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Derivative Securities in Germany: An Examination of the Price Discovery and Extreme Value Processes.

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DERIVATIVE SECURITIES IN GERMANY: AN EXAMINATION OF THE PRICE DISCOVERY AND EXTREME VALUE PROCESSES

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ABSTRACT

This dissertation examines the price discovery and extreme value processes found in Germany's stock index and stock index futures markets. These two concepts are framed within the fundamental relationship between risk and return found in the financial economics literature.

Results from the price discovery analysis indicate that the stock index futures market processes information more quickly than the underlying spot market. However, this processing can be characterized by a feedback loop because sometimes the spot market processes information more quickly than the futures market.

An indepth analysis of the information processing relationship implies that the futures market processes information faster than most of the individual stock index component stocks. However, two securities sometimes lead the futures market. The reasons these two securities lead the futures market are of particular interest.

Additionally, the processing speed of the futures market tends to be increased when there is market-wide, as opposed to security-specific, information affecting the securities market. Also, analyses of up and down markets and different trading activity proxies are performed. They reveal that the lead-lag relation is conditional on the information set available to market participants.

The results of the extreme value section indicate that extreme price declines for most FDAX contracts are larger in absolute terms than extreme price increases. The results of the extreme value analysis also indicate that the data generation process of the extreme price changes originate from a Type II extreme value process.

An examination of prudent margin setting procedures is made as a practical application of extreme value theory. The results of this part of the study indicate that the extreme value distribution approximates the empirical extreme value observations better than the normal distribution process.

CHAPTER 1

INTRODUCTION

The risk/return trade-off relationship is a central paradigm in the financial economics literature and is used extensively as a pedagogical concept in financial economics education. In particular, this trade-off relationship is essential to the argument of efficient asset allocation of society's precious resources. One avenue used to investigate this relationship is to examine the price discovery process and/or risk characteristics of a particular security, market or basket of securities. Derivative securities offer an interesting avenue for examining the impact of price discovery and risk processes on resource allocation.

The purpose of this dissertation is to examine both the price discovery and risk processes of Germany's derivative security markets. The price discovery process is examined in a lead-lag context. The particular risk process analyzed here is via probabilities of observing extreme values. These two elements are important in understanding how derivative securities are used by investors to transfer their information into efficient asset allocation decisions.

Extant research implies that derivative securities (especially stock index futures) process information more quickly than their underlying securities. This research

documents that returns from derivative securities usually lead the returns of their underlying assets. However, documentation of a weak feedback of information processing from the underlying asset to the contingent claim also exists.

This dissertation uses vector autoregressive (VAR) methods, as described by Granger (1969), to investigate the lead-lag relationship between Germany's futures and spot markets in an attempt to determine the sources of any lead-lag, or feedback relationship existing in the data. Due to leverage effects, transaction costs, and institutional constraints, it is hypothesized that the derivative securities markets will tend to process information more quickly than the spot market.

To examine whether derivative securities process information faster than the underlying securities, a number of hypotheses are examined. The first hypothesis examined is whether DAX index futures returns lead DAX spot returns over a large time series of spot and futures index data. The results of this analysis indicate that derivative securities process information more quickly than the underlying securities. However, a significant feedback information loop is also documented.

To further investigate the causes of the information processing ability of stock index futures, a number of more detailed hypotheses are examined. First, an examination is

made of the lead-lag relation between the stock index futures and the individual component securities of the DAX index. The results of this inspection indicate that the futures market processes information more quickly than most (28 out of 30) individual securities. However, there is an apparent information processing feedback loop between two of the individual securities (Allianz and Deutsche Bank) and the futures contract. One implication of this finding is that information processing on most individual securities is slower than that taking place in the futures market. With respect to Allianz and Deutsche Bank, each of these firms hold asset portfolios consisting of many other firms. In a sense, these two firms may be proxies for the market as a whole.

There may be many reasons why there exists a lead-lag relation in the DAX and DAX index futures contracts. One of these reasons relates to the difficulty German investors have in short-selling individual securities. An examination of up and down markets is made to explore this issue. The result of this section is surprising in that the lead time of the futures market is substantially reduced, though feedback still exists. Apparently, the short selling restrictions in Germany do not entice participants with bad news to trade their information in the derivative securities market. Market expectation alignment during extreme up and down markets is given as a

reason for the reduction in processing speed in the futures market.

Much attention has been paid by financial market research to defining information proxies. One of these proxies comes under the rubric of trading activity. In particular, the number of transactions, trading volume, and the number of securities trading per time periods have been postulated as proxies for information. Hence, examining the lead-lag relation considering these proxies of trading activity can be an important indication as to whether information processing is affected by differential levels of market activity. The results of this test, however, are mixed. Essentially, the lead-lag structure depends upon the definition given to trading activity. The implication here is that more research related to information proxies is needed.

If investors wish to decrease trading costs, derivative securities offer one route to obtain this objective. In particular, stock index futures contracts allow investors an option to trade market-wide, or macro-based information with lower transaction costs than trading individual securities. Depending on whether an investor possesses market-wide (macro related) or security-specific (micro related) information, he may choose the derivative or underlying security. Examining this issue in a lead-lag context allows one to determine the information processing

speed of each market when investors are confronted with different types of economic information. The results of this analysis indicate that under heavy market-wide movements, the derivative market's information processing advantage is expanded. The implication here is that the leverage effects and low transaction costs of the derivative securities market are an attractive alternative to investors endowed with macro or market-wide information.

Regarding the risk process, much research has been done using ARCH and GARCH models for modelling risk conditional on past information. This dissertation takes a different but complementary path in that the risk process considered is found in the probabilities of observing extreme values. The idea is that extreme values may well be considered the "ultimate" risk measure because they represent precipitous changes in wealth. If abrupt changes in wealth are undesirable, the contribution of this analysis is determining the probability of observing large negative wealth effects found in extreme values.

Extreme value theory - as applied to financial markets by Longin (1994), Jansen and De Vries (1991), Koedijk, et. al. (1992) and Akgiray, et. al. (1988b) - is used to examine the tail distribution of the futures return series. Since extreme value analysis is a relatively new branch of the financial literature, this part of the dissertation adds much to the body of financial knowledge.

The results of this section indicate two facts related to the DAX futures data: (1) price declines are larger in absolute value than price increases, and (2) the extreme price changes follow a Type II extreme value distribution. The Type II extreme value process indicates highly leptokurtotic tail behavior and an increased probability of observing large stock price changes. Examples of parent distributions that generate Type II extreme values are the t-distribution, the Cauchy distribution and other leptokurtotic data generation processes, such as ARCH and GARCH. This result is intuitively pleasing because it conforms to extant research indicating non-normality of stock return distributions.

As a practical application of extreme value analysis, prudent margin setting requirements are examined. The thrust of this section is related to curbing losses due to extreme price movements in Germany's stock index futures market. Findings are that the extreme distribution is better suited to curbing losses than using a normal distribution process when setting margin levels. A normative application of this result is that margin setting committees should use extreme value theory when setting prudent margin levels.

CHAPTER 2

PRICE DISCOVERY

2.1 LITERATURE REVIEW

Derivative securities are defined as financial assets that derive their value from other financial assets. Stock index futures fall under the category of derivative securities because they are assets based on the value of a basket of securities. In particular, the basket of securities are those securities that make up the particular stock index of interest.

According to the no arbitrage condition of the spot futures parity theorem, the value of a stock index futures contract is a function of the underlying stock index, a factor to account for a risk free level of interest rates, a factor to account for leakage (usually a dividend yield) if any, and a factor to account for the time to maturity. The spot futures parity theorem, also called the cost of carry relationship, is shown in its functional form in Equation 1.

$$F=f(I,R_f,D,T), \tag{1}$$

where F is the futures price, I is the value of the index in question, R_f is the risk free rate of interest, D is an appropriate dividend yield, and T is the time to maturity of the futures contract.

In a perfect world, futures prices will instantaneously reflect all information related to the underlying stock index, interest rates and appropriate dividend yields. However, research related to the price discovery processes of stock index and stock index futures markets infers that the derivative asset processes information more quickly than the underlying asset. This result may lead one to infer that the underlying asset derives its value from the derivative asset.

Examination of lead-lag relationships is not specific to the spot and futures return relationship, however. Manaster and Rendleman (1982) examine the lead-lag relationship between stocks and their associated stock options. The authors find that the returns for stock options usually lead the returns on the underlying stocks. However, Stephan and Whaley (1990) find that the lead-lag relationship is the opposite of the result found by Manaster and Rendleman (1982). Returns on the individual stocks appear to lead the returns on their options. Brockman (1994) provides evidence supporting Manaster and Rendleman's explanation when he finds that returns to primes and scores lead those of their underlying stocks.

Finally, Kawaller, Koch and Koch (1990), and Chan, Chan and Karolyi (1991) examine the lead-lag relationship of volatility in the S&P 500 spot and futures markets. The

results from these studies indicate that volatility is transmitted much more quickly than price changes.

Finnerty and Park (1987) were the first to examine the price discovery processes of stock index futures markets. They analyze the relationship between the futures contract of the Major Market Index and its associated spot index. Their model accounts only for the futures price change that occurred one minute before the spot return. Even though they include dummy and interaction variables for contract expiration effects, they examine only the transmission of information from the futures to the spot market and do not consider the possibility of information being transmitted from the spot to the futures markets. The results of their analysis show that stock index futures usually lead the spot market in price discovery - a phenomenon the authors label "a case of the tail wagging the dog."

Kawaller, Koch and Koch (1987) examine the lead-lag relationship of the S&P 500 futures and spot markets for various trading days in 1984 and 1985. Using minute-by-minute data, for different daily time periods of the contract (88, 60, 30, 14, and 1 day(s) prior to expiration and expiration day), the authors find that futures price changes lead spot price changes up to 45 minutes, while the

spot price changes lead the futures price changes by no more than 2 minutes.[1]

Stoll and Whaley (1990) also study the lead-lag relationship between the S&P 500 and Major Market spot and futures markets (from 1982-1987 for the S&P and from 1984-1987 for the Major Market). The authors find that the S&P 500 futures tend to lead the S&P 500 index up to 15 minutes. However, the leading market direction is not found to be unidirectional, i.e. hints of the spot market leading the futures market are also documented. Results for the Major Market index and associated futures contract are similar to those found for the S&P 500 market, except that the feedback relationship from spot to futures is almost non-existent.

In a related study, Chan (1992) examines the lead-lag relationship between the S&P 500 and Major Market spot and futures markets for the time period covering 1984-1987. Using an approach similar to Stoll and Whaley (1990), Chan (1992) documents the existence of a lead-lag relationship (also up to 15 minutes).

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[1]Their model (a bivariate VAR-type model) is similar to the type used in this paper; however, they allow the contemporaneous price change of the futures and spot indices to enter the model when the spot and future price changes are the dependent variables. Contemporaneous price changes are usually constructed for convenience of analysis purposes. In reality, very few observations are actually "contemporaneous."

The first study on the price discovery process of the stock index futures market in Germany was carried out by Grünbichler, Longstaff, and Schwartz (1994). These authors find that the lead time for returns in Germany's futures market over its spot market is longer than that documented in the U.S. market. Specifically, evidence is presented that the electronically traded futures market leads the floor-based spot market by approximately 20 minutes instead of the 15 minutes found in the S&P and Major Market studies of Stoll and Whaley (1990) and Chan (1992). Interestingly though, Grünbichler, Longstaff, and Schwartz (1994) also find that the spot market leads the futures market by approximately five minutes, although this lead is weak.

If spot and futures prices are assumed to follow the paths set out under the spot-futures parity relationship, one would expect to see price changes in the spot market move in tandem with price changes in the futures market.[2] However, empirical results indicate that the futures market tends to process information more quickly than the underlying spot market. Researchers have argued that arbitrage opportunities, infrequency of trading, bid-ask spread effects, mechanical time delays, transactions costs, and other factors may explain the information processing

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[2]Technically, contemporaneous movements of both spot and futures price series would only occur if the component stock dividend yields and applicable interest rates were non-stochastic.

advantage of the stock index futures market. "Herding" theories, similar to those found in Admati and Pfleiderer (1988), Bhushan (1991), and Chowdry and Nanda (1991) have also been used to explain the information processing advantage. Discretionary traders "herd" during the same time period, on the same asset, or in the same market, respectively. The herding theories imply that uninformed investors tend to concentrate their trading in order to reduce losses to informed traders. On the other hand, informed traders will want to trade in the market where it is less costly to reveal their information.

Kawaller, Koch and Koch (1987) state that market sentiment and arbitrage trading may be two phenomena affecting the temporal linkages between spot and futures markets. Since changes in investor sentiment can only be transmitted through the spot index after all the relevant stocks trade at different prices from the previous index calculation, the index may reflect updated market sentiment with a lag. Market sentiment can cause the futures market to lead the spot market when investors react to bullish or bearish macro-economic factors.

The futures market could also more quickly reflect new macro-economic information because of the lower initial investment required. Additionally, portfolio rebalancing or stock selection decisions are not required. However, futures traders may rely on recent changes in the

underlying spot market for an indication of the direction of future prices.

Since the transactions costs of a futures transaction are less than the transactions costs of trading the component stocks of an index, market participants who have expectations about market-wide movements, rather than individual stock movements, may elect to trade in the futures market instead of the spot market. Loistl and Kobinger (1993) document that round-trip transaction costs of a futures transaction are approximately 1/100 as costly as the round-trip transaction costs of trading all the stocks comprising the DAX index. If investors want to trade where it is least costly, it is hypothesized that investors informed with macro-economic information in Germany will tend to trade in the futures market. However, it may still be possible for an investor to become informed on an individual stock, or sub-group of stocks, and reveal his information through trades in the spot market.

Chan (1992) also acknowledges that the lead-lag relationship may depend on whether information arriving to the market is market-wide or firm-specific. If information is market-wide, informed investors may prefer to trade in the lower cost market, instead of having to engage in individual stock selection and to incur higher transactions costs. When information is macro in nature, the futures market is in a position to lead the spot market by a longer

time period than when there is not a large amount of market-wide information. Conversely, if information is firm-specific or even industry-specific, the spot market may lead the futures market when traders respond to firm-specific news related to their individual stock holdings more quickly than futures traders.

Chan (1992) deduces that the information processing advantage of the futures market is due primarily to market-wide movements of asset returns, as opposed to the infrequency or intensity of trading, or good or bad news events. Chan (1992) finds that after accounting for a changing infrequent trading structure (news events or trading intensity effects) the lead-lag relationship is stronger the more individual stocks move together (market-wide movements).

Chan (1992) stipulates that when a larger number of component stocks make up an index, the futures market leads the spot market more strongly. He concludes that the asymmetric lead-lag relationship between the futures and the spot market is attributable to faster information processing and a more efficient ability to recognize market-wide information by the futures market.

If trading in both markets is largely dominated by little or no arbitrage opportunities, market sentiment activities affect the spot and futures prices in the same direction. However, if arbitrage opportunities persist,

arbitrageurs begin to take opposite positions in each market, causing any "normal" lead-lag relationship to alter. According to Kawaller, Koch, and Koch (1987), changes in the lead-lag relationship during arbitrage opportunities may manifest themselves either when both markets move in the same direction (with one series moving more quickly than the other), or when they move in opposite directions. Hence, there may be a dynamic lead-lag relationship between the spot and futures index markets, depending on whether market sentiment or arbitrage conditions are present.

Stoll and Whaley (1990) also discuss some of the factors that may account for the existence of a lead-lag relationship between the S&P 500 and Major Market futures and spot markets. Infrequent trading, negative serial correlation induced by the bid-ask spread of individual stocks in an index, and the mechanical time delays in reporting stock trades and/or the relevant index are each mentioned as possible ways for a lead-lag relationship to exist. These authors use an ARMA (Autoregressive Moving Average) model to mitigate infrequent trading and bid-ask problems. The autoregressive (AR) portion of the model is shown to moderate infrequent trading problems whereas the moving average (MA) portion is shown to temper noise introduced by the bid-ask spread.

Chan (1992) discusses additional phenomena that may cause the futures market to lead the spot market. For example, short-selling restrictions are discussed as one of the reasons for the existence of a lead-lag relationship. Since Diamond and Verrecchia (1987) document that short-selling restrictions retard the adjustment of prices to private information, Chan (1992) postulates that short-selling restrictions placed on institutional or insider traders in the spot market will cause the futures market to lead the spot market, especially in the presence of bad news.

Bamberg and Röder (1994) note that only institutional traders are eligible to short-sell individual securities in Germany. Therefore, when individual investors possess adverse private information, and want to trade on that information, they must go through the futures market. Since there are little or no short-selling restrictions in the futures market, the futures price discovery process may tend to lead the spot market, especially in down markets.

Chan (1992) notes that there may also be a relationship between price discovery and the intensity of trading in each market. Due to Admati and Pfleiderer's (1988) finding that both liquidity and informed traders prefer to trade when the market is thick, either through a high level of trading volume or transaction activity, more information may be released in thick, rather than thin,

markets. Chan (1992) postulates that the increased information released through thick trading directly impacts upon any existing lead-lag relationship.

Another factor that may impact the differential information processing capabilities of the spot or futures market is the advent of fully computerized trading systems. Huang and Stoll (1992) discuss some of the important issues to consider when designing automated trading systems, and Domowitz (1993) develops a taxonomy of automated trading systems. Domowitz (1993) classifies different automated trading systems along the lines of priority of trade execution, degree of automation of the price discovery process, and transparency of the system. He finds a broad spectrum of systems in existence. In general, however, most automated trade execution systems contain some level of sophistication in that there exists a trade-matching algorithm combined with information display and transmission mechanisms.

The futures market found in Germany's Futures and Options Exchange, operating under the Frankfurt Stock Exchange (FSE), is the automated Deutsche Termnibörse (DTB). As of 1993 the DTB had approximately 75 members utilizing approximately 550 terminals for order entry, order confirmation, and examination of trading activity.[3] Even though the system was recently only operational in

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[3]Information obtained from Table 1 in Domowitz (1993).

Germany, an agreement with the MATIF, France's futures and options exchange, has allowed access to the system for traders not physically located in Germany. A thorough discussion on the market microstructure issues in Germany is found in Grünbichler, Longstaff, and Schwartz (1994), and Booth et.al. (1995). Specific plans concerning who will obtain access to the DTB outside of Germany is found in German Stock Exchanges -- Annual Report 1992.

The first classification scheme used by Domowitz (1993) is the priority of trade execution. This classification scheme determines the priority given to orders in the system that await execution. The DTB's priority of trade execution is a combination of price and time priority. This combination of priority gives preference to the best price available for purchase or sale, and then accounts for the time an order spends at a particular price, not necessarily the amount of time the order has remained unmatched in the system. As compared with other automated systems used on futures and options exchanges, the DTB maintains an average priority of trading algorithm.

The degree of automation in the price discovery process is closely related to the economic efficiency of the automated trading algorithm because it dictates how prices are determined. The differences in algorithm capabilities examined by Domowitz (1993) range from a

system having to receive transaction prices from outside (basically an input of a transaction occurring off the system) to a fully automated continuous double auction system using some type of pricing model to determine the price of any transaction. The DTB uses the most popular type of price discovery algorithm used by automated trading systems - the automated continuous double auction algorithm. Like other systems employing this algorithm, DTB transactions occur when orders are crossed. A price is determined within the system (as determined by the previously mentioned priority rules) and a transaction occurs when the best offer to buy is greater than or equal to the best offer to sell. According to Huang and Stoll (1992), a continuous double auction trading system, like that found on the DTB, is the preferred algorithm for efficient price discovery. Therefore, DAX (Deutscher Aktienindex) futures contracts are traded on a system with one of the highest levels of automated price discovery actually used by computerized trading exchanges.

The final classification discussed by Domowitz (1993) is the transparency and anonymity of the automated system. Huang and Stoll (1992) define transparency of a system as "the degree to which trading information is made publicly available." When more trading information is available (on transaction prices and volume for instance), the trading system becomes more transparent. On the other hand,

anonymity is defined as the degree to which traders can transact without revealing their identity. The less information revealed by the system about a trader's identity, the more anonymous the system.

For the most part, screen-based trading systems are extremely anonymous. Very few systems offer any kind of identification of the trader on the other side of the transaction, while none offer counterparty information to the public. Domowitz implies that stock and bond trading systems appear to offer more information to the interested public than futures and options systems. Therefore, an information asymmetry is being introduced between direct and indirect system participants where informed traders may be able to hide more of their private information if they participate in an automated market rather than on a regular floor-traded system. The DTB is extremely transparent in that it displays the last transacted price, as well as the prices and volume for transactions in the automated order book. The DTB is also completely anonymous in that no information related to the counterparties of transactions is displayed or transmitted. Therefore, informed traders may be well-hidden when transacting through the DTB.

Huang and Stoll (1992) discuss some of the main concerns with increased transparency and anonymity.[4] In

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[4]Massimb and Phelps (1994) compare and contrast the operational efficiencies and loss of liquidity due to electronic trading systems. Even though they conclude that

particular, a situation similar to Akerlof's (1970) lemons market may cause trading to cease, due to the increased level of asymmetric information. However, these concerns may be mitigated by preferencing of order flow. In general, automated systems must balance transparency and anonymity with the reputation capital of traders (market makers). If market makers' identities are completely anonymous, they will not be able to assume responsibility for the quality of the market (i.e. show their fairness to both sides of a transaction) and possibly may be unable to attract sufficient order flow to unwind adverse positions or to provide necessary immediacy to the market. Huang and Stoll's suggestion is to allow for a system to be flexible and afford some type of preference-based trading based on past or current order flow or possibly on reputation. The DTB, like many of the other automated futures and options systems, does not allow for preference-based transactions.

Design-based classifications may have an effect on the lead-lag relationship found in Germany's spot and futures markets. Massimb and Phelps (1994) discuss the mechanical characteristics of an automated trading system (increased information dissemination, decreased settlement time, decreased number of wrongly-entered trades, etc...), which

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the loss of liquidity dominates the gains in efficiency offered by today's technology, they suggest that applications of advanced technology to the traditional floor trading systems may alter the loss and gain relationship.

decrease the time period necessary to report spot and futures transactions. If the computerized system is used to facilitate the mechanical operations of markets, operational efficiencies could possibly be increased. If the increased operational efficiencies are greater in the spot market than in the futures market, one could hypothesize that any lead-lag relationship advantage (often attributed to the futures market) would be shortened. However, if the operational efficiency gains are greater in the futures market than in the spot market, any existing lead-lag relationship favoring the futures market may be increased.[5] Analyzing the information processing capability between a spot and futures market where one market maintains a traditional floor trading technology, and the other market adopts a purely electronic trading system may be one way to probe technological or mechanical efficiency gains from adopting an electronic trading system.

Germany's stock exchange is composed of both an "old-fashioned" floor trading system for its spot market and an electronic screen trading system that handles its futures transactions. Both the S&P 500 spot and futures markets are traded on traditional floor traded systems. In

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[5]Discussions related to lowering costs of market operation via automated exchanges are also found in Harris (1990). Increased operational efficiency arguments are found in Grossman (1990) as well.

reality, however, Germany's spot market is a hybrid floor-automated market, where an electronically traded spot market, IBIS (Integrietes Börsenhandels- und Informations-System), accounts for nearly 15-25% of the spot markets trades.

Analyzing the lead-lag relationship between the spot and futures markets using German data and comparing the results to the S&P 500 lead-lag relationship potentially adds valuable data to the information sets of policy makers evaluating the prospects of incorporating screen trading systems technology into their markets. If the technology provided from electronic trading systems can increase information processing speed, then markets utilizing the new technology could perhaps boast faster price discovery, higher operational efficiency, and possibly lower costs to market participants.[6] These operational and economically desirable exchange characteristics could, in effect, create a strategic advantage useful in the increasingly competitive market for security traders.

Even though the consensus of extant empirical research implies an information processing advantage to futures and or electronic markets, it maintains the possibility that spot and/or traditional floor markets periodically have the advantage. At this point, it is useful to recall two

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[6]Massimb and Phelps (1994) provide evidence refuting the lower cost claims often extolled by electronic trading system advocates.

factors that may affect the information processing advantage of the technology based futures market found in Germany. First, Loistl and Kobinger (1993) document a significantly lower futures market transaction cost in Germany. Second, IBIS trades essentially make the spot market a hybrid between old-fashioned floor trading activities and one embracing new technological efficiencies. Therefore, attributing any price discovery advantages directly to technology, or transaction costs, is not as straightforward as that discussed in Grünbichler, Longstaff and Schwartz (1994)

To examine empirically the information processing relationship between spot and futures and electronic and traditional floor systems, this study analyzes the lead-lag relationships between the price changes for German DAX and S&P 500 stocks by employing a bivariate VAR system.[7] Results of this research find that the S&P 500 futures returns lead the S&P 500 spot returns by about 35 minutes, and that Germany's futures returns lead spot returns by approximately 23 minutes.

However, both markets exhibit evidence that the spot returns lead futures returns: up to five minutes for the

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[7]This study employs a system related more closely to the Granger (1969) approach rather than the Sims (1972) approach. Since most of the extant literature focuses on U.S. markets, the S&P 500 data will be used only as a comparison. No indepth analysis of the lead-lag relation will be made for the S&P 500 data.

S&P and up to two minutes for the DAX. Discovering the phenomenon that each market leads the other implies that there is a significant information feedback relationship present for both markets; therefore, no complete price discovery domination by either market exists. Implications of the feedback relationship are that traders in the futures market appear to transmit information to the spot market; on occasion, however, traders in the spot market appear to transmit information to the futures market, regardless of the technology or transactions costs of the trading system. Therefore, from an information processing, or price discovery, standpoint, it is not readily apparent that the traditional floor traded S&P 500 futures market or the German electronic screen-traded futures market completely dominates its corresponding spot markets in information processing capabilities.

An additional result found is that the S&P 500 spot and futures markets exhibit cointegration. The associated error correction model does not appear to alter the feedback relationship found in the non-error corrected model. However, the DAX spot and futures markets do not exhibit cointegration. Due to the significant feedback relationship, it appears that the electronic trading system found in Germany does not completely dominate the floor trading system in information processing capability, as implied by Grunbichler, Longstaff and Schwartz (1994).

The contribution of this dissertation (as related to the S&P 500 lead-lag relationship) is that the model employed here allows for explicit testing of Granger causality and cointegration between the spot and futures market. When not accounting for cointegration, the S&P 500 results parallel those of Kawaller, Koch, and Koch (1987), i.e., futures returns lead spot returns by approximately 35 minutes and spot returns lead futures returns by approximately 5 minutes.

The results here find that the S&P 500 spot and futures markets are cointegrated. Thus, by the Granger Representation theorem, the correct model specification to examine the lead-lag relationship must incorporate an error correction term.[8] After including the error correction term, however, the lead-lag structure remains relatively unchanged.

The contribution of this dissertation (as it relates to the German spot futures lead-lag relationship) is to investigate more closely the lead-lag relationship found on the FSE between the spot and futures markets. Using a finer time grid of data (1 minute instead of 5 minutes) and a different method of analysis (bivariate VAR, instead of

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[8]Error correction terms indicate that there is a long-run equilibrium condition relating the spot and futures markets to one another. That is, economic forces exist which prevent either market's deviation from the spot futures parity theorem, at least for extended periods of time.

Sims) than Grünbichler, Longstaff, and Schwartz (1994), this paper investigates the causal relationships between the DAX spot and futures markets. Also, the hypotheses examined in this dissertation are based on information-linked explanations, not technology based notions, as found in Grünbichler, Longstaff, and Schwartz (1994).

The results of this paper also match well with Grünbichler, Longstaff, and Schwartz's (1994) results. The lead of the futures price changes is found to be approximately 23 minutes, not 20. Even though the lead of the price changes of the spot market over the futures market appears to remain around 5 minutes, the results of this paper more closely examine the lead time. It is hypothesized that the significant feedback relationship is due to information-based ideas, and not the hybrid nature of the spot trading system.

2.2 HYPOTHESES TO BE TESTED

2.2.1 Hypothesis #1

Ho: There is no lead-lag structure to the DAX stock and stock index futures market.
Ha: There exists a lead-lag structure to the DAX stock and stock index futures markets.

Stoll and Whaley (1990), Kawaller, Koch and Koch (1987) and Chan (1992) all indicate that the stock index futures market processes information faster than the underlying stock market in the United States. Grünbichler, Longstaff and Schwartz (1994) also find a lead-lag

structure to the German DAX and DAX index futures market. This hypothesis examines the information processing issue in Germany's security markets using a much longer time series of data and a much finer time grid of observations than that employed by Grünbichler, Longstaff and Schwartz (1994). Examining this hypothesis on this unique dataset is useful because it gives researchers an indication of the persistence of Germany's DAX futures markets information processing advantage, if one exists.

2.2.2 Hypothesis #2

Ho: The DAX futures market leads all component stocks in fashion similar to the index.
Ha: The DAX futures market leads component stocks differently than the index.

According to Chan (1992), testing this hypothesis is important for two reasons. First, determining which, if any, stocks lead the futures is useful information for investors constrained from participating in the futures markets. Second, testing this hypothesis allows a closer inspection of the lead-lag relation through a decreased importance of the infrequent trading problem.[9]

2.2.3 Hypothesis #3

Ho: The lead-lag relation is the same in up and down markets.
Ha: The lead-lag relation is different in up and down markets.

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[9]Even though the infrequent trading problem is virtually eliminated via examining individual stock activity, the return interval is increased from a one-minute to five-minute interval in order to maximize observations.

As mentioned previously, individual investors in Germany cannot short-sell individual stocks. Therefore, the alternative hypothesis would be that the futures market tends to lead the spot market in down markets because individual investors cannot short-sell individual stocks for whatever reason.

Chan (1992) defines up and down markets as those markets that have large negative or positive returns.[10] Movements in the DAX spot market are used as the proxy for up and down markets. Essentially, each spot market's intradaily return (minute-by-minute) will be ranked into deciles according to each data point's position in that day's returns. Then, the lead-lag relationship will be examined only on the lowest and highest deciles (the down and up markets).

Examining the data in this fashion allows for a clearer picture of the short-selling restrictions found in Germany. *A priori*, the down-market expectation is that any feedback relationship will cease to exist and that the price discovery process of the futures market will be accelerated. *A priori* up-market expectations are not as clear.

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[10]Strictly speaking, Chan (1992) coins the terms "good news and bad news" instead of "up market and down market" as used here.

2.2.4 Hypothesis #4

Ho: The lead-lag relation is similar under different trading activity.
Ha: The lead-lag relation is different under different trading activity.

This hypothesis examines and tests the Admati and Pfleiderer (1988), Bhushan (1991), and Chowdry and Nanda (1991) uninformed traders' "herding" behavior hypotheses. Essentially, uninformed investors will want to protect themselves from informed traders' activities by grouping together either through time of trades, securities or in particular markets. Additionally, Easley and O'Hara (1987) suggest that informed investors want to trade their information as quick and in as large amounts as possible, creating a link between the information and the volume associated with a transaction. Informed traders will want to trade when many uninformed traders are trading.

Since the data set used in this dissertation is rich in transaction information (i.e. transactions, and volume information are available) for the spot market, a significant advantage over the analysis of Chan (1992) is made.[11] As proxies for the trading intensity of the spot market, trading intensity will be defined as the number of firms traded per time interval, number of transactions per time interval, and the volume of shares traded per time

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[11]Chan's (1992) proxy of trading intensity only accounts for the number of transactions taking place in both the spot and futures markets.

interval. Finally, to examine Easley and O'Hara's (1987) informed trader impacts, an average volume per transaction variable will be created as a proxy for trading intensity.

The analytical approach here will be similar to that used in the up and down market hypothesis. Each trading intensity proxy will be ranked daily. Then the lead-lag examination will be performed on the top and bottom decile for each market. Due to the unique data set available, it is expected that much information related to how traders reveal their information will be obtained from this hypothesis test.

2.2.5 Hypothesis #5

Ho: The lead-lag relation between the spot and futures markets is the same under heavy market-wide price movements as it is under security specific price movements.
Ha: The lead-lag relation between the spot and futures markets is different under heavy market-wide price movements as it is under security specific price movements.

One of the advantages of trading through the futures market is the ability to decrease transactions costs when a trader has market-wide information. Since the tremendous cost differential between trading in Germany's futures contracts and trading in the spot market has previously been mentioned, expectations are that this hypothesis will be rejected in favor of its alternative. A method of counting the number of securities moving in one direction at any given time will be used to test this hypothesis. This method is similar to Chan's (1992) definition of

market-wide information. Again, DAX spot returns will be grouped into deciles according to the ratio of securities moving in the same direction (this is the proxy for market-wide movements) and the lead-lag relation of the top and bottom decile will be analyzed using the same methods as previously mentioned in the other testable hypotheses.

2.3 DATA DESCRIPTIONS

2.3.1 S&P 500 Data

The S&P 500 spot and futures data used in this study consist of intradaily data from Tick Data Corporation. The period covered is from January 1, 1986 to December 31, 1993. The S&P 500 index calculation is based on the market value of the component stocks and is calculated by the following formula:

$$SP500_t = \frac{\sum_{j=1}^{500} n_{j,t} P_{j,t}}{BaseValue} x10, \tag{2}$$

where $n_{j,t}$ is the number of outstanding shares for firm j at time t, $P_{j,t}$ is the current stock price for firm j, and *Base Value* is the average value of the index during 1941-1943 (assigned to be 10).[12] Dividends paid by the component stocks do not enter into the index calculation.

S&P 500 futures contracts are traded on the Chicago Mercantile Exchange between the hours 08:30 and 15:15

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[12] Details about the composition of the S&P 500 come from Tucker (1991).

central time. Expiration is based on quarterly contracts (March, June, September, and December) settled on the third Friday of each expiring month.

The S&P 500 is made up of 400 industrial firms, 40 utilities, 20 transportation firms, and 40 financial institutions comprising approximately 75% of the total market value of the NYSE. The intradaily time period examined is that when the NYSE is open (08:30 to 15:00 central time). However, an additional 15 minutes is examined to catch any lagging observations added to the data set after market closure. Even though there are many trading observations made within any given minute, the data used for contemporaneous observations are the last price change for every minute of the time period analyzed.

The range of the S&P 500 index data is 203.44 to 470.91 while the range of the S&P 500 futures data is 202.00 to 471.80. An overlay plot of opening index and futures values is found in Figure 1. A casual observance of Figure 1 indicates that the S&P 500 spot and futures markets generally trended upward, except for the notable market downturns due to the 1987 crash and bearish market environment found at the end of 1990. Figure 1 indicates that the two series moved in synchronous fashion over the time period analyzed, and hence, do not appear to show any information being processed more quickly by either market - at least not on a daily basis.

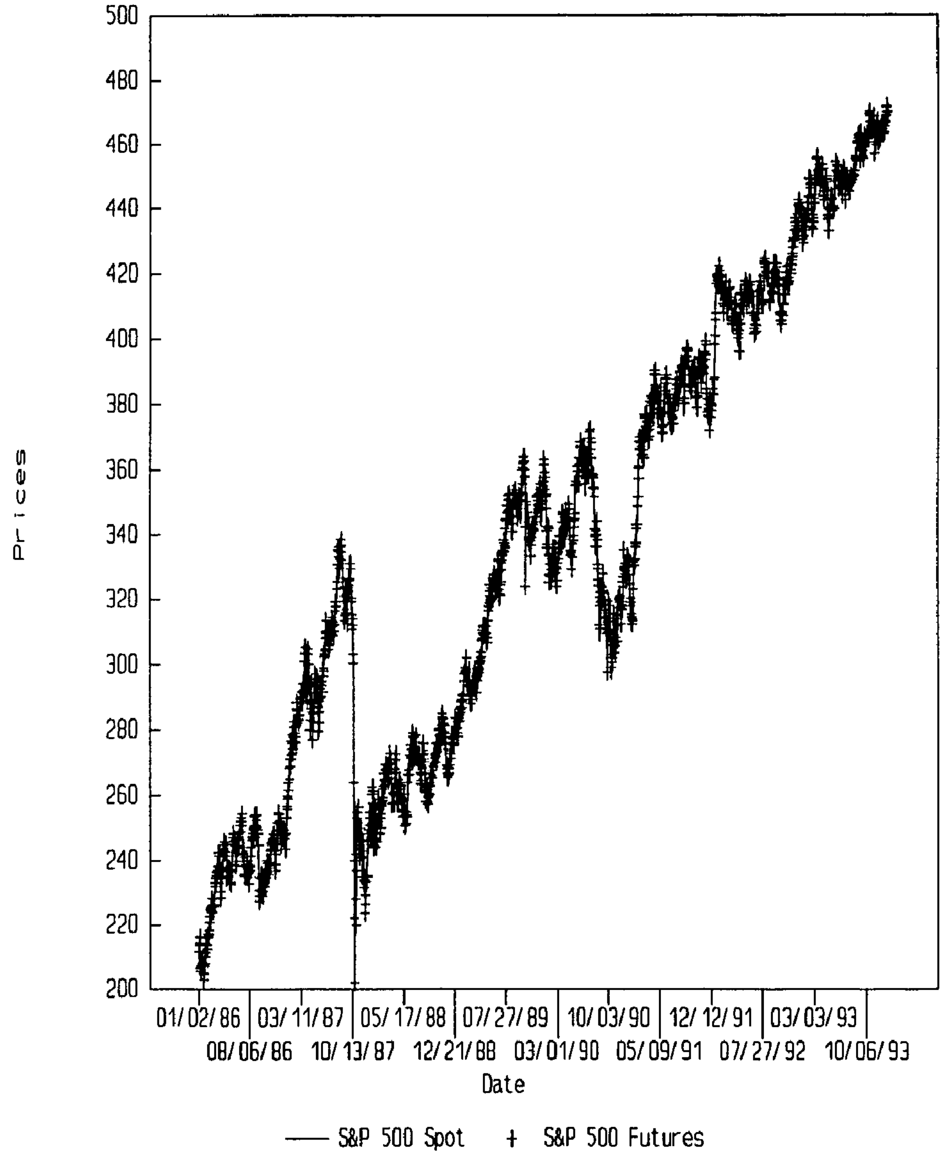

Figure 1
Overlay of S&P 500 Spot and Futures
Daily Opening Values

General statistical information regarding the S&P 500 spot and futures returns is found in Table 1. Non-normality of both series is indicated by the Kolmogorov D-statistic. The spot return series appears to be negatively skewed, while the futures return series exhibits positive skewness. Both series, however, are highly leptokurtotic. Also, even though both series have essentially zero returns, the futures return series is 6.58 times as variable as the spot return series.

Table 1
Average S&P 500 Index and Futures Returns.
816,168 observations.

	Index Returns	Futures Returns
Mean	9.939E-7	1.068E-7
Variance	4.459E-8	2.934E-7
Skewness	-0.107	3.972
Kurtosis	55.702	1035.15
D*	0.136	0.121
Minimum	-0.008	-0.042
Maximum	0.009	0.079

* Kolmogorov D-statistic, critical value at 0.1% significance level is 0.009.
Standard error for excess Kurtosis is 0.05. Standard error for excess Skewness is 0.003.

2.3.2 DAX Index Data

The DAX index data used in this study consist of intradaily data provided by the Frankfurt Stock Exchange (FSE) and covers the time period January 1, 1992 to March 31, 1994. The DAX index is a total-performance index

consisting of 30 stocks, where the weights used in the calculation are based on each component firm's listed capital. The formula for calculating the DAX index is as follows:

$$DAX_t = K_t \frac{\sum_{i=1}^{30} P_{it} Q_{it} C_{it}}{\sum_{i=1}^{30} P_{i0} Q_{i0}} x1000. \tag{3}$$

K_t is a general correction factor used once a year to avoid jumps in the index when a component firm's capital figures are brought up to date. P_{it} is the current stock price for firm i, Q_{it} is the weight used for weighting each firm's market value, and C_{it} is the correction factor used for stock option and dividend information. Note that even though market values change over time, the weights used in calculating the DAX change only once a year. Dividends paid by component stocks of the DAX are treated as if they are reinvested in their respective stocks when calculating the index.

The intradaily time period analyzed is between 10:30 am and 1:45 pm (the FSE is open from 10:30 am to 1:30 pm). Even though the FSE opens at 10:30 am, DAX calculations are not made until trading on any component stock is completed. That is, DAX calculations do not necessarily begin at exactly 10:30 am. Also, to allow for instances where some

trades require extra time to be posted to the system, this study examines DAX index postings until 1:45 pm.[13]

DAX index data are stamped with date and time to the nearest second. However, calculation of the index is done only once a minute and only after at least one component stock is traded. When there are lulls in trading, and no component stocks trade, no new date- and time-stamped DAX calculations are made for the next minute. Since returns in this study are calculated as $ln(P_t/P_{t-1})$, missing DAX quotations would cause some returns to be minute returns, two-minute returns, three-minute returns, etc.

To ensure that returns are generated by a minute-by-minute time series of prices, DAX index values are carried over to fill time gaps in the data. In essence, this process creates a zero return for any minute that does not have a DAX observation, thereby creating a truer process of index returns not captured by the furnished database. Carryover of the observations also replicates more accurately the information set available to market participants watching information displayed on their terminals.

The DAX index data series contains 96,988 intradaily observations, of which, 5,238 (5.4%) carryover observations

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[13]The earliest observation is at 10:33 am and the latest observation is at 1:40 pm.

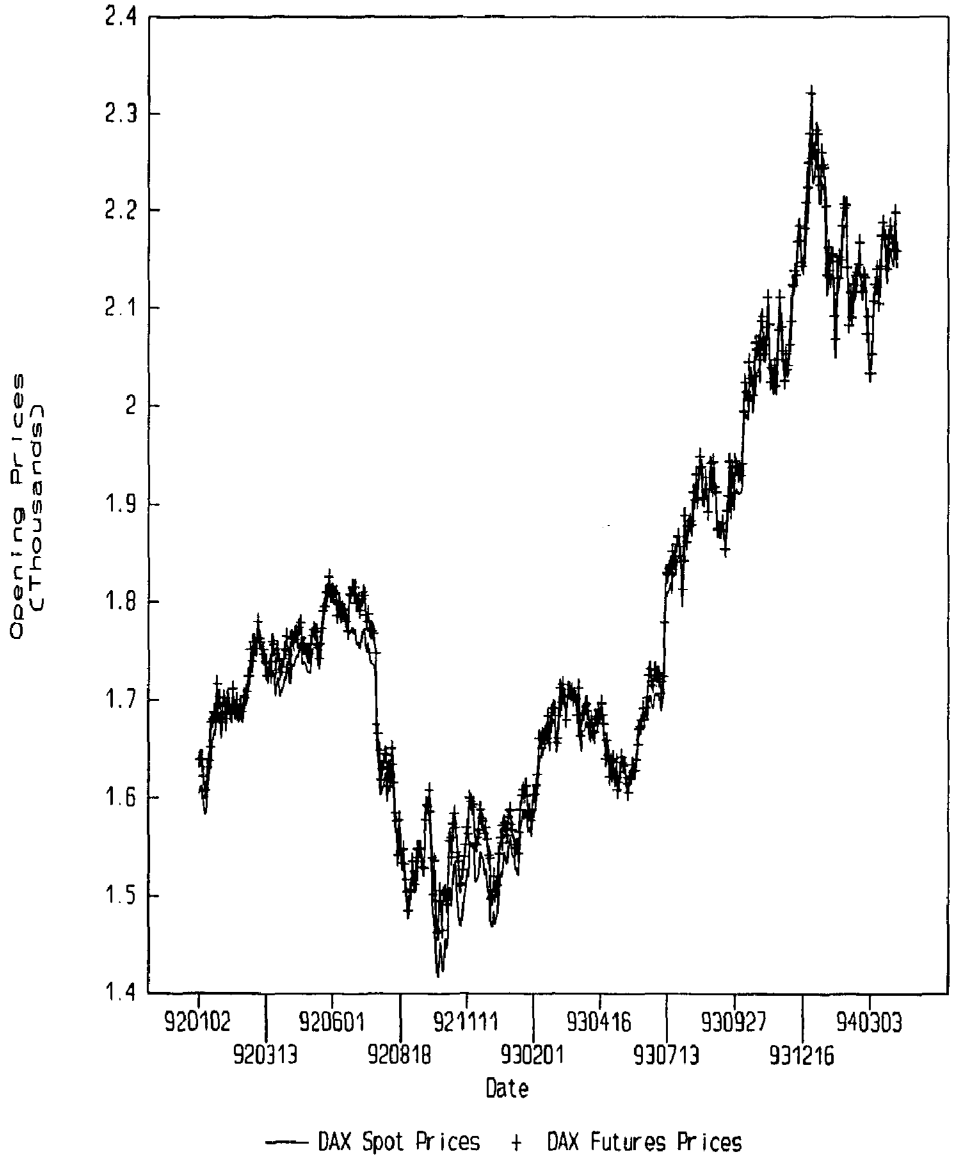

Figure 2
Overlay of DAX Spot and Futures
Daily Opening Prices

were added to the data. The range of the DAX index for the time period is 1416.52 to 2322.00. A plot of opening DAX values over time is found in Figure 2.

Cursory observation of Figure 2 indicates that the DAX Index rose steadily until June 1992. A bearish market environment then ensued until early April 1993. The last year or so of data appear to show the DAX on an upward trend.

2.3.3 DAX Futures Data

The DAX futures data used in this study consist of intradaily data provided by the electronically based futures market, the DTB. Trading in futures contracts occurs from 10:30 to 16:00. The futures data are generated by individual futures transactions and recorded with date and time stamps to the nearest hundredth of a second. For the entire sample period and entire time the futures market is open, there are 530,781 futures transactions available for analysis.

Similar to the DAX Index market, the futures market periodically experiences lulls in activity that cause time gaps in the data. To ensure minute-by-minute data, carryover of futures prices into gaps found in the futures data set is made. Even though it can be argued that carrying over futures observations creates stale prices, only 3% of the futures data were replicated. One justification for the carryover of these prices is to have

a consistent interpretation of the regression results.[14] Essentially, in order to make time-based inferences of the regression results, a consistent minute-by-minute lag structure must be maintained.

DAX Futures contracts are based on a quarterly expiration cycle. Expiration of the DAX contracts occurs on the third Friday of the expiration month. Therefore, the last trading done on an expiring contract occurs on the Thursday before expiration Friday. As stated in Bühler and Kempf (1993), settlement on expiration day is based on the DAX calculation the first minute after at least 50 percent of the DAX component stocks trade. Therefore, the futures settlement price can consist of trades that take place at different times during the day. In this study, all 1992, 1993, and the March 1994 futures contracts are examined.

Following the convention set out by Kawaller, Koch and Koch (1987), Stoll and Whaley (1990), Chan (1992), and Grünbichler, Longstaff and Schwartz (1992), this study examines only the nearest futures contracts, defined as the contract with the nearest expiration date. The nearest

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[14]Kofman and Moser (1994) experience the same missing data problem in their analysis of the BUND futures data from the DTB. They also use carryover observations in their examination of the lead-lag relationship between BUND trading on the DTB and the LIFFE (London International Financial Futures Exchange).

contract is followed until maturity.[15] A plot of the first daily futures transactions over time can be found in the overlay of spot and futures data found in Figure 2. The futures price pattern followed that of the DAX Index. One interesting feature seen in Figure 2, however, is that the opening futures price appeared to be generally higher than the spot market during the bear market experienced in 1992. The overlay indicates that the two price series did not appear to diverge often over the time period examined. Therefore, Figure 2 does not appear to suggest that information was processed consistently faster by the futures markets on a daily basis.

2.3.4 DAX Component Stocks Data

As previously stated, the basket of DAX stocks consists of 30 individual securities. These securities represent firms in the financial and industrial sectors and comprise the majority of market value and trading volume on the FSE. The dataset for the individual securities was provided by the FSE and contains date, price and time-stamp information. Beginning April 1, 1993, the dataset also includes volume information. A listing of the specific securities is found in Table 2.

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[15]Ma, Mercer, and Walker (1992) indicate that switching contracts on the expiration date induces excessive volatility into the futures price series. Since this portion of the dissertation examines only the first moment instead of the second moment of the future price series, examination of the nearest futures contracts similar to the aforementioned research is done here.

Table 2
DAX Component Stocks

Firm Name	Mean	Var	Skew	Kurt	D
Allianz	-0.001	0.020	-0.001	7.520	0.259
BASF	0.002	0.021	0.362	8.296	0.241
Bayer	0.001	0.018	0.171	5.085	0.223
Bayrische Hypobank	-0.000	0.018	-0.021	10.920	0.340
BMW	-0.000	0.023	0.386	12.714	0.332
Bayrische Vereinsbank	-0.000	0.017	0.069	10.725	0.353
Commerzbank	-0.002	0.019	-0.179	7.094	0.308
Continental	-0.001	0.046	0.630	21.181	0.368
Daimler	-0.002	0.015	-0.057	3.896	0.214
Deutsche Babcock	0.003	0.061	0.020	29.648	0.364
Deutsche Bank	-0.001	0.008	-0.057	5.060	0.226
Degussa	0.003	0.046	-0.037	19.424	0.358
Dresdner Bank	-0.001	0.016	0.149	9.180	0.327
Henkel	-0.000	0.020	0.292	18.534	0.364
Hoechst	0.003	0.022	0.310	7.395	0.244
Karstadt	-0.001	0.032	0.240	15.560	0.363
Kaufhof Holding	-0.002	0.047	-0.201	25.197	0.337
Lufthansa	-0.005	0.087	-0.400	14.096	0.366
Linde	0.000	0.024	0.166	14.645	0.374
MAN	0.002	0.038	0.614	21.720	0.338
Metallgesellschaft	-0.005	0.094	-0.789	24.191	0.343
Mannesmann	0.000	0.028	0.330	9.494	0.285
Preussag	0.003	0.029	0.586	17.157	0.329
RWE	0.000	0.015	0.509	19.306	0.324
Schering	0.001	0.033	0.221	26.610	0.283
Siemens	-0.001	0.011	-0.406	5.832	0.206
Thyssen	0.001	0.033	0.110	8.906	0.327
Veba	-0.000	0.010	0.230	10.008	0.259
Viag	0.002	0.024	0.708	22.876	0.328
Volkswagen	0.001	0.027	-0.058	4.347	0.235

A preliminary examination of the firm-specific dataset indicated that calculating minute-by-minute returns would have caused too many carry over observations to be entered in the data. Therefore, 5-minute price change intervals are used to calculate return information and to perform analyses related to the individual stock related data.

Table 2 also provides basic statistical information related to the 5-minute return series generated for each security. All stocks have essentially an average zero 5-minute return, various skewness positions and exhibit excess kurtosis. Finally, the Kolmogorov D statistic indicates that the firm-specific data is non-normal. This non-normality is probably a result of the leptokurtotic data generation process.

2.3.5 Contemporaneous Observations Data

Contrary to the five-minute contemporaneous return convention used in Stoll and Whaley (1990), Chan (1992), and Grünbichler, Longstaff and Schwartz (1992), this study maintains the informational content of the minute-by-minute data inherent in the DAX spot data set when examining Hypotheses #1 and #3. However, since the futures database contains approximately six observations per minute, and the DAX spot data contain only one observation per minute, a

criterion for selecting which futures observations are contemporaneous to the spot data has to be formulated.[16]

The criterion for selecting contemporaneous observations in this study is to select the closest futures observations that precede DAX observations by up to 59 seconds.[17] The criterion for selecting contemporaneous observations resulted in 93,977 contemporaneous spot and futures returns. Futures observations precede spot observations an average of 17 seconds.

General statistical information regarding the contemporaneously generated DAX spot and futures returns is found in Table 3. Non-normality of both return series is indicated by the Kolmogorov D-statistic. The index return series is positively skewed whereas the futures returns data exhibit negative skewness. Both series, however, have high levels of kurtosis.

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[16]Since only 122 observations had precisely the same time stamp, very few observations are "truly" contemporaneous.

[17]Selecting contemporaneous observations in the manner described introduces a bias for spot returns to lead futures returns. That is, more information is incorporated in a later time series. For example, if a futures transaction is recorded 20 seconds past the minute, whereas the index calculation is not made until 50 seconds past the minute, the spot market incorporates the information present at 20 seconds past the minute plus any information reaching the market before the 50-second mark. Analyzing the data where the futures observations were chosen as the nearest before or after observation, or to follow spot observations by 59 seconds, did not alter the results.

Even though both series have essentially a zero return, the futures return series is 3.111 times as variable as the spot return series. Higher volatility in the DAX futures market is also documented by Grünbichler, Longstaff, and Schwartz (1994) (variance ratio average of 1.27 for 5-minute data) and Bühler and Kempf (1993) (variance ratio average of 3.08 for minute-by-minute data).[18]

Table 3
Average DAX Index and Futures Returns and Average seconds Futures Prices precede DAX prices.
93,997 observations.

	DAX Spot Returns	DAX Futures Returns
Mean	1.200E-7	-2.560E-6
Variance	5.560E-8	1.730E-7
Skewness	0.113	-0.812
Kurtosis	61.174	240.06
D*	0.13	0.26
Minimum	-0.006	-0.028
Maximum	0.006	0.019

* Kolmogorov D-statistic, critical value at 0.1% significance level is 0.014.
Standard error for excess Kurtosis is 0.026. Standard error for excess Skewness is 0.008.

[18]The variance ratio found on the DAX is approximately 50% less than that found in the S&P 500 data set. Whether this difference can be attributed to differential levels of noise or information between floor and electronic trading is unclear.

2.4 METHOD OF ANALYSIS

2.4.1 Causality, Sims Approach

The lead-lag relationship, as described in Sims (1972) and used in Stoll and Whaley (1990), Chan (1992), and Grünbichler, Longstaff and Schwartz (1994), can be represented by a model similar to Equation 4:

$$R^{s}{}_{t}=\alpha+\sum_{i=-n}^{i=n} R^{f}{}_{t+i}+e_{t}, \tag{4}$$

where R^s_t is the return in the spot market, R^f_t is the return in the futures market, and e_t is the error term.

Sims (1972) gives a practical test for unidirectional causality that requires a joint test of significance of the parameters on the future values of R^f. If the future values of R^f_t *(i.e. i>0)* are jointly insignificantly different from zero, and assuming that past values exhibit some reasonable significance, then unidirectional causality from the futures to spot markets is implied.

Also, Sims (1972) proposes that a simple inspection of the size of the coefficients on the future values can be an indication to reject the null of unidirectional causality, regardless of the significance of the joint tests. Results from Stoll and Whaley (1990) display that the size of the future values of R^f are as large, and in some cases larger, than the coefficients of the past values (see Table 4 in Stoll and Whaley (1990)). Therefore, even with no explicit

significant tests, results from Stoll and Whaley (1990) imply bidirectional causality (feedback) between the S&P 500 spot and futures markets.

As noted by Chan (1992), examining the lead-lag relationship by testing the significance of lead-lag coefficients of models similar to Equation (4) does not necessarily mean that price movements in one market *cause* price movements in the other market. More appropriately, the "lead" refers to one market processing information faster than the market that "lags" behind in its information reaction time. Chan's (1992) significance tests on the future values of the futures data indicate a significant feedback relationship existing between both the Major Market and S&P spot and futures markets (See Table 4 in Chan (1992)).

From an intuitive standpoint, an additional comment can be made about the Sims (1972) lead-lag relationship (Equation (4)) adopted by Stoll and Whaley (1990), Chan (1992), and Grünbichler, Longstaff and Schwartz (1994). Often, when one thinks about regression techniques, the concept of using independent variables to "predict" dependent variables comes to mind. With the concept of prediction in mind, Equation (4) uses past values of futures data to predict future values of spot data. Then, Equation (4) uses future futures data to predict past values of spot data. Beyond finding statistical

significance of the coefficients on the future futures data, it is difficult to make inferences about future futures data "predicting" past spot data. That is, using the Sims approach makes it difficult to grasp, intuitively, which information set is being used by the investor.

Chan (1992), Stoll and Whaley (1990) and Grünbichler, Longstaff and Schwartz (1994) all find that futures markets appear to lead their respective spot markets in information processing ability. However, they also provide evidence that the spot markets appear to lead their respective futures markets. This result appears to indicate bidirectional causality (feedback) between spot and futures markets. As a direct test for possible feedback, and to avoid the "predictability" problem, Granger Causality tests are used.

2.4.2 Causality, Granger Approach

The *Granger Causality Theorem* is proposed in Granger (1969). In its simplest form, the null of Granger noncausality is depicted by Equation (5):

$$H_o: f(x_t|x_{t-n}) = f(x_t|x_{t-n}, y_{t-n}) \,. \tag{5}$$

That is, variable y will not cause variable x, if the distribution of x (given only past values of x) is equal to the distribution of x (given past values of x and y). Therefore, y will cause x if predictions of x using past values of x and y are better than predictions only using x. If y causes x and x causes y, then a feedback system is

said to exist. Taking expectations of Equation (5) allows the hypothesis of causality to be tested by ordinary least squares regression techniques. For instance, Equation (5) can be represented by the regression format symbolized by Equation (6):

$$x_t=\alpha_0+\sum_{i=1}^{n}\delta_i x_{t-i}+\sum_{i=1}^{n}\beta_i y_{t-i}+e_t. \tag{6}$$

Jointly testing the null hypothesis that the β_i's are zero is accomplished by calculating an F-statistic from the restricted and unrestricted regressions of Equation (6).[19] If the F-statistic is significant at some *a priori* determined level of significance, then rejection of the null that the β_i's are zero infers that y causes x. Lindley (1957) notes that with a large number of observations, significance levels should be lowered. Therefore, unless otherwise noted, this study uses the 0.01% level of significance for its rejection criteria instead of the usual 5% or 1% significance levels.

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[19]Strictly speaking, using the Wald test statistic (Chi-Squared distributed) is the only test required. However, using an F-distributed random variable (the Wald statistic divided by the number of restrictions being tested) as the test statistic is more conservative (requiring a larger statistic before rejection of the null) than the Chi-squared statistic. Therefore, the test statistic chosen to examine joint hypotheses in this portion of the dissertation is the F-test.

2.4.3 Bivariate Vector Autoregression

Regressions similar to Equation (4) were used by Stoll and Whaley (1989), Chan (1992), and Grünbichler, Longstaff and Schwartz (1994) to analyze lead-lag relationships between American and German spot and futures markets. However, this paper analyzes results from the following bivariate vector autoregressive equation:[20]

$$R^s_t=\alpha_1+\sum_{i=1}^{n}\gamma_{i1}R^s_{t-i}+\sum_{i=1}^{m}\beta_{i1}R^f_{t-i}+e_{t1}, \tag{7}$$

$$R^f_t=\alpha_2+\sum_{i=1}^{n}\gamma_{i2}R^f_{t-i}+\sum_{i=1}^{m}\beta_{i2}R^s_{t-i}+e_{t2}, \tag{8}$$

where R^s_t is the spot market return at time t and R^f_t is the futures market return at time t. Use of the bivariate vector autoregressive process in the form represented by Equations (7) and (8) explicitly allows causality and feedback issues to be addressed.

Stoll and Whaley (1990) show that an index return is well-described by an ARMA process. The AR (Autoregressive) portion is shown to mitigate the effects of infrequent trading of the stocks comprising the index. Furthermore, the MA (Moving Average) portion is shown to moderate the effects of the bid-ask spread. Hence, Equation (8) also

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[20]Note the difference between this equation and Kawaller, Koch, and Koch's (1987) model, i.e. contemporaneous Beta coefficients are not found in the model employed in this dissertation.

allows the infrequent trading bias of index returns to be addressed.

Haller and Stoll (1989) use Roll's (1984) method for calculating implied bid-ask spreads in the German market. Even though they find statistically significant implied spreads for small stocks, the implied spread for the largest DAX stocks is statistically insignificant in both the continuous dealer and noon auction markets. Since this study only examines large DAX stocks, the MA component is not considered and the AR convention as used by Chan (1992) and Grünbichler, Longstaff and Schwartz (1994) is adopted in this part of the dissertation.[21]

Therefore, the bivariate vector autoregressive framework adopted in this study, Equations (7) and (8), works around the "predictability" problem previously noted by using only regressors that are lagged with respect to the dependent variable. Secondly, the framework simultaneously accounts for infrequent trading effects. Finally, the equations used in this study test directional causality and examine any feedback relationships between both spot and futures markets.

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[21]To temper the effect of the infrequent trading bias, previous studies performed an AR regression on the index and then used the return innovations created from that regression as the dependent variable for Equation (4). Use of Equation (8) serves the dual purpose of simultaneously moderating infrequent trading effects and allowing a directional causality relationship to be tested in one regression.

2.4.4 Cointegration Considerations

Theoretically, there is a no-arbitrage condition that drives the relationship between spot and futures prices, as Equation (9) suggests:

$$F_t = S_t (1 + r_f - d)^T, \tag{9}$$

where F_t is the futures index price at time t, S_t is the actual spot index price at time t, r_f is the risk-free interest rate, d is the dividend yield paid by stocks in the index, and T is the time to maturity of the futures contract. Equation (9) is usually designated as the *spot-futures parity theorem* or *cost-of-carry relationship.* This parity relationship is an arbitrage relationship, since deviations of actual prices from theoretically predicted prices allow risk-free returns to be obtained with zero net investment.

Economic theory suggests that if deviations from the parity relationship are large, economic agents would attempt to obtain a "free lunch." The quest for this "free lunch" would induce forces that diminish deviations to the level where transactions costs erase any arbitrage profits. Therefore, activities undertaken to temper arbitrage profits are likely to bring spot and futures prices together so that they do not drift too far apart.

Research on price deviations from the parity relationship can be found in work conducted by Stoll and

Whaley (1986), MacKinlay and Ramaswamy (1988), and Modest and Sundaresean (1983). Results from those studies indicate that violations of the parity relationship occur less than 15% of the time in U.S. markets. Evidence that the S&P 500 spot and futures prices move closely together is also provided in Figure 1.

Loistl and Kobinger (1992) show that some short-term arbitrage opportunities existed in the September 1991 DAX futures contract, but very few long-term arbitrage opportunities were available. Evidence that German spot and futures index prices remain close together is also provided in Figure 2. Additionally, Bühler and Kempf (1993) show that arbitrage opportunities in the DAX futures market drastically diminished within the first year of operation. Therefore, equilibrium forces that reduce arbitrage profits imply a long-term relationship probably exists between spot and futures prices.

Cointegration tests are designed to analyze long-run economic relationships. If spot and futures prices are found to be cointegrated, then the regression formulations set out in Equations (7) and (8) are misspecified and must be modified to include an error correction term. Specifically, if the data are cointegrated, Equations (7) and (8) should be modified to yield:

$$R^s{}_t=\alpha_1+\sum_{i=1}^{n}\gamma_{i1}R^s{}_{t-i}+\sum_{i=1}^{m}\beta_{i1}R^f{}_{t-i}+\phi_1(F_{t-1}-S_{t-1})+e_t, \tag{10}$$

$$R^f{}_t=\alpha_2+\sum_{i=1}^{n}\gamma_{i2}R^f{}_{t-i}+\sum_{i=1}^{m}\beta_{i2}R^s{}_{t-i}+\phi_2(F_{t-1}-S_{t-1})+e_t. \tag{11}$$

The second-to-last terms in equations (10) and (11) are called the error correction terms and are designed to reflect the current error that the model contains in achieving long-run equilibrium.[22] In essence, the error correction terms act as the long-term economic forces that diminish arbitrage opportunities presented by short-term perturbations causing deviations from the spot-futures parity relationship.

The error correction terms in equations (10) and (11) have another economic definition; they are the *basis* between the futures and spot prices. If the basis is exceptionally large, meaning that the futures price is above (or that the spot price is below) its equilibrium level, then two alternatives may occur: the futures price adjusts downward, or the spot price adjusts upward. Therefore, ϕ_1 in equation (10) is hypothesized to be non-positive, while ϕ_2 in Equation (11) is hypothesized to be non-negative.

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[22]Technically, the error correction terms are the errors resulting from a cointegrating regression, not just the difference between the two level variables.

To test for cointegration between spot and futures, this study follows a three-step process. First, a check for stationarity and equivalent integration of the two price series is made using the methodology set out by Dickey and Fuller (1979):

$$R_t=\alpha+\beta lnP_{t-1}+\sum_{i=1}^{m}\gamma_i R_{t-i}+\lambda t+e_t, \tag{12}$$

$$\Delta R_t=\alpha+\beta R_{t-1}+\sum_{i=1}^{m}\gamma_i \Delta R_{t-i}+\lambda t+e_t. \tag{13}$$

If the β from Equation (12) is insignificantly different from zero and the β from Equation (13) is significantly different from zero, then the price series are I(1) variables and may be cointegrated. Results of regressions from Equations (12) and (13) are located in Table 4. t-statistics for the β's from Equation (12) are -1.898 and -2.113 for the DAX spot and futures, and -3.052 and -2.367 for the S&P 500 spot and futures. Equation (13) yields t-statistics of -49.577 and -51.367 for the DAX spot and futures and -236 and -196 for the S&P 500 spot and futures.

Results from Table 4 indicate that the spot and futures prices for both the DAX and S&P 500 are I(1) variables, i.e. their first differences (returns) are stationary and their prices may be cointegrated.

Table 4
Tests for Unit Roots

Equation (12)
Levels

SPOT MARKET	t-statistic	FUTURES MARKET	t-statistic
DAX	-1.898	DAX	-2.113
S&P 500	-3.052	S&P 500	-2.367

Equation (13)
First Differences of
Levels

SPOT MARKET	t-statistic	FUTURES MARKET	t-statistic
DAX	-49.577	DAX	-51.367
S&P 500	-236.44	S&P 500	-196.514

MacKinnon (1991) has calculated the appropriate t-values for the 5% and 1% significance levels to be respectively -3.7809 and -4.3266. Even though this study uses 0.01% as its rejection criteria, it is assumed that a statistic of -10 or smaller is significant at the 0.01% level.

The second step followed to test for cointegration is to run the following cointegrating regressions:

$$\ln P^{s}_{t}=\alpha_1+\beta\ln P^{f}_{t}+\lambda t+v_{t1}, \tag{14}$$

$$\ln P^{f}_{t}=\alpha_2+\beta\ln P^{s}_{t}+\lambda t+v_{t2}. \tag{15}$$

The final step in testing for cointegration is to take the errors from Equations (14) and (15) and analyze them for stationarity similar to the analysis carried out by equations (12) and (13):

$$\Delta v_t = \beta v_{t-1} + \sum_{i=1}^{m} \gamma_i \Delta v_{t-i} + u_t . \tag{16}$$

If β from Equation (16) is significantly negative, then the price series are cointegrated. Results from regressions run on Equation (16) are found in Table 5. t-statistics are -1.241 and -1.322 for the DAX errors of Equations (13) and (14), and -25.179 and -25.146 for the S&P 500 errors of Equations (13) and (14). MacKinnon (1991) calculates the 1% significance level to be -4.3266. Therefore, results from Table 5 indicate that the German spot and futures markets are not cointegrated and that Equations (7) and (8) may be used without the error correction terms. However, the S&P 500 spot and futures markets are cointegrated, requiring Equations (10) and (11) to be used when analyzing the lead-lag relationship.

At first glance, finding no cointegration in the DAX data series appears to be counter-intuitive to the explanation of the spot-futures parity concept discussed earlier.[23] There may be a straightforward explanation as

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[23]Dwyer and Wallace (1992) indicate that finding cointegration and/or not finding cointegration does not directly imply efficient or inefficient market conditions. They state that finding cointegration is a phenomenon specific to the model used for testing for cointegration. One example cited is the case of examining exchange rates written in terms of a common currency. The fact that the stochastic trend between two countries' cancels out has no implication towards market efficiency or inefficiency. Rather it is a consequence of the no arbitrage, zero transactions costs model.

to why the DAX data series is found not to be cointegrated while the S&P 500 series is found to be cointegrated.

If natural logs of Equation (9) are taken, the following equation results:

$$lnF_t = lnS_t + Tln(1+r_f-d)\,. \tag{17}$$

Examining Equation (17) in a cointegrating regression format yields:

$$lnF_t = a + blnS_t + c[\ln(1+r_f-d)]T + e_t\,. \tag{18}$$

The parity theorem suggests that e_t is stationary, i.e. an I(0) variable, and that $\ln F_t$ and $\ln S_t$ are cointegrated. Brenner and Kroner (1995) document that there is only one scenario that may yield a cointegrating relationship between the spot and futures price, and that occurs when the interest rate and dividend yield are cointegrated.[24] Since the subtraction of two I(1) (nonstationary) variables may yield an I(0) (stationary) variable, it appears that the data for the S&P 500 indicate cointegrated intradaily interest rates and dividend yields. This finding is important since Bradley and Lumpken (1992) provide evidence that interest rates are I(1) variables.

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[24]Even though Brenner and Kroner's proposition is based on a proof using realized spot and current futures prices, the stationary basis scenario also applies to the cointegration of contemporaneous spot and futures prices via the no-arbitrage parity relationship.

However, research on the level of integration in dividend yields has not yet been published.

Table 5
Stationary tests for Cointegration residuals, v_t, from Equations (14) and (15).

V_t from regression of Spot on Futures (Equation (14)).

Market	t-stat
DAX	-1.241
S&P 500	-25.179

V_t from regression of Futures on Spot (Equation (15)).

Market	t-stat
DAX	-1.322
S&P 500	-25.146

MacKinnon (1991) has calculated the appropriate t-values for the 5% and 1% significance levels to be respectively -3.7809 and -4.3266. Even though this study uses 0.01% as its rejection criteria, it is assumed that a statistic of -10 or smaller is significant at the 0.01% level.

Even though Brenner and Kroner (1995) state that "the question of whether spot and futures prices are cointegrated has not been addressed in the literature," evidence of cointegration in the S&P 500 spot and futures markets has recently been presented by Ghosh (1993) and Dwyer, Locke and Yu (1994). Ghosh (1993) examines 15-minute intradaily return data for every Wednesday in 1988 for the S&P 500 and finds that the two series are cointegrated and that cointegration is helpful in predicting movement from one market to the other. Dwyer, Locke and Yu (1994) examine intradaily minute return data for the last 13 weeks of the nearest futures contracts in

1989 and 1990 for the S&P 500 and find that the majority (but not all) of the contracts exhibit cointegration. They support their hypothesis of a dynamic nonlinear relationship between the spot and futures prices with the fact that cointegration is present when constructing a threshold error correction model. Therefore, the finding that the S&P 500 is cointegrated adds to the sparse literature on the existence of cointegration between equity spot and futures markets.[25]

There may be a simple explanation as to why the DAX spot and futures markets are not cointegrated.[26] Looking back on the definition and calculation of the DAX Index (see Equation (2)), one notes that dividends are included in calculation. Bühler and Kempf (1993) state that inclusion of the dividend makes the DAX a "total performance index" and that the appropriate parity relationship between the spot and futures price is:

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[25]Brenner and Kroner (1993) state that fixing the expiration date and varying the time to maturity of the futures contract, as done in this dissertation, induces a time-varying variance in the cointegrating residuals. Since the test statistics of the cointegration tests appear to be large (around -25), it is assumed here that cointegration will be robust to the presence of heteroskedastic cointegrating errors.

[26]The author wishes to thank Paul Brockman for help with this explanation.

$$F_t=S_t(1+r_f)^T, \tag{19}$$

where the variables maintain the same definition as in Equation (9). If natural logs are taken in Equation (19), the following relationship exists:

$$lnF_t=\ln S_t+Tln(1+r_f). \tag{20}$$

Examining Equation (20) in a cointegrating regression format yields:

$$lnF_t=a+blnS_t+c[\ln(1+r_f)]T+e_t. \tag{21}$$

Comparing Equation (21) to Equation (18) yields insight as to why the DAX data series is not cointegrated while the S&P 500 series is cointegrated.

If interest rates are I(1), as evinced by Bradley and Lumpkin (1992), then their impacts will be transmitted to the error of the cointegrating regression. Since the stochastic nature of I(1) variables always dominates the stochastic characteristics of I(0) variables, there will be no I(1) dividend yield to cancel the interest rate effect. Hence, a unit root test of the cointegrating errors will never reject the unit root null. Instead it will fail to reject the null of no cointegration between the two series. In the case of the DAX, or other total performance indices, Brenner and Kroner (1995) state that the cointegrating relationship must now contain the futures price, the spot

price, and the interest rate information.[27]
Thus, it is the misspecification of the cointegrating regression that generates the nonstationary errors, not the incorrect nature of the parity theorem. Since rejection of the null that e_t is an I(1) variable is central to determining whether the variables are cointegrated, using a model that generates non-stationary error terms will never allow cointegration to be concluded.

2.5 CAUSALITY RESULTS

Since the results of cointegration tests imply that the DAX spot and futures data are not cointegrated, this research analyzes the relationship between the German Spot and Futures markets using Equations (7) and (8). However, since the cointegration tests imply that S&P 500 spot and futures markets are cointegrated, analysis of the lead-lag relationship is accomplished using both Equations (7) and (8), and (10) and (11). In this manner, the effect of including the error correction term can be analyzed.

For the S&P 500 data, this paper follows the convention set out by Kawaller, Koch and Koch (1987) by setting the lag length of the lagged dependent variable to

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[27]In technical terms, the cointegrating vector will now be trivariate (1,-1,-1), instead of the bivariate cointegrating vector (1,-1) apparently present in the S&P 500 data. An examination of the impact of intradaily interest rate information on the cointegration test for the DAX and DAX Futures is an interesting issue and will be conducted in future research.

60 minutes while setting the lag length of the cross market to 45 minutes. For the German data, Grünbichler, Longstaff and Schwartz (1994) indicate that DAX Index Futures returns lead Dax Index returns by about 20 minutes. However, since this dissertation uses minute-by-minute data, the lag lengths for Equations (7) and (8) are set to 30 minutes to account for any additional information possibly not captured in the 5-minute dataset.[28]

Even though extending the lag length of the DAX data may reduce the efficiency of the OLS estimator in this case, Gonzalo (1990) shows that the efficiency loss is small. More importantly, however, is to assure that the residual term in a lagged dependent variable regression, is a white noise process. That is, the residual term must exhibit no autocorrelation pattern. This white noise characteristic is critical to obtain since OLS standard errors are inconsistent when autocorrelation is present in these models. Inconsistent standard errors cause inferences drawn from hypothesis tests to be wrong. White noise tests (not reported) on the error terms from the applicable DAX regressions indicate that autocorrelation, to lag 24, is not present. Therefore, setting the lag length to 30 minutes for the DAX data

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[28]Overnight returns are not computed. That is, a previous day's returns do not enter into the long lags of the regression.

ensures the analysis to err on the side of obtaining consistent, rather than efficient standard errors.

2.5.1 Hypothesis #1 Results[29]

Hypothesis #1 was stated as:

Ho: There is no lead-lag structure to the DAX stock and stock index futures markets.
Ha: There exists a lead-lag structure to the DAX stock and stock index futures markets.

The next four sections discuss the results of this hypothesis test.

2.5.1.1 S&P 500 Spot Results, No Error Correction Term

Figure 3 is a graphic representation of the parameter estimates for the regression of S&P 500 Spot returns as the dependent and independent variables with a 99.99% confidence interval around the null of a zero value. Significant parameters are found to lag 6. Thereafter, they become insignificant. Figure 4 displays a similar graph for the parameter estimates of the lagged S&P 500 Future returns as independent variables. Significant lagged future returns are found approximately to lag 33. An F-test testing the significance of the lagged future returns yields a value of 1013.29, which has an associated p-value of <0.0001. Therefore, S&P 500 future returns Granger-cause S&P 500 spot returns.

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[29]Recall that the S&P 500 analyses are made for comparison purposes only.

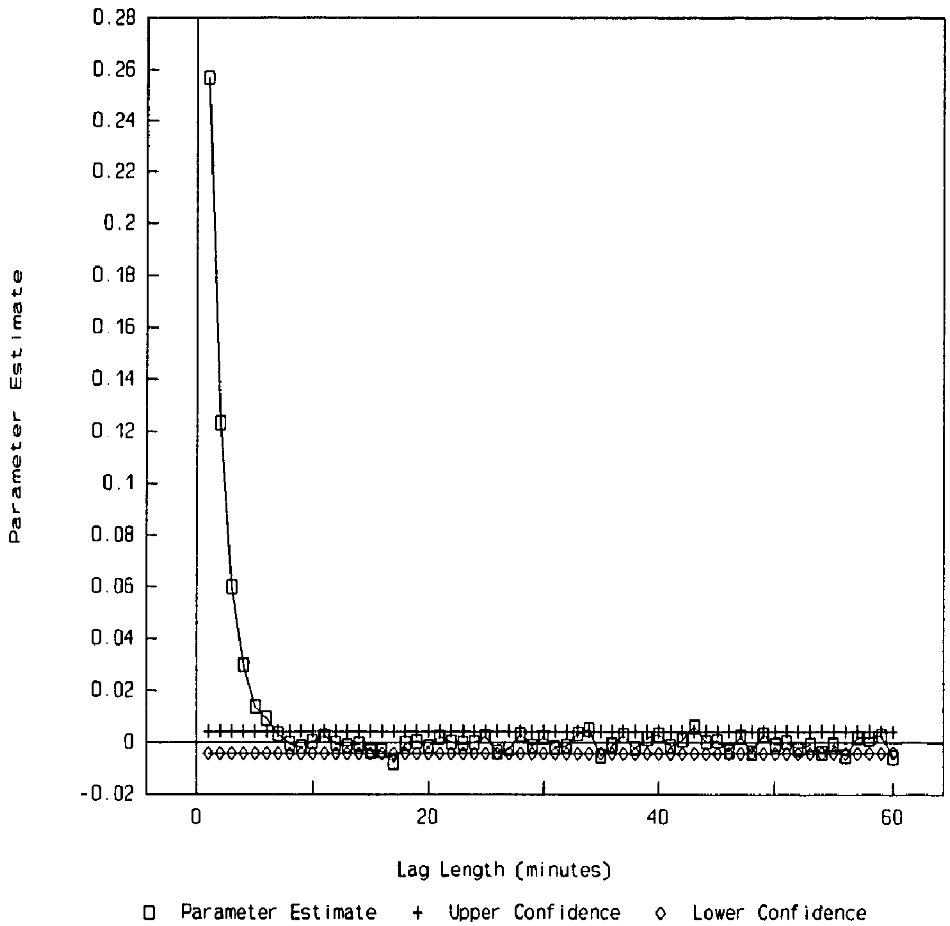

Figure 3
S&P 500 Spot Return as Both
Dependent and Independent Variables

Figure 3's graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression:

$$R^s_t=\alpha_1+\sum_{i=1}^{60}\gamma_{i1}R^s_{t-i}+\sum_{i=1}^{45}\beta_{i1}R^f_{t-i}+e_{t1}.$$

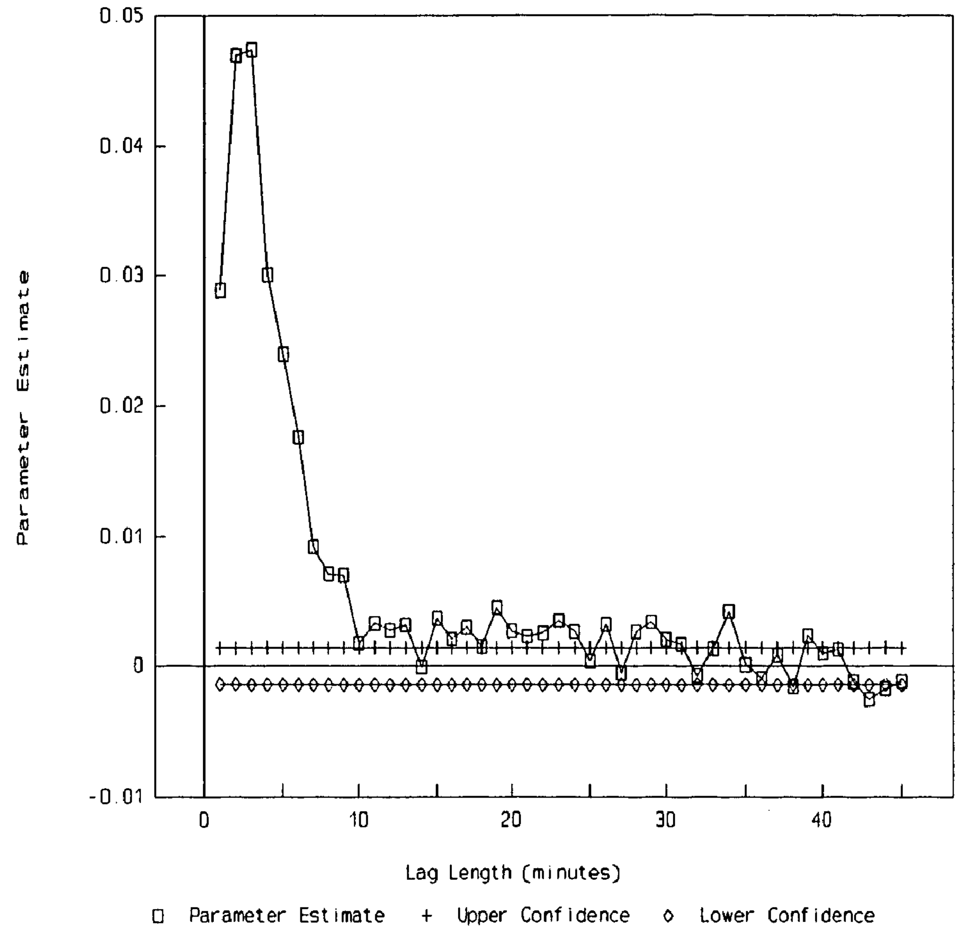

Figure 4
S&P 500 Spot Return Dependent Variable
and S&P 500 Futures Returns as Independent Variable

This graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression:

$$R^s_t=\alpha_1+\sum_{i=1}^{60}\gamma_{i1}R^s_{t-i}+\sum_{i=1}^{45}\beta_{i1}R^f_{t-i}+e_{t1}.$$

2.5.1.2 S&P 500 Future Results, No Error Correction Term

Figure 5 is the graphical representation for the regression with S&P 500 futures returns as both dependent and independent variables. The parameter estimates bounce frequently between negative and positive values. The negative parameter for lag 1 may be indicative of a bid-ask spread bounce in the futures market.

Figure 6 displays a similar graph for the parameter estimates of the lagged spot returns. Significant spot returns are only found to lag 3, and after, they are not significantly different from zero. An F-test for the significance of all the lagged spot return parameter estimates being equal to zero results in a value of 79.217, which has an associated p-value of <0.0001. Therefore, S&P 500 spot returns Granger-cause S&P 500 future returns.

The results from sections 2.5.1 and 2.5.2 are similar to those presented by Kawaller, Koch and Koch (1987). The lead-lag relationship (without an error correction term) found in this work coincides well with their analyses. Apparently, the faster information processing speed of the S&P 500 futures market is persistent over time. However, this study documents that a significant feedback relationship between the S&P 500 spot and futures markets also exists.

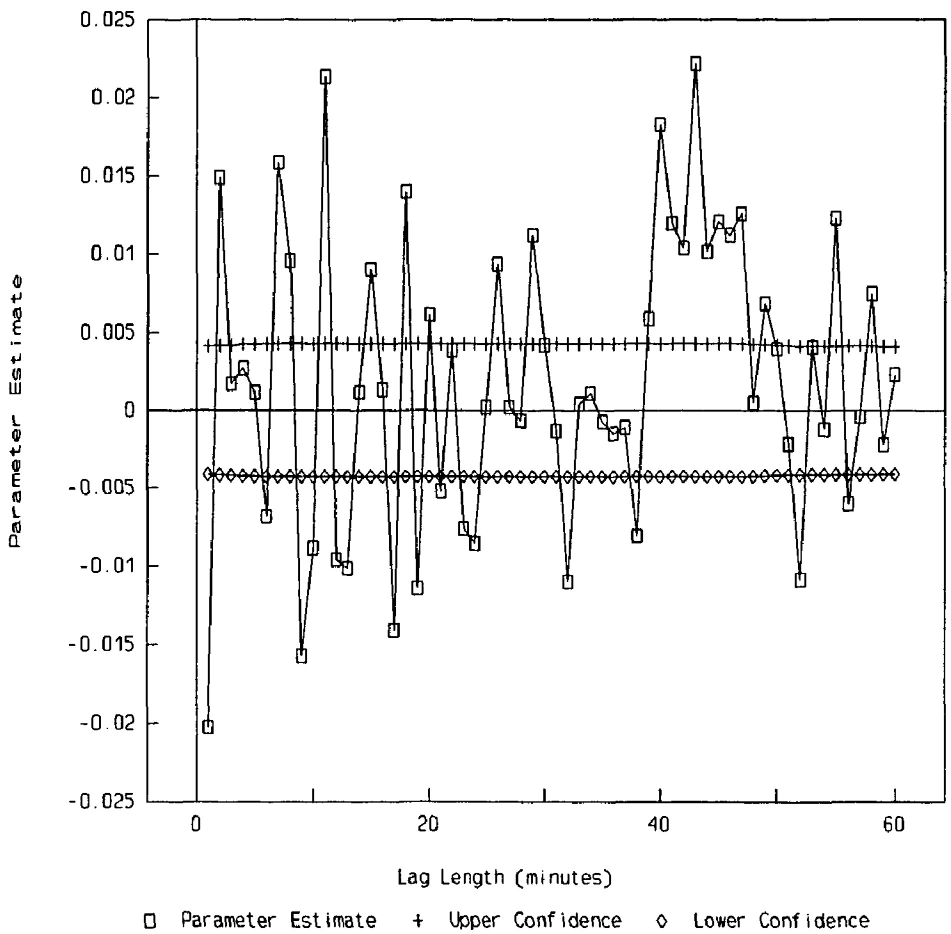

Figure 5
S&P 500 Futures Return Dependent Variable
and S&P 500 Futures Returns as Independent Variable

Figure 5's graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression.

$$R^{f}_{t}=\alpha_{2}+\sum_{i=1}^{60}\gamma_{i2}R^{f}_{t-i}+\sum_{i=1}^{45}\beta_{i2}R^{s}_{t-i}+e_{t2},$$

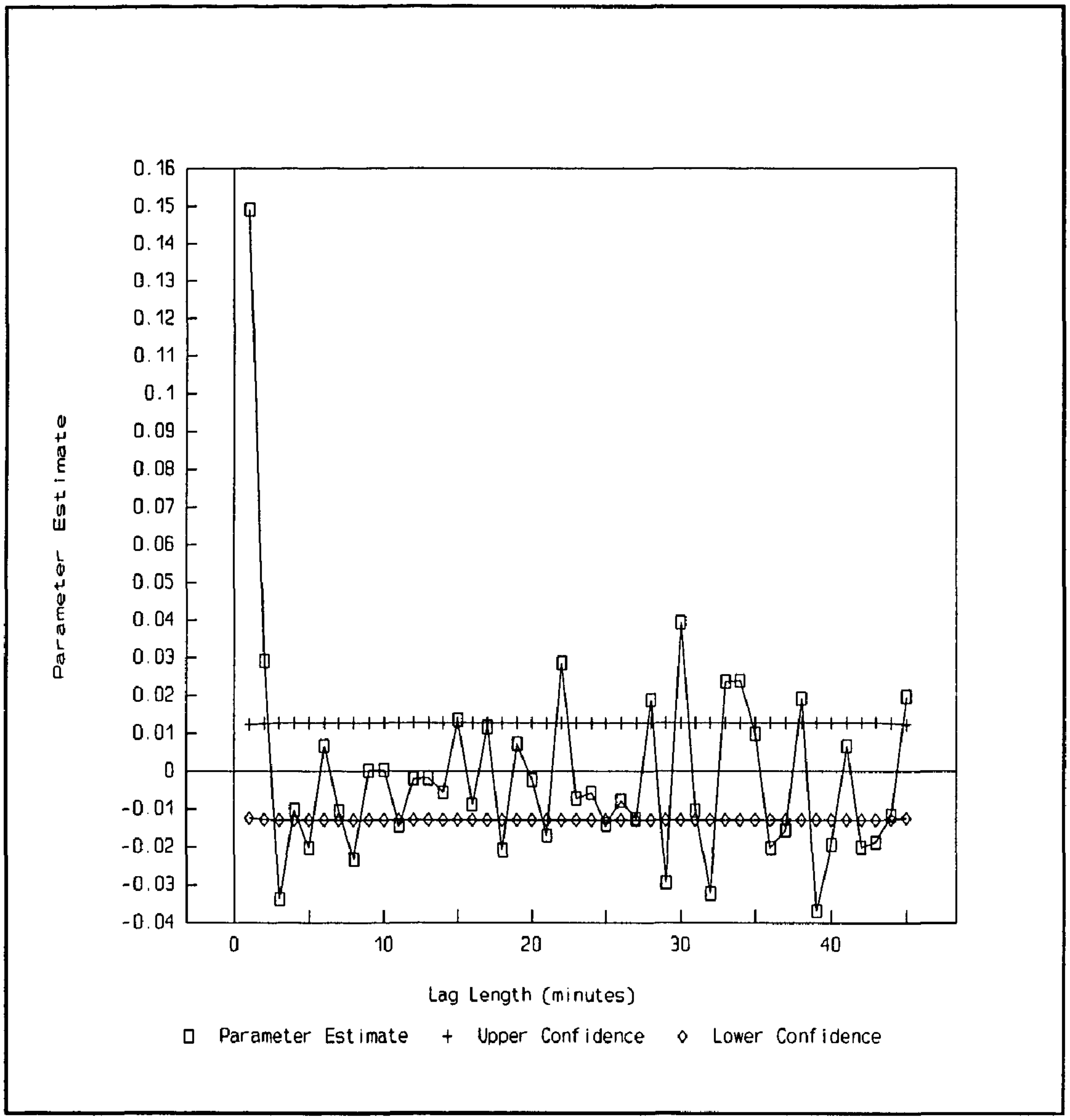

Figure 6
S&P 500 Futures Return Dependent Variable
and S&P 500 Spot Returns as Independent Variable

Figure 6's graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression.

$$R^f_t=\alpha_2+\sum_{i=1}^{60}\gamma_{i2}R^f_{t-i}+\sum_{i=1}^{45}\beta_{i2}R^s_{t-i}+e_{t2},$$

2.5.1.3 S&P 500 Spot and Future Results, With Error Correction Term

Accounting for the error correction term does not alter the lead-lag structure found in the non-error corrected analysis. Therefore, only a discussion of the error correction parameter estimates will be made.

The parameter estimates on the error correction term in Equation (10) are negative, and significantly different from zero (p-value < 0.0001). The parameter estimate on the error correction term in Equation (11) is positive and also significantly different from zero (p-value < 0.0001). The signs of the parameter estimates on both error correction terms are as hypothesized given the appropriate correcting mechanism. Apparently, large deviations from the spot-futures parity relationship are corrected through either market for this data and time period analyzed.

2.5.1.4 DAX Spot Results

Figure 7 is the graphical representation of the parameter estimates of Equation (7) with DAX spot returns as both the dependent and independent variables. White noise tests on the errors imply that a lag length of thirty minutes is a sufficient AR process to mitigate an autocorrelated error term.

Figure 8 is the graphic of parameter estimates, along with the confidence limits of the regression of Equation (8). Examining the coefficients on the lagged future returns reveals significance to approximately lag 23. This

lag length is longer than that documented by Grünbichler, Longstaff and Schwartz (1994). An F-test for the significance of the coefficients on the futures data yields a value 254.67, which is significant at the 0.0001 level. Therefore, the DAX futures returns Granger-cause the spot returns.

2.5.1.5 DAX Futures Results

Figure 9 is the graphic representing the regression with DAX Futures as both the dependent and independent variables. White noise tests also indicate that a lag length of 30 sufficiently reduces the possibility of autocorrelated errors.

As far as the regression with DAX Futures as the dependent variable and lagged spot data as independent variable is concerned, statistically significant coefficients are found only to lag 2 (See Figure 10). After this, the parameters fluctuate randomly around zero. This result supports those found in Grünbichler, Longstaff, and Schwartz (1994) that the DAX spot market leads the futures market by up to 5 minutes. However, the finer time grid of data used here allows a closer inspection of the relationship.

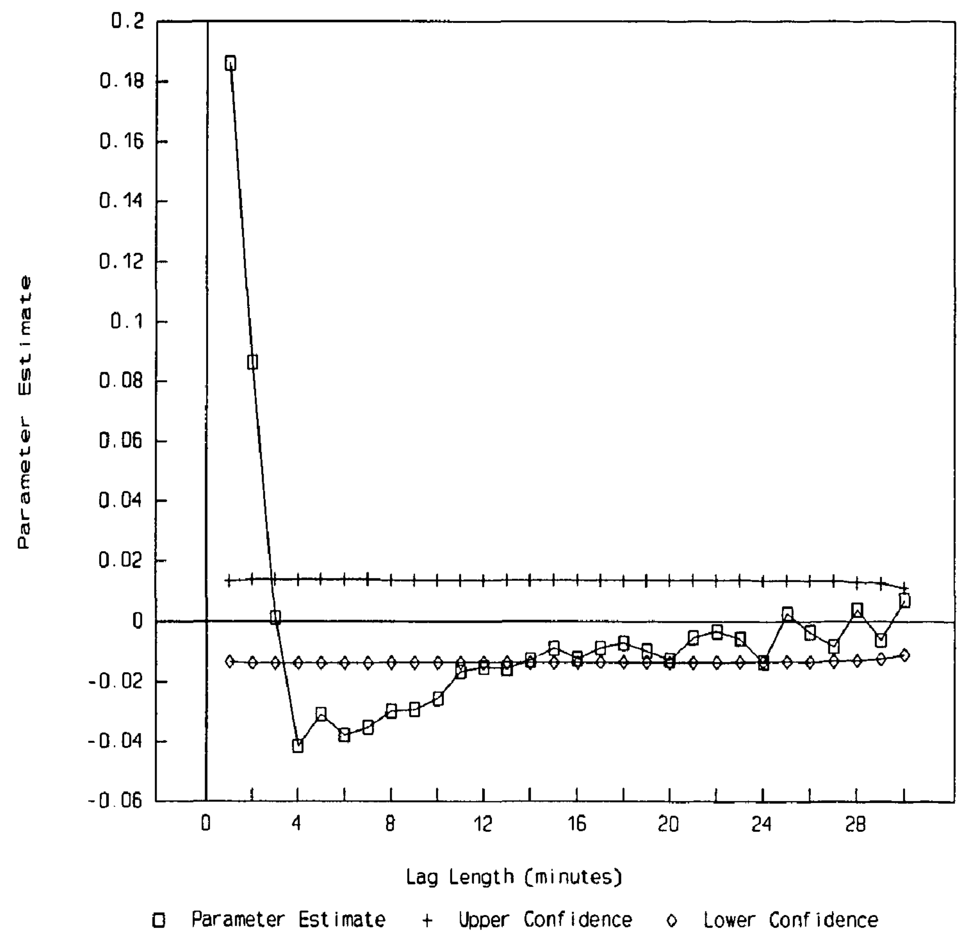

Figure 7
DAX Spot returns as Both Dependent and Independent Variables

Figure 7's graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression.

$$R^{s}{}_{t}=\alpha_{1}+\sum_{i=1}^{30}\gamma_{i1}R^{s}{}_{t-i}+\sum_{i=1}^{30}\beta_{i1}R^{f}{}_{t-i}+e_{t1}.$$

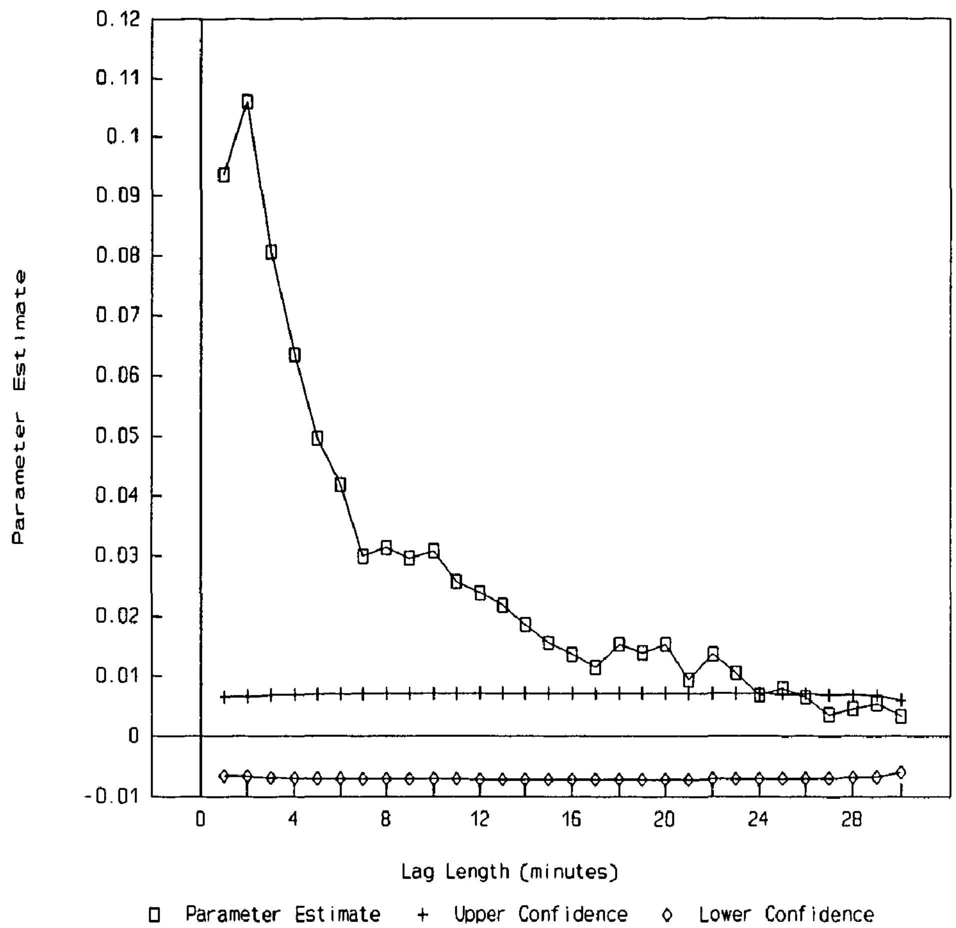

Figure 8
DAX Spot returns as Dependent and
DAX Futures returns as Independent Variables

Figure 8's graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression:

$$R^{s}{}_{t}=\alpha_1+\sum_{i=1}^{30}\gamma_{i1}R^{s}{}_{t-i}+\sum_{i=1}^{30}\beta_{i1}R^{f}{}_{t-i}+e_{t1}.$$

An F-test for the significance of all the lagged spot parameter estimates yields a value of 103.19, which is significant at the 0.0001 level. Therefore, the spot returns appear to Granger-cause the future returns.

Evidence is presented supporting the notion that the DAX futures market leads the DAX spot market by at least 23 minutes. However, the spot market has significant parameters to 2 minutes. Therefore, a significant feedback relationship also exists in Germany's DAX index and DAX index futures markets.

The fact that the lead length of the futures market over the spot market is long tends to infer that the futures market always dominates the information processing characteristics of the spot market. However, the documented feedback relationship indicates that this is not always the case, and that a conclusion of "futures markets returns always leading spot market returns" is incorrect.

Hence, the documented feedback relationship in this data provides evidence supporting the null of this hypothesis. That is, a feedback relationship means that both markets lead each other and suggests that there is no persistent one-sided lead or lag structure in the DAX stock index and stock index futures market, even though the futures market processing time appears faster.

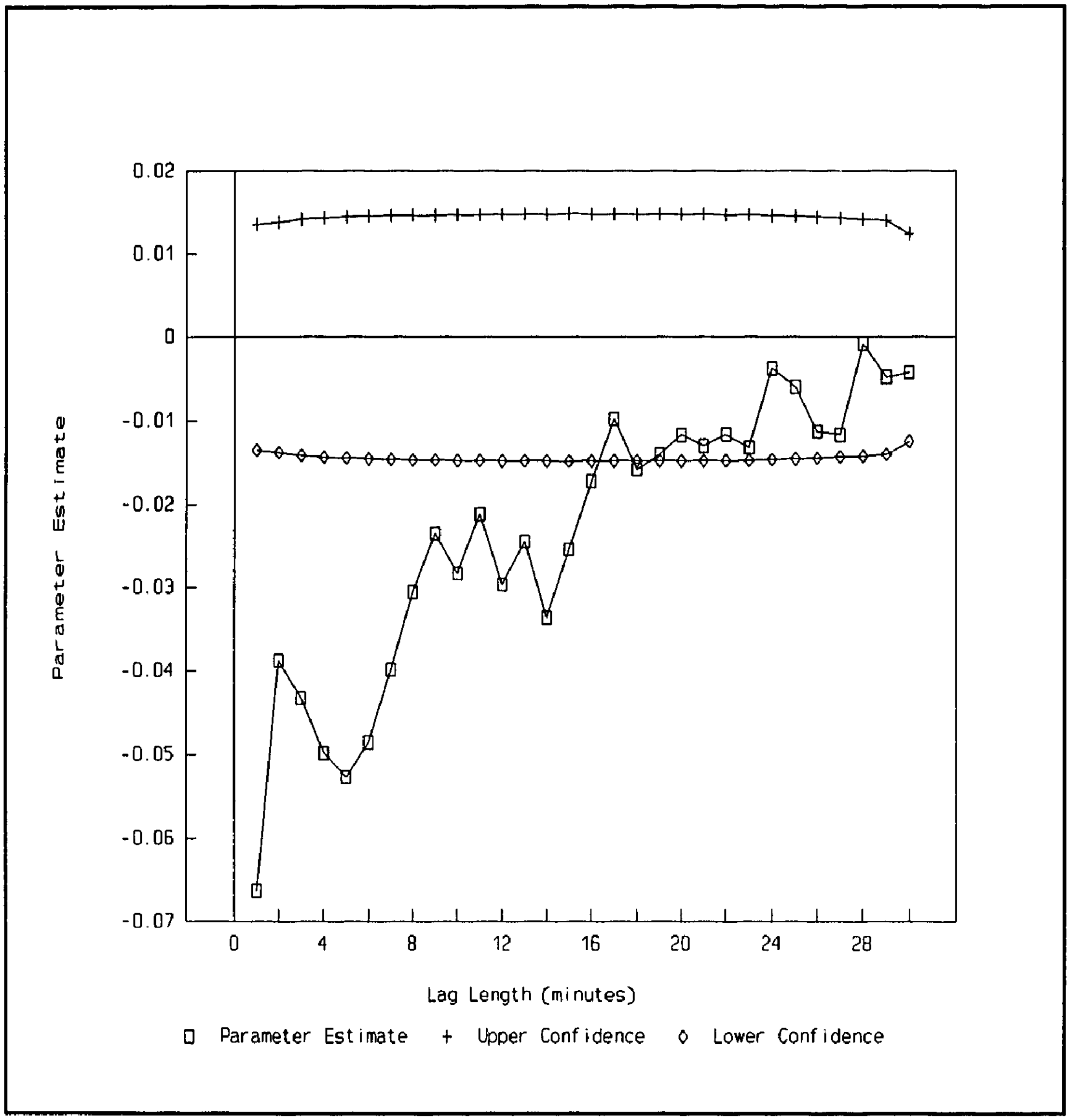

Figure 9
DAX Futures Returns as Both the Dependent and Independent Variables

Figure 9's graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression.

$$R^{f}_{t}=\alpha_1+\sum_{i=1}^{30}\gamma_{i1}R^{f}_{t-i}+\sum_{i=1}^{30}\beta_{i1}R^{s}_{t-i}+e_{t1}.$$

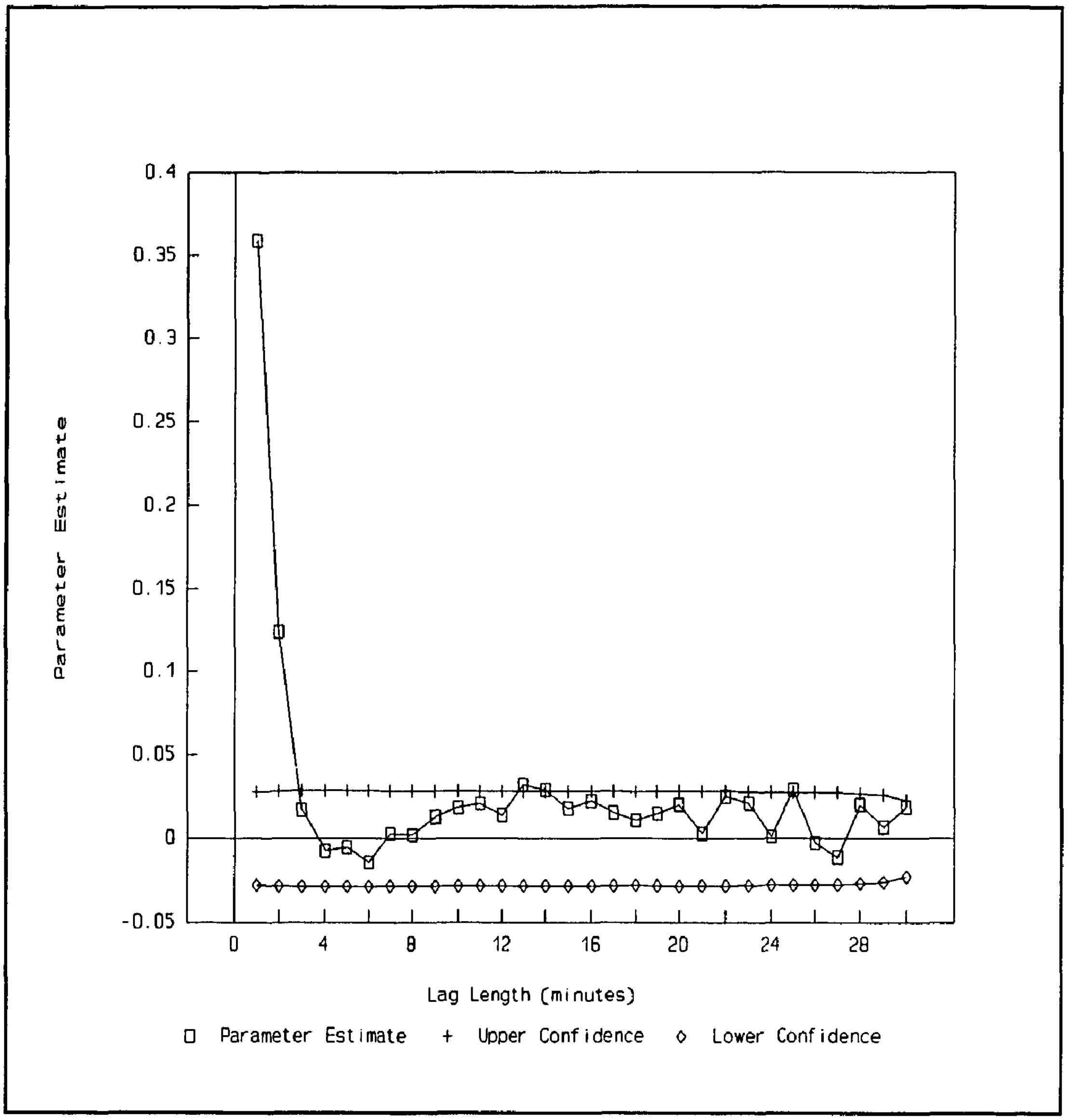

Figure 10
DAX Futures Returns as the Dependent and DAX Spot as the Independent Variable

This graphic was generated by the parameter estimates and upper and lower 99.99% confidence limits from the following regression.

$$R^f{}_t=\alpha_1+\sum_{i=1}^{30}\gamma_{i1}R^f{}_{t-i}+\sum_{i=1}^{30}\beta_{i1}R^s{}_{t-i}+e_{t1}.$$

2.5.2 Hypothesis #2 Results

Hypothesis #2 is stated as:

Ho: The DAX futures market leads all component stocks in fashion similar to the index.
Ha: The DAX futures market leads component stocks differently than the index.

To test this hypothesis, five minute returns for each security are generated. Then, the corresponding five minute returns for the DAX futures contracts are matched by date and time to the DAX component stock data. To maintain a 30 minute lead-lag time window, the lag lengths in Equations (7) and (8) are set to 6. Parameter estimates, and their corresponding significance levels (p-values) in parenthesis, from the lead-lag regressions for the individual DAX component stocks are presented in Table 6.

The table is read in the following manner. First, Table 6 is broken into panels of information related to each stock. Within each individual stock panel, there are two subpanels: one for the regression with the company's return as the dependent variable (Equation (7)), and one for the regression with the DAX futures return as the dependent variable (Equation (8)).

For example, BASF, the first company listed in Table 6, shows that its own return lagged one period results in a parameter estimate of -0.1998 that is significant at a p-value of 0.0001. The lagged futures data indicate significant parameters out to lag 6. On the other hand,

when the futures returns are the dependent variable, BASF's lagged returns do not show any significant parameters at the 0.0001 level. The F-test for causality in this example indicates that the futures market Granger causes BASF's stock return, but not vice-versa. There is no feedback of information in this example, only unidirectional causation from the futures to the individual stock.

An examination of Table 6 indicates that there is no discernable information processing advantage attributed to 28 out of 30 individual stocks. That is, none of the 28 individual stocks appear to lead the futures market in information processing. However, the futures market leads each individual stock from around 10 to 30 minutes, depending on the stock in question.

The test for Granger causality, however, is a joint test of the hypothesis that the cross-market variables are zero. This joint hypothesis test is carried out for each stock and the calculated F-statistic with associated significance level is found in Table 7.

The results presented in Table 7 complement those found in Table 6 and can be summarized as follows. First, For 28 out of 30 DAX component stocks, the DAX futures market Granger causes the individual security. Since no feedback of information processing is present, the causation is unidirectional. This result simply means that

Table 6
Lead-Lag Regression Results
for the Individual Component DAX Stocks

BASF					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1998	-0.1595	-0.0577	-0.0446	-0.0419	-0.0123
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1479)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4901	0.2332	0.1097	0.0873	0.0702	0.0651
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0117	-0.0588	-0.0285	0.0234	0.0204	0.0283
(0.2071)	(0.0001)	(0.0039)	(0.0167)	(0.0345)	(0.0029)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0006	-0.0158	0.0215	-0.0028	0.0023	0.0072
(0.9282)	(0.0135)	(0.0008)	(0.6615)	(0.7063)	(0.1966)
BMW					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1131	-0.0798	-0.0686	-0.0323	-0.0401	-0.0074
(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0001)	(0.3857)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4281	0.1853	0.1458	0.0935	0.0526	0.0114
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.4394)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0034	-0.0510	-0.0174	0.0305	0.0278	0.0325
(0.7177)	(0.0001)	(0.076)	(0.0017)	(0.0042)	(0.0007)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0137	-0.0194	0.0090	-0.0001	-0.0079	0.0084
(0.0283)	(0.0019)	(0.1464)	(0.9841)	(0.1796)	(0.1279)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Continental					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0179	-0.0116	-0.0199	-0.0182	0.0028	-0.0176
(0.0588)	(0.2116)	(0.0294)	(0.0404)	(0.7435)	(0.0312)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3408	0.2351	0.1749	0.1156	0.0280	0.0186
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1698)	(0.3551)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0142	-0.0676	-0.0280	0.0292	0.0249	0.0367
(0.1188)	(0.0001)	(0.0022)	(0.0013)	(0.0059)	(0.0001)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0050	-0.0021	0.0021	0.0061	-0.0031	-0.0052
(0.232)	(0.6135)	(0.6069)	(0.1231)	(0.416)	(0.1495)

Daimler Benz					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2688	-0.1374	-0.0322	0.0005	0.0136	0.0106
(0.0001)	(0.0001)	(0.0039)	(0.9645)	(0.2129)	(0.2908)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.5133	0.1562	0.0546	0.0457	0.0171	0.0176
(0.0001)	(0.0001)	(0.0003)	(0.0022)	(0.2462)	(0.2174)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0172	-0.0511	-0.0330	0.0213	0.0182	0.0324
(0.1102)	(0.0001)	(0.0046)	(0.065)	(0.1093)	(0.0032)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0065	-0.0249	0.0183	0.0033	0.0026	0.0019
(0.4305)	(0.0039)	(0.0338)	(0.6971)	(0.759)	(0.8077)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

DT. Babcock					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0723	-0.0420	-0.0446	-0.0222	-0.0244	-0.0078
(0.0001)	(0.0001)	(0.0001)	(0.0163)	(0.0074)	(0.3812)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3344	0.2298	0.1740	0.1181	0.0658	0.0572
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0076)	(0.0194)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0133	-0.0649	-0.0229	0.0328	0.0213	0.0298
(0.1452)	(0.0001)	(0.012)	(0.0003)	(0.0172)	(0.0008)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0058	-0.0024	0.0044	-0.0044	0.0002	-0.0019
(0.0985)	(0.4876)	(0.1975)	(0.1881)	(0.9585)	(0.5528)

Degussa					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0456	-0.0265	-0.0114	-0.0387	-0.0166	0.0014
(0.0001)	(0.0036)	(0.1939)	(0.0001)	(0.0496)	(0.865)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.2770	0.1947	0.1297	0.1190	0.0652	0.0522
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0012)	(0.009)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0120	-0.0682	-0.0298	0.0212	0.0189	0.0301
(0.1799)	(0.0001)	(0.0009)	(0.0167)	(0.0318)	(0.0006)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0018	-0.0009	0.0177	0.0000	0.0004	-0.0070
(0.6563)	(0.8235)	(0.0001)	(0.9947)	(0.9244)	(0.0478)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Bayer

Dependent Variable = Company Return

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2313	-0.1485	-0.0995	-0.0371	-0.0125	-0.0091
(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.2048)	(0.3089)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.5202	0.2242	0.1094	0.0860	0.0179	0.0065
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.2158)	(0.6434)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0108	-0.0614	-0.0278	0.0214	0.0098	0.0221
(0.2645)	(0.0001)	(0.0076)	(0.0388)	(0.3368)	(0.0266)

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0046	-0.0067	0.0117	0.0072	0.0140	0.0071
(0.5084)	(0.352)	(0.1057)	(0.3119)	(0.0458)	(0.2606)

Hoechst

Dependent Variable = Company Return

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1954	-0.1500	-0.0541	-0.0329	-0.0169	-0.0016
(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0696)	(0.8547)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.5487	0.2547	0.1182	0.0927	0.0462	0.0185
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0029)	(0.2224)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0084	-0.0513	-0.0187	0.0276	0.0218	0.0375
(0.3638)	(0.0001)	(0.0594)	(0.0052)	(0.0262)	(0.0001)

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0080	-0.0234	0.0110	-0.0026	0.0009	-0.0042
(0.1798)	(0.0001)	(0.0709)	(0.6651)	(0.8837)	(0.4395)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Man AG					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0573	-0.0823	-0.0116	-0.0035	-0.0058	-0.0044
(0.0001)	(0.0001)	(0.1801)	(0.6777)	(0.4727)	(0.5707)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4289	0.2617	0.1670	0.1201	0.0521	-0.0086
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0038)	(0.627)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0095	-0.0612	-0.0247	0.0256	0.0138	0.0304
(0.2885)	(0.0001)	(0.0071)	(0.0049)	(0.1272)	(0.0007)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0077	-0.0038	0.0053	0.0106	0.0041	-0.0053
(0.0955)	(0.3959)	(0.2207)	(0.0119)	(0.3166)	(0.1753)

Henkel					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0907	-0.0521	-0.0407	-0.0194	-0.0067	-0.0054
(0.0001)	(0.0001)	(0.0001)	(0.0291)	(0.4414)	(0.5121)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.2145	0.1666	0.1095	0.0811	0.0623	0.0064
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.6381)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0156	-0.0650	-0.0205	0.0266	0.0196	0.0296
(0.0884)	(0.0001)	(0.0261)	(0.0034)	(0.03)	(0.0009)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0055	-0.0032	0.0134	-0.0007	0.0058	-0.0088
(0.3801)	(0.5976)	(0.0235)	(0.9105)	(0.3025)	(0.1002)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Karstadt					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0361	-0.0471	-0.0254	-0.0418	-0.0003	-0.0122
(0.0001)	(0.0001)	(0.005)	(0.0001)	(0.9721)	(0.1441)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.2843	0.1420	0.1142	0.0996	0.0576	0.0722
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0001)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0128	-0.0689	-0.0276	0.0273	0.0222	0.0314
(0.1594)	(0.0001)	(0.0025)	(0.0025)	(0.013)	(0.0004)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0010	-0.0001	0.0142	0.0009	0.0031	0.0129
(0.8449)	(0.9768)	(0.0025)	(0.8511)	(0.4913)	(0.0027)

Linde					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0755	-0.0738	-0.0455	-0.0365	-0.0326	-0.0100
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.2346)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.2541	0.1581	0.1083	0.0991	0.0617	0.0542
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0118	-0.0663	-0.0257	0.0260	0.0208	0.0331
(0.1956)	(0.0001)	(0.0052)	(0.0042)	(0.0214)	(0.0002)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0005	-0.0069	0.0141	-0.0043	0.0019	-0.0024
(0.9307)	(0.2159)	(0.0094)	(0.4202)	(0.7212)	(0.6244)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Mannesmann					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1590	-0.0975	-0.0405	-0.0225	0.0242	0.0131
(0.0001)	(0.0001)	(0.0001)	(0.0173)	(0.0094)	(0.1349)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.5666	0.2140	0.1194	0.0486	0.0079	-0.0211
(0.0001)	(0.0001)	(0.0001)	(0.0042)	(0.6414)	(0.2051)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0096	-0.0642	-0.0316	0.0156	0.0091	0.0154
(0.3116)	(0.0001)	(0.0015)	(0.1134)	(0.3547)	(0.111)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0039	-0.0039	0.0145	0.0115	0.0161	0.0123
(0.4798)	(0.4814)	(0.0094)	(0.0368)	(0.0031)	(0.0153)

Metallgesellschaft					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0296	-0.0366	-0.0185	-0.0132	-0.0109	0.0093
(0.0012)	(0.0001)	(0.0341)	(0.1258)	(0.1953)	(0.2507)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3766	0.1576	0.1392	0.1424	0.1004	0.1051
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0007)	(0.0003)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0175	-0.0665	-0.0297	0.0307	0.0183	0.0346
(0.0526)	(0.0001)	(0.0009)	(0.0005)	(0.0367)	(0.0001)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0003	0.0033	-0.0007	-0.0013	0.0052	-0.0043
(0.9003)	(0.212)	(0.7907)	(0.5978)	(0.0353)	(0.0745)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Preussag					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0536	-0.0442	-0.0070	-0.0183	0.0086	-0.0224
(0.0001)	(0.0001)	(0.4259)	(0.035)	(0.313)	(0.0061)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3761	0.1818	0.1136	0.0745	0.0459	0.0197
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0055)	(0.2275)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0139	-0.0614	-0.0239	0.0302	0.0268	0.0377
(0.1208)	(0.0001)	(0.0088)	(0.0008)	(0.0027)	(0.0001)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0015	-0.0145	0.0101	-0.0102	-0.0022	-0.0027
(0.7584)	(0.0031)	(0.0349)	(0.0306)	(0.6279)	(0.5427)

RWE					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1672	-0.1117	-0.0824	-0.0387	-0.0414	-0.0155
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0679)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4006	0.1790	0.1531	0.0773	0.0659	0.0350
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.005)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0079	-0.0610	-0.0259	0.0252	0.0179	0.0265
(0.395)	(0.0001)	(0.0079)	(0.0092)	(0.0624)	(0.005)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0086	-0.0056	0.0100	-0.0008	0.0059	0.0010
(0.2397)	(0.4477)	(0.1713)	(0.9129)	(0.3966)	(0.8713)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Schering

Dependent Variable = Company Return

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0293	-0.0472	-0.0281	-0.0175	-0.0059	-0.0099
(0.0013)	(0.0001)	(0.0015)	(0.0428)	(0.4892)	(0.2041)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3857	0.1546	0.0641	0.0418	0.0046	0.0178
(0.0001)	(0.0001)	(0.0004)	(0.0192)	(0.7968)	(0.3121)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0173	-0.0701	-0.0309	0.0299	0.0265	0.0364
(0.0537)	(0.0001)	(0.0007)	(0.0009)	(0.0029)	(0.0001)

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0086	0.0027	0.0043	-0.0102	-0.0022	-0.0001
(0.0591)	(0.552)	(0.3282)	(0.0186)	(0.6079)	(0.9749)

Siemens

Dependent Variable = Company Return

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.3353	-0.1933	-0.0765	-0.0234	-0.0009	0.0121
(0.0001)	(0.0001)	(0.0001)	(0.0288)	(0.93)	(0.2025)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4747	0.2070	0.0838	0.0633	0.0186	0.0013
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1322)	(0.9166)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0108	-0.0496	-0.0321	0.0238	0.0198	0.0290
(0.2843)	(0.0001)	(0.0037)	(0.0299)	(0.0659)	(0.0052)

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0026	-0.0268	0.0224	-0.0016	0.0035	0.0068
(0.7726)	(0.0038)	(0.0164)	(0.8633)	(0.6966)	(0.4089)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Thyssen

Dependent Variable = Company Return

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1357	-0.1105	-0.0612	-0.0427	-0.0513	-0.0137
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1078)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.5832	0.2597	0.1471	0.0385	0.0568	0.0500
(0.0001)	(0.0001)	(0.0001)	(0.0318)	(0.0014)	(0.0044)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0109	-0.0646	-0.0314	0.0168	0.0179	0.0311
(0.2372)	(0.0001)	(0.0012)	(0.0792)	(0.0598)	(0.0009)

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0030	-0.0053	0.0151	0.0070	-0.0051	0.0041
(0.5439)	(0.2897)	(0.0024)	(0.1535)	(0.291)	(0.3636)

Veba

Dependent Variable = Company Return

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1673	-0.1192	-0.0556	-0.0665	-0.0368	-0.0027
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.7553)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3862	0.1580	0.0817	0.0313	0.0491	0.0399
(0.0001)	(0.0001)	(0.0001)	(0.003)	(0.0001)	(0.0001)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0153	-0.0596	-0.0314	0.0197	0.0166	0.0249
(0.109)	(0.0001)	(0.0022)	(0.0532)	(0.0993)	(0.0115)

Independent Variable = Lagged Company Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0046	-0.0201	0.0264	0.0067	0.0066	0.0090
(0.6217)	(0.0348)	(0.0054)	(0.4723)	(0.471)	(0.2858)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Viag					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0301	-0.0505	-0.0189	-0.0086	-0.0275	0.0056
(0.0012)	(0.0001)	(0.0368)	(0.3364)	(0.0016)	(0.4981)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3465	0.1391	0.0893	0.0259	0.0388	-0.0033
(0.0001)	(0.0001)	(0.0001)	(0.0853)	(0.0096)	(0.8229)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0176	-0.0684	-0.0289	0.0252	0.0210	0.0327
(0.0516)	(0.0001)	(0.0017)	(0.0058)	(0.021)	(0.0003)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0101	0.0010	0.0068	-0.0051	-0.0025	0.0058
(0.0727)	(0.8505)	(0.2127)	(0.3475)	(0.6377)	(0.2472)

Volkswagen					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2243	-0.1195	-0.0456	0.0040	0.0398	0.0199
(0.0001)	(0.0001)	(0.0001)	(0.6886)	(0.0001)	(0.0303)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.6556	0.1831	0.0767	0.0345	-0.0112	-0.0291
(0.0001)	(0.0001)	(0.0001)	(0.0565)	(0.5323)	(0.0973)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0068	-0.0516	-0.0248	0.0239	0.0080	0.0161
(0.499)	(0.0001)	(0.0203)	(0.0237)	(0.4442)	(0.1161)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0090	-0.0153	0.0076	0.0038	0.0152	0.0119
(0.1252)	(0.0102)	(0.2021)	(0.5139)	(0.0089)	(0.0267)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Kaufhof Holding					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0626	-0.0536	-0.0312	-0.0315	-0.0266	0.0027
(0.0001)	(0.0001)	(0.0005)	(0.0003)	(0.0023)	(0.7454)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3830	0.2012	0.1249	0.1047	0.0730	0.0460
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0241)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0160	-0.0712	-0.0308	0.0232	0.0195	0.0294
(0.0793)	(0.0001)	(0.0008)	(0.0108)	(0.0312)	(0.0011)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0043	0.0062	-0.0011	0.0022	-0.0001	0.0107
(0.2873)	(0.1243)	(0.7718)	(0.574)	(0.9754)	(0.0037)

Bay. Hypobank					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1144	-0.0716	-0.0698	-0.0609	-0.0331	-0.0121
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1403)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3455	0.2022	0.1409	0.0975	0.0953	0.0445
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0009)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0177	-0.0731	-0.0372	0.0219	0.0227	0.0371
(0.0504)	(0.0001)	(0.0001)	(0.0178)	(0.0132)	(0.0001)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0084	0.0033	0.0138	-0.0066	0.0062	-0.0038
(0.1771)	(0.5916)	(0.0232)	(0.2758)	(0.2899)	(0.4895)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Bay. Vereinsbank					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0988	-0.0769	-0.0430	-0.0521	-0.0385	-0.0053
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.5155)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3153	0.1573	0.1084	0.0971	0.0685	0.0614
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0125	-0.0637	-0.0242	0.0287	0.0203	0.0350
(0.1635)	(0.0001)	(0.0081)	(0.0016)	(0.0241)	(0.0001)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0006	-0.0164	0.0028	0.0086	0.0003	-0.0052
(0.9228)	(0.0107)	(0.656)	(0.1663)	(0.9579)	(0.3581)

Commerzbank					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1780	-0.0999	-0.0430	-0.0049	-0.0200	0.0289
(0.0001)	(0.0001)	(0.0001)	(0.5944)	(0.0254)	(0.0005)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4072	0.1837	0.0997	0.0509	0.0532	0.0185
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.1533)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0181	-0.0747	-0.0367	0.0216	0.0179	0.0253
(0.0479)	(0.0001)	(0.0001)	(0.0226)	(0.0568)	(0.0062)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0148	0.0094	0.0145	-0.0002	0.0085	0.0086
(0.0253)	(0.1592)	(0.0283)	(0.9796)	(0.1844)	(0.1484)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

Deutsche Bank					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.3182	-0.1915	-0.1098	-0.0402	0.0002	-0.0084
(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.9864)	(0.3899)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4395	0.1693	0.1060	0.0664	0.0398	0.0249
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0181)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0041	-0.0384	-0.0231	0.0166	-0.0031	0.0282
(0.6968)	(0.0008)	(0.0464)	(0.1512)	(0.7871)	(0.0103)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0343	-0.0333	0.0122	0.0193	0.0352	-0.0080
(0.0018)	(0.0038)	(0.2934)	(0.0954)	(0.0019)	(0.4326)
Dresdner Bank					
Dependent Variable = Company Return					
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2074	-0.1630	-0.0662	-0.0487	-0.0109	-0.0115
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.2257)	(0.1649)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.4323	0.2258	0.1491	0.1004	0.0593	0.0458
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0075	-0.0545	-0.0254	0.0237	0.0156	0.0252
(0.4136)	(0.0001)	(0.0084)	(0.0133)	(0.0991)	(0.0069)
Independent Variable = Lagged Company Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0225	-0.0112	0.0136	0.0053	0.0110	0.0106
(0.0012)	(0.1103)	(0.0524)	(0.4404)	(0.1036)	(0.0867)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

(table con'd.)

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
Lufthansa						
Dependent Variable = Company Return						
Independent Variable = Lagged Company Return						
	-0.0402	-0.0183	-0.0221	-0.0342	-0.0223	0.0200
	(0.0001)	(0.0485)	(0.0164)	(0.0002)	(0.0126)	(0.0198)
Independent Variable = Lagged DAX Futures Return						
	0.5201	0.2189	0.1452	0.1636	-0.0217	0.0642
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.4537)	(0.0251)
Dependent Variable = DAX Futures Return						
Independent Variable = Lagged DAX Futures Return						
	-0.0159	-0.0659	-0.0253	0.0283	0.0218	0.0385
	(0.0772)	(0.0001)	(0.0049)	(0.0015)	(0.0138)	(0.0001)
Independent Variable = Lagged Company Return						
	0.0070	-0.0057	0.0007	-0.0029	0.0004	-0.0010
	(0.0144)	(0.0455)	(0.813)	(0.2916)	(0.8878)	(0.6979)
Allianz						
Dependent Variable = Company Return						
Independent Variable = Lagged Company Return						
	-0.2281	-0.1675	-0.0857	-0.0619	-0.0111	-0.0179
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.2359)	(0.0364)
Independent Variable = Lagged DAX Futures Return						
	0.5133	0.2222	0.1435	0.0986	0.0780	0.0576
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Dependent Variable = DAX Futures Return						
Independent Variable = Lagged DAX Futures Return						
	-0.0032	-0.0464	-0.0284	0.0200	0.0146	0.0236
	(0.7386)	(0.0001)	(0.0054)	(0.0485)	(0.1465)	(0.0161)
Independent Variable = Lagged Company Return						
	-0.0173	-0.0216	0.0185	0.0054	0.0080	0.0097
	(0.0104)	(0.0015)	(0.0064)	(0.4248)	(0.2204)	(0.1067)

Regressions are as in Equations (7) and (8) where the dependent variable is either the individual company's returns (Equation (7)), or the DAX futures returns (Equation (8)). p-values are in parenthesis.

Table 7
Hypothesis Tests of Lead-Lag Between the
Individual Securities Lead and the DAX Futures

Firm Name	Futures Leads Security	Security Leads Futures
Allianz	260.127 (0.0001)	**5.221 (0.0001)**
BASF	233.392 (0.0001)	4.137 (0.0004)
Bayer	260.964 (0.0001)	1.498 (0.1744)
Bayrische Hypobank	156.556 (0.0001)	1.779 (0.0992)
BMW	170.918 (0.0001)	3.563 (0.0016)
Bayrische Vereinsbank	138.018 (0.0001)	1.707 (0.1150)
Commerzbank	190.800 (0.0001)	2.088 (0.0513)
Continental	76.446 (0.0001)	1.190 (0.3083)
Daimler	226.851 (0.0001)	3.351 (0.0027)
Deutsche Babcock	52.480 (0.0001)	1.192 (0.3070)
Deutsche Bank	327.222 (0.0001)	**5.582 (0.0001)**
Degussa	53.876 (0.0001)	4.365 (0.0002)
Dresdner Bank	254.857 (0.0001)	3.866 (0.0007)
Henkel	73.525 (0.0001)	1.768 (0.1013)
Hoechst	260.610 (0.0001)	3.931 (0.0006)
Karstadt	64.700 (0.0001)	3.050 (0.0056)
Kaufhof Holding	78.408 (0.0001)	1.970 (0.0662)
Lufthansa	66.328 (0.0001)	1.981 (0.0646)
Linde	73.793 (0.0001)	1.691 (0.1186)
MAN	135.911 (0.0001)	2.450 (0.0228)
Metallgesellschaft	37.523 (0.0001)	1.621 (0.1368)
Mannesmann	218.444 (0.0001)	3.717 (0.0011)
Preussag	107.705 (0.0001)	3.219 (0.0037)
RWE	215.337 (0.0001)	0.847 (0.5334)
Schering	87.132 (0.0001)	1.850 (0.0855)
Siemens	291.113 (0.0001)	3.886 (0.0007)
Thyssen	217.706 (0.0001)	2.628 (0.0151)
Veba	274.815 (0.0001)	2.745 (0.0115)
Viag	103.341 (0.0001)	1.205 (0.3004)
Volkswagen	247.362 (0.0001)	3.441 (0.0021)

Table displays F-test statistic ad p-values (in parenthesis).

information is processed more quickly in the futures market than the markets for the individual securities. However, this data reveal a feedback of information processing between two stocks and the Futures market, Allianz and Deutsche Bank.

This second finding is extremely interesting given the fact that the majority of the other firms appear to have no impact, individually, on the futures market. Chan (1992) finds that none of the 20 MMI stocks exhibit this characteristic. Since these two companies hold large stock portfolios of many other German firms, this result possibly indicates that these firms may simply be proxies of the stock market as a whole. Essentially, it could be that Allianz and Deutsche Bank play the role of a widely diversified mutual fund of German equities.

On the other hand, given the fact that Allianz's and Deutsche Bank's weighted effect (the P*Q found in Equation (2)) on the DAX index is large (comprising approximately 20% of the index), the result that these two firms lead the futures market could be an artifact of the way the DAX is calculated. However, Siemens's weight impact on the index is approximately 10%, and its stock returns do not appear to lead the futures market returns. The finding in this hypothesis test warrants additional attention.

In summary, testing Hypothesis #2 finds unidirectional information processing (with futures as the lead processor) for 28 of the 30 DAX component stocks. However, 2 of the

stocks, Deutsche Bank and Allianz exhibit a feedback of information processing with the DAX futures market. That is, these two stocks Granger cause the futures market. Therefore, the null hypothesis of a fixed lead-lag structure across all DAX component securities can be rejected in favor of its alternative.

2.5.3 Hypothesis #3 Results

Hypothesis #3 is stated as:

Ho: The lead-lag relation is the same in up and down markets.
Ha: The lead-lag relation is different in up and down markets.

The purpose of this hypothesis is to examine the effects of short-selling restrictions facing investors in the German equities market. Recall that short-selling individual securities in Germany is a difficult process for institutional investors and practically impossible for individual investors. Therefore, if investors have information that forecasts market downturns, their best opportunity to transact on that information is through the futures market, which has no short-selling restrictions.

Hence, down market related information portends two outcomes: (1) extending the lead time of futures information processing over spot market processing and, (2) unidirectional causation from the futures to the spot market. However, *a priori*, no forecast is made of the lead-lag relation in an up market.

To test this hypothesis, intradaily DAX index returns are ranked into deciles. The lowest ranked decile contains the largest downward intradaily price movements, whereas the highest ranked decile contains the largest upward intradaily price movements. The lead-lag relationship in each decile is then examined via Equations (7) and (8).

Figures 11 and 12 portray a graphical representation of the regression relationship between DAX index returns, as the dependent variable, to itself lagged and to the futures returns lagged for observations in the lowest ranked decile of intradaily spot returns. Figure 11 indicates that the parameter estimates of the lagged dependent variable become insignificant after 5 lags.

The surprising result of this hypothesis test is found in Figure 12, the graphical representation of the parameter estimates of the lagged futures returns. When the lead-lag relationship between all DAX indexes and the DAX index futures observations was examined in Hypothesis #1, the result was that the futures series tended to lead the spot series by approximately 23 minutes. However, in a down market, the lead is truncated to no longer than 12 minutes!

Given the fact that investors have a difficult, if not impossible, time short-selling German equities, this result is surprising. The F-statistic testing for Granger-Causality of the futures returns is significant (27.643, p-

value < 0.0001), indicating that futures still Granger-cause index returns in a down market.

Explanations for this result may come from the following sources: (1) either the short-selling restrictions are not as restrictive as implied by Bamberg and Röder (1994), or (2) conservative German investors do not worry about selling securities they do not own, and substitute short-selling activities with selling their own positions, or (3) simply that investors react more quickly to extreme price movements than non-extreme price movements. Whatever, the reason, the decrease in the lead time of the futures market in a down market is surprising.

Figures 13 and 14 represent the results of the regression using futures data as the dependent variable. Figure 13 indicates that the lagged dependent parameter estimates become insignificant around lag 5, implying that the lag length is sufficient to reduce the incidence of autocorrelated errors. Figure 14 shows that the lagged DAX index return's parameter estimates become insignificant after 1 minute. Hence the lead from the spot market has decreased by 1 minute, as was found in testing Hypothesis #1.

The F-test statistic for Granger-Causality from the spot to futures markets is 8.259, which is also significant at the 0.0001 significance level. Since each return series

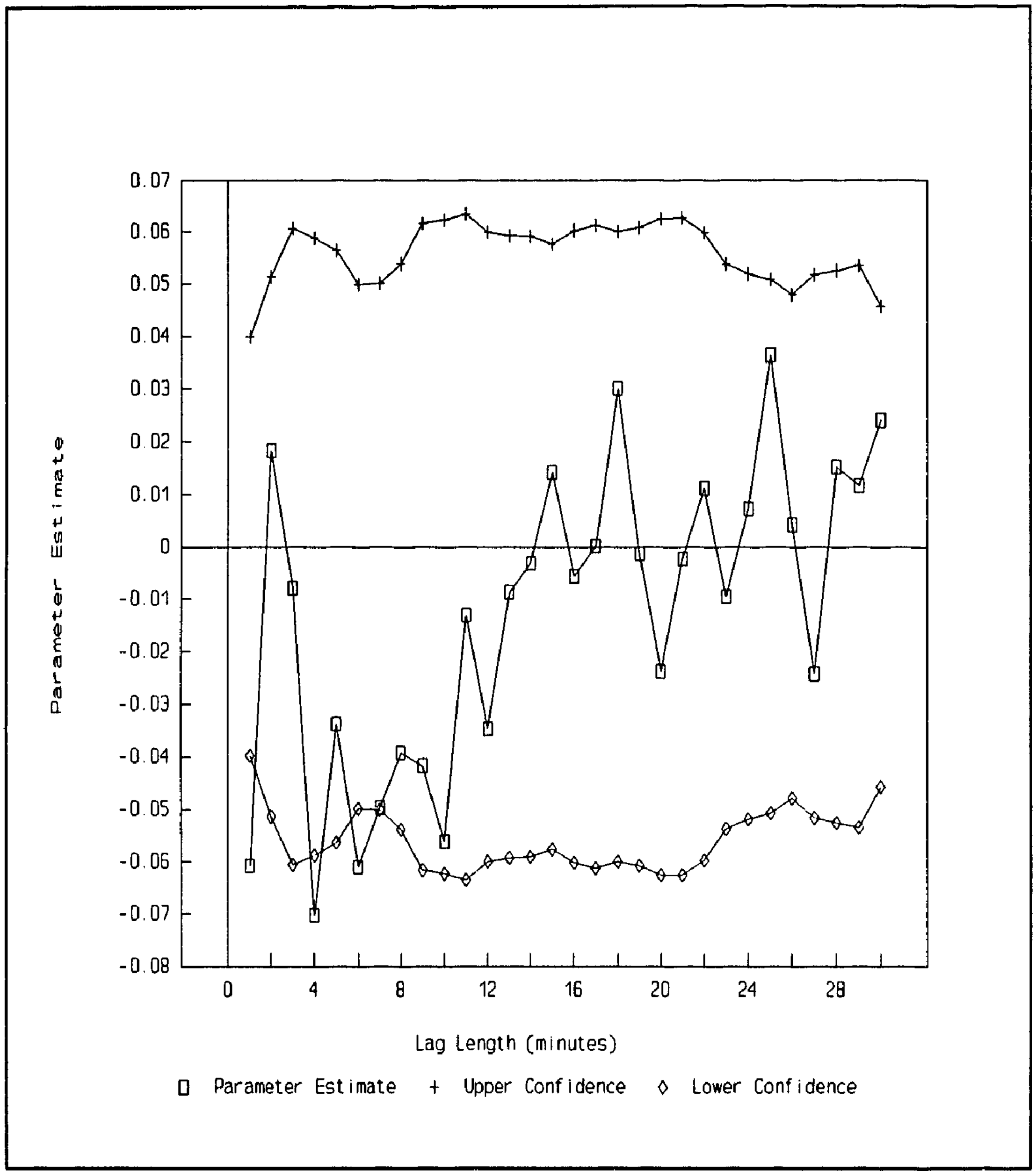

Figure 11
DAX Returns as Dependent and Independent Variable, Observations from the Lowest Intradaily Spot Returns: A Down Market

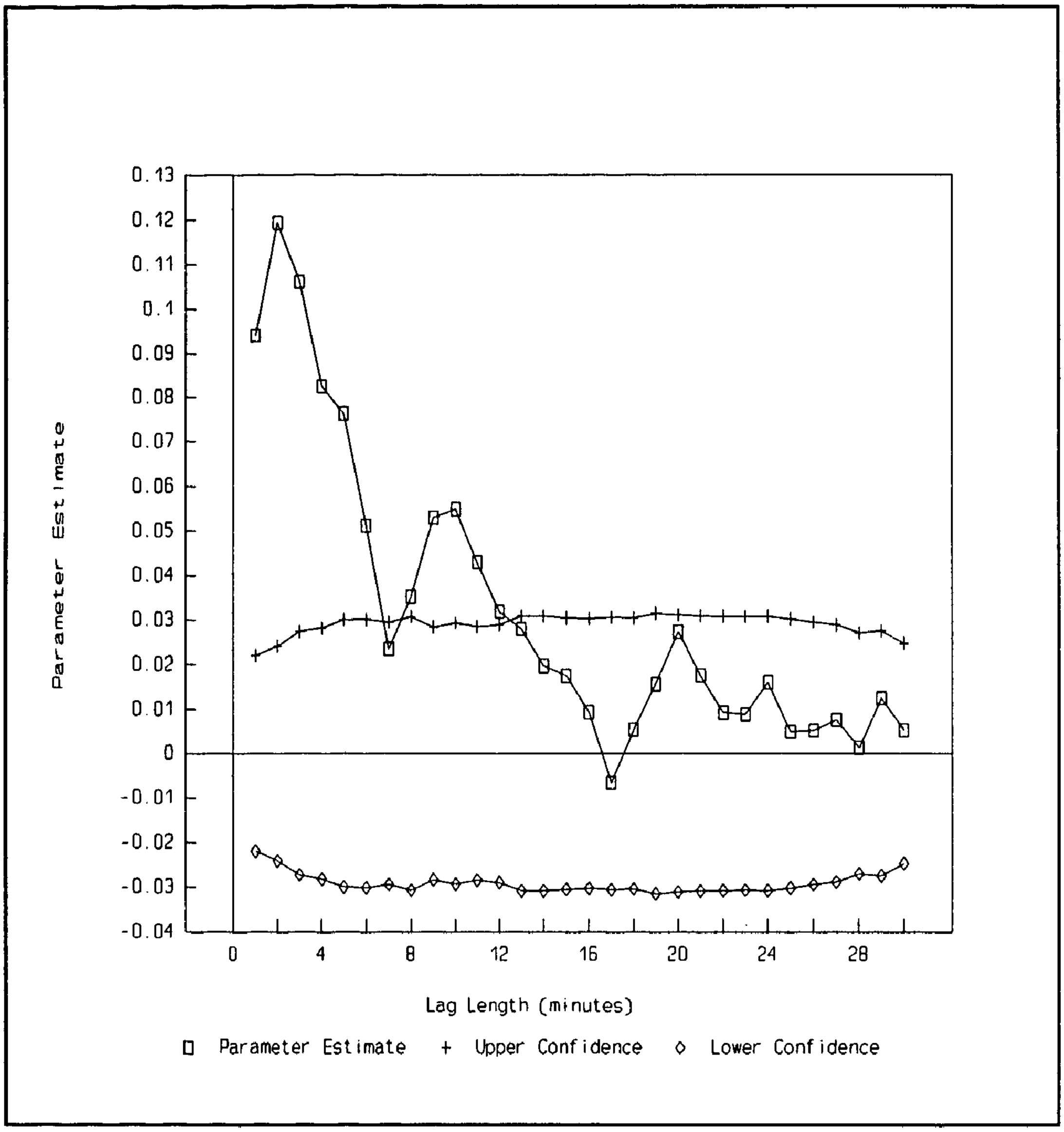

Figure 12
DAX Returns as Dependent and Futures Returns as Independent Variable, Observations from the Lowest Intradaily Spot Returns: A Down Market

leads the other, the feedback of information found in the test of Hypothesis #1 still holds, even in a down market. However, the information processing advantage exhibited by the futures market (up to 23 minutes) has decreased substantially in the down market dataset.

Figures 15 and 16 graphically represent the parameter estimates, and their 99.99% confidence limits for the case of the DAX Index returns as the dependent variable in the data containing the highest intradaily spot returns (the up market data series). Figure 15 indicates that the lagged dependent spot return parameters become insignificant quickly. Figure 16, however, presents the result that the lead of the futures market is trimmed even further in the up market than in the down market. Significant parameters are only found to lag 5.

This result may provide some light on the unexpected outcome revealed in the down market analysis. For instance, suppose that extreme price movement markets reveal more information about the expectations of market participants than at other locations of the price change distribution. If more information is revealed in these extreme up and down markets, then the expectations of both spot market and futures market participants may become aligned, and therefore, their trading patterns may also become aligned.

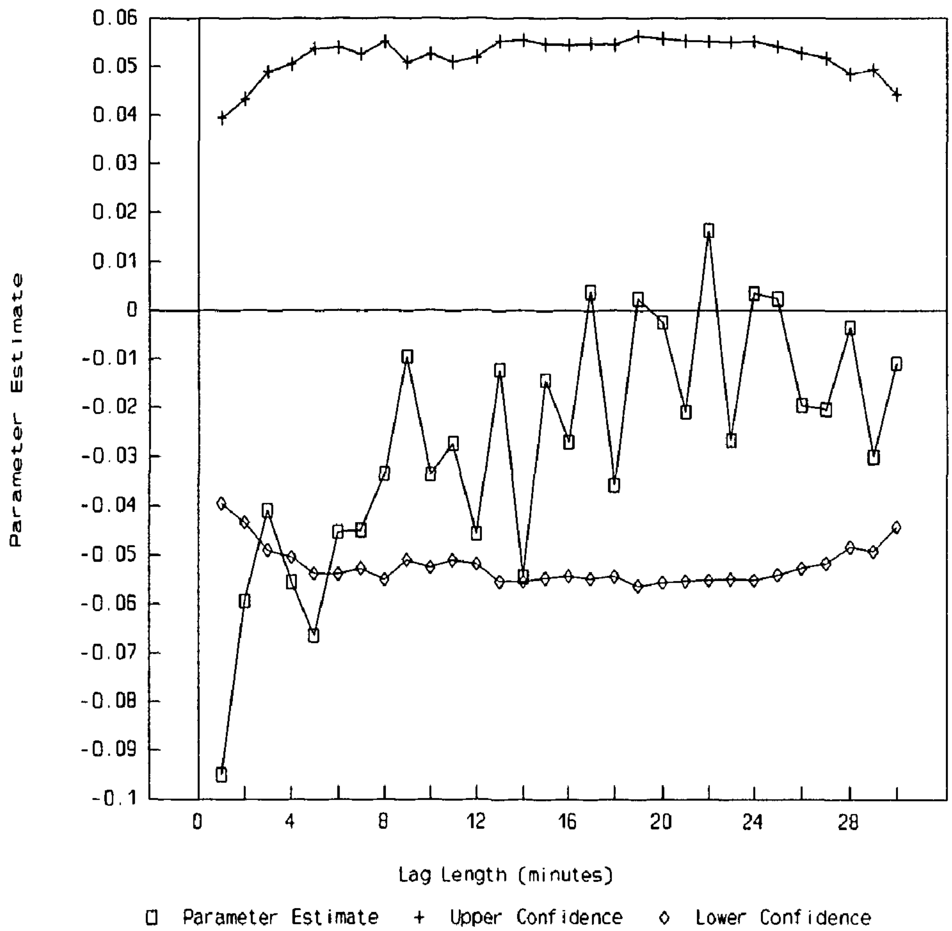

Figure 13
DAX Futures Returns as Both Dependent and Independent Variables for the Lowest Decile Intradaily Spot Returns: The Case of a Down Market

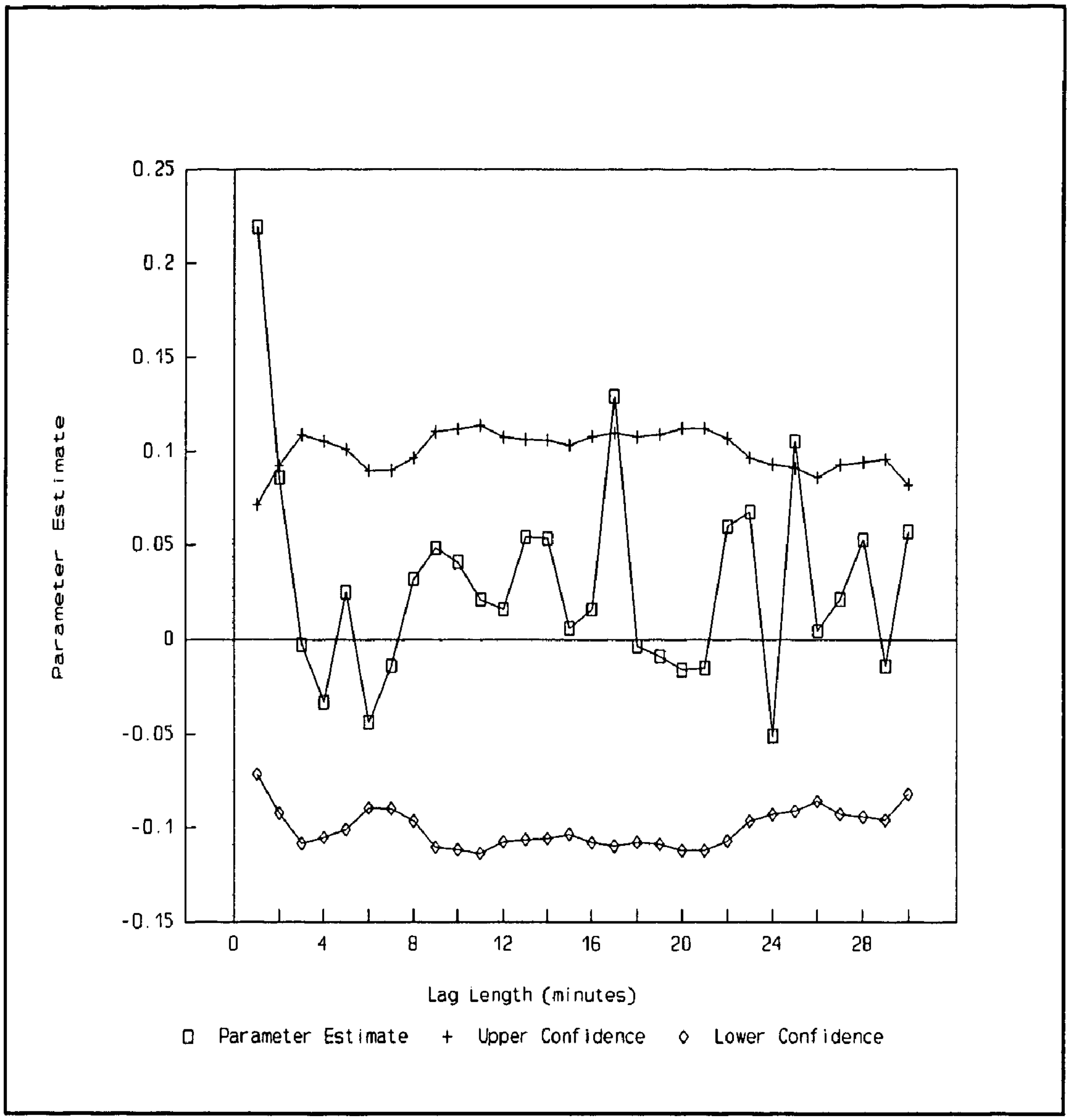

Figure 14
DAX Futures Returns as the Dependent and DAX Index Returns as the Independent Variable for the Lowest Decile Intradaily Spot Returns: The Case of a Down Market

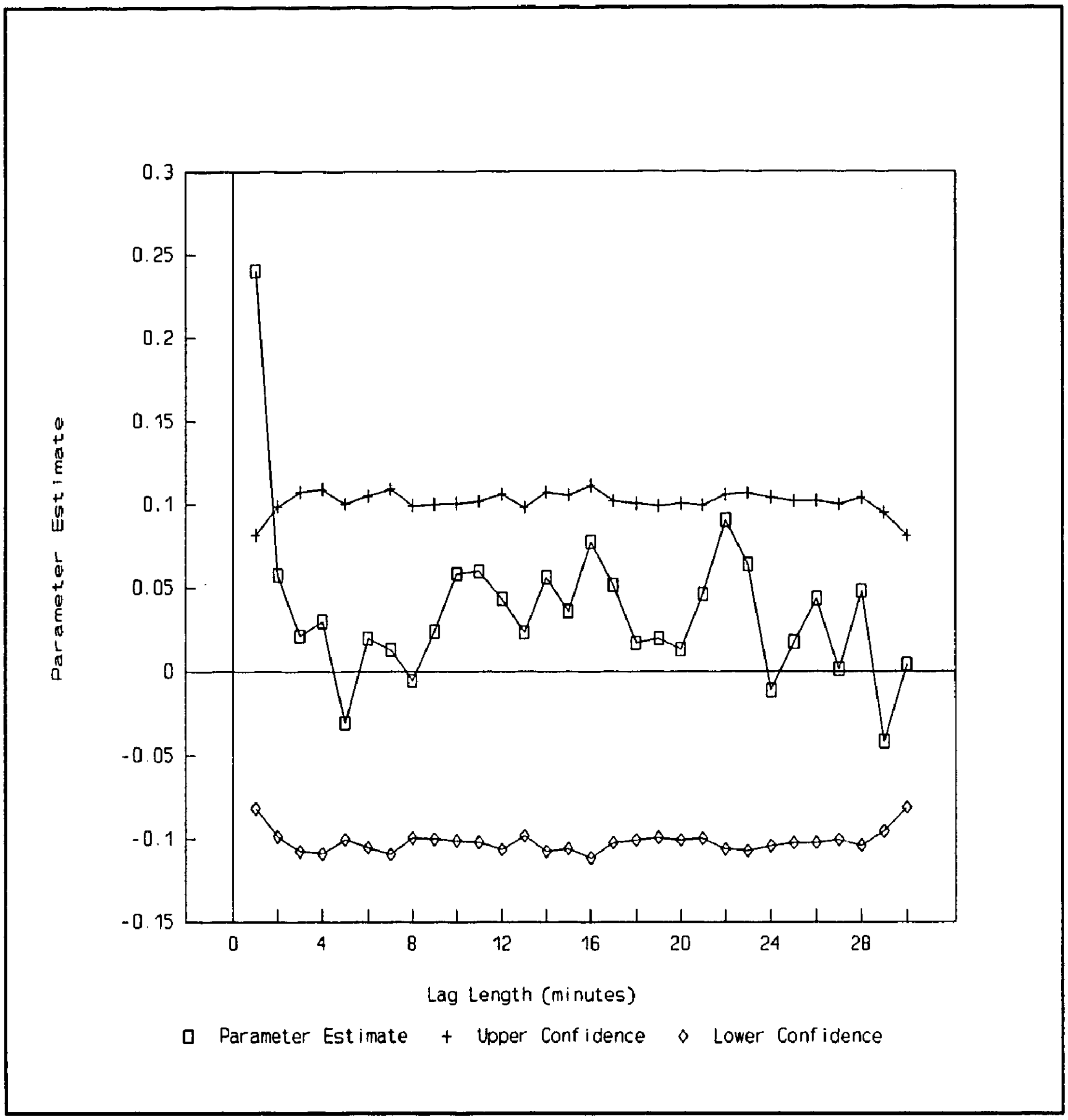

Figure 15
DAX Spot Returns as Both Dependent and Independent Variables for the Highest Decile Intradaily Spot Returns: The Case of an Up Market

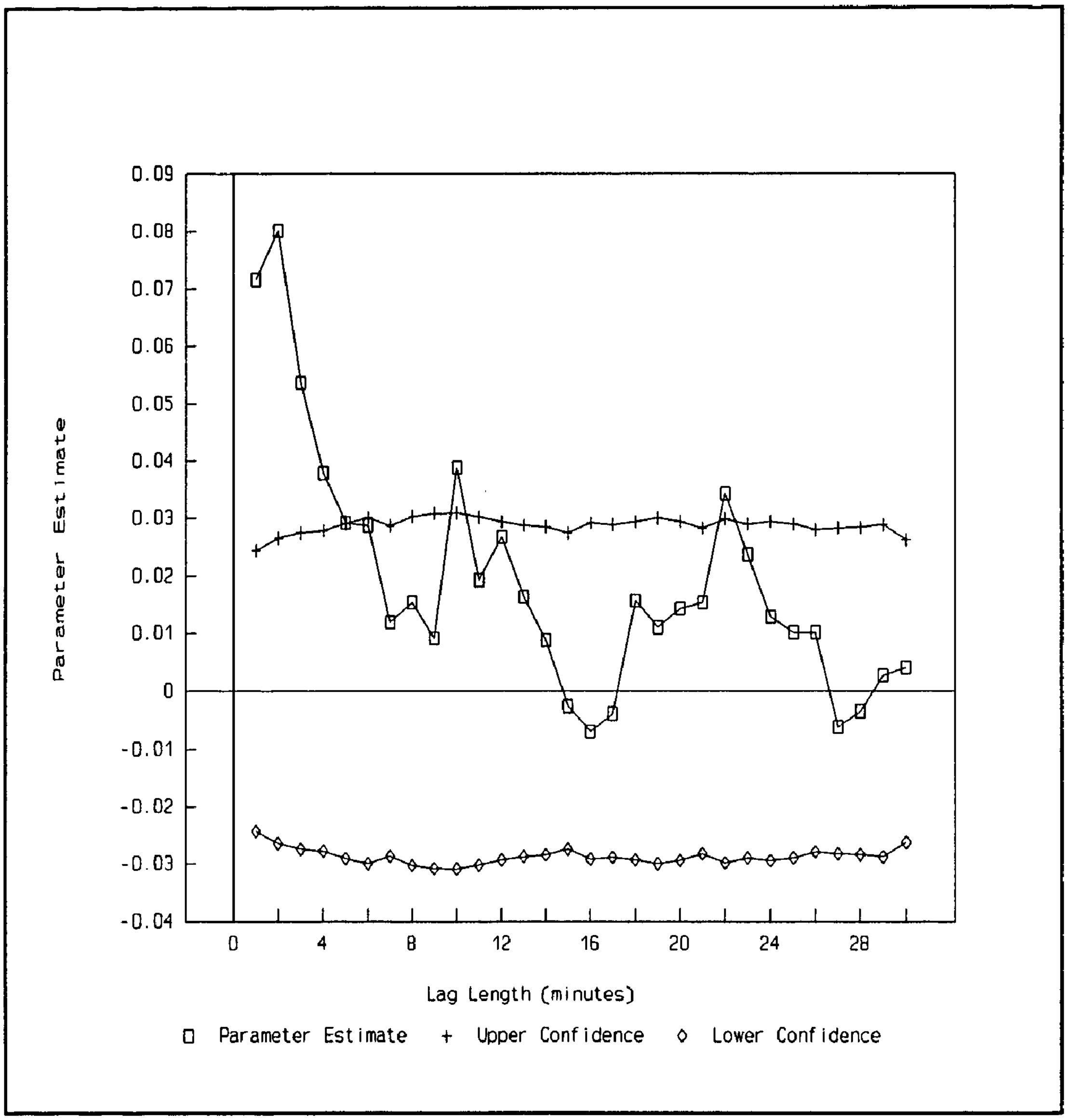

Figure 16
DAX Returns as Dependent and Futures Returns as Independent Variable, Observations from the Highest Intradaily Spot Returns: The Case of an Up Market

This additional information, coupled perhaps with investor sentiment, could cause spot market participants to transact quickly before prices become too low or too high. If the beneficial effects of leverage, lower transaction costs, etc... attributed to the futures market remain the same during extreme price movements, the relative advantages of trading through the futures market may be offset during periods of extreme price movements. Even though the absolute transactional advantages remain the same for the futures participants, the extreme price movements may create opportunities for spot market players to more easily recover higher transactions costs and possibly security selection and information gathering costs.

This explanation, however, is not meant to be rigorous, only cursory. The results of testing Hypothesis #3 are unique in that Chan (1992), does not document this effect in the U.S. markets. Essentially, his results indicate a constant lead-lag relationship in both up and down markets. His work does not show a decrease in the futures lead position. The results point to the fact that information processing in extreme markets may be different than at other times. Additional investigation of this phenomenon is warranted.

Figures 17 and 18 indicate that the information processing effects on the futures market are the same in up and down markets (compare to Figures 13 and 14). Their

presentation is made for completeness only. The statistical test for causality generates a value of 8.259 (p-value < 0.0001) for futures causing spot returns, and 6.769 (p-value < 0.0001) for the spot returns causing futures price changes. Thus, the feedback of information is also present in the up market data.

In summary, the results related to Hypothesis Test #3 indicate that the null cannot be rejected. Both the up and down markets appear to generate a significant feedback of information processing between the spot and futures markets. Given the short-selling restrictions found in Germany, this result was unexpected. It is conjectured that the extreme price change distributions cause the expectations of both spot and futures participants to become more closely aligned, which manifests the feedback relationship. No support is found here for short-selling restrictions to cause the futures market additional information processing advantages.

2.5.4 Hypothesis #4 Results

The null and alternative hypotheses for Hypothesis #4 are:

Ho: The lead-lag relation is similar under different trading activity.
Ha: The lead-lag relation is different under different trading activity.

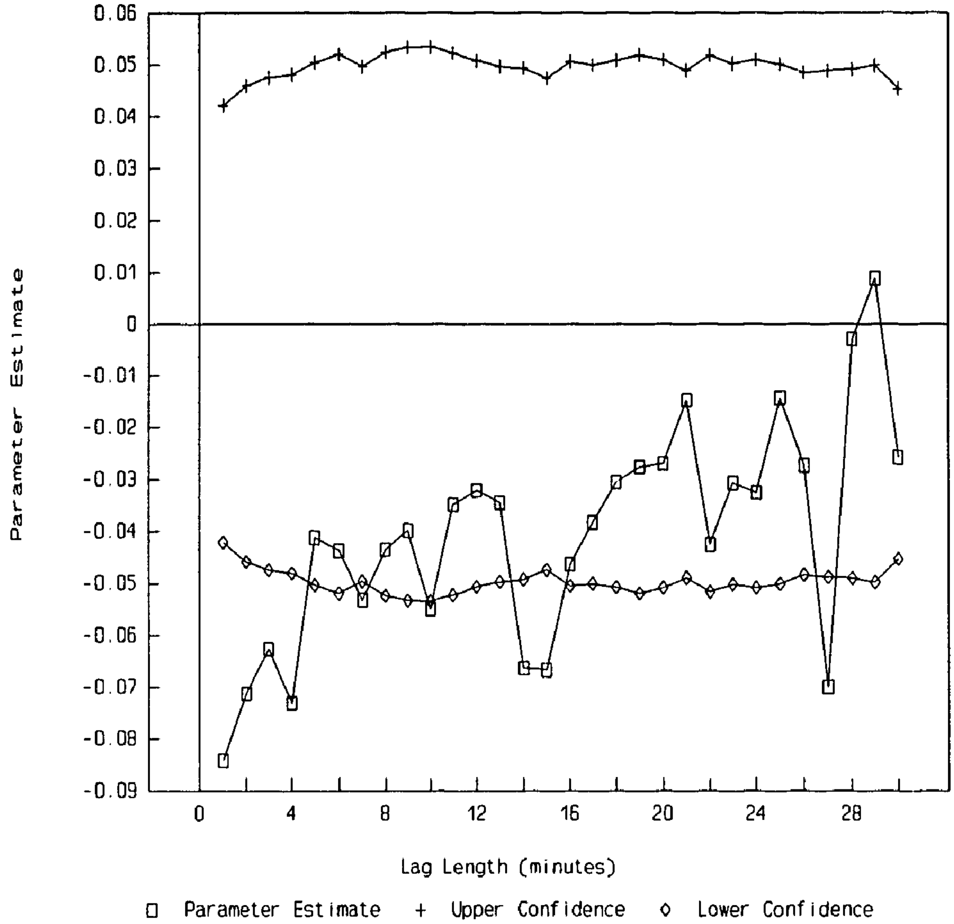

Figure 17
DAX Spot Returns as Both Dependent and Independent Variables for the Highest Decile Intradaily Spot Returns: The Case of an Up Market

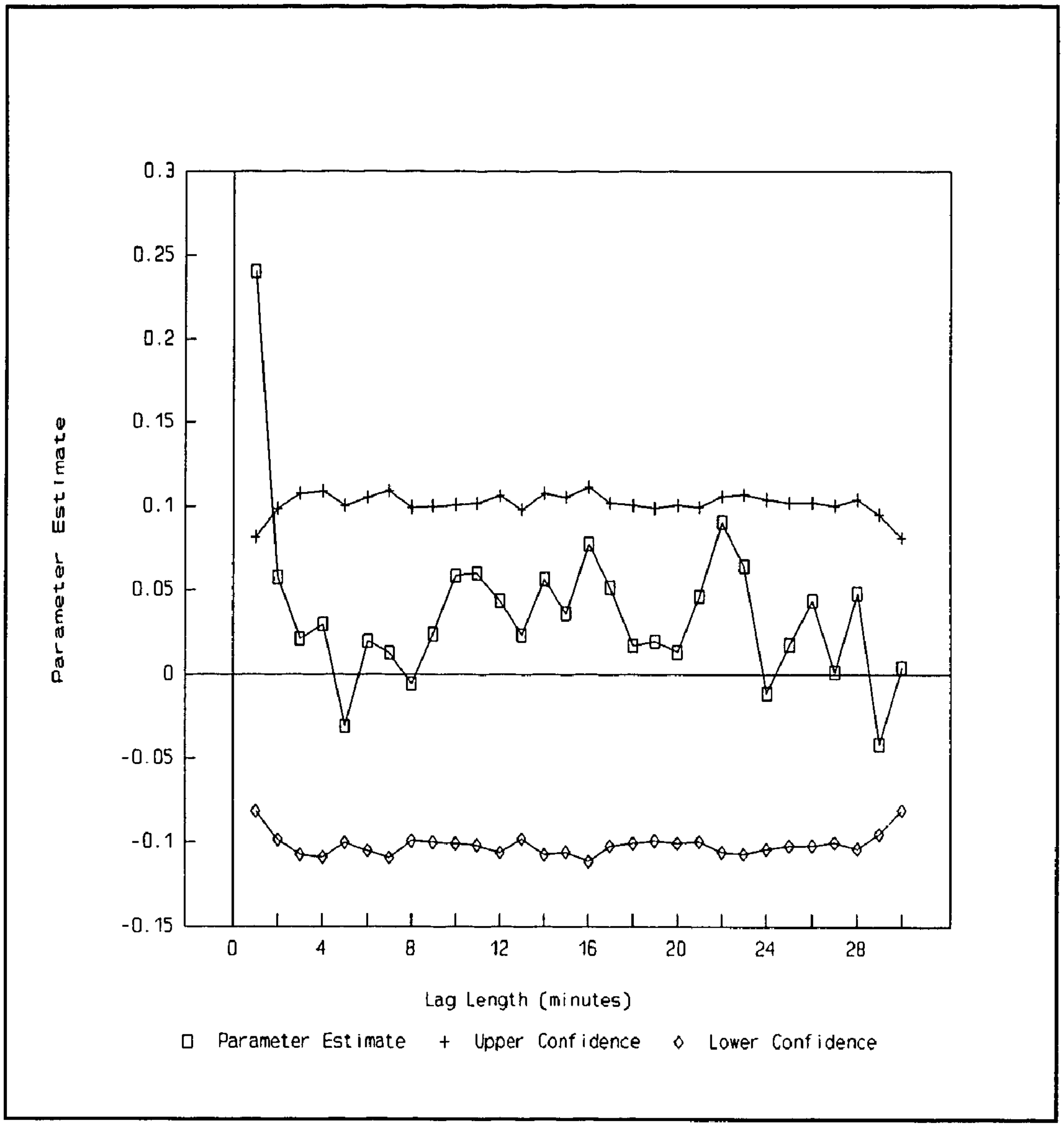

Figure 18
DAX Futures Returns as Dependent and Spot Returns as Independent Variable, Observations from the Highest Intradaily Spot Returns: The Case of an Up Market

The herding hypotheses of Admati and Pfleiderer (1988), Bhushan (1991) and Chowdry and Nanda (1991) indicate that uninformed investors "herd" together in order to protect themselves from being "fleeced" by informed investors. The suggestion from these papers is that uninformed investors will want to trade together during time of day, trade similar securities or trade in the same market.

Hypothesis #4 is a test of the herding notions through analyzing the lead-lag relationship for different levels of trading activity. Three proxies for trading activity are presented: the number of firms trading per time interval, total number of transactions per time interval, and total volume of shares traded per time interval. Since the data are dependent on the security-specific dataset, five minute returns for the DAX index and DAX index futures data are generated and used for the analysis.

A parallel to the herding notion is found in Easley and O'Hara (1987) where it is stated that informed investors will want to trade their information quickly and in as large amounts as possible, so that the market impacts are minimized. To test whether Easley and O'Hara's (1987) trading activity proxy has an effect on the lead-lag relationship an average volume per transaction variable is created. This variable is calculated as the total volume traded in a five minute interval divided by the total number of transactions occurring in that interval.

Each one of these proxies is calculated per five minute time period and then ranked intradaily into quintiles.[30] The lowest and highest intradaily quintile rankings for each proxy are then used to examine the lead-lag relation between the spot and futures markets. The results of the examination of a differential lead-lag structure for each trading activity proxy are found in Tables 8 through 11.

The regression results found in Table 8 can be summarized as follows. For the lowest activity data series, the futures leads the spot by only 5 minutes. The F-test for Granger Causality from the futures to the spot is 29.553 and is significant at the 0.0001 level. There is no discernable pattern of the lagged spot returns in the DAX futures regression. The F-test for causality from the spot to the futures is 2.138 (p-value = 0.0464), which is insignificant at the prescribed level required in this dissertation. Therefore, the direction of causality in the lowest trading activity quintile, proxied by the number of firms trading in a 5 minute time period, is unidirectional from the futures to the spot.

For the highest activity data series, the lead of the futures over the spot increases from 5 to 20 minutes. The causality test yields a value of 156.419 (p-value < 0.0001), indicating causality from the futures to the spot.

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[30]Quintiles are used since the volume information is only present for the last 10 months of the dataset.

However, the lagged DAX index returns have a significant parameter at five minutes in the DAX futures regression. The Granger test yields a value of 9.131, which is significant at the 0.0001 level. This result indicates a feedback relationship between the spot and futures market existing in the high trading activity data series.

Therefore, when using the number of firms traded as a proxy for trading activity, the null of Hypothesis #3 is rejected in favor of its alternative.

The results found in Table 9, where trading activity is defined as the total number of security transactions in a 5 minute period, are as follows. Quintile 1 (the lowest activity series) indicates that futures price changes lead spot price changes by approximately 10 minutes. The causality test yields 39.891 (significant at 0.0001) indicating a causal relationship from the futures market to the spot market when market participants are confronted with low trading activity.

None of the lagged spot market return parameters are individually significant in the futures regression. The joint hypothesis testing the significance of all the lagged spot return parameters simultaneously generates a test statistic of 2.374 (p-value = 0.0274), which does not meet the significance level criteria of 0.0001. Therefore, in low trading activity, defined by the number of transactions per 5 minute time period, the direction of causation is unidirectional from the futures to the spot market.

Table 8
Examination of the Lead-Lag Relationship
Under Different Trading Activity:
Proxy - Number of Firms Trading in 5 Minute Period

Quintile 1 (Lowest Activity)					
Dependent Variable = DAX Index Return					
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0232	-0.0651	-0.0282	-0.0253	-0.0053	-0.0171
(0.138)	(0.0001)	(0.0462)	(0.0815)	(0.6996)	(0.0992)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0194	0.0054	0.0056	0.0028	0.0037	0.0025
(0.0001)	(0.0013)	(0.0009)	(0.0807)	(0.0224)	(0.0805)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2604	-0.1257	-0.0434	-0.0341	0.0271	0.0214
(0.0001)	(0.0001)	(0.1084)	(0.2365)	(0.3434)	(0.3966)
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.5241	-0.5878	0.2969	-0.0738	0.0205	0.1263
(0.0583)	(0.0272)	(0.2365)	(0.7745)	(0.933)	(0.4924)
Quintile 5 (Highest Activity)					
Dependent Variable = DAX Index Return					
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.4339	-0.3716	-0.1967	-0.2039	-0.1490	-0.0140
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.6477)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.1032	0.0563	0.0323	0.0324	0.0255	0.0130
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0031)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.1981	0.1453	-0.0272	0.1429	0.1453	0.0723
(0.0001)	(0.0003)	(0.5309)	(0.0016)	(0.0005)	(0.0561)
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-2.1715	-0.6758	0.1628	-1.1428	-0.7071	-0.0509
(0.0001)	(0.0578)	(0.6685)	(0.0019)	(0.0472)	(0.8476)

Table 9
Examination of the Lead-Lag Relationship
Under Different Trading Activity:
Proxy - Total Security Transactions in 5 Minute Period

Quintile 1 (Lowest Activity)

Dependent Variable = DAX Index Return

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0282	-0.0781	-0.0219	-0.0507	-0.0072	-0.0099
(0.0692)	(0.0001)	(0.1242)	(0.0006)	(0.6049)	(0.3356)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0226	0.0091	0.0055	0.0045	0.0032	0.0017
(0.0001)	(0.0001)	(0.0012)	(0.0052)	(0.0481)	(0.2551)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2650	-0.1324	-0.0520	-0.0257	0.0262	0.0166
(0.0001)	(0.0001)	(0.0725)	(0.3554)	(0.3477)	(0.5057)

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.2422	-0.6066	0.1634	-0.5235	0.2095	0.1007
(0.3639)	(0.0159)	(0.5045)	(0.0386)	(0.3837)	(0.5685)

Quintile 5 (Highest Activity)

Dependent Variable = DAX Index Return

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.4665	-0.3841	-0.1431	-0.1569	-0.1467	-0.0195
(0.0001)	(0.0001)	(0.0012)	(0.0002)	(0.0005)	(0.5095)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.1097	0.0623	0.0276	0.0308	0.0248	0.0151
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0005)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.2801	0.1948	-0.0532	0.1375	0.1063	0.0738
(0.0001)	(0.0001)	(0.2603)	(0.0041)	(0.0167)	(0.0643)

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-2.4819	-0.5986	0.6472	-0.5566	-0.4979	0.0336
(0.0001)	(0.1383)	(0.1123)	(0.1505)	(0.2008)	(0.902)

The lead time of the futures market in high activity periods increases from 5 to at least 25 minutes. The causal test statistic is still significant (F-statistic = 181.12, p-value < 0.0001), indicating causation from the futures market to the spot. However, there also appears to be causation from the spot market to the futures market. The F-test in this case is 9.578 with an associated p-value of < 0.0001. Hence a feedback of information appears to exist when high trading activity is defined as the total number of security transactions in a 5 minute time period.

The accept/reject decision for this proxy of trading activity is to reject the null in favor of its alternative. This result is distinctive because Chan (1992) does not find a difference of information processing using this trading activity proxy in the U.S. markets. There appears to be a differential level of information processing in high trading activity time periods in Germany's securities markets.

Table 10 presents the results of the lead-lag examination when trading activity is defined as total volume traded per 5 minute interval. The results for this trading activity proxy are different than the previous two proxies of trading activity.

For instance, there is only unidirectional causality from the futures to the spot when trading activity is defined as volume. The causality test shows low and high

Table 10
Examination of the Lead-Lag Relationship
Under Different Trading Activity:
Proxy - Total Volume in 5 Minute Period

Quintile 1 (Lowest Activity)					
Dependent Variable = DAX Index Return					
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2154	-0.1868	-0.1100	-0.0507	-0.0390	-0.0521
(0.0001)	(0.0001)	(0.0001)	(0.0664)	(0.1006)	(0.0045)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0343	0.0231	0.0158	0.0102	0.0034	0.0041
(0.0001)	(0.0001)	(0.0001)	(0.0005)	(0.2405)	(0.0981)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2338	-0.0857	-0.0220	-0.0244	0.0071	-0.0130
(0.0001)	(0.0581)	(0.6144)	(0.5678)	(0.8673)	(0.72)
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2392	-0.7873	-0.4016	-0.0579	-0.4849	0.1506
(0.5562)	(0.0493)	(0.2903)	(0.8852)	(0.1598)	(0.5708)
Quintile 5 (Highest Activity)					
Dependent Variable = DAX Index Return					
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1337	-0.2740	-0.0320	-0.1502	-0.1465	0.0204
(0.0217)	(0.0001)	(0.6274)	(0.0166)	(0.0147)	(0.6556)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0853	0.0514	0.0232	0.0263	0.0156	0.0150
(0.0001)	(0.0001)	(0.0011)	(0.0005)	(0.0231)	(0.0131)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.1614	0.1615	-0.0242	0.1253	0.0362	0.1083
(0.0005)	(0.0083)	(0.7164)	(0.0766)	(0.5721)	(0.0552)
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1531	-0.9892	1.3878	-0.4300	-0.4261	-0.2028
(0.7782)	(0.0851)	(0.0242)	(0.4623)	(0.4469)	(0.6348)

activity quintiles to be 30.426 and 51.627 respectively. Both test statistics pass the significance level criteria. Testing causation from the spot to the futures market results in insignificant test statistics under both trading activity quintiles, 1.188 (p-value = 0.31) and 2.134 (p-value = 0.0437), the low and high trading activity quintiles respectively.

Therefore, when trading activity is defined to be volume, the lead-lag relationship is the same under high and low trading activity levels. Unidirectional causation from the futures market to the spot market is indicated in both scenarios. Therefore, the null for Hypothesis #4 cannot be rejected when using this proxy for trading activity.

The result from Germany is important because Chan (1992) does not examine volume's relationship to the lead-lag structure in the U.S. market. Essentially, trading volume may be helpful in explaining the longer lead time of the futures market. The volume/lead-lag relationship should be examined in more detail.

The final proxy for examining trading activity relates to Easley and O'Hara's (1987) average volume per transaction variable. The results using this proxy for trading activity are found in Table 11 and are qualitatively similar to those found in Table 10. The futures market Granger causes the spot market in both quintiles of trading activity. The F-statistics are

Table 11
Examination of the Lead-Lag Relationship
Under Different Trading Activity:
Proxy - Average Volume Per Transaction in 5 Minute Period

Quintile 1 (Lowest Activity)

Dependent Variable = DAX Index Return

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.3765	-0.3369	-0.2083	-0.1074	-0.1438	-0.0954
(0.0001)	(0.0001)	(0.0001)	(0.0012)	(0.0001)	(0.0001)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0474	0.0353	0.0265	0.0158	0.0082	0.0107
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0212)	(0.0005)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.1812	-0.0410	-0.0051	-0.0280	-0.0280	-0.0296
(0.0001)	(0.3611)	(0.9093)	(0.5397)	(0.5126)	(0.4234)

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.9513	-0.9309	-0.5202	-0.1450	-0.7271	-0.2246
(0.0129)	(0.0172)	(0.1975)	(0.7165)	(0.0329)	(0.4004)

Quintile 5 (Highest Activity)

Dependent Variable = DAX Index Return

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0238	-0.0479	0.0166	-0.0585	0.0575	0.0389
(0.6224)	(0.3265)	(0.7617)	(0.2667)	(0.2391)	(0.3191)

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0618	0.0231	0.0168	0.0118	0.0034	0.0054
(0.0001)	(0.0001)	(0.0036)	(0.0532)	(0.557)	(0.2688)

Dependent Variable = DAX Futures Return

Independent Variable = Lagged DAX Futures Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0578	-0.0119	-0.0197	0.0876	0.0033	0.0884
(0.1909)	(0.8254)	(0.735)	(0.1568)	(0.9553)	(0.0761)

Independent Variable = Lagged DAX Index Return

Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3327	-0.1582	0.6327	-0.2948	0.9286	0.0697
(0.4969)	(0.7492)	(0.2536)	(0.5809)	(0.0608)	(0.8601)

statistically significant. Their values are 42.155 and 34.106 for the low and high trading activity quintiles.

The test for spot to futures causality does not reject the null of zero parameters in each category. Test statistics are 2.166 (p-value = 0.0441) for the low trading activity quintile and 1.074 (p-value = 0.3762) for the high trading activity quintile.

This analysis indicates that the unidirectional causal relation is the same in low and high trading activity quintiles when using average volume per transaction as the proxy for trading activity. Therefore, the null of Hypothesis #4 cannot be rejected when using this proxy.

In summary, when trading activity is defined as number of firms trading per period, or total transactions occurring per period of time, the null of Hypothesis #4 is rejected. That is, a differential lead-lag structure exists under different trading activities. However, when volume is used as the proxy for trading activity, either total volume or average volume per transaction, the null of Hypothesis #4 cannot be rejected.

This result is interesting because it implies that the proxy for trading activity is sensitive to which variables are used. If trading activity is a proxy for the amount of information available in securities markets, research by Lamoureaux and Lastrapes (1990) indicates that volume is the proxy for information. However, Harris (1987)

indicates that the number of transactions is the better proxy.

The results of this hypothesis test are useful because they indicate that differential information characteristics may be attributed to both of these measures. The debate should not be focused on whether information is proxied by volume or number of transactions, but rather, what type of information is contained in each variable. For instance, does volume proxy for an informed investor's transactions? Do the number of securities transacted proxy for a noise trader's transactions? These are issues that should be addressed in subsequent research.

2.5.5 Hypothesis #5 Results

Ho: The lead-lag relation between the spot and futures markets is the same under heavy market-wide price movements as it is under security specific price movements.
Ha: The lead-lag relation between the spot and futures markets is different under heavy market-wide price movements as it is under security specific price movements.

This hypothesis examines the issue of which market investors choose to transact with market-wide (macro related) or security-specific (micro related) information. Essentially, the idea is that macro economic information affects the whole economy: hence, to leverage its impact, traders prefer to transact in the futures market, where transactions costs are low in comparison to the spot market. This notion portends that market-wide information

enhances the futures information processing speed over that of the spot market.

On the other hand, if investors have information related to individual companies, or sub-groups of companies, they may prefer to transact through the equity as opposed to derivative markets. Therefore, if the information tends to be security-specific, the lead of information processing attributed to the futures market should be decreased. Table 12 presents the results of examining this hypothesis.

Quintile 1, in Table 12, presents results for the data series of lowest market-wide movements. The contrapositive definition of the lowest market-wide quintile is the highest security-specific related quintile. That is, the data used in this quintile contain the highest level of security-specific information.

The regression results indicate that the futures market leads the spot market by only 15 minutes for the security-specific data series. The Granger causality tests indicate that lagged futures price changes cause spot price changes (test statistic is 13.771, p-value < 0.0001), and that lagged spot price changes cause futures price changes (test statistic is 3.725, p-value < 0.0001). Therefore, there appears to be a feedback of information processing present in low levels of macro-economic related information.

Table 12
Examination of the Lead-Lag Relationship
Under Different Market-Wide Movements:
Proxy - Number of Firms Moving Together in 5 Minute Period

Quintile 1 (Lowest Market-Wide Movements)					
Dependent Variable = DAX Index Return					
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.0414	-0.0810	-0.0357	-0.0383	-0.0094	-0.0180
(0.0024)	(0.0001)	(0.0035)	(0.0014)	(0.3921)	(0.0344)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.0107	0.0048	0.0053	0.0040	0.0009	0.0027
(0.0001)	(0.0006)	(0.0001)	(0.0037)	(0.5229)	(0.0202)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.3762	-0.2227	-0.1262	-0.0872	-0.0293	-0.0145
(0.0001)	(0.0001)	(0.0001)	(0.0013)	(0.2658)	(0.5282)
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.7533	0.1170	0.8895	-0.0035	0.4534	-0.0674
(0.0052)	(0.6415)	(0.0002)	(0.9882)	(0.0368)	(0.6875)

Quintile 5 (Highest Market-Wide Movements)					
Dependent Variable = DAX Index Return					
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-0.2434	-0.2975	-0.1003	-0.1833	-0.1173	0.0316
(0.0001)	(0.0001)	(0.0336)	(0.0001)	(0.011)	(0.3621)
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.1140	0.0559	0.0283	0.0300	0.0228	0.0073
(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.116)
Dependent Variable = DAX Futures Return					
Independent Variable = Lagged DAX Futures Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
0.3297	0.1571	-0.0512	0.1490	0.0912	0.0286
(0.0001)	(0.0003)	(0.2676)	(0.0015)	(0.0464)	(0.4879)
Independent Variable = Lagged DAX Index Return					
Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
-1.0917	-0.2978	0.8533	-0.8481	-0.6308	0.5230
(0.0035)	(0.4572)	(0.0402)	(0.0334)	(0.1207)	(0.0872)

Quintile 5 contains data corresponding to the largest levels of market-wide information. The regression results indicate that the futures market now processes information 25 minutes before the spot market. This is consistent with the notion that investors want to trade through the derivative market when their information is related to the macro economy. Testing the causal relation from the futures to the spot market results in a test statistic of 187.397, which is significant at the 0.0001 level. Testing the causal relation from the spot to the futures market yields a test statistic of 4.482. Even though its significance level is close to the cutoff, p-value = 0.0002, it does not meet the significance levels required in this study. Therefore, a unidirectional causation relation holds from the futures market to the spot in periods of market-wide information.

Since the results of this hypothesis test indicate a feedback of information when market-wide price movements are low, and a unidirectional lead of information processing when market-wide price movements are high, the null of this hypothesis test is rejected in favor of its alternative. This result was found by Chan (1992) in the U.S. markets and adds support to the idea that derivative securities provide an alternative avenue for price discovery. Due to their lower costs, and leverage effects, informed investors, especially when they hold macro-

economic related information, will transmit the information through the derivative, as opposed to the underlying security.

2.6 CHAPTER 2 SUMMARY

The existence of faster information processing by derivative securities is well documented in the financial economics literature. Since, theoretically, derivative security prices are based on information impounded in the underlying asset, this phenomenon is puzzling.

The thrust of Chapter 2 is to examine the price discovery issue by examining possible explanations for this phenomenon through the use of data found in Germany's security markets. Using data from Germany is useful because examining price discovery mechanisms in another market offers an opportunity to test the robustness of ideas formulated to explain the deriviative security lead-lag phenomena observed in the United States.

In order to examine the factors affecting the information processing advantage attributed to derivative securities in general, and stock index futures in particular, a number of hypotheses are formulated. These hypotheses can be summarized as: (1) documenting a lead-lag relationship in the DAX stock index and DAX stock index futures markets, (2) examining the lead-lag relationship between the DAX component stocks and the DAX futures market, (3) testing whether short-selling restrictions impact the lead-lag relationship, (4) evaluating trading

activity proxies and the effects on the lead-lag relationship, and finally, (5) weighing the influence of macro- or micro-based economic information on the lead-lag structure. The results of these hypothesis tests are as follows.

First, there exists a significant feedback of information processing between the DAX spot and DAX futures markets. Even though the lead time of the futures return series is much longer than that found in Grunbichler, Longstaff, and Schwartz (1994), Granger causality from the spot to futures market is also documented. Therefore, on occasion, information in the spot market hits the spot market first and then is transmitted to the futures market.

The examination of the lead-lag relationship between the futures market and each DAX component stock yields an interesting result. Most (28/30) of the component stock's return series are Granger caused by the futures market. However, two stocks, Allianz and Deutsche Bank exhibit a significant feedback of information relationship with the futures market. That is, at times, the price changes in these two stocks lead the price changes in the futures market. The reason for this result could be that these securities are themselves market proxies, or just an artifact from the way these two stocks affect the calculation of the DAX index. Given the evidence (of no MMI component stock leading the MMI index) established in

the U.S. market by Chan (1992), this finding is surprising and deserves more in-depth study.

Short-selling restrictions are especially onerous in Germany. These restrictions suggest that the lead-lag structure may be altered, especially when security prices are declining. Therefore, examining the lead-lag relationship in extreme up- and down-markets may offer additional insight into explaining the price discovery advantage attributed to derivative securities.

The surprising result in evaluating the short-selling restriction hypothesis is not that short-selling restrictions do not appear to affect the lead-lag structure, because a feedback relationship exists in both markets, but that the lead time of the futures price changes decreases drastically (from 23 to 15 minutes in a down market and 23 to 5 minutes in an up-market). An alignment of investor expectations during extreme price movements is used to explain this surprising result.

The trading activity hypothesis test results are multi-faceted since different proxies of trading activity are defined. Whenever a transactional based variable (number of transactions, or number of firms traded) is used, the lead-lag relationship changes with low to high levels of trading activity. However, when a volume based variable (total of average volume) is used, the lead-lag relationship remains unchanged with changes in trading activity.

This result implies that the trading activity variable chosen is a proxy for different types of information. Given the fact that efficient capital markets suggest that all relevant information is impounded in prices, the results of these hypothesis tests support additional research into ascertaining which market factors are proxies for information. Establishing what factors proxy for information and how these factors are used by market participants would be a worthwhile endeavor.

Examining the impact of macro- or micro-economic information on the lead-lag relationship can add support to the notion that the observed price discovery process in derivative securities markets is due to lower transactions costs and increased leverage opportunities. The macro-economic explanation is supported here because the results imply that the lead-lag structure changes from a feedback of information in security-specific defined markets, to a unidirectional lead in market-wide defined markets. The implications are that investors use derivative assets as their vehicle to disseminate macro based economic information because of lower transactions costs and leverage effects.

Through the use of a different dataset and method of analysis than appears in previous work, this research provides information related to the price discovery processes in Germany's securities markets. In particular, information is provided that helps explain the often

observed phenomenon that price discovery in derivative securities is faster than their underlying assets.

The results of this study indicate that the DAX futures market often processes information more quickly than the DAX spot market, but this advantage does not hold in all circumstances. Essentially, the processing speed is dependent on the market conditions confronting investment participants. Market-wide information tends to increase the lead time, but extreme price movements tend to decrease the lead time. However, in a majority of the cases, a feedback of information exists between the 2 markets. This implies that Germany's securities participants use a wide range of information when making investment decisions, and that this information set is useful in discovering the correct price for assets.

CHAPTER 3

EXTREME VALUE

3.1 OBJECTIVE

Futures market officials are confronted with the difficult task of setting appropriate margin levels that must balance the costs of trader default and the benefits of increased market liquidity. One way to guard against default is prudent margin setting practices designed to protect futures positions from extreme price movements. The objective of this chapter is to concentrate on protecting against margin violation via accurately extrapolating the probabilities of encountering extreme price movements. This chapter suggests that using extreme value theory is the preferred tool to use in setting prudent margin levels.

3.2 LITERATURE REVIEW

3.2.1 Extreme Values[31]

According to Gumbel (1958) and Kinnison (1985), the impetus for research on extreme value statistics originated from early astronomers. Like most researchers, astronomers were having a difficult time handling outlying observations. The difficulty arose from the fact that the tools provided by Gaussian probability and statistical theory were mainly concerned with calculating measurements

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[31]The first two paragraphs of this section rely heavily on Gumbel's (1958) and Kinnison's (1985) exposition on the history of extreme value research.

for averages, not extreme observations. Hence, the well-known rule-of-thumb "if it's plus or minus three standard deviations away from the mean, throw it out" was created. A conundrum arises, however, if the underlying distribution has infinite sample size (as in the case of asymptotic distributions). The magnitude and frequency of outliers increases because there is greater opportunity for them to occur.

The main problem with trying to quantify extreme value probabilities is that large values are actually new random variables with distributional properties different from the parent distribution. This observation was made by Bortkiewicz (1922), the individual credited with being the first to clearly state the extreme value problem.

In order to generate reliable statistical tools that address large values, a new tractable theory had to be developed. Fisher and Tippet (1928) determined the three asymptotic distributions that accurately describe extreme value behavior of all other distributional forms. Their work independently replicated the asymptotic distribution result of Fréchet (1927) and added two additional asymptotic distributions to the literature.

Essentially, their distributions provided tractable solutions for determining the extreme value behavior of all data generation processes. Further applications and refinements of extreme value theory were then made in the

statistical inference literature by Gumbel (1941), Gnedenko (1943), and Jenkinson (1955).[32]

Arriving at the three different extreme value distributional forms is as follows.[33] Consider a sequence of stationary i.i.d. random variables X_1, X_2, ..., X_n with some probability density function F. The statistic of interest is determining the probability that the maximum

$$M_n = \max(X_1, X_2, \ldots, X_n) \tag{22}$$

value of the first n variables is below a certain level x, where the cumulative probability distribution is stated as being:

$$P(M_n \leq x) = F^n(x)\ . \tag{23}$$

Extreme value theory boils down to studying the asymptotic distribution of the scaled order statistic M_n.

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[32]Three textbooks that summarize and expand extreme value theory and its applications are Gumbel (1958), Galambos (1978), and Leadbetter, Lindgren and Rootzèn (1983). Galambos (1978) lists a number of non-financial cases where extreme value analysis is valuable. For example, engineering designs of dams, dikes and other structures can be modified to account for extreme weather conditions such as hurricanes or floods. Other examples include failure of components in equipment, corrosion effects on the failure of structures, or extreme levels of pollutants and their effects on the inhabitants in a particular environment.

[33]This description is an annotation of what can be found in most of the extreme value references mentioned in this section. Extreme value research found in the statistical inference literature basically states the problem in the same way as that found here and in papers applying extreme value concepts to financial data by Jansen and deVries (1991), Koedijk, Stork and deVries (1992), Kofman and deVries (1989), and Kofman (1993).

Extreme value research depends on finding an appropriate situation where the following is satisfied:

$$P(a_n(M_n - b_n) \le x) \overset{W}{\rightarrow} G(x)$$
$$\text{or in terms of } F;$$
$$F^n(x/a_n + b_n) \overset{W}{\rightarrow} G(x)\,. \tag{24}$$

In other words, the probability that an appropriately scaled maximum value is less than or equal to some value of interest (x) is given by the function *G(x)*. *G(x)* is one of the three distributional forms determined by Fisher and Tippet (1928) and *w* means "to weakly converge." If there is a situation that satisfies (24), then *F* belongs to the domain of attraction of *G*, which takes the following three forms:

$$\begin{aligned}
&\textit{Type I}: && G(x) = \exp(-e^{-x}) && \text{if } -\infty < x < \infty; \\
&\textit{Type II}: && G(x) = 0 && \text{if } x \le 0, \\
& && = \exp(-x^{-\alpha}) && \text{if } x > 0; \\
&\textit{Type III}: && G(x) = \exp(-(-x)^{\alpha}) && \text{if } x < 0, \\
& && = 1 && \text{if } x \ge 0.
\end{aligned} \tag{25}$$

The double exponential form of the Type I distribution represents cases where the tail of the underlying distribution is approaching its asymptote exponentially. This situation is representative of the tail behavior of the normal distribution. However, Type II distributions represent cases where the tail of the underlying distribution does not decay rapidly at an appreciable rate. Type II generated data are indicative of cases where second or higher moments do not exist, such as observations generated by distributions with "fat" tails. Finally, the

Type III limiting result contains an upper bound and represents extreme value behavior from truncated data generation processes. Since there are numerous studies indicating that fat tailed distributions, and not the normal distribution, generate financial asset returns, the underlying assumption in most financial research employing extreme value theory is that extreme asset returns exhibit Type II limiting behavior.[34]

3.2.2 Parallels with Stable Paretian research

Even though extreme value theory is documented thoroughly in the statistical inference literature, applications to financial market data are less numerous. Stable Paretian related research, however, which takes tail parameters into account, and thus extreme observations, is more common. This section reviews the extant literature on stable Paretian research and its relation to extreme value concepts.

Fama (1965) develops a portfolio optimization model using Paretian distributions. However, his analysis concentrates on the dispersion parameter of the entire distribution, not specifically the extreme values. Fama (1965) concludes that even when asset return distributions

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[34]A brief listing of the studies documenting non-normality for asset returns is Mandlebrot (1963), Fama (1965), Frankfurter and Lamoureaux (1987), and Akgiray and Booth (1988). Examples of studies assuming the Type II limiting behavior are Jansen and deVries (1991), Koedijk, Stork and deVries (1992), Kofman (1993), and Kofman and deVries (1989).

contain infinite variances, there is a diversification benefit similar to the well-known Markowitz (1952) result. That is, even though the portfolio variance is not reduced, because it is infinite in Paretian distributions, the magnitude of the dispersion parameter, from the stable distribution, is reduced by holding a diversified portfolio.

Frankfurter and Lamoureaux (1987) examine Fama's (1965) hypothesis and conclude that even though asset return distributions are not strictly normal, assumption of a Gaussian distribution is preferable to Paretian distributions in normative portfolio theory models. The preference of assuming a normal distribution follows from the fact that simulations of *ex-post* portfolio returns assuming Paretian distributions never outperform the *ex-post* portfolio returns generated by a normal distribution. Since the Paretian hypothesis is more difficult to employ, Frankfurter and Lamoureaux (1987) conclude "it is of no use to a portfolio manager--given extant estimation techniques."

Akgiray and Booth (1988) use stable Paretian distributions in their analysis of U.S. traded stocks and find that most of the stocks do not strictly conform to stable law distribution properties. The data in their sample exhibit tail properties significantly thinner than those expected from a Paretian distribution. Additionally, Akgiray, Booth, and Loistl (1989a, 1989b) show that

Paretian distributions do not accurately describe returns on German securities. Here too, German stock returns exhibit thinner tail behavior than that expected from a Paretian distribution. These two papers show that while the tail parameters of some securities indicate a Paretian distribution, the other descriptive parameters are not stable with respect to time. Hence, there is a preference for using finite variance models over using stable Paretian models.

Loretan and Phillips (1994) also examine stable Paretian distributions using a variety of heavy-tailed financial time series. Their emphasis is on tests of covariance stationarity, not specifically the stable Paretian distributional properties. They also provide evidence of data containing finite variances, but high probabilities of achieving observations in the tails of each distribution.

The literature cited so far indicates that financial time-series data do not strictly conform to stable Paretian laws. However, the existence of high levels of extreme observations is still problematic. Therefore, how does one account for these extreme observations? Extreme value analysis may be helpful in understanding the distributional properties of these outlying financial time-series data.

Akgiray, Booth, and Seifert (1988) apply extreme value concepts in a generalized Pareto context when examining

black-market exchange rates. Specifically, they employ DuMouchel's (1983) maximum likelihood technique to estimate the tail parameter of the black market exchange rate distribution and find that this particular set of financial data exhibit infinite variances. This result contrasts the findings of Akgiray and Booth (1988), Akgiray, Booth, and Loistl (1989a, 1989b) and Loretan and Phillips (1994).

Koedijk, Stork and DeVries (1992) apply a non-parametric index calculation, as found in Hill (1975), to examine differences between exchange rate regimes. They find that the non-parametric estimator is more efficient than the maximum likelihood estimator employed by Akgiray, Booth, and Seifert (1988) and that their data do not exhibit Paretian properties during floating exchange rate regimes.

Jansen and DeVries (1991) also employ Hill's estimator to extreme price movement data in the U.S. stock market. Their result generates realistic probabilities for anticipating an abrupt market downturn, such as the one occurring in 1987. Similar to the results of Mandlebrot (1963) and Fama (1965), their tail behavior result indicates that the data generation process for stock returns is not from a normal distribution or stable Paretian but probably from another leptokurtotic distribution, such as the student-t. Kofman and DeVries (1989) examine the tail behavior of potato futures returns also using the Hill (1975) estimator. Their findings also

support a data generation process from the student-t, and not from the stable Paretian distribution.

McCullough (1994) indicates that studies inferring non-Paretian distributions may be flawed in their approach. The criticism is that the tail index estimate generated by the maximum likelihood technique advocated by DuMouchel (1983) cannot be used to reject the presence, or absence, of a stable Paretian distribution. Specifically, the DuMouchel (1983) technique is unable to distinguish the contribution of an infinite variance distribution when the tail behavior of the data in question is similar to a normal distribution. His results indicate why there may be some discrepancy between Akgiray, Booth, and Seifert's (1988) result, and the other studies indicating preference for finite variance models.

For instance, Akgiray, Booth and Seifert (1988) calculate tail parameter estimates close to one, indicating tail behavior drastically different from the normal distribution. In contrast, the other studies report tail index parameters close to two, indicating tail behavior similar to the normal distribution. Therefore, McCullough's (1994) result may be an explanation for the conflicting evidence presented in the literature for and against using finite versus using infinite variance models to describe financial data generating processes.

Whatever the outcome of the controversy generated by the conflicting results of Akgiray et. al. (1988), Kojdick

et. al. (1993), Jansen and DeVries (1991) and Kofman and DeVries (1989), they all suggest that examining the probability of encountering extreme value observations is an alternative to unconditional volatility when measuring risk. This suggestion is based on the fact that extreme values shed a brighter light on the probabilities of anticipating abrupt changes in wealth than using models based on data generated from normal processes.

3.2.3 MARGIN MAINTENANCE

3.2.3.1 General Margin Issues

Margin requirements of futures market participants are unique in that they do not represent either a premium for participation or a down payment on an asset. Futures margins are performance bonds used to enforce performance of a futures contract. With the evolution of organized and advanced futures markets, it can be argued that futures margins have become insurance payments by market participants to insure against default on the terms of a futures contract.

On the other hand, purchasers of option contracts pay an option "premium" for the *right* to either buy or sell a certain asset at a prespecified price in the future. The option premium is effectively the purchase price of the *right* to either buy or sell the security. The purchaser is not obligated to exercise his *right* if it is not profitable

to do so.[35] Additionally, when common stock is purchased on margin, a margin payment is required. However, in this case, the margin can be seen as a down payment or collateral for the securities.

In setting futures margin levels, the clearinghouse must examine the cost/benefit tradeoff of having either too low or too high of a margin level. If the margin requirement is set too low, the incidence of trader default may become unacceptable. On the other hand, if the margin requirement is set too high, the costs of transacting through the futures market may become exorbitant, decreasing the liquidity and price discovery advantages often attributed to futures market activity.

Every organized futures exchange (or in general, every derivative security exchange) maintains a clearinghouse that guarantees contractual performance of all futures traders.[36] Essentially, the clearinghouse breaks every futures trade into two distinct contracts: one contract between the buyer and the clearinghouse, and one contract between the seller and the clearinghouse. The clearinghouse is an independent organization whose

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[35]Of course, the seller of the option is obliged to live up to the option's agreement if exercised upon. Margin requirements similar to those of futures participants usually apply to sellers of option contracts, especially those sold naked.

[36]The general characteristics of the margin process as found in Tucker (1991), Hull (1993), and Duffie (1989) are used in this section.

stockholders are clearing member firms, entities with a clear stake in maintaining the integrity of the futures trading process. Futures traders must maintain an account with a clearing member firm, either directly or indirectly through a brokerage firm (futures commodity merchant) in order to trade futures contracts.

Since the clearinghouse is completely hedged by assuming offsetting positions on every futures trade, its exposure to direct market fluctuations is nil. However, the credit risk of every futures trader, through his clearing member account, impacts the clearinghouse's ability to maintain confidence in the futures trading process. In order to minimize its loss from potential credit defaults, the clearinghouse sets initial margin requirements for every clearing members' accounts, and requires that every broker maintain acceptable maintenance margins for his own clients. Margin requirements vary across different futures contracts and are usually tied, but not limited to the individual contract's maximum daily price limit, if one exists, and the liquidity of the contract. Of course, the factor most often cited as the determinant of the margin level is the volatility of the underlying asset.

One tie-in between extreme value theory and optimal margin setting may be through this price limit. The daily price limit is established to limit extreme daily price fluctuations in either direction. However, the limit is

usually set so wide as to not impede (truncate) valuable price discovery information to the market.

This chapter proposes that the difficult process for setting margin requirements can be improved by examining the probability of observing values in the tails of price change distributions, i.e. extreme returns in either direction. A detailed examination of the prudent margin setting process is beneficial due to the fact that setting the margin too low may result in an increased incidence of trader default.[37] On the other hand, setting the margin too high may impede important price discovery processes inherent in the futures trading process by increasing the opportunity costs of derivative traders.

Margin requirements are usually set by experienced futures market participants through a consensus committee decision. Brenner (1981) indicates that the exchanges' margin committees are best suited to properly set and oversee margin requirements because of their first-hand experience with market conditions. Additionally, Brenner (1981) notes that margin committees' propensity to quickly increase or decrease margin levels "in response to changes in market conditions" is a testament to the committee's flexibility.

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[37]In addition to the possible increased incidence of trader default, setting the margin too low may also result in increased noise levels in security prices. This increase of noise would serve to decrease the importance of the price discovery process provided by derivative trading.

Factors that may affect the margin committees' decisions to set appropriate margin levels are (1) underlying asset price levels, (2) underlying asset price volatility, (3) volume, (4) levels of speculative and hedging positions etc... as discussed in Rutz (1988) and Gay, Hunter and Kolb (1986). Hull (1993) states that variability in the underlying security is the primary factor affecting the optimal margin setting decision. An interesting twist on the notion that higher volatility "causes" higher margin levels is found in Hardouvelis, Pericli, and Theodossiou (1995), where the authors provide evidence that volatility is a function of the margin level. In particular, higher margin levels cause lower subsequent volatility.

The fundamental and overriding reason for setting optimal margin levels is to accomplish two goals; maximize trading activity, and minimize the probability of margin violation. Baer, France and Moser (1994) term these two objectives "opportunity costs and prudentiality." The authors show that amenably resolving the opposing goals of these two objectives are the *raison d'être* of the margin committee. Their paper goes beyond the scope of the work presented here but is unique in that their model explicitly accounts for the opportunity costs of margin deposits and examines the tradeoffs between lowering these costs and maintaining a comfortable level of prudentiality. Their result implies that it is the internalization of the

opportunity costs and prudentiality that justifies the existence of the clearinghouse and the associated margin committee.

A reputational based explanation for margin requirements is found in Telser (1981). He implies that minimum margin levels are constraints against imprudent behavior and are used to maintain a certain respectable reputation level for futures market participants.[38] A preference based model introduced by Hunter (1986) indicates that there is a positive relationship between the minimum margin level and a participant's degree of risk aversion.[39] The higher the risk aversion, the higher the margin level.

In relation to some empirical work on margin setting, Figlewski (1984) develops and tests a model designed to compute the probability of the first margin violation given a certain margin level. Gay, Hunter and Kolb (1986) reverse the process, and develop a model that calculates the appropriate margin level required given the probability of margin violation during any specified time period.

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[38]Evidence of the high level of reputational capital held by futures participants is given in Duffie (1989) when he states that "no U.S. clearinghouse has ever defaulted on its obligations, and that there are relatively few defaults by individual traders."

[39]One constraint in Hunter's (1986) model is that the rational margin level not "exceed the maximum possible loss over one trading day." Therefore, extreme value theory may be used to test empirically the rationality of minimum margin levels.

Additional empirical analyses have been accomplished by Tomek (1985) who examines predicted and actual margin calls and their relationship to set margins. These empirical papers indicate that margin levels are set quite conservatively.

Warshawsky (1989) uses time series data to examine the constancy of margins whereas Edwards and Neftci (1988) extend his work to a multivariate setting. The results of these two papers, however, seem to provide evidence contradicting the conservative margin setting results previously mentioned. For instance, Warshawsky (1989) shows that Figlewski's (1984) and Gay, Hunter and Kolb's (1986) distributional assumptions are not met, causing incorrect inferences to be drawn. Specifically, the underlying data generation process does not follow a normal distribution. He uses a non-parametric test to show that margin levels were not set as conservatively as implied from Figlewski's (1984) and Gay, Hunter and Kolb's (1986) papers.

Edwards and Neftci (1988) add further doubt to the conservatively set margin issue by examining multiple contracts. They find that margin committees usually concentrate only on a single contract and do not account for the possibility that traders hold multiple contracts. Basically, holding multiple contracts increases the probability of default by an individual trader. Edwards and Neftci's (1988) implication is that setting margin

requirements should also account for the multivariate nature of price movements and contract positions.

Except for the Warshawsky (1989) and Edwards and Neftci (1988) papers, most of the extant literature uses models assuming that price changes of futures contracts, and its related assets, follow a normal distribution. Chapter two of this dissertation documents that intraday price changes in Germany's spot and futures markets are highly leptokurtotic, and fail the Kolmogorov normality test. This result implies that Germany's spot and futures data do not originate from a normal distribution and that the elevated levels of kurtosis imply a higher than expected incidence of extreme observations.

If margins are set assuming a normally distributed data generation process, the nonnormality may affect the determination of an optimal margin. In particular, methods that rely on the normality assumption do not take into account the added risk present in leptokurtotically generated extreme values. These models may tend to underestimate both the incidence of maintenance margin violations and the prudent margin required for reducing margin violations at prescribed probability levels. On the other hand, if an ad hoc increase in the margin level is made to counteract the underestimation, information related to price discovery may be lost by decreased trading levels.

3.2.3.2 Germany Specific Margin Issues[40]

In Germany, the derivatives product clearinghouse is the Deutsche Terminbörse (DTB) GmbH. This is the central organization for clearing both options and futures transactions. Similar to clearinghouses on the U.S. market, the primary goal of the DTB's clearinghouse is to guarantee all transactions on the exchange. It executes this goal in a number of different ways. First, the clearinghouse assumes its role as counterpart for every transaction on the system. Second, the clearinghouse acts as intermediary for delivery of funds and financial instruments at settlement. Third, calculation and collection of variation margins are accomplished by the clearinghouse through monitoring real-time information on the options and futures positions of members. Finally, the clearinghouse provides usual "banking" functions such as member account deposits, withdrawals, and cash payment receipts for activity fees.

All DTB trading members fit into one of three categories; 1)General Clearing Member (GCM), 2)Direct Clearing Member (DCM), and 3)Non-Clearing Member (NCM). The GCM is a trader who can clear his own trades, client trades, and transactions from NCM's. The DCM can settle transactions only for its own or its client's accounts. As

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[40]Information on the DTB's clearing and margining activities was gathered from personal contacts with DTB personnel and DTB provided literature.

inferred by the GCM definition, the NCM's must settle their transactions through a GCM. GCM's and DCM's are directly responsible to the DTB for all obligations they have agreed to clear. NCM's and clients of member firms have no direct responsibility to the DTB.

To become a DTB trading member, or exchange participant, and gain access to the DTB trading system, there are a few requirements that need to be met. The particulars are available directly from the exchange, but generally, the member firm must be an operating business establishment with meaningful exchange business conducted on the DTB. There are restrictions and basic training qualifications that must be met by the participants' personnel. Finally, since the DTB is a totally electronic exchange, with no trading floor, the exchange participants must equip themselves with DTB authorized hardware and software. Periodically, members will be required to update both hardware and software to meet the changing technological landscape.

To maintain a certain level of security against default, the exchange has set minimum financial requirements of its clearing members. GCM's must maintain a minimum DM250 million of net equity capital whereas DCM's are only required to maintain a net equity position of DM25 million. The additional capital required for the GCM's is a direct consequence of its ability to clear NCM transactions. Additionally, the GCM's and DCM's must have

third party bank letters of credit in the amounts of DM10 million and DM2 million, respectively.

To facilitate payment of exchange fees and margin calls, every member must maintain an account (called the LZB account) at the Landeszentralbank Hessen, Haupstelle Frankfurt am Main (State Central Bank in Hessen, Main Office, Frankfurt). In addition, every participant must also maintain a security deposit account (DKV account) at the Deutscher Kassenverein AG, in Frankfurt. The purpose of the DKV account is to facilitate delivery of stock and or bond certificates.

At the present time, the DTB has implemented only daily margin settlement procedures. Margin calls are generated when the margin requirement of a participant's option or futures positions goes beyond the market value of securities or cash deposited as collateral. The DTB arrives at the appropriate margin requirement or excess in an account by netting positions in 21 margin classes. These classes are maintained in order to project potential impacts of price changes in individual assets.

For example, the DAX margin class contains the Futures on the DAX contracts (FDAX), the Options on the DAX contracts (ODAX), and the Options on the Futures DAX (OFDX) contracts. The total margin requirement is made up of

three components: the futures spread margin, the premium margin, and the additional margin.[41]

If an investor holds only FDAX contracts, his daily margin requirement would presently be set in the following fashion. First, whatever the contract price of the underlying DAX, the clearinghouse would add and subtract 130 points. The resulting DAX values would then be multiplied by 100 (the futures contract size) and then multiplied by the requisite number of short and long positions. The long or short position that results in the larger margin requirement is used to determine the requisite margin level that must be deposited in an LZB account. Currently, the approximate level of the DAX (around 2000) and the margin requirement for a futures contract (DM13,000 per contract) results in an initial margin of approximately 6.5%, a historically targeted figure.

The contribution made by the extreme value analysis to the German stock index futures markets is its ability to examine the impacts of extreme values on intraday margin violation probabilities. Because the exchange does not presently have intradaily margin requirements, the information provided in this dissertation should be beneficial to the DTB exchange officials. Naturally, the

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[41]Edwards and Nefcti's (1988) result indicates that examining the impacts of extreme values on multi-contract margin requirements is an interesting topic and is an area for potential future research.

information contained within this dissertation should be useful to decision makers at other markets when examining alternatives to existing margin setting procedures.

3.3 DATA EMPLOYED

The transactional data used in this paper are provided by the DTB and cover all contracts with at least 6 months worth of trading data from January 1992 through September 1994. This selection process allowed for the analysis of all futures contracts from June 1992 to September 1994. During this time, the DAX has achieved lows of around 1400 and highs around 2300. Towards the end of the time period analyzed, the DAX was trading at a level around 2000.

Only trading days with more than two transactions and having both positive and negative price changes were considered. Finally, the data examined were cleaned of mistrades. Mistrades are transactions where some error either on the buyer or seller side of a transaction was made in entering the transaction. For example, inadvertent keystrokes could have caused too high a price, or too many contracts to be entered in the system. Obviously, wrong price entries would have direct consequences on the extreme value analysis.

Recall that the objective of this chapter is to analyze and provide the DTB with information regarding intradaily price change extremes. Since the DTB's daily margin requirements are in existence, it was decided that the extreme value would focus on the intradaily aspects of

margin levels. Hence, the results of this chapter are important since they provide information on the intradaily aspects of the DAX futures price changes not previously documented, and they provide information on intradaily margin setting procedures not presently used by the DTB.

In order to examine maximum and minimum intradaily price changes, this paper calculates all possible combinations of intradaily price changes. Price changes are calculated by taking the log of a later transaction's price level and subtracting the log of an earlier transaction's price level ($\ln P_t - \ln P_{t-b}$). After all possible combinations of transactional price changes are calculated, maximums and minimums for each day are generated.[42]

When applying extreme value theory to any set of data, one of the most important variables that must be controlled is the "return period." According to Kinnison (1985), extreme measurements should be made at equal distant points in time, daily periods in this case. This research differs from previous applications of extreme value theory to financial market data in that it uses maximums and minimums from intradaily price changes. The selection procedure

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[42]The intradaily price changes are calculated using SAS's PROC IML routine to create dynamic vector sizes. Each daily maximum and minimum are chosen from an (N(N-1)/2)x1 vector where N is the number of transactions occurring in that day. Calculation time was extensive, taking over eight days to complete.

used here results in a natural and consistent holding period (one day).

Longin (1994) chooses the maximum and minimum price changes of the S&P500 index over 60 non-overlapping trading days. Even though it is reasonable to incorporate a maximal and minimal price change every quarter, what would happen if one chose one every month, or one every week? The subjectiveness of Longin's procedure in selecting observations and holding periods is not present in this work.

Additionally, research work applying Hill's (1975) estimator must choose which sections of the distribution to include in the analysis. Usually, a "Hill Horror Plot" is examined to test the sensitivity of the estimated tail parameter value to the number of observations chosen.[43] This judgmental method for choosing the number of observations is similar to the old practice of examining a correllogram when attempting to determine whether a series was stationary. Again, the subjectiveness of this procedure is readily apparent, and not employed in this chapter.

3.4 METHOD OF ANALYSIS

This dissertation applies a generalized extreme value parametric model first used on financially related data by

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[43]The term "Hill Horror Plot" was coined by Sid Resnick at the *Conference on Multivariate Extreme Value Estimation with Applications to Economics and Finance*, Erasmus University, Rotterdam, May 26-28, 1994.

Longin (1994). The method calculates the domain of attraction for the maximal and minimal intradaily observations. Longin's (1994) model is not "new" in the sense that the distributional form has never been described before. In reality, his model is a reparameterization of Maritz and Munro's (1967) Generalized Extreme Value distribution. However, Longin's approach is important because it had not been applied to financial market data before. For continuity purposes, this paper uses approximately the same symbols and letters found in Longin's equations.

Longin (1994) begins his analysis by assuming that log price changes of a futures contract, for instance, are random occurrences and can be measured by the random variable R (for returns). He lets f_R and F_R represent the probability density and the cumulative probability density functions of R, respectively. Also, he lets $R_1, R_2, \ldots R_n$ be the random variables measuring the returns at time 1, 2, ... n, with the extreme values of each random variable defined as the minima and maxima. Finally, Longin designates *MIN* and *MAX* as the minimum and maximum values, respectively, achieved from the n random variables $R_1, R_2, \ldots R_n$.

If *MIN* and *MAX* are independent and identically distributed, that is, they follow the random walk theory of speculative security prices, Longin (1994) states that the exact distributions of *MIN* and *MAX* are given by:

$$F_{MIN}(r)=1-[1-F_R(r)]^n \tag{26}$$

$$F_{MAX}(r)=[F_R(r)]^n. \tag{27}$$

Since the exact distributional form is a power exponential function, values close to the center of the distribution have little effect on the distributional properties of extreme values. Hence, the distribution of both the minima and maxima extreme values depends heavily on the properties of the distribution of large negative or large positive values of return observations.

Like any investigation of the distributional forms for a set of data, the exact sample distribution of Equations (26) and (27) is not known with certainty. Therefore, Longin (1994), relying on results found in Gnedenko (1943), Jenkinson (1955) and Tiago de Oliveira (1973), presents a central limit theorem result for the normalized *MIN* and *MAX* random variables (where each variable is normalized by an appropriate location (β) and dispersion parameter (α) e.g. $((MINn-\beta^{MIN})/\alpha^{MIN})$ and $(MAXn-\beta^{MAX})/\alpha^{MAX}))$ *MINNORM* and *MAXNORM*. The limiting results become the following:

$$F_{MINNORM}=1-\exp[-(1+\tau^{\min}r_s)^{\frac{1}{\tau^{\min}}}] \tag{28}$$

$$F_{MAXNORM}=\exp[-(1-\tau^{\max}r_s)^{\frac{1}{\tau^{\max}}}] \tag{29}$$

Longin's (1994) parameter τ (the tail index) is responsible for determining the type (i.e. Type I, Type II, or Type III) of distribution from which extreme values are drawn.

The τ may be either less than, equal to, or greater than zero. For instance, when $\tau=0$, the limiting distribution corresponds to the Type I extreme value distribution (also called a Gumbel distribution). When $\tau>0$, the limiting distribution corresponds to the Type III extreme value distribution (also called a Weibull distribution), and when $\tau<0$, the limiting distribution is of the Type II extreme value distribution (called a Fréchet distribution). τ is similar to the tail index of Paretian distributions, and is representative of the impact extreme values have on the underlying distribution. In particular, τ gives an indication of the thickness of the tails found in the underlying distribution.

One useful result of extreme value theory is that the limiting distribution of the extreme values follows the same form as the tail behavior of the random variable's parent distribution. That is, normally distributed data exhibiting an exponentially decreasing tail structure will generate tail indexes equal to zero. These tail observations will follow a Gumbel (Type I) extreme value distribution. Fat-tailed distribution generated extreme values, such as stable Paretian, student-t, or other leptokurtotic distributions will generate tail indexes less than zero, indicating that these extreme values are drawn from a Fréchet (Type II) distribution. Weibull (Type III), or possibly Gumbel (Type I), distributions may generate

tail observations for random variables containing some sort of bounds (truncated data).[44]

Another interesting feature of extreme value theory is that violations of the i.i.d. assumption do not alter the domain of attraction for the extreme values. For example, Berman (1963) replicates the tail index results on serially correlated data. He finds that extreme values follow Gumbel, Weibull, or Fréchet distributions, even when they are not independent.

ARCH and GARCH models explicitly allow for conditional dependence in the second moment and are often useful in explaining time series behavior when the underlying data generating process exhibits leptokurtosis.[45] DeHaan, Resnick, Rootzèn and DeVries (1989) document that if the random variable of interest follows an ARCH process, the extreme values found from the data generation process follow a Fréchet distribution. Therefore a linkage between ARCH process and extreme values exists.

Mixture of normal distributions are frequently used to explain arrival of information processes. Harris (1987) documents that daily arrival of information for stock

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[44]Futures contracts often have daily price limits attached which cause trading to cease when the limits are reached. These price limits may represent bounds on extreme observations, and possibly increase the probability of observing Weibull distributions.

[45]Engle's (1982) ARCH and Bollerslev's (1986) GARCH models have been studied extensively in the financial literature.

returns can be explained in a mixture of distributions context. In an examination of information arrival defined as a mixture of distributions, Lamoureaux and Lastrapes (1990) present evidence that volume is the mixing variable that accounts for information flow by showing diminished GARCH effects when accounting for volume.[46] Leadbetter, Lindgren and Rootzèn (1983) document the link between extreme value theory and mixture of normal distributions by showing that extreme observations derived from mixture of normal distributions follow Gumbel (Type I) distributions. Hence, there may be some benefit to combining mixture of distributions research with extreme value research.

Estimation of the appropriate distributional parameters is accomplished using standard nonlinear regression techniques on the following regression equations:

$$-Log[-Log(\frac{m}{N+1})] = \frac{1}{\tau^{\max}} Log\alpha^{\max} - \frac{1}{\tau^{\max}} Log[\alpha^{\max} - \tau^{\max}(MAX^{m} - \beta^{\max})] + u_{m} \tag{30}$$

[46]Recent refinements of mixture of distributions research are made by Richardson and Smith (1994). The authors demonstrate the usefulness of mixture of distributions concepts by improving on the mixture of distributions property estimation technique. Specifically, they apply a general method-of-moment estimator in their examination of the Dow Jones 30 firms' information arrival processes.

$$-Log[-Log(\frac{m}{N+1})]=\frac{1}{\tau^{\min}}Log\alpha^{\min}-\frac{1}{\tau^{\min}}Log[\alpha^{\min}-\tau^{\min}(\beta^{\min}-MIN^{m})]+u_{m}. \quad (31)$$

Recall that τ is the tail index parameter, α is the dispersion parameter and β is the location parameter of the appropriate tail distribution. Also, MAX^m (MIN^m) is the maximum (minimum) observation for the particular sequence of observations being analyzed. These regressions are an extension of plotting data on extreme value probability paper. Kinnison (1985) notes that the goal of this regression is to fit the expected cumulative probability frequencies to their observed extreme values. Essentially, the regression is a straight forward curve fitting exercise of regressing plotting positions against extreme values.

After estimation of the associated tail distribution parameters, an analysis of the appropriate margin setting level given various probabilities of margin violations is made. This test is accomplished using the normal distribution as a benchmark for comparison, and then using the distribution dictated by the sign of the tail parameter.[47] For example, a sample's unconditional mean and unconditional variance are substituted into a normal

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[47]Following the convention set in Jansen and deVries (1991), Kofman and deVries (1989), Koedijk, Stork, and deVries (1992) and Kofman (1993), only those contracts exhibiting Type II extreme value behavior will be considered.

distribution equation, and then the appropriate margin values are solved using Equations (30) and (31).

Longin (1994) gives the analytical relationship between the margin level and probability of margin violation for long and short positions assuming normal distributions to be:

$$\pi^{long}=1-[1-\Phi(\frac{r-\mu}{\sigma})]^{n} \tag{32}$$

$$\pi^{short}=1-[\Phi(\frac{r-\mu}{\sigma})]^{n} \tag{33}$$

where Φ = CDF for N(0,1). Additionally, he shows the relationship between margin violation and margin levels assuming the extreme value distribution as being:

$$\pi=1-\exp[-[1-\tau[\frac{\pm r\pm\beta}{\alpha}]]^{\frac{1}{\tau}}] \tag{34}$$

where the appropriate *max* or *min* superscripts are substituted depending on whether it is a long (min) or short (max) position. Additionally, r is preceded with a minus (plus) and β is preceded with a plus (minus) for long (short) positions. Finally, both of these theoretical distributions are compared to the resultant empirical probability exhibited by the data and given as:

$$\pi^{long} = \frac{\#\{MIN < r\}}{N} \tag{35}$$

$$\pi^{short} = \frac{\{\#MAX > r\}}{N}. \tag{36}$$

These distributional forms are used to determine whether the normal distribution assumption causes inadvertent margin violation expectations vs. those from the appropriate extreme value distribution.

Longin's (1994) results using S&P 500 stock index data indicate that the normal distribution underestimates the appropriate margin level at most margin violation probabilities. His results also indicate that the normal distribution underestimates the probability of margin violation given various maintenance margin levels. Whether or not this pattern is exhibited in Germany is an empirical question.

The estimation procedure of the parameters from the limiting distributions of extreme values is relatively straight-forward. All that is required is to estimate three parameters: the tail index, the location and the dispersion parameters. Most importantly, not only does the tail index yield the appropriate distribution of the extreme values, but it also yields information about the thickness of the tails for the underlying return distribution.

3.5 REGRESSION RESULTS, AND EFFECTS ON OPTIMAL MARGIN LEVELS

3.5.1 Regression Results

Table 13 lists the results of using the regression found in Equation (30) for the maximal intradaily returns. The values for maximal transactional returns range from 1.707% to 3.705%. The average maximum price change is around 3%.

All parameter estimates for τ^{max}, α^{max}, and β^{max} are significant at p-values less than 0.01, except for the December 1992 contract.[48] Since the majority of the contracts appear to follow a Type II extreme value limiting distribution, these results are similar to those found in Longin (1994), and forecasted by Jansen and DeVries (1989), Kofman and DeVries (1989), and Kofman (1993). That is, the extreme values resulting from increases in future contract prices appear to follow a Type II limiting distribution. However, it is noteworthy that the maximum values for the March 1993 contract appear to follow a Type III limiting distribution, whereas the December 1992 contract's maximal returns appear to follow a Type I extreme value limiting distribution.

Table 14 lists the results of using the regression found in Equation (31) for the minimal intradaily returns. The values for minimal transactional returns range from -

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[48]The author is using the 1% level as a cutoff for statistical significance.

1.527% to -4.788%. The average minimum price change is around -3.5%, higher in magnitude than the average maximum price change. Apparently, the observance of extreme values is not symmetric around the center of the parent distribution. The extreme negative price changes appear to be larger in magnitude than the extreme positive price changes.

The estimated parameters for the minimum returns, τ^{max}, α^{max}, and β^{max} indicate limiting distribution inferences similar to the maximum price changes. For the most part, the parameters are significant and indicate that the extreme minimum price changes originate from a Type II limiting distribution. However, the extreme negative price changes for the September 1993 and December 1993 contracts are apparently generated from a Type I limiting distribution.

One characteristic revealed in Tables 13 and 14 is noteworthy. It appears that both the dispersion and location parameters of the contracts have increased over time. One explanation for the result indicates that extreme intradaily price changes are becoming more frequent and are achieving larger magnitudes. On the other hand, this result may indicate that the extreme values possesses non-stationary characteristics, causing the noted trend. Further investigation into why this is occurring would be an interesting extension of this study.

Table 13
Estimated Parameters for Maximum
Intradaily Price Changes
See Equation (30)

Contract	N	Maximum Price Change	τ^{max}	α^{max}	β^{max}
Jun 92	115	1.707	-0.202	0.212	0.365
Sep 92	179	2.906	-0.269	0.277	0.375
Dec 92	186	2.690	-0.017*	0.446	0.496
Mar 93	187	2.424	0.035	0.414	0.607
Jun 93	174	3.705	-0.154	0.299	0.472
Sep 93	175	2.813	-0.141	0.315	0.448
Dec 93	174	2.747	-0.072	0.367	0.494
Mar 94	165	3.706	-0.087	0.455	0.607
Jun 94	176	3.546	-0.112	0.387	0.619
Sep 94	162	2.845	-0.068	0.421	0.647

Estimation of the extreme value parameters is by Equation (30):

$$-Log[-Log(\frac{m}{N+1})] = \frac{1}{\tau^{max}} Log\alpha^{max} - \frac{1}{\tau^{max}} Log[\alpha^{max} - \tau^{max}(MAX^{m} - \beta^{max})] + u_{m}$$

All parameter estimates are significant at p-values < 0.0001, except for * which is insignificantly different from zero with p-value of 0.1667.

3.5.2 Effects on Margin Levels and Violation Probabilities

The appropriate intradaily price changes resulting from the extreme value distribution are solved from the appropriately signed parameters found in Equation (34) for long and short positions. To calculate these

price changes, the following equations are used:

$$r_{\min}=\beta^{\min}-\frac{\alpha^{\min}}{\tau^{\min}}\left[1-[-\ln(1-\pi)]^{\tau^{\min}}\right] \tag{38}$$

for the long positions and,

$$r_{\max}=\frac{\alpha^{\max}}{\tau^{\max}}\left[1-[-\ln(1-\pi)]^{\tau^{\max}}\right]+\beta^{\max} \tag{39}$$

for the short positions. Where r_{min} and r_{max} are the calculated margin levels given the violation probabilities (π) found in the Table 3. Note that the terms margin levels and price changes are interchangeable in this analysis.

Rearranging Equations (32) and (33) allows calculation of the minimal and maximal intradaily price changes assuming normally distributed data for both long and short positions. These formulas are:

$$r^{\min}=\Phi^{-1}\left[1-(1-\pi)^{\frac{1}{n}}\right]\sigma+\mu \tag{40}$$

for the long positions and,

$$r_{\max}=\Phi^{-1}\left[(1-\pi)^{\frac{1}{n}}\right]\sigma+\mu \tag{41}$$

for the short positions. Φ^{-1} is the inverse function of a standard normal variate and σ and μ are the standard deviation and mean of the underlying series.

Rearranging Equations (35) and (36) allows the empirical maximums and minimums to be found in the data.

These equations are:

$$r_{\min}\# = \pi^{long} * N \tag{42}$$

for the long positions and,

$$r_{\max}\# = \pi^{short} * N. \tag{43}$$

Here, $r_{max}\#$ and $r_{min}\#$ are the calculated rank numbers given each probability (π) level.

Table 14
Estimated Parameters for Minimum
Intradaily Price Changes
See Equation (31)

Contract	N	Minimum Price Change	$\tau^{\min}$	$\alpha^{\min}$	$\beta^{\min}$
Jun 92	115	-1.527	-0.206	0.189	-0.359
Sep 92	179	-4.684	-0.341	0.291	-0.395
Dec 92	186	-4.788	-0.229	0.397	-0.504
Mar 93	187	-4.687	-0.210	0.359	-0.589
Jun 93	174	-4.341	-0.202	0.312	-0.458
Sep 93	175	-2.180	0.003**	0.365	-0.488
Dec 93	174	-2.157	0.031***	0.412	-0.519
Mar 94	165	-4.034	-0.140	0.462	-0.602
Jun 94	176	-3.226	-0.097	0.503	-0.610
Sep 94	162	-3.478	-0.108	0.456	-0.661

Estimation of the extreme value parameters is by Equation (31):

$$-Log[-Log(\frac{m}{N+1})] = \frac{1}{\tau^{\min}} Log\alpha^{\min} - \frac{1}{\tau^{\min}} Log[\alpha^{\min} - \tau^{\min}(\beta^{\min} - MIN^{m})] + u_{m}.$$

All parameter estimates are significant at p-values < 0.0001, except for ** p-value=0.719, *** p-value=0.025.

Finally, recall that the minimal price changes for the September 1993 and December 1993 contracts and the maximal price changes for the December 1992 and March 1993 contracts do not follow a Type II limiting extreme value distribution. Hence, the extreme value analysis is not carried out on these contracts. The extreme value results for these non-conforming contracts are represented as "na" in both Tables 15 and 16. Table 15 contains the results for the margin violation probability analysis for long and short futures positions.

Interpretation of Table 15's Panels is as follows. The first column contains given probabilities of margin violation that are input into Equations (39) through (44). The next three columns represent the intradaily price change (margin level) calculated from those equations for a long position. For instance, when examining Table 15, Panel B, the intradaily price changes associated with a margin violation probability of 0.04 are -1.681% assuming a normal distribution, -2.083% assuming the appropriate extreme value distribution, and -1.947% actually observed in the data. An intuitive interpretation of these results is as follows.

If the margin committee is willing to accept intradaily margin violations four out of every 100 trading days, the normal distribution suggests setting the margin requirement at 1.68% of the transacted contract value. The extreme value distribution, on the other hand, recommends

setting the margin requirement at 2.083% for this margin violation probability. The actual sample data probability, as represented in the Empirical column, shows that there were only four out of every 100 minimal price change observations greater (in negative terms) than 1.947%.

An analogous example can be made using the short position information found in the last three columns of each Panel. For instance, Table 15 Panel E shows that at an acceptable margin violation probability of 1 out of 100 trading days, the extreme value distribution recommends a required margin of 2.474% of the contract value. The normal distribution requires only a 1.078% margin. Empirically, the data show that 1 out of every 100 trading days had intradaily price changes exceeding 2.207%.

The pattern found in Table 15 can be summed up in two statements. First, the extreme value distribution generates larger required margin levels than those recommended by assuming normally distributed data, and the extreme value's data more closely track the observed extremes, shown by the empirical distribution results.

The pattern of the extreme value distribution generating larger required margin levels than the normal distribution, and the pattern of more closely tracking the empirical distribution is shown in all contracts and for both long and short futures positions. However, the better fit criteria is not the only information that can be garnered from Table 15.

The power of the extreme value analysis is its ability to extrapolate required margin levels above and beyond those observed in the empirical distribution. For example, Table 15 Panel E indicates that if the margin setting committee did not want to see an intradaily margin violation for a long position except once every 4 years or so (probability = 0.001), it should set the margin level to 5.160% of the contract value. This margin requirement is much larger than the value suggested by the normal distribution (1.332%) and helps the margin committee make better informed decisions about margin violations that have not occurred, but still have positive probability of happening. Essentially, the results found in Table 15 indicate that prudent margin levels should be set using extreme value theory.

Table 16 contains 10 panels (A-J) corresponding to the margin violation examination for each of the contracts. However, in this case, a set margin level is used to calculate the probability of margin violation. In essence, the Panels in Table 4 answer the question, "If margin levels are set to a given percentage, how many trading days should intradaily price changes cause margin violations?"

An example using Table 16 Panel E may provide some direction for answering that question. Take the information pertinent to setting the margin level for a long position first. If margin levels are set at 3% of contract value, the extreme value distribution predicts

that intradaily price declines greater than 3% will happen about eight trading days out of 1000. The normal distribution forecasts no intradaily price changes exceeding that level. The sample data suggest that at least six trading days out of 1000 experienced intradaily price changes greater than 3%.

On the other hand, data pertinent to short positions indicate a different result. The extreme value analysis indicates that only four out of 1000 trading days will experience price increases at the 3% level. The normal distribution predicts none, while the sample data for the June 1993 contract had six days where price increases above 3% were observed.

An examination of all Table 16's Panels indicates that the extreme value distribution generates a positive probability of margin violation at higher margin levels than the normal distribution suggests. Additionally, the extreme value probabilities track those generated by the sample much better than those generated from the normal distribution. This latter result is quite evident by the fact that the normally distributed model usually only generates two or three useful probabilities per contract position, i.e. only a small number of the probabilities are less than one. Even if the probabilities are less than one, they are often farther away from those probabilities observed empirically than those generated from extreme value theory.

Table 15
Panel A
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the June 1992 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-0.646	-0.900	-0.921	0.676	0.968	1.031
0.050	-0.689	-1.328	-1.220	0.719	1.227	1.188
0.040	-0.703	-1.214	-1.268	0.733	1.317	1.202
0.030	-0.720	-1.324	-1.304	0.750	1.439	1.425
0.020	-0.743	-1.491	-1.395	0.773	1.623	1.530
0.010	-0.781	-1.807	-1.527	0.811	1.972	1.707
0.005	-0.817	-2.172	-1.527	0.847	2.373	1.707
0.004	-0.828	-2.301	na	0.858	2.514	na
0.003	-0.843	-2.476	na	0.873	2.707	na
0.002	-0.862	-2.740	na	0.893	2.996	na
0.001	-0.896	-3.247	na	0.926	3.550	na
0.0005	-0.928	-3.832	na	0.958	4.187	na
0.0004	-0.938	-4.038	na	0.968	4.412	na
0.0003	-0.951	-4.319	na	0.981	4.717	na
0.0002	-0.969	-4.744	na	0.999	5.178	na
0.0001	-0.999	-5.559	na	1.029	6.060	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel B
Intradaily Price Changes Associated with
Given Margin Violation Probabilities for
the September 1992 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.563	-1.380	-1.406	1.391	1.231	1.230
0.050	-1.653	-1.892	-1.809	1.482	1.633	1.640
0.040	-1.681	-2.083	-1.947	1.510	1.778	1.760
0.030	-1.717	-2.350	-2.250	1.545	1.978	2.016
0.020	-1.765	-2.772	-2.454	1.593	2.285	2.127
0.010	-1.844	-3.641	-2.859	1.672	2.892	2.419
0.005	-1.920	-4.739	-4.684	1.748	3.621	2.906
0.004	-1.944	-5.152	-4.684	1.772	3.886	2.906
0.003	-1.974	-5.731	-4.684	1.802	4.252	2.906
0.002	-2.016	-6.651	na	1.844	4.818	na
0.001	-2.085	-8.551	na	1.914	5.941	na
0.0005	-2.153	-10.957	na	1.982	7.293	na
0.0004	-2.174	-11.861	na	2.003	7.784	na
0.0003	-2.201	-13.132	na	2.030	8.463	na
0.0002	-2.239	-15.150	na	2.068	9.514	na
0.0001	-2.302	-19.318	na	2.131	11.598	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel C
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the December 1992 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.448	-1.672	-1.641	1.420	na	1.598
0.050	-1.536	-2.192	-2.054	1.507	na	1.846
0.040	-1.563	-2.376	-2.229	1.534	na	1.915
0.030	-1.597	-2.626	-2.251	1.569	na	2.012
0.020	-1.643	-3.005	-2.598	1.615	na	2.245
0.010	-1.720	-3.739	-4.636	1.691	na	2.596
0.005	-1.793	-4.596	-4.788	1.764	na	2.690
0.004	-1.816	-4.902	-4.788	1.787	na	2.690
0.003	-1.845	-5.320	-4.788	1.816	na	2.690
0.002	-1.886	-5.957	na	1.857	na	na
0.001	-1.953	-7.193	na	1.924	na	na
0.0005	-2.018	-8.641	na	1.990	na	na
0.0004	-2.039	-9.158	na	2.010	na	na
0.0003	-2.065	-9.865	na	2.036	na	na
0.0002	-2.101	-10.944	na	2.073	na	na
0.0001	-2.162	-13.035	na	2.134	na	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel D
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the March 1993 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.109	-1.620	-1.547	1.087	na	1.485
0.050	-1.156	-2.067	-2.026	1.153	na	1.880
0.040	-1.177	-2.224	-2.062	1.173	na	2.008
0.030	-1.202	-2.436	-2.064	1.199	na	2.044
0.020	-1.238	-2.756	-2.259	1.234	na	2.068
0.010	-1.295	-3.367	-4.103	1.292	na	2.207
0.005	-1.351	-4.071	-4.687	1.348	na	2.424
0.004	-1.368	-4.321	-4.687	1.365	na	2.424
0.003	-1.390	-4.660	-4.687	1.388	na	2.424
0.002	-1.214	-5.173	na	1.418	na	na
0.001	-1.472	-6.158	na	1.469	na	na
0.0005	-1.522	-7.297	na	1.519	na	na
0.0004	-1.537	-7.701	na	1.534	na	na
0.0003	-1.557	-8.249	na	1.554	na	na
0.0002	-1.585	-9.081	na	1.582	na	na
0.0001	-1.631	-10.676	na	1.628	na	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel E
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the June 1993 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-0.995	-1.349	-1.320	0.897	1.277	1.215
0.050	-1.054	-1.730	-1.610	0.955	1.599	1.498
0.040	-1.072	-1.863	-1.641	0.973	1.709	1.559
0.030	-1.095	-2.043	-1.799	0.996	1.855	1.571
0.020	-1.126	-2.314	-2.062	1.027	2.072	1.599
0.010	-1.177	-2.830	-2.147	1.078	2.474	2.008
0.005	-1.225	-3.422	-4.341	1.127	2.920	3.705
0.004	-1.241	-3.631	-4.341	1.142	3.047	3.705
0.003	-1.260	-3.914	-4.341	1.162	3.280	3.705
0.002	-1.287	-4.342	na	1.189	3.586	na
0.001	-1.332	-5.160	na	1.233	4.156	na
0.0005	-1.375	-6.100	na	1.277	4.789	na
0.0004	-1.389	-6.432	na	1.291	5.007	na
0.0003	-1.407	-6.883	na	1.308	5.300	na
0.0002	-1.431	-7.564	na	1.332	5.736	na
0.0001	-1.471	-8.867	na	1.373	6.547	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel F
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the September 1993 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.233	na	-1.325	1.211	1.282	1.286
0.050	-1.308	na	-1.535	1.287	1.609	1.558
0.040	-1.331	na	-1.708	1.310	1.720	1.568
0.030	-1.361	na	-1.826	1.339	1.878	1.856
0.020	-1.401	na	-1.829	1.379	2.085	1.918
0.010	-1.466	na	-2.022	1.445	2.486	2.501
0.005	-1.529	na	-2.180	1.508	2.926	2.813
0.004	-1.549	na	-2.180	1.527	3.077	2.813
0.003	-1.574	na	-2.180	1.553	3.279	2.813
0.002	-1.609	na	na	1.587	3.577	na
0.001	-1.667	na	na	1.645	4.128	na
0.0005	-1.723	na	na	1.701	4.738	na
0.0004	-1.741	na	na	1.719	4.944	na
0.0003	-1.763	na	na	1.742	5.222	na
0.0002	-1.795	na	na	1.773	5.635	na
0.0001	-1.847	na	na	1.825	6.397	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel G
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the December 1993 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.142	na	-1.473	1.128	1.389	1.465
0.050	-1.212	na	-1.758	1.198	1.708	1.628
0.040	-1.234	na	-1.810	1.219	1.812	1.817
0.030	-1.261	na	-1.857	1.247	1.949	2.012
0.020	-1.298	na	-1.921	1.284	2.145	2.177
0.010	-1.359	na	-1.974	1.345	2.492	2.209
0.005	-1.418	na	-2.157	1.403	2.856	2.747
0.004	-1.436	na	-2.157	1.422	2.977	2.747
0.003	-1.459	na	-2.157	1.445	3.135	2.747
0.002	-1.492	na	na	1.477	3.364	na
0.001	-1.545	na	na	1.531	3.772	na
0.0005	-1.598	na	na	1.583	4.199	na
0.0004	-1.614	na	na	1.600	4.342	na
0.0003	-1.635	na	na	1.621	4.529	na
0.0002	-1.664	na	na	1.650	4.799	na
0.0001	-1.713	na	na	1.699	5.279	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel H
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the March 1994 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.711	-1.824	-1.754	1.633	1.783	1.783
0.050	-1.815	-2.301	-2.159	1.737	2.150	2.096
0.040	-1.874	-2.466	-2.579	1.769	2.286	2.162
0.030	-1.888	-2.682	-2.808	1.809	2.465	2.584
0.020	-1.943	-3.001	-3.118	1.864	2.723	2.606
0.010	-2.034	-3.586	-3.344	1.955	3.183	2.907
0.005	-2.121	-4.229	-4.034	2.042	3.671	3.706
0.004	-2.148	-4.450	-4.034	2.069	3.835	3.706
0.003	-2.182	-4.744	na	2.104	4.050	na
0.002	-2.230	-5.180	na	2.152	4.362	na
0.001	-2.310	-5.984	na	2.232	4.922	na
0.0005	-2.388	-6.869	na	2.309	5.517	na
0.0004	-2.412	-7.173	na	2.333	5.716	na
0.0003	-2.443	-7.579	na	2.364	5.978	na
0.0002	-2.486	-8.180	na	2.408	6.360	na
0.0001	-2.559	-9.290	na	2.480	7.044	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel I
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the June 1994 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.460	-1.875	-1.773	1.306	1.609	1.674
0.050	-1.545	-2.340	-2.486	1.392	1.982	1.957
0.040	-1.571	-2.495	-2.724	1.418	2.107	2.136
0.030	-1.604	-2.699	-2.906	1.451	2.271	2.179
0.020	-1.650	-2.994	-2.947	1.496	2.511	2.207
0.010	-1.724	-3.523	-3.168	1.570	2.945	2.670
0.005	-1.795	-4.087	-3.226	1.642	3.413	3.546
0.004	-1.817	-4.277	-3.226	1.664	3.571	3.546
0.003	-1.846	-4.527	-3.226	1.692	3.781	3.546
0.002	-1.855	-4.892	na	1.732	4.089	na
0.001	-1.951	-5.549	na	1.797	4.647	na
0.0005	-2.014	-6.252	na	1.861	5.520	na
0.0004	-2.034	-6.488	na	1.881	5.454	na
0.0003	-2.060	-6.801	na	1.906	5.725	na
0.0002	-2.095	-7.256	na	1.942	6.122	na
0.0001	-2.154	-8.076	na	2.001	6.843	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 15
Panel J
Intradaily Price Changes Associated with Given Margin Violation Probabilities for the September 1994 Contract

	Intradaily Price Changes (Margin Levels)					
	Long Futures Position			Short Futures Position		
Probability	Normal	Extreme	Empirical	Normal	Extreme	Empirical
0.100	-1.448	-1.822	-1.874	1.493	1.670	1.766
0.050	-1.539	-2.257	-2.362	1.585	2.033	2.056
0.040	-1.568	-2.402	-2.631	1.613	2.151	2.116
0.030	-1.603	-2.594	-2.667	1.649	2.306	2.132
0.020	-1.652	-2.873	-2.922	1.697	2.528	2.668
0.010	-1.732	-3.377	-3.064	1.777	2.921	2.710
0.005	-1.808	-3.918	-3.478	1.854	3.331	2.845
0.004	-1.833	-4.101	-3.478	1.878	3.467	2.845
0.003	-1.863	-4.343	na	1.908	3.646	na
0.002	-1.905	-4.698	na	1.951	3.903	na
0.001	-1.976	-5.341	na	2.021	4.360	na
0.0005	-2.044	-6.033	na	2.089	4.838	na
0.0004	-2.065	-6.268	na	2.111	4.997	na
0.0003	-2.093	-6.578	na	2.138	5.205	na
0.0002	-2.131	-7.033	na	2.176	5.506	na
0.0001	-2.195	-7.856	na	2.240	6.040	na

Intradaily price changes are calculated using Equations (39) and (40) for the extreme value distribution, Equations (41) and (42) for the normal distribution, and Equations (43) and (44) for the empirical distributions.

Table 16
Panel A
Margin Violation Probabilities Given Associated Price Changes for the June 1992 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	0.000	0.000
10%	0.000	0.001	0.000	0.000	0.000	0.000
5%	0.000	0.004	0.000	0.000	0.002	0.000
4%	0.000	0.008	0.006	0.000	0.004	0.000
3%	0.000	0.016	0.006	0.000	0.009	0.000
2%	0.002	0.044	0.034	0.000	0.029	0.034
1%	0.982	0.188	0.218	0.784	0.157	0.162
0.5%	1.000	0.509	0.480	1.000	0.480	0.458
0.4%	1.000	0.626	0.609	1.000	0.600	0.575
0.3%	1.000	0.757	0.760	1.000	0.734	0.709
0.2%	1.000	0.883	0.888	1.000	0.865	0.860
0.1%	1.000	0.969	0.983	1.000	0.958	0.989
0.05%	1.000	0.990	0.994	1.000	0.984	1.000
0.04%	1.000	0.992	0.994	1.000	0.987	1.000
0.03%	1.000	0.994	0.994	1.000	0.990	1.000
0.02%	1.000	0.996	1.000	1.000	0.992	1.000
0.01%	1.000	0.997	1.000	1.000	0.994	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel B
Margin Violation Probabilities Given
Associated Price Changes for
the September 1994 Contract

	Margin Violation Probability					
Absolute Margin Level	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	0.000	0.000
10%	0.000	0.000	0.000	0.000	0.000	0.000
5%	0.000	0.000	0.000	0.000	0.000	0.000
4%	0.000	0.000	0.000	0.000	0.001	0.000
3%	0.000	0.001	0.000	0.000	0.002	0.000
2%	0.000	0.007	0.000	0.000	0.010	0.000
1%	0.000	0.073	0.078	0.000	0.091	0.113
0.5%	0.582	0.394	0.365	0.722	0.423	0.409
0.4%	0.946	0.555	0.530	0.983	0.573	0.522
0.3%	1.000	0.750	0.783	1.000	0.747	0.754
0.2%	1.000	0.920	0.913	1.000	0.903	0.922
0.1%	1.000	0.993	0.991	1.000	0.986	1.000
0.05%	1.000	0.999	1.000	1.000	0.997	1.000
0.04%	1.000	1.000	1.000	1.000	0.998	1.000
0.03%	1.000	1.000	1.000	1.000	0.999	1.000
0.02%	1.000	1.000	1.000	1.000	0.999	1.000
0.01%	1.000	1.000	1.000	1.000	1.000	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel C
Margin Violation Probabilities Given Associated Price Changes for the December 1992 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	na	0.000
10%	0.000	0.000	0.000	0.000	na	0.000
5%	0.000	0.004	0.000	0.000	na	0.000
4%	0.000	0.008	0.011	0.000	na	0.000
3%	0.000	0.020	0.011	0.000	na	0.000
2%	0.001	0.064	0.059	0.000	na	0.032
1%	0.906	0.283	0.306	0.863	na	0.274
0.5%	1.000	0.636	0.613	1.000	na	0.586
0.4%	1.000	0.730	0.710	1.000	na	0.661
0.3%	1.000	0.822	0.812	1.000	na	0.737
0.2%	1.000	0.902	0.882	1.000	na	0.860
0.1%	1.000	0.959	0.973	1.000	na	0.973
0.05%	1.000	0.977	1.000	1.000	na	0.995
0.04%	1.000	0.980	1.000	1.000	na	0.995
0.03%	1.000	0.982	1.000	1.000	na	0.995
0.02%	1.000	0.985	1.000	1.000	na	1.000
0.01%	1.000	0.987	1.000	1.000	na	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel D
Margin Violation Probabilities Given Associated Price Changes for the March 1993 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	na	0.000
10%	0.000	0.000	0.000	0.000	na	0.000
5%	0.000	0.002	0.000	0.000	na	0.000
4%	0.000	0.005	0.011	0.000	na	0.000
3%	0.000	0.015	0.011	0.000	na	0.000
2%	0.001	0.055	0.048	0.000	na	0.037
1%	0.230	0.301	0.299	0.225	na	0.321
0.5%	1.000	0.724	0.738	1.000	na	0.695
0.4%	1.000	0.825	0.818	1.000	na	0.824
0.3%	1.000	0.911	0.888	1.000	na	0.882
0.2%	1.000	0.967	0.973	1.000	na	0.941
0.1%	1.000	0.993	0.984	1.000	na	0.979
0.05%	1.000	0.998	0.995	1.000	na	0.989
0.04%	1.000	0.998	0.995	1.000	na	0.989
0.03%	1.000	0.999	0.995	1.000	na	0.989
0.02%	1.000	1.000	1.000	1.000	na	1.000
0.01%	1.000	1.000	1.000	1.000	na	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel E
Margin Violation Probabilities Given
Associated Price Changes for
the June 1993 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	0.000	0.000
10%	0.000	0.000	0.000	0.000	0.000	0.000
5%	0.000	0.001	0.000	0.000	0.000	0.000
4%	0.000	0.003	0.006	0.000	0.001	0.000
3%	0.000	0.008	0.006	0.000	0.004	0.006
2%	0.000	0.032	0.023	0.000	0.023	0.011
1%	0.095	0.202	0.236	0.029	0.189	0.218
0.5%	1.000	0.584	0.586	0.995	0.598	0.580
0.4%	1.000	0.702	0.701	1.000	0.721	0.713
0.3%	1.000	0.819	0.828	1.000	0.838	0.856
0.2%	1.000	0.916	0.908	1.000	0.930	0.931
0.1%	1.000	0.975	0.966	1.000	0.981	0.966
0.05%	1.000	0.990	0.989	1.000	0.992	0.983
0.04%	1.000	0.992	0.989	1.000	0.994	0.983
0.03%	1.000	0.993	1.000	1.000	0.995	1.000
0.02%	1.000	0.995	1.000	1.000	0.996	1.000
0.01%	1.000	0.996	1.000	1.000	0.997	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel F
Margin Violation Probabilities Given Associated Price Changes for the September 1993 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	na	0.000	0.000	0.000	0.000
10%	0.000	na	0.000	0.000	0.000	0.000
5%	0.000	na	0.000	0.000	0.000	0.000
4%	0.000	na	0.000	0.000	0.001	0.000
3%	0.000	na	0.000	0.000	0.004	0.000
2%	0.000	na	0.011	0.000	0.023	0.017
1%	0.536	na	0.234	0.477	0.188	0.183
0.5%	1.000	na	0.594	1.000	0.573	0.611
0.4%	1.000	na	0.726	1.000	0.689	0.691
0.3%	1.000	na	0.806	1.000	0.804	0.771
0.2%	1.000	na	0.886	1.000	0.901	0.909
0.1%	1.000	na	0.960	1.000	0.964	0.966
0.05%	1.000	na	0.994	1.000	0.982	1.000
0.04%	1.000	na	0.994	1.000	0.985	1.000
0.03%	1.000	na	1.000	1.000	0.987	1.000
0.02%	1.000	na	1.000	1.000	0.989	1.000
0.01%	1.000	na	1.000	1.000	0.991	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel G
Margin Violation Probabilities Given Associated Price Changes for the December 1993 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	na	0.000	0.000	0.000	0.000
10%	0.000	na	0.000	0.000	0.000	0.000
5%	0.000	na	0.000	0.000	0.000	0.000
4%	0.000	na	0.000	0.000	0.001	0.000
3%	0.000	na	0.000	0.000	0.004	0.000
2%	0.000	na	0.006	0.000	0.027	0.017
1%	0.332	na	0.264	0.299	0.235	0.183
0.5%	1.000	na	0.626	1.000	0.626	0.611
0.4%	1.000	na	0.724	1.000	0.726	0.691
0.3%	1.000	na	0.822	1.000	0.820	0.771
0.2%	1.000	na	0.902	1.000	0.898	0.909
0.1%	1.000	na	0.954	1.000	0.953	0.966
0.05%	1.000	na	0.977	1.000	0.971	1.000
0.04%	1.000	na	0.977	1.000	0.974	1.000
0.03%	1.000	na	0.983	1.000	0.977	1.000
0.02%	1.000	na	1.000	1.000	0.980	1.000
0.01%	1.000	na	1.000	1.000	0.981	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel H
Margin Violation Probabilities Given
Associated Price Changes for
the March 1994 Contract

	Margin Violation Probability					
Absolute Margin Level	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	0.000	0.000
10%	0.000	0.000	0.000	0.000	0.000	0.000
5%	0.000	0.002	0.000	0.000	0.001	0.000
4%	0.000	0.006	0.006	0.000	0.003	0.000
3%	0.000	0.020	0.024	0.000	0.013	0.006
2%	0.013	0.077	0.055	0.000	0.064	0.067
1%	0.995	0.358	0.376	0.977	0.352	0.364
0.5%	1.000	0.714	0.700	1.000	0.718	0.721
0.4%	1.000	0.792	0.794	1.000	0.796	0.800
0.3%	1.000	0.863	0.842	1.000	0.865	0.848
0.2%	1.000	0.921	0.921	1.000	0.921	0.915
0.1%	1.000	0.961	0.982	1.000	0.960	0.970
0.05%	1.000	0.975	1.000	1.000	0.974	0.988
0.04%	1.000	0.978	1.000	1.000	0.976	0.988
0.03%	1.000	0.980	1.000	1.000	0.978	0.988
0.02%	1.000	0.982	1.000	1.000	0.980	1.000
0.01%	1.000	0.984	1.000	1.000	0.982	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel I
Margin Violation Probabilities Given Associated Price Changes for the June 1994 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	0.000	0.000
10%	0.000	0.000	0.000	0.000	0.000	0.000
5%	0.000	0.002	0.000	0.000	0.001	0.000
4%	0.000	0.006	0.000	0.000	0.002	0.000
3%	0.000	0.020	0.017	0.000	0.009	0.006
2%	0.001	0.083	0.079	0.000	0.048	0.040
1%	0.934	0.377	0.381	0.643	0.325	0.313
0.5%	1.000	0.713	0.705	1.000	0.745	0.756
0.4%	1.000	0.784	0.790	1.000	0.834	0.830
0.3%	1.000	0.849	0.841	1.000	0.907	0.903
0.2%	1.000	0.904	0.898	1.000	0.958	0.966
0.1%	1.000	0.945	0.949	1.000	0.986	0.983
0.05%	1.000	0.961	0.966	1.000	0.993	0.994
0.04%	1.000	0.964	0.977	1.000	0.994	1.000
0.03%	1.000	0.967	0.977	1.000	0.995	1.000
0.02%	1.000	0.969	1.000	1.000	0.996	1.000
0.01%	1.000	0.971	1.000	1.000	0.997	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

Table 16
Panel J
Margin Violation Probabilities Given
Associated Price Changes for
the September 1994 Contract

Absolute Margin Level	Margin Violation Probability					
	Long Futures Position			Short Futures Position		
	Normal	Extreme	Empirical	Normal	Extreme	Empirical
20%	0.000	0.000	0.000	0.000	0.000	0.000
10%	0.000	0.000	0.000	0.000	0.000	0.000
5%	0.000	0.001	0.000	0.000	0.000	0.000
4%	0.000	0.005	0.000	0.000	0.002	0.000
3%	0.000	0.017	0.012	0.000	0.009	0.000
2%	0.001	0.075	0.080	0.001	0.053	0.068
1%	0.873	0.387	0.377	0.930	0.357	0.346
0.5%	1.000	0.762	0.759	1.000	0.759	0.747
0.4%	1.000	0.836	0.840	1.000	0.838	0.852
0.3%	1.000	0.899	0.901	1.000	0.903	0.926
0.2%	1.000	0.946	0.951	1.000	0.951	0.975
0.1%	1.000	0.976	0.969	1.000	0.980	0.981
0.05%	1.000	0.986	0.988	1.000	0.988	0.981
0.04%	1.000	0.987	0.994	1.000	0.990	0.988
0.03%	1.000	0.989	0.994	1.000	0.995	0.988
0.02%	1.000	0.990	1.000	1.000	0.991	1.000
0.01%	1.000	0.991	1.000	1.000	0.993	1.000

The margin violation probabilities are calculated from Equation (34) for the extreme value distribution, Equations (32) and (33) for the normal distribution, and Equations (35) and (36) for the empirical distribution.

The extreme value distribution appears to be a much better representation of the empirical distribution than the normal distribution function. This relationship is evident in almost every panel found in both Tables 15 and 16, and is relatively robust to whatever contract chosen. Not only are the extreme value distribution results closer to the empirical distribution calculations, they also exhibit a greater sensitivity to changes in given margin violation probabilities than the normal figures.

3.6 CHAPTER 3 SUMMARY

The objective of Chapter 3 was to provide information related to the distributional characteristics of extreme intradaily price changes of DAX futures contracts and to provide accurate probabilities of observing those extreme values. This objective was framed within a margin setting example. The practical goal of this exercise was to contribute valuable insight on the feasibility of using extreme value theory by the DTB's margin setting committee when setting intradaily margin requirements.

The results of the analysis can be summarized as follows. First, the intradaily extreme price movements of DAX stock index futures contracts appear to follow a Type II extreme value limiting distribution. This result is intuitive and provides additional evidence that high frequency financial data are generated by non-normal data generation processes.

Secondly, the extreme value distribution generates extreme intradaily price movements, given set probability levels, and probability levels, given set intradaily price changes, that are closer to those observed in the data samples than the normal distribution. These results indicate that the extreme value statistical technique is a useful tool to apply when extrapolating the probability of observing extremes outside the boundaries set by the data.

The normative implication of this study is that margin setting committees should use extreme value theory as an aid in setting prudent margin levels. The prudent action is being able to better protect against trader default resulting from extreme price movements of the invested asset. The extreme value statistical technique is shown to be a superior statistical tool for generating realistic probabilities of margin default than assuming normally distributed data.

CHAPTER 4

SUMMARY AND SUGGESTIONS FOR FUTURE RESEARCH

The objective of this dissertation was to examine the price discovery and risk processes of Germany's stock index and stock index futures market. The price discovery process was analyzed using the information processing speed, via lead-lag, between each market. The risk process was examined via the properties of the extreme values found in the futures market.

The results of the lead-lag analysis indicate that, on average, the futures market tends to process information more quickly than the spot market. However, there exists a feedback of information processing indicating that the futures market does not completely dominate the information processing capability of the spot market.

The futures market processing time appears to be increased when market participants posses market-wide information, but decreased when the market experiences large (extreme) price movements. Suggestions for future research in this area should concentrate on: (1) Why Deutsche Bank and Allianz appear to lead the futures market on occasion (2) the differential information processing aspects found in extreme price movement markets, and (3) the impacts of defining trading activity in different ways, either by volume or number of transactions.

The results of the extreme value analysis indicate that extreme price changes of the futures market follow a

Type II limiting extreme value distribution. Applying this result in a prudent margin setting framework indicates that using the extreme value distribution yields better protection against price movements than assuming normally distributed data.

Suggested future research in this area is related to determining the stationary/non-stationary characteristics of the extreme value parameters, and examining multi-contract price movement impacts on the extreme value distribution.

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