Price Formation in Spot and Futures Markets: Exchange Traded Funds vs. Index Futures

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Abstract

This paper reconsiders the process of price discovery in spot and futures markets. In our study, we examine the contribution of two derivative products of the German blue chip index DAX: Exchange traded funds and index futures. In order to eliminate noise caused by differences in the microstructure of the markets, we use transaction data only from electronic-trading markets. We apply a linear vector error correction model for our estimations and we use the common factor weights, first proposed by Schwarz and Szakmary (1994), to quantify the contribution of each market to the process of price discovery. Our results indicate that the futures market leads in the process of price discovery. Furthermore, we show that volatility, and not liquidity, as would be conjectured by the transaction-costs hypothesis, is the driving factor for relative price leadership between the two markets.

JEL classification: G13, G14, G19.

Keywords: Index Futures, Exchange Traded Funds, Vector Error Correction Model, Common Factor Weights.

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1 Introduction

In recent years, there has been a move in financial markets towards the trading of identical or closely related assets in parallel markets. For instance, futures contracts have been introduced for the indices, such as the US-based Dow Jones Industrial Average (DJIA), the S&P 500, as well as the German index DAX 30. More recently, a new market segment, the so-called exchange traded funds (ETFs), has drawn considerable attention. ETFs are closely related to mutual funds in that they hold portfolios of financial assets. However, unlike mutual funds, ETFs are traded or priced continuously during exchange trading sessions, similarly to stocks. The arrival of basket securities, such as financial futures and ETFs, facilitates market participation of uninformed traders and allows inexpensive index arbitrage (e.g., Subrahmanyam (1991) and Gorton and Pennacchi (1993)).

According to the efficient market hypothesis, new information should be impounded simultaneously in all markets. Yet, due to institutional differences, such as the magnitude of transaction costs, markets may differ in the speed of information dissemination. It is therefore an interesting research question to investigate which market incorporates new information faster and consequently contributes more to the process of price discovery. This question has drawn considerable attention in the financial literature. Due to the fact that indices and its derivative products are cointegrated, the model commonly used to investigate price formation in financial markets is some version of the vector error correction model (VECM) introduced by Hasbrouck (1995). Cointegration theory suggests that price differences between markets do not diverge infinitely. Rather, there exists a long-term relationship between prices in parallel markets. The VECM directly links changes in futures and spot prices to deviations from the long-run relation. The VECM specification stipulates that prices may deviate from their common long-run relation. However, arbitrage forces ensure that prices converge to their theoretically stipulated relation. One difficulty when estimating the VECM using spot and futures prices is the fact that the cointegration relation, which is induced by the cost-of-carry relation between the two markets, is time-varying. One possible solution is demeaning of the log price series for each trading day. This approach, which removes any average daily level difference between the spot and futures price series while leaving intraday returns unaffected, was introduced by Dwyer, Locke, and Yu (1996) and adopted by Theissen (2005), among others. In our analysis, we follow a different approach, applied by a variety of authors, such as Martens, Kofman, and Vorst (1998) and Tse (2001). Using a pre-specified cointegrating vector, we take the cost-of-carry relationship directly into account and base our analysis on discounted futures prices.

Despite all methodological differences, the majority of studies have shown that the futures market leads the index market in price discovery. Stoll and Whaley (1990) and Chan (1992) for the S&P 500 index, and Tse (1999), Tse (2001), and Tse, Bandyopadhyay, and Shen (2006) for the DJIA index report the dominance of the futures market in price discovery. For the German market, Booth, So, and Tse (1999), who consider the DAX index, index futures and index options in their investigation on price leadership in the German market, show that index futures dominate in the process of price formation. Similarly, Theissen (2005) finds that the futures market leads the spot market in terms of relative contribution to price discovery.

The empirical investigations have so far focused mainly on the index itself and the corresponding futures market. Despite the tremendous growth in ETF trading, few studies have been conducted on the relative price discovery of ETFs and index futures. Since the majority of previous studies have reported a leadership of the futures market relative to the index, the examination of whether the ETF market, in turn, leads the futures market in price discovery is the logical next step. Given their lower transaction costs and absence of short-sale restrictions, ETF markets may potentially incorporate new information faster than cash indices. Hence, the price leadership of the futures market, relative to the spot market, might be weakened in the new setting where the ETF market is considered in place of the index itself. Hasbrouck (2003) analyzes price leadership among the three S&P 500 index derivatives, the

ETF, the electronically-traded small-denomination futures contract "E-mini," and the regular floor-traded futures contract. His main finding states that the "E-mini" leads the process of price discovery by contributing roughly 90% to price formation. However, his results are based on ETF data obtained from Amex, which uses floor-trading. Since electronic trading offers the advantages of lower trading costs and trader anonymity, the results of Hasbrouck (2003) may shift in favor of the ETF market. Tse, Bandyopadhyay, and Shen (2006) address this issue by including electronically-traded ETFs from ArcaEx, a computer-mediated trading system, in their examination of the price leadership of the DJIA index and its derivatives (ETFs, floor-traded futures contracts, and electronically-traded "E-mini futures"). In this setting, the authors find that the ETFs make a significant contribution to the process of price discovery.

Our goal is to examine the relative contribution to price discovery of the ETF market and the futures market in Germany, two derivative products of the German blue chip index DAX. We estimate the VECM using DaxEx (ETF) prices and DAX futures prices adjusted for the cost-of-carry. The contribution of this paper to the existing literature is twofold: First, even though previous papers have investigated price discovery in the German market, none of them has thus far included the increasingly important ETFs in their analysis. For instance, Grünbichler, Longstaff, and Schwartz (1994), Kempf and Korn (1998), and Theissen (2005) analyze the lead-lag relationship for the German spot and futures market, but do not consider the market for ETFs. Hence, our paper is the first empirical investigation of price discovery with respect to the ETF market and the futures market in Germany. Our results indicate that the futures market leads in the process of price discovery. Second, we extend the literature on price leadership in spot and futures markets by investigating which factors drive the price leadership of the futures market and potentially lead to a shift in price formation in favor of the ETF market. Precisely, we analyze whether liquidity and/or volatility affect relative price formation. Our results show that when volatility is high the contribution of the ETF market to the process of price discovery increases. Liquidity turns out to have no impact on price leadership.

In order to quantify the contribution of the two markets to the process of price discovery, we use the so-called common factor weights (CFW), first introduced by Schwarz and Szakmary (1994). This intuitive measure can be simply calculated from the coefficients of the VECM. In order to eliminate undesirable effects on the results due to differences in the microstructure of the markets, our analysis is based on data from electronic-trading markets. This procedure closely follows Tse, Bandyopadhyay, and Shen (2006).

The remainder of this paper is organized as follows. Section 2 presents the relevant economic and econometric models and discusses the measure we use in our study to assess the contributions to price discovery. Section 3 provides some details about the ETF market and the product itself. Section 4 describes the data used in our analysis and presents some descriptive statistics, as well as the results of the stationarity tests. Section 5 documents the empirical results, and in Section 6 the determinants for price leadership are analyzed. Finally, Section 7 concludes.

2 Methodology

2.1 The Economic Model

The relation between spot and futures prices is described by the cost-of-carry model. Under the no-arbitrage condition, i.e., a situation where a futures contract is priced at its "fair value," which rules out arbitrage opportunities between the spot and the futures market, the model takes the following form:

$$F_{t,T} = S_t e^{(r_{t,T} - \kappa_{t,T})(T-t)}, \tag{1}$$

where $F_{t,T}$ is the price of a futures contract expiring at time T, S_t is the spot price, $r_{t,T}$ is the risk-free interest rate on an investment for the time period (t,T), and $\kappa_{t,T}$ is the expected dividend yield on the underlying asset.[1] Any deviation from the relation described by equation (1) creates arbitrage opportunities. If, for instance, $F_t > S_t e^{(r_{t,T}-\kappa_{t,T})(T-t)}$, arbitrageurs can earn a profit by taking a long position in the index, i.e., by buying the stocks in the index and shorting the futures contract. For $F_t < S_t e^{(r_{t,T}-\kappa_{t,T})(T-t)}$, the reverse arbitrage strategy should be executed.

Following the cost-of-carry relation, we define the pricing error as

$$z_t = p_t^S - (\underbrace{f_t - (r_{t,T} - \kappa_{t,T})(T-t)}_{\equiv p_t^F}), \tag{2}$$

where $f_t = \ln(F_t)$ and $p_t^S = \ln(S_t)$;[2] hence, z_t may be considered the percentage change of mispricing. Values of the pricing error different from zero indicate arbitrage opportunities, given that we assume zero transaction costs associated with index arbitrage. Since it takes time for arbitrageurs to take appropriate positions in the spot and the futures markets, this arbitrage opportunity has to be lagged by d periods of time, where d is the delay inherent in the arbitrage process. Hence, arbitrage activity takes place when the following inequality holds:

$$z_{t-d} \neq 0. \tag{3}$$

When arbitrageurs enter into the market, the next observations of the pricing error move fast towards zero.

2.2 The Econometric Model

In this section, we provide motivation and details of an econometric model for describing arbitrage activity and investigating whether the spot market or the futures market leads the

[1] Henceforth, for convenience we drop subscript T, indicating the expiration day of the futures contract.
[2] Note that p_t^F denotes the log futures prices adjusted for the cost-of-carry.

process of price discovery.

Previous empirical literature (e.g., Martens, Kofman, and Vorst (1998) and Dwyer, Locke, and Yu (1996)) has concluded that spot indices and futures have unit roots, i.e., are non-stationary, whereas the respective pricing error, as defined above, is stationary. This, in turn, implies that spot and futures prices adjusted for the cost-of-carry are cointegrated with a coefficient of unity. As such, the relation between these time series can be characterized by an error correction representation (see Engle and Granger (1987)).[3] Such an error correction model directly links changes in futures and spot prices to deviations from the arbitrage relation, i.e., the pricing error. The error correction specification stipulates that prices undergo some short-term disruption, i.e., they deviate from the long-run relation (1). However, since prices possess the same long-run properties, this implies that they adjust due to arbitrage trading aimed at exploiting mispricing.

We follow other studies in this field, such as Dwyer, Locke, and Yu (1996) and Theissen (2005), and model current futures and spot returns by lagged futures and spot returns and by deviations from the cost-of-carry relation in the previous period, $z_{t-1} = p^S_{t-1} - p^F_{t-1}$.[4] Formally, the linear vector error correction model works as follows:

$$\begin{aligned} \Delta p^S_t &= \alpha^S + \sum_{i=1}^{k} \gamma_{11i} \Delta p^S_{t-i} + \sum_{i=1}^{k} \gamma_{12i} \Delta p^F_{t-i} + \delta^S (p^S_{t-1} - p^F_{t-1}) + u^S_t, \\ \Delta p^F_t &= \alpha^F + \sum_{i=1}^{k} \gamma_{21i} \Delta p^S_{t-i} + \sum_{i=1}^{k} \gamma_{22i} \Delta p^F_{t-i} + \delta^F (p^S_{t-1} - p^F_{t-1}) + u^F_t, \end{aligned} \tag{4}$$

where Δp_t are logarithmic futures (F) and spot (S) returns and superscripts S and F identify

[3]See Brenner and Kroner (1995) for a summary of various applications of cointegration relations in financial research.

[4]Since in our study we use transaction prices rather than quotes, the time in our framework is transaction time rather than continuous clock time. Therefore, the time index t refers to observations in transaction time.

coefficients relating to the respective markets.[5]

Following Martens, Kofman, and Vorst (1998) and Tse (2001), we use a pre-specified cointegrating vector which enters the model as the error correction term z_{t-1}, defined by equation (2).[6] This procedure takes the cost-of-carry relation explicitly into account and at the same time captures the time-variability of the cointegration relation.[7]

The coefficients on the error correction term, δ^S and δ^F, indicate which market dominates the process of price formation and how the system adjusts to deviations from the long-run equilibrium. If the futures market impounds information faster than the spot market, δ^F should be insignificant whereas δ^S will be significantly negative, indicating that the spot price exhibits adjustment tendencies. In other words, the futures market reflects information first and thus does not show adjustment movements. If instead information disseminates in the spot market first, δ^S will be insignificant and δ^F will be positive and significant.

2.3 Measure for the Contribution to Price Discovery: Common Factor Weights

In order to assess the contribution to price discovery of each market, we use the common factor weights (CFW) of Schwarz and Szakmary (1994) who propose a measure that is calculated

[5]These two equations stem from the general vector error correction model developed to investigate the long-run and short-run relationships between price series that are cointegrated. This general model can be specified as

$$\Delta\mathbf{p}_t = \alpha + \mathbf{\Gamma}_1\Delta\mathbf{p}_{t-1} + \mathbf{\Gamma}_2\Delta\mathbf{p}_{t-2} + \ldots + \mathbf{\Gamma}_p\Delta\mathbf{p}_{t-p} + \delta(\beta'\mathbf{p}_{t-1} - \mu_e) + \mathbf{u}_t, \qquad (5)$$

where $\mathbf{\Gamma}_i$ is the coefficient matrix of the ith lag in the returns of the price vector, α is the constant term, δ is the error correction coefficient, β is the cointegration vector, and $\mu_{\mathbf{e}}$ is the expected value of the cointegration relation. In our case, the term μ_e is expected to be zero ($\mu_e = 0$) and the cointegration vector is supposed to be $(1, -1)$.

[6]Note that in the following analysis the expected dividend yield does not enter the cost-of-carry relation, since we consider DAX derivative products and the calculation of the DAX as a performance index is based on the presumption that dividends are reinvested.

[7]Dwyer, Locke, and Yu (1996) and Theissen (2005), among others, follow a different approach to avoid the problem arising due to the non-constant cointegration relation. In their empirical analyses, they modify spot and futures time series by subtracting the daily mean from the logarithms of the spot and the futures price series.

by using the coefficients on the error correction term in model (4). The relative magnitude of these coefficients quantifies the contribution of the two markets to price discovery. Formal justifications, which are based on Gonzalo and Granger (1995), are given, for instance, by Theissen (2002) and Booth, Lin, Martikainen, and Tse (2002). Specifically, the common factor weights are obtained as follows:[8]

$$CFW^S = \frac{\delta^F}{\delta^F - \delta^S} \text{ and } CFW^F = \frac{-\delta^S}{\delta^F - \delta^S}. \tag{7}$$

As mentioned in the previous section, the coefficients δ^S and δ^F indicate the way of adjustment of the system to deviations from the cost-of-carry relation. The higher the magnitude of δ^j $(j = \{S, F\})$, the slower the market impounds new information or, stated differently, the more the market has to adjust toward the new equilibrium price. That is, the market which leads the process of price formation does not follow but rather initiates the deviation from the cost-of-carry relation. For instance, if the futures market impounds information faster than the spot market, δ^S will be significant, indicating that the spot price exhibits adjustment tendencies, and δ^F will be insignificant. If price discovery occurs only in the futures market, $CFW^F = 1$; conversely, if price discovery occurs exclusively in the spot market, $CFW^F = 0$. If both markets contribute equally to the process of price discovery, $CFW^F = CFW^S = 0.5$.

The sum of the coefficients δ^j can be interpreted as the total adjustment of the system to a shock in at least one market. The common factor weights quantify the part of the total reaction attributed to a particular market. Simultaneous small/large values of the error correction coefficients for both markets indicate slow/fast adjustment dynamics. In the extreme case, where the coefficients δ^j are equal to zero, the supply of arbitrage services is

[8] This is equivalent to

$$CFW^S = \frac{|\delta^F|}{|\delta^F| + |\delta^S|} \text{ and } CFW^F = \frac{|\delta^S|}{|\delta^F| + |\delta^S|}, \tag{6}$$

as long as the coefficients δ^F and δ^S have the correct signs, i.e., $\delta^F > 0$ and $\delta^S < 0$.

zero. In this case, spot and futures prices are independent random walks and, as a result, not cointegrated. Standardizing the common factor weights, so that they sum up to one, yields a measure to quantify the relative price leadership.

3 Exchange Traded Funds

In the past few years, a substantial growth in trading volume and product coverage occurred in the ETF market showing the increasing popularity of those funds. Table 1 displays the increase in trading volume for the DaxEx, the most liquid ETF traded on XTF Xetra provided by Deutsche Boerse AG. ETFs cover a broad spectrum of investment options across domestic and global markets, diverse market capitalization, and investment styles. Thus, ETFs offer a great opportunity for diversification and therefore an interesting investment alternative. Trading ETFs allows to trade a whole basket of stocks in one transaction, a feature common with futures and certificates. For this reason, ETFs, similarly to other basket securities (such as index futures), facilitate market participation of uninformed traders, but simultaneously attract informed traders. We have informally been told that trades by institutional investors amount to 90-95% of the trading volume, indicating that the ETF market is a valid counterpart for the index itself in terms of information arrival. This fact, in connection with the previously mentioned advantages of the ETF market over the index, provides reason for the conjecture that relative price leadership between spot and futures markets may have shifted in favor of the spot market (ETF market).

In Germany, ETFs are traded on the electronic market XTF, provided by Deutsche Boerse AG. In our study, we use data of the DaxEx (ISIN: DE0005933931) which represents one product on this market.[9] The DaxEx is (now) issued by Barclays Global Investors (Deutsch-

[9]Due to a recent acquisition of INDEXCHANGE Investment AG through Barclays Bank PLC in 2007, the DaxEx was renamed and is now iShares DAX (DE). However, throughout this paper we refer to the ETF as the DaxEx.

land) AG and replicates the German blue chip index DAX.[10] Hence, as soon as the index composition or the relative weights of the DAX index are changed, the ETF fund management is forced to change the composition of the DaxEx. For replication purposes, it is allowed to solely use stocks of the index, certificates on the index, certificates on stocks of the index, forward contracts on the stocks of the index, and forward contracts on the index. Among these alternatives, the stocks in the index have absolute priority. ETF managers are supposed to meet a required degree of duplication of 95%.[11]

The DaxEx is an ETF which retains its profits, that is all dividends of the stocks in its portfolio are not distributed to the shareholders but are reinvested, as is the case for the DAX index. This feature allows the fund to hold a very close replication of the underlying index. Furthermore, administrative fees are deducted every day and a small fraction of the assets are held in cash. These features cause the fund to slightly underperform the index. The fund might also outperform the index, when markets are falling (this is referred to as cashdrag).

4 Data

We use high-frequency observations of transaction prices for both the DaxEx and the DAX futures (FDax). The starting point of our sample is the first trading day of July 2005 and the last data point is the final trading day of December 2005.

Futures contracts on the DAX are traded on EUREX exchange. These futures expire on the third Friday of the months of March, June, September, and December. Hence, our price series includes three expiration dates for futures contracts, the third Friday of September 2005, the third Friday of December 2005 and the third Friday of March 2006. All data are

[10]The DAX is a value-weighted index calculated from the prices of the 30 most liquid German stocks.

[11]The degree of duplication (DG) is calculated by the following formula: $DG = 100\% - \frac{\sum_{i=1}^{n} |w_i^I - w_i^F|}{2}$, where w_i^I is the weight of stock i in the index in percent, w_i^F is the weight of stock i in the fund in percent, and n is the number of stocks in the index.

obtained from Deutsche Boerse AG.

Since the data include many more transaction prices for the FDax than for the DaxEx, we have to eliminate some futures prices in order to synchronize the two price series. We opt for an approach described in Harris, McInish, Shoesmith, and Wood (1995) where for every transaction price of the DaxEx we identify the most recent transaction price of the FDax and by this match the price series for our model.[12] Therefore, in each pair of transaction prices the observation of the FDax is usually slightly older (but never more recent) than the matched observation of the DaxEx. Consequently, this synchronization works clearly to the disadvantage of the futures market.

Another difficulty arises due to differences in the microstructure between the two markets, XTF (Deutsche Boerse's ETF segment) for the DaxEx and EUREX for the FDax. On XTF, there are three auctions for the DaxEx per trading day, but no such auction takes place on EUREX for the FDax. Both markets are electronic continuous trading markets, except for the three auction periods on XTF. Since differences in the market structure could influence our estimations, we only consider prices of the simultaneous continuous trading time of both markets and discard prices recorded during the auction periods on XTF.[13] Regular trading on XTF starts after the morning auction at 9.04 a.m. and extends until 5.30 p.m., when the final auction is held. We therefore eliminate all price data before 9.04 a.m. and from 5.30 p.m. onwards. We further discard all prices within a five minute interval from the time of the intraday auction which takes place from 1.10 p.m. to 1.12 p.m.

As outlined earlier, a time-varying cointegration relation between futures and spot prices

[12]There are, of course, alternative ways to synchronize the data. Harris, McInish, Shoesmith, and Wood (1995) provide a good comparison of alternative methods to synchronize transaction data. Their study finds that the results for alternative synchronizations are quite similar. We also checked for potential changes in the results due to variations of the synchronization method but the results are similar and the conclusions remain the same.

[13]Previous papers, such as Grünbichler, Longstaff, and Schwartz (1994) and Kempf and Korn (1998), analyze various spot and futures markets. Their attention is focused on possible implications of different trading protocols for the process of price discovery.

is implied by the cost-of-carry relationship. In order to appropriately consider the time-variation of this cointegrating relation, we calculate adjusted futures prices by discounting the futures data series. As an approximation for the risk-free interest rate we use Eonia (Euro OverNight Index Average).[14] The daily risk-free interest rate is a good approximation for the interest rate in the cost-of-carry relation for futures traded on EUREX, since investors have to pay a collateral for their position.[15] The amount of the margin is calculated on a daily basis and the collaterals are invested at daily risk-free interest rates.

Table 2 gives some descriptive statistics for the return series of the two markets. The standard deviations (adjusted for autocorrelation) in both markets are nearly equal. Both markets show negative skewness and excess kurtosis, with both being more pronounced in the futures market. The return series show negative serial correlation, most likely due to the bid-ask bounce. The autocorrelation is considerably lower in the futures market, which may be due to the elimination of a significant number of DAX futures observations.

An important prerequisite for estimating an error correction model is that the price series are integrated of order one (I(1)), which means that the first differences have to be integrated of order zero (I(0)). Another necessary condition for our estimation is that the two series are cointegrated. Table 3 presents the results of the Augmented Dickey-Fuller test and of the Phillips-Perron test for the level and the first difference of the series, respectively. The results of the two tests indicate clearly that both time series are I(1). That is, for the levels the null hypothesis of non-stationarity is not rejected, whereas for the first differences it is clearly rejected. Further tests indicate that the two price series are cointegrated according to the cost-of carry relation.[16]

[14]Eonia was extracted from Thomson Financial Datastream.

[15]For further information, visit www.eurexchange.com.

[16]The results of the Augmented Dickey-Fuller test (p-value 0.0000) and of the Phillips-Perron test (p-value 0.0001) applied to the difference between the adjusted futures time series and the DaxEx time series suggest stationarity of the pricing error. The results of the Johansen tests (not shown in the paper) clearly indicate that the adjusted futures time series and the DaxEx time series are cointegrated.

5 Empirical Results

Model (4) is estimated by using ordinary least squares (OLS). Both the Schwarz information criterion (SIC) and the Akaike information criterion (AIC) suggest to include 16 lags. Table 4 thus shows the results of the estimation with $k = 16$ lags included. In order to conserve space, we only report the coefficients on the first four lags. The results show that the independent variables for the cash market have much more explanatory power than the independent variables for the futures market, as indicated by an adjusted R^2 of 0.058 in the spot market and 0.015 in the futures market.[17] The returns of both markets depend negatively on their own lagged returns, probably due to the bid-ask bounce, and positively on the lagged returns of the respective other market. Bi-directional causality is indicated by the F-statistic. However, the t-statistics of the coefficients reveal that the cash market depends much more on the lagged returns of the futures market than the futures market on lagged returns of the spot market.

The coefficient on the error correction term shows that the spot market responds to the futures market, as indicated by a negative sign on the error correction term ($\delta^S = -0.0487$). The impact of the error correction term in the futures market is much less significant than it is in the spot market ($\delta^F = 0.0165$), though it has the expected positive sign. While both markets contribute to the process of price discovery, the futures market appears to dominate the process. According to the CFW, which are reported in Table 4, the futures market clearly leads the process of price formation. It is assigned a 74.7% contribution to price formation, while the DaxEx contributes only the remainder of 25.3%. These results correspond to the findings of Theissen (2005) who studies the process of price formation of the DAX index itself and DAX futures. When interpreting the results, one should keep in mind that the DaxEx prices are matched with the most recent corresponding futures prices, which is to the disadvantage of the futures market. Consequently, our results are even likely to understate

[17] Throughout the paper, we use the terms cash market and spot market interchangeably.

the contribution of the futures market to the process of price discovery.

6 Determinants of Price Leadership

In this section, we investigate which factors drive the price leadership of the futures market. Precisely, we analyze to what extent liquidity and volatility affect relative price formation. One would expect market liquidity to be a determining factor, since (informed) traders prefer to trade in the market with the lowest transaction costs (or the highest liquidity). The trading-costs hypothesis is supported, for instance, by Fleming, Ostdiek, and Whaley (1996) in their analysis of relative price formation in stock, index futures, and option markets and by Kim, Szakmary, and Schwarz (1999) who test for lead-lag return relations across index futures markets and across cash markets. Both studies find that the highest trading activity is found in the low-cost market and that the magnitude of trading costs is the main determinant of price leadership. This, in turn, implies that measures for price leadership, such as the common factor weights, are correlated with trading activity (see, for instance, Theissen (2002)).

Bamberg and Dorfleitner (1998) find that the overall trading volume of DAX futures increases significantly just before contract expiration. This increase is particularly significant in the last two weeks of a quarter year, which, in this case, is the time interval between two contract expiration dates. This increase amounts to 70%, on average. Hence, one might expect that during periods with low trading volume in the futures market the price leadership of the FDax is weaker compared to periods just before expiration dates, i.e., in the last two weeks of each quarter. In addition, Bamberg and Dorfleitner (1998) and Bamberg and Dorfleitner (2000) find that the overall trading volume is heavily concentrated on the nearby contract, i.e., the contract with the shortest time-to-expiration, which is the only type of contract that we study in this paper. Hence, assuming the trading-costs hypothesis holds and using relative trading volume as a proxy for liquidity, one would expect time-varying trading intensity in the nearby futures contract to translate into time-varying price leadership of the futures market relative to the ETF market (unless similar trading patterns are found in the ETF market as well).

In order to illustrate the time variation of the relative trading volume and of the CFW, we plot the evolution of both measures on a daily basis.[18] Figure 1 plots the daily relative trading volume of the two markets, defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market (thin blue line). We also show the average relative trading volume over the entire sample period, represented by the horizontal thick red line in Figure 1. The figure indicates that the relative trading volume fluctuates heavily over time with sharp peaks around the expiration days of the futures contracts. The CFW are calculated for each trading day separately and are plotted in Figure 2.[19] The figure indicates that also the CFW series is noticeably unstable over time.

In contrast to the findings by Theissen (2002), among others, that price leadership is positively correlated with relative trading volume, Martens (1998) in his study of Bund futures contracts traded on LIFFE (floor market) and DTB (screen market) shows that not relative trading volume, but volatility is the driving force for relative price discovery. Precisely, he finds that in periods with low volatility relative trading volume on LIFFE increases, whereas the contribution to the process of price formation decreases. However, in their analysis of price leadership in floor-based and screen-based trading systems in several FX futures markets, Ates and Wang (2006) fail to find support for volatility as a determinant of price

[18] Note that the CFW are solely calculated from the coefficients on the error correction term in model (4). Thus, we run stability tests for the coefficients, since instability of the coefficients implies instability of the CFW. Test results of the cumulative sum of recursive residuals (CUSUM) and CUSUM of squares test (see Brown, Durbin, and Evans (1975)), which are not shown in the paper, reject the parameter stability hypothesis.

[19] Since the coefficients on the error correction term do not have the expected sign for all trading days, we use formula (6) to calculate the common factor weights.

discovery.

In Section 5, we have shown that the futures market clearly dominates the process of price discovery for the entire sample period. We now examine to what extent liquidity and/or volatility drive the price leadership of the futures market relative to the ETF market. Specifically, we run the following regression with daily estimates for liquidity and volatility as explanatory variables:

$$\mathrm{CFW}_t^F = \beta_0 + \beta_1 \mathrm{RTV}_t^F + \beta_2 \mathrm{Vola}_t + \varepsilon_t, \tag{8}$$

where CFW_t^F denotes the common factor weight of the futures market on day t, RTV_t^F is the daily relative trading volume of the two markets, defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market, and Vola_t denotes the sum of the realized volatilities of the two markets ($\mathrm{Vola}_t = \mathrm{Vola}_t^F + \mathrm{Vola}_t^S$), which are estimated for each trading day according to Hansen and Lunde (2005a) and Hansen and Lunde (2005b). The estimation procedure for the realized volatilities requires the choice of a sampling interval. Because of market microstructure noise, one should not use every tick for the estimation. In fact, the range between one and five minutes is often found to be the optimal sampling frequency (see, for instance, Hansen and Lunde (2006)). We choose a sampling interval of five minutes, which is rather on the upper end of the commonly used intervals, in order to minimize potential effects due to market microstructure noise.[20] In Appendix A.1, the estimation procedure of realized variances is described in more detail.

We estimate several specifications of model (8) using OLS and present the results in Table 5; the reported t-statistics are adjusted for time-series correlation using the Newey and West (1987) methodology. It can be seen from the table that the coefficients β_1 have the expected sign in all specifications. The coefficients on the relative trading volume are positive, but

[20] As a robustness check, we have also tried sampling intervals of one minute and ten minutes; the results are similar and the conclusions remain the same.

statistically insignificant in all specifications. However, the coefficients on the measures of volatility are significant in all specifications, with the volatility of the futures market being even more significant than the sum of the volatilities for the two markets. As can be seen from specifications (3)-(5), including each variable separately in the regression does not qualitatively change the findings. Our results show that, as indicated by the negative coefficient on volatility, higher volatility in the markets causes the price leadership of the futures market to decrease.

We now investigate to what extent the price leadership shifts to the ETF market during high volatility periods. In order to shed more light on the contribution of the two markets to price discovery conditional on volatility, we calculate their CFW during high and low volatility periods. Similar to Martens (1998), we first classify trading days based on the sum of the realized volatilities of the two markets, Vola_t, into "high volatility" and "low volatility" days according to the following rule:

$$\begin{aligned} &\text{if } \text{Vola}_t > \text{quantile}_{90^{th}} \quad : \quad \text{day } t \text{ is a high volatility day,} \\ &\text{if } \text{Vola}_t < \text{quantile}_{10^{th}} \quad : \quad \text{day } t \text{ is a low volatility day,} \end{aligned}$$

where $\text{quantile}_{x^{th}}$ is the x^{th} quantile of the sample distribution of Vola_t. Following Martens (1998), in addition to the quantiles, we also employ $\mu + \sigma$ and $\mu - \sigma$ as boundaries for high volatility and low volatility days, where μ and σ are the mean and the standard deviation of the sample distribution of Vola_t. Second, we estimate the error correction model (4) for each volatility subsample separately and from the obtained coefficients calculate the CFW for the two markets.[21] The results for the coefficients on the error correction term and the CFW for high and low volatility periods are summarized in Table 6. We also report the average trading volume (in millions of EURO), the average relative trading volume, and the

[21] Tsay (1998) shows that under certain assumptions the consistency of conditional least-squares parameter estimates and variance-covariance matrices holds.

average number of contracts traded in the two markets conditional on volatility. Panel A presents the results for the case when the $90^{th}/10^{th}$ quantiles serve as boundaries for high/low volatility periods (specification I), whereas in Panel B the definition of high/low volatility periods is based on the thresholds $\mu + \sigma$ and $\mu - \sigma$ (specification II).[22] As can be seen from Panel A, for both the futures market and the ETF market, trading volume and the number of contracts traded are higher in high-volatility than in low-volatility periods. However, for the ETF market, the rate of increase is much lower than for the futures market. For instance, trading volume in the ETF market during high-volatility periods is almost three times higher than in low-volatility periods, whereas in the futures market it is almost four times as high, leading to an increase in the relative trading volume of the futures market. According to the trading-costs hypothesis, higher (relative) trading volume should translate into a higher contribution to the process of price discovery. However, the results for the CFW fail to support the hypothesis, but show that the price leadership of the futures market decreases by 22.5% from low to high volatility periods. The contribution of the ETF market rises from roughly 5.5% to almost 27%. Hence, in high volatility periods the contribution of the ETF market is higher than its unconditional contribution (25.3%).

As can be seen from Panel B, using $\mu + \sigma$ and $\mu - \sigma$ as boundaries for high/low volatility periods does not qualitatively change the results.[23] The decrease in the CFW for the futures market from low to high volatility periods equals 14.3% and the drop is obviously less pronounced than in the specification of Panel A. Compared to low volatility periods, the relative trading volume increases by 15.3% and the increase is smaller than in specification I.

In order to provide formal statistical evidence for these findings, we evaluate, for both the DaxEx and the FDax, the null hypotheses that the average trading volume, the average relative trading volume, and the average CFW do not differ in high and low volatility peri-

[22] We have also tried the $5^{th}/95^{th}$ quantiles as boundaries for low and high volatility periods; the results are similar and the conclusions remain the same.

[23] Note that the boundaries and hence the market characteristics for the high volatility period are the same as in specification I.

ods.[24] More specifically, we test whether the increase in trading volume for both markets, the increase in relative trading volume, and the decrease in the CFW of the FDax—and therefore its lower contribution to the process of price discovery—from low to high volatility periods are statistically significant. Table 7, Panel A reports the p-values of the corresponding t-tests for the case when the $90^{th}/10^{th}$ quantiles are used as boundaries for high/low volatility periods. The p-values presented in Panel B are from tests based on the thresholds $\mu + \sigma$ and $\mu - \sigma$ as boundaries for high/low volatility periods. The results in Panel A show that for both the DaxEx and the FDax the increase in trading volume from low to high volatility periods is significant (p-values are equal to 0.0000), whereas the increase in relative trading volume is insignificant. The p-value for the decrease in the CFW from low to high volatility periods, which is significant at the 5% level, provides statistical evidence for the previous finding that the price leadership of the futures market is lower when volatility is high, and vice versa. The results in Panel B, where the thresholds $\mu + \sigma$ and $\mu - \sigma$ define high/low volatility periods, are qualitatively the same as the ones in Panel A. The only quantitative difference is that the decrease in the CFW of the FDax is statistically significant at the 1% level.

In summary, the results above show that volatility is the significant determinant of the degree of price leadership of the futures market. As volatility increases, trading volume and the number of contracts traded increase in both markets, and the relative trading volume of the futures market rises. This, however, does not imply an increase in the price leadership of the futures market. On the contrary, the contribution to price formation of the ETF market rises substantially, indicating a shift in informational efficiency in favor of the ETF market.

Since all our data are obtained from electronic-trading systems, but do not include transactions from floor-trading systems, our results might be explained by a potential shift of informational efficiency from floor-based to screen-based trading. In other words, from low to high volatility periods the screen-based ETF market apparently "gains" a substantial

[24] The test for the change in the CFW is based on the statistical properties of the daily estimates of the CFW on low and high volatility days, respectively.

share of price discovery from the corresponding floor-based trading system. Due to the fact that the FDax is traded exclusively electronically, this shift in informational efficiency cannot occur in the futures market. If this conjecture held true, these results would be in contrast to Martens (1998) who finds that for the case of Bund futures contracts the share in the process of price discovery of the screen-based trading system decreases during high volatility periods.

7 Conclusions

This paper examines the process of price discovery in spot and futures markets which are linked by the cost-of-carry relationship. Our analysis assesses the contribution to price formation of the ETF market and the futures market in Germany. This question is important, since in recent years trading of basket securities, such as ETFs and futures contracts, has gained popularity among financial market participants. In order to investigate the process of price discovery in this new environment of electronically-traded basket securities, we estimate a vector error correction model using transaction data for the DaxEx and the FDax. In order to quantify the contributions of the two markets to the process of price discovery, we calculate the common factor weights for both markets. Our results indicate a clear price leadership of the futures market over the ETF market, although our chosen method for matching the two price series works to the disadvantage of the futures market. These results are in line with the findings of Theissen (2005) who argues that the futures market leads the cash index in terms of relative contribution to price discovery.

Furthermore, we extend similar studies on price leadership between spot and futures markets, as we investigate which factors influence the process of price discovery. More specifically, our paper is the first to analyze to what extent liquidity and volatility affect the process of price formation in spot (ETF) and futures markets. We find that volatility, but not liquidity is the driving force in the process of price discovery. From low to high volatility periods the share of price formation of the futures market decreases, whereas trading volume increases relative to the ETF market.

A Appendix

A.1 Calculation of Realized Variances

We use realized variance (RV) as an estimate of integrated variance (IV). Assume that the efficient log-price process can be described by the stochastic differential equation

$$dp^*(t) = \mu(t)dt + \sigma(t)dw(t), \tag{9}$$

where $\mu(t)$ and $\sigma(t)$ are smooth time-varying functions and w is a standard Brownian motion. We further assume that μ and σ are independent of w. Following the notation in Hansen and Lunde (2005b), we let integer values of t refer to trading day closing times and use trading days as the unit of time. Therefore, the close-to-close return on day t is defined as the difference between two log prices, i.e., $r_t \equiv p(t) - p(t-1)$. Unfortunately, the efficient price process cannot be observed and we, therefore, describe the observed price process as the efficient price process plus microstructure noise:

$$p^*(t) \equiv p(t) + \varepsilon(t). \tag{10}$$

Integrated variance over the time interval $[a, b]$, $\mathrm{IV}_{[a,b]}$, is defined as

$$\mathrm{IV}_{[a,b]} \equiv \int_a^b \sigma^2(t)dt. \tag{11}$$

Integrated variance is usually estimated with realized variance from intraday tick data. We follow Hansen and Lunde (2005b) and denote times at which prices are observed by $a = t_0 < t_1 < ... < t_m = b$. We define a partition of $[a, b]$, $\Xi \equiv \{t_0, .., t_m\}$. The RV sampled from this partition is thus given by

$$\mathrm{RV}^{\Xi}_{[a,b]} \equiv \sum_{i=1}^{m} (p(t_i) - p(t_{i-1}))^2, \tag{12}$$

where $p(t_i) - p(t_{i-1})$ represents intra-day returns. Note that $\mathrm{RV}^{\Xi}_{[a,b]}$ is specific to the partition.

As $\mathrm{RV}^{\Xi}_{[a,b]}$ incorporates only prices that occurred during the trading day, it ignores information that arrives when the market is closed. Therefore, we employ the scaling estimator of Hansen and Lunde (2005a) and Hansen and Lunde (2005b). The scaling estimator incorporates the overnight return by scaling the RV by λ, which is given by

$$\lambda = \frac{\sum_{t=1}^{n}(r_t - \bar{r})^2}{\sum_{t=1}^{n}\mathrm{RV}^{\Xi}_{[a,b]}}. \tag{13}$$

Thus, our estimator of RV_t is defined as

$$RV_t = \lambda \mathrm{RV}^{\Xi}_{[a,b]}. \tag{14}$$

References

Ates, A., and G. H. Wang (2006): "Liquidity and Price Discovery on Floor versus Screen-based Trading Systems: An Analysis of Foreign Exchange Futures Markets," Financial Management Association Annual Meetings.

Bamberg, G., and G. Dorfleitner (1998): "Haltedauern von DAX-Futures-Positionen und die Konzentration auf den Nearby-Kontrakt," *Zeitschrift für Betriebswirtschaft, Ergänzungsband*, 2, 55–74.

——— (2000): "Concentration on the Nearby Contract in Financial Futures Markets: A Stochastic Model to Explain the Phenomenon," *Journal of Economics and Finance*, 24, 246–259.

Booth, G. G., J.-C. Lin, T. Martikainen, and Y. Tse (2002): "Trading and Pricing in Upstairs and Downstairs Stock Markets," *Review of Financial Studies*, 15, 1111–1135.

Booth, G. G., R. W. So, and Y. Tse (1999): "Price Discovery in the German Equity Index Derivatives Markets," *Journal of Futures Markets*, 19, 619–643.

Brenner, R., and K. Kroner (1995): "Arbitrage, Cointegration, and Testing the Unbiasedness Hypothesis in Financial Markets," *Journal of Financial and Quantitative Analysis*, 30, 23–42.

Brown, R., J. Durbin, and J. Evans (1975): "Techniques for Testing the Constancy of Regression Relationships over Time," *Journal of the Royal Statistical Society Series B*, 37, 149–192.

Chan, K. (1992): "A Further Analysis of the Lead-Lag Relationship Between the Cash Market and Stock Index Future Market," *Review of Financial Studies*, 5, 123–152.

Dwyer, G., P. Locke, and W. Yu (1996): "Index Arbitrage and Nonlinear Dynamics Between the S&P 500 Futures and Cash," *Review of Financial Studies*, 9, 301–332.

ENGLE, R., AND C. GRANGER (1987): "Co-integration and Error Correction: Representation, Estimation, and Testing," *Econometrica*, 55, 251–276.

FLEMING, J., B. OSTDIEK, AND R. E. WHALEY (1996): "Trading Costs and the Relative Rates of Price Discovery in Stock, Futures, and Option Markets," *Journal of Futures Markets*, 16, 353–387.

GONZALO, J., AND C. GRANGER (1995): "Estimation of Common Long-Memory Components in Cointegrated Systems," *Journal of Business & Economic Statistics*, 13, 27–35.

GORTON, G. B., AND G. G. PENNACCHI (1993): "Security Baskets and Index-Linked Securities," *Journal of Business*, 66, 1–27.

GRÜNBICHLER, A., F. A. LONGSTAFF, AND E. S. SCHWARTZ (1994): "Electronic Screen Trading and the Transmission of Information: An Empirical Examination," *Journal of Financial Intermediation*, 3, 166–187.

HANSEN, P. R., AND A. LUNDE (2005a): "A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH(1,1)?," *Journal of Applied Econometrics*, 20, 873–889.

——— (2005b): "A Realized Variance for the Whole Day Based on Intermittent High-Frequency Data," *Journal of Financial Econometrics*, 3, 525–554.

HANSEN, P. R., AND A. LUNDE (2006): "Realized Variance and Market Microstructure Noise," *Journal of Business & Economic Statistics*, 24, 127–161.

HARRIS, F. H., T. H. MCINISH, G. L. SHOESMITH, AND R. A. WOOD (1995): "Cointegration, Error Correction, and Price Discovery on Informationally Linked Security Markets," *Journal of Financial and Quantitative Analysis*, 30, 563–579.

HASBROUCK, J. (1995): "One Security, Many Markets: Determining the Contributions to Price Discovery," *Journal of Finance*, 50, 1175–1199.

——— (2003): "Intraday Price Formation in US Equity Index Markets," *Journal of Finance*, 58, 2375–2400.

KEMPF, A., AND O. KORN (1998): "Trading System and Market Integration," *Journal of Financial Intermediation*, 7, 220–239.

KIM, M., A. C. SZAKMARY, AND T. V. SCHWARZ (1999): "Trading Costs and Price Discovery Across Stock Index Futures and Cash Markets," *Journal of Futures Markets*, 19, 475–498.

MARTENS, M. (1998): "Price Discovery in High and Low Volatility Periods: Open Outcry Versus Electronic Trading," *Journal of International Financial Markets, Institutions and Money*, 8, 243–260.

MARTENS, M., P. KOFMAN, AND T. VORST (1998): "A Threshold Error-Correction Model for Intraday Futures and Index Returns," *Journal of Applied Econometrics*, 13, 245–263.

NEWEY, W. K., AND K. D. WEST (1987): "A Simple, Positive-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, 55, 703–708.

SCHWARZ, T. V., AND A. C. SZAKMARY (1994): "Price Discovery in Petroleum Markets: Arbitrage, Cointegration, and the Time Interval of Analysis," *Journal of Futures Markets*, 14, 147–167.

STOLL, H. R., AND R. E. WHALEY (1990): "The Dynamics of Stock Index and Stock Index Futures Returns," *Journal of Financial and Quantitative Analysis*, 25, 441–468.

SUBRAHMANYAM, A. (1991): "A Theory of Trading in Stock Index Futures," *Review of Financial Studies*, 4, 17–51.

THEISSEN, E. (2002): "Price Discovery in Floor and Screen Trading Systems," *Journal of Empirical Finance*, 9, 455–474.

——— (2005): "Price Discovery in Spot and Futures Markets: A Reconsideration," working paper, University of Bonn, Institute BWL1.

TSAY, R. S. (1998): "Testing and Modeling Multivariate Threshold Models," *Journal of the American Statistical Association*, 93, 1188–1202.

Tse, Y. (1999): "Price Discovery and Volatility Spillovers in the DJIA Index and Futures Market," *Journal of Futures Markets*, 19, 911–933.

——— (2001): "Index Arbitrage with Heterogeneous Investors: A Smooth Transition Error Correction Analysis," *Journal of Banking & Finance*, 25, 1829–1855.

Tse, Y., P. Bandyopadhyay, and Y.-P. Shen (2006): "Intraday Price Discovery in the DJIA Index Markets," *Journal of Business Finance & Accounting*, 33, 1572–1585.

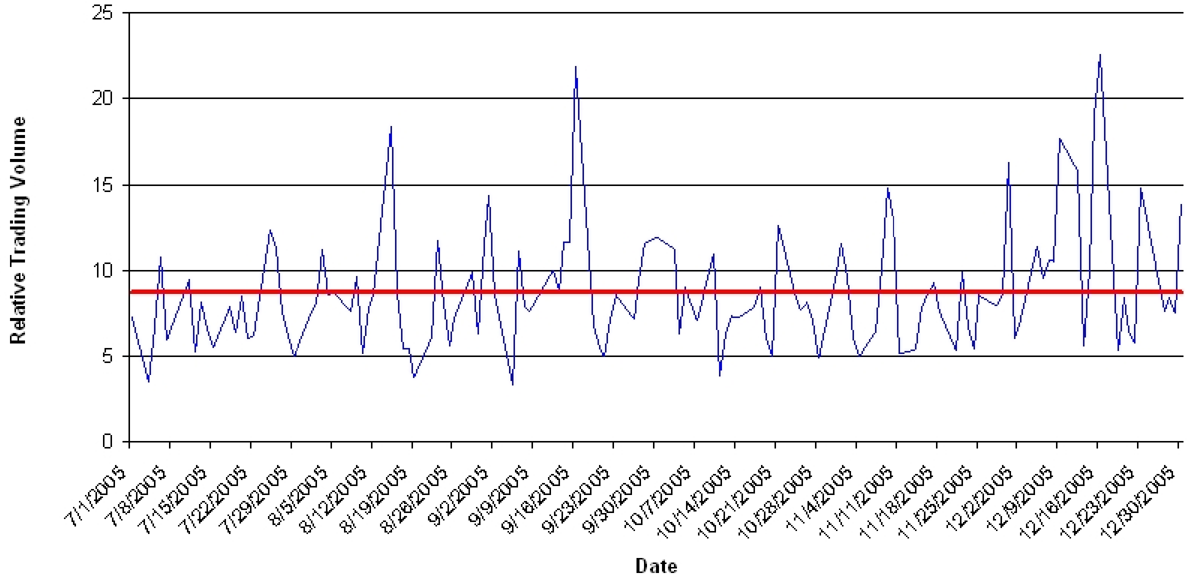

Figure 1: Relative Trading Volume: The figure shows the relative trading volume of the futures and the ETF market, defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market (thin blue line). The horizontal thick red line represents the average relative trading volume over the entire sample period.

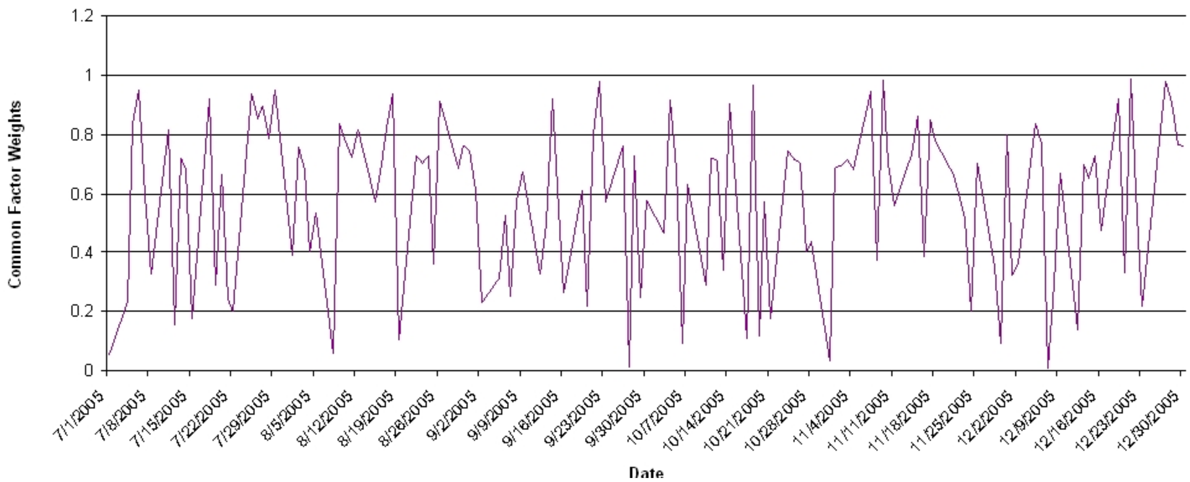

Figure 2: Common Factor Weights of the Futures Market: The figure shows the evolution of the common factor weights for the futures market. The common factor weights are calculated according to formula (6).

Table 1: Volume DaxEx

Year	Volume in millions of EURO
2001	14,541
2002	13,654
2003	18,851
2004	14,897
2005	18,570
2006	27,965
2007	41,173

Table 2: Descriptive Statistics

	DaxEx	FDax
Return standard deviation	0.000550	0.000522
Skewness	−0.819285	−0.873453
Kurtosis	213.3106	249.9899
First order serial correlation	−0.078	−0.045

The table presents descriptive statistics for the DaxEx and the DAX futures returns series. The returns are calculated using transaction prices. The return standard deviations are corrected for autocorrelation.

Table 3: Stationarity Tests

	level		first difference	
	ADF	Phillips-Perron	ADF	Phillips-Perron
log(DaxEx)	0.5062	0.4565	0.0001	0.0001
log(FDax)	0.5304	0.5353	0.0001	0.0001

The table presents the p-values from the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test applied to both the levels and the first differences of the time series.

Table 4: Summary Results of the Vector Error Correction Model

	DaxEx	FDax
Constant	0.0018	-0.0006
	(-5.68)	(2.00)
DaxEx(-1)	-0.4456	0.2032
	(-33.80)	(15.87)
DaxEx(-2)	-0.3448	0.1554
	(-23.31)	(10.82)
DaxEx(-3)	-0.2722	0.1206
	(-17.41)	(7.94)
DaxEx(-4)	-0.2196	0.0902
	(-13.66)	(5.77)
FDax(-1)	0.423	-0.2275
	(31.94)	(-17.40)
FDax(-2)	0.341	-0.1634
	(22.60)	(-11.15)
FDax(-3)	0.2801	-0.1205
	(17.58)	(-7.79)
FDax(-4)	0.2168	-0.0957
	(13.23)	(-6.01)
Error correction term	-0.0487	0.0165
	(-5.69)	(1.99)
Common factor weights	0.253	0.747
R^2	0.058	0.015
F-statistic	67.76	17.04
Lags included	16	16

The table presents the results of the error correction model:

$$\Delta p_t^S = \alpha^S + \sum_{i=1}^{k} \gamma_{11i} \Delta p_{t-i}^S + \sum_{i=1}^{k} \gamma_{12i} \Delta p_{t-i}^F + \delta^S (p_{t-1}^S - p_{t-1}^F) + u_t^S,$$

$$\Delta p_t^F = \alpha^F + \sum_{i=1}^{k} \gamma_{21i} \Delta p_{t-i}^S + \sum_{i=1}^{k} \gamma_{22i} \Delta p_{t-i}^F + \delta^F (p_{t-1}^S - p_{t-1}^F) + u_t^F,$$

where p_{t-1}^S denotes the lagged log price of the DaxEx, p_{t-1}^F denotes the lagged log of the adjusted futures price, and Δp_t^j denotes the log returns for the two markets $j = \{S, F\}$. We estimate the model using OLS, including 16 lags as suggested by both the SIC and the AIC criterion, but report the coefficients for the first four lags only. The cointegration vector is pre-specified as $(1, -1)$. The t-statistics of the coefficients are reported in parentheses. The last line reports the common factor weights for the DaxEx and the FDax, respectively.

Table 5: Regression Analysis of Factors Affecting Price Leadership

Specification	Intercept	RTV_t^F	Vola_t	Vola_t^F	Adj. R^2	F-statistic
(1)	0.7355^{***}	0.0010	-0.6614^{***}	-	0.0245	2.6211
	(8.62)	(0.16)	(-2.75)			
(2)	0.7051^{***}	0.0027	-	-1.2198^{***}	0.0456	4.0810
	(11.19)	(0.42)		(-4.03)		
(3)	0.5754^{***}	0.0004	-	-	-0.0078	0.0027
	(8.98)	(0.06)				
(4)	0.7436^{***}	-	-0.6597^{***}	-	0.0320	5.2622
	(11.63)		(-2.77)			
(5)	0.7258^{***}	-	-	-1.2000^{***}	0.0519	8.0620
	(16.81)			(-4.10)		

The table presents the results of the regression :

$$\mathrm{CFW}_t^F = \beta_0 + \beta_1 \mathrm{RTV}_t^F + \beta_2 \mathrm{Vola}_t + \varepsilon_t,$$

where CFW_t^F denotes the common factor weight of the futures market (calculated according to formula (6)), RTV_t^F is the relative trading volume of the two markets, defined as the ratio of trading volume in the futures market to the trading volume in the ETF market, and Vola_t denotes the sum of the realized volatilities of the two markets (Vola_t^F and Vola_t^S), which are estimated according to Hansen and Lunde (2005a) and Hansen and Lunde (2005b). The t-statistics of the coefficients are adjusted for time-series correlation using the Newey and West (1987) methodology and reported in parenthesis. *,**,*** indicates significance at the 10%, 5%, and 1% level.

Table 6: Market Characteristics During High and Low Volatility Periods

Panel A: Quantiles

	FDax		DaxEx	
	high volatility	low volatility	high volatility	low volatility
Trading volume	1,126	309	150	50
Relative trading volume	8.2632	7.0731	-	-
Number of contracts	231,542	60,368	3,222,854	1,014,282
Error correction term	0.0262	-0.0006	-0.0717	-0.0105
Common factor weight	0.7326	0.9451	0.2674	0.0549

Panel B: Mean plus/minus standard deviation

	FDax		DaxEx	
	high volatility	low volatility	high volatility	low volatility
Trading volume	1,126	285	150	46
Relative trading volume	8.2632	7.1681	-	-
Number of contracts	231,542	55,026	3,222,854	940,830
Error correction term	0.0262	-0.0028	-0.0717	-0.0164
Common factor weight	0.7326	0.8545	0.2674	0.1455

The table presents the average trading volume (in millions of EURO), the average relative trading volume, the average number of contracts, the coefficient on the error correction term, and the common factor weights of the futures market (FDax) and the spot market (DaxEx) conditional on high/low volatility. The relative trading volume is defined as the ratio of the trading volume in the futures market to the trading volume in the ETF market. The coefficients on the error correction term are denoted by δ^F and δ^S in the error correction model (4). The common factor weights are calculated as specified in formula (6). In Panel A, the 90^{th} quantile and the 10^{th} quantile serve as boundaries for high/low volatility periods as described in the text. In Panel B, the mean plus/minus one standard deviation of the empirical distribution of the sum of the realized volatilities are used to define high/low volatility periods.

Table 7: Statistical Test Results

Panel A: Quantiles

	FDax	DaxEx
Trading volume (p-value)	0.0000***	0.0000***
Relative trading volume (p-value)	0.2128	-
Common factor weight (p-value)	0.0154**	-

Panel B: Mean plus/minus standard deviation

	FDax	DaxEx
Trading volume (p-value)	0.0000***	0.0000***
Relative trading volume (p-value)	0.3403	-
Common factor weight (p-value)	0.0093***	-

This table presents the results of the t-test for the null hypothesis that the average trading volume, the average relative trading volume, and the average common factor weights are equal for the high and low volatility samples. The tests in Panel A are performed on samples which are constructed by using the 90^{th} quantile and the 10^{th} quantile to define high/low volatility periods as described in the text. In Panel B, the tests are performed on samples constructed by using boundaries specified by the mean plus/minus one standard deviation of the empirical distribution of the sum of the realized volatilities. *,**,*** indicates significance at the 10%, 5%, and 1% level.