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Error-Correction Relationships between High, Low and Consensus Prices

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Abstract

The paper models the return generation process of asset prices by incorporating the observed daily Close, High and Low prices as a vector error correction process. In addition, various transformed prices, such as the Weighted Close, the Typical Price and the Median Price, are investigated as alternatives to the Close for depicting "consensus" prices.

The vector error correction models reveal some interesting stylised facts for the US daily Dow Jones Industrial *DJI*30 Index data from *1990* to *1999* (*10* years). The empirical results show, via the cointegrated models as specified, that the "cointegrating" errors significantly capture the behaviour of observed and transformed returns. In addition, goodness-of-fit tests fail to reject the extreme-value distribution as implied by the cointegrating vectors, thus suggesting an extreme-valued behaviour in the error-correction process. As the error-correction terms are extreme-valued and significant in the compound models as investigated, it can be said that the distribution of the observed returns will consequently be non-normal.

Key words: High and Low prices, Vector Error Correction, Cointegration and Extreme-Valued Distributions.

JEL classification: *C32* (Time-Series Models)

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[1] This paper was presented at the First International Workshop on Intelligent Finance (IWIF-1), Crown Promenade Hotel, Melbourne, Australia (University of Ballarat, Victoria) in December, 2004 under the title "Compound Models of High-Low Speculative Prices: A Cointegration-based Approach".

1 Introduction

Daily closing prices are typically used as proxies for daily security prices and other financial timeseries data. Empirical observations on these financial data, however, usually not only include the closing prices $(C(t))$, but also the opening, the highest and the lowest prices $(O(t), H(t), L(t))$ for specific horizons such as days, weeks and months. Obviously, a multivariate vector of prices $(H(t), L(t), O(t), C(t))$ will be more informative than just the closing prices $C(t)$ for modelling and forecasting asset prices and returns[2].

The insight of this paper is that the High $H(t)$ and Low $L(t)$ prices can be used to model the return generation process of asset prices as illustrated by Fiess and MacDonald [2002]. In addition, we also analyse price behaviour using various "technical" price types: the Weighted Close $(WC(t))$, the Typical Price $(TP(t))$ and the Median Price $(MP(t))$. These "technical" price types are based on the notion of an "average" or "consensus" price.

The Weighted Close is computed by multiplying the Close by two, adding the High and the Low to this product, and dividing the result by four and is given as:

(1)
$$WC(t) = \frac{H(t) + L(t) + 2 * C(t)}{4}$$

The result is the average price with extra weight given to the closing price.

The Typical Price is calculated by adding the High, Low, and closing prices together, and then dividing by three and is given as:

(2)
$$TP(t) = \frac{H(t) + L(t) + C(t)}{3}$$

The result is the average, or typical price.

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[2] The "Open and Close refer to the price at the opening and the closing of the market respectively, High and Low prices correspond to the two extremes: the highest and lowest prices of the day" Fiess and MacDonald [2002].

The Median Price is calculated by adding the High and Low price and dividing by two and is given as:

(3)
$$MP(t) = \frac{H(t) + L(t)}{2}$$

The Median Price indicator is simply the midpoint of each day's price range.

In Section 2 the observed and transformed data as used in the paper are described and discussed. In Section 3 the modeling methodology is described. The findings are tabulated and described in Section 4. The conclusions are presented in Section 5.

2 Data

The dataset used in this paper is the daily *DJI30* Index prices from 1/1/1990 to 1/1/2000 covering a period of *10* years (*2527 observations*) as shown in the top panel in Figure 2-1. We use the Highs, Lows and Closes of the *DJI30* Index, instead of a typical stock price like *IBM* , as the aggregated index generally reflects better the systematic aspects of the market as a whole. The choice of the *DJI30* Index is because it relates to the New York Stock Exchange (*NYSE*) which is one of the largest and most researched markets in the world. We also compute the Weighted Close, the Typical Price and the Median Price for *DJI30* Index.

The bottom panel in Figure 2-1 illustrates the temporal movements of the various price types *(H(t), L(t), C(t), WC(t), TP(t) and MP(t))* using the *DJI30* Index series for the period 29/4/93 to 26/7/93 as an example.

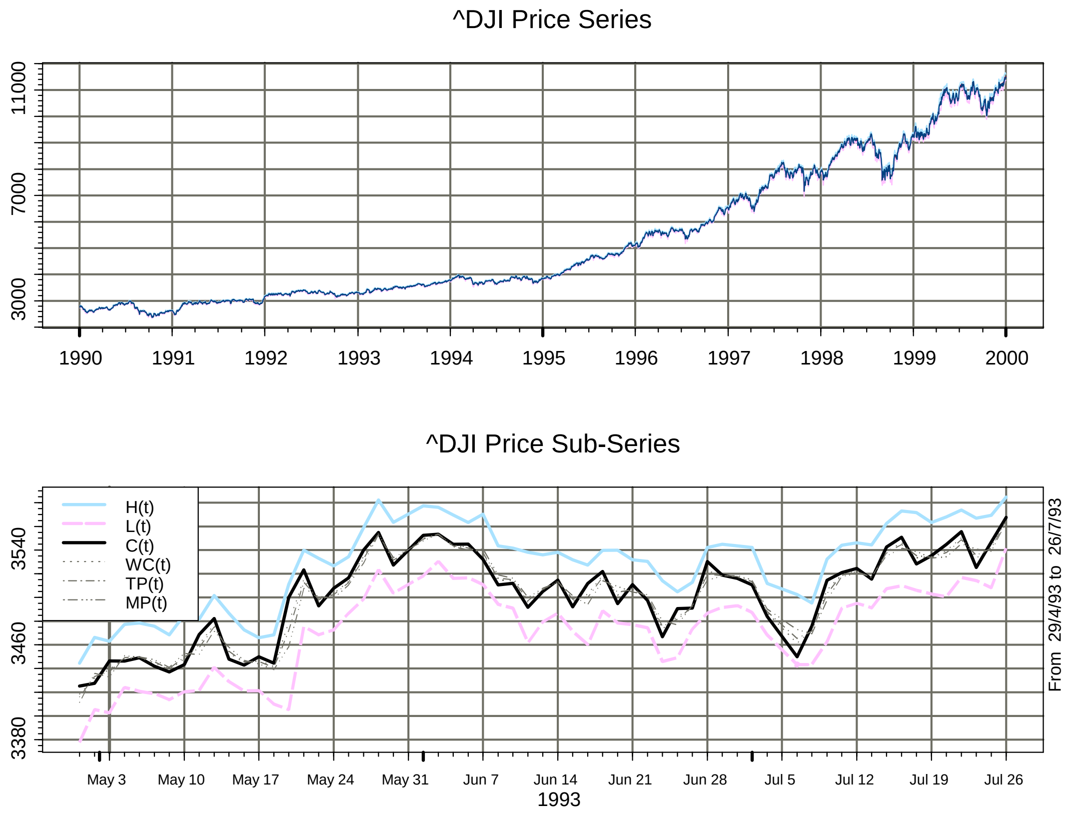

Figure 2-1: DJI30 Price Data
Notes: H(t)=High; L(t)=Low; C(t)=Close; WC(t)=Weighted Close; TP(t)=Typical Price; MP(t)=Median Price.

Note that the Highs and Lows bound the other price types and accordingly can be termed as "extremal" prices. In contrast, the other price types are may be termed as "central" prices. Of the central price types, the Close is the most volatile. The Weighted Close, the Typical Price and the Median Price tend to be more of an "average" price. Non-stationary of the log-prices for all variables *(H(t), L(t), C(t), WC(t), TP(t) and MP(t))* cannot be rejected as the results of the augmented Dickey-Fuller test shown in Table 2-1 suggest.

H(t)		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.873061	0.9952
Test critical values:	1% level	-3.432746	
	5% level	-2.862484	
	10% level	-2.567318	
L(t)		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.719196	0.9926
Test critical values:	1% level	-3.432746	
	5% level	-2.862484	
	10% level	-2.567318	
C(t)		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.743036	0.9931
Test critical values:	1% level	-3.432744	
	5% level	-2.862484	
	10% level	-2.567317	
WC(t)		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.788019	0.9939
Test critical values:	1% level	-3.432746	
	5% level	-2.862484	
	10% level	-2.567318	
TP(t)		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.815585	0.9943
Test critical values:	1% level	-3.432746	
	5% level	-2.862484	
	10% level	-2.567318	
MP(t)		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.821153	0.9944
Test critical values:	1% level	-3.432746	
	5% level	-2.862484	
	10% level	-2.567318	

*MacKinnon (1996) one-sided p-values.

Table 2-1: Augmented Dickey-Fuller test statistic

Figure 2-2 depicts the timeseries plots of the differenced logarithmic prices (logarithmic returns) for the High, Low and Close. The log-return series appear similar but are not identical, meaning they seem to have similar shocks or disturbances and even common volatilities over time. The plots also suggest that the $D(C), D(H)$ *and* $D(L)$ series are stationary.

In fact as the results in Table 2-2 show, the $D(C)$ log-difference series is stationary. The null hypothesis that $D(C)$ has a unit root can be rejected. Similar results are obtained for the other variables, i.e. *(D(H), D(L), D(WC), D(TP) and D(MP))*. Thus, for all our price vectors, the logarithmic price series are non-stationary and the logarithmic returns series are stationary.

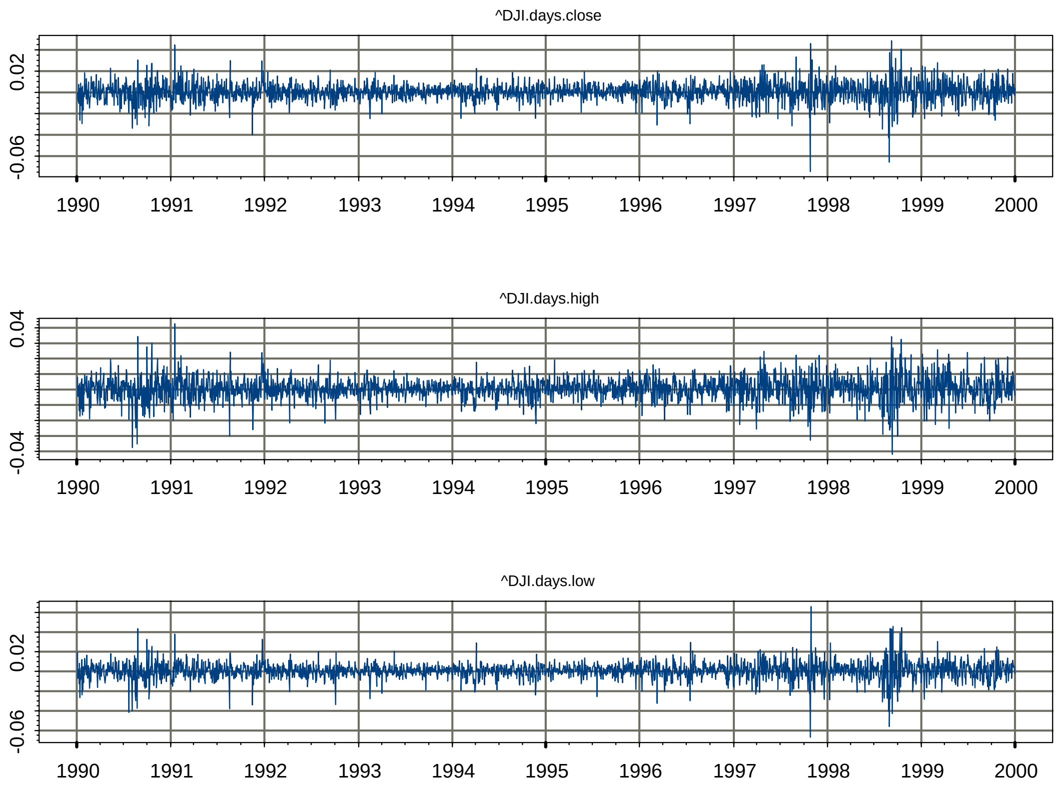

Figure 2-2: Timeseries Plots [D(C) D(H)) D(L)]

D(C)		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-51.23833	0.0001
Test critical values:	1% level	-3.432512	
	5% level	-2.862381	
	10% level	-2.567262	

*MacKinnon (1996) one-sided p-values.

Table 2-2: Augmented Dickey-Fuller test statistic for D(C) Log-Returns

	D(C)	D(H)	D(L)	D(MP)	D(TP)	D(WC)
Mean	0.000558	0.000561	0.000564	0.000566	0.000561	0.000560
Median	0.000605	0.000884	0.000792	0.000801	0.000751	0.000809
Maximum	0.048605	0.042695	0.065996	0.040326	0.041937	0.043608
Minimum	-0.074549	-0.042032	-0.067045	-0.049971	-0.057689	-0.061851
Std. Dev.	0.008917	0.007470	0.008677	0.007671	0.007460	0.007611
Skewness	-0.409517	-0.187177	-0.306406	-0.278563	-0.400895	-0.455001
Kurtosis	8.201366	5.698868	9.528487	6.793541	7.608653	7.999361
Jarque-Bera	2919.214	781.6887	4527.192	1547.929	2304.050	2718.811
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	2527	2527	2527	2527	2527	2527

Table 2-3: DJI30 Log-returns Summary Statistics

Table 2-3 lists the summary statistics for the dataset used. As can be seen, all the variables have negatively skewed distributions with moderately high kurtosis. As to be expected, the Jarque-Bera statistics significantly rejects the null hypothesis that these variables have normal distributions.

In Figure 2-3 the correlations are shown for the four “central” price types investigated in this paper. The process of averaging involved in the definition of the “technical” prices seems to result in autocorrelations in the log-return series.

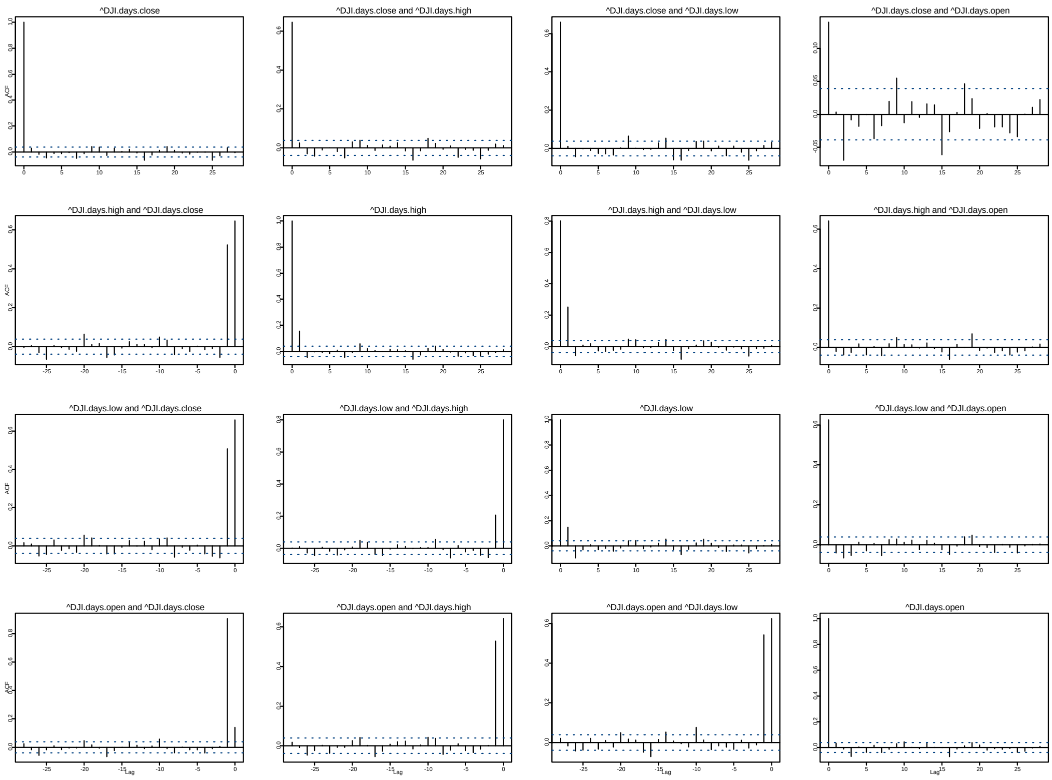

Figure 2-3: Correlograms [D(C) D(WC) D(TP) D(MP)]

More specifically, from Figure 2-3, the log-returns series using High and Low prices exhibit high (first-order) autocorrelations, whereas those log-return series using just the Close prices do not have any significant autocorrelations. This implies that any modeling incorporating the “extremal” prices will have more predictive ability compared to the ones based on just the closing prices.

	D(C)	D(WC)	D(TP)	D(MP)
D(C(-1))	0.030262	0.289916	0.382313	0.541707
D(WC(-1))	0.027403	0.228773	0.300272	0.423320
D(TP(-1))	0.025178	0.195668	0.256122	0.360015
D(MP(-1))	0.019085	0.117264	0.151893	0.211057

Table 2-4: First-Order Correlations [D(C) D(WC) D(TP) D(MP)]

In Table 2-4 the estimated values of the first-order autocorrelation are listed. Note that the values of the first-order auto-correlations for the Weighted Close, Typical Price and the Median Price are of the same magnitude.

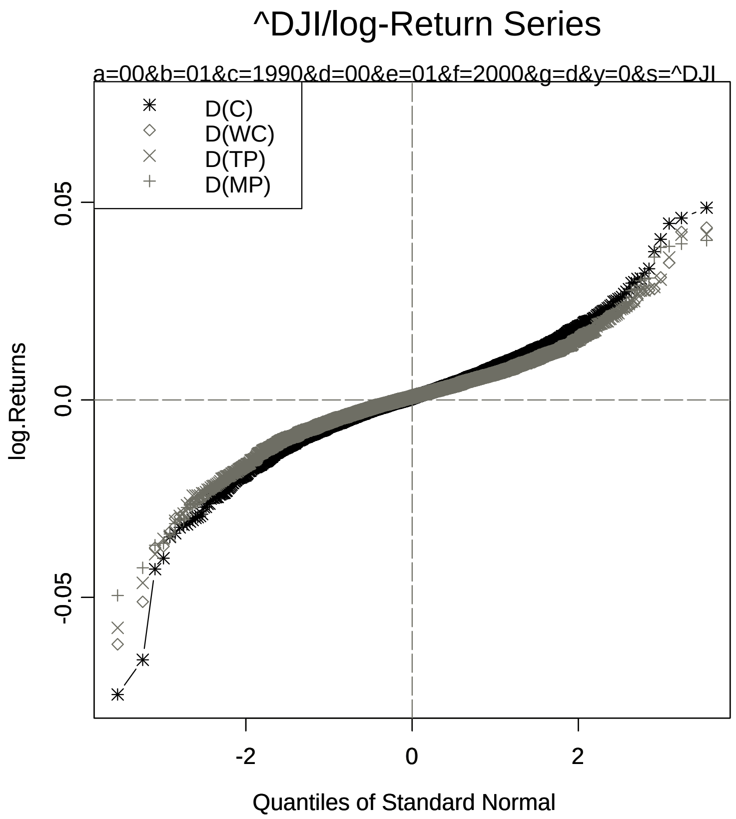

Figure 2-4: Log-Returns Data
Notes: D(C)=Close log-Returns; D(WC)=Weighted Close log-Returns; D(TP)=Typical Price log-Returns; D(MP)=Median Price log-Returns.

As the Close is also sometimes either the High or the Low price for the day, it may not be a good proxy for the “typical” or “consensus” price of the day. Accordingly, we investigate the relevance of “technical” prices for depicting “consensus” prices. In Figure 2-4, the outliers present in the Close log-Returns series have been circumvented by taking the “averages” of the price data in the other central-type returns. The QQ-plots for the various other central-type log-returns types have similar "shapes" indicating the similarity of the distributions of these "technical" log-returns.

Hence, we can infer from Figure 2-1 and Figure 2-4 that the "technical" prices and returns are not very dissimilar from the Close prices and returns, as far as their distributions and realizations are concerned. In addition, the "technical" returns have fewer outliers and are auto-correlated.

3 Methodology

The returns generation process in this paper is specified to be based on a modified Vector Error Correction Model $(VECM)$ defined as:

$$\Delta P(t)=\sum_{i=1}^{p}\alpha(i)\Delta P(t-i)+\left\{\alpha^{+}\xi^{+}(t)+\alpha^{-}\xi^{-}(t)\right\}+\varepsilon(t) \tag{4}$$

where $\Delta P(t\text{-}i); i=1,2,...,p$ are the past changes in observed or transformed prices[3] and ε_t is the current error. The terms within the brackets $\left\{\alpha^{+}\xi^{+}(t)+\alpha^{-}\xi^{-}(t)\right\}$ are the current error-correction residuals. The error-correction residuals are implicitly defined to be the functions $f\{H(t),P(t-1)\}$ and $f\{L(t),P(t-1)\}$ and consequently are "current" asymmetric disturbances in our formulation.

Fiess and MacDonald [1999] used a similar cointegration approach to illustrate the structural relationship between High, Low and Close prices. In this paper, we differ from Fiess and MacDonald [1999] by having the current High and Low prices in the error-correction terms and transforming the Close price to obtain the various price types commonly used in technical analysis. We also equate these transformed "technical" prices to the notion of "consensus" prices as used by economists to highlight their relevance and similarities.

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[3] The prices can be the closing prices, the weighted closes, the typical prices or the median prices.

First we undertake a Vector Auto-Regressive (VAR) Lag Order selection process. The results for various selection criteria are listed in Table 3-1. The SC selects 7 lags, the HQ selects 12 lags and the rest select the set maximum of 20 lags, including the AIC. In this paper we adopt the SC criteria and use 7 lags.

VAR Lag Order Selection Criteria
Endogenous variables: D(H(1)) D(L(1)) D(C)
Exogenous variables: C
Sample: 1 2528
Included observations: 2506

Lag	LogL	LR	FPE	AIC	SC	HQ
0	27072.54	NA	8.32E-14	-21.60378	-21.59681	-21.60125
1	28681.18	3212.136	2.32E-14	-22.88043	-22.85253	-22.87030
2	29116.11	867.4383	1.65E-14	-23.22036	-23.17153	-23.20264
3	29357.05	479.9482	1.37E-14	-23.40546	-23.33571	-23.38014
4	29501.76	287.9322	1.23E-14	-23.51378	-23.42310	-23.48086
5	29571.15	137.8814	1.17E-14	-23.56197	-23.45037	-23.52146
6	29633.23	123.2223	1.13E-14	-23.60433	-23.47181	-23.55623
7	29666.95	66.85902	1.10E-14	-23.62407	-23.47062 *	-23.56836
8	29691.82	49.24136	1.09E-14	-23.63673	-23.46236	-23.57343
9	29719.19	54.12607	1.07E-14	-23.65139	-23.45609	-23.58050
10	29753.63	68.01943	1.05E-14	-23.67169	-23.45547	-23.59320
11	29779.43	50.90665	1.04E-14	-23.68510	-23.44795	-23.59901
12	29800.06	40.65892	1.03E-14	-23.69439	-23.43631	-23.60070*
13	29811.74	22.96774	1.03E-14	-23.69652	-23.41752	-23.59524
14	29824.81	25.70849	1.02E-14	-23.69977	-23.39985	-23.59090
15	29837.53	24.95787	1.02E-14	-23.70273	-23.38188	-23.58626
16	29851.16	26.72833	1.02E-14	-23.70643	-23.36466	-23.58236
17	29866.13	29.32135	1.01E-14	-23.71120	-23.34850	-23.57953
18	29876.71	20.69186	1.01E-14	-23.71246	-23.32883	-23.57320
19	29886.07	18.30335	1.01E-14	-23.71275	-23.30820	-23.56590
20	29907.77	42.33164*	1.00E-14*	-23.72288*	-23.29741	-23.56843

Table 3-1: VAR Lag Order Selection Criteria
Notes: * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

Based on the VAR lag order selection criteria, $VECM$ models with 6 lags are then fitted using the four “technical” price types: the Close, the Weighted Close, the Typical Price and the Median Price. The High and Low prices were modeled as lead prices in order to obtain “current” (and not lagged) error-correction terms on the RHS of Equation (4).

4 Findings

As mentioned in Section 3, we use $H(t+1), L(t+1)$ *and P(t)* and not $H(t), L(t)$ *and P(t)* in our *VECM* formulation to ensure that the error correction terms reflect the price changes relative to the last-period closing prices. We also restrict the error correction process in our *VECM* model to be of an order analogous to $\{H(t) - P(t-1)\}$ and $\{L(t) - P(t-1)\}$.

4.1 H(1)-L(1)-C VECM

Series: H(1) L(1) C
Unrestricted Cointegration Rank Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.832957	5113.965	29.68	35.65
At most 1 **	0.209317	593.6747	15.41	20.04
At most 2	0.000167	0.422925	3.76	6.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Trace test indicates 2 cointegrating equation(s) at both 5% and 1% levels

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.832957	4520.291	20.97	25.52
At most 1 **	0.209317	593.2517	14.07	18.63
At most 2	0.000167	0.422925	3.76	6.65

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Max-eigenvalue test indicates 2 cointegrating equation(s) at both 5% and 1% levels

Table 4-1: Unrestricted Cointegration Rank Test

Two cointegrating equations are significant at the 1% level as shown in Table 4-1.

2 Cointegrating Equation(s):		Log likelihood	29822.89
Normalized cointegrating coefficients (std.err. in parentheses)			
H(1)	L(1)	C	
1.000000	0.000000	-1.003641	
		(0.00026)	
0.000000	1.000000	-0.996798	
		(0.00028)	
Adjustment coefficients (std.err. in parentheses)			
D(H(1))	0.094165	0.314111	
	(0.02839)	(0.02521)	
D(L(1))	0.543547	-0.058504	
	(0.03276)	(0.02908)	
D(C)	0.737079	0.618202	
	(0.01610)	(0.01429)	

Table 4-2: CIs and ACs [EC(C,2) 1 6 H(1) L(1) C]

Table 4-2 displays the cointegrating coefficients and adjustment coefficients for the cointegrating vectors. The adjustment coefficients are estimated to be 0.737079 and 0.618202 respectively. Figure 4-1 shows the timeseries plots of the two cointegrating errors series as defined by the cointegrating vectors $1.000000 \bullet H_t - 1.003641 \bullet C_{t-1}$ and $1.000000 \bullet L_t - 0.996798 \bullet C_{t-1}$.

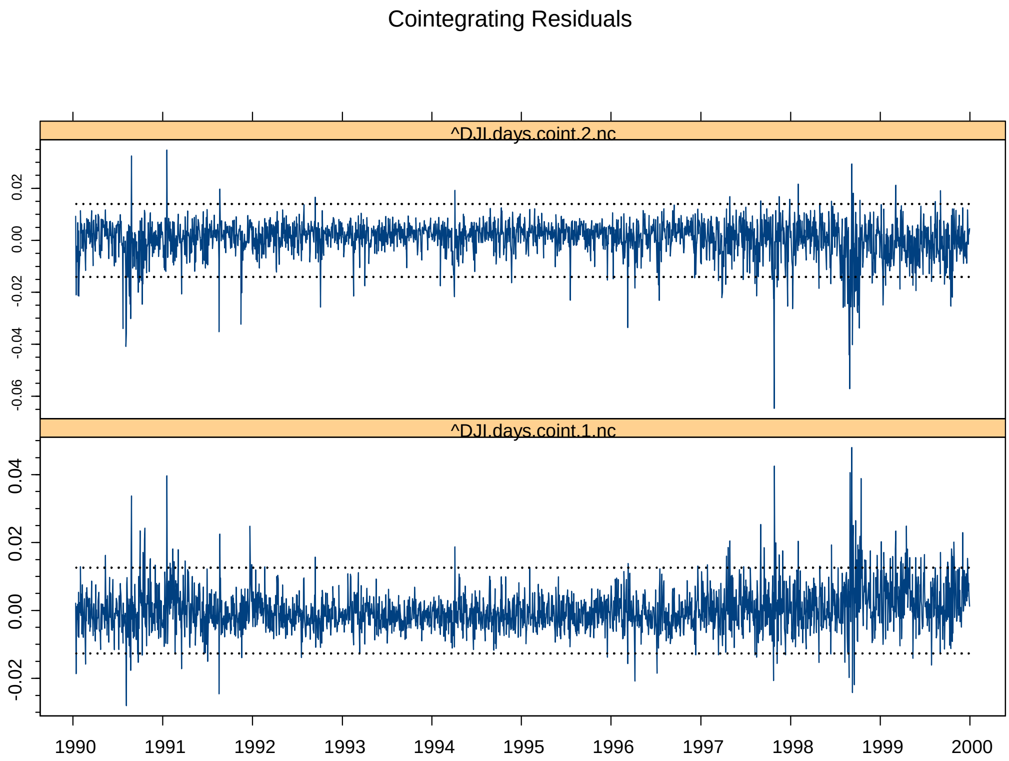

Figure 4-1: CI Residuals [EC(C,2) 1 6 H(1) L(1) C]

The cointegrating errors appear to exhibit volatility clustering and share common shocks overtime. Higher volatilities are accompanied by higher and lower prices. The volatilities are also in tandem with the $D(C)$ log-returns shown in Figure 2-2 indicating that the $VECM$ modeling process maintains the inherent temporal dependencies in the data.

The histograms of the cointegrating errors are illustrated in Figure 4-2. The cointegrating error historgrams are skewed and kurtotic in appearance. The cointegrating residual 1 series $(CR1)$ is positively skewed and the cointegrating residual 2 series $(CR2)$ is negatively skewed. This asymmetry is a direct consequence of the cointegrating variables as defined, since the Highs and Lows are the maximum and minimum values of the price series as observed.

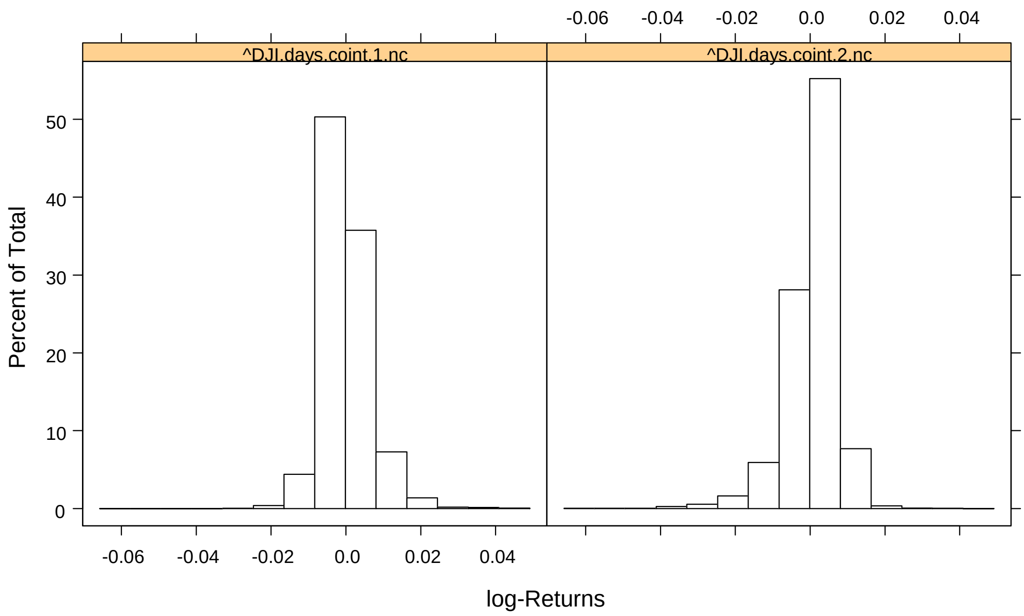

Figure 4-2: CI Histograms [EC(C,2) 1 6 H(1) L(1) C]

As the Highs and Lows are the maximum and minimum values of the observed series, we have attempted to fit an "extreme-value" distribution to each of the two cointegrating error series. The results as tabulated in Table 4-3 and Table 4-4 are both significant at the 1% level.

Hypothesis: Extreme Value Max

Method	Value	Adj. Value	Probability
Cramer-von Mises (W2)	7.657184	7.686293	< 0.01
Watson (U2)	7.657032	7.686140	< 0.01
Anderson-Darling (A2)	48.71436	48.89954	< 0.01

Table 4-3: Empirical Distribution Test for CR1 Series

Hypothesis: Extreme Value Min

Method	Value	Adj. Value	Probability
Cramer-von Mises (W2)	6.479187	6.503817	< 0.01
Watson (U2)	6.475729	6.500346	< 0.01
Anderson-Darling (A2)	40.44428	40.59802	< 0.01

Table 4-4: Empirical Distribution Test for CR2 Series

Vector Error Correction Estimates
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2	
H	1.000000	0.000000	
L	0.000000	1.000000	
C(-1)	-1.001218	-0.998721	
	(3.2E-05)	(3.4E-05)	
	[-31668.2]	[-29367.9]	
Error Correction:	D(H(1))	D(L(1))	D(C)
CointEq1	0.423503	0.688261	0.792681
	(0.07958)	(0.09271)	(0.04527)
	[5.32155]	[7.42342]	[17.5098]
CointEq2	0.433406	0.365643	0.718228
	(0.07419)	(0.08643)	(0.04220)
	[5.84222]	[4.23068]	[17.0195]
R-squared	0.161750	0.155601	0.809742
Adj. R-squared	0.155379	0.149183	0.808296

Table 4-5: EC(C,2) 1 6 H(1) L(1) C

Table 4-5 shows a significant result for the $HLC-VECM$ model. The R-squared is 0.809742 and the adjustment coefficients are 0.792681 and 0.718228, both of which are very significant for depicting the $D(C)$ variable, indicating that the current-period's closing log-returns are significantly explained by current-period's cointegrating errors as modeled. The R-square values become 0.161750 and 0.155601, when $D(C)$ is replaced by $D(H(1))$ and $D(L(1))$ respectively, indicating that the model formulation implicitly captures the $D(C)$ series better than the $D(H(1))$ series or the $D(L(1))$ series.

This is also confirmed by results of the fitted Ordinary Least Squares (OLS) regression $D(C)=A(1)+A(2)*(H-C(-1))+A(3)*(L-C(-1))$ as is tabulated in Table 4-6. The R-squared in this case is 0.810820.

Dependent Variable: D(C)
Method: Least Squares
D(C)=A(1)+A(2)*(H-C(-1))+A(3)*(L-C(-1))

	Coefficient	Std. Error	t-Statistic	Prob.
A(1)	-3.83E-05	0.000226	-0.169900	0.8651
A(2)	0.701555	0.012055	58.19487	0.0000
A(3)	0.666991	0.010979	60.74954	0.0000
R-squared	0.810820	Mean dependent var		0.000484
Adjusted R-squared	0.810684	S.D. dependent var		0.009372
S.E. of regression	0.004078	Akaike info criterion		-8.165517
Sum squared resid	0.046157	Schwarz criterion		-8.159116
Log likelihood	11348.99	Durbin-Watson stat		2.222758

Table 4-6: LS D(C)=A(1)+A(2)*(H-C(-1))+A(3)*(L-C(-1))

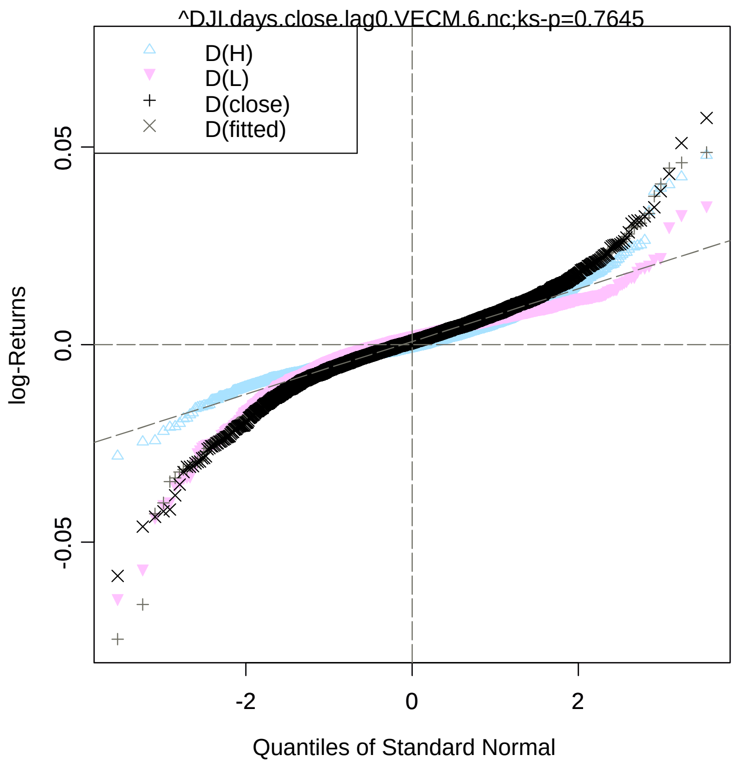

Figure 4-3: Log-Returns [EC(C,2) 1 6 H(1) L(1) C]

As shown by the QQ-plots in Figure 4-3, the distribution of the fitted data cannot be distinguished from the Close log-returns data with the exception of some “outliers”. Note that the Close QQ-plot tends to trace the Low log-returns for low values of log-returns and the High log-returns for High values of log-returns.

4.2 H(1)-L(1)-WC VECM

The results for the H-L-WC VECM model are tabulated in Table 4-7.

Vector Error Correction Estimates
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2	
H	1.000000	0.000000	
L	0.000000	1.000000	
WC(-1)	-1.001228	-0.998733	
	(3.2E-05)	(3.4E-05)	
	[-31232.9]	[-29606.2]	
Error Correction:	D(H(1))	D(L(1))	D(WC)
CointEq1	0.850589	1.209470	0.774300
	(0.14522)	(0.16910)	(0.04129)
	[5.85715]	[7.15243]	[18.7545]
CointEq2	0.852924	0.881647	0.727418
	(0.13760)	(0.16022)	(0.03912)
	[6.19867]	[5.50268]	[18.5952]
R-squared	0.162566	0.157287	0.934832
Adj. R-squared	0.156202	0.150882	0.934337

Table 4-7: EC(C,2) 1 6 H(1) L(1) WC

The R-squared value is 0.934832 and the adjustment coefficients are 0.774300 and 0.727418 for $D(WC)$.

4.3 H(1)-L(1)-TP VECM

The results for the H-L-TP VECM model are tabulated in Table 4-8.

Vector Error Correction Estimates
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2	
H	1.000000	0.000000	
L	0.000000	1.000000	
TP(-1)	-1.001232	-0.998737	
	(3.2E-05)	(3.4E-05)	
	[-31088.1]	[-29680.8]	
Error Correction:	D(HIGH(1))	D(LOW(1))	D(TPRICE)
CointEq1	1.293104	1.754050	0.771573
	(0.21301)	(0.24801)	(0.04037)
	[6.07062]	[7.07248]	[19.1148]
CointEq2	1.283745	1.412634	0.733201
	(0.20348)	(0.23692)	(0.03856)
	[6.30891]	[5.96260]	[19.0148]
R-squared	0.162898	0.157771	0.969871
Adj. R-squared	0.156536	0.151370	0.969642

Table 4-8: EC(C,2) 1 6 H(1) L(1) TP

The R-squared value is *0.969871* and the adjustment coefficients are *0.771573* and *0.733201* for $D(TP)$.

4.4 H(1)-L(1)-MP VECM

The Median Price *VECM* model is a tautology[4] as the MPrice is a simple average of the High and Low prices. Consequently, any attempt to empirically fit the defined *VECM* model results in a singular matrix. To circumvent this impasse, we use OLS regression for *D(MP)=A(1)+A(2)*(H-MP(-1))+A(3)*(L-MP(-1))* to obtain estimates of the adjustment coefficients and the results are listed in Table 4-9.

Dependent Variable: D(MP)
Method: Least Squares
D(MP)=A(1)+A(2)*(H-MP(-1))+A(3)*(L-MP(-1))

	Coefficient	Std. Error	t-Statistic	Prob.
A(1)	4.14E-18	3.85E-17	0.107470	0.9144
A(2)	0.500000	2.05E-15	2.43E+14	0.0000
A(3)	0.500000	1.82E-15	2.75E+14	0.0000
R-squared	1.000000	Mean dependent var		0.000562
Adjusted R-squared	1.000000	S.D. dependent var		0.007662
S.E. of regression	5.84E-16	Sum squared resid		8.59E-28
Durbin-Watson stat	1.969278			

Table 4-9: LS D(MP)=C(1)+C(2)*(H-MP(-1))+C(3)*(L-MP(-1))

The R-squared value is *1.0* and the adjustment coefficients are *0.500000* and *0.500000* for $D(MP)$. The R-square of *1.0* indicates an exact fit. The adjustment coefficients reflect the fact that the Median Price is a simple average of the High and Low prices. This is also confirmed by the QQ-plots in Figure 4-4 where the fitted data cannot be distinguished from the computed Median Price log-returns.

[4] This tautology was pointed out by Professor Dipankor Coondoo, whilst proof reading a draft of this paper. Professor Coondoo is attached to the Economic Research Unit, Indian Statistical Institute, Kolkata.

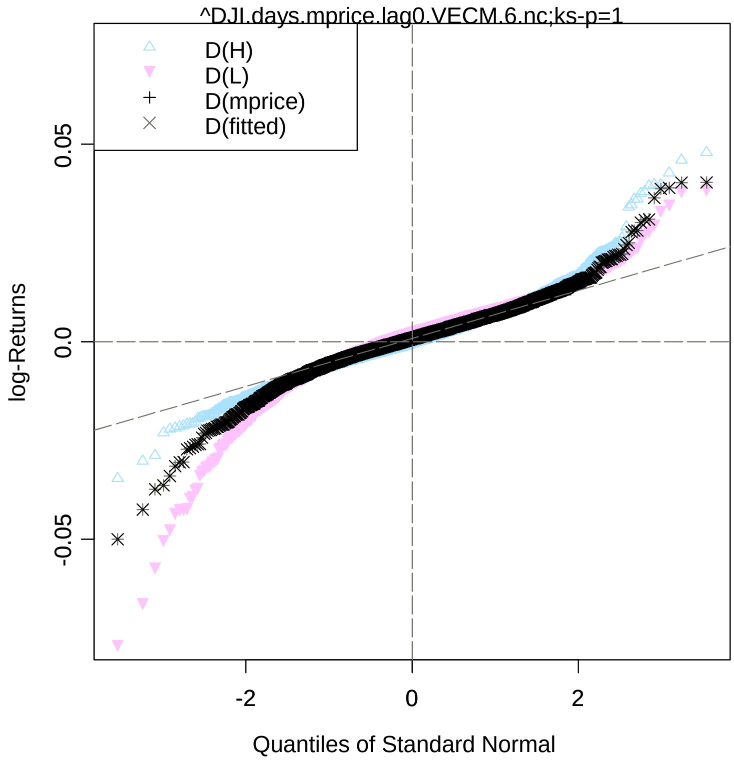

Figure 4-4: QQ-Plots [LS D(MP)=C(1)+C(2)*(H-MP(-1))+C(3)*(L-MP(-1))]

Note that the Median Price QQ-plots falls in the middle of the High and Low QQ-plots as would be expected of log-returns based on Median prices. Thus, as we go from using the Close prices to using the Median Prices, the distributions of the “consensus” prices move from being influenced by the “tails” of the High and Low distributions to the weighted sum causing these “consensus” prices to be less influenced by the “outliers”.

5 Conclusions

By using an econometric model, we are perhaps able to show that the “technical” prices heuristically computed and empirically used by technical traders are nothing more that the “consensus” prices much sought after by economists. This raises doubts about the validity of the Close price as the “true” measure of the “consensus” price. The “technical” prices are by construct “average” prices and hence are more amenable to depict the “consensus” prices as implied by economists.

We also show that there is a statistically increasing and significant relationship between changes in "technical" prices and the cointegrating residuals of a $VECM$ model constructed from the $H(1)$, $L(1)$ and the four "technical" prices, $C, WC, TP\ and\ MP$. As we move from the Close to the Median Price representation of consensus value, we find that the explanatory power of the corresponding $VECM$ model increases. This is not surprising due to the fact that the computed "technical" prices are functions of the High, Low and Close prices. The Median Price OLS model (as the $VECM$ model was indeterminate) gives the best fit of the various models considered with an R-square of 1.0[5]. The worst fit is the Close Price $VECM$ model with a R-square of 0.809742. It is reasonable to assume that one should be able to make better estimates of Median Prices as compared to Close Prices. The values of the adjustment coefficients also decrease as we progress from Close prices to Median Prices. This is consistent with the fact that sometime Close price are also the High or Low prices, but the "technical" prices are by definition functions of both the High and Low prices, thus displaying lower weightings on the cointegrating error terms.

We also empirically show that the distribution of the daily returns, whatever the "technical" proxy used to model the log-returns, is not normally distributed but is skewed with a high kurtosis. We find that the empirical distributions of the cointegrating errors as captured by the High, Low and the last-period Close prices have shapes not dissimilar from the shape of the density function of an extreme-value distribution. This suggests that the "fat-tails" of log-returns are possibly the consequence of hidden extreme-valued drivers in the daily price generation process. In this paper, the error-correction vectors in the $VECM$ models are shown to empirically proxy these hidden extreme-valued drivers.

[5] The perfect value for R-square is a consequence of the formulation and is only relevant for its descriptive ability, and not its predictability.

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