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International Evidence on Autocorrelation Patterns of Stock Index and Futures Returns

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Abstract

This paper investigates the relation between returns on stock indices and their corresponding futures contracts in order to evaluate potential explanations for the pervasive yet anomalous evidence of positive, short-horizon portfolio autocorrelations. Using a simple theoretical framework, we generate empirical implications for both microstructure and behavioral models. These implications are then tested using futures data on 24 contracts across 15 countries. The major findings are (i) return autocorrelations of indices tend to be positive even though their corresponding futures contracts have autocorrelations close to zero, (ii) these autocorrelation differences between spot and futures markets are maintained even under conditions favorable for spot-futures arbitrage, and (iii) these autocorrelation differences are most prevalent during low volume periods. These results point us towards a market microstructure-based explanation for short-horizon autocorrelations and away from explanations based on current popular behavioral models.

1 Introduction

Arguably, one of the most striking asset pricing anomalies is the evidence of large, positive, short-horizon autocorrelations for returns on stock portfolios, first described in Hawawini (1980), Conrad and Kaul (1988,1989,1998) and Lo and MacKinlay (1988,1990a). The evidence is pervasive both across sample periods and across countries, and has been linked to, among other financial variables, firm size (Lo and MacKinlay (1988)), volume (Chordia and Swaminathan (1998)), analyst coverage (Brennan, Jegadeesh and Swaminathan (1993)), institutional ownership (Badrinath, Kale and Noe (1995) and Sias and Starks (1997)), and unexpected cross-sectional return dispersion (Connolly and Stivers (1998)).[1] The above results are puzzling to financial economists precisely because time-variation in expected returns is not a high-frequency phenomenon; asset pricing models link expected returns with changing investment opportunities, which, by their nature, are low frequency events.

As a result, most explanations of the evidence have centered around the so-called lagged adjustment model in which one group of stocks reacts more slowly to aggregate information than another group of stocks. Because the autocovariance of a well-diversified portfolio is just the average cross-autocovariance of the stocks that make up the portfolio, positive autocorrelations result. While financial economists have put forth a variety of economic theories to explain this lagged adjustment, all of them impose some sort of underlying behavioral model, i.e., irrationality, on the part of some agents, that matters for pricing. (See, for example, Holden and Subrahmanyam (1992), Brennan, Jegadeesh and Swaminathan (1993), Jones and Slezak (1998), and Daniel, Hirshleifer and Subrahmanyam (1998).) Alternative, and seemingly less popular, explanations focus on typical microstructure biases (Boudoukh, Richardson and Whitelaw (1994)) or transactions costs which prevent these autocorrelation patterns from disappearing in financial markets (Mech (1993)). The latter explanation, however, does not explain why these patterns exist in the first place.

This paper draws *testable* implications from the various theories by exploiting the relation between the spot and futures market.[2] Specifically, while much of the existing focus in the

[1] Another powerful and related result is the short-term continuation of returns, the momentum effect, documented by Jegadeesh and Titman (1993). While this evidence tends to be firm-specific, it also produces positive autocorrelation in short-horizon stock returns (see Grinblatt and Moskowitz (1998) as recent examples). Moreover, this evidence holds across countries (e.g., Rouwenhorst (1998)) and across time periods.

[2] Miller, Muthuswamy and Whaley (1994) and Boudoukh, Richardson and Whitelaw (1994) also argue that the properties of spot index and futures returns should be different. Miller, Muthuswamy and Whaley (1994) look at mean-reversion in the spot-futures basis in terms of nontrading in S&P 500 stocks, while

literature has been on the statistical properties of artificially constructed portfolios (such as size quartiles), there are numerous stock indices worldwide which exhibit similar properties. Moreover, many of these indices have corresponding futures contracts. Since there is a direct link between the stock index and its futures contract via a no arbitrage relation, it is possible to show that, under the aforementioned economic theories, the futures contract should take on the properties of the underlying index. In contrast, why might the properties of the returns on the index and its futures contract diverge? If the index, or for that matter, the futures prices are constructed based on *mismeasured* prices (e.g., stale prices, bid or ask prices), then the link between the two is broken. Alternatively, if transaction costs on the individual stocks comprising the index are large enough, then the arbitrage cannot be implemented successfully. This paper looks at all of these possibilities in a simple theoretical framework and tests their implications by looking at spot and futures data on 24 stock indices across 15 countries.

The results are quite remarkable. In particular,

- The return autocorrelations of indices with less liquid stocks (such as the Russell 2000 in the U.S., the TOPIX in Japan, and the FTSE 250 in the U.K.) tend to be positive even though their corresponding futures contracts have autocorrelations close to zero. For example, the Russell 2000's daily autocorrelation is 22%, while that of its respective futures contract is 6%. The differences between these autocorrelation levels are both economically and statistically significant.

- Transactions costs cannot explain the magnitude of these autocorrelation differences as the magnitude changes very little even when adjusting for periods favorable for spot-futures arbitrage. We view this as strong evidence against the type of irrational models put forth in the literature.

- Several additional empirical facts point to microstructure-type biases, such as staleness of pricing, as the most probable source of the difference between the autocorrelations of the spot and futures contracts. For example, in periods of generally high volume, the

Boudoukh, Richardson and Whitelaw (1994) look at combinations of stock indices, like the S&P 500 and NYSE, in order to isolate portfolios with small stock characteristics. While the conclusions in those papers are consistent with this paper, those papers provide only heuristic arguments and focus on limited indices over a short time span. This paper develops different implications from various theories and tests them across independent, international data series.

return autocorrelation of the spot indices drops dramatically. The futures contract's properties change very little, irrespective of the volume in the market.

- All of these results hold domestically, as well as internationally. This is especially interesting given that the cross-correlation across international markets is fairly low, thus providing independent evidence in favor of our findings.

The paper is organized as follows. In Section 2, we provide an analysis of the relation between stock indices and their corresponding futures contracts under various assumptions, including the random walk model, a nontrading model, and a behavioral model. Of special interest, we draw implications for the univariate properties of these series with and without transactions costs. Section 3 describes the data on the various stock index and futures contracts worldwide, while Section 4 provides the main empirical results of the paper. In Section 5, we make some concluding remarks.

2 Models of the Spot-Futures Relation

There is a large literature in finance on the relation between the cash market and the stock index futures market, and, in particular, on their lead-lag properties. For example, MacKinlay and Ramaswamy (1988), Stoll and Whaley (1990), and Chan (1992), among others, all look at how quickly the cash market responds to market-wide information that has already been transmitted into futures prices. While this literature shows that the cash and futures market have different statistical properties, there are several reasons why additional analysis is needed. First, while there is strong evidence that the futures market leads the cash market, this happens fairly quickly. Second, most of the analysis is for indices with very active stocks, such as the S&P 500 or the MMI, which possess very little autocorrelation in their return series. Third, these examinations have been at the intraday level and not concerned with longer horizons that are more relevant for behavioral-based models.

In this section, we provide a thorough look at implications for the univariate statistical properties of the cash and futures markets under various theoretical assumptions about market behavior with and without transactions costs. In order to generate these implications, we make the following assumptions:

- The index, S, is an equally-weighted portfolio of N assets with corresponding futures contract, F.[3]

- To the extent possible (i.e., transactions costs aside), there is contemporaneous arbitrage between S and F. That is, the market is rational with respect to index arbitrage.

- Prices of individual securities, $S_i,\ i = 1, ..., N$, follow a random walk in the absence of irrational behavior. This assumption basically precludes any "equilibrium" time-variation in expected returns at high frequencies. All lagged adjustment effects, therefore, are described in terms of irrational behavior on the part of some agents, i.e., some form of market inefficiency.

- The dividend processes for each asset, d_i, and the interest rate, r, are independent of the index price, S. Violations of this assumption are investigated in Section 4 and evaluated for their effect on the relation between the cash and futures market

Under these assumptions, we consider three models. The first is the standard model with no market microstructure effects or irrational behavior. The implications of this model are well known, and are provided purely as a benchmark case. The second model imposes a typical market structure bias, namely nontrading on a subset of the stocks in the index. The third model imposes a lagged adjustment process for some of the stocks in the index. In particular, we assume that some stocks react to market-wide information more slowly due to the reasons espoused in the literature. Transaction costs are then placed on the individual stocks in the index, as well as on the futures contract, to better understand the relation between the cash and futures markets.

2.1 Case I: The Random Walk Model

Applying the cost of carry model and using standard arbitrage arguments, the futures price is simply the current spot price times the compounded rate of interest (adjusted for paid dividends):[4]

$$F_{t,T} = S_t e^{(i-d)(T-t)}$$

[3]The assumption of equal weights is used for simplicity.

[4]See, for example, MacKinlay and Ramaswamy (1988). Note that, for the moment, we assume that interest rates and dividend yields are constant. In practice, this assumption is fairly robust due to the fact that these financial variables are significantly less variable than the index itself. Violations of this assumption are explored in Section 4.

where $F_{t,T}$ is the futures price of the index, maturing in T-t periods,

S_t is the current level of the index,

i is the continuously compounded rate of interest,

d is the continuously compounded rate of dividends paid, and

T is the maturity date of the futures contract.

Thus, under the cost of carry model, we can write the return on the futures as

$$r_F = r_S, \tag{1}$$

where r_F is the continuously compounded return on the futures and r_S is the excess return of the underlying spot index (i.e., in excess of the risk-free interest rates). Note that the change in the continuously compounded interest rate (adjusted for the dividend rate), $\Delta(i-d)$, drops out due to the assumption of constant interest rates and dividend yields. For the more realistic assumption that these variables are stochastic (yet perhaps independent) of stock returns, $\Delta(i-d)$ would represent an additional term in equation (1).

Several observations are in order. First, under the random walk model, and assuming that $\Delta(i-d)$ has either low volatility or little autocovariance, the autocorrelation of futures' returns will mimic that of the spot market, i.e., it will be approximately zero. Second, the variance of futures' returns should exceed that of the spot market by the variance of $\Delta(i-d)$, assuming no correlation between the index returns and either dividend changes or interest rate changes. Third, even in the presence of transaction costs, these results should hold as the futures price should still take on the properties of the expected future stock index price, which is the current value of the index in an efficient market.

2.2 Case II: A Nontrading Model

The market microstructure literature presents numerous examples of market structures which can induce non-random walk behavior in security prices. Rather than provide an exhaustive analysis of each of these structures, we focus on one particular characteristic of the data that has received considerable attention in the literature, namely nonsynchronous trading. Nontrading refers to the fact that stock prices are assumed to be recorded at a particular point in time from period to period when in fact they are recorded at irregular points in time during these periods. For example, stock indices are recorded at the end of trading using the last transaction price of each stock in the index. If those stocks (i) did not trade at the same time, and (ii) did not trade exactly at the close, then the index would be subject to nontrading-induced biases in describing its characteristics. The best known characteristic, of course, is the spurious positive autocorrelation of index returns, as well as the lower variance of measured returns on the index.

Models of nontrading, and corresponding results, have appeared throughout the finance literature, including, among others, Fisher (1966), Scholes and Williams (1977), Cohen, Maier, Schwartz and Whitcomb (1978), Dimson (1979), Atchison, Butler and Simonds (1987), Lo and MacKinlay (1990b), and Boudoukh, Richardson and Whitelaw (1994). In this paper, we choose the simple model of Lo and MacKinlay (1990b) to illustrate the relation between the spot and futures markets. In their model, in any given period, there is an exogenous probability π_i that stock S_i does not trade. Furthermore, each security's return, r_i, is described by one zero-mean, i.i.d. factor, M, with loading, β_i. Lo and MacKinlay (1990b) show that the measured excess returns on an equally-weighted portfolio of N securities, denoted $r_{\hat{S}}$, can be written as

$$r_{\hat{S},t} = \mu_S - i + (1 - \pi_S)\beta_S \sum_{k=0}^{\infty} \pi_S^k M_{t-k},$$

where μ_S and β_S are the average mean and average beta of the portfolio of the N stocks, and π_S is the probability of nontrading assuming equal nontrading probabilities across the stocks. Of course, the true excess returns are simply described by

$$r_{S,t} = \mu_S - i + \beta_S M_t,$$

where any idiosyncratic risk has been diversified away.

In a no arbitrage world, the price of the futures contract will reflect the present value of the stock index at maturity. That is,

$$F_{t,T} = \mathrm{PV}(\hat{S}_T) e^{(i-d^*)(T-t)}, \tag{2}$$

where d^* is the previous dividend rate, d, adjusted for the fact that some stocks in the index don't trade. Note that, due to nontrading, the present value of the index is no longer its true value, but instead a value that partly depends on the current level of nontrading. This is because the futures price is based on the measured value of the index at maturity, which includes stale prices. Within the Lo and MacKinlay (1990b) model, nontrading today has some, albeit small, information about the staleness of prices in the distant future. However, as long as the contract is not close to expiration, the effect, which is of order π^{T-t}, is miniscule. In particular, it is possible to show that the corresponding futures return is:

$$r_{F_{t,T}} = (1 - \pi^{T-t}) r_{S,t}. \tag{3}$$

Not surprisingly, in contrast to the measured index returns, futures returns will not be autocorrelated due to the efficiency of the market and the no arbitrage condition between the cash and futures market. However, the futures return will differ from the true excess spot return because it is priced off the *measured* value of the spot at maturity. This difference leads to a lower volatility of the futures return than the true spot return, though by a small factor for long-maturity contracts. Specifically, within the framework of this model, the variance ratio between futures returns and true spot returns is $(1-\pi^{T-t})^2$, whereas the ratio between measured index returns and true returns is $\frac{(1-\pi)^2}{1-\pi^2}$. Except for very short maturity contracts, futures returns volatility will be greater than that of the measured index return.[5]

2.3 Case III: The Partial-Adjustment Model

As an alternative to market microstructure-based models, the finance literature has developed so-called partial adjustment models. Through either information transmission, noise trading or some other mechanism, these models imply that some subset of securities partially adjust, or adjust more slowly, to market-wide information. While there is some debate about whether these models can be generated in both a *reasonable* and rational framework, all the models impose some restrictions on trading so that the partial adjustment effects cannot get arbitraged away. There are a number of models that produce these types of partial adjustment effects (e.g., see Holden and Subrahmanyam (1992), Foster and Viswanathan (1993), Badrinath, Kale and Noe (1995), Chordia and Swaminathan (1998) and Llorente, Michaely, Saar and Wang (1998)).

Here, we choose one particular model, which coincides well with Section 2.2 above, namely Brennan, Jegadeesh and Swaminathan (1993). We assume that the index is made up of two

[5] It can be shown that futures returns volatility will be greater than that of the measure index return if

$$\begin{aligned} (T-t) \quad &> \quad \frac{\ln\left(1-\sqrt{\frac{1-\pi}{1+\pi}}\right)}{\ln \pi} \\ &\approx \quad \sqrt{\frac{1}{1-\pi^2}}. \end{aligned}$$

Even when π is 50%, which is a unrealistically large number, the volatility ratio will be greater than one if the maturity of the futures contract is greater than 1.25 days.

equally-weighted portfolios of stocks, S_F and S_P, which for better terminology stand for full (i.e., F) and partial (i.e., P) response stocks. (Brennan, Jegadeesh and Swaminathan (1993) consider stocks followed by many analysts versus those followed by only a few analysts.) Assume that the returns on these two portfolios can be written as

$$\begin{aligned} R_{F,t} &= \mu_F + \beta_F M_t \\ R_{P,t} &= \mu_P + \beta_P M_t + \gamma_P M_{t-1}. \end{aligned}$$

Thus, for whatever reason, the return on the partial response stocks is affected by last period's realization of the factor. One offered explanation is that market-wide information is only slowly incorporated into certain stock prices, yielding a time-varying expected return that depends on that information. Note that similar to Lo and MacKinlay (1990b) and Section 2.2 above, we have also assumed that these two portfolios are sufficiently well-diversified that there is no remaining idiosyncratic risk.

Assume that the index contains ω of the fully adjusting stock portfolio and $1-\omega$ of the partially adjusting portfolio. Under the assumption of no transactions costs and no arbitrage, it is possible to show that the excess returns on the index and its corresponding futures contract can be written as:

$$\begin{aligned} r_{S,t} &= \mu_S - i + \beta_S M_t + \gamma_S M_{t-1} \qquad (4) \\ r_{F,t} &= r_{S,t} \\ \text{where } \mu_S &= \omega\mu_F + (1-\omega)\mu_P \\ \beta_S &= \omega\beta_F + (1-\omega)\beta_P \\ \gamma_S &= (1-\omega)\gamma_P. \end{aligned}$$

The returns on both the stock index and its futures contract coincide, and therefore pick up similar autocorrelation properties. In fact, their autocorrelations can be solved for

$$\frac{[\omega\beta_F + (1-\omega)\beta_P](1-\omega)\gamma_P}{[\omega\beta_F + (1-\omega)\beta_P]^2 + [(1-\omega)\gamma_P]^2}.$$

For indices with relatively few partial-adjustment stocks (i.e., high ω) or low lagged response coefficients (i.e., small γ_P), the autocorrelation reduces to approximately :

$$\frac{(1-\omega)\gamma_P}{\omega\beta_F + (1-\omega)\beta_P}.$$

With the additional assumption that the beta of the index to the factor is approximately one, an estimate of the autocorrelation is $(1-\omega)\gamma_P$. That is, the autocorrelation depends on the proportion of partially adjusting stocks in the index and on how slowly these stocks respond. These results should not seem surprising. With the no arbitrage condition between the cash and futures market, the price of the futures equals the present value of the future spot index, which is just the current value of the index. That is, though the spot price at maturity includes lagged effects, the discount rate does also, leading to the desired result. With nontrading, because the lagged effects are *spurious*, discounting is done at μ_S, which leads to zero autocorrelation of futures returns.

In response, a behavioralist might argue that the futures return does not pick up the properties of the cash market due to the inability of investors to actually conduct arbitrage between the markets. Of course, the most likely reason for the lack of arbitrage is the presence of transactions costs, that is, commissions and bid-ask spreads paid on the stocks in the index and the futures contract. The level of these transactions costs depend primarily on costs borne by the institutional index arbitrageurs in these markets. Abstracting from any discussion of basis risk and the price of that risk, we assume here that arbitrageurs buy or sell all the stocks in the index, at a multiplicative cost of δ. Thus, round-trip transactions costs per arbitrage trade are equal to 2δ. In this environment, it is possible to show that, in the absence of arbitrage, the futures price must satisfy the following constraints:

$$-(2\delta + \delta i) \leq F_{t,T} - S_t e^{(i-d)(T-t)} \leq (2\delta + \delta i). \tag{5}$$

In other words, the futures price is bounded by its no arbitrage value plus/minus round-trip transactions costs.

What statistical properties do futures returns have within the bounds? There is no obvious answer to this question found in the behavioral literature. If the futures is priced off the current value of the spot index, then, as described above, futures returns will inherit the autocorrelation properties of the index return. Alternatively, suppose investors in futures markets are more sophisticated, or at least respond to information in M fully. That is, they price futures off the future value of the spot index, discounted at the rate μ_S. In this case, the futures returns will not be autocorrelated, and expected returns on futures will just equal $\mu_S + E[\Delta(i-d)]$.

Of course, if the futures-spot parity lies outside the bound, then arbitrage is possible, and futures prices will move until the bound is reached. It is possible to show that futures prices at time t will lie outside the bound (in the absence of arbitrage) under the following condition:

$$|M_t| \geq \frac{2\delta + \delta i}{(1-\omega)\gamma_P}. \tag{6}$$

That is, three factors increase the possibility of lying outside the bound: (i) large recent movement in the stock index (i.e., $|M_t|$), (ii) low transactions costs (i.e., δ), (iii) large autocorrelation in the index (i.e., $(1-\omega)\gamma_P$). If condition (6) is met, then, even in the case of sophisticated futures traders, expected returns on futures will not be a constant, but instead capture some of the irrationality of the index. Specifically, if (6) is true, then

$$E_t[r_{F,t}] = (1-\omega)\gamma_P M_t - (2\delta + \delta i). \tag{7}$$

Figure 1 illustrates the pattern in expected futures returns under this model. Within the bounds, expected futures returns are flat. Outside the bound, futures begin to take on the properties of the underlying stock index, and futures returns are positively autocorrelated for more extreme past movements. Figure 1 provides the basis for an analysis of the implications of futures markets in the presence of index return autocorrelation.

Similarly, we can calculate the volatility of the returns on the index and the volatility of the returns on its corresponding futures contract. Within the bound, using equation (4), it is possible to show that the return variances are:

$$\begin{aligned} \sigma^2_{r_S} &= (\beta_S^2 + \gamma_S^2)\sigma_M^2 \\ \sigma^2_{r_F} &= (\beta_S + \gamma_S)^2\sigma_M^2. \end{aligned}$$

In other words, as long as γ_S is positive (which is the prevailing view), the volatility of futures returns will be higher than the volatility of the spot index excess returns. However, volatility of interest rate changes aside (i.e., $\sigma^2_{\Delta(i-d)}$), the volatility of the spot and futures returns will start to converge when condition (6) is realized. This is because the futures return takes on the properties of the index return as index arbitrage forces convergence of the two.

2.4 Implications

The above models for index and corresponding futures prices are clearly stylized and very simple. For example, the Lo and MacKinlay (1988) model of nontrading has been generalized to heterogeneous nontrading and heterogeneous risks of stocks within a portfolio which provides more realistic autocorrelation predictions (see, for example, Boudoukh, Richardson and Whitelaw (1994)). Which model is best, however, is besides the point for this paper. The purpose of the models is to present, in a completely transparent setting, different implications of two opposing schools of thought. The first school believes that the time-varying patterns in index returns are not tradeable, and in fact may actually be completely spurious, i.e., an artifact of the way we measure returns. The second school believes that these patterns are real and represent actual prices, resulting from some sort of inefficient information transmission in the market. The implications we draw from these models are quite general and robust to more elaborate specifications of nontrading or agent's ability to incorporate information quickly.

In particular, according to the models described in Sections 2.2 and 2.3, it is possible to make several observations about the relative statistical properties of index and futures returns:

- Under a market microstructure setting, the index returns will be positively autocorrelated while the futures returns will not be autocorrelated (bid-ask bounce aside). Moreover, the magnitude of these differences will be related to the level of microstructure biases. In contrast, the behavioral model predicts spot index and futures returns will inherit the same autocorrelation properties.

- Similar implications occur for the volatility of the index and futures returns. Behavioral models predict spot and futures returns will have approximately the same volatility (interest rate volatility aside), while market microstructure models imply different volatilities. Again, the difference in volatilities will be related to the magnitude of the microstructure biases.

- In the presence of transactions costs, behavioral models can potentially form a wedge between the statistical properties of spot index and futures returns. However, this wedge leads to particular implications, namely that the spot index and futures returns will behave similarly in periods of big stock price movements and possibly quite differently in periods of small movements. For example, the autocorrelation of futures returns should be zero for small movements, and positive for large movements. Likewise, the relative volatility between the futures and spot market should be higher in the futures market for small past movements versus large past movements.

- Finally, a nontrading-based explanation of the patterns in spot index and futures returns implies the following characteristic of the data. As the nontrading probability π goes down, i.e., higher volume, the spot index return's properties, such as its autocorrelation, should look like the true return process. Moreover, while the properties of the index return change with volume, the properties of the futures return should remain the same for long maturity contracts.

These observations are the basis for an empirical comparison of spot index and corresponding futures returns. To build up as much independent evidence as possible, this analysis is performed on over 24 indices across 15 countries. Because the daily index returns across these countries are not highly correlated, the results here will have considerably more power to differentiate between the implications of the two schools.

3 The Data

All the data are collected from Datastream; specifically, price levels of each stock index and corresponding futures contract at the close of trade every day, daily volume on the overall stock market in a given country, daily open interest and volume for each futures contract, short-term interest rates and dividend yields. The data are collected to coincide with the length of the available futures contract. For example, if the futures contract starts on June 1, 1982 (as did the S&P 500), all data associated with this contract start from that date.

The futures data are constructed according to usual conventions. In particular, a single time series of futures prices is spliced together from individual futures contracts prices. For liquidity, the nearest contract's prices are used until the first day of the expiration month, then the next nearest is used, and so on. For a futures contract to be used, we require at least four years of data (or roughly 1000 observations) to lower the standard errors of the estimators. This leads us to drop a number of countries such as the Eastern European block, emerging countries in Asia like Thailand, Korea and Malaysia, as well as some small stock based indices like the MDAX in Germany. Given this criteria, we are left with 24 futures contracts on stock indices covering 15 countries. Table 1 gives a brief description of each contract, the exchange it is traded on, its country affiliation, its starting date, as well as some summary statistics on the futures' returns, open interest and trading volume. Summary statistics on the underlying index returns are also provided.

Some observations are in order. First, given the wide breadth of countries used in this analysis as seen in Table 1, and the fact that daily returns across countries have relatively small contemporaneous correlations (e.g, with a mean of .39 and a median of .32), the data in this study provide considerable independent information about the economic implications described in Section 2. Second, while the unconditional means of the index returns and corresponding futures returns are basically the same for all contracts, their volatilities are substantially different. While part of these differences can be explained by interest rate volatility, the majority of the differences come from some other source (see Section 4). As shown in Section 2, these types of differences are more commonly associated with market microstructure biases since behavioral models imply the volatility will be picked up in both markets. Third, the futures contracts have considerable open interest and daily volume in terms of the number of contracts. Table 1 provides the mean for these contracts, and, for less liquid ones such as the Russell 2000 and Value Line, these means are still high relative to less liquid stocks, e.g., 455 and 197 contracts per day respectively. The fact that these contracts are liquid allows us to focus primarily on market microstructure biases related to the stocks in the underlying index. Section 4 of the paper addresses any potential biases related to the futures contracts.

4 Empirical Results

In this section, we focus on providing evidence for or against the implications derived from the models of Section 2. In particular, we investigate (i) the autocorrelation properties of the spot index and corresponding futures returns, (ii) the relative time-varying properties of spot index and future returns conditional on recent small and large movements in returns, and (iii) the relation between these time-varying properties and underlying stock market volume.

4.1 Autocorrelations

Table 2 presents the evidence for daily autocorrelations of spot indices and their corresponding futures returns across 24 contracts. The most startling evidence is that, for every contract, the spot index autocorrelation exceeds that of the futures. This cannot be explained by common sampling error as many of the contracts are barely correlated given the 15 country cross-section. Figure 2 presents a scatter plot of the autocorrelations of the futures and spot indices, i.e., a graphical representation of these results. On the 45 degree line, the spot and futures autocorrelations coincide; however, as the graph shows, all the points lie to the right of this line. Thus, all the spot autocorrelations are higher than their corresponding futures.

Moreover, other than the Nikkei 225 contracts (which have marginally negative values), all of the spot index returns are positively autocorrelated. Some of these indices, such as the Russell 2000 (small firm US), ValueLine (equal-weighted US), FTSE 250 (medium-firm UK), TOPIX (all firms Japan), OMX (all firms Sweden) and Australian All-Share index, have fairly large autocorrelations — .22, .19, .21, .10, .12 and .10, respectively. Interestingly, these indices also tend to be ones which include large weights on firms which trade relatively infrequently. In contrast, the value-weighted indices with large, liquid, actively-traded stocks, such as the S&P 500 (largest 500 US firms), FTSE 100 (100 most active U.K. firms), Nikkei 225 (active 225 Japan stocks), and DAX (active German firms), are barely autocorrelated — .03, .08, -.014 and .02, respectively.

Note that while the autocorrelations of both the index and futures alone are difficult to pinpoint due to the size of the standard errors, the autocorrelation differences should be very precisely estimated given the high contemporaneous correlation between the index and futures. In terms of formal statistical tests, for 21 out of 24 contracts we can reject the hypothesis that the spot index autocorrelation equals that of its futures contract at the 5% level. To the extent that this is one of the main comparative implications of market microstructure versus behavioral models, this evidence supports the microstructure-based explanation.[6] The evidence is particularly strong as 17 of the differences are significant the 1% level. These levels of significance should not be surprising given that the index and its futures capture the same aggregate information, yet produce in 12 cases autocorrelation differences of at least 10% on a daily basis!

4.2 Time-Varying Patterns of Returns

The results in Section 4.1 are suggestive of differences between the time-varying properties of spot index and futures returns. While this tends to be inconsistent with behavioral-based explanations of the data, we showed in Section 2.3 that it is possible to construct a *reasonable* scenario in which large differences can appear. Specifically, the reason why behavioral models imply a one-to-one relation between spot and futures returns is that they are linked via spot-futures arbitrage. If spot-futures arbitrage is not possible due to transactions costs, then theoretically spot and futures prices might diverge if their markets are driven by different investors. Figure 1 shows that the implication of this transaction-

[6] Of course, futures returns, due to either nontrading or bid-ask bounce, should have negative autocorrelations, which could partially explain the differences even without index microstructure biases. Section 4 looks at the extent to which futures biases can explain the result.

based model is that, conditional on extreme recent movements, the statistical properties of spot and futures returns should be similar; for small movements, they can follow any pattern, including the spot return being positively autocorrelated and its futures return being serially uncorrelated.

In order to test this implication directly, consider a piecewise linear regression of the futures return on its most recent lag. In particular:

$$r_{F,t+1} = a + b_1 r_{F,t} + (b_2 - b_1)\text{Max}[0, r_{F,t} - a_1] + (b_3 - b_2)\text{Max}[0, r_{F,t} - a_2] + \epsilon_{t+1}, \quad (8)$$

where a_1 and a_2 are the breakpoints of the piecewise regression. These breakpoints are equivalent to the transactions costs bounds described in Section 2.3. Here, we choose these points as -1.0% and 1.0%, respectively. Thus, any daily return of plus/minus 1% or greater in magnitude allows index arbitrage to take place. The coefficients b_1, b_2 and b_3 reflect the slopes of the piecewise relation. In the context of Figure 1, b_1 and b_3 are positive while b_2 is zero under the behavioral model. In the market microstructure model, bid-ask bounce aside, these coefficients should be zero.

Table 3A presents the regression results from equation (8) for each contract across the 15 countries. From the behavioral viewpoint, equation (8) implies, as its null hypothesis, a series of inequality constraints, $b_1 \geq 0$ & $b_3 \geq 0$. Because the constraints are inequalities, these restrictions are very weak. Nevertheless, thirteen of the twenty-five contracts reject the behavioral theory at conventional levels using an inequality restrictions-based test statistic (see Wolak (1987) and Boudoukh, Richardson and Smith (1993) for a description of the test methodology).[7] More important, however, is that, for these cases, all of them give estimates which are consistent with $b_1 \leq 0$ and $b_3 \leq 0$, the exact opposite implication of the behavioral model. This suggests some amount of symmetric behavior at the extremes. Perhaps the strongest evidence is that across all 24 contracts, $b_1 > 0$ only five times, though not significantly! Thus, for the circumstances most favorable to spot-futures arbitrage, there is little evidence of local positive autocorrelation of the futures return.

Figure 3 provides a graphical presentation of these results for three contracts which contain illiquid stocks, namely the Russell 2000, TOPIX and FTSE 250. The graph represents a kernel estimation of the mean of $r_{F,t+1}$, conditional on the value of $r_{F,t}$. As seen from these three somewhat independent graphs, the implications of the behavioral model (i.e., Figure 1)

[7] To understand the nature of how weak inequality restrictions are, consider the test from the perspective of the microstructure viewpoint, i.e., the null of $b_1 = 0 \& b_3 = 0$ versus the alternative of $b_1 \geq 0 \& b_3 \geq 0$. Performing tests of this restriction yields not one rejection in favor of the behavioral theory.

are not borne out. Time-variation of expected futures returns, if any, occur for low current values of returns. Conditional on high values, the relation looks quite flat.[8] Of course, the strongest evidence in the graph is that there is not much time-variation in the estimated expected return on the futures anywhere, which is not a prediction of behavioral-based models.

One potential point of discussion is that the model described in Figure 1 implies a linear relation between next period's return and the current period's return. While this is consistent with almost all the behavioral models described in the literature, it is not necessarily an appropriate assumption. The more general implication is that, outside the transaction costs bounds, the spot and futures return take on similar characteristics, linear or nonlinear as the case may be. In order to address this issue more completely, we provide an analogous regression to (8) above, namely

$$r_{S,t+1} - r_{F,t+1} = a + b_1 r_{F,t} + (b_2 - b_1)\mathrm{Max}[0, r_{F,t} - a_1] + (b_3 - b_2)\mathrm{Max}[0, r_{F,t} - a_2] + \epsilon_{t+1}. \quad (9)$$

Under more general versions of the model of Section 2.3, we would expect $b_1 = b_3 = 0$, that is, the spot index and futures return to behave the same under conditions for spot-futures arbitrage. Table 3B provides results for the regression in (9) across all the countries.

In contrast to this behavioral-based implication, 21 of the 24 contracts reject the hypothesis, $b_1 = b_3 = 0$, in favor of the microstructure alternative, $b_1 \geq 0, b_3 \geq 0$, at the 5% level. This is especially surprising given that some of these contracts include, for the most part, actively traded stocks. Almost all the b_1 and b_3 coefficients are positive (i.e., only 4 negative estimates amongst 50), which again implies that the time-variation of the expected spot index returns is both greater than that of its corresponding futures contract and more positively autocorrelated. To the extent that the microstructure based theory would imply that all three coefficients (b_1, b_2, b_3) should be positive, 70 of 75 of them are. Since these coefficients represent relations over different (and apparently independent) data ranges and across 15 somewhat unrelated countries, this evidence, in our opinion, is strong.

4.3 Autocorrelations and Volume

One obvious implication of the nontrading-based model of Section 2.2 is that there should be some relation between the spot index properties and volume on that index, whereas the

[8] The exception here is the FTSE 250 for current values of $r_{F,t} > 1.5\%$. However, for the post 1994 sample period we have here for this contract, there are hardly any observations. Thus, the results fall into the so-called Star-Trek region of the data, and are unreliable.

futures should for the most part be unrelated to volume. Of course, behavioral-based models may also imply some correlation between volume and autocorrelations (e.g., as in Chordia and Swaminathan (1998)), but it is clearly a necessary result of the nontrading explanation.

In order to investigate this implication, we collected data from Datastream on overall stock market volume for each of the 15 countries. While this does not represent volume for the stocks underlying the index, it should be highly correlated with trading in these stocks because all the indices we look at are broad-based, market indices. That is, on days in which stock market volume is low, it seems reasonable to assume that large, aggregate subsets of this volume will also be relatively low. During the sample periods for each country, there has been a tendency for volume to increase (partly due to increased equity values and greater participation in equity markets). The standard approach is to avoid the nonstationarity issue and look at levels of detrended volume. For the US stock market, Figure 4 graphs the two volume series, and illustrates the potential differences between the two series. For the purposes of estimation, the detrended series looks more useful.

In order to investigate the effect of trading volumes on autocorrelations of the spot index and its futures return, we consider the following nonlinear regressions:

$$\begin{aligned} r_{S,t+1} &= \alpha_0^s + \left[\alpha_1^s + \alpha_2^s \left(\mathrm{Max}(\mathrm{Vol}^s) - \mathrm{Vol}_t^s\right)\right] r_{S,t} + \epsilon_{t+1}^s \\ r_{F,t+1} &= \alpha_0^f + \left[\alpha_1^f + \alpha_2^f \left(\mathrm{Max}(\mathrm{Vol}^s) - \mathrm{Vol}_t^s\right)\right] r_{F,t} + \epsilon_{t+1}^f, \end{aligned} \tag{10}$$

where $\mathrm{Max}(\mathrm{Vol}^s)$ is the maximum volume of the stock market during the sample period. Note that these regressions represent fairly logical representations of the relation between next period's return and current returns and volume. Specifically, there are two components to the time-variation of expected returns: (i) the magnitude of last period's return, and (ii) the level of volume in the market.

The hypothesis that the trading volume is a *factor* that influences autocorrelation differentials can be represented as follows:

(1) The trading volume reduces the autocorrelation of the spot, but not the futures contract:

$$\begin{aligned} \alpha_2^s &> 0 \\ \alpha_2^f &= 0 \end{aligned}$$

(2) We can interpret α_1^s and α_1^f as the autocorrelations of the spot index and the futures contact returns when the trading volume of the spot is highest. In that case, the

autocorrelation of the spot as well as the futures should be close to zero:

$$\alpha_1^s = 0$$
$$\alpha_1^f = 0$$

Some observations are in order. Hypothesis (1) is an obvious implication of index returns being driven by nontrading-based models, and the most important component of our hypotheses. Note that it is possible that $\alpha_2^s = 0$, in which case α_1^s represents the autocorrelation of the index return in a world in which volume plays no role. With respect to hypothesis (2), it appears to be redundant given (1). However, we want to be able to test whether the negative relation is strong enough to bring forth the desired result that the spot index return autocorrelation becomes zero at the highest level of the trading volume. Finally, an important hypothesis to test is whether the futures contract's autocorrelation is independent of trading volume.

Table 4 provides results for each of the 24 stock indices across the 15 countries. First, there is a negative relation between the trading volume and the autocorrelation of the spot index return for most of the countries (i.e., $\alpha_2^s > 0$). While the estimators are individually significant at the 5% level for only a few of the indices (e.g., the Russell 2000's estimate is 0.54 with standard error 0.19), 21 of 24 of them are positive. Moreover, relative to the futures return coefficient on volume (i.e., α_2^f), about 70% have values of $\alpha_2^s > \alpha_2^f$. While only a few of these are individually significant at the 5% level (i.e., S&P 500, Russell 2000, NYSE, FTSE 250, Switzerland, Amsterdam, Hong Kong, and Belgium), only one contract goes in the direction opposite to that implied by the nontrading-based theory.

Second, independent of volume, the relation between futures return autocorrelations and trading volume is very weak. Even though many of the autocorrelation coefficients, α_2^f, are positive, they tend to be very small in magnitude and are thus both *economically* and statistically insignificant. Furthermore, the estimates at high levels of nontrading imply negative autocorrelation in futures returns, which is consistent with the Table 2 results. Combining the estimates of α_1^f and α_2^f together in equation (10) implies that the autocorrelations of futures returns are rarely positive irrespective of volume levels. This result is consistent with the bid-ask bounce effect which will be looked at in Section 4.5.

Third, at the highest level of trading, the autocorrelations of the spot and futures return are for the most part insignificantly different from zero. For example, only 3 contracts, all of which are based on Japanese stock indices (i.e., Nikkei 225, Nikkei 300, and TOPIX), violate this hypothesis. However, for each of these cases, the autocorrelations are negative at high volume, and thus do not contradict the nontrading-based theory per se. In fact, 21 of the 24 indices imply negative autocorrelation of the spot index return during periods of highest volume. While these autocorrelations are not estimated precisely, it does point out that adjustments for trading volume lead to changes in the level of autocorrelations. For example, the Russell 2000's autocorrelation changes from Table 2's estimate of 0.22 to -0.09 at highest volume levels in Table 4. The most obvious explanation for the negative values is misspecification of the regression model in (10).

In order to address this issue, we perform a nonparametric analysis of the effect of trading volumes on autocorrelations of the spot and futures return for the Russell 2000 contract. Specifically, using multivariate density estimation methods, we look at the expected return differential, $r_{S,t+1} - r_{F,t+1}$, on detrended market volume and the most recent stock market innovation, estimated by current futures returns $r_{F,t}$. For multidimensional estimation problems like this, it is important to document the area of relevant data. Figure 5 provides a scatter plot of detrended volume and futures returns, which represents the applicable space. Any results using observations outside this area should be treated cautiously.

Figure 6 graphs the relation between futures returns and past returns and volume, i.e., the nonparametric alternative to the regression described in equation (10). For low volume periods, the differential is positive and particularly steep when past returns are high, and negative when past returns are low. In other words, low volume periods seem to be an important factor describing differences in the statistical properties of spot and futures returns. Interestingly, for average and heavy-volume days, there appears to be little difference in their time-varying properties. As a finer partition of this graph, Figure 7 presents cut-throughs of the relation between spot-future return differentials and past market innovations for four different levels of volume within the range of the data. As seen from Figure 7, while there are positive differentials for all levels of volume (as consistent with the one-dimensional analysis of Sections 4.1 and 4.2), the most striking evidence takes place during low volume periods. To the extent that low volume periods are associated with nontrading, these results provide evidence supportive of the type of models described in Section 2.2. It is, of course, possible for researchers to devise a behavioral model that fits these characteristics as well, but they must do so in the presence of spot-futures arbitrage.

4.4 Volatility Ratios

Section 2 provides implications for the variance ratio between the futures and the underlying index return. The ratios given in Table 1 do not support the behavioral explanation as futures return volatility exceeds that of the spot index. In this subsection, we explore these results more closely by addressing two issues: (I) the effect of the volatility of interest rates and dividend yields, and (II) the behavior of the volatility ratios in periods most suited to spot-futures arbitrage.

With respect to (I), Table 5 provides the ratio of the futures return variance over the measured spot index return variance, adjusted for the variance (and covariance) of the cost of carry, $\Delta(i-d)$. Not surprisingly, due to the fact that stock volatility is so much greater than interest rate volatility, the results from Table 1 carry through here. For every single contract, the variance ratio exceeds 1, and significantly so for all but one. This result provides strong evidence in favor of a nontrading-based explanation.

With respect to (II), Section 2.4 showed that the behavioralists imply, for extreme lagged returns, the variance ratio should be closer to one than for small lagged returns. In practice, due to heteroskedasticity, one would expect variances to increase during the extreme periods, but that the ratios stay relatively constant. Since extreme values are more suitable for spot-futures arbitrage, spot and futures volatility should be closer together (at least outside the transactions cost range). In contrast to the previous results regarding behavioral hypotheses, Table 5 provides some (albeit weak) support for the theory. Nineteen of the twenty-five contracts produce greater variance ratios in normal periods; however, only eight of these are significant at conventional levels. Microstructure-based explanations do not address this issue per se. However, if extreme moves tend to be associated with high volume environments, then rational theories would also suggest that the volatility ratio decline here (i.e., due to the better measurement of the stock index). In any event, the main prediction, namely that futures volatility exceeds spot volatility, is strongly supported in the data.

4.5 Can Bid-Ask Bounce Explain the Autocorrelation Differences?

One possible explanation for the differences between spot index and futures' return autocorrelations is that the futures contract themselves suffer from microstructure biases. That is, a behavioralist might argue that the true autocorrelation is large and positive, yet the futures' autocorrelation gets reduced by bid-ask bounce and similar effects. In fact, it is well known that bid-ask bias leads to negative serial correlation in returns (see, for example, Roll (1984) and Blume and Stambaugh (1983)). How large does the bid-ask spread need to be to give credibility to this explanation?

Consider a variation of the Blume-Stambaugh (1983) model in which the measured futures price, F^m, is equal to the true price, F, adjusted for the fact that some trades occur at the offer or asking price, i.e.,

$$F_t^m = F_t(1 + \theta_t),$$

where θ_t equals the adjustment factor. In particular, assume that θ_t equals $\frac{s}{2}$ with probability $\frac{p}{2}$ (i.e., the ask price), $-\frac{s}{2}$ with probability $\frac{p}{2}$ (i.e., the bid price), or 0 with probability $1 - p$ (i.e., a trade within the spread). Here, s represents the size of the bid-ask spread, and can be shown to be directly linked to the volatility of θ_t. Specifically, we can show that $\sigma_\theta^2 = p\frac{s^2}{4}$. In words, the additional variance of the futures price is proportional to the size of the spread and the probability that trades take place at the quotes. Using the approximation $\ln(1 + x) \approx x$, it is possible to show that the implied autocorrelation of futures returns is given by

$$\frac{-ps^2}{4\sigma_{R_F}^2 + 2ps^2}. \tag{11}$$

Table 6 reports the autocorrelation differences between the stock index and futures returns. If these differences were completely due to bid-ask bias in the futures market, then equation (11) can be used to back out the relevant bid-ask spread. The last two columns of Table 6 provide estimates of the size of this spread in percentage terms of the futures price. The two columns represent two different values of p, the probability of trading at the ask or bid, equal to either 0.5 or 1.0. Of course, a value of 1.0 is an upper bound on the effect of the bid-ask spread. The implied spreads in general are much larger than those that occur in practice. To see this, we document actual spreads at the end of the sample over a week period, and find that they are approximately one-tenth the magnitude (i.e., see column (4) of Table 6). Alternatively, using the actual spreads, and the above model, we report implied autocorrelations, which are all close to zero. Therefore, the differences in the autocorrelations across the series is clearly not driven by bid-ask bounce in the futures market.

5 Concluding Remarks

The simple theoretical results in this paper, coupled with the supporting empirical evidence, lead to several conclusions. First, there are significant differences between the statistical properties of spot index and corresponding futures returns even though they cover the same underlying stocks. These differences can most easily be associated with market microstructure-based explanations as behavioral models do not seem to capture the characteristics of the data. Second, in the presence of transactions costs and the most favorable conditions for behavioral models, the empirical results provide very different conclusions. When futures-spot arbitrage is possible, the spot and futures contract exhibit the most different behavior, the opposite implication of a behavioral model. Third, an important factor describing these different properties is the level of volume in the market, which is consistent with nontrading-based explanations as well as possibly behavioral-based models linked to volume.

The unique aspect of this paper has been to differentiate, rather generally, implications from two very different schools of thought and provide evidence thereon. Our conclusion is generally not supportive of the behavioral, partial-adjustment models that have become popular as of late. What then is going on in the market that can describe these large daily autocorrelations of portfolio returns?

Previous authors (e.g., Conrad and Kaul (1989) and Mech (1993), among others) have performed careful empirical analyses of nontrading by taking portfolios that include only stocks that have traded. Their results, though somewhat diminished, suggest autocorrelations are still positive and large for these portfolios. It cannot be the case that exchange-based rules, like price continuity on the NYSE, explain these patterns because these results hold across exchanges and apparently across countries. Whatever the explanation, it must be endemic to all markets.

Rational models predict that the price of a security is the discounted value of its future cash flow. Within this context, how should we view a trade for 100 shares when there is little or no other trading? Does it make sense to discard a theory based on a single investor buying a small number of shares at a stale over- or undervalued (relative to market information) price, or a dealer inappropriately not adjusting quotes for a small purchase or sale? Our view is that the important issue is how many shares can trade at that price (either through a large order or numerous small transactions). What would researchers find if we took portfolios of stocks that trade meaningfully, and then what would happen if these portfolios got segmented via size, number of analysts, turnover, et cetera? These are questions which seem very relevant given the results of this paper.

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Table 1: Sample Statistics for Indices and Futures Contracts

Reported for each contract are the exchange, country, number of observations, start date, end date, mean and standard deviation of index return and futures return, open interest and futures trading volume.

			Returns							Open Interest		Trading Volume	
						Index		Futures					
Contract	**Exchange**	**Country**	*No*	*Start*	*End*	*Mean*	*Std*	*Mean*	*Std*	*Mean*	*Std*	*Mean*	*Std*
S&P 500	CME	US	4350	06/01/82	02/03/99	0.0559	0.9851	0.0560	1.1911	274693.78	130827.85	62089.07	32102.39
RUSSELL 2000	CME	US	1558	02/11/93	02/03/99	0.0396	0.7813	0.0396	0.9418	5466.76	4002.12	455.17	705.14
NIKKEI 225	CME	US	2169	10/10/90	02/03/99	-0.0215	1.4357	-0.0204	1.5385	20324.65	8122.63	1732.23	1905.72
NYSE-STOCK	NYSE	US	4368	05/06/82	02/03/99	0.0495	0.9081	0.0495	1.1799	6740.36	3691.51	6132.52	3975.41
MAXI VALUE LINE	KCBT	US	2791	05/23/88	02/03/99	0.0503	0.6635	0.0512	0.9025	2498.05	2006.71	197.13	303.51
FTSE 100	LIFFE	UK	3848	05/03/84	02/03/99	0.0430	0.9486	0.0432	1.0964	93947.63	67882.48	9041.89	10053.11
FTSE 250	LIFFE	UK	1287	02/25/94	02/03/99	0.0214	0.5607	0.0211	0.6330	5232.38	1872.38	N/A	N/A
TOPIX	TSE	Japan	2716	09/05/88	02/03/99	-0.0241	1.1789	-0.0241	1.3280	61164.59	41705.49	9940.63	6469.21
NIKKEI 225	OSX	Japan	2716	09/05/88	02/03/99	-0.0242	1.4150	-0.0244	1.4166	152646.3	75833.12	37204.19	23681.51
NIKKEI 300	OSX	Japan	1296	02/14/94	02/03/99	-0.0214	1.1622	-0.0208	1.3256	120634.89	29613.88	7940.81	12508.13
DAX	EUREX	Germany	1981	07/01/91	02/03/99	0.0580	1.1717	0.0576	1.2450	175100.14	90140.25	18856.4	11907.66
SWISS MARKET	EUREX	Switzerland	2147	11/09/90	02/03/99	0.0760	1.0570	0.0757	1.0970	23893.42	28975.27	6623.03	8699.17
AEX	AMSTERDAM	Netherlands	2681	10/24/88	02/03/99	0.0577	1.0526	0.0579	1.1169	21538.75	14465.87	4751.23	5574.94
BELFOX-20	BELFOX	Belgium	1372	10/29/93	02/03/99	0.0665	0.8718	0.0667	0.9214	6616.48	4061.94	1429.17	1933.21
HANG SENG	HKFE	Hong Kong	2881	01/18/88	02/03/99	0.0462	1.7099	0.0459	1.9631	31604.23	24939.12	11800.48	12777.53
IBEX 35 PLUS	MEFF	Spain	1771	04/20/92	02/03/99	0.0729	1.2625	0.0725	1.4750	36196.55	21435.12	14519.69	15056.57
MIB 30	MIF	Italy	1091	11/28/94	02/03/99	0.0792	1.5513	0.0776	1.6605	19685.53	9234.24	14008.73	9486.82
OMX-STOCK	OMX	Sweden	2370	01/02/90	02/03/99	0.0530	1.3241	0.0524	1.5853	59106.35	68598.88	N/A	N/A
ATX	OTOT	Austria	1692	08/07/92	02/03/99	0.0248	1.1096	0.0258	1.2468	30523.44	15544.54	1596.17	1489.93
NIKKEI 225	SIMEX	Singapore	3148	01/06/87	02/01/99	-0.0084	1.4153	-0.0088	1.6491	13222.81	11834.87	152646.30	75833.12
NIKKEI 300	SIMEX	Singapore	1042	02/03/95	02/03/99	-0.0196	1.2327	-0.0194	1.3230	14816.72	8380.19	N/A	N/A
TORONTO 35	TFE	Canada	2071	02/25/91	02/03/99	0.0328	0.8464	0.0324	1.0129	14508.86	7204.8	645.20	997.97
AUSTRALIA	SFE	Australia	3937	01/03/84	02/03/99	0.0334	0.9983	0.0331	1.4475	23745.64	34674.36	1345984.04	868007.19
CAC 40	MATIF	France	2698	01/03/88	02/03/99	0.0401	1.1692	0.0399	1.2503	47530.65	62667.04	4910.75	7712.68

Table 2: Daily Autocorrelations of Index and Futures Returns

Reported are daily autocorrelations of index and futures returns. The χ_1^2 statistic tests $\rho^{Index} = \rho^{Future}$. Standard errors are serial correlation and heteroskedasticity-adjusted using Newey and West (1987).

Contract	**Exchange**	$\rho^{\mathbf{Index}}$	*s.e.*	$\rho^{\mathbf{Future}}$	*s.e.*	χ_1^2	*p-value*
S&P 500	CME	0.0267	0.0269	-0.0386	0.0278	26.5625	0.0000
RUSSELL 2000	CME	0.2155	0.0457	0.0668	0.0399	45.5922	0.0000
NIKKEI 225	CME	-0.0346	0.0261	-0.0910	0.0264	6.6635	0.0098
NYSE-STOCK	NYSE	0.0589	0.0282	-0.0582	0.0288	45.3751	0.0000
MAX VALUE LINE	KCBT	0.1877	0.0309	-0.0270	0.0357	61.6370	0.0000
FTSE 100	LIFFE	0.0836	0.0312	0.0262	0.0284	12.3201	0.0004
FTSE 250	LIFFE	0.2082	0.0663	0.1201	0.0563	4.6523	0.0310
TOPIX	TSE	0.0985	0.0260	-0.0114	0.0260	44.6339	0.0000
NIKKEI 225	OSX	-0.0141	0.0242	-0.0275	0.0246	1.1324	0.2873
NIKKEI 300	OSX	0.0132	0.0347	-0.0760	0.0322	33.8410	0.0000
DAX	EUREX	0.0249	0.0277	0.0010	0.0297	4.2482	0.0393
SWISS MARKET	EUREX	0.0539	0.0299	0.0298	0.0288	4.9607	0.0259
AEX	AMSTERDAM	0.0356	0.0254	0.0034	0.0278	6.5739	0.0103
BELFOX-20	BELFOX	0.1510	0.0390	0.1008	0.0355	4.0746	0.0435
HANG SENG	HKFE	0.0124	0.0429	-0.0529	0.0450	21.8761	0.0000
IBEX 35 PLUS	MEFF	0.1270	0.0294	0.0076	0.0311	37.6380	0.0000
MIB 30	MIF	0.0108	0.0369	-0.0379	0.0375	10.0323	0.0015
OMX-STOCK	OMX	0.1179	0.0262	-0.0357	0.0370	18.0804	0.0000
ATX	OTOT	0.0897	0.0374	-0.0102	0.0395	67.2461	0.0000
NIKKEI 225	SIMEX	-0.0163	0.0263	-0.0433	0.0299	0.6547	0.4184
NIKKEI 300	SIMEX	0.0091	0.0379	-0.0435	0.0369	10.7257	0.0011
TORONTO 35	TFE	0.0841	0.0311	-0.0799	0.0702	5.2843	0.0215
AUSTRALIA	SFE	0.1025	0.0290	-0.0744	0.0385	23.5963	0.0000
CAC 40	MATF	0.0474	0.0217	0.0129	0.0222	12.4701	0.0004

Table 3A: Daily Autocorrelations of Futures Returns: Piecewise Regression Analysis

Reported are daily autocorrelations of futures returns. Extreme movements in lagged futures returns are based on the cut-off points -1.0% and 1.0%. The regression is

$$r_{t+1}^F = a + b_1 r_t^F + (b_2 - b_1)\ \text{Max}[0, r_t^F - a_1] + (b_3 - b_2)\ \text{Max}[0, r_t^F - a_2] + \epsilon_{t+1}^F,$$

where $a_1 = -0.01$ and $a_2 = 0.01$. The $\bar{\chi_2}^2$ statistic tests $H_0:\ b_1 \geq 0\ \&\ b_3 \geq 0$ vs $H_a:\ b_1 \not\geq 0$ or $b_3 \not\geq 0$. Standard errors are serial correlation and heteroskedasticity-adjusted using Newey and West (1987).

Contract	**Exchange**	$\mathbf{b_1}$	*s.e.*	$\mathbf{b_2}$	*s.e.*	$\mathbf{b_3}$	*s.e.*	$\bar{\chi_2}^2$	*p-value*
S&P 500	CME	-0.1398	0.0687	0.0136	0.0358	0.0316	0.0876	4.1394	0.0540
RUSSELL 2000	CME	-0.1910	0.1209	0.2241	0.0517	-0.0793	0.1855	3.0496	0.0931
NIKKEI 225	CME	-0.1901	0.0810	-0.0931	0.0524	0.0129	0.0710	5.5107	0.0255
NYSE-STOCK	NYSE	-0.1435	0.0730	0.0005	0.0334	-0.0320	0.0774	3.8699	0.0626
MAX VALUE LINE	KCBT	-0.3946	0.1107	0.1233	0.0421	-0.0106	0.0804	12.7142	0.0006
FTSE 100	LIFFE	0.0651	0.1253	0.0552	0.0349	-0.1109	0.1344	0.6804	0.3871
FTSE 250	LIFFE	-0.2898	0.2225	0.3097	0.0594	-0.4351	0.2919	3.3905	0.0800
TOPIX	TSE	-0.1021	0.0843	0.0211	0.0429	0.0153	0.0807	1.4645	0.2332
NIKKEI 225	OSX	-0.0556	0.0799	-0.0504	0.0468	0.0350	0.0740	0.4832	0.4402
NIKKEI 300	OSX	-0.2271	0.1076	0.0129	0.0600	-0.0994	0.1061	6.0696	0.0184
DAX	EUREX	0.0071	0.1330	0.0211	0.0478	-0.0484	0.0877	0.3270	0.5123
SWISS MARKET	EUREX	0.0298	0.1401	0.0891	0.0470	-0.1158	0.0799	2.1042	0.1591
AEX	AMSTERDAM	-0.0921	0.0936	0.1053	0.0374	-0.1173	0.0875	2.5778	0.1238
BELFOX-20	BELFOX	0.2066	0.1667	0.1107	0.0435	-0.0411	0.0972	0.1789	0.5600
HANG SENG	HKFE	-0.1892	0.0932	0.2104	0.0792	-0.1329	0.0827	4.3282	0.0517
IBEX 35 PLUS	MEFF	0.0207	0.0873	0.1000	0.0557	-0.1616	0.1065	2.2996	0.1432
MIB 30	MIF	0.0930	0.1213	0.0473	0.0790	-0.2656	0.0729	13.2769	0.0005
OMX-STOCK	OMX	-0.2223	0.0766	0.2455	0.0517	-0.2149	0.1334	13.5719	0.0004
ATX	OTOT	-0.2811	0.1118	0.1996	0.0608	-0.1043	0.0932	6.3696	0.0172
NIKKEI 225	SIMEX	-0.0693	0.0929	0.0638	0.0489	-0.1303	0.0805	4.5310	0.0405
NIKKEI 300	SIMEX	-0.2587	0.1209	0.0602	0.0690	-0.0454	0.1133	5.5742	0.0235
TORONTO 35	TFE	-0.2504	0.0888	0.2113	0.0523	-0.4903	0.1806	24.1307	0.0000
AUSTRALIA	SFE	-0.1290	0.0557	0.0433	0.0517	-0.1726	0.1775	5.6866	0.0238
CAC 40	MATF	-0.0049	0.0886	0.0452	0.0421	-0.0372	0.0703	0.2809	0.5121

Table 3B: Daily Autocorrelations of Spot-Futures Return Spread: Piecewise Regression Analysis

Reported are daily autocorrelations of the spot-futures return spread. Extreme movements in lagged futures returns are based on the cut-off points -1.0% and 1.0%. The regression is

$$r^S_{t+1} - r^F_{t+1} = a + b_1 r^F_t + (b_2 - b_1)\ \text{Max}[0, r^F_t - a_1] + (b_3 - b_2)\ \text{Max}[0, r^F_t - a_2] + \epsilon^{S-F}_{t+1},$$

where $a_1 = -0.01$ and $a_2 = 0.01$. The $\bar{\chi_2}^2$ statistic tests $H_0 :\ b_1 = b_3 = 0$ vs $H_a :\ b_1 \geq 0\ \ \&\ \ b_3 \geq 0$. Standard errors are serial correlation and heteroskedasticity-adjusted using Newey and West (1987).

Contract	**Exchange**	$\mathbf{b_1}$	*s.e.*	$\mathbf{b_2}$	*s.e.*	$\mathbf{b_3}$	*s.e.*	$\bar{\chi_2}^2$	*p-value*
S&P 500	CME	0.0602	0.0339	0.1288	0.0119	-0.0105	0.0472	5.5935	0.0268
RUSSELL 2000	CME	0.1666	0.0332	0.1339	0.0183	0.1363	0.0548	28.0097	0.0000
NIKKEI 225	CME	0.3706	0.0669	0.2150	0.0332	0.2163	0.0445	48.8751	0.0000
NYSE-STOCK	NYSE	0.0988	0.0419	0.1727	0.0147	0.0722	0.0657	5.7848	0.0244
MAX VALUE LINE	KCBT	0.3470	0.0873	0.1323	0.0222	0.0990	0.0555	19.4654	0.0000
FTSE 100	LIFFE	0.1654	0.0291	0.0516	0.0124	0.0790	0.0359	41.0167	0.0000
FTSE 250	LIFFE	-0.0462	0.0420	0.0164	0.0275	0.4978	0.2388	7.5059	0.0097
TOPIX	TSE	0.1204	0.0391	0.1818	0.0170	0.0257	0.0286	9.4947	0.0034
NIKKEI 225	OSX	0.0186	0.0271	0.0735	0.0204	0.0004	0.0374	0.4875	0.4325
NIKKEI 300	OSX	0.0588	0.0400	0.1373	0.0204	0.0449	0.0357	3.8178	0.0623
DAX	EUREX	0.1035	0.0362	0.0025	0.0149	0.0381	0.0170	13.0757	0.0005
SWISS MARKET	EUREX	0.0192	0.0198	0.0708	0.0113	0.0325	0.0164	4.6248	0.0409
AEX	AMSTERDAM	0.0114	0.0282	0.0485	0.0114	0.0350	0.0172	4.2490	0.0498
BELFOX-20	BELFOX	-0.0665	0.0621	0.0956	0.0202	0.0009	0.0405	0.0341	0.6553
HANG SENG	HKFE	0.0816	0.0329	0.1525	0.0292	0.0866	0.0332	8.7237	0.0053
IBEX 35 PLUS	MEFF	0.1110	0.0271	0.1388	0.0267	0.2095	0.0681	24.9556	0.0000
MIB 30	MIF	0.0376	0.0247	0.0967	0.0255	0.0737	0.0286	8.1299	0.0066
OMX-STOCK	OMX	0.1972	0.0610	-0.0023	0.0298	0.2689	0.0980	20.1802	0.0000
ATX	OTOT	0.1320	0.0229	0.0892	0.0167	0.1209	0.0257	53.1407	0.0000
NIKKEI 225	SIMEX	-0.0455	0.1398	0.1008	0.0473	0.0924	0.0199	22.8572	0.0000
NIKKEI 300	SIMEX	0.0375	0.0405	0.0901	0.0224	0.0486	0.0485	1.9027	0.1803
TORONTO 35	TFE	0.1020	0.0666	0.0509	0.0403	0.4369	0.1803	11.5582	0.0010
AUSTRALIA	SFE	0.6983	0.1019	0.1796	0.0557	0.4143	0.1250	52.1736	0.0000
CAC 40	MATF	0.0046	0.0237	0.0711	0.0122	0.0073	0.0133	0.3108	0.4951

Table 4: Daily Autocorrelations and Trading Volume

Reported are the regression coefficients describing the relationship between the daily autocorrelations of spot and futures returns and the trading volume of the lagged spot index. The regressions are

$$\begin{aligned} r_{t+1}^S &= \alpha_0^S + \left[\alpha_1^S + \alpha_2^S \left\{\mathrm{Max}(\mathrm{Vol}^S) - \mathrm{Vol}_t^S\right\}\right] r_t^S + \epsilon_{t+1}^S \\ r_{t+1}^F &= \alpha_0^F + \left[\alpha_1^F + \alpha_2^F \left\{\mathrm{Max}(\mathrm{Vol}^S) - \mathrm{Vol}_t^S\right\}\right] r_t^F + \epsilon_{t+1}^F \end{aligned}$$

The χ_2^2 statistic tests $\alpha_1^S = \alpha_1^F = 0$, and the $z-value$ statistic tests $\alpha_2^S - \alpha_2^F > 0$. Standard errors are serial correlation and heteroskedasticity-adjusted using Newey and West (1987).

Contract	**Exchange**	α_1^S	*s.e.*	α_1^F	*s.e.*	α_2^S	*s.e.*	α_2^F	*s.e.*	χ_2^2	*p-value*	**z-value**	*p-value*
S&P 500	CME	-0.0912	0.1038	-0.0541	0.0839	0.0791	0.0553	0.0122	0.0464	0.9858	0.6108	2.7059	0.0034
RUSSELL 2000	CME	-0.0909	0.1374	-0.0649	0.1255	0.5395	0.1894	0.2231	0.1751	0.4411	0.8021	2.6527	0.0040
NIKKEI 225	CME	-0.0767	0.1469	-0.0420	0.1891	0.0092	0.0261	-0.0070	0.0339	0.2726	0.8726	0.4862	0.3134
NYSE-STOCK	NYSE	-0.0646	0.1078	-0.0447	0.0825	0.0831	0.0570	-0.0100	0.0449	0.3589	0.8357	3.0447	0.0012
MAX VALUE LINE	KCBT	-0.0368	0.1351	-0.1708	0.1436	0.2412	0.1221	0.1543	0.1269	1.6147	0.4460	0.7341	0.2315
FTSE 100	LIFFE	-0.0385	0.1890	-0.0300	0.1502	0.0868	0.1249	0.0345	0.1016	0.0421	0.9792	1.0850	0.1390
FTSE 250	LIFFE	0.0794	0.2135	0.1037	0.1722	0.2252	0.2464	0.0363	0.2029	0.7737	0.6792	1.9764	0.0241
TOPIX	TSE	0.0603	0.0813	-0.1411	0.0756	0.0144	0.0231	0.0385	0.0197	10.4209	0.0055	-1.1928	0.8835
NIKKEI 225	OSX	-0.0812	0.0773	-0.1120	0.0829	0.0213	0.0214	0.0248	0.0227	1.8738	0.3918	-0.3197	0.6254
NIKKEI 300	OSX	-0.1241	0.1263	-0.2255	0.1316	0.1162	0.0865	0.1138	0.0897	5.4123	0.0668	0.0650	0.4741
DAX	EUREX	-0.1711	0.2144	-0.3306	0.1905	0.0733	0.0787	0.1246	0.0688	5.9837	0.0502	-1.4791	0.9304
SWISS MARKET	EUREX	-0.0363	0.0878	0.0325	0.0662	0.0546	0.0436	0.0004	0.0312	2.7580	0.2518	2.2095	0.0136
AEX	AMSTERDAM	0.1622	0.0853	-0.0030	0.1167	-0.0268	0.0141	0.0014	0.0207	14.4554	0.0007	-2.3730	0.9912
BELFOX-20	BELFOX	-0.1362	0.2184	0.0990	0.1569	0.1410	0.1021	-0.0009	0.0730	2.6858	0.2611	1.8761	0.0303
HANG SENG	HKFE	-0.2912	0.1232	-0.2384	0.1472	0.1926	0.0609	0.1192	0.0708	12.2509	0.0022	3.5046	0.0002
IBEX 35 PLUS	MEFF	0.0822	0.1563	0.0687	0.1302	0.0226	0.0665	-0.0241	0.0556	0.3068	0.8578	1.1286	0.1295
MIB 30	MIF	-0.1473	0.1332	-0.2030	0.1246	0.1538	0.1052	0.1551	0.0994	4.3753	0.1122	-0.0391	0.5156
OMX-STOCK	OMX	0.0610	0.2270	-0.2349	0.2342	0.0154	0.0584	0.0538	0.0619	2.2468	0.3252	-0.6963	0.7569
ATX	OTOT	-0.3985	0.2680	-0.3835	0.2846	0.1840	0.0907	0.1376	0.0939	2.2953	0.3174	1.6024	0.0545
NIKKEI 225	SIMEX	-0.0816	0.0772	-0.2536	0.1015	0.0213	0.0214	0.0545	0.0244	6.4681	0.0394	-1.5575	0.9403
NIKKEI 300	SIMEX	-0.1217	0.1404	-0.1154	0.1451	0.1177	0.0977	0.0487	0.1072	0.7569	0.6849	1.0256	0.1525
TORONTO 35	TFE	-0.0789	0.0753	-0.3695	0.2108	0.2183	0.0798	0.3976	0.2261	3.5942	0.1658	-0.8296	0.7966
AUSTRALIA	SFE	-0.2421	0.0912	-0.6325	0.2734	0.1391	0.0348	0.1978	0.0925	7.6987	0.0213	-0.7807	0.7825
CAC 40	MATF	-0.1311	0.0953	-0.1198	0.1030	0.0685	0.0341	0.0501	0.0378	1.9053	0.3857	0.9663	0.1670

Table 5: Volatility Ratios

Reported are volatility ratios of the futures and spot returns. ϕ is $\sigma^2(R^F)/\sigma^2\left(R^S+\triangle(i-d)\right)$. $\triangle(i)$ is defined as $\left[\ln(1+i^a_{t+1})-\ln(1+i^a_t)\right]/6$, i.e., the change in continuously compounded 2-month interest rates. $\triangle(d)$ is similarly computed. ϕ_n and ϕ_e stand for the volatility ratios for the normal range and extreme range of M_t, respectively. Specifically, extreme movements in lagged futures returns are based on the cut-off points -1.0% and 1.0%. The regressions are

$$\begin{aligned} r^S_{t+1} &= \mu^S_n(1-I_e)+\mu^S_e\, I_e+\epsilon^S_{t+1} & r^F_{t+1} &= \mu^F_n(1-I_e)+\mu^F_e\, I_e+\epsilon^F_{t+1} \\ {\epsilon^S_{t+1}}^2 &= {\sigma^S_n}^2(1-I_e)+{\sigma^S_e}^2\, I_e+\varepsilon^S_{t+1} & {\epsilon^F_{t+1}}^2 &= \phi_n{\sigma^S_n}^2(1-I_e)+\phi_e{\sigma^S_e}^2\, I_e+\varepsilon^F_{t+1} \end{aligned}$$

where $I_e=0$ if $-0.01\le r^F_{t+1}\le 0.01$; otherwise $I_e=1$. The *z-value* statistic tests $\phi_n-\phi_e>0$. Standard errors are serial correlation and heteroskedasticity-adjusted using Newey and West (1987).

Contract	**Exchange**	ϕ	*s.e.*	$\phi_{\mathbf{n}}$	*s.e.*	$\phi_{\mathbf{e}}$	*s.e.*	**z-value**	*p-value*
S&P 500	CME	1.4488	0.1231	1.2764	0.0208	1.6581	0.2048	-1.8529	0.9681
RUSSELL 2000	CME	1.4456	0.0530	1.5522	0.0557	1.3154	0.0869	2.5419	0.0055
NIKKEI 225	CME	1.1450	0.0430	1.2572	0.0721	1.0586	0.0550	2.1472	0.0159
NYSE-STOCK	NYSE	1.6714	0.1171	1.5368	0.0376	1.8408	0.2123	-1.3907	0.9178
MAX VALUE LINE	KCBT	1.8343	0.0980	1.9619	0.0986	1.5944	0.1269	3.0624	0.0011
FTSE 100	LIFFE	1.3237	0.0356	1.4133	0.0529	1.2004	0.0850	1.7271	0.0421
FTSE 250	LIFFE	1.2570	0.0807	1.2663	0.0777	1.2350	0.1540	0.2104	0.4167
TOPIX	TSE	1.2660	0.0391	1.3805	0.0555	1.1646	0.0704	2.0736	0.0191
NIKKEI 225	OSX	1.0002	0.0236	1.0539	0.0258	0.9580	0.0361	2.1363	0.0163
NIKKEI 300	OSX	1.2975	0.0575	1.3466	0.0983	1.2378	0.0506	0.9608	0.1683
DAX	EUREX	1.1296	0.0337	1.1595	0.0415	1.0891	0.0338	1.7010	0.0445
SWISS MARKET	EUREX	1.0731	0.0209	1.0925	0.0190	1.0477	0.0378	1.0930	0.1372
AEX	AMSTERDAM	1.1189	0.0251	1.1337	0.0267	1.1004	0.0433	0.6728	0.2505
BELFOX-20	BELFOX	1.1133	0.0430	1.1357	0.0557	1.0644	0.0464	1.1090	0.1337
HANG SENG	HKFE	1.3138	0.0396	1.3422	0.0333	1.2956	0.0625	0.6587	0.2550
IBEX 35 PLUS	MEFF	1.3639	0.0495	1.4767	0.0698	1.2508	0.0533	2.8952	0.0019
MIB 30	MIF	1.1397	0.0294	1.1750	0.0418	1.1065	0.0365	1.3303	0.0917
OMX-STOCK	OMX	1.4433	0.0875	1.3577	0.0656	1.5153	0.1497	-0.9774	0.8358
ATX	OTOT	1.2588	0.0250	1.2780	0.0339	1.2342	0.0410	0.7972	0.2127
NIKKEI 225	SIMEX	1.1303	0.0499	1.0986	0.0408	1.1613	0.0883	-0.6478	0.7414
NIKKEI 300	SIMEX	1.1483	0.0338	1.1595	0.0514	1.1378	0.0418	0.3325	0.3697
TORONTO 35	TFE	1.4338	0.2347	1.1669	0.0620	1.9188	0.6497	-1.1478	0.8745
AUSTRALIA	SFE	2.0811	0.3024	2.4615	0.1780	1.8776	0.4293	1.3342	0.0911
CAC 40	MATF	1.1442	0.0184	1.1367	0.0253	1.1541	0.0232	-0.5358	0.7039

Table 6: Futures Return Autocorrelations and the Bid-Ask Spread

Table 6 reports the difference between autocorrelations of the spot index and futures return for each contract, and the actual estimated bid-ask spread of each futures contract. Using a Blume-Stambaugh (1993) bid-ask model, the table provides (I) implied autocorrelation differences based on actual spreads, and (II) the implied spread necessary to explain the actual autocorrelation differences. Low probability (i.e., 50%) and high probability (i.e., 100%) states refer to the probability that the trades take place at the quotes rather than within the quoted spreads.

Contract	AC Diff.	Vol.	Spread	Implied AC		Implied Spread	
				low prob.	*high prob.*	*low prob.*	*high prob.*
S&P 500	0.0653	1.1911	0.037	0.0001	0.0002	0.86	0.61
Russell 200	0.1487	0.9418	0.150	0.0032	0.0063	1.03	0.73
Nikkei 225	0.0564	1.5385	0.060	0.0002	0.0004	1.03	0.73
NYSE	0.1171	1.1799	0.040	0.0001	0.0003	1.14	0.81
Value Line	0.2147	0.9025	0.100	0.0015	0.0031	1.18	0.84
FTSE 100	0.0574	1.0964	0.150	0.0023	0.0047	0.74	0.53
FTSE 250	0.0881	0.6330	NA	NA	NA	0.53	0.38
TOPIX	0.1099	1.3280	0.038	0.0001	0.0002	1.25	0.88
Nikkei 225	0.0134	1.4166	0.059	0.0002	0.0004	0.46	0.33
Nikkei 300	0.0892	1.3256	0.500	0.0178	0.0356	1.12	0.79
DAX	0.0239	1.2450	0.060	0.0003	0.0006	0.54	0.38
Swiss	0.0241	1.0970	0.014	0.0000	0.0000	0.48	0.34
AEX	0.0322	1.1164	0.089	0.0008	0.0016	0.57	0.40
BELFOX 20	0.0502	0.9214	0.217	0.0069	0.0139	0.58	0.41
Hang Seng	0.0653	1.9631	0.037	0.0000	0.0001	1.42	1.00
IBEX 35	0.1194	1.4750	0.070	0.0003	0.0006	1.44	1.02
MIB 30	0.0487	1.6605	0.068	0.0002	0.0004	1.04	0.73
OMX	0.1536	1.5853	0.032	0.0001	0.0001	1.76	1.24
ATX	0.0999	1.2468	0.308	0.0076	0.0153	1.11	0.79
Nikkei 225	0.0270	1.6491	0.060	0.0002	0.0003	0.77	0.54
Nikkei 300	0.0526	1.3230	0.375	0.0100	0.0201	0.86	0.61
Toronto 35	0.1640	1.0129	0.127	0.0020	0.0039	1.16	0.82
Australia	0.1769	1.4475	0.032	0.0001	0.0001	1.72	1.22
CAC 40	0.0345	1.2503	NA	NA	NA	0.66	0.46

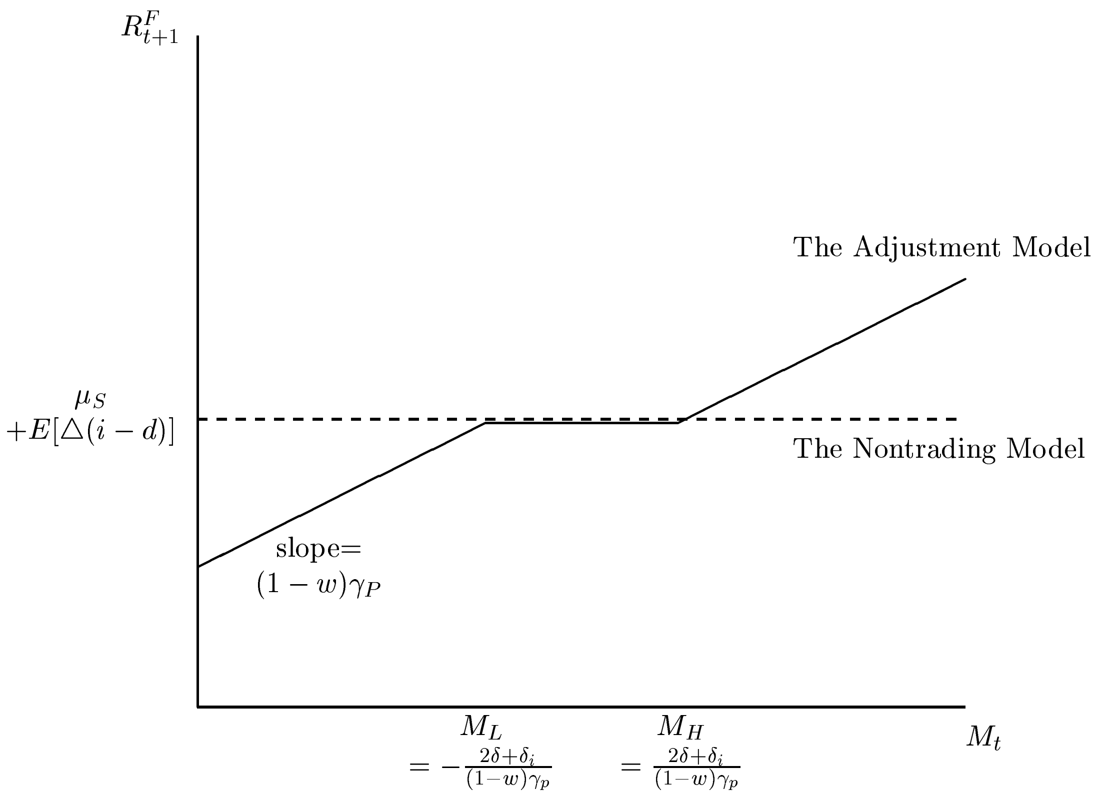

Figure 1: The theoretical relation between the futures return (R^F_{t+1}) and the lagged market innovation (M_t) in the lagged adjustment model with transaction costs (solid line) and the nontrading model (dashed line).

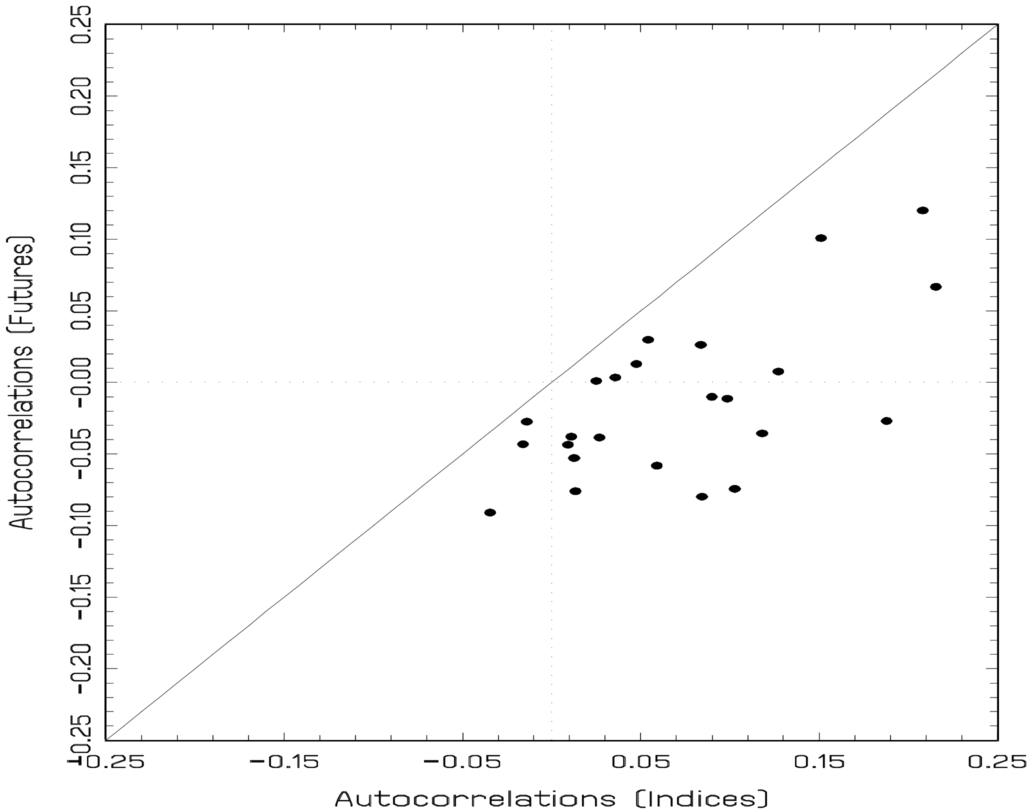

Figure 2: Autocorrelations of futures and spot returns for 24 indices. The solid line is the 45 degree line.

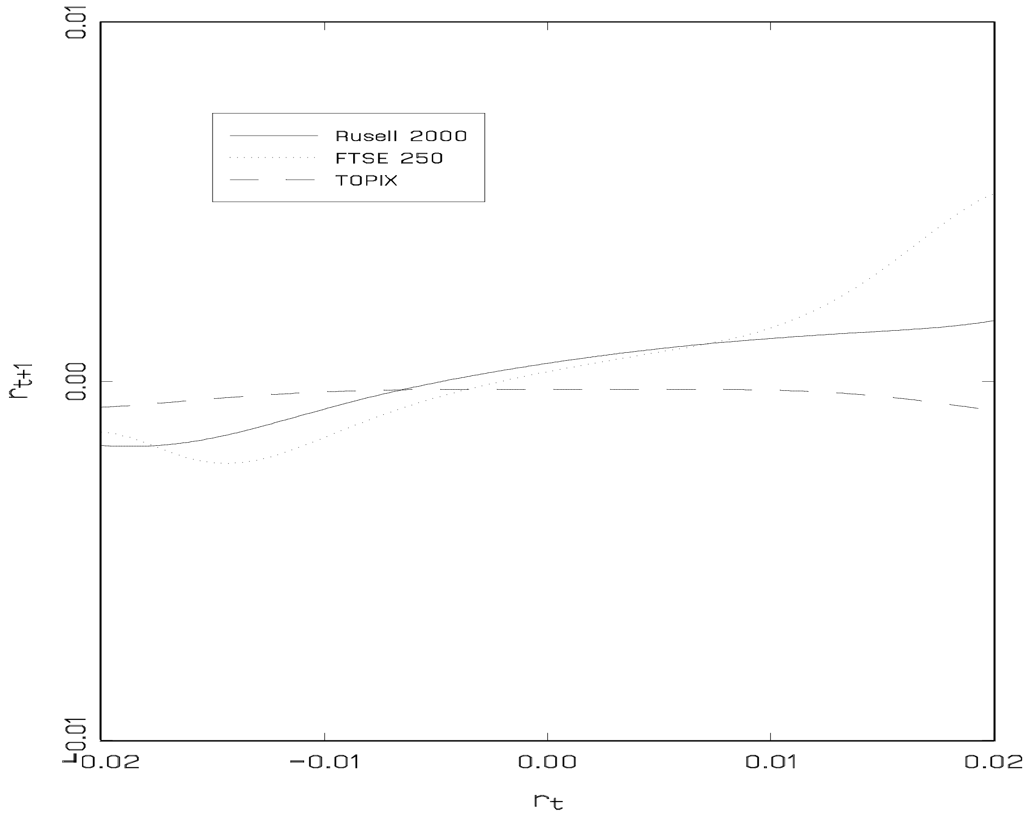

Figure 3: Nonparametric kernel estimates of the relation between the lagged return (r_t^F) and the return (r_{t+1}^F) on three futures contracts: the Russell 2000, FTSE 250, and TOPIX.

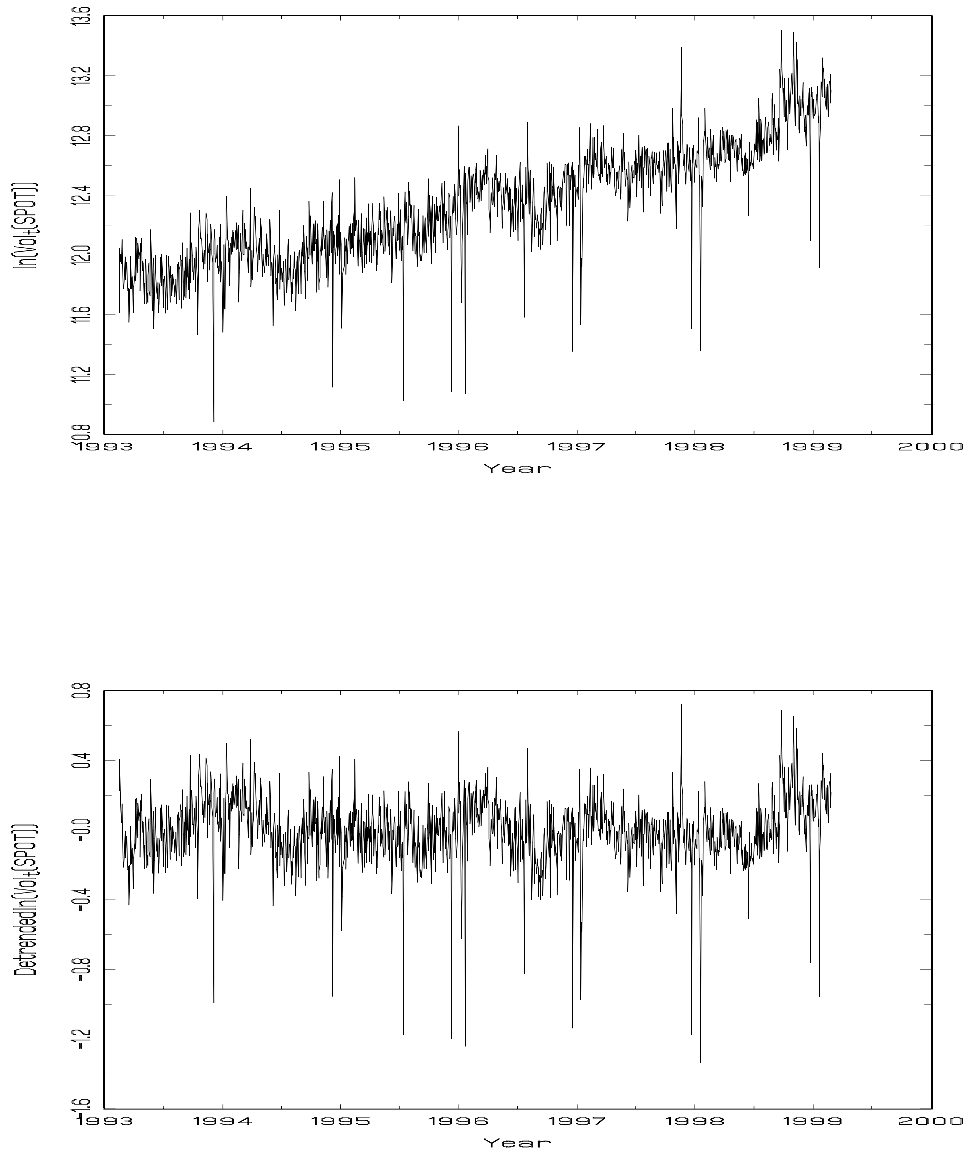

Figure 4: Trading volume in the U.S. spot market $(\ln(1 + vol_t^S))$ and detrended trading volume.

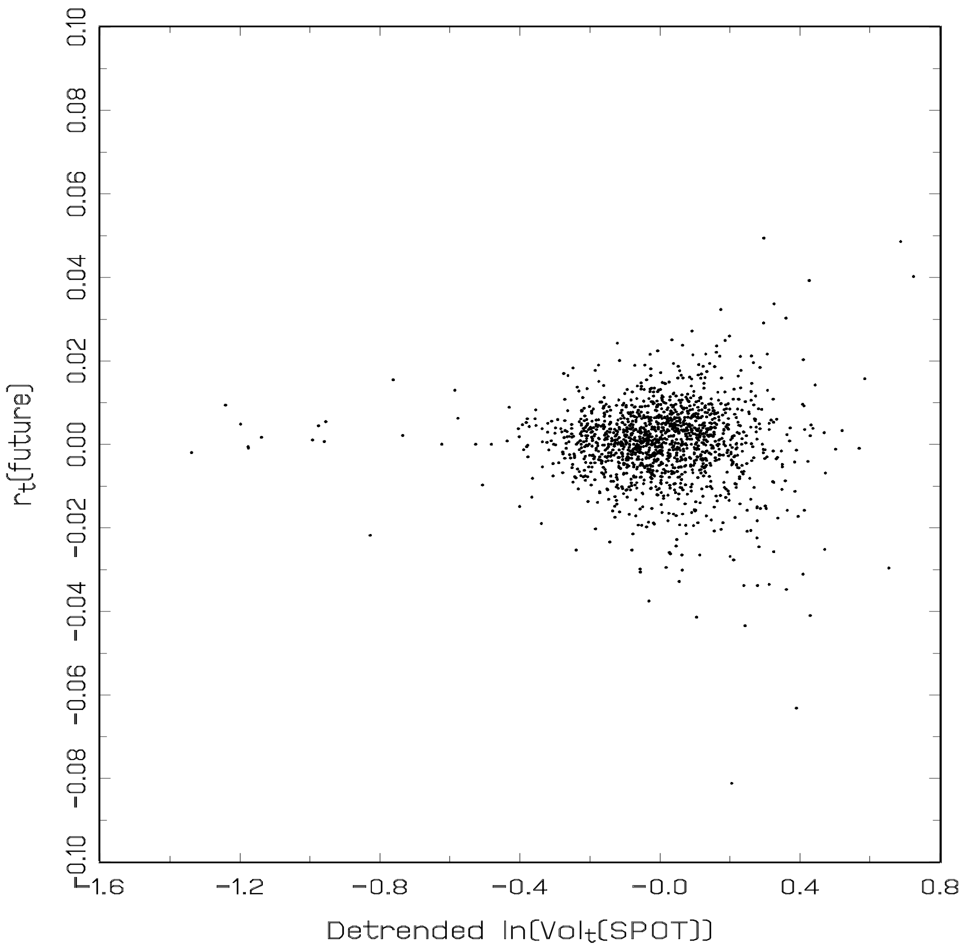

Figure 5: Scatter plot of detrended trading volume in the U.S. spot market and the return on the Russell 2000.

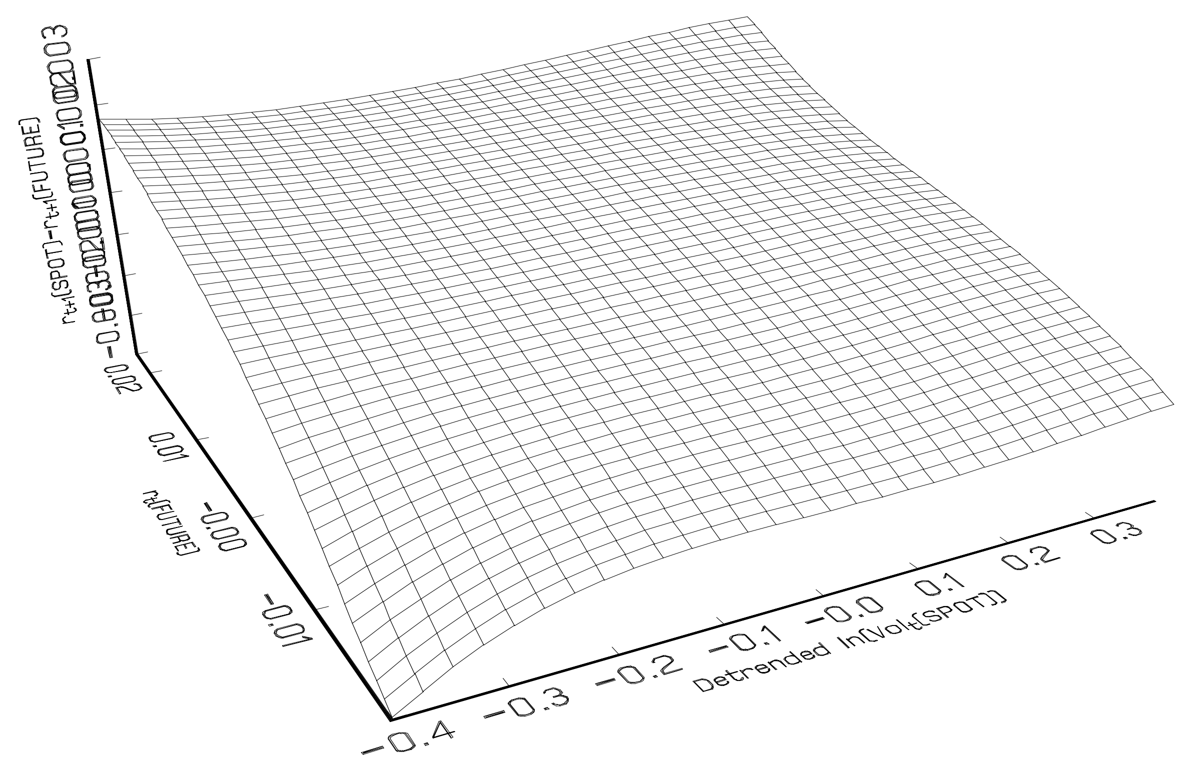

Figure 6: Three dimensional plot of the kernel estimate of the relation between the spot-futures return spread, the lagged return on the futures and detrended trading volume for the Russell 2000.

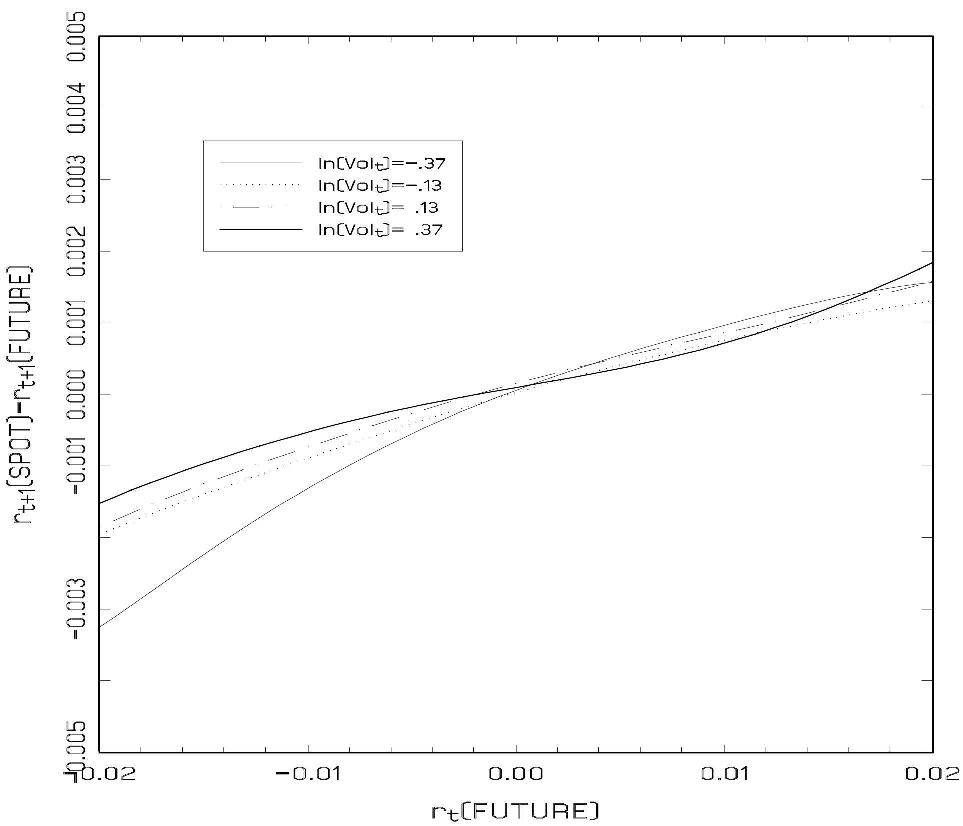

Figure 7: Two-dimensional cut-through of the relation between the lagged futures return (r_t^F) and the current spot-futures spread ($r_{t+1}^S - r_{t+1}^F$) of the Russell 2000 at different values of the lagged log-volume ($\ln(1 + vol_t^S)$).