MARKET ARCHITECTURE AND NONLINEAR DYNAMICS OF AUSTRALIAN STOCK AND FUTURES INDICES*

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This paper studies the All Ordinaries Index in Australia, and its futures contract known as the Share Price Index. We use a new form of smooth transition model to account for a variety of nonlinearities caused by transaction costs and other market/data imperfections, and given the recent interest in the effects of market automation on price discovery, we focus on how the nonlinear properties of the basis and returns have changed, now that floor trading in the futures contract has been replaced by electronic trading.

I. Introduction

Researchers have studied the dynamic relationship between the price of stock futures contracts and the underlying cash market ever since 1982, when the Chicago Mercantile Exchange first introduced futures contracts based on Standard and Poor's (S&P) 500 Stock Index. Compelling empirical evidence that future indices lead stock indices and weaker evidence of feedback has attracted considerable attention, because standard 'no arbitrage' arguments predict that in perfectly functioning markets there should only be contemporaneous correlations between the two return series, and zero cross-correlations at non-zero lags and leads. Several reasons for the observed 'lead-lag' relationship between stock market and future indices have been put forward, and these include infrequent trading in components of the stock index, the use of transactions data rather than bid-ask quote data in index calculations, time delays in the computation and reporting of the stock index, and transaction costs associated with buying portfolios of stocks and futures contracts. Stoll and Whaley (1990) provide a useful discussion on possible causes of the 'lead-lag' relationship, and Abhyankar (1998) surveys the empirical evidence on this issue.

The factors that give rise to the 'lead-lag' relationship between stock indices and futures

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also imply nonlinearities in the behaviour of index returns. The most obvious of these is the nonlinear effect of transaction costs on portfolio adjustment, but infrequent trading in stocks can also introduce nonlinearities, as can the delays and other problems associated with the reporting of the stock index. The literature that studies nonlinearities in index returns is currently small, and it mostly focuses on thresholds caused by transaction costs. Authors such as Yadav *et al*. (1994), Dwyer *et al*. (1996) and Martens *et al*. (1998) have studied the effects of transaction costs on arbitrage, by estimating threshold models of the basis and/or returns in the United States. These models assume identical transaction costs for all investors, and behavioural regimes that depend on whether arbitrage generates net profits after transaction costs. Statistically significant evidence of thresholds supports these models, but reconciliation of the estimated thresholds with independent estimates of transaction costs has been difficult.

One problem with threshold vs transaction cost comparisons is that both vary over different investors and different types of stocks. Individual investor and market specific thresholds then become blurred in an aggregate setting, and it becomes hard to relate any estimate of an ‘aggregate threshold’ back to a simple measure of transaction costs. Anderson (1997) studies this problem in a paper on arbitrage between bills of different maturity within the U.S. Treasury Bill Market. She models the yield adjustment process using a smooth transition error correction model in which transaction costs vary across market participants. The smooth transition allows for a continuum of regimes, which in the context of modelling stock returns can account for the nonlinear effects of infrequent trading and data reporting problems as well as heterogenous transaction costs. Taylor *et al*. (2000) use smooth transition error correction models to study the heterogeneity in transaction costs associated with trading FTSE100 stocks and futures.

This paper studies the All Ordinaries Index in Australia, and its futures contract known as the Share Price Index. Several papers have analysed the lead-lag relationship in the Australian context (see, for example, West (1997), Lin and Stevenson (1999) and Frino *et al*. (2000)), but little direct work has been done on examining the nonlinearities in Australian markets. We introduce a new type of smooth transition model to account for nonlinearities caused by transaction costs and other market/data imperfections, and given the recent interest in the effects of market automation on price discovery, our study focuses on how the nonlinear properties of the basis and the returns have changed, now that floor-trading in the futures contract has been replaced by electronic trading.

The effects of screen trading have been studied by Grünbichler *et al*. (1994) who studied the German DAX index, and more recently, by Taylor *et al*. (2000) who studied the U.K. FTSE100 index. The Australian case differs from these other cases in that the recent automation involved the futures market, and created a situation in which both the spot and futures markets were then automated. In the German case, only the futures market was automated and stocks continued to be floor-traded, while in the UK case the stock market was automated while futures continued to be floor-traded. While one might expect screen trading to reduce the nonlinear effects of transaction costs in all three of these cases, one would also expect that the automation in the Australian case would remove asymmetries in dynamic behaviour that had been present because of the operational differences between trading in the spot market and trading in the futures market.

We find strong evidence of nonlinearity before the futures trading went on-line, and weaker evidence of nonlinearity after on-line trading. Our analysis suggests that the automation of the futures market has removed the nonlinear properties of the basis, and made the nonlinear properties of the two returns series more similar. A particularly interesting finding is that prior to the automation of the futures market, the nonlinearities that characterise each market are different, whereas after the introduction of on-line futures trading, the returns in each market have a common nonlinear factor. Futures returns lead stock returns (with feedback) both before and after the introduction of screen-trading, and the futures lead increases only slightly after automation. The speed of mean-reversion in the basis is slow, and appears to be unchanged.

The remainder of this paper is organised as follows. Section II of this paper discusses the theoretical basis for our work, together with various econometric specifications that account for lead-lag relationships and nonlinearities. This section introduces our new smooth transition error correction model, which accounts for the possible effects of transaction costs, infrequent trading and asymmetries between trading in spots vs futures contracts. Section III discusses the institutional detail that underlies the Australian markets for equities and futures, and then provides details on the samples that are studied in this paper. Section IV contains our empirical results, which compare the properties of the data before and after the cessation of floor trading in the futures market. Section V concludes.

II. Theoretical Basis

The relationship between the futures price of shares underlying a futures contract and the spot price on the cash market for the same shares is often described by the cost-of-carry model, which postulates that

$$F_t = S_t e^{(r-y)(T-t)}, \tag{1}$$

where F_t is the futures price of the index at time t, S_t is the spot price of the index at time t, r is the interest rate foregone while carrying the underlying stocks, y is the dividend yield on the stocks and $T - t$ is the remaining life of the futures contract. Equation (1) is justified by a 'no-arbitrage' assumption, since $F_t > S_t e^{(r-y)(T-t)}$ would enable investors to profit by selling futures and buying stocks, while $S_t e^{(r-y)(T-t)} > F_t$ would allow profits by buying futures and short selling stocks. The assumptions that underlie these arguments are that markets are perfectly efficient, and that transaction costs are zero. This simple version of the model also assumes that the interest rate and dividend yield are constant over the life of the futures contract, although in practice they will vary, as will $r - y$, the net cost of carry of the underlying stocks.

Market efficiency implies that $\ln S_t$ is a random walk, and that the returns denoted by $s_t = \Delta \ln S_t$ are serially uncorrelated. The cost of carry model then implies that $\ln F_t$ will be the sum of the random walk process in $\ln S_t$ and the series $(r - y)(T - t)$. The dynamic properties of $\ln F_t$ then depend on the assumptions about $(r - y)(T - t)$. When working with tick by tick data it is reasonable to assume that T is sufficiently distant to justify the treatment of $(T - t)$ as a constant, and together with the assumptions that r and y are constant, the basis given by $b_t = \ln F_t - \ln S_t$ is simply a constant.[1] Constant b_t are not observed in practice, but in this over-simplified case, $\ln F_t$ follows the same random walk process as $\ln S_t$, and the returns denoted by $f_t = \Delta \ln F_t$ are perfectly correlated with s_t and serially uncorrelated. The two return series f_t and s_t will have zero cross-correlations at all

[1] In practice, researchers working with tick by tick data often account for daily changes in $(r - y)(T - t)$ by removing the daily averages of $\ln S_t$ and $\ln F_t$ from the data. See, eg, Dwyer *et al.* (1996).

non-zero leads and lags. Given that b_t is not constant, it is common to allow for this by writing

$$b_t = \ln F_t - \ln S_t = \mu + v_t \tag{2}$$

in which μ is interpreted as the expected cost of carry, and $v_t = b_t - \mu$ (with $E(v_t) = 0$) is known as the mis-pricing error. See Brenner and Kroner (1995) for further discussion on the stochastic implications of equation (1).

Empirical work has shown that $\ln S_t$ and $\ln F_t$ are not pure random walks, and that both include significant mean reverting components. There is also considerable evidence that $\ln S_t$ and $\ln F_t$ are cointegrated (i.e. they share the same random walk component). The literature has typically dealt with the observed correlations in returns data by attempting to 'correct' for them (some examples include Stoll and Whaley (1990), and Shyy *et al.* (1996)), or by explicitly modeling these dynamics (see, e.g., Wahab and Lashgari (1993), Brenner and Kroner (1995)). The latter approach, which also accounts for the cointegration is based on an error correction formulation given by

$$\begin{aligned} f_t &= c_f + \alpha_f(L) f_{t-1} + \beta_f(L) s_{t-1} + \gamma_f\, b_{t-d} + \varepsilon_t^f \\ s_t &= c_s + \alpha_s(L) f_{t-1} + \beta_s(L) s_{t-1} + \gamma_s\, b_{t-d} + \varepsilon_t^s \end{aligned} \tag{3}$$

in which $\alpha_f(L)$, $\beta_f(L)$, $\alpha_s(L)$, and $\beta_s(L)$ are polynomials in the lag operator, and ε_t^f and ε_t^s are zero mean, serially uncorrelated errors that can be contemporaneously correlated. Equation (3) implies that returns will respond to movements in the basis, consistent with arbitrage activities and corresponding mean reversion in the basis. As noted by Miller *et al.* (1994), some of the mean reversion is due to corrections for infrequent trading, as stock indices 'catch up' with futures. The parameter d takes no special meaning in a linear setting (since one can always reparameterise the lagged polynomials to obtain equivalent models regardless of d), but it becomes important in the nonlinear models below. The assumption that the γ are not zero corresponds to a 'no frictions' assumption, because it implies that returns respond to *all* movements in the basis. The presence of the lagged polynomials allows for short run dynamics, which might arise because of problems associated with the calculation and reporting of the indices.

The adaptation of equation (3) to account for transaction costs is based on the intuition that arbitrage will only occur when it generates net profits to investors. Defining c to be investors' transaction cost and d to be a delay associated with making the appropriate trades, the arbitrage condition is given by $|b_{t-d} - \mu| > c$, which implies a no-arbitrage band given by $-c < (b_{t-d} - \mu) < c$. The transaction costs are assumed to be the same for all investors, and the same regardless of whether one is going short or long in the underlying stocks. The corresponding error correction model becomes

$$\begin{aligned} f_t &= c_{fi} + \alpha_{fi}(L) f_{t-1} + \beta_{fi}(L) s_{t-1} + \gamma_{fi}\, b_{t-d} + \varepsilon_t^f \\ s_t &= c_{si} + \alpha_{si}(L) f_{t-1} + \beta_{si}(L) s_{t-1} + \gamma_{si}\, b_{t-d} + \varepsilon_t^s \end{aligned} \tag{4}$$

which is a threshold error correction model (see Balke and Fomby (1997)). The basis b_{t-d} drives the error correction process, and the threshold c defines three behavioural regimes in which

$$i = 1 \qquad \text{if } b_{t-d} - \mu < -c \ (i.e. \ if \ v_{t-d} < -c) \tag{4a}$$

$$i = 2 \qquad \text{if } -c < b_{t-d} - \mu < c \ (i.e. \ if \ -c \leqslant v_{t-d} \leqslant c)$$

$$i = 3 \qquad \text{if } b_{t-d} - \mu > c \ (i.e. \ if \ v_{t-d} > c)$$

We expect γ_{f2} and γ_{s2} to be zero because arbitrage will not generate net profits when $|b_{t-d} - \mu| < c$, (or equivalently when $|v_{t-d}| < c$). One can generalise this model to allow for non-symmetric thresholds, and more than three behavioural regimes. The papers by Yadev (1994), Dywer *et al.* (1996) and Martens *et al.* (1998) are all set within this framework. They find statistically significant evidence in favour of transaction cost thresholds, but have difficulty in relating the estimated thresholds to average transaction costs. Martens *et al.* (1998) find evidence of many thresholds in their data, and attribute some of these thresholds to transaction costs and other thresholds to the effects of infrequent trading. These thresholds are not symmetrically distributed around μ, which suggests differences between the responses to negative and positive pricing errors.

The smooth transition error correction model modifies equation (4) to obtain

$$\begin{aligned} f_t &= c_f^1 + \alpha_f^1(L) f_{t-1} + \beta_f^1(L) s_{t-1} + \gamma_f^1 b_{t-d} \\ &\quad + \Psi_f(v_{t-d})[c_f^2 + \alpha_f^2(L) f_{t-1} + \beta_f^2(L) s_{t-1} + \gamma_f^2 b_{t-d}] + \varepsilon_t^f \\ s_t &= c_s^1 + \alpha_s^1(L) f_{t-1} + \beta_s^1(L) s_{t-1} + \gamma_s^1 b_{t-d} \\ &\quad + \Psi_s(v_{t-d})[c_s^2 + \alpha_s^2(L) f_{t-1} + \beta_s^2(L) s_{t-1} + \gamma_s^2 b_{t-d}] + \varepsilon_t^s, \end{aligned} \tag{5}$$

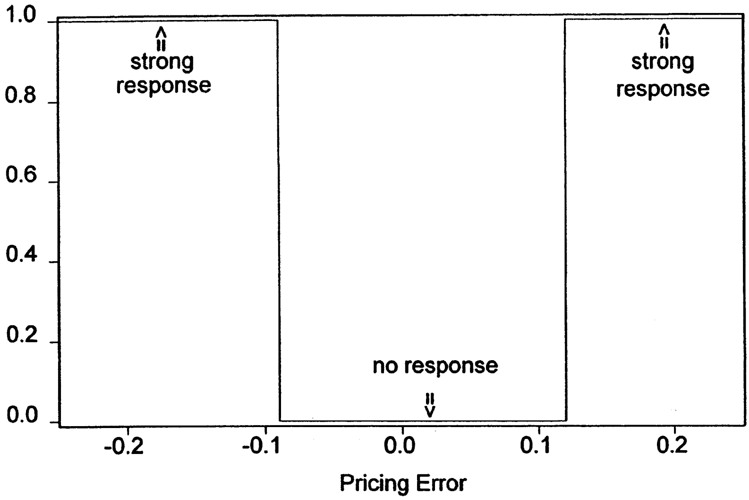
in which Ψ_f and Ψ_s are exponential (ESTAR) transition functions, defined by

$$\Psi_j = \left[1 - \exp\left(-\frac{\lambda_j}{\sigma_v^2}(v_{t-d})^2\right)\right] \quad \text{for } j = f, s. \tag{5a}$$

The Ψ_j take values between zero and one, and they are monotonically increasing with the absolute size of the pricing error. As the Ψ_j vary, the VECM parameters also vary, implying that the nature of the price adjustment process changes with the size of the pricing error. As discussed in Anderson (1997), if one views the transition function Ψ as a cumulative density for the distribution of (non-negative) transaction cost thresholds, then relative to a baseline case without frictions, the parameters change more, when $|v_{t-d}|$ is larger and a greater proportion of investors find the prospect of arbitrage more profitable. Taylor *et al.* (2000) interpret their models in this way, setting $\gamma_f^1 = \gamma_s^1 = 0$, and then letting the smooth transition inherent in the Ψ_j account for multiple regimes implied by heterogenous transaction costs. In their model, the response to pricing errors becomes more pronounced, the larger the absolute size of that error, and error correction is effective only when $|v_{t-d}|$ is sufficiently large.

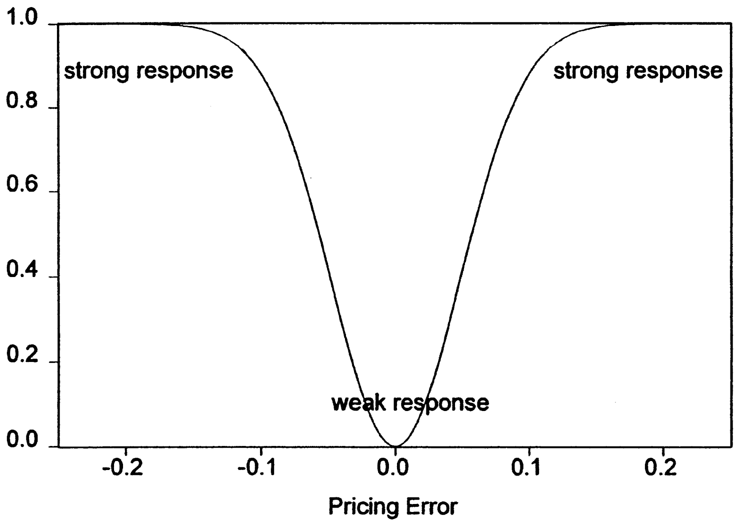
One shortcoming of using smooth transition functions defined by the Ψ_j, rather than thresholds is that the symmetry in Ψ_j does not allow for asymmetries between the responses to negative and positive pricing errors. The use of transition functions such as Ψ_j also restrict the effective width of the implied 'no-arbitrage bands'', unless the λ_j are very small and Ψ_j is approximately zero over a large range of v_{t-d}. Figure 1 compares the responses to pricing errors using the asymmetric threshold and a symmetric (ESTAR) smooth-transition approach. While it is possible to modify the ESTAR model to account for asymmetries

Threshold Transition Function (γ in eqn (4))



In this illustration, $\gamma_1 = \gamma_3 = 1$,and $\gamma_2 = 0$. The symmetric thresholds (i.e. -c and c in eqn (4a)) have been replaced by asymmetric thresholds (-.09 and .12).

ESTAR Transition Function (Ψ in eqn (5))



In this illustration, $\frac{\lambda_j}{\sigma_v^2} = 1$ in eqn (5a).

Figure 1. Response to pricing errors
Threshold transition function (γ in eqn (4))
ESTAR Transition Function (Ψ in eqn (5))

(see Anderson 1997), this paper specifies and employs a new smooth transition function that allows for wide 'no-arbitrage' bands as well as asymmetries. This function allows for different behaviour, depending on whether the pricing error is positive or negative, and it is defined by

$$\Phi_{Pj} = \left[\frac{1}{1+\exp\left(-\frac{\lambda_{Pj}}{\sigma_v}(v_{t-d}-c_P)\right)} - \frac{1}{1+\exp\left(\frac{\lambda_{Pj}}{\sigma_v}c_P\right)} \right] \cdot \left[\frac{1+\exp\left(\frac{\lambda_{Pj}}{\sigma_v}c_P\right)}{\exp\left(\frac{\lambda_{Pj}}{\sigma_v}c_P\right)} \right] \tag{6a}$$

for $v_{t-d} > 0$, and

$$\Phi_{Nj} = \left[\frac{1}{1+\exp\left(\frac{\lambda_{Nj}}{\sigma_v}(v_{t-d}+c_N)\right)} - \frac{1}{1+\exp\left(\frac{\lambda_{Nj}}{\sigma_v}c_N\right)} \right] \cdot \left[\frac{1+\exp\left(\frac{\lambda_{Nj}}{\sigma_v}c_N\right)}{\exp\left(\frac{\lambda_{Nj}}{\sigma v}c_N\right)} \right] \tag{6b}$$

for $v_{t-d} \leqslant 0$. The subscripts P and N respectively indicate those portions of the transition function that relate to positive and negative pricing errors. We call Φ a U-STAR transition function, because its main characteristic is that it is shaped like a drunken U. The constants in the right hand brackets of these equations scale Φ so that $0 < \Phi < 1$, and the constants inside the first brackets ensure that $\Phi = 0$ at $v_{t-d} = 0$, and that Φ is continuous at $v_{t-d} = 0$. See Figure 2 for some illustrations.

The U-STAR model then uses (6a) and (6b) in a specification given by

$$\begin{aligned}
f_t &= c_f^0 + \alpha_f^0(L)f_{t-1} + \beta_f^0(L)s_{t-1} + \gamma_f^0\, b_{t-d} \\
&+ I(v_{t-d} > 0).\Phi_{Pf}(v_{t-d})[c_f^P + \alpha_f^P(L)f_{t-1} + \beta_f^P(L)s_{t-1} + \gamma_f^P\, b_{t-d}] \\
&+ I(v_{t-d} \leqslant 0).\Phi_{Nf}(v_{t-d})[c_f^N + \alpha_f^N(L)f_{t-1} + \beta_f^N(L)s_{t-1} + \gamma_f^N\, b_{t-d}] + \varepsilon_t^f \\
s_t &= c_s^0 + \alpha_s^0(L)f_{t-1} + \beta_s^0(L)s_{t-1} + \gamma_s^0\, b_{t-d} \\
&+ I(v_{t-d} > 0).\Phi_{Ps}(v_{t-d})[c_s^P + \alpha_s^P(L)f_{t-1} + \beta_s^P(L)s_{t-1} + \gamma_s^P\, b_{t-d}] \\
&+ I(v_{t-d} \leqslant 0).\Phi_{Ns}(v_{t-d})[c_s^N + \alpha_s^N(L)f_{t-1} + \beta_s^N(L)s_{t-1} + \gamma_s^N\, b_{t-d}] + \varepsilon_t^s,
\end{aligned} \tag{6}$$

which implies a total response to pricing errors of $\gamma_j^0 + I(v_{t-d} > 0).\ \gamma_j^P\Phi_{jP}(v_{t-d}) + I(v_{t-d} \leqslant 0).\gamma_j^N\Phi_{jN}(v_{t-d})$. Since the automation of the futures market should lower transaction costs and make the adjustment of portfolios easier, we expect smaller 'no arbitrage bands' in the latter part of our sample. For $\gamma_j^0 \simeq 0$ this corresponds to a thinner U ($|c_P|$, and $|c_N|$ will be smaller), with steeper sides (λ_P and λ_N will be bigger). Since the stock market in Australia was automated prior to that in the futures market, the automation of the futures market should also reduce the differences between trade based on each index, and therefore reduce the presence of asymmetries. This corresponds to a decrease in the *difference* between $|c_P|$, and $|c_N|$, and a decrease in the *difference* between λ_P and λ_N. Similar patterns in Φ_j might also be expected even when $\gamma_j^0 \neq 0$, although some response to pricing errors (i.e γ_j^0) is now present at all times.

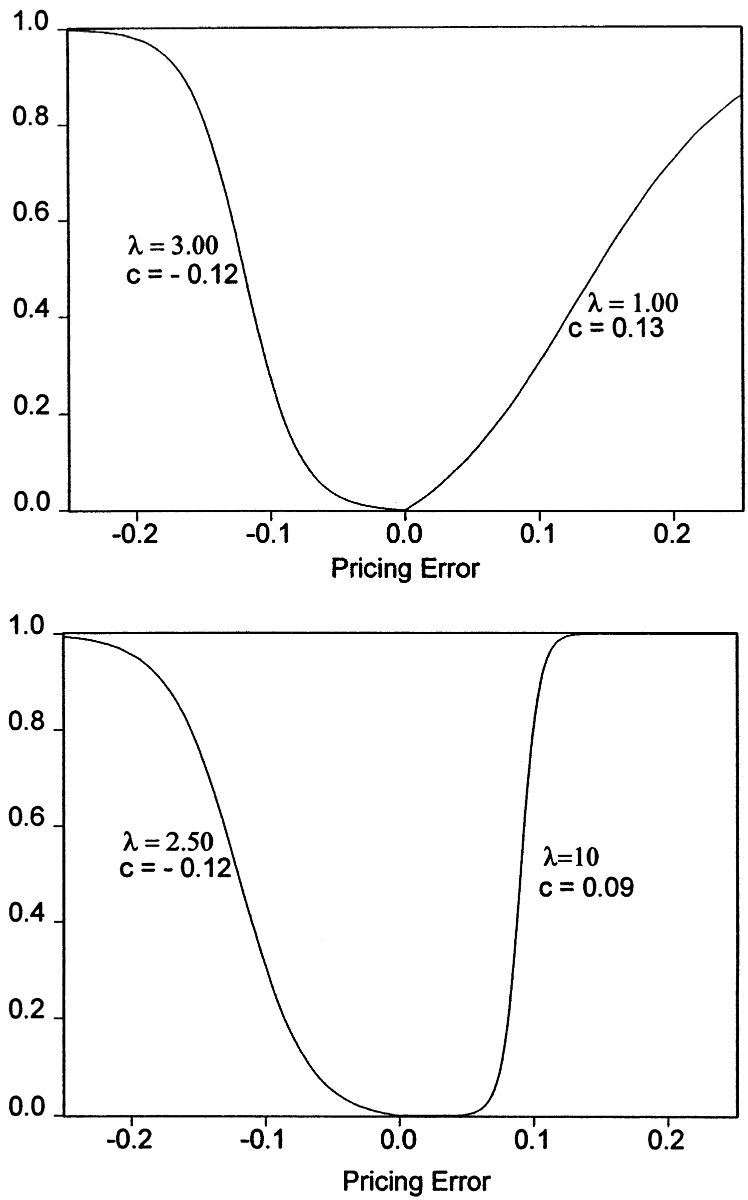


Figure 2: U-STAR transition functions

III. Institutional Details and Data

Our empirical analysis is based on the All Ordinaries Index (AOI), calculated by the Australian Stock Exchange (ASX). Based on market capitalisation, the ASX is the 12th largest share market in the world, and the second largest in the Asia Pacific Region. At the end of 1999, the AOI was based on 253 actively traded stocks and it accounted for 91% of listed Australian equities. The Australian Stock Exchange trades between 10.00 am and 4.00 pm (EST) from Monday to Friday (public holidays excluded). Opening times for individual stocks are staggered but all stocks are trading by 10.10, and at the end of the day additional trading at volume weighted prices may continue until 4.20 pm. Stock trading has been fully automated since 1991, when the Stock Exchange Automated Trading System (SEATS) was introduced. SEATS continuously matches bids and offers during normal trading hours, and updates the price indices. It also disseminates this updated information to data vendors, at frequencies which are usually more than once every minute.

The Sydney Futures Exchange (SFE) has been trading Share Price Index (SPI®) futures contracts based on the AOI since 1983, when it became the first exchange outside the USA to list index futures. Almost 20,000 SPI® contracts are traded each day, with most trading occurring in contracts with the next expiry month. Contracts mature at the end of March, June, September and December each year. Unlike the ASX, the SFE has not been fully automated until very recently, with trading in SPI® futures becoming fully automatic on October 4, 1999. Trading on the floor occurred between 9.50 am to 12.30 pm, and then from 2.00 pm until 4.10 pm (EST) from Monday to Friday (public holidays excluded) until November 12, 1999. Since then, day-time trading hours have been extended, with trading starting at 9.30 am and continuing until 4.30 pm.

Standard P/ASX 200 and the S&P/ASX 300, which are respectively based on 200 and 300 stocks. SPI® futures contracts based on the old All Industries Index are still being issued, but are being phased out as new futures contracts (called SPI200 and based on the S&P/ASX200) are being phased in. The first SPI200 contracts were listed in May 2000 and expired in June 2000, while the last SPI® contracts will expire in September 2000. The old All Ordinaries Index (based on 253 stocks) is still calculated, but will be discontinued after September 2001.

The data used in this study is tick by tick AOI data obtained from IRESS (Integrated Real Time Equity System) and matching tick by tick SPI® data obtained from the SFE. The samples covered the last two weeks of August in 1999, and the first two weeks of November 1999. The AOI is updated on IRESS approximately twice a minute, (to the nearest 0.1 index point), and this was converted to one observation per minute by using the last observation for each minute. The SPI data for August listed the time (to the nearest second), volume (number of contracts) and index value (to the nearest integer) for each transaction, but the November data recorded trade times in minutes, rather than in seconds. Minute by minute futures index values were obtained by weighting the index for each trade by its volume. The last available observation was used when data was missing. Only those contracts for futures expiring in September 1999 were included in the August data set, and only those contracts for futures expiring in December 1999 were included in the November data set.

Both markets were open between 10.00 am to 12.30 pm and then from 2.00 pm to 4.00, which led to 271 matched observations each day. However, the first 15 minutes of each day were discarded to avoid anomalies related to the staggered opening of the ASX. The daily samples of the stock and futures indices were each demeaned using the remaining observations (from 10.16 to 12.30 and 2.00 pm to 4.00 pm); demeaning the futures index accounted for dividends and interest rates (which were assumed to be constant for each day), while demeaning the stock index allowed the scaling of the basis to be centered on zero.[2] The

[2] The assumptions that are made when demeaning the daily samples are that r and y are constant throughout each day, and that the futures contract expiry date T is far enough into the future to ensure that $(T - t)$ is approximately constant throughout each day. The demeaning implies that $b_t = v_t$ in our empirical work.

analysis was then based on samples covering 10.30 am to 12.30 pm and 2.15 pm to 4.00 pm (226 observations) for each day, which allowed for the inclusion of up to 15 contiguous lags in our autoregressions. In total, there were thirteen days of data for August 1999 (2938 observations) and ten days of data for November 1999 (2260 observations), making 5198 observations altogether.

IV. Empirical Analysis

It is useful to examine the properties of the returns and the basis prior to modelling their dynamics, and some summary statistics relating to the demeaned data are provided in Table I. Returns for futures were more volatile than those for stocks, and the variability of futures increased slightly after the automation of that market. The basis was slightly skewed, and although its variability increased after the automation of the futures market, its range decreased. All reported first order autocorrelation coefficients (excepting the futures return for November) were statistically significant, and formal tests indicated stronger first order

Table IA Summary statistic relating to the indices and returns

	August		*November*		*Full Sample*	
	Futures	*Stocks*	*Futures*	*Stocks*	*Futures*	*Stocks*
Max Price Index	3113.8	3083.4	3018.7	3009.0	3113.8	3083.4
Min Price Index	2905.5	2934.1	2880.2	2887.2	2880.2	2887.2
ADF for *ln*(Price)	−1.349	−1.327	−1.629	−1.855	−1.471	−1.557
Max Return	0.1360	0.1169	0.1296	0.1171	0.1360	0.1171
Min Return	−0.1240	0.1238	−0.1602	−0.1023	−0.1602	−0.1238
St Dev Return	0.0299	0.0209	0.0319	0.0197	0.0308	0.0204
ρ_1 for Return	0.1590	0.2294	0.0049	0.0837	0.0874	0.1705
ADF for Return	−4.330	−4.262	−4.229	−4.670	−4.389	−4.158
No of Observations	2938	2938	2260	2260	5198	5198

Table IB Summary statistics relating to the basis

	August	*November*	*Full Sample*
Mean	0.0000	0.0000	0.0000
Median	−0.0007	−0.0026	−0.0013
Max	0.3896	0.2377	0.3896
Min	−0.3113	−0.2122	−0.3113
St Dev	0.0688	0.0785	0.0732
Skewness	0.1511	0.1263	0.1388
Kurtosis	5.1954	2.6947	3.8450
ρ_1 for Δb_t	−0.1336	−0.1727	−0.1528
ADF	−2.1157	−2.1333	−2.1233
No of Observations	2938	2260	5198

Notes: ρ_1 is the first order autocorrelation coefficient. The reported ADF statistics are arithmetic averages of the ADF test statistics for the daily samples. The ADF regressions for the ln(price) contained a constant and 12 lags, while the ADF regressions for the returns and the basis contained 12 lags.

autocorrelation in returns prior to the cessation of floor-trading in futures, and stronger negative first order autocorrelation in basis changes after the shift to electronic trading. The reported statistics for unit root analysis are the *averages* of Dickey Fuller unit root test statistics for each of the daily samples. Tests relating to the full samples would have been misleading given the removal of overnight returns and the use of different demeaning transformations for different days. The averages of the Dickey Fuller are indicative only, but compared to the usual critical values (-2.88 for *ln*(price) and -1.95 for the returns and the basis) they suggest that the log prices have a unit root, and that returns and the basis are stationary. All 46 of the underlying tests on daily data supported a unit root in *ln*(prices), all but four[3] of the tests rejected a unit root in returns, and all but six[3] rejected a unit root in the basis.

Table II reports some summary statistics relating to three linear VECM(12) specifications that provide the point of departure for our nonlinear modelling exercise. These models are based on the full sample, the August sample and the November sample, and full details are

Table II Linear error correction models of returns for futures and stocks

FULL SAMPLE

Model of Futures Returns:
Last statistically significant (at 5% level) lag of stock returns: s_{t-4}
Error correction coefficient (υ_{t-1}) with het. c.t-stat: -0.0287 (-3.9731)
Summary statistics: $R^2 = 0.049$, $s.e. = 0.030$

Model for Stock Returns:
Last statistically significant (at 5% level) lag of futures returns: f_{t-10}
Error correction coefficient (υ_{t-1}) with het. c.t-stat: 0.0254 (5.369)
Summary statistics: $R^2 = 0.161$, $s.e. = 0.019$

AUGUST SAMPLE

Model of Futures Returns:
Last statistically significant (at 5% level) lag of stock returns: s_{t-5}
Error correction coefficient (υ_{t-1}) with het. c.t-stat: -0.0276 (-2.5394)
Summary statistics: $R^2 = 0.069$, $s.e. = 0.029$

Model for Stock Returns:
Last statistically significant (at 5% level) lag of futures returns: f_{t-8}
Error correction coefficient (υ_{t-1}) with het. c.t-stat: 0.0280 (3.9015)
Summary statistics: $R^2 = 0.212$, $s.e. = 0.019$

NOVEMBER SAMPLE

Model of Futures Returns:
Last statistically significant (at 5% level) lag of stock returns: s_{t-2}
Error correction coefficient (υ_{t-1}) with het. c.t-stat: -0.0301 (-3.1313)
Summary statistics: $R^2 = 0.044$, $s.e. = 0.031$

Model for Stock Returns:
Last statistically significant (at 5% level) lag of futures returns: f_{t-10}
Error correction coefficient (υ_{t-1}) with het. c.t-stat: 0.0215 (3.5346)
Summary statistics: $R^2 = 0.121$, $s.e. = 0.019$

[3] Two of these exceptions relate to Melbourne Cup Day, when Australians are much more interested in a horse race than they are in the stock market.

provided in Appendix 1. The above ADF tests justified our error correction representation, and while AIC suggested that five lags would be sufficient to model the *linear* dynamics of returns, we worked with a longer lag structure to allow for the possibility that AIC might not choose the optimal lag structure for our *nonlinear* models. The longer lag structure also provides a broader picture of the 'lead-lag' relationship.

For the full sample, the error correction term is negative in the futures equation and positive in the stocks equation (as expected), with both results being statistically significant. Each of the first ten lags of futures returns are statistically significant in the stock returns equation, in line with previous findings that returns for futures lead returns for stocks. The effect of lagged stock returns on futures is statistically significant for two lags, but changes sign at lag three and becomes insignificant after lag four.

The VECM(12)s for the August and November subsamples are similar to the full sample model, in that the error correction coefficients are statistically significant and negative in the future returns equations and statistically significant and positive in the stock returns equations. Comparing the August and November equations, the future returns equation changes very little, although more lags of stocks have predictive power for futures in August (5 lags), than in November (2 lags). A heteroscedasticity corrected test of no change has a p-value of 0.1013. The changes in the equation for stock returns are more pronounced, with the futures lead increasing from about eight minutes in August to ten minutes in November. For this equation, a heteroscedasticity corrected test of no change strongly rejects the null, with a p-value of 0.0001. For each return, the overall level of significance (as measured by the p-value for the overall F-test) is lower in November than August, suggesting that returns have become less predictable since the automation in the futures market.

Table III reports the results of heteroscedasticity corrected tests of the linear VECM(12) against various ESTAR alternatives. Each of these alternatives uses the lagged basis as a transition variable, but the transition lag is allowed to vary from one up to twelve. The tests are performed on a model of the basis as well as on the returns equations, because ESTAR behaviour in the basis will imply ESTAR behaviour in the returns; this model of the basis

Table III P-Values of heteroscedasticity consistent tests of H_0 : No Nonlinearity vs H_1 : ESTAR type nonlinearity

Transition	*August*			*November*		
Lag	*Stocks*	*Futures*	*Basis*	*Stocks*	*Futures*	*Basis*
1	0.0004	0.0000	0.0041	0.0466	0.3900	0.8914
2	0.0009	0.0000	0.0016	0.2432	**0.0029**	0.4106
3	0.0000	0.0011	0.0026	0.0258	0.1892	0.5832
4	0.0004	0.0001	0.0009	0.1360	0.6489	0.7423
5	0.0001	0.0000	0.0000	0.0789	0.0789	**0.1068**
6	**0.0000**	**0.0000**	**0.0000**	0.0211	0.0202	0.1611
7	0.0000	0.0001	0.0000	0.0057	0.0797	0.3576
8	0.0014	0.0032	0.0313	0.1149	0.5574	0.7632
9	0.0615	0.0142	0.0586	0.0100	0.4731	0.8928
10	0.0034	0.0067	0.0200	0.0380	0.0750	0.3305
11	0.0373	0.0330	0.0407	0.0436	0.1842	0.8670
12	0.0004	0.0184	0.0231	**0.0001**	0.2348	0.9009

Note: The minimum p-value found for each set of linearity tests is indicated in bold type.

had the same explanators as the VECM(12). Given the similarities between the ESTAR and USTAR specifications, one would expect the ESTAR tests to have power against USTAR alternatives. The tests are based on second order approximations to the nonlinear alternative, and they assess whether the explanatory power of the linear equations increase, when one adds additional regressors that interact v_{t-d}^2 with all of the VECM explanators.

Given the differences between the August and the November models noted above, and the fact that we wanted to assess the effect of closing futures floor trading, the nonlinearity tests were performed on each subsample separately. For August, nearly all of the tests found strong evidence of nonlinearity associated with movements in the basis. The p-values of the tests on returns and the basis were all minimised when $d = 6$, which suggests a lag of six minutes between pricing errors and nonlinear adjustment in returns. For November, the results were less significant and not as clear, but they supported a specification using $d = 6$ for each of the returns equation. The basis did not show evidence of nonlinearity for any value of d, which together with the contrasting August results suggests that the process for pricing errors has changed since automation. Linearity in the basis also casts doubt about the presence of a 'no-arbitrage band'. The fact that $d = 6$ is not a suitable transition variable for the basis despite its suitability for each return is interesting for another reason, because this is consistent with a common nonlinear factor in returns. See Anderson and Vahid (1998) for details on common nonlinear factors.

We next set $d = 6$ and then estimated the implied USTAR models. Given the long lag structure and the complicated nature of the nonlinearity, we used a two stage estimation process, that involved a grid search for the transition parameters during the first stage. For the August sample we chose to work with estimates of the transition function for the basis, since the nonlinearity in the returns was associated with the nonlinear movement in the basis. The estimated transition parameters for the basis were then incorporated as fixed transition parameters in the second stage of estimation, which involved estimating the other parameters for the equations for stock returns and futures returns. For November we adopted a different approach, since the basis was linear. Here, we first used a grid search to estimate the transition function for the stock returns (which we chose in preference to the futures equation because stock returns are more predictable than futures returns), and we then estimated the other parameters for the stock return equation. We then used this, together with an estimated linear equation for the basis, to deduce the futures equation. This latter technique imposed the common factor restriction implied by the nonlinearity tests.

Summary statistics relating to each nonlinear VECM(12) are presented in Table IV, and the estimated transition functions are illustrated in Figure 3. Full details are provided in Appendix 2. The lag structure in these nonlinear models was richer than than that in the linear VECMS. In the nonlinear model, the futures lead over stocks was 10 minutes in August and increased to 11 minutes in November, while stocks could predict futures for up to 12 minutes ahead in August, but for only 8 minutes in November. An important property of these models is that the predictability of each type of return decreased after automation (the R^2 dropped quite substantially), consistent with a decline in the *strength* of the lead-lag relationship. The error correction terms were statistically significant in most regimes for the August equations (including the middle regimes), which provides evidence against restricting $\gamma_{f1} = 0$ and $\gamma_{s1} = 0$ (as in Taylor *et al.* (2000)). Thus, although the strength of error correction changes with the pricing error, the usual transactions cost interpretation of 'no-arbitrage' bands does not provide the whole story in this case. There are other factors affecting the mean reversion process, which include infrequent trading and complications associated with trading portfolios of stocks. For November, the error correction terms were

Table IVA Nonlinear error correction model of returns for futures and stocks

AUGUST SAMPLE

Model of Futures Returns:

Last statistically significant (at 5% level) lag of stock returns: s_{t-12}

Coefficients and heteroscedasticity corrected t-stats for error correction terms:

γ^N:	0.0375	(0.692)
γ^0:	−0.0442	(−2.528)
γ^P:	−0.1321	(−1.256)

Summary statistics: $R^2 = 0.102$, $s.e. = 0.028$

Model of Stock Returns:

Last statistically significant (at 5% level) lag of futures returns: f_{t-10}

Coefficients and heteroscedasticity corrected t-stats for error correction terms:

γ^N:	−0.1076	(−2.648)
γ^0:	0.0518	(4.788)
γ^P:	0.1664	(2.492)

Summary statistics: $R^2 = 0.248$, $s.e. = 0.018$

Correlation between errors for the two equations is 0.365

Implied s.e. of basis = 0.028.

Transition Function:

$$\Phi_{Pt} = \left[\frac{1}{1+\exp\left(-\frac{3.42}{0.0688}(v_{t-6}-0.13)\right)} - \frac{1}{1+\exp\left(\frac{3.42}{0.0688}\times 0.13\right)}\right]\cdot\left[\frac{1+\exp\left(\frac{3.42}{0.0688}\times 0.13\right)}{\exp\left(\frac{3.42}{0.0688}\times 0.13\right)}\right]$$

for $v_{t-6} > 0$

$$\Phi_{Nt} = \left[\frac{1}{1+\exp\left(\frac{10}{0.0688}(v_{t-6}+0.09)\right)} - \frac{1}{1+\exp\left(\frac{10}{0.0688}\times 0.09\right)}\right]\cdot\left[\frac{1+\exp\left(\frac{10}{0.0688}\times 0.09\right)}{\exp\left(\frac{10}{0.0688}\times 0.09\right)}\right]$$

for $v_{t-6} < 0$

The transition variable v_{t-6} is < -0.09 for 216 observations, between -0.09 and 0.13 for 2616 observations, and > 0.13 for 106 observations.

Table IVB Nonlinear error correction model of returns for futures and stocks

NOVEMBER SAMPLE

Model of Futures Returns:

Last statistically significant (at 5% level) lag of stock returns: s_{t-8}

Coefficients and heteroscedasticity corrected t-stats for error correction terms:

γ^N:	-0.0929	(-1.294)
γ^0:	-0.0091	(-0.282)
γ^P:	-0.0171	(-0.395)

Summary statistics: $R^2 = 0.043$, $s.e. = 0.031$

Model for Stock Returns:

Last statistically significant (at 5% level) lag of future returns: f_{t-11}

Coefficients and heteroscedasticity corrected t-stats for error correction terms:

γ^N:	0.0560	(1.379)
γ^0:	0.0208	(1.180)
γ^P:	0.0146	(0.567)

Summary statistics: $R^2 = 0.163$, $s.e. = 0.018$

Correlation between errors for the two equations is 0.274.

Implied s.e. of basis $= 0.031$.

Transition Function:

$$\Phi_{Pt} = \left[\frac{1}{1+\exp\left(-\frac{10}{0.0785}(v_{t-6}-0.04)\right)} - \frac{1}{1+\exp\left(\frac{10}{0.0785}\times 0.04\right)}\right]\cdot\left[\frac{1+\exp\left(\frac{10}{0.0785}\times 0.04\right)}{\exp\left(\frac{10}{0.0785}\times 0.04\right)}\right]$$

for $v_{t-6} > 0$

$$\Phi_{Nt} = \left[\frac{1}{1+\exp\left(\frac{10}{0.0785}(v_{t-6}+0.09)\right)} - \frac{1}{1+\exp\left(\frac{10}{0.0785}\times 0.09\right)}\right]\cdot\left[\frac{1+\exp\left(\frac{10}{0.0785}\times 0.09\right)}{\exp\left(\frac{10}{0.0785}\times 0.09\right)}\right]$$

for $v_{t-6} < 0$

The transition variable v_{t-6} is < -0.09 for 216 observations, between -0.09 and 0.04 for 2009 observations, and > 0.04 for 713 observations.

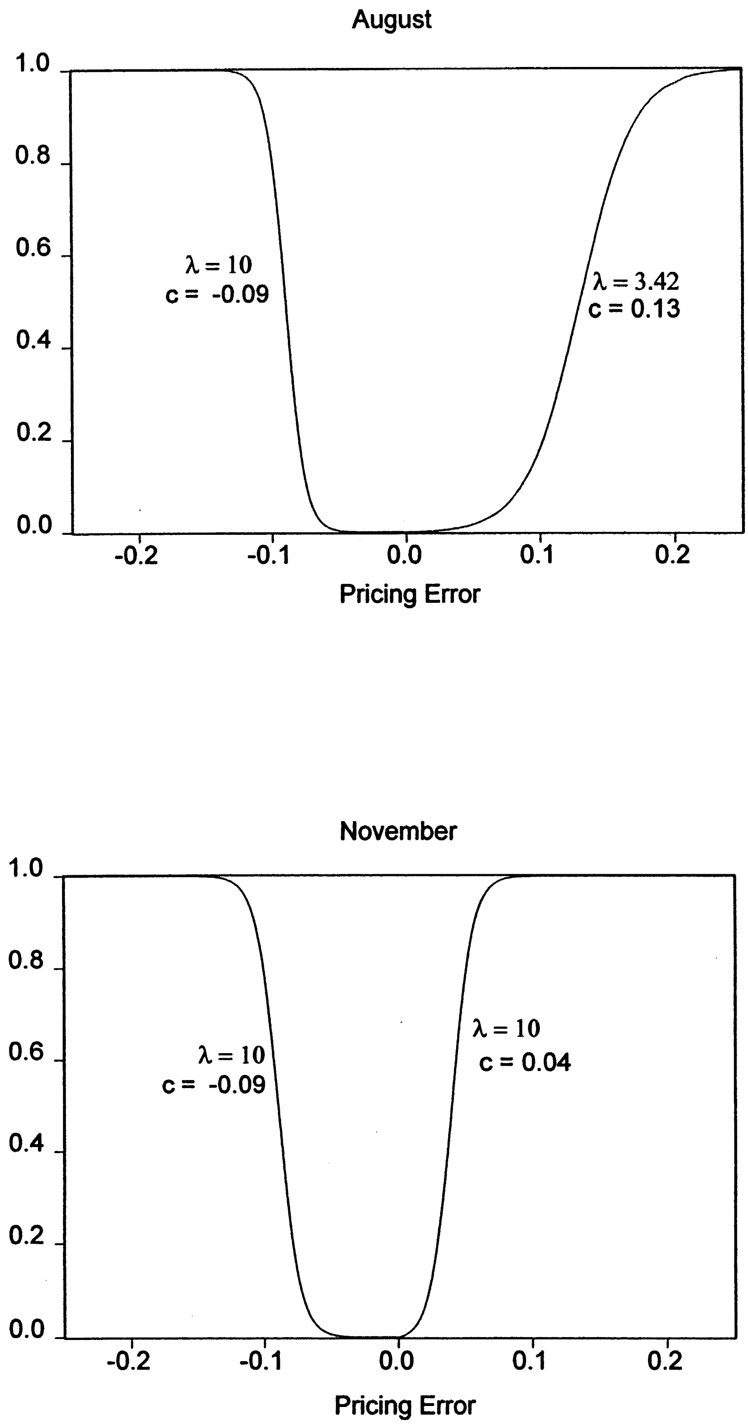


Figure 3: Estimated transition functions

not statistically significant, although the lagged basis still played a crucial role in that it generated the transition between different behavioural regimes.[4]

Figure 3 shows that the boundaries of the behavioural regimes for August and November are different, with the inner band for pricing errors being more symmetric for November than for August, and thinner. The increased symmetry suggests that the automation of the futures market has reduced some of the practical differences between responding to positive and negative pricing errors, and the thinner band implies that smaller pricing errors will now induce regime shifts.

It is hard to interpret autoregressive parameters in time series models, and nonlinearity further complicates interpretation. We therefore study the dynamic properties of our models by analysing their generalised impulse response functions.[5] We trace the impacts of shocks to futures and stocks on movements in the basis, assuming that the basis is initially zero and the market is in equilibrium. The size of the shocks that we consider are approximately one standard deviation of the basis (about 0.07) and two standard deviations, and given that it is often believed that shocks to the stock index are firm specific and different from shocks to the futures index which reflect macroeconomic shocks (see Frino *et al.*, 2001), we consider two extreme cases. In the first case a positive (negative) shock to the basis is caused purely by a positive (negative) shock in the futures market, and we call this sort of shock a 'macroeconomic' shock. In the second case a positive (negative) shock to the basis is caused purely by a negative (positive) shock to the stock index, and we call this sort of shock a 'firm specific' shock.

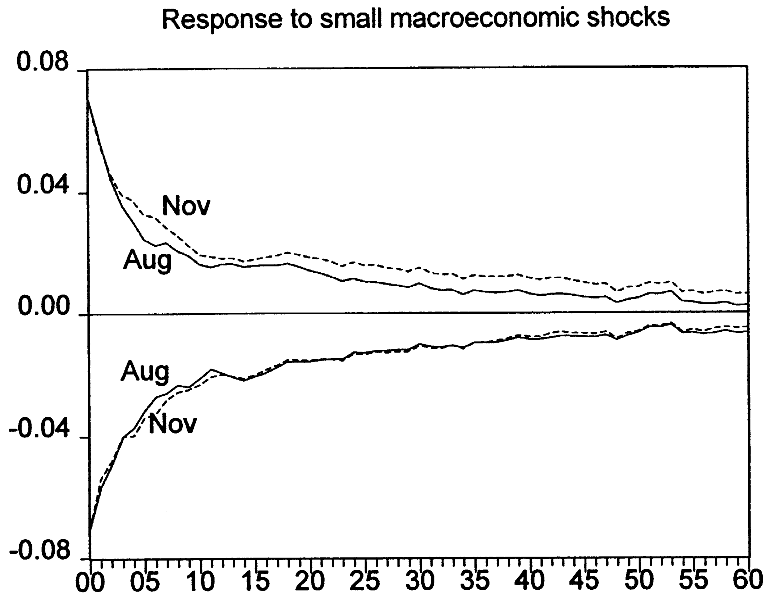
The generalised impulse response functions are illustrated in Figures 4 and 5. There are minor differences between the effects of the two types of shocks, and minor asymmetries between the effects of positive and negative shocks. There are no significant differences between the response functions for August and November. The half lives of all shocks are short, but in each case it takes more than an hour for equilibrium to be restored.

V. CONCLUSION

This paper examines the impact of screen trading in futures on the nonlinear properties of the basis and returns. We use a new form of smooth transition model to account for nonlinearities caused by transaction costs and other market/data imperfections, and we study the properties of these models by inspecting their implied responses to various shocks. We find strong evidence of nonlinearity before the futures trading went on-line, and weaker evidence of nonlinearity after on-line trading. Our analysis suggests that the automation of the futures market has made the nonlinear properties of the stock market and the futures market more similar, and that after the introduction of on-line futures trading, the returns in each market have a common nonlinear factor. Futures returns lead stock returns (with feedback) both before and after the introduction of screen-trading, and the futures lead increases only slightly after automation. The speed of mean-reversion in the basis is slow, and appears to be unchanged. We find that even though the models are statistically different, their implications as shown by their impulse response functions are virtually the same.

[4] Further exploration based on unit root tests for the basis found weak evidence of 'no-arbitrage bands' given by $-0.009 < b_{t-6} < 0.009$ for August and $-0.003 < b_{t-6} < 0.003$ for November, but we do not pursue this issue further here.

[5] Unlike linear models, the expected response to shocks cannot be derived analytically, and are therefore derived by averaging over many simulated response paths (See Koop *et al.*, 1996).



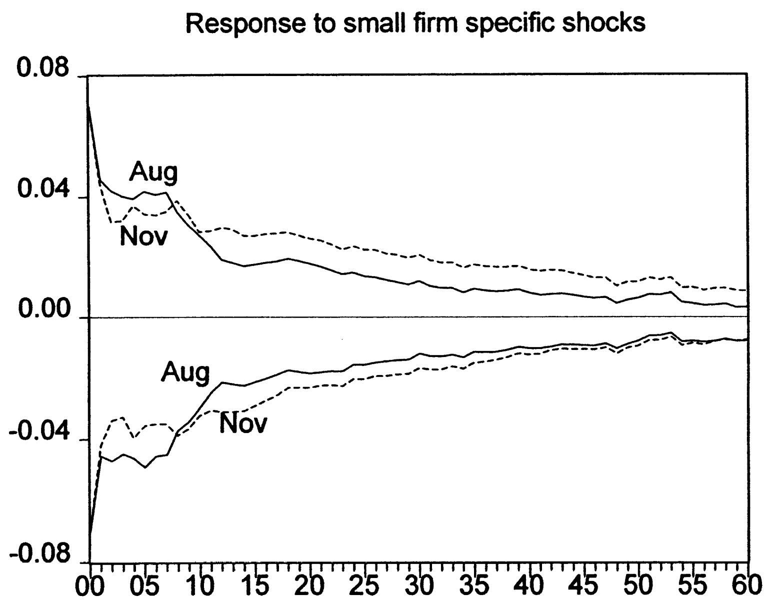


Figure 4: Mean reversion in the basis

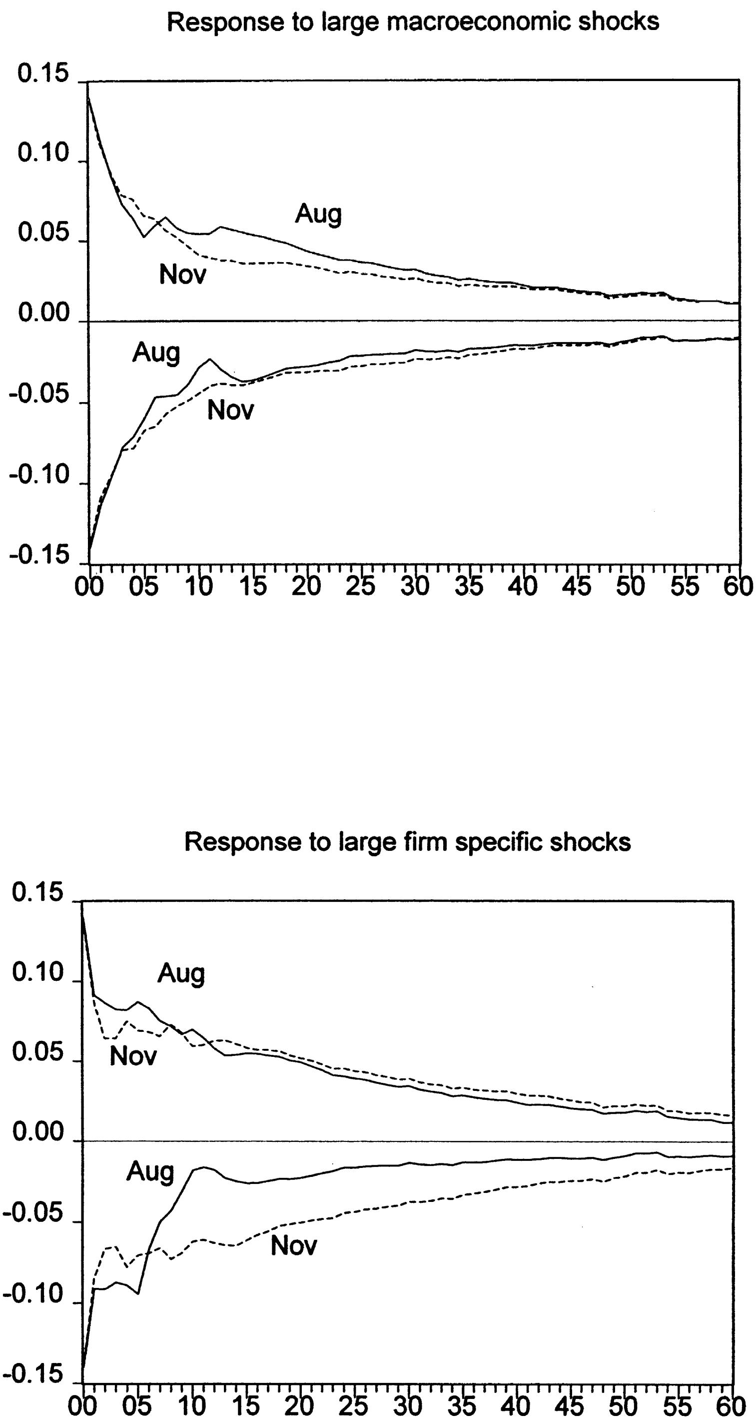


Figure 5: Mean reversion in the basis

APPENDIX 1A: LINEAR ERROR CORRECTION MODEL FOR THE FULL SAMPLE

	Returns for Futures		*Returns for Stocks*	
Variable	*Coef*	*het.c t-stat*	*Coef*	*het.c. t-stat*
const	−0.0002	−0.4523	−0.0000	−0.1316
v_{t-1}	−0.0287	−3.9731	0.0254	5.3686
f_{t-1}	0.0400	2.0193	0.1771	15.6057
f_{t-2}	−0.0340	−1.8107	0.1117	10.3028
f_{t-3}	−0.0296	−1.5672	0.0933	8.2279
f_{t-4}	−0.0006	−0.0320	0.0545	4.9544
f_{t-5}	−0.0095	−0.5568	0.0565	5.0410
f_{t-6}	−0.0034	−0.1933	0.0246	2.2409
f_{t-7}	0.0103	0.6051	0.0264	2.4878
f_{t-8}	−0.0027	−0.1648	0.0233	2.0659
f_{t-9}	0.0015	0.0853	0.0213	1.9916
f_{t-10}	−0.0149	−0.8755	0.0206	1.9126
f_{t-11}	−0.0104	−0.6304	0.0190	1.777
f_{t-12}	0.0059	0.3594	0.0087	0.8354
s_{t-1}	0.2903	10.92224	−0.0084	−0.4713
s_{t-2}	0.0627	2.3194	−0.0413	−2.2830
s_{t-3}	−0.0186	−0.7046	−0.0548	−3.1965
s_{t-4}	−0.06422	−2.4054	−0.0349	−2.0721
s_{t-5}	−0.0276	−1.0767	−0.0338	−1.9466
s_{t-6}	−0.0059	−0.2295	−0.0191	−1.1448
s_{t-7}	−0.0444	−1.8100	−0.0437	−2.6382
s_{t-8}	−0.0149	−0.6180	−0.0169	−1.0355
s_{t-9}	0.0337	1.4646	0.0032	0.2001
s_{t-10}	0.0147	0.6366	−0.0242	−1.6130
s_{t-11}	0.0233	1.1217	−0.0140	−0.9581
s_{t-12}	−0.0033	−0.1593	−0.0265	−1.7854
R^2	0.0488		0.1612	
s.e	0.0301		0.0187	

Note: The pricing error $v_{t-1} = b_{t-1} - \mu$ is used as the error correction term.

APPENDIX 1B: LINEAR ERROR CORRECTION MODEL FOR THE AUGUST SAMPLE

	Returns for Futures		*Returns for Stocks*	
Variable	*Coef*	*het.c t-stat*	*Coef*	*het.c. t-stat*
const	−0.0003	−0.5047	0.0000	0.0220
v_{t-1}	−0.0276	−2.5394	0.0280	3.9015
f_{t-1}	0.1030	4.1596	0.2168	13.3864
f_{t-2}	−0.0370	−1.5210	0.1243	8.2632
f_{t-3}	−0.0035	−0.1317	0.0985	6.1992
f_{t-4}	−0.0173	−0.7257	0.0466	2.8822
f_{t-5}	0.0067	0.2765	0.0567	3.4756
f_{t-6}	0.0064	0.2541	0.0332	2.1668
f_{t-7}	0.04487	1.8601	0.0242	1.6036
f_{t-8}	0.0140	0.5904	0.0321	2.0885
f_{t-9}	−0.0069	−0.2797	0.0154	0.9983

	Returns for Futures		*Returns for Stocks*	
Variable	*Coef*	*het.c t-stat*	*Coef*	*het.c. t-stat*
f_{t-10}	−0.0266	−1.1316	0.0093	0.6117
f_{t-11}	−0.0030	−0.1288	0.0214	1.4354
f_{t-12}	0.0138	0.5723	0.0015	0.1025
s_{t-1}	0.2831	7.9086	0.0000	0.0040
s_{t-2}	0.0205	0.5771	−0.0336	−1.4428
s_{t-3}	−0.0291	−0.8341	−0.0643	−2.7648
s_{t-4}	−0.0673	−1.8982	−0.0516	−2.2869
s_{t-5}	−0.0773	−2.2647	−0.0536	−2.3922
s_{t-6}	−0.0188	−0.5383	−0.0211	−0.9796
s_{t-7}	−0.0553	−1.6394	−0.0533	−2.4407
s_{t-8}	−0.0056	−0.1738	−0.0483	−2.2176
s_{t-9}	0.0325	1.0124	−0.0031	−0.1376
s_{t-10}	0.0184	0.6242	−0.0036	−0.1712
s_{t-11}	0.0384	1.3737	−0.0090	−0.4696
s_{t-12}	0.0054	0.1945	−0.0362	−1.7486
R^2	0.0694		0.2121	
$s.e$	0.0290		0.0187	

Note: The pricing error $v_{t-1} = b_{t-1} - \mu$ is used as the error correction term.

Appendix 1C: Linear Error Correction Model for the November Sample

	Returns for Futures		*Returns for Stocks*	
Variable	*Coef*	*het.c t-stat*	*Coef*	*het.c. t-stat*
const	0.0000	0.0116	−0.0001	−0.2701
v_{t-1}	−0.0301	−3.1313	0.0215	3.5346
f_{t-1}	−0.0294	−0.9750	0.1334	8.5887
f_{t-2}	−0.0402	−1.4318	0.0930	6.0773
f_{t-3}	−0.0554	−2.1399	0.0861	5.4026
f_{t-4}	0.0063	0.2420	0.0640	4.289
f_{t-5}	−0.0243	−1.0098	0.0617	4.0238
f_{t-6}	−0.0186	−0.7495	0.0194	1.2551
f_{t-7}	−0.0278	−1.1550	0.0311	2.0984
f_{t-8}	−0.0307	−1.3406	0.0141	0.8690
f_{t-9}	0.0033	0.1357	0.0268	1.8369
f_{t-10}	−0.0080	−0.3314	0.0318	2.1267
f_{t-11}	−0.0177	−0.7459	0.0171	1.1424
f_{t-12}	−0.0085	−0.3784	0.0145	1.0294
s_{t-1}	0.2850	7.2584	−0.0483	−1.8785
s_{t-2}	0.1211	3.0051	−0.0645	−2.2729
s_{t-3}	0.0202	0.5010	−0.0433	−1.6646
s_{t-4}	−0.0392	−0.9514	−0.0099	−0.3764
s_{t-5}	0.0431	1.0931	−0.0015	−0.0567
s_{t-6}	0.0178	−0.4589	−0.0009	−0.0365
s_{t-7}	−0.0269	−0.7348	−0.0161	−0.6480
s_{t-8}	−0.0213	−0.5792	0.0328	1.3321
s_{t-9}	0.0347	1.0309	0.0175	0.7482

continued overleaf

	Returns for Futures		*Returns for Stocks*	
Variable	*Coef*	*het.c t-stat*	*Coef*	*het.c. t-stat*
s_{t-10}	0.0026	0.0711	−0.0482	−2.2835
s_{t-11}	−0.0118	−0.3730	−0.0273	−1.2324
s_{t-12}	−0.0306	−0.9448	−0.0293	−1.3929
R^2	0.0436		0.1205	
$s.e$	0.0313		0.0186	

Note: The pricing error $v_{t-1} = b_{t-1} - \mu$ is used as the error correction term.

APPENDIX 2A: NONLINEAR ERROR CORRECTION MODEL OF FUTURES (AUGUST SAMPLE)

	Superscript 0 Regime		*Superscript P Regime*		*Superscript N Regime*	
Variable	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
const	−0.001	−1.525	0.035	1.987	0.0003	0.0325
v_{t-6}	−0.044	−2.528	−0.132	−1.256	0.037	0.692
f_{t-1}	0.093	3.151	0.299	2.320	0.052	0.510
f_{t-2}	−0.027	−0.941	0.034	0.250	0.065	0.642
f_{t-3}	−0.026	−0.839	0.463	2.773	0.210	1.812
f_{t-4}	−0.015	−0.536	0.154	1.208	0.003	0.024
f_{t-5}	−0.021	−0.736	0.530	3.158	0.044	0.400
f_{t-6}	0.005	0.174	−0.084	−0.650	0.005	0.054
f_{t-7}	0.042	1.579	0.163	1.363	−0.082	−0.846
f_{t-8}	0.044	1.661	−0.318	−2.727	−0.197	−2.261
f_{t-9}	0.025	0.926	−0.230	−2.230	−0.168	−1.549
f_{t-10}	−0.012	−0.449	0.179	1.276	−0.282	−3.322
f_{t-11}	−0.006	−0.224	0.238	1.423	−0.141	−1.420
f_{t-12}	0.020	0.746	−0.009	−0.068	−0.052	−0.567
s_{t-1}	0.266	6.564	−0.165	−0.769	0.031	0.219
s_{t-2}	0.014	0.341	−0.277	−1.255	0.007	0.053
s_{t-3}	−0.022	−0.546	−0.249	−1.324	−0.094	−0.630
s_{t-4}	−0.042	−1.016	−0.430	−1.751	−0.136	−0.847
s_{t-5}	−0.089	−2.221	−0.229	−1.121	0.129	0.850
s_{t-6}	−0.027	−0.710	0.073	0.373	0.174	1.312
s_{t-7}	−0.088	−2.361	0.270	1.278	0.240	2.034
s_{t-8}	−0.022	−0.635	−0.161	−0.888	0.243	1.986
s_{t-9}	0.006	0.180	0.170	0.946	0.221	2.010
s_{t-10}	0.011	0.331	−0.238	−1.472	0.155	1.327
s_{t-11}	0.016	0.514	0.007	0.044	0.220	1.916
s_{t-12}	0.030	0.967	0.032	0.221	−0.213	−2.097
Transition λ	not applicable		3.42		10	
Transition c	not applicable		0.13		−0.09	

Note: See equations (6), (6a) and 6(b) for the model specification. All t statistics are corrected for heteroscedasticity. The R^2 is 0.102 and the $s.e.$ is 0.028.

APPENDIX 2B: NONLINEAR ERROR CORRECTION MODEL OF STOCKS (AUGUST SAMPLE)

	Superscript 0 Regime		*Superscript P Regime*		*Superscript N Regime*	
Variable	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
const	0.0001	0.277	−0.030	−2.700	−0.009	−1.552
v_{t-6}	0.052	4.788	0.166	2.492	−0.108	−2.648
f_{t-1}	0.185	9.761	−0.019	−0.231	0.116	1.544
f_{t-2}	0.094	5.437	−0.103	−1.175	0.188	2.660
f_{t-3}	0.068	3.852	−0.090	−0.964	0.180	2.090
f_{t-4}	0.015	0.830	−0.266	−2.612	0.250	2.989
f_{t-5}	0.021	1.040	−0.147	−1.755	0.191	2.286
f_{t-6}	0.017	0.991	−0.168	−2.309	0.186	3.466
f_{t-7}	0.017	1.029	0.037	0.440	0.073	1.224
f_{t-8}	0.042	2.443	−0.096	−1.472	−0.059	−1.059
f_{t-9}	0.007	0.384	−0.074	−0.920	0.119	1.735
f_{t-10}	0.001	0.052	−0.050	−0.572	0.019	0.356
f_{t-11}	0.011	0.697	−0.048	−0.553	0.057	0.740
f_{t-12}	0.009	0.558	−0.242	−2.578	−0.012	−0.202
s_{t-1}	0.014	0.521	0.097	0.692	−0.041	−0.362
s_{t-2}	0.023	0.906	0.027	0.203	−0.336	−3.266
s_{t-3}	−0.022	−0.899	0.434	3.408	−0.412	−4.426
s_{t-4}	−0.020	−0.819	0.224	1.722	−0.236	−2.368
s_{t-5}	−0.011	−0.432	0.030	0.268	−0.244	−2.449
s_{t-6}	−0.018	−0.779	0.048	0.345	−0.091	−1.115
s_{t-7}	−0.024	−0.986	−0.196	−1.839	−0.176	−2.446
s_{t-8}	−0.067	−2.868	0.063	0.461	0.140	1.856
s_{t-9}	−0.006	−0.253	0.118	0.989	−0.018	−0.206
s_{t-10}	0.010	0.417	0.070	0.601	−0.151	−2.049
s_{t-11}	−0.026	−1.280	0.176	1.481	0.124	1.751
s_{t-12}	−0.038	−1.778	0.266	2.799	−0.115	−1.654
Transition λ	not applicable		3.42		10	
Transition c	not applicable		0.13		−0.09	

Note: See equations (6), (6a) and 6(b) for the model specification. All t statistics are corrected for heteroscedasticity. The R^2 is 0.248 and the $s.e.$ is 0.018.

APPENDIX 2C: NONLINEAR ERROR CORRECTION MODEL OF FUTURES (NOVEMBER SAMPLE)

	Superscript 0 Regime		*Superscript P Regime*		*Superscript N Regime*	
Variable	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
const	0.0004	0.372	−0.001	−0.294	−0.008	−0.875
v_{t-6}	−0.009	−0.282	−0.017	−0.395	−0.093	−1.294
f_{t-1}	−0.137	−2.367	0.194	2.421	0.316	3.018
f_{t-2}	−0.061	−1.197	−0.005	−0.070	0.098	1.012
f_{t-3}	−0.099	−1.961	0.092	1.327	0.069	0.653
f_{t-4}	0.020	0.380	−0.065	−0.873	0.007	0.070

continued overleaf

	Superscript 0 Regime		*Superscript P Regime*		*Superscript N Regime*	
Variable	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
f_{t-5}	−0.003	0.056	−0.090	−1.335	0.028	0.258
f_{t-6}	0.022	0.551	−0.077	−1.269	−0.067	−0.802
f_{t-7}	−0.062	−1.706	0.121	2.143	−0.016	−1.192
f_{t-8}	−0.042	−1.275	0.034	0.624	0.060	0.750
f_{t-9}	−0.007	−0.224	0.019	0.309	0.032	0.359
f_{t-10}	−0.023	−0.650	0.046	0.800	−0.049	−0.601
f_{t-11}	−0.003	−0.082	−0.040	−0.706	−0.024	−0.285
f_{t-12}	0.006	0.197	−0.019	−0.363	−0.043	−0.518
s_{t-1}	0.355	5.128	−0.104	−1.073	−0.203	−1.443
s_{t-2}	0.171	2.454	−0.027	−0.262	−0.249	−1.884
s_{t-3}	0.056	0.764	−0.086	−0.848	0.007	0.049
s_{t-4}	−0.053	−0.728	0.034	0.317	−0.010	−0.075
s_{t-5}	0.055	0.720	−0.029	−0.280	0.095	0.727
s_{t-6}	−0.084	−1.307	0.197	2.144	0.144	1.183
s_{t-7}	0.066	−1.076	−0.167	−1.903	−0.256	−2.205
s_{t-8}	−0.066	−1.141	0.058	0.657	0.229	1.917
s_{t-9}	0.034	0.670	−0.001	−0.008	−0.106	−0.838
s_{t-10}	0.063	1.049	−0.099	−1.186	−0.095	−0.769
s_{t-11}	−0.010	−0.217	−0.098	−1.313	0.172	1.667
s_{t-12}	−0.069	−1.348	0.083	1.130	0.067	0.650
Transition λ	not applicable		10		10	
Transition c	not applicable		0.04		−0.09	

Note: See equations (6), (6a) and 6(b) for the model specification. All t statistics are corrected for heteroscedasticity. The R^2 is 0.043 and the $s.e.$ is 0.031.

Appendix 2D: Nonlinear Error Correction Model of Stocks (November Sample)

	Superscript 0 Regime		*Superscript P Regime*		*Superscript N Regime*	
Variable	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
const	−0.001	−1.322	0.0002	0.097	0.011	1.990
v_{t-6}	0.021	1.180	0.015	0.567	0.056	1.379
f_{t-1}	0.105	3.657	0.049	1.191	0.028	0.436
f_{t-2}	0.082	3.108	−0.011	−0.255	0.045	0.807
f_{t-3}	0.096	3.505	−0.018	−0.412	−0.127	−2.458
f_{t-4}	0.075	2.683	−0.037	−0.874	−0.089	−1.585
f_{t-5}	0.076	2.974	−0.027	−0.595	−0.065	−1.097
f_{t-6}	0.020	0.987	−0.008	−0.211	0.036	0.729
f_{t-7}	0.038	1.881	−0.002	−0.042	−0.012	−0.255
f_{t-8}	0.034	1.595	−0.053	−1.357	−0.025	−0.469
f_{t-9}	0.018	0.934	0.006	0.152	0.069	1.240
f_{t-10}	0.018	0.902	0.044	1.225	−0.023	−0.430
f_{t-11}	0.005	0.296	0.029	0.813	0.005	0.092
f_{t-12}	0.010	0.535	0.003	0.093	0.029	0.521
s_{t-1}	−0.030	−0.786	−0.069	−1.074	0.085	0.946
s_{t-2}	−0.089	−2.377	0.072	1.095	0.050	0.572
s_{t-3}	−0.075	−1.791	0.060	0.927	0.127	1.380

	Superscript 0 Regime		Superscript P Regime		Superscript N Regime	
Variable	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
s_{t-4}	−0.034	−0.833	0.029	0.436	0.201	2.216
s_{t-5}	−0.064	−1.637	0.144	2.189	0.106	1.308
s_{t-6}	−0.035	−1.030	0.068	1.100	0.020	0.229
s_{t-7}	0.028	0.786	−0.095	−1.587	−0.136	−1.752
s_{t-8}	0.055	1.786	−0.063	−1.147	−0.008	−0.092
s_{t-9}	0.035	1.126	−0.039	−0.712	−0.036	−0.393
s_{t-10}	0.011	0.399	−0.123	−2.587	−0.115	−1.473
s_{t-11}	0.022	0.831	−0.093	−1.936	−0.080	−0.825
s_{t-12}	−0.010	−0.330	0.005	0.103	−0.103	−1.234
Transition λ	not applicable		10		10	
Transition c	not applicable		0.04		−0.09	

Note: See equations (6), (6a) and 6(b) for the model specification. All t statistics are corrected for heteroscedasticity. The R^2 is 0.163 and the $s.e.$ is 0.018.

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