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DIRECT MARKET ACCESS IN EXCHANGE-TRADED DERIVATIVES: EFFECTS OF ALGORITHMIC TRADING ON LIQUIDITY IN FUTURES MARKETS

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Algorithmic trading (AT) and high frequency trading (HFT) afforded by direct market access (DMA) may have a greater impact on the exchange-traded derivatives markets than has been seen in the equity markets. This study breaks new ground to provide empirical evidence for the positive effects of AT on liquidity in the U.S. futures markets. To analyze the potential effects of electronic trading, this study provides an extensive review of the research in both equity and derivatives market microstructure. Using a unique dataset that directly and explicitly identifies algorithmic trading activity in exchange-traded derivatives, our research presents empirical evidence that AT decreases spreads (market width) and increases market depth in the Crude Oil, Euro FX, Eurodollar, S&P 500 E-mini, and 10-year U.S. Treasury Note futures contracts traded at the CME Group exchanges.

Electronic trading has been one of the most significant catalysts throughout the evolution of financial markets, especially for exchange-traded instruments. Emergence of electronic communication and/or crossing networks (ECNs) and their widespread use by various market participants resulted in a substantial change in the ownership and organizational structure of exchanges starting with the equity markets. Advances in technologies that directly impact trading in financial markets (e.g., telecommunication capacity, computational power) coupled with changes in the regulatory environment helped competitive market forces establish various trade execution venues. This increase in competition intensified the need to analyze and manage various components of trading costs and led to enhanced trading sophistication. As a result of these fundamental changes, techniques such as direct market access (DMA), smart order routing (SOR), algorithmic trading (AT), and high frequency trading (HFT) became the focus of attention for market participants,

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exchanges, and regulators. Recently market and exchange characteristics of transparency, best execution, and latency have been the subject of research and analysis in addition to the more traditional factors of liquidity, volatility, and efficiency. Of course, given the recent turmoil in financial markets and high-profile losses, these factors have also attracted the attention of politicians and the public at large.

Extensive use of algorithmic trading (AT) activities emerged relatively more recently in the exchange-traded derivatives in comparison to the equity markets.[1] However, the impact of DMA, AT, and HFT on market quality and risk management may be more substantial for derivatives.[2] In order to analyze the potential effects of DMA, AT, and their resultant changes in exchange-traded derivatives markets, this study provides an extensive review of the research in both equity and derivatives market microstructure. Historically, exchanges in equity and derivatives markets had varying degrees of differences; however, the implementation of electronic trading has made these two markets more connected and trading practices are now more similar than ever before.

Based on a unique dataset that identifies algorithmic trading activity directly and explicitly, our research finds that AT decreases spreads and increases market depth in the Crude Oil, Euro FX, Eurodollar, S&P 500 E-mini, and 10-year U.S. Treasury Note futures contracts electronically traded at the CME Group exchanges. To the best of our knowledge, this study is the first to provide empirical evidence for effects of AT on liquidity in the U.S. futures markets. Similar to the findings for the U.S. equity markets by Hendershott, Jones, and Menkveld (2011) and for the German equity markets by Hendershott and Riordan (2009), we find that for the U.S. futures markets algorithmic trading has a positive effect on liquidity.

Section I presents an overview of concepts related to direct market access. Section II provides a review of the existing literature on equity and futures market microstructure; recent work on DMA, AT, and HFT; and draws conclusions for the exchange-traded derivatives markets. Section III describes the data used in this paper while section IV introduces the empirical methodology. Empirical results are discussed in section V and section VI offers conclusions.

I. OVERVIEW OF DIRECT MARKET ACCESS CONCEPTS

As with any major structural change and the emergence of new technology, the use of innovative trading technologies in financial markets had a profound impact on returns from short-term trading, long-term performance of investment portfolios, measurement and management of risk, as well as interconnectivity of various markets both domestically and globally. Market microstructure research (MMR) has focused

1. Electronic trading in CME's Globex platform started in 1992, and the Open Access Policy was implemented in 2000. The Open Access Policy allows customers to trade directly on CME Globex if their clearing firm provides a financial guarantee for their trading activity. This effectively means that CME provided DMA to investors starting in 2000. However, explicit identification of AT through "Tag 50" designation started more recently, in 2006.

2. The existence of multiple contract months and relatively more inter- and intra- market trading suggests that DMA, AT, and HFT may have a higher impact on the exchange-traded derivatives markets than on the equity markets.

on analyzing the effects of the changes in trading and execution rules, different trading venues, regulatory changes, impact of technological advances, and behavior of market participants in response to the developments in financial markets. MMR initially focused on equity markets primarily due to the availability of detailed transactions data and rapid changes in trading practices. Following the advent of electronic trading in derivatives markets, microstructure research focusing on exchange-traded derivatives, especially futures markets trading, increased significantly.

Similar to the developments in equity trading, participants in derivatives market are demanding more direct access to the markets (DMA) for reduced transaction costs, increased speed of executions, and decreased information leakage. As in the case of equities, electronic trading in futures enables the use of computers to execute trades, reducing errors as well as enabling more efficient post-trade reporting and analysis. Electronic trading in exchange-traded derivatives facilitates direct access to markets, which in turn allows algorithms to be used to generate quote updates and orders; eventually, increased sophistication and speed of trading systems — including exchanges' execution capabilities — leads to the high (and ultra-high) frequency trading.

DMA enables traders to connect directly to an exchange, using the exchange's native application programming interface (API) through its dedicated network.[3] In its purest form, exchanges may provide DMA to market participants without explicit electronic order handling/authentication by intermediaries/brokers, called naked access. In other cases, intermediaries or brokerage houses facilitate DMA access. Different levels of DMA provided to various types of market participants have significant implications for transparency, fairness, and risk management.

Initially in equity markets, algorithmic trading (AT) referred to the use of computer programs to submit orders and execute trades in order to minimize the market impact costs. AT replicated the actions of human traders by determining the size and timing of purchases and sales of shares based on various mathematical models (algorithms).[4] Contemporary AT encompasses almost all tasks that can be carried out by human market makers and traders. For example, posting of bid and/or ask quotes generated by computer models may be considered algorithmic market making and concurrent execution of several transactions across different assets/markets is algorithmic arbitrage. Additionally, electronic execution of trades to achieve various positions generated by financial models, both short- and longer-term investments in a range of assets, is also a form of algorithmic trading.

High frequency trading (HFT) occurs when the pace of transactions generated

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3. Aitken, Harris, and Ji (2009) suggest that DMA is defined as electronic facilities that allow brokers to offer clients direct access to the exchange trading system through the broker's infrastructure without manual intervention by the broker.

4. Hendershott, Jones, and Menkveld (2011) provide a simple definition for algorithmic trading (AT) as "the use of computer algorithms to manage the trading process." They suggest that many observers view algorithms and AT from the standpoint of institutional buy-side investor and indicate correctly that "algorithms can also be used to formulate trading decisions and strategies as well as implement them."

by algorithms reaches a speed which human traders would not have been able to achieve.[5] Increased competition and intensive use of AT and HFT necessitate that participants be physically closer to the order-matching engines of exchanges, creating the phenomenon called co-location.[6] High frequency trading is a subset of algorithmic trading and AT is a subset of DMA activities. Direct market access includes "point-and-click" trading (e.g., by individual investors), automated trading activities that encompass low frequency trades, and the HFT with significantly large and fast submission of quotes and trades solely by computer programs.[7]

In an electronic trading environment in futures markets, DMA basically recreates the advantages of pit trading by allowing numerous market makers (locals) and traders to access and act on timely trade information. As a result, the efficiency of the pit environment is augmented with the use of technology in an electronic setting. DMA creates infinitely large electronic trading pits that can be interconnected in ways that were not possible in the physical pit-trading environment.

Another way to represent DMA from the point of view of an investor or a financial institution is that, rather than executing trades via a broker, trades are executed through a member of the exchange who has transaction privileges on the floor. In this case, co-locating could be analogous to such an individual or institution purchasing or renting the right to be physically present and trade at the floor of the exchange. The futures trading floor analogy for AT and HFT would be a local having beyond-human capabilities to analyze vast amounts of data, announce bids and asks with extreme rapidity, and confirm trades with others who could match his or her speed in announcing prices and quantities. In an electronic version of the above scenario, DMA, AT, HFT, and co-location enable access to prices and markets and offer the capabilities to transact that are not bound by location, distance, and human limitations. In this perspective, these new trading practices increase liquidity, decrease transaction costs, and improve the price discovery in exchange-traded derivatives markets.

The existence of multiple contract months and relatively more inter- and intra-market trading suggests that DMA as well as its by-products AT and HFT may have a higher impact on the exchange-traded derivatives markets than on the equity markets. Although there is a significant body of academic work in market microstructure research (MMR) covering both the equity and derivatives markets, empirical evidence on the effects of DMA, AT, and HFT in equity markets is new and limited. Even more, such research is very rare in exchange-traded derivatives markets.

Exchange-traded derivatives markets are in the process of experiencing the

5. Brogaard (2010) indicates that there are no clear and commonly accepted definitions for many of the terms in rapid trading and in computer controlled trading, and uses the definition HFT that Securities and Exchange Commission (SEC) uses, "professional traders acting in a proprietary capacity that engages in strategies that generate a large number of trades on a daily basis" (SEC, 2010, p. 3606).

6. SEC refers to co-location as "a service offered by trading centers that operate their own data centers and by third parties that host the matching engines of trading centers" (SEC, 2010, p. 3610).

7. We thank John Labuszewski at the CME Group for clarifying these subtle differences.

implementation of these innovative approaches at various levels. This research paper is intended to provide guidance to market participants, exchanges, and regulators by synthesizing the findings in equity MMR; the recent empirical work on the effects of DMA, AT, and HFT in stock markets; and microstructure research in derivatives markets. It presents empirical evidence on early stages of DMA and AT in futures markets and discusses the implications of these developments for exchange-traded derivatives markets.

II. REVIEW OF LITERATURE

Literature on direct market access and algorithmic trading in equity markets is limited and in exchange-traded derivatives markets, almost nonexistent. However, previous research focusing on various aspects of equity and derivatives market microstructure provides insights about how DMA, AT, and HFT impact derivatives trading.

A. Equity Market Microstructure

Considering the importance of price discovery and contributions of various market participants to this process, analyzing the relative informational advantages of these agents is important because DMA, AT, and HFT may cause changes in different agents' participation in trading while possibly altering the balance of asymmetric information.

It has been shown that electronic access to equity markets increases liquidity, reduces trade size, alters volatility, reduces returns to market making/specialist systems, and increases transparency. However, DMA may eventually lead to alternative trading venues and fragmentation of liquidity. Based on these findings, is there a chance that DMA, AT, and HFT will also result in the fragmented liquidity and creation of alternative execution venues observed in equity markets? If so, what might be the results of these changes in futures markets? Exchanges and regulators need to examine implications of such potential developments in exchange-traded derivatives markets.

Conrad, Johnson, and Wahal (2003) investigate the execution costs of trades sent to traditional and alternative trading systems in equity markets and conclude that orders sent to traditional brokers have higher execution costs than those executed by alternative trading systems such as electronic communication networks (ECNs). Barclay, Hendershott, and McCormick (2003) examine the competition among different trading venues in the United States and show that ECNs attract more informed orders than NASDAQ market makers.

Anand and Subrahmanyam (2008) compare the informational advantages of intermediaries with those of other investors using confidential transactions data from the Toronto Stock Exchange (TSX). They find that intermediaries account for greater price discovery than other institutional and individual investors, in spite of

8. They also note that TSX is a completely electronic and highly transparent environment, and in the context of individual stocks, the potential for informational effects is known to be stronger than in basket securities, derivatives, and futures indexes.

initiating fewer trades and volume.[8] Their empirical results indicate that intermediaries contribute more to price discovery and hence tend to be more informed, even in a transparent electronic market where such an advantage is not driven by a privileged view of the market on a trading floor.

Saar (2001) shows that market intermediaries possess important order flow information that gives them an informational advantage. However, there is a possibility that the higher information share of market intermediaries may be a result of front running or stepping ahead by brokers. But Anand and Subrahmanyam (2008) investigate these activities and find no evidence of such trading by intermediaries on the TSX.

These findings suggest that with the increased use of DMA, AT, and HFT in derivatives markets, the informational role of intermediaries and entities with co-location privileges needs to be closely monitored for potential information asymmetry generation. The potential impact of DMA in terms of fragmenting liquidity in exchange-traded derivatives needs to be investigated. The nature of the intermediation provided by futures commission merchants (FCMs) may change, and, in turn, could equalize access to markets.

The influence of market transparency on market quality is investigated in several papers. Hendershott and Jones (2005) find that more transparency is associated with better market quality, which has been a crucial competitive advantage for ECNs in the United States. Bessembinder, Maxwell, and Venkataraman (2006) focus on the impact of transaction reporting on execution costs for corporate bonds and find a significant reduction of execution costs following the introduction of transaction reporting. Avgouleas and Degiannakis (2005) examine the impact of pre-trade transparency on market volume by using trading volume data before and after the introduction of a central order book at the London Stock Exchange (LSE). They conclude that when trading shifts from the quote-driven to the order-driven market structure, transparency increases significantly.

Bloomfield and O'Hara (2000) suggest that the demand for sunshine trading and order splitting reduces the competitive advantage of low-transparency markets; they question the long-term viability of transparent markets particularly in large, well-monitored markets with low information asymmetries where such regulated transparency may be of less value. Tuttle (2003) finds that NASDAQ traders tend to use hidden orders more in stocks with high idiosyncratic risk and high volatility, and he concludes that this is consistent with the idea that hidden orders reduce the adverse selection risk for liquidity providers. Tuttle's findings provide a competing hypothesis to Bloomfield and O'Hara that anonymity becomes more appealing when adverse selection risk and volatility are low, as this lowers the free option value of limit orders. Theissen (2002) also finds that, while the adverse selection component is larger in the anonymous electronic trading system in the German market for stocks of all sizes, small stocks also exhibit larger realized spreads when traded anonymously.

The implication of these results for the exchange-traded derivatives is that the level of transparency of the limit order book has a significant impact on the trading costs for market participants with differential liquidity-related trading orientation. Given that there are multiple contract months and relatively more inter- and intra-market trading in derivatives markets, higher levels of limit order book transparency may be more desirable.

Anonymity plays a key role in market participants' trading strategies as part of their efforts to obtain best execution. In recent years, the SEC has been requiring higher standards of intermediary accountability in order execution practices, while exchanges are attempting to respond to market's demand for greater anonymity. Barclay et al. (2003) find that informed traders prefer using anonymous ECNs compared to transacting non-anonymously with NASDAQ dealers. Anecdotal evidence also indicates that institutional direct market access participants usually conduct their algorithmic trades anonymously. Furthermore, Frino, Johnstone, and Zheng (2010) examine whether the identity of a broker involved in transactions contains information. Using a sample of transactions from the Australian Stock Exchange — where broker identity is transparent — they provide evidence that consecutive buyer- and/or seller-initiated transactions by the same broker have a relatively high permanent price impact. Their findings imply that broker identity conveys information to market participants, and that markets in which broker identity is disclosed are likely to be more efficient.

Grammig, Schiereck, and Theissen (2001) find that for the German stock market the probability of informed trading is higher in the anonymous electronic trading system compared to the non-anonymous trading floor, while Reiss and Werner (2005) find that in London informed traders tend to go to the non-anonymous direct interdealer market. They conclude that adverse selection is less prevalent in anonymous brokered markets.

De Winne and D'hondt (2007) investigate why traders hide their orders and how other traders respond to hidden depth. Their empirical findings suggest that traders use hidden orders to manage both exposure risk and picking off risk. They show that hidden depth increases order aggressiveness, and when hidden depth is discovered, order submissions are adjusted to seize the opportunity for depth improvement, suggesting that either this hidden depth is not associated with informed trading or the risk of trading with an informed trader is offset by the improvement in depth. However, Anand and Weaver (2004) report that hidden quantity can be used to reduce price impact if the probability of non-execution is small. Pardo and Pascual (2007) show that the execution of hidden volume increases during periods of intense trading when aggressive orders are clustered. To minimize the non-execution risk, hidden order traders can wait for a higher trading aggressiveness on the opposite side of the market, reduce implicit trading costs, and find faster trading executions.

Comerton-Forde and Tang (2009) characterize the impact of anonymous orders in a limit order market where identity disclosure is voluntary. They find that anonymously initiated trades tend to be more informative than non-anonymous ones, with cumulative excess returns positively related to trade size and security activity levels. Their empirical results indicate that anonymous orders are traded at lower spreads than non-anonymous orders only for the most actively traded stocks; market orders that are anonymous result in higher price impact (pointing to high adverse selection cost) and in lower realized spreads (suggesting lower order processing and inventory management costs) than non-anonymous market orders. They conclude that anonymous trading is dependent on the order aggressiveness and the type of order originator.

Increased use of the DMA to submit quote-revisions and orders generated by algorithms in exchange-traded derivatives is likely to increase the merits of allowing voluntary disclosure rules for specific futures markets and contract months. Given that many expiration (contract) months are traded in futures markets, DMA and AT increase the spread trading as well as pricing efficiency of deferred-month contracts. However, any adverse selection cost impact of anonymous orders in longer-dated contracts is likely to be transmitted to more liquid front-month contracts. Therefore, the optimal level of anonymity in algorithmic and high frequency trading in exchange-traded derivatives needs to be investigated.

Aitken et al. (2009) investigate trade-based manipulation, as proxied by the daily incidence of ramping alerts, in 34 security markets worldwide during the 2000–2005 period. They suggest that closing call auctions, direct market access, specific regulations, and real-time surveillance (RTS) procedures and enforcement assure better market integrity and enhance market efficiency.[9] They conclude that reduction in liquidity caused by higher volatility affects the order submission of liquidity suppliers who submit orders less aggressively. Specifically, their findings indicate that direct market access (DMA) reduces ramping manipulation, which Aitkin et al. interpret as "DMA facilitates algorithmic countertrading strategies that can circumvent the pump and dump tactics of a ramping manipulator." Cumming and Johan (2008) examine trading regulations with corresponding surveillance technology to monitor alerts and find that comprehensive rules prohibiting trade-based manipulation generate higher turnover and larger market caps.

These findings point to the importance of both pre- and post-trade real-time risk analysis. One possible solution is to co-locate the risk control algorithms of clearing houses and financial intermediaries with the exchanges' trade-matching engines where the servers of market participants engaging in AT and HFT activities are co-locating. Also, a regulator or self-regulator algorithm trader might co-locate at that physical location in order to facilitate detection and rapid response to improper trading activity that might be taking place at extreme speeds.

B. Microstructure of Exchange-Traded Derivatives

A significant amount of research in exchange-traded derivatives markets focuses on the effects of the move from floor-based trading to electronic trading. Various authors study the effects of such a move on the liquidity, bid-ask spreads, trading

9. Cumming and Johan (2008) suggest that trading activity increases if exchanges adopt surveillance procedures and regulations that assure market integrity (similar to findings of Eleswarapu and Venkataraman 2006). Pagano and Schwartz (2003) and Comerton-Forde and Rydge (2006) investigate implementation of closing call auctions to improve market quality.

volume, and behavior of market participants in both U.S. and global exchanges. More recent articles focus on the changes in market structures and market quality using higher frequency trading and quote data in futures markets.

Liquidity costs are considerably lower in the electronic market than in the open outcry market (Shah and Brorsen 2010). Huang (2004) analyzes the determinants of bid-ask spreads for the Taiwan Futures Exchange (TAIFEX) and Singapore Exchange-Derivatives Trading (SGX-DT) futures and finds that volatility and the information asymmetry are the major factors affecting the spreads and that the information asymmetry component is significantly lower in the electronically traded TAIFEX contract than in the open-outcry SGX-DT futures.

Ates and Wang (2005), focusing on the electronic and floor-traded contracts based on S&P 500 and NASDAQ 100 indexes, investigate the relative efficiency in terms of contributions to price discovery and find that contribution of electronically traded contracts is higher. Tse and Zabotina (2001) examine the FTSE 100 index futures trading following the transition to electronic trading and find a decrease in bid-ask spreads; however, they also find that the open-outcry trading has higher market quality and higher information content.

Frino, Lepone, and Wearin (2008) study the intraday pattern of quoted depth in interest rate futures contracts traded at the Sidney Futures Exchange (SFE), which is a competitive dealer market, and find that depth is lowest at the open, considerably higher during the final hours of trading, and highest at the close, which is a pattern at odds with the ones observed in specialist markets. Their results show that an increase in quoted depth is due to a narrowing in bid-ask spreads, and they conclude that this observation at the close of trading is driven by dealers' rebalancing inventories.

Chung and Chiang (2006) examine the price clustering in the DJIA, S&P 500, and NASDAQ-100 index futures by comparing the electronically and floor-traded contracts and find that prices are significantly more clustered in open-outcry trading; they attribute this to higher levels of human participation in trading on the floor.

Frino et al. (2008) investigate the influence of large trades executed by outside customers on futures prices at the CME and find that the permanent price impact (information effect) of large buyer-initiated trades is greater than that of large seller-initiated trades, while the temporary price impact (liquidity effects) of seller-initiated trades is greater.

Chakravarty and Li (2003) find that dual traders in futures markets are informed and act as liquidity suppliers. Anand and Chakravarty (2007) analyze price discovery across trade sizes in options markets and find that small- and medium-size trades are responsible for the majority of price discovery.

Wagener and Riordan (2009) study the lead-lag effect between the Deutscher Aktien Index (DAX) spot index and DAX index futures under asymmetric latency in the exchange infrastructure by focusing on the introduction of the exchange electronic trading platform Xetra Release 8.0, which significantly reduced the trading latency. Their empirical results suggest that a decrease in relative latency between the Deutsche Böerse systems Xetra and Eurex leads to a higher degree of market integration, and they conclude that "a significant improvement in the cash market infrastructure cutting network latency reduces the execution risk."[10]

Webb, Muthuswamy, and Segara (2007) investigate the frequency of market clearing and the changes in trading hours for stock index futures contracts at the TAIFEX and SGX to measure the effect of increases in clearing on the volatility of futures prices. They find that simultaneous opening times for the TAIFEX, which batches orders at the open, and the SGX, which does not, is associated with a significant reduction in the volatility in SGX.

Bortoli et al. (2006) investigate the effects of an increase in pre-trade transparency on trading behavior in the Share Price Index (SPI) futures traded at the SFE. Their research covers the time period in 2001 when the exchange increased the limit order book disclosure from depth at the best bid-ask prices to depth at the three best bid-ask prices. They find a decline in depth at the best quotes and an increase in the proportion of market orders exceeding depth at the best quotes. Their conclusion is that when pre-trade transparency increases, "limit order traders charge market order traders a higher premium for execution certainty by withdrawing depth from the best quotes, but not by increasing bid-ask spreads."

Tse, Xiang, and Fung (2006), investigating the Euro FX and Yen FX futures traded at the CME, show that electronic futures trading contributes more to price discovery than both online spot and floor futures trading while online spot trading dominates electronic futures. Cabrera, Wang, and Yang (2009) find that the Electronic Broking Services (EBS) electronic interdealer broker dominates both electronic and floor traded currency futures. Poskitt (2010), using high frequency data on Sterling FX futures traded at the CME, shows that information share of electronically traded futures prices is marginally lower than the forward prices at Reuters D3000 and variations in "GLOBEX's information share on an intraday basis can be explained by variations in relative liquidity, spreads and price volatility."[11]

C. Algorithmic and High Frequency Trading

Academic research on the effects of algorithmic trading (AT) is quite new as detailed trade and quote data identifying AT activity is very limited. However, research suggests that direct market access facilitates more efficient price discovery as well as quantity discovery.

Riordan and Storkenmaier (2009) find that the latency reduction (from 50 ms to 10 ms round trip) of Xetra Release 8.0 (used by the Deutsche Böerse) improves the market liquidity, decreasing trading costs by 1 to 4 basis points. They interpret their findings as "evidence of algorithmic traders using the increase in exchange system speed to process information faster, thereby increasing liquidity and the informativeness of prices." Hendershott and Riordan (2009) investigate the impact of algorithmic trading on price discovery process in the 30 DAX stocks on the

10. Easley, Hendershott, and Ramadorai (2008) point to the importance of low latency when trading simultaneously in multiple securities and suggest that the execution speed is a significant factor in trading decisions.

11. Poskitt (2009) also finds that GLOBEX's information share declines sharply when returns are computed from a mixture of GLOBEX transaction prices and Reuters D3000 midquotes.

Deutsche Böerse. They find that AT affects liquidity almost equally in supply (when liquidity is expensive) and demand (when it is cheap), and they also show that algo trades and quotes are more informative than those generated by humans. They suggest that this is achieved by AT "placing more efficient quotes and demanding liquidity to move the prices towards the efficient price." Chaboud et al. (2009) investigate the effects of AT in the spot foreign exchange markets and find that AT activity and volatility are not correlated, and that the order flow generated by AT does not affect the return variance.

Hendershott et al. (2011) investigate the impact of algorithmic trading on market liquidity by using the electronic message traffic as a proxy for algorithmic trading activity in the NYSE stocks and find that AT and liquidity are positively related. By considering the implementation of auto-quoting on the NYSE as an exogenous event, the authors show that algorithms result in more message traffic, and as quoted and effective spreads narrow adverse selection declines. They interpret this as an "indication that algorithmic trading does causally improve liquidity."

Brogaard (2010) investigates the impact of high frequency traders on equities markets by considering how the strategies utilized are related to liquidity, price efficiency, and volatility. The study shows that contribution to price discovery of trades and quotes of HFT is greater than others and their activity reduces volatility. Empirical results indicate that high frequency traders demand liquidity at smaller order sizes and that trades surrounding a demanded HFT execute faster. These results suggest that high frequency trading does not increase volatility. Brogaard interprets these findings to suggest that "HFT plays a very important role in price efficiency and the price discovery process and high frequency trading provides more useful information to the price generation process." Castura, Litzenberger, and Gorelick (2010), focusing on Russell 1000 and Russell 2000 stocks, investigate the impact of HFT on equity market quality. They find that while the ratio of HFT to total market activity is growing, equity markets appear to become more efficient with tighter spreads, greater liquidity at the inside, and less mean reversion of mid-market quotes; they correlate this with the growth in automation and speed on equity exchanges.

Hasbrouck and Saar (2009) find that, in electronic markets with the increase in AT, limit orders are cancelled very quickly, and they often correspond to modifications resulting in a new limit order at an updated price or in a market order. Hendershott et al. (2011) point out that the Regulation National Market System (Reg NMS) is designed to increase competition among liquidity suppliers, and their findings suggest that algorithmic liquidity suppliers play an important role in the supply of liquidity.

Chordia, Roll, and Subrahmanyam (2008) suggest that recent increases in trading volume and the reduction in the average trade size can be attributed to AT.[12] Garvey and Wu (2010) investigate the execution quality of electronic trading with

12. Brownlees, Cipollini, and Gallo (2010) develop a dynamic model for intraday volume which incorporates the existence of algorithmic trading.

geographically dispersed locations and trading speeds and find that "speed differences are costly to traders and that speed-advantaged traders engage in strategies that are more conducive to speed."

Gerig and Michayluk (2010) develop a theoretical model that explains the increase in the high frequency automated trading volume. Their model shows that automated liquidity providers are able to price securities more precisely than traditional market makers so that they are able to transact the majority of order flow and cause prices to be more efficient. Model predictions also include that the informed investors' profits decrease, uninformed investors lose less money, and trading activity of uninformed traders increases as a result of lower transaction costs.

Overall, empirical evidence to date suggests that the increased use of algorithmic and high frequency trading, facilitated by direct market access, has a positive effect on market liquidity in equity markets both domestically and globally. When this result is coupled with the lack of empirical evidence pointing to an increased price volatility attributed to AT and HFT, it is not too optimistic to expect that their impact is likely to be positive in exchange-traded derivatives markets as well.

III. DATA AND DESCRIPTIVE STATISTICS

A. Algorithmic Trading and Liquidity Measures

This study uses a unique dataset obtained from the CME Group for five futures contracts (Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note) traded at the CME Group exchanges. It includes several microstructure variables: percentage of volume attributed to automated trading systems in the specific market that day (***ATS***); percent of message traffic attributed to automated trading systems (***MSG***); the average bid-ask spread for a given size order during a trading day (***Width***); and the number of contracts displayed at the "top-of-the-book," showing average size-in terms of contracts-of the best bid and best ask quotes in the limit order book (***Depth***).[13]

Among the many surveillance measures the CME Group's market regulation division uses are the "Tag 50 ID" numbers to analyze the effect of algorithmic trading activities on the liquidity and quality of futures and options contracts traded on its exchanges (CME, CBOT, NYMEX, and COMEX). Identification of algorithmic trading activity "is facilitated by CME Globex policy that requires automated trading systems (ATSs) to declare themselves as such" where ATS is referred to as "a system that automates the generation and routing of orders to Globex."[14]

Market participants trading at the CME Group exchanges are required by the

13. CME Group, Algorithmic Trading and Market Dynamics, July 15, 2010. CME refers to the Depth variable as market resilience, which is the average width of the bid–offer spread for a specified size order. Depth is defined as the number of contracts on average at the "top of the book" or best bid or offer.

14. CME Group, Algorithmic Trading and Market Dynamics, July 15, 2010.

CME Group Rule 576 to include an operator ID, also referred to as the "Tag 50 ID" or "User ID" with each order they enter into the CME Globex electronic trading system.[15] Although CME required its members who use algorithmic trading systems (ATS) to identify themselves with the "Tag 50 ID" starting in 2006, full implementation by all trading systems was not immediate. Therefore, microstructure data on ***ATS*** and ***MSG*** variables appear to be more reliable after mid 2008. As a result, this study covers the time period May 1, 2008, to May 27, 2010.[16]

The uniqueness of the dataset used in this study is due to the explicit identification of algorithmic trading (AT) volume, which is the proportion of executed orders originated from an ATS compared to the total electronic orders executed (***variable ATS***). CME Group data also provides the proportional volume of electronic message traffic attributed to ATS (***variable MSG***). Identification of the amount of electronic messages generated by AT, in addition to the actual AT trades, is necessary because the literature and anecdotal evidence indicate that ATSs generate a large amount of bid and ask quotes which they cancel/lift over a short horizon. We believe that our study is the first to use such detailed identifiers of AT in exchange-traded U.S. derivatives markets.

B. Price and Trading Data on Futures Contracts

Daily open, high, low, and settlement prices, the daily total trading volume (***TrdVolu***), and open interest (***OpInt***) for the five contracts under investigation are obtained from the Reuters/CRB database. The Reuters/CRB database also contains the implied volatility (***ImpVola***) for each of the contracts based on the near-the-money futures options and the 200-day rolling historical volatility measure (***HisVola***).

C. Market Control Variables

In order to control for changes in the market conditions, various other variables are extracted from the Reuters/CRB database: AAA-corporate bond yield (***CorpAAA***); BAA corporate bond yield (***CorpBAA***); corporate credit spread (***CorpSprd*** = CorpBAA – CorpAAA); yield on 3-month Treasury Bill (***Tbill3mo***); difference between the AAA-corporate bond yield and the yield on 10-year Treasury Note (***DefSprd***); difference between the yields on 10-year Treasury Note and the 3-month Treasury Bill (***TermSprd***); daily stock index levels for Dow Jones Industrial Average (***DOW***), NASDAQ composite (***NASDAQ***), New York Stock Exchange Composite (***NYSE***), Russell 1000 (***Russell1000***), and S&P 500 (***SP500***); daily values of Goldman Sachs Commodity Index (***GSCI***), U.S. Dollar Index (***DollarInd***),

15. See CME Group, Market Regulation Advisory Notice RA0915-5, "Operator ID ('Tag 50 ID') Required on All CME Globex Orders." These IDs are "unique to the party who entered the order. For orders entered manually, the Tag 50 ID must be unique to the individual entering the order into CME Globex. For orders entered by an automated trading system ('ATS'), the Tag 50 ID must be unique to the person, or the identified team of persons on the same shift, who are responsible for the operation of the ATS. All Tag 50 IDs must be unique at the level of the clearing member firm" (p. 1).

16. The data for the ***ATS***, ***MSG***, ***Width***, and ***Depth*** variables are from the regular trading hours.

spot Gold price (***GOLD***), Reuters/CRB Commodity Index (ReutersCRBind), and the CBOE's Volatility Index (***VIX***).[17]

Table 1 presents the descriptive statistics on the futures microstructure variables. Percentage of trading volume from algorithmic trading systems appears to be highest in Euro FX (72.17%) and lowest in Crude Oil (32.43%) while for other contracts ***ATS*** ranges from 40% to 50%. A possible explanation for this observation is the existence of a highly liquid, electronic market for FX forwards that facilitates high frequency cross-market and cross-currency trades.[18] Figure 1 displays the relative ***ATS*** and its time variation for the five contracts. Results for the percentage of electronic message (***MSG***) traffic emanating from AT indicate that the Euro FX contract has the highest proportion (88.33%) while the Eurodollar contract attains the lowest (55.87%). This suggests that almost half of the electronic message traffic in Eurodollar futures is generated by non-algorithmic activity. Figure 2 shows the ***MSG*** and its time-variation. Figure 3 graphs the ***ATS*** and Figure 4 graphs the ***MSG***.[19]

Observations for the ***Width*** (bid-ask spread) and market ***Depth*** indicate that Eurodollar futures has the smallest width and largest depth among the five contracts, suggesting that the high liquidity of this contract attracts more "human" electronic orders/quotes, which tend to be revised more frequently than the ones from algorithms. We observe that the Crude Oil contract has the widest spread and least depth. Crude Oil futures did not start trading on an electronic system as early as other financial futures such as Euro FX and E-mini S&P 500. Spread trading is more prevalent in a physical commodity market such as crude oil, and spreads move more slowly compared to the outright futures prices. These market-specific characteristics may explain the relatively low algorithmic trading activity in the Crude Oil contract, and as a result its low liquidity can be attributed to limited electronic cross-market and cross-commodity trading. There are relatively more liquid and electronic cross-market and cross-asset trading possibilities for both E-mini and Treasury note futures. Figures 5 and 6 display the ***Width*** and ***Depth*** across five contracts and their time variation. These two graphs show the relative increases in spreads and decreases in market depth during the third quarter of 2008 as a result of the recent financial crisis.

Descriptive statistics for the trading volume, open interest, and volatility variables are provided in Table 2. In order to understand variation in the market variables prior to the start of our microstructure data period, comparison of these statistics for two time periods is presented: the "before" period is April 10, 2006, to April 30, 2008; the "after" period is May 1, 2008, to May 27, 2010.[20] Figures 7 and 8 graph

17. These control variables chosen to take into account the changes in the commodity, corporate debt, credit, currency, energy, equity fixed-income markets as well as the changes in volatility.

18. Findings of Tse, Xiang, and Fung (2006) and Cabrera, Wang, and Yang (2009) may point to this interpretation.

19. Figure 3 graphs the ATS and Figure 4 graphs the MSG approximately one month before and after May 6, 2010, the day referred to as the "Flash Crash." A casual inspection of these figures does not suggest an extraordinary change in ATS and MSG on that day.

20. Mean and median of market variables (using both parametric and non-parametric tests) are found to be different during the 2-year period before and after May 1, 2008 (except for mean of GSCI).

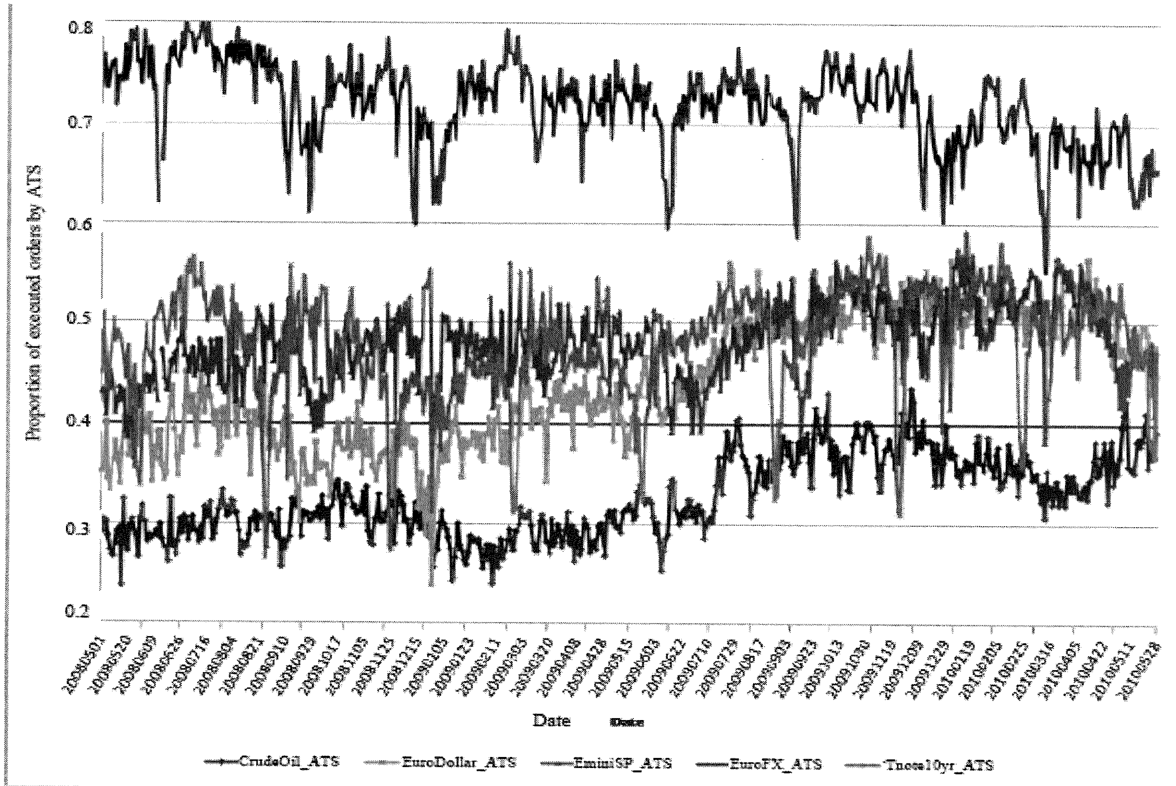
Table 1. Descriptive Statistics on Futures Microstructure Variables: ATS, MSG, Width and Depth, May 1, 2008, to May 27, 2010.

	CrudeOil	EuroFX	EuroDollar	EminiSP	Tnote10yr
Mean	32.43%	72.17%	44.10%	48.09%	47.48%
Median	31.50%	72.89%	42.98%	47.91%	48.03%
Max	43.50%	80.97%	56.42%	59.22%	58.08%
Min	23.95%	55.24%	31.71%	36.56%	26.69%
Std. Dev.	3.98%	4.32%	5.80%	4.02%	5.35%
Skewness	0.3550	-0.9213	0.1340	0.1039	-1.0271
Kurtosis	2.2348	3.9365	1.8630	2.6756	4.5370
			MSG		
	CrudeOil	EuroFX	EuroDollar	EminiSP	Tnote10yr
Mean	70.67%	88.33%	55.87%	71.48%	65.89%
Median	68.96%	89.01%	55.12%	71.51%	66.57%
Max	85.65%	95.07%	85.65%	81.44%	84.18%
Min	57.74%	75.07%	21.53%	59.47%	48.20%
Std. Dev.	6.12%	3.83%	7.36%	3.78%	4.88%
Skewness	0.5050	-0.7179	0.2774	-0.0478	-0.1736
Kurtosis	2.1064	3.0393	4.9103	2.7085	3.4623
			Width		
	CrudeOil	EuroFX	EuroDollar	EminiSP	Tnote10yr
Mean	48.08349	22.80801	18.34247	21.60916	28.57527
Median	41.35478	18.7203	13.7488	20.74676	25.93447
Max	107.8332	75.27579	58.69449	62.13548	95.25045
Min	13.53045	13.0642	12.59267	12.50082	15.63671
Std. Dev.	18.97225	9.878861	9.992397	9.022524	13.55803
Skewness	0.6779	1.2075	2.0948	1.3547	1.2368
Kurtosis	2.4031	4.5995	6.3964	5.2716	4.5477
			Depth		
	CrudeOil	EuroFX	EuroDollar	EminiSP	Tnote10yr
Mean	6.10853	21.53783	1279.785	397.1073	409.0063
Median	6.051945	21.44758	717.1916	348.3574	343.4008
Max	11.13911	48.83141	10062.65	1244.024	1350.825
Min	3.20584	6.041679	93.03325	68.40597	75.09946
Std. Dev.	1.936459	9.209597	1723.291	213.2097	264.3048
Skewness	0.4160	0.2744	3.0227	1.1495	1.1995
Kurtosis	2.1246	2.2577	12.5923	4.5287	4.1469

Note: ***ATS*** is the percentage of volume attributed to automated trading systems in the specific market that day; ***MSG*** is the percent of message traffic attributed to automated trading systems; ***Width*** is the average bid-ask spread for a given size order during a trading day; ***Depth*** is the number of contracts displayed at the "top-of-the-book" (i.e., average size-in terms of contracts-of the best bid and best ask quotes in the limit order book). The data for the ***ATS***, ***MSG***, ***Width***, and ***Depth*** variables are from regular trading hours.

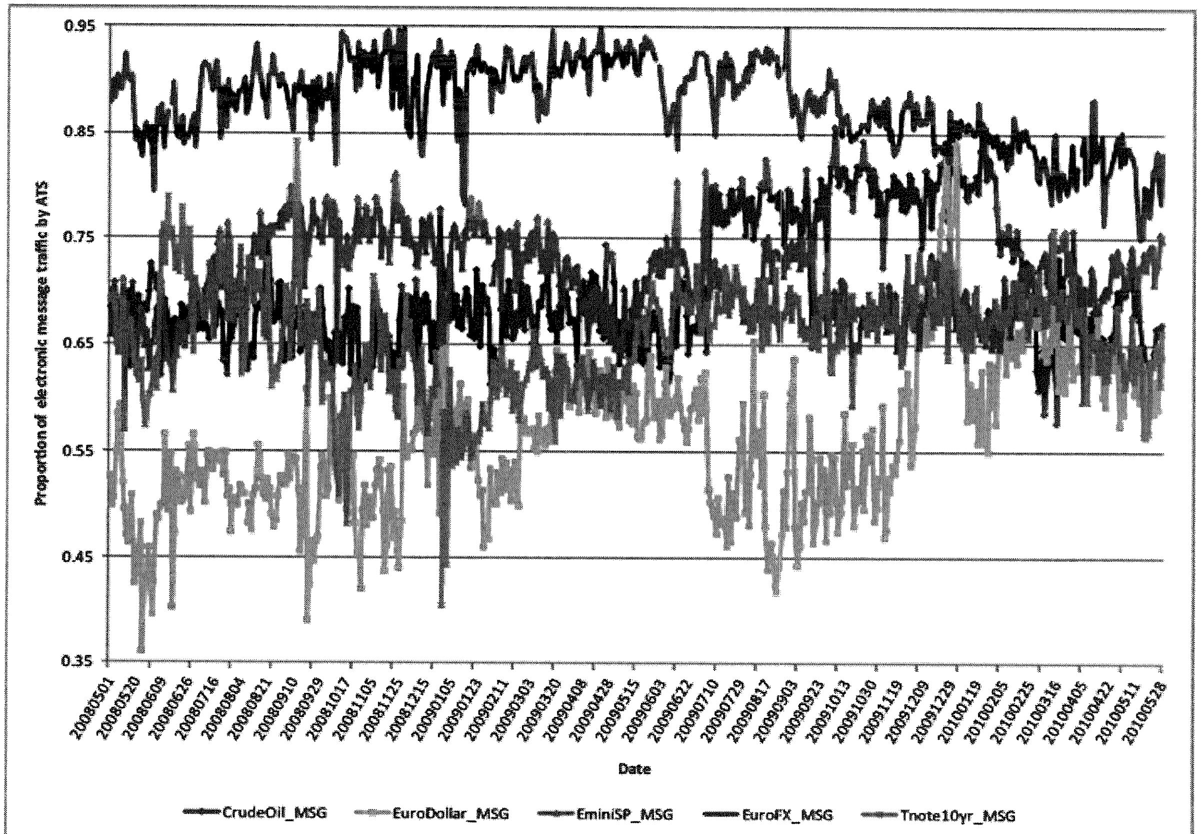
Data source: CME Group

Figure 1. Proportion of Electronically Executed Orders Originated by Algorithmic Trading.



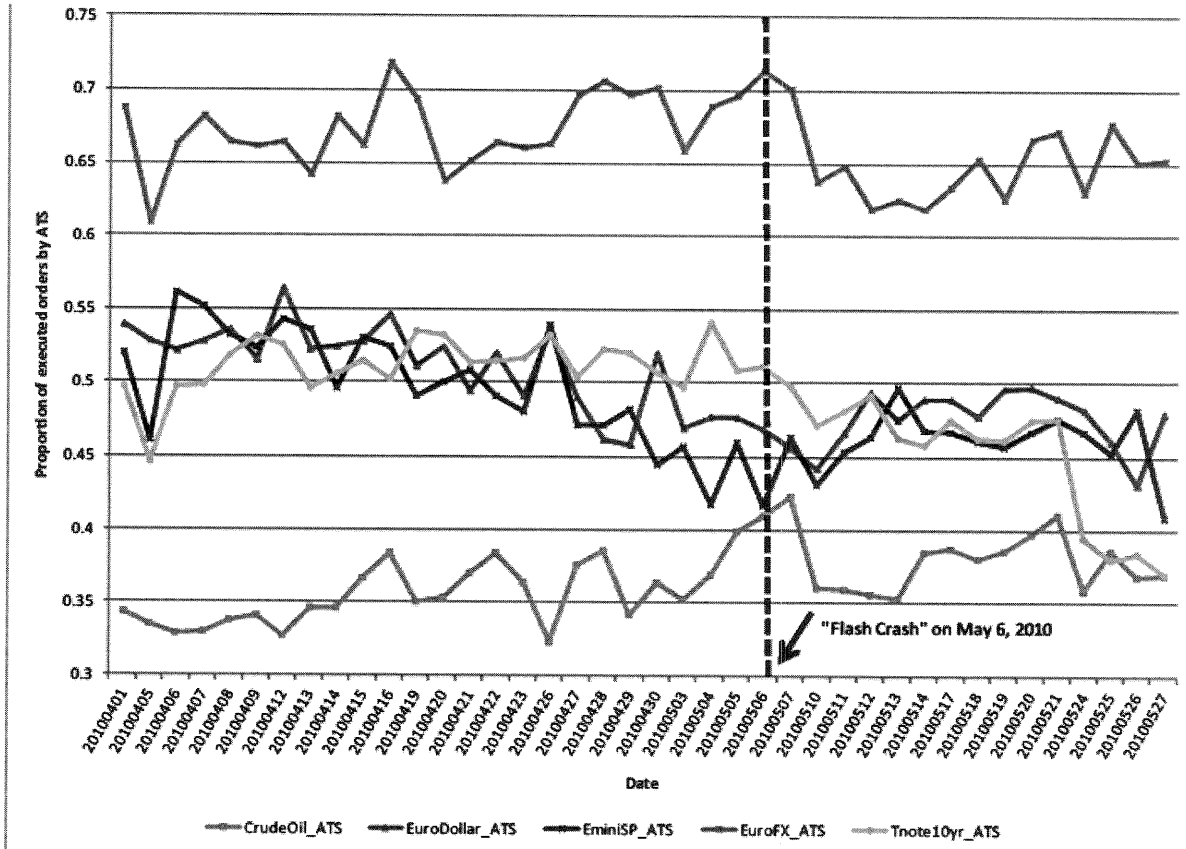
Proportion of Electronically Executed Orders Originated by Algorithmic Trading, ATS by Contract: May 1, 2008, to May 27, 2010 for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts.
Data source: CME Group; the data for the ***ATS***, ***MSG***, ***Width***, and ***Depth*** variables are from the regular trading hours.

Figure 2. Proportion of Electronic Messages (orders/quotes) Emanating from Algorithmic Trading (MSG).



Proportion of Electronic Messages (orders/quotes) Emanating from Algorithmic Trading (MSG) by Contract: May 1, 2008, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts.
Data source: CME Group; the data for the ***ATS***, ***MSG***, ***Width*** and ***Depth*** variables are from the regular trading hours.

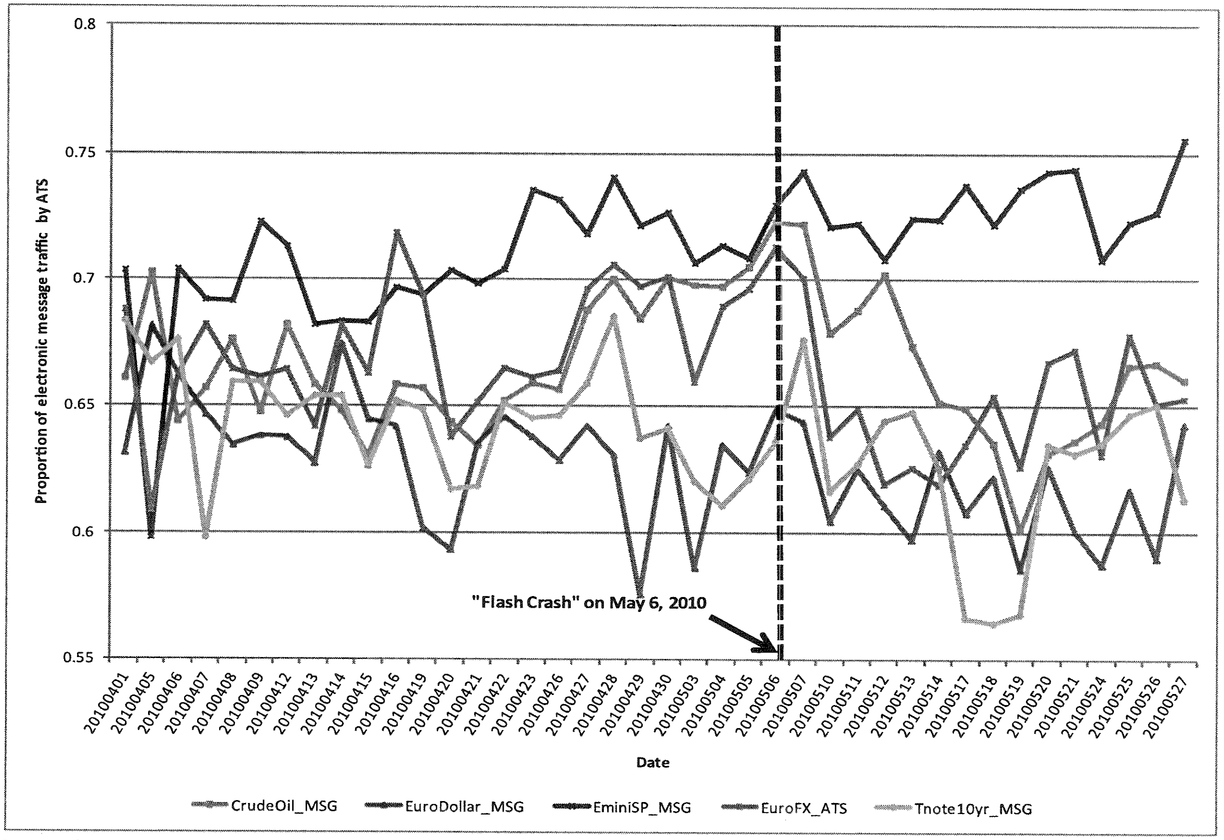
Figure 3. Proportion of Electronically Executed Orders Originated by Algorithmic Trading.



Proportion of Electronically Executed Orders Originated by Algorithmic Trading for the Period April 1, 2010, to May 27, 2010, showing "Flash Crash" of May 6, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts.

Data source: CME Group; the data for the ***ATS***, ***MSG***, ***Width*** and ***Depth*** variables are from the regular trading hours.

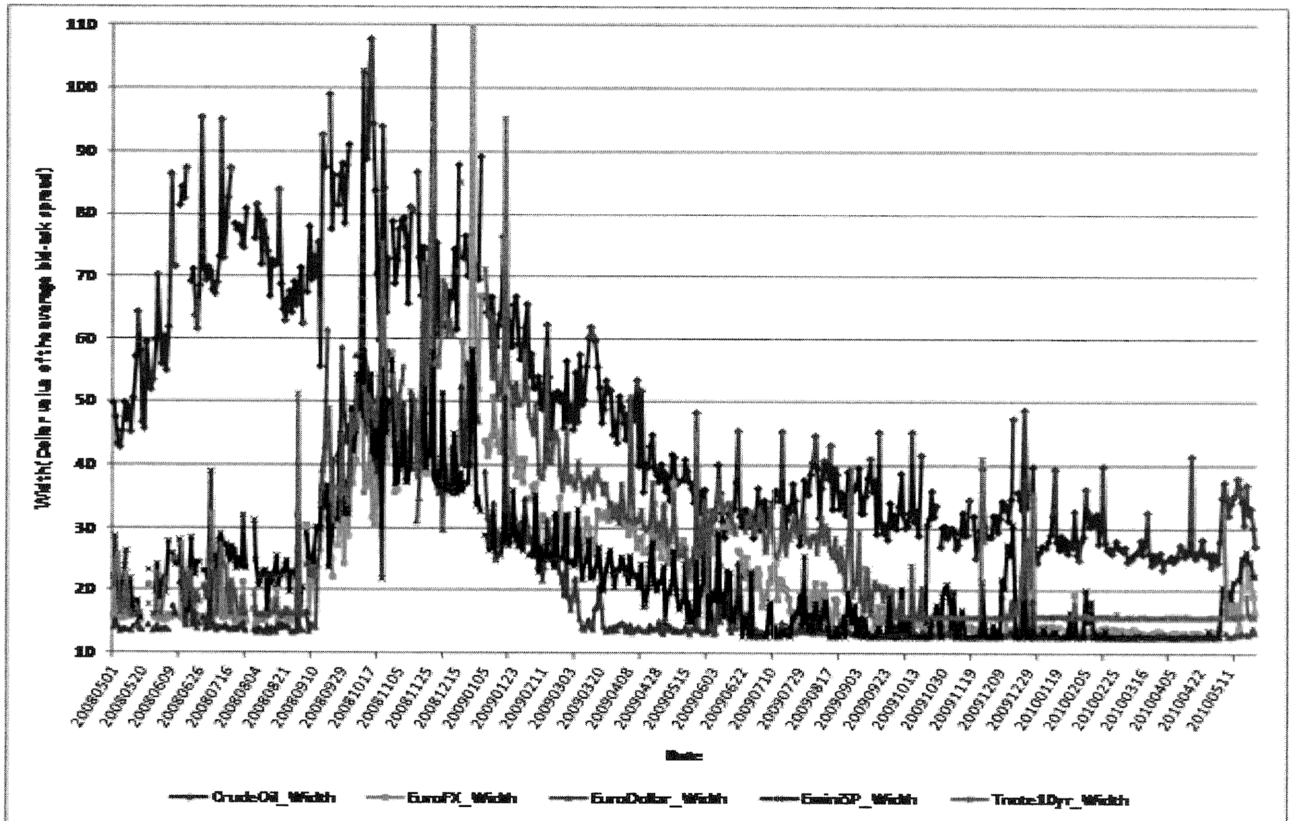
Figure 4. Proportion of Electronic Messages (orders/quotes) Emanating from Algorithmic Trading.



Proportion of Electronic Messages (orders/quotes) Emanating from Algorithmic Trading for the Period April 1, 2010, to May 27, 2018, showing "Flash Crash" of May 6, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts.

Data source: CME Group; the data for the ***ATS***, ***MSG***, ***Width*** and ***Depth*** variables are from the regular trading hours.

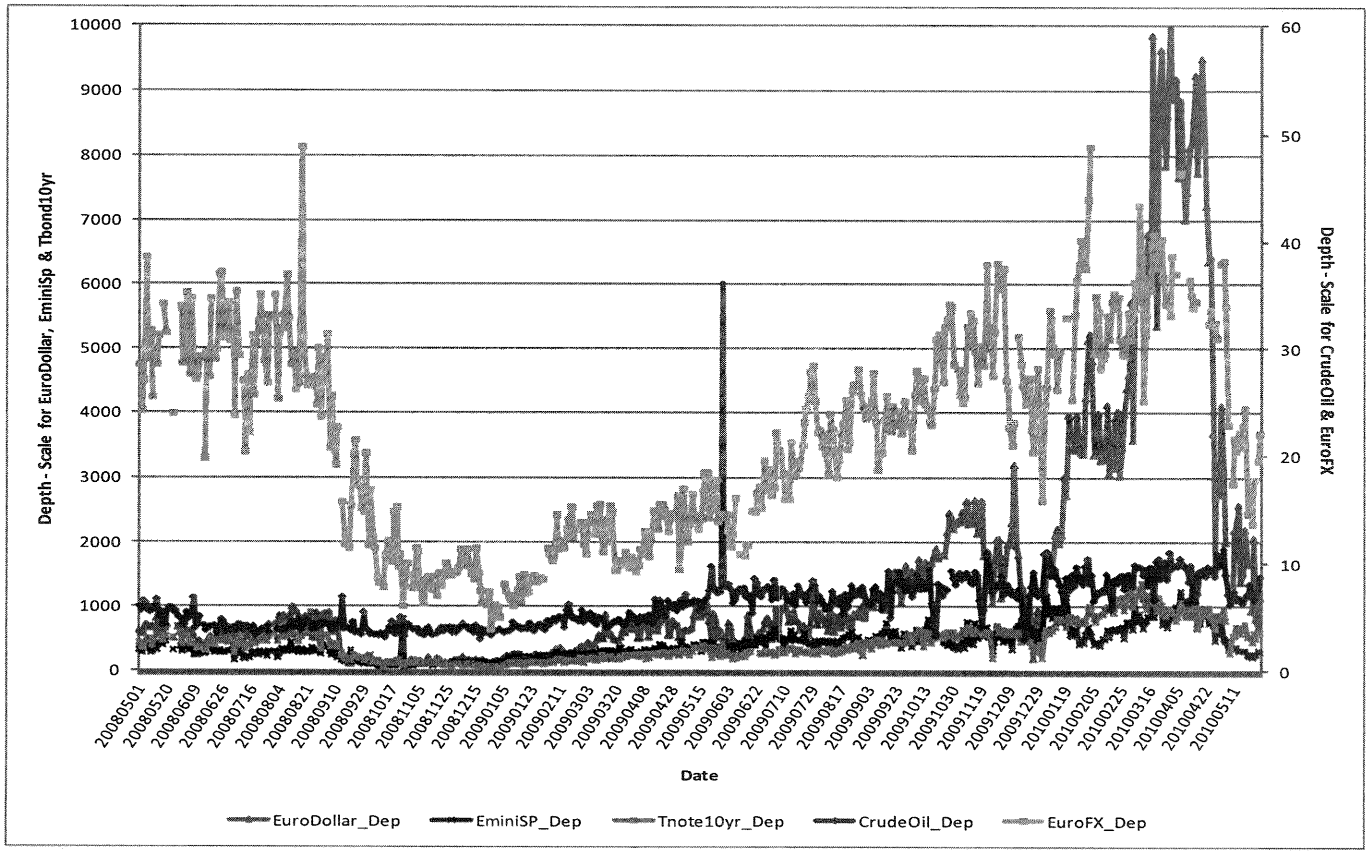
Figure 5. Market Width for the Period May 1, 2008, to May 27, 2010.



Market Width for the Period May 1, 2008, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts.

Data source: CME Group; the data for the ***ATS***, ***MSG***, ***Width*** and ***Depth*** variables are from the regular trading hours.

Figure 6. Market Depth for the Period May 1, 2008, to May 27, 2010.



Market Depth for the Period May 1, 2008, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts.

Data source: CME Group; the data for the ***ATS***, ***MSG***, ***Width*** and ***Depth*** variables are from the regular trading hours.

Table 2. Descriptive Statistics on Five Futures Contracts: Daily Volume, Open Interest, and Volatility.

		Trading Volume & Open Interest		Volatility Implied & Historical		Intraday Volatility			
(1)	CrudeOil								
Time	Statistic	Ln(TrdVolu)	Ln(OpInt)	ImpVola	HisVola	GarKla	Pakinson	Range	RSY94
Before	Mean	12.87936	14.07090	0.31037	0.26492	0.01386	0.00032	0.02782	0.00032
	Median	12.95356	14.10261	0.29780	0.26180	0.01291	0.00024	0.02585	0.00025
	Std. Dev.	0.39796	0.12323	0.04809	0.06619	0.00517	0.00028	0.01052	0.00037
	Skewness	-1.02338	-0.57196	1.04733	0.68003	1.45966	3.47890	1.47393	9.75343
	Kurtosis	5.43091	2.29499	4.45689	3.46680	6.88324	23.56477	6.81036	148.58290
After	Mean	13.21007	14.02149	0.52866	0.45146	0.02365	0.00105	0.04692	0.00103
	Median	13.21756	14.00876	0.45900	0.36910	0.01934	0.00055	0.03900	0.00056
	Std. Dev.	0.29514	0.07379	0.20988	0.21182	0.01410	0.00138	0.02675	0.00137
	Skewness	-0.65126	0.44812	1.07943	0.93223	1.82701	3.97193	1.54600	3.78359
	Kurtosis	6.31197	2.72576	3.16691	2.64784	7.95801	30.94680	6.35204	24.69317

Table 2, continued. Descriptive Statistics on Five Futures Contracts: Daily Volume, Open Interest, and Volatility.

(2)	EuroFX	Trading Volume & Open Interest		Volatility Implied & Historical		Intraday Volatility			
Time	Statistic	Ln(TrdVolu)	Ln(OpInt)	ImpVola	HisVola	GarKla	Pakinson	Range	RSY94
Before	Mean	12.01282	12.16782	0.07649	0.06626	0.00359	0.00002	0.00720	0.00002
	Median	12.03239	12.18965	0.07420	0.06250	0.00334	0.00002	0.00669	0.00002
	Std. Dev.	0.33997	0.14822	0.01750	0.01862	0.00153	0.00002	0.00308	0.00002
	Skewness	-0.87207	-0.29675	0.51258	0.40865	1.09825	2.16552	1.09303	4.38765
	Kurtosis	7.31627	2.40108	2.62918	2.03892	4.18738	8.60837	4.16081	36.96949
After	Mean	12.32943	11.99436	0.13971	0.12240	0.00648	0.00008	0.01304	0.00008
	Median	12.33109	12.01053	0.11620	0.10530	0.00565	0.00005	0.01133	0.00005
	Std. Dev.	0.40165	0.23707	0.04953	0.04336	0.00323	0.00009	0.00654	0.00010
	Skewness	-1.22556	0.26549	1.25194	0.80376	1.54021	2.99151	1.54917	3.25996
	Kurtosis	10.71546	2.76698	4.00326	2.50596	5.83391	13.93990	5.86484	17.20603

Table 2, continued. Descriptive Statistics on Five Futures Contracts: Daily Volume, Open Interest, and Volatility.

(3) EuroDollar

Time	Statistic	Trading Volume & Open Interest		Volatility Implied & Historical		Intraday Volatility			
		Ln(TrdVolu)	Ln(OpInt)	ImpVola	HisVola	GarKla	Pakinson	Range	RSY94
Before	Mean	14.61597	16.16021	0.12799	0.13504	0.00027	0.00000	0.00113	0.00000
	Median	14.63891	16.14970	0.07510	0.07575	0.00018	0.00000	0.00100	0.00000
	Std. Dev.	0.40724	0.07360	0.10976	0.17608	0.00030	0.00000	0.00063	0.00000
	Skewness	-0.88732	0.15756	1.24030	2.27956	3.13282	3.47453	1.52332	4.57961
	Kurtosis	5.78757	2.02780	3.79660	7.64453	19.34330	19.57783	6.19571	34.65420
After	Mean	14.40346	15.82571	0.72905	0.58973	0.00034	0.00000	0.00144	0.00000
	Median	14.40958	15.80338	0.78230	0.54810	0.00023	0.00000	0.00117	0.00000
	Std. Dev.	0.42409	0.14628	0.30475	0.32711	0.00040	0.00000	0.00107	0.00001
	Skewness	-1.91023	0.48073	-0.24035	0.87563	3.01185	19.06164	6.34548	21.91379
	Kurtosis	14.69838	2.22836	2.66144	3.66717	15.17884	404.52580	78.41297	493.27890

Table 2, continued. Descriptive Statistics on Five Futures Contracts: Daily Volume, Open Interest, and Volatility.

		Trading Volume & Open Interest		Volatility Implied & Historical		Intraday Volatility			
(4)	Emini S&P 500								
Time	Statistic	Ln(TrdVolu)	Ln(OpInt)	ImpVola	HisVola	GarKla	Pakinson	Range	RSY94
Before	Mean	14.13279	14.42281	0.15564	0.13727	0.00678	0.00010	0.01370	0.00010
	Median	14.08976	14.44146	0.13480	0.13130	0.00553	0.00004	0.01110	0.00005
	Std. Dev.	0.49210	0.20364	0.05956	0.06304	0.00431	0.00015	0.00876	0.00020
	Skewness	-0.11723	-0.03448	0.71801	0.56820	1.89127	4.32681	1.88043	7.95242
	Kurtosis	3.19595	2.36717	2.36358	2.35308	8.09170	29.54153	7.89987	86.37391
After	Mean	14.59885	14.77799	0.28511	0.27249	0.01326	0.00041	0.02688	0.00039
	Median	14.59838	14.75500	0.22930	0.20040	0.01017	0.00015	0.02044	0.00015
	Std. Dev.	0.41200	0.12662	0.13799	0.19326	0.00991	0.00077	0.02051	0.00077
	Skewness	-1.81441	0.71461	1.49343	1.75631	2.08392	3.92632	2.16004	4.62776
	Kurtosis	12.97335	3.67853	5.21569	5.49366	7.88584	20.86218	8.34482	29.37146

Table 2, continued. Descriptive Statistics on Five Futures Contracts: Daily Volume, Open Interest, and Volatility.

		Trading Volume & Open Interest		Volatility Implied & Historical		Intraday Volatility			
(5)	**Treasury Note (10-year)**								
Time	**Statistic**	**Ln(TrdVolu)**	**Ln(OpInt)**	**ImpVola**	**HisVola**	**GarKla**	**Pakinson**	**Range**	**RSY94**
Before	**Mean**	13.93702	14.69171	0.05746	0.05007	0.00258	0.00001	0.00530	0.00001
	Median	13.95781	14.67468	0.05070	0.04340	0.00221	0.00001	0.00462	0.00001
	Std. Dev.	0.45410	0.10604	0.01885	0.02062	0.00138	0.00002	0.00285	0.00002
	Skewness	-0.49608	0.41215	0.81686	1.21966	1.53552	3.51397	1.57170	5.06524
	Kurtosis	4.75827	2.49628	2.57332	3.72802	6.24795	20.79764	6.35896	45.21718
After	**Mean**	13.56462	14.09699	0.08919	0.08430	0.00408	0.00003	0.00837	0.00003
	Median	13.60130	14.03630	0.08385	0.07840	0.00363	0.00002	0.00756	0.00002
	Std. Dev.	0.52420	0.23324	0.02445	0.03132	0.00210	0.00005	0.00429	0.00004
	Skewness	-1.42213	0.56219	0.48520	1.04812	2.20825	7.72542	2.38856	4.71498
	Kurtosis	9.65794	2.08146	2.21400	3.39042	11.86176	92.58063	15.02140	33.75686

Note: Before Time: April 10, 2006, to April 30, 2008; After Time: May 01, 2008, to May 27, 2010. Daily total trading volume (***TrdVolu***), daily total open interest (***OpInt***), and implied volatility (***ImpVola***) based on the near-the-money options traded on futures, 200-day rolling historical volatility measure (***HisVola***).

Data source: CME Group; ATS and MSG data is available from May 01, 2008, to May 27, 2010.

the trading volume and open interest for the five contracts during the two years before and after the start of our AT data. While Figures 7 and 8 show no obvious trend, the ratio of trading volume to open interest presented in Figure 9 suggests a positive time trend across all contracts with differing magnitudes. Figures 10 and 11 display the estimates of the implied and the intraday volatility of futures prices. Although the main focus of the paper is not to statistically analyze these factors individually, these graphs help visualize the market conditions specific to the futures contracts under investigation.

We also include in our analysis various variables to control for conditions in the overall financial markets. Table 3 contains the statistics for the market control variables and provides before and after comparisons. Figure 12 graphs select market control variables (VIX, CorpSprd, GSCI, Gold, and S&P 500) over the four years (April 2006 to May 2010).

Using parametric and non-parametric tests for the mean and median of contract specific variables, we investigate potential changes in trading volume, open interest, implied and historical volatility, and four different measures of intraday volatility (Garman-Klass, Parkinson, Range, and RSY94). For all five contracts, we observe an increase in all volatility measures before (April 10, 2006, to April 30, 2008) and after (May 1, 2008, to May 27, 2010) availability of ATS data in our study. Except for the E-mini S&P 500 contract, open interest appears to decrease in the after period.

These descriptive statistics are casual graphical observations and simple univariate comparisons of means and medians. Our intention is not to model the before and after effects based on ATS data availability but rather to use these variables in a microstructure model to control for changes in markets specific to each contract in addition to the overall economy.

IV. EMPIRICAL METHODS

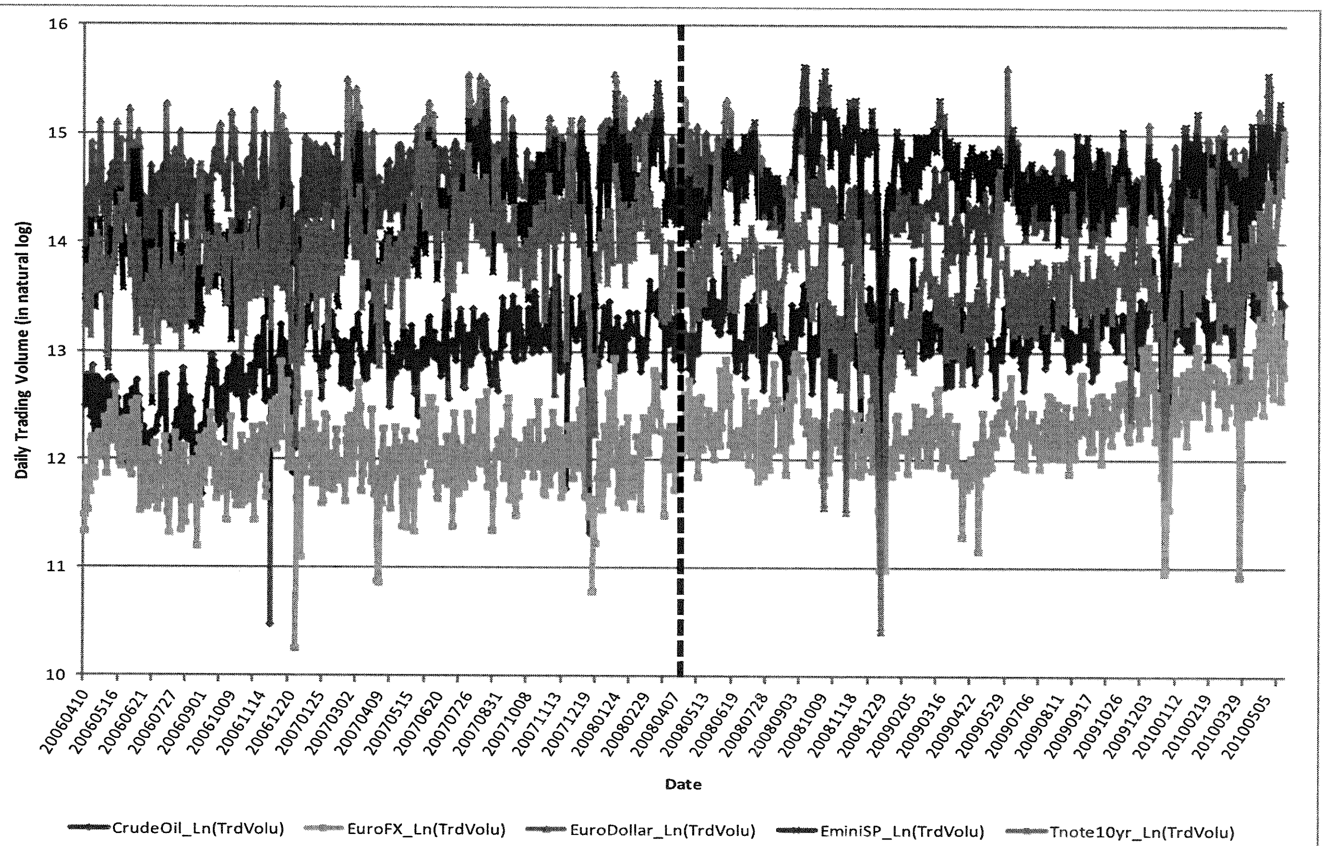
In this section we describe the empirical methods used in estimating the intraday price volatility and the models used in investigating the effects of DMA and algorithmic trading on futures market liquidity. Liquidity measures used are the daily average width and depth provided by the CME and calculated using the intraday quotes and transaction prices.

A. Estimating Intraday Volatility

In addition to the implied and historical volatility measures provided by the Reuters/CRB dataset, we estimate the intraday volatility (***IntVola***) of the futures prices using various methods, expecting that both short-term and long-term volatility affect market liquidity.

Finance literature, in particular futures markets research, contains numerous methods to estimate intraday volatility using the daily open (OP_t), high (HP_t), low (LP_t), and closing (CP_t) prices. The simplest estimator is the difference between the high and the low prices of the day:

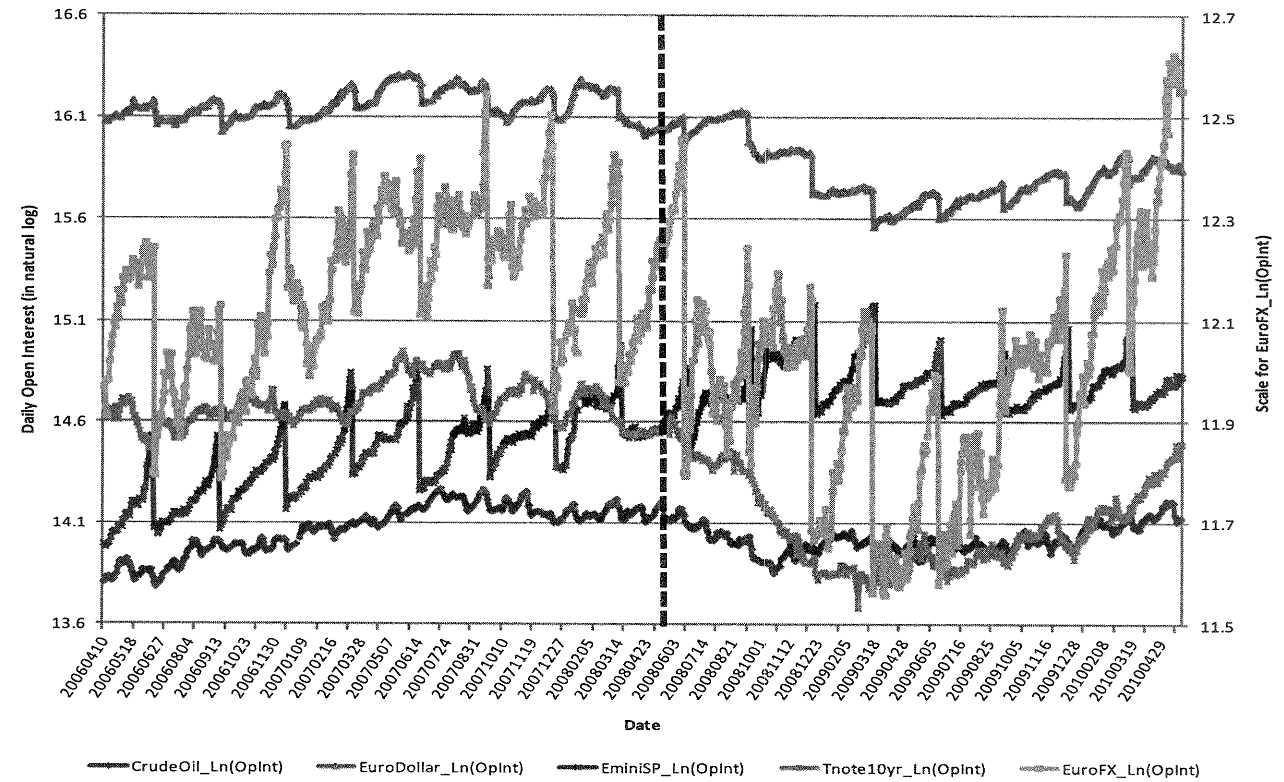
Figure 7. Daily Trading Volume for the Period April 10, 2006, to May 27, 2010.



Daily Trading Volume for the Period April 10, 2006, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts. Data Source: Reuters/CRB database.

Note: Casual observation of the graph suggests that there is no evident change in the trading volume after May 1, 2008 (start of the microstructure dataset used in this study).

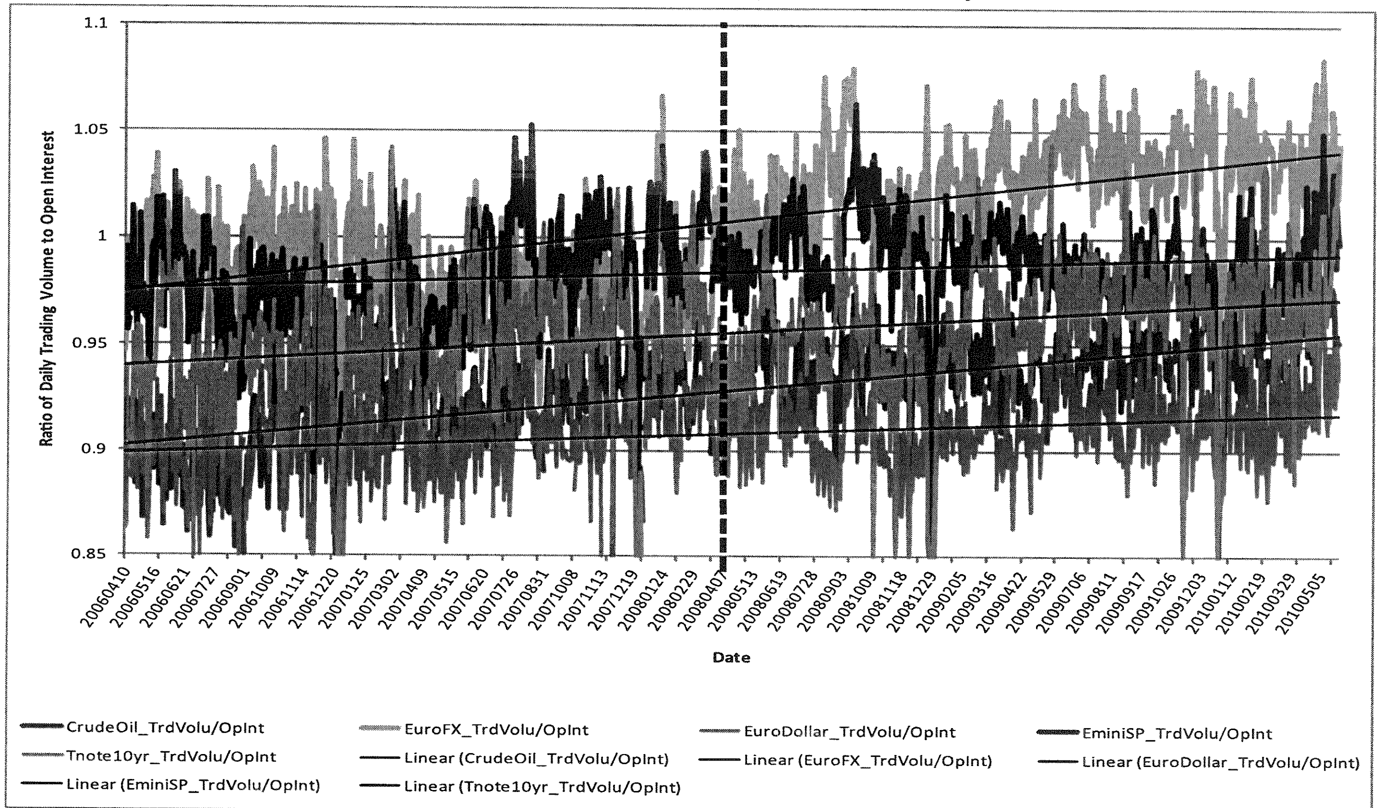
Figure 8. Daily Total Open Interest for the Period April 10, 2006, to May 27, 2010.



Daily Total Open Interest for the Period April 10, 2006, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts. Data Source: Reuters/CRB database.

Note: Casual observation of the graph suggests that there is no evident change in the open interest after May 1, 2008 (start of the microstructure dataset used in this study).

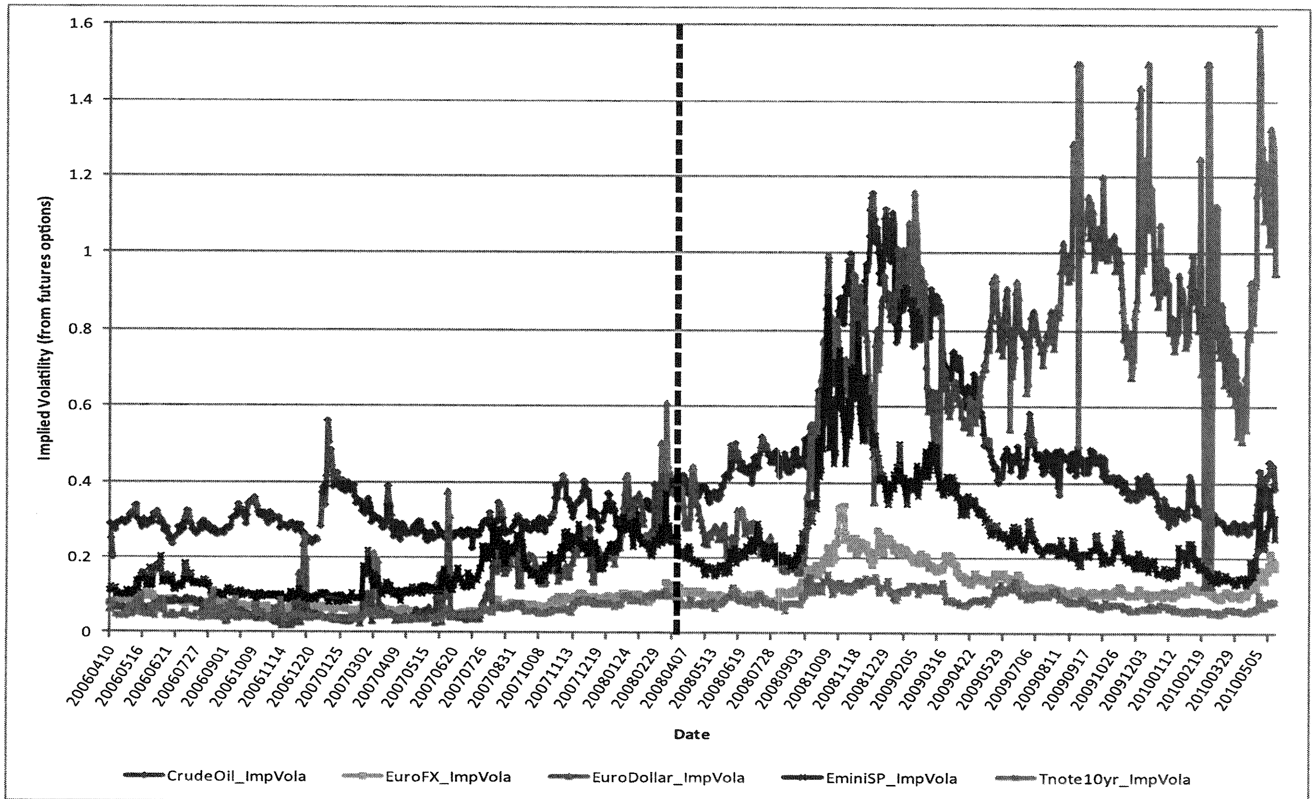
Figure 9. Ratio of Trading Volume to Open Interest for the Period April 10, 2006, to May 27, 2010.



Ratio of Trading Volume to Open Interest for the Period April 10, 2006, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts. Data source: Reuters/CRB database.

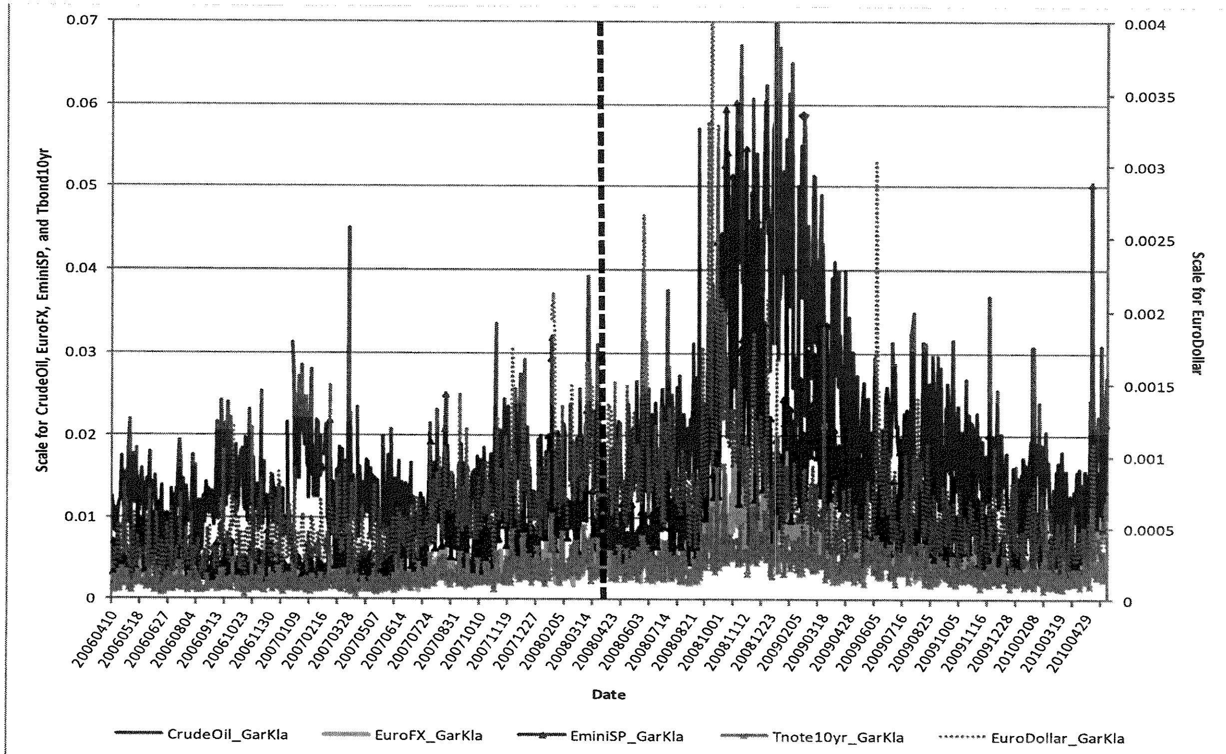
Note: Casual observation of the graph suggests that ratio of trading volume to open interest is increasing during the time frame under investigation, indicating an improvement in liquidity.

Figure 10. Implied Volatility for the Period April 10, 2006, to May 27, 2010.



Implied Volatility for the Period April 10, 2006, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, and 10-year U.S. Treasury Note Contracts. Data source: Reuters/CRB database. Note: Implied volatility (***ImpVola***) for each of the contracts based on the near-the-money options traded on those futures. This graph suggests that there is a marked increase in volatility starting with the third quarter of 2008 (in line with recent turmoil in financial markets). However, this does not appear to be immediately after May 1, 2008 (start of the microstructure dataset used in this study).

Figure 11. Garman-Klass Estimate of Intraday Volatility for the Period April 10, 2006, to May 27, 2010.



Garman-Klass Estimate of Intraday Volatility for the Period April 10, 2006, to May 27, 2010, for Crude Oil, Euro FX, Eurodollar, E-mini S&P 500, 10-year Treasury Note. Intraday volatility is estimated using the Garman-Klass (***GarKla***) estimator. This graph suggests that there is a period of heightened intraday volatility for all contracts from the September 2008 until April 2009. Another observation is that the Garman-Klass estimate of the intraday volatility of Eurodollar contract is very small (order of 10-2) compared to the other four contracts. However, this high intraday volatility period does not appear to be around May 01, 2008 (start of the microstructure dataset used in this study). Data Source: Reuters/CRB database.

Table 3. Descriptive Statistics on Market Control Variables: April 10, 2006, to May 27, 2010.

Horizon	Statistic	Corp AAA	Corp BAA	Corp Sprd	Tbill 3mo	Def Sprd	Term Sprd
April 10, 2006 to April 30, 2008	Mean	5.5793	6.5536	0.9743	4.2186	1.0265	0.3373
	Median	5.55	6.56	0.91	4.853	0.803	0.152
	Std. Dev.	0.2108	0.2250	0.1732	1.1955	0.4110	0.7982
	Skewness	0.2511	0.0775	1.4610	-1.4156	1.2110	1.2355
	Kurtosis	2.0095	2.2059	3.9512	3.7450	3.1567	3.7752
	IQ Range	0.3600	0.3500	0.0900	1.2640	0.4940	0.9390
	CV	0.0378	0.0343	0.1778	0.2834	0.4004	2.3664
May 01, 2008 to May 27, 2010	Mean	5.4245	7.2348	1.8102	0.4505	1.9621	3.0086
	Median	5.365	7.075	1.48	0.155	1.7715	3.203
	Std. Dev.	0.3362	0.9504	0.8153	0.6267	0.4125	0.5584
	Skewness	0.9436	0.5829	0.7015	1.5112	0.6760	-0.4200
	Kurtosis	4.6777	2.2126	1.9179	3.5224	1.9874	1.7661
	IQ Range	0.3700	1.7250	1.6300	0.2120	0.7275	0.9730
	CV	0.0620	0.1314	0.4504	1.3912	0.2102	0.1856
April 10, 2006 to May 27, 2010	Mean	5.5021	6.8935	1.3915	2.3291	1.4947	1.6807
	Median	5.475	6.64	1.095	1.787	1.57	2.1105
	Std. Dev.	0.2908	0.7692	0.7220	2.1123	0.6232	1.5029
	Skewness	0.4506	1.5055	1.5710	0.2067	0.2739	-0.1190
	Kurtosis	4.1149	4.5344	4.1597	1.2876	2.0547	1.4215
	IQ Range	0.3700	0.7200	0.5700	4.6980	1.0160	3.0525
	CV	0.0529	0.1116	0.5189	0.9069	0.4169	0.8942

Table 3, continued. Descriptive Statistics on Market Control Variables: April 10, 2006, to May 27, 2010.

Horizon	Statistic	DOW	NASDAQ	NYSE	Russell1000	SP500
April 10, 2006 to April 30, 2008	Mean	4,217.73	2,425.01	9,128.36	762.99	1,401.80
	Median	4,225.97	2,430.86	9,139.57	766.33	1,408.21
	Std. Dev.	259.89	190.07	641.76	48.58	88.34
	Skewness	-0.1904	-0.0457	-0.1427	-0.1047	-0.1018
	Kurtosis	1.9050	2.3005	2.0043	1.9074	1.9160
	IQ Range	421.72	268.17	1,029.14	80.27	148.15
	CV	0.0616	0.0784	0.0703	0.0637	0.0630
May 01, 2008 to May 27, 2010	Mean	3,400.42	2,012.76	6,789.97	574.95	1,051.88
	Median	3,379.32	2,123.93	6,899.68	584.91	1,066.19
	Std. Dev.	533.86	346.05	1,234.00	96.84	173.12
	Skewness	0.2752	-0.3308	0.2761	0.1321	0.1614
	Kurtosis	2.3995	1.7879	2.4248	2.1651	2.2283
	IQ Range	746.30	608.04	1,690.72	153.96	265.63
	CV	0.1570	0.1719	0.1817	0.1684	0.1646
April 10, 2006 to May 27, 2010	Mean	3,807.11	2,217.90	7,953.55	668.52	1,226.00
	Median	3,898.49	2,300.05	8,320.19	696.61	1,277.58
	Std. Dev.	586.33	347.26	1,528.84	121.36	222.63
	Skewness	-0.5618	-0.7831	-0.4731	-0.5187	-0.4874
	Kurtosis	2.2776	2.8530	2.1000	2.1420	2.0934
	IQ Range	911.08	385.46	2,319.66	183.40	344.65
	CV	0.1540	0.1566	0.1922	0.1815	0.1816

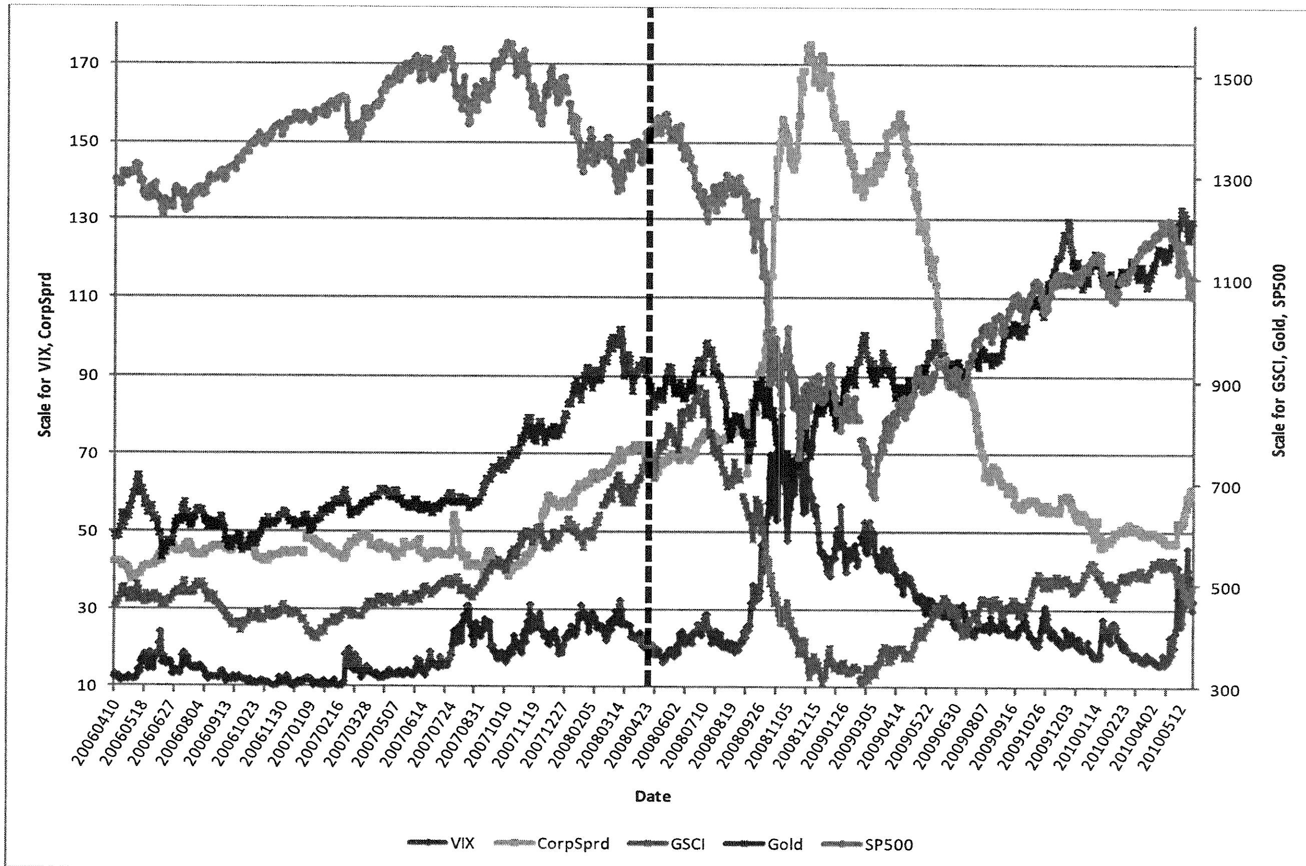
Table 3, continued. Descriptive Statistics on Market Control Variables: April 10, 2006, to May 27, 2010.

Horizon	Statistic	Gold	DollarInd	GSCI	ReutersCRB	VIX
April 10, 2006 to April 30, 2008	Mean	706.62	81.41	512.43	424.35	17.14249
	Median	663.53	82.53	483.44	404.98	15.235
	Std. Dev.	110.51	4.4409	83.43	52.04	5.7511
	Skewness	1.0993	-0.6508	1.0789	1.2762	0.6121
	Kurtosis	2.9892	2.3270	3.2554	3.6471	2.1157
	IQ Range	138.14	7.4610	121.55	61.41	10.2900
	CV	0.1564	0.0546	0.1628	0.1226	0.3355
May 01, 2008 to May 27, 2010	Mean	964.55	79.87	510.85	442.37	31.23839
	Median	938.36	79.85	486.96	450.95	25.45
	Std. Dev.	124.10	4.4334	144.36	67.00	13.6837
	Skewness	0.2608	0.0943	0.9555	0.3701	1.2994
	Kurtosis	2.2023	2.0955	3.1350	2.3668	4.0689
	IQ Range	206.22	7.2350	130.40	98.05	18.1800
	CV	0.1287	0.0555	0.2826	0.1515	0.4380
April 10, 2006 to May 27, 2010	Mean	835.71	80.63	511.63	433.40	24.22429
	Median	848.48	80.87	484.11	413.41	21.68
	Std. Dev.	174.48	4.5017	117.99	60.67	12.6548
	Skewness	0.3015	-0.2644	1.0575	0.7580	1.6549
	Kurtosis	2.0330	2.0103	3.9091	2.7847	5.9705
	IQ Range	281.60	7.8910	104.27	86.22	11.9300
	CV	0.2088	0.0558	0.2306	0.1400	0.5224

Notes: ***CorpAAA***—AAA-corporate bond yield; ***CorpBAA***—BAA corporate bond yield; ***CorpSprd***—corporate credit spread (= ***CorpBAA*** – ***CorpAAA***); ***Tbill3mo*** —yield on 3-month Treasury Bill; ***DefSprd*** —difference between the AAA-corporate bond yield and the yield on 10-year Treasury Note; ***TermSprd*** —difference between the yields on 10-year Treasury Note and the 3-month Treasury Bill; ***DOW***—daily stock index levels for Dow Jones Industrial Average; ***NASDAQ*** —NASDAQ composite; ***NYSE*** —New York Stock Exchange Composite; ***Russell1000***—Russell 1000; ***SP500***—S&P 500; *GSCI* —daily values of Goldman Sachs Commodity Index; ***DollarInd***—U.S. Dollar Index; *GOLD* —spot Gold price; ***ReutersCRB*** —Reuters/CRB Commodity Index; and ***VIX***—the CBOE's Volatility Index.

Data sources: Reuters/CRB database; CME Group's ATS and MSG data is available from May 1, 2008, to May 27, 2010.

Figure 12. Market Control Variables, VIX, CorpSprd, GSCI, Gold, and SP500, April 10, 2006, to May 27, 2010.



Note: ***VIX*** is the CBOE's Volatility Index, ***CorpSprd*** is the corporate credit spread (calculated as the difference between the AAA rated and BAA rated corporate bond yields), ***GOLD***, ***GSCI***, and ***SP500*** are the daily spot levels of Gold, Goldman Sachs Commodity Index, and S&P 500 Index, respectively. Data source: Reuters/CRB database.

$$Range_t = Ln(HP_t) - Ln(LP_t) \tag{1}$$

Some researchers also used the simple difference of the two prices (Chan and Lien 2003). Parkinson (1980) proposes a revised version of the range estimator:

$$Parkinson_t = \left[Ln(HP_t) - Ln(LP_t)\right]^2 / \left[4Ln(2)\right] \tag{2}$$

Garman and Klass (1980) incorporate the opening and low prices of the day into the following estimate of intraday volatility:[21]

$$GarKla_t = \left\{\frac{1}{2}\left[Ln(HP_t) - Ln(LP_t)\right]^2\right\} - \left\{\left[2\ln(2)-1\right]\left[Ln(CP_t) - Ln(OP_t)\right]^2\right\} \tag{3}$$

A version of the Garman-Klass estimator independent of the drift is proposed by Rogers, Satchell, and Yoon (1994):[22]

$$\begin{aligned} RSY94_t = &\left\{\left[Ln(HP_t) - Ln(OP_t)\right]\left[Ln(HP_t) - Ln(CP_t)\right]\right\} - \\ &\left\{\left[Ln(LP_t) - Ln(OP_t)\right]\left[Ln(LP_t) - Ln(CP_t)\right]\right\} \end{aligned} \tag{4}$$

All four of these intraday volatility estimators rely on the daily range based analysis with varying levels of efficiency. Based on the futures markets research, we use the Garman-Klass estimates of intraday volatility in our empirical analysis. We also repeat empirical tests using other estimators and find that our results do not materially change.

B. Modeling Liquidity and AT

In order to investigate the effects of DMA and AT on the liquidity of futures contracts traded at the CME, we use a model similar to the one used by Hendershott, Jones, and Menkveld (2011). They model the relationship between the liquidity and their proxy of algorithmic trading as:

$$Liq_{i,t} = \alpha_i + \beta \mathrm{AT}_{i,t} + \delta' \mathrm{X}_{i,t} + \varepsilon_{i,t} \tag{5}$$

where Liq_{it} is a measure of liquidity for stock i on day t, AT_{it} is their proxy for the algorithmic trading, and X_{it} is a vector of control variables (which they choose to be share turnover, volatility, the inverse of share price, and log market cap).[23] They

21. Chen, Daigler, and Parhizgari (2006) and Shu and Zhang (2006) illustrate that volatility estimates using the Garman-Klass method and the high frequency realized volatility measures provide equivalent results.
22. Yang and Zhang (2000) discuss modifications to the RSY94 estimator.
23. Hendershott et al. (2011) include both fixed effects and time dummies in their model.

estimate the panel regressions in equation (5) using standard errors that are robust to general cross-section and time-series heteroskedasticity and within-group autocorrelation (Arellano and Bond 1991).

Our empirical tests use two different direct measures of algorithmic trading provided by the CME: ATS, percentage of trading volume identified as originating from algorithms, and MSG, percentage of message traffic identified as originating from algorithms. Our empirical tests do not suffer as much from the measurement error as Hendershott, Jones, and Menkveld's (2011) proxy for AT, normalized measure of electronic message traffic.[24] We also use two measures of liquidity, average market width and depth, for each contract. Our control variables include those specific to the contracts GSCI, gold price, and CBOE's volatility index VIX: estimates of intraday and implied volatility, trading volume and open interest, as well as market-related factors.

We estimate the following general model using various cross-sectional time series (CSTS) techniques:

$$Liq_{i,t} = \alpha_i + \beta_i \mathrm{Algo}_{i,t} + \delta_i^{'} \mathrm{X}_{i,t} + \varphi_i^{'} Z_{i,t} + \varepsilon_{i,t} \tag{6}$$

where $\boldsymbol{Liq}_{i,t}$ is either of our liquidity measures ***ATS*** or ***MSG***; $\mathbf{Algo}_{i,t}$ is either of our direct measure of algorithmic trading, $\mathbf{X}_{i,t}$ is a vector of control variables on each futures contract (***IntVola***, intraday volatility; ***ImpVola***, implied volatility; ***OpInt***, open interest; ***TrdVolu***, trading volume) and $\mathbf{Z}_{i,t}$ is a vector of market controls (***GSCI***, Goldman Sachs Commodity Index; ***Gold***, price of gold; ***VIX***, CBOE's volatility index). Explicitly, we first estimate models without market controls:

$$\begin{aligned} Liq_{i,t} &= \alpha_i + \beta_i \mathrm{A}_{i,t} + \delta_{1,i}\mathrm{IntVola}_{i,t} + \delta_{2,i}\mathrm{ImpVola}_{i,t} + \\ &\delta_{3,i}\mathrm{OpInt}_{i,t} + \delta_{4,i}\mathrm{TrdVol}_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where
$$Liq_{i,t} = \begin{cases} Width_{i,t} \\ Depth_{i,t} \end{cases}, \text{ and } A_{i,t} = \begin{cases} ATS_{i,t} \\ MSG_{i,t} \end{cases}. \tag{8}$$

In order to provide robust estimation results, we use the following alternative panel estimation methods: (a) random-effects GLS regressions with autoregressive errors AR(1); (b) standard fixed-effects panel regression using the between-regression estimator (when we exclude market controls from the independent variables). When we include the vector of market controls in our analysis, we estimate the following models using (c) standard fixed-effects panel regression with using the between regression estimator and (d) fixed-effects cross-sectional time-series regression with first-order autoregressive disturbances:

24. Hendershott et al. (2011) state that they "cannot directly observe whether a particular order is generated by a computer algorithm," which is due to the nature of the NYSE data they use in their analysis. They indicate that "the rate of electronic message traffic may be a useful proxy for the amount of algorithmic trading taking place," which they normalize by dividing number of electronic messages by trading volume of each stock on a given day.

$$Liq_{i,t} = \alpha_i + \beta_i A_{i,t} + \delta_{1,i}\text{IntVola}_{i,t} + \delta_{2,i}\text{ImpVola}_{i,t} + \delta_{3,i}\text{OpInt}_{i,t} + \delta_{4,i}\text{TrdVol}_{i,t} + \varphi_1\text{GSCI}_t + \varphi_2\text{Gold}_t + \varphi_3\text{VIX}_t + \varepsilon_{i,t} \quad (9)$$

where $$Liq_{i,t} = \begin{cases} Width_{i,t} \\ Depth_{i,t} \end{cases}, \text{ and } A_{i,t} = \begin{cases} ATS_{i,t} \\ MSG_{i,t} \end{cases}. \quad (10)$$

We estimate equation (6) with various market control variables and find that the results do not materially change; therefore, we report our findings using the vector of market controls that include the GSCI, Gold, and the VIX.

V. EMPIRICAL RESULTS

Table 4 presents the empirical results for the effects of algorithmic trading on liquidity using only the contract specific factors as control variables (specifically equations 7 and 8). The results using both the random-effects GLS regressions with AR(1) and the fixed-effects models are consistent. After controlling for intraday and implied volatilities, trading volume and open interest, we find that an increase in the proportion of trading associated with algorithmic trading systems (***ATS***) decreases the width (spreads) and increases the market depth. When an AT's proportion of electronic message traffic (***MSG***) is used as a measure of algorithmic trading, we observe the same results. Our models explain relatively large portions of within and between variation in the cross-sectional time series data, and coefficient estimates of ***ATS*** and ***MSG*** are all significant at 1%.

Estimated coefficients of volatility, volume, and open interest are consistent with the findings in futures MMR. (See, e.g., Wang, Yau, and Baptiste 1997; Wang and Yao 2000; Girma and Mougoue 2002; Bryant and Haigh 2004; and Frank and Garcia 2009.) ***Width*** (spreads) increases with both measures of volatility and decreases with trading volume and open interest; their effect on ***Depth*** is reversed. Our results for the volatility are robust to the measurement of short-term (intraday) volatility and longer-term (implied) volatility.

The changes we observe by considering only the futures contract–specific factors may in fact be influenced by other dynamics of overall financial markets. Table 5 presents findings when we include both futures contract and market control variables in our cross-sectional time series regressions (specifically equations 9 and 10). Results based on cross-sectional time series estimation using both the fixed-effects and fixed-effects with AR(1) disturbances are consistent and confirm the findings presented in Table 4.

We again observe that trading volume of ATS (as well as their proportion of electronic message traffic, ***MSG***) decreases the ***Width*** while increasing the market ***Depth***, after controlling for both futures contract-specific and market-wide factors. While the coefficient estimates of futures contract–specific control factors retain their signs and significance, the inclusion of market-wide factors increases the

Table 4. Effects of Algorithmic Trading on Liquidity, May 1, 2008, to May 27, 2010: Cross-Sectional Time Series (Panel) Data Analysis for $Liq_{i,t} = \alpha_i + \beta_i \text{Algo}_{i,t} + \delta_i^{'} X_{i,t} + \varepsilon_{i,t}$

	Random-effects GLS Regression with AR(1)				CSTC with Fixed-effects			
	Width		*Depth*		*Width*		*Depth*	
ATS	-63.07		3346.60		-105.99		7793.50	
	(-15.22)*		(14.23)*		(-20.57)*		(22.99)*	
MSG		-23.7574		1601.95		-42.93		3631.73
		(-5.29)*		(7.44)*		(-9.71)*		(12.13)*
IntVola(GarKla)	437.20	510.89	-737.35	-2485.84	671.62	879.31	-6535.28	-19995.16
	(13.21)*	(15.03)*	(-0.51)	(-1.73)***	(17.74)*	(22.71)*	(-2.44)**	(-7.17)*
ImpVola	12.88	14.37	383.50	336.90	14.1302	8.9302	637.61	932.66
	(8.96)*	(9.32)*	(4.69)*	(4.1)*	(9.4)*	(5.66)*	(5.74)*	(7.87)*
OpInt	-9.84E-07	-2.63E-07	2.02E-04	2.09E-04	-2.6874	-2.1926	1.73E-04	1.62E-04
	(-3.62)*	(-0.82)	(12.41)*	(13.19)*	(-1.73)***	(-1.32)	(5.89)*	(5.09)*
TrdVolu	-3.20E-06	-3.25E-06	-6.39E-05	-7.13E-05	-8.9189	-10.9461	1.68E-05	5.25E-05
	(-6.94)*	(-6.63)*	(-3.01)*	(-3.33)*	(-11.84)*	(-13.75)*	(0.49)	(3.53)*
Constant	57.00	39.64	-1783.76	-1239.88	227.94	226.78	-4003.83	-2740.68
	(22.75)*	(10.92)*	(-12.11)*	(-7.08)*	(11.46)*	(10.49)*	(-20.87)*	(-11.64)*

Table 4, continued. Effects of Algorithmic Trading on Liquidity, May 1, 2008, to May 27, 2010: Cross-Sectional Time Series (Panel) Data Analysis for $Liq_{i,t} = \alpha_i + \beta_i \text{Algo}_{i,t} + \delta_i' X_{i,t} + \varepsilon_{i,t}$

	Random-effects GLS Regression with AR(1)				CSTC with Fixed-effects			
	Width		*Depth*		*Width*		*Depth*	
R2 within	0.3577	0.2667	0.1881	0.0531	0.4276	0.3456	0.2223	0.0989
R2 between	0.7803	0.7105	0.5991	0.8214	0.9013	0.7325	0.1308	0.6126
R2 overall	0.4734	0.4292	0.2752	0.2897	0.5617	0.4851	0.1203	0.2696
# of obs.	2220	2220	2267	2267	2210	2210	2267	2267
Wald $Chi^2(6)$	805.12	510.62	348.78	220.98	328.75	232.39	129.05	49.54

*, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Note: Two direct measures of algorithmic trading ($\text{Algo}_{i,t}$) are ***ATSi,t*** – percentage of volume attributed to automated trading systems and ***MSG***$_{i,t}$ – percent of message traffic attributed to automated trading systems. Two measures of the liquidity ($\text{Liq}_{i,t}$) are ***Width***$_{i,t}$ – average bid–ask spread for a given size order during a trading day, and ***Depth***$_{i,t}$ – number of contracts displayed at the "top-of-the-book" (i.e., average contract size of the best bid and best ask quotes). ***Xi,t*** is a vector of control variables on each futures contract; ***TrdVolu*** is daily total trading volume, ***OpInt*** is daily total open interest, ***IntVola(GarKla)*** is the Garman-Klass estimate of intraday volatility, and ***ImpVola*** is implied volatility for each of the contracts based on the near-the-money options traded on those futures. The data for the ***ATS***, ***MSG***, ***Width*** and ***Depth*** variables are from regular trading hours.

Table 5. Effects of Algorithmic Trading on Liquidity, Controlling for Market Factors, May 1, 2008, to May 27, 2010: Cross-Sectional Time Series (CSTS) Data Analysis for $Liq_{i,t} = \alpha_i + \beta_i \mathrm{Algo}_{i,t} + \delta_i^{'} \mathrm{X}_{i,t} + \varphi_i^{'} Z_{i,t} + \varepsilon_{i,t}$

	CSTS with Fixed-effects				CSTC with Fixed-effect & AR(1)			
	Width		*Depth*		*Width*		*Depth*	
ATS	-56.33		5570.94		-32.3193		1616.71	
	(-13.01)*		(15.61)*		(-8.57)*		(7.66)*	
MSG		-22.9863		2826.60		0.0549		326.01
		(-6.91)*		(10.35)*		(0.02)		(1.86)***
IntVola(GarKla)	132.48	170.14	18219.66	14330.60	82.08	101.51	4492.32	3581.77
	(3.99)*	(5)*	(6.65)*	(5.11)*	(2.87)*	(3.51)*	(3.2)*	(2.55)**
ImpVola	13.10	10.29	651.74	907.62	12.28	11.44	563.24	559.02
	(10.4)*	(8.12)*	(6.23)*	(8.6)*	(9.05)*	(8.31)*	(6.8)*	(6.68)*
OpInt	-11.27	-10.18	211.34	96.52	-6.12E-07	-3.97E-07	1.55E-04	1.51E-04
	(-8.41)*	(-7.41)*	(1.91)***	(0.85)	(-2.28)**	(-1.44)	(10.41)*	(9.92)*
TrdVolu	-4.64	-4.93	-168.45	-121.32	-2.82E-06	-2.74E-06	-6.25E-05	-6.46E-05
	(-7.71)*	(-7.99)*	(-3.68)*	(-2.59)**	(-7.18)*	(-6.86)*	(-3.08)*	(-3.15)*
VIX	0.6435	0.6539	-14.30	-14.99	0.7785	0.7180	-23.86	-21.75
	(25.99)*	(25.71)*	(-7.08)*	(-7.21)*	(37.65)*	(31.89)*	(-18.2)*	(-15.46)*
GSCI	0.0362	0.0342	0.1630	0.3841	0.0387	0.0339	-0.9603	-0.8004
	(19.06)*	(17.52)*	(1.05)	(2.39)**	(22.35)*	(18.73)*	(-8.04)*	(-6.44)*
GOLD	-0.0123	-0.0191	1.4233	2.0784	-0.0083	-0.0192	0.4533	0.8794
	(-5.63)*	(-8.77)*	(7.86)*	(11.51)*	(-4.71)*	(-10.71)*	(4.11)*	(7.63)*
Constant	246.23	231.13	-4379.05	-3435.29	9.3851	7.5402	-169.85	-135.10
	(14.63)*	(13.33)*	(-3.15)*	(-2.39)**	(14.94)*	(11.83)*	(-7.96)*	(-6.29)*

Table 5, continued. Effects of Algorithmic Trading on Liquidity, Controlling for Market Factors, May 1, 2008, to May 27, 2010: Cross-Sectional Time Series (CSTS) Data Analysis for $Liq_{i,t} = \alpha_i + \beta_i \mathrm{Algo}_{i,t} + \delta_i^{'} \mathrm{X}_{i,t} + \varphi_i^{'} Z_{i,t} + \varepsilon_{i,t}$

	CSTS with Fixed-effects				CSTC with Fixed-effect & AR(1)			
	Width		*Depth*		*Width*		*Depth*	
R2 within	0.6562	0.6376	0.3051	0.0993	0.589	0.5744	0.2187	0.1991
R2 between	0.4978	0.145	0.0066	0.7223	0.7664	0.7158	0.8302	0.7898
R2 overall	0.5539	0.3468	0.0913	0.2898	0.643	0.5475	0.42	0.3855
# of obs.	2210	2210	2257	2257	2212	2212	2259	2259
F(8,2197)/(8,2244)	524.2	483.17	123.14	100.96	393.99	370.96	78.57	69.79

*, **, and *** denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Note: Two direct measures of algorithmic trading (**Algo**$_{i,t}$) are ***ATS***$_{i,t}$ – percentage of volume attributed to automated trading systems and ***MSG***$_{i,t}$ – percentage of message traffic attributed to automated trading systems. Two measures of the liquidity (**Liq**$_{i,t}$) are ***Width***$_{i,t}$ – average bid–ask spread for a given size order during a trading day, and ***Depth***$_{i,t}$ – number of contracts displayed at the "top-of-the-book" (i.e., average size-in terms of contracts-of the best bid and best ask quotes). **X**$_{i,t}$ is a vector of control variables on each futures contract where ***TrdVolu*** is daily total trading volume, ***OpInt*** is daily total open interest, ***IntVola(GarKla)*** is the Garman-Klass estimate of intraday volatility, and ***ImpVola*** is implied volatility for each of the contracts based on the near-the-money options traded on those futures. **Z**$_{i,t}$ is a vector of market controls where ***GSCI*** is the Goldman Sachs Commodity Index, ***GOLD*** is spot Gold price, and ***VIX*** is the CBOE's Volatility Index. The data for the ***ATS, MSG, Width*** and ***Depth*** variables are from regular trading hours.

within and between R-squared values of our models.[25]

Our empirical results for the effects of AT on the liquidity in futures markets using direct measures that identify algorithm-generated trades and quote revisions confirm the findings for the U.S. equity markets by Hendershott, Jones, and Menkveld (2011) and the findings for the German equity markets by Hendershott and Riordan (2009). While we employ a very similar model to the one used by Hendershott, Jones, and Menkveld, our measures of AT activity do not suffer from their measurement errors. Results presented in our Tables 4 and 5 are based on four different cross-sectional time series modeling techniques and two separate direct measures of AT activity; after controlling volatility, trading volume, open interest and other market-wide factors, the findings indicate that algorithmic trading has a significant positive impact on market liquidity. This is evidenced by a decrease in spreads and an increase in depth. The nature of our dataset obtained from the CME Group precludes us from analyzing the informativeness of individual AT generated trades and quotes.

VI. CONCLUSIONS

Although the extensive use of algorithmic trading (AT) activities emerged relatively more recently in the exchange-traded derivatives in comparison to the equity markets, their impact on market quality and risk management may be more substantial. In order to analyze the potential effects of DMA, AT, and their accompanied changes in exchange-traded derivatives markets, this study provides an extensive review of the research in both equity and derivatives market microstructure.

After synthesizing the very recent and limited empirical evidence for the effects of algorithmic trading in equity markets, our research presents empirical results based on a unique dataset of algorithmic trading activity in five futures contracts electronically traded at the CME Group exchanges. To the best of our knowledge, this study is the first to provide such empirical evidence for the U.S. futures markets.

The uniqueness of the dataset used in this study is due to the explicit identification (direct measurement) of algorithmic trading volume — the proportion of executed orders originated from ATS to the total electronic orders executed (***variable ATS***). CME Group data also include the proportional volume of electronic message traffic attributed to ATS (***variable MSG***). Our empirical results are based on the Crude Oil, Euro FX, Eurodollar, S&P 500 E-mini, and 10-year U.S. Treasury Note futures, for the time period between May 1, 2008, and May 27, 2010.

After controlling for short- and longer-term volatility, trading volume, and open interest, as well as other market-wide factors, we find that an increase in the proportion of trading associated with algorithmic trading systems (***ATS***) decreases the width (spreads) and increases the market depth in futures trading. When an AT's proportion of electronic message traffic (***MSG***) is used as a measure of

25. We estimate equations (9) and (10) using various combinations of market control variables and find no material change in our overall results for the impact of AT on liquidity.

algorithmic trading activity, we observe similar statistically significant results. Our models explain relatively large portions of within and between variations in the cross-sectional time series data, and our coefficient estimates for the volatility, volume, and open interest all have the expected signs and significance. Similar to recent research in equity markets, our results for the U.S. futures markets conclude that algorithmic trading has a positive impact on market liquidity.

It is our intent that this paper will provide guidance to market participants, exchanges, and regulators because it presents empirical evidence on early stages of DMA and AT in futures markets and discusses the implications of these developments for exchange-traded derivatives markets.

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