New strategies and asset classes for increased performance

New Strategies and Asset Classes for Increased Performance

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Declaration and Acknowledgements

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Abstract

This thesis explores several topics related to generating yield through new strategies and asset classes. We introduce new investment strategies based on trading Futures contracts in the copper market, thus making important contributions to the literature. We expand the opportunity set of asset strategies by revisiting the concept of transaction time, shed some light on the significance of the forward curve for fundamental as well as technical traders in the commodity market and finally show how low interest rates and capital account restrictions encourage commodity-inventory related asset strategies.

After an Introduction chapter, we follow in Chapter 2 upon the transaction time of Geman and Ane (1996) and the temperature of a stock as defined in Derman (2002) and extend them in two ways: the temperature is now a time-varying entity and the analysis is extended to a portfolio of stocks. We use the portfolio temperature in order to assess the cross-section of stock returns creating a long/short factor portfolio within the S&P500 IT Index based on the temperature of the stock and examine its performance on a high frequency database. We show the significance of the risk premium associated with the heat of stocks during turbulent times, focusing on a particular 3-month period in autumn 2015 that was characterized by higher equity market volatility and equity price losses.

In Chapter 3, we focus our attention on the fundamental role of inventories in explaining copper price volatility. Copper price volatility has been trading in a range until 2001 but has shown signs of heat afterwards. Using a three-factor model we derive a fundamental long-term value for copper. Second, we emphasis the significance of this fundamental long-term value by considering an agent based model approach in which mean-reversion focused fundamental investors trade with chartists who follow price trends. We show that fundamental investors take increasing positions in copper when the spot price of copper deviated from its fundamental value (i.e. the fundamental value is higher than the spot price) and chartists loose relative significance.

In Chapter 4, we expand on the role of inventories in the Theory of Storage and turn our attention to commodity inventory financing in China. In the aftermath of a copper financial scandal in a major Chinese port in 2014 and unprecedented queues in London Metal Exchange - related warehouses in the US acquired by financial institutions, the age-old concept of inventory is becoming elusive. The goal of this chapter is threefold: i) present the motivation and mechanism of the activity of commodity inventory financing in the specific case of copper in China as of 2009; ii) exhibit, through a database of Shanghai bonded warehouse volumes during the years 2008 to 2015, an estimate of the amount of copper involved in inventory financing. iii) Using Shanghai Exchange Futures and spot prices, we also show how interest rate arbitrage via commodity inventory financing has impacted the relationship of the copper forward curve to Shanghai copper inventories. We confirm the validity of the Theory of Storage in the case of the Shanghai copper market and show that adding bonded warehouse data to Shanghai copper inventories weakens the relationship of the forward curve to inventories.

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Chapter 1. Introduction

Motivation

Commodities can be classified into the major subclasses of metals, energy and agricultural. They are a major input in the production process and vital to economic growth. The price dynamics are mainly driven by supply, demand and inventories.

In the early days, the commodity was anything from precious metals to grain and rubber. The collateral should not degrade rapidly over time, nor should it be expensive to store. Copper, the world's oldest mined commodity, has this merit, being crucial in the growth of economies and storable at a reasonable cost.

Over the past 50 years the role of commodities in financial markets has changed substantially. The rise of China, the development of Commodity Futures Exchanges and rapid technological advances across the entire processing chain of commodities are just a few examples of factors contributing to the significance of commodities for the global economy.

Of particular focus has been China, partly because of its sheer size of its economy – the second largest in the world - partly because of its regulations on funding. Strong growth in China attracted vast amounts of foreign direct investments. The commodity boom in China has been unprecedented and Figure 1 provides an illustration of the extreme commodity usage caused by Chinese infrastructure projects. The economic relevance of China to the global economy has increased considerably over the past 25 years. This trend is likely to continue though the Chinese demand structure in commodities is changing as Chinese authorities aim to rebalance economic growth away from infrastructure spending towards domestic consumption.

The case of China highlights both, the fundamental demand for commodities in the traditional production process as well as the financial demand because of its capital account restrictions. The interaction in the commodity market, between domestic and foreign commodity investors as well as regulators is crucial in reconciling fundamental theories in commodity markets and appreciating the concepts highlighted in the early 20th century by Kaldor (1939) and Working (1949).

Figure 1: Chinese total cement consumption illustrated as a block covering Chicago

Source: https://www.wired.com/2014/06/how-much-cement-has-china-used/

In this thesis we highlight the application to commodities, specifically copper, beyond the traditional production process. An environment of increased globalization and integration of financial markets has resulted in unprecedented financial innovation. Commodities have been vital collateral for centuries (dating back to the 15th century). Increased financial innovation meant that the role of commodities has broadened to areas ranging from helping to generate higher returns in a low interest rate environment to circumventing capital account restrictions in order to obtain cheaper funding.

We address those applications of commodities to new asset strategies from several angels. We explain the rationale and motivation behind each strategy highlight the risks involved and also provide evidence of the risk premia that can be harvested.

Financial and technological progress resulted in new types of market participants in commodity markets. Technical traders are able to trade commodity contracts intra-day and Futures markets reflect incoming information quickly. Short-term moves are amplified by technical traders making it more difficult for fundamental traders to filter relevant information. Fundamental theories in commodity markets - we wish to highlight the Theory of Storage - have been challenged lately. This thesis will provide evidence for the robustness of this fundamental theory in an environment of rapidly changing commodity market conditions.

In this thesis we focus on three particular avenues of financial innovation. Technological progress on an unprecedented scale has meant that intra-day trading has gained significance in financial markets. We expand the concept of a temperature of a stock as in Derman (2002) in a time-varying setting and broaden it to a portfolio of stocks. We show that a systematic strategy of trading "high temperature" stocks against low temperature stocks in the transaction time introduced by Geman and Ane (1996) is able to generate a positive risk premium. In Chapter 3 we expand on the notion of systematic or technical trading and include fundamental traders in an agent-based model. We show that the forward curve contains valuable information about the long-term fundamental value of commodity prices. Systematic as well as fundamental traders are able to benefit from this information in their trading strategies. Copper spot price volatility has shown signs of a structural break after 2001 supported by increased demand from China as well as increased financial speculation. Increased financial speculation is partly reflected in the Temperature concept introduced in Chapter 2 and crucial in understanding shorter-term copper price moves. However the information contained in the forward curve remains valid despite financial innovation adding complexity in understanding commodity inventory dynamics. We use the example of Chinese copper inventories and show how financial innovation has enabled Chinese copper dealers to circumvent capital account restrictions in order to obtain cheaper funding in China acquired with loans from US banks. This has led to artificial copper inventory. Despite the creativity around this financial innovation we show that the information about supply and demand backed out of the forward curve as defined in the Theory of Storage exhibited by Working (1949) and Brennan (1958) is robust.

Structure of the thesis

The following three chapters focus on the financial innovation in commodity markets and new strategies to harvest positive risk premia; we develop the topic sequentially. The strategies and results we provide are relevant to academics, market participants as well as regulators. Since the mid-2000s, there has been a remarkable increase in the popularity of investing in commodity markets. Investors can obtain exposure via physical assets, commodity related stocks, Exchange traded funds or derivatives like Futures and swap contracts.

Financial and technical innovation has made it possible to exploit more sophisticated trading strategies that enable isolating a specific risk premium while mitigating market risk. Consequently these trading strategies often involve derivatives, leverage and short positions. Investors as well as regulators need to be aware of the risks involved while considering the robustness of the fundamentals of physical commodity markets.

We use Futures prices as well as physical commodity prices in our research, showing the flexibility of asset strategies across different investment instruments. Buying the physical commodity involves costs and other operational considerations. Many investors prefer the liquidity of Futures markets over the spot market providing the flexibility of going short as well. We exploit the fundamental relationship between the spot and Futures markets in Chapter 3 and use the information embedded in the forward spread to derive a fundamental value for copper prices. We also show that this fundamental value keeps its relevance in the context of commodity inventory financing and new Exchanges.

We introduce trading strategies that provide positive risk premia for short-term as well as fundamental longer-term focused investors, making several important contributions to the literature. Chapter 2 is providing short-term investors with a strategy to exploit the relative trading frequency and Chapter 3 builds upon the notion of speculative excitement embedded in the temperature of commodities by considering the interaction between short-term and long-term investors in the case of the copper market. Chapter 4 provides regulators with information about the significance and dangers of commodity shadow inventory. Lastly, in Chapter 5, we present our final remarks, a summary of our main findings and potential for further research.

Contributions

The focus of Chapter 2 is twofold: follow upon the transaction time of Geman and Ane (1996) and the temperature of a stock as defined in Derman (2002) and extend them in a time-varying setting to a portfolio of stocks. We show the usefulness of the portfolio temperature in explaining the cross-section of stock returns by creating a long/short temperature factor portfolio. We provide evidence for a positive risk premium associated with the temperature of stocks.

Chapter 3 explains the importance of inventories in explaining copper spot price volatility. We use a three factor model to derive a fundamental long-term value for copper. This long-term value proxy is used as input in an agent based model comprised of technical short-term traders and longer-term fundamental traders. The model provides evidence of the relevance of the fair value to both technical as well as fundamental traders.

Chapter 4 confirms the validity of commodity inventories used in Chapter 3 by examining Chinese copper inventories and the impact of commodity inventory financing. We use a database of Shanghai copper inventories and bonded warehouses to examine the relationship between the forward curve and copper inventories. We confirm the validity of the Theory of Storage and the relevance of the forward curve in reflecting copper supply and demand despite the dramatic surge in Chinese copper bonded warehouses.

Lastly, in Chapter 5, we present our final remarks, a summary of our main findings and potential for further research.

References

Brennan, M.J, 1958, “The Supply of Storage”, *American Economic Review*, 48(1), pp 50-72.

Derman, E., 2002. “The Perception of Time, Risk and Return During Periods of Speculation”, Goldman Sachs & Co.

Geman H., and T. Ane, T., 1996. “Stochastic subordination”, *Risk*, 9, pp. 145-149.

Kaldor, Nicholas, 1939. “Speculation and Economic Stability”, *Review of Economic Studies*, 7 (1), pp. 1-27

Working, Holbrook, 1949. “The Theory of the Price of Storage”, *American Economic Review*, 39, pp. 1254-1262.

Chapter 2. The temperature of a stock – An order flow-adjusted asset pricing approach

Section 1: Introduction

We investigate the effect of speculative excitement, i.e., short-term investor behaviour influencing stock prices, by moving from calendar time to transaction time. A dimensionless time scale that counts the number of trades provides us with an alternative expression for risk and return.

After the proposal by Mandelbrot and Taylor (1967) of introducing stable processes Clark (1973) in his pioneer work exhibited that returns are normally distributed after subordination directed by the volume of transactions. Returns are driven by a subordinated Brownian motion leading to heavy-tailed distributions. This concept has been tested in a univariate framework as well as multi-variate dimension (Huth and Abergel, 2010). Since the 1980s a large body of literature has addressed the relationship between trading opportunities, volume and price behaviour (see Karpoff 1987 as an example) as the lack of normality in calendar-time stock returns (Mandelbrot, 1963, Bouchaud and Potters 2004) is due to the randomly varying time between trades (Geman and Ane, 1996 and Plerou et al., 2000). Harris (1982), Tauchen and Pitts (1983) and Schwert (1989) related trading volumes and price movements to new information. The reference to what in earlier studies was called ‘economic time’ goes back to Burns and Mitchell (1946) who analyse business cycles or in the case of Barro (1970) focus on macroeconomic variables by investigating the high inflation period of the 1920s. In 1994, Jones et al had exhibited that conditional on trades, volume did not bring any valuable information in explaining volatility as the positive volume-volatility relationship is due to the positive relationship between the number of transactions and volatility. The lack of trading has been shown to dampen volatility during the break of the Tokyo Stock Exchange shown by Ito and Lin (1992). Volume in contrast may reflect the disagreement in the market on information available (Epps and Epps 1976).

The use of the number of transactions for a stochastic time change more general than a subordinator was introduced by Geman and Ane (1996). They showed that asset prices can be represented as continuous processes in what they term 'business time'. Ane and Geman (2000) then exhibited that the cumulative number of trades, instead of the trading volume, was a better stochastic clock in order to recover normality of assets returns close to Gaussian. Several authors use this so-called business time to speed up the calendar time as market activity increases and achieve normality under a suitable rescaling transformation (Andersen et al., 2003). Velasco-Fuentes and Ng (2008) show that normality is not always obtained by conditioning on re-centered cumulative number of trades as suggested by Ane and Geman (2000) and instead use a non-linear function containing trades and volumes as stochastic clock. Huth and Abergel (2010) apply the concept of what they call 'event time' to a stochastic covariance matrix to model a time-dependent correlation as opposed to volatility testing the concept on high frequency data for the CAC 40.

The random behaviour of market activity through the arrival of new trades provides a clear explanation for the time-varying behaviour of volatility. We apply the concept of stochastic time to the relationship between risk and high frequency returns of S&P500 Information Technology stocks. We show that short-term speculation will result in the expected return of a stock being proportional to a stocks' traditional volatility multiplied by the square root of its trading frequency (i.e., number of trades) labelled as temperature of a stock. Similar to Derman (2002) we will use a modified Capital Asset Pricing Model in which we define the frequency adjusted beta for each stock. Further we show the cross-sectional pricing of the temperature of a stock by creating a long/short factor portfolio, i.e. long the stocks with a high temperature and short the stocks with a low temperature, using the S&P500 IT stock universe as a base.

The structure of the paper is as follows. Section 2 describes the general framework and related work for the approach as well as a brief fundamental rationale for the temperature of a stock. Section 3 derives the theoretical framework for the heat of a stock in a Capital asset pricing model context. Section 4 calculates the temperature of stock while Section 5 relates the concept of frequency-adjusted beta to a risk premium priced within a Capital Asset pricing framework. This is done by forming "heat" based long/short portfolios measuring the cross-sectional significance of trading opportunities as a return driver. In Section 6 we provide possible explanations for the existence of a "heat premium". A summary and concluding remarks are given in Section 7.

Section 2: General Framework

Returns are generally evaluated on a time continuous clock which is common to all market participants. However the numbers of trades, supply and demand patterns influencing the trading frequency are important as stocks are traded at discrete times. During highly speculative markets, when market sentiment is turning quickly, investors' trade horizon might become very short-term. This is likely resulting in a higher trading frequency in certain stocks. For example the hype around biotechnology companies in early 2014 resulted in a strong outperformance of the Nasdaq 100 Index compared to blue chip stocks in the S&P 500 Index. In markets like these a strong interplay between trading frequency and expected return can be observed. Technological advances made it possible to trade most of these stocks intra-day but also enable us to base our analysis on intra-day tick-by-tick data for technology shares.

It is realistic to assume that each stock has its own trading frequency or trading opportunities per calendar time. As in Derman (2002) we define the trading frequency as a linear mapping of a stocks' trading opportunities between its intrinsic time (e.g. ticks per second, or the inverse of trading opportunities) and the standard calendar time t. Derman (2002) assumes an average trading frequency of a stock and thus ignores the effects of its fluctuations.

If every stock has its own intrinsic time scale, trading opportunities per calendar time t (like the chance to perform a trade of a fixed amount per calendar time or the inverse of the time interval between trades), short-term traders are likely to care about the risk and return measured in frequency-adjusted terms rather than calendar time.

In order to highlight this concept of time change we begin by characterizing the stock price as Geometric Brownian motion where d_{τ_i} represents the marginal change in the frequency-adjusted time τ_i that measures the rate of trading opportunities per calendar time t. The symbol μ_i represents the expected return of stock I per unit of frequency adjusted return and σ_i is the stock i's volatility in intrinsic time which is similarly to the volatility in calendar time defined as the square root of the variance of stock returns over an intrinsic time interval:

$$\frac{dS_i}{S_i} = \mu_i d\tau_i + \sigma_i dW_i \tag{1}$$

Similar to standard Brownian motion we can write

$$dW_i^2 = d\tau_i \tag{2}$$

and

$$dW_i dW_j = \rho_{ij}\sqrt{d\tau_i}\sqrt{d\tau_j}$$

$$d\tau_i = v_i dt$$

$$\mu t_i = v_i \mu_i \tag{3}$$

The time based return thus represents the intrinsic time return multiplied by the number of trading opportunities while the volatility in the time dimension is adjusted by the square root of trading opportunities. In this chapter we aggregate trading opportunities by minute over the 3 months at the end of 2014. Since intrinsic time correlation π_i and calendar-time correlation ρ_i are both dimensionless they are identical.

$$\sigma t_i = \sqrt{v_i}\sigma_i \tag{4}$$

$$\pi_i = \rho_i \tag{5}$$

$$\frac{dS_i}{S_i} = \frac{\mu t_i}{v_i} d\tau_i + \frac{\sigma t_i}{\sqrt{v_i}} dW_i \tag{6}$$

The stock price in intrinsic time thus represents a trading opportunity scaled version of the original stock price process.

So far we have derived the analytical framework for the one asset case. In the next section we will widen the application to a multi-stock framework using a frequency adjusted Capital asset pricing model. We use the Standard and Poors (S&P) 500 Information Technology universe consisting of 65 stocks at the time of evaluation (end of 2014). We use three months of minute data starting at the 8th of December 2014. For simplification reasons we assume that the stocks in our universe are correlated with the overall market, in our paper proxied with the wider S&P500 index. The statistics calculated in the following sections are additionally smoothed by using a 60-minute rolling time window.

Section 3: Theoretical Framework - Heat of a single stock and extension to several stocks

We briefly highlight below the multi-stock case with S being a stock price evolving according to a geometric Brownian motion with a positive drift, the same as the market index I.

$$\frac{dS_i}{S_i} = \frac{\mu_i}{v_i} d\tau \quad + \frac{\sigma_i}{\sqrt{v_i}} dW_i \tag{7}$$

$$\frac{dI}{I} = \frac{\mu_I}{v_I} d\tau \quad + \frac{\sigma_I}{\sqrt{v_I}} dW_I \tag{8}$$

Both are correlated via the following equation:

$$dW_i = \rho_{iI}\, dW_I + \sqrt{1 - \rho_{iI}^2}\varepsilon_i \tag{9}$$

And ε_i is a random normal variable that represents the idiosyncratic risk of stock i and is uncorrelated with dW_I.

We assume we can create a market-neutral portfolio by using part of the Index exposure I to beta hedge our stock exposure S and thus derive a beta neutral version

$$\widetilde{S_i} = S_i - \Delta_i I \tag{10}$$

The evolution of this beta-neutral portfolio in intrinsic time is given by:

$$d\widetilde{S_i} = dS_i - \Delta_i dI \tag{11}$$

Substituting for S and I and combining terms:

$$= S_i(\frac{\mu_i}{v_i}d\tau \quad + \frac{\sigma_i}{\sqrt{v_i}}dW_i) - \Delta_i I(\frac{\mu_I}{v_I}d\tau \quad + \frac{\sigma_I}{\sqrt{v_I}}dW_I)$$

$$= \frac{\mu_i}{v_i}S_i d\tau \quad + \frac{\sigma_i}{\sqrt{v_i}}S_i(\rho_{iI}\, dW_I + \sqrt{1-\rho_{iI}^2}\varepsilon_i) - \Delta_i I(\frac{\mu_I}{v_I}d\tau \quad + \frac{\sigma_I}{\sqrt{v_I}}dW_I)$$

$$= (\frac{\mu_i}{v_i}S_i - \Delta_i I\,\frac{\mu_I}{v_I})d\tau \quad + (\rho_{iI}\,\frac{\sigma_i}{\sqrt{v_i}}S_i - \frac{\sigma_I}{\sqrt{v_I}}I)dW_I + \frac{\sigma_I}{\sqrt{v_I}}S_i\sqrt{1-\rho_{iI}^2}\varepsilon_i \tag{12}$$

If we choose dW_I such that the systematic part of the stock risk S is fully eliminated (perfect beta hedge)

$$\rho_{iI}\,\frac{\sigma_i}{\sqrt{v_i}}S_i - \frac{\sigma_I}{\sqrt{v_I}}I = 0 \tag{13}$$

And solving for share of Index I we need to use to hedge S, namely Δ_i, we obtain

$$\Delta_i = \frac{\rho_{iI}\,\sigma_i S_i}{\sigma_I I}\sqrt{\frac{v_I}{v_i}} = \frac{\rho_{iI}\,\sigma_i\sigma_I S_i}{\sigma_I^2 I}\sqrt{\frac{v_I}{v_i}} = \beta_{iI}\sqrt{\frac{v_I}{v_i}}\frac{S_i}{I} \tag{14}$$

which is the familiar capital asset pricing model. By substituting Δ_i into $\widetilde{S_i} = S_i - \Delta_i I$ we derive

$$\widetilde{S_i} = (1 - \beta_{iI}\sqrt{\frac{v_I}{v_i}})S_i \tag{15}$$

Using a similar process as in (7) we can see that the log change in $\widetilde{S_i}$ can be written as

$$\frac{d\widetilde{S_i}}{\widetilde{S_i}} = \frac{\widetilde{\mu_i}}{v_i}d\tau \quad + \frac{\widetilde{\sigma_i}}{\sqrt{v_i}}dW_i \tag{16}$$

where

$$\widetilde{\mu_i} = \frac{\mu_i - \beta_{iI}\mu_I\sqrt{\frac{v_i}{v_I}}}{(1 - \beta_{iI}\sqrt{\frac{v_I}{v_i}})}$$

$$\widetilde{\sigma_i} = \frac{\sigma_i\sqrt{1-\rho_{iI}^2}}{(1-\beta_{iI}\sqrt{\frac{v_I}{v_i}})} \tag{17}$$

These equations describe the stochastic intrinsic-time evolution of the market-hedged component of stock i. We know that the expected return of 2 portfolios that are both market neutral should earn the same return, namely the risk-free rate. If not, arbitrage would be possible by selling the portfolio with the lower return and investing into the portfolio with the higher return.

We thus consider another portfolio $\tilde{X}$ that evolves similar to portfolio $\tilde{S}$, namely:

$$\frac{\widetilde{dX}}{\tilde{X}} = \frac{\widetilde{\mu_x}}{v_x}d\tau \quad + \frac{\widetilde{\sigma_x}}{\sqrt{v_x}}\varepsilon_x \tag{18}$$

Since we can create portfolios of stocks $\tilde{S}$ and $\tilde{X}$ that carry the same instantaneous risk by combining them with a risk free asset, the invariance principle (namely that two portfolios with the same perceived risk should have the same expected return) demands that they carry the same expected return as stated earlier, so that $\widetilde{\mu_s} = \widetilde{\mu_x}$ and thus

$$\frac{\widetilde{\mu_s}-r}{\widetilde{\sigma_s}} = \frac{\widetilde{\mu_x}-r}{\widetilde{\sigma_x}} \tag{19}$$

Thus for any stock we conclude that the intrinsic-time Sharpe Ratio SR is equal to:

$$SR = \frac{\frac{\mu_i}{v_i} - \frac{r}{v_B}}{\frac{\sigma_i}{\sqrt{v_i}}} \tag{20}$$

Section 4: Defining the temperature of a Stock

We derived these equations in order to define the heat of a stock. We based the work on Derman (2002) and we are aiming to extend the initial concept in two directions:

- Providing a time varying version of the temperature of a stock
- Giving evidence of a cross-sectional "Heat premium

Earlier we made the statement that the heat of a stock relates the volatility (time period) to trading opportunities. We can rewrite the last equation, for simplification reasons we are assuming interest rates are zero, to the following expression:

$$\mu_s = SR\sigma_s\sqrt{v_s} \tag{21}$$

which expresses that the expected return of stock S is proportional to the product of its volatility and the square root of its trading frequency where

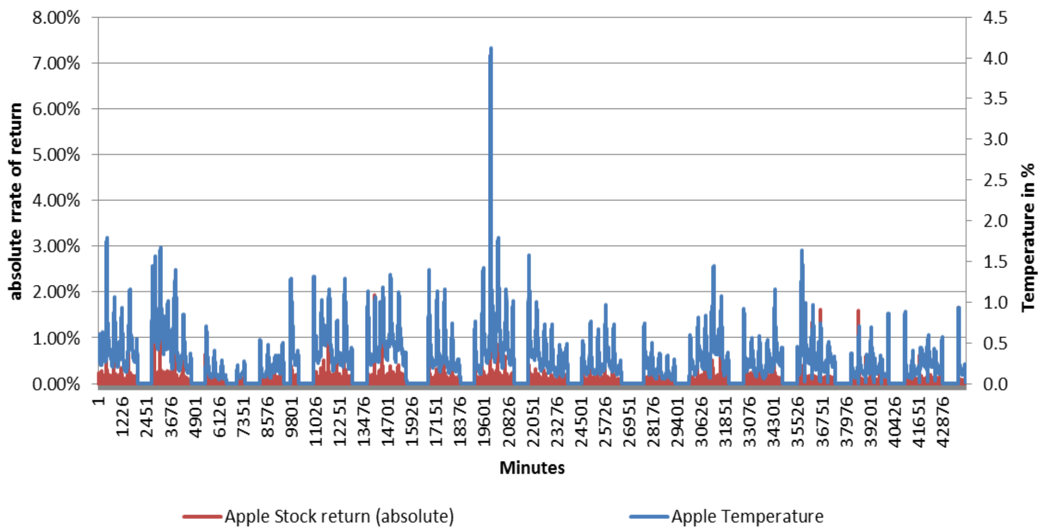
$$\sigma_s\sqrt{v_s} = sig_s * v_s = temperature\ of\ a\ stock(\mathrm{t}) \tag{22}$$

The heat of a stock thus combines a calendar-based measure of volatility with a frequency adjustment for trading opportunities, the higher the trading opportunities the higher the temperature of a stock. Rather than using rolling historical volatility (which is the case in this thesis) we would like to highlight the possibility of using a generalized autoregressive conditional heteroscedasticity or GARCH process as an alternative. A White test (White, 1980) is often best practice when testing for heteroscedasticity and autocorrelation in econometric modelling while using a GARCH approach is best practice for time series data. For ease of computation and acknowledging that the rolling historical volatility approach captures most of the underlying dynamics we choose not to model a GARCH process.

In the application to follow and as a main contribution of this paper we define the temperature of a stock as time-varying. We use a rolling window of 60 minutes to dynamically update the temperature for each stock in the universe and thus assess the reactivity and significance of the concept of temperature for each stock and in a portfolio context. Figure 2 and Figure 3 below show the evolution of the absolute return of Apple and Oracle over a three month period (using minute data) from 08/12/2014 to 08/03/2015 and contrast it to the temperature (using a 60 minute rolling window for calculating all statistics) for the two respective stocks. The absolute return of each stock in the S&P IT universe is defined as

$$|\log P_t - logP_{t-1}| \tag{23}$$

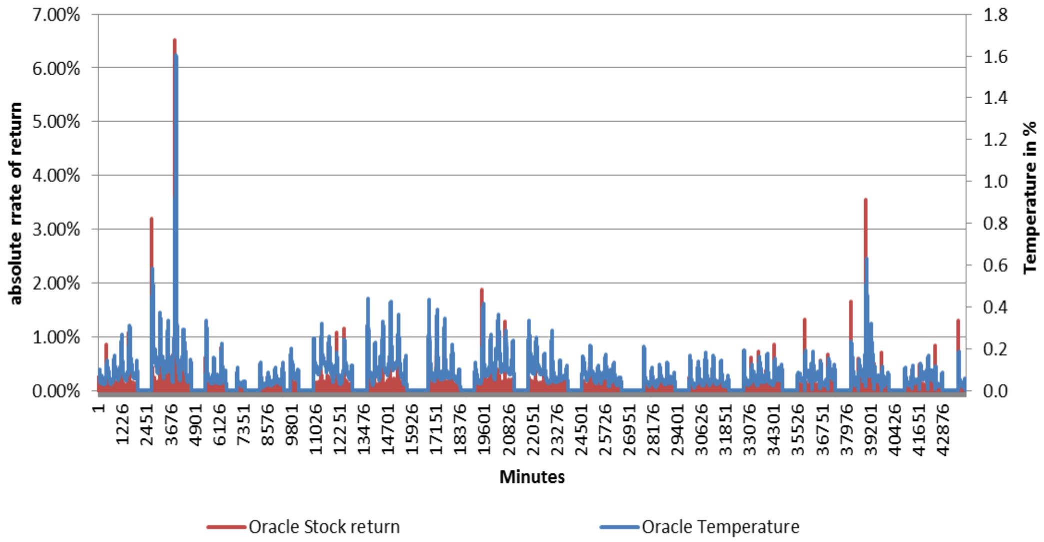
Figure 2: Apple stock return absolute (lhs) versus temperature (rhs) - x-axis represents number of observations (minute data)



Source: Bloomberg, Authors' calculations

From visual inspection we can see that periods of marked moves in the Apple stock return coincide with an increase in the temperature statistic. There are also periods of no trading with a zero return and temperature over short intervals of time during the trading day. During December 2014 we saw a flaring-up of the Greek debt crisis as new elections surprised the market negatively. The stock price of Oracle below shows a similar pattern though it is worth noting that Oracle shares were less frequently traded than Apple shares during the measurement period. This might explain the smaller return changes for the Oracle share price over the period caused by lower liquidity. The overall development of the Oracle temperature is generally more muted but spikes at exceptions.

Figure 3: Oracle stock price (rhs) versus temperature (lhs) – x-axis represents number of observations (minute data)



Source: Bloomberg, Authors' calculations

We next perform linear and non-linear statistical tests to get a better understanding of the characteristics of the data and the potential links between the performance of stocks and their temperature.

A multi-variate regression using the temperature of a stock as the dependent variable and the stock return as well as the overall market return as the independent variable shows a negative beta of the temperature statistic to market returns (significant t-statistic). The R-squared is close to zero though which would indicate an overall weak relationship of stock and market returns together in explaining the temperature. The high F-statistic would indicate large differences in mean values for market returns and stock returns as independent variables and these differences seem to be significant (low p values).

$$y_t = \alpha + \beta_{stock} * stock_{return} + \beta_{market} * market_{return} + \epsilon \qquad (24)$$

Table 1: Multi-variate regression statistics (t-statistic in brackets)

	Average across all S&P IT stocks
α	0.00
β_{stock} (t-stat)	0.00 (1.93)
β_{market} (t-stat)	-1.09 (2.32)
R^2	0.00
F-statistic	34.49
p value	0.04

Source: Authors' calculations

Additionally we perform an augmented Dickey-Fuller univariate root test. The test assumes that the true underlying process is a zero drift unit root process, specifically, under the null hypothesis the true underlying process is a zero drift ARIMA (P,1,0) model

$$y_t = y_{t-1} + \theta_1 \Delta y_{t-1} + \cdots \theta_p \Delta y_{t-p} + \varepsilon_t \qquad (25)$$

which is equivalent to an integrated AR(P+1) model. We use a 0.05 significance level, 60 lags (as we use 60 minutes of rolling data) for a t-test of the AR coefficients. For each stock in the S&P500 IT Index the null hypothesis can be easily rejected as we show below for the temperature of Apple and Oracle.

Table 2: Multi-variate regression statistics

ADF Test	Apple	Oracle	Critical value	p value
temperature t-1	-4.82	-5.65	-1.94	0.01
D_temperature t-1	-5.78	-6.52	-1.94	0.01
D_temperature t-2	-6.57	-7.42	-1.94	0.01
D_temperature t-3	-7.28	-8.12	-1.94	0.01
D_temperature t-4	-7.85	-8.64	-1.94	0.01
D_temperature t-5	-8.61	-9.15	-1.94	0.01
D_temperature t-6	-9.10	-9.85	-1.94	0.01
D_temperature t-7	-9.67	-10.22	-1.94	0.01
D_temperature t-8	-9.96	-10.61	-1.94	0.01
D_temperature t-9	-10.46	-10.99	-1.94	0.01
D_temperature t-10	-10.89	-11.29	-1.94	0.01
D_temperature t-60	-8.39	-9.51	-1.94	0.01

Source: Authors' calculations

So far we have leveraged off Derman (2002) and looked at the single and multi-stock case. In the following sections we introduce comparative temperature statistics that allow us to capture divergence, convergence and overall temperature tendencies in the stock universe we monitor (S&P IT universe).

Section 5: Defining a Heat premium

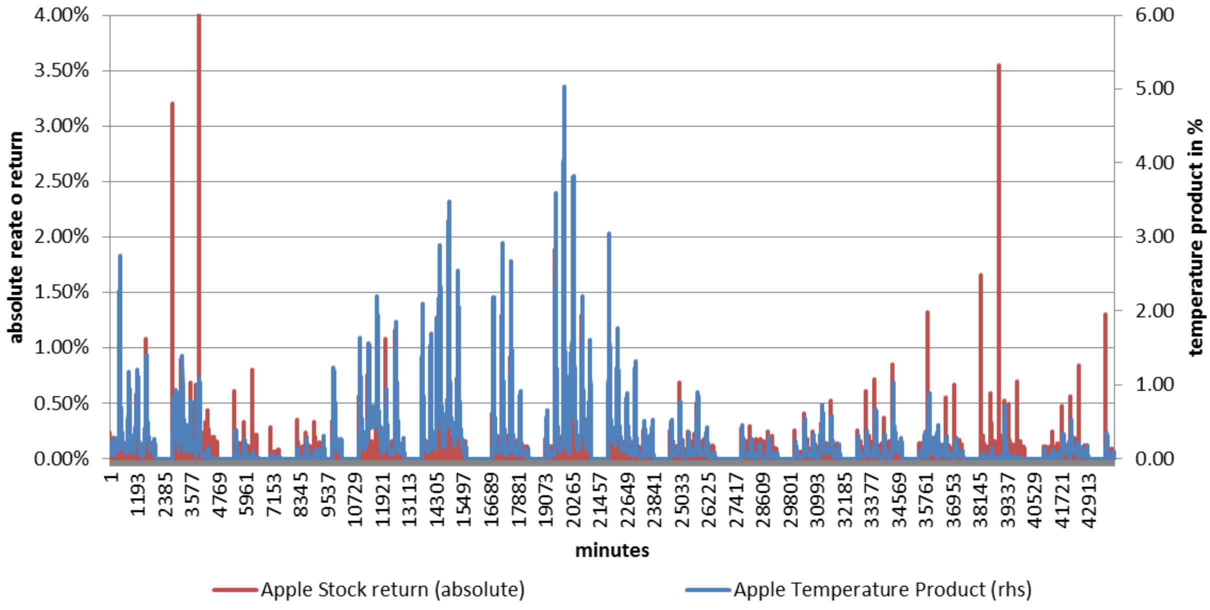
We have derived the temperature of a stock theoretically and in practical context (Apple and Oracle as part of the S&P IT universe). At the time of analysis (June 2015) this universe comprised 65 stocks, from very actively traded stocks like Apple to less frequently traded stocks. In order to capture the dynamics amongst this stock universe we are proposing the following simple temperature statistics:

- Product of temperature of two stocks (measuring concentration in liquidity)
- Ratio of temperature of two stocks (measuring divergence in liquidity)
- Minimum of temperature across stocks at time t (measuring systematic liquidity or the minimum time to re-allocate a portfolio)

Each of these statistics adds additional value assessing the usefulness of the concept of temperature of a stock. In order to make the product and ratio comparable across stocks we use the overall S&P 500 index as the denominator in the ratio and as the second input for the product next to each individual stock's temperature.

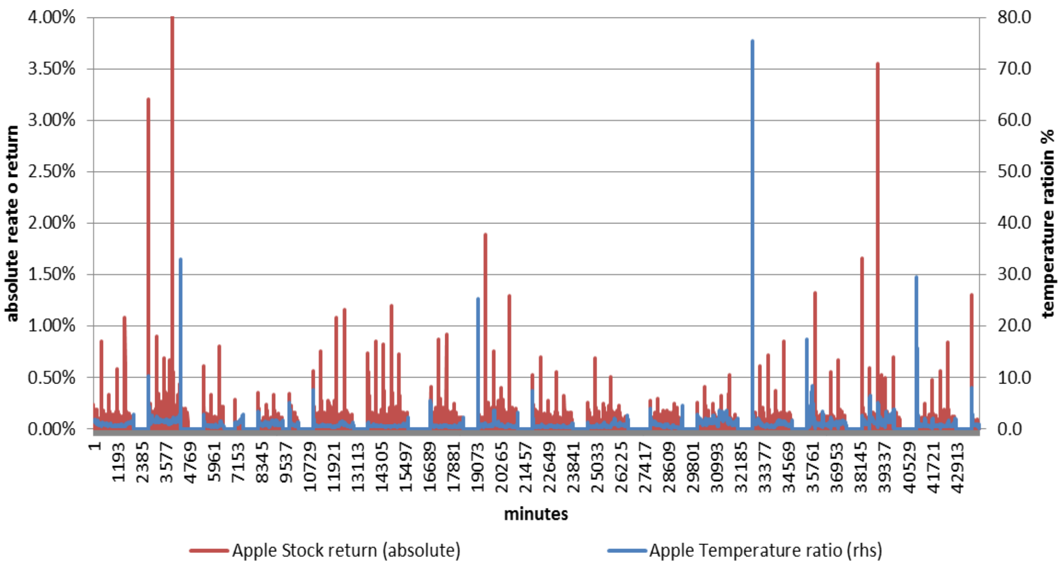
Similar to the earlier section we use the example of the Apple share price to highlight the potential benefits of the product, ratio and minimum temperature. As in the analysis above we use 60 minutes rolling prices to derive the statistics necessary to compute the variates of temperature. Figure 4 below shows the product of the temperature between Apple and the S&P500 Index. Compared to Figure 3 which shows the temperature of Apple in isolation we can observe more temperature spikes. The product is thus also able to capture wider "Heat" or trading activity in the market.

Figure 4: Apple temperature product (versus S&P500 Index) and Apple stock return absolute- lhs (minute data)



Source: Bloomberg, Authors' calculations

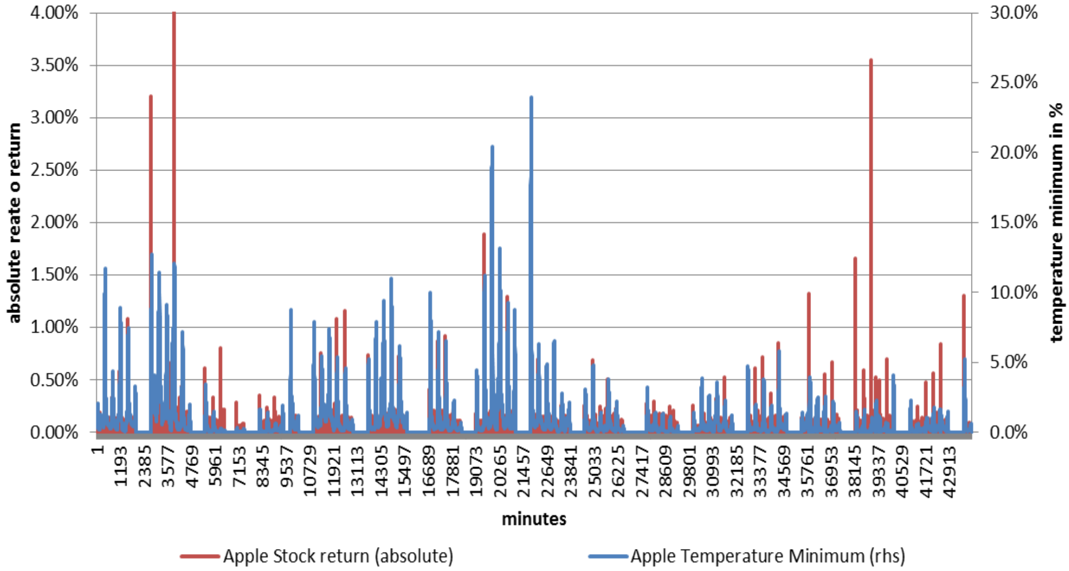
Figure 5: Apple temperature ratio with S&P500 and Apple stock return absolute lhs (minute data)



Source: Bloomberg, Authors' calculations

Another interesting component to us was to look at the divergence of temperature ratios to assess if the rise in temperature of one stock is more an idiosyncratic move or represents a wider systematic move. The ratio of Apple's stock in Figure 5 compared to the wider S&P500 Index suggests that the temperature spike of Apple after around 20,000 data observations looks to be more idiosyncratic as Apple's temperature diverged significantly from the broader market index during that period. This data point refers to December 2014. Apple just won a court-case against Samsung concerning copy-right laws and the idiosyncratic nature of the Apple stock price move during that period is confirmed by the spike in the temperature ratio.

Figure 6: Apple temperature minimum across S&P500 IT sector and Apple stock return absolute lhs (minute data)



Source: Bloomberg, Authors' calculations

Figure 6 however gives additional details on this move in Apple at around 20,000 data points as it would suggest that the S&P500 IT Index was more active than the overall S&P500 Index. The minimum temperature across the S&P500 IT stocks has generally been higher during that period and would thus suggest that the sub-sector of IT stocks showed a higher trading activity and Apple was one of the most actively traded stocks. The minimum temperature can thus also be seen as a systematic measure of portfolio liquidity versus the liquidity of a single stock.

In order to assess the correlation between the temperature of a stock and the realized return in more depth we look at the correlation and cross-correlation of each stock in the S&P500 IT sector with its own temperature as well as with the temperature of the other stocks in this index. Table 3 shows the minimum, maximum, average and median reading for this analysis of the lower triangular of the correlation matrix of S&P500 IT stocks versus temperature (2,145 combinations).

Table 3: Relationship of temperature with return (S&P500 IT universe)

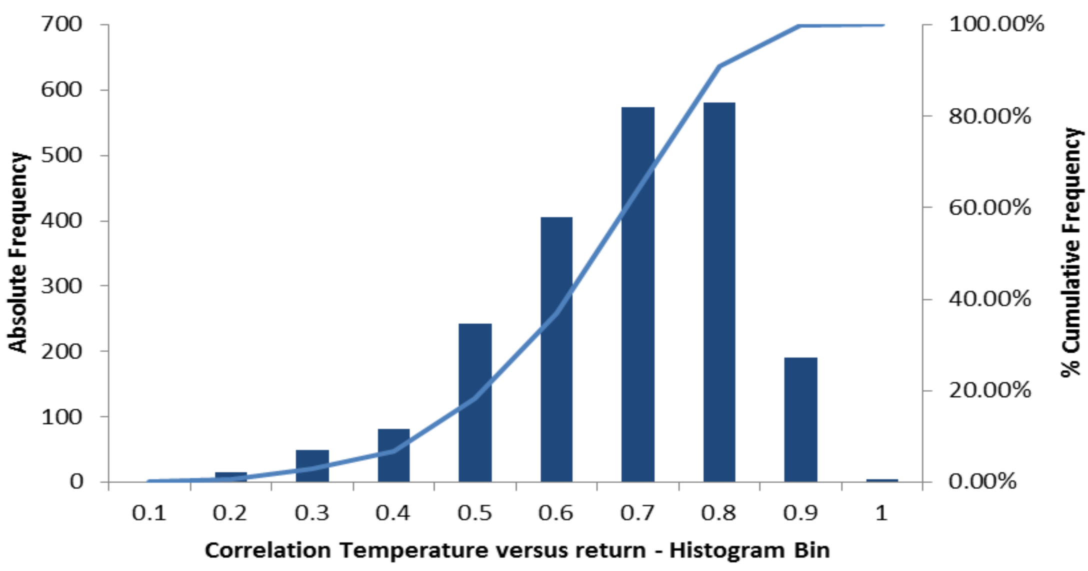
	Cross-sectional analysis of Temperature versus return
Minimum	0.11
Maximum	0.97
Average	0.63
Median	0.66

Source: Authors' calculations

The average and the median are both well above 0.5 and thus indicating a strong positive relationship between the temperature and returns of S&P500 IT stocks.

Figure 7 shows the same data but in form of a histogram providing indication of the distribution of correlations. 10% of correlations are below +0.1 with 50% of correlation pairs above 0.6.

Figure 7: Distribution analysis temperature and return for S&P500 IT universe



Source: Authors' calculations

The example of using the Product, Ratio and Minimum of the temperature to evaluate trading activity for the Apple stock shows that using the temperature of a stock from different angles might add additional information about market behaviour. We are specifically interested in the influence of temperature on individual stock pricing. In order to do so we need to define a factor premium for Temperature that all stocks in our universe relate to. We perform a cross-sectional analysis to proof the concept of temperature across the universe of stocks we analyse. We cross-sectional rank each stock based on the temperature from high to low into 6 buckets (1 is the bucket with the lowest statistic and 6 the bucket with the highest statistic). We thus create a factor basket for the temperature which we are able to use in an arbitrage pricing model (Ross 1976).

By using an arbitrage pricing model we will show the heat premium of a stock defined as the excess return over the market return of a stock. We are thus focused on excess returns – i.e. in excess of the market beta of the stock. We would like to isolate the temperature related premium of individual stocks as well as the overall market temperature by systematically going long the stocks with a high temperature and short the stocks with a low temperature.

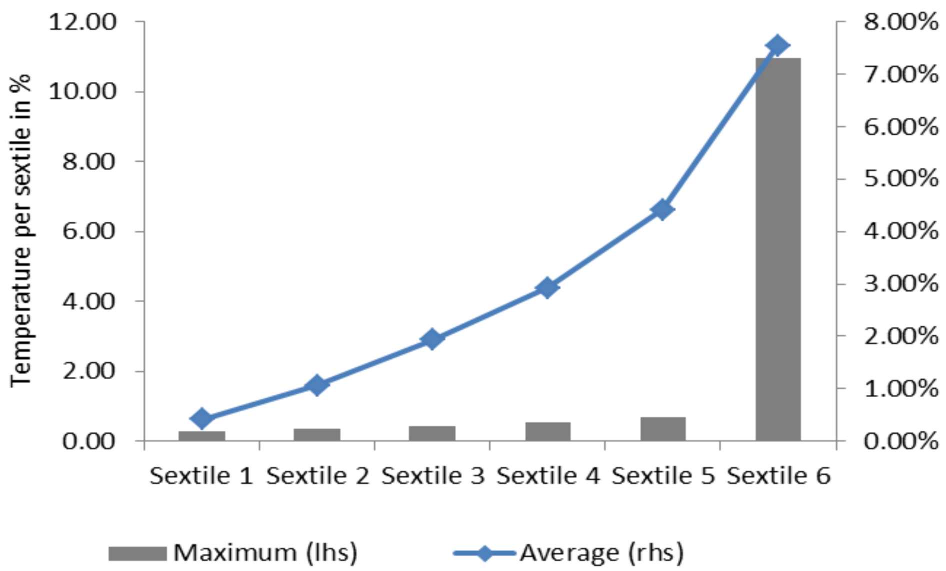
With the help of the risk/return ratio for a stock derived earlier we are able to isolate this premium. We go back to the previous section about defining the return of a stock. We use the formulation for $\widetilde{\mu_i}$ in Formula 17 to relate the frequency adjusted return of a stock to the frequency adjusted excess return of a stock over the overall market.

$$ {}_{Temperature}^{High/Low} r_t = \frac{\mu_i - \beta_{iI}\mu_I\sqrt{\frac{v_i}{v_I}}}{(1-\beta_{iI}\sqrt{\frac{v_I}{v_i}})} \tag{26} $$

Investors thinking of a stock in intrinsic time the benchmark for the investor should be the market return times the market beta, but crucially adjusted by the square root of the relative trading frequency of the stock versus the market. As Derman (1996) has shown this excess return over that benchmark is proportional to the stock's temperature rather than simply its volatility and to stocks with a higher trading frequency this represents an excess return or an additional premium.

We assess the distributional characteristics of each temperature sextile by calculating the average value, the maximum as well as the minimum value of heat within each sextile. The highest temperature sextile in Figure 8 (Sextile 6 containing the high temperature stocks) shows a wider distribution of temperature with a higher average temperature. Figure 8 would suggest that the temperature rises exponentially across the sextiles.

Figure 8: Temperature statistics sorted by Temperature sextile from 1 (low) to 6 (high)



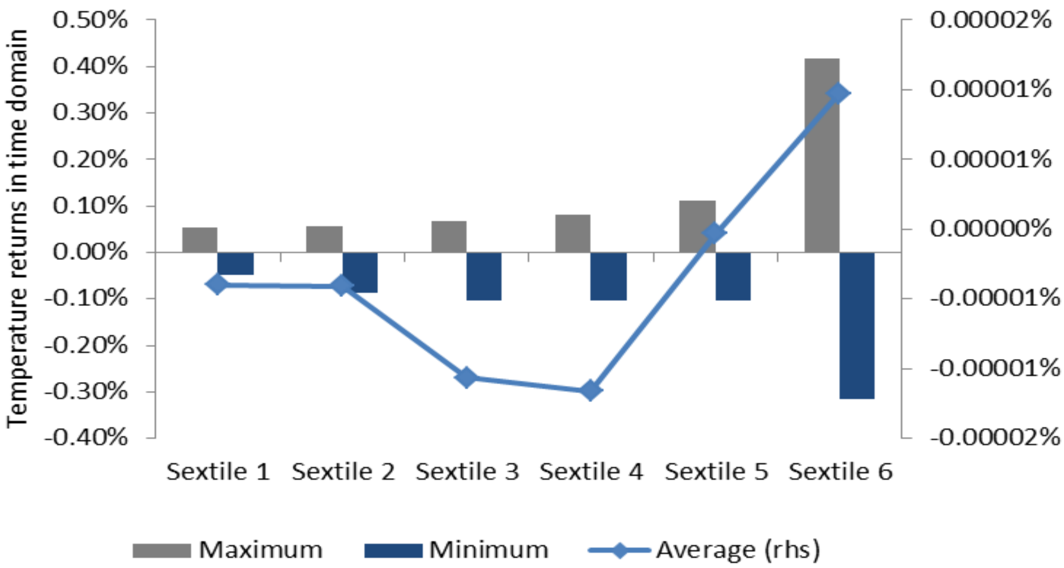
Source: Authors' calculations

Further Figure 9 shows the distributional characteristics of the return profile associated with each temperature sextile by calculating the average value, the maximum as well as the minimum value of performance within each sextile. In order to highlight the use of the temperature concept we perform the sextile analysis on both, time frequency returns and frequency adjusted returns according to the relative temperature in Formula 26. In both cases, time and frequency domain we use beta adjusted returns and thus eliminate the impact from the market.

Many investors might not be able to implement trades on a frequency adjusted basis because of operational reasons. The analysis below however suggests that in time as well as in temperature domain the return profile develops according to the temperature sextiles with high temperature stocks on average showing a positive excess return and low temperature stocks showing a negative excess return.

The performance profile is similar to the temperature sextile profile and is not monotonically increasing across sextiles. Rather the extreme sextiles on the upside show positive return on average with a wider distribution. The middle sextiles between the extreme bottom and extreme top are the ones with a negative average though a wider distribution compared to the bottom sextiles. The returns underlying this sextile analysis have been calculated by removing the market beta from each stock. Figure 9 would suggest that it is possible to build a long/short basket of stocks, long the stocks with a high temperature and short the stocks with a low temperature which is able to deliver a positive excess return.

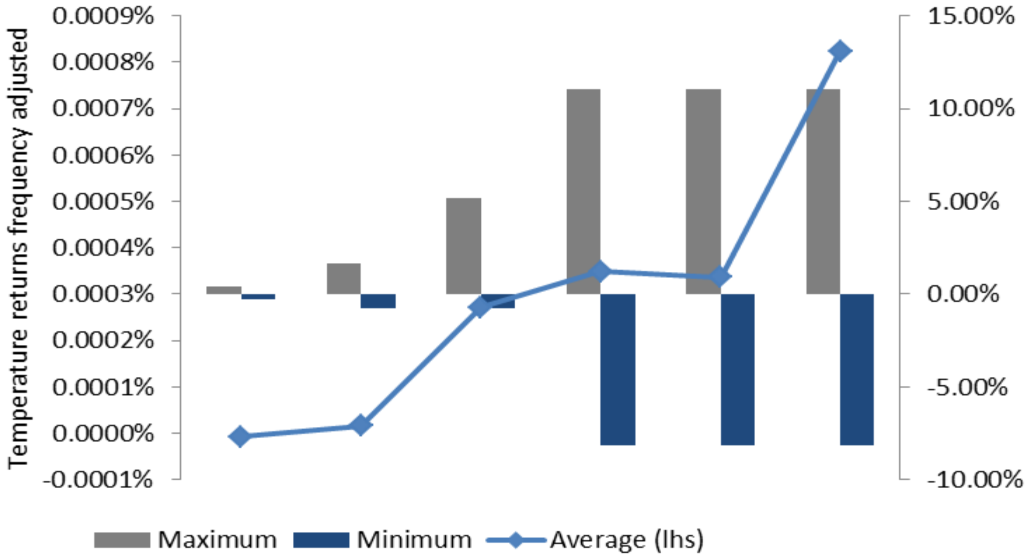
Figure 9: Return statistics sorted by Temperature sextile from 1 (low) to 6 (high) – using time based returns (in %)



Source: Authors' calculations

Figure 10 highlights the concept of temperature returns across sextiles in frequency-adjusted domain. Similar to time-domain the excess return of high temperature stocks (beta-adjusted again) is higher compared to low temperature stocks. The relationship between the ranking and the average return is stronger in the case of frequency-adjusted returns compared to time domain returns. The average excess return increases steadily from low temperature sextile (1) to high temperature sextile (6).

Figure 10: Return statistics sorted by Temperature sextile from 1 (low) to 6 (high) – using frequency adjusted returns (in %)



Source: Authors' calculations

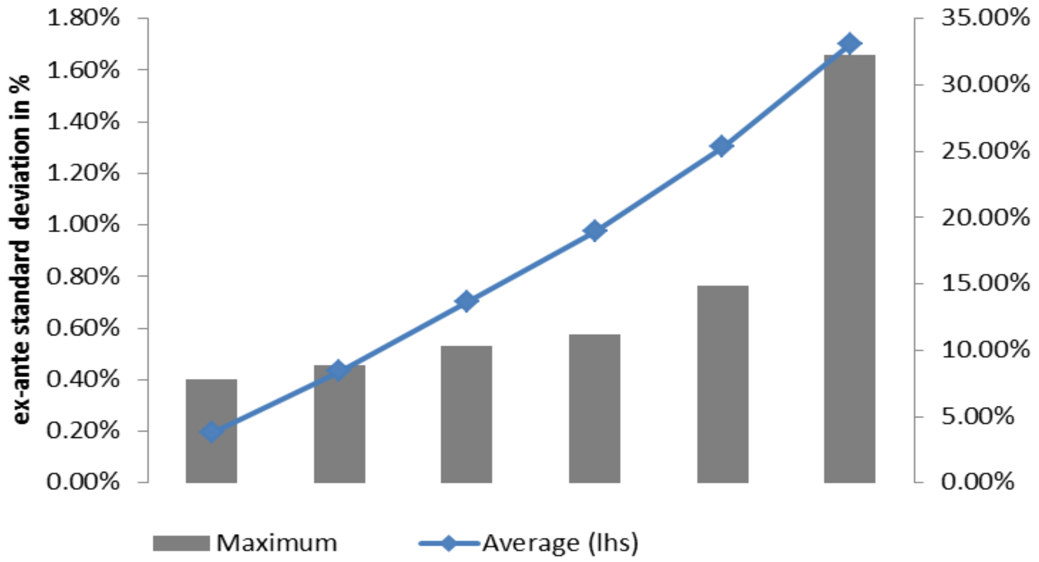
We have shown that high temperature stocks are more likely to outperform low temperature stocks after accounting for the beta of each stock to the S&P IT Index. In the next section we will provide more insight from an ex-post perspective of what could have driven this heat premium.

Section 6: Possible explanations for a Heat premium

There can be various fundamental reasons for high temperature stocks to outperform low temperature stocks. Part of it could be driven by the higher inherent risk of high temperature stocks. In the previous section we showed the beta-adjusted returns across temperature sextiles indicated higher returns for higher temperature stocks compared to low temperature stocks. The difference between ex-ante and ex-post beta provides more insight into a potential risk bias inherent in high temperature stocks. A beta higher 1 can indicate either an investment with higher volatility than the market, or a volatile investment whose price movements are highly correlated with the market.

Figure 11 below shows that ex-ante high temperature stocks tend to have a higher volatility compared to low temperature stocks.

Figure 11: Ex-ante standard deviation of log returns sorted by Temperature sextile from 1 (low) to 6 (high)

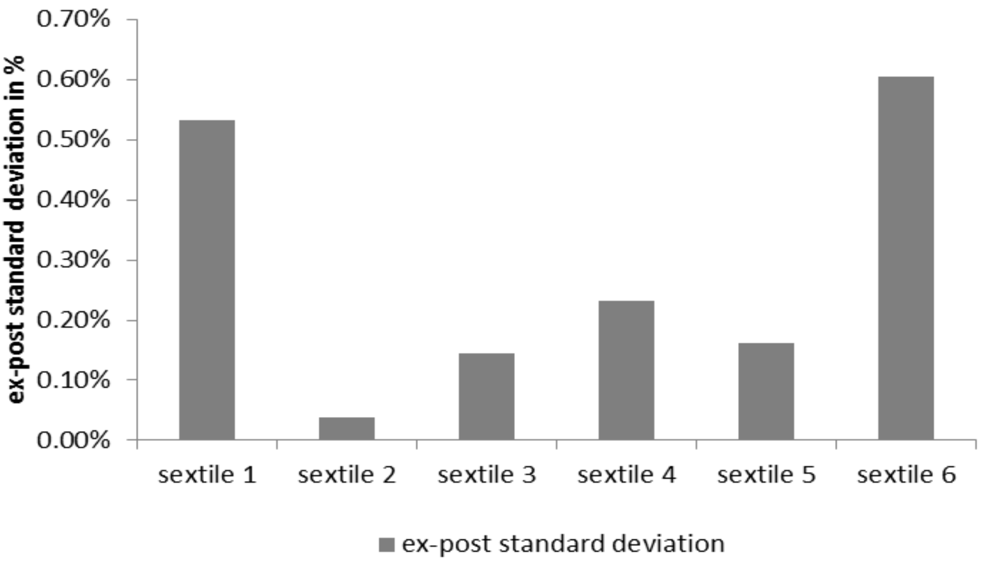


Source: Authors' calculations

We sort the risk of each stock in our S&P IT universe by sextiles, from lowest risk (sextile 1) to high risk (sextile 6). It would suggest that ex-ante there is a positive relationship between higher temperature stocks (higher sextile) and higher risk while lower temperature stocks (lower sextile) within our universe tend to show a lower risk on average. The range however does not change a lot across the first 5 sextiles, only the highest temperature stocks (sextile 6) tend to show a much wider range of risk on the upside.

However once we adjust for the beta of frequency-adjusted returns and measure the ex-post volatility, Figure 12 shows that the higher temperature sextile (sextile 6) does not indicate higher risk any longer. Higher temperature stocks show lower ex-post risk than low temperature stocks. Adjusting for the beta removes higher ex-ante risk effectively.

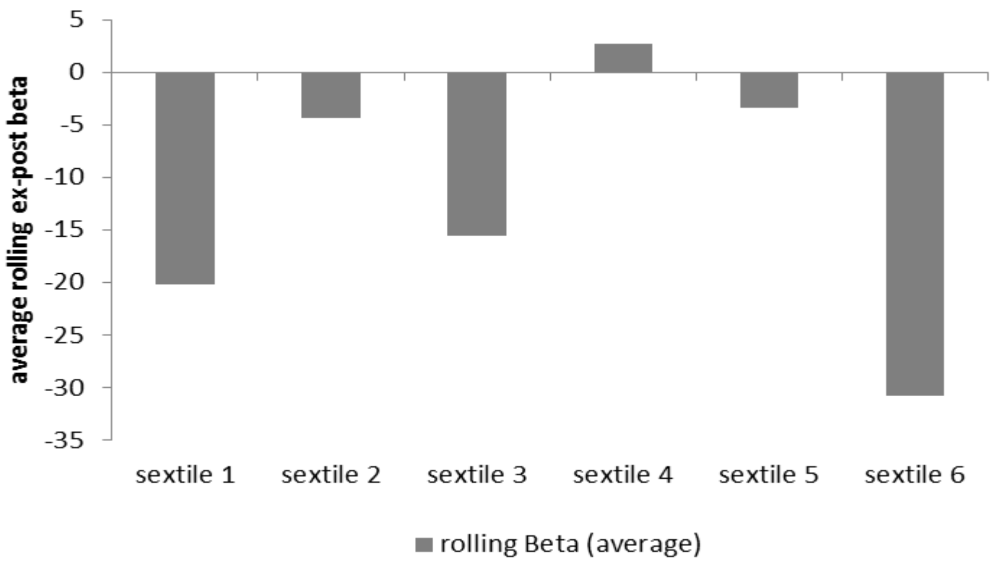
Figure 12: Ex-post standard deviation of log returns sorted by Temperature sextile from 1 (low) to 6 (high)



Source: Authors' calculations

This is also confirmed from Figure 13 which shows the ex-post beta across temperature sextiles. Higher temperature stocks show a lower ex-post beta compared to low temperature stocks.

Figure 13: Ex-post rolling beta sorted by Temperature sextile from 1 (low) to 6 (high)



Source: Authors' calculations

This would suggest that there is no additional compensation for risk contained in high temperature stocks once adjusted for the beta. There could be several other reasons for additional compensation though we have basically eliminated two of them, namely market risk (by correcting frequency-adjusted returns by the market beta) as well as liquidity (by using a liquid subset of the S&P500 Index). In the introduction we highlighted the time period over which we measure returns and our deliberate choice of a higher market volatility environment which might associate the heat premium with other intra-day effects.

Table 4 highlights the relative performance of the temperature sorted stock baskets. It gives an indication of the signal decay. The data would indicate a rather rapid signal decay with the Highest temperature stocks outperforming the lowest temperature stocks by 19% cumulative over the period measured while the relative performance of the middle sextiles is less positive or in the case of temperature sextile 4 relative to temperature sextile 3 indicating negative performance. The more extreme the temperature gap is the more rewarding is the premium while the middle of the temperature distribution is likely to pick up noise and hence does not show a positive temperature premium.

Table 4: Relative cumulative performance of Temperature sorted baskets (S&P500 IT universe)

Basket	Cumulative Performance
Sextile 6 minus sextile 1	+19.2%
Sextile 5 minus sextile 2	+0.4%
Sextile 4 minus sextile 3	-8.4%

Source: Authors' calculations

A more explicit approach to show that there is a premium associated with the performance of high temperature stocks compared to low temperature stocks during market turbulence is using an asset pricing framework explaining the time series characteristics of each stock against a market factor and a temperature factor represented by a portfolio overweighting high temperature stocks and underweighting low temperature stocks.

Further to the sextile analysis earlier we use below an Asset Pricing framework (Ross, 1976). We showed above that the concept of temperature is likely to hold in time domain too. Most investors are not able to consider trades on a frequency adjusted basis. In order to avoid a beta effect in our long/short basket which in a market neutral setting serves as our heat risk factor input into the APT we beta-adjust the long and the short side of the temperature premium basket for every stock. We beta-adjust the returns of our stock universe and create a proxy for our temperature risk premium by creating a long/short portfolio of stocks, long the stocks with the highest temperature and short the stocks with the lowest temperature.

$$\mu_t = \frac{1}{\beta_t^H} r_t^{Highest\ sextile} - \frac{1}{\beta_t^L} r_t^{Lowest\ sextile} \tag{27}$$

where r_t represents the beta-adjusted equally weighted basket return for heat ranked stocks. We use the performance gap between the top and bottom sextile heat-ranked stocks as heat premium proxy in equation 28.

We model the expected return of our 65 S&P500 IT stocks (j) as a linear function of the stock's sensitivities to the market factor and to the temperature factor.

$$E_{r_j} = \alpha + \beta_{j1} MarketRiskPremium_1 + \beta_{j2} temperatureRiskFactor_2 \tag{28}$$

We use minute data for the period 8th of December to 8th of March 2015. Below we show the output of the APT model explaining time-based returns of our S&P500 IT universe through the market risk factor and through the Temperature risk factor. We did not consider additional risk factors common in the literature (like Value, Size or Momentum) as we would expect investors not to focus on these factors over very short period of times but this could be part of future research. We focus on time-based returns rather than transaction-based returns as we do acknowledge that most institutional investors are not able to exploit this premium in transaction time because of operational constraints.

We run the regression for each stock in the S&P500 IT universe (65 stocks) separately and average the factor exposure.

Table 5 below indicates that market beta dominates S&P500 IT stock returns short-term though the inclusion of a temperature risk factor yields a positive premium.

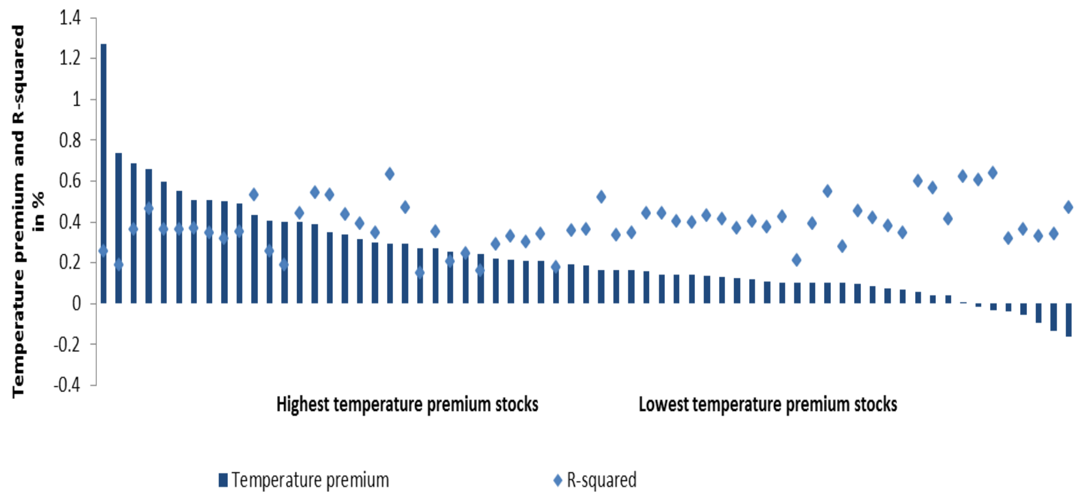
Table 5: APT output considering market beta and temperature risk factor (S&P500 IT universe) – t-statistic in brackets

	Excluding temperature risk factor	Including temperature risk factor
α	0.00	0.00
β_1 (t-statistic)	1.00 (4.0)	0.87 (3.8)
β_2 (t-statistic)		0.24 (1.8)
R^2	0.38	0.37
F-statistic	14,986.87	25,101.47
p value	0.00	0.00

Source: Authors' calculations

The inclusion of a heat premium preserves the statistical significance of the model with an explanatory power of 37%.

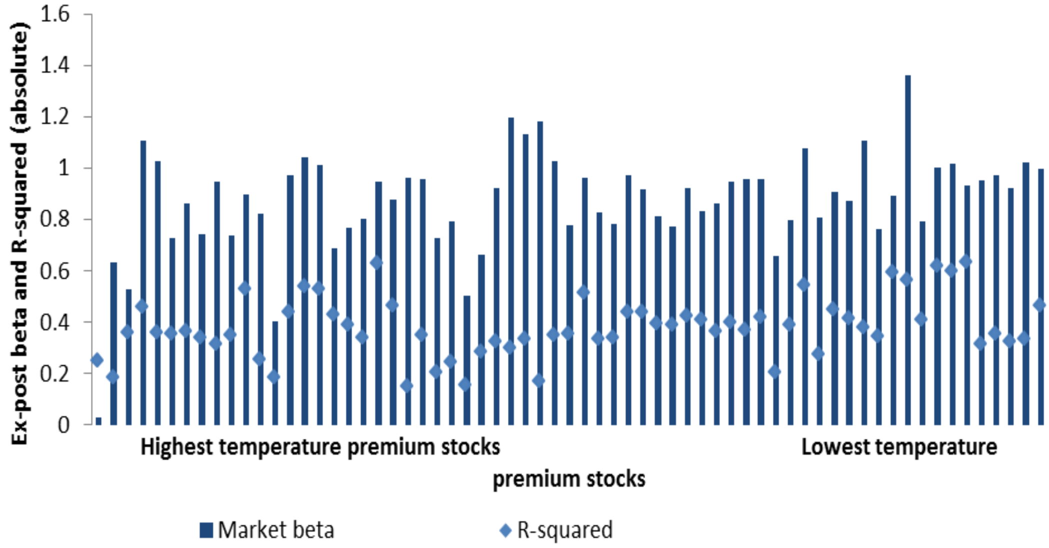
Figure 14: Stocks sorted by Temperature premium 6 (high) to 1 (low) and corresponding R-squared



Source: Authors' calculations

Figure 14 and Figure 15 rank the stock universe by temperature premium from high temperature to low temperature premium. The idiosyncratic nature of the premium is confirmed as the R-squared of the asset pricing model tends to decrease with increasing temperature premium.

Figure 15: Ex-post rolling beta sorted by Temperature sextile from 6 (high) to 1 (low) and corresponding R-squared



Source: Authors' calculations

Figure 15 highlights the market beta for each stock ranked by temperature premium confirming similar to the previous analysis that on a frequency-adjusted basis there does not seem to be a market beta bias within the temperature premium.

Section 7: Conclusion

We have extended a notion of temperature of a stock originally defined by Derman (2002). We have used the S&P 500 IT sub index comprising 65 IT stocks and looked at a time varying version of the temperature, thus introducing dynamics in the existing framework. We specifically applied the time varying temperature concept to a particular turbulent period of three months witnessing high market volatility in order to show the significance of the temperature premium during market turmoil. We show that the temperature of a stock is a concept that is able to explain part of a stock return – a “heat premium” - that could also be relevant in a cross-sectional analysis of stock returns as we highlight within an asset pricing context.

References

Andersen, T.G., T. Bollerslev, F.X. Diebold and P. Labys, 2003. “Modelling and forecasting realized volatility”, *Econometrica*, 71, pp. 579-625

Ane, T., and Helyette Geman, 2000. “Order Flow, Transaction Clock, and Normality of Asset Returns”, *Journal of Finance,* Vol. 55, No 5 (Oct. 2000), pp. 2259-2284.

Barro, R.J., 1970. “Inflation, the payments period, and the demand for money.”, *Journal of Political Economy,* Vol. 78, pp. 1228-1263.

Bouchaud, J.-P. and M. Potters, 2004. “Fluctuations and response in financial markets: The subtle nature of ‘Random’ price changes.”, *Quantitative Finance*, 4, pp. 176-190.

Burns, A.F. and W.C. Mitchell, 1946. “Measuring Business Cycles”. New York Columbia University Press, for NBER.

Carr, P., Geman, H., Madan, D. and Mark Yor, 2002. “The fine structure of asset returns: an empirical investigation, *Journal of Business*, 75, pp. 305-332.

Clark, P.K.A., 1973. “A subordinated stochastic process model with finite variance for speculative prices”, *Econometrica*, 41 (1), pp. 135-155.

Derman, E., 2002. “The Perception of Time, Risk and Return During Periods of Speculation”, Goldman Sachs & Co.

Epps, T.W. and M.L. Epps, 1976. “The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis”, *Econometrica*, 44, 2, pp. 305-321.

Geman H., and T. Ane, T., 1996. “Stochastic subordination”, *Risk*, 9, pp. 145-149.

Gillemot, L., Farmer, J.D. and F. Lillo, 2006. “There’s more to volatility than volume”, *Quantitative Finance*, 6(5), pp. 371-384.

Harris, L., 1982. "A theoretical and empirical analysis of the distribution of speculative prices and of the relation between absolute price change and volume", Ph.D. thesis, University of Chicago.

Huth N. and Freedeeric Abergel. 2010. "The times change: multivariate subordination. Empirical facts", *Quantitative Finance.*

Ito, T. and W.L. Lin, 1992. "Lunch break and intraday volatility of stock returns", Economic Letters, 39, 1, pp. 85-90.

Jones, C., Gautam Kaul, and Marc L. Lipson, 1994. "Transactions, volume and volatility". *Review of Financial Studies*, 7, pp. 631-651.

Karpoff, Jonathan M., 1987. "The relation between price changes and trading volume: A survey". *Journal of Financial and Quantitative Analysis*, 22, pp. 109-126.

Mandelbrot, B.B. and H.M. Taylor, 1967. "On distribution of stock price differences", *Operations Research*, 15(6), pp. 1057-1062

Plerou V., P. Gopikrishnan, L. Amaral, X. Gabaix and H.E. Stanley, 2000. "Economic Fluctuations and Anomalous Diffusion", *Physical Review E*, 62, R3023-R3026.

Ross, Stephen, 1976. "The arbitrage theory of capital asset pricing." *Journal of Economic Theory*, 13 (3), pp. 341-360.

Schwert, G.W., 1989. "Why does stock market volatility change over time?". *Journal of Finance*, 44, pp. 1115-1153

Silva, Christian A., 2005. "Applications of physics to finance and economics: returns, trading activity and income", PhD thesis, University of Maryland.

Tauchen, G. and M. Pitts, 1983. "The price variability-volume relationship on speculative markets", *Econometrica*, 51, pp. 485-505.

Velasco-Fuentes, R. and W.L. Ng, 2008. "Nonlinearities in Stochastic Clocks: Trades and Volume as Subordinators of Electronic Markets", Centre for Computational Finance and Economic Agents, Working Paper Series.

White, Halbert, 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity", *Econometrica*, 48, pp. 817-838.

Chapter 3. Spot Price Modelling of Industrial Metals – An heterogeneous agent based model for Copper

Section 1: Introduction

We propose an empirical model based on the heterogeneous agents literature. Price changes are induced by fundamental as well as technical demand. The model is estimated for copper. In this type of model, the market price is formed by the trading behaviour of heterogeneous agents, who condition their buying and selling on a number of forecast rules. The relative weights put on these rules are determined by the past performance error of the different forecasts, so agents can change their strategy of how to behave. The model is based on an approach proposed by Lux&Marchesi (1999, 2000) and Lux (1998) which we will follow throughout this document. Additionally we will explicitly model the fundamental value that will be used by the experts as input variable for their recommendation. This fundamental value – the long-term equilibrium spot price - against which fundamentally driven experts make their recommendation, is calculated out of the forward curve of copper.

The model to calculate the long-term equilibrium price is combining two different strings of literature. One is that commodity prices follow a "random walk" described by geometric Brownian motion. This is the model of stock price uncertainty underlying the famous Black-Scholes option pricing formula and it leads to closed-form solutions in some interesting cases. In this model, prices are expected to grow at some constant rate with the variance in future spot prices increasing in proportion to time. If prices increase (or decrease) more than anticipated in one time period, all future forecasts are increased (or decreased) proportionally.

The other direction of authors has been focusing on the use of mean-reverting price models and argued that these models are more appropriate for many commodities. Intuitively, when the price of a commodity is higher than some long-run mean or equilibrium price level, the supply of the commodity will increase because higher cost producers of the commodity will enter the market—new production comes on line, older production expected to go off line stays on line—thereby putting downward pressure on prices. Conversely, when prices are relatively low, supply will decrease since some of the high-cost producers will exit, putting upward pressure on prices.

When these entries and exits are not instantaneous, prices may be temporarily high or low but will tend to revert toward the equilibrium level. There are elements of truth in each of these simple models of commodity prices. For most commodities, there appears to be some mean reversion in prices but there is also uncertainty about the equilibrium price to which prices revert.

In this article, we develop a simple three-factor model of commodity prices that captures all of the effects mentioned before; In our model, the equilibrium price level is assumed to evolve according to a geometric Brownian motion with drift reflecting expectations of the exhaustion of existing supply, improving technology for the production and discovery of the commodity, inflation, as well as political and regulatory effects. The short-term deviations—defined as the difference between spot and equilibrium prices—are expected to revert toward zero following an Ornstein-Uhlenbeck process. These deviations may reflect, for example, short-term changes in demand resulting from variations in the weather or intermittent supply disruptions, and are tempered by the ability of market participants to adjust inventory levels in response to changing market conditions.

Although neither of these factors is directly observable they can be calculated indirectly if forward curve data (especially for long-term contracts) are available via a recursive technique like the Kalman Filter.

Section 2: Related Work

This paper adds to a debate that models commodity spot prices oscillating around a long-run trend rather than showing mean reversion.

Finding mean-reversion in commodity spot prices has some crucial implications like return variance that does not increase linearly with time or the implications on the value of real options such as mines as well as the consequences on monetary policy as higher trending commodity prices will have direct impact via higher inflation. In another example Casassus et al (2005) show that if commodity prices revert to a constant mean, the prices of options on commodity futures will be significantly smaller than in case of a random walk.

Most commodity pricing papers on commodity futures use a mean-reverting process to a constant level to model the spot prices of commodities like the one-factor model of Schwartz (1997) or Geman and Nguyen (2005).

However there has been a series of papers aiming to show that this reversion to a constant mean has often to be rejected as Cashin, Liang and McDermott (2000) have shown that shocks to commodity prices can be persistent while Grilli and Yang (1988), use a dataset from 1900 to 1986 to proof that commodity prices (real prices in this case) show a positive trend over time.

We follow Geman and Nguyen (2005) and introduce a three factor stochastic volatility model for copper prices. In contrast to Geman and Nguyen (2005) the long-term trend to which the mean reversion process for the copper spot price reverts over time is modelled by a geometric Brownian motion with drift. This is based on the work of Geman (2000) which takes a long-term trend around which the commodity price oscillates over time. This is in contrast to most three factor commodity models which use a second mean reversion process to explain the price trajectory of a fundamental value or convenience yield (see Schwartz 1996 as an example). In order to introduce fat tails into the distribution of copper prices we use the fundamental value gained from our three factor model and introduce financial investors, labelled fundamentalists who use this price input as an internal benchmark or fair value to assess the value of copper prices. These fundamentalists interact with what we will label as technical investors who follow a trend-following approach to assess the fair value of copper prices.

A simple heterogeneous agents based model will be presented in this paper to assess the effect of fundamental as well as technical traders on the price of copper. As the model is based on the fundamentals of copper it makes sense to take supply and demand into consideration. Rapidly growing countries like India or China are dominant on the demand side yet this cannot fully explain the dramatic moves of copper since 2007. A possible cause of this larger price volatility is the existence of speculators in the copper market (Geman, 2005). Similar observations have been made for other commodities like oil over the last couple of years where inventory speculation caused a run-up in oil prices during the 1970s (Danielsen, 1979). This poses a strong challenge towards the Efficient Market Hypothesis of Fama (1970). The Efficient Market hypothesis assumes rational expectations and thus the current price of copper should reflect all available information.

One of the deviations from the Efficient Market Hypothesis is represented by heterogeneous agents. Brock and Hommes (1997) account for different types of investors. A cobweb type demand-supply model was used by Brock and Hommes (1997) where agents choose between naive and rational expectations. Investors switch between different forecasting strategies based on the past performance of these strategies. The switching of investors introduces non-linearity into the system and thus local instability and complicated dynamics can be observed in a fully rational notion of equilibrium.

Frankel and Froot (1988) classified two types of investors, fundamentally based investors and technical traders in an environment of exchange rates. Later models like Foellmer et al. (2004) also introduce liquidity traders to account for volatility in an equity market which is close to equilibrium. In general, fundamental traders are comparing the current price of a financial asset with their fair value and thus have a stabilizing effect as they would buy in case of a lower current price compared to the spot price and vice versa. Technical traders in contrast base their investment decision on past prices, e.g. trend followers buy if they observed a price increase in the past and sell in case of falling prices. Hommes (2006) gives a detailed overview of heterogeneous agents models. Reitz and Westerhoff (2007) and Reitz and Slopek (2009) have been some of the recent authors to estimate heterogeneous agents models for commodities though research in the 1960s by Smidt (1965) already indicated the existence of speculation in commodity markets.

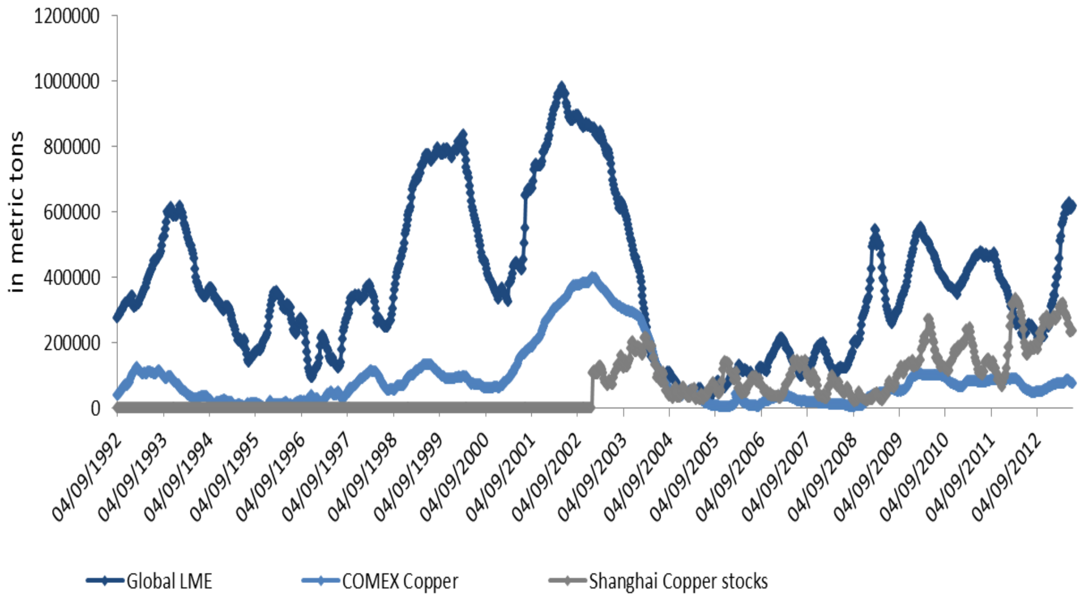
The aim of this paper is to wrap a three-factor commodity model into a heterogeneous agents model where the Fundamental price input is directly derived from the three-factor model for copper. The heterogeneous agents model is based on the work of Lux&Marchesi (1999, 2000) who introduced an algorithm combining fundamental and noise traders (which will be denoted chartist in our paper). The input of the fundamental price (which is used by fundamentally driven investors to compare with the current price of copper) is directly generated via a three-factor copper price model where it is calculated out of the model spot price. The spot price is based on a long-term price (which is represented by a Geometric Brownian motion with positive drift) of copper combined with short-term fluctuations (via a mean-reversion process) and considering stochastic volatility. It is this long-term fundamental price of copper calculated via the modelled spot price which serves as an input in the heterogeneous agents model.

Chile, the United States, Peru and China represent the largest producers of Copper (http://www.bgs.ac.uk/mineralsuk/statistics/worldStatistics.html). With the rapid expansion of Chinese economic growth over the last decade China now represents also the largest importer of Copper followed by the United States and Europe (Source: International Trade Center). For years the London Metal Exchange (LME) and the Chicago Mercantile Exchange (COMEX) in the US have been the main locations for trading Copper forward contracts. A very small fraction of futures contracts at COMEX and LME are physically unwound at maturity (as in all commodity futures markets). Over the years as Chinese significance in copper trading rose the Shanghai exchange became the third major player in the copper space as can be seen on the chart below.

Weekly copper inventory data for the LME and COMEX are available since September 1992 while Chinese weekly copper inventory data are available from January 2003. Figure 1 shows Global copper inventory data since 1992 (in metric tons) and the gain in significance of China on copper inventories.

The chart also shows the cyclical nature of copper, often labelled “Dr. Copper” in financial markets. The period of 2000/2001 and the 2008 recession have both led to a sharp rise in copper inventories as demand collapsed.

Figure 16: Global Copper Inventory data (in metric tons)



Source: Shanghai Futures Exchange, LME, COMEX

The aftermath of the 2001/2002 recession has resulted in a sharp decrease in overall copper inventories while from 2005 onwards a general upward trend could be observed despite the volatility around the financial crisis in 2008.

Table 6: Global Copper Inventory statistics

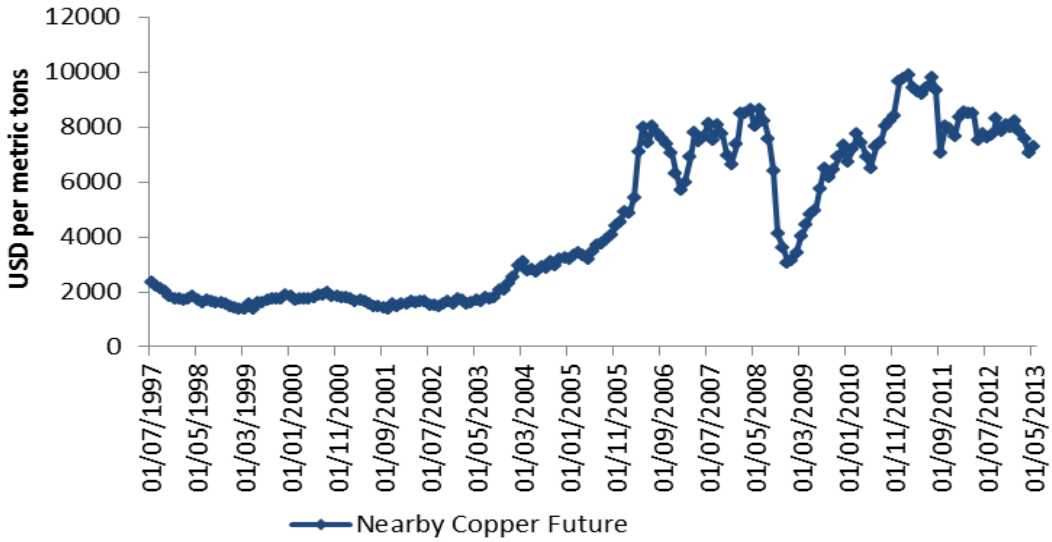
Test Statistics	LME Copper Inventory	COMEX Copper Inventory	Shanghai Copper Inventory
Average	380,104.65	90,451.36	60,732.90
Median	342,125.00	65,211.00	23,731.00
Maximum	980,075.00	399,368.00	336,387.00
Minimum	25,525.00	1,478.00	-
Standard Deviation	11,695.20	3,178.62	13,074.37
Dickey Fuller Test Statistic	- 6.23	- 5.60	- 9.94
p-value	0.01	0.01	0.01
Lag order	10	10	10

Source: Authors' calculations, Shanghai Futures Exchange, LME, COMEX

The table above summarizes key statistics for the three inventory markets (LME, COMEX and Shanghai). The Dickey Fuller Test statistics are statistically significant and reject the null hypothesis of a unit root.

Turning to copper prices, our analysis comprises monthly copper future data since 1997. We use Chicago Mercantile Exchange data (COMEX). The nearby contract represents the proxy for the cash price and we also obtained data for the 3 month, 6 month, 9month, 12 month, 15 month and 21 month forward contract since 1997. The chart below shows the price development of the nearby contract over time.

Figure 17: Monthly copper price since 1997

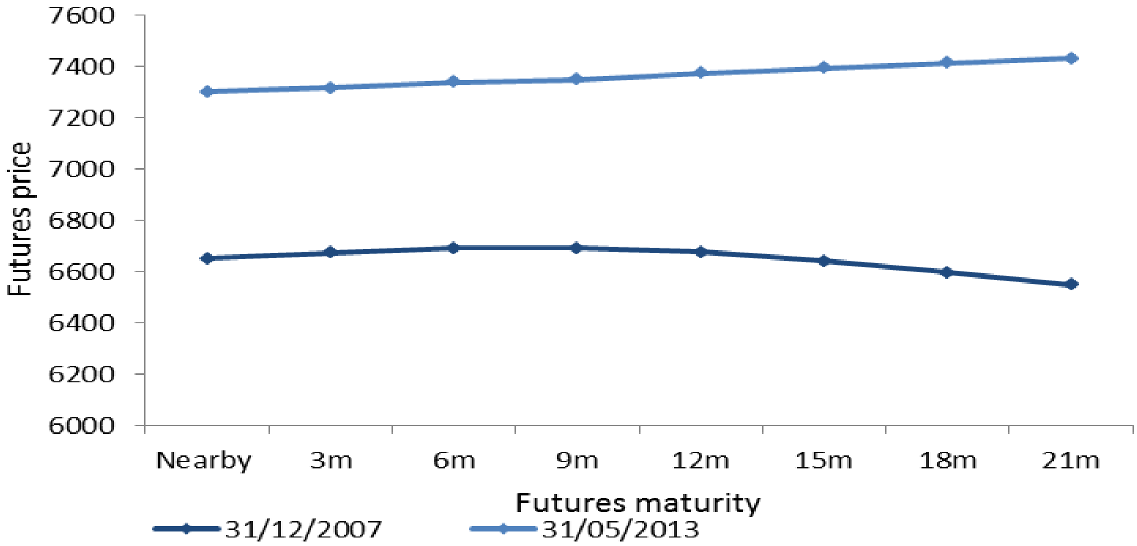


Source: COMEX

The sharp increase in commodity prices from 2002 to 2007 was also observed in copper prices with a quadrupling of prices over this period. The Financial Crisis in 2008 led to a sharp correction with more than -50%.

Financial investors (as in so many other commodities) have not only contributed to the higher volatility in commodity prices over the last couple of years but also influenced the shape of the forward curve. The chart below shows that the copper forward curve was inverted before the Financial crisis but has been in contango lately.

Figure 18: Copper forward curve over time – December 2007 versus May 2013 (in USD)



Source: COMEX

We also look more in detail on the statistical properties of each copper future maturity over the period 1997 to 2013 using monthly log prices. As with many commodity markets all maturities of copper futures observed show a negative skewness (relatively few low values) while the excess Kurtosis is positive and thus indicates fait tail behaviour.

Table 7: Copper futures statistical analysis 1997 to 2013 (using log prices)

	Nearby Contract	3m Future	6m Future	9m Future	12m Future	15m Future	18m Future	21m Future
Mean	8.18	8.18	8.18	8.17	8.17	8.16	8.16	8.15
Standard Deviation (annualized)	27.66%	27.45%	26.85%	26.22%	25.66%	25.27%	24.84%	24.47%
Standard Error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Skew	- 0.89	- 0.90	- 0.94	- 1.00	- 1.05	- 1.08	- 1.09	- 1.10
Excess Kurtosis	2.54	2.32	2.62	2.81	2.92	2.87	2.96	2.96

Source: COMEX, Authors' calculations

The table above also picks up the so called "Samuelson effect" which states that futures price volatility decreases with increasing maturity.

Next to looking at copper future prices over various maturities we also analyse in more detail the volatility behaviour of nearby copper futures. We introduce the scarcity variable, here denoted as $s_t$and defined as inverse inventory at time t (see Geman et al. 2005). We take the copper stock for the US and Global markets at the end of period t (here monthly) and calculate the scarcity as the inverse of inventories. In order to understand the impact of inventories on spot price volatility (σ_t)we run the following multi-variant regression that includes a constant, a variable that accounts for possible trends over time (δ) as well as the sensitivity β which should be positive if high inventories reduce nearby copper future volatility.

$$\sigma_t = \alpha + \delta t + \beta s_{t-1} + \epsilon_t \quad (1)$$

We run this regression for different inventory data, namely a global inventory proxy which includes LME, COMEX as well as Shanghai data and for a US inventory proxy (COMEX only). σ_t is the monthly volatility of nearby copper futures calculated from daily data. s_{t-1} represents the scarcity at the end of the previous month (inverse of inventories).

Using the entire data series (from 1997 to 2013) as input the F-Test and the T-statistics for each input variable show that the scarcity variable cannot be rejected at a 1% significance level as driver of copper price volatility. The US scarcity variable has been more volatile over the observation period which explains the lower scarcity beta.

Table 8: Monthly copper price volatility regression output (based on monthly inventory data) with t-statistics in brackets

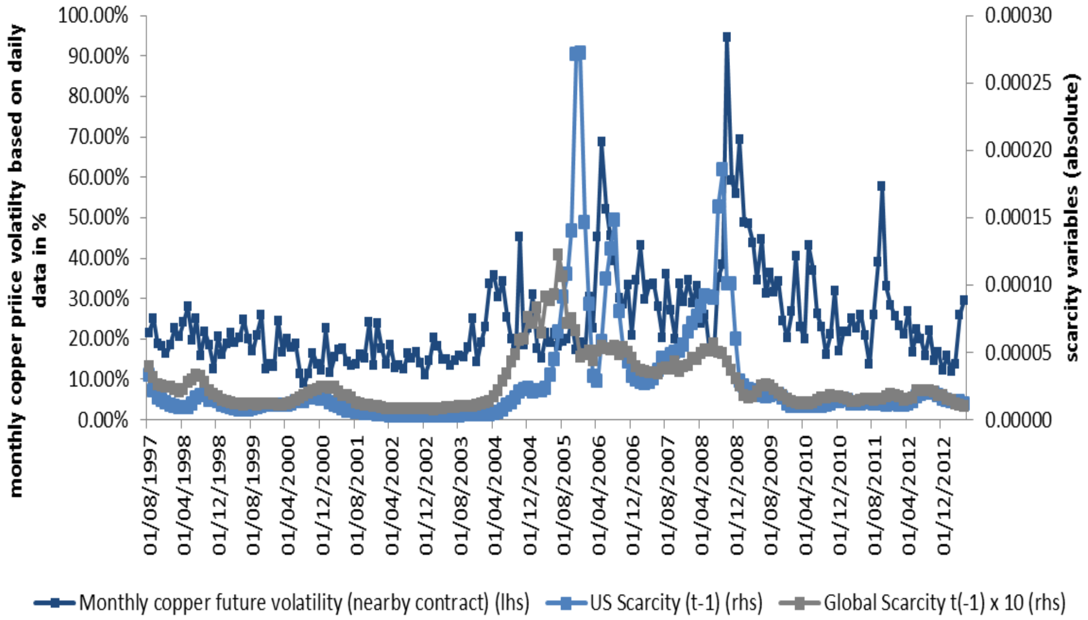
	Global Copper Inventories	US Copper Inventories
α (t-statistic)	0.15 (7.92)	0.16 (9.99)
δ (t-statistic)	0.00 (4.91)	0.00 (4.55)
β (t-statistic)	10,279.48 (2.62)	631.62 (3.20)
R-squared	0.15	0.17
F-test	16.58	18.49
Standard error	0.11	0.11

Source: Shanghai Futures Exchange, LME, COMEX, Authors' calculations

Despite adding Chinese stock data to the global stock variable US inventories show a higher R-squared in explaining copper nearby futures volatility. It is worth mentioning that the time effect does not seem to influence spot price volatility because the coefficient is close to 0 for both, global copper inventories as well as US inventories only.

In the next chart we contrast the 2 derived scarcity variables versus daily copper spot price volatility on a monthly basis. The scarcity variables show 2 events of significant spikes, namely in 2005 and just before the Financial crisis. The positive beta confirms that our scarcity proxy shows a positive relationship to subsequent copper price volatility. Thus when inventories get lower a rise in copper spot price volatility is more likely. Beside these 2 events the scarcity proxies did not signal tight inventories for most of the last 15 years.

Figure 19: Monthly copper price volatility based on daily data versus Global and US scarcity variables

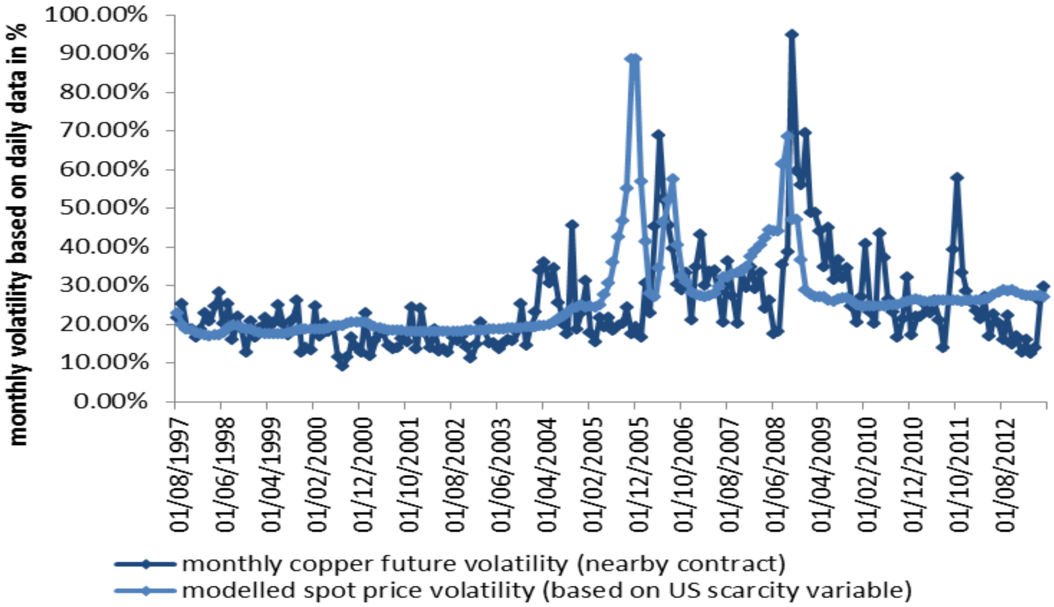


Source: Shanghai Futures Exchange, LME, COMEX, Authors' calculations

Looking further into the historical behaviour of copper spot prices we use the regression outputs for an in-sample period (1997 to 2004) and approximate copper spot price volatility for the out-of-sample period (2005-2013) and compare it with realized volatility. We use the period from 2005 onwards for out-of-sample testing as the data suggest a structural break from a low copper price volatility regime before 2005 to a higher copper price volatility regime after 2005.

$$\widehat{\sigma_t} = \hat{\alpha} + \hat{\delta} t + \hat{\beta} s_{t-1} \tag{2}$$

Figure 20: Monthly copper price volatility based on daily data versus modelled volatility



Source: COMEX, Authors' calculations

As could have been suspected from the previous chart looking at the scarcity variable over time the estimated volatility anticipates the 2 spikes in copper future volatility in late 2005 and during the financial crisis while the spot price volatility spike in 2011 seems having been driven by financial market volatility (Euro-Zone debt crises) rather than fundamental (supply/demand) reasons.

Section 3: Reference level or fundamental spot price of copper for fundamentally driven investors

In this section we describe the role of the financial players present in our model more in detail. We described the general market characteristics of copper markets in the previous chapter while this chapter will provide a framework for modelling the demand and supply relationship via the fundamental value of copper prices. We will distinguish between two different types of market participants, fundamental agents and technical agents. The agent of our model takes the expected price for the next time interval [t;t+], called the reference level, from a financial expert. Indeed, we need to describe how these experts choose this reference level. We consider a finite set of financial experts I = {1,2,......,M}.

The fundamental value or benchmark of each expert, denoted L_t^i, is the value, on a logarithmic scale, at which this expert i ϵ I I expects the price to return in the long run. The long-run price of copper is based on a three-factor model for commodity prices where the equilibrium price level is assumed to evolve according to a geometric Brownian motion with drift, reflecting themes like exhaustion of existing supply, improved technology for production or inflation (Geman, 2000) This long-term equilibrium price is not directly observable in the market though in the case of long-term futures prices this information can be estimated over time. Additionally, the long-term equilibrium price level will be refined with a short-term deviation term which is expected to revert to zero following an Ornstein-Uhlenbeck process. These short-term deviations are representing short-term changes in demand or supply e.g. because of weather. The third factor introduced will be a scarcity parameter for copper which represents the inverse of global copper stocks at the end of each time period t ϵ T.

As often done in financial literature we define returns as changes in log prices. We denote the spot price of copper by S_t at time t. First we introduce a scarcity variable similar to Geman and Nguyen (2005) denoted as s_t and defined as inverse inventory at time t. The same notation as in Geman and Nguyen (2005) is used to denote the world stock of copper at the end of period t, I_t and thus the scarcity s_t=1/I_t follows. To gain more insight into the effects of inventories on volatility we use the following equation introduced in the previous section.

$$\sigma_t = \alpha + \delta_t + \beta s_{t-1} + \varepsilon_t, \tag{3}$$

where t denotes the time period (month), s_{t-1} is the scarcity variable at time t-1, and σ_t is the standard deviation of the nearby returns over period t. α accounts for the possibility of a trend in either the volatility or scarcity series. The constant β, the sensitivity of volatility to past inventory data is positive if high inventories reduce volatility. If on the other side inventories are very low then an additional unit of inventory will have a greater effect on volatility.

The copper spot price is decomposed into three stochastic factors

$$\ln(S_t) = X_t \tag{4}$$

where X_t will be the short-term deviations from the copper equilibrium price modelled as a mean reversion process with a stochastic long-term equilibrium price L_t.

The variance of the spot return is assumed to be stochastic and represented by the following equation:

$$var_t = (\alpha + \beta s_t)^2 \tag{5}$$

where α as well as β are constant and β being positive.

The dynamics of the stochastic component of the spot price under the real probability measure are driven the following stochastic differential equations:

$$dX_t = (\kappa(L_t - X_t) + \lambda_x v_t)dt + \sqrt{var_t}\,dz_t^x \tag{6}$$

where L_t is represented by a geometric Brownian motion with constant drift μ and λ_χ represents the market price of commodity risk:

$$dL_t = (\mu + \lambda_L \sigma_L v_t)dt + \sigma_L dz_t^L \quad (7)$$

where λ_L represents the risk premium on the long-term mean uncertainty. The variance of the stochastic component of the spot price can thus be written by

$$dvar_t = (a(b - v_t) + \lambda_v \sigma_v var_t)dt + \sigma_v \sqrt{var_t}dz_t^v \quad (8)$$

We thus assume that the two state variables Xt and vol_t follow a mean-reversion process and L_t a geometric Brownian Motion respectively. Further there exists a correlation ρ_{xL} (respectively ρ_{vL} and ρ_{xv}) assumed between the Brownian Motions z_x and z_L and z_v. We assume no arbitrage opportunities because we have more instruments than sources of risk and hence the market is complete. The variables a, b and σ_v are positive and λ_v is the market price of volatility risk.

The existence by arbitrage does hold (a risk-neutral probability measure Q can be assumed).

$$dX_t = \kappa(L_t - X_t)dt + \sqrt{var_t}d\hat{z}_t^x \quad (9)$$

$$dL_t = \mu dt + \sigma_L d\hat{z}_t^L \quad (10)$$

$$dvar_t = a(b - var_t)dt + \sigma_v \sqrt{var_t}d\hat{z}_t^v \quad (11)$$

The choice of the square root process in equation (9) ensures positivity of the solution while mean reversion implies bounded values. The fact that var_t is observable means that the Kalman Filter procedure used to calculate the parameters involved is based on normally distributed quantities.

Our representation of the spot price has the features of a mean-reverting behaviour with a stochastic trend and stochastic volatility.

The assumptions above imply the following dynamics of the copper spot price under the Q measure:

$$dS_t = k[(L_t - \ln S_t) + \frac{1}{2k} var_t] S_t dt + \sqrt{var_t} S_t d\hat{z}_t^x \tag{12}$$

Because the future price is a Q-martingale based on assumptions (3) and (4) the price F_t^T at time t of a future contract maturing at time T can be written as

$$F_t^T = E_Q\left(\frac{S_T}{\mathcal{F}_T}\right) = e^{A(t,T)+B(t,T)lnS_t+C(t,T)L_t+D(t,T)var_t} \tag{13}$$

The solution of this form yields the system of the following ordinary differential equations:

$$B' + kB = 0 \tag{14}$$

$$C' - kB = 0 \tag{15}$$

$$-D' + \frac{\sigma_v^2}{2} D^2 - D(a + \rho_{xv}\sigma_v B) + \frac{\sigma_L^2}{2} C^2 + \frac{1}{2} B^2 = 0 \tag{16}$$

$$A' - \mu C - abD = 0 \tag{17}$$

with initial conditions A(T,T)=0, B(T,T)=1, C(T,T)=0 and D(T,T)=0. The solutions to (14) and (15) are elementary and plugging into (12) and (13) results in the following expressions:

$$B(t,T) = e^{-\kappa(T-t)} \tag{18}$$

$$C(t,T) = e^{\kappa(T-t)} \tag{19}$$

$$A(t,T) = \mu \frac{1-e^{\kappa(T-t)}}{k} \quad + ab\int_t^T D(u,T)du \tag{20}$$

Where D(t,T) is the solution to the following ordinary differential equation

$$D'(t,T) = -\frac{\sigma_v^2}{2} D^2 + D(a - \rho_{xv}\sigma_v B) - \frac{\sigma_L^2}{2} C^2 - \frac{1}{2} B^2 - \rho_{LX}\sigma_L BC \tag{21}$$

The integral in (20) will be solved using the numerical procedure of the trapezoidal rule. The solution to equation (21) is not available in closed form but will be solved numerically with high precision by methods like Runge-Kutta.

Section 4: The Kalman Filter approach for a three-factor copper price model

The Kalman Filter will be used to calculate unobserved state variables (long-term equilibrium price and stochastic component of the spot price) based on observations (in this case the log of Future prices for copper) that depend on these state variables. We will work in a discrete setting and given a prior distribution on the initial values of the state variables and a model describing the likelihood of the observations as a function of the true values, the Kalman Filter will generate updated posterior distributions for these state variables.

In the three-factor model only the stochastic component of the spot price and its stochastic long-term equilibrium mean are unobservable whereas the scarcity variable is directly obtained by taking the inverse of the inventory numbers.

Two equations are crucial for the Kalman Filter, namely the measurement equation and the transition equation. The measurement equation relates the observable vector $\mathrm{Y_t^F}$ to the state vector $\mathrm{Z_t}$ where $\mathrm{Z_t}$ is defined as $\mathrm{Z_t} = [\mathrm{X_t}, \mathrm{L_t}]$ via the following relationship:

$$Y_t^F = M_j + L_j Z_j + \omega_j, j = 1, \ldots., J \tag{22}$$

where

$M_j = [A\left(t_j, T_i\right) + D\left(t_j, T_i\right) var_t\big]\big], i = 1, \ldots. N, N \times 1\ vector$

$L_j = [B\left(t_j, T_i\right), C\left(t_j, T_i\right)\big]\big], i = 1, \ldots. N, N \times 2\ vector$

ω_j is a $N \times 1\ vector$ of serially uncorrelated disturbances with $\mathrm{E}[\omega_j] = 0, Var\left[\omega_j\right] = \Omega$ where Ω is a diagonal matrix.

Equations (21) and (22) can be used to derive the transition equation for the copper spot price as

$$dZ_t = (U_t + HZ_t)dt + V_t dW_t \tag{23}$$

Where $U_t = [\lambda_x v_t, \mu + \lambda_L \sigma_L var_t]'$ and $H = \begin{bmatrix} -\kappa & \kappa \\ 0 & 0 \end{bmatrix}$ and V_t is such that

$$V_t V_t' = \begin{bmatrix} 1 & \rho_{XL}\sigma_L \\ \rho_{XL}\sigma_L & \sigma_L^2 \end{bmatrix} var_t$$

and the discrete-time transition equation for the Kalman Filter is obtained as:

$$Z_j = e^{H\Delta} Z_{j-1} + G_{12}(\Delta_j) + \widetilde{V_j}\epsilon_j \tag{24}$$

ϵ_j is a 2 x 1 vector of serially uncorrelated disturbances with $E(\epsilon_j) = 0$ and $Var(\epsilon_j) = IdentityMatrix(2x2)$. $G_{12}(\Delta_j) = \int_0^{\Delta} e^{H(\Delta_j - u)} U_j du$ is the approximate discrete-time version of $\mathrm{U_t}$ in the transition equation.

The Kalman Filter allows estimating the state variables over time by updating the estimator $\widehat{\mathrm{Z_{J/J}}}$ but this is assuming a specific assumption about the parameters of the process. The equations above assumed the prior knowledge of these parameters. In practice however the parameters are unknown so they have to be estimated, e.g. by Maximum likelihood:

$$\log Likelihood = -\frac{NJ}{2} log 2\pi - \frac{1}{2}\sum_{j=1}^{J} log|R_j| - \frac{1}{2}\sum_{j=1}^{J} \hat{v}_j' R_j^{-1} \hat{v}_j \tag{25}$$

Where the conditional distribution of $\hat{v}_{j+1}$is normal with mean zero and a covariance matrix R_j.

4.1. Three-factor copper price model - results

In this section we estimate the model parameters developed earlier. We apply the Kalman filtering procedure to the time series of nine maturity copper futures prices (N=9) for up to 2 years out the forward curve. We use monthly data from July 1997 to May 2013.

The Kalman filter is a recursive method for computing the unobserved state variables and works best for normally distributed data. These state variables are described in a transition equation while the link between the observable futures prices and the state variables is explained by the measurement equation. The Kalman filter optimizes a log-likelihood function that minimizes the error between the model output and the real-world data used as input. In our three-factor model only the stochastic component of the spot price and its long-term mean (we use this long-term mean as the fundamental value input for our financial agent model later) are unobservable while the scarcity variable is directly obtained as the inverse of the inventory numbers.

The table below gives the estimated parameters and standard errors of the three-variable model and shows the estimated values of the common parameters.

Table 9: Parameter output – three factor model (standard error in brackets)

Parameter	Three-factor model results
κ	0.78 (0.03)
μ	8.62 (0.05)
σ_L	0.80 (0.26)
a	2.34 (0.17)
b	0.23(0.04)
σ_v	2.95 (0.34)
$corr_{xv}$	0.51 (0.08)

Variable a is much higher than κ indicating that the stochastic volatility process shows a stronger mean-reversion behaviour compared to the stochastic component of the spot price. The correlation between the stochastic component of the spot price and spot price volatility is positive and statistically significant, in conformity with the Theory of Storage.

Section 5: Heterogeneous agent based model considering co-movement for Copper prices

In the previous section we derived the long-term fundamental value for copper. We will use this value as a fair value proxy in an agent based model approach. A simple heterogeneous agent based model will be presented in this chapter to assess the effect of fundamental as well as technical traders on the price of copper.

As mentioned earlier the aim of this paper is to wrap a three-factor commodity model into a heterogeneous agents model where the Fundamental price input is directly derived from the three-factor model for copper.

This section describes the approach towards the heterogeneous agent model chosen while the next section applies the output from the three-factor model to the agents model and calibrates the parameters to copper prices observed.

5.1. Demand/Supply relationship

Before going into detail about the various strategies that investors can apply this section focuses on simple demand and supply functions in order to characterize the copper market. Similar to Geman and Nguyen (1995) who use a linear regression to see the impact of inventories on volatility it makes sense to evaluate the overall demand and supply for copper in a simplified linear regression which takes into account exogenous factors as well as endogenous price-sensitive factors.

In the case of copper as with most commodities we can distinguish between real demand and investment demand, namely demand of fundamental investors and demand of technically driven investors.

The link of real and speculative demand with the price dynamics of copper will be modelled via the following equation:

$$\dot{P} = \beta D = \beta[D_c + D_f] = \beta[(\dot{n}_+ - n_-)s_c + n_f s_f(p_f - p)] \qquad (26)$$

where $\dot{P}$ represents the price change of copper which is a function of excess demand from fundamentalist (D_f) and chartists (D_c). We further follow Lux (1995) and distinguish between optimistic chartists (their absolute number is n_+) and pessimistic chartists (their absolute number is n_-). When we multiply the absolute number of chartists (N=n_-+n_+) with the amount of shares they hold (denoted s) then we derive the total demand of chartists. In this setting we are interested in the excess demand of chartists which according to equation (26) represents the difference of positive minus pessimistic chartists.

The interaction between chartists and fundamentalists is defined by two ratios, namely:

$$x := \frac{n_{+} - n_{-}}{n_c} \tag{27}$$

describing the excess of optimistic chartists over pessimistic chartists and

$$z := \frac{n_c}{N} \tag{28}$$

where z represents the fraction of chartists amongst the entire population of traders.

5.2. Fundamentalists

Fundamentalists base their demand for copper on the difference between the current expectation (at time t) of the future spot price (at time t+1) and the current price of copper. The expected excess return of fundamentalists is thus given by $\mathrm{d}|(\mathrm{p_f} - \mathrm{p})/\mathrm{p}|$ where d is a discount factor. This represents the present value of the trading profit expected by the fundamentalist which would occur when the price p has reverted back to the fundamental value $\mathrm{p_f}$.

5.3. Chartists

The second type of strategies which is considered in this paper is chartists. Chartists base their investment decision on past price patterns. In contrast to fundamentalists, who tend to have a stabilizing effect on financial assets via contrarian trades chartists are more likely to invest with the trend and thus encourage current trends in the market further. In line with what has been proposed in previous heterogeneous agents models (e.g. Hommes 2006) we focus on a pure trend following approach where chartists look at the past price at t-1 and thus try to assess short-term trends.

The distinction between optimists and pessimists adds further refinement to the price dynamics of our agent-based model approach. Both benefit from a price move $\dot{p}$ above a refinancing rate r_f (we are focusing on excess returns above risk free rate r_f). Thus the profit of an optimistic chartist can be modelled as:

$$optimists\ trading\ profit = \frac{r+\dot{p}/w}{p} - r_f \quad (29)$$

where w represents a speed of transition parameter between the chartists and the fundamentalists.

$$pessimists\ trading\ profit = r_f - \frac{r+\dot{p}/w}{p} \quad (30)$$

Optimists are long the stock and thus pay the refinancing rate r_f whereas pessimists are short the stock and thus receive r_f.

After we defined the trading profits of both groups, fundamentalists and chartists, the next step is to combine both in a systematic interaction approach. This is based on the utility function of both groups which is in simple terms a function of performance.

5.4. Interaction between fundamentalists and chartists

The transition probability of a chartist from positive to negative and vice versa is determined by Utility

$$U_1 = \alpha_c x + \beta_c \frac{\dot{p}}{v} \quad (31)$$

which directly feeds into the transition probability of moves between optimists and pessimists where v is a variable for the speed of change from optimists to pessimists

$$p_{\mp\pm} = v(\frac{n_c}{N}\exp(\pm U_1)) \quad (32)$$

The utility is thus a function of the relative weight of optimists versus pessimists (x) and the price change. The transition probability function is an exponential function (Lux 1995) and considers moves from pessimists to optimists in the case of rising prices and a higher transition probability of optimists switching to pessimist in the case of falling copper prices in equation (32).

The transition probability of moving from fundamentalists to chartists is modelled in a similar way as

$$p_{f\pm} = w\frac{n_\pm}{N}\exp(U_{2,\pm}) \tag{33}$$

and vice versa as

$$p_{\pm f} = w\frac{n_f}{N}\exp(-U_{2,\pm}) \tag{34}$$

where the utility of moving from fundamentalist group to the chartist group $U_{2,\pm}$ and from the chartist to fundamentalists -$U_{2,\pm}$ is given by

$$U_{2,+} = \alpha_3(\left(\frac{r+\frac{\dot{p}}{w}}{p} - r_f\right) - d\left|\frac{p_f - p}{p}\right|) \tag{35}$$

The utility of moving from the optimist to the fundamentalist is derived as the difference of the performance of the optimist (who is long copper and short cash) and the discounted expected performance of the fundamentalist.

Similarly the utility from pessimists to fundamentalists, denoted $U_{2,-}$ can be described as the difference of the performance of a pessimist (who is short copper and long cash) minus the discounted expected profit of the fundamentalist

$$U_{2,-} = \alpha_3(\left(r_f - \frac{r+\frac{\dot{p}}{w}}{p}\right) - d\left|\frac{p_f - p}{p}\right|) \tag{36}$$

As mentioned in the previous section this paper will explicitly derive the input for the fundamental investors, namely the long-run equilibrium price of copper which was labelled L_t. The next section will give a brief overview of the derivation of this long-term equilibrium spot-price for copper.

$$\frac{dx}{dt} = \frac{\frac{dn_+}{dt} - \frac{dn_-}{dt}}{n_c} - (\frac{n}{n_c^2})dn_c/dt$$

$$n_+ = \frac{(1+x)zN}{2}$$

$$n_- = \frac{(1-x)zN}{2}$$

$$\frac{dx}{dt} = z[(1-x)p_{\mp} - (1+x)p_{\pm}] + \frac{(1-z)(1-x^2)(p_{f+} - p_{+f} + p_{-f} - p_{f-})}{2} \quad (37)$$

As $p_{\pm-}$ and $p_{\mp}$ are of the form of exponential functions (as shown in equations (32-34) above) we can use the following trigonometric identities to solve the deterministic analogue of what originally represented a system of stochastic equations with state variables x, z and p:

$$\mathrm{Sinh}(x) = \frac{(e^x - e^{-x})}{2}, Cosh(x) = \frac{(e^x + e^{-x})}{2} \; and \; Tah(x) = \frac{Sinh(x)}{Cosh(x)}$$

From the definition of z we can follow that $\frac{dz}{dt} = \frac{\frac{dn_c}{dt}}{N}$ which can be derived from the subgroup of pessimists

$$\frac{dn_-}{dt} = (n_+ p_{+\,-} - n_- p_{-+})\left(1 - \frac{n_f}{N}\right) + n_f\left(\frac{n_-}{N}\right)p_{f-} - n_-\left(\frac{n_f}{N}\right)p_{-f} - (a-b)n_- \quad (38)$$

where the first two terms mimic contagion the third and fourth term express changes of strategies and the last term represents market entry and exit. Performing a similar exercise for the subgroup of optimists

$$\frac{dn_+}{dt} = (n_- p_{-+} - n_+ p_{+-})\left(1 - \frac{n_f}{N}\right) + n_f\left(\frac{n_+}{N}\right)p_{f+} - n_+\left(\frac{n_f}{N}\right)p_{+f} - (a-b)n_+ \quad (39)$$

and combining (38) and (39) eliminates the last term (entry and exit of agents) and leads to

$$\frac{dz}{dt} = \frac{(1-z)z(1+x)\left(p_{f+}-p_{+f}\right)}{2} + \frac{(1-z)z(1-x)\left(p_{f-}-p_{-f}\right)}{2} + a(1-z) \qquad (40)$$

We assumed at the start that chartists adjust their position for a fixed amount t_c (of shares). Chartists who are bullish try to increase their stake while those who are bearish will try to decrease their shares. This leads to an excess demand from chartists

$$D_c = (n_+ - n_-)t_c = nt_c = xzNt_c = xzs_c \qquad \text{where } s_c = Nt_c \qquad (41)$$

Fundamentalists on the other side will buy copper when the price has fallen below their fair value proxy and sell when the price is above their fair value. We can thus formulate the excess demand of fundamentalists as

$$D_f = t_f\delta\left(p_f - p\right) = (1-z)N\delta\left(p_f - p\right) = (1-z)s_f\left(p_f - p\right) \quad \text{where } s_f = N\delta \qquad (42)$$

Combining equations (41) and (42) for dp/dt results in equation (26) and we have thus proofed the aggregate demand equation.

5.5. Agent based modelling approach - results

In this section we present the results of the agent based model introduced before. This Poisson-type dynamics of updating strategies and opinion index will be approximated within a simulation framework. We chose small time increments in order to avoid synchronicity of decisions and because the phenomenon of volatility bursts requires higher precision between the time steps modelled. We are using the long-term fundamental value derived from the three-factor model as benchmark for fundamental traders. We assume for the simulation a total number of 500 agents. In order to make sure the system is able to calibrate and in order to avoid degenerate situations in which either the group of chartists or fundamentalists has declined to zero we ensure a minimum number of 4 agents in each group, fundamental and technical agents. Despite the fact that this scenario of an absorbing state decreases with a sufficient number of agents it still has a positive probability of occurring and thus we prefer to apply a lower limit on each agent category.

We show in the table below the fixed parameter values for dividends and average rate of return. It is worth noting, as shown in several academic studies applying this model, that this approach is not very sensitive to those parameters and we have thus chosen values that are in line with previous applications (Lux, 1998, Lux et al. 2000).

Table 10: Fixed parameters for agent based model

Fixed Parameter	Assumed Value
Number of steps per integer time step	50
Number of microsteps for dp/dt	100
Number of agents	500
Minimum number of agents in a strategy	4
Nominal dividends of the asset	0.4%
Risk free rate	0.04%
Frequency of optimist/pessimist revaluation	3
Frequency of chartist/fundamentalist revaluation	2
Discount factor	0.75
Imprecision in excess demand perception	0.05

Source: Authors' calculations

We estimate the importance of the opinion index for chartists (α_c), the importance of price changes for chartist expectations (β_c), the importance of profit differentials for a switch between chartists and fundamentalists (α_3) as well as the reaction speed of auctioneers (β) with the help of the Generalized method of moments technique (GMM). This method requires that a certain number of moment conditions ($g(X, \theta)$ are specified for the model for which we show the generalized form below.

$$m(\theta_0) \equiv E[g(X_t, \theta_0)] = 0 \tag{43}$$

These moment conditions are functions of the model parameters and data such that their expectation is zero at the true values of the parameters. The GMM method minimizes a certain norm of the sample average of our moment conditions and can thus be written as:

$$\hat{\theta} = arg \min_{\theta \epsilon \Theta} (\tfrac{1}{T} \textstyle\sum_{t=1}^{T} g(X_t, \theta))' \widehat{W} \, (\tfrac{1}{T} \textstyle\sum_{t=1}^{T} g(X_t, \theta)) \tag{44}$$

where W represents the positive-definite weighting matrix.

Based on 14 years of monthly data we derive estimates for the parameters shown in the table below. All four parameters are positive as expected and statistically significant. It is worth noting that the importance of profit differentials for a switch between chartists and fundamentalists (α_3) as well as the reaction speed of auctioneers (β) are reasonably small. The importance of the opinion index of chartists and the importance of price changes for chartist expectations are closely linked and show a high positive correlation. The importance of profit differentials for a switch from chartists to fundamentalists is negatively correlated to the importance of price changes for chartist expectations as well as to the opinion index of chartists. Thus the higher the optimism (pessimism) amongst chartists the lower (higher) the probability of chartists to move to the fundamentalist group and the less (more) attention chartists are paying to past profit differentials for their strategy assessment.

Table 11: Agent based model output (standard error in brackets)

Number of observations: 169

Number of parameters: 4

Number of degrees of freedom: 165

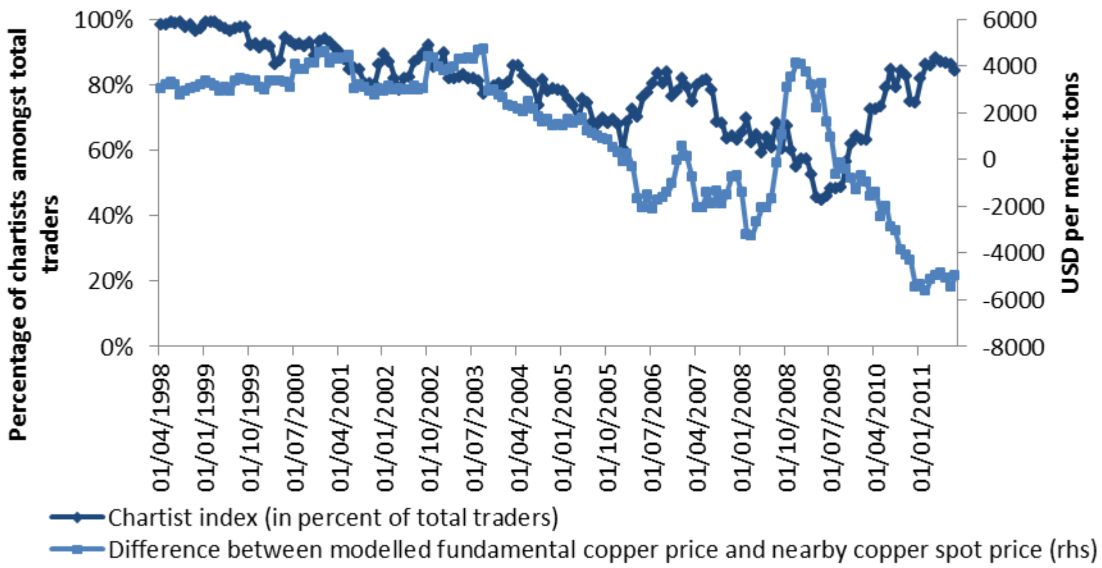
Orthogonality conditions: 5

Parameter	Estimate (standard error)			
α_c	0.55 (1.07E-09%)			
β_c	0.23 (7.59E-11%)			
α_3	0.10 (2.20E-10%)			
β	0.10 (8.54E-12%)			
correlation of parameters	α_c	β_c	α_3	β
α_c	1			
β_c	0.88	1		
α_3	-0.99	-0.92	1	
β	0.33	0.60	-0.39	1

Source: Authors' calculations

In order to provide some further insight into the model over time we show below the fraction of chartists modelled over time based on our approach. Based on the copper price data evaluated we can see that the number of chartists started to drop before the financial crisis. The copper spot price was considerably lower than the fundamental value and the difference narrowed which made the mean reversion trade very profitable. Strong copper demand by China after 2001 has likely been one of the reasons for this narrowing between the copper spot price and its fundamental value. Copper prices retreated sharply during the financial crisis and fell well below the fair value assumed by fundamental traders. This coincided with technical traders gaining in relative performance again (momentum was more profitable) after 2009.

Figure 21: Percentage of chartist amongst trader universe versus difference between modelled copper fair value and copper spot price (rhs)



Source: Authors' calculations

Section 6: Conclusion

We have shown in this paper that inventory plays a role in explaining copper price volatility. Using a three factor model we derived a fundamental long-term value for copper. The addition of a stochastic component in the spot price shows a positive correlation to copper spot price volatility. Second, we emphasis the significance of this fundamental long-term value by considering an agent based model approach in which mean-reversion focused fundamental investors trade with chartists who follow price trends. We showed that fundamental investors take increasing positions in copper when the spot price of copper deviated from its fundamental value (i.e. the fundamental value is higher than the spot price) and chartists loose relative significance.

References

Amilon, H., 2008. Estimation of an adaptive stock market model with heterogeneous agents, Journal of Empirical Finance 15, pp. 342-362

Boswijk, H.P., C.H. Hommes, and S. Manzan, 2007. Behavioral heterogeneity in stock prices, Journal of Economic Dynamics & Control, pp. 1938-1970

Brock, W.A., and C.H. Hommes, 1997. A Rational Route to Randomness, Econometrica, 65 (5), pp. 1059–1096

Brock, W.A., and C.H. Hommes, 1998. Heterogeneous beliefs and routes to chaos in a simple asset pricing model, Journal of Economic Dynamics and Control 22, pp. 1235-1274

Danielsen, A.L., 1979. The role of speculation in the oil price ratchet process, Resources and Energy 2, pp. 243-263

De Jong, E., W.F.C. Verschoor, and R.C.J. Zwinkels, 2009. Behavioural heterogeneity and shift-contagion: Evidence from the Asian Crisis, Journal of Economic Dynamics & Control 33 (11), pp. 1929-1944

Ellen, t.S., and R.C.J. Zwinkels, 2010. Oil price dynamics: A behavioural finance approach with heterogeneous agents, Energy Economics

Fama, E., 1970. Efficient capital markets: A review of theory and empirical work, The Journal of Finance 25 (2), pp. 28-30

Foellmer, H., U. Horst, and A. Kirman, 2004. Equilibria in Financial Markets with Heterogeneous Agents: A Probabilistic Perspective, Working Paper

Foellmer, H., and M. Schweizer, 1993. A Microeconomic Approach to Diffusion Models for Stock Prices, Mathematical Finance, 3, pp. 1-23

Foellmer, H., 1994. Stock Price Fluctuations as a Diffusion in a Random Environment, Philos.Trans R. Soc. Lond., Ser. A, 1684, pp. 471-483

Forbes, K.J., and R. Rigobon, 2002. No Contagion, Only Interdependence: Measuring Stock Market Comovements, Journal of Finance, Vol. 57, No.5, pp. 2223-2261

Frankel, J.A. and K.A. Froot, 1988. Chartists, fundamentalists and the demand for dollars, American Economic Review 10, 49-102

Geman, H., 2000. Scarcity and Price Volatility in Oil Markets, EDF Tading Technical Report

Geman, H., and V.N. Nguyen, 2005. Soybean inventory and forward curve dynamics, Management Science, Vol. 51, No. 7, pp. 1076-1091

Geman, H., 2005. Commodities and Commodity Derivatives, Modelling and Pricing for Agriculturals, Metals and Energy, John Wiley & Sons Ltd. West Sussex, England

Karolyi, G.A. and R.M. Stulz, 1996. Why Do Markets move together? An Investigation of US-Japan Stock Return Comovements, Journal of Finance, Vol. 51, No.3, pp. 951-986

Kirman, A. and G. Teyssiere, 2002. Microeconomic Models for Long-Memory in the Volatility of Financial Time Series, Studies in Nonlinear Dynamics and Econometrics, 5, pp. 281–302.

Longin, F., and B. Solnik, 2001. Extreme Correlation of International Equity Markets, Journal of Finance, Vol. 56, No.2 (April 2001), pp. 649-676

Lux, T., 1995. Herd Behavior, Bubbles and Crashes, The Economic Journal, Vol. 105, No. 431 (Jul. 1995) pp.881-896

Lux, T., 1998. The socio-economic dynamics of speculative markets: interacting agents. Chaos, and the fat tails of return distributions, Journal of Economic Behavior & Organization, Vol. 33 (1998), pp. 143-165

Lux, T. & M. Marchesi, 2000. Volatility clustering in financial markets: A microsimulation
of interacting agents. International Journal of Theoretical and Applied Finance 3:4, pp. 675—702

Pindyck, R.S., and J.J. Rotemberg, 1990. The Excess Co-Movement of Commodity Prices, The Economic Journal, Vol. 100, No. 403, pp. 1173-1189

Pindyck, R.S., 1990. Inventories and the short-run dynamics of commodity prices, MIT's center for Energy Policy Research

Pindyck, R.S., 1990. The long-run evolution of energy prices, The Energy Journal, 20, pp.1-27

Schwartz, E. and J.E. Smith, 2000. Short-Term Variations and Long-Term Dynamics in Commodity Prices, Management Science, Vol. 46, No. 7

Pindyck, R.S., 2004. Volatility and Commodity Price Dynamics, The Journal of Futures Markets, Vol.24, No.11, pp. 1029-1047

Reitz, S., and U.Slopek, 2009. Nonlinear oil price dynamics – a tale of heterogeneous speculators?, German Economic Review 10 (3), pp. 270-283

Reitz, S. And F.H.Westerhoff, 2007. Commodity price cycles and heterogeneous speculators: a STAR-GARCH model, Empiricial Economics 33 (2), pp. 231-244

Smidt, S., 1965. Amateur Speculators: A survey of trading strategies, information sources and patterns of entry and exit from commodity futures markets by non-professional speculators, Cornell University, Cornell Studies in Policy and Administration.

Steinsaltz, D., 1999. Locally Contractive Iterated Function Systems, Annals of Probability, 4, pp. 546–588

Chapter 4. Commodity Inventory Financing and the robustness of the Theory of Storage- The case of China

Section 1: Introduction

The use of commodities in securing a financial deal has existed for a long time in the history of humankind. The simplest commodity deals involved the use of a commodity as collateral to obtain a loan; failure to pay back resulted in the lender taking possession of the physical commodity. In the early days, the commodity was anything from precious metals and stones to grain and rubber. Obviously, the collateral should not degrade rapidly over time, nor should it be expensive to store, hence a high value-to–density is desirable. Copper, the world's oldest mined commodity, has the merit of not degrading with time, being crucial in the growth of economies and storable at a reasonable cost.

Back in the 15th century it was meant to provide loans at a low rate to people in need. The borrower would give in deposit (the terminology 'collateral' did not exist yet) an item of value (e.g. a jewel) and the loan was worth about two-thirds of the value of the asset deposited. Advancing fast-forward 500 years in time, we find commodities becoming in the last twenty years part of new 'structured trade finance' activities that include prepayment finance, traditional export finance, receivables-backed programs and tolling. Commodity inventory financing was first used by financial players wishing to also offer trade partners in emerging countries effective liquidity tools overcoming domestic capital account restrictions.

Of particular focus has been China, partly because of its sheer size of its economy – the second largest in the world - partly because of its strict regulations on funding. Strong growth in China attracted vast amounts of foreign direct investments though strict capital account restrictions made it often difficult for local market players to get sufficient funding. High capital demand in China also meant that domestic interest rates were higher than its main trading partners the US and European Union. In this context the role of commodity inventories changed from being a classic trade finance tool across countries and markets to becoming collateral for interest rates or FX arbitrage. The growing size of this activity in China led financial players to introduce in the 2000s the use of the acronym CCFDs to represent Chinese commodity financing deals.

Practitioners (Lewis et al. ,2014 and Yuan et al., 2014) as well as academics (Xiao and Balding, 2015) describe the process of commodity inventory financing structures as a way to circumvent capital account restrictions and arbitrage high domestic Chinese interest rates against cheaper foreign funding. Various modifications to this structure, currency hedged or unhedged, underlying commodity hedged or not, meant that the structure closely resembled a carry trade in which higher interest rate assets were bought against low interest rate assets. Like ourselves, Tang and Zhu (2016) analyze inventory financing in China through copper, aluminum and six other commodities. Introducing a 'Theory of Inventory', they conclude to the 'financialization' of commodity markets because of the deviations from the Theory of Storage their model exhibits.

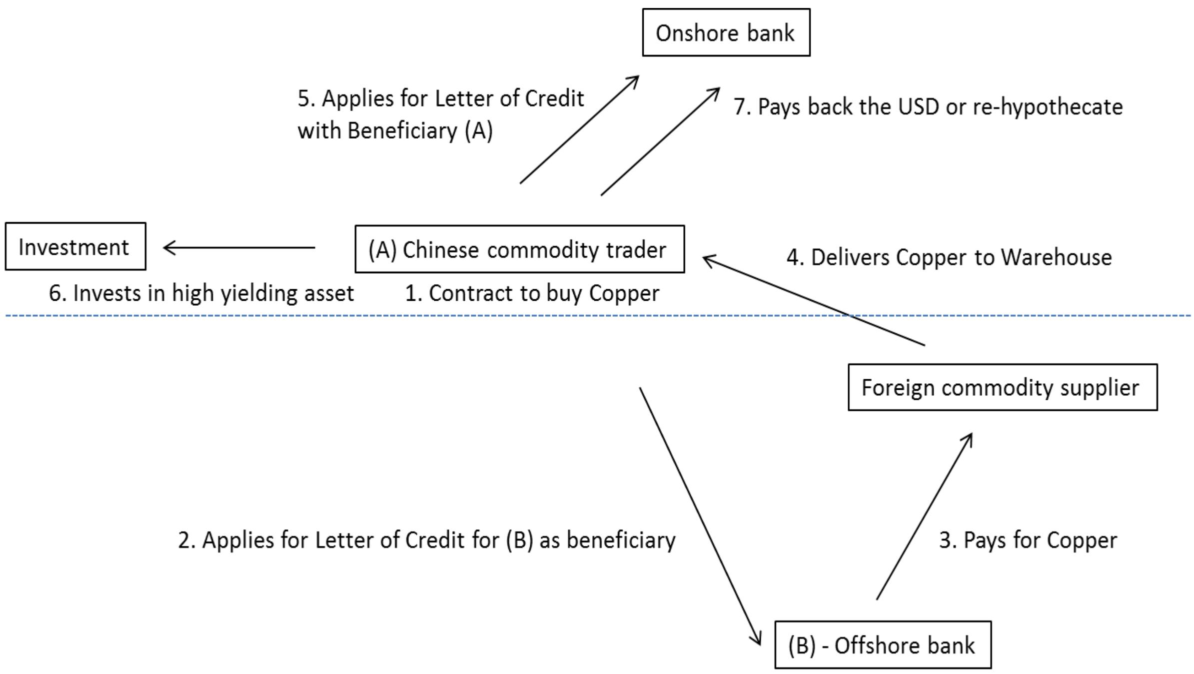
Focusing on copper, a crucial commodity in the Chinese construction boom, our aim in this paper is to investigate the extent to which commodity inventory financing transactions have impacted Chinese copper demand as well as the Shanghai copper forward curve. Using a database related to Chinese bonded copper warehouses we are able to proxy the magnitude of copper demand coming from structured trades. We provide a theoretical framework, based on the fundamental Theory of Storage and traditional definition of inventory, as well as previous research of ours (Geman and Nguyen (2005); Geman and Ohana (2009); Geman and Smith (2009), in line with the founding work of Kaldor (1939) and Working (1949)), to assess its effects on the Shanghai copper forward curve over the years 2009 to 2015.

The remaining of the paper is as follows. In Section 2 we provide a detailed description of commodity inventory financing in China (CCFD), and the financial and economic variables influencing this trade. We describe the shape of the Shanghai copper forward curve over time and show consistency with the Theory of Storage. Section 3 provides a proxy for the extent of Chinese copper bonded warehouses. Further we explain the effects of commodity inventory financing within the Theory of Storage and describe the potential for a weakening of the relationship between the forward curve and inventories provoked by the effects of commodity inventory financing. Section 4 concludes the paper.

Section 2: The General Framework of Inventory Financing and its interpretation within the Theory of Storage

In order to convey the general concept of commodity inventory financing for capital account arbitrage, Figure 22 presents the simplest framework which involves an offshore entity. We focus in our analysis on copper - other metals like aluminium have been used as underlying collateral as well. We use Chinese SHFE inventory data obtained from the Shanghai Futures Exchange and World Bureau of Metal statistics data for Chinese copper consumption. Because of its easy storability and liquid derivatives market - for hedging purposes - copper has likely benefited the most. There is evidence that other non-perishable commodities have been used for financing purposes, gold in particular; different types of regulation in less liquid Futures markets make it more difficult to implement those financing trades.

Figure 22: Simple case of commodity inventory financing



Source: Authors

1. The Chinese commodity trader instructs (often via an offshore subsidiary) to buy copper from a foreign producer
2. In order to obtain financing for this trade, the Chinese commodity trader applies for a letter of credit from an offshore bank and is typically required to

pay a margin (haircut, in the banking language) of about 20% of the notional amount. The maturity of the letter of credit varies but is often short-term (3-6 months) in nature. The underlying currency for this financing is US dollars

3. Upon reception by the bank of the Bill of Lading produced by the shipper of the copper, the offshore bank pays the foreign producer
4. The copper is delivered to a bonded warehouse – and no import duties have to be paid at that point
5. The Chinese trader pledges the copper in inventory as collateral to borrow money from an onshore bank in Chinese Yuan (CNY) at a cheap rate
6. The Chinese trader invests the proceeds in Chinese real estate or high yielding investment products, hence earning the spread between onshore CNY investment yields and cheap financing
7. At maturity, the trader/investor has two choices:
    a. Close the transaction by selling the copper, selling the domestic investment vehicle and repaying both the Chinese loan and USD loan
    b. Repeat the financing procedure. He/she obtains funding through re-hypothecated collateral, without any physical move of copper this time

To avoid losses in the case of decline of copper price, the party holding the industrial metal in a financing deal would sell on the Shanghai Exchange copper Futures contracts with the same maturity as its loan. In the case of the situation 8.a above where the copper is re-hypothecated, the hedge is ‘rolled over’, which is costly if the copper forward curve is backwardated (Future prices decreasing with maturity) at maturity of the initial transaction as she/he would buy back a short maturity and sell a more distant maturity at a lower price. The same method applies when hedging the currency risk involved in the transaction if it is not denominated in US dollars.

We further illustrate with a numerical example the mechanism involved in commodity inventory financing and detail the financial variables impacting the trade namely interest rate differentials, copper forward curve prices, hedging and storage costs as well as potential administrative charges.

We place ourselves at the end of December 2013 and use LME and Shanghai Futures Exchange data for copper spot and forward closing prices; storage costs are based on their average value across LME warehouses in Asia:

- On the 31st of December 2013, the LME copper price was quoted as $ 7,394.5/ton. The difference between the Shanghai copper spot price (source: Shanghai Futures Exchange) and the LME SHFE spot price was $177.5/ton and if we assume a conservative discount of 20% taken by the financing bank (which equals the cash deposit the Chinese commodity trader would commit to this transaction), the amount borrowed by the commodity trader would be $6,057/ton.
- We assume a six-month refinancing at USD Libor of 0.35% plus a risk premium of 3%, thus implying refinancing costs of $101.5/ton based on the copper price after applying a 20% haircut
- Storage costs of around $0.2/ton/day add total storage costs of $36/ton.
- Immediately using the proceeds of the refinancing activity and investing 80% (considering the haircut) into a 12% yielding Chinese wealth management product would earn a six month return of $363/ton.
- We have not considered any hedging costs of the copper collateral or the currency which could further reduce the profit. At the end of December 2013, the copper forward curve was in backwardation with a slope of 0.8% if defined by the spot and the six-month forward. Additionally, the FX forward rate for a CNY hedge would have implied costs of 0.31% (i.e., the FX forward curve was in contango implying a weaker CNY six-month forward), which would have resulted in total hedging costs of $81.4/ton.
- Hence the original transaction would have generated a profit of approximately 9.5% over the six-month period based on the 20% cash committed by the commodity trader. In reality administrational charges slightly reduce the return yield and the commodity trader is still exposed to basis risk between the LME Future and the Shanghai copper Future if the transaction is hedged by using LME Futures.

- This profit could then be further increased by rolling the trade and hedge more frequently than every six-month in the case of a favourable (contangoed) forward curve.

The example above emphasizes the economic and financial variables influencing the profitability of the trade. The main variables to consider are the interest rate differential between onshore Chinese interest rates and external financing rates (we compare CNY onshore interest rates with USD refinancing rates) and the shape of the copper forward curve. Both determine the original funding costs (interest rate differential) as well as FX and collateral hedging costs which depend on the shape of the FX Forward curve. This inventory financing structure represents a type of carry trade and is influenced by the FX and collateral volatility because it impacts funding costs via a higher risk premium (i.e., the higher the volatility of interest rates, copper price and currencies involved in the trade, the more likely is the bank to increase the risk premium at stake in inventory financing).

2.1. Interest rate differential between the Chinese CNY and USD

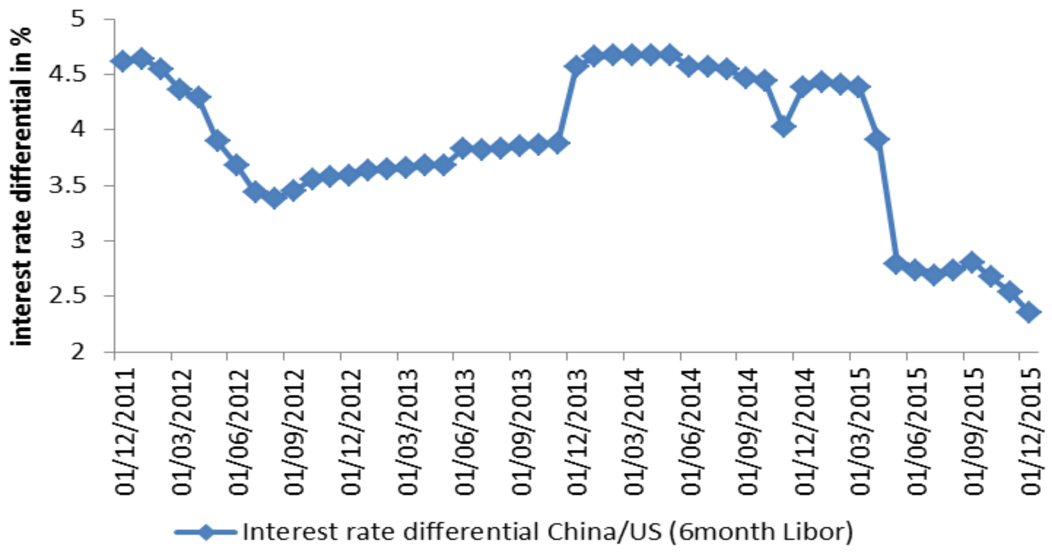
According to the uncovered interest rate parity, the expected return on a domestic asset (like an interest rate deposit) will equal the exchange-rate adjusted expected return on foreign currency assets (USD deposit in this case). However there are two assumptions central to this theorem, namely perfect substitutability of domestic and foreign assets and capital mobility, both somehow restricted in the Chinese case.

Hence the original incentive and one of the core drivers to implement a commodity inventory financing trade is the interest differential between the onshore domestic market and the offshore USD funding market.

Figure 23 depicts the spread of Chinese domestic 6month Libor rates over equivalent USD rates. It can be seen that the spread has been greater than 3.5% for most of the past 5 years. The spread has also been fairly stable within a range of +/-0.5% around 4% as the Chinese monetary authorities actively managed their currency against the

US Dollar in contrast to the early 2000s in which the spread showed much higher fluctuations.

Figure 23: 6-month Libor interest differential China over US (in %)

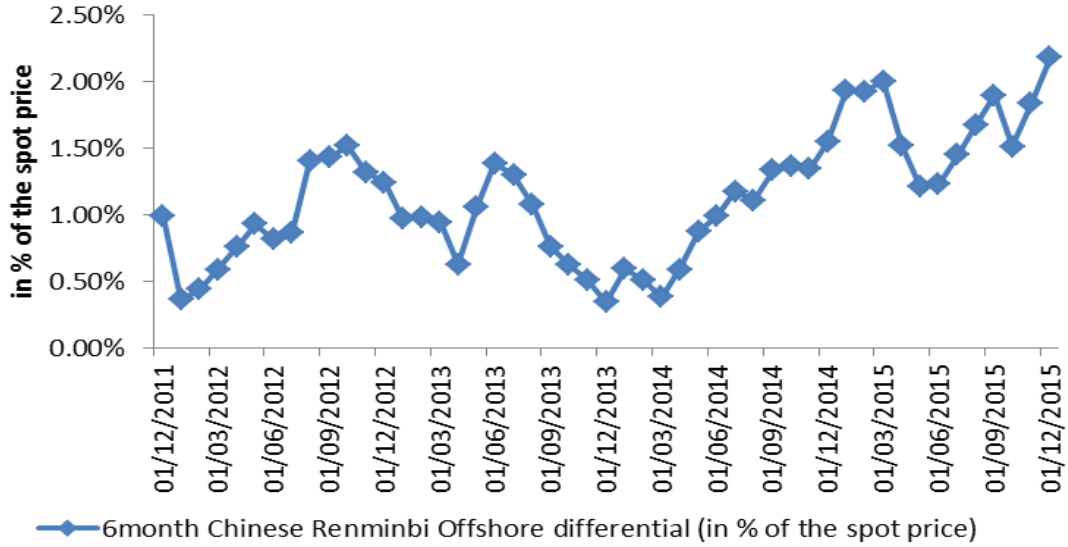


Source: Bloomberg, Authors' calculations

The People Bank of China (PBOC) actively controlled the currency to ensure a stable relationship of the Chinese Renminbi to its main trading partners. Figure 24 highlights this stable relationship by plotting the differential between the 6-month forward contract and the USD/CNY spot price (as a % of the spot price) indicating only a limited depreciation pressure on the Chinese currency.

In the case of commodity inventory financing foreign exchange volatility and commodity volatility are the underlying sources of risk.

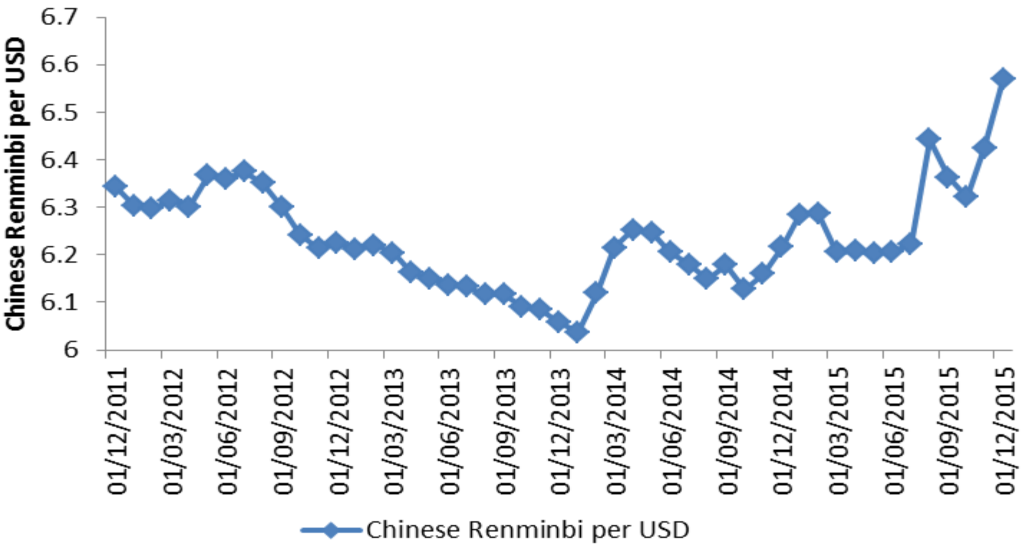
Figure 24: 6-month China offshore currency differential over spot price (in % of spot price)



Source: Bloomberg, Authors' calculations

Figure 25 shows that the CNY strengthened until 2014. This period was associated with the Renminbi offshore volatility trading in a close range as highlighted in Figure 26.

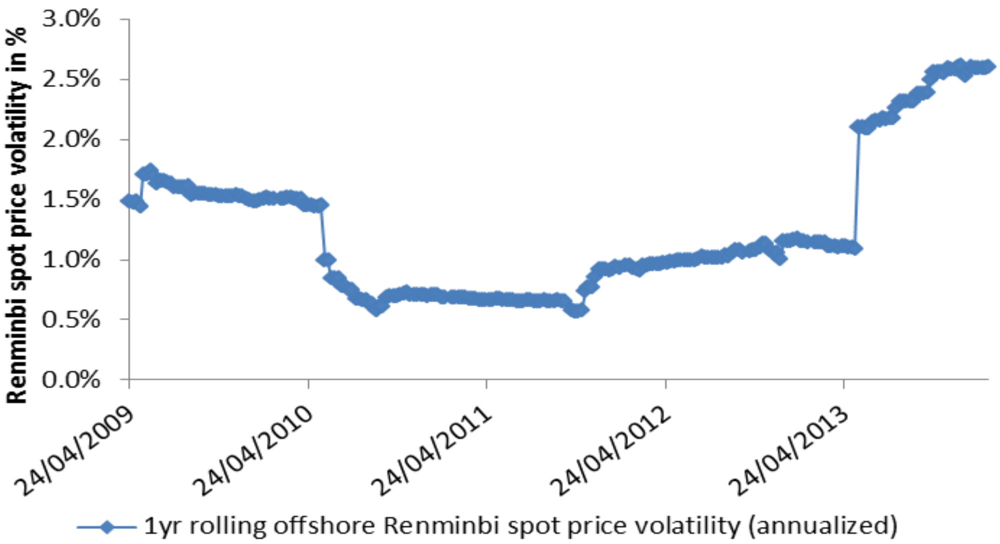
Figure 25: Chinese Renminbi in USD



Source: Bloomberg

The risk arising from foreign exchange in CCFD was low but likely reduced by the active management of the Chinese currency.

Figure 26: Chinese Renminbi offshore spot price volatility (rolling one year)



Source: Bloomberg, Authors' calculations

2.2. Copper Forward curves

Besides the interest rate differential, the copper price is the other major source of risk in our example of a structured commodity trade.

The onshore commodity trader can choose to hedge this risk at initiation of the trade. This might come at an additional cost if the copper forward curve is in backwardation. The commodity trader is exposed to the spot price risk and hedging it by shorting Futures involves a negative roll in the case of a backwardated copper forward curve.

2.2.1. Shape of the copper forward curve on Shanghai Exchanges and relationship to copper inventories

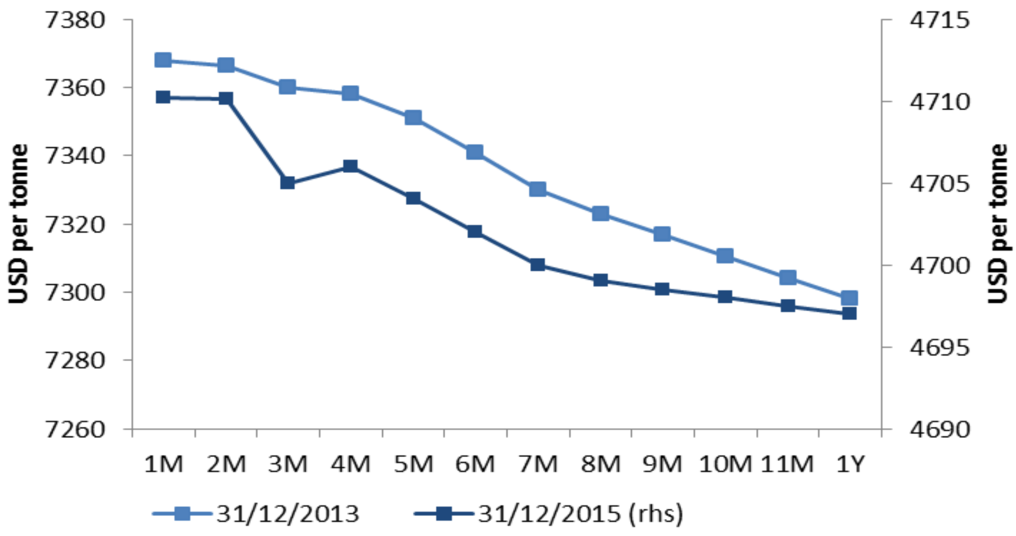
The role of inventory in explaining the shape of the forward curve and spot price volatility is central in the Theory of Storage developed by the founding papers of Kaldor (1939), 'Speculation and Economic Stability', and Working (1949), 'The

Theory of the Price of Storage'. In particular, a backwardated forward curve (negative slope), itself represented by the adjusted spread (Future minus spot divided by spot) signals a low inventory; and a low inventory implies a high volatility of the spot price. In their reference paper, Fama and French (1987) used the adjusted spread of the forward curve as a proxy for inventory to study the relationship between inventory and spot price volatility in a number of metals and agriculture markets.

Reconstructing a database of soybeans world prices, Geman and Nguyen (2005) exhibited directly over the period 1994- 2004 a quasi-perfect affine relationship between spot volatility and the inverse of the inventory, this inverse inventory becoming a state variable in a parsimonious factor model of the soybean forward curve. Geman and Ohana (2009) analyzed the inventory/volatility relationship in the case of a database of US natural gas and crude oil. While the standard relationship prevailed at all times for natural gas, it was more visible in crude oil during times when inventory was lower than in average, i.e., times of scarcity.

We wish to analyze the observed forward curves using Shanghai Future exchange data and compare the months of December 2013 and December 2015. Figure 27 and Figure 28 highlight a difference in the term structure of copper on the Shanghai copper Futures in 2013 compared to 2015. The Shanghai copper Future curve was in contango in 2013 (in contrast to the LME copper forward curve which was in backwardation at that time).

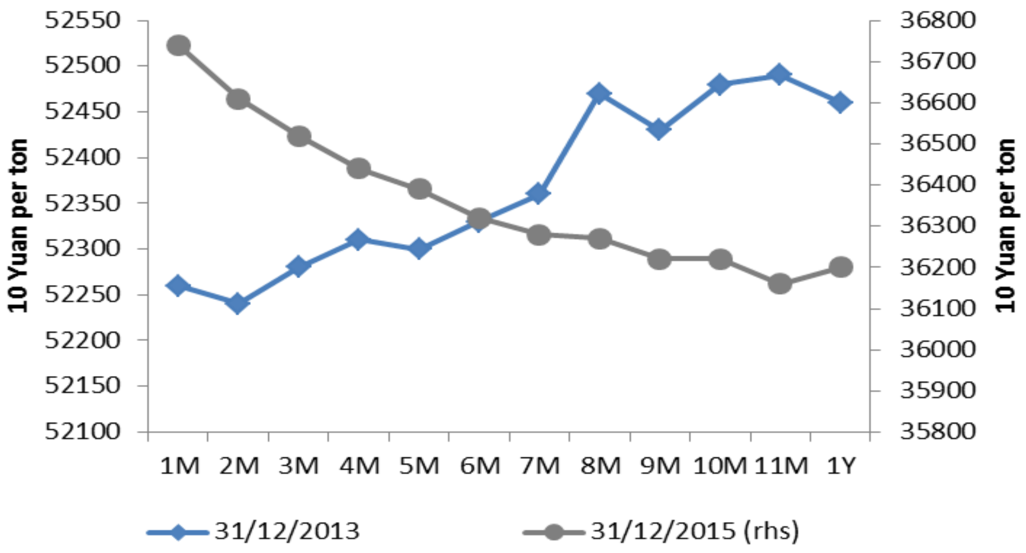
Figure 27: LME Copper forward curves as of 31/12/2013 and 31/12/2015 (USD per tonne)



Source: LME

Idiosyncratic factors including a large copper holder on the LME (effectively eliminating substantial LME inventory available) as well as regulatory changes made by China's State Administration of Foreign Exchange (SAFE) to CCFDs (short-term dampening CCFD demand and releasing more copper inventory) led to this difference in the forward structures meaning that the Shanghai Copper forward curve showed a positive spread between the Futures price and the spot price.

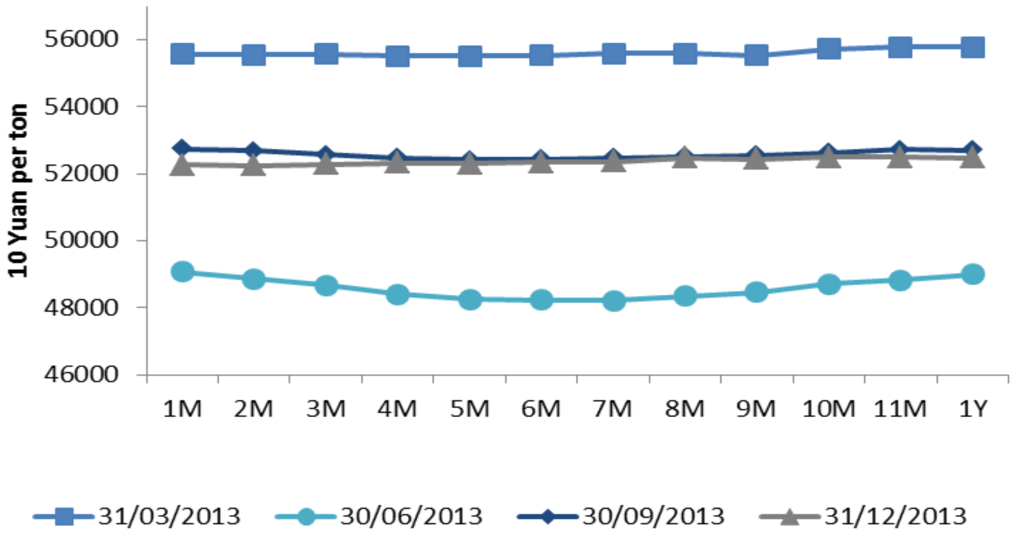
Figure 28: Shanghai Copper forward curves as of 31/12/2013 and 31/12/2015 (10 Yuan per ton)



Source: Shanghai Futures Exchange

The Shanghai copper forward curve showed a different shape at the end of 2015 compared to 2013, with the spot price significantly below 2013 levels and the forward curve in backwardation as uncertainty around Chinese economic growth triggered a significant correction in industrial metals over the period 2013-2015. Figure 29, Figure 30 and Figure 33 highlight the evolution of the Shanghai copper forward curve over the period 2013-2015.

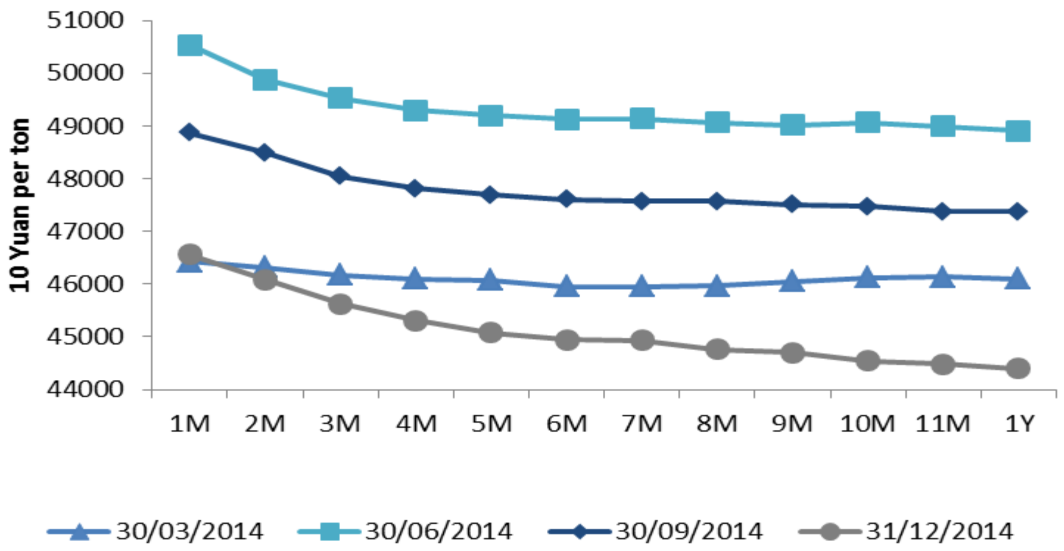
Figure 29: Shanghai Copper forward curve as of March, June, September and December 2013 (10 Yuan per ton)



Source: Shanghai Futures Exchange

Figure 29 contrasts the changes of the Shanghai copper forward curves from March 2013 to December 2013. The forward curves saw the entire forward curve dropping sharply until the mid of the year as with some recovery in forward prices from June to December 2013. Figure 30 confirms the continuation of this trend through 2014. The Shanghai copper forward curve flattened substantially over the first half of 2014 with the front-month copper forward price rising sharply by roughly 9 percent over the 2nd quarter while the 12-month forward contract continued to drop. Copper bonded warehouse inventories peaked at the beginning of 2014 which coincides with a sharp increase during the first 2 months of 2014. The port of Qingdao scandal increased public attention to those structured commodity deals and the time series of copper bonded warehouses dropped sharply over summer 2014. This resulted in a sharp increase in SHFE copper inventories as shadow inventory was released into the official market. Consequently the second half of 2014 saw a renewed weakness in copper prices again with the front-month copper forward price falling -8 percent resulting in a less backwardated forward curve at the end of 2014.

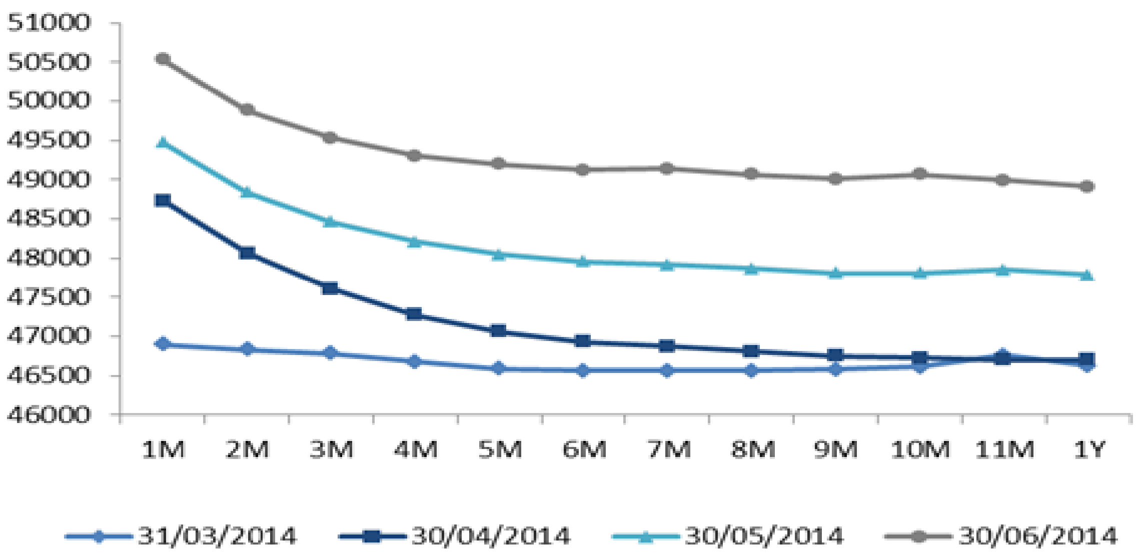
Figure 30: Shanghai Copper forward curve as of March, June, September and December 2014 (10 Yuan per ton)



Source: Shanghai Futures Exchange

This was in line with what the LME copper forward curve experienced over the same period – a sharp rise in the first half of the year followed by a drop of copper prices across the forward curve during the second half of 2014.

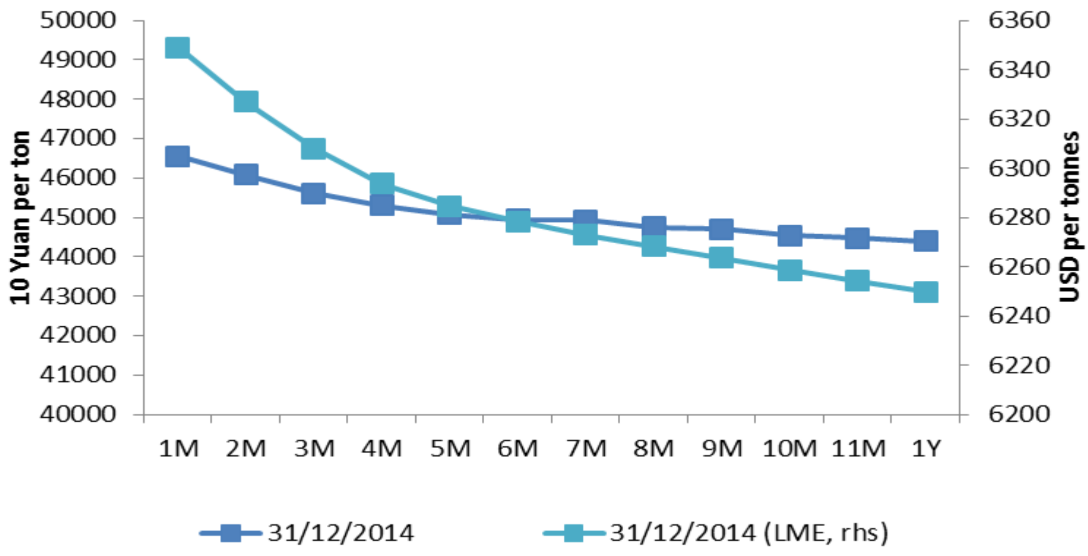
Figure 31: Shanghai Copper forward curve as of March, April, May and June 2014 (10 Yuan per ton)



Source: Shanghai Futures Exchange

Figure 32 highlights a similar shape of the copper forward curve in Shanghai and for the LME at the end of 2014.

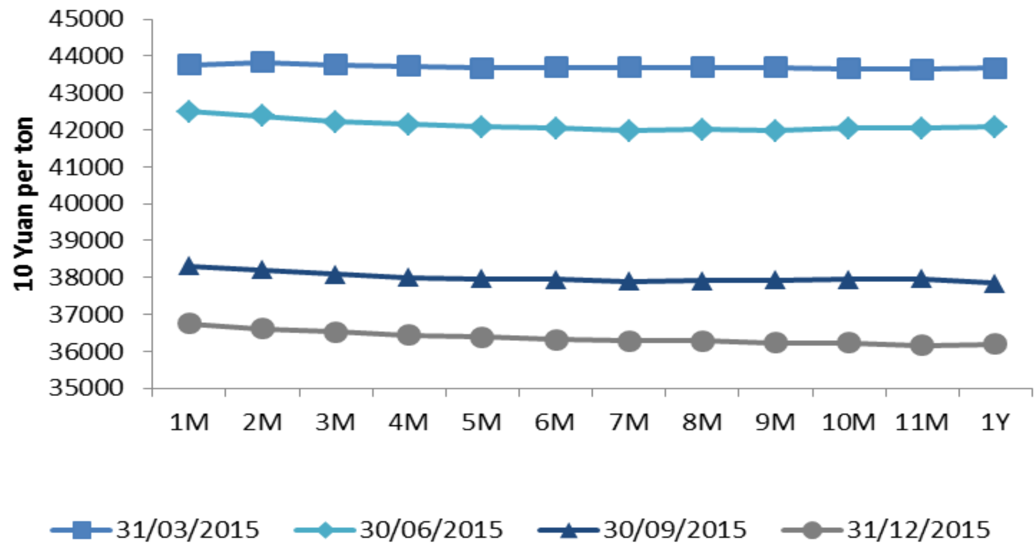
Figure 32: LME (USD per tonne) and SHFE Copper forward curve (10 Yuan per ton) as of December 2014



Source: LME, Shanghai Futures Exchange

The Shanghai copper forward curve experienced a parallel downward shift in 2015. Figure 33 shows the continuous drop of copper across the entire forward curve during that year. Similar to the previous two years the front-end copper forward price continued to marginally outperform the 12-month forward contract and as a consequence the curve showed a stronger backwardation at the end of 2015.

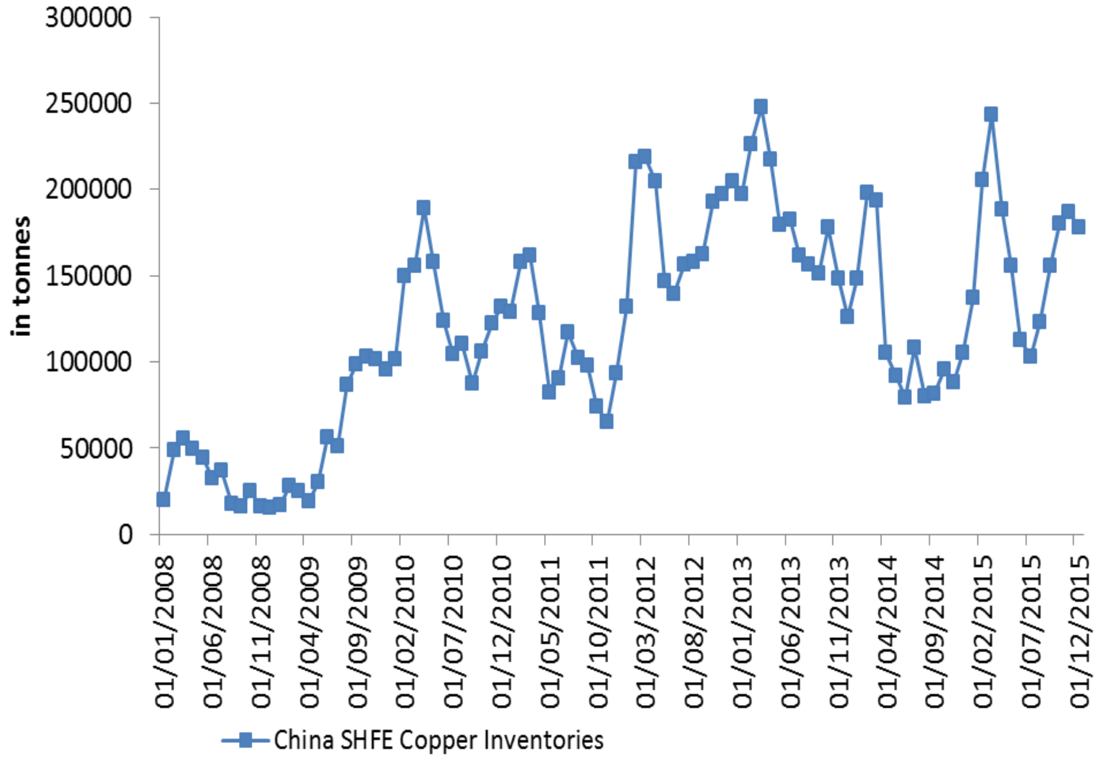
Figure 33: Shanghai Copper forward curve as of March, June, September and December 2015



Source: Shanghai Futures Exchange

Lower inventories have led to a backwardated copper forward curve which was also confirmed by an inversion of the LME copper forward curve with the spot price trading above the forward price at the end of 2015.

Figure 34: Shanghai Copper inventory 2008 to 2015 (in tonnes)



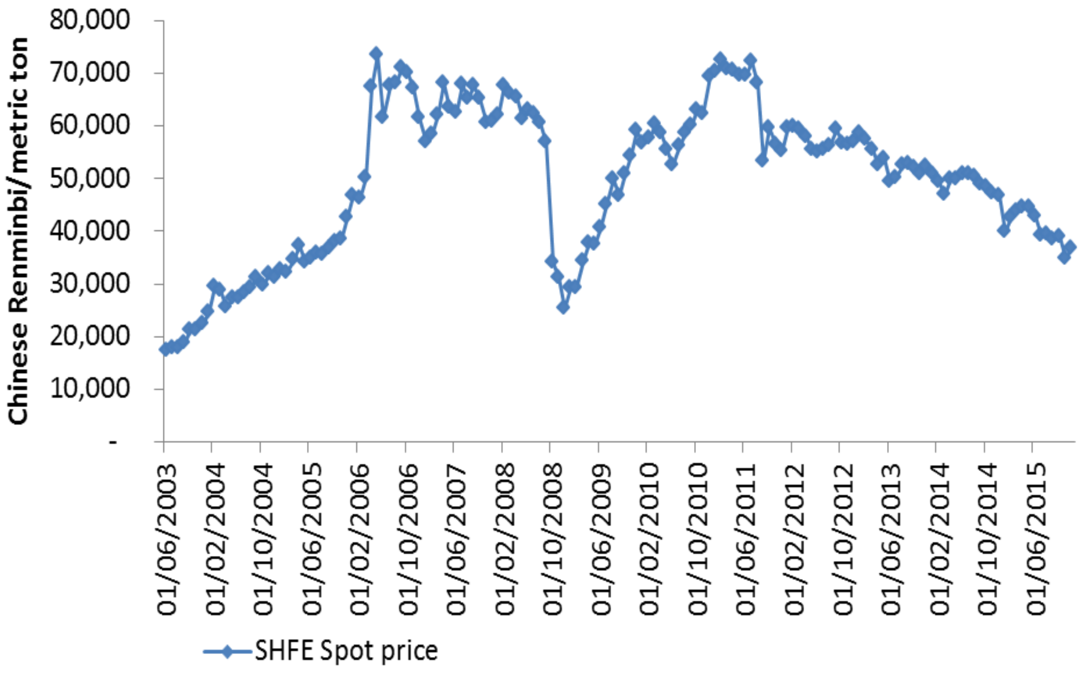
Source: Shanghai Futures Exchange

Figure 34 shows SHFE available Shanghai copper inventories. No SHFE data on CCFD copper inventory activity exist and bonded warehouse data have only been available recently. The copper forward curve is reflecting publicly available demand and supply. As a consequence the analysis of the forward curves from 2013 to 2015 and the highly positive correlation of the forward spread with Shanghai copper inventories validate the relationship described in the Theory of Storage.

2.2.2. Copper Spot Price Volatility

Similar to the analysis conducted for the Chinese Renminbi, Figure 35 shows the Shanghai copper spot price which was characterized by a marked increase in volatility over the period 2008-2009 that coincides with the Global Financial crisis and a sharp drop in the copper spot price. We display in Table 12 the yearly average and standard deviation of the copper spot price volatility and recognize the marked drop in volatility and volatility-of-volatility after the global financial crisis.

Figure 35: Shanghai copper spot price



Source: Shanghai Futures Exchange

From 2012 onwards the copper spot price volatility started to increase steadily though volatility-of-volatility continued to stay very low. This feature probably positively impacted the Chinese Commodity Inventory Deals as it might have pushed investors not to hedge the commodity risk and led to lower risk premia charged by banks involved in the commodity deals.

Table 12: Shanghai copper spot price volatility (per calendar, annualized)

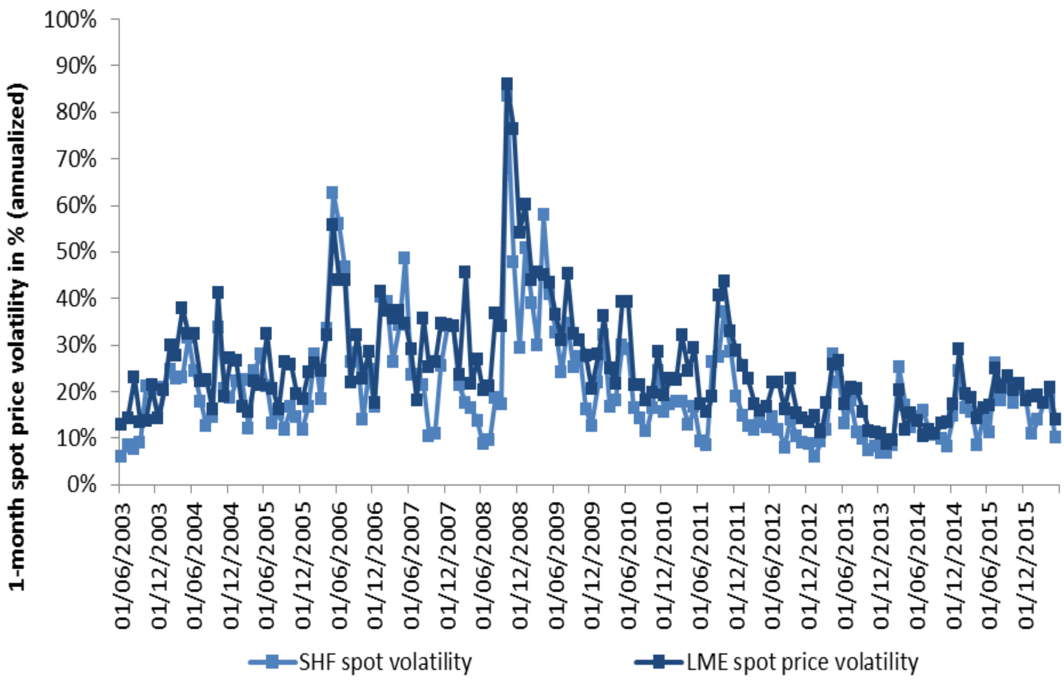
	annualized mean	annualized standard deviation
31/12/2004	22.2%	6.2%
31/12/2005	17.7%	5.6%
31/12/2006	31.0%	16.0%
31/12/2007	28.2%	11.6%
31/12/2008	26.5%	21.1%
31/12/2009	32.6%	13.2%
31/12/2010	20.5%	6.8%

31/12/2011	19.9%	8.5%
31/12/2012	11.7%	2.3%
31/12/2013	12.6%	6.8%
31/12/2014	12.9%	5.1%
31/12/2015	17.8%	5.0%

Source: Shanghai Futures Exchange, Authors' calculations

Figure 36 and Table 15 show the one- month volatility (annualized, based on daily data) for the LME and Shanghai copper spot and 6 month Future prices and confirm a consistent pattern making us comfortable to use Shanghai copper price data, the ones in fact more relevant to our analysis.

Figure 36: One- month annualized volatility based on daily LME and Shanghai spot price data



Source: LME, Shanghai Futures Exchange, Authors' calculations

In this order, we use the "excess volatility" defined as excess spot price volatility over Futures price volatility as defined in Equation (1) to emphasize the general behaviour of the copper forward curve during the period 2011 to 2015 characterized by higher CCFD transactions.

$$\sigma_{\text{excess,t}} = \sigma_{spot,t} - \sigma_{forward,t} \quad (1)$$

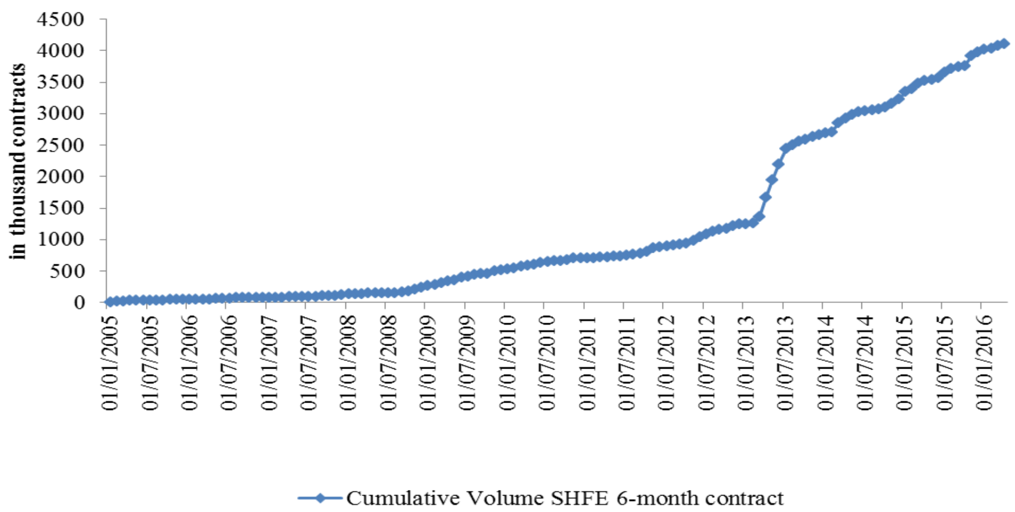
We choose the maturity of the Future contract to be six months not to artificially reduce the volatility of the Futures contract because of the Samuelson (1965) effect of volatility declining with the maturity of the Future contract; while being in agreement with the maximum duration of most inventory finance deals.

Table 15 in the Appendix shows monthly data on the excess volatility of spot over 6-month Future for the Shanghai and LME data since 2011.

The excess copper spot price volatility on the Shanghai Futures exchange was most of the time observed lower compared to the excess copper spot price volatility on the LME. The Shanghai excess copper spot price volatility rose from 2011 to 2014 though seem to have dropped after the Qingdao port scandal. Increased CCFD activity has increased the volatility of the Futures contract and reduced excess Shanghai copper spot price volatility.

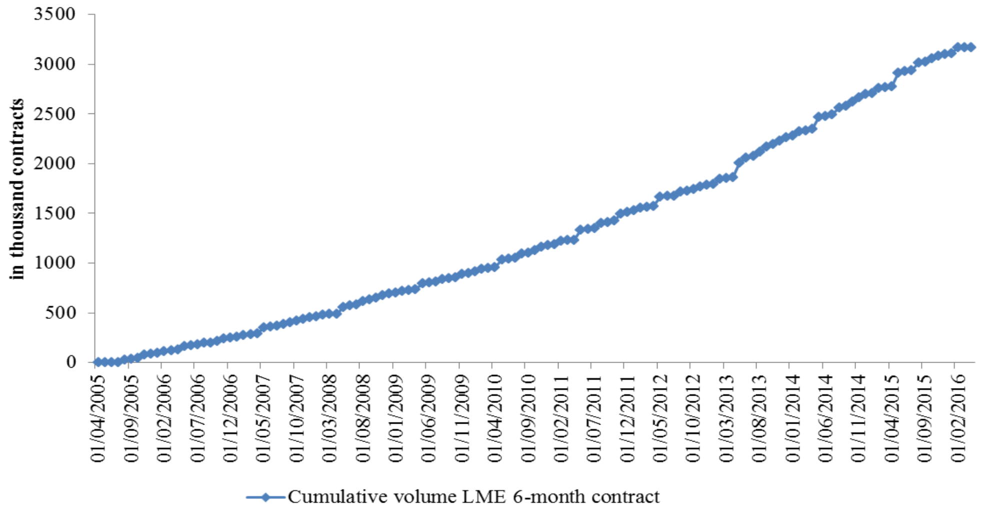
Figure 37 and Figure 38 show that the monthly volume of 6-month Shanghai copper Future contract sharply increased from 2011 onwards while the LME 6-month copper Future contract did not experience the same exponential growth.

Figure 37: 6-month Shanghai copper Future contract volumes (cumulative)



Source: Shanghai Futures Exchange, Authors' calculations

Figure 38: 6-month LME copper Future contract volumes (cumulative)



Source: Shanghai Futures Exchange, Authors' calculations

2.3. Recent developments

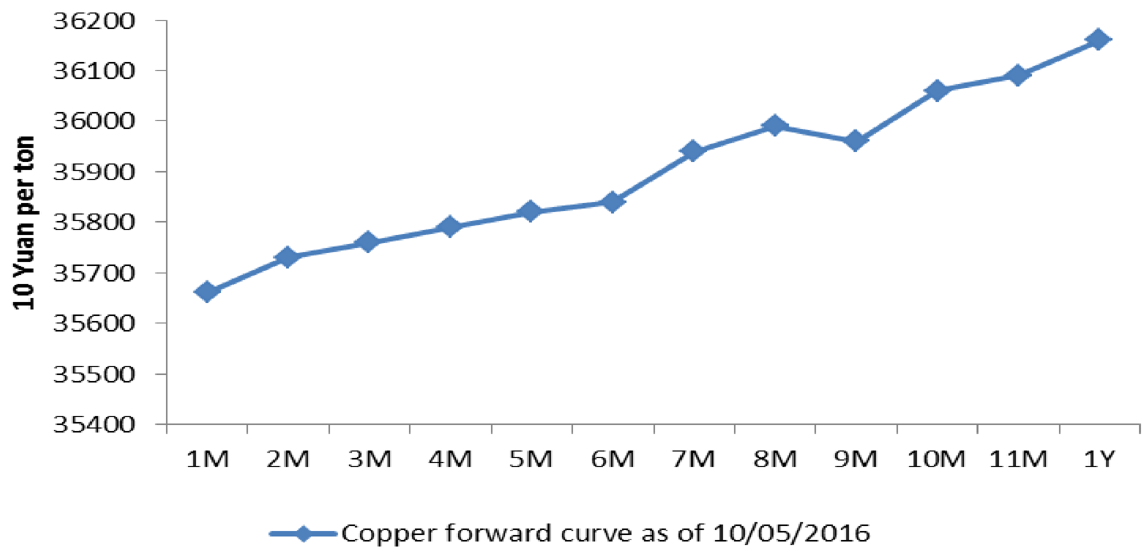
Over the years 2013 to 2015, the carry trade activity from commodity inventory financing was challenged from several angles. A higher volatility in the copper spot price, a convergence of interest rates between China and the US as well as higher hedging costs made it more difficult to generate attractive yields in CCFDs.

In a parallel way, the tightening of financing conditions in China's shadow banking system over the same two years revealed the legal and operational risks involved as Chinese authorities implemented a series of reforms in the financial sector to gain better control over the credit channel.

An inventory scandal around the Dangdang Terminal in Qingdao was probably the triggering incident. The same collateral was seemingly pledged multiple times by a Chinese metal trader in commodity financing trades and led to an investigation by China's Central Commission for Discipline Inspections as well as litigation in front of the London High Court among high profile global financial players and commodity houses – in particular between Mercuria and Citi, its favourite funding bank, around a \$270million missing inventory.

By the end of 2015, FX hedging costs had increased to 1% on a 6-month forward basis compared to our example of December 2013. The increased uncertainty around Chinese economic growth and the surprise currency devaluation in 2015 resulted in a steeper contango of the FX forward curve.

Figure 39: Shanghai Copper forward curve as of 10/05/2016



Source: Shanghai Futures Exchange

Section 3: Commodity Inventory Trade, bonded warehouses and the effects on the Theory of Storage

According to the World Bureau of Metal statistics, China accounts for 46% of global copper demand. Our view is that the large number of CCFDs created a distortion of the true underlying copper demand. In the previous section we showed that Chinese copper demand was facing headwinds going forward. China's unprecedented infrastructure boom has been slowing down, the Chinese Renminbi falling versus the US Dollar in an environment where copper mines estimate production should rise by 9% in 2016.

In this section we aim to shed more light on the copper demand artificially created to take advantage of lower offshore USD interest rates compared to Chinese domestic interest rates. We will adjust SHFE Chinese copper inventories by a proxy for copper bonded warehouses. We will show to what extent the fundamental relationship between the forward spread and copper inventories as described in Kaldor (1939) and Working (1949) would have been impacted and we will provide an explanation for the validity of the Theory of Storage under these circumstances.

We wish now to analyze how commodity inventory financing might have influenced the copper forward curve, keeping in mind the results of the Theory of Storage (Kaldor, 1939; Working, 1949, Geman and Nguyen, 2005) recalled earlier.

For this purpose we focus on Shanghai copper spot and Futures data to measure the impact of bonded warehouse data on the copper forward curve. Table 16 provides an overview of the Shanghai copper spot price and Future price characteristics from 2008 to 2015. We analyse the adjusted spread which is defined as the Future price minus the spot price normalized by the spot price. In Table 17 in the Appendix we calculate the 1-year rolling correlation between the adjusted spread and Shanghai copper inventories (normalized by Chinese consumption). A high positive correlation between the adjusted spread and copper inventories can be observed over the time period analysed signalling a strong positive relationship between the shape of the Futures curve and Shanghai copper inventories as explained in the Theory of Storage. Increasing copper inventories result in a higher adjusted spread, i.e. the Futures curve shows more contango which is confirmed by the consistent and positive correlation between the forward spread and inventories except for a short period of time in 2010 and 2014. During both periods, 2010 and 2014, Chinese copper bonded warehouses decreased sharply and SHFE inventories increased as shadow inventory was released into the market. Copper spot price volatility increased during those periods making the correlation less stable. Recalling the concept of temperature from earlier speculative sentiment in the market has likely increased causing this temporary rise in copper spot price volatility.

In order to assess the effects of CCFD in more depth we use a dataset for China bonded warehouses provided by the LME, CRU and Bloomberg. Shanghai bonded warehouse data are based on a monthly survey. Each month 10-15 bonded warehouses, copper traders and other industry participants are surveyed. The results are aggregated to an overall bonded warehouse number that has been published since March 2008.

Table 13 provides more detail on Chinese bonded warehouse data. The data show a positive trend until mid-2014 though with periods of sharp declines at the end of 2010 and the end of 2013.

SHFE Shanghai copper inventories (Figure 34) show a similar pattern in 2010-11 and 2013-14. The rolling 1-year correlation between SHFE Shanghai copper inventories and bonded warehouse inventories highlights a close relationship between the two inventory measures during the 2011-2014 period from which onwards the correlation started to weaken possibly linked to the awareness of the magnitude of CCFDs and government measures implemented to reduce those transactions.

Table 13: China bonded warehouses (in 000s metric tons)

Shanghai copper bonded warehouse (in 000s metric tons)	2009	2010	2011	2012	2013	2014	2015
January	250	350	450	450	775	600	580
February	250	350	550	500	825	750	570
March	275	300	625	600	725	825	560
April	300	250	550	650	650	850	590
May	250	225	450	560	550	810	650
June	350	200	300	495	475	750	680
July	300	200	250	550	350	660	650
August	325	250	200	600	425	620	540
September	250	250	200	650	425	570	420
October	225	300	250	700	450	570	430
November	250	300	250	800	525	590	440
December	300	400	400	775	550	600	450

Source: Bloomberg, Authors' calculations

Following Tufano (1996) and Geman and Vergel (2014) we analyse below the linear relationship between SHFE inventories, bonded warehouse inventories (we use changes in inventories) and the normalized forward spread over the period 2008 to 2015.

$$Forward\ spread \quad = \alpha + \beta_1 * SHFE_{inventories} + \beta_2 bonded\_warehouses + \varepsilon \quad (2)$$

We see from Table 14 that only SHFE inventories are statistically significant. The coefficient sign is positive for SHFE inventories confirming the relationship described in the Theory of Storage. The close-to-zero coefficient for bonded warehouses as well as the low t-statistic however indicates that adding bonded warehouse data does not add information on forward curve dynamics beyond what was described in Kaldor (1939) and Working (1949).

Table 14: Regression output normalized forward spread against SHFE and bonded warehouse inventories (in 000s metric tons)

Regression Statistics			
R-Squared	0.09		
Observations	93		
	Coefficients	*Standard Error*	*P-value*
α (t-statistic)	-1.08 (-3.70)	0.291	0.000
β_1 (t-statistic)	0.03 (2.82)	0.011	0.006
β_2 (t-statistic)	0.00(0.75)	0.005	0.456

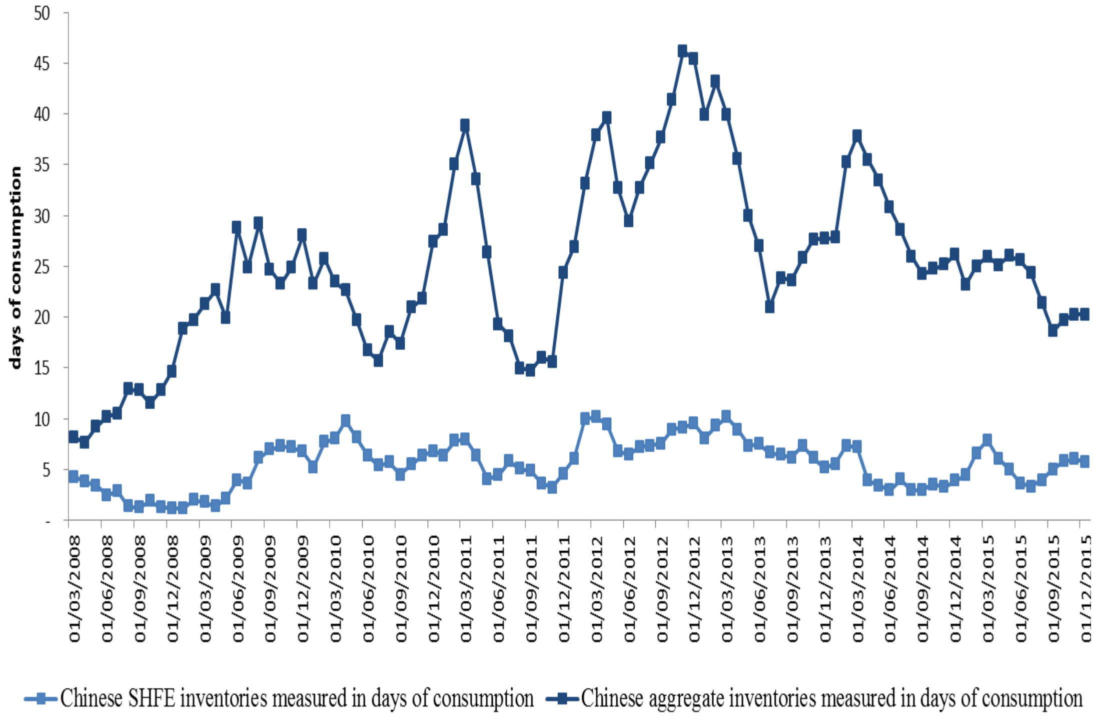
Source: Bloomberg, Shanghai Futures Exchange, Authors' calculations

Table 16 provides an overview of the adjusted spread which is defined as the Future price minus the spot price normalized by the spot price compared to aggregate inventories we aggregate SHFE inventories and bonded warehouse data introduced above. In Table 17 in the Appendix we calculate the 1-year rolling correlation between the adjusted spread and aggregate copper inventories. Periods of lower or even negative correlation between the adjusted spread and aggregate copper inventories can be observed compared to the relationship between SHFE inventories and the adjusted forward spread analyzed earlier signaling a weaker relationship between the shape of the Futures curve and Shanghai copper inventories as explained in the Theory of Storage once we adjust for bonded warehouses.

We wish to prove further the impact of commodity inventory financing on copper spot price volatility by making use of China bonded warehouse data. For calibration purposes we choose to normalize SHFE Shanghai copper exchange data dividing it by Chinese copper consumption using both Chinese SHFE inventory and aggregate copper inventory data that include bonded warehouse data.

This removes factors affecting the long-term volatility expected to influence both, spot price volatility as well as Futures volatility and allows us to show a much clearer relationship between copper inventory and copper volatility.

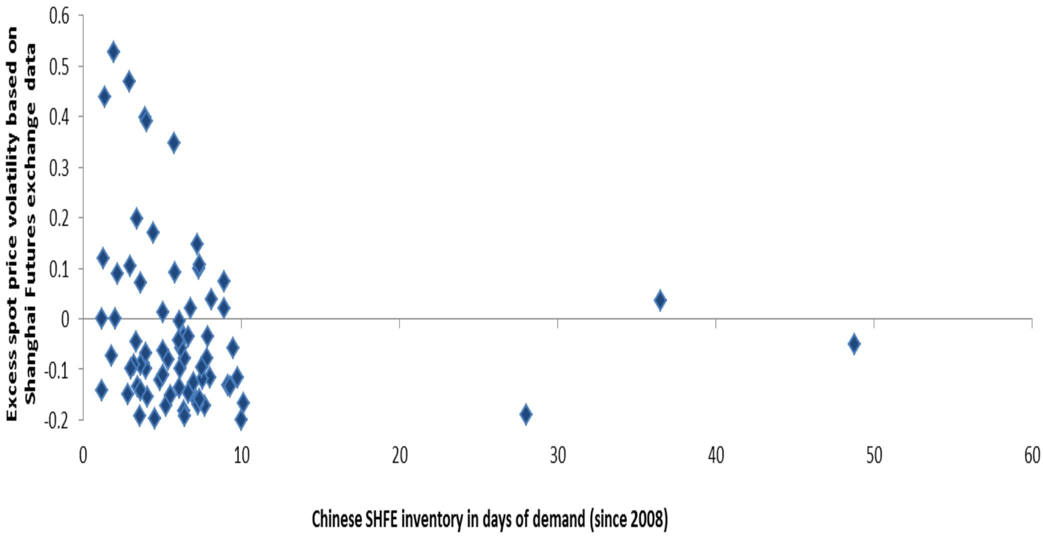
Figure 40: Chinese inventories expressed in days of copper demand (excluding and including bonded warehouse data)



Source: Bloomberg, Shanghai Futures Exchange, Authors' calculations

Figure 40 highlights the difference in Inventory-to-Demand ratio expressed in days of SHFE reported and aggregate copper inventories. The adjustment of SHFE inventory data by bottom-up approximation to bonded warehouses leads to a higher Inventory-to-Demand ratio as inventories were artificially boosted by CCFDs.

Figure 41: Excess spot volatility versus Chinese copper Inventories in days of Chinese consumption



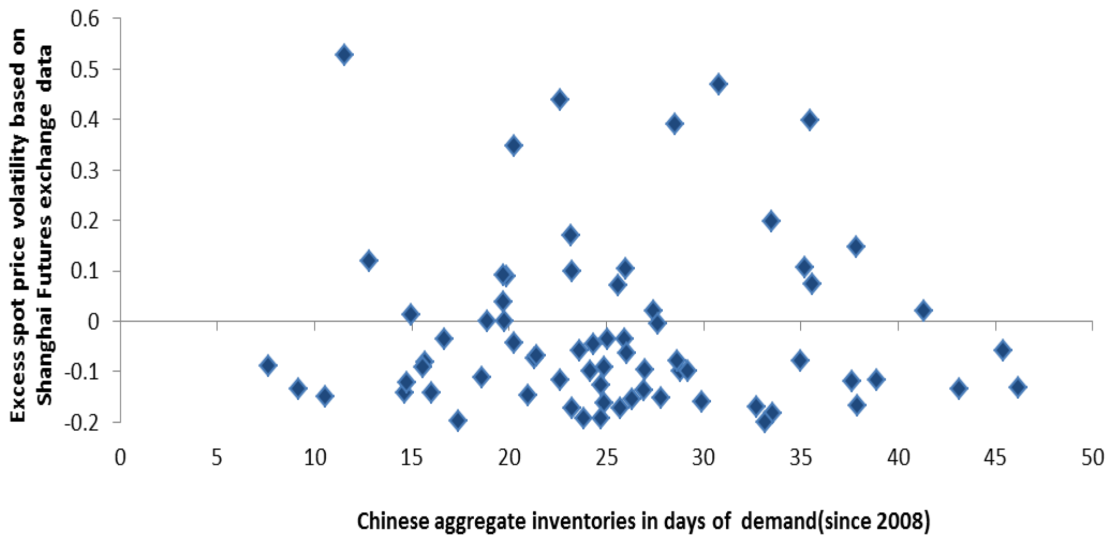
Source: Shanghai Futures Exchange, Authors' calculations

If inventory is more than 6 days of Chinese consumption, then spot price volatility and Futures volatility are roughly equal indicating parallel shifts in the curve. At low inventory to consumption levels, spot price volatility tends to exceed Futures price volatility and the relationship becomes exponential because of scarcity.

We also show the relationship of Shanghai inventories to aggregate Chinese copper inventories including Shanghai bonded warehouse data and contrast versus excess Shanghai copper spot price volatility. The functional relationship between inventories and demand is similar to the one described in Geman and Smith (2012). Figure 42 suggests a similar exponential relationship for bottom-up Chinese copper inventories to Chinese demand though the relationship is less convex dampened by bonded warehouse inventories. This shows the potential of CCFD activity to distort the inventory-to-demand relationship in the Shanghai copper market.

The growth of Chinese copper bonded warehouses over the years 2009-2015 encouraged a build-up of physical copper inventory. The fundamental relationship between Shanghai copper inventories and the Shanghai copper forward spread as described in the Theory of Storage remained valid throughout this period however as CCFD inventory was not generally known to the market.

Figure 42: Excess Spot Volatility versus Shanghai Inventories in days of aggregate Chinese copper inventories



Source: Bloomberg, Shanghai Futures Exchange, Authors' calculations

Table 16 shows in detail the relationship between the forward spread and the aggregate Shanghai copper inventories including bonded warehouses (from 2011-2015). The 1-year rolling correlation numbers highlighted in Table 18 show a positive relationship of SHFE inventories (normalized by Chinese copper consumption) with the forward spread until March 2014 while the inclusion of bonded warehouse data dampened the relationship considerably from 2014 onwards (reduction of bonded warehouses after the Qingdao scandal dampening the relationship to the forward curve).

We use both, the more common Pearson correlation as well as the Spearman (1904) rank correlation statistic. The Spearman rank correlation coefficient is more reliable in the case of missing data and measuring the correlation not on the data itself but the ranking. It shows similar properties to the Pearson correlation coefficient but can be used for continuous as well as ordinal data and does not require a normal distribution of the underlying data.

Both correlation measures show a positive relationship between the forward-to-spot price spread and the inventory-to-demand ratio based on SHFE data. When we include bonded warehouses, we observe that a higher inventory-to-demand ratio (e.g. driven by higher inventories caused by CCFDs) leads to a weaker relationship. Confirming earlier results the weaker correlation of aggregate inventories to the forward spread highlights the potential of bonded warehouses distorting the relationship as described in the Theory of Storage.

Further we choose to analyse the relationship between the normalized 6-month forward spread and inventory-to-demand ratio after the financial crisis which has likely been supportive to higher CCFD activity. The rank correlation measure is positive for most of the period analysed except for 2010 and early 2013 during which both rank correlation measures, SHFE and aggregate inventories, move closer to zero. It is also during these periods when the statistical significance falls. The gap between the SHFE correlation to forward spread and aggregate inventories (including bonded warehouses) to forward spread has widened lately again and could indicate increased CCFD activity during the second half of 2015 similar to what was observed during the period 2011-2012.

The extent of commodity inventory financing remains potentially significant as the aggregate inventories-to-demand correlation to the forward spread moved below the correlation to forward spread based on SHFE inventories during that period with the SHFE data continuing to confirm the Theory of Storage. The negative correlation from mid-2015 onwards in the case of aggregate inventories (including bonded warehouses) indicates that the extent of CCFD has remained significant despite the Qingdao scandal and subsequent regulatory measures to dampen CCFD activity.

Section 4: Conclusion

We described in this paper the motivation and mechanism of commodity inventory financing in the context of China (CCFD). Benefiting from a database allowing us to infer China copper bonded warehouses since 2008, we argue that commodity inventory financing is likely to have contributed to a weakening of the relationship between the copper forward curve and inventories as described in the Theory of Storage. Hedging activity motivated by CCFD has the potential to distort the copper futures curve by weakening the positive relationship between the forward spread and copper inventories. Market participants in the Shanghai Futures market did not know the extent of CCFD investing though as long as they perceived the Futures price a fair representation of the future spot price they would have willingly taken the other side of the hedging activity. The CCFD activity lowered mid of 2014 for a number of reasons, including the breaking news in June 2014 of multiple uses of the same collateral copper by a metal trader broke out in Qingdao – an event viewed by some market analysts as important as the collapse of crude oil prices. Nevertheless our analysis would suggest that CCFDs remained significant over the past 2 years.

References

Balding, C. and David Garcia, 2016. "How Chinese Banks Reduce Lending While Expanding Credit and the Hidden 2 Trillion RMB in Liquidity: A Case Study on the Bank of Chongqing and Huishang Bank", Forthcoming in the *Journal of Financial Perspectives*.

Belke, A., I.G. Bordon and Torben W. Hendricks, 2010. "Monetary Policy, Global Liquidity and Commodity Price Dynamics", Ruhr Economic Papers, Number 167, University of Duisburg, Essen.

Bloomberg Intelligence. 2008-2015. Bloomberg Intelligence Copper Global Dashboard (accessed May 2016)

Fama, E.F., 1984. "Forward and spot exchange rates.", *Journal of Monetary Economics*, 14(3), pp. 319-338.

Fama, E.F. and K.R. French, 1987. "Commodity futures prices: Some evidence on forecast power, premiums and the theory of storage", *Journal of Business,* 60(1), pp. 55-73.

Fama, E.F. and K.R. French, 1988. "Business Cycles and the Behavior of Metal Prices", *The Journal of Finance*, 43(5), pp. 1075-1093.

Frankel, Jeffrey A., 2014. "Effects of speculation and interest rates in a "carry trade" model of commodity prices", *Journal of International Money and Finance*, 42, pp. 88-112.

Garvey, M. and Andrew Shaw, 2014. "Base Metals: Copper – Collateral Damage", Credit Suisse Fixed Income Research, Commodities Research.

Geman, H. and Vu-Nhat Nguyen, 2005. "Soybean Inventory and Forward Curve Dynamics", *Management Science,* 51 (7), pp. 1076-1091.

Geman, H. and Steve Ohana, 2009. "Forward curves, scarcity and price volatility in oil and natural gas markets", *Energy Economics*, 31 (4), pp. 576-585.

Geman H., and William O. Smith, 2013. "Theory of storage, inventory and volatility in the LME base metals", *Resources Policy,* 38, pp. 18-28, ISSN 0301-4207.

Geman, H. and Pedro Vergel Eleuterio, 2013."Investing in fertilizer-mining companies in times of food scarcity", *Resources Policy,* 38(4), pp. 470-480.

Kaldor, Nicholas, 1939. "Speculation and Economic Stability", *Review of Economic Studies,* 7 (1), pp. 1-27

Lewis, M. M. Hsueh and X. Fu, 2014. "Copper & Iron Ore: Are Chinese Financing Deal Fears overdone?", Deutsche Bank Market Research, Commodities Weekly, pp.3-12.

Roache, S.K., and Marina Rousset, 2015. "China: Credit, Collateral, and Commodity Prices", Hong Kong Institute for Monetary Research, Working Paper No. 27/2015.

Spearman, C., 1904. "The Proof and Measurement of Association Between Two Things", The American Journal of Psychology, 15, pp. 72-101.

Tang, K., and Haoxiang Zhu, 2016. "Commodities as Collateral",*Review of Financial Studies,* 2016, 29 (8) pp. 2110-2160.

Tufano, P. 1996. "The Determinants of Stock Price Exposure: Financial Engineering and the Gold Mining Industry", *Journal of Finance*, 111 (3), pp. 1015-1052

Working, Holbrook, 1949. "The Theory of the Price of Storage", *American Economic Review,* 39, pp. 1254-1262.

Xiao, Z. and C. Balding, 2015. "Carry Trade Dynamics under Capital Controls: The Case of China", Working Paper, HSBC Business School.

Yuan, R., M. Layton, J. Currie and D. Courvalin, 2014. "Days numbered for Chinese commodity financing deals", Goldman Sachs Commodities Research, Metal Detector.

Appendix

Table 15: SHFE and LME copper spot price and 6-month forward contract volatility, SHFE and LME excess (spot minus forward) copper spot price volatility (annualized)

	Shanghai copper spot price volatility	Shanghai 6 month copper future volatility	LME copper spot price volatility	LME 6 month copper future volatility	Excess spot volatility LME	Excess spot volatility Shanghai
31/01/2011	17.1	18.6	22.8	20.5	2.3	-1.4
28/02/2011	17.9	19.4	22.3	22.0	0.3	11.9
31/03/2011	17.9	20.3	32.2	25.0	7.2	-2.4
30/04/2011	12.7	15.5	24.4	23.8	0.5	-2.8
31/05/2011	16.7	19.7	29.4	27.9	1.5	-3.0
30/06/2011	9.4	12.4	17.3	20.2	-2.8	-3.0
31/07/2011	8.5	12.7	15.6	13.5	2.1	-4.3
31/08/2011	26.4	26.0	19.0	26.6	-7.6	0.3
30/09/2011	27.3	31.1	40.6	40.1	0.5	-3.7
31/10/2011	37.1	43.3	43.6	57.0	-13.4	-6.2
30/11/2011	28.6	31.5	32.8	27.5	5.3	-2.9
31/12/2011	19.0	26.0	28.8	34.1	-5.4	-7.1
31/01/2012	14.8	17.2	25.6	25.8	-0.2	-2.4
29/02/2012	12.6	15.8	22.7	23.0	-0.3	-3.1
31/03/2012	11.8	14.2	17.2	20.7	-3.5	-2.4
30/04/2012	13.4	17.7	15.8	28.7	-12.8	-4.2
31/05/2012	12.2	15.5	16.6	17.3	-0.8	-3.3
30/06/2012	14.4	19.2	21.9	23.3	-1.4	-4.8
31/07/2012	11.8	14.1	21.8	20.2	1.6	-2.4
31/08/2012	8.0	10.4	16.0	15.5	0.5	-2.4
30/09/2012	14.0	15.8	22.7	21.2	1.5	-1.9
31/10/2012	10.3	10.1	15.4	14.7	0.7	0.2

30/11/2012	9.1	10.4	14.2	15.9	-1.8	-1.4
31/12/2012	8.6	9.2	13.5	13.8	-0.2	-0.5
31/01/2013	6.0	7.9	14.8	15.6	-0.7	-1.9
28/02/2013	9.2	10.6	11.1	12.0	-1.0	-1.4
31/03/2013	11.9	15.1	17.6	13.7	3.9	-3.2
30/04/2013	28.0	26.1	25.8	26.9	-1.0	1.9
31/05/2013	21.9	26.0	26.5	30.5	-4.0	-4.1
30/06/2013	13.2	14.6	17.2	18.6	-1.4	-1.4
31/07/2013	18.0	21.1	20.7	23.7	-2.9	-3.1
31/08/2013	11.1	13.8	20.4	17.3	3.1	-2.7
30/09/2013	9.9	10.5	15.6	16.4	-0.8	-0.6
31/10/2013	7.3	9.4	11.5	14.9	-3.4	-2.0
30/11/2013	8.0	8.1	11.1	10.5	0.6	0.0
31/12/2013	6.7	8.5	11.0	11.4	-0.4	-1.9
31/01/2014	6.9	8.1	8.7	11.1	-2.4	-1.2
28/02/2014	8.6	7.7	9.6	8.8	0.8	0.8
31/03/2014	25.3	22.1	20.2	23.2	-3.0	3.2
30/04/2014	17.0	12.1	11.8	11.3	0.5	4.8
31/05/2014	12.2	10.1	15.2	12.8	2.4	2.0
30/06/2014	14.6	9.9	13.8	11.8	2.0	4.7
31/07/2014	15.9	11.4	10.4	10.9	-0.5	4.5
31/08/2014	11.2	10.1	11.6	13.4	-1.8	1.1
30/09/2014	10.6	11.7	10.8	13.1	-2.3	-1.1
31/10/2014	9.8	12.2	13.0	17.8	-4.8	-2.4
30/11/2014	8.2	11.0	13.4	14.7	-1.3	-2.8
31/12/2014	14.8	18.7	17.4	13.6	3.8	-3.9
31/01/2015	24.5	20.9	29.2	28.0	1.2	3.6
28/02/2015	16.3	16.9	19.4	21.0	-1.6	-0.6
31/03/2015	15.7	16.3	18.7	24.9	-6.1	-0.6
30/04/2015	8.5	11.5	14.3	14.2	0.1	-3.0
31/05/2015	14.7	15.7	16.3	18.8	-2.5	-1.0
30/06/2015	11.2	10.4	16.9	16.8	0.1	0.7
31/07/2015	26.2	27.4	24.9	26.0	-1.1	-1.2

31/08/2015	18.1	19.4	20.7	28.7	-8.0	-1.3
30/09/2015	20.9	23.5	23.2	25.7	-2.5	-2.6
31/10/2015	17.6	16.1	20.3	20.3	0.0	1.5
30/11/2015	20.8	21.7	21.6	22.1	-0.5	-0.9
31/12/2015	18.9	14.0	17.9	21.1	-3.2	4.9

Table 16: Forward spread (normalized by the spot price), SHFE inventories, aggregate inventories and inventory/demand ratio based on SHFE and aggregate inventories

	Forward spread (normalized by spot price)	SHFE inventories	Aggregate inventories	Inventory/Demand based on SHFE inventories	Inventory/Demand based on aggregate inventories
27/02/09	-3.44	28332	278332	2.01	19.73
31/03/09	-3.11	25181	300181	1.79	21.28
30/04/09	-3.13	19064	319064	1.35	22.62
29/05/09	1.11	30217	280217	2.14	19.86
30/06/09	3.11	56088	406088	3.98	28.79
31/07/09	2.42	51135	351135	3.62	24.89
31/08/09	1.67	86625	411625	6.14	29.18
30/09/09	3.25	98689	348689	7.00	24.72
30/10/09	2.99	102835	327835	7.29	23.24
30/11/09	3.69	101277	351277	7.18	24.90
31/12/09	3.06	95315	395315	6.76	28.02
29/01/10	0.44	101210	451210	5.21	23.24
26/02/10	2.44	149478	499478	7.70	25.73
31/03/10	3.80	155465	455465	8.01	23.46
30/04/10	1.11	189441	439441	9.76	22.64
31/05/10	0.83	157698	382698	8.12	19.71
30/06/10	-0.84	123939	323939	6.38	16.69
30/07/10	0.51	104507	304507	5.38	15.69
31/08/10	0.70	110582	360582	5.70	18.57
30/09/10	0.69	87447	337447	4.50	17.38
29/10/10	0.98	106091	406091	5.46	20.92
30/11/10	1.02	122612	422612	6.32	21.77
31/12/10	4.60	131891	531891	6.79	27.40
31/01/11	5.36	129250	579250	6.39	28.63
28/02/11	2.92	158101	708101	7.81	35.00
31/03/11	0.27	161916	786916	8.00	38.89
29/04/11	-1.92	128268	678268	6.34	33.52

31/05/11	-1.88	82309	532309	4.07	26.31
30/06/11	-0.56	90089	390089	4.45	19.28
29/07/11	1.68	117067	367067	5.79	18.14
31/08/11	0.32	102258	302258	5.05	14.94
30/09/11	1.25	97911	297911	4.84	14.72
31/10/11	-1.15	73768	323768	3.65	16.00
30/11/11	-2.72	65205	315205	3.22	15.58
30/12/11	-0.69	93219	493219	4.61	24.38
31/01/12	2.21	131645	581645	6.10	26.94
29/02/12	2.29	216086	716086	10.01	33.17
30/03/12	1.49	218814	818814	10.13	37.92
30/04/12	1.11	204762	854762	9.48	39.59
31/05/12	-2.19	147044	707044	6.81	32.75
29/06/12	-0.50	139442	634442	6.46	29.38
31/07/12	-1.29	156510	706510	7.25	32.72
31/08/12	-1.71	158065	758065	7.32	35.11
28/09/12	-0.21	162547	812547	7.53	37.63
31/10/12	-0.35	192761	892761	8.93	41.35
30/11/12	0.07	197088	997088	9.13	46.18
31/12/12	0.80	204773	979773	9.48	45.38
31/01/13	0.86	197091	972091	8.09	39.89
28/02/13	-0.40	226201	1051201	9.28	43.13
29/03/13	-2.03	247591	972591	10.16	39.91
30/04/13	-2.71	217180	867180	8.91	35.58
31/05/13	-3.55	179317	729317	7.36	29.92
28/06/13	-3.76	182493	657493	7.49	26.98
31/07/13	-4.03	161564	511564	6.63	20.99
30/08/13	-2.66	156568	581568	6.42	23.86
30/09/13	-1.93	150994	575994	6.20	23.63
31/10/13	-1.82	178343	628343	7.32	25.78
29/11/13	-2.31	148670	673670	6.10	27.64
31/12/13	-1.41	125849	675849	5.16	27.73
31/01/14	-1.69	148581	748581	5.52	27.80
28/02/14	-1.33	198286	948286	7.36	35.21
31/03/14	-2.34	193725	1018725	7.19	37.83
30/04/14	-7.09	105156	955156	3.90	35.47
30/05/14	-4.86	91947	901947	3.41	33.49
30/06/14	-4.45	78975	828975	2.93	30.78
31/07/14	-1.94	108393	768393	4.02	28.53
29/08/14	-3.18	79778	699778	2.96	25.98
30/09/14	-3.75	81554	651554	3.03	24.19
31/10/14	-3.94	95824	665824	3.56	24.72
28/11/14	-4.19	88278	678278	3.28	25.19
31/12/14	-4.14	105522	705522	3.92	26.20
30/01/15	-3.56	137042	717042	4.43	23.16

27/02/15	-1.00	205146	775146	6.62	25.03
31/03/15	-0.33	243592	803592	7.87	25.95
30/04/15	-1.70	188165	778165	6.08	25.13
29/05/15	-1.51	156053	806053	5.04	26.03
30/06/15	-2.18	112921	792921	3.65	25.61
31/07/15	-2.77	103117	753117	3.33	24.32
31/08/15	-0.65	123223	663223	3.98	21.42
30/09/15	-1.18	155515	575515	5.02	18.59
30/10/15	-0.97	180157	610157	5.82	19.70
30/11/15	-0.06	187152	627152	6.04	20.25
31/12/15	-0.93	177854	627854	5.74	20.28

Table 17: 1-year rolling Pearson and Spearman correlation between 6-month forward spread (normalized) and changes in inventories (SHFE and aggregate inventories)

	Rank correlation SHFE inventories	Rank correlation aggregate inventories	Pearson correlation SHFE inventories	Pearson correlation aggregate inventories
27/02/2009	-0.34	-0.29	-0.18	-0.46
31/03/2009	-0.34	-0.30	-0.18	-0.45
30/04/2009	-0.26	-0.16	-0.15	-0.37
29/05/2009	0.07	-0.46	0.07	-0.55
30/06/2009	0.57	0.11	0.50	0.08
31/07/2009	0.38	-0.12	0.38	-0.11
31/08/2009	0.55	0.04	0.58	-0.02
30/09/2009	0.56	-0.19	0.57	-0.21
30/10/2009	0.59	-0.33	0.54	-0.29
30/11/2009	0.42	-0.31	0.35	-0.31
31/12/2009	0.27	-0.25	0.22	-0.27
29/01/2010	0.23	-0.06	0.19	-0.04
26/02/2010	0.41	-0.07	0.30	-0.03
31/03/2010	0.33	-0.13	0.16	-0.11
30/04/2010	-0.24	-0.15	-0.30	-0.09
31/05/2010	0.11	-0.06	0.01	-0.03
30/06/2010	0.42	0.10	0.30	0.07
30/07/2010	0.50	0.18	0.37	0.12
31/08/2010	0.48	0.06	0.40	0.05
30/09/2010	0.48	0.23	0.41	0.21
29/10/2010	0.45	0.26	0.37	0.19
30/11/2010	0.50	0.23	0.42	0.16
31/12/2010	0.60	0.36	0.44	0.40
31/01/2011	0.53	0.49	0.33	0.50

28/02/2011	0.54	0.51	0.36	0.50
31/03/2011	0.51	0.57	0.34	0.58
29/04/2011	0.63	0.71	0.53	0.69
31/05/2011	0.74	0.82	0.64	0.76
30/06/2011	0.63	0.81	0.55	0.74
29/07/2011	0.68	0.74	0.54	0.73
31/08/2011	0.67	0.75	0.55	0.75
30/09/2011	0.69	0.74	0.56	0.75
31/10/2011	0.73	0.67	0.62	0.71
30/11/2011	0.71	0.61	0.60	0.65
30/12/2011	0.56	0.42	0.48	0.40
31/01/2012	0.70	0.45	0.73	0.47
29/02/2012	0.71	0.44	0.75	0.46
30/03/2012	0.69	0.50	0.72	0.50
30/04/2012	0.55	0.45	0.63	0.43
31/05/2012	0.57	0.47	0.65	0.45
29/06/2012	0.61	0.47	0.67	0.46
31/07/2012	0.48	0.48	0.60	0.46
31/08/2012	0.49	0.49	0.60	0.47
28/09/2012	0.54	0.59	0.64	0.53
31/10/2012	0.50	0.59	0.62	0.53
30/11/2012	0.43	0.53	0.61	0.49
31/12/2012	0.50	0.51	0.65	0.57
31/01/2013	0.34	0.40	0.57	0.51
28/02/2013	0.11	0.28	0.25	0.37
29/03/2013	-0.03	0.34	0.13	0.38
30/04/2013	0.35	0.44	0.41	0.50
31/05/2013	0.41	0.47	0.50	0.58
28/06/2013	0.40	0.60	0.45	0.67
31/07/2013	0.51	0.69	0.53	0.76
30/08/2013	0.52	0.61	0.54	0.69
30/09/2013	0.52	0.58	0.54	0.67
31/10/2013	0.42	0.51	0.45	0.62
29/11/2013	0.42	0.37	0.44	0.51
31/12/2013	0.31	0.47	0.38	0.59
31/01/2014	0.57	0.71	0.55	0.74
28/02/2014	0.54	0.71	0.53	0.74
31/03/2014	0.54	0.73	0.52	0.79
30/04/2014	0.63	0.76	0.79	0.63
30/05/2014	0.61	0.77	0.75	0.67
30/06/2014	0.68	0.78	0.76	0.68
31/07/2014	0.64	0.66	0.76	0.61
29/08/2014	0.66	0.71	0.76	0.61
30/09/2014	0.64	0.75	0.75	0.64
31/10/2014	0.51	0.69	0.69	0.61

28/11/2014	0.58	0.65	0.74	0.58
31/12/2014	0.72	0.65	0.83	0.61
30/01/2015	0.63	0.56	0.80	0.57
27/02/2015	0.63	0.49	0.82	0.48
31/03/2015	0.70	0.54	0.85	0.49
30/04/2015	0.42	0.42	0.39	0.36
29/05/2015	0.22	0.43	0.22	0.35
30/06/2015	0.11	0.33	0.12	0.21
31/07/2015	0.11	0.41	0.08	0.31
31/08/2015	0.14	0.06	0.11	-0.06
30/09/2015	0.20	-0.13	0.16	-0.27
30/10/2015	0.30	-0.02	0.23	-0.16
30/11/2015	0.23	0.06	0.17	-0.06
31/12/2015	0.31	0.23	0.26	0.10

Table 18: 1-year rolling Pearson and Spearman correlation between 6-month forward spread (normalized) and changes inventories-to-demand (SHFE and aggregate inventories)

	Rank correlation SHFE inventories	Rank correlation aggregate inventories	Pearson correlation SHFE inventories	Pearson correlation aggregate inventories
27/02/2009	-0.28	-0.31	-0.13	-0.44
31/03/2009	-0.33	-0.27	-0.16	-0.40
30/04/2009	-0.24	-0.07	-0.13	-0.30
29/05/2009	0.10	-0.45	0.08	-0.51
30/06/2009	0.58	0.01	0.51	0.13
31/07/2009	0.38	-0.25	0.39	-0.07
31/08/2009	0.54	-0.07	0.59	0.01
30/09/2009	0.56	-0.28	0.58	-0.18
30/10/2009	0.61	-0.43	0.56	-0.26
30/11/2009	0.44	-0.37	0.37	-0.26
31/12/2009	0.28	-0.27	0.24	-0.21
29/01/2010	0.23	-0.10	0.19	0.01
26/02/2010	0.44	-0.06	0.33	0.05
31/03/2010	0.43	-0.01	0.26	0.07
30/04/2010	0.22	0.33	0.00	0.27
31/05/2010	0.42	0.36	0.21	0.28
30/06/2010	0.55	0.37	0.38	0.28
30/07/2010	0.61	0.42	0.43	0.31
31/08/2010	0.59	0.30	0.49	0.26
30/09/2010	0.58	0.46	0.48	0.43
29/10/2010	0.51	0.47	0.43	0.39

30/11/2010	0.54	0.43	0.46	0.33
31/12/2010	0.64	0.48	0.48	0.50
31/01/2011	0.47	0.44	0.29	0.43
28/02/2011	0.47	0.46	0.32	0.45
31/03/2011	0.45	0.51	0.29	0.52
29/04/2011	0.57	0.67	0.48	0.64
31/05/2011	0.69	0.79	0.59	0.72
30/06/2011	0.58	0.77	0.50	0.71
29/07/2011	0.62	0.72	0.49	0.69
31/08/2011	0.62	0.73	0.51	0.72
30/09/2011	0.63	0.72	0.51	0.72
31/10/2011	0.68	0.65	0.58	0.68
30/11/2011	0.65	0.58	0.56	0.62
30/12/2011	0.50	0.38	0.43	0.36
31/01/2012	0.70	0.42	0.72	0.44
29/02/2012	0.70	0.41	0.74	0.42
30/03/2012	0.68	0.48	0.71	0.46
30/04/2012	0.54	0.42	0.62	0.40
31/05/2012	0.56	0.44	0.64	0.41
29/06/2012	0.60	0.44	0.66	0.41
31/07/2012	0.47	0.43	0.58	0.41
31/08/2012	0.47	0.44	0.58	0.42
28/09/2012	0.53	0.54	0.63	0.48
31/10/2012	0.49	0.53	0.60	0.47
30/11/2012	0.42	0.48	0.59	0.43
31/12/2012	0.50	0.47	0.63	0.53
31/01/2013	0.28	0.29	0.51	0.39
28/02/2013	0.05	0.18	0.16	0.22
29/03/2013	-0.10	0.21	0.03	0.19
30/04/2013	0.23	0.30	0.27	0.29
31/05/2013	0.29	0.34	0.32	0.35
28/06/2013	0.27	0.46	0.28	0.44
31/07/2013	0.37	0.56	0.37	0.56
30/08/2013	0.37	0.49	0.37	0.50
30/09/2013	0.37	0.45	0.36	0.46
31/10/2013	0.26	0.36	0.26	0.39
29/11/2013	0.26	0.19	0.25	0.24
31/12/2013	0.13	0.23	0.14	0.26
31/01/2014	0.55	0.68	0.54	0.73
28/02/2014	0.51	0.66	0.51	0.72
31/03/2014	0.51	0.67	0.49	0.76
30/04/2014	0.62	0.68	0.77	0.59
30/05/2014	0.60	0.68	0.73	0.62
30/06/2014	0.66	0.69	0.74	0.64
31/07/2014	0.64	0.58	0.74	0.57

29/08/2014	0.65	0.64	0.74	0.57
30/09/2014	0.63	0.68	0.73	0.60
31/10/2014	0.49	0.62	0.66	0.56
28/11/2014	0.55	0.57	0.72	0.53
31/12/2014	0.69	0.54	0.81	0.53
30/01/2015	0.68	0.58	0.82	0.53
27/02/2015	0.69	0.47	0.84	0.42
31/03/2015	0.72	0.50	0.85	0.45
30/04/2015	0.42	0.44	0.41	0.38
29/05/2015	0.23	0.44	0.24	0.39
30/06/2015	0.13	0.37	0.14	0.29
31/07/2015	0.12	0.43	0.11	0.37
31/08/2015	0.15	0.16	0.13	0.09
30/09/2015	0.21	0.00	0.19	-0.09
30/10/2015	0.32	0.13	0.27	0.04
30/11/2015	0.26	0.26	0.22	0.20
31/12/2015	0.38	0.51	0.35	0.47

Chapter 5. Conclusions

Section 1: Final remarks

This thesis is focused on equity and commodity related new strategies providing attractive returns in a low interest rate environment. Commodity Futures market are used for hedging purposes as well as investing. We exploit the relationship between the spot price and the forward price, the relationship of the forward curve as described in the Theory of Storage to showcase new ways of generating alternative returns.

Section 2: Important findings and contributions to the literature

The research in this thesis contributes to the existing literature in various ways. We follow upon the transaction time of Geman and Ane (1996) and the temperature of a stock as defined in Derman (2002) and extend them in a time-varying setting to a portfolio of stocks. We show the usefulness of the portfolio temperature in explaining the cross-section of stock returns by creating a long/short temperature factor portfolio and we provide evidence for a positive risk premium associated with the temperature of stocks. We highlight the usefulness of this approach to intra-day data. The technological progress over the past 20 years has enabled hedge funds and other sophisticated market players to access markets instantaneously. Not only investors but also regulators are interested in better understanding of intra-day data after several instances of “flash crashes” or very abrupt intra-day moves in single stocks as well as in broad indices like the Dow Jones Industrial Average. Our research contributes to the existing literature by providing a simple transaction based approach to intraday moves during volatile market periods. In our model, short-term technical traders get rewarded for providing liquidity in the market. We show that the “heat” of a stock is relevant to short-term focused market participants. We create a portfolio of long the most liquidly traded stocks and short the less liquidly traded stocks and provide evidence of a positive return during market turbulence. This would suggest that short-term traders remain represented in the market despite market volatility and contrary to many market commentary blaming short-term traders for causing volatility and liquidity crisis.

In Chapter 3 we show the importance of inventories explaining copper spot price volatility. We introduce a three factor model to derive a fundamental long-term value for copper in which the copper spot price is modelled as geometric Brownian motion with positive drift. We derive a long-term value proxy and show the relevance by using it as input in an agent based model. Our model allows distinguishing between cyclical and structural moves in the copper forward curve. We are interested in the structural trend which we use as a fair value proxy for market participants. Our agent-based model is comprised of short-term traders introduced in Chapter 2 and longer-term fundamental traders who focus on mean reversion in contrast to technical traders exploiting short-term momentum. The model provides evidence of the relevance of the fair value to both technical as well as fundamental traders. Not only investors but also regulators are keen to understand the supply and demand relationship caused by the interaction of different types of traders. Regulators are already distinguishing between speculators and other investors. We see our research in Chapter 3 as a natural extension to this classification of traders similar to the regularly published Commodity Futures Trade Commission (CFTC) reports. Technical traders are vital to market functioning as they provide liquidity (e.g. by going short) and the flexibility the market needs to adjust positioning. Despite the critique around short-term market participants like hedge funds the research shows that they too are taking commodity fundamentals – in this case commodity supply and demand - into account when designing trading strategies.

Chapter 4 confirms the validity of commodity inventories used in Chapter 3 by examining Chinese copper inventories and the impact of commodity inventory financing. We use a database of Shanghai copper inventories and bonded warehouses to examine the relationship between the forward curve and copper inventories. China has grown rapidly over the past 30 years and so has its commodity consumption. After the Financial crisis however commodity demand remained much stronger than what would have been suggested by economic growth. At the same time funding conditions in China remained tight as the central bank actively controlled asset bubbles. Commodity traders are able to circumvent capital account restrictions through commodity inventory financing and hence to obtain cheap US dollar funding. These transactions created shadow inventory in copper which reached its high in 2014 just before the Qingdao inventory scandal. The temperature of the copper spot has likely increased with higher copper spot price volatility. Despite this artificial distortion of copper inventories, we confirm the validity of the Theory of Storage and the relevance of the forward curve in reflecting copper supply and demand despite the dramatic surge in Chinese copper bonded warehouses. The paper contributes to the existing literature on financialization of commodity markets by rejecting some of the recent claims that the forward spread is a distorted measure of supply and demand. We show the robustness of the forward spread in explaining supply and demand in China and view commodity inventory financing as an artificial inventory making that has no significance on official copper inventories.

Section 3: Directions for further research

We wish to highlight several ways for further research. In the case of our transaction-time based approach in Chapter 2 it would be interesting to exploit possible further reasons for the premia or exclude them by examining other market periods. It could also be of value to use our fundamental copper price proxy derived in Chapter 3 in different models than an agent-based model in order to confirm its validity. Lastly it remains important to monitor the developments around commodity inventory financing in China. The recent further tightening in funding conditions through the restriction of wealth management products is likely to encourage an increase in commodity inventory activity. Further research focusing on the links between those funding conditions, shadow inventories and official inventories calibrated against the forward curve would help the investment community and regulators to understand the dynamics behind commodity inventory financing better and avoid unintended negative consequences similar to what high-profile western investors experienced during the Qingdao scandal in 2014.