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Herding, anti-herding behaviour in metal commodities futures: a novel portfolio-based approach

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The purpose of this article is twofold. Motivated by the heated debate on the financialization of commodities, we examine the existence of herding behaviour in metal commodities futures. In order to identify any time-dependent properties reflected in time-varying parameters, we employ the overlapping rolling window regression technique. The empirical evidence confirms a time-varying anti-herding behaviour before the global financial crisis and the absence of herding or anti-herding behaviour during the crisis. Next we attempt to formally establish the link between the documented anti-herding behaviour and portfolio management with the use of dynamic conditional correlations via the DCC-GARCH family multivariate modelling. After specifying the correlations, an in-sample recursive dynamic Markowitz portfolio is constructed and monitored. By doing so, we attribute the anti-herding behaviour to different portfolio positioning and rebalancing. On the other hand, in the absence of herding or anti-herding behaviour, we document a shift in the correlations and covariances of the commodity futures especially during the crisis, resulting in a decrease of the portfolio weights together with a substantial cash flow towards the risk-free asset.

Keywords: metal commodities; herding and anti-herding behaviour; cross-sectional absolute dispersion; rolling window regression; dynamic conditional correlations

JEL Classification: C22; C32; G12; G10

I. Introduction

This article explores the existence of herding behaviour in metal commodities market and contributes to the discussion of commodities markets financialization. The term financialization refers to the changing nature of commodities markets that have become strongly integrated with traditional financial markets.

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The reasons behind this development are mainly focused on the extensive use of commodities as diversification and hedging tool by financial investors. Investing in commodities has been widely considered as an effective portfolio diversification strategy since their returns move to a great extent in an opposite direction compared to those of stocks or bonds (Gorton and Rouwenhorst, 2006). However, the financialization of commodity trading poses a sizeable threat to the traditional role of commodity markets. In particular, commodity exchanges offer at least two important functions to their participants, i.e. price discovery and protection against price risk. These two functions are distorted to the degree that investors' trading actions and sometimes speculative actions result in larger price swings and push prices away from what would be determined by the forces of physical commodity supply and demand. As a result, commodity prices no longer solely convey shifts in the demand and supply of the physical product but they are sensitive to information spillovers from financial markets and to small shocks. Finally, commodity prices exhibit large variability and are most likely to experience speculative bubbles.

Although it is heavily explored, herding is still masked with an ambiguity in terms of magnitude and observed patterns. Researchers identify two broad categories of herding, namely intentional and unintentional or spurious. In the former case, investors tend to neglect their own private information and intentionally imitate the actions of the others assuming that they possess superior information, whereas in the latter case unintentional herding refers to market-wide homogeneous reaction to readily available information and signals (see *inter alia* Bikhchandani and Sharma, 2001). However, herding does not always constitute an irrational investment behaviour. For example, as Bikhchandani and Sharma (2001) point out, a rise in interest rates could lead investors to reduce their portfolio equity exposure since stocks have become less attractive compared to fixed-income securities. This situation is described as a fundamentally driven spurious herding behaviour.

Herding is a very interesting phenomenon to explore that entails serious implications for investors and market regulators. Additionally, in periods of market turbulence, herding behaviour may lead to inefficiency, cause excessive volatility, enhance financial fragility and generally disrupt the productive flow of funds within the financial system through irrational pricing. Gathering on the same side of the market can also intensify the co-movement among asset returns, and hence cast doubt on the benefit of portfolio diversification (Chang *et al.*, 2000; Baur, 2006; Chiang and Zheng, 2010; Morelli, 2010).

Literature explores the existence of herding behaviour by monitoring the shifts of asset returns dispersion in response to market movements. The idea behind this test lies in the argument put forward by Christie and Huang (1995), who argued that herding reveals itself as a market-wide phenomenon causing a common response of asset prices irrespective of available information. Therefore, Christie and Huang (1995) pointed out that whenever cross-sectional dispersion in individual stock returns contracts herding is present. A series of studies have employed the above measures in order to explore herding effects in the US market (Christie and Huang, 1995) and in international markets as well. In particular, Chiang *et al.* (2010), Demirer and Kutan (2006),and Tan *et al.* (2008) investigated the existence of herding effects in the Chinese stock markets, whereas Chiang and Zheng (2010) examined a large sample of 18 global markets. Demirer *et al.* (2010) has examined herding behaviour in Taiwanese stock market. Along the same lines, Economou *et al.* (2011) provided evidence for four south European markets and Philippas *et al.* (2013) investigated the existence of herding effects in the US Real Estate Investment Trust market. In a related study, Gleason *et al.* (2004) explored herding in the US market by employing data on nine sector S&P 500 Exchange Traded Funds listed on the American Stock Exchange. There has been a number of studies (Christie and Huang, 1995; Chiang *et al.*, 2010; Economou *et al.*, 2011; testing for herding with an external market; Gleason *et al.*, 2004; Goodfellow *et al.*, 2009; for Polish individual investors; Henker *et al.*, 2006) reporting instances of excessively high cross-sectional return dispersion, which was termed by Gębka and Wohar (2013) as 'negative herding'. More recently, Balcilar *et al.* (2014), for a sample of Gulf Arab stock markets, documented significant evidence of herding. Their results indicated that market volatility plays a pivotal role among a series of international factors in explaining the occurrence of herding behaviour.

As for the commodity markets, the literature on herding behaviour is scarce and inconclusive. On the one hand, Pindyck and Rotemberg (1990) suggested that correlated trading actions in the market may give rise to intense co-movements among commodity prices. Wiener (2006), in his study of speculative behaviour in the international oil market, reveals that herding might be present among specific sub-groups of investors. Similarly, Gilbert (2009) reports some evidence of short-lived excessive behaviour in nonferrous metals markets that is driven by speculators' actions. Demirer *et al.* (2015), employing data on various commodities sectors, report significant evidence of herd behaviour only for grains. However, evidence against herding in commodity markets was provided by Chunrong *et al*. (2006). Adrangi and Chatrath (2008), employing trading data, documented that investors tended to mimic each other but their actions do not constitute herding behaviour. Likewise, Boyd *et al*. (2013), relying on trading data, found that the correlated actions among hedge fund managers do not threat the well-functioning of the crude oil market. More recently, Steen and Gjolberg (2013) report no significant evidence in favour of herding, whereas in the same vein Pierdzioch *et al.* (2013), employing an extensive sample of analyst forecasts, document significant evidence of forecaster anti-herding behaviour.

As already stated, herding behaviour could induce excessive volatility in commodities markets. In fact, during the recent global financial crisis the prices of many commodities have experienced a speculative bubble, triggering a heated discussion over the significance of investors' actions in commodity markets. Moreover, metals constitute a rather important segment of tradable commodities for both developed economies whose industries are heavily dependent on metals' imports and for developing countries as well whose revenues are closely related to metals' exports. Thus, excessive variability of metal prices could have a sizeable detrimental effect on the interests of the market participants and that is a reason for which policymakers, regulators and investors in general closely monitor the behaviour of metal prices.

Therefore, in the context of the present study we examine for the first time any herding behaviour for the US metal commodities consisting of aluminium, copper, gold, lead, nickel, platinum, silver and zinc. We report an anti-herding behaviour of the series under examination. In order to identify any changing properties and capture potential time-varying parameters, the data set is further examined employing the overlapping rolling window regression methodology. Consistent with Pierdzioch *et al.* (2013), who document evidence of anti-herding among oil and metal price forecasters, our results indicate anti-herding behaviour before and after the Global Financial Crisis (GFC) and an in-line with the market behaviour during the GFC. As an attempt to shed further light on the anti-herding behaviour, the conditional covariance matrix is calculated via DCC-GARCH multivariate modelling. Constructing a dynamic recursive in-sample Markowitz portfolio, we managed to establish a link between the anti-herding behaviour and an upward shift in the short and long positioning of the portfolio weights. At the same time, when herding is detected portfolio weights are diminishing, resulting in a cash flow towards the risk-free asset.

The remainder of the article is organized as follows. Section II outlines the data and the econometric methodology employed, whereas Section III reports the results and the relevant discussion. The concluding remarks are provided in Section IV.

II. Econometric Methodology and Data

The data

The data set under examination includes the widely accepted Standard & Poor's Goldman Sachs Commodities sub-indices that represent a reliable benchmark of investing in US metal commodities. The metals under examination are aluminium, copper, gold, lead, nickel, platinum, silver and zinc, and the daily closing values of the relevant indices were obtained from Bloomberg. We consider only weekdays and in case of holidays the previous day index closing price is considered. The data set consists of 4787 observations from Friday 6 January 1995, when the lead commodity futures were launched, to Tuesday 31 December 2013, and the return is defined as the sequential difference of the natural logarithm of the prices, $R_t = \ln(P_t/P_{t-1})$ where P_t denotes the value of the index at time t. The time series under consideration are plotted in Fig. 1.

Econometric methodology

Herding model. In order to quantify herding, a measure of dispersion is needed. There are two alternative measures of dispersion, the cross-sectional standard deviation (CSSD) used in Christie and Huang (1995),

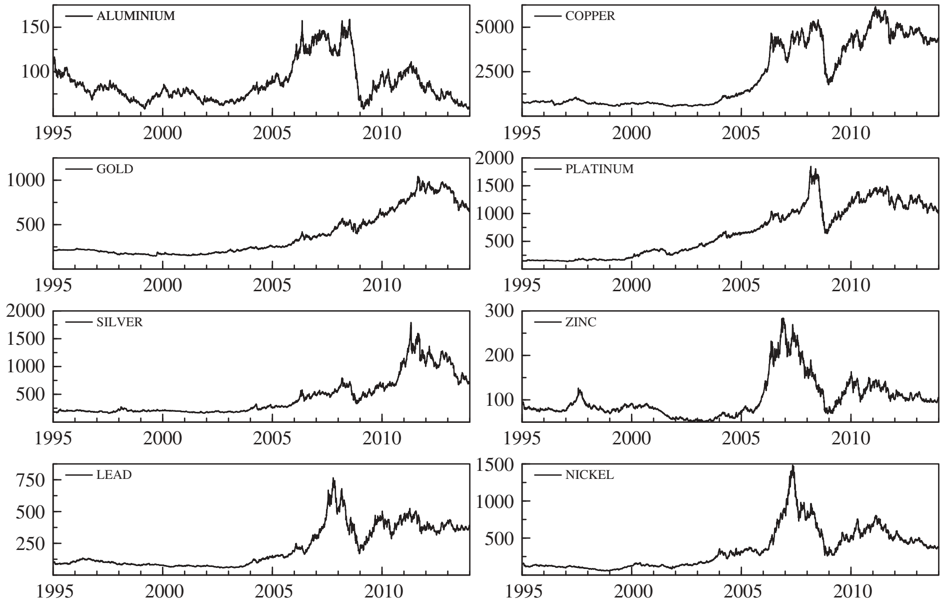

Fig. 1. Metal commodities time series

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} \left(R_{i,t} - R_{m,t}\right)^2}{N-1}} \tag{1}$$

where $R_{i,t}$ is the return of the ith asset at time t, and $R_{m,t}$ is the average of the $R_{i,t}$s.

An alternative measure of dispersion is provided by Chang *et al.* (2000), who defined the cross-sectional absolute deviation (CSAD) as

$$CSAD_t = \frac{1}{N} \sum_{i=1}^{N} \left| R_{i,t} - R_{m,t} \right| \tag{2}$$

The CSSD definition in Equation 1 calculated by squared return-deviations might be sensitive and considerably affected by the existence of outliers. Both of these dispersion models are used to identify any possible herding behaviour and provide an easily utilized approach on the market information. The approach taken by Christie and Huang (1995) was to argue that herding will be more prevalent during periods of market stress, and they consider the equation for herding identification using a dummy variable approach,

$$CSSD_t = \alpha + \beta_1 D_t^u + \beta_2 D_t^L + \varepsilon_t \tag{3}$$

where $D_t^u = 1$ ($D_t^L = 1$) if the return on the asset is for the time period t lies in the extreme upper (lower) tail of the returns distribution, and 0 otherwise, respectively. On the other hand, Chang *et al.* (2000), hereinafter called CCK, argued that the model in Equation 3 requires defining what is meant by market stress. Under normal circumstances, the conditional CAPM specifies a linear relationship between CSAD and market returns. Following this assumption, during period of market stress, if herding occurs a nonlinear relationship will also exist, and this nonlinear relationship can be modelled as

$$CSAD_t = \alpha + \gamma_1 \left| R_{m,t} \right| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{4}$$

If herding is present, then γ_2 will be significantly negative, implying that the deviation of returns contracts during periods of market stress.

We utilize the most commonly used measure of dispersion of returns in the literature, the CSAD measure defined by Equation 2, where $R_{m,t}$ is the value of an equally weighted average of the indices returns, and the CCK approach of Equation 4 to quantify for any herding phenomena. In the context of the present study, we extend the static CCK analysis considering one-sided overlapping rolling window regression of 500 days rolled by one day, to account for any dynamic properties of the herding phenomenon.

The t-cDCC multivariate approach. A useful feature of the DCC family models is that the parameters governing the variance and correlation dynamics can be estimated separately. Correlation models are based on the decomposition of the conditional covariance matrix into conditional SDs and correlations. For the specification of the covariance matrix $\mathbf{\Sigma_t}$, Engle (2002) considered the decomposition $\mathbf{\Sigma_t} = D_t R_t D_t$, where

$$D_t = \begin{pmatrix} \sqrt{h_{1,t}} & & & 0 \\ & \sqrt{h_{2,t}} & & \\ & & \ddots & \\ 0 & & & \sqrt{h_{n,t}} \end{pmatrix} \quad (5)$$

is the $n \times n$ diagonal matrix of the univariate conditional volatilities, and

$$R_{t-1} = \begin{pmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1n,t} \\ \rho_{21,t} & 1 & \cdots & \rho_{2n,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{n1,t} & \rho_{n2,t} & \cdots & 1 \end{pmatrix} \quad (6)$$

is the symmetric $R_t = (\rho_{ij,t}) = (\rho_{ji,t})$, $n \times n$ correlation matrix of the standardized residuals $\varepsilon_t = D_t^{-1} r_t \sim N(0, R_t)$. To ensure the positive definiteness of the covariant matrix H_t in all calculations steps, and the fact that in the conditional correlation matrix the absolute value of all elements has to be less or equal to one, R_t is decomposed to $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$, where Q_t is a positive definite matrix describing the structure of the dynamics, and

$$Q_t^{*-1} = \begin{pmatrix} 1/\sqrt{q_{11,t}} & & & 0 \\ & 1/\sqrt{q_{22,t}} & & \\ & & \ddots & \\ 0 & & & 1/\sqrt{q_{nn,t}} \end{pmatrix} \quad (7)$$

rescales the elements of Q_t to ensure $|q_{ij}| \leq 1$. For the correlation estimation, one typically first estimates Q as the empirical correlation matrix of the standardized residuals.

The tractability of the DCC model proposed by Engle (2002) can be substantially improved by reformulating the correlation driving process as

$$Q_t = (1 - A - B)\overline{Q} + A Q_{t-1}^{*1/2} \varepsilon_{t-1} \varepsilon_{t-1}' Q_{t-1}^{*1/2} + B Q_{t-1} \quad (8)$$

where $\overline{Q}$ is the unconditional covariance of the standardized residuals. This leads to the corrected DCC (cDCC) model (Aielli, 2008, 2013), where the conditional correlations are given by

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \; i \neq j = 1, .., n \quad (9)$$

and in this work the estimation of the parameters A and B of the cDCC model assumes a t-Student multivariate distribution to account for fat tails (t-cDCC), and variance targeting for parsimony. For the individual GARCH models in the first part of the t-cDCC procedure, we use an ARMA(1,1) model for the mean equation

$$r_t = \mu + \phi r_{t-1} + \theta \varepsilon_{t-1} + \varepsilon_t \quad (10)$$

where $\varepsilon_t = \sigma_t z_t$ and $z_t \sim N(0, 1)$, and an APARCH (1,1) model for the variance equation

$$\sigma_t^\delta = \omega + a(|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^\delta + \beta \sigma_{t-1}^\delta \quad (11)$$

while Equations 8 and 9 govern the dynamics of the second step of the t-cDCC. All calculations have been performed with the MATLAB® computing language, and the GARCH models with the OxMetrics™ (Lambert and Laurent, 2000; Laurent and Peters, 2002; Laurent, 2009) econometric software.

III. Results and Discussion

Descriptive statistics and stylized facts

The stylized facts of the time series under consideration are shown in Table 1, where we report information on the annualized mean and SD in per cent, the skewness coefficient, the kurtosis coefficient, the

Table 1. Descriptive statistics and stylized facts

	Aluminium	Copper	Gold	Platinum	Silver	Zinc	Lead	Nickel
Ann. mean (%)	−3.22	9.10	6.06	10.42	7.22	0.72	7.04	4.90
Ann. SD (%)	20.98	26.74	17.40	22.39	30.95	28.59	31.45	35.90
Skewness	−0.25	−0.17	−0.13	−0.45	−0.85	−0.24	−0.2	−0.13
Kurtosis	5.58	7.52	10.29	7.16	10.65	6.73	6.81	6.9
J.B.	1382.2	4089.5	10601	3613.7	31.1	2822.9	2922.3	3047.8
ARCH(10)	33.04*	98.23*	27.98*	61.89*	31.14*	58.82*	69.39*	52.24*
L.B.(10)	14.91	44.05*	22.09*	39.13*	15.5	27.79*	36.80*	8.94

Note: *denotes statistical significance at the 5% and 1% level.

Jarque–Bera (J.B.) normality test, the ARCH Lagrange multipliers (LM) test for heteroscedasticity and the Ljung–Box (L.B.) test for serial correlation where the number of lags for the ARCH-LM and L.B. statistic to be tested was set to 10. All series under consideration are leptokurtic with high kurtosis deviating from normality and negatively skewed, and except aluminium, for the time interval under examination, the rest of the metals have a positive mean. The J.B. test reveals the typical non-normality feature of the time series. The ARCH-LM test indicates the presence of heteroscedasticity, and the time series exhibit serial correlation according to the L.B. test statistic.

The unconditional correlations are shown in Table 2 which shows that the unconditional correlations of the metal commodity futures are relatively low, ranging from 0.205 (gold–nickel) to 0.737 (gold–silver).

Since almost all time series under examination exhibit serial correlation and heteroscedasticity, for all regressions, static or rolled, estimated with OLS method, the statistical inference is based on Newey and West (1987) SEs corrected for heteroscedasticity and serial correlation in the error terms.

Herding and anti-herding behaviour in the metals market

The CSAD and the CSAR are shown in Fig. 2 (top and bottom, respectively).

Applying the CCK model, the obtained coefficients indicate a statistically significant anti-herding behaviour,

$$\begin{aligned} CSAD_t &= 0.0065 + 0.2367\left|R_{m,t}\right| + 1.542R_{m,t}^2 \\ &\quad\;\; (52.45) \qquad (10.91) \qquad\quad (-2.78) \end{aligned} \tag{12}$$

The upwards nonlinear deviation from the CAPM linearity, evidence of anti-herding behaviour, is shown in Fig. 3.

Under these conditions, the usual null and alternative hypotheses in the herding literature have to be modified and reformulated, to test H_0 against one of the following alternative hypotheses depending on the question posed:

H_0. *In the absence of herding effects, we expect in the model* $\gamma_1 > 0$ *and* $\gamma_2 = 0$.

Table 2. Unconditional correlations

	Aluminium	Copper	Gold	Platinum	Silver	Zinc	Lead	Nickel
Aluminium	1	0.687	0.273	0.304	0.336	0.634	0.539	0.518
Copper	0.687	1	0.306	0.324	0.371	0.693	0.603	0.584
Gold	0.273	0.306	1	0.534	0.737	0.274	0.233	0.205
Platinum	0.304	0.324	0.534	1	0.538	0.299	0.274	0.233
Silver	0.336	0.371	0.737	0.538	1	0.344	0.296	0.262
Zinc	0.634	0.693	0.274	0.299	0.344	1	0.645	0.544
Lead	0.539	0.603	0.233	0.274	0.296	0.645	1	0.491
Nickel	0.518	0.584	0.205	0.233	0.262	0.544	0.491	1

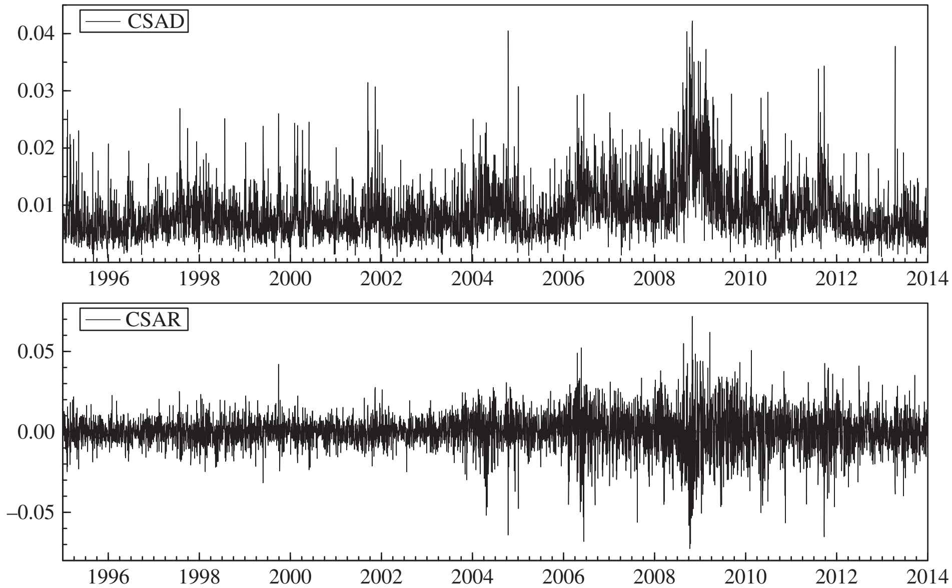

Fig. 2. CSAD (top) and CSAR (bottom) for the metal commodity futures

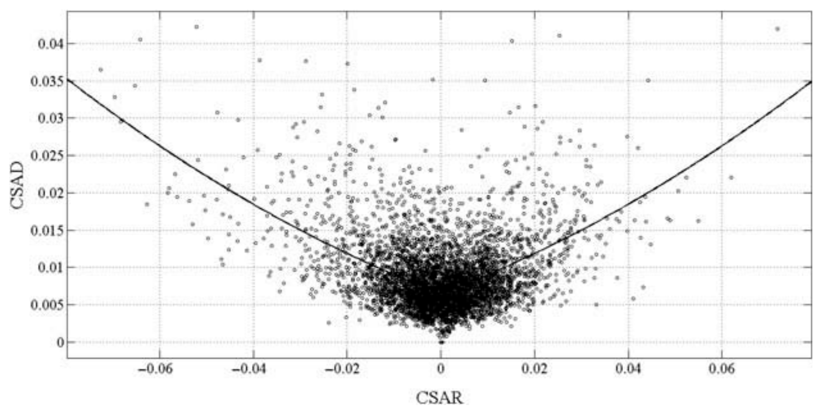

Fig. 3. CSAR–CSAD nonlinear regression indicating the anti-herding behaviour upward curving

H_1. *If herding effects are encountered, we expect* $\gamma_2 < 0$.
H_2. *If* $\gamma_2 > 0$, *anti-herding behaviour occurs*.

The asymmetric response of volatility to general market state has gained significant prominence in recent studies (Bekaert and Wu, 2000). In particular, Tan *et al.* (2008) and Chiang and Zheng (2010) confirm the existence of asymmetric herding behaviour under different market returns. In an international framework, Chiang *et al.* (2007) claimed that news exhibit asymmetric effects on stock returns and volatility. Thus, in light of the previous studies, we set off to examine whether herding behaviour presents an asymmetric reaction on days when the market is rising vis-à-vis days when the market is falling. For this purpose, Equation 2 is reformulated conditional on the following two regimes:

$$CSAD_t^+ = a^+ + \gamma_1^+ \left|R_{m,t}^+\right| + \gamma_2^+ \left(R_{m,t}^+\right)^2 = \underset{(38.4)}{0.0063} + \underset{(7.32)}{0.2228}\left|R_{m,t}^+\right| + \underset{(1.95)}{1.8269}\left(R_{m,t}^+\right)^2 \quad (13)$$

$$CSAD_t^- = a^- + \gamma_1^- \left|R_{m,t}^-\right| + \gamma_2^- \left(R_{m,t}^-\right)^2 \\ = \underset{(37.3)}{0.0066} + \underset{(8.70)}{0.2523}\left|R_{m,t}^-\right| + \underset{(1.97)}{1.2179}\left(R_{m,t}^-\right)^2 \quad (14)$$

In order to check if there is a statistically significant difference between the up and down markets, a nested model can be used:

$$CSAD_t = a + \gamma_1 \left|R_{m,t}\right| + \gamma_2^+ \left(R_{m,t}^+\right)^2 + \gamma_2^- \left(R_{m,t}^-\right)^2 \\ = \underset{(51.0)}{0.0064} + \underset{(10.5)}{0.2415}\left|R_{m,t}\right| + \underset{(1.36)}{1.0788}\left(R_{m,t}^+\right)^2 \\ + \underset{(2.85)}{1.624}\left(R_{m,t}^-\right)^2 \quad (15)$$

and testing the hypothesis H$_0$: $\gamma_2^+ - \gamma_2^- = 0$, the p-value is $p = 0.2926$, indicating no significant difference between the up and down markets.

Taking into account that standard linear regression technique summarizes the average relationship between the variables, the use of quantile regression (Koenker, 2005) provides estimates of multiple range of change from minimum to maximum response in order to provide a more accurate picture of the empirical distribution. The results of the quantile regression are shown in Table 3.

Examining the relationship between CSAD and CSAR of the metals' futures in various points of their distribution, we infer a consistent anti-herding behaviour as reflected in a positive and statistically significant γ_2 coefficient. However, a slight different picture is revealed in the upper part of the distribution (90th quantile) where no significant anti-herding is detected.

Table 3. Quantile regression results for the CCK model of Equation 4

Quantile		Coefficient	SE	t-Statistic	p-Value
q10	α	0.0033	0.0001	31.35	0
	γ_1	0.1314	0.0190	6.92	0
	γ_2	1.7831	0.6137	2.91	0.004
q20	α	0.0041	0.0001	46.21	0
	γ_1	0.1438	0.0186	7.74	0
	γ_2	1.9757	0.6007	3.29	0.001
q30	α	0.0048	0.0001	49.45	0
	γ_1	0.1546	0.0171	9.03	0
	γ_2	2.0124	0.4504	4.47	0
q40	α	0.0054	0.0001	54.67	0
	γ_1	0.1723	0.0194	8.9	0
	γ_2	2.2196	0.6780	3.27	0.001
q50	α	0.0054	0.0001	54.67	0
	γ_1	0.1723	0.0194	8.9	0
	γ_2	2.2196	0.6780	3.27	0.001
q60	α	0.0068	0.0001	56.85	0
	γ_1	0.2043	0.0250	8.18	0
	γ_2	2.4485	0.7648	3.2	0.001
q70	α	0.0075	0.0001	54.61	0
	γ_1	0.2550	0.0269	9.48	0
	γ_2	1.9811	0.8691	2.28	0.023
q80	α	0.0086	0.0002	51.64	0
	γ_1	0.2768	0.0313	8.83	0
	γ_2	2.6111	1.0669	2.45	0.014
q90	α	0.0105	0.0002	46.39	0
	γ_1	0.3591	0.0475	7.55	0
	γ_2	1.6964	1.4054	1.21	0.227

Employing the rolling window regression methodology

After examining the static CCK behaviour for the whole sample, the more robust procedure of rolling window regression methodology is employed to assess the stability of the model's parameters and capture potential time-varying parameters. The existence of herding or not in most of the studies in the literature is rarely focused on possible time-varying parameters in the model's estimations. A line of criticism rests on the static character of the traditional methods that can be found in the seminal studies of Christie and Huang (1995) and Chang *et al.* (2000). These tests fail to explicitly accommodate the dynamic nature of the observed pattern. Along these lines and following the suggestions of Hwang and Salmon (2004), current research on the field has focused on a time-varying measure of herding. A few recent studies regarding dynamic approaches are by Balcilar *et al.*, 2013, 2014), who used the regime switching approach, Gębka and Wohar (2013), using quantile regressions, and Klein (2013), who use Markov switching seemingly unrelated regressions. Since the values of the coefficients in the static model are sensitive to the selected sample period, it is necessary to carefully consider possible changes in the estimation results by changing the sample period. Although the model's parameters are assumed to be constant over time in the time-series analysis, this assumption may not be true because the

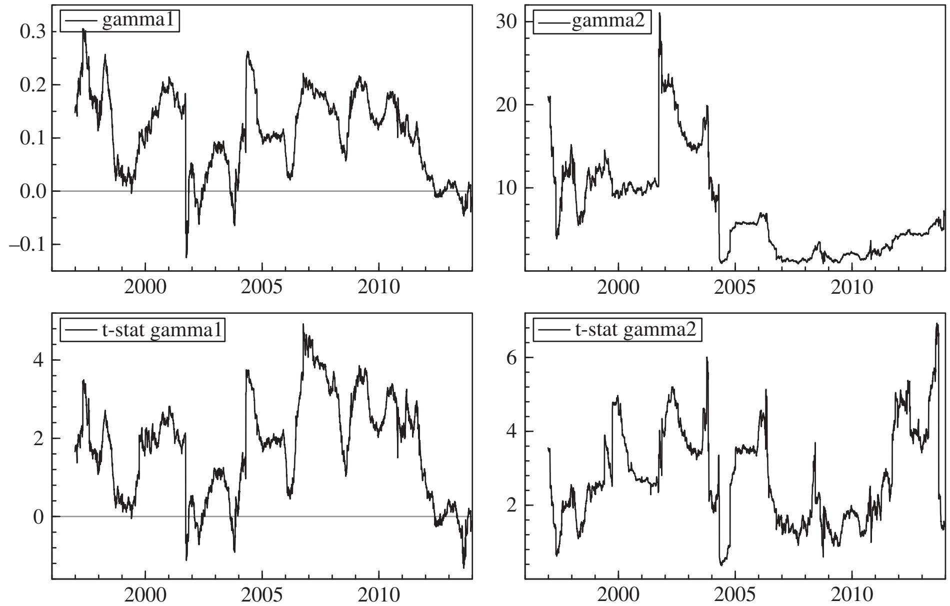

Fig. 4. Rolling window regression results showing the time evolution of the γ_1 coefficient (top, left), the γ_2 coefficient (top, right) and the *t*-statistics for the γ_1 (bottom, left) and γ_2 (bottom, right)

economic environment often changes. If a crisis occurs, then the OLS regression estimates over the full sample will estimate a relationship that holds on the average, regardless of the position and the size of the crisis, and there is no information regarding the dynamics of the system near or after a shock. If the parameters are truly constant over the entire sample, then the estimates over the rolling windows should not deviate significantly. However, if the parameters change during the period of analysis, then the rolling estimates should capture this instability. The size of the rolling window is related to the timescales of the system (response times) and the aim of the research (Su and Hwang, 2009). For systems with fast timescales, short windows can be appropriate, whereas systems with slow timescales require longer rolling windows for the metrics to be able to capture changes in the signature of the time series. Short rolling windows may lead to irregular trends in the estimates of the metrics, whereas long rolling windows smooth out the trends, and the shorter the rolling window is, the less accurate the estimate of the metric becomes. There is no golden rule for the right size of the rolling window and there is a trade-off between having a long enough window to estimate the metrics, and short enough to have a sufficient number of windows in order to be able to derive a trend.

Since we are interested in the behaviour of the data set during the last financial crisis, we use a rolling window of 500 observations which is very close to the December 2007–June 2009 peak to trough business cycle reference dates given by the National Bureau of Economic Research. The results are shown in Fig. 4 for the γ_1 coefficient (top, left), the γ_2 coefficient (top, right), the *t*-statistic of the γ_1 coefficient (bottom, left) and the *t*-statistic for the γ_2 coefficient (bottom, right). The first point in every subfigure is assigned to the end of the rolling window. The results of the rolling-estimation window analysis indicate that the anti-herding was somewhat less prevalent in 1995−2000, and that with few exceptions it became more prevalent since then. It is also evident that the γ_2 coefficient demonstrated significant fluctuations of over time but without assuming any negative value which is indicative of herding behaviour. It is worth noting that we observe significant anti-herding behaviour before and after the GFC, and a reduction of the γ_2 coefficient to a nonsignificant positive value as the window passes through the crisis time period. In general, our results are consistent with those of Pierdzioch *et al.* (2010) and Pierdzioch *et al.* (2013), who documented evidence of anti-herding among oil and metal price forecasters, respectively.

Dynamic conditional correlations of metal commodities

The results of the two steps of the multivariate GARCH model are reported in Table 4.

The AR(1) coefficient ϕ in the mean equation was positive and statistically significant for aluminium, copper, gold and zinc, while it was statistically significant and negative for nickel. The MA(1) coefficient θ was statistically significant and negative for aluminium, copper, gold and zinc, while it was statistically significant and positive for platinum, lead and nickel. The leverage coefficient γ accounting for the leverage effect was statistically significant and negative for platinum and silver. A positive leverage coefficient means negative information has stronger impact than the positive information on the price volatility. Similarly, a negative leverage coefficient means that positive information has stronger impact than the negative information on the price volatility, a case appearing often in commodities. The coefficient δ plays the role of a Box–Cox transformation on the volatility, accounting for the Taylor effect that autocorrelations of the absolute returns are often larger than autocorrelations of the squares, and it was statistically significant for all cases. The volatility persistence measure, which in the case of the APARCH model, the condition for a stationary solution to exist is $a\mathrm{E}(|z| + \gamma z)^{\delta} + \beta < 1$, was found close to one for all the metals examined which is an indication of high persistence. In general, this condition depends on the assumptions made on the innovation process, but since in the first step of the DCC model a Gaussian distribution is used, the aforementioned stationarity condition holds.

Since the results employ 28 conditional covariances, the 8 conditional variances of the metal commodity futures are shown in Fig. 5 for clarity, and pairwise co-movement can be inferred. There are several maxima of the conditional volatilities which are associated with small or large decrements of the market indices, in agreement with the maxima of the CSAD measure shown in Fig. 2 (top).

There is evidence for different behaviour of the volatility of the metals during the Asian/Russian crisis (11/1997–10/1998), the dotcom bubble (03/2000–09/2002), the 2006 rise of the metals' future prices and in the period after the GFC, while there is a co-movement of the volatilities during the GFC. The pairwise correlations of the metal commodity futures with the CSAR are shown in Fig. 6.

We observe increase of the correlations after the 2006 rise of the metals' future prices which start to decouple again after the GFC. The majority view among economists and market commentators is that high prices for oil and nonferrous metals in 2006–2008 were driven primarily by rapid demand growth in China and other parts of Asia, in the context of more modest growth in oil supply. If correlation between the future returns is high, a loss in an asset is likely to be accompanied by a loss in other assets as well. Diversifications benefits are greater when the correlation between asset returns is low. On the other hand,

Table 4. Multivariate ARMA(1,1)–APARCH(1,1) model

Variable	$\mu X10^4$	φ	θ	$\omega\ X10^4$	α	β	γ	δ	*Pers.*	*Log-likelihood*
Panel A: univariate GARCH models										
Aluminium	−1.790	0.809*	−0.822*	0.013	0.039*	0.955*	−0.033	1.976*	0.9932	14269.5
Copper	2.100	0.470*	−0.481*	0.027	0.052*	0.940*	0.087	1.948*	0.9920	13414.6
Gold	1.170	0.871*	−0.880*	0.021	0.054*	0.954*	−0.182	1.565*	1.0025	15447.2
Platinum	4.430*	−0.180	0.233*	0.167	0.071*	0.935*	−0.125*	1.438*	0.9948	14156.7
Silver	2.850	−0.187	0.170	0.143	0.054*	0.953*	−0.231*	1.445*	0.9998	12681.9
Zinc	−0.670	0.730*	−0.750*	0.093	0.041*	0.964*	−0.143	1.400*	0.9986	13233.4
Lead	1.110	−0.142	0.202*	0.025	0.035*	0.964*	−0.111	1.791*	0.9974	12662.9
Nickel	0.970	−0.761*	0.765*	0.052	0.040*	0.950*	−0.002	1.984*	0.9899	11727.0
Panel B: multivariate GARCH model										
α	0.029*									
B	0.966*									
Dof	8.347*									
Log-likelihood	159651									

Note: *denotes statistical significance at the 5% and 1% level.

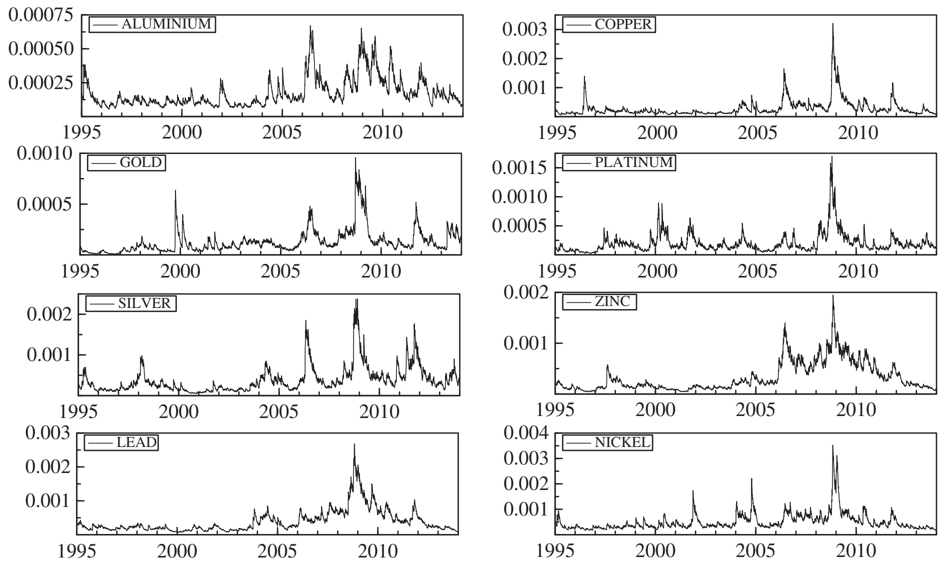

Fig. 5. Conditional volatilities of the metal commodity futures

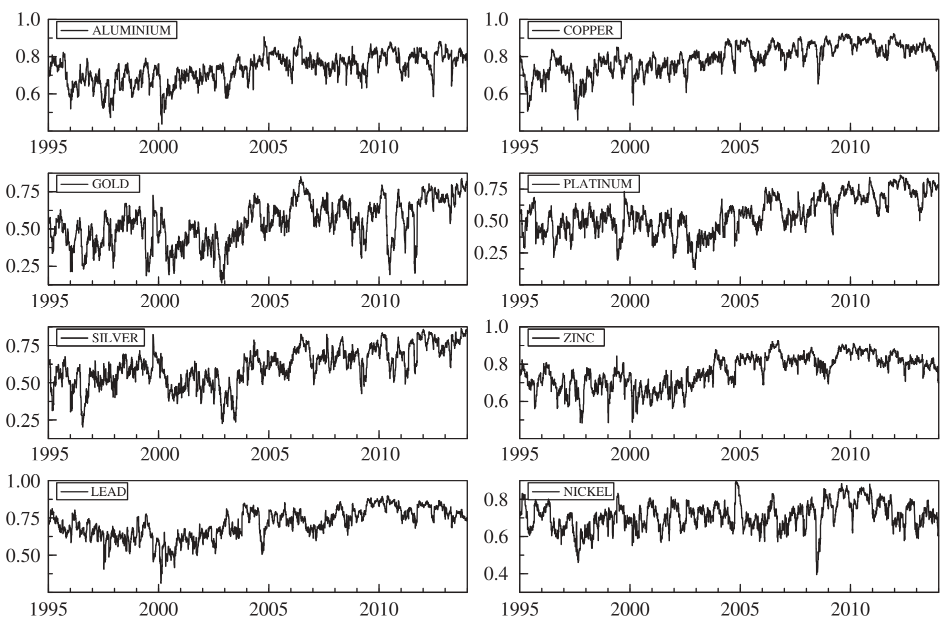

Fig. 6. Conditional pairwise correlations of the metal commodities with the CSAR measure

the identification of significantly increased correlation of asset returns denotes co-movement, while any continuous high correlation suggests strong linkages between the two assets. Having obtained the trailing covariance matrix $\mathbf{\Sigma}$ for every day from the t-cDCC model, we construct an in-sample recursive dynamic Markowitz portfolio and calculate its return μ using the expressions $\mathbf{w} = \mathbf{\Sigma}^{-1}\mathbf{r}$ and $\mu = \mathbf{wr}$, where $\mathbf{r}$ is the vector of the metals' future returns. This is equivalent to an unconstrained Markowitz portfolio with a risk-free asset of zero return and an implied coefficient of risk aversion of one. The concept of a budget constraint is used to limit the degree of total market exposure assumed by an investor, by requiring that the total value of the portfolio equals the available wealth. The unconstrained case implies that the investor may arbitrarily borrow additional funds in order to leverage the effective realized returns.

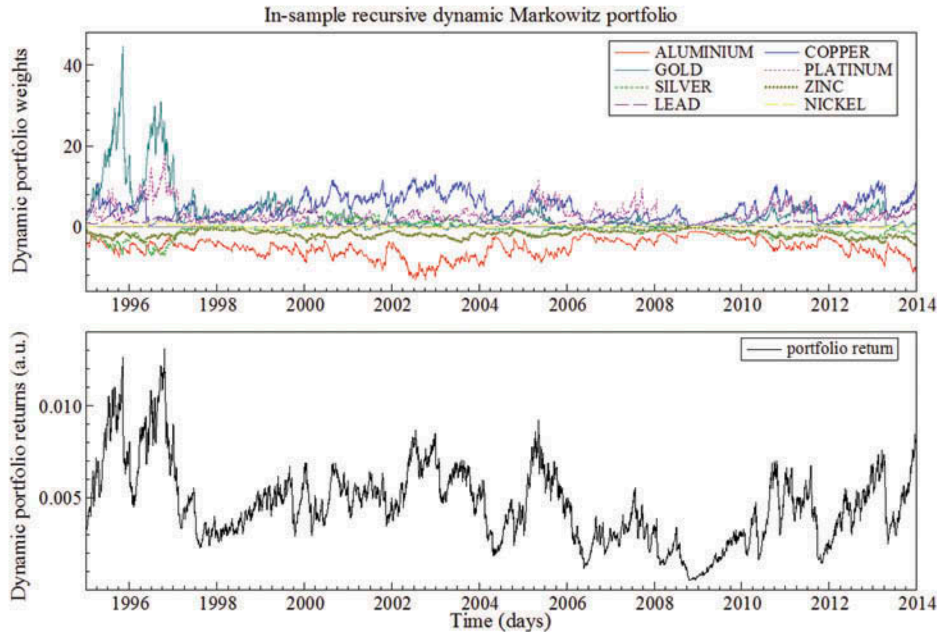

Fig. 7. In-sample recursive dynamic unconstrained Markowitz portfolios showing the portfolio weights (top) and the portfolio returns (bottom)

The optimal mean-variance recursive dynamic weights and the associated portfolio return are plotted in Fig. 7 (top and bottom, respectively).

In order to explain the limited number of static instances of anti-herding behaviour, Gebka and Wohar (2013) provide three different behavioural-based explanations: localized herding, excessive 'flight to quality' and overconfidence. Starting with the first term, localized herding is observed every time a subgroup of investors increases or decreases simultaneously its position into a subset of assets/markets. As a result, the prices of the subset of assets that investors prefer (reject) will register an increase (decrease). This could lead to increased CSAR and CSAD measures across the entire portfolio studied as the sum of the two subsets. The second term known as 'flight to quality' refers to portfolio rebalancing which is more likely to occur during periods of market turbulence and uncertainty. Under these circumstances, investors' funds flow from the riskier positions/markets into the more secure ones as an attempt to minimize potential losses.

If this safety-driven investment strategy exceeds the limits of a single market, it could get universal dimensions and trigger an adverse price movements for risky versus safe markets. A higher dispersion of returns would be again a natural development. At this point, it should be emphasized that the tendency of investors to favour domestic assets over foreign ones known as home bias could drive the dispersion of returns at even higher levels in times of market stress. Positive, rather than negative, γ_2 coefficient implies that returns dispersion is higher than what the CAPM equilibrium model would predict (Fig. 2). Our results are consistent with an anti-herding behaviour in times of high market volatility, which as Goodfellow *et al.* (2009) suggest could be attributed to investors' overconfidence. Simply put, investors that have recently experienced large positive returns in their portfolios are more likely to ignore market signals and place more attention on their ability to process available information and make the right investment decision. In the same vein, Noth and Weber (2003) show in an experimental study that information cascades market-wide, as opposed to localized herding, collapse if there is sufficient overconfidence in the quality of private information received by the agents. Hence, overconfidence causes an increase in heterogeneity of beliefs, trading consequently of price movements. From our point of view, a positive γ_2 coefficient in times of high market returns can be attributed to different portfolio diversification positions, different rebalancing timing and different strategies either to attribute highest returns to their portfolios, like in the case of a hedge fund, or follow a more passive approach like a pension fund.

Furthermore, any influence by decisions of domestic and international policymakers as well as by the reactions of those in other countries and international markets can lead to different portfolio diversification strategies and portfolio position rebalancing. Bringing the findings together, the three phenomena discussed in Gębka and Wohar (2013), localized herding, excessive ‘flight to quality’ and overconfidence, as a possible explanation of the anti-herding behaviour should reflect to weight rebalancing on the short and long positions of a portfolio consisting of the metal commodities.

As a first attempt to quantify these findings, a linear model of the CSAD measure of dispersion and the time-varying portfolio return μ_t^{port} is constructed in order to examine any significant dependency. The obtained coefficients and the t-statistics are in agreement with the aforementioned analysis, indicating a negative dependence,

$$\begin{array}{l} CSAD_t = 1.73351 - 28.7727\ \mu_t^{\text{port}} \\ \qquad\qquad (32.86) \qquad (-12.34) \end{array} \tag{16}$$

with an explanatory power of adjusted R^2 13.5%, a practically zero p-value of the F-statistic, and a Durbin–Watson test value $DW = 1.80$. In case there is a co-movement in the metals’ market, the correlation of the assets is increasing and the diversification benefits of the portfolio are reduced, leading to a dynamic rebalancing of the weights with a cash flow towards the risk-free asset. In case the correlations are reduced, then the diversification benefits are enhanced and there should be a cash flow from the risk-free asset to the portfolio, leading to positive γ_2 values. This is majorly observed during the GFC where the value of the γ_2 coefficient, the return of the portfolio and the weights are reduced. After the GFC, the conditional variances are reduced and the portfolio weights are increasing, depending on the long or short position.

IV. Conclusion

In this work, we have examined for the first time the dynamic herding and anti-herding behaviour of the US metal commodities consisting of aluminium, copper, gold, lead, nickel, platinum, silver and zinc. The period of analysis extends from Friday 6 January 1995, when the lead commodity futures were launched, to Tuesday 31 December 2013. The results reveal statistically significant anti-herding behaviour and the absence of herding during the recent global financial turmoil. Our results are in line with Pierdzioch *et al.* (2013), who reported evidence of anti-herding among oil and metal price forecasters, and Demirer *et al.* (2015) for all commodities sectors except for grains. Analysis of the market’s microstructure via rolling window regression indicates significant anti-herding behaviour before and after the GFC. As an attempt to reconcile the documented anti-herding behaviour with portfolio restructuring processes as outlined by Gebka and Wohar (2013), we calculate the conditional covariant matrix via DCC-GARCH multivariate modelling. Constructing a dynamic recursive in-sample Markowitz portfolio, the anti-herding behaviour is associated with the increase in the short and long positioning of the portfolio weights, while in the case of increasing correlations and covariances, the weights are diminishing, resulting in a cash flow towards the risk-free asset. Our results provide novel insights regarding behavioural patterns across alternative financial assets markets during tranquil and turbulent periods.

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