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Applications of nonferrous metal price volatility to prediction of China's stock market

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Abstract: The aim of the present work is to examine whether the price volatility of nonferrous metal futures can be used to predict the aggregate stock market returns in China. During a sample period from January of 2004 to December of 2011, empirical results show that the price volatility of basic nonferrous metals is a good predictor of value-weighted stock portfolio at various horizons in both in-sample and out-of-sample regressions. The predictive power of metal copper volatility is greater than that of aluminum. The results are robust to alternative measurements of variables and econometric approaches. After controlling several well-known macro pricing variables, the predictive power of copper volatility declines but remains statistically significant. Since the predictability exists only during our sample period, we conjecture that the stock market predictability by metal price volatility is partly driven by commodity financialization.

Key words: commodity futures; nonferrous metals; price volatility; stock return; predictability

1 Introduction

The world commodity market has witnessed a big metal price boom in the last decade. Metal prices have risen to recorded nominal highs since the turn of the millennium. According to the data from LME, among all the six Commodity Research Bureau (CRB) categories of primary commodities, metals experienced the greatest dramatic price fluctuation in the 2002−2008 commodity boom. Especially in the commodity market collapse during the financial crisis, the prices of basic metals fell 60%−75% from the peak to the bottom.

The integration of metal prices fluctuation with macroeconomic business cycles and financial market has been of recent interest. LABYS et al [1] documented that the commonality in metal prices reflects the tendency of commodity markets to respond to common business cycles and trend factors. The common factors in metal price can be related to macroeconomic influences, such as industrial production, consumer prices, interest rates, stock prices, and exchange rates. A more recent work by CHEN [2] investigated the time-serial properties of the prices of 21 metals and found that 34% of price volatility can be attributed to global macroeconomic factors over the period of 1972−2007. A large body of empirical evidence suggested that the commodity index investment was the major driver of the current spike in commodity futures, aggravating the integration of commodity market and financial market in the process of financialization [3−8].

The trade-off between risk and expected return is essential in any equilibrium theory of finance. From an aggregate perspective, as systematic risk increases, risk-averse investors require a higher risk premium to hold aggregate wealth, and the equilibrium expected return must rise. However, the questions posted are that the systematic risks are unobserved. Although the measure of stock market variance is thought to be a proxy of systematic risk, stock market volatility may itself be poor forecast of future stock market returns [9]. According to the trading data from 2004 to 2011 in the commodity markets in China, metal futures, such as copper and aluminum, attract the greatest interest of speculation and hedge trading, with its price fluctuating with sorts of macro shocks. Since commodity risk begins to be regarded as part of the macro risk source, it is intuitive to take commodity price volatility into our consideration to proxy systematic risk. Can the volatility of metal prices predict the aggregate stock market returns

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in China since the emergence of commodity financialization?

To find the answer to the question above, we collect the data from China's metal futures and stock market and examine whether there is a substantial predictive relationship between lagged metal volatility and aggregate stock market returns. For the availability of data, we choose two typical nonferrous metals, copper and aluminum, as representatives of all kinds of metals on the commodity market. In-sample and out-of-sample regression results show that the volatilities of copper and aluminum are capable of forecasting stock market return at various horizons, which is consistent with our conjecture. Additionally, the results remain stable after controlling several well-known macro-economic variables and are quantitatively similar by alternative measurement of variables. However, the predictive significance loses when we replicate our results at an earlier period from 1995 to 2003, which lends part of the predictability in our sample period to the prevailing commodity financialization.

The work contributes to the literature on metal volatility. A large amount of them study the volatility of precious metals [10−15]. A few of them [16−19] focus on the time-series property of industrial metals volatility, especially the spillover effect between commodity markets and the financial markets. COCHARN et al [19] showed that the implied volatility of the stock return plays a significant role in determining metal risk and return. In the present work, authors attempt to examine the forecasting power of metal volatility, through a standard procedure of predicting stock returns, instead of complex time-series model using high-frequency data.

2 Methodology

To analyze the predictability of metal volatility for stock market return, we run monthly long-horizon predictive regressions as follows:

$$r_{t+1,\,t+K}=a_K+b_K x_t+u_{t+1,\,t+K} \tag{1}$$

where $r_{t+1,\,t+K}$ is the continuously compounded return measured over K months in the future, and x_t is a forecasting variable known at time t. The forecasting horizons are 1, 3, 6, 9 and 12 months ahead.

The statistical inference for the slope estimates is based on both asymptotic t-statistics and empirical p-values obtained by NEWEY and WEST [20] from a Bootstrap experiment [21]. This bootstrap simulation produces an empirical distribution for the estimated predictive slopes that should represent a better approximation of the finite sample distribution of these estimates. In this simulation, the market return and the forecasting variables are simulated (10000 times) under the null of no predictability of the market return.

First, estimate the original regression Eq. (1) using ordinary least squares (OLS), save the slop estimate $\widehat{b}_k$: and assume that the predictor, x_t, follows an AR(1) process and estimate Eqs. (2) and (3)

$$r_{t+1,\,t+K}=a_K+u_{u+1,\,t+K} \tag{2}$$

$$x_{t+1}=\varphi+\phi x_t+\varepsilon_{t+1} \tag{3}$$

The time-series of OLS residuals, $\hat{u}_{t+1,t+K}$ and $\hat{\varepsilon}_{t+1}$, and the OLS estimates, $\hat{a}_K$, $\hat{\varphi}$, $\hat{\phi}$ are saved. In each replication, m=1, ⋯, 10000, the pseudo-samples for the innovations in the market return and the predictor are constructed by drawing with replacement from the two residuals:

$$\{\hat{u}^m_{t+1,\,t+K}\},\quad t=s^m_1,\, s^m_2,\, \cdots,\, s^m_T \tag{4}$$

$$\{\hat{\varepsilon}^m_{t+1}\},\, t=s^m_1,\, s^m_2,\, \ldots,\, s^m_T \tag{5}$$

The time indices $s^m_1, s^m_2, \cdots, s^m_T$, are created randomly from the original time sequence, 1, ⋯, T. The innovations in both the return and predicator have the same time sequence to account for their contemporaneous cross-correlation. For each replication, m=1, ⋯, 10000, a pseudo-sample of the market return and predictor are constructed

$$r_{t+1,\,t+K}=\hat{a}_K+\hat{u}^m_{t+1,\,t+K} \tag{6}$$

$$x^m_{t+1}=\hat{\varphi}+\hat{\phi}x^m_t+\hat{\varepsilon}^m_{t+1} \tag{7}$$

Use the artificial data rather than the original data to estimate the following equation:

$$r^m_{t+1,\,t+K}=a^m_K+b^m_K x^m_t+v^m_{t+1,\,t+K} \tag{8}$$

The initial value for $x_t(x_0)$ is picked at random from one of the observations of x_t. In result we get an empirical distribution of the regression slope estimates, $\{\hat{b}^m_K\}^{10000}_{m=1}$.

$$p(\hat{b}_K)=\mathrm{Num}\{\hat{b}^m_K\geq|\hat{b}_K|\}+\mathrm{Num}\{\hat{b}^m_K\leq-|\hat{b}_K|\} \tag{9}$$

where $\mathrm{Num}\{\hat{b}^m_K\geq|\hat{b}_K|\}$ denotes the number of bootstrapped slop estimates that are higher than the absolute of original slop estimate.

GOYAL and WELCH [22] suggested that most forecasting variables with in-sample forecasting power do not demonstrate an ability to forecast returns out-of-sample. Following CAMPBELL and WELCH [23], GOYAL and THOMPSON [22], GUO [24], RAPACH et al [25] and FERREIRA et al [26], we use R^2_{os} to test the out-of-sample predictability.

The R^2_{os} is calculated as

$$R^2_{\mathrm{OS}}=1-\frac{\sum_{t=n}^{T}(R_t-\hat{R}_t)^2}{\sum_{t=n}^{T}(R_t-\overline{R}_t)^2} \tag{10}$$