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Microstructure Characteristics of U.S. Futures Markets

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Ahmet Senol Oztekin

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To: Dean David R. Klock
College of Business Administration

This dissertation, written by Ahmet Senol Oztekin, and entitled Microstructure Characteristics of U.S. Futures Markets, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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ABSTRACT OF THE DISSERTATION

MICROSTRUCTURE CHARACTERISTICS OF U.S. ELECTRONIC FUTURES MARKETS

by

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Prior finance literature lacks a comprehensive analysis of microstructure characteristics of U.S. futures markets due to the lack of data availability. Utilizing a unique data set for five different futures contract this dissertation fills this gap in the finance literature. In three essays price discovery, resiliency and the components of bid-ask spreads in electronic futures markets are examined. In order to provide comprehensive and robust analysis, both moderately volatile pre-crisis and volatile crisis periods are included in the analysis.

The first essay entitled “Price Discovery and Liquidity Characteristics for U.S. Electronic Futures and ETF Markets” explores the price discovery process in U.S. futures and ETF markets. Hasbrouck’s information share method is applied to futures and ETF instruments. The information share results show that futures markets dominate the price discovery process. The results on the factors that affect the price discovery process show that when volatility increases, the price leadership of futures markets declines.

Furthermore, when the relative size of bid-ask spread in one market increases, its information share decreases.

The second essay, entitled "The Resiliency of Large Trades for U.S. Electronic Futures Markets," examines the effects of large trades in futures markets. How quickly prices and liquidity recovers after large trades is an important characteristic of financial markets. The price effects of large trades are greater during the crisis period compared to the pre-crisis period. Furthermore, relative to the pre-crisis period, during the crisis period it takes more trades until liquidity returns to the pre-block trade levels.

The third essay, entitled "Components of Quoted Bid-Ask Spreads in U.S. Electronic Futures Markets," investigates the bid-ask spread components in futures market. The components of bid-ask spreads is one of the most important subjects of microstructure studies. Utilizing Huang and Stoll's (1997) method the third essay of this dissertation provides the first analysis of the components of quoted bid-ask spreads in U.S. electronic futures markets. The results show that order processing cost is the largest component of bid-ask spreads, followed by inventory holding costs. During the crisis period market makers increase bid-ask spreads due to increasing inventory holding and adverse selection risks.

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CHAPTER 1: PRICE DISCOVERY AND LIQUIDITY CHARACTERISTICS FOR U.S. ELECTRONIC FUTURES AND ETF MARKETS

1.1. Introduction

Futures contracts, electronically traded exchange traded funds (ETFs), and their underlying cash markets are three different types of instruments used for speculative, investment, and/or hedging purposes. The inter-related nature of these securities allows us to address the issue of market completeness versus redundancy. Thus, we ask which inter-related instrument(s) incorporate new information and which instrument(s) simply derives its prices from the other markets. Moreover, analyzing the price discovery process provides important information on where informed traders focus their attention. Thus, such knowledge allows participants to determine which markets are most fair and orderly.

The microstructure issues of U.S. futures markets have received little attention compared to equity markets, mainly because of the historical lack of bid-ask quotes from floor-traded futures contracts. Thus, previous authors needed to proxy futures bid-ask spreads from the futures price series. However, Locke and Venkatesh (1997) show that spread estimators ineffectively proxy floor-traded futures bid-ask spreads. In addition, futures floor-traded data incorporates inaccurate recording problems, including the time displacement of the sequence of trades and prices on the official price record.

In order to analyze the dynamic and time-varying nature of the relative price discovery process of these markets we employ Hasbrouck's (1995) information share methodology. Furthermore, we extend our analysis by examining the determinants of the price discovery process in these markets. We then explore the effects of large trades and the depth of the market by computing the time series and cross-sectional differences in these liquidity measures across asset classes. Included in our analysis is a comparison of the 2008 financial crisis to the pre-crisis period to show how the different characteristics of market behavior affect the price discovery shares of various financial instruments for different market conditions. Hasbrouck's information share method is based on the Law of One Price. Thus, prices of the same or related instruments cannot deviate from one another in the long run because of arbitrage activity. Consequently, the same or related assets share a common value. Therefore, the information share method measures the contribution of each instrument to this common value.[1]

Our examination of ETFs in the price discovery process is consistent with the importance of ETFs as an important investment tool in modern financial markets. During the 2008 financial crisis 716 ETFs traded in U.S. equity markets, with the daily average trading volume for the SPY ETF alone approaching 42 billion dollars. Moreover, the initiation of electronic trading in futures markets and the subsequent growth in high frequency trading in the new millennium (Karazoglu, 2011) represents a major structural change in markets.[2] In order to capture the microstructure effects in these markets we employ bid-ask spread data for electronically traded futures contracts on stock index, currency, and gold and their associated electronically traded ETFs. The literature conflicts on the importance of ETFs in price discovery: for example, see Hasbrouck

[1] Hasbrouck's (1995) information share method provides maximum and minimum values for each futures and ETF pair. In the regression we first employ the ratio of the daily average values of the information shares. Then we repeat our regression analysis using the daily maximum and minimum information share values separately.

[2] A rich literature highlights the increased trading efficiency obtained by electronic trading (e.g., Jain 2005).

(2003) versus Tse, Bandyopadhyay and Shen (2006). Using both U.S. equity index futures and ETF data, Hasbrouck determines that the e-mini S&P 500 futures contributes more to price discovery than does the floor-traded SPY ETF. Alternatively, Tse, Bandyopadhyay and Shen show that the contribution made by the DIA ETF to price discovery is greater than the contribution made by floor-traded futures.

In order to explore the effects of liquidity measures as determinants of the price discovery process we utilize two methods that have rarely been used in this context before. We calculate the price impact of trades using Hasbrouck's (2004) sequential trading based model and then examine the market depth of futures and ETFs with Engle and Lange's (2001) VNET method. With Hasbrouck's model we analyze not only the first component of transactions costs (the bid-ask spread), but also the second component (the price impact of trades). These additions provide a more comprehensive analysis than previous studies (Ates and Wang 2005, Schlusche 2009). Moreover, Engle and Lange argue that the best quoted depth does not provide the full depth in markets, whereas VNET depth captures the realized market depth by measuring the actual trade volume required to move prices. Finally, our approach differs from previous studies in the literature by examining the *determinants* of price discovery for various U.S. electronic futures relative to their corresponding ETFs.[3] We also compare these results for a highly volatile period versus an average volatility period. Thus, we determine whether analyzing two distinctly different volatility periods provides evidence concerning differing determinants of the price discovery process.

[3] The stated objective of the ETFs used in our sample is to replicate the returns achieved in the associated spot markets. However, ETF prices do include tracking error (Shin and Soydemir, 2010; Petajisto, 2011).

Previous studies that explore the determinants of the price discovery process document different variables as significant factors. For example, Theissen (2002) employs German DAX equity index futures and spot data to show that trading volume positively affects price leadership of a market. Alternatively, Martens (1998) uses Bund futures and Schlusche (2009) employs DAX futures and ETFs to document that a market's relative contribution to price discovery depends *solely* on the level of volatility. Both of these results contradict the transactions costs hypothesis (Fleming, Ostdiek, Whaley., 1996) which relies on the actual costs of transactions.[4] Alternatively, Ates and Wang (2005) use floor and *electronically* traded currency futures in U.S. markets to show that price discovery is affected by the relative liquidity in the floor-traded and electronic markets, whereas volatility does not affect price discovery. Regarding the research here, the use of extensive intraday data enables us to analyze the effects of specific factors (i.e., the price impact of trades and market depth) that are overlooked in previous studies on price discovery. In addition, we examine how market characteristics such as volatility and other time-varying factors affecting price discovery help us to resolve conflicting results regarding price discovery and its determinants. Our results find support for *both* the transactions cost and leverage hypotheses,[5] as well as the significance of volatility in the price discovery process in these markets.

Overall, our study contributes to the literature by investigating the price discovery process of electronically traded futures and ETFs across a variety of asset classes, and

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[4] The Transactions Cost Hypothesis states that markets with lower transactions costs (higher liquidity) exhibit a higher information share.

[5] The leverage hypothesis states that leveraged financial instruments attract more informed trading than non-leveraged instruments. The reason is that informed traders prefer leveraged instruments to take advantage of their information to increase their profits.

then examining the determinants of the price discovery process in these markets. Specifically, our study contributes to the literature in the following ways. First, we use electronic markets data instead of floor-traded prices (especially for futures markets), which provides almost instantaneous trade execution and therefore a more accurate representation of when information is fully disseminated into market prices. Second, our real time bid-ask spread databases make it possible to present the first major analysis of bid-ask *quotes* for U.S. electronic futures markets, such that our results are not affected by floor-traded bid-ask estimator bias. A third contribution to the literature is our examination of three different inter-related markets (futures, their corresponding ETFs, and the related underlying cash instruments), as well as studying different asset classes (stock market indexes, currency, and metal futures/ETFs), with both of these factors adding to previous research on price discovery. Moreover, although a number of studies examine price discovery, they do not compare ETFs with futures on automated trading platforms.[6] Fourth, we not only analyze the market microstructure liquidity characteristics of futures contracts and their corresponding ETFs, but we also explore how price discovery is affected by market depth, volatility, informed trading and liquidity, including employing the bid-ask spread and the price impact of larger trades. Thus, our results provide a depth and breadth of results not available elsewhere, especially in terms of whether information shares are invariant to asset classes. Finally, and perhaps most importantly, previous studies employ data from relatively stable periods, whereas we examine the volatile financial crisis of 2008 versus the less volatile pre-crisis period of 2007 in order to understand the relative importance of liquidity,

[6] In addition, we examine ETFs that are electronically traded, rather than floor traded ETFs as with Hasbrouck (2003).

volatility, and VNET depth for price discovery in futures and ETFs in different market environments.

Our results show that price discovery occurs mainly in the highly liquid and highly leveraged futures markets. These findings support the transaction cost hypothesis, as well as the leverage hypotheses. Besides futures and ETF data, we also employ spot market data for currencies and the stock market cash index to analyze the price discovery process of these underlying markets. Our results show that futures markets lead the price discovery process, followed by the spot market and then ETFs.

The results also show that *both* the ratio of the quoted percentage spreads between the futures contracts and the corresponding ETFs, and the level of their overall volatility, determine the relative information shares of these markets. This result holds for all three types of instruments (stock market indexes, currencies, and metal futures/ETFs). Other variables (such as the ratio of the impact of trades on prices and the ratio of the daily average dollar volume of futures and ETFs) do not significantly change the value of the information shares.

The presentation in the following sections is organized as follows: Section 2 provides a brief literature review of price discovery for futures and ETFs. Section 3 describes the data. Section 4 presents our research methods and section 5 discusses our results. Concluding remarks and suggestions for future research are summarized in the last section.

1.2. Literature Review

Previous studies (Pirrong, 1996; Grammig, Schireck, Theissen, 2001; Hasbrouck, 2003; Kurov and Lasser, 2004) compare electronic markets to floor trading (mostly in equities), showing that electronic markets provide anonymity, fast execution and higher information efficiency advantages to traders relative to floor trading.[7] In fact, Hasbrouck (2003) shows that e-mini electronically traded futures contracts are the dominant source of information compared to floor traded equity futures, ETFs, and the associated cash index. However, Tse, Bandyopadhyay and Shen (2006) show that electronically traded Dow Jones ETFs contributes significantly to the price discovery process relative to the Dow futures. Therefore, instead of asking which instrument dominates price discovery, the more relevant question to ask is what characteristics and market conditions cause one instrument to provide a greater contribution to the price process?

Futures contracts provide anonymity, execution speed, leverage and information efficiency advantages to investors, as noted above. Alternatively, Alexander and Barbosa (2008) argue that ETFs' popularity among *individual* investors has increased due to the ability to be sold short and their low transactions costs for small size trades. Deville (2008) states that ETFs are more convenient as trading instruments compared to futures for smaller orders and liquidity traders. Hegde and McDermott (2004) say that lower prices per share and smaller contract sizes for ETFs make them more suitable investment vehicles for many investors. ETFs also represent quick ways of taking exposure in particular sectors and strategies. As such, ETF have the potential to lead price discovery in terms of industry specific information and information that is more dispersed across many traders. Consequently, ETFs provide an interesting alternative to futures contracts and the cash market.

[7] Subrahmanyam (p. 529, 2009) defines information efficiency as "the amount of private information revealed in the market price."

Another line of research analyzes the *determinants* of the price discovery process. Admati and Pfleiderer (1988) theoretically show that both informed and liquidity traders prefer to trade in liquid markets. In this sense liquidity enhances the incorporation of private information into prices by attracting informed traders. Analyzing stocks, futures, and options in U.S. markets, Fleming, Ostdiek, Whaley (1996) document that a traders' choice on which market to use depends on the relative transaction costs in alternative markets. They show that the market with the smallest transactions costs attracts informed traders and therefore dominates the price discovery process. Martikainen and Puttonen (1994) and Zhong, Darrat, and Otero. (2004) find similar results for Finnish and Mexican stock markets. Consequently, in order to examine the relation between price discovery and transactions costs, several authors study the effect of a reduction in tick size on price discovery in futures and stocks: Baillie, Booth, Tse and Zabotina (1999) uses the information-share approach, Chu, Hsieh and Tse, (1999) and Hsieh (2004) employ a common-factor decomposition approach, and So and Tse (2004), Roope and Zurbruegg (2002), and Covrig, Ding, and Low (2004) employ both approaches. They all find that price discovery improves with a reduction in the tick size, which reduces transactions costs. Regarding bid-ask spreads, Theissen (2002) finds that the size of the *relative* bid-ask spread across different markets only weakly explains the contribution to price discovery, whereas Wang and Ates (2005) show that using the ratio of spreads with currency futures provides a much stronger evidence of spreads affecting price discovery. Unlike our study, none of the studies mentioned here use data from a financial crisis period, when price discovery is particularly important.

Volatility is another potential determinant of price discovery. Schlusche (2009) reports that the price discovery process for DAX futures and its associated ETF is only affected by its volatility, not its liquidity. Martens (1998) and Franke and Hess (2000) empirically document that the German bund futures using the Automated Pit Trading System (APT) on the London International Financial Futures Exchange's (LIFFE's) made a greater contribution to price discovery during periods of higher volatility, whereas the Deutsche Terminborse (DTB) futures made a larger contribution to price discovery during periods of low volatility.[8] Our study helps resolve this debate by focusing on the difference between a highly volatile crisis period and a normal period, a factor that is not examined in these studies. Finally, Theissen (2002) finds that the contribution made to price discovery by the trading system employed was positively related to the size of the market share. In conclusion, different studies document different variables as the main determinant of price discovery. Our goal is to resolve this debate by providing a more comprehensive study of the factors most closely related to price discovery.

1.3. Data

We employ electronic market transactions and bid-ask quotes for five different futures contracts. The futures employed are chosen to represent a cross-section of different asset classes; the associated ETFs represent the top ranking ETFs by trading volume in their respective categories. The futures data are from CQG and the ETF trade and quotes data are obtained from TAQ. Our sample includes the E-mini S&P 500, E-mini NASDAQ 100, British pound, the Euro currency, and gold futures. The

[8] We use electronic market data as it is the dominant venue for futures trading during our period of study. For example, according to CME's website during the pre-crisis period in 2007 electronic futures markets created 77% of the trading volume, whereas floor trading only caused 23%. Similarly, during the crisis period the volume share of the electronic market was 84%, with floor trading being 16%.

corresponding ETFs trade with ticker symbols of SPY, QQQ, GLD, FXE and FXB. Our sample period covers the September through December 2008 financial crisis as well as the January through March 2007 pre-crisis "normal" time period.[9] The instrument specifications for the futures contracts are described in Table 1.1 Panel A. The ETFs used in this study and the markets they follow are listed in Panel B of Table 1.1. Following Engle and Lange (2001), the first five minutes of each trading session are excluded.[10]

1.4. Empirical Methodology

1.4.1. Price Discovery

In the finance literature the price discovery process across related instruments are typically analyzed using Hasbrouck's (1995) information share (IS) or Gonzalo Granger's (1995) component share (CS) methods. Baillie et al. (2002) argue that although the IS and CS methods seem different, they share a lot in common, since both techniques are based on the vector error correction models. In this study we utilize Hasbrouck's IS method in order to determine the price discovery ability of electronically traded futures contracts versus their related ETFs; for some tests their associated cash markets also are examined.

Hasbrouck's information share methodology is the first process we employ to analyze the price discovery process in the futures, ETF and spot markets. This price

[9] The selection of these periods is based on the logic provided by Anand, Irvine, Puckett and Venkataraman (2013). Following their paper we use the first quarter of 2007 as the benchmark period and the last quarter of 2008 (the Lehman Brothers bankruptcy) as the crisis period. We examine the active nearby expiration contracts and roll the contracts to the next expiration when either the volume of the deferred contract becomes dominant, or at least one week prior to the expiration of the nearby contract. Furthermore, trades that occur on the same side of the market, at the same price, and within the same minute are combined into one transaction. Bid-ask spreads that are more than $5 per unit price are discarded as misprints or outliers.

[10] When the first five minutes are included the quantitative results change by less than 1% and qualitative inferences are unchanged.

discovery model is based on the assumption that arbitrage prevents prices of these related securities from widely diverging. The information share of an instrument is measured as that instrument's contribution to the total variance of the common (random-walk) component. If p_t^X represents the price of asset X and p_t^Y represents the price of asset Y, then a vector error correction model of order K lags of the price changes can be represented as:

$$\Delta p_t = A_t \Delta p_{t-1} + \ldots + A_k \Delta p_{t-k} + \gamma (z_{t-1} - \mu_z) + u_t \tag{1.1}$$

where $p_t = \begin{bmatrix} p_t^x \\ p_t^y \end{bmatrix}$ is the column vector of prices, A_i is the squared autoregressive coefficient matrix of order n for the number of instruments analyzed, γ is vector of the speed of adjustment coefficients, $\mu_z = E(p_t^X - p_t^Y)$ stands for the mean vector of deviations representing the long-run average price difference between the two markets, $z_t = p_t^X - p_t^Y$ is the price difference matrix, and the γ $(z_{t-1} - \mu_z)$ term equals the error correction coefficients. Also, $u_t = \begin{bmatrix} u_t^x \\ u_t^y \end{bmatrix}$ is the vector of random innovations with the covariance matrix of $\begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$. The linear combinations of the random innovations in the prices of X and Y provides the innovations of the common price:

$$\eta_t = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} u_t^x \\ u_t^y \end{bmatrix} \tag{1.2}$$

where the a_{ij} are determined from the VECM parameters. The variance of the common price is then:

$$\mathrm{Var}(\eta_t) = [a_{11} \quad a_{12}] \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{12} \end{bmatrix} \tag{1.3}$$

When the covariance matrix is diagonal ($\sigma_{12} = 0$):

$$\mathrm{Var}(\eta_t) = \mathrm{Var}(\eta t A) \ = \ a_{11}^2\sigma_1^2 + a_{12}^2\sigma_2^2 \tag{1.4}$$

The information share for security X is then equal to

$$\mathrm{IS}_x = \frac{a_{11}^2\sigma_1^2}{\sigma_\eta^2} \tag{1.5}$$

Similarly, the information share for security Y is:

$$\mathrm{IS}_y = \frac{a_{12}^2\sigma_2^2}{\sigma_\eta^2} \tag{1.6}$$

Hasbrouck's method constructs upper and lower bounds for the information shares by orthogonalizing (rotating) the covariance matrix to determine the explanatory power of a particular market. Following Hasbrouck (2003) we use the quote mid-points for prices in order to avoid the bid-ask bounce issue.[11]

1.4.2. Determinants of the Price Discovery Process in Futures and ETFs

After determining which market(s) dominate the price discovery process, for both the crisis and pre-crisis periods, we then explore the relative importance of the determinants of the daily variation in information share of the futures and ETF markets. Specifically, using a regression model we test how the price discovery process is affected

[11] Bid-ask bounce is the constant reversal of trade prices between the bid and ask sides of the market. Using trade prices causes the price series to appear to oscillate between the bid and ask prices, even though the true value of the asset does not change.

by the relative liquidity (the price impact of trades and the bid-ask spread), market depth (as measured by VNET, i.e. the volume needed to move prices 0.5%), daily dollar volume, declining average trade size, increasing adverse selection cost, and the aggregate volatility of the futures and ETFs.

We employ the bid-ask spread and the price impact of trades in order to explore the effects of liquidity on price discovery. VNET measures the realized depth; by including VNET we test the effect that market depth has on price discovery. Adverse selection cost (Glosten and Harris (1987)) and higher average trade size are used to capture informed trading activity (O'Hara, 1987).

1.4.2.1. The Bid-Ask Spread

Trading costs have three main components (Fleming, Ostdiek, and Whaley, 1996). These costs are the bid-ask spread, the market impact of trades, and brokerage commissions. Fleming, Ostdieck, and Whaley state that in a perfectly frictionless and rational market, new information should be incorporated simultaneously into the prices of similar securities traded in different markets. However, their results show that the price discovery process is dominated by the lowest-cost market.

In order to explore the effects of the first component of transactions costs (the bid-ask spread) on price discovery we calculate the average of the percentage quoted spreads for each day and each instrument. We obtain the percentage spread by dividing the dollar quoted spread by the midpoint of the bid and ask quotes. Ates and Wang (2005) show, that the ratio of the spreads between the electronic market and floor trading is the *only* significant factor affecting the price discovery process. According to their results, when the relative spread increases in one market, its contribution to the price discovery process decreases. In our analysis we employ the ratio of the daily average electronic futures spread to the ETF electronic spread to examine price discovery.

1.4.2.2. Trade Impact

According to the transaction cost hypothesis a second factor that can affect information share is the market impact of transactions on prices. Market impact measures the percentage of the price variation that can be attributed to trade size, and is determined using Hasbrouck's (2004) sequential-trading-based regression equation. Hasbrouck) develops a Markov Chain Monte Carlo (MCMC) based method to assign trade direction for floor traded markets. Since bid-ask quotes are available from our electronic markets, we classify trade direction by using the methodology introduced by Lee and Ready (1991) to obtain a more powerful test than the MCMC method, which is based only on *inferred* spreads from transactions prices.

We use the following regression model in order to analyze the impact of trades on the futures and ETF markets:

$$\Delta m_t = \sum_{J=0}^{J} q_{t-j} \lambda_j v_{t-j} + u_t \tag{1.7}$$

where m is the midpoint of the ask and bid quotes, q is the trade direction (which takes the value of 1 for buy orders and -1 for sell orders based on the Lee and Ready algorithm),[12] λ (1x2) is the two element coefficient vector for the impact of these trades, which is multiplied by the associated two element vector v:

[12] The Lee and Ready (1991) algorithm classifies a trade as a buy (sell) if the trade price is closer to the ask (bid). Trades that occur exactly at the mid-quote are classified according to the tick rule of the previous trade. In such cases if the trade price is larger (smaller) than the previous price then it is classified as a buy (sell).

$v_{t-j} = [1\ \sqrt{volume}]'$. (1.8)

where volume is the dollar trade volume of each transaction. Hasbrouck argues that the square-root transformation in (8) is motivated by trade-price impact studies in equity markets that generally find concavity in the relation.

For our information share regression, one of the key explanatory factors is λ, which represents the daily ratio of the trade impact values between the futures contract and the ETF. As discussed previously, we expect the market with a lower price impact to have a higher information share. The ratio λ captures the relative transactions costs of the two instruments in terms of the price impact of the trades of these instruments. We expect the coefficient to be negative according to the transaction cost hypothesis, since the transaction costs and its information share in a given market are negatively correlated. In addition, in our regression the ratio of the daily dollar volumes of the instruments determines the relative activity of the two instruments.

1.4.2.3. VNET Market Depth

We calculate the net directional volume (VNET depth) values in order to measure the market depth in the futures and ETF markets, as well as allowing us to examine the effect of market depth on information share price discovery in the three inter-related markets. VNET (Engle and Lange, 2001) is based on the assumption that price changes occur due to the imbalance between buyer and seller initiated trades. Thus, VNET is the net directional volume (i.e., the difference between the volume of buyer-initiated volume and the volume of seller-initiated volume) causing a given price change over a time interval (called the price duration). Engle and Lange (2001) argue that on an ex-post basis the VNET measure captures the realized market depth. The formula for VNET is:

$$\text{VNET} = \left|\sum q_i \, \text{Vol}_i\right| \tag{1.9}$$

where q_i is the direction of the trade (1 for buy, -1 for sell) and Vol_i is the dollar trade volume. Engle and Lange (2001) determine VNET by picking price level thresholds in order to obtain a daily average number of price durations. Since the price levels of futures and ETFs are substantially different, we define the "price duration" as the amount of time *between* 0.5% cumulative price changes.[13] In this context, VNET measures the realized depth that is associated with a certain percentage price change. For example, when market depth is low, a smaller net directional volume is sufficient to change prices 0.5% and the VNET value is lower compared to the periods when a higher volume is required to move prices. Engle and Russell (1998) show that the expected length of the price durations is inversely proportional to volatility. Accordingly, lower VNET values would be expected in a time series of a crisis compared to a non-crisis period, whereas a cross-section of the market with higher depth should have larger VNET values.

1.4.2.4. Regression Model for the Determinants of Price Discovery

We examine how liquidity affects the price discovery process by analyzing the effects of the ratio of bid-ask spreads, daily dollar volume, trade impact, average dollar trade size,[14] VNET depth values, and volatility on the information shares of futures and ETFs. In order to minimize the effects of microstructure noise (as discussed by Andersen and Bollerslev, 1998), we employ a five-minute sampling frequency in order to measure the daily volatility in markets, as done by Schlusche (2009). Since the daily volatility in

[13] The results are consistent when 0.1% and 0.25% price changes are used for the price durations.

[14] O'Hara (1987) argues that informed traders use larger orders compared to uninformed traders. To analyze whether relative order sizes affect the price discovery in futures and ETF markets we use the ratio of the futures and ETF average dollar trades sizes.

both the futures and ETF markets show an extremely high correlation,[15] we employ the aggregate standard deviations of the futures and corresponding ETFs, which is consistent with Andersen and Bollerslev (1998) and Schlusche (2009). The regression equation to examine what factors affect information share (IS) is given in (1.10):

$$IS_t = \beta_0 + \beta_1 Rspread_t + \beta_2 Rvolumet_t + \beta_3 Volatility_t + \beta_4 Rvnet_t + \beta_5 Rtrade\_impacts_t + \beta_6 Rtrade\_size_t \quad (1.10)$$

where Rspread is the ratio of the percentage spreads, Rvnet is the ratio of the VNET values, Rvolume is the daily average dollar volume ratio, Rsize is the ratio of the average dollar trade sizes, Rtrade value is the ratio of the liquidity coefficients in the futures and ETF markets, and volatility is the aggregate of the two market's volatility on day t, where the daily volatility is calculated as the sum-of-squares of the five-minute intraday returns (Andersen and Bollerslev, 1998). Each variable in the model employs trade-by-trade data to determine the daily value. The t-statistics are calculated using Newey-West corrected standard errors to adjust for any potential serial correlation.

We also test the effects of the adverse selection component of effective spreads on price discovery (Glosten and Harris, 1987; Hendershott, Jones and Menkveld, 2011). The adverse selection cost of a spread is calculated as:

$$Adv\_selection_{jt} = q_{jt}\,(m_{j,t+5min} - m_{j,t})/m_{j,t} \quad (1.11)$$

[15] Average dollar volume, trade size, percentage spreads and other factors are different in futures and ETF markets, but volatility is similar as they follow the same underlying cash or spot market and the ratio is almost equal to1. Therefore, instead of using the ratio of volatility, we employ the aggregate value for volatility.

where q_{jt} is the trade direction indicator, $m_{j,t}$ is the midpoint of the prevailing quote, $m_{j,t+5min}$ is the quote midpoint five minutes after the trade and q takes the value of +1 for purchases and -1 for sales.

Grammig and Peter (2013) argue that the upper and lower bounds of the information share values diverge at higher sampling frequencies. Thus, since we employ trade by trade high frequency data, we also execute the regressions given above for the ratios of the maximum values and the ratios of the minimum values of the information share as a robustness check.

1.5. Results

1.5.1. Price Discovery, Liquidity and Market Depth in Futures and ETF Markets

1.5.1.1. Information Share Results

We start our empirical analysis by exploring the price discovery process of futures, ETFs, and the underlying spot markets. Panel A of Table 1.2 (left columns) shows the mean information share values obtained using Hasbrouck's (1995) model for the inter-related futures and ETF instruments. In Panel B we extend the scope of the analysis of the inter-related markets, determining the information share values for futures, ETFs, and their underlying spot markets.

The results in both panels show that the price discovery process is dominated by futures, both for the pre-crisis and crisis periods. The implication is that informed traders engage in futures markets more than in ETFs. The dominance of futures over ETFs is most prominent for currency markets. Specifically, the British pound futures possess an information share)of 0.983 versus the information share of 0.017 for the British pound ETFs during the pre-crisis; for the crisis period the pound futures and ETF information share values are 0.973 and 0.027, respectively. Similarly, the Euro futures possess a large information share of 0.963 and a value of 0.037 for the ETFs during the pre-crisis and 0.941 and 0.059 for the crisis period, respectively. The dominance of futures over the ETFs is least prominent for metals: comparing gold futures to the gold ETF shows the smallest difference in information shares between the two markets (an information share of 0.762 for futures vs. a value of 0.238 for ETFs during the pre-crisis, and values of 0.731 for futures and 0.269 for the ETF during the crisis). These results show that the gold ETF (GLD) attracts more informed trading relative to the currency and equity ETFs[16].

Panel B of Table 1.2 reports our information share results for the expanded set of inter-related securities of futures, ETFs, *and* spot markets. These results show that futures remain the main venue for price discovery, followed by the spot market, then the ETFs. In fact, spot markets have a higher information share than ETFs for *all* asset classes in this study, with these results being consistent for both the pre-crisis and crisis periods.

Next we analyze the changes in the price discovery shares of these instruments during the crisis period. The general conclusion is the information share of the (leveraged) futures market declines during the volatile crisis period. We arrive at this conclusion for all asset classes when we compare the information share of futures during the pre-crisis period with the information share during crisis period in any given row of Table 1.2. This pattern is particularly obvious in Panel B when all three instruments are

[16]Daigler and Padungsaksawasdi (2014) document that gold exhibits a positive risk-return relation, opposite to stocks and currencies. The reasoning is that gold "crashes" upward, whereas the stock market crashes downward; currencies can have large moves in either direction. They argue that gold is considered a safe haven and generally used for hedging purposes. Consequently, ETFs could be suitable for hedgers as they are not leveraged and thus less risky than futures markets.

analyzed. For example, the E-mini S&P 500 futures information share declines from 0.722 in the normal period to 0.633 during the crisis period, whereas the information share of ETFs and cash indexes increase. Specifically, the information share for the SPY ETF increases from 0.081 in the pre-crisis period to 0.136 in the crisis period. Similarly, the cash index's IS increase from 0.157 in the pre-crisis period to 0.231 in the crisis period. Thus, the analysis of changes in information share values show that the price discovery share of cash indexes and ETFs increase during the crisis period, whereas the contribution of the futures correspondingly decline.

In Table 1.3 we report the information share values for the futures and ETFs in our sample for each month during the crisis period. According to these results, the futures contracts consistently dominate their ETF pairs during *each* of the four months. This shows that our results are not driven by an extreme value in one month, rather they are consistent throughout the crisis period.

1.5.1.2. Liquidity in the Futures and ETF Markets

After documenting that futures contracts possess higher information share values than the ETFs, we now turn our attention to the study of the determinants of price discovery. Here we examine the liquidity of these instruments as a potential determinant of the relative information shares. Table 1.4 shows our results for the size of the percentage spreads and Hasbrouck's (2004) sequential trading model on the price impact of trades. The first two numerical columns of Table 1.4 report the average percentage spreads for the futures and ETFs for the two time periods. The ETFs possess much larger percentage spreads than the futures. The next set of columns shows that the trade impact coefficients from the regression are significantly smaller for futures than for ETFs, which is consistent with the percentage spread results.

Brunnermeier and Pedersen (2009) and Chiu et al. (2012) show that the borrowing constraints of investors during the crisis period adversely affected liquidity in financial markets. The pre-crisis versus crisis comparison of the bid-ask spreads shows that the percentage spreads of every instrument in our sample increased during the crisis period, which is consistent with the worsening of liquidity in the futures and ETF markets during the crisis period. Also, the effect of the trade impact aspect of liquidity for both the futures and ETFs deteriorate (become larger) during the crisis period.

Hasbrouck (2004) argues that the R-squared values for the sequential trading-based regression model show to what extent traders are informed in one market. In other words, the R-squared values in Hasbrouck's model measure the proportion of price changes that originates from the trading activity. Consistent with our information share results, the R-square values for the futures contracts are higher than the ETFs, both in the pre-crisis and crisis periods. Also during the crisis period trades explain a lesser percentage (smaller R-square values) of the price changes for both the futures and ETF markets. The last column of the table reports the standard deviations of returns, which shows the increased volatility existing during the crisis period. The results for the R-squared values and standard deviations show the heightened uncertainty in the futures and ETF markets during the crisis period. Using the crisis period provides the opportunity to analyze how price discovery and other microstructure characteristics of futures and ETFs are affected by the increased uncertainty during this period. Previous studies (Ates and Wang, 2005; Schlusche, 2009) only employ stable time periods.

Table 1.5 continues our examination of liquidity variables as determinates of price discovery, employing variables such as the average bid-ask quote sizes and the trade sizes of the futures and ETFs. Consistent with our liquidity analysis in Table 1.4, these results show that both the average bid-ask quote sizes and the trade sizes decline during the crisis. The decline in the liquidity of futures and ETFs in terms of increased trade impact, increased percentage spread, wider quotes, and lower trade sizes during the financial crisis shows the different adverse effects of the crisis on the futures and ETF markets. Thus, the volatility and liquidity results show that the pre-crisis and crisis periods provide an interesting environment to examine the effects of decreased liquidity and increased volatility on the price discovery process between futures and ETFs.

1.5.1.3. Market VNET Depth in Futures and ETF Markets

In Table 1.6 we report the average daily dollar volume and the average VNET depth, where VNET is the dollar volume needed to change prices by 0.5%. The higher the VNET, the deeper and more liquid the markets. We first discuss the levels of VNET followed by the changes in VNET. The dollar VNET values for the futures are much higher than the VNET values for the ETFs, with currency futures showing the largest difference – especially during the crisis period.[17] As Hasbrouck (2004) states, there are several other venues for currency trading (e.g., the interbank market), which could be the reason why currency ETFs exhibit less VNET depth values compared to other ETFs in our sample. Comparatively, relative to the other futures contracts, higher net directional dollar volumes (VNET) are required to change the prices of stock index ETFs. The larger VNETs for the stock index ETFs during the crisis is consistent with the increased

[17] During the crisis period of 2008 those trading currencies turned from the interbank market to the futures market to avoid the credit risk of money center banks during this time period.

popularity and volume of the ETFs during this time period, as discussed in the introduction.

Next we discuss changes in VNET from the pre-crisis period to the crisis period. During the crisis period there were a large number of 0.5% price changes compared to the pre-crisis period for all the asset classes in our sample. Moreover, the price durations (the length of the time interval when a 0.5% price change occurred) are much shorter during the crisis period (not shown here). For example, during the first quarter of 2007 there were 64 price durations for the e-mini S&P 500 futures, whereas in the last quarter of 2008 more than 3,000 0.5% price changes occurred for the same futures contract. Thus, in normal times the net directional dollar volume (VNET) needed for the futures contracts to change 0.5% is substantially less. However, the VNET results for the ETFs show that average VNET values for the ETFs are actually higher during the crisis period compared to the pre-crisis period. Consequently, changes in the daily trading volume during the crisis shows that a similar pattern occurs between the futures and ETFs, since the daily trading volumes of the ETFs are actually *higher* during the crisis period relative to the pre-crisis period.

Overall, our results show that one important development during the crisis period was the worsening of the market depth of futures markets (as measured by VNET). In contrast, the realized depth for ETFs improved.

1.5.1.4. Discussion of the Information Share, Liquidity, and Market Depth Results

The results reported above show that futures contracts are more liquid and possess larger information shares and market depth compared to the ETFs. These results are consistent with the transactions cost and leverage hypotheses, as the more liquid and leveraged futures market dominates the price discovery process. Our analysis for the crisis period shows that high volatility affects futures and ETF markets in terms of price discovery, liquidity and market depth.

We documented that both the average daily dollar trading volume and the VNET values of the ETFs increased during the crisis period, whereas both trading volume and VNET values of futures contracts declined. The liquidity measures of the percentage spread and trade impacts highlight the adverse effect of high volatility on the liquidity of both futures and ETF markets.

The significantly different information share results for futures and ETFs for the pre-crisis period versus the crisis period shows that the relative price discovery in futures and ETFs was significantly affected by the 2008 financial crisis. Thus, although futures dominate the price discovery process in both time periods, the information shares of ETFs increased (the information shares of futures declined) during the crisis period. In the next section our goal is to explore the factors that significantly affect the day-to-day variation in information share values of futures and ETFs.

1.5.2. The Determinants of Price Discovery

Using the information shares of futures contracts as the dependent variable, we test the impact of relative liquidity using the ratios of percentage spreads and of trade impacts, market depth (VNET), informed trading (average trade size and the adverse selection component of effective spreads), and aggregate volatility on price discovery. In Tables 1.7 and 1.8 we document our regression results for these potential determinants of price discovery. Unlike previous studies (Ates and Wang 2005; Schlusche 2009) that find only one factor as significant, our results in Table 1.7 show that the coefficients for volatility and the ratio of percentage spreads are significantly negative for explaining information shares. Thus, when the ratio of the percentage spreads of the futures to the ETFs decreases (i.e., the futures spreads become smaller relative to the ETF spreads), then the information share of the futures markets increases, and vice-versa. This result is consistent with the transaction cost hypothesis. Moreover, our results show that volatility also affects the information shares of futures and ETFs. This finding means that the information shares of the leveraged futures markets decline and the information shares of ETFs increase during more volatile time periods. Other variables in our model (such as the ratio of depth, trade impact, and average trade size) are not significant factors. Thus, our results show that only the percentage spread and volatility significantly affect price discovery for both the pre-crisis and crisis periods. These results support the transaction cost hypothesis. Moreover, our price discovery results show that the first component of transaction costs (namely the spread, Fleming, Ostdiek, and Whaley, 1996), is the most important measure of liquidity. Consequently, we find that during periods of high volatility the futures information shares decline, although futures still dominate the price discovery process. Table 1.8 employs the ratios of the adverse selection costs in futures and ETF markets in place of the average trade sizes. Similar to our findings in Table 1.7, Table 1.8 shows that the ratio of the spreads and the aggregate volatility are the only two significant factors affecting the price discovery process.

One potential issue with our results is the use of high frequency data to examine the information share. In particular, Grammig and Peter (2013) state that at higher sampling frequencies, such as five and ten minutes, the upper and lower bounds of the information share values diverge. Since we employ trade by trade data in our analysis we test the robustness of our results by re-examining the information shares by separately testing the minimum values in Table 1.9. We report our regression results for the determinants of price discovery using the ratios of the *minimum* values of the daily information shares of the futures relative to the ETF as the dependent variable. Our results are similar to the findings we document in Tables 1.7 and 1.8. These results also show that when the aggregate volatility in futures and ETF markets increases, the information share of futures markets declines. Moreover, the relative liquidity in one market is inversely related to its information share. Table 10 documents the results for the ratios of the maximum values of the information shares. Consistent with previous results we find that the relative liquidity and volatility variables are significant variables that affect price discovery. Overall, our results are robust, whether we employ the mean, maximum, or minimum values of the information shares.

1.6. Conclusion

Two of the most important functions of a financial market are to provide price discovery and liquidity (O'Hara 1987). The price discovery and liquidity characteristics of futures markets have received limited attention compared to equity markets. Historically, the key reason for this dearth of futures microstructure studies was the lack of bid-ask quote data, since such data is not available for floor trading transactions that dominated futures trading until recently. Alternatively, electronic exchanges gather such information. In addition, we compare the price discovery and liquidity characteristics of ETFs to futures contracts.

Using electronic quote and transaction data for futures and ETFs we analyze the price discovery processes for five different instruments during a normal and a volatile time period. We find that the futures dominate the price discovery processes during both the volatile financial crisis and the pre-crisis periods.

We also examine the liquidity characteristics of the futures and ETFs in our sample in terms of percentage spreads and the price impact of large trades. We find that currency futures are the most liquid contracts among futures, with gold being the least liquid contract. Alternatively, currency ETFs are the least liquid and equity ETFs are the most liquid among the ETFs. The lack of liquidity for currencies is consistent with the other venues of currency trading that exist, as well as the relative lack of interest in currency trading by individual investors compared to equities. Our results also show that the liquidity of both futures and ETFs decline during the crisis.

Our analysis on volume and realized market depth documents the adverse effects of a financial crisis on futures markets. Compared to the pre-crisis period both the daily dollar volume and market depth (as measured by VNET) declined in the futures market during the crisis. Alternatively, these measures are higher for the ETFs for the crisis, showing the increased interest from traders for these financial instruments during this time period (see Alexander and Barbosa, 2009, for their discussion of ETFs).

We investigate whether these liquidity changes affect price discovery in futures and ETF markets by regressing the information shares on these instruments' ratio of the bid-ask spread, the average trade size, dollar volume, the trade impact on prices, and aggregate volatility. The regression results support the transaction cost hypothesis in terms of the importance of the *relative* bid-ask spread. Moreover, our results show that volatility is another significant factor that affects the price discovery process between futures and ETF markets. Consistent with Kyle and Obhizhaeva's (2011) market microstructure invariance theorem, the determinants on price discovery are the same two factors for currency, stock index and gold futures, as well as their corresponding ETFs.

Future research projects could extend this paper to include options market data, where options on futures and options on ETFs are employed as underlying instruments. The results would determine the contribution of options to price discovery and how their contribution changes based on different market conditions.

Table 1.1 – Panel A

Futures Contract Specifications

Contract	E-mini S&P 500	E-mini Nasdaq 100	Gold
Symbol	ES	NQ	GL
Related ETF	SPY	QQQ	GLD
Tick Size	$0.25	$0.25	$0.1
Contract Size	$50 x index price	$20 x index price	100 troy oz
Expiration Months	Mar,Jun,Sep,Dec	Mar,Jun,Sep,Dec	Feb,Apr,Jun,Aug,Oct,Dec
Price Quoted in	Index points	Index points	$/oz

Contract	British pound	Euro
Symbol	M6B	M6E
Related ETF	FXB	FXE
Tick Size	$0.0001 USD/GBP	$0.0001 USD/Euro
Contract Size	6,250 British pounds	125,000 Euros
Expiration Months	Mar,Jun,Sep,Dec	Mar,Jun,Sep,Dec
Price Quoted in	USD/GBP	USD/EUR

Table 1.1 – Panel B

ETF Definitions

	Definition
SPY	Provide investment results that correspond to the price and divident performance of the S&P 500 Index.
QQQ	Provides investment results that correspond to the price and dividend performance of the Nasdaq 100 Index.
GLD	Replicate the performance of the price of gold bullion.
FXE	Tracks the price of the Euro.
FXB	Tracks the price of the British pound.

Panel A reports the specifications of the futures contracts. Contracts are traded electronically on the Chicago Mercantile Exchange's GLOBEX electronic trading platform. Panel B provides the definitions of the ETFs. Unlike the futures in our sample, these ETFs are not leveraged. All ETF performances are net of expenses. *Source*: The CMEX website.

Table 1.2
Information Shares of Futures, ETFs, and Related Cash Markets

Panel A			Panel B		
Instrument	*Pre-Crisis*	*Crisis*	*Instrument*	*Pre-Crisis*	*Crisis*
E-mini S&P 500	0.879	0.857**	E-mini S&P 500	0.722	0.633**
SPY ETF	0.121	0.143**	SPY ETF	0.081	0.136**
			Cash Index	0.157	0.231**
E-mini NASDAQ 100	0.894	0.849**	E-mini NASDAQ 100	0.770	0.661**
QQQ ETF	0.106	0.151**	QQQ ETF	0.108	0.130**
			NASDAQ 100 Cash Index	0.112	0.209**
Euro Futures	0.963	0.941*	Euro Futures	0.609	0.547*
FXE ETF	0.037	0.059*	FXE ETF	0.110	0.152*
			Euro Spot	0.281	0.351*
British Pound Futures	0.983	0.973*	British Pound Futures	0.614	0.602*
FXB ETF	0.017	0.027*	FXB ETF	0.030	0.071*
			British Pound	0.356	0.327*
Gold Futures	0.762	0.731**			
GLD ETF	0.238	0.269**			

Panel A of this table (left columns) reports the Hasbrouck (1995) information share values for the futures and ETFs in our sample. Panel B (right columns) report the results for our three-way analysis of futures, ETFs, and spot markets. The pre-crisis period covers January-March 2007 and the crisis period covers September-December 2008. The data source is CQG database for futures and TAQ for ETFs. The notations * and ** refer to the significance of the difference between the crisis and pre-crisis periods at the 5% and 1% levels, respectively.

Table 1.3
Crisis Period Monthly Information Share Values of Futures and ETFs

Instrument	*September*	*October*	*November*	*December*
E-mini S&P 500	0.864	0.842	0.847	0.876
SPY ETF	0.136	0.158	0.153	0.124
E-mini NASDAQ 100	0.858	0.832	0.827	0.879
QQQ ETF	0.142	0.168	0.173	0.121
Euro Futures	0.962	0.921	0.933	0.947
FXE ETF	0.038	0.079	0.077	0.053
British Pound Futures	0.982	0.960	0.977	0.974
FXB ETF	0.018	0.040	0.023	0.026
Gold Futures	0.741	0.725	0.719	0.747
GLD ETF	0.059	0.075	0.081	0.053

This table reports the Hasbrouck (1995) monthly information share values for the futures and ETFs in our sample during the crisis period (September-December 2008). The data source is CQG database for futures and TAQ for ETFs.

Table 1.4
Liquidity and Volatility Measures of Futures and ETFs during the Pre-Crisis and Crisis Periods

	Average Percentage Spread		*Trade Impact Coefficients*				*R-sq*		*St. Deviation of Returns*	
			Trade Direction		*Trade Volume*					
Contract	*Pre-Crisis*	*Crisis*	*Pre-Crisis*	*Crisis*	*Pre-Crisis*	*Crisis*	*Pre-Crisis*	*Crisis*	*Pre-Crisis*	*Crisis*
S&P 500 Futures	0.011	0.02	0.41	0.98	0.10	0.12	41%	31%	1.12	2.54
SPY ETF	0.018	0.04	0.54	1.32	0.23	0.36	10%	1%	0.89	2.03
NASDAQ Futures	0.013	0.02	0.53	1.11	0.09	0.12	34%	30%	1.23	2.77
QQQ ETF	0.028	0.06	0.82	1.52	0.11	0.13	08%	01%	1.21	2.59
Gold Futures	0.023	0.04	0.81	1.24	0.14	0.18	25%	22%	1.61	2.91
GLD ETF	0.088	0.20	1.14	2.05	0.51	0.92	07%	01%	1.31	2.88
Euro Futures	0.006	0.01	0.23	0.33	0.04	0.05	49%	42%	0.22	1.58
FXE ETF	0.312	0.39	3.30	4.20	0.93	1.17	01%	01%	1.47	2.23
Brit. Pound Futures	0.008	0.01	0.34	0.43	0.06	0.09	45%	43%	0.16	0.58
FXB ETF	0.366	0.72	2.20	4.42	0.86	1.46	02%	01%	1.70	2.70

This table reports the spreads and trade impact coefficients. Higher values for the trade impact coefficients are associated with lower liquidity. Trade impacts are analyzed using $\Delta m_t = \sum_{j=0}^{j} q_{t-j}\, \lambda_j v_{t-j} + u_t$ where $\lambda_j = (\lambda_{j,intercept}\ \ \lambda_{j,slope})$, $v_{t-j} = [1\ \sqrt{volume}]$, Δm_t is the change in the efficient price; the R^2 value of this regression model provides the price variation that is attributable to the trades. Trade direction $\lambda_{j,intercept}$ and trade volume $\lambda_{j,slope}$ impact coefficients are multiplied by 10,000, where trade direction (q) is equal to +1 for buy orders and -1 for sell orders. The pre-crisis period covers January-March 2007 and crisis period covers September-December 2008. The data source is CQG database for futures and TAQ for ETFs.

Table 1.5
Bid-Ask and Trade Sizes

Contract	Average Bid Size		Average Ask Size		Average Trade Size		Average Dollar Trade Size	
	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisi	Crisis
S&P 500	599.63	151.28	601.37	150.90	17.88	7.48	1,277,242	390,996
SPY ETF	318.61	72.77	303.35	77.22	8.99	4.31	129,467	38,694
NASDAQ 100	67.24	17.42	66.47	17.98	29.31	16.53	1,468,526	572,826
QQQ ETF	2006.52	462.94	1968.65	467.26	20.96	6.96	82,891	23,706
Gold Futures	6.51	3.91	6.36	3.97	4.37	2.68	294,748	207,240
GLD ETF	111.79	23.43	111.90	23.67	6.59	2.79	42,595	21,207
Euro Futures	16.58	12.39	17.64	12.06	5.63	2.59	1,008,617	417,621
FXE ETF	43.80	35.37	48.55	37.92	5.39	3.18	67,903	44,527
British Pound Futures	12.35	10.07	14.27	10.45	4.17	2.31	874,971	342,843
FXB ETF	23.18	21.28	27.92	21.38	4.38	2.87	84,713	51,947

This table provides the average quote and trades sizes. The values for ETFs are reported in lots where one lot is equal to one hundred shares. Average dollar trade volumes of transactions are reported in the last two columns. The pre-crisis period covers January-March 2007 and crisis period covers September-December 2008. The data source is CQG database for futures and TAQ for ETFs.

Table 1.6

VNET Market Depth Values

Contract	*Daily Avg. Dollar Volume (in billions)*		*Average VNET (in thousands)*		*Number of Price Durations*	
	Pre-Crisis	*Crisis*	*Pre-Crisis*	*Crisis*	*Pre-Crisis*	*Crisis*
S&P 500	73.211	56.493	3,596.502	640.391	56	3,131
SPY ETF	13.656	41.945	304.617	463.805	64	3,322
NASDAQ 100	21.464	19.399	2,817.432	582.662	77	3,361
QQQ ETF	3.342	7.818	243.256	359.186	61	3,652
Gold Futures	1.643	1.420	321.717	258.644	159	516
GLD ETF	0.371	1.343	142.216	160.259	127	492
Euro Futures	16.824	14.211	4,913.213	573.463	128	623
FXE ETF	0.011	0.103	42.916	89.666	164	782
British Pound Futures	14.345	11.853	4,214.215	549.713	133	741
FXB ETF	0.002	0.015	21.739	46.095	179	932

This table reports the daily average dollar volume market depth of futures contracts and ETFs as measured by VNET. Average VNET values show the average net directional dollar volume needed that leads to a 0.5% price change. Every interval where a 0.5% price change occurs is defined as a price duration. VNET values are calculated using the formula: VNET=Σ|qiVoli|, where “q” is the trade direction and “Vol” is the volume traded. Larger VNET values are associated with higher market depth, which means it takes greater net directional volume to change the price. The number of price durations is inversely related to market liquidity. The pre-crisis period covers January-March 2007 and crisis period covers September-December 2008. The data source is CQG database for futures and and TAQ for ETFs.

Table 1.7
Determinants of Price Discovery

Panel A: Full Sample

	E-Mini S&P 500	*E-mini NASDAQ 100*	*Euro*	*British Pound*	*Gold*
Ratio of Spreads	-1.60	-1.71	-0. 44	-0.37	-1.41
	(-7.71)	(-7.67)	(-4.87)	(-4.74)	(-5.84)
Volume	-0.35	-0.31	-0.19	-0.83	-0.19
	(-0.57)	(-0.69)	(-0.10)	(-0.88)	(-0.13)
Volatility	-2.33	-1.91	-1.51	-0.65	-1.24
	(-8.16)	(-7.14)	(-4.43)	(-3.74)	(-4.25)
VNET	-0.08	0.12	-0.29	-0.28	-0.31
	(-0.03)	(-0.05)	(-0.08)	(-0.07)	(-0.11)
Trade Impact	0.25	0.48	-0.11	0.27	0.52
	(-0.04)	(0.16)	(-0.07)	(0.09)	(0.05)
Trade Size	0.19	-0.24	0.13	-0.52	-0.20
	(0.12)	(-0.19)	(-0.15)	(-0.13)	(-0.19)
Dummy	2.81	3.14	2.24	1.63	1.03
	(-2.44)	(-2.51)	(-2.36)	(-2.49)	(-2.33)
Adjusted R-sq	27%	28%	23%	25%	17%

Panel B: Pre-Crisis

Ratio of Spreads	-1.43	-1.51	-0.89	-0.78	-1.33
	(-7.24)	(-7.49)	(-5.96)	(-5.24)	(-6.77)
Volume	0.26	0.36	0.79	-0.40	-0.58
	(-0.22)	(-0.27)	(-0.41)	(-0.33)	(-0.38)
Volatility	-2.27	-1.43	-1.29	-0.92	-1.42
	(-5.17)	(-4.11)	(-3.16)	(-3.01)	(-3.74)
VNET	-0.12	-0.19	-0.12	-0.61	-0.83
	(-0.04)	(-0.07)	(-0.13)	(-0.25)	(-0.31)
Trade Impact	0.42	0.73	-0.66	0.17	0.74
	(-0.15)	(-0.64)	(-0.73)	(-0.05)	(-0.54)
Trade Size	-0.26	-0.67	0.42	0.38	0.73
	(0.13)	(-0.22)	(0.13)	(0.08)	(0.25)
Adjusted R-sq	27%	22%	24%	21%	16%

Panel C: Crisis Period

	E-Mini S&P 500	*E-mini NASDAQ 100*	*Euro*	*British Pound*	*Gold*
Ratio of Spreads	-1.96	-1.83	-0.54	-0.47	-1.33
	(-9.26)	(-9.43)	(-6.35)	(-5.45)	(-7.12)
Volume	-0.18	-0.13	-0.27	-0.15	-0.41
	(-0.49)	(-0.45)	(-0.65)	(-0.48)	(-0.66)
Volatility	-2.14	-1.66	-1.14	-1.33	-1.06
	(-7.41)	(-6.32)	(-4.29)	(-5.42)	(-4.02)
VNET	-0.11	-0.29	-0.51	-0.46	-0.39
	(-0.05)	(-0.07)	(-0.20)	(-0.18)	(-0.15)
Trade Impact	-0.33	-0.21	-0.77	-0.29	-0.67
	(-0.08)	(-0.13)	(-0.19)	(-0.14)	(-0.16)
Trade Size	-0.61	-0.44	-0.53	-0.26	-0.69
	(-0.84)	(-0.55)	(-0.67)	(-0.18)	(-0.91)
Adjusted R-sq	29%	25%	17%	21%	18%

This table reports the OLS regression results for futures contracts information share on the spread, volume, trade size, trade impact coefficients, volatility and VNET market depth values. Every variable in the model (except volatility) is calculated using the ratio of daily values from the futures and ETFs. The model we use can be represented as: $ISt = \beta_0 + \beta_1 Spread_t + \beta_2 Volume_t + \beta_3 Volatility_t + \beta_4 Vnet_t + \beta_5 Trade\_impacts_t + \beta_6 Trade\_size_t$, where spread is the ratio of percentage spreads, Vnet is the ratio of Vnet values, Volume is the total dollar trading volume ratio, Size is the ratio of the average trade sizes, and Trade Impact is the ratio of the liquidity coefficients for futures and ETFs. Volatility is the sum of the two markets' volatility on day t, where the daily volatility is calculated as the sum of squares of the 5-minute intraday returns (Andersen & Bollerslev, 1998). We obtain the percentage spread by dividing the dollar spread by the midpoint of the bid and ask prices. Every variable in the model is calculated for each day and the information shares of the futures are regressed on these variables. T-values are reported in parentheses. Coefficients and t-values in bold values are significant at the 5% level. The t-statistics are calculated using Newey-West, which corrects standard errors to adjust for any potential serial correlation.

Table 1.8
Determinants of Price Discovery with Adverse Selection Cost

Panel A: Full Sample

	E-Mini S&P 500	*E-mini NASDAQ 100*	*Euro*	*British Pound*	*Gold*
Ratio of Spreads	-1.58	-1.75	-0. 49	-0.41	-1.53
	(-7.43)	(-7.24)	(-4.85)	(-4.61)	(-5.43)
Volume	-0.34	-0.31	-0.24	-0.74	-0.23
	(-0.55)	(-0.69)	(-0.11)	(-0.79)	(-0.16)
Volatility	-2.31	-1.93	-1.54	-0.63	-1.22
	(-8.16)	(-7.14)	(-4.39)	(-3.69)	(-4.21)
VNET	-0.11	-0.12	-0.29	-0.28	-0.31
	(-0.04)	(-0.05)	(-0.08)	(-0.07)	(-0.11)
Trade Impact	0.22	0.48	-0.11	0.27	0.52
	(-0.04)	(0.16)	(-0.07)	(0.09)	(0.05)
Adverse Selection Cost	0.64	0.37	0.29	0.57	0.83
	(0.87)	(0.64)	(0.79)	(0.63)	(0.72)
Dummy	-2.79	-3.14	-2.25	-1.66	-1.02
	(-2.38)	(-2.48)	(-2.31)	(-2.46)	(-2.31)
Adjusted R-sq	26%	28%	22%	24%	17%

Panel B: Pre-Crisis

Ratio of Spreads	-1.38	-1.53	-0.89	-0.79	-1.21
	(-7.18)	(-7.42)	(-5.96)	(-5.21)	(-6.72)
Volume	0.27	0.35	0.71	-0.45	-0.55
	(-0.23)	(-0.25)	(-0.40)	(-0.35)	(-0.34)
Volatility	-2.29	-1.45	-1.26	-0.98	-1.38
	(-5.15)	(-4.10)	(-3.11)	(-2.97)	(-3.68)
VNET	-0.13	-0.16	-0.14	-0.63	-0.81
	(-0.05)	(-0.09)	(-0.11)	(-0.23)	(-0.29)
Trade Impact	0.40	0.75	-0.63	0.20	0.71
	(-0.17)	(-0.62)	(-0.76)	(-0.05)	(-0.52)
Adverse Cost	0.53	0.38	0.48	0.73	0.62
	(0.54)	(0.71)	(0.65)	(0.71)	(0.82)
Adjusted R-sq	26%	21%	25%	23%	15%

Panel C: Crisis Period

	E-Mini S&P 500	*E-mini NASDAQ 10(*	*Euro*	*British Pound*	*Gold*
Ratio of Spreads	-1.93	-1.86	-0.57	-0.49	-1.31
	(-9.21)	(-9.38)	(-6.31)	(-5.42)	(-7.06)
Volume	-0.17	-0.16	-0.29	-0.17	-0.40
	(-0.45)	(-0.43)	(-0.63)	(-0.43)	(-0.68)
Volatility	-2.11	-1.62	-1.17	-1.29	-1.03
	(-7.29)	(-6.25)	(-4.25)	(-5.22)	(-4.01)
VNET	-0.12	-0.27	-0.53	-0.48	-0.37
	(-0.06)	(-0.09)	(-0.18)	(-0.19)	(-0.13)
Trade Impact	-0.32	-0.22	-0.75	-0.28	-0.64
	(-0.08)	(-0.12)	(-0.22)	(-0.15)	(-0.18)
Adverse Cost	0.61	0.65	0.43	0.56	-0.69
	(0.84)	(0.71)	(0.82)	(0.77)	(-0.91)
Adjusted R-sq	28%	24%	19%	20%	19%

This table reports the OLS regression results using the adverse selection component of effective spread instead of average trade sizes employed in Table 6. Every variable in the model (except volatility) is calculated using the ratio of daily values from the futures and ETFs. The model we use can be represented as: $ISt = \beta_0 + \beta_1 Spread_t + \beta_2 Volume_t + \beta_3 Volatility_t + \beta_4 Vnet_t + \beta_5 Trade\_impacts_t + \beta_6 Adverse\_cost_t$, where spread is the ratio of percentage spreads, Vnet is the ratio of Vnet values, Volume is the total dollar trading volume ratio, Adverse is the adverse selection cost component of effective spreads, and Trade Impact is the ratio of the liquidity coefficients for futures and ETFs. Volatility is the sum of the two markets' volatility on day t, where the daily volatility is calculated as the sum of squares of the 5-minute intraday returns (Andersen & Bollerslev, 1998). We obtain the percentage spread by dividing the dollar spread by the midpoint of the bid and ask prices. Every variable in the model is calculated for each day and the information shares of the futures are regressed on these variables. T-values are reported in parentheses. Coefficients and t-values in bold values are significant at the 5% level. The t-statistics are calculated using Newey-West, which corrects standard errors to adjust for any potential serial correlation.

Table 1.9
Determinants of Price Discovery Using Minimum Values of the Information Shares

	E-Mini S&P 500	*E-mini NASDAQ 100*	*Euro*	*British Pound*	*Gold*
Ratio of Spreads	-1.45	-1.59	-0.52	-0.45	-1.22
	(-7.32)	(-7.41)	(-4.46)	(-4.51)	(-5.79)
Volume	-0.39	-0.51	-0.16	-0.73	-0.17
	(-0.47)	(-0.34)	(-0.13)	(-0.92)	(-0.15)
Volatility	-2.44	-1.82	-1.62	-0.65	-1.21
	(-8.06)	(-6.89)	(-4.43)	(-3.74)	(-4.21)
VNET	-0.12	-0.18	-0.22	-0.24	-0.22
	(-0.03)	(-0.04)	(-0.08)	(-0.05)	(-0.12)
Trade Impact	-0.22	-0.54	-0.13	-0.33	-0.44
	-0.16	-0.16	0.07	-0.12	-0.07
Adverse Cost	-0.19	-0.24	-0.11	-0.47	-0.23
	(-0.12)	(-0.19)	(-0.15)	(-0.16)	(-0.17)
Dummy	-2.73	-2.92	-2.14	-1.59	-1.26
	(-2.29)	(-2.41)	(-2.36)	(-2.49)	(-2.29)
Adjusted R-sq	26%	25%	23%	24%	14%

This table reports the OLS regression results using the daily ratio of the minimum values of the information share as the dependent variable (rather than the mean values of the information shares employed in Table 7). Every variable in the model (except volatility) is calculated using the ratio of daily values from the futures and ETFs. The model we use can be represented as: $ISt = \beta_0 + \beta_1 Spread_t + \beta_2 Volume_t + \beta_3 Volatility_t + \beta_4 Vnet_t + \beta_5 Trade\_impacts_t + \beta_6 Adverse\_cost_t$, where spread is the ratio of the percentage spreads, Vnet is the ratio of Vnet values, Volume is the total dollar trading volume ratio, Adverse is the adverse selection cost component of the effective spreads, and Trade Impact is the ratio of the liquidity coefficients for futures and ETFs. Volatility is the sum of the two markets' volatility on day t, where the daily volatility is calculated as the sum of squares of the 5-minute intraday returns (Andersen & Bollerslev, 1998). We obtain the percentage spread by dividing the dollar spread by the midpoint of the bid and ask prices. Every variable in the model is calculated for each day and the information shares of the futures are regressed on these variables. T-values are reported in parentheses. Coefficients and t-values in bold are significant at the 5% level. The t-statistics are calculated using Newey-West, which corrects standard errors to adjust for any potential serial correlation.

Table 1.10
Determinants of Price Discovery Using Maximum Values of the Information Shares

	E-Mini S&P 500	*E-mini NASDAQ 100*	*Euro*	*British Pound*	*Gold*
Ratio of Spreads	-1.51	-1.48	-0.49	-0.42	-1.16
	(-7.39)	(-7.22)	(-4.48)	(-4.54)	(-5.92)
Volume	-0.44	-0.56	-0.23	-0.66	-0.21
	(-0.38)	(-0.41)	(-0.09)	(-0.86)	(-0.16)
Volatility	-2.38	-1.76	-1.69	-0.71	-1.17
	(-7.95)	(-6.77)	(-4.51)	(-3.88)	(-4.16)
VNET	-0.16	-0.22	-0.17	-0.28	-0.16
	(-0.04)	(-0.08)	(-0.07)	(-0.09)	(-0.13)
Trade Impact	-0.26	-0.33	-0.46	-0.33	-0.44
	-0.19	-0.33	-0.31	-0.41	-0.17
Adverse Cost	-0.11	-0.28	-0.17	-0.37	-0.12
	(-0.17)	(-0.24)	(-0.20)	(-0.15)	(-0.17)
Dummy	-2.73	-2.86	-2.03	-1.63	-1.33
	(-2.29)	(-2.47)	(-2.26)	(-2.41)	(-2.15)
Adjusted R-sq	27%	25%	22%	22%	13%

This table reports the OLS regression results using the daily ratio of the maximum values of the information share as the dependent variable (rather than the mean values of the information shares employed in Table 7. Every variable in the model (except volatility) is calculated using the ratio of daily values from the futures and ETFs. The model we use can be represented as: $ISt = \beta_0 + \beta_1 Spread_t + \beta_2 Volume_t + \beta_3 Volatility_t + \beta_4 Vnet_t + \beta_5 Trade\_impacts_t + \beta_6 Adverse\_cost_t$, where spread is the ratio of the percentage spreads, Vnet is the ratio of Vnet values, Volume is the total dollar trading volume ratio, Adverse is the adverse selection cost component of the effective spreads, and Trade Impact is the ratio of the liquidity coefficients for futures and ETFs. Volatility is the sum of the two markets' volatility on day t, where the daily volatility is calculated as the sum of squares of the 5-minute intraday returns (Andersen & Bollerslev, 1998). We obtain the percentage spread by dividing the dollar spread by the midpoint of the bid and ask prices. Every variable in the model is calculated for each day and the information shares of the futures are regressed on these variables. T-values are reported in parentheses. Coefficients and t-values in bold values are significant at the 5% level. The t-statistics are calculated using Newey-West, which corrects standard errors to adjust for any potential serial correlation.

CHAPTER 2: THE RESILIENCY OF LARGE TRADES FOR U.S. ELECTRONIC FUTURES MARKETS

2.1. Introduction

Market liquidity is considered to be the most important criterion for evaluating market quality (Clemons and Weber 1992). Kyle (1985) identifies three components of market liquidity: bid–ask spread, depth, and resiliency. Bid–ask spread measures the difference between the prices at which the dealer is willing to buy and sell the instrument. Depth is defined as the size of the order flow required to change prices. Resiliency is the speed that prices return to equilibrium following a large trade. Thus, resilient markets are those where the price effects of large trades are small and short-lived. In this respect, resiliency is the time dimension of liquidity.

Resiliency is an important aspect of liquidity affecting trading strategies and investor performance. Traders prefer resilient markets, as transaction costs increase when the market is not resilient. Obizhaeva and Wang (2005) and Alfonsi, Fruth, and Schied (2005) argue that an optimal trading strategy, one which minimizes execution costs, depends on the resiliency of an investor's book. Regulators and exchanges both have an interest in more resilient markets, whose lower transaction costs attract more investors, increasing exchange profits and helping to prevent price manipulations.

Despite its importance, the resiliency of U.S. electronic futures markets has not been analyzed in previous studies (since actual bid-ask prices were not available for floor trading), causing existing literature to focus on the resiliency of U.S. equity markets. My study contributes to the literature in the following ways: 1) For the first time, the resiliency of U.S. electronic futures markets is examined; 2) Changes in market resiliency are investigated over types of markets by comparing the resiliency of U.S. futures markets in pre-crisis versus crisis periods; and 3) By using different asset classes, the study is able to assess the resiliency of a wide spectrum of futures contracts.

My results show that markets are more resilient when they are less volatile. Moreover, different types of assets show different resiliencies. In particular, according to our results, currency futures are more resilient than the equity index and gold futures. Markets also respond differently to large buy and sell orders during a volatile period, when large sell trade effects outweigh those of large buy trades.

2.2. Literature Review

Numerous studies analyze the effects of large trades on stock price behavior. These studies document that the price impacts of large trades are larger than the price impacts of smaller trades. Although these pioneering studies establish the importance of "resiliency" i.e. the time dimension of liquidity in microstructure literature, they majorly focus on the equity market. Thus, "resiliency" as a fundamental measure of market quality/liquidity can be better understood by examining an asset market other than equity. Our study adds to this very nascent literature on "resiliency" by examining several assets in the US futures market. This will also help shed more light on the connection between various aspects of market quality namely spread, depth and resiliency.

For example, Easley and O'Hara (1987) theoretically and empirically show that large trades affect stock prices more than small trades because large trades contain private information. Hasbrouck (1991) finds that large trades in stock markets contain information and thus their bid–ask spreads are wider for large trades. Lee, Mucklow, and Ready (1993) document that in equity market the bid–ask spreads widen and depths decline after large trades. Lee and Radhakrishna (2000) document that a majority of institutional trades in equity markets are indeed large trades. Koski and Michaely (2000) show that liquidity suppliers in equity markets adjust bid–ask spreads when they face adverse selection risk. Similar effects of large trades on equity markets are documented empirically by Kraus and Stoll 1972; Holthausen, Leftwich, and Mayers 1987, 1990; Gemmill 1996; and Keim and Madhavan 1996.

Saar (2001) theoretically shows that the price impact of trades depends on economic conditions. Chiyachantana, et al. (2004) empirically supports the theoretical model of Saar (2001), arguing that institutional traders pay for liquidity when they sell in declining markets or buy in rising markets.

Subrahmanyam (1991) and Gorton and Pennacchi (1993) theoretically prove that individual, equity-specific private information is negligible for futures and other types of basket securities. However, Fleming, Ostdiek, and Whaley (1996) state that futures markets attract informed traders, because of their low transaction costs and leverage. In fact, their empirical results show that futures prices incorporate new information faster than index and option prices. They argue that futures prices lead other markets because informed traders prefer to trade in this market. Subrahmanyam (1991) states that frictions, such as nonsynchronous trading in the underlying stocks, can explain the lead of index futures prices over cash index prices. Berkman, Brailsford, and Frino (2005) find that trades in U.K. futures markets are mainly liquidity-motivated. Similarly, using data from the Sydney Futures Exchange, Frino and Oetomo (2005) show that price effects of large trades in futures markets are smaller than those of large trades in equity markets. Frino and Oetomo (2005) also do not find asymmetry between the effects of buy and sell trades. These results, as well as the theoretical models of Subrahmanyam (1991) and Gorton and Pennacchi (1993), show that differences exist in the trading dynamics between futures and equity markets.

Coppejans, Domowitz, and Madhavan (2003) provide evidence for the high degree of resiliency of the Swedish stock index futures market, showing that the reduction of liquidity dissipates quickly following a volatility shock (disappearing within an hour after the shock). They attribute this rapid adjustment to the self-correcting nature of automated auctions. Frino and Cummings (2010) report that the 3 Year Commonwealth Treasury Bond Futures on the Sydney Futures Exchange recover after 12 trades following a block trade.

The research in this paper differs from prior studies that focus on the effects of large trades and the resiliency of markets in several aspects. First, prior research does not analyze the resiliency of the U.S. electronic futures markets. Previous studies on futures floor trading did not provide an accurate and precise time sequence of trades, unlike the futures data employed here. Second, prior studies only employ one type of futures contract, whereas here the resiliencies of five different futures contracts are analyzed and compared. Third, this study examines the effect of different market conditions (the volatility of the 2008 financial crisis) on resilience.[18] To sum up, both the wide spectrum of data and uniqunes of data period makes this study fill the gaps in literature that have not been explored by prior studies.

2.3. Data

I employ electronic market transactions and bid–ask quote data for five different futures contracts from the CQG futures database. Use of electronic prices is an important extension of past studies since floor trading price data does not provide bid–ask prices (and approximations from formulas are notoriously inaccurate) and floor prices provide imprecise time sequences of trades; thus, only with electronic trade data is the current study possible with accuracy. My sample includes the E-mini S&P 500, E-mini NASDAQ 100 equity index, gold, British pound, and the euro currency futures to represent a wide spectrum of different asset classes. My sample time periods are the volatile financial crisis time span of September 2008 through December 2008 and the less volatile pre-crisis period of January 2007 through March 2007.

Trades that occur at the same price, in the same trade direction (buy or sell), and within the same minute are aggregated. Nearby contracts are employed in the analysis, since they are the most active contracts. Trades are categorized into 10 groups, based on the empirical distribution of transaction sizes of each contract. Block trades are associated with the 10th group since they possess the largest transaction sizes.

[18] As Brunnermeier (2009) states, the 2008 financial crisis was the most severe crisis since the Great Depression.

2.4. Methodology

Following Koski and Michaely (2000) and Frino and Cummings (2009), quoted prices and bid–ask spreads are used for the return and liquidity analyses in order to avoid the bid–ask bounce. In accordance with the Lee and Ready (1991) algorithm, trades that are closer to the ask (bid) are classified as buy (sell) trades. Trades that occur at the midquote are classified according to the price of the previous trade. If the trade price is larger (lower) than the previous trade price, then it is classified as a buy (sell).

Following Holthausen, Leftwich, and Mayers (1990); Koski and Michaely (2000); and Frino Cummings (2009), block trades are designated as trade 0 and then benchmark returns (BENR) are calculated for each contract from the returns for quotes sequenced from –20 through –11 relative to the block trades

$$\text{BENR} = \frac{\sum_{j=1}^{N} \sum_{t=-20}^{-11} Rj,t}{N} \quad , \qquad (2.1.)$$

where N is the total number of trades during the period (pre-crisis or crisis), and $R_{j,t}$ is the return for quote t. Returns are computed using the ask quote prices for purchases and bid quote prices for sales.

Using the benchmark for the ask quotes, mean excess returns for block purchases (MRP) are computed as

$$\text{MRP}_t = \frac{\sum_{j}^{Npur} Rjt - BENR}{Npur}, \qquad t = -10, \ldots, +20, \qquad (2.2)$$

where N_{pur} is the total number of block purchases. Mean excess returns for block sales (MRS) are calculated using the total number of sales and the bid quotes. After analyzing the price impacts around large trades, the changes in the bid-ask quote sizes surrounding large trades are examined using the following formulas.

First, benchmarks spreads for each futures contract are computed as

$$BENSPR = \frac{\sum_{j=1}^{N}\sum_{t=-20}^{-11} Sj,t}{N}, \qquad (2.3.)$$

where is $S_{j,t}$ is the bid-ask spread for quote t.

Mean excess spreads are computed using the equation

$$MS_t = \frac{\sum_{j}^{Npur} Sjt - BENSPR}{Npur} \qquad t= -10, \ldots , +20 \qquad (2.4.)$$

Using these equations above, the effects of large trades are analyzed in terms of returns and liquidity.

2.5. Results

The summary statistics reported in Table 2.1. show that the average number of contracts for each block trade were less during the crisis period compared to the pre-crisis period. Furthermore, the number of block sales and purchases per day were also lower during the crisis period. These results reflect the declining degree of trading activity in the futures markets during the crisis period.

2.5.1. Returns around Large Trades

In this section the returns after large trades are analyzed for each of the five futures contracts, both before and during the crisis periods. The results in Tables 2.2. through 2.5. show that among all the contracts in my sample, currency futures exhibit the smallest returns following large trades. Of the two currency futures, after block trades euro futures have smaller returns than British pound futures. Moreover, gold futures exhibit the highest returns after large trades. Comparing returns for the two index futures following large trades, we can see that returns in the E-mini NASDAQ 100 futures market are larger than the returns in the E-mini S&P 500 futures market. These results show that E-mini S&P 500 futures contracts are more liquid than the E-mini NASDAQ 100 futures.

Saar (2001) theoretically shows that price reactions to trades depend on the economic condition. My empirical results examine the 2008 pre-crisis to crisis periods, concluding that the results here support his argument. In particular, during the crisis period the returns after block trades are much larger than those during the pre-crisis period (see Figures 2.1.–2.5.). The results show that most of the price adjustment occurs within the first few trades for electronic futures markets. The larger returns for block trades during the crisis period reflect a decline in liquidity during that time period. Furthermore, the crisis period exhibits an asymmetry between the price effects of large buy and large sell trades, unlike the pre-crisis period. Thus, during the crisis period the returns after large sell trades are greater than returns after large buy trades. However, during the pre-crisis period, returns exhibit similar return patterns after large buy and sell trades. For example, the instant return for the E-mini S&P 500 index futures after *both* purchases and sells is around 0.3% during the pre-crisis period (Figure 2.1.), whereas after 20 trades the return increases to approximately 0.5%. Alternatively, during the crisis period the instant return for large buy trades is 0.46% and for large sales is 0.62%, whereas after 20 trades the cumulative return for large purchases is 0.8% and for large sales is 1.0%. Using the E-mini NASDAQ 100 index futures one finds similar results (Figure 2.2). Comparison of Figures 2.1. and 2.2. shows that the E-mini S&P 500 futures market is slightly more liquid than the E-mini NASDAQ 100 futures market for both the pre-crisis and crisis periods. For example the instant returns following large purchases and large sales (0.42% and –0.44%, respectively) are larger than the instant returns for the E-mini S&P 500 market. Similarly during the crisis period, the initial returns following a large purchase (0.56%), and the return following a large sale (0.65%), are also larger than the initial returns in the E-mini S&P 500 market. Returns following large trades in the gold futures market are higher than the returns in any other markets that are analyzed in this study (Figure 2.3.). During the pre-crisis period, large trades are associated with a 0.5% initial price change, whereas during the crisis period the initial returns are 0.7% for buy trades and –0.75% for sell trades. Returns following large trades in currency futures are lower than those in equity indexes and gold futures (Figures 2.4. and 2.5.). Both the initial returns and cumulative returns after block trades in the currency futures markets show that euro futures are more liquid than the British pound futures. For example during the crisis period, the initial returns are 0.35 and –0.49% after the large buy and sell trades, respectively, of British pound futures, whereas in the euro currency futures market the initial returns on average were 0.33% and –0.40% for large buy and sell trades, respectively.

2.5.2. Bid–Ask Spreads around Large Trades

In this section, the effects of large trades on the liquidity in futures markets in terms of the bid–ask spreads are examined. Using equation (2.4.) the mean excess spreads before and after large trades are computed and reported in Tables 2.6.–2.9. Consistent with the results of previous studies, these results show that block trades cause bid–ask spreads to widen. The results for the crisis period exhibit three major differences from the pre-crisis period. First, the bid–ask spreads widen much more after block trades during the crisis period. Second, there is a difference in the number of trades it takes for bid–ask spreads to return to their levels prior to the block trades. Specifically, during the crisis period it takes more trades for the liquidity level to recover from the adverse effects of block trades. Finally, block purchases and sales show asymmetrical effects during the crisis period, when the effects of block sales on bid–ask spreads are larger than those of block purchases. In fact, more trades are required to restore liquidity to pre-block trade levels after block sales than to restore liquidity after block purchases

Our results show liquidity recovers in currency contracts faster than in the equity index and gold futures (Figures 2.6.–2.15.) and that the euro futures contract is the most resilient futures contract. In the euro currency futures market during the pre-crisis period, liquidity reverts back to the pre-block trade level after 7 trades (Figures 2.12. and 2.13.). However, during the crisis period liquidity recovers after 10 trades following large purchases, whereas it takes 11 trades to recover after large block sales.

The British pound futures contract is the second-most resilient futures contract in our sample, after euro futures. In the British pound futures market during the pre-crisis period, liquidity recovers following block transactions after 8 trades (Figures 2.14. and 2.15.). In the crisis period following large purchases the bid-ask spreads remain above average levels for 10 trades. After large sales it takes 12 trades until liquidity returns to pre-block trade levels.

The gold futures market is the least resilient market in our sample (Figures 2.10. and 2.11.). Even during the pre-crisis period, bid–ask spreads stay above average levels for 12 trades following block trades. The adverse effects of the crisis on the liquidity of gold futures can be seen in Figures 2.10 and 2.11. For example during the crisis period, it takes 15 trades until liquidity is recovered following large purchases, whereas liquidity is recovered after 17 trades following large sales.

Our results show that the E-mini S&P 500 and E-mini NASDAQ 100 futures markets exhibit similar resiliencies (Figures 2.6–2.9.). Specifically, after block trades liquidity recovers in 9 trades in these markets during the pre-crisis period, whereas during the crisis period the E-mini S&P 500 futures market shows slightly more resiliency than the E-mini NASDAQ 100 futures market, with liquidity recovering after block purchases in 12 trades for the former as opposed to 13 trades for the latter. After block *sales*, the bid–ask spreads return to normal levels in 14 and 15 trades for E-mini S&P 500 and E-mini NASDAQ 100 contracts, respectively.

2.6. Conclusion

Understanding how markets respond to large trades is important not only to traders who want to minimize the price impacts of their transactions but also to regulators who establish the rules for well-functioning markets. Although studies exist that analyze the price impact of trades in U.S. markets, no previous studies compare the speed of the adjustment process after large trades in volatile versus normal times in electronic U.S. futures markets. This study fills that gap in the literature by using high-frequency quote and trade data from U.S. electronic futures markets to compare the effects of block trades on quote returns and bid-ask spreads during volatile and less volatile periods. Our results show that the effects of block trades are larger during the volatile period of the financial crisis used for this study compared to the pre-crisis period. Specifically, more trades are required for prices to adjust to a new equilibrium and liquidity to recover after large trades during the crisis period than during the pre-crisis period. Moreover, during the crisis period the effects of block sales are larger than the effects of block purchases. However, during the pre-crisis period, the effects of purchases and sales are similar. This study could be extended using ETF, options, and less liquid futures in order to compare the speed of adjustment processes in different and less liquid instruments.

Table 2.1. – Descriptive Statistics

	E-mini S&P 500		E-mini NASDAQ 100		Gold	
Period	Crisis	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisis
Average size of purchases	6.76	11.5	5.44	9.84	2.78	4.11
Average size of block purchases	41.77	56.03	37.22	44.37	14.55	19.06
Number of block purchases per day	882.70	498.94	774.43	453.72	245.97	214.22
Average size of sales	6.87	11.31	5.63	9.68	3.02	4.01
Average size of block sales	48.44	56.51	42.48	43.96	17.35	18.93
Number of block sales per day	909.82	487.78	847.32	448.28	266.26	211.74
	Euro		British Pound			
Average size of purchases	5.23	9.14	4.45	8.74		
Average size of block purchases	29.37	36.04	24.31	32.43		
Number of block purchases per day	672.48	572.29	612.49	542.18		
Average size of sales	5.61	8.97	4.92	8.66		
Average size of block sales	36.22	35.47	31.14	31.48		
Number of block sales per day	714.67	575.12	633.51	537.62		

This table contains sample characteristics for the following electronically traded futures contracts: E-mini S&P 500, E-mini NASDAQ-100, gold, British pound, and the euro. The trades are categorized into trade groups based on the percentiles of the empirical trade size distribution. Transactions with a trade size equal to or larger than the 90th percentile are classified as block trade.

Table 2.2. - Quote Returns around Large Sales

		Trade Relative to Block Trade (t=0)				
		–2	–1	0	1	2
E-Mini S&P (Pre-Crisis)	Mean Excess Return	–0.01	0.01	–0.29	–0.05	–0.02
	t-value: Excess return = 0	–1.4	1.6	–40.2	–4.5	–4.4
E-Mini S&P (Crisis)	Mean Excess Return	–0.01	-0.01	–0.62	–0.09	–0.04
	t-value: Excess return = 0	–1.8	-1.7	–45.3	–9.8	–4.6
E-Mini NASDAQ (Pre-Crisis)	Mean Excess Return	–0.01	–0.01	–0.44	–0.04	–0.02
	t-value: Excess return = 0	–0.8	–1.2	–47.4	–4.9	–3.3
E-Mini NASDAQ (Crisis)	Mean Excess Return	0.01	–0.02	–0.65	–0.11	–0.06
	t-value: Excess return = 0	0.9	–1.5	–54.2	–7.5	–5.3
Gold (Pre-Crisis)	Mean Excess Return	0.01	–0.01	–0.51	–0.05	– 0.02
	t–value: Excess return = 0	0.6	–0.9	–45.2	–6.2	–3.4
Gold (Crisis)	Mean Excess Return	–0.01	0.02	–0.69	–0.16	–0.06
	t-value: Excess return = 0	–1.3	1.6	–52.8	–14.4	–8.3
Euro (Pre-Crisis)	Mean Excess return	–0.02	–0.01	–0.23	–0.03	–0.02
	t-value: Excess return = 0	–2.5	–1.3	–28.3	–4.5	–3.1
Euro (Crisis)	Mean Excess Return	–0.01	–0.01	–0.42	–0.07	–0.04
	t-value: Excess return = 0	–1.9	–2.2	–48.8	–7.5	–7.2
British Pound (Pre-Crisis)	Mean excess trade size	–0.01	0.01	–0.24	–0.04	–0.03
	t-value: Excess return = 0	–1.3	0.8	–26.5	–4.7	–3.6
British Pound (Crisis)	Mean Excess Return	–0.03	–0.01	–0.49	–0.09	–0.05
	t-value: Excess return = 0	–1.5	–0.9	–49.5	–9.7	–9.5

Quote-to-quote returns are computed from one bid quote to the next bid quote for sales. The excess return for quote 0 relative to the block trade is defined as the excess return from the prevailing quote to the block trade. The excess return for quote +1 is defined as the excess return from the block trade to the first quote after the block trade.

Table 2.3. – Quote Returns around Large Purchases

		Trade Relative to Block Trade (t=0)				
		-2	–1	0	1	2
E-Mini S&P (Pre-Crisis)	Mean Excess Return	0.02	0.01	0.31	0.03	0.02
	t-value: Excess return = 0	0.8	1.2	40.3	8.5	8.4
E-Mini S&P (Crisis)	Mean Excess Return	–0.01	0.01	0.46	0.04	0.04
	t-value: Excess return = 0	–0.7	0.8	35.3	5.1	5.2
E-Mini NASDAQ (Pre-Crisis)	Mean Excess Return	–0.02	0.01	0.42	0.04	0.03
	t-value: Excess return = 0	–1.3	0.7	49.5	9.1	7.3
E-Mini NASDAQ (Crisis)	Mean Excess Return	0.01	–0.01	0.56	0.05	0.03
	t-value: Excess return = 0	1.8	–1.7	43.5	4.6	3.9
Gold (Pre-Crisis)	Mean Excess Return	–0.01	–0.01	0.49	0.04	0.02
	t-value: Excess return = 0	–0.7	–0.4	44.1	10.4	4.2
Gold (Crisis)	Mean Excess Return	0.02	0.01	0.71	0.06	0.05
	t-value: Excess return = 0	1.6	1.2	53.4	14.1	13.9
Euro (Pre-Crisis)	Mean Excess Return	–0.01	0.01	0.32	0.03	0.01
	t-value: Excess return = 0	–0.9	0.5	29.2	6.7	6.1
Euro (Crisis)	Mean Excess Return	0.01	0.01	0.44	0.03	0.03
	t-value: Excess return=0	1.1	1.2	47.2	7.5	7.2
British Pound (Pre-Crisis)	Mean Excess Return	–0.01	0.01	0.34	0.03	0.03
	t-value: Excess return = 0	–1.1	1.4	27.1	11.5	11.2
British Pound (Crisis)	Mean Excess Return	–0.01	–0.01	0.49	0.03	0.02
	t-value: Excess return = 0	–1.4	–0.8	50.3	7.9	7.4

Quote-to-quote returns are computed from ask quote to ask quote for purchases. The excess return for quote 0 relative to the block trade is defined as the excess return from the prevailing quote to the block trade. The excess return for quote +1 is defined as the excess return from the block trade to the first quote after the block trade.

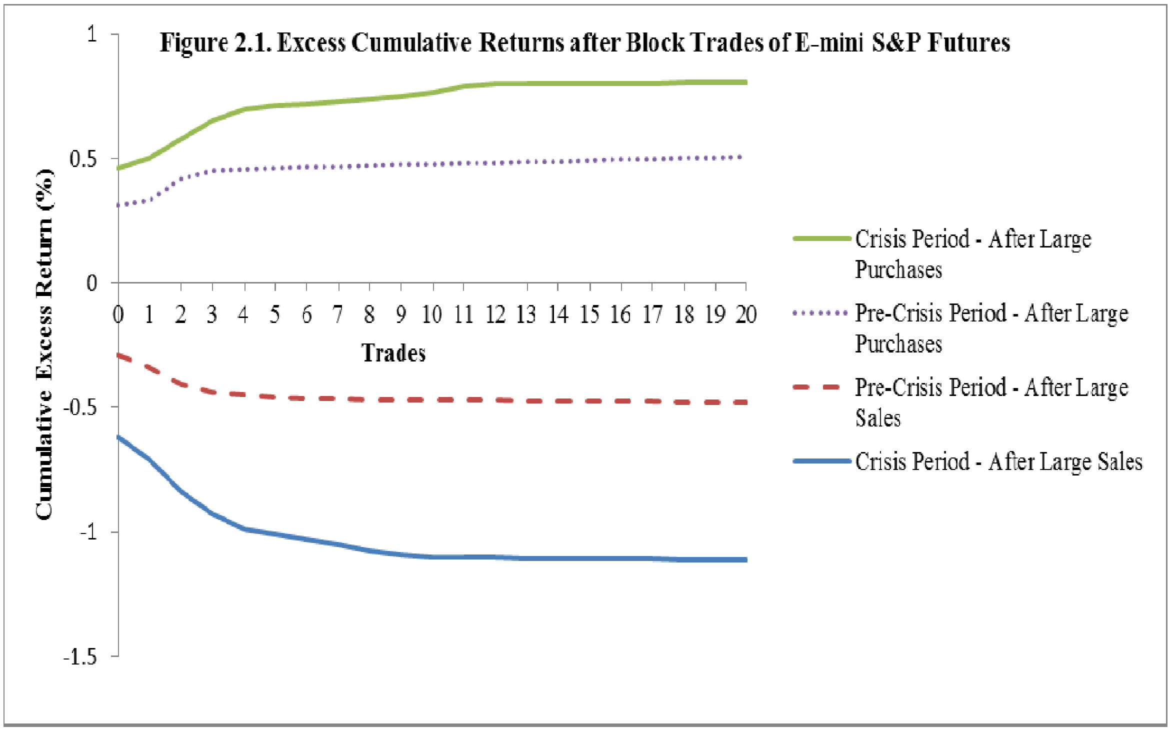


Figure 2.1. Excess Cumulative Returns after Block Trades of E-mini S&P Futures
Cumulative Excess Return (%)
1
0.5
0
-0.5
-1
-1.5
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Trades
Crisis Period - After Large Purchases
Pre-Crisis Period - After Large Purchases
Pre-Crisis Period - After Large Sales
Crisis Period - After Large Sales

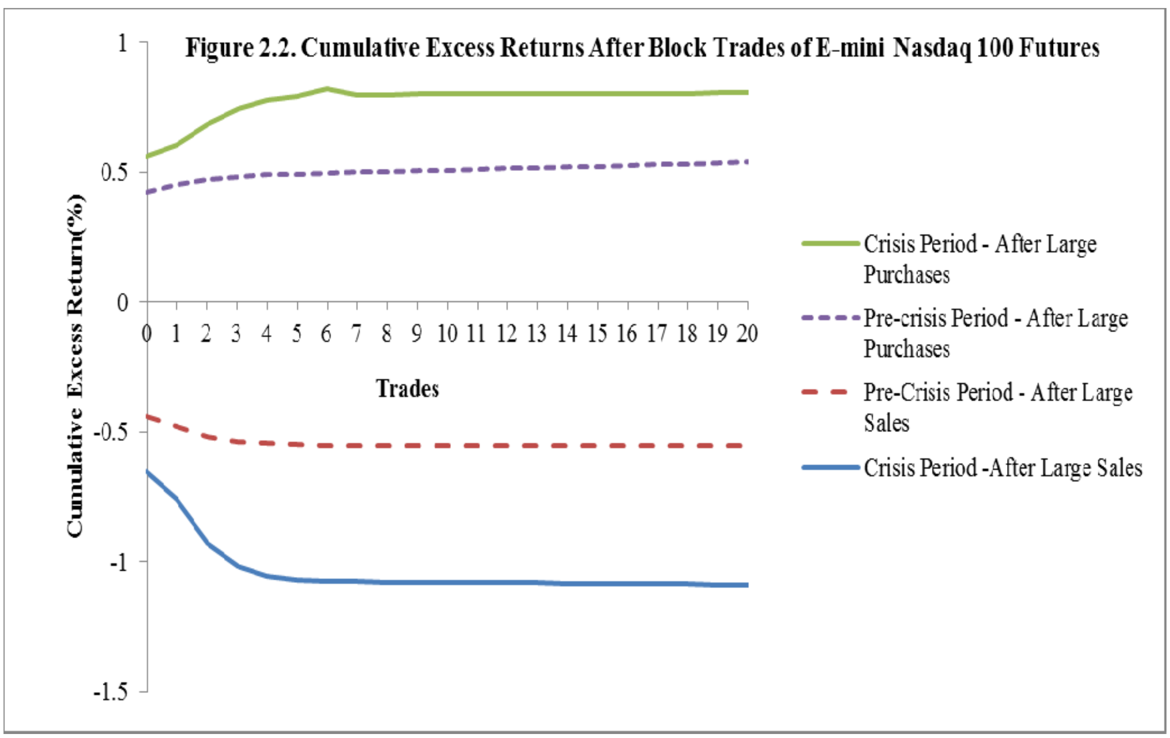


Figure 2.2. Cumulative Excess Returns After Block Trades of E-mini Nasdaq 100 Futures
Cumulative Excess Return(%)
1
0.5
0
-0.5
-1
-1.5
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Trades
Crisis Period - After Large Purchases
Pre-crisis Period - After Large Purchases
Pre-Crisis Period - After Large Sales
Crisis Period -After Large Sales

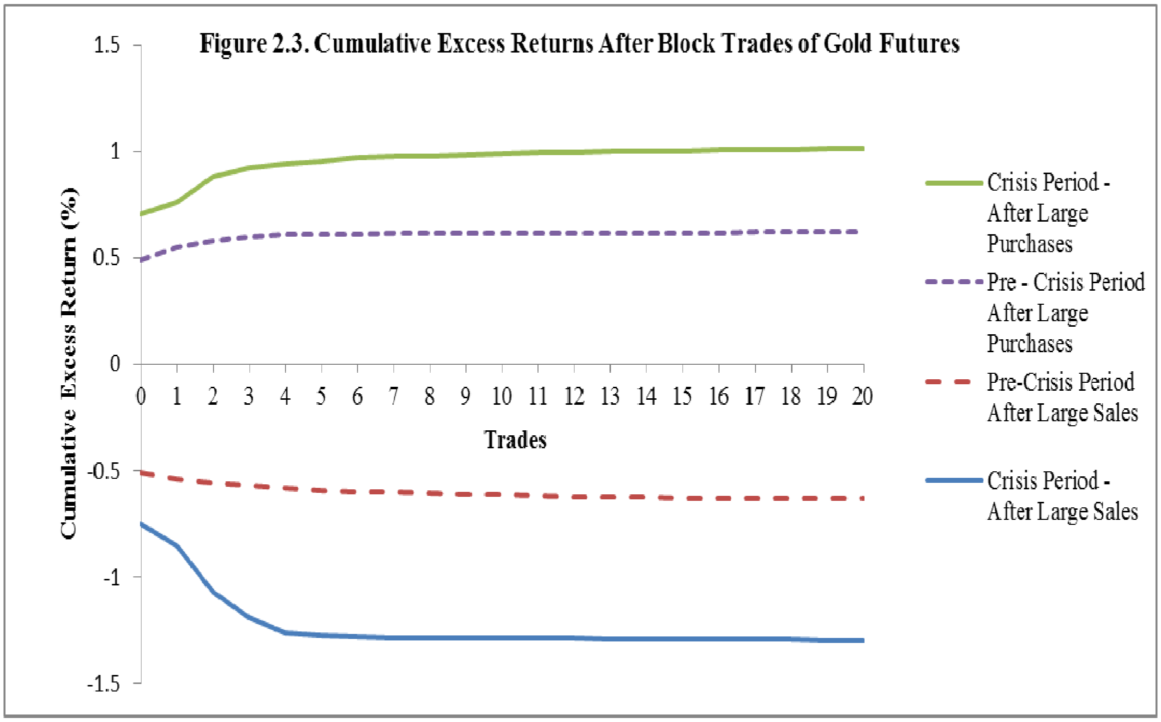


Figure 2.3. Cumulative Excess Returns After Block Trades of Gold Futures
1.5
1
0.5
0
-0.5
-1
-1.5
Cumulative Excess Return (%)
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Trades
Crisis Period - After Large Purchases
Pre - Crisis Period After Large Purchases
Pre-Crisis Period After Large Sales
Crisis Period - After Large Sales

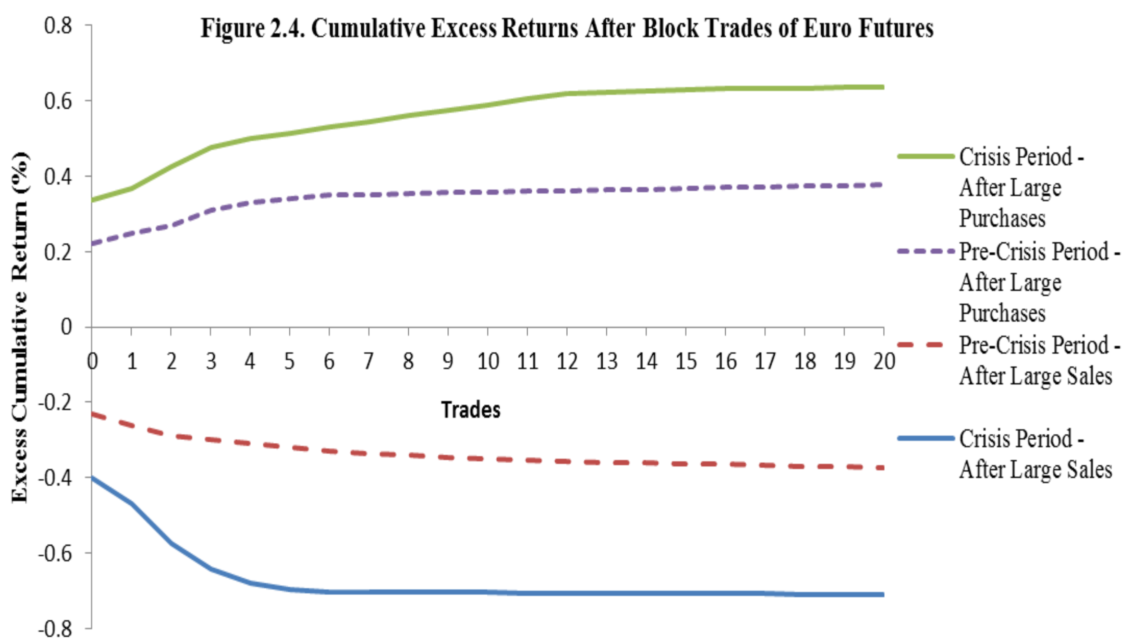


Figure 2.4. Cumulative Excess Returns After Block Trades of Euro Futures
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
Excess Cumulative Return (%)
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Trades
Crisis Period - After Large Purchases
Pre-Crisis Period - After Large Purchases
Pre-Crisis Period - After Large Sales
Crisis Period - After Large Sales

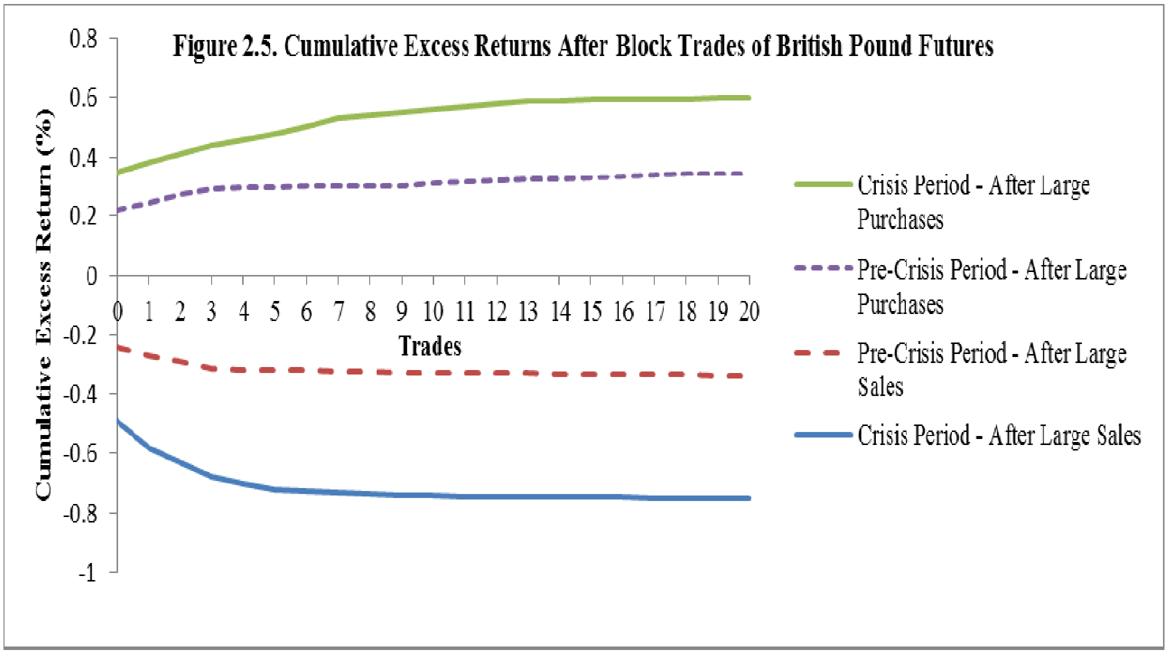


Figure 2.5. Cumulative Excess Returns After Block Trades of British Pound Futures
Cumulative Excess Return (%)
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20
Trades
Crisis Period - After Large Purchases
Pre-Crisis Period - After Large Purchases
Pre-Crisis Period - After Large Sales
Crisis Period - After Large Sales

Table 2.4. – Bid-Ask Spreads around Large Sales

		Trade Relative to Block Trade				
		–2	–1	0	1	2
E-Mini S&P (Pre-Crisis)	Bid–Ask Spread	0.251	0.282	0.452	0.448	0.447
	Mean Excess Spread	–0.019	0.012	0.182	0.178	0.177
	t-value: Excess Spread = 0	–0.6	1.4	8.3	8.5	8.4
E-Mini S&P (Crisis)	Bid–Ask Spread	0.431	0.409	0.982	0.954	0.942
	Mean Excess Spread	–0.019	–0.041	0.532	0.504	0.492
	t-value: Excess Spread = 0	1.6	–0.8	17.2	15.1	14.3
E-Mini Nasdaq (Pre-Crisis)	Bid–Ask Spread	0.289	0.285	0.541	0.537	0.533
	Mean Excess Spread	–0.011	–0.015	0.241	0.237	0.233
	t-value: Excess Spread = 0	–0.8	–1.2	9.7	8.9	9.3
E-Mini Nasdaq (Crisis)	Bid–Ask Spread	0.583	0.488	1.022	1.027	0.962
	Mean Excess Spread	0.053	–0.042	0.492	0.497	0.432
	t-value: Excess Spread = 0	1.8	–1.7	13.5	12.6	12.7
Gold (Pre-Crisis)	Bid–Ask Spread	0.0101	0.0103	0.0174	0.0178	0.0175
	Mean Excess Spread	–0.0009	–0.0007	0.0064	0.0068	0.0065
	t-value: Excess Spread = 0	–1.3	–1.1	11.4	12.3	11.7
Gold (Crisis)	Bid–Ask Spread	0.0162	0.0171	0.0346	0.0362	0.0354
	Mean Excess Spread	–0.0018	–0.0009	0.0166	0.0182	0.0174
	t-value: Excess Spread = 0	–1.6	–1.2	13.4	14.1	13.9
Euro (Pre-Crisis)	Bid–Ask Spread	0.025	0.023	0.052	0.055	0.054
	Mean Excess Spread	–0.002	–0.004	0.025	0.028	0.027
	t-value: Excess Spread = 0	–2.3	–3.9	8.8	7.5	7.2
Euro (Crisis)	Bid–Ask Spread	0.044	0.041	0.095	0.099	0.097
	Mean Excess Spread	–0.009	–0.012	0.042	0.046	0.044
	t-value: Excess Spread = 0	–2.1	–2.4	8.8	7.5	7.2
British Pound (Pre-Crisis)	Bid–Ask Spread	0.021	0.022	0.057	0.061	0.059
	mean excess trade size	–0.008	–0.007	0.028	0.032	0.030
	t-value: Excess Spread = 0	–2.3	–2.1	6.5	7.5	7.2
British Pound (Crisis)	Bid–Ask Spread	0.042	0.052	0.103	0.106	0.105
	mean excess trade size	–0.015	–0.005	0.046	0.049	0.048
	t-value: Excess Spread = 0	–2.3	–0.9	10.5	10.9	10.7

Excess spreads are spreads in excess of a benchmark level, computed using spreads -20 through -11 relative to trades of a given size. For excess spreads, reported results include Mean excess spread and t: Excess spread = 0 (the t-statistic for the test of the null hypothesis that the mean excess spread equals zero)

Table 2.5. – Bid-Ask Spreads around Large Purchases

		Trade Relative to Block Trade (t=0)				
		–2	–1	0	1	2
E-Mini S&P (Pre-Crisis)	Bid–Ask Spread	0.251	0.282	0.452	0.448	0.447
	Mean Excess Spread	–0.019	0.012	0.182	0.178	0.177
	t-value: Excess Spread = 0	–0.6	1.4	8.3	8.5	8.4
E-Mini S&P (Crisis)	Bid–Ask Spread	0.422	0.473	0.945	0.949	0.938
	Mean Excess Spread	–0.028	0.023	0.495	0.499	0.488
	t-value: Excess Spread = 0	–1.8	1.6	10.2	8.5	8.4
E-Mini Nasdaq (Pre-Crisis)	Bid–Ask Spread	0.289	0.285	0.541	0.537	0.533
	Mean Excess Spread	–0.011	–0.015	0.241	0.237	0.233
	t-value: Excess Spread = 0	–0.8	–1.2	9.7	8.9	9.3
E-Mini Nasdaq (Crisis)	Bid–Ask Spread	0.521	0.512	0.932	0.961	0.964
	Mean Excess Spread	–0.009	–0.018	0.402	0.431	0.434
	t-value: Excess Spread = 0	–0.9	–1.5	8.4	8.9	9.3
Gold (Pre-Crisis)	Bid–Ask Spread	0.0101	0.0103	0.0174	0.0178	0.0175
	Mean Excess Spread	–0.0009	–0.0007	0.0064	0.0068	0.0065
	t-value: Excess Spread = 0	–1.3	–1.1	11.4	12.3	11.7
Gold (Crisis)	Bid–Ask Spread	0.0154	0.0174	0.0316	0.0342	0.0324
	Mean Excess Spread	–0.0026	–0.0006	0.0138	0.0162	0.0144
	t-value: Excess Spread = 0	2.3	1.2	8.3	8.4	9.3
Euro (Pre-Crisis)	Bid–Ask Spread	0.025	0.023	0.052	0.055	0.054
	Mean Excess Spread	–0.002	–0.004	0.025	0.028	0.027
	t-value: Excess Spread =	–2.3	–3.9	8.8	7.5	7.2
Euro (Crisis)	Bid–Ask Spread	0.046	0.042	0.088	0.096	0.094
	Mean Excess Spread	–0.007	–0.011	0.035	0.043	0.041
	t-value: Excess Spread =	–1.9	–2.2	8.8	7.5	7.2
British Pound (Pre-Crisis)	Bid–Ask Spread	0.021	0.022	0.057	0.061	0.059
	Mean Excess Spread	–0.008	–0.007	0.028	0.032	0.030
	t-value: Excess Spread =	–2.3	–2.1	6.5	7.5	7.2
British Pound (Crisis)	Bid–Ask Spread	0.047	0.048	0.094	0.097	0.095
	Mean Excess Spread	–0.010	–0.009	0.037	0.040	0.038
	t-value: Excess Spread =	–2.1	–1.9	9.2	9.7	9.5

Excess spreads are spreads in excess of the benchmark level, computed using spreads -20 through -11 relative to trades of a given size. For excess spreads; reported results include the Mean Excess Spread and t: Excess spread = 0 (the t-statistic for the test of the null hypothesis that the mean excess spread equals zero).

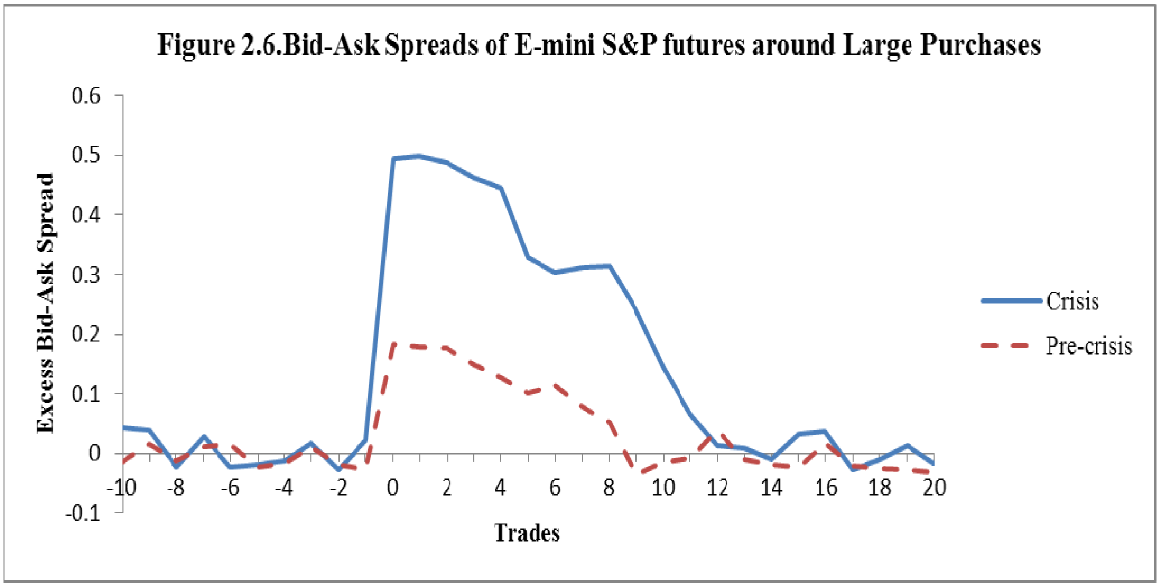


Figure 2.6.Bid-Ask Spreads of E-mini S&P futures around Large Purchases
Excess Bid-Ask Spread
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-10
-8
-6
-4
-2
0
2
4
6
8
10
12
14
16
18
20
Trades
Crisis
Pre-crisis

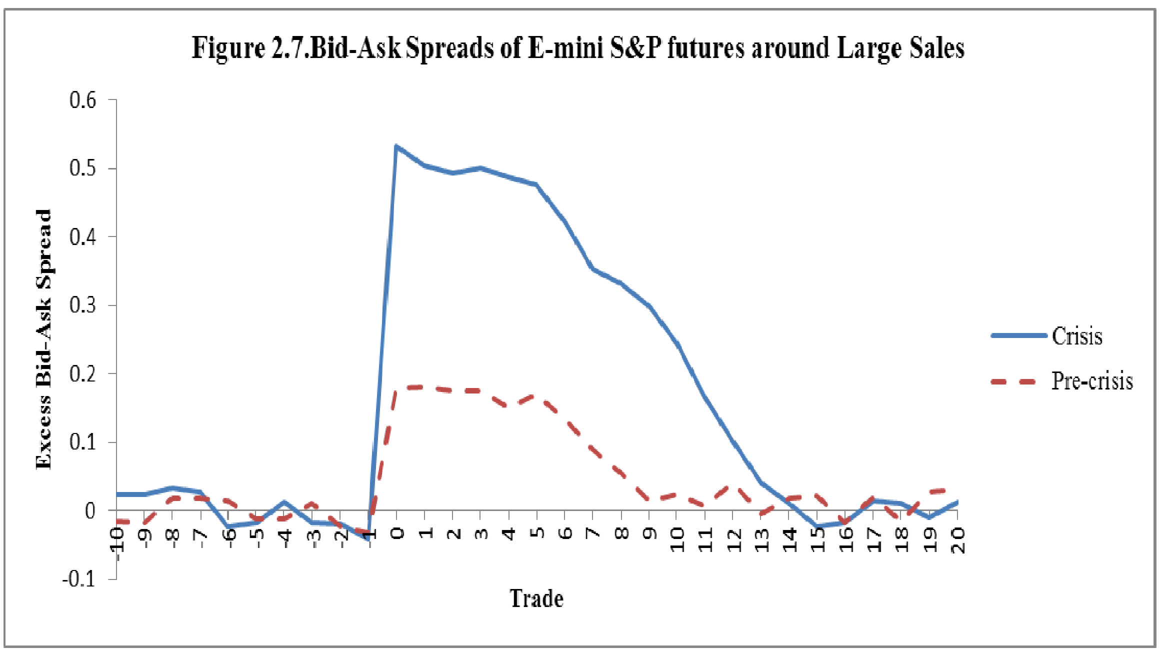


Figure 2.7.Bid-Ask Spreads of E-mini S&P futures around Large Sales
Excess Bid-Ask Spread
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
-10
-9
-8
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
Trade
Crisis
Pre-crisis

Figure 2.8. Bid-Ask Spreads of E-Mini Nasdaq Futures around Large Purchases

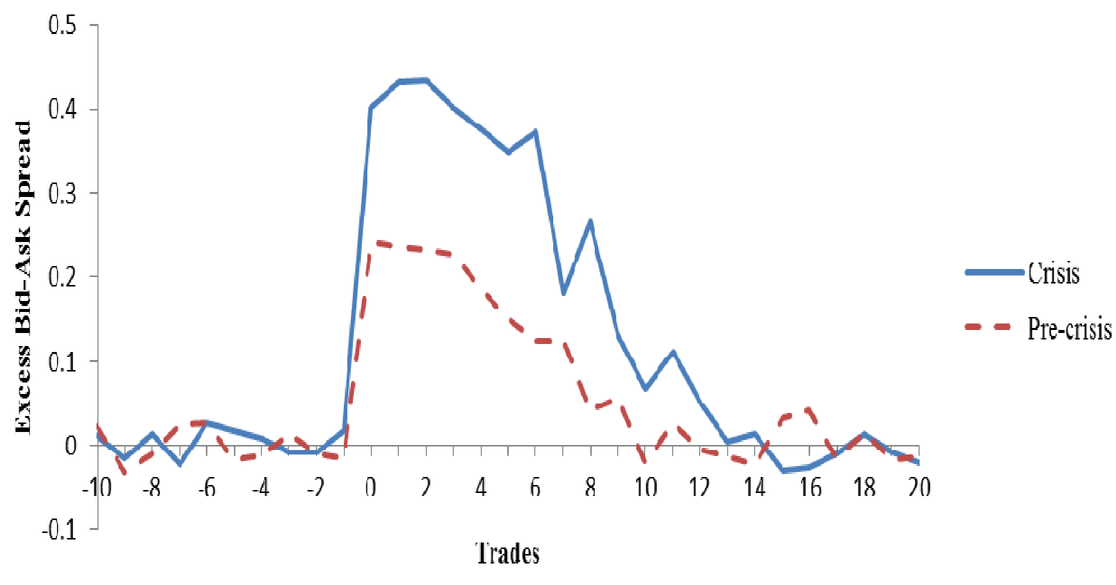
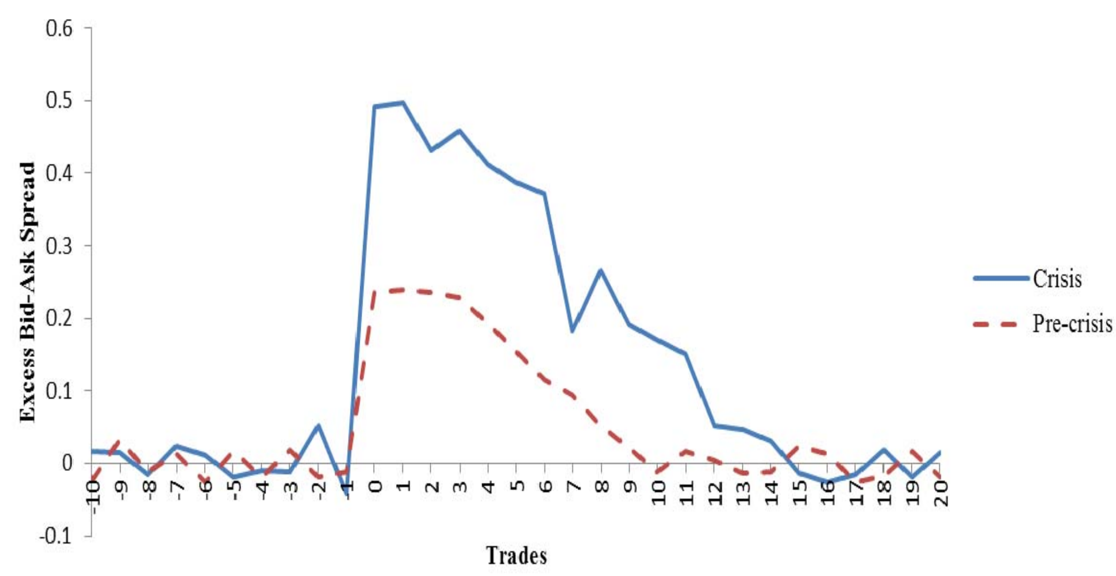


Figure 2.9. Bid-Ask Spreads of E-Mini Nasdaq Futures around Large Sales



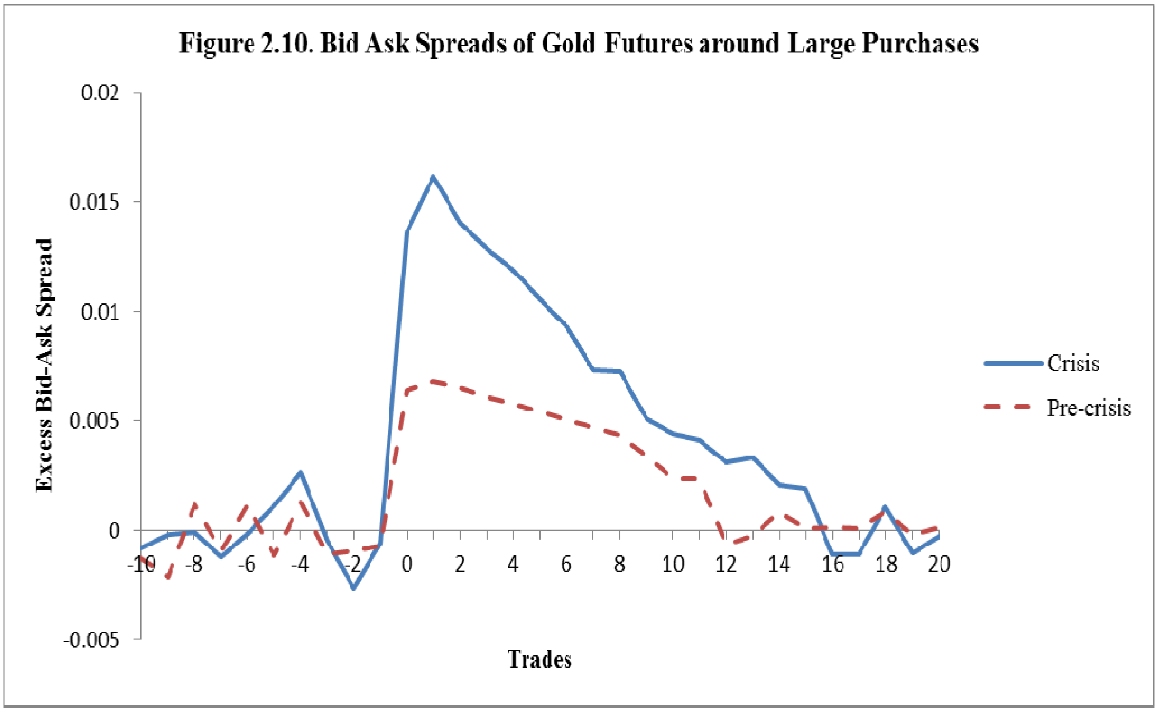


Figure 2.10. Bid Ask Spreads of Gold Futures around Large Purchases
0.02
0.015
0.01
0.005
0
-0.005
Excess Bid-Ask Spread
-10
-8
-6
-4
-2
0
2
4
6
8
10
12
14
16
18
20
Trades
Crisis
Pre-crisis

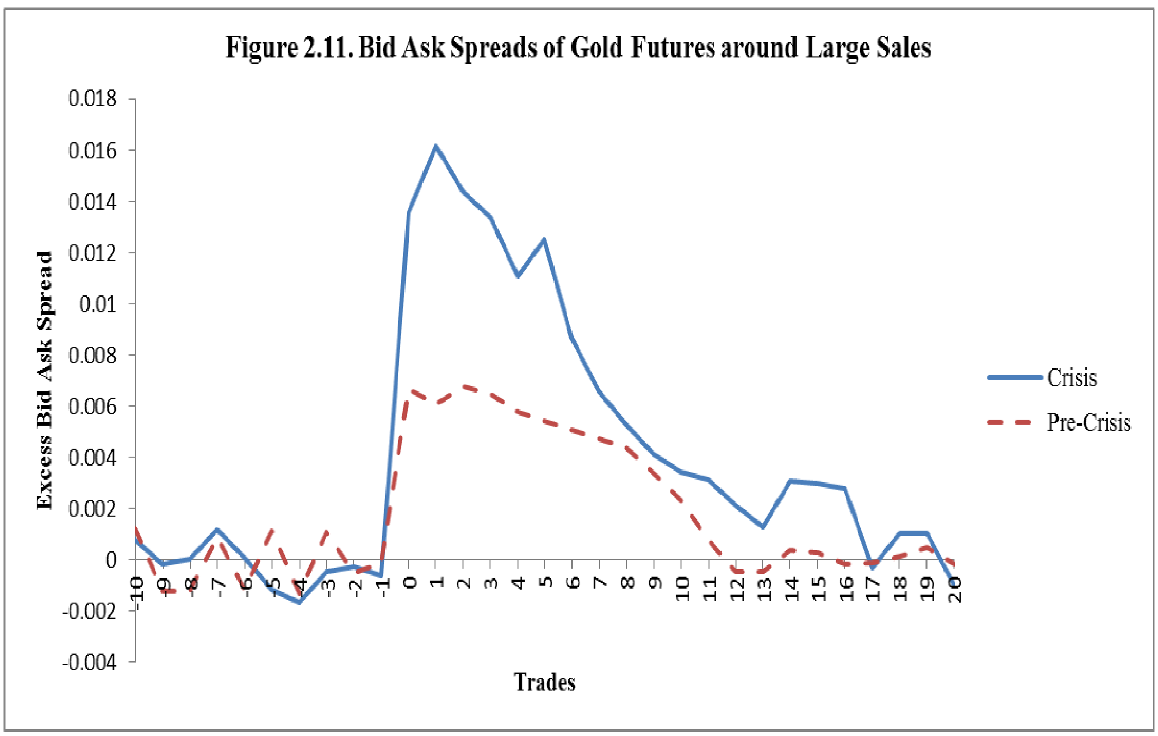


Figure 2.11. Bid Ask Spreads of Gold Futures around Large Sales
0.018
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
-0.002
-0.004
Excess Bid Ask Spread
-10
-9
-8
-7
-6
-5
-4
-3
-2
-1
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
Trades
Crisis
Pre-Crisis

Figure 2.12. Bid Ask Spreads of Euro Futures around Large Purchases

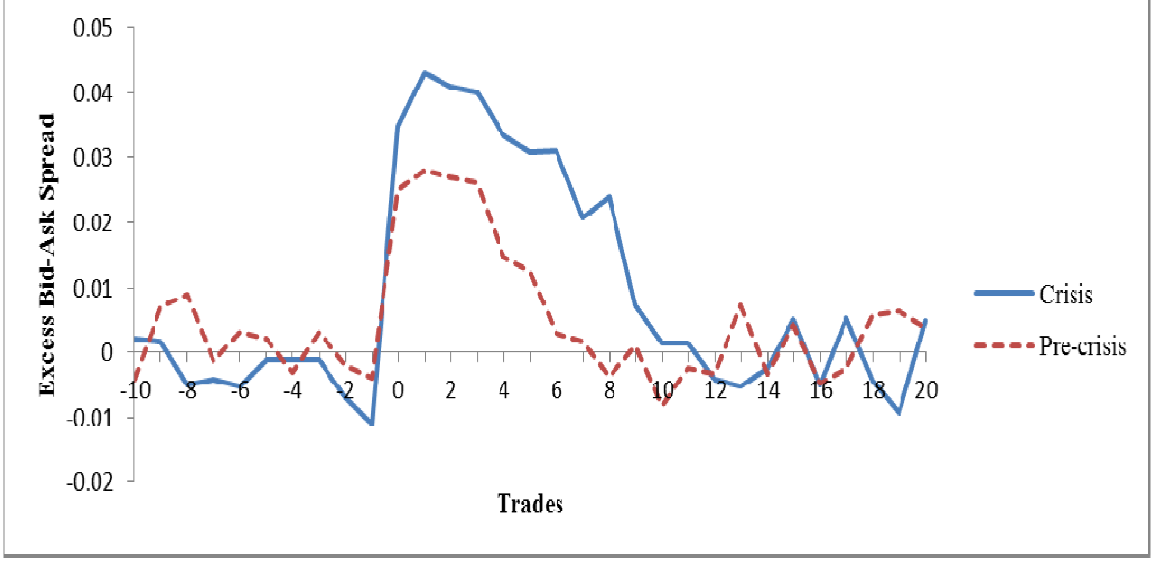


Figure 2.13.Bid Ask Spreads of Euro Futures around Large Sales

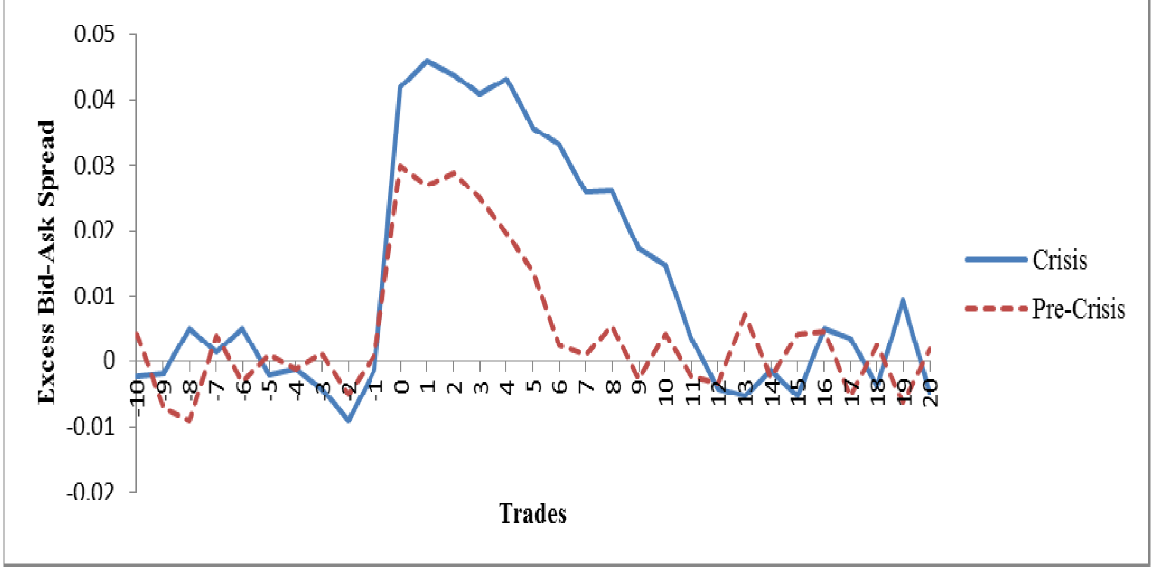


Figure 2.14. Bid Ask Spreads of British Pound Futures around Large Purchases

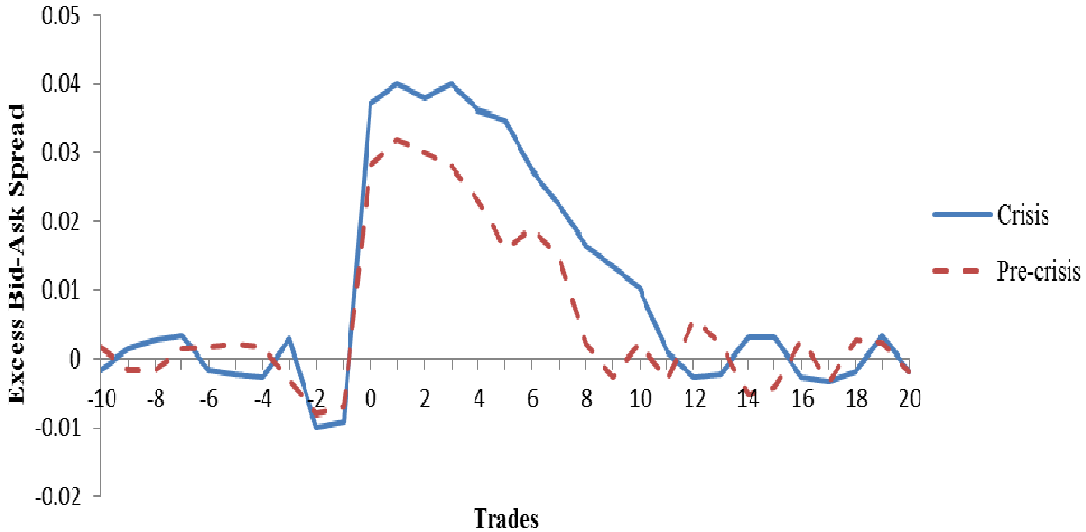
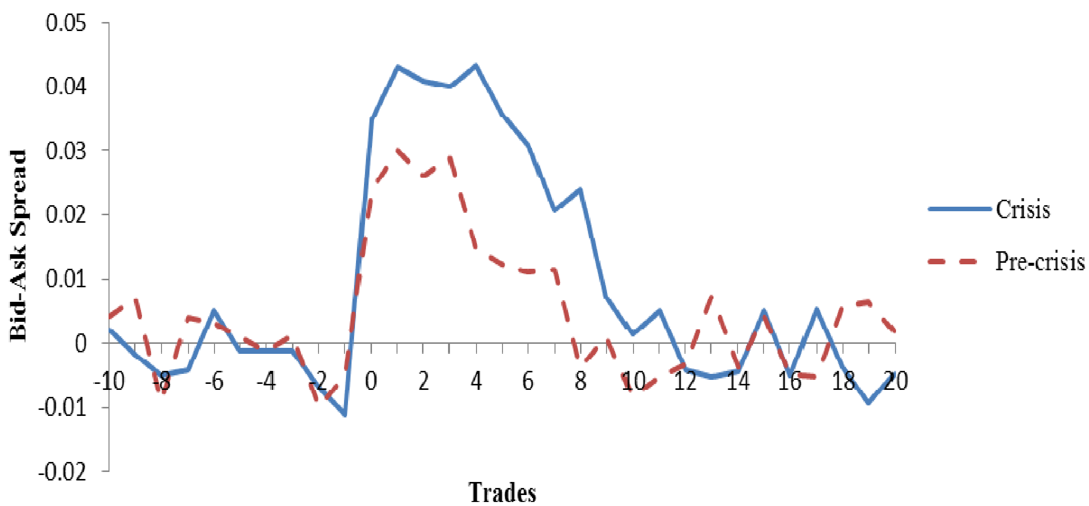


Figure 2.15. Bid Ask Spreads of British Pound Futures around Large Sales



CHAPTER 3: COMPONENTS OF QUOTED BID-ASK SPREADS IN U.S ELECTRONIC FUTURES MARKETS

3.1. Introduction

The bid-ask spread represents a major component of a trader's transactions cost. Much of the literature finds that bid-ask spreads reflect the three costs that market makers incur: order processing costs (Roll 1984), adverse selection costs (Kyle 1985; Glosten and Milgrom; 1985; and Glosten 1994), and inventory costs (Stoll 1978). Several studies concerning bid-ask spreads focus their analyses on the empirical determinants of bid-ask spreads in the equity markets (Roll 1984; Glosten and Milgrom, 1985; Glosten, 1987; Glosten and Harris, 1988; Copeland and Galai, 1983; Haller and Stoll, 1989; Stoll, 1989; George, Kaul, and Nimalendran, 1991; McInish and Wood, 1992; Huang and Stoll 1997). Whereas previous studies focused on the behaviour and components of bid-ask spreads in U.S. equity markets, no studies exist in the literature analyzing bid ask spreads in U.S. electronic futures markets.

In this study, I analyze how adverse selection, order processing, and inventory holding costs affect bid–ask spreads for a wide spectrum of futures contracts in both volatile and less volatile periods. The purpose of this study is to understand how market makers adjust quotes during different market conditions. These bid-ask spreads are decomposed into their components using Huang and Stoll's (1997) model. According to Van Ness et al. (2001), Huang and Stoll's method accurately captures the adverse selection component of the spread without being affected by the instrument's price volatility. This property of Huang and Stoll's technique makes it particularly suitable for this study, since adverse selection costs are measured for both volatile and less volatile periods.

This study contributes to the literature by comparing for the first time the three cost components for equity index, currency, and precious metal futures during volatile (in this case, the financial crisis of 2008) and less volatile periods (the pre-crisis period), using intraday, high-frequency data from five different futures contracts that are electronically traded in U.S. markets.

Our results show that during the more volatile period of 2008, market makers increase bid–ask spreads, mostly because of the increased risks associated with information asymmetry (calculated as adverse selection costs) and inventory holding costs. However, we find that order processing costs represent the largest component of bid–ask spread in both periods.

3.2. Literature Review

Several studies show that market makers widen spreads when information arrival is suspected. Kyle's (1985) theoretical model is based on informed investors taking advantage of uninformed investors and profiting from trading on private information about the value of an asset. Kyle's model emphasizes the importance of the adverse selection cost component of the bid-ask spread as it affects dealers and uninformed liquidity traders. Further empirical research shows that adverse selection costs comprise an important component of the bid–ask spread in equities markets (Easley and O'Hara, 1987; Glosten and Milgrom, 1985; Copeland and Galai, 1983). These studies analyze the impact of informed traders in a market setting, where the other players are uninformed traders and market makers. Informed trading has considerable negative impact on market makers, who therefore inflate bid and ask quotes to compensate for the losses from informed traders.

Subrahmanyam (1991) extends Kyle's model to a multi-asset economy setting, where baskets of stocks are available for trading. Subrahmanyam's model predicts that because private information about individual assets plays a smaller role at the portfolio level, less of an informational disadvantage exists to market makers holding baskets of stocks; an example of such assets is equity index futures. Neal and Wheatley (1998) find that although the adverse selection cost component of closed-end funds is indeed smaller than that of common stocks, the difference is not as great as hypothesized by Subrahmanyam (1991).

In the market microstructure literature (Kyle 1985; Glosten and Milgrom 1985), three investor categories are proposed—market makers, informed traders, and liquidity (uninformed) traders. Market makers, or other limit order investors, possess an information disadvantage relative to informed investors, whereas liquidity investors trade without access to private information. To market makers, informed and liquidity investors are indistinguishable. Informed investors profit from trading with market makers, and liquidity investors. Market makers post bid–ask quotes wide enough to compensate for trading with informed investors. Therefore, spreads increase with asymmetric information.

Inventory holding cost is another component of the bid ask spread. As market makers buy (sell) and as inventory increases (decreases), market makers try to sell (buy) back, thereby adjusting their quotes in to control order flow and bring inventory back to a preferred position (Stoll 1978; Amihud and Mendelson 1980; Ho and Stoll 1981; Ho and Stoll 1983). The third and last component of bid ask spread is order processing cost. The order processing cost represents a fee charged by market makers for matching buy and sell orders

In the market microstructure literature of decomposing the bid-ask spread two classes of models exist: the serial covariance spread estimation model and the order flow spread estimation model. In the serial covariance spread estimation model the spread measures are derived from the serial covariance properties of transaction price changes (the most common empirical serial covariance estimation model was developed by Roll (1984)). If trade prices fluctuate between bid and ask prices then the observed price changes become negatively autocorrelated. Roll's (1984) model estimates the bid-ask spread based on this negative serial correlation property of transaction prices. In another class of models, the bid-ask spread is estimated via order flow regression models. Glosten and Harris (1988) applied this concept to estimate the adverse selection spread component by developing an order flow transaction costs model. Huang and Stoll (1997) extend the Roll (1984) and Glosten and Harris (1988) models, by combining order processing, inventory, and asymmetric information (adverse selection) cost components. Van Ness, Van Ness, and Warr (2001) show that Huang and Stoll's method accurately captures the adverse selection cost component of bid–ask spreads without being affected by market conditions. This study examines the bid–ask spreads of futures contracts using Huang and Stoll's (1997) method, reported for the first time in the literature.

3.3. Data

This study employs intraday, high-frequency data from five different futures contracts that are electronically traded in U.S. markets. Data from different asset classes and from different time periods are used in order to determine how the bid-ask spreads behave for different asset classes. Our data set includes the E-mini S&P 500, E-mini NASDAQ 100 equity index, gold, the British pound, and euro currency futures. The sample periods include the volatile time span of September 2008 through December 2008, during the financial crisis, as well as the less volatile, pre-crisis period of January 2007 through March 2007.

Trades that occur at the same price, in the same direction (buy or sell), and within the same minute are aggregated. Nearby contracts are used in the analysis, since they are the most active contracts. The data source is the CQG transactions database.

3.4. Methodology

I implement the Huang and Stoll (1997) model by first establishing a basic trade indicator model, then I employ two extensions to distinguish between all three bid–ask spread components. This technique uses the generalized method of moments to directly provide consistent estimates of the components of the bid-ask spread. The first part of the model, the basic trade indicator, makes no assumptions about the conditional probability of trades and measures the order processing cost. The basic model (explained in more detail later) is based on substituting observable values into the unobservable price, V_t, which leads to

$$\Delta P_t = \frac{S}{2}(Q_t - Q_{t-1}) + \lambda \frac{S}{2} Q_{t-1} + e_t \tag{3.1.}$$

where S is the estimated traded spread; Q is the trade indicator and takes the value of –1, or 1, for sell and buy trades respectively. $\lambda = \alpha + \beta$, where α is the adverse selection cost component and β is the inventory-holding cost component of the bid-ask spread. From this equation the cost component of the spread that is not due to adverse selection or inventory holding costs, $(1 - \lambda)$, which represents the order processing cost component of the spread.

In the second part the basic model is extended by using the conditional expectation of the trade indicator. Since quote revisions follow each trade, every subsequent trade is dependent on the one prior to it. This data serves as a basis for a probability estimator, π, which is defined as the probability that the current trade is opposite in sign to the trade that occurred just before. The basic model is extended to estimate all three cost components of the bid ask spread .

$$E(Q_{t-1}|Q_{t-2}) = (\ 1 - 2\pi)Q_{t-2} \tag{3.2.}$$

$$\Delta M_t = (\alpha + \beta)\frac{S_{t-1}}{2} Q_{t-1} - \alpha(1 - 2\pi)\frac{S_{t-2}}{2} Q_{t-2} + \epsilon_t \tag{3.3.}$$

where St is the quoted spread at the transaction at time t, M_t is the midpoint of the bid–ask quote that prevails just before the transaction at time t, Q_t is the buy–sell indicator for the trade price, P_t , and π is the probability that the trade at time t is opposite in sign to the trade at $t - 1$. α and β represent the percentage of the half spread attributable to adverse selection costs and inventory costs respectively. Order processing cost component is equal to $(1 - \alpha - \beta)$.

3.5. Results

Utilizing Huang and Stoll's (1997) method, the bid ask spreads of five futures contracts are decomposed into three components to examine the pre-crisis and crisis periods of this study. The contract specifications given in Table 3.1 reflect the size and thus the risk traders and market makers take with each trade.

Our results in Table 3.2 show that order processing is the largest cost component of bid–ask spreads in the futures markets examined here. The sum of the adverse selection and inventory holding costs is smaller than the order processing cost for all five contracts, during both the pre-crisis and the crisis period. However, order processing costs decline and the sum of the adverse selection and inventory risk costs increase during the volatile crisis period as compared with the pre-crisis period. This result shows that when uncertainty increases in futures markets, market makers increase bid–ask spreads in response to higher information asymmetry and inventory holding risks. Among the contracts in our sample, gold futures have the smallest order processing costs (0.68 in the pre-crisis and 0.58 in the crisis periods), although they also possess the highest adverse selection and inventory holding costs. Equity index futures are associated with the least adverse selection and inventory holding costs. Specifically, in the E-mini S&P futures market the sum of the inventory holding and the adverse selection cost components are higher than for the E-Mini Nasdaq 100 futures market.

Order processing, adverse selection, and inventory holding costs are reported separately in Table 3.3. In this analysis, sequential trades are not aggregated. The results reported in this table are consistent with the results reported in Table 3.2. Order processing costs still represent the largest component of the bid–ask spreads in futures markets. The second-largest cost component is the inventory holding costs. An exception is the gold futures adverse selection cost, which are negative due to trade clustering. In the next section the results are reported after the sequential trades that occur at the same price without any quote change are combined.

Following Huang and Stoll (1997), who also find negative adverse selection costs due to trade clustering, we aggregate sequential trades that occur at the same price. Table 3.4. shows the order processing, inventory holding, and adverse selection costs for sequential trades that occur at the same price, which are aggregated and treated as one large order. The results show that the gold futures market possesses the highest adverse selection and inventory holding costs in our sample, both in the pre-crisis and crisis periods. Consistent with Subrahmanyam (1991), our results show that adverse selection costs are the smallest, and the order processing costs are the largest components of the bid–ask spreads for all five futures markets. Moreover, the inventory holding costs are the second largest component of spreads after order processing costs. During the crisis period, the order processing cost components of the bid–ask spreads decrease, whereas the adverse selection and inventory holding cost components increase.

3.6. Conclusion

In this study I analyze the bid-ask spread components of a wide spectrum of futures contracts, in both volatile and less volatile periods, in order to understand how market makers adjust quotes during different market conditions. The cost components of bid–ask spreads are analyzed using intraday, high-frequency data from five different futures contracts that are electronically traded in U.S. markets to understand how market makers adjust quotes during different market conditions.

Our results show that during more volatile periods, market makers increase bid–ask spreads, mostly because of the increased risks associated with information asymmetry, calculated as adverse selection costs, and inventory holding costs. Although adverse selection and inventory holding costs are higher during the crisis period as compared with the pre-crisis period, order processing costs represent the largest cost component of bid–ask spread in both periods.

A theoretical model predicts that in markets using baskets of securities, adverse selection costs are diversified away (Subrahmanyam 1991). However, there is no prior empirical study that tests this hypothesis using data from U.S. electronic futures markets. Among the contracts we analyzed, our results show that the adverse selection cost component of equity index futures bid–ask spreads are smaller than those of gold and currency futures. Adverse selection and inventory holding cost components are larger for gold futures than for the equity index and currency futures.

This study can be extended in the future to compare adverse selection, inventory holding and order processing costs in different markets and subsequent time periods, especially using data from options markets and data from the post-crisis period.

Table 3.1: Contract Specifications

This table reports the contract specifications of the five different futures contracts in this study.

Contract	Tick Size (Pts.)	Contract Size	Point Value (US$)
E-Mini S&P 500	0.25	$50 times the index	50
E-Mini NASDAQ 100	0.25	$20 times the index	20
Gold	0.10	100 troy ounces	100
Euro	0.0001	EUR 125,000	125,000
British Pound	0.0001	GBP 62,500	62,500

Table 3.1. Traded Spread and Order Processing Cost Components

This table reports the results from estimating $\Delta P_t = \frac{S}{2}(Q_t - Q_{t-1}) + \lambda \frac{S}{2} Q_{t-1} + e_t$. The results show the estimated traded spread (S) and the proportion of bid-ask spread due to adverse selection and inventory holding (λ) costs. The proportion of the traded spread due to order processing is calculated as 1 – λ.

	S (Estimated Spread)		Λ (Sum of Adverse Selection and Inventory Holding Cost)		1-λ (Order Processing Cost)	
	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisis	Crisis
E-Mini S&P	0.270	0.450	0.11	0.19	0.89	0.81
E-Mini NASDAQ	0.300	0.530	0.14	0.23	0.86	0.77
Gold	0.010	0.018	0.32	0.42	0.68	0.58
Euro	0.026	0.052	0.17	0.28	0.83	0.72
British Pound	0.029	0.057	0.19	0.31	0.81	0.69

Table 3.3. Components of the Bid–Ask Spreads, Estimates Based on Serial Correlation in Trade Flows

This table reports the results from computing the extended model, which is based on serial correlation in trade flows. The extended model is used to simulatenously estimate the three components of the bid–ask spread: adverse selection (α), inventory holding (β), and order processing (1-α-β). The extended model consists of the following equations

$$E(Q_{t-1}|Q_{t-2}) = (1-2\pi)Q_{t-2} + \varepsilon_t$$

$$\Delta M_t = (\alpha+\beta)\frac{S_{t-1}}{2}Q_{t-1} - \alpha(1-2\pi)\frac{S_{t-2}}{2}Q_{t-2} + e_t.$$

	α (Adverse Selection)		β (Inventory Holding)		π		1-α-β (Order Processing)	
	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisis	Crisis
E-Mini S&P	–0.03	–0.01	0.13	0.16	0.31	0.36	0.90	0.85
E-Mini NASDAQ	–0.04	–0.03	0.15	0.17	0.26	0.32	0.89	0.86
Gold	0.02	0.04	0.22	0.24	0.44	0.48	0.76	0.72
Euro	–0.05	–0.04	0.16	0.19	0.27	0.31	0.89	0.85
British Pound	–0.07	–0.02	0.19	0.23	0.22	0.35	0.88	0.79

Table 3.4. Components of the Bid–Ask Spreads, Estimates Based on Serial Correlation in Trade Flows with Trade Clusters

This table reports the results from computing the extended model, which is based on serial correlation in trade flows. Sequential trades without quote revision are considered as one large order. The extended model is used to simulatenously estimate the three components of the bid–ask spread: adverse selection (α), inventory holding (β), and order processing (1-α-β). The extended model consists of the following equations: $E(Q_{t-1}|Q_{t-2}) = (1-2\pi)Q_{t-2} + \varepsilon_t$ and $\Delta M_t = (\alpha+\beta)\frac{S_{t-1}}{2}Q_{t-1} - \alpha(1-2\pi)\frac{S_{t-2}}{2}Q_{t-2} + e_t$.

	α (Adverse Selection)		β (Inventory Holding)		π		1-α-β (Order Processing)	
	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisis	Crisis	Pre-Crisis	Crisis
E-Mini S&P	0.01	0.02	0.18	0.22	0.52	0.56	0.81	0.76
E-Mini NASDAQ	0.01	0.02	0.20	0.23	0.52	0.59	0.79	0.75
Gold	0.07	0.09	0.31	0.34	0.54	0.55	0.62	0.57
Euro	0.02	0.04	0.23	0.28	0.57	0.53	0.75	0.68
British Pound	0.03	0.05	0.25	0.30	0.54	0.59	0.72	0.65

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FMA 2013 in Chicago, “Liquidity, Characteristics and Price Discovery in U.S. Electronic Futures and ETF Markets”

GFC 2013 in Monterey, California, “Global Equity Market Innovations through Volatility Measures”

SWFA 2012 in New Orleans, “Liquidity, Volatility and Market Depth in U.S. Electronic Futures Market”