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Analysis of Volatility and Correlation for CME Steel Products

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1. Introduction

Correlation and volatility between commodity prices is a very important factor to consider when designing risk management and investment strategies. The efficiency of hedging strategies for instance, depends on the existence of strong and stable correlation between spot and futures commodity prices; the absence of correlation on the other hand, or even sudden changes in the level of correlations may have detrimental implications not only for hedging and risk management but also in shaping the efficiency of a country's energy, manufacturing and food policies. In general, co-movements between commodity markets may be attributed to common macroeconomic shocks on world markets, and the complementarity or substitutability in the production or consumption of related commodities. It is also an established fact that although the prices for related commodities are correlated, correlation changes over time and, in particular, correlation changes have become more erratic over the last five years. Recent research by Buyuksahin et. al (2010) and Silvennoinen and Thorp (2010) has found that returns correlation between commodities has increased substantially during the recent financial crisis. Tang and Xiong (2011) also highlight that the increase in the correlations between the returns of different commodity futures started long before the crisis and cannot be simply attributed to the onset of the crisis.

In this report we attempt to identify whether the co-movement of HRC CRU, which is the underlying asset for the CME contract, and a basket of related steel commodities is strong enough.

The motivation for investigating this issues stems from the fact that although commodity prices, and in particular prices for related commodities such as the different steel products, tend to be correlated in the "long-run", over shorter periods of time this relationship may break down and prices may exhibit greater independence in their behaviour. This is because short-term supply demand factors are more independent across the different commodities, due to regional imbalances between supply and demand, differences in transportation costs, other external factors that are unique for each market etc. Whether this is the case, is important for participants in the market as it implies that hedging policies may be less effective over short periods of time due to the higher basis risk.

In order to identify these issues we investigate the correlation between the various steel products and the raw materials used in their production process. The results indicate that whereas price correlation in levels is high, return correlation for all the commodity pairs with the HRC CRU is low. As a result, we could argue that in the long term, same steel commodities tend to move together, however, over shorter periods of time, short term co-movement between steel related commodities is substantially lower. To support the above finding, we use a measure of co-movement called concordance which indicates that, during long-term cycles steel commodities tend to move together as they ride along the same industrial cycle, however, this relationship breaks down during short-term cycles.

The report is organized as follows. Section 2 reports the steel commodities used in the analysis and their descriptive statistics. Section 3 discusses the correlation analysis; and section 4 investigates the extent to which concordance is present in the prices of the steel related commodities. Finally, section 5 concludes the report.

2. Data and descriptive statistics

We examine nine closely related commodities, scrap, billet, HCC, Rebar, HRC and iron ore. These commodities are related in that they are either: co-produced; used as inputs to the production of another and, constitute either substitutes or complements in demand. Table 1 summarises the specifications of each of the commodities used and reports the start date of the available data; all series end on June 14, 2011.

Table 1: Steel & Steel Products Dataset and Abbreviations				
Commodity		***Name***	***Specifications***	***Start Date***
Iron ore	1	Ironore_Platts	Platts "IODEX" Iron ore fines 62% Fe CFR China Port $/t	06/02/2008
	2	Ironore_TSI	TSI iron ore (CFR Tianjin China)	11/17/2008
Scrap	1	Scrap_US	Platts US shredded scrap Del US Mid West $/MT	09/04/2007
Billet	1	Billet_LME	LME Billet - Cash settlement $/t	02/25/2008
HCC	1	HCC_M_Platts	Platts Prem Mid Vol HCC FOB Aus $/t	03/15/2010
HRC	1	HRC_Ruhr	Platts HRC E-works Ruhr Euro/t	11/17/2006
	2	HRC_CRU	CRU US Mid West HRC $/MT	10/05/2009
	3	HRC_Platts	Platts US Mid West HRC $/MT	01/04/2010
Rebar	1	Rebar_Platts	Platts Turkish rebar FOB $/MT	11/17/2006

Descriptive statistics of the commodities' prices and returns are reported in Table 2. In Panel B, we can see that the risk-return profile of the commodities is markedly different. For instance, the annualised volatilities for Billet and Scrap price changes are more than double that of the other commodities of the group. The coefficients of skewness and excess kurtosis indicate departures from normality for all the returns series. In particular, the observed negative skewness coefficients for most of the commodities (apart from HRC CRU, HRC Ruhr and HCC_M_Platts) imply that long positions are associated with greater risk since more extreme losses are placed on the left side of the returns distribution. The existence of fat-tails in the underlying series is also evidenced by calculating the empirical critical values of the standardised returns from the historical distributions. These imply that all returns series are fat-tailed relative to the 1% left and right tail regions, since the historical quantiles are greater in absolute value than the 1% critical value of standard normal distribution, i.e. 2.326. Fat tails at the 1% regions imply that extreme events have higher probability of occurrence relative to the standard normal distribution**.** Moreover, estimating time-varying volatilities based on the RiskMetrics procedure confirms that Billet and Scrap price returns are not only more volatile but volatility is also more erratic.

Table 2: Descriptive Statistics & Preliminary Analysis

	Ironore Platts	***Ironore TSI***	***Scrap US***	***Billet LME***	***HCC_M Platts***	***HRC Ruhr***	***HRC CRU***	***HRC Platts***	***Rebar_Platts***
Panel A: Log-Prices									
Mean	4.754	4.741	5.819	6.188	5.455	5.901	6.369	6.411	6.406
Maximum	5.263	5.257	6.413	7.147	5.817	6.295	6.683	6.688	7.303
Minimum	4.007	4.079	4.883	5.541	5.170	5.446	6.156	6.190	5.940
Std. Dev.	38.6%	37.9%	33.7%	38.0%	18.5%	22.0%	15.6%	15.2%	28.9%
Skewness	-0.419	-0.345	-0.288	0.914	0.386	-0.371	0.561	0.360	1.303
Kurtosis	1.714	1.645	2.636	3.148	1.685	2.177	2.079	1.851	4.662
Jarque-Bera	76.87	63.84	18.74	119.2	31.37	57.66	38.32	28.65	448.5
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	783	663	971	851	324	1127	437	374	1127
Panel B: Log-Returns									
Mean (Annual.)	-0.138%	40.597%	13.230%	-8.215%	24.520%	0.814%	17.766%	21.748%	6.275%
Maximum	0.073	0.111	0.353	0.321	0.101	0.0853	0.123	0.095	0.138
Minimum	-0.105	-0.097	-0.405	-0.294	-0.049	-0.139	-0.095	-0.044	-0.194
Std. Dev. (Annual.)	24.16%	22.76%	50.81%	64.96%	22.60%	22.04%	20.81%	14.30%	29.26%
Coeff. Of Variation	175.6	0.56	3.84	7.91	0.92	27.08	1.17	0.66	4.66
Skewness	-1.126	-0.084	-0.829	-0.191	2.332	-0.851	1.489	2.738	-1.831
Kurtosis	10.788	18.042	71.889	14.517	17.493	21.744	35.013	37.792	38.480
Jarque-Bera	2,141	6,242	191,917	4,703	3,120	16,619	18,779	19,280	59,690
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	782	662	970	850	323	1126	436	373	1126
Panel C: Time-Varying Volatility (RiskMetrics)									
Mean Vol (Annual.)	21.6%	21.2%	40.5%	54.5%	20.4%	19.8%	18.3%	12.8%	23.8%
Std of Vol	10.7%	7.9%	30.6%	35.0%	8.9%	9.3%	7.8%	5.3%	17.0%
Standardised Returns – Tails									
1% tail (Left)	-3.057	-2.852	-4.337	-2.801	-2.436	-3.052	-4.076	-4.422	-3.184
99% Tail (Right)	2.684	3.168	5.566	3.316	6.212	4.261	5.134	5.745	4.734

Figure 1 displays the volatility processes for different product prices[1]. Time variation in the volatility dynamics is confirmed, whereas the high volatility levels the industry experienced from the second half of 2008 and 2009 are also apparent. However, in the short term, we can note divergences in the processes, and, whether increases in volatility are transmitted to all markets is not obvious. The average correlation of the time series of volatilities is around 30% excluding CRU US

[1] RiskMetrics uses a weighted average of the estimated volatility and the last change in price at any point in time to estimate volatility. This is a simple Exponentially Weighted Moving Average (EWMA) procedure which essentially assigns different weights to each observation. In particular, the basic EWMA specification allows more recent observations to carry largest weights whereas weights associated with previous observations decline exponentially over time. Thus more recent observations have a stronger impact on volatility. Let be the squared returns (daily) and λ the weight/decay factor. The decay factor could be estimated but usually it is set at 0.94 as recommended by RiskMetrics. Then, the standard EWMA model of RiskMetrics can be represented as :

$$\sigma_{t+1}^2 = (1-\lambda)\sum_{j=0}^{\infty}\lambda^{j-1}R_t^2 \;\Rightarrow\; \sigma_{t+1}^2 = \lambda\sigma_t^2 + (1-\lambda)R_t^2$$

Mid West HRC (black line in Figure 1) which seems to be negatively correlated to all other products (-27% on average).

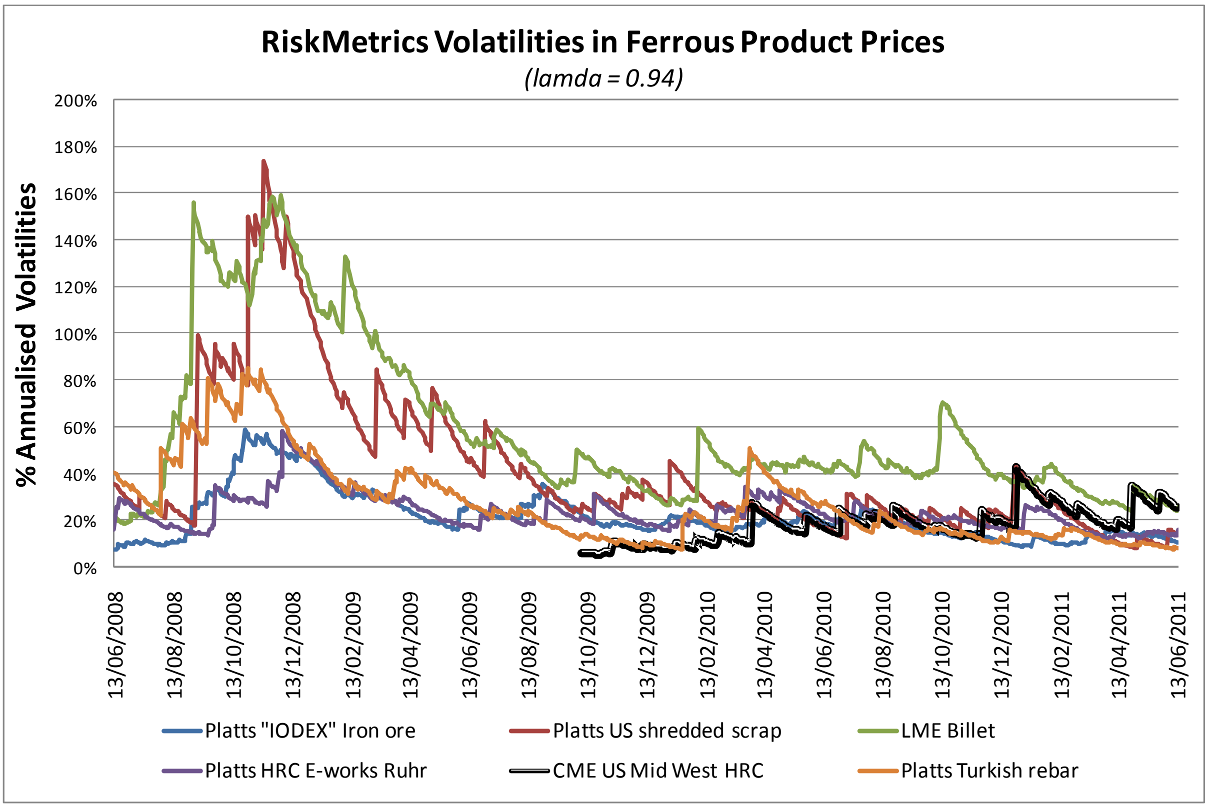


Figure 1: Conditional Annualised Volatilities in Ferrous Product Prices

Furthermore, the fat tails and the high kurtosis in log returns (Table 2) mean that more of its volatility can be explained by infrequent extreme events (excessive deviations from the mean – relatively large shocks). This illustrates the uncertainty and risk underlying the return process in the industry. As it has already been noted, the risk-return profile of the commodities is found to be markedly different.

Figure 2 attempts to isolate some large shocks in different products. We define as a jump, those returns with absolute values greater than three times the standard deviation (stdev) of the returns of the series. The +/- stdev bounds are displayed in the graphs for illustration purposes (red lines); jumps are also highlighted in green. Results show that extreme events in one market do not necessarily occur simultaneously in all cases. Moreover, this is a first indication that interdependencies during extreme events might not be frequent.

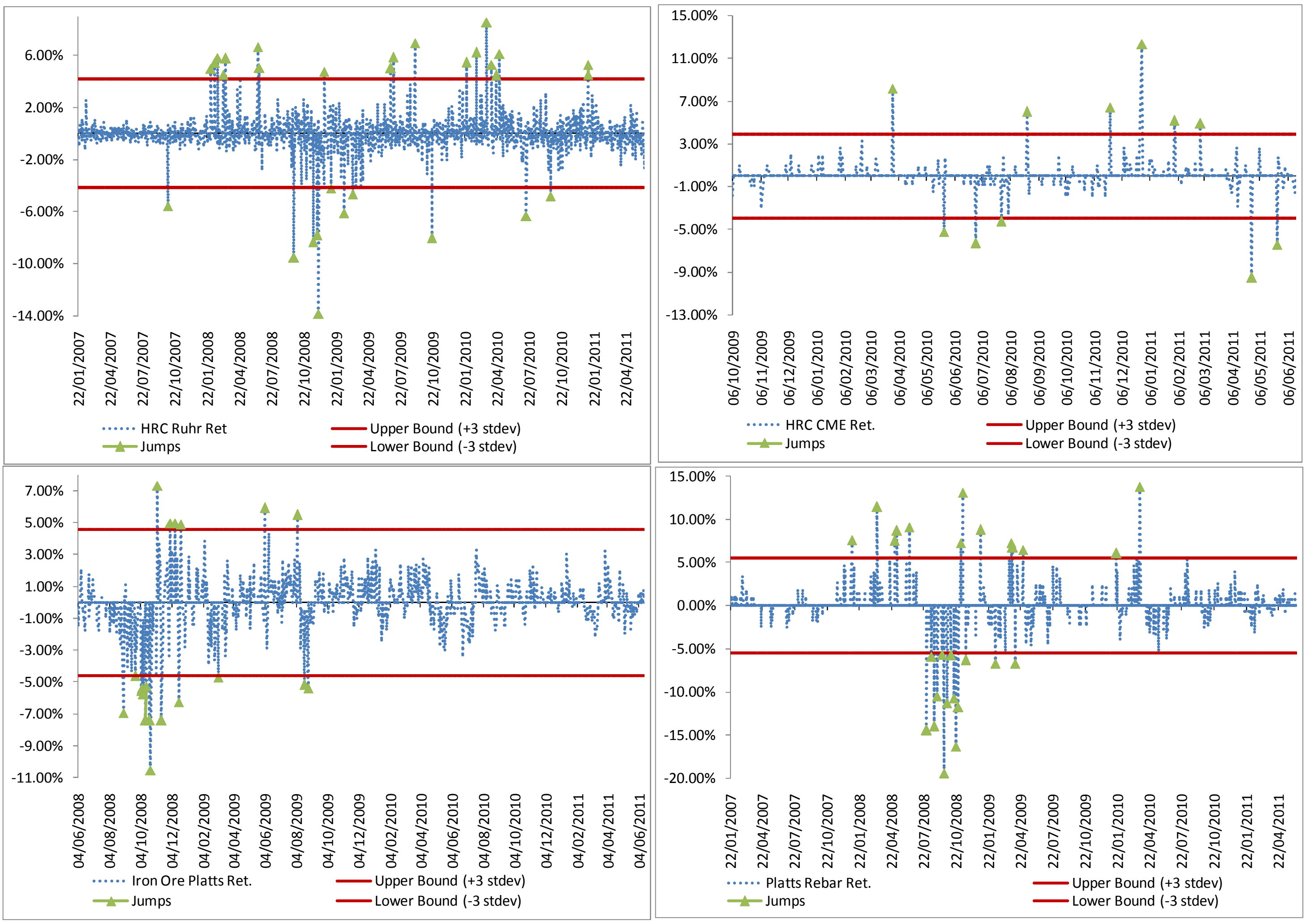


Figure 2: Jumps in Ferrous Product Prices

3. Correlation analysis

Table 3 shows the correlation results for the logarithm of the nominal commodity prices (Panel A) as well as the daily change in the logarithmic prices (Panel B). We also perform a test to confirm whether the estimated correlations are significantly positive. The 5 percent critical value is calculated as $1.96/T^{0.5}$, where T is the number of observations (see notes in Table 3; for more details the reader is referred to Pindyck and Rotemberg, 1990). Looking first, in panel A (log-prices), all the 36 correlations are significantly positive. However, in Panel B, only 11 out of 36 correlations are significantly positive, whereas the magnitude of the figures is now much lower. For instance the correlation of prices for HRC CRU lies within 63.9% to 90.6%, whereas the corresponding figure for the price changes is -3.86% to 7.27%. This finding, i.e. high correlation between a commodity pair in the long run, together with the relatively lower correlation in the short run are two essential indicators that one should examine before initiating a hedging strategy, or constructing a portfolio, since these measures provide information on the frequency of divergence from the long run linkages.

Table 3: Correlation Matrix of Steel Products

	Iron ore Platts	Iron ore TSI	*Scrap* US	Billet LME	HCC Platts (Mid)	HRC Ruhr	HRC CRU	HRC Platts	Rebar Platts
Panel A : Log-Prices									
Iron ore Platts	1								
Iron ore TSI	0.9986*	1							
Scrap US	0.9260*	0.9592*	1						
Billet LME	0.7593*	0.9359*	0.8739*	1					
HCC Platts (Mid)	0.8162*	0.8015*	0.9034*	0.6727*	1				
HRC Ruhr	0.6067*	0.7355*	0.6553*	0.6049*	0.2288*	1			
HRC CRU	0.7421*	0.7298*	0.8161*	0.7075*	0.9064*	0.6393*	1		
HRC Platts	0.7320*	0.7162*	0.8356*	0.6211*	0.9230*	0.5012*	0.9825*	1	
Rebar Platts	0.6964*	0.9033*	0.8490*	0.9742*	0.7699*	0.6379*	0.7613*	0.6989*	1
Panel B: Log Returns									
Iron ore Platts	1								
Iron ore TSI	0.3188*	1							
Scrap US	0.0563	0.0910*	1						
Billet LME	0.0705*	0.1085*	-0.0898	1					
HCC Platts (Mid)	0.1556*	0.1441*	0.0055	0.0238	1				
HRC Ruhr	0.0253	0.0476	0.1133*	-0.0176	0.0942	1			
HRC CRU	-0.0386	0.0349	0.0467	0.0003	0.0571	0.0727	1		
HRC Platts	0.0266	0.0666	0.1429*	-0.0388	0.0633	0.0427	0.1072*	1	
Rebar Platts	0.1367*	0.0292	0.0213	0.1095*	0.0979	-0.0128	0.0423	0.0315	1

In Panel A each series is the logarithm of the commodity price. In Panel B each series is the first difference of the logarithm of the price. The 5% critical value is calculated as $1.96/T^{0.5}$, where T is the number of observations. Note that individual cross-correlations are calculated using all the available data points of each pair of commodities. For instance, for the Iron ore pair (Platts-TSI) the sample spans from November 17, 2008 to June 14, 2011 resulting 663 daily obs. for each series, and a 5% critical value of 0.076 (the individual cross-correlation exceeding 0.076 will be significantly positive); for the Scrap pair (US-EU) the sample is from December 1, 2010 to June 14, 2011 resulting 138 daily obs. for each series, and a 5% critical value of 0.167 (the individual cross-correlation exceeding 0.167 will be significant);Significance is denoted by an asterisk (*).

Overall, we find that correlations are statistically significant and positive only for prices and not for price changes. This implies that the long run co-movement is relatively strong and there is evidence of a common trend that drives these markets. On the other hand, the low or even negative correlation for price changes indicate that short-run dynamics (returns) are independent. This can be attributed to the fact that, in the short-term, self-governing high volatility periods make spot prices to diverge. The implications for a portfolio of steel products are far-reaching since any diversification effects from holding that portfolio are not clear-cut. In addition, divergence between prices in the short-run means that managing risk in the short-run may be riskier as the basis risk between the different benchmarks is going to be higher.

Table 4: Average Rolling Correlation of HRC CRU with commodities

	Based on 20Day Correlation		*Based on 40Day Correlation*		*Based on 60Day Correlation*		*Whole Sample*
	$Mean(\rho_t)$	$Median(\rho_t)$	$Mean(\rho_t)$	$Median(\rho_t)$	$Mean(\rho_t)$	$Median(\rho_t)$	
Panel A: Correlation of Log-Prices							
Ironore (Platts)	0.085*	0.282	0.146*	0.499	0.198*	0.542	0.742*
Ironore (TSI)	0.078*	0.182	0.141*	0.465	0.192*	0.543	0.730*
Scrap (US)	0.212*	0.394	0.393*	0.564	0.392*	0.582	0.816*
Billet (LME)	0.097*	0.200	0.122*	0.161	0.158*	0.229	0.708*
HCC Medium (Platts)	0.308*	0.530	0.463*	0.722	0.463*	0.723	0.906*
HRC (Ruhr)	0.403*	0.632	0.536*	0.755	0.538*	0.775	0.639*
HRC (Platts)	0.585*	0.733	0.806*	0.863	0.806*	0.864	0.983*
Rebar (Platts)	0.174*	0.418	0.278*	0.470	0.276*	0.493	0.761*
Panel B: Correlation of Volatilities (RiskMetrics)							
Ironore (Platts)	0.048*	0.032	-0.032	-0.129	-0.018	-0.074	-0.476
Ironore (TSI)	0.034	-0.013	-0.114	-0.167	-0.091	-0.125	-0.569
Scrap (US)	0.192*	0.193	0.197*	0.119	0.200*	0.106	-0.255
Billet (LME)	0.180*	0.173	0.120*	0.125	0.146*	0.161	-0.176
HCC Medium (Platts)	0.039	-0.007	0.132*	0.143	0.133*	0.144	0.435*
HRC (Ruhr)	0.026	-0.017	0.109*	0.098	0.130*	0.129	-0.171
HRC (Platts)	0.106*	0.056	0.154*	0.196	0.153*	0.195	0.544*
Rebar (Platts)	0.092*	0.084	0.086*	0.078	0.125*	0.108	0.020

In Panel A (Panel B), $Mean(\rho_t)$ is the average time varying correlation coefficient between the log-price (conditional volatility) of HRC CRU and the corresponding commodity log-price (conditional volatility); * indicates significance at the 5 percent level (the null hypothesis is that the average time-varying correlation is positive). $Median(\rho_t)$ is the median time varying correlation coefficient between the log-price (conditional volatility) of HRC CRU and the corresponding commodity log-price (conditional volatility).

To provide a more comprehensive overview into the behaviour of correlation across time, rolling conditional correlations are estimated based on a 20-, 40 and 60 day windows. The 20-day rolling correlations represent a relatively fast changing estimate (short-term view) where more recent observations are taken into account (a period of 1 month) whereas the 60-day rolling correlations represent a relatively slower changing estimate (long-term view) where more past observations are taken into account (a period of 3 months). These correlation coefficient estimates are displayed in Figure 3 for HRC Ruhr and HRC Platts (versus HRC CRU). Average and median figures are provided in Table 4, Panel A. It seems that, overall, correlations drop significantly in comparison to their corresponding unconditional estimate. (column entitled “Whole Sample” or the dashed green line in the graph). Furthermore correlations increase as we increase the estimation window; this confirms the previous finding that, in the short term, prices do not move together, however, in the long term, they present similar trends. For instance, the correlation of HRC CRU with HRC Platts is on average 58.5% in the short-term (20-day window), and 80.6% in the longer-term windows (40- and 60- days), whereas for the whole sample this figure increases to 98.3%; the medians also present a similar increasing pattern.

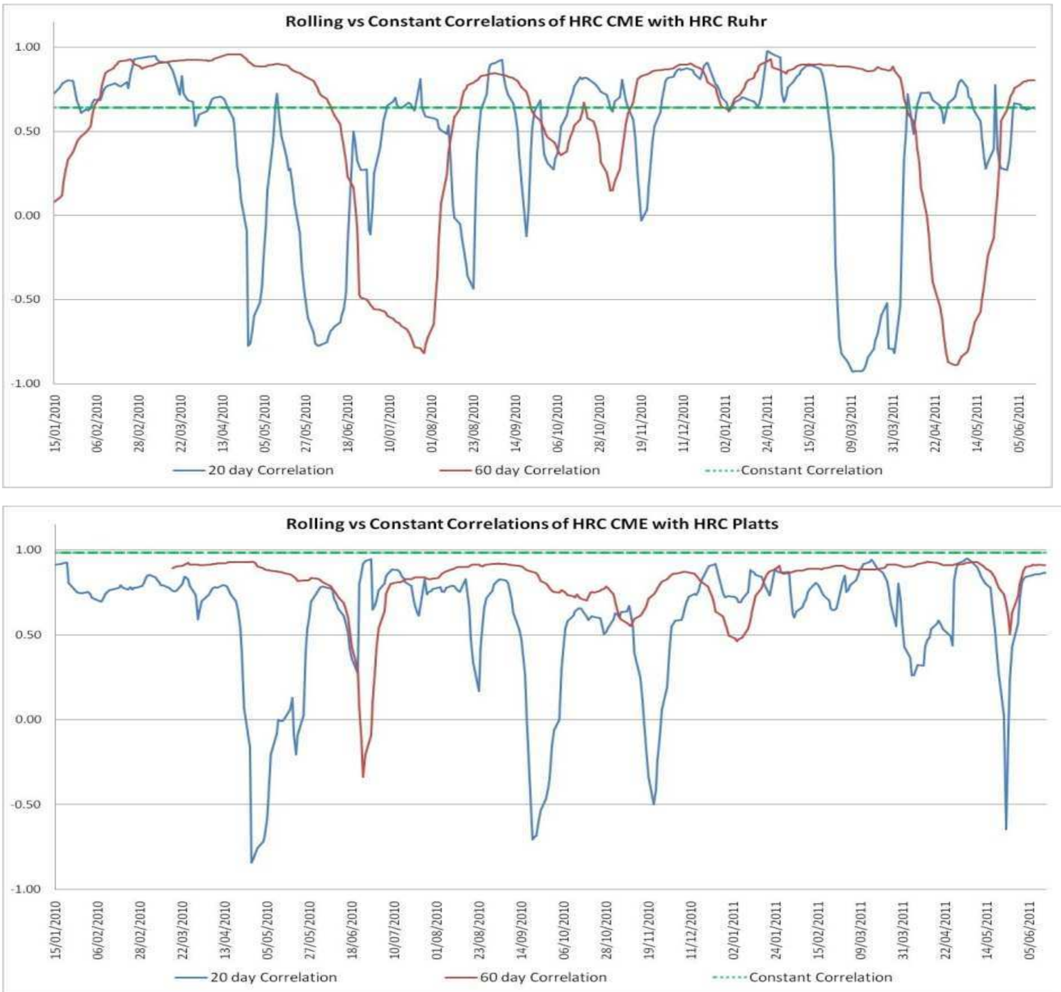


Figure 3: Rolling vs. Constant Correlation of HRC CRU with HRC Ruhr (top) and HRC Platts (bottom)

Co-movements in volatility influence the distribution of portfolio returns, and therefore play a key role in risk management as well as derivative pricing. Joint movements in volatility also help our understanding of the markets on issues such as contagion and the transmission of shocks. While each of the volatility series was assumed to evolve independently of the HRC CRU, a simple measure to examine volatility linkages across the studied commodities is the correlation between the estimated volatilities of two commodities. This is presented in Table 4, Panel B. Overall, the volatilities of the steel markets were not found to be correlated. In fact, apart from the Platts HRC and HCC Medium Vol., correlation is on average negative. For instance, the correlation of the volatility of Iron ore (Platts) returns was -47.6% over the entire sample; the 20- day rolling correlation produces an average value of almost 5% (but significantly positive at the 5% level), however, as we increase the window to 40 or 60 days, this figure becomes negative.

Finally, we use principal component analysis and examine whether the prices or returns of the steel related commodities can be explained by common factors. As the correlation analysis has indicated, returns correlation is low and price correlation is high. Hence, we should also expect that there are no common factors explaining the returns structure of the commodities; on the other hand, it should also provide support that the price structure of the steel related commodities can be explained by a few common factors. Indeed, the results of the PCA (Table 5) show that in order to explain 95% of the variation in the returns we would need 8 principal components, out of a possible maximum of 9, whereas in the case of prices, the results show that the first three principal components of commodity prices can explain up to 94% in price variation.

Table 5: Explanatory power of principal components

Principal Component	*Variation Explained*	*Cumulative Variation Explained*
Prices		
1	0.73	0.73
2	0.17	0.90
3	0.05	0.94
4	0.03	0.97
5	0.01	0.98
6	0.01	0.99
7	0.01	1.00
8	0.00	1.00
9	0.00	1.00
Returns		
1	0.19	0.19
2	0.13	0.32
3	0.13	0.45
4	0.12	0.57
5	0.10	0.67
6	0.10	0.77
7	0.09	0.86
8	0.09	0.95
9	0.05	1.00

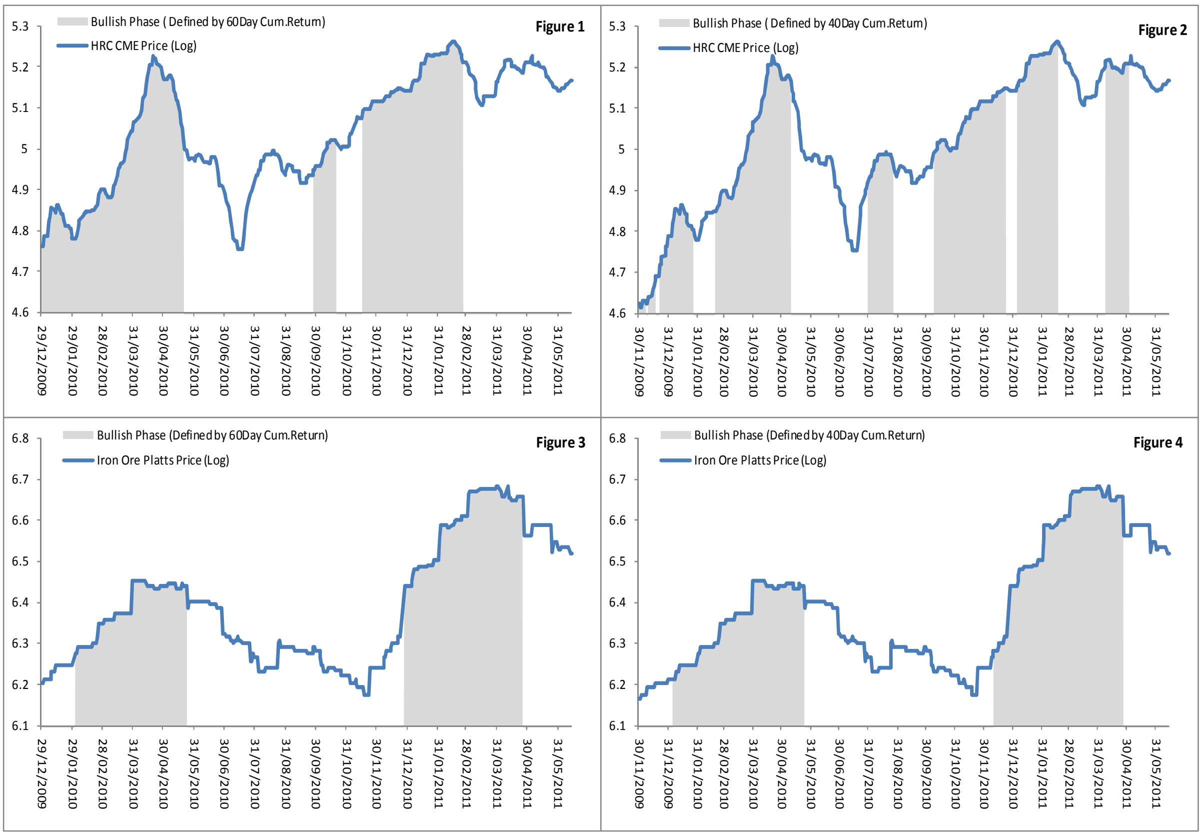
4. Synchronization of phases

In this section we use a measure of co-movement of time series called concordance statistic (Harding and Pagan, 2002). Concordance measures the extent to which the cycles/phases of two series are synchronized. For our purposes it is employed to calculate the proportion of time that the prices of two commodities are concurrently in the same phase (i.e. bullish or bearish period). Furthermore, concordance may represent a way to summarise information on the clustering of turning points, i.e. whether bullish phases for different commodities turn into bearish phases at the same time.

To use the concordance statistic, we first need to identify the bull-bear phases for the different commodities. While it is easy to say what a bullish or bearish market is, there is no formal definition in the literature. One general definition would describe a bullish (bearish) commodity market as a period of general rising (falling) prices. For our purposes we define bullish and bearish phases in 3 ways by employing the 20, 40, and 60 days cumulative return[2]:

$$CumR_t^z \geq \frac{1}{N}\sum_{t=1}^{N} CumR_t$$

where, $CumR_t^z$ is the z days cumulative return on day t . For example, when the 20 days cumulative return on day t for commodity(x_i) is greater than or equal to the average cumulative return of the commodity(x_i), then the phase is defined as bullish; otherwise bearish. For illustration purposes Figures 1-4 show the bullish phases for HRC CRU and Iron Ore (Platts) commodities when the phases are defined by the 60 and 40 days cumulative return.



[2] We are constrained when defining bullish-bearish phases due to the fact that observations are not sufficient – for all price series – to run an algorithm such as the Bry-Boschan (1971).

Next, let there be two commodities (x_i, x_j) and define two binary variables $S_{i,t}$ and $S_{j,t}$. When commodity x_i is in a bullish phase, $S_{i,t} = 1$, otherwise $S_{i,t} = 0$; similarly, when commodity x_j is in a bullish phase, $S_{j,t} = 1$, otherwise $S_{j,t} = 0$. Then following Harding and Pagan (2002), the degree of concordance of the two commodities is defined as:

$$C_{ij=}T^{-1}\left[\sum_{t=1}^{T}(S_{i,t}S_{j,t}) + (1 - S_{i,t})(1 - S_{j,t})\right]$$

where, T is the sample size.

The concordance index $C_{i,j}$ measures the proportion of time that the two commodities are in the same phase, with a $C_{i,j}$ of unity implying that the two commodities are in the same phase 100 percent of the time. To test whether the concordance index is statistically significant we follow Harding and Pagan (2006), who suggest using the correlation coefficient ρ_S between $S_{i,t}$ and $S_{j,t}$ to test for no concordance[3]. The correlation coefficient ρ_S can be obtained from the regression:

$$\frac{S_{i.t}}{\sigma_{S_i}\sigma_{S_j}} = \alpha + \rho_S\frac{S_{j.t}}{\sigma_{S_i}\sigma_{S_j}} + \varepsilon_t$$

where, σ_{S_i} and σ_{S_j} are the estimated standard deviations of $S_{i,t}$ and $S_{j,t}$, respectively. The t-statistic[4] associated with ρ_S can be used to evaluate the statistical significance of the null hypothesis of no concordance between the two commodities.

Table 5: Concordance of HRC CRU with commodities

	Phase based on 20Day Cumulative Returns		***Phase based on 40Day Cumulative Returns***		***Phase based on 60Day Cumulative Returns***	
	$C_{i,j}$	ρ_s	$C_{i,j}$	ρ_s	$C_{i,j}$	ρ_s
Ironore (Platts)	0.592	0.186*	0.592	0.185*	0.698	0.400***
Ironore (TSI)	0.542	0.083	0.584	0.168	0.690	0.384***
Scrap (US)	0.703	0.407***	0.469	-0.062	0.796	0.587***
Billet (LME)	0.561	0.122	0.481	-0.038	0.653	0.303***
HCC Medium (Platts)	0.799	0.582***	0.637	0.236*	0.735	0.452***
HRC (Ruhr)	0.808	0.616***	0.723	0.448***	0.809	0.615***
HRC (Platts)	0.938	0.877***	0.838	0.682***	1.000	1.000***
Rebar (Platts)	0.688	0.381***	0.479	-0.044	0.653	0.321***

$C_{i,j}$ is the concordance index between HRC CRU and the corresponding commodity; $\rho_s$is the correlation coefficient between the HRC CRU phase and the phase of the corresponding commodity; standard errors are HAC; ***,**,* indicates significance at the 1, 5, and 10 percent levels, respectively.

[3] The null hypothesis of no concordance between commodities x_i and x_j corresponds to a correlation coefficient of zero.

[4] To get the correct t-statistic for ρ_s it is necessary to use heteroskedastic and autocorrelation consistent (HAC) standard errors (Harding and Pagan, 2006).

Table 6 presents the concordance index $C_{i,j}$, which allows us to examine if the price of HRC CRU and the price of the rest of the commodities move together. Two interesting results can be identified: a) when the bullish/bearish phase is defined by the 60 day cumulative return, the null hypothesis of no concordance in the bilateral relationship of HRC CRU and the rest of the commodities is rejected for any of the pairs; whereas, when the bullish/bearish phase is determined according to the 40 day cumulative return, the null of no concordance is not rejected in some pairs; 2) the proportion of time that the prices of HRC CRU and another commodity are concurrently in the same phase is greater when a phase is defined according to the 60 day cumulative return.

It seems that during short phases, it is difficult for commodities to be in the same phase. This is evident by the statistically insignificant concordance indices during short-time phases; and the fact that during long phases (defined by the 60 day cumulative return) concordance is higher and statistically significant. Furthermore, HRC CRU appears to have the highest concordance with HRC (Ruhr) and HRC (Platts), a logical result since we are dealing with the same commodity but different price reference source. In respect to the rest of the HRC CRU commodity pairs, we can observe much lower concordance during short phases and only the pairs of HRC CRU with HCC Medium (Platts) and Iron Ore (Platts) being statistically significant.

Overall, concordance statistics for short and long phases give contradictory results leading to the conclusion that, although commodities may move together through longer cycles, the co-movement relationship may break down during shorter cycles.

5. Conclusion

The aim of this report was to identify whether there is variation in the correlation between the various steel products and whether this relationship changes under different trading horizons. The motivation for investigating this issues stems from the fact that although in the long-run commodity prices reflect a common trend driven by the conditions of the World economy, over shorter periods prices may exhibit greater independence in their behaviour. This is an important issue for market participants as it implies that hedging policies may be less effective over short periods of time due to the higher basis risk.

To identify these issues we investigate the correlation between the various steel products and the raw materials used in their production process. The results indicate that whereas price correlation is high, returns correlation for all the commodity pairs is generally low. As a result, we could argue that in the long term, same steel commodities tend to move together, however, over shorter periods of time, co-movement between steel related commodities is substantially lower.

The implications of these findings are as follows. Basis Risk can be quite high for hedging short-term positions. In the absence of specialised steel futures contracts, hedging against price fluctuations using existing contracts involves a cross-hedge, resulting in a critical disadvantage: reduced hedging effectiveness. The fact that - in the short term - there seems to be a certain degree of independence, implies that the industry's risk factors affect steel-related commodities in a non-uniform way and this in turn highlights the need for individual financial solutions i.e. more products, adequate to cover the needs of all parts of the supply chain. Basis risk, arising from differences in the derivative contract written and the actual underlying asset could prove disastrous in hedging due to fragile correlation structure. The steeper the basis risk, the larger the disincentive to hedge. In other words specialist hedging tools may be required to hedge short-term positions.

Even for longer-term positions, basis risk can also be high due to the short-term fluctuations in prices. There is evidence that wide variations in steel price differentials are common and a single unified price cannot serve the industry accurately. Even if two commodities move in proximity to one another, extreme short term variations can be a very challenging task to deal with. In fact, large basis risk can be equally problematic to unhedged positions (or even worse, since it falsely creates a deceptive sense of security). Ignoring the stochastic behaviour of the correlation of steel prices and, most importantly, the cash flow requirements to support potential day-to-day losses of a hedging scheme for long term positions, can lead to a debacle. The risk matrix function of the corporation contains many risks apart from price risk such as basis, liquidity and credit risk.

Finally, the rationale for the existence of derivative markets is to facilitate price discovery and offer the means to price and hedge risk. After the development of organised exchanges, derivatives products expanded giving easy access to commodities. They increasingly gained importance, motivating the entry of new financial players. However the steel industry is still on its infancy regarding that matter. In markets characterised with uncertainty and risk, price risk exposure can be and should be managed and controlled. In search for appropriate futures contracts it seems that the correlations of products in the industry is not sufficiently strong and - with the exception of some financial institutions, offering OTC derivatives products such as swaps and options- for many products there is no tradable contract. Steel markets, have become increasingly volatile; fat-tails and volatility clusters are a new feature in this market illustrating the importance of risk management in the industry. As a result, the market surely will benefit from new financial products that will assist participants to mitigate price risk across the supply chain.

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