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Keywords: Price discovery, futures markets, threshold error correction, common factor weights

JEL classification: G13, G14

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1 Introduction

Which market impounds new information faster into prices, the index futures market or the spot market? Transaction costs are lower in the futures market. Given that the magnitude of the transaction costs determines whether a trader can profitably trade on a given piece of information, the adjustment of prices to market-wide information (e.g. announcements of macroeconomic variables) should be faster in the futures market. On the other hand, traders possessing information about the value of individual stocks will most likely trade that stock rather than the whole index. [1] Consequently, stock-specific information should be reflected in the spot market first.

The issue of the relative contributions of spot and futures markets to the process of price discovery is of obvious importance, and consequently has received considerable attention in the literature. Most previous studies (to be surveyed briefly in section 2) have compared index values computed from the prices of the component stocks to index futures prices. However, investors nowadays can also trade in shares of exchange traded funds (ETFs) which replicate the index. ETF shares are a close substitute for the index portfolio, and their bid ask spreads are low. Consequently, ETF shares should allow for low-cost index arbitrage.

The standard methodology to analyze price discovery is to estimate an error correction model. Applying this methodology to data on equity index values and futures prices is fraught with several problems which make straight estimation of the model troublesome. First, the constituent stocks of the index trade infrequently. Consequently, index values are partially based on stale prices. The infrequent trading effect together with bid-ask bounce introduces distinct serial correlation patterns into the time series of index returns which may induce a spurious lead of the futures market. Although Stoll and Whaley (1990) have proposed a method to purge the return data of the infrequent trading effects, it is much less clear how the index level data needed in the estimation of the ECM can be purged of those effects. Second, the cointegrating relation between index levels and index futures prices implied by the cost-of-carry model is not constant over time but rather changes daily. Third, the standard error correction model implies that the speed of adjustment of prices to deviations from the long-run equilibrium relation is independent of the size of the deviation. This is not necessarily the case, however, because arbitrageurs will start trading when the deviation is larger than the expected roundtrip transaction cost. Their trading activity is likely to speed the adjustment. ETF prices do not suffer from an infrequent trading problem. All other problems alluded to above, however, are also relevant in analyses using ETF data instead of equity index values.

One potential solution to the infrequent trading (and bid-ask bounce) problem, first proposed by Shyy et al. (1996), is to use quote midpoints rather than prices. The time-variability of the cointegrating relationship can be accounted for by either demeaning the log price series as proposed by Dwyer et al. (1996) or by using discounted futures prices as is done by Kempf and Korn (1996) and Martens et al. (1998). Finally, a threshold error correction model allows the adjustment coefficients to depend on the magnitude of the deviation from the long-run equilibrium relation and is thus able to account for the presence of arbitrageurs (Dwyer et al., 1996).

The present paper contributes to this line of research. We use data from the German blue chip index DAX, the most liquid ETF replicating the DAX, and the DAX futures contract traded on the EUREX to assess the contributions to price discovery of the spot and the futures market. As suggested above, we use quote midpoint data, we use demeaned log price series, and we use a threshold error correction model. The contribution of our paper is twofold. First, we modify the threshold error correction model to allow for time-varying transaction costs. Previous papers

(Dwyer et al., 1996; Martens et al., 1998) have estimated the threshold transaction costs (i.e., the size of the deviation of prices from their long-run equilibrium that allows arbitrageurs to break even) and implicitly assumed the costs to be constant. It is, however, well established that bid-ask spreads follow a distinct intraday pattern. In our data set the third quartile of the spread distribution is between 1.5 and 2 times larger than the first quartile, and the 95% quantile is between 2 and 6 times larger than the 5% quantile. Consequently, the price deviation that allows for profitable arbitrage varies substantially. Our paper is the first to allow for this time-variation by making the threshold dependent on the bid-ask spreads in the two markets. Second, this is the first paper to estimate a threshold error correction model using midquote data. This is potentially important because arbitrage signals should be based on tradable prices (i.e., bid and ask quotes) rather than on past transaction prices. Another distinctive feature of our paper is that all markets under scrutiny are electronic limit order markets. Consequently, the results are unlikely to be caused by differences in market microstructure.

Our results can be summarized as follows. The futures market dominates the price discovery process. Returns in the spot market depend much more heavily on lagged returns in the futures market than vice versa. When measuring the contributions to price discovery we also find that the futures market leads. We further find that the dynamics of the adjustment process is different when arbitrage opportunities exist. This finding underpins the importance of taking the existence of arbitrage opportunities explicitly into account.

The paper is structured as follows. Section 2 provides a brief survey of the literature. Section 3 describes the data set and presents some descriptive statistics. Methodology and results of our empirical analysis are presented in section 4. Section 5 concludes.

2 A Brief Review of the Literature

Empirical analysis of the relation between stock index values and index futures prices is complicated by methodological problems. Stocks in the spot market are not traded simultaneously. Consequently, the index is partially calculated from stale prices.[2] This introduces positive serial correlation in the index returns which, in turn, may introduce a spurious lead-lag relation. Further, bid-ask bounce may induce negative serial correlation in the return series. Stoll and Whaley (1990) propose to estimate an ARMA model for the index returns and to use the innovations from the model rather than the index returns to analyze the lead-lag relation between the spot and the futures market. Using a VAR model they find that the futures market leads the stock market by about 5 minutes. The general result that the futures market leads the spot market has, despite all methodological differences, been confirmed in subsequent research. A notable exception is Shyy et al. (1996). These authors confirm the result of a lead of the futures markets when basing their estimates on price data. Estimation based on quote midpoints, on the other hand, leads to the reverse conclusion that the spot market leads.

The VAR approach does not take into account that index values and futures prices are cointegrated. What is required instead is an error correction model (ECM). Different approaches at estimating an ECM have been proposed. Some authors have estimated the cointegrating relationship (e.g. Shyy et al. 1996; Bose, 2007) but the more common approach is to use a pre-specified cointegrating vector based on the theoretical cost-of-carry relation (e.g. Dwyer et al., 1996; Fleming et al., 1996; Kempf and Korn, 1996; Martens et al., 1998; Booth et al., 1999; Tse, 2001; Schlusche, 2009).

Two issues deserve attention. First, the cost-of-carry relation $F_t = S_t e^{r(T-t)}$ implies that the cointegrating relation is not constant over time but rather changes daily.[3] Many previous papers do not take that into account. There are, however, some notable exceptions. Dwyer et al. (1996) subtract the daily mean from the time series of log prices before estimating the ECM. Kempf and Korn (1996), Martens et al. (1998) and more recently Schlusche (2009) use discounted futures prices. These should, according to the cost-of-carry relation, be equal to the spot prices.

The second issue is related to the infrequent trading problem. The ECM is usually estimated using simple log returns. These returns do, however, suffer from the infrequent trading problem addressed above. Some authors (e.g. Fleming et al., 1996; Kempf and Korn, 1996; Pizzi et al., 1998) have used ARMA residuals rather than log returns when estimating the ECM. The problem with this approach is that it combines an error correction term directly derived from the index and futures price levels with the ARMA residuals in one model, thereby introducing a sort of inconsistency into the model. A convenient way to circumvent this problem[4] is to use quote midpoints rather than transaction prices (e.g. Shyy et al., 1996). Midpoints are based on firm quotes and thus should not suffer from an infrequent trading problem. Further, there is no bid-ask bounce in quote data.

The standard ECM specification implies that, whenever prices deviate from the long-run equilibrium relation (which, in turn, is given by the cost-of-carry relation), there is a tendency for prices to adjust. The size of the adjustment coefficient is independent of the magnitude of the deviation. Several authors have argued that this is likely to be an incomplete description of the adjustment process. When deviations from the long-run equilibrium are larger than the round-trip transaction costs, arbitrageurs step in, thereby speeding the adjustment process. The resulting dynamics can be captured by a threshold error correction model (TECM). This approach was pioneered by Yadav et al. (1994) and subsequently adopted by Dwyer et al., (1996), Kempf and Korn (1996) and Martens et al. (1998).

In these papers the TECM is estimated using transaction price data. Thus, it is assumed that a sufficiently large deviation between lagged futures prices and lagged spot index values triggers an arbitrage signal. However, arbitrageurs cannot trade at these prices. This is particularly true for the spot index because the calculation of the index value is partially based on stale prices. It would be preferable to construct the arbitrage signal from quote data because trades can actually be executed at these prices. Data on bid and ask quotes is, however, not usually available from open outcry futures markets.

A second implicit assumption made in previous papers is that the transaction cost and, consequently, the price difference triggering an arbitrage signal, is constant. This is not necessarily the case, though. The most important determinant of the transaction cost is the bid-ask spread. The spread, however, is time-varying. Some of the variation is caused by distinct intraday patterns. Consequently, a model that assumes constant roundtrip transaction costs may fail to fully capture the dynamics of the adjustment process. The methodology used in the present paper takes the time-varying nature of transaction costs explicitly into account.

Analyzing the relation between index ETF prices and index futures prices poses less problems because ETF prices do not suffer from an infrequent trading problem. The other issues addressed above - the specification of the cointegrating relationship and the implications of the (potentially time-varying) transaction costs for the adjustment process - are, however, still relevant. We are aware of four papers that analyze price discovery in ETF and futures markets. None of these papers has estimated a threshold error correction model. Hasbrouck (2003) and Schlusche (2009) find that the futures market dominates price discovery. Tse et al. (2006) report more differentiated results. The contribution of the ETF market to price discovery is negligible when ETF prices from a floor-based trading system (the Amex) are used. When prices from an electronic trading system (Archipelago) are used instead, the estimated contribution to price discovery of the ETF market increases substantially. Hendershott and Jones (2005) find that ETF prices from the Island ECN dominated price discovery until, in 2002, Island stopped displaying quotes on its trading screens.

3 Data

We use data from three different markets, the German stock market, the index ETF market and the index futures market. From this data we compile two data sets. The first one combines DAX index values from the spot equity market with DAX index futures data while the second data set combines data for the most liquid DAX ETF with index futures data.

Data Set 1

The sample period for data set 1 is the first quarter of 1999 and covers 61 trading days. All data was obtained from Bloomberg. We use data for the German blue chip index DAX and the DAX futures contract. The DAX is a value-weighted index calculated from the prices of the 30 most liquid German stocks. The index is calculated from share prices in Xetra.[5] Index values are given with a precision of two digits after the decimal point. The DAX is a performance index, i.e., the calculation of the index is based on the presumption that dividends are reinvested. Consequently, the expected dividend yield does not enter the cost of carry relation.

During our sample period Deutsche Börse AG also calculated an index from the current best ask prices (ADAX) and an index from the current best bid prices (BDAX).[6] These indices are value-weighted averages of the inside quotes, and the difference between them is equivalent to a value-weighted average bid-ask spread.

Futures contracts on the DAX are traded on the EUREX. The contracts are cash-settled and mature on the third Friday of the months March, June, September and December. The DAX futures contract is a highly liquid instrument. In the first quarter of 1999 more than 3.6 million contracts were traded. The open interest at the end of the quarter was more than 290,000 contracts.[7] The minimum tick size in the futures market corresponds to 1/2 index point.

Both Xetra and EUREX are electronic open limit order books. Therefore, the results of our empirical analysis are unlikely to be affected by differences in the microstructure of the markets.[8] The trading hours in the two markets differ. Trading in Xetra starts with a call auction held between 8.25 am and 8:30 am. After the opening auction, continuous trading starts and extends until 5 pm, interrupted by an intraday auction which takes place between 1:00 pm and 1:02 pm. Trading of the DAX futures contract starts at 9 am and extends until 5 pm.

Our data set comprises the values of the DAX index and the two quote-based indices ADAX and BDAX at a frequency of 15 seconds. The values in our data set correspond to the last observation in each interval. From the quote-based indices we calculate a midquote-index, denoted $MQDAX_t$, and a time series of percentage bid-ask spreads, denoted S_t. The data set further comprises a time series of all bid and ask quotes and all transaction prices of the nearby DAX futures contract.

We only use data for the period of simultaneous operation of both markets. We further discard all observations before 9 am and from 4:55 pm onwards. We also discard all observations within 5 minutes from the time of the intraday call auction (held between 1:00 pm and 1:02 pm). When estimating the ECM we assure that all lagged returns are from the same trading day.

In order to synchronize the data from the spot and the futures market we proceeded as follows. For each index level observation we identify the most recent transaction price and the most recent quote midpoint from the DAX futures data. Thus, in each pair of observations the observation from the futures market is older (though by some seconds only) than the matched observation from the spot market. This procedure clearly works to the disadvantage of the futures market.

The cost-of-carry relation implies that the spot index and the futures contract are cointegrated. In order to eliminate the time-variation of the cointegrating relation we follow the procedure introduced by Dwyer et al. (1996). We calculate the mean of the log price series for each trading day and subtract the mean from the original series. This procedure leaves the intraday returns unaffected but eliminates the average daily level difference between the futures prices and the spot index level.[9] All error correction models are estimated using these demeaned series.

Panel A of Table 1 shows descriptive statistics for data set 1. The first line displays the frequency of zero return observations. Zero returns for the DAX are observed in 5% of the return intervals. For the midquote returns this frequency is substantially lower, amounting to only 0.53%. These low values are not too surprising because a transaction or a quote change, respectively, will be observed whenever there is a transaction or a quote change in at least one of the 30 constituent stocks of the index. Things look different for the futures market. Here, we observe zero returns in 21.1% of the case when we consider returns calculated from prices and in 16.7% of the cases when considering midquote returns. These figures, also being considerably higher than those for the DAX, are still low enough to suggest that our data frequency is adequate.

Insert Table 1 about here

Besides the frequency of zero returns Table 1 provides a variety of further descriptive statistics. The return standard deviation is higher in the futures market, and in both markets it is higher for the price returns than for the midquote returns. This is most likely due to the fact that price returns are affected by bid-ask bounce whereas midquote returns are not. The DAX returns exhibit positive serial correlation ($\rho = 0.12$). This comes as no surprise given that the constituent stocks of the index trade infrequently and non-synchronously. What is a surprise, however, is the observation that the first order serial correlation of the midquote returns is even higher, amounting to 12.9%. This contrasts with the negative serial correlation at the individual stock level documented by Hasbrouck (1991) and others. A possible explanation for the positive serial correlation is that a quote change in one stock may trigger a quote change in other stocks. This would induce positive serial correlation in the returns of the midquote index. This correlation, then, would be a characteristic feature of the modus operandi of the spot market. We therefore did not attempt to remove the serial correlation by applying an ARMA filter to the data.

The autocorrelation pattern for the futures market is in line with what one would expect. The returns calculated from prices are negatively correlated, most likely because of bid-ask bounce. The midquote returns are weakly positively correlated ($\rho = 0.04$).

The last line of Panel A of Table 1 shows the average bid-ask spreads. They amount to 0.28% for the DAX but to only 0.03% for the DAX futures contract. These figures are consistent with results for the UK reported in Berkman et al. (2005) and substantiate our earlier claim that transaction costs are lower in the DAX futures market.

As a prerequisite for our empirical analysis we have to establish that the time series are I(1) and are cointegrated. Panel A of Table 2 presents the results of augmented Dickey-Fuller tests and Phillips-Perron tests applied to the log of the levels and their first differences. Four time series are considered, the DAX index itself, the DAX midquote index and the prices and the quote midpoints of the DAX futures. The results of the stationarity tests clearly suggest that all series are I(1). Results of Johansen tests (not shown) applied to pairs of log time series (DAX level and DAX futures prices, DAX midquote index and DAX futures midquotes) provide clear evidence that the time series are cointegrated.

Insert Table 2 about here

Data Set 2

Our second data set covers 61 trading days in the last quarter of 2010. It combines data for the most liquid exchange-traded fund (the DAX EX) and data for the DAX futures contract. The data was obtained from Bloomberg.

The iShares DAX (DAX EX) is an exchange-traded fund (ETF) issued by BlackRock Asset Management.[10] It tracks the blue chip index DAX. The fund exists since December 2000 and is the largest ETF replicating the DAX. Its net asset value at year-end 2010 was more than € 4.3 billion. The average monthly trading volume in the fourth quarter of 2010 was more than € 1.3 billion. Trades by institutional investors account for 90-95% of the total volume (Schlusche 2009). The DAX EX is traded on Xetra. The price of a fund certificate corresponds to 1/100 of the index value. We therefore multiplied all ETF prices and quotes by 100. The minimum tick size corresponds to one index point. It is thus twice as large as the minimum tick size in the futures market.

The DAX futures market was already described in the previous subsection. It was even more liquid in 2010 than it was in 1999. The number of contracts traded in the last quarter of 2010 was 9.2 million (as compared to 3.6 million in Q1 1999) and the average percentage spread declined from 0.029% to 0.011% (see Table 1).

The data set comprises a complete record of all transaction prices, bid and ask quotes for the DAX EX and the nearby DAX futures contract. We only use data for the period of simultaneous operation of both markets. We discard all observations before 9:05 am and from 5:30 pm onwards. We also discard all observations around the intraday call auction in the DAX EX market which is held at a randomly chosen point in time between 1:10 pm and 1:12 pm. We construct a simultaneous data set by recording the last transaction price and the last bid and ask quote at the end of each minute.[11] As in data set 1 we eliminate the time-variation in the cointegrating vector by demeaning the log price series. Further, we again use the pre-specified cointegrating vector (1; -1). When estimating the ECM we assure that all lagged returns are from the same trading day.

Panel B of Table 1 shows descriptive statistics for data set 2. The zero return frequencies reflect the differing liquidity of the DAX EX and the DAX futures contract. While we observe 63.7% zero returns for the DAX EX the corresponding figure for the DAX future is much lower, at 13.6%. Quote changes are much more frequent in both markets. The percentage of intervals with no quote change is 18.6% for the DAX EX and 7.9% for the DAX future. Our main conclusions are obtained from error correction models estimated on quote midpoint data.

In both markets the standard deviation of price returns is higher than the standard deviation of midquote returns. This may be due to the presence of bid-ask bounce in the time series of transaction prices. All for time series display negative serial correlation. It is more pronounced for the price returns than for the midquote returns (-0.027 versus -0.011 for the DAX EX and -0.017 versus -0.005 fir the DAX future). This may, again, be due to bid ask bounce. The last line of Panel B of Table 1 shows the average bid-ask spreads. They amount to 0.038% for the DAX EX and to 0.011% for the DAX futures contract. The spread difference between the two markets under scrutiny is thus much lower in data set 2 than in data set 1.

Panel B of Table 2 presents the results of unit root tests applied to the log of the levels and their first differences. The results clearly suggest that all series are I(1). Results of Johansen tests (not shown) applied to pairs of log time series (DAX EX level and DAX futures prices, DAX EX quote midpoints and DAX futures quote midpoints) provide clear evidence that the time series are cointegrated.

4 Methodology and Results

4.1 Base Model

Having established that the time series are I(1) and cointegrated we can proceed by estimating the error correction model

$$\begin{aligned} r_t^X &= \alpha^X + \sum_{\tau=1}^{k} \beta_\tau^X r_{t-\tau}^X + \sum_{\tau=1}^{k} \gamma_\tau^X r_{t-\tau}^F + \delta^X \left(p_{t-1}^X - p_{t-1}^F \right) + \varepsilon_t^X \\ r_t^F &= \alpha^F + \sum_{\tau=1}^{k} \beta_\tau^F r_{t-\tau}^F + \sum_{\tau=1}^{k} \gamma_\tau^F r_{t-\tau}^X + \delta^F \left(p_{t-1}^X - p_{t-1}^F \right) + \varepsilon_t^F \end{aligned} \qquad (1)$$
,

where *p* denotes a demeaned log price series and *r* denotes a log return. The indices X and F identify observations and coefficients relating to the spot market (the stock market in data set 1 and the ETF market in data set 2, denoted X for Xetra in both cases) and the futures market (F). We follow the literature (e.g., Dwyer et al., 1996; Fleming et al., 1996; Kempf and Korn, 1996; Martens et al., 1998; Booth et al., 1999; Tse, 2001; Schlusche, 2009) by using the pre-specified cointegrating vector (1; -1).[12]

We estimate model (1) using OLS, for both prices and quote midpoints. This allows us to check whether we can replicate the result obtained by Shyy et al. (1996), i.e., to check whether prices and quote midpoints yield different conclusions as to which market leads in the process of price discovery. Because there is evidence of heteroscedasticity and serial correlation of the residuals all t-statistics are based on Newey-West standard errors. The number of lags is (based on the Schwartz information criterion (SIC)) set to 16 for data set 1 and to 10 for data set 2.[13]

We measure both markets' contributions to price discovery using the common factor weight (CFW) measure.[14] It has first been proposed by Schwarz and Szacmary (1994) on intuitive grounds. A formal justification, based on the work of Gonzalo and Granger (1995), has been provided by Booth et al. (2002), deB Harris et al. (2002) and Theissen (2002). The common factor weights are easily obtained from the coefficients on the error correction terms in (1):

$$CFW^X = \frac{\delta^F}{\delta^F - \delta^X}, CFW^F = \frac{-\delta^X}{\delta^F - \delta^X}. \tag{2}$$

The results are presented in Table 3. To conserve space we only report coefficients for the first four lags.

We discuss the results obtained from data set 1 (shown in Panel A of Table 3) first. Starting with the model estimated from transaction price data, we note that the independent variables have considerable explanatory power for the spot market returns, as is evidenced by an adjusted R^2 of 0.18. They have much less explanatory power for the returns in the futures markets. The adjusted R^2 for the futures market equation is a mere 0.01. Returns in both markets depend negatively on their own lagged values. This may be due to bid-ask bounce. We further find that returns in both markets depend positively on lagged returns in the other market. The F statistic indicates bi-directional Granger causality. A look at the values of the F statistics and at the coefficient values and their t-statistics reveals, however, that the impact of lagged futures returns on the spot market is far stronger than the impact of spot market returns on the futures market.

In both equations the coefficient on the error correction term has the expected sign and is significant. Thus, both markets contribute to price discovery. Apparently, however, the futures market dominates the process of price discovery. According to the common factor weights the futures market contributes 71.7% to price discovery while the contribution of the spot market is only 28.3%. The results thus imply that the futures market is the clear leader in the process of price discovery.

The results obtained when estimating (1) with quote midpoint data are comparable. The R^2 for the spot market equation is higher at 0.23 whereas the R^2 for the futures market equation drops to 0.007. Midquote returns in the spot market depend negatively on their own lagged values. We do not observe a similar pattern for the futures market. Returns in both markets depend positively on lagged returns in the other market. Although the F statistic again indicates bi-directional Granger causality it is obvious from the estimation results that the futures market dominates.

The common factor weights assign the spot market a slightly higher contribution to price discovery than in the transaction price model (40.2% as compared to 28.3%). Still, the results indicate that the futures market leads in the process of price discovery. This contrasts with the results of Shyy et al. (1996) who find that the spot market leads in the process of price discovery when the estimation is based on quote midpoints. When interpreting our results it should be kept in mind that the construction of our data set puts the futures market at a disadvantage. Thus our results are likely to even understate the role of the futures market in the process of price discovery.

<u>Insert Table 3 about here</u>

The results for data set 2 are shown in Panel B of Table 3. They share several similarities with those from data set 1. The explanatory variables again have much higher explanatory power for the spot market returns than for the futures market returns. The futures market clearly dominates the process of price discovery. The F-statistic indicates that the futures returns Granger-cause the returns in the ETF market. Evidence for Granger causality in the opposite direction is much weaker; the corresponding F-statistic is insignificant when the estimation is based on transaction prices and significant only at the 10% level when the estimation is based on midquote returns. The coefficient estimate for the error correction term is insignificant in the futures market equation which already indicates that the futures market does not adjust to deviations from the long-run relation given by the cost of carry model. This is confirmed by the common factor weights which also indicate that the futures market dominates price discovery. Its share is estimated to be 98.5% and 91.1% in the transaction price and quote midpoint model, respectively. These values are much higher than the corresponding value of 74.7% reported by Schlusche (2009) for data from 2005.

4.2 Threshold Error Correction Model

As noted previously, model (1) assumes that the speed of adjustment to deviations of the price levels from their long-run equilibrium relation is independent of the size of these deviations. This is unlikely to be the case, however, as arbitrageurs stand ready to take opportunity of any profits available. Thus, when the deviations are large enough to make arbitrage profitable (i.e., when they are larger than the transaction costs) we should expect faster adjustment.

In order to pursue this issue further we first have to define an arbitrage signal. Previous papers assumed that arbitrage will set in when the price deviation exceeds a constant threshold level. However, it is well known that transaction costs are time varying. Table 4 provides evidence on the variation of percentage bid-ask spreads. In the DAX futures market the 75% quantile of the spread distribution is about twice as large as the 25% quantile. The corresponding ratio for the spreads on the spot market is about 1.5. This holds for both data sets. When we consider the 95 and 5% quantiles instead we obtain (of course) larger differences. The ratios range from 2.2 for the Xetra DAX to more than 6 for the DAX futures contract in the first quarter of 1999.

Insert Table 4 about here

In order to take advantage of profit opportunities, arbitrageurs have to trade fast. They are thus likely to use market orders and consequently have to pay the spread. An arbitrage trade consists of selling at the bid price in one market and buying at the ask price in the other market. In both cases, the total transaction cost is the half spread in the spot market plus the half spread in the futures market.[15] We assume that arbitrage is profitable when the price deviation exceeds this threshold. We thereby assume that there are no other relevant transaction costs besides the spread, and we assume that the position is either held until maturity or can be unwound at zero cost.[16] This corresponds to the conjecture by Dwyer et al. (1996, p. 312) that "the trigger for index arbitrage is about one-half of the round-trip transaction costs".

As both markets under scrutiny are fully automated, arbitrage trades may be executed as program trades. We therefore do not consider the possibility of delays between the occurrence of price deviations and the onset of arbitrage.[17] We thereby implicitly assume that the reaction time is no more than our data frequency.

Table 5 takes a closer look at the arbitrage opportunities. In data set 1 the deviation between the (demeaned) spot and futures market quote midpoints exceeds the transaction costs in about 5.46% of the cases. In 2.42% of the observations, the spot index is larger than the futures price whereas in 3.03% the reverse is true.[18] In most cases, the price deviation exceeds the transaction cost only by a small amount. The average value is 1.83 index points. Larger deviations do occur, however, as is evidenced by a maximum value of almost 19 points. We observe more arbitrage opportunities in data set 2. The deviation between the quote midpoints exceeds the transaction costs in more than 25% of the cases. The higher percentage of arbitrage opportunities is due to the very low bid ask spreads in data set 2. Remember from Table 1 that the average percentage spread is 0.038% for the DAX EX and 0.011% for the DAX futures contract. In most cases the arbitrage profits are small. The mean profit is about 1.1 index points. Large deviations occur occasionally, as is evidenced by a maximum value of 38 index points.[19]

Insert Table 5 about here

We define a dummy variable D_t taking on the value 1 if there is an arbitrage opportunity as defined above and zero otherwise. We then augment model (1) to obtain

$$\begin{aligned} r_t^X &= \alpha^X + \sum_{\tau=1}^{k} \beta_\tau^X r_{t-\tau}^X + \sum_{\tau=1}^{k} \gamma_\tau^X r_{t-\tau}^F + \delta_1^X \left(p_{t-1}^X - p_{t-1}^F \right) + \delta_2^X D_{t-1} \left(p_{t-1}^X - p_{t-1}^F \right) + \varepsilon_t^X \\ r_t^F &= \alpha^F + \sum_{\tau=1}^{k} \beta_\tau^F r_{t-\tau}^F + \sum_{\tau=1}^{k} \gamma_\tau^F r_{t-\tau}^X + \delta_1^F \left(p_{t-1}^X - p_{t-1}^F \right) + \delta_2^F D_{t-1} \left(p_{t-1}^X - p_{t-1}^F \right) + \varepsilon_t^F \end{aligned} \quad (3)$$

.

The coefficients δ_2^X and δ_2^F measure whether the adjustment to price deviations is different in the presence of arbitrage opportunities. We expect these coefficients to have the same sign as δ_1^X and δ_1^F, respectively.

As already noted, arbitrage either requires to sell in the spot market and buy in the futures market or to do the reverse. The price dynamics in the two cases may be different because selling in the spot market may require short sales. We therefore estimate an additional model in which we allow the coefficient on the error correction term to be different in the two cases alluded to above. The model is

$$\begin{aligned} r_t^X &= \alpha^X + \sum_{\tau=1}^{k} \beta_\tau^X r_{t-\tau}^X + \sum_{\tau=1}^{k} \gamma_\tau^X r_{t-\tau}^F \\ &\quad + \delta_1^X \left(p_{t-1}^X - p_{t-1}^F \right) + \delta_2^X D_{t-1}^1 \left(p_{t-1}^X - p_{t-1}^F \right) + \delta_3^X D_{t-1}^2 \left(p_{t-1}^X - p_{t-1}^F \right) + \varepsilon_t^X \\ r_t^F &= \alpha^F + \sum_{\tau=1}^{k} \beta_\tau^F r_{t-\tau}^F + \sum_{\tau=1}^{k} \gamma_\tau^F r_{t-\tau}^X \\ &\quad + \delta_1^F \left(p_{t-1}^X - p_{t-1}^F \right) + \delta_2^F D_{t-1}^1 \left(p_{t-1}^X - p_{t-1}^F \right) + \delta_3^F D_{t-1}^2 \left(p_{t-1}^X - p_{t-1}^F \right) + \varepsilon_t^F \end{aligned} \quad (4)$$

,

where D_t^1 and D_t^2 are dummy variables identifying those arbitrage opportunities that require selling in the spot market (D_t^1) and selling in the futures market (D_t^2).

We can construct suitable extensions of the common factor weights as follows:

$$CFW_2^X = \frac{\left(\delta_1^F + \delta_2^F\right)}{\left(\delta_1^F + \delta_2^F\right) - \left(\delta_1^X + \delta_2^X\right)}, CFW_2^F = \frac{-\left(\delta_1^X + \delta_2^X\right)}{\left(\delta_1^F + \delta_2^F\right) - \left(\delta_1^X + \delta_2^X\right)} . \tag{5}$$

CFW_2^X and CFW_2^F measure the contribution to price discovery in the presence of arbitrage opportunities. Analogous to (5) we can also define CFW measures for the two "arbitrage regimes" in model (4).

We have argued earlier that the identification of arbitrage opportunities should be based on quote data rather than on transaction price data. Consequently, we estimate models (3) and (4) using quote midpoint data. To enhance comparability with our previous results we include the same number of lags (16 for data set 1 and 10 for data set 2).

The results for data set 1 are presented in Panel A of Table 6. They are comparable to those shown in Table 3. The spot market returns depend negatively on their own lagged values and depend strongly and positively on lagged futures returns. Futures returns, on the other hand, depend positively on lagged spot market returns but depend on their own lagged values significantly only at lag 1. As before we find bi-directional Granger causality, and as before we can conclude from the magnitude of the coefficient estimates and the test statistics that the dependence of the spot market on the futures market is much stronger than the reverse dependence. These results hold for model (3) as well as for model (4).

The estimates of the coefficient on the error correction term in the "no-arbitrage regime" have the same sign but are smaller in magnitude than those presented before. Based on these estimates, the CFW measure attributes both markets almost equal contributions to price discovery (47.1% for the spot market and 52.9% for the futures market). It should be kept in mind, though, that we are likely to understate the contribution of the futures market. The coefficients CFW_2^X and CFW_2^F have the expected sign and are significant. The contributions to price discovery in the arbitrage regime, measured using equation (5), reveal that the share of the spot market drops to 36.3% in the presence of arbitrage opportunities whereas the share of the futures market rises to 63.7%. The results thus suggest that the leading role of the futures market in the price discovery process is particularly pronounced when price deviations are large (i.e., when arbitrage opportunities exist).

The estimates of the parameters $\delta_2^X, \delta_3^X, \delta_2^F$ and δ_3^F in model (4) have the expected sign and are significant. The result that the contribution of the futures market to the price discovery process is higher when price deviations are large is confirmed. Additionally, we observe that the share of the spot market is lowest when there are arbitrage opportunities and the spot market index is larger than the futures price. This is the case where arbitrage requires selling in the spot market.

Insert Table 6 about here

The results for data set 2, shown in Panel B of Table 5, resemble those shown in Table 3. There is clear evidence that returns in the futures market Granger-cause returns in the ETF market. Evidence of causality in the reverse direction is much weaker; the corresponding F-statistics are significant only at the 10% level. In the absence of arbitrage opportunities prices in the futures market do not adjust to deviations from the cost of carry relation. The coefficient of the error correction term is insignificant and even has the wrong sign. As a consequence equation (2) would yield a common factor weight for the futures market in excess of 100% and a negative weight for the spot market. We therefore set the weights to 100% and 0%, respectively. All these results indicate that, absent arbitrage signals, only the futures market contributes to price discovery.

The contributions to price discovery change considerably in the presence of arbitrage signals. The common factor weight for the spot market jumps to 40.8% in the presence of arbitrage signals.

Model (4) implies that the spot market contributes 31.9% when arbitrage involves selling in the spot market and contributes 55.2% when arbitrage involves buying in the spot market. Taken together the results imply that under normal market conditions price discovery occurs only in the futures market. In the presence of arbitrage signals the spot market catches up and contributes significantly to price discovery. The latter finding is at odds with the results obtained using data set 1. There, we concluded that the lead of the futures market becomes stronger in the presence of arbitrage opportunities. The most likely reason for these apparently contradictory findings is the difference in the spot market instruments considered in the two data sets. In data set 1 we considered an index (which cannot be traded) while in data set 2 we consider an ETF.

In summary, our results imply that a) the futures market leads in the process of price discovery and that b) the presence of arbitrage opportunities has a strong impact on the nature of the price discovery process.

5 Summary and Conclusion

In this paper we reconsider the issue of price discovery in spot and futures markets. Its contribution is twofold. First, we modify the threshold error correction model to allow for time-varying transaction costs. Second, we estimate a threshold error correction model using midquote data whereas previous papers used price data. Midquote data is conceptually superior because arbitrage signals should be based on tradable prices (i.e., bid and ask quotes) rather than on past transaction prices.

Our basic finding that the futures market leads in the process of price discovery is consistent with most previous results. We do not confirm the finding of Shyy et al. (1996) that the spot market leads when the estimation is based on quote midpoints rather than on transaction prices. We further document that the presence of arbitrage opportunities has a strong impact on the nature of the price discovery process.

Our results imply that the futures market generally impounds new information faster than the spot market. As a consequence, researchers investigating into the market response to macroeconomic news, or into informational linkages between markets in different countries, should consider using futures market data rather than spot market data.

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Table 1: Descriptive Statistics

Panel A displays descriptive statistics for data set 1 (the index sample). It shows statistics for four return series: DAX returns, DAX midquote returns, DAX futures returns and DAX futures midquote returns. The returns are calculated over intervals of 15 seconds. The last line shows the average quoted bid-ask spread. For the spot market this is the value-weighted average of the spreads of the constituent stocks.

Panel B displays similar statistics for data set 2 (the ETF sample). There are again four return series: DAX EX returns, DAX EX midquote returns, DAX futures returns and DAX futures midquote returns. The returns are calculated over intervals of 1 minute. The last line shows the average quoted bid-ask spread.

Panel A: Data set 1

	DAX	DAX midquote	FDAX price	FDAX midquote
Percentage of zero returns	5.00%	0.53%	21.05%	16.7%
Return standard deviation	0.000298	0.000223	0.000404	0.000340
First order serial correlation	0.120	0.129	-0.079	0.040
Average bid-ask spread	0.2846%		0.0292%	

Panel B: Data set 2

	DAX EX price	DAX EX midquote	FDAX price	FDAX midquote
Percentage of zero returns	63.65%	18.63%	13.55%	7.91%
Return standard deviation	0.000396	0.000362	0.000368	0.000362
First order serial correlation	-0.027	-0.011	-0.017	-0.005
Average bid-ask spread	0.0382%		0.0105%	

Table 2: Stationarity Tests

The table presents the p-values from augmented Dickey Fuller tests and Phillips-Perron tests applied to both the levels and to the first differences of the time series. Panel A (Panel B) shows the results for data set 1 (data set 2).

Panel A: Data set 1

	level		first difference	
	Augmented DF	Philipps / Perron	Augmented DF	Philipps / Perron
log(DAX)	0.349	0.412	0.000	0.000
log(MQ DAX)	0.401	0.519	0.000	0.000
log(FDAX)	0.439	0.399	0.000	0.000
log(MQ FDAX)	0.370	0.396	0.000	0.000

Panel B: Data set 2

	level		first difference	
	Augmented DF	Philipps / Perron	Augmented DF	Philipps / Perron
log(DAX EX)	0.510	0.405	0.000	0.000
log(MQ DAX EX)	0.501	0.397	0.000	0.000
log(FDAX)	0.349	0.330	0.000	0.000
log(MQ FDAX)	0.373	0.360	0.000	0.000

Table 3: Results of Error Correction Models

The table presents the results of the error correction model

$$r_t^X = \alpha^X + \sum_{\tau=1}^{k} \beta_\tau^X r_{t-\tau}^X + \sum_{\tau=1}^{k} \gamma_\tau^X r_{t-\tau}^F + \delta^X \left(p_{t-1}^X - p_{t-1}^F\right) + \varepsilon_t^X$$

$$r_t^F = \alpha^F + \sum_{\tau=1}^{k} \beta_\tau^F r_{t-\tau}^F + \sum_{\tau=1}^{k} \gamma_\tau^F r_{t-\tau}^X + \delta^F \left(p_{t-1}^X - p_{t-1}^F\right) + \varepsilon_t^F$$

where *p* denotes a demeaned log price series and *r* denotes a log return. The indices X and F identify observations and coefficients relating to the spot market (the DAX index in data set 1 and the DAX EX in data set 2) and the futures market (F). We use a pre-specified cointegrating vector. The models are estimated by OLS with Newey West standard errors. Only the coefficients for lags 1-4 are shown. Asterisks ** (*) denote significance at the 5% (10%) level. At the bottom of the table we report the R squared and the F-statistic for a test of the null hypothesis that the coefficients for the lagged returns of the other market (i.e., the spot market in the futures equation and vice versa) are jointly zero. We further report the lag order of the models. The last line reports the common factor weights. Results for data set 1 are shown in Panel A, those for data set 2 in Panel B.

Panel A: Data set 1

	Transaction Prices		Quote Midpoints	
	XDAX	FDAX	XDAX	FDAX
Constant	-4.26E-06**	-7.96E-07	-2.65E-06**	-7.04E-07
EC	-0.056556**	0.022349**	-0.029377**	0.019736**
XDAX(-1)	-0.007426	0.064078**	-0.071744**	0.043607**
XDAX(-2)	-0.034063**	0.048440**	-0.062804**	0.042332**
XDAX(-3)	-0.031447**	0.042881**	-0.048973**	0.047461**
XDAX(-4)	-0.036544**	0.024176**	-0.038622**	0.038573**
FDAX(-1)	0.150425**	-0.073297**	0.191583**	0.048087**
FDAX(-2)	0.123504**	-0.030181**	0.139903**	-0.003362
FDAX(-3)	0.107591**	-0.017890**	0.104424**	-0.005091
FDAX(-4)	0.084878**	-0.006991	0.082565**	0.003325
R^2	0.180021	0.014389	0.227733	0.007471
F statistic	143.77**	14.22**	291.24**	8.32**
Lags included	16		16	
CFW	0.283	0.717	0.402	0.598

Panel B: Data set 2

	Transaction Prices		Quote Midpoints	
	DAX EX	FDAX	DAX EX	FDAX
Constant	9.03E-07	1.58E-06	7.05E-07	1.55E-06
EC	-0.404736**	0.006068	-0.522558**	0.051058
XDAX(-1)	-0.047799**	0.019743	-0.291539**	0.039016
XDAX(-2)	-0.003253	-0.007547	-0.277453**	-0.006837
XDAX(-3)	-0.002759	0.002917	-0.314209**	-0.108706
XDAX(-4)	0.005678	0.007943	-0.059857	0.093721*
FDAX(-1)	0.113850**	-0.028950*	0.287857**	-0.041466
FDAX(-2)	0.048352**	-0.020270	0.260817**	-0.011556
FDAX(-3)	0.032030**	-0.005183	0.299833**	0.096120
FDAX(-4)	-0.013971	-0.024223	0.051562	-0.101816*
R^2	0.239293	0.002502	0.044766	0.005020
F statistic	8.91**	1.21	4.69**	1.80*
Lags included	10		10	
CFW	0.015	0.985	0.089	0.911

Table 4: Distribution of Bid-Ask Spreads

The table shows the 5%, 25%, 50%, 75% and 95% percentiles of the distribution of percentage bid ask spreads. Figures for data set 1 (data set 2) are provided in Panel A (Panel B).

Panel A: Data set 1

	5%	25%	50% (Median)	75%	95%
XDAX	0.1877	0.2347	0.2740	0.3225	0.4194
FDAX	0.0097	0.0189	0.0211	0.0396	0.0622

Panel B: Data set 2

	5%	25%	50% (Median)	75%	95%
DAX EX	0.0159	0.0311	0.0325	0.0480	0.0641
FDAX	0.0071	0.0073	0.0077	0.0147	0.0158

Table 5: Arbitrage Opportunities

An arbitrage signal, in our definition, occurs when the absolute difference between the demeaned spot and futures prices is larger than the transaction cost (the sum of the half-spread in the spot market and the half-spread in the futures market). The table shows the number of arbitrage opportunities, the mean and median arbitrage profit and the maximum profit. Profits are measured in index points. The last line shows the lowest number of arbitrage opportunities observed on any individual day of the sample period. Columns 1 and 2 show separate figures for arbitrage opportunities where the spot index value (data set 1) and the value of the DAX EX (data set 2), respectively, is larger [smaller] than the futures price.

Panel A: Data set 1

	DAX > FDAX	FDAX > DAX	Both
number of cases	2,658 2.42%	3,331 3.03%	5,989 5.46%
mean arbitrage profit	1.4788	2.1086	1.8291
median arbitrage profit	1.0751	1.2503	1.1559
maximum arbitrage profit	16.9659	18.9944	18.9944
lowest daily number of observations	1	1	9

Panel B: Data set 2

	DAX EX > FDAX	FDAX > DAX EX	Both
number of cases	3,542 12.01%	3,936 13.34%	7,478 25.35%
mean arbitrage profit	1.2078	0.9441	1.0690
median arbitrage profit	0.8292	0.6165	0.7221
maximum arbitrage profit	37.9671	7.6698	37.9671
lowest daily number of observations	0	0	0

Table 6: Results of Threshold Error Correction Models

The table presents the results of the error correction models

$$r_t^X = \alpha^X + \sum_{\tau=1}^{k} \beta_\tau^X r_{t-\tau}^X + \sum_{\tau=1}^{k} \gamma_\tau^X r_{t-\tau}^F + \delta_1^X \left(p_{t-1}^X - p_{t-1}^F\right) + \delta_2^X D_{t-1} \left(p_{t-1}^X - p_{t-1}^F\right) + \varepsilon_t^X$$

$$r_t^F = \alpha^F + \sum_{\tau=1}^{k} \beta_\tau^F r_{t-\tau}^F + \sum_{\tau=1}^{k} \gamma_\tau^F r_{t-\tau}^X + \delta_1^F \left(p_{t-1}^X - p_{t-1}^F\right) + \delta_2^F D_{t-1} \left(p_{t-1}^X - p_{t-1}^F\right) + \varepsilon_t^F$$

(columns 1 and 2) and

$$r_t^X = \alpha^X + \sum_{\tau=1}^{k} \beta_\tau^X r_{t-\tau}^X + \sum_{\tau=1}^{k} \gamma_\tau^X r_{t-\tau}^F + \delta_1^X \left(p_{t-1}^X - p_{t-1}^F\right) + \delta_2^X D_{t-1}^1 \left(p_{t-1}^X - p_{t-1}^F\right) + \delta_3^X D_{t-1}^2 \left(p_{t-1}^X - p_{t-1}^F\right) + \varepsilon_t^X$$

$$r_t^F = \alpha^F + \sum_{\tau=1}^{k} \beta_\tau^F r_{t-\tau}^F + \sum_{\tau=1}^{k} \gamma_\tau^F r_{t-\tau}^X + \delta_1^F \left(p_{t-1}^X - p_{t-1}^F\right) + \delta_2^F D_{t-1}^1 \left(p_{t-1}^X - p_{t-1}^F\right) + \delta_3^F D_{t-1}^2 \left(p_{t-1}^X - p_{t-1}^F\right) + \varepsilon_t^F$$

(columns 3 and 4). *p* denotes a demeaned log price series and *r* denotes a log return. The indices X and F identify observations and coefficients relating to the spot market (the DAX in data set 1 and the DAX EX in data set 2) and the futures market (F). We use a pre-specified cointegrating vector. The dummy variable D_t identifies all arbitrage signals. The dummy variables D_t^1 [D_t^2] identify those arbitrage signals where the spot market midquote index is larger [smaller] than the midquote in the futures market. The models are estimated by OLS with Newey West standard errors. Only the coefficients for lags 1-4 are shown. Asterisks ** (*) denote significance at the 5% (10%) level. At the bottom of the table we report the R squared and the F-statistic for a test of the null hypothesis that the coefficients for the lagged returns of the other market (i.e., the spot market in the futures equation and vice versa) are jointly zero. We further report the lag order of the models. The last lines report the common factor weights. Results for data set 1 are shown in Panel A, those for data set 2 in Panel B.

Panel A: Data set 1

	Arbitrage signals pooled (equation 3)		Separate arbitrage signals (equation 4)	
	XDAX	FDAX	XDAX	FDAX
Constant	-2.83E-06	-6.20E-07	4.26E-07	-1.44E-06
EC / no arbitrage	-0.013674**	0.012159**	-0.014775**	0.012437**
EC / arbitrage	-0.050915**	0.024569**		
EC / arb. X-F			-0.091940**	0.034925**
EC / arb. F-X			-0.026632**	0.018439**
XDAX(-1)	-0.073381**	0.044397**	-0.071992**	0.044047**
XDAX(-2)	-0.063698**	0.042763**	-0.062631**	0.042494**
XDAX(-3)	-0.049866**	0.047892**	-0.048698**	0.047598**
XDAX(-4)	-0.039288**	0.038894**	-0.038021**	0.038574**
FDAX(-1)	0.187369**	0.050121**	0.183106**	0.051197**
FDAX(-2)	0.139643**	-0.003237	0.137180**	-0.002615
FDAX(-3)	0.105444**	-0.005583	0.103422**	-0.005073
FDAX(-4)	0.084098**	0.002586	0.082477**	0.002995
R^2	0.235761	0.008265	0.240010	0.008372
F statistic	265.90**	8.44**	291.14**	8.39**
Lags included	16		16	
CFW / no arbitrage	0.471	0.529	0.457	0.543
CFW / arbitrage	0.363	0.637		
CFW / arb. X-F			0.307	0.693
CFW / arb. F-X			0.427	0.573

Panel B: Data set 2

	Arbitrage signals pooled (equation 3)		Separate arbitrage signals (equation 4)	
	DAX EX	FDAX	DAX EX	FDAX
Constant	7.56E-07	1.61E-06	1.29E-06	2.13E-06
EC / no arbitarge	-0.648522**	-0.095461	-0.650214**	-0.097114
EC / arbitrage	0.292950**	0.340754**		
EC / arb. X-F			0.240208**	0.289217**
EC / arb. F-X			0.382039**	0.427808**
XDAX(-1)	-0.305934**	0.022272	-0.304022**	0.024141
XDAX(-2)	-0.287087**	-0.018042	-0.285533**	-0.016524
XDAX(-3)	-0.321308**	-0.116964	-0.320338**	-0.116016
XDAX(-4)	-0.065216	0.087487*	-0.065020	0.087679*
FDAX(-1)	0.304588**	-0.022005	0.302479**	-0.024066
FDAX(-2)	0.270784**	0.000037	0.269360**	-0.001354
FDAX(-3)	0.307254**	0.104752	0.306279**	0.103799
FDAX(-4)	0.057405	-0.095020*	0.057220	-0.095201*
R^2	0.046096	0.006821	0.046204	0.006921
F statistic	4.97**	1.79*	4.90**	1.79*
Lags included	10		10	
CFW / no arbitrage	0	1	0	1
CFW / arbitrage	0.408	0.592		
CFW / arb. X-F			0.319	0.681
CFW / arb. F-X			0.552	0.448

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[1] Alternatively, investors could trade in single stock futures. However, the market for single stock futures is rather illiquid. The monthly statistics for December 2010 available on the EUREX website (see http://www.eurexchange.com/market/statistics/monthly/2010_en.html) reveals that the number of traded contracts is very low for most constituent stocks of the DAX; there is even one DAX member firm (Heidelberger Zement AG) for which there was no trade in the entire month.

[2] Trading activity in today's markets is, of course, much higher than it used to be when the first papers addressing the infrequent trading problem were written. However, since then not only the trading intensity but also the data resolution used in empirical studies has increased tremendously. Relative to the frequency of observations there are still stale prices today. This is evidenced by significant positive serial correlation in index returns at high data frequencies. Using data (obtained from Bloomberg) at the 1-second frequency (a resolution used in several recent papers, e.g. Tse et al. 2006) we found that the serial correlation of DAX returns exceeded 0.1 in six out of the ten trading days (March 7 - 18, 2011) we considered.

[3] If, as is usual, the model is estimated using logs, the relation becomes $\ln(F_t) = \ln(S_t) + r(T-t)$. This implies that, in a regression of $\ln(F_t)$ on $\ln(S_t)$, the slope is constant and equal to one, whereas the intercept changes daily. Note that we do not include the expected dividend yield in the cost-of-carry relation. The reason is that the DAX is a performance index, i.e., calculation of the index is based on the presumption that dividends are reinvested.

[4] There is an alternative. Jokivuolle (1995) developed a procedure (based on the Beveridge-Nelson decomposition) which allows estimation of the true index level. Using these estimates rather than the observed index levels allows to formulate an ECM in which both the error correction term and the lagged returns are purged of infrequent trading effects. To the best of our knowledge this procedure has not yet been applied to test the lead-lag relation between spot and futures markets.

[5] During our sample period Xetra accounted for 79.9% of the total order book turnover in the constituent stocks of the DAX on all German exchanges. See the fact book 1999 of Deutsche Börse AG, p. 33. Note that, during our sample period, Deutsche Börse AG also calculated DAX values based on the prices of the Frankfurt Stock Exchange.

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[6] The calculation of these quote-based indices was discontinued in 2005. Bloomberg did provide intraday data but deleted it after 30 trading days. Consequently, intraday data on the quote-based indices is no longer available. We therefore had to rely on data that we had collected for a different research project (see Freihube and Theissen 2001). It is for this reason that we use data from 1999 in this paper.

[7] See the fact book 1999 of Deutsche Börse AG, p. 88.

[8] Some previous papers, most notably Grünbichler et al. (1994), Kempf and Korn (1998) and Frino and McKenzie (2002), analyze spot and futures markets with different trading protocols. The focus of these papers is to assess the implications of the trading protocol for price discovery.

[9] As noted previously, an alternative procedure would be to use discounted futures prices (as in Martens et al., 1998). However, futures prices appear to deviate systematically from the values implied by the cost of carry relation (see, e.g., Bühler and Kempf (1995) for the German market), most likely because of different tax treatment of dividends in spot and futures markets. In this case, discounting futures prices will produce biased arbitrage signals. Demeaning, on the other hand, removes any systematic deviation of futures prices from the cost of carry relation.

[10] BlackRock bought the investment unit from Barclays plc in 2009.

[11] We opted for one minute intervals because the trading frequency of the DAX EX is not high enough to sustain a data frequency of 15 seconds. As can be seen from Panel B of Table 1, even at the one-minute frequency the probability of observing no transaction in an interval is above 0.6. The probability of observing no quote change is much lower, at 18.6%. Our main conclusions are derived from ECMs estimated on quote midpoint data.

[12] We use this pre-specified cointegrating vector because the cost-of-carry relation gives us a strong theoretical reason to believe that the demeaned log prices from the spot and futures markets should be equal.

[13] To enhance the comparability of the results we decided to use the same number of lags in the models based on transaction prices and quote midpoints. The SIC suggests to include 16 (12) lags in the price (midquote) model for data set 1 and 2 (10) lags in the price (midquote) model for data set 2.

[14] A very popular alternative is the Hasbrouck (1995) information share. We decided against this measure for two reasons. First, the measure cannot be calculated for our extended models which take the existence of arbitrage

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opportunities into account. Second, Grammig and Peter (2008) and Yan and Zivot (2010) have pointed out that the information shares have limitations when the estimates are based on high sampling frequencies.

[15] We note that this measure may overstate the true transaction costs in data set 1. Arbitrageurs do not necessarily have to trade all 30 DAX stocks. They can instead trade a tracking portfolio consisting of fewer stocks (thereby, of course, introducing tracking error). As this portfolio is likely to be tilted towards liquid stocks, the average spread will be lower than the average spread of all DAX stocks. This argument does obviously not apply to data set 2 because the DAX EX is a basket.

[16] There is a positive probability that an arbitrageur will be able to unwind her position early at a profit. The value of the early unwinding option (Brennan and Schwartz, 1988, 1990) reduces the price differential necessary to make arbitrage profitable.

[17] In contrast, Dwyer et al. (1996) use data from open outcry markets. In such an environment delays are likely. They address the issue empirically and estimate delays ranging from 1 minute to 5 minutes.

[18] These figures are clearly lower than the corresponding values in Dwyer et al. (1996, p. 324). They report that slightly less than 9% of their observations are in each of the two tail regimes that are associated with arbitrage opportunities.

[19] The extreme values were observed on one day on which the DAX lost more than 1% shortly after the opening. As a robustness check we re-estimated all our models excluding this day. The results were very similar.

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