Linkages between asset classes during the financial crisis, accounting for market microstructure noise and non-synchronous trading

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Abstract

In this paper we analyse market co-movements during the global financial crisis. Using high frequency data and accounting for market microstructure noise and non-synchronous trading, interdependencies between differing asset classes such as equity, FX, fixed income, commodity and energy securities are quantified. To this end multivariate realised kernels and GARCH models are employed. We find that during the current period of market dislocations and times of increased risk aversion, assets have become more correlated when applying these intra-day measures. FX pairs seemingly lead the other variables, but commodities remain entirely unaffected.

Keywords: Financial crisis, high frequency data, kernel based estimation

JEL Classification Numbers: C32, E44, G01

1 Introduction

The subprime crisis and the following credit crunch which began in the second half of 2007 has been characterised by the transmission of financial shocks across various markets and by interlinkages between and co-movement of differing asset classes. The current market dislocations were initially triggered by a credit event, namely a shock to the U.S. housing market caused by cheap credit and a subsequent reversal of interest rates and falling house prises. Through the securitisation process by the disintermediated banking system this shock was amplified and spread across differing assets, leading to disruption of the interbank money, commercial paper, foreign exchange and credit markets. Furthermore, these effects, driven by increased levels of risk aversion, were not limited to the U.S. but affected markets in most developed and emerging market economies.

Due to the severity of the crisis an increasing body of literature has emerged in this area, such as Frank *et al.* (2008) who provide a detailed overview of the increased transmission of liquidity shocks across U.S. financial markets. This is also related to existing work on financial contagion which flourished following the Asian Crisis. The identification of channels of shock transmission across countries is, for instance, discussed in Dungey, Fry, Gonzalez-Hermosillo and Martin (2005), Dornbusch, Park and Claessens (2000) and Pericoli and Sbacria (2003). Changes in conditional correlations between asset returns during the crisis are examined for structural breaks by Forbes and Rigobon (2002), King, Sentana and Wadhwani (1994), King and Wadhwani (1990) and Caporale, Cippollini and Spagnolo (2005).

This paper extends the empirical literature along several dimensions. Unlike in the aforementioned studies, high frequency data are exploited for a wide range of differing asset classes, such as equity, FX, commodities, energy and fixed income securities, whilst accounting for market microstructure noise and non-synchronous trading. This allows for the analysis of realised volatility for these variables during the crisis based on an intra-day measure, thus broadening existing work on equities. Furthermore, changes in interdependencies between markets are quantified, whereby information loss by merely employing daily returns is avoided. This question is especially of importance during the current market conditions as it can help identify affected asset classes and evaluate whether these market dislocations are indeed systemic. Also, it is essential for investors in the context of portfolio diversification during times of widespread market illiquidity. Finally, the realised covariance estimates are combined with daily data within a multivariate GARCH framework in order to improve the explanatory power of these volatility models across a wide range of assets.

It has been argued that the emergence of new transmission mechanisms of financial shocks and the increased co-movements of assets following the onset of the subprime crisis is due to excess liquidity in markets and portfolio reoptimisation. Concerning the latter, hedge funds holding asset-backed securities and other structured products have been burdened by increased margin requirements, driven in turn by greater market volatility. As a consequence they attempted to offload the more liquid parts of their portfolios in order to meet these margin calls and also respond to redemptions by investors. As argued by Khadani and Lo (2007), quantitatively driven hedge funds were especially engaged in liquidation sales across different asset classes such as through the unwind of carry trades. This flight to both liquidity and transparency by investors increased demand for assets such as fixed income and gold securities, which is reflected by their recent price developments and their respective trading volumes during the crisis.

In this paper we present evidence supporting this argumentation. Increased correlations across a wide range of assets are found during the current financial crisis, compared to those from the pre-crisis period. It is shown that FX pairs moved approximately 6 months prior to the emergence of any market dislocations, thus implying their potential as early indicators of future turbulence. Furthermore, fixed income securities became more correlated amongst each other and with currencies. Interdependence between risk aversion measures such as the VIX index and gold also became more pronounced. Finally, despite simultaneous increases in the price levels of commodities, we do not find evidence of any co-movement when measured at an intra-daily frequency.

The outline of this paper is as followed. In section 2 we briefly discuss the data and potential linkages between differing asset classes during the financial crisis. In section 3 the econometric methodology is provided, followed by the results of the realised (kernel based) volatility and cross-correlation analysis in sections 4 and 5, respectively. In section 6 a recent strand of literature is explored, whereby the realised covariances are combined with daily data for estimation within a multivariate GARCH framework. Finally, section 7 concludes.

2 Data and interlinkages between variables

As outlined in the introduction, this paper provides a detailed analysis of the realised volatility of assets across equity, FX, fixed income, commodity and energy markets during the ongoing global financial crisis. Furthermore, potential changes in the co-movements between these securities are quantified by providing estimates of realised correlations, whilst accounting for non-synchronous trading and market microstructure noise.

2.1. Data description

The historical market data are obtained from the commercial providers TickData and Taq Data, whereby the former have cleaned them by filtering for misreporting and decimal errors.[1] The sample spans January 3rd 2006 until September 31st 2008, such that it includes a control period before the onset of the subprime crisis and ends after the Lehman Brothers bankruptcy. Opening and closing hours differ across asset classes, ranging from 7:20 for FX and fixed income futures to 16:00 for the VIX index and the Exchange Traded Funds. All securities are traded on either the New York Stock Exchange (NYSE), New York Mercantile Exchange (NYMEX), Chicago Mercantile Exchange (CME) or on the Chicago Board of Trade (CBOT), whereby differences in the respective time zones have been corrected. This heterogeneity with regard to trading hours does provide challenges for the realised correlation analysis below, and will be discussed further.

In this paper mainly futures are used in order to achieve consistency across as-

[1] An overview of the variable names, their respective abbreviations, sources and trading locations can be found in Table 4 in the appendix.

sets as well as ensuring sufficient market liquidity. Here an auto-roll strategy is adopted by which the roll-over date is determined by when the daily tick volume of the back-month contract exceeds that of the current front-month contract. In the appendix the closing prices of these variables are reported.[2] With regard to fixed income securities both the Eurodollar and the 10 year Treasury note futures contracts are included. The motivation for this is their inverse pricing relative to interest rates, in addition to their demand being related to investor risk aversion and preference for liquid and transparent assets. As it can be seen from Figure 5, prices for both these securities increased significantly during the onset of the crisis in the second half of 2007 and have remained at this elevated level since.

Concerning FX variables, $U.S. vs Australian Dollar (AUD hereafter), Swiss Franc (CHF), Euro (EUR) and Japanese Yen (JPY) futures are used. From the beginning of 2006 until early 2008 the $U.S. depreciated significantly against these major currencies, after which it experienced a relative rebound as the financial crisis spread to other markets.

Rising commodity prices received much attention in 2008 with focus on whether their respective sharp increases were driven by economic fundamentals or rather by speculative forces. Towards the end of the sample period, these price movements are reversed for the corn, cattle, soy beans and cotton futures.

Measures of risk aversion in financial markets are included in the form of a gold

[2] The Exchange Traded Funds for the energy (XLE), technology (XLK) and health care (XLV) sectors have been omitted. Their respective price movements are very similar to those of the Industrial Sector SPDR (XLI)

futures contract and the VIX index, which is a function of the implied volatility of S&P 500 index options. During the beginning of the crisis in the second half of 2007 the former increased significantly and eventually peaked at a historical high in excess of $1000 following the rescue of Bear Stearns in March 2008. The VIX on the other hand, exhibited a number of sharp upwards movements, most noticeably during the Chinese stock market correction in February 2007, during the beginning of market dislocations in the summer of the same year and finally during the collapse of Lehman Brothers in September 2008.

In this paper stock markets are proxied by Exchange Traded Funds (ETFs), which mimic the performance of an underlying industry index. These entities are similar to mutual funds but differ in that continuous market trading rather than the Net Asset Value (NAV) determines their respective prices. Furthermore, creation and redemption of shares by specialised dealers allows for arbitrage to restrict divergence from their NAVs, unlike closed ended funds which may exhibit premia or discounts. In Figure 7 in the appendix it can be seen from the differing sector SPDRs that U.S. stocks for all industries were affected during the market downturn. Interestingly, the decline of the financial sector (XLF) led that of the others by approximately 6 months.

Finally, energy futures in the form of crude oil and natural gas contracts are used. Both follow a similar price evolution, whereby simultaneous peaks are reached in mid 2008. It is most likely that these patters are driven by both speculation and high demand from emerging markets until summer 2008, after which the steep fall in prices can be attributed to collapsing demand as the real economic effects of

	OtC Vol.	CtO Vol.		OtC Vol.	CtO. Vol.
Eurodollar	0.0004	0.0005	Corn	0.0166	0.0132
TNotes	0.0032	0.0022	Cotton	0.0122	0.0121
USDAUD	0.0045	0.0058	Soy Beans	0.0133	0.0107
USDCHF	0.0043	0.0046	XLB	0.0126	0.0077
USDEUR	0.0036	0.0036	XLE	0.0152	0.0090
USDJPY	0.0042	0.0052	XLF	0.0179	0.0130
VIX	0.0652	0.0350	XLI	0.0099	0.0061
Crude	0.0159	0.0105	XLK	0.0113	0.0071
Gas	0.0254	0.0220	XLP	0.0070	0.0040
Gold	0.0104	0.0087	XLU	0.0099	0.0050
Cattle	0.0078	0.0064	XLV	0.0078	0.0043

Table 1: Open-to-Close and Close-to-Open Daily Volatility as measured by the standard deviations of daily returns.

the crisis spread.

In Table 1 the open-to-close and close-to-open daily volatilities for all respective variables are reported. First, inspecting the values for the Exchange Traded Funds, we find that they are consistent with the existing literature, both in terms of absolute and relative magnitudes. The volatility of the Financial Sector SPDR (XLF) is greatest, which is to be expected as the sample includes times of financial market turbulence. Furthermore, the volatilities of all industries during the open hours of the exchange are greater than those during the closed period, which is determined by the distribution of information arrival throughout the day. Concerning the other asset classes, volatility patterns differ in that the overnight variability as a percentage of the corresponding open-to-close quantity is significantly greater. We believe that there are two reasons for this. Firstly, many of the futures contracts have shorter trading hours as compared to the ETFs, and secondly, in some cases the underlying asset is continuously traded for 24 hours. This for instance is the case for the FX futures, and where we find that the overnight volatility exceeds that of when the U.S. markets are open.

Next, a more detailed data description of the price evolution, as reported by trades, of the USD-EUR and the Eurodollar futures contracts on a tranquil trading day, namely November 27th, 2007 is provided. Both markets are open from 7:20 until 14:00 (EST) and 13104 observations for the former and 4914 for the latter are recorded during this time. In the first row of Figure 1 the market prices are reported, whereby the \$U.S. marginally devalued against the Euro and the price of the Eurodollar increased. From the scale it can be seen that the times of the observations are not uniformly distributed during the day, but rather less trades were observed around the midday hours. Next, the tick-by-tick price changes are presented in the center of Figure 1.[3] For both securities price movements most commonly occurred by one tick, with a few exceptions being a 2 tick change at once. Finally, we provide the corresponding autocorrelation functions for lags 2 through to 100, whereby confidence intervals are based on heteroskedasticity robust standard errors.[4] There is some evidence of negative autocorrelation in the data, which is attributed to market microstructure noise such as the bid/ask bounce. In what follows this effect is explicitly taken into account when motivating the econometric methodology.

[3]The tick size for the USDEUR futures contract is 0.0001, whereas for the Eurodollar it is 0.0025. The reason for the latter is that it is based on 3 month Libor such that this day count fraction leads to a minimal price movement of 25 \$U.S. per 1 million face value.

[4]The first lags are omitted for clarity. Their values for both assets are -0.2223 and -0.1868, respectively.

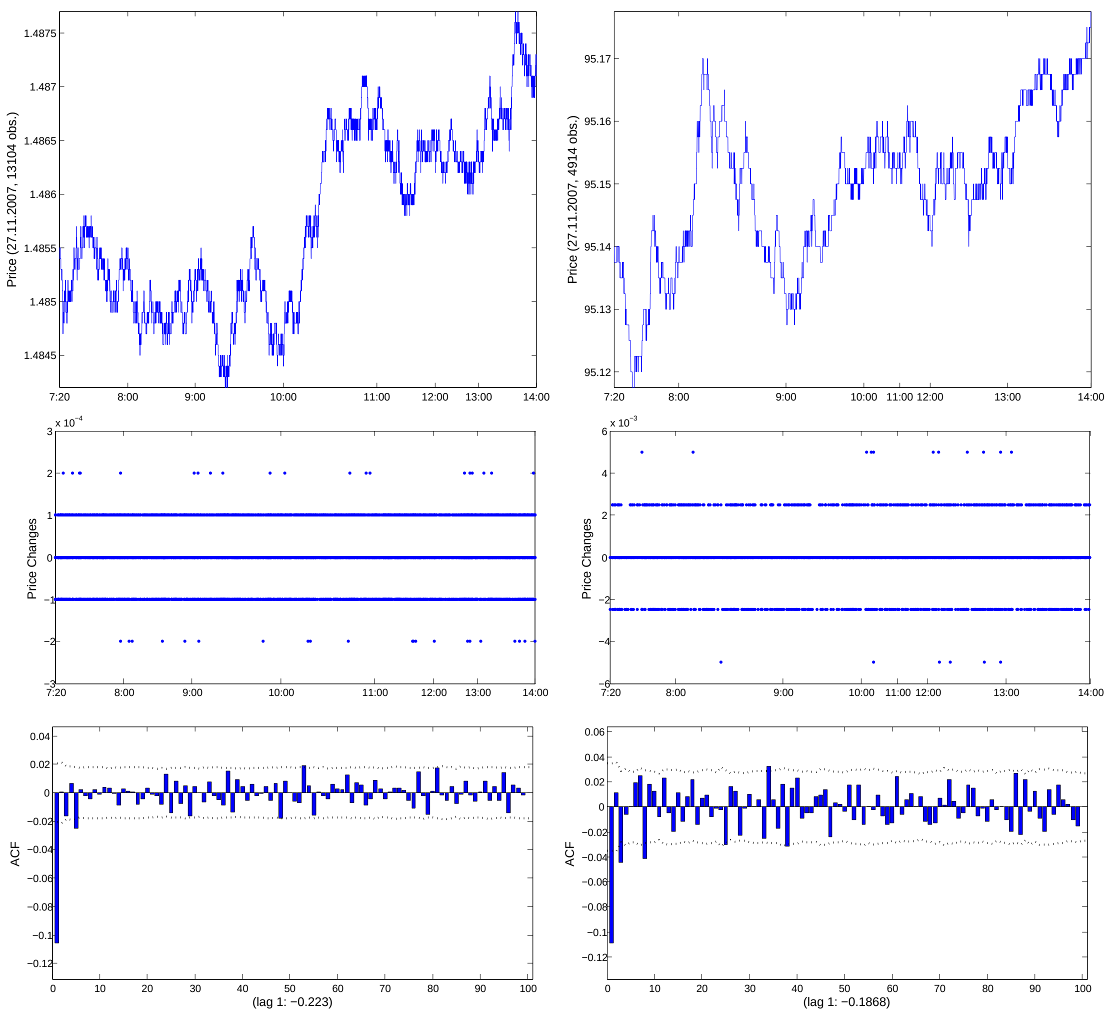

Figure 1: Prices, returns and autocorrelations for the USD-EUR (left column) and Eurodollar futures contracts (right column) for November 27th, 2007. There are 13104 observations for the former and 4914 for the latter on this trading day. The ACF functions are reported for lags 2 through to 100, together with their respective heteroskedasticity robust standard errors. The first lags for these assets are -0.2223 and -0.1868, respectively

2.2. Interlinkages between asset classes

This section is concluded by discussing the mechanisms by which linkages between equity, fixed income, commodity and energy markets may have increased during the financial crisis. The main argumentation is that these asset classes have become more interconnected due to increased investor risk aversion, subsequent portfolio rebalancing and due to excess liquidity which had previously built up in the financial markets, fueled in part by cheap credit and excess leverage. Following the initial shock to the U.S. subprime mortgage market, investors faced uncertainty surrounding the valuation of securitised products, exacerbated by downgrades by rating agencies and a repricing of risk more generally, and thus withdrew funds from such investments and from the commercial paper markets. Following the illiquidity of these complex financial products, a flight to transparency set in, a result of which the demand for fixed income securities such as Treasury notes and bonds increased, in turn suppressing their respective yields. Presumably, absolute returns were not central to this behaviour as investors rather sought a storage of value which insured them against capital losses and allowed for rapid liquidation in deep markets. This is reflected by the sharp increase in the prices of the Eurodollar and the 10 year Treasury notes futures contracts during the second half of 2007. As market conditions did not improve since the onset of the crisis these have remained at an elevated level, as illustrated in Figure 5.

Concerning other asset classes, exchange rates exhibited systematic price movements during the financial crisis. Between the beginning of 2006 and 2008, the $U.S. continuously depreciated against major currencies such as EUR, JPY, AUD and CHF. As market dislocations subsequently spread to these economies during the second half of 2008, this trend was reversed due to real economic effects and the resulting narrowing of the interest rate gap as central banks globally slashed rates towards zero. A further feature of the FX markets during the crisis were the unwinds of carry trades between high yielding currencies such as the Australian Dollar and the Icelandic Krona (ISK), and the Japanese Yen. As investor risk aversion increased due to the deterioration of the health of the financial system, funds were shifted back into markets which were perceived as being less risky.

As has been widely documented, commodity and energy prices increased significantly during this recent period of financial turbulence, before retreating sharply. Firstly, it has been argued that these asset prices were driven by strong fundamentals from emerging markets until the summer of 2008, after which demand contracted, as the real economic effects of the financial crisis spread globally. Secondly, it has been put forward that the rapid price increase and its subsequent decline have mostly been due to speculative forces, such as hedge funds trading the respective futures contracts in order to take advantage of the sustained price dynamics. These price increases are consistent with the aforementioned notion of portfolio rebalancing and with cross-asset spillovers resulting from excess liquidity in financial markets. Due to widespread falling asset prices and the preference for transparent securities, investment strategies were changed through the purchase of commodity contracts, independently of economic linkages or fundamentals.

Finally, the impact on U.S. stock markets in the form of Exchange Traded Funds is analysed. From Figure 7 it follows that these liquid instruments, reflecting the return on underlying industry indices, initially increased in price and peaked during the end of 2007 and beginning of 2008, after which equity markets exhibited a systematic sell off. Interestingly, the Financial Sector SPDR (XLF) started to decline by mid 2007, and is subsequently characterised by the greatest percentage fall whereby values halved by the end of the sample period.

Investor behaviour across all of these different asset classes can in part be explained by repricing of risk in general. In this paper, risk aversion is proxied by the VIX index, which is a function of the implied volatility of S&P 500 index options. During times of greatest market uncertainty and when this measure was highest, assets which were perceived as being most risky were sold, and substituted by securities with truncated downside risks, as illustrated above.

3 Methodology

In this paper high frequency data is employed to estimate realised volatility and correlation measures separately for each trading day during the sample window. To this end the notation and methodology by Barndorff-Nielsen *et al.* (2008a) is adopted. It is assumed that the variables outlined above follow an n-dimensional log price process $X = (X^{(1)}, X^{(2)}, ..., X^{(n)})'$ on the interval [0,T], where n denotes the number of assets. Furthermore, the observation times and numbers for asset i are defined as $t_1^{(i)}, t_2^{(i)}, ...$ and N^i, respectively. The asset price process X is comprised of the efficient price Y and market microstructure noise U in the form of $X(t) = Y(t) + U(t)$, whereby $U(t)$ is due to market illiquidity, inaccurate recording or the bid/ask bounce. It is assumed that $E(U(t)) = 0$, such that the mean of each element of the n-dimensional $U(t)$ vector is zero. Furthermore, $Var(U(t)) = \omega^2$ is a diagonal $n \times n$ matrix whereby the assumptions are made the market microstructure noise is uncorrelated and that its variance is constant across assets and time within any trading day. Y is defined as the following Brownian semimartingale on probability space $(\Omega, \Im, P)$:

$$Y(t) = \int_0^t a(u)du + \int_0^t \sigma(u)dW(u), \tag{1}$$

where a is a bounded drift, σ is a cadlag process and where W is a vector of independent Brownian motions, all of which are adapted with regard to the filtration $\Im$. The focus of this paper is the measure of covariation between differing assets for which it can be shown that

$$[Y](T) = \int_0^T \Sigma(u)du \qquad where \qquad \Sigma = \sigma\sigma' \tag{2}$$

and where

$$[Y](T) = \lim_{N\to\infty} \sum_{j=1}^{N} \{Y(t_j) - Y(t_{j-1})\}\{Y(t_j) - Y(t_{j-1})\}', \tag{3}$$

for $0 = t_0 < t_1 < ...t_N = T$ with $sup_j\{t_{j+1} - t_j\} \to 0$ and for $N \to \infty$.[5]

As a result, (3) is estimated which provides a consistent estimate of $[Y](T)$ when using high frequency data. It should be noted though that when making inference

[5]Importantly, practical implementation of (3) and the estimation of the multivariate kernel requires that all assets are observed at the same time. Correction for possible non-synchronous trading is discussed at the end of the methodology section.

with regard to this expression, biases can arise due to data characteristics. Firstly, the realised variance (RV) may be overstated as the sampling frequency increases due to market microstructure noise in the form of the bid/ask bounce. Secondly, as first shown by Epps (1979), the realised covariance measure is downward biased because of non-synchronous trading. As a result, the quantity of interest in this paper, namely the realised cross-correlation between asset classes, will be severely skewed towards zero.

In order to overcome this bias differing approaches have been proposed in the literature. Firstly, Bandi and Russel (2005) determine the optimal sampling frequency. Zhang *et al.* (2005) introduce the concept of subsampling, whereby the RV measure is calculated for each possible sparse grid and subsequently averaged. Finally, Hansen and Lunde (2006) propose the RV^{AC_1} estimator which takes the negative autocorrelations implied by the bid/ask bounce into account.

In this paper we adopt the multivariate realised kernel put forward by Barndorff-Nielsen *et al.* (2008a). As in the case of the RV^{AC_1} estimator above, the multivariate kernel, which is shown to be positive semi-definite, is of the form of the heteroskedasticity and autocorrelation consistent (HAC) estimator as proposed by Newey and West (1987). Thus the tick-by-tick negative autocorrelation in asset returns, as described in Figure 1 for the USD-EUR and the Eurodollar contracts, is accounted for. The kernel estimator is defined as $K(X) = \sum_{h=-m}^{m} k(\frac{h}{H+1})\Gamma_h$ whereby the h-step autocovariance is given by

$$\Gamma_h = \begin{cases} \sum_{j=|h|+1}^{m} x_j x'_{j-h} & h \geq 0 \\ \sum_{j=|h|+1}^{m} x_{j-h} x'_j & h < 0, \end{cases} \tag{4}$$

and where x_j denotes asset returns defined as the first difference of the observed log price process X. The conditions that $k(0) = 1$ and $k'(0) = 0$ are required and imply that the first few autocovariances receive close to a unit weight. In order to satisfy these properties the Parzen kernel function is utilised, whereby

$$k_P(x) = \begin{cases} 1 - 6x^2 + 6x^3 & 0 \leq x \leq 1/2 \\ 2(1-x)^3 & 1/2 \leq x \leq 1 \\ 0 & x > 1. \end{cases} \tag{5}$$

Subsequently, the realised cross-correlations between assets which are of interest are defined as

$$\hat{\rho}^{(i,j)} = \frac{K(X^{(i)}, X^{(j)})}{\sqrt{K(X^{(i)})K(X^{(j)})}}. \tag{6}$$

As discussed above, it is assumed that the price process is defined as $X^{(t)} = Y^{(t)} + U^{(t)}$ where $Y^{(t)}$ is the efficient price and $U^{(t)}$ denotes the market microstructure noise. It can be shown that if $K(U) \xrightarrow{\text{P}} 0$ and $K(Y) \xrightarrow{\text{P}} [Y](T)$ then $K(X) \xrightarrow{\text{P}} [Y](T)$, implying that asymptotically independence between U and Y need not be assumed. In order to take any autocorrelation in the returns into account and to achieve consistency of the kernel estimator, its optimal bandwidth H which determines the lag length of the autocovariances, is to be estimated. In this context Barndorff-Nielsen *et al.* (2008a) show that $H \propto n^{3/5}$ is optimal and that this condition is met by

$$H^* = c^* \xi^{4/5} n^{3/5} \quad where \quad c^* \left\{ \frac{k''(0)^2}{k_\bullet^{0,0}} \right\} \quad and \quad \xi^2 = \frac{\omega^2}{\sqrt{T \int_0^T \sigma_u^4 du}}, \tag{7}$$

and where $k_\bullet^{0,0} = \int_0^1 k(x)^2 dx$.[6] Thus the determination of H involves the estimation of ω^2 and the integrated quarticity.

A further point of importance are end effects. Asymptotically, the econometric theory of the multivariate realised kernel requires averaging of prices at the beginning and the end of each trading day due to noise affecting the realised autocovariances at these limits. This is because $K(U) \xrightarrow{P} U_0^2 + U_T^2 \neq 0$, implying inconsistency of the estimator. Defining $\bar{U}_0^2$ and $\bar{U}_T^2$ as the local averages at the beginning and the end of the trading day, respectively, it can be shown that $K(U) = \bar{U}_0^2 + \bar{U}_T^2 + o_p(1)$. If subsequently ergodicity of the market microstructure noise is assumed in addition to $E(U_t) = 0$ it follows that $K(U) \xrightarrow{P} 0$ such that consistency of the realised covariance estimator is assured. In this context the local averages of the price process are constructed by

$$X_0 = \frac{1}{m} \sum_{j=1}^{m} X(\tau_j) \quad and \quad X_N = \frac{1}{m} \sum_{j=1}^{m} X(\tau_{N-m+j}),$$

where N is defined as the number of observations. With regard to the optimal averaging length, a trade-off between accounting for the start and end of trading day noise, and the loss of information in constructing the kernel estimates arises.

[6] For the Parzan kernel adopted in this paper this implies that the constant of proportionality $c^* = ((12)^2/(0.269)^{1/5} = 3.5134$. Many thanks to Kevin Sheppard for the estimation procedure, as proposed Bandi and Russel (2005).

In practice it has been shown by Barndorff-Nielsen *et al.* (2008b) that when the magnitude of the quadratic variation vastly exceeds that of $\bar{U}_0^2 + \bar{U}_T^2$, such as in liquid futures markets, the end effects can be ignored, which is done in this paper.

As previously mentioned, the multivariate realised kernel is motivated due to the existence of market microstructure noise in the high frequency returns. In the left column of Figure 2 variance signature plots, as widely seen in the existing literature for equities, are provided for the Eurodollar and the USD-JPY futures contracts, whereby (3) is estimated using returns at differing sampling frequencies. These indicate that the realised variance also increases as the time between observations falls for differing asset classes such as FX and fixed income securities (blue). Furthermore, the variance based on daily open-to-close returns (red) and heteroskedasticity and autocorrelation consistent (HAC) confidence intervals are reported. In the right column, the realised variance implied by the kernel estimator is given as a function of the bandwidth H. The average optimal $H^* = c^* \xi^{4/5} n^{3/5}$ for both contracts are 37.1 and 33.9, respectively. At bandwidths above 10 lags, which with at an average sampling frequency of 10 to 15 seconds imply positive kernel weights across 2 minutes, most of the negative autocorrelation in the data has been accounted for. In Figure 3 covariance signature plots for FX, fixed income, commodities and energy futures are provided, again based on the estimation of (3). As argued above, this measure is biased towards zero due to the Epps effect at higher sampling frequencies, thus underlying the necessity of the multivariate kernel when calculating realised correlations.

Finally, as mentioned in footnote 5, before estimation of (3) and the kernel based

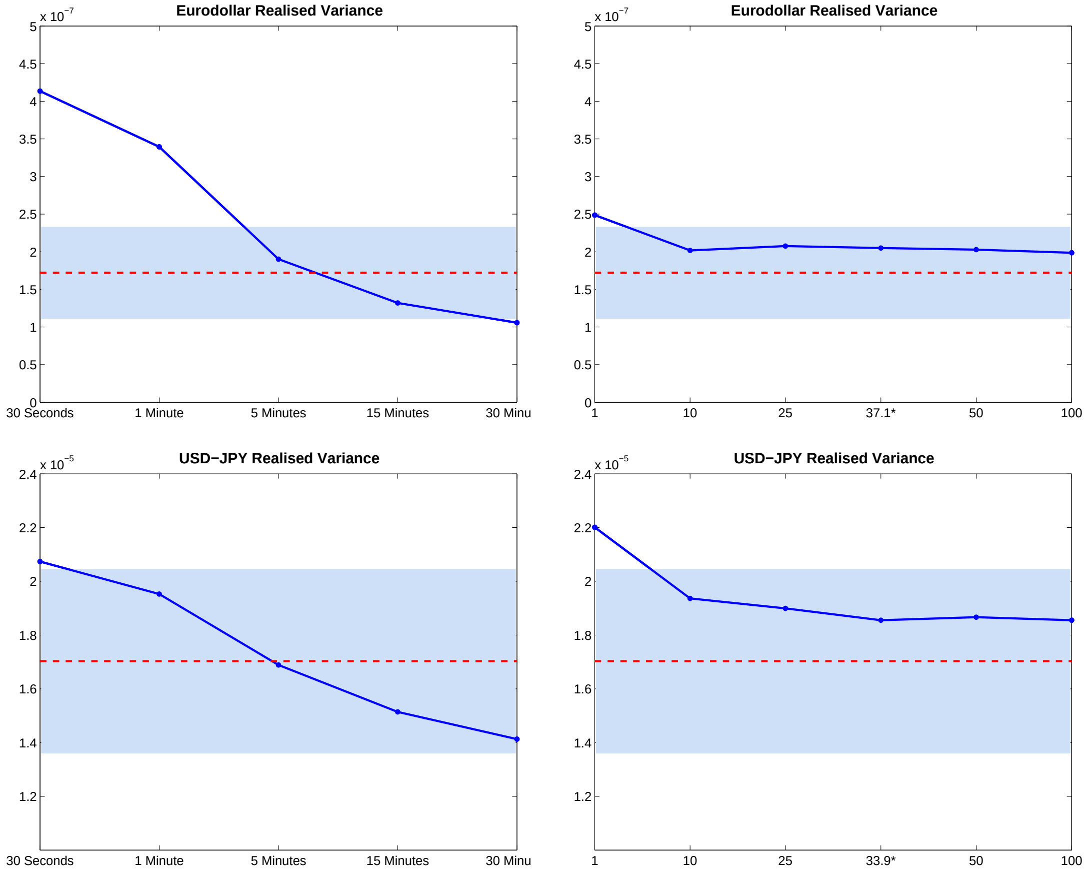

Figure 2: Variance signature plots for the Eurodollar and the USD-JPY futures contracts. In the left column, the realised variance (blue) is provided as a function of the sampling frequency. Furthermore, the variance from open-to-close daily returns (red) and 95% HAC confidence intervals are reported. As the sampling frequency increases the market microstructure noise becomes more prominent. In the right column, the realised variance implied by the kernel estimator is given as a function of the bandwidth H. The average optimal $H^* = c^* \xi^{4/5} n^{3/5}$ for both contracts are 37.1 and 33.9, respectively. At small values of the bandwidth, the autocorrelation in the data is not sufficiently taken into account.

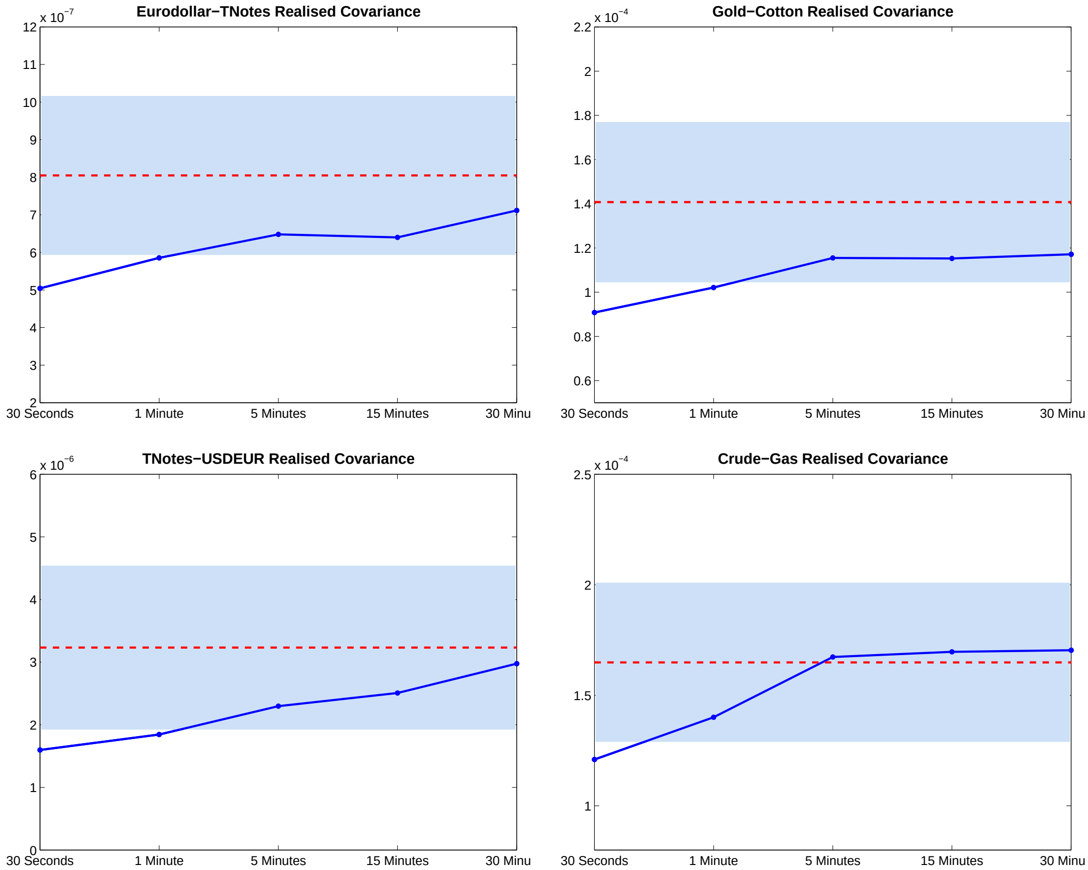

Figure 3: Covariance signature plots for FX, fixed income, commodities and energy futures. As the sampling frequency increases the realised covariances (blue) are biased towards zero due to the Epps effect. Also, the average covariance based on open-to-close daily returns (red) and 95% HAC confidence intervals are reported.

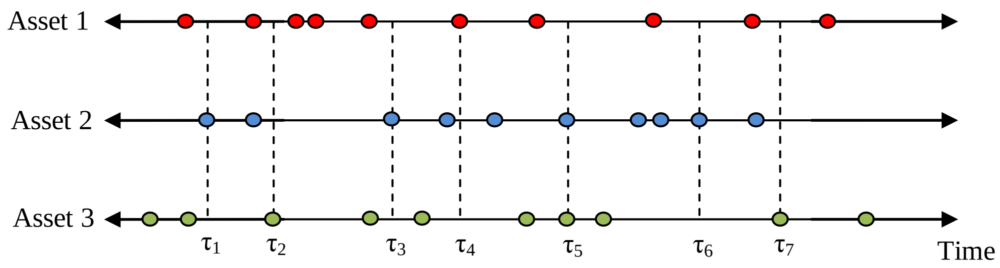

Figure 4: Refresh Times for 3 assets

measures can be conducted, the data has to be corrected for non-synchronous trading, heterogeneous market opening times and missing observations. To this end Barndorff-Nielsen *et al.* (2008a) introduce the notion of Refresh Time which is defined as $\tau_j = max(t^{(1)}_{N^{(1)}_{\tau_j}}, ..., t^{(n)}_{N^{(n)}_{\tau_j}})$. Figure 4 provides an example of this for the case of 3 assets. The first Refresh Time τ_1 is constructed as the time it takes for all assets to trade once. At τ_1 the stale prices for assets 1 and 3 are used in order to form $X(\tau_1)$. This procedure is then repeated over $[0, T]$. In our analysis, the resulting information loss is potentially severe as certain assets, such as commodities futures, trade less frequently than the liquid Exchange Traded Funds. As a result, the construction of the synchronised data sets using Refresh Times and the estimation of kernel based volatilities and correlations are conducted in a bivariate fashion.

4 Realised (Kernel Based) Volatility

In this section a first comprehensive overview of realised kernel based volatility (KVol hereafter), which is a nonparametric ex-post estimate of the return variation as defined by $K(X) = \sum_{h=-m}^{m} k(\frac{h}{H+1})\Gamma_h$ on page 87, across a wide range of asset classes is provided whilst taking non-synchronous trading and market microstructure noise into account. Importantly, as will be evident in what follows, the respective KVol measures based on the multivariate realised kernel do not increase uniformly across all assets during the financial crisis.

In Figure 8 the KVol estimates for the fixed income securities and FX futures are provided. With regard to the former, the volatilities of both the Eurodollar and the 10 year Treasury note contracts approximately double after mid 2007. This corresponds to the period discussed previously during which the prices for fixed income products increased as investors were seeking safe short run havens in times of market uncertainty and rising risk aversion. KVol patterns for the FX futures are not uniform during the crisis but do share some common features. In terms of the magnitude of the KVol all currency pairs in the sample exhibit volatility of approximately 0.004 to 0.006. Also, all currencies are affected by the bankruptcy of Lehman Brothers in September 2008. More specifically, for the USD-AUD contract KVol doubles rapidly in mid July 2007 and remains elevated after that. Furthermore, there is a spike in the intra-day volatility on August 17th 2007 which potentially corresponds to the aforementioned unwind of carry trades. For CHF there is less evidence that volatility increased systematically during the crisis, as the KVol in mid 2006 was not significantly lower than during the latter stages of the sample period. Similar patterns can be observed for the EUR future, albeit excluding the Lehman Brothers episode. Finally, the KVol measure for the USD-JPY contract nearly trebles from approximately 0.002 just before the onset of the crisis. As in the case of the AUD future, this currency pair exhibits a spike in intra-day volatility on August 17th 2007, which may correspond to the reverse position of the unwinding carry trades.

During the financial crisis the volatility of commodities did not increase homogeneously. As can be seen in Figure 9, the KVol measures for the corn, cattle and cotton futures do not exhibit a systematic rise, except for a large spike in volatility for the latter on March 3rd 2008. The soy beans contract on the other hand did become more volatile with KVol doubling at the beginning of 2008. With regard to gold, there is no evidence of an upward trend in the realised kernel volatility, despite the aforementioned price increase during the crisis to $1000 per ounce around the time of the Bear Stearns rescue. Noteworthy is the magnitude of the KVol measure in September 2008 during the bankruptcy of Lehman Brothers, a time of heightened risk aversion and subsequent demand for fixed income and gold securities. Finally, in Figure 9, the KVol for the VIX index is presented. Its long run average remains approximately constant, but the measure exhibits short periods of increased intra-day volatility. These corresponds to a 25% stock market correction in Turkey due to repricing of risk and over-dependence on foreign investment in June 2006, the Shanghai stock market crash in February 2007, the onset of the subprime crisis in July 2007 and the Lehman bankruptcy in September 2008, respectively.

In Figure 10, the realised kernel based volatilities for the Exchange Traded Funds are provided.[7] In accordance with the literature, uncertainty with regard to the health of the financial system began to rise after the summer of 2007. During this

[7] It should be noted that the volatility estimates for the Exchange Traded Funds are of similar magnitudes as the VIX index in levels in Figure 6. Differences arise though as the former are based on historical stock market data, whereas the latter is a function of forward looking implied volatility from S&P 500 index options.

time, KVol increased for all industries. As the crisis deepened and solvency issues became apparent in addition to market and funding illiquidity, volatility increased further and peaked following the Lehman Brothers bankruptcy in September 2008. When comparing the KVol measures for differing industries it is to be noted that the volatility of the Financial Sector SPDR (XLF) is highest and approximately double compared to that of the Industry (XLI) and Utilities (XLU) Sector SPDRs.

Finally, we present the realised kernel based volatilies of the crude oil and the natural gas futures in Figure 11. During the time of the sharp rise and subsequent fall in oil prices in 2008 the volatility showed a slight upward trend increasing from approximately 0.015 to 0.025. Natural gas on the other hand did not become systematically more volatile during the crisis.

Using the multivariate realised kernel, this section provided a broad overview of realised volatility estimates by using high frequency data across differing asset classes during the global financial crisis. In this context it is shown that changes in volatility are not homogenous during this period. Consistent with existing literature, the KVol measure sharply rises for the Exchange Traded Funds with the Financial Sector SPDR being most affected. More modest increases are identified for fixed income products. With regard to the FX and commodities contracts findings are mixed. These results are of importance as they highlight that investors do not face equal increases in uncertainty across tradable securities, and which will in turn have an influence on any optimal (minimal variance) portfolio weights.

5 Realised (Kernel Based) Correlations

As outlined in the introduction, this paper also tests whether during the financial crisis new channels of shock transmission emerged and whether unrelated asset classes co-moved to a greater extent. It has been previously argued that such process is driven by widespread increases in risk aversion, portfolio reoptimisation and excess liquidity in financial markets. From an investors' point of view the degree the increased correlations across unrelated markets is also of importance in the context of diversification.

In the data description it was pointed out that the different assets in the sample exhibit heterogeneous market hours despite all exchanges being in the same time zone. This provides challenges for our analysis of realised cross-correlations as the construction of the Refresh Times requires simultaneous trading. As a result the bivariate intersections of these trading hours are constructed for estimation of the realised kernels, thus implying a degree of information loss. Furthermore, a downward bias of the correlations may arise if news arrival occurs before markets open. In this case assets will sequentially react to the new information despite potentially exhibiting similar price movements due to the event, as result of which the correlation may underreport the true degree of interdependency across markets.

In Figure 12 the realised kernel based correlations between FX futures are presented. During the onset of the crisis in the second half of 2007 there are very pronounced changes in this measure of co-movement, especially amongst those currency pairs including AUD. As market stress eased at the beginning of 2008 after the rescue of Bear Stearns, these relationships seem to normalise, but heightened interaction is observed again during the Lehman Brothers bankruptcy. In 2006 the correlation between the USD-AUD and the USD-JPY FX futures remains at approximately 0.5 indicating that returns of these currencies are positively related. By mid 2007 this correlation had dropped to 0, after which this measure falls to -0.6 during the crisis. This is consistent with the aforementioned unwinding of carry trades due to increased risk aversion, whereby investors sold high yielding currencies such as AUD or ISK and fled to JPY and to a lesser extent into CHF. One further point of interest is that the correlations for all currency pairs begin to fall around January 2007, which is 6 months prior to the onset of the crisis. Thus this is evidence that FX pairs may be suitable to develop predictions of future market dislocations.

The first examples of realised kernel correlations across differing asset classes, namely between FX and fixed income futures, are provided in Figure 13. Before the crisis, both the Eurodollar and the 10 year Treasury note contracts were hardly correlated with the Australian Dollar, with this measure being approximately 0.1. During the period of financial turbulence this correlation dropped to -0.2 and -0.4, respectively, due to increased risk aversion. As investors indiscriminately sold risky assets, such as high yielding currencies, their portfolios were rebalanced towards fixed income securities. This behaviour is also reflected by the increased correlations between the Eurodollar and the Treasury note contracts, and currencies such as JPY and CHF, whereby this realised measure of co-movement rises from approximately 0.1 at the beginning of 2006 to between 0.4 and 0.5 for both FX pairs. Finally, the lower left panel of Figure 13 provides evidence that both fixed income futures became closer substitutes during the financial crisis as their correlations increased in mid 2007. This is consistent with the interpretation that investor demand for Treasuries was not solely driven by yield or maturity considerations, but rather these securities were used as a short-run transparent liquidity storage.

Realised correlations between gold, the VIX index and the energy futures are presented in Figure 14. The former two are both measures of risk aversion and market uncertainty, as the first is perceived as being a safe haven during turbulent times whereas the second is a function of the implied volatility of S&P 500 index options. From the top left panel it can be seen that in 2008 the correlation between these two measures increases to about 0.2, implying that during times of increased stock market volatility the gold price rises. The other plots in Figure 14 are consistent with the notion of asset prices being driven by excess liquidity and portfolio re-optimisation during the crisis. For example, the energy contracts of crude oil and natural gas have become highly correlated with gold and the VIX index. Thus, as market conditions deteriorated and gold prices and risk aversion rose, investors also continuously drove up energy prices, despite the real negative effects of the financial crisis on the world economy.

Next, the correlations between between energy futures and stock prices in the form of the Exchange Traded Funds are described and it is shown that these effects are not homogenous across differing industries. More specifically, the realised correlation between natural gas and the Energy Sector SPDR (XLE) is positive throughout the sample period, increasing from 0.2 before the crisis to 0.4. This is contrasted by the degree of co-movement between crude oil and the Industry

Sector SPDR (XLI), for instance. Before the financial crisis these two asset classes are uncorrelated, but in 2008 this realised measure falls to -0.4. This in turn implies that as the dislocations of financial markets deepened and real effects spread, increases in energy prices became associated with falls in industrial stocks. Similar heterogeneity in the correlations can be found between gold and the differing industries. For example, the XLE SPDR becomes increasingly more correlated with this proxy of risk aversion, whereas this relationship with XLI turns negative during the crisis, being consistent with investors liquidating cyclical industrial stocks and buying gold. Concerning the relationship between the VIX index and the Exchange Traded Funds, as expected, it is found that the Financial Sector SPDR (XLF) is highly negatively correlated with the former, whereas this relationship is not as strong in the case of the Utilities Sector SPDR (XLU).

Finally, in the left column of Figure 16 realised correlations amongst Exchange Traded Funds are provided. During the financial crisis the interdependencies between the individual sectors have grown, a result which is consistent with existing literature. In the right column, the correlations amongst a subset of commodities are presented. Interestingly, despite simultaneous price increases for cattle, corn, cotton and soy beans, we find absolutely no evidence that these futures have become more correlated with each other or with any of the other assets.

This section presented results with regard to realised kernel based correlations between differing asset classes. We find that the co-movements between FX pairs changed approximately 6 months prior to those of all other variables and before the onset of the subprime crisis. This would indicate that it is potentially possible to use these measures as an early indicator of future market dislocations. Furthermore, we provide evidence that fixed income securities became more correlated, in absolute value, with both high and low yielding currencies. Interdependence between risk aversion measures such as the VIX index and gold with energy also became more pronounced during the financial crisis. Finally, it is shown that, despite simultaneous increases in the price levels of commodities, their co-movement amongst themselves and with other securities did not increase. With regard to interpretation of these results, we believe that these findings are consistent with the notion that prices became more heavily interrelated during the crisis due to excess liquidity, heightened risk aversion and portfolio rebalancing.

6 GARCH Modeling

In this final section the estimates from the multivariate realised kernel are combined with daily data and modelled within a multivariate GARCH framework. Examples of this can be found in Engle and Gallo (2003) who extend the Multiplicative Error Model (MEM) by including exogenous regressors such as realised volatility, absolute returns and the daily high-low range in the conditional variance of asset returns. Incorporating realised measures in this way allows for exploitation of additional intra-day information and it is subsequently shown that out-of-sample forecasting performance of this model class can be improved.

In this paper, the same methodology as in Barndorff-Nielsen *et al.* (2008a) is adopted, where a scalar BEKK model, as initially proposed by Engle and Kroner (1995), is amended to include realised estimates of the implied covariance matrix as exogenous regressors. As their analysis is conducted for stocks, we are able to build on this seminal work by comparing their results with those of differing asset classes, such as FX, fixed income, commodity and energy securities.

In addition to the kernel estimate of the covariance matrix as described throughout, a further one based on 5 minute asset returns is included in the multivariate GARCH model. Recalling earlier methodological discussion, it was argued that biases may arise when calculating (3), which in turn motivated the adoption of the multivariate realised kernel. More specifically, it was pointed out that as the sampling frequency increases the RV measure exhibits an upward bias due to market microstructure noise such as the bid/ask bounce, whereas the opposite is true for the realised covariance due to the Epps effect. In Figures 2 and 3 we showed that this phenomenon, which has been observed in the literature, also holds for a wide range of asset classes. As a result, the 'naive' estimation of (3) is conducted using 5 minute returns, such as to avoid these issues arising due to high sampling frequencies.

Following Barndorff-Nielsen *et al.* (2008a) multivariate GARCH models are estimated whereby daily returns, constructed from closing prices, are mean zero $E(r_t|\Im_{t-1}^{HF}) = 0$ and where the conditional variance is specified as $Cov(r_t|\Im_{t-1}^{HF}) = H_t$. $\Im_{t-1}^{HF}$ denotes the high frequency information set and thus includes the lagged realised kernel covariance K_{t-1} and that based on 5 minutes returns $RCov_{t-1}^{5m}$.

More specifically, five differing scalar BEKK models are specified.

$$H_t = C'C + \alpha r_{t-1} r'_{t-1} + \beta H_{t-1} \tag{8}$$

$$H_t = C'C + \alpha K_{t-1} + \beta H_{t-1} \tag{9}$$

$$H_t = C'C + \alpha r_{t-1} r'_{t-1} + \beta H_{t-1} + \gamma K_{t-1} \tag{10}$$

$$H_t = C'C + \alpha r_{t-1} r'_{t-1} + \beta H_{t-1} + \delta RCov^{5m}_{t-1} \tag{11}$$

$$H_t = C'C + \alpha r_{t-1} r'_{t-1} + \beta H_{t-1} + \gamma K_{t-1} + \delta RCov^{5m}_{t-1} \tag{12}$$

In Tables 2 and 3 the results are presented for a subset of Exchange Traded Funds, FX, fixed income, commodity and energy securities. It should be noted that both realised measures do not include overnight effects, unlike the daily returns, in explaining the conditional variance. As a general pattern it is found that the inclusion of the realised covariances reduces the α and β terms in the scalar BEKK models, whilst respective coefficients of between 0.1 and 0.4 are attributed to the kernel and the 5 minutes covariance estimates. Based on the log-likelihood values of nested specifications, it follows that the standard scalar BEKK model (8) is rejected for most assets in favour of one incorporating intra-day information such as (10) and (11).

Barndorff-Nielsen *et al.* (2008a) provide very similar findings for stocks, both in terms of magnitudes of coefficients and model selection. As a result we conclude that the inclusion of realised measures increases the explanatory power of models for a wider range of underlying asset classes and may be of use in developing more precise volatility forecasts.

Asset Class	H_{t-1}	$r_{t-1}r'_{t-1}$	K_{t-1}	RV^{5m}_{t-1}	$\log L$
AUD-CHF	0.8577 (0.0399)	0.0168 (0.0121)	0.1165 (0.0366)	-	7254.2
	0.8394 (0.0498)	0.0219 (0.0127)	-	0.1180 (0.0408)	7254.5
	0.9466 (0.0114)	0.0530 (0.0097)	-	-	7231.7
	0.8505 (0.0414)	-	0.1373 (0.0371)	-	7253.2
	0.8344 (0.0518)	-	0.0832 (0.0629)	0.0627 (0.0674)	7253.7
AUD-JPY	0.8802 (0.0216)	0.03311 (0.0129)	0.08339 (0.0231)	-	7230.2
	0.8832 (0.0217)	0.0373 (0.0126)	-	0.0718 (0.0210)	7229.5
	0.9316 (0.0108)	0.0701 (0.0106)	-	-	7214.9
	0.8629 (0.0236)	-	0.1266 (0.0231)	-	7226.8
	0.8615 (0.0244)	-	0.1044 (0.0556)	0.0223 (0.0521)	7226.8
AUD-TN	0.9118 (0.0263)	0.0153 (0.0107)	0.0693 (0.0258)	-	7205.3
	0.9057 (0.0227)	0.0169 (0.0112)	-	0.0737 (0.0230)	7207.6
	0.9511 (0.0124)	0.0487 (0.0097)	-	-	7190.4
	0.9031 (0.0283)	-	0.0913 (0.0247)	-	7204.3
	0.9007 (0.0228)	-	0.000 (0.0395)	0.0870 (0.0399)	7207.1
Cattle-Corn	0.8448 (0.0736)	0.0047 (0.0127)	0.1575 (0.0775)	-	5436.1
	0.9222 (0.0270)	0.000 (0.0096)	-	0.0638 (0.0226)	5437.4
	0.9533 (0.0166)	0.0232 (0.0070)	-	-	5428.1
	0.8351 (0.0712)	-	0.1738 (0.0679)	-	5436.1
	0.8924 (0.0486)	-	0.0562 (0.0487)	0.0501 (0.02153)	5438.8

Table 2: Bivariate Scalar BEKK Models for Selected Asset Classes

Asset Class	H_{t-1}	$r_{t-1}r'_{t-1}$	K_{t-1}	RV^{5m}_{t-1}	log$L$
Cotton-Soy	0.9640 (0.0127)	0.0236 (0.0064)	0.0070 (0.0075)	-	5346.2
	0.9565 (0.0180)	0.0224 (0.0067)	-	0.0083 (0.0065)	5347.5
	0.9678 (0.0104)	0.0245 (0.0061)	-	-	5345.7
	0.9312 (0.0229)	-	0.0651 (0.0205)	-	5327.8
	0.8824 (0.0502)	-	0.0000 (0.0268)	0.0593 (0.0276)	5339.6
Gold-Crude	0.8748 (0.0451)	0.0149 (0.0120)	0.1330 (0.0558)	-	5432.5
	0.8328 (0.0441)	0.0000 (0.0145)	-	0.1373 (0.0388)	5442.8
	0.9623 (0.0083)	0.0333 (0.0064)	-	-	5422.4
	0.8552 (0.0409)	-	0.1738 (0.0468)	-	5431.8
	0.8329 (0.0444)	-	0.0000 (0.0540)	0.1373 (0.0451)	5442.8
Gold-Gas	0.8249 (0.0452)	0.0000 (0.0143)	0.2086 (0.0568)	-	5080.7
	0.7358 (0.0942)	0.0000 (0.0190)	-	0.2128 (0.0691)	5088.5
	0.9475 (0.0112)	0.0421 (0.0085)	-	-	5056.5
	0.8249 (0.0451)	-	0.2086 (0.0527)	-	5080.7
	0.7358 (0.0897)	-	0.000 (0.0853)	0.2128 (0.0902)	5088.5
XLK-XLF	0.6476 (0.0685)	0.0049 (0.0061)	0.4058 (0.07543)	-	5900.5
	0.5802 (0.0833)	0.000 (0.000)	-	0.4144 (0.0854)	5896.8
	0.8972 (0.0123)	0.1136 (0.1042)	-	-	5801.3
	0.6937 (0.0343)	-	0.3608 (0.0445)	-	5900.1
	0.6244 (0.0686)	-	0.2746 (0.0727)	0.1389 (0.08791)	5901.9

Table 3: Bivariate Scalar BEKK Models for Selected Asset Classes

7 Conclusion

In this paper the existing empirical literature on the current financial crisis is extended. First, using high frequency data across a wide range of asset classes, we provide an analysis of realised kernel based volatility of Exchange Traded Funds, FX, fixed income, commodity and energy securities, whilst accounting for market microstructure noise and non-synchronous trading. Second, changes in interdependencies between these distinct markets are quantified and it is shown that correlations increased during periods of heightened market dislocations.

More specifically, it is found that the co-movements between FX pairs changed approximately 6 months prior to the onset of the subprime crisis, which is believed to be driven by the unwinding of carry trades. This also suggests that these assets may be utilitsed in constructing predictors of future financial turbulence.

Furthermore, fixed income securities became more correlated, in absolute value, with both high and low yielding currencies. Interdependence between risk aversion measures such as the VIX index and gold with energy also became more pronounced during the financial crisis. Finally, it is shown that, despite simultaneous increases in the price levels of commodities, their comovement amongst themselves and with other securities did not increase. With regard to interpretation of these results, we believe that this is consistent with the notion that prices became more heavily interrelated during the crisis due to excess liquidity, heightened risk aversion and portfolio rebalancing.

Finally, we build on existing work by combining realised covariance estimates with daily data. In this context it is shown that their inclusion within a multivariate GARCH framework may increase the explanatory power of volatility models and we extend these existing findings for stock market securities to cover other asset classes.

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Asset	Abbreviation	Trading Market	Data Source
Eurodollar Futures	Eurodollar	CME	TickData
Treasury Notes Futures	TNotes	CBOT	TickData
Australian Dollar Futures	USDAUD	CME	TickData
Swiss Franc Futures	USDCHF	CME	TickData
Euro Futures	USDEUR	CME	TickData
Japanese Yen Futures	USDJPY	CME	TickData
VIX Index	VIX	CBOE	TickData
Crude Oil Futures	Crude	NYMEX	TickData
Natural Gas Futures	Gas	NYMEX	TickData
Gold Futures	Gold	NYMEX	TickData
Live Cattle Futures	Cattle	CME	TickData
Corn Futures	Corn	CME	TickData
Cotton Futures	Cotton	NYBOT	TickData
Soy Beans Futures	Soy Beans	CME	TickData
Materials SPDR	XLB	NYSE	Taq Data
Energy SPDR	XLE	NYSE	Taq Data
Finance SPDR	XLF	NYSE	Taq Data
Industrials SPDR	XLI	NYSE	Taq Data
Technology SPDR	XLK	NYSE	Taq Data
Consumer Staples SPDR	XLP	NYSE	Taq Data
Utilities SPDR	XLU	NYSE	Taq Data
Health Care SPDR	XLV	NYSE	Taq Data

Table 4: CME = Chicago Mercantile Exchange, CBOT = Chicago Board of Trade, CBOE = Chicago Board of Options Exchange, NYMEX = NY Mercantile Exchange, NYBOT = NY Board of Trade, NYSE = NY Stock Exchange

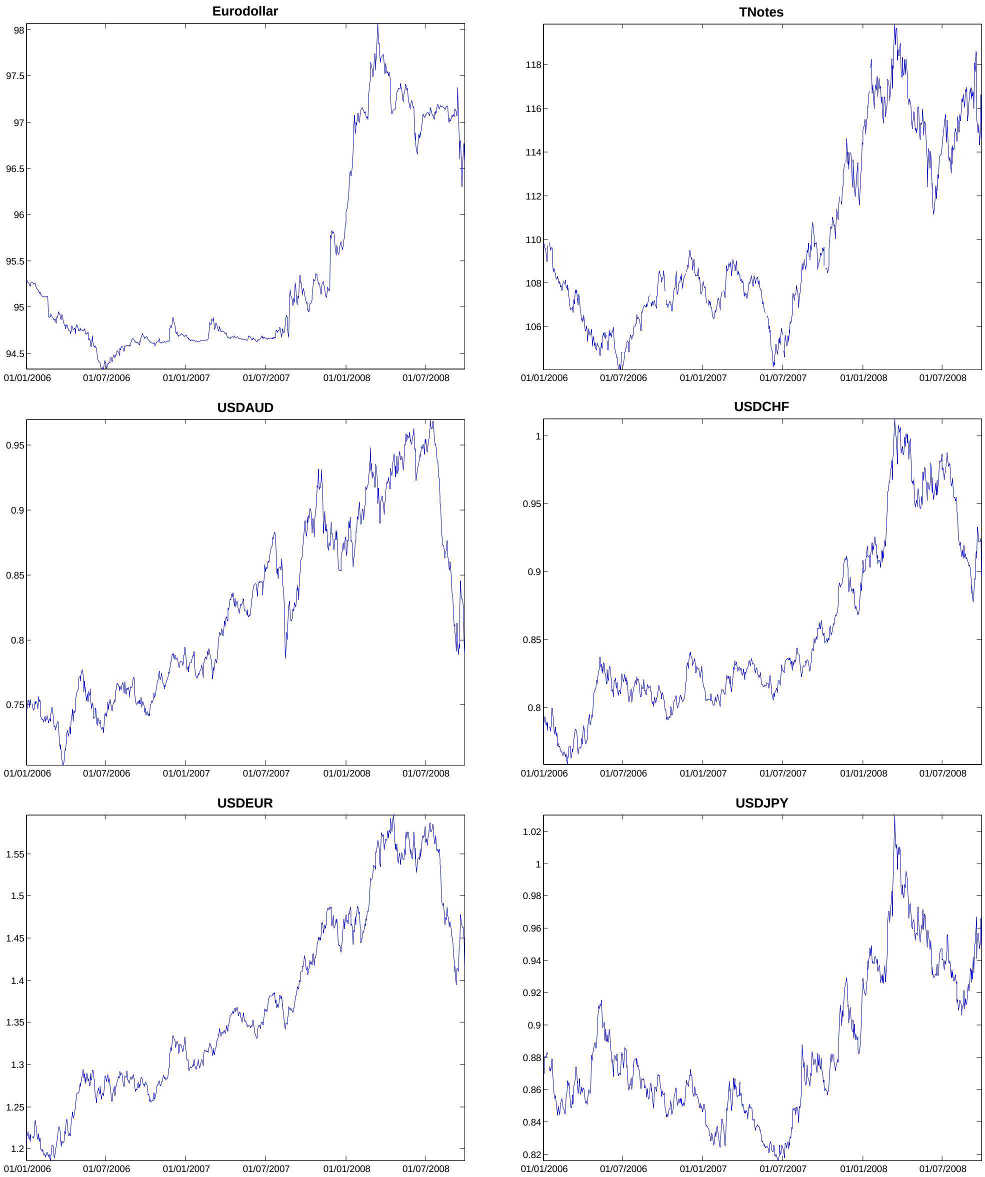

Figure 5: Fixed Income Securities, FX, Commodities and ETFs

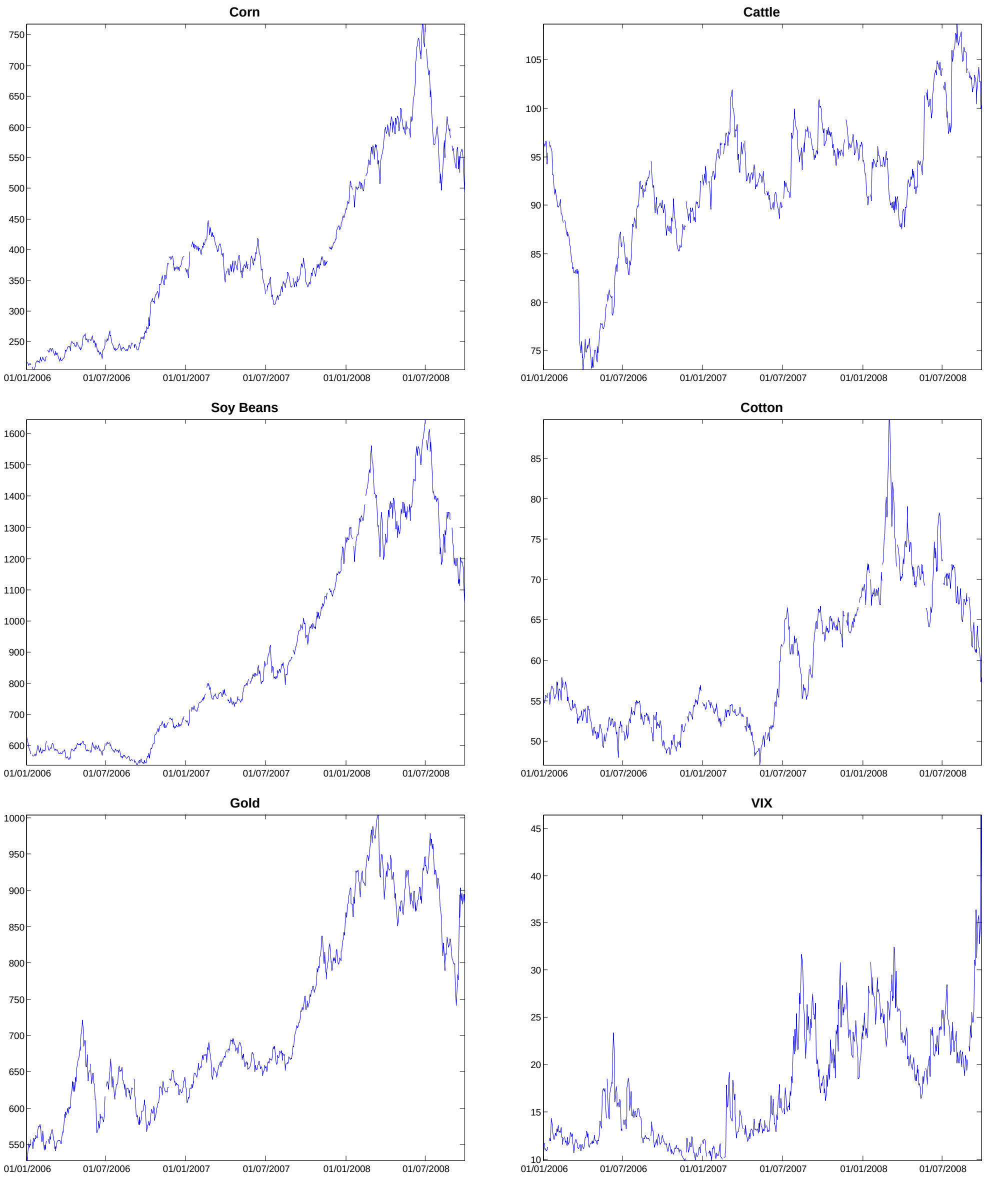

Figure 6: Fixed Income Securities, FX, Commodities and ETFs

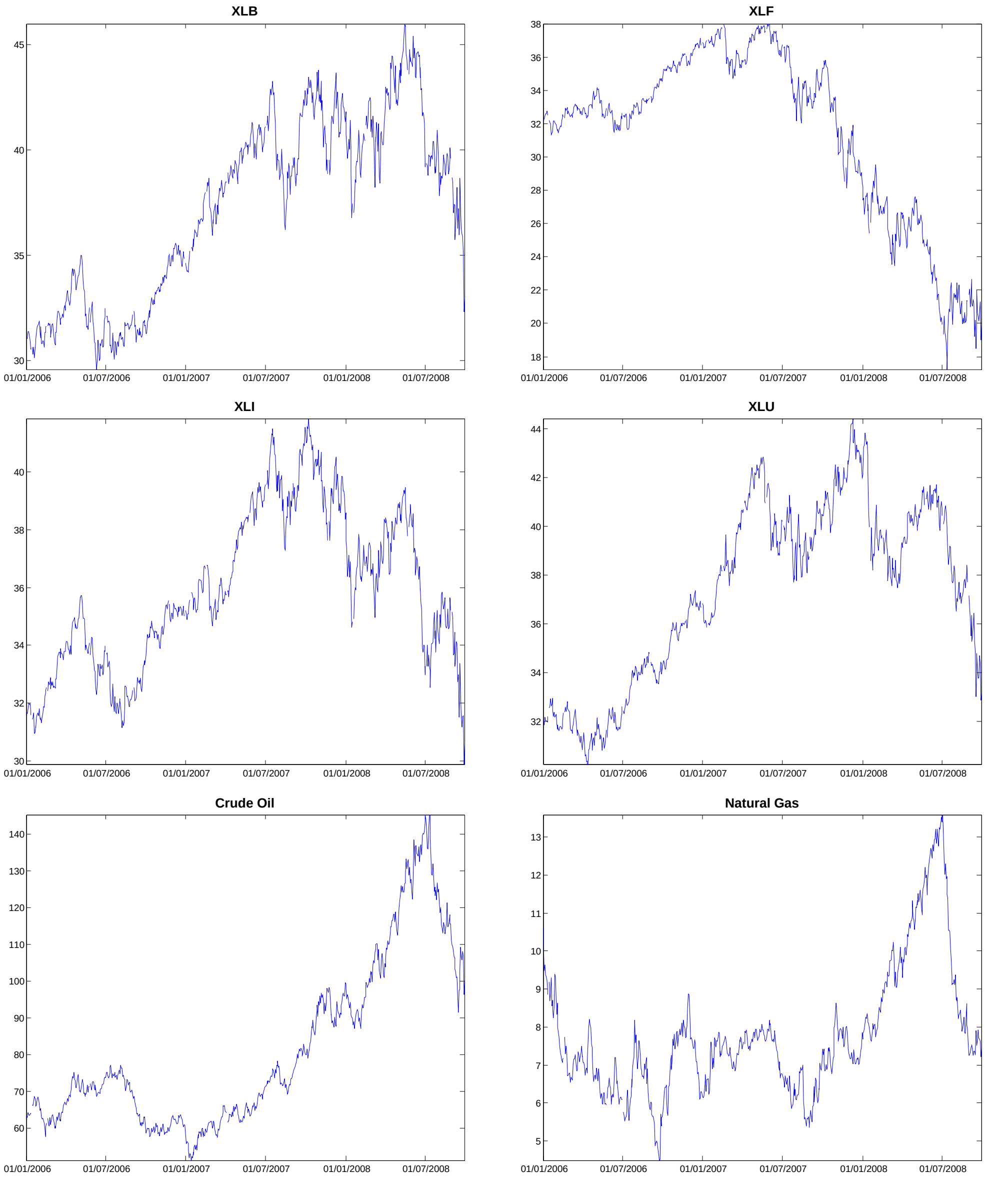

Figure 7: Fixed Income Securities, FX, Commodities and ETFs

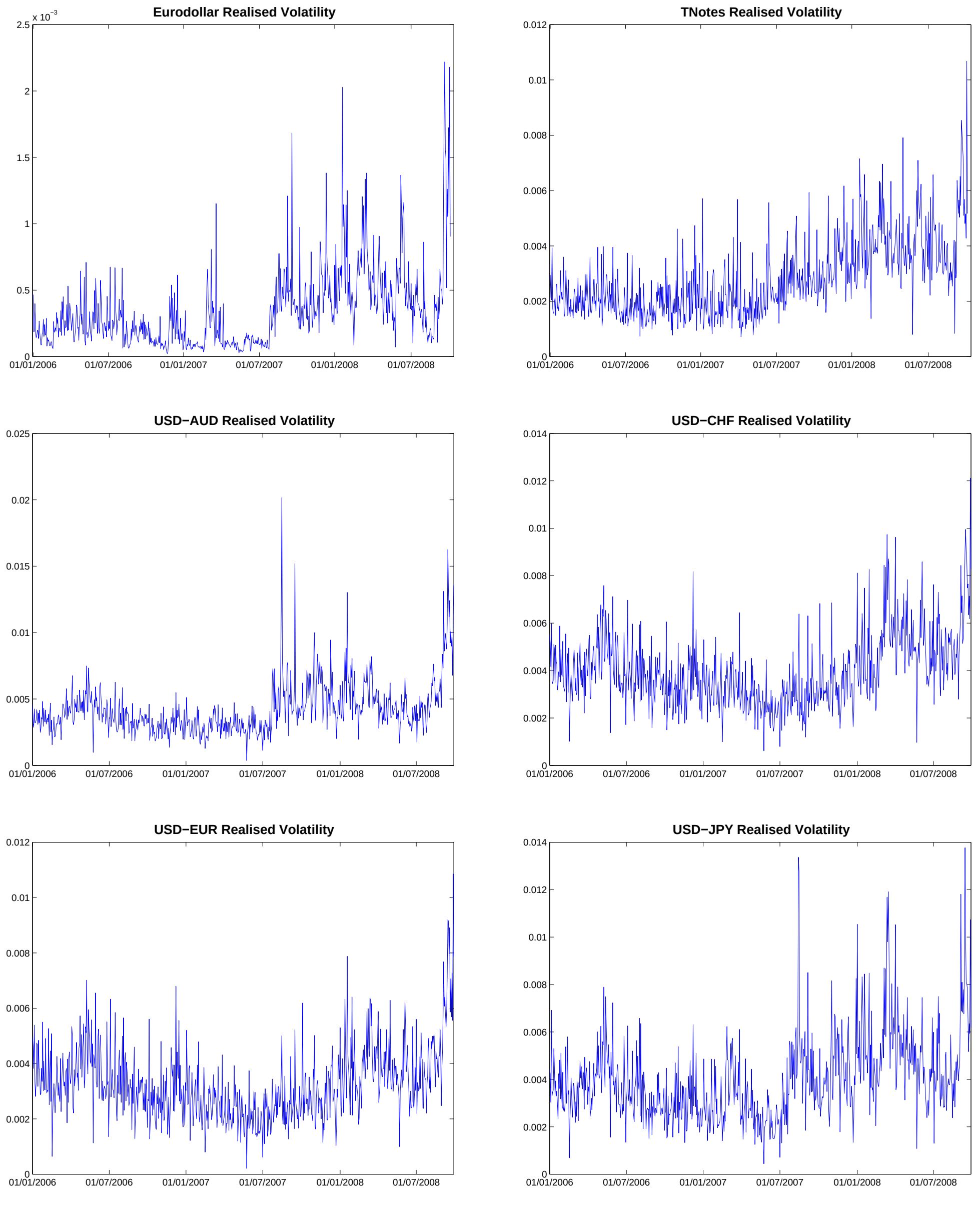

Figure 8: Realised Volatility for Fixed Income and FX Futures

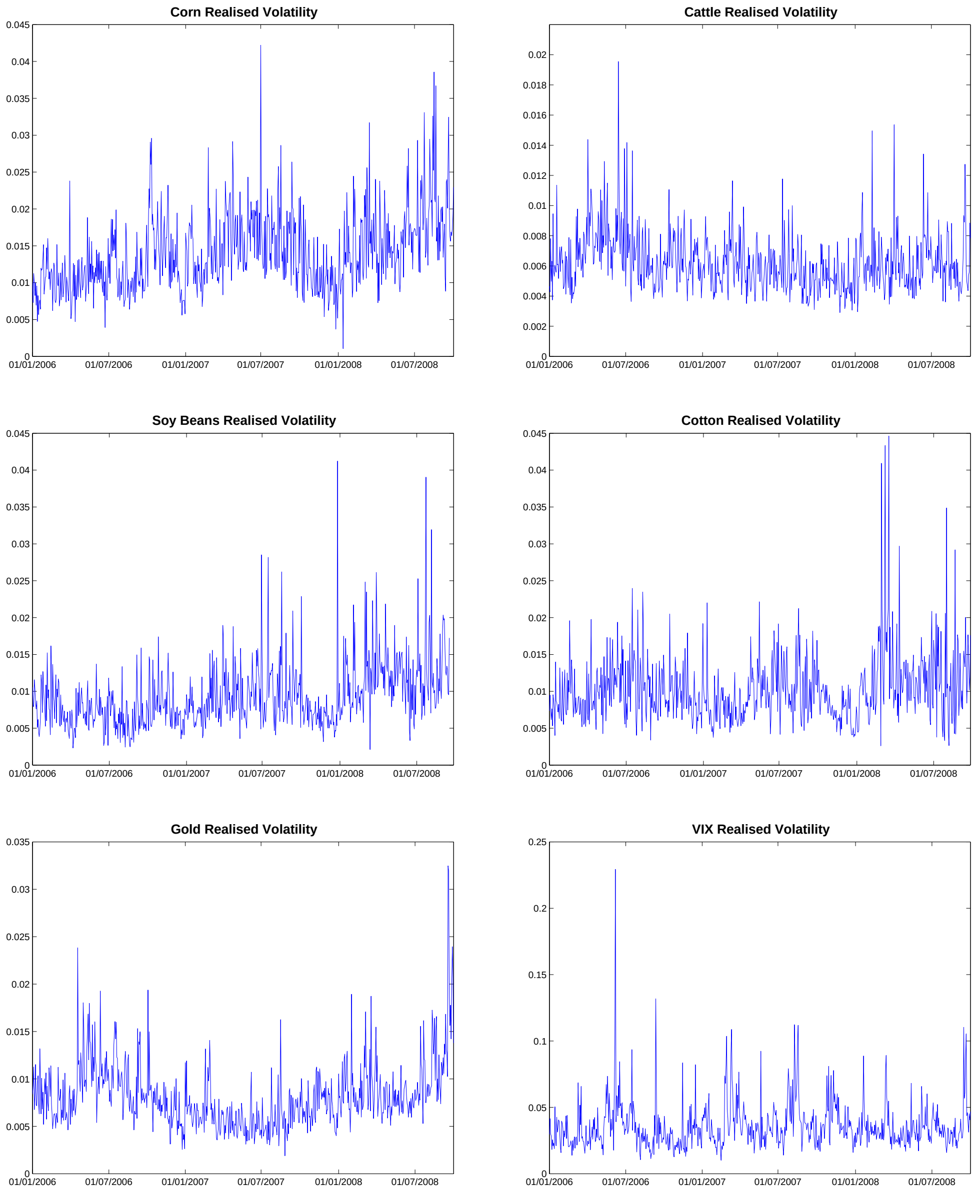

Figure 9: Realised Volatility for Commodities Futures

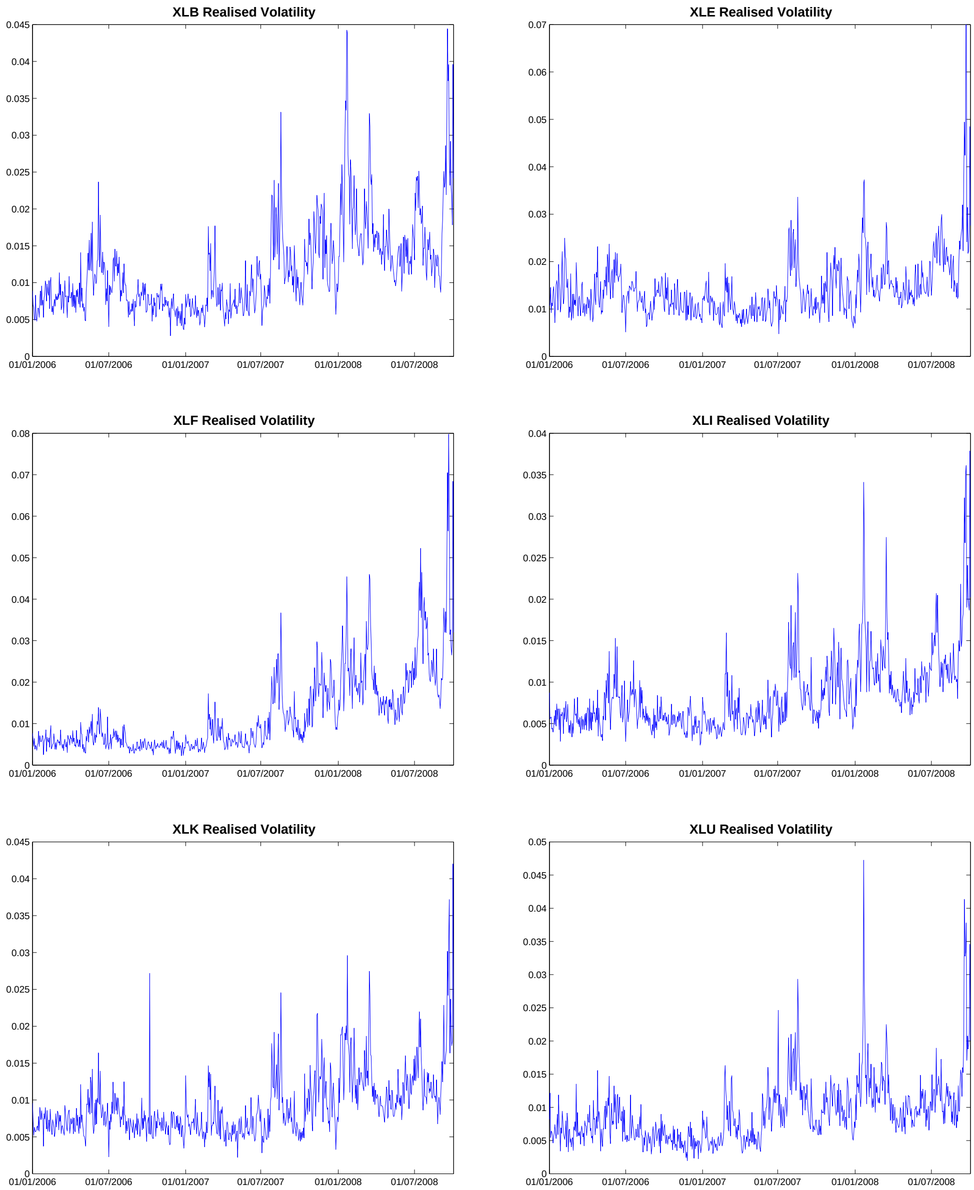

Figure 10: Realised Volatility for Exchange Traded Funds

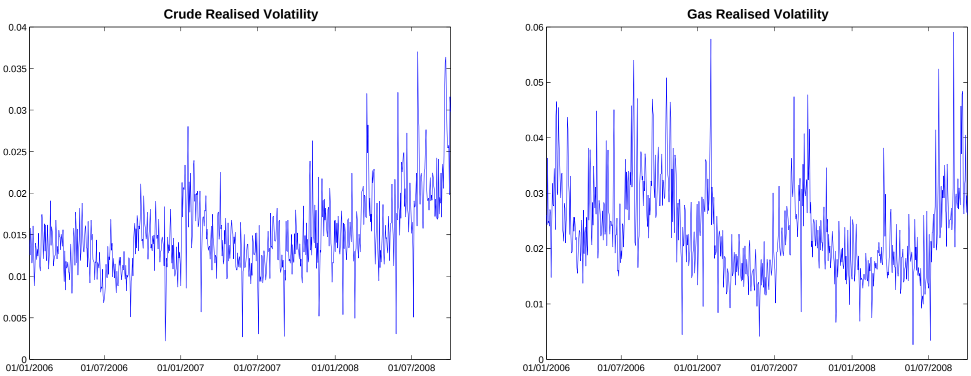

Figure 11: Realised Volatility for Energy Futures

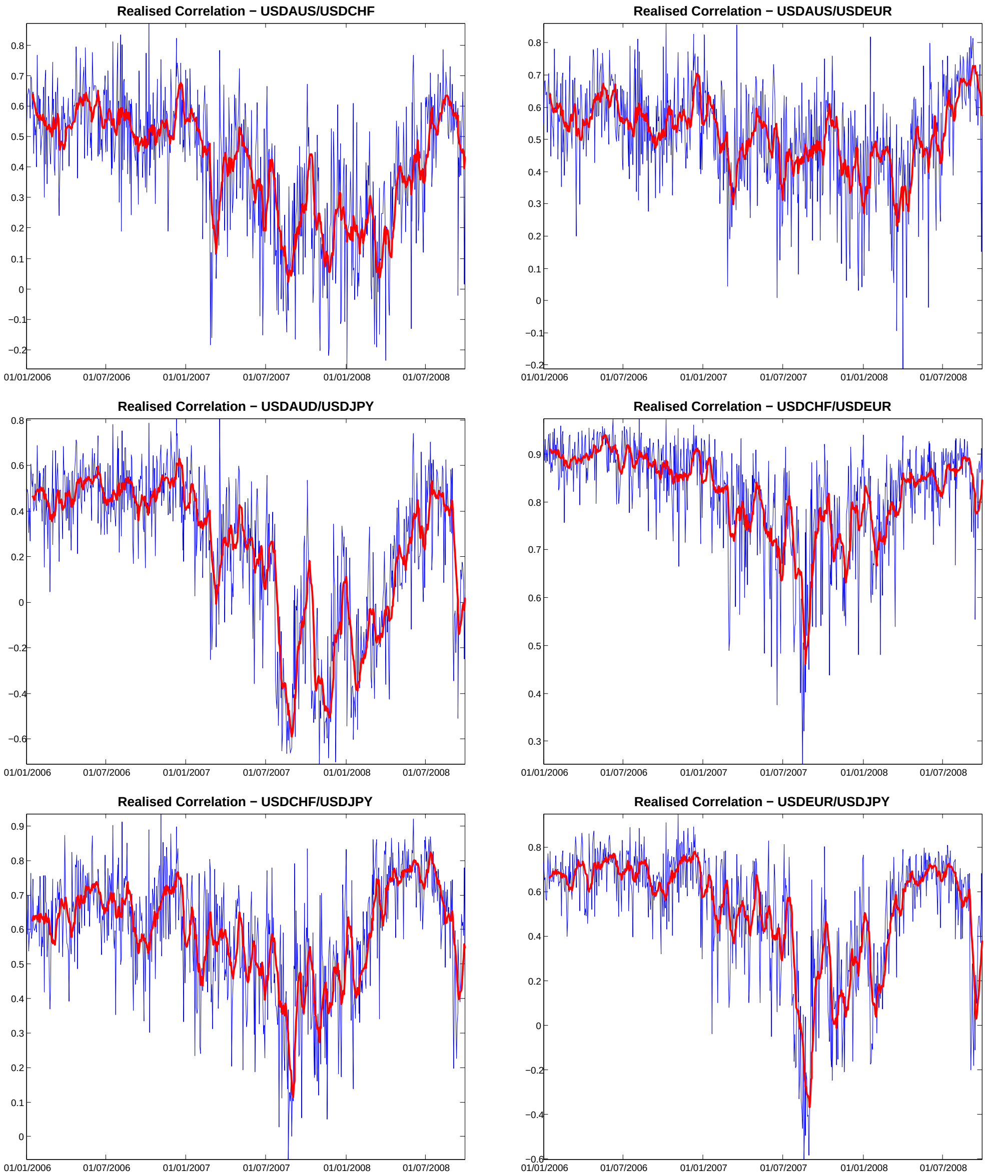

Figure 12: Realised Correlations for FX Futures (blue); 10 Day Moving Average (red)

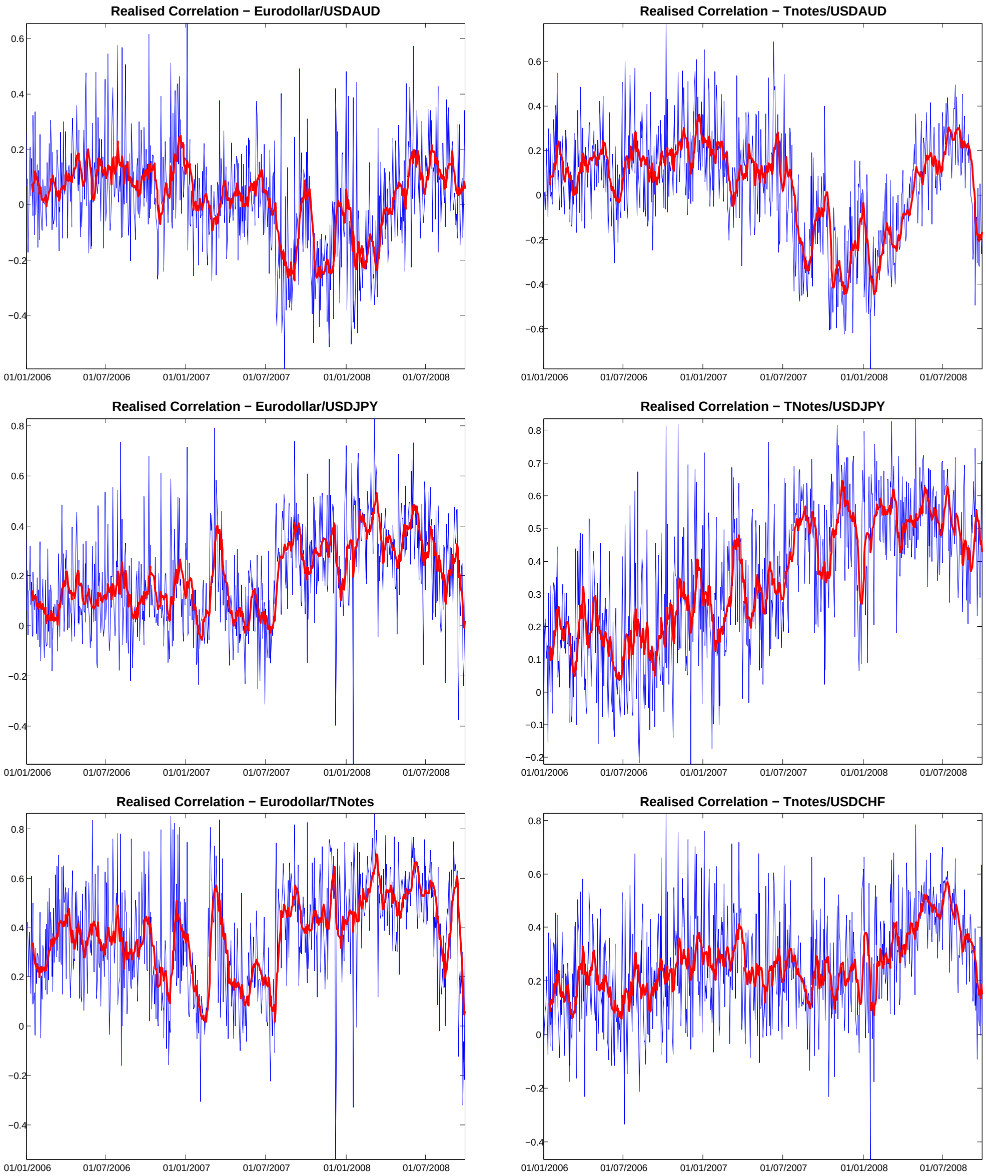

Figure 13: Realised Correlations for Fixed Income and FX Futures (blue); 10 Day Moving Average (red)

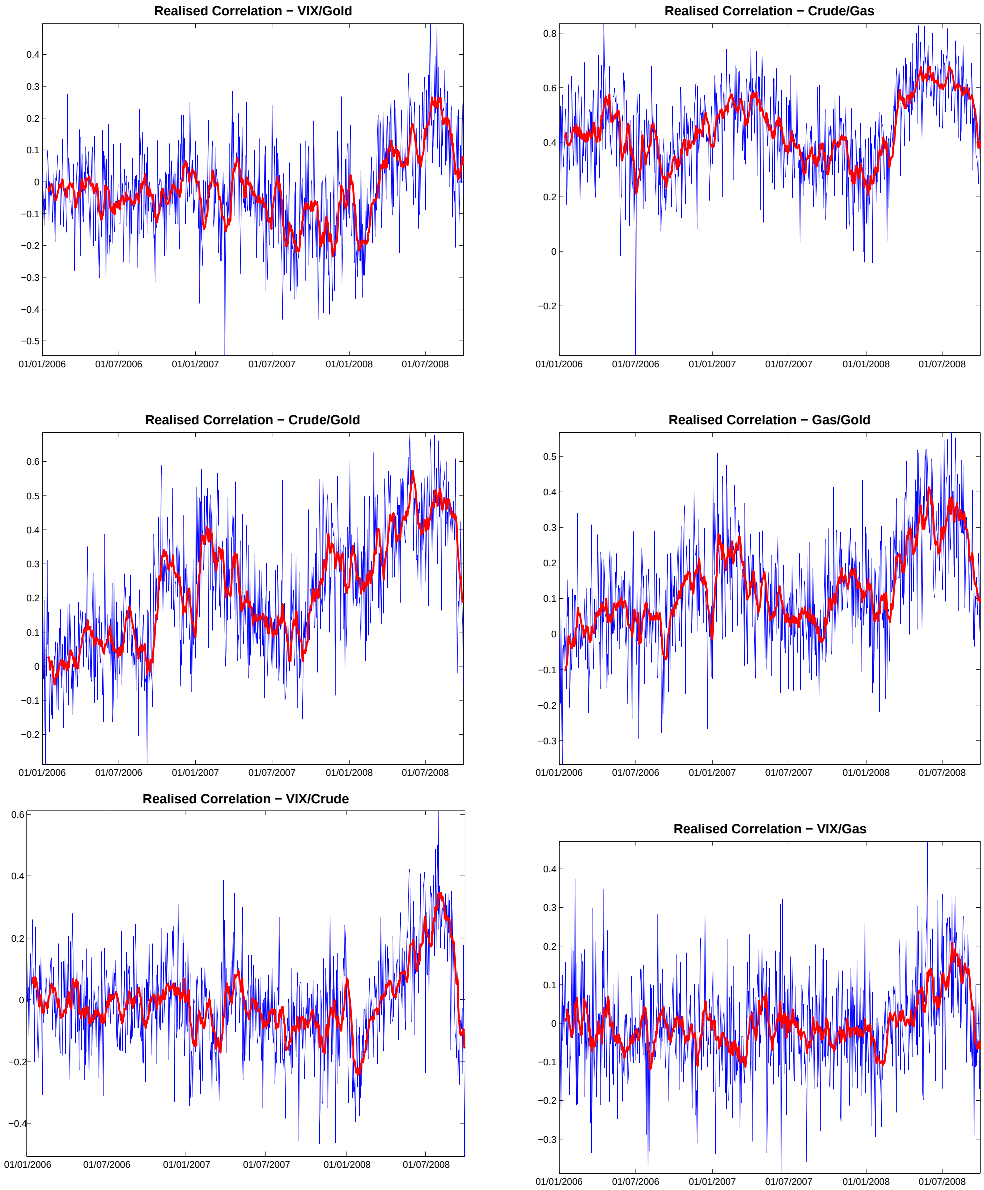

Figure 14: Realised Correlations for VIX, Gold and Energy (blue); 10 Day Moving Average (red)

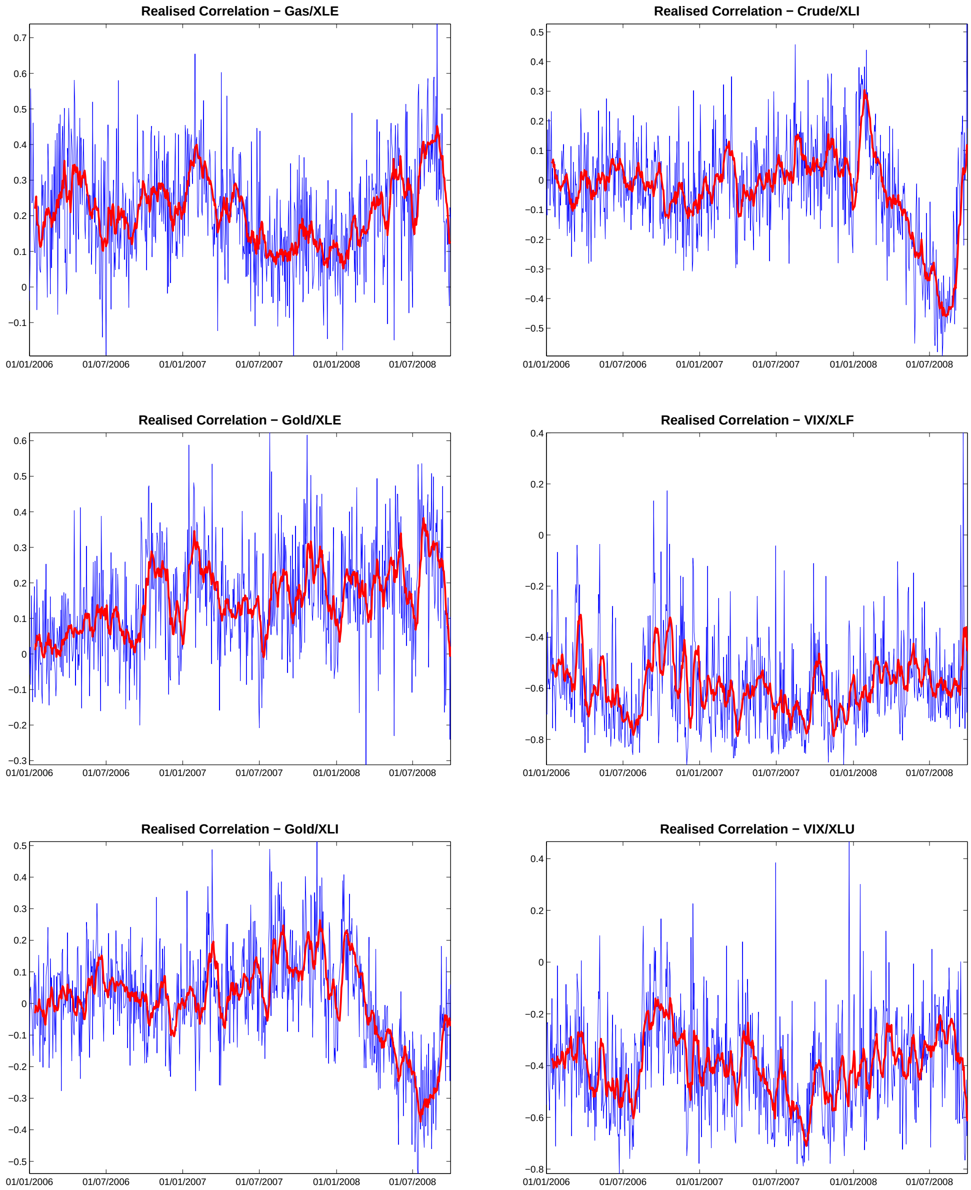

Figure 15: Realised Correlations for VIX, Gold, Energy and ETFs (blue); 10 Day Moving Average (red)

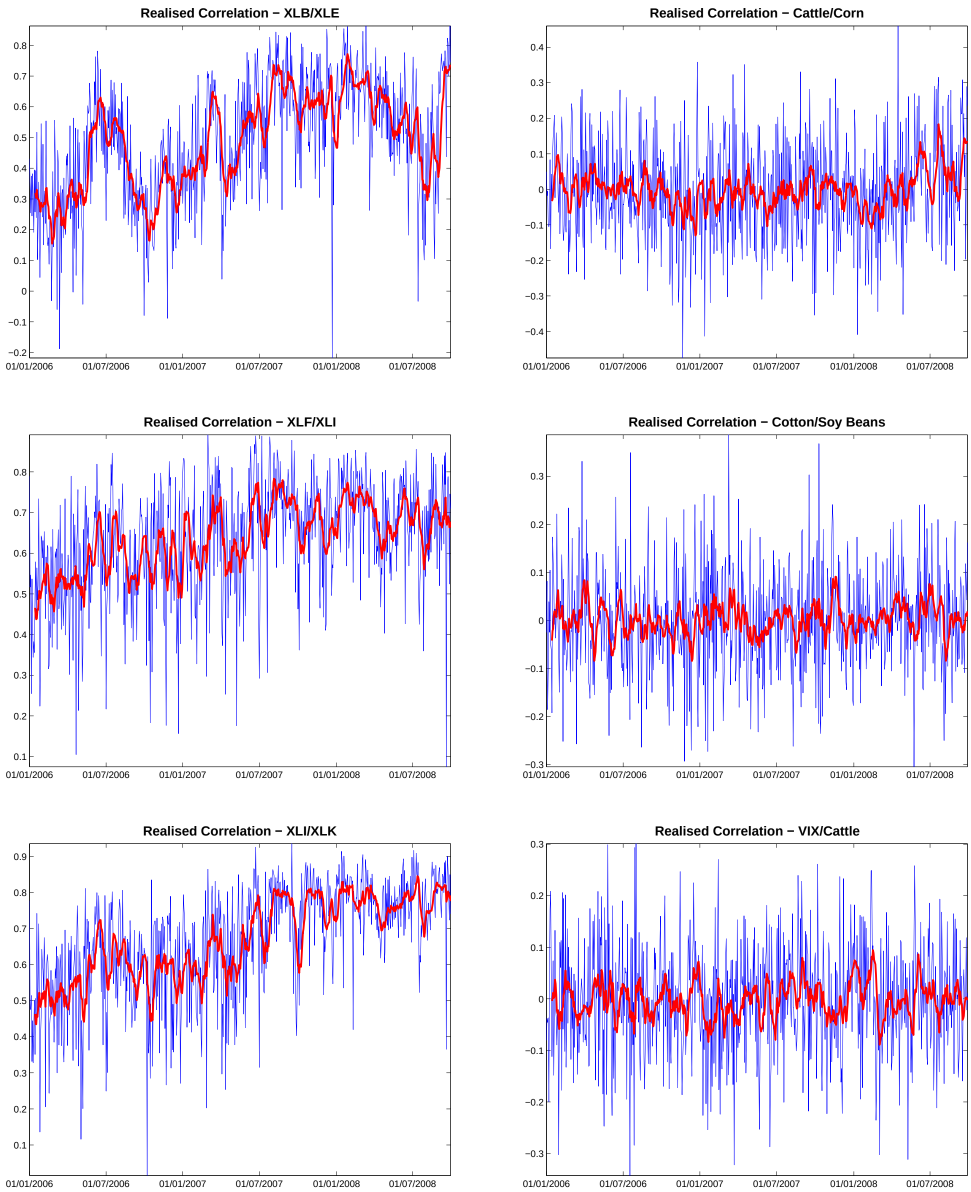

Figure 16: Realised Correlations for ETFs and Commodities (blue); 10 Day Moving Average (red)