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Abstract

We employ a large dataset of physical inventory data on 21 different commodities for the period 1993-2011 to empirically analyze the behaviour of commodity prices and their volatility as predicted by the theory of storage. We examine two main issues. First, we explore the relationship between inventory and the shape of the forward curve. Low (high) inventory is associated with forward curves in backwardation (contango), as the theory of storage predicts. Second, we show that price volatility is a decreasing function of inventory for the majority of commodities in our sample. This effect is more pronounced in backwardated markets. Our findings are robust with respect to alternative inventory measures and over the recent commodity price boom period.

JEL classification: C22, C58, G00, G13

Keywords: Forward curves, inventory, commodity price volatility, theory of storage, convenience yield.

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1. Introduction

Over the past few years, the flow of funds to commodities has increased substantially, primarily through investments in exchange-traded funds (ETFs) and commodity indices.[1] This widespread interest in commodity investments is partly associated with the view of commodities as a good diversification tool, since their correlations with stocks and bonds have been low or negative (Gorton and Rouwenhorst, 2006; Buyuksahin et al., 2010). Recently, Daskalaki and Skiadopoulos (2011) point out that these diversification benefits are preserved only during the recent commodity price boom (2003-2008), but in their study vanish in an out-of-sample context. It is also a common belief that commodities provide a good hedge against inflation (Bodie, 1983; Edwards and Park, 1996). Moreover, recent evidence suggests that momentum and term-structure based strategies in commodities can generate significant profits (Miffre and Rallis, 2007; Fuertes et al., 2010).[2]

The behaviour of commodity prices is strikingly different from that of stocks and bonds. For instance, such factors as seasonal supply and demand, weather conditions, and storage and transportation costs, are specific to commodities and do not affect, or at least not directly, the prices of stocks and bonds. In the light of these stylised facts, understanding the determinants of commodity prices and their volatilities is an issue of great importance.

The mainstream theory in commodity pricing, namely the theory of storage, explains the behaviour of commodity prices based on economic fundamentals. Furthermore, it has major implications for the volatility of commodity prices. Since its inception, this theory has been the central topic of many theoretical and empirical papers in the economics literature. Nevertheless, most studies employ proxies for inventory, such as the sign of the futures basis (e.g., Fama and French, 1988), thus providing only indirect evidence on the effect of inventory on commodity prices and their volatilities.

In this paper, we employ real inventory data to test two of the main predictions of the theory of storage. Specifically, we show how inventory affects

[1]The Financial Times characteristically reports: "... inflows into the sector reached a new high of \$7.9bn in October 2010, taking total investor commodity holdings to a record \$340bn."

[2]See also Fabozzi et al. (2008) for practical aspects of commodity investing.

the slope of the forward curve (the basis) as well as the price volatility for a wide spectrum of 21 different commodities. Analyzing the relationship between inventory and the term structure of futures prices is important for various reasons. First, if inventory indeed has a significant effect on the shape of the forward curve ("contango" vs "backwardation"), then it should also affect the profitability of various term-structure based investment strategies. Additionally, the strength of this relationship will provide further evidence on whether the basis should be employed as a proxy for inventory in empirical studies. Furthermore, the results from our research are of substantial academic and practical interest since volatility underlies a variety of key financial decisions such as asset allocation, hedging and derivatives pricing.

Our study contributes to the empirical literature on the theory of storage in several ways. Gorton et al. (2007) employ physical inventory data to document a negative non-linear relationship between inventory and the futures basis for a large cross-section of commodities. They do not examine the link between inventory and volatility in detail as we do. Also, Geman and Ohana (2009) examine the relationship between inventory and the adjusted futures spread in the oil and natural gas markets, using end-of-month inventory data. The present paper adds to the evidence of the aforementioned studies by thoroughly analyzing the link between real inventories and the slope of the forward curve at several different maturities whereas previous research has only examined the short end of the curve. Furthermore, the sample used for our analysis includes the recent commodity price boom, which offers a great opportunity to test our hypothesis over varying market conditions (for an analysis of the recent commodity price boom, see Baffes and Haniotis, 2010).

Second, and more importantly, using our extensive inventory dataset, we document a negative relationship between inventory and commodity returns volatility. We characterise the time series variability of futures returns and spreads with respect to inventory levels for each individual commodity. From this perspective, our analysis is related to Geman and Nguyen (2005), who analyze the relationship between scarcity (inverse of inventory) and returns volatility in the soybean market. However, given the heterogeneous nature of commodities as an asset class (Erb and Harvey, 2006; Brooks and Prokopczuk, 2011; Daskalaki et al., 2012), it is quite intuitive to examine the inventory-volatility relationship for a broader set of commodities. For example, Fama and French (1987) find that the implications of the theory of storage are not empirically supported for certain commodities.

Our analysis provides a number of interesting results. First, we find a strong positive relationship between logarithmic inventory and the slope of the forward curve, the latter approximated by the interest-adjusted basis at different maturities. In particular, lower (higher) inventory for a commodity is associated with lower (higher) basis and forward curves in "backwardation"[3] ("contango") as the theory of storage predicts. Since the interest-adjusted basis represents storage costs and convenience yields, our findings provide insights regarding the relationship between convenience yield and inventory. Our research also implicitly builds on the competing "hedging pressure" literature, which is based on the existence of a risk premium earned by investors in futures for bearing the risk of spot price changes. Recent empirical evidence has shown that there exists a link between futures basis and risk premiums (Gorton and Rouwenhorst, 2006).

Second, we find that price volatility is a decreasing function of inventory for the majority of commodities in our sample. To do this, we estimate for each commodity univariate regressions of monthly price volatility against end-of-month inventory. Monthly price volatility is measured by the standard deviation of daily nearby futures returns/adjusted basis for each month. The magnitude of the reported relationship appears to be higher for commodities that are more sensitive to fundamental supply and demand factors, which determine storage. Moreover, heterogeneity is a possible explanation for the difference in the sizes of the coefficients across individual commodities. Some commodities are more difficult to store, and some of them are seasonal

[3]Backwardation is observed when the spot price is higher than the contemporaneous futures price, or the price of the nearby futures contract is higher than the price of longer maturity contracts. Contango describes the opposite case. According to the early hedging pressure hypothesis (Keynes, 1930; Hicks, 1939), the net supply of futures contracts, namely "hedging pressure", gives rise to risk premia in futures prices (compensation for risk transferring from producers to speculators).

or perishable, while others are not. Our evidence generally supports the implications of theoretical studies (Williams and Wright, 1991; Deaton and Laroque, 1992).

Lastly, we investigate the hypothesis that the effect of inventory varies across different states of the market. To this end, we estimate OLS regressions of commodity returns/futures basis volatility on the interest-adjusted basis, decomposing the basis into positive and negative values that indicate the state of inventories (positive basis – high inventory and vice versa). In line with the implications of the theory, our estimation results suggest that the relationship between inventory and volatility is stronger in backwardation (low inventory). Furthermore, the results for energy commodities (crude oil and natural gas) lend support for the existence of the asymmetric V-shaped relationship between inventory and volatility reported by previous studies (Kogan et al., 2009). For crude oil (natural gas), positive deviations from the long-run inventory level (positive basis) have larger (smaller) impacts than negative deviations of the same magnitude.

As mentioned in Gorton et al. (2007), there exist some problems when dealing with inventory data. These are basically associated with the definition of the appropriate measure of inventory (e.g. world vs domestic supplies) and also with the timing of information releases regarding inventory levels. Another potential pitfall concerns the difference in the quality of the corresponding data from commodity to commodity, which hampers the ability to draw universal conclusions. This is an inherent problem in any study that uses physical inventories in the analysis. Therefore, any results using inventories should be interpreted cautiously.

The remainder of the paper is organized as follows. Section 2 briefly discusses the theory of storage and the relevant literature. Section 3 presents the datasets used for the empirical analysis. Section 4 examines the relationship between inventory and the slope of the forward curve. Section 5 analyzes the relationship between scarcity and price volatility. Section 6 tests the stability of the results obtained through various robustness tests. The final section presents concluding remarks.

2. Theoretical background and relevant literature

The theory of storage, introduced in the seminal papers of Kaldor (1939), Working (1948), Brennan (1958) and Telser (1958), links the commodity spot price with the contemporaneous futures price through a no-arbitrage relationship known as the "cost-of-carry model". This theory is based on the notion of "convenience yield", which is associated with the increased utility from holding inventories during periods of scarce supply. This no-arbitrage relationship between spot and futures prices is given by:

$$F_{t,T} = S_t(1 + R_{t,T}) + w_{t,T} - y_{t,T} \tag{1}$$

where $F_{t,T}$ is the price at time t of a futures contract maturing at T, S_t is the time t spot price of the commodity, $R_{t,T}$ is the interest rate for the period from t to T, $w_{t,T}$ is the marginal cost of storage per unit of inventory from t to T, and $y_{t,T}$ is the marginal convenience yield per unit of storage.

Within the context of the theory of storage, convenience yield can be regarded as an option to sell inventory in the market when prices are high, or to keep it in storage when prices are low. Milonas and Thomadakis (1997) show that convenience yields exhibit the characteristics of a call option with a stochastic strike price, which can be priced within the framework of Black's model (Black, 1976). Evidence has also shown that convenience yield is a convex function of inventories (Brennan, 1958; French, 1986).

A high convenience yield during periods of low inventory drives spot prices to be higher than contemporaneous futures prices and the adjusted basis becomes negative. Specifically, as inventories decrease, convenience yield increases at a higher rate due to the convex relationship between the two quantities. In contrast, at high levels of inventory, convenience yield is small and futures prices tend to be higher than contemporaneous spot prices to compensate inventory holders for the costs associated with storage. The theory of storage also predicts a negative relationship between price volatility and inventory. In particular, at low inventory states, the lower elasticity of supply and the inability to adjust inventories in a timely manner without significant costs (e.g., imports from other locations) make spot and futures prices more volatile. As a result, basis also becomes more volatile. The opposite happens at high inventory conditions.

Moreover, such factors as non-continuous production of some commodities (e.g., agriculturals), storage costs, and weather conditions, exacerbate the effect of demand shocks on current and future prices and thus have a significant impact on price volatility.[4] Fama and French (1987) use a dataset on 21 commodity futures and show that variation in the basis is driven by seasonals in supply and demand, storage costs and interest rates. Also, Fama and French (1988) employ the sign of the interest-adjusted basis as well as the phase of the business cycle as proxies for inventory to analyze the relative variation of spot and futures prices for metals. They find that when inventories are low, the interest-adjusted basis is more volatile and also spot metal prices tend to be more volatile than futures prices in line with the Samuelson hypothesis.

In a different version of the theory of storage, Williams and Wright (1991) build a quarterly model with annual production and point out that price volatility is highest shortly before the new harvest when inventories are low. Deaton and Laroque (1992) suggest an equilibrium competitive storage model, and show that conditional volatility is positively correlated with the price level (the "inverse leverage effect"). Routledge et al. (2000) develop an equilibrium model for commodity futures prices and show that backwardation, driven by inventory and supply/demand shocks, is positively related to volatility. A number of recent papers report an asymmetric V-shaped relationship between inventory proxies and price volatility, meaning that both high and low levels of inventory induce high price volatility (Lien and Yang, 2008; Kogan et al., 2009). Carbonez et al. (2010) provide contrasting evidence on the existence of this V-shaped relationship in the case of agricultural

[4]For instance, in agricultural commodities the uncertainty about the future level of stocks shortly before the end of the new harvest, when inventory is usually low, leads to more volatile prices (see Williams and Wright, 1991). Moreover, weather conditions may affect the total level of supply and induce periodicity in the prices of these commodities (Chambers and Bailey, 1996).

commodities.

The majority of the aforementioned studies employ indirect measures for inventory, such as the (adjusted) futures basis to support their basic arguments. Nevertheless, very few papers employ observed inventory data. For instance, Geman and Nguyen (2005) construct a sample of US and global inventories for soybeans at various frequencies and show that price volatility is a monotonically increasing function of scarcity, the latter defined as the inverse of inventory. Gorton et al. (2007) employ physical inventory data on a large set of 31 commodities and conclude that the basis is a non-linear, increasing function of inventory.

Apart from the theory of storage, the alternative view of commodity futures prices, namely the hedging pressure hypothesis, is based on the idea of a risk premium earned by long investors in commodity futures. According to the very first version of the theory (Keynes, 1930; Hicks, 1939), speculators earn a positive risk premium for bearing the risk short hedgers (producers) are seeking to avoid. Later extensions show that producers can take both long and short positions (Cootner, 1960), inducing risk premiums that vary with the net positions of hedgers. This literature suggests that hedging pressure arises from the existence of frictions (transaction costs, limited participation, etc), which cause segmentation of commodity markets from other asset markets. Another strand of the same literature relates risk premiums to systematic risk factors based on the traditional CAPM (Dusak, 1973) or CCAPM framework (Jagannathan, 1985; De Roon and Szymanowska, 2010). Finally, later studies allow risk premiums to depend on both systematic risk and the positions of hedgers (Hirshleifer, 1989; Bessembinder, 1992; De Roon et al., 2000) and provide evidence that risk premiums vary with net hedging demand. In general, the existence of risk premiums in futures prices and their determinants has been a debatable issue among academics and practitioners.

It is therefore evident that gaining insights on the determinants of commodity prices and their volatility is an issue of paramount importance, not only for academics and practitioners, but also for policy makers (Bhar and Hamori, 2008). In this spirit, Dahl and Iglesias (2009) analyze the dynamic relationship between commodity spot prices and their volatilities. Furthermore, the issue of whether and under which conditions investors should include commodities in their portfolios still remains an open question. Bodie and Rosansky (1980) argue that including commodities in a portfolio of stocks improves the risk-return profile of a typical investor. In contrast, Daskalaki and Skiadopoulos (2011) cast doubt on the diversification benefits from investing in commodities and find that these benefits exist only during periods of infrequent bursts in commodity prices.

Moreover, some recent empirical work has focused on the so-called "financialization" of commodities. This term indicates the increase in co-movements of commodities with other assets (e.g. Silvennoinen and Thorp, 2010) or between seemingly unrelated commodities (Tang and Xiong, 2010). This effect is widely considered a consequence of the increased participation of new commodity investors and primarily hedge funds. Buyuksahin and Robe (2010) argue that the positions of traders, especially hedge funds, led to the recent increase in commodity volatility and comovement of commodities and equities beyond what can be explained by macroeconomic fundamentals. This is an issue of great importance for global policy makers since the increase in volatility and comovement can exercise upward pressure on food and energy prices, raising inflation concerns.

3. Data and preliminary analysis

3.1. Price data

The primary datasets employed in this study consist of daily futures prices with several maturities for 21 commodities traded on the major US commodity exchanges (NYMEX, CBOE, CBOT and ICE) and the London Metal Exchange (LME). The full dataset covers the period from 31 December 1992 to 31 December 2011. The dataset for our analysis begins at the end of 1992 because this corresponds to a common starting point of most inventory series in our sample. The particular commodities are selected to cover, as far as possible, such major categories as grains, livestock, industrials, energy and metals. All price series except for metals are obtained from the Commodity Research Bureau (CRB), which assembles data from all major commodity exchanges worldwide. Metal price data are collected from Bloomberg. All prices are expressed in US dollars. Since our study involves calculation of the futures basis, we need the prices of futures contracts with different maturities. The number of available maturities varies across different commodities from four to twelve per year. Table 1 contains a description of the commodity price dataset.

For the purpose of our analysis, prices of the first nearby futures contract are treated as spot prices, similar to Geman and Nguyen (2005). Since futures contracts have fixed maturity months, we need to construct a continuous series of futures prices for each commodity. To avoid expiration effects (Fama and French, 1987) and low liquidity effects due to thin trading, we roll over from the nearest to maturity to the next nearest to maturity contract on the last trading day of the month preceding delivery. Since we also need longer maturity contracts to compute the futures basis, we apply the same procedure for the futures prices of the second nearest to maturity contract and so forth. We then calculate the return of commodity i on day t as the daily change in logarithmic prices:

$$r_{i,t} = log(\frac{F_{i,t,T}}{F_{i,t-1,T}}) \tag{2}$$

where $F_{i,t,T}$ is the closing price on day t of the futures contract on commodity i maturing at T. In calculating the returns we exclude the prices of the first day of each delivery month in order to ensure that the computed returns always correspond to contracts with the same expiry date (see, Fuertes et al., 2010).

Table 2 provides summary statistics for the daily nearby futures returns series. Means and standard deviations of each series are expressed annualized and as percentages. As seen from the table, the mean annualized returns of metals and crude oil are the highest overall. Also, most of the agricultural and animal commodities had negative average daily returns during the time period considered. However, the result of a t-test fails to reject the null hypothesis of a non-significant mean in all cases. We also observe substantial returns volatility for all commodities. This is consistent with evidence in Erb and Harvey (2006). Among the main drivers of this high price volatility are: the non-continuous production of some commodities (e.g., agricultural), storage costs (Fama and French, 1987), weather conditions (Geman, 2005), especially for the agricultural and energy commodities, as well as the uncertainty regarding the future macroeconomic conditions (e.g., changes in inflation, exchange rates fluctuations, etc). Overall, gold exhibits the lowest amount of annual variation. The annualized daily volatility of 47.39% for natural gas is the highest among all commodities in our sample, followed by 39.24% for coffee. Crude oil and heating oil nearby returns also exhibit significant amounts of daily variation (33.7% and 32.1% respectively).

The sign of skewness is mixed, yet it is close to zero for most commodities. However, the kurtosis coefficients are all significantly higher than three (except for lumber), a standard evidence of non-normality. These non-Gaussian features of commodity returns are also confirmed by the Jarque–Bera test statistic, which clearly rejects the null hypothesis of normality in all cases.

3.2. Inventory data

Apart from the commodity price data, we also compile a large set of inventory data, using various sources. Most datasets correspond to end of month stocks covering the period from December 1992 to December 2011. In those cases when the inventory level is reported on the first day of a calendar month, we shift to the end of the previous month. For some commodities, inventory data are not available from 1993 (soybean oil, cotton, coffee, aluminium and tin) and thus we utilize the subsequent date when those became available as the starting point of our series. Also, due to the non availability of reliable data for oats after 2003, we stop our sample at the end of 2003 for this specific commodity. The data for agricultural and animal products are obtained from the US Department of Agriculture (USDA). For soybeans, corn, oats and wheat, the original datasets are available at a weekly frequency and thus we consider the inventory level of the last week of month as a proxy for end of month inventory. For the three energy commodities, we gather data from the

US Energy Information Administration (EIA). Finally, data for metal stocks stored in the Commodity Exchange (COMEX) for gold, silver and copper, and the London Metal Exchange (LME) for aluminium and tin, are collected from Datastream.

As discussed in Gorton et al. (2007), there are some problems when dealing with inventory data. The first of those concerns the appropriate definition of inventory. For example, in a global market such as that for crude oil, international inventories may provide a better proxy for available supplies compared to inventories stored at the various delivery locations across the US. However, in a recent study, Geman and Ohana (2009) provide empirical evidence that using either domestic US or global petroleum inventories leads to very similar conclusions. Geman and Nguyen (2005) also find that the relationship between inventory and spot price volatility for soybeans is significant regardless of whether US or world soybeans inventory is employed. Moreover, one can argue that a proper definition of inventory should take into account all quantities that can be effectively used in case of a shortage, including government or off-exchange stocks. Another problem is that in some cases inventory data are released with a lag and are sometimes revised later. This may create a problem when synchronizing these data with asset prices.

To alleviate the first concern, in the case of oil we employ some additional measures for inventory, such as the volumes of all petroleum products in the US and OECD countries. We also consider global inventories for corn, soybeans and wheat in addition to domestic US inventories. Unfortunately, we lack availability of global inventory data for the remaining commodities in our study.

Figure 1 plots the inventory series for a subset of commodities along with the fit of a seasonal function where applicable. An inspection of the graphs and of inventory datasets reveals that the inventories of agricultural and animal commodities, as well as those of natural gas and heating oil, exhibit strong periodicity. To formally test for seasonality in inventories, we regress the inventory of each commodity on monthly dummy variables. We then use the F-statistic to test whether the coefficients of all seasonal dummies are equal in each regression. As expected, corn, soybeans, and wheat exhibit very strong seasonal variation, which is mainly driven by their non-continuous production (crop cycles) and also by exogenous factors, such as weather conditions. Most of the agricultural commodities in the domestic US market are harvested once a year, and thus their inventory level reaches its peak immediately after the harvest and is lowest shortly before the beginning of the new harvest.

Natural gas and heating oil stocks are also highly seasonal. This seasonal variation is basically determined by higher demand during heating seasons (cold winter months) combined with capacity constraints of the available systems. Animal commodities (cattle, hogs and pork bellies) also produce strong evidence of seasonality in their inventories. Seasonals in production, perishability as well as seasonal variations in slaughter levels are among the main drivers of this seasonal pattern. On the other hand, soybean oil inventory does not exhibit seasonals, most likely because of its conversion process from soybeans.

Also coffee, cotton, cocoa and lumber do not provide any evidence of seasonal inventories. For the first two, this is most likely because of their production process. For lumber, a possible explanation is that its demand is determined by longer term factors, such as manufacturing activity and also its production is more easily adjusted to demand (see, Fama and French, 1987). Finally, metal stocks are not subject to short-term seasonal variations, since there is no *a priori* reason for seasonality in supply or demand. Finally, crude oil is continuously produced and consumed, and thus its stocks are not subject to seasonal variations.

Our subsequent analysis is based on the logarithm of inventory to capture the non-linear relationship between inventory and convenience yield/basis documented by well-established studies (e.g., Telser, 1958; Deaton and Laroque, 1992; Ng and Pirrong, 1994). We express our logarithmic inventory as a deviation from the mean in order to remove the effect of measurement units and also to allow for comparability of coefficients across different commodities.

4. Adjusted basis and inventory

Using our inventory dataset, we analyse the relationship between scarcity and the slope of the forward curve individually for each commodity. The forward curve slope is approximated by the interest-adjusted basis (henceforth, adjusted basis) at three different maturities. Specifically, we construct the series of adjusted basis for 2-, 6- and 10- month maturities. The theory of storage implies that basis becomes more negative (positive) as inventory decreases (increases).

In order to calculate the adjusted basis, we collect daily data on the Treasury-bill (T-bill) yields of the corresponding maturities from Thomson Reuters Datastream. We subsequently define the adjusted basis ($b_{i,t}$) of commodity i on day t, as follows:

$$b_{i,t} = \frac{F_{i,t,T_2} - F_{i,t,T_1}}{F_{i,t,T_1}} - R_{f,t}\,\delta \tag{3}$$

where F_{i,t,T_1} is the price on day t of the first nearby futures contract maturing in T_1 days, which is used as the spot price in our study. Also, F_{i,t,T_2} is the time t price of a futures contract with T_2 days to maturity ($T_2 > T_1$) and $R_{f,t}$ is the annualised T-bill rate of the corresponding maturity on day t. $\delta = \frac{T_2 - T_1}{365}$ is the difference between the time to maturity of the two futures contracts expressed in years. This difference is always as close as possible to the horizon over which the basis is computed (i.e., 2, 6 or 10 months). Finally, $b_{i,t}$ is the daily adjusted basis, which represents the slope of the forward curve on day t. Since monthly data are employed for inventory in our framework, we further compute the monthly forward curve slope as the average of the daily 6-month adjusted basis for each month in the sample period.[5]

For three commodities (lumber, oats, and pork bellies), illiquidity of long term future contracts did not allow calculation of the 10-month basis. In general, an issue when calculating the basis concerns the fact that futures contracts of different commodities do not expire every month. Thus, the computed daily basis does not always correspond, for instance, to six months. To address this, similar to Fuertes et al. (2010) and Daskalaki et al. (2012), we take the price of the next futures contract whenever there is no traded contract with six months to maturity. The same applies to the nearby futures price treated as the spot price in our study. For instance, to calculate the 6-month basis of corn on 15 January, we need the price of the February contract, maturing at the end of January, as the spot price, and the August contract, maturing at the end of July, as the 6-month futures price. If there is no February contract for this particular commodity, we consider the next to maturity contract, i.e., the March contract, as the first nearby contract, and therefore the September contract as the 6-month futures contract. Accordingly, if there is no contract maturing in September for the specific commodity, we consider the next to maturity contract (i.e., October), and so on.

4.1. Empirical Evidence

Our first objective is to empirically test the relationship between inventory and the slope of the forward curve (adjusted basis). To this end, we estimate

[5] It is more standard to synchronize single futures prices with monthly inventories rather than considering the average from daily values. However, the use of averages presents the advantage that it accounts for the effects of revisions in the reported inventory data, which are essentially an average; they are not necessarily recorded at the end of the month even if they are published at that time. Moreover, Geman and Ohana (2009) apply the same method and mention that even in the case when the term structure switches from contango to backwardation taking averages is a good procedure. We repeated the estimations using individual monthly observations to compute the 2-month basis and got very similar results. Also, an inspection of the basis series from daily and monthly observations, respectively, indicated that in almost all cases they provide the same signal regarding backwardation or contango for a particular month. Given that this signal is employed as an inventory proxy in empirical studies (e.g. Fama and French, 1988), our results are robust to the different data frequencies.

for each commodity i the following regression:

$$\tilde{b}_{i,\tau} = \alpha_i + \beta_i \tilde{I}_{i,\tau} + u_{i,\tau} \tag{4}$$

where $\tilde{b}_{i,\tau}$ is the deseasonalized forward curve slope of commodity i in month τ, computed as the monthly average of the daily adjusted basis of the respective maturity (2-, 6, or 10-month) over each month τ, and $\tilde{I}_{i,\tau}$ is the deseasonalized logarithmic inventory at the beginning of that month τ (or equivalently the end of month $\tau - 1$). The basis and inventories of some commodities exhibit seasonality. To deseasonalize these variables, we estimate regressions against monthly dummies and use the residuals as the deseasonalized adjusted basis and inventory in our regressions.[6] A time trend is included in the seasonal regressions of monthly logarithmic inventory when it is statistically at the 5% level.

Adjustment for seasonality in the adjusted basis and inventory series of each commodity is based on the significance of the F-test statistic, which evaluates the null hypothesis that the coefficients of all monthly dummies are equal. As a result, dummy regressions are not considered for metals, crude oil, soybean oil, cotton, coffee and lumber, since there is no indication of periodicity in either their basis or inventory. For these commodities, inventories are expressed in deviations from their means to facilitate comparison across different commodities and to remove the effects of measurement units.

Table 3 presents the results from the univariate OLS regressions of equation (4). Our results strongly support a positive and significant relationship between inventory and the slope of the forward curve (adjusted basis) for all maturities considered. More specifically, using a two-tailed test we conclude that for the 21 commodities considered, 17 (18) coefficients are statistically significant at the 5% (10%) level for the 2-month basis. The only exceptions are lumber, cattle and gold. Moreover, the statistically significant coefficients are positive in all cases. Adjusted basis for longer maturities (6, 10 months)

[6] We also applied two additional methods to remove seasonality from the series: a) a moving average filter and b) a fit of sine/cosine functions. All methods gave very similar results.

allow for very similar conclusions. This demonstrates the robustness of our results with respect to the considered maturities.

Regarding the magnitude of the coefficients, we observe that all three energy commodities and lean hogs exhibit the strongest link with inventory. Overall, the largest in size coefficient is reported for crude oil, followed by natural gas across all maturities considered. In particular, the coefficient of the 6-month basis for crude oil is equal to 0.668. This means that a deviation of 1% from the average inventory level for crude oil results in a 0.67% increase in the crude oil adjusted basis. The large coefficients for energy commodities can be explained by high storage and transportation costs as well as capacity constraints of available systems that deter storage and make prices more sensitive to inventory withdrawals. An interpretation for the strong significance in animal commodities could be the high storage costs and perishability that lead to low inventory levels relative to demand. In general, our results support the evidence of Gorton et al. (2007).

Apart from the energy and animal commodities, a strong association is also observed for most of the agricultural and soft commodities. Significant coefficients for these commodities are mainly related to the fact that most of these commodities are harvested once or twice a year in the domestic US market and the available inventory must satisfy demand over the whole year. Given that total imports for these commodities represent a very small proportion of annual production in the US, the prices of agricultural commodities are highly sensitive to the levels of available stocks in the domestic US market. Metals, and gold in particular, exhibit the lowest correlation with inventory. The coefficient for gold is insignificant, while for the rest the coefficients are usually very small in size (of order $10^{-3} forshort-termbasis$). Low storage costs relative to their value and sufficiently high inventory levels relative to demand, especially for precious metals, are the main reasons for these low correlations.

Also, in line with evidence in Geman and Ohana (2009), who used a slightly shorter sample period (1993-2006), we find that the petroleum stock in OECD countries is a stronger measure for oil inventories in terms of explanatory power (having a higher R^2 coefficient). Moreover, the coefficient estimates for global inventories in respect of corn, soybeans and wheat are all highly significant at the 1% level and their corresponding t-statistics are higher than those of US inventories.

Overall, our results lend support to one of the main implications of the theory of storage that inventory is positively associated with the slope of the forward curve (the basis). Lower (higher) available inventory leads to wider and more negative interest-adjusted basis and thus more backwardated (contagoed) markets. Differences in magnitude across commodities are related to their varying dependence on the fundamentals of storage. Our evidence is robust for the forward slope at different maturities.

5. Inventory and price volatility

Theoretical as well as empirical evidence on the theory of storage suggests that price volatility is inversely related to inventory. For example, Deaton and Laroque (1992) show in their theoretical model that next period spot price volatility decreases with higher inventories. Also Ng and Pirrong (1996) analyse the dynamic basis-volatility relationship in gasoline and heating oil markets. Motivated by this strand of the literature, we use our physical inventory data to directly test how inventory is related to subsequent commodity price volatility. We distinguish between two alternative cases for price volatility: i) adjusted basis volatility, and ii) the volatility of nearby futures returns.

To obtain a measure for adjusted basis volatility, we first compute for each commodity the annualised standard deviation from the daily adjusted basis series for each month τ. Then we estimate the following regression:

$$\tilde{\sigma}_{i,\tau} = \alpha_i + \gamma_i \tilde{I}_{i,\tau} + \epsilon_{i,\tau} \tag{5}$$

where $\tilde{\sigma}_{i,\tau}$ is the annualized standard deviation of the daily adjusted basis series of commodity i in month τ, and $\tilde{I}_{i,\tau}$ is the inventory of commodity i at the beginning of month τ (or equivalently, at the end of month $\tau - 1$). We deseasonalise both the inventory and the adjusted basis volatility as discussed above.

Estimation results are reported in Table 4. The coefficients of these commodity-by-commodity regressions indicate a negative relationship between inventory and adjusted basis volatility. Regarding the volatility of the 2-month basis we see that for the 21 commodities considered, 14 (15) inventory coefficients are statistically significant at the 5% (10%) level. From those 12 (13) are negative whereas two are positive. If we analyse the results across the separate commodity groups, we see that the relationship is particularly strong for most of the agricultural and energy commodities in terms of the sizes of the regression coefficients. Specifically, all inventory coefficients are negative and strongly significant at the 5% level in the agricultural commodity group, except for oats.

Concerning the animal commodities, the coefficients for hogs and pork bellies are statistically significant at the 1% level and quite high, although of the opposite sign than anticipated (positive). This looks counter-intuitive at first sight. However, a plausible explanation for this reversal in the inventory-volatility relationship is that during periods of low demand when inventories are usually high, the difficulty to increase storage due to capacity constraints may lead to big price drops increasing price volatility. For the animal commodities, this effect is further exacerbated by their perishable nature. In an attempt to empirically test this line of reasoning we estimate the same regression for hogs, decomposing deseasonalised logarithmic inventory into negative versus positive values. The results indicate that the inventory coefficient is positive for higher than average inventory, whereas it is negative for lower than average inventory (a non-linear pattern).

From the three energy commodities, the coefficients of crude oil and heating oil are both highly negative and significant at the 1% level. Surprisingly given the sensitivity of its prices to storage levels, the coefficient of natural gas is insignificant. However, the empirical evidence in Geman and Ohana (2009) suggests that the negative inventory-volatility relationship for natural gas is mainly observed during periods of low inventory (or equivalently, high scarcity), e.g. during winter. Indeed, if we estimate the same regression separately for negative and positive values of deseasonalised inventory, we observe a high negative correlation during periods of negative deseasonalised inventory. Finally, the inventory coefficients of industrial metals are all significant, whereas those of precious metals are always insignificant. The absence of significance for precious metals does not come as a surprise since variations in their prices are primarily determined by investment demand and also inventories are sufficient in general to limit variations in convenience yields. Also, the estimation results for the volatility of 6-month basis lead to very similar conclusions.

Turning our focus to spot return volatility, we first compute for each commodity the annualised standard deviations of daily nearby futures returns over each month τ in the sample. The volatility series obtained are then employed as dependent variables in the following regression:

$$\sigma_{i,\tau} = \omega_i + \zeta_i \tilde{I}_{i,\tau-1} + u_{i,\tau} \tag{6}$$

where $\sigma_{i,\tau}$ is the annualised standard deviation of the daily nearby futures returns of commodity i over each month τ in the sample and $\tilde{I}_{i,\tau-1}$ is the logarithm of inventory of commodity i at the end of month τ-1. Similar to the regressions of the adjusted basis volatility given by equation (5), we deseasonalize inventory and nearby futures volatility by estimating regressions against monthly seasonal dummies, as discussed above.

Estimation results are reported in Table 5. The coefficient on the inventory variable is statistically significant for 11 (14) out of the 21 commodities at the 5% (10%) level. Moreover, all significant coefficients are negative except for those of hogs and pork bellies. Regarding the magnitude of the coefficients, we observe that the relationship appears to be particularly strong for energy, agricultural and animal commodities. The strong relationship for energy commodities is mainly associated with high storage costs and also with capacity constraints in production and transmission systems, which increase the sensitivity of prices to supply or demand shocks. For agricultural commodities, on the other hand, the non-continuous nature of production, significant storage costs and the inability to import supplies from other locations during the cycle at a low cost, reduce the elasticity of supply and thus increase the responsiveness of prices to supply and demand shocks. The coefficient for soybeans is in consistent with Geman and Nguyen (2005). Coefficients of hogs and pork bellies are significant, but positive. A possible explanation is provided above. Finally, we observe relatively lower coefficients for metals in comparison with the other commodities. The only notable exception is copper, with a much higher coefficient relative to the other metals. From metals group, only copper and tin provide support for a significant relationship with inventory. This result for copper is most likely related to the difficulty of storing this commodity.

Evidence from this last section suggests that commodity price volatility is negatively associated with inventory fluctuations. However, this evidence is not universal for all commodities because of their heterogeneity as an asset class. For instance, some commodities such as the agriculturals are periodically produced and therefore variation in inventory levels throughout the year affects the sensitivity of their spot and futures prices to demand shocks. Gorton et al. (2007) mention that high storage costs provide incentives to economise on inventories and also limit the variation in available supplies. This can partly explain the observed positive inventory-volatility relationship. The difficulty in injecting into storage when demand is high and inventories sufficiently large leads to a price drop and also to higher volatility. Energy commodities are continuously produced and their prices are more demand driven. For example, natural gas volatility is basically determined by demand shocks during the heating season given the inability to increase production due to capacity constraints of available systems. Gold, in contrast, is more of a financial than a commodity contract as argued by many authors and therefore its prices and volatility are expected to be more related to economic conditions (e.g. inflation) than to inventory considerations. It is thus evident that the different characteristics of each commodity affect the responsiveness of its prices to supply and demand conditions. These findings are in line in with those of Erb and Harvey (2006), who observe significant differences in excess returns and also in the sensitivity of these returns to inflation across various commodities.

5.1. The effect of market states

Ng and Pirrong (1996) analyse the dynamics of gasoline and heating oil prices and find that spot returns are more volatile in backwardation compared to contangoed markets. Also, Fama and French (1988) show that the volatility of metal prices is higher when interest-adjusted basis is negative. To test whether this hypothesis is empirically supported by our data, we separate the adjusted basis of each commodity into positive and negative values and then estimate for each commodity two regressions using as dependent variable: i) the adjusted basis volatility, and ii) the nearby futures volatility. The specification is:

$$\sigma_{i,\tau} = \phi_0 + \phi_1 I_{\{b_{i,\tau-1}>0\}} b_{i,\tau-1} + \phi_2(1 - I_{\{b_{i,\tau-1}>0\}}) b_{i,\tau-1} + e_{i,\tau} \quad (7)$$

where: $\sigma_{i,\tau}$ is the nearby futures/the adjusted basis volatility, respectively, of commodity i in month τ and $I_{\{b_{i,\tau-1}>0\}}$ the indicator function that takes the value of 1 if the 2-month adjusted adjusted basis of the previous month $(\tau-1)$ is positive and 0 otherwise, and $b_{i,\tau-1}$ is the adjusted basis of commodity i at the end of month $\tau-1$. Therefore, if negative basis has indeed a larger impact on volatility, then we expect the coefficient of the negative basis (ϕ_2) to be significant and higher in absolute value than the corresponding coefficients of the positive basis.

The results are presented in Table 6. Columns 2 and 3 report the number of months in backwardation and contango for each commodity. We see that the majority of commodities were mostly in contango. The only exceptions are crude oil, pork bellies and tin. This observation for crude oil is in accordance with Erb and Harvey (2006). Columns 4 and 5 contain coefficient estimates when nearby futures volatility is employed as the dependent variable in the regressions, whereas columns 6 and 7 report estimates for basis volatility as the dependent variable. We exclude gold and silver from the analysis since their prices were in contango almost every month, so it is not possible to distinguish between the impact of negative from positive basis. Again, the observation of contango market for precious metals is consistent with Erb and Harvey (2006).

The results for nearby futures volatility support, in general, a stronger link between inventory and volatility during backwardated markets. This effect seems to be more pronounced for agricultural and soft commodities, for which most positive basis coefficients are insignificant, whereas the negative basis coefficients are negative and significant. Exceptions are soybean oil and orange juice, where the coefficients are not significant in any case. Significance is also absent for industrial metals. In addition, results for the three energy commodities are of particular interest. Specifically, for crude oil and natural gas, the results provide support for an asymmetric V-shaped relationship between inventory and volatility, with both positive and negative basis inducing higher volatility, consistent with previous studies (e.g. Kogan et al., 2009). For crude oil (natural gas), positive basis has a larger (smaller) impact than negative basis of the same size. Finally, among the three animal commodities, only hogs provides significant estimates which supports a V-shaped relationship. For heating oil, only the coefficient on negative basis is significant at the 1% level.

For basis volatility, where the basis is defined as the difference between the first and the second nearby futures contracts in excess of the interest rate, we obtain slightly different results. Coefficients for many of the agricultural commodities are now significant and negative in contango states, supporting a universally negative correlation between inventory and volatility. However, negative basis coefficients (backwardation) are always higher in absolute value than those for positive basis (contango) of the same magnitude. From the soft commodities, coffee and cotton provide significant coefficients only in backwardation states, whereas cocoa and orange juice do not provide significant coefficients in any state. The coefficients for energy commodities lead to very similar conclusions to the case of nearby futures volatility. Finally, copper and tin support a globally negative relationship with inventory in contrast to the case of nearby futures volatility, where only the coefficients on the backwardation states were significant.

6. Robustness analysis

We perform a series of tests to check the robustness of the results obtained in the previous sections. First, to check the stability of our results, we repeat our estimations using sub-samples. Initially, we divide the entire sample of each commodity into two equal sub-samples and re-perform the relevant estimations. Apart from a few cases, our results are robust across the two sub-periods considered.

The rapid growth in commodity prices between 2003 and 2008 provides a motivation to analyze our main empirical relationships over this period and to test whether any significant structural change occurred. We thus separate our full sample in two sub-periods: 1993-2002 and 2003-2008, and re-perform our estimations. The results over the commodity price boom period are very similar to those obtained for the 1992-2002 period, as well as for the full sample period and in some cases are even stronger. This provides some evidence that variations in fundamental supply and demand factors continued to play an important role during the period of sharp rises in commodity prices in addition to the effect of increased participation from commodity index investors (Irwin and Sanders, 2011).

Second, to provide additional evidence regardless of distributional assumptions, we perform all significance tests in our analysis additionally using a non parametric test, Spearman's rank order correlation. This technique is distribution independent. Our results remain qualitatively similar.

Lastly, we test the relationship between inventory and the slope of the forward curve using the 12-month adjusted basis as a proxy for the slope of the forward curve. We compute the 12-month basis from equation (3) considering the first nearby as well as the year ahead futures contract. The 12-month basis has the advantage that it implicitly takes seasonality into consideration, since taking the difference between the nearby and the year ahead futures prices is similar to applying seasonal differences. Overall, our estimation results strongly support those obtained for the other maturities.

7. Conclusions

This paper analyses the fundamental role of inventory in explaining commodity futures prices and their volatilities within the economic framework of the theory of storage. Using an extensive dataset of monthly inventories for 21 different commodities for the period from 1993 to 2011, we empirically test two of the main predictions of the theory of storage. First, we document a negative relationship between inventory and the slope of the forward curve. The latter is approximated by the interest adjusted basis at different maturities, namely 2, 6, 10 and 12 months, respectively. In particular, lower inventories are associated with wider and more negative futures basis and therefore more backwardated forward curves. This result also implies that the convenience yield is an increasing function of inventory. Moreover, our evidence suggests that (adjusted) basis can serve as a sufficiently good proxy for inventory in empirical studies. These results also provide further support to those in Gorton et al. (2007).

Second, in line with the implications of the theory of storage, we find that inventory is negatively related to commodity price volatility. More specifically, price volatility is a decreasing function of inventory. The documented relationship appears to be stronger for energy, animal and agricultural commodities and weaker for metals, and especially for precious metals. Furthermore, conditioning our analysis on market states (contango vs backwardation) we observe that a negative basis (low inventory) has a more pronounced impact on volatility than a positive basis (high inventory). Also, for energy commodities we document a V-shaped relationship between volatility and the slope of the forward curve, consistent with previous empirical studies (see, Kogan et al., 2009). These findings are preserved during the recent commodity price boom (2003-2008).

Our purpose for this study is to test the theoretical considerations relating to the theory of storage in a more direct way than in many existing studies using real inventories. Nevertheless, the current study is not attempting to suggest using physical inventories instead of proxies, such as the futures basis. Inventory data still exhibit problems, such as measurement errors or sometimes unavailability at higher frequencies, such as daily. Instead, our main purpose was concentrated in two main directions: first, to test the validity of these inventory proxies and second, to provide useful evidence on the fundamental relationships the theory predicts using any useful part of information contained in inventory datasets.

Our main conclusions offer additional support for the evidence of Ng and Pirrong (1994) that fundamentals drive commodity prices and their volatilities. From a practical point of view, our results have important implications for derivatives pricing, asset allocation and hedging. For instance, Geman and Nguyen (2005) find that including scarcity (the inverse of inventory) as an additional factor in a state-variables model significantly improves the pricing performance for soybean futures. Our evidence suggests that this can possibly be extended to other commodities. However, due to the heterogeneity of individual commodities, universal conclusions cannot be extracted.

References

Baffes, J. and T. Haniotis (2010). Placing the 2006/08 commodity price boom into perspective. *Policy Research Working paper, World Bank*.

Bessembinder, H. (1992). Systematic risk, hedging pressure, and risk premiums in futures markets. *Review of Financial Studies 5*(4), 637–667.

Bhar, R. and S. Hamori (2008). Information content of commodity futures prices for monetary policy. *Economic Modelling 25*(2), 274–283.

Black, F. (1976). The pricing of commodity contracts. *Journal of Financial Economics 3*(1-2), 167–179.

Bodie, Z. (1983). Commodity futures as a hedge against inflation. *Journal of Portfolio Management 9*(3), 12–17.

Bodie, Z. and V. Rosansky (1980). Risk and return in commodity futures. *Financial Analysts Journal 36*(3), 27–39.

Brennan, M. (1958). The supply of storage. *American Economic Review 48*(1), 50–72.

Brooks, C. and M. Prokopczuk (2011). The dynamics of commodity prices. *Working paper. SSRN*.

Buyuksahin, B., M. Haigh, and M. Robe (2010). Commodities and equities: Ever a market of one? *Journal of Alternative Investments 12*(3), 76–95.

Buyuksahin, B. and M. Robe (2010). Speculators, commodities and cross-market linkages. *Working paper, SSRN*.

Carbonez, K., T. Nguyen, and P. Sercu (2010). The asymmetric effects of scarcity and abundance on storable commodity price dynamics and hedge ratios. *Working paper. Katholieke Universiteit Leuven*.

Chambers, M. and R. Bailey (1996). A theory of commodity price fluctuations. *Journal of Political Economy 104*(5), 924–957.

Cootner, P. (1960). Returns to speculators: Telser versus keynes. *The Journal of Political Economy 68*(4), 396–404.

Dahl, C. and E. Iglesias (2009). Volatility spill-overs in commodity spot prices: New empirical results. *Economic Modelling 26*(3), 601–607.

Daskalaki, C., A. Kostakis, and G. Skiadopoulos (2012). Are there common factors in commodity futures returns? *working paper, University of Piraeus*.

Daskalaki, C. and G. Skiadopoulos (2011). Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking and Finance 35*(10), 2606–2626.

De Roon, F., T. Nijman, and C. Veld (2000). Hedging pressure effects in futures markets. *The Journal of Finance 55*(3), 1437–1456.

De Roon, F. and M. Szymanowska (2010). The cross-section of commodity futures returns. *Working paper. SSRN*.

Deaton, A. and G. Laroque (1992). On the behaviour of commodity prices. *Review of Economic Studies 59*(1), 1–23.

Dusak, K. (1973). Futures trading and investor returns: An investigation of commodity market risk premiums. *The Journal of Political Economy*, 1387–1406.

Edwards, F. and J. Park (1996). Do managed futures make good investments? *Journal of Futures Markets 16*(5), 475–517.

Erb, C. and C. Harvey (2006). The strategic and tactical value of commodity futures. *Financial Analysts Journal*, 69–97.

Fabozzi, F., R. Fuess, and D. Kaiser (2008). A primer on commodity investing. *The Handbook of Commodity Investing*.

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

Fama, E. and K. French (1988). Business cycles and the behavior of metals prices. *Journal of Finance 43*(5), 1075–1093.

French, K. (1986). Detecting spot price forecasts in futures prices. *Journal of Business 59*(2), 39–54.

Fuertes, A., J. Miffre, and G. Rallis (2010). Tactical allocation in commodity futures markets: Combining momentum and term structure signals. *Journal of Banking and Finance 34*(10), 2530–2548.

Geman, H. (2005). *Commodities and commodity derivatives*. Wiley. England.

Geman, H. and V. Nguyen (2005). Soybean inventory and forward curve dynamics. *Management Science 51*(7), 1076–1091.

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

Gorton, G., F. Hayashi, and K. Rouwenhorst (2007). The fundamentals of commodity futures returns. *forthcoming, Review of Finance*.

Gorton, G. and K. Rouwenhorst (2006). Facts and fantasies about commodity futures. *Financial Analysts Journal 62*(2), 47–68.

Hicks, J. (1939). *Value and capital*, Volume 2. Oxford U.P., Cambridge.

Hirshleifer, D. (1989). Determinants of hedging and risk premia in commodity futures markets. *Journal of Financial and Quantitative Analysis 24*(03), 313–331.

Irwin, S. and D. Sanders (2011). Index funds, financialization, and commodity futures markets. *Applied Economic Perspectives and Policy 33*(1), 1–31.

Jagannathan, R. (1985). An investigation of commodity futures prices using the consumption-based intertemporal capital asset pricing model. *Journal of Finance*, 175–191.

Kaldor, N. (1939). Speculation and economic stability. *Review of Economic Studies 7*(1), 1–27.

Keynes, J. (1930). *Treatise on money: Pure theory of money*, Volume 1. Macmillan, London.

Kogan, L., D. Livdan, and A. Yaron (2009). Oil futures prices in a production economy with investment constraints. *Journal of Finance 64*(3), 1345–1375.

Lien, D. and L. Yang (2008). Asymmetric effect of basis on dynamic futures hedging: Empirical evidence from commodity markets. *Journal of Banking and Finance 32*(2), 187–198.

Miffre, J. and G. Rallis (2007). Momentum strategies in commodity futures markets. *Journal of Banking and Finance 31*(6), 1863–1886.

Milonas, N. and S. Thomadakis (1997). Convenience yields as call options: An empirical analysis. *Journal of Futures Markets 17*(1), 1–15.

Newey, W. and K. West (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica 55*(3), 703–708.

Ng, V. and S. Pirrong (1994). Fundamentals and volatility: Storage, spreads, and the dynamics of metals prices. *Journal of Business 67*(2), 203–230.

Ng, V. and S. Pirrong (1996). Price dynamics in refined petroleum spot and futures markets. *Journal of Empirical Finance 2*(4), 359–388.

Routledge, B., D. Seppi, and C. Spatt (2000). Equilibrium forward curves for commodities. *Journal of Finance 55*(3), 1297–1338.

Silvennoinen, A. and S. Thorp (2010). Financialization, crisis and commodity correlation dynamics. *Working paper. University of Technology Sydney*.

Tang, K. and W. Xiong (2010). Index investment and financialization of commodities. Technical report, National Bureau of Economic Research.

Telser, L. (1958). Futures trading and the storage of cotton and wheat. *Journal of Political Economy 66*(3), 233–255.

Williams, J. and B. Wright (1991). *Storage and commodity markets.* Cambridge University Press. US.

Working, H. (1948). Theory of the inverse carrying charge in futures markets. *Journal of Farm Economics 30*(1), 1–28.

Table 1: **Details of commodity contracts**

Commodity	**Exchange**	**Delivery months**
A. Agricultural		
Corn	CBOT	Mar, May, Jul, Sep, Dec
Oats	CBOT	Mar, May, Jul, Sep, Dec
Soybeans	CBOT	Jan, Mar, May, Jul, Aug, Sep, Nov
Soybean oil	CBOT	Jan, Mar, May, Jul, Aug, Sep, Oct, Dec
Wheat	CBOT	Mar, May, Jul, Sep, Dec
B. Softs		
Cocoa	ICE†	Mar, May, Jul, Sep, Dec
Coffee	ICE	Mar, May, Jul, Sep, Dec
Cotton	ICE	Mar, May, Jul, Oct, Dec
Lumber	CME	Jan, Mar, May, Jul, Sep, Nov
Orange juice	ICE	Mar, May, Jul, Sep, Nov
C. Livestock and meats		
Live Cattle	CME	Feb, Apr, Jun, Aug, Oct, Dec
Lean Hogs	CME	Feb, Apr, Jun, Jul, Aug, Oct, Dec
Pork bellies	CME	Feb, Mar, May, Jul, Aug
D. Energy		
Heating oil	NYMEX	all months
Natural gas	NYMEX	all months
Crude oil (WTI)	NYMEX	all months
E. Metals		
Aluminium	LME	all months
Copper	COMEX	Jan, Mar, May, Jul, Oct, Dec
Gold	COMEX	Feb, Mar, Apr, Jun, Aug, Oct, Dec
Silver	COMEX	Jan, Feb, Mar, Apr, May, Jul, Sep, Dec
Tin	LME	all months

∗*CBT: Chicago Board of Trade, CME: Chicago Mercantile Exchange, NYMEX: New York Mercantile Exchange, ICE: Intercontinental Exchange, COMEX: Commodity Exchange and LME: London Metal Exchange*
†*Formerly New York Board of Trade (NYBOT)*

Table 2: **Summary Statistics**

This table presents summary statistics for commodity futures returns. The sample period is 1 January 1993 to 31 December 2011. In addition to the first four central moments, the table reports the value of the Jarque–Bera (J–B) normality test statistic and the first order serial correlation coefficient, denoted AR(1). The mean and standard deviation are both expressed annualised and as percentages. * and ** indicate statistical significance at the 10% and 5% level respectively for the AR(1) coefficient and rejection of normality at the same significance level for the J–B statistic.

A. Agricultural	**Mean**	**St. Dev.**	**Skew**	**Kurt**	**J-B**	**AR(1)**	**Obs**
Corn	-7.02	25.87	-0.03	5.66	1383.0	0.05**	4690
Oats	-4.75	31.07	-0.08	5.70	1429.7	0.07**	4690
Soybeans	2.64	23.31	-0.26	5.51	1272.5	-0.01	4652
Soybean oil	-1.27	23.26	0.06	5.02	790.5	0.01	4633
Wheat	-10.18	29.21	0.01	5.29	1018.1	-0.01	4690
B. Softs							
Cocoa	-0.42	30.16	-0.04	5.43	1145.6	0.00	4654
Coffee	-1.81	39.24	0.36	10.35	10570.8	0.00	4653
Cotton	-3.18	27.49	0.00	4.86	670.2	0.04**	4660
Lumber	-16.44	30.54	0.09	2.64	32.2	0.11**	4673
Orange juice	-7.41	31.67	0.40	12.21	16512.4	0.01	4641
C. Livestock							
Cattle	-0.61	14.45	-0.14	4.60	513.8	0.05**	4672
Hogs	-7.53	24.05	-0.13	4.28	329.0	0.04**	4643
Pork bellies	1.83	31.93	0.02	3.43	34.6	0.08**	4575
D. Energy							
Heating oil	5.03	32.08	-0.13	5.02	781.2	-0.03	4534
Natural gas	-19.56	47.39	0.05	5.21	918.7	-0.02	4533
Crude oil	6.10	33.69	-0.25	6.32	2124.1	-0.02	4533
E. Metals							
Aluminium	-1.81	21.73	-0.27	5.39	870.0	-0.05**	3474
Copper	5.93	28.37	-0.25	7.01	3174.4	-0.06**	4667
Gold	5.11	16.64	0.07	9.82	8998.7	0.02	4649
Silver	6.57	30.29	-0.84	11.04	13110.3	0.00	4667
Tin	8.37	1.72	-0.32	10.16	7476.58	0.05**	3474

Table 3: **Adjusted basis and inventory**

This table displays results from estimating commodity-by-commodity OLS regressions of monthly adjusted basis (forward curve slope) on the logarithm of end of month inventory. Inventories of seasonal commodities are the residuals from regressions against monthly dummies. For non-seasonal commodities, inventories are deviations from historical mean. Futures basis is computed for three different maturities: 2, 6 and 10 months. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively. t-statistics of coefficients are reported in parentheses. Newey and West (1987) HAC standard errors and covariances were employed in the OLS estimations.

		2-month		6-month		10-month	
Commodity	**Obs**	α_i	β_i	α_i	β_i	α_i	β_i
Corn	227	-0.001	0.038***	0.000	0.079***	0.000	0.115***
		(-0.219)	(-3.047)	(-0.028)	(-3.130)	(-0.005)	(-2.929)
Oats	134	-0.009	0.025*	-0.017	0.055*	-	-
		(-1.213)	(-1.728)	(-1.016)	(-1.907)	-	-
Soybeans	227	0.000	0.011***	-0.001	0.030***	-0.002	0.033**
		(-0.061)	(-4.028)	(-0.214)	(-2.928)	(-0.272)	(-2.320)
Soyoil	156	0.001	0.015***	0.010*	0.081***	0.002	0.124***
		(-0.673)	(-3.008)	(-1.669)	(-3.145)	(-0.283)	(-3.307)
Wheat	227	0.000	0.036***	0.000	0.106***	0.000	0.153***
		(-0.005)	(-5.208)	(-0.059)	(-5.045)	(-0.024)	(-5.671)
Coffee	201	-0.004	0.018***	-0.010	0.045***	0.029***	0.057***
		(-1.525)	(-6.438)	(-1.348)	(-5.321)	(-2.655)	(-5.390)
Cocoa	227	-0.001	0.018***	-0.002	0.036***	-0.003	0.049***
		(-0.675)	(-3.603)	(-0.654)	(-3.389)	(-0.593)	(-3.320)
Cotton	185	0.016***	0.055***	0.037***	0.178***	0.047***	0.025
		(-6.479)	(-6.310)	(-5.601)	(-5.947)	(-2.670)	(-6.778)
Lumber	227	0.000	0.057	0.000	0.135	-	-
		(-0.021)	(-0.656)	(-0.032)	(-0.935)	-	-
Orange juice	227	0.011***	0.089***	0.033***	0.225***	0.044***	0.103***
		(-4.116)	(-4.299)	(-4.600)	(-4.189)	(-5.201)	(-4.102)
Cattle	227	0.001	0.008	0.002	-0.056	0.002	0.110
		(-0.216)	(-0.469)	(-0.304)	(-1.602)	(-0.300)	(1.599)
Hogs	227	0.000	0.167***	-0.003	0.461***	-0.005	0.631***
		(-0.066)	(-3.852)	(-0.217)	(-3.819)	(-0.311)	(-4.033)
Pork bellies	224	-0.001	0.045***	-0.003	0.115***	-	-
		(-0.158)	(-3.530)	(-0.356)	(-4.242)	-	-
Heating oil	227	0.000	0.170***	0.000	0.417***	0.001	0.582***
		(-0.030)	(-6.804)	(-0.066)	(-6.729)	(-0.121)	(-7.777)
Natural gas	227	0.002	0.172***	0.003	0.486***	0.003	0.638***
		(-0.338)	(-4.619)	(-0.238)	(-5.917)	(-0.215)	(-7.079)
Crude oil	227	0.000	0.279***	0.001	0.668***	0.000	0.950***
		(-0.026)	(-7.565)	(-0.153)	(-8.643)	(-0.021)	(-9.007)
Aluminium	171	0.004***	0.007***	0.003	0.017***	0.005	0.031***
		(-3.626)	(-5.144)	(-0.843)	(-4.034)	(-0.871)	(-4.316)
Copper	227	-0.001	0.010***	-0.032***	0.027***	-0.053***	0.041***
		(-0.488)	(-6.960)	(-6.784)	(-6.356)	(-7.561)	(-6.412)
Gold	227	0.001	0.004	0.000	0.005	-0.000	0.006
		(0.254)	(1.123)	(-0.117)	(1.383)	(-0.129)	(1.572)
Silver	227	0.000	0.006***	-0.001	0.020***	-0.003**	0.038***
		(-0.170)	(-5.912)	(-1.158)	(-6.345)	(-2.384)	(-7.868)
Tin	171	-0.005***	0.009***	-0.017***	0.022***	-0.027***	0.034***
		(-6.950)	(-6.583)	(-8.434)	(-7.049)	(-9.560)	(-6.614)

Table 4: **Inventory and adjusted basis volatility**

This table presents estimation results from the following regression:

$$\tilde{\sigma}_{i,\tau} = \alpha_i + \gamma_i \tilde{I}_{i,\tau-1} + \epsilon_{i,\tau}$$

where $\tilde{\sigma}_{i,\tau}$ is the adjusted basis volatility of commodity i in month τ and $\tilde{I}_{i,\tau-1}$ is the (deseasonalized) inventory level of commodity i at the end of month τ-1. Monthly basis volatility is computed as the annualised standard deviation of the daily 2- and 6-month adjusted basis respectively, over each month τ. For seasonal commodities, both inventory and adjusted basis volatility refer to the residuals from regressions against monthly seasonal dummies. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels respectively, using a two-tailed test. Newey and West (1987) HAC standard errors and covariances were used in the estimations.

		2 month basis volatility			6 month basis volatility		
Commodity	Obs	α_i	γ_i	*R-sq.*	α_i	γ_i	*R-sq.*
Corn	227	0.001	-0.039**	5.59%	0.017	-0.034**	5.45%
		(-0.033)	(-2.193)		(-1.139)	(-1.986)	
Oats	133	0.010	-0.006	0.02%	-0.009	-0.005	0.01%
		(-0.693)	(-0.168)		(-0.481)	(-0.108)	
Soybeans	227	-0.001	-0.031***	4.59%	-0.001	-0.036**	2.25%
		(-0.139)	(-3.290)		(-0.096)	(-2.278)	
Soybean oil	156	0.027***	-0.047***	24.58%	0.082***	-0.137***	17.87%
		(-10.012)	(-2.795)		(-8.515)	(-2.691)	
Wheat	227	0.000	-0.038***	4.62%	0.003	-0.064**	3.10%
		(-0.023)	(-2.911)		(-0.142)	(-2.126)	
Cocoa	227	0.000	-0.006	0.13%	0.000	-0.017	0.42%
		(-0.008)	(-0.442)		(-0.014)	(-0.809)	
Coffee	202	-0.005	-0.020***	12.53%	-0.011	-0.025**	7.81%
		(-0.722)	(-3.373)		(-0.793)	(-2.400)	
Cotton	184	0.002	-0.075**	4.70%	0.001	-0.088***	4.31%
		(-0.182)	(-2.119)		(-0.092)	(-2.658)	
Lumber	227	0.000	-0.071*	0.93%	0.001	-0.106*	1.01%
		(-0.042)	(-1.683)		(-0.045)	(-1.732)	
Orange juice	227	0.000	-0.027	0.04%	0.001	-0.047	2.07%
		(-0.005)	(-0.352)		(-0.097)	(-1.452)	
Cattle	227	0.094***	-0.001	0.00%	0.153***	0.015	0.00%
		(-19.808)	(-0.044)		(-21.108)	(-0.394)	
Hogs	227	0.200***	0.437***	6.95%	-0.004	0.962***	7.91%
		(-20.063)	(3.781)		(-0.170)	(3.059)	
Pork bellies	224	0.148***	0.145***	2.24%	0.263	0.224	3.96%
		(8.535)	(2.029)		(9.819)	(-0.342)	
Heating oil	227	0.000	-0.192***	9.19%	0.000	-0.253**	5.60%
		(-0.005)	(-2.816)		(-0.004)	(-2.011)	
Natural gas	227	-0.002	-0.136	0.92%	0.003	0.210	1.02%
		(-0.087)	(-1.058)		(-0.086)	(-1.070)	
Crude oil	227	0.110***	-0.338***	4.77%	0.208***	-0.697***	7.04%
		(-14.383)	(-3.095)		(-16.330)	(-3.829)	
Aluminium	171	0.033***	-0.022***	2.27%	0.060***	-0.031***	2.29%
		(-6.545)	(-3.196)		(-15.103)	(-6.659)	
Copper	227	0.000	-0.017***	1.46%	0.000	-0.029***	2.07%
		(-0.078)	(-5.691)		(-0.072)	(-4.852)	
Gold	227	0.000	-0.004***	0.00%	0.000	-0.006***	0.46%
		(-0.067)	(-2.833)		(-0.058)	(-2.799)	
Silver	227	0.009***	-0.027	1.93%	0.021***	-0.052	0.42%
		(-7.644)	(-1.407)		(-8.090)	(-1.310)	
Tin	171	0.028***	-0.022***	0.76%	0.051***	-0.031***	0.04%
		(-10.667)	(-4.551)		(-10.015)	(-4.237)	

Table 5: **Inventory and nearby futures volatility**

This table reports commodity-by-commodity results for the following regression:

$$\sigma_{i,\tau} = \omega_i + \zeta_i \tilde{I}_{i,\tau-1} + u_{i,\tau}$$

where $\sigma_{i,\tau}$ is the nearby futures returns volatility of commodity i in month τ and $\tilde{I}_{i,\tau-1}$ is the (deseasonalised) inventory of commodity i at the end of month τ-1. The monthly nearby futures volatility is calculated as the annualised standard deviation of the daily nearby futures returns over each month τ. For seasonal commodities, both inventory and nearby futures volatility are the residuals from regressions against monthly seasonal dummies. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels. Newey and West (1987) HAC standard errors and covariances were employed in the estimations.

commodity	**Obs.**	ω_i	ζ_i	$R-sq.$
Corn	227	-0.118***	-0.048*	0.41%
		(-8.240)	(-1.791)	
Oats	133	-0.078***	-0.057*	9.82%
		(-3.896)	(-1.798)	
Soybeans	227	0.211***	-0.030***	5.93%
		(-38.118)	(-3.856)	
Soybean oil	156	0.231***	-0.095***	6.89%
		(-20.948)	(-3.024)	
Wheat	227	-0.123***	-0.055***	3.29%
		(-11.380)	(-2.682)	
Cocoa	227	0.287***	-0.097***	9.20%
		(-32.682)	(-4.548)	
Coffee	202	0.643***	-0.021*	5.91%
		(-4.022)	(-1.897)	
Cotton	184	0.010	-0.008	0.14%
		(-0.734)	(-0.197)	
Lumber	227	0.001	-0.228***	10.90%
		(-0.169)	(-6.479)	
Orange juice	227	0.000	-0.016	0.20%
		(-0.026)	(-0.512)	
Cattle	227	0.138***	0.018	0.25%
		(-28.002)	(-0.604)	
Hogs	227	-0.001	0.333***	21.97%
		(-0.221)	(-4.071)	
Pork bellies	224	0.298***	0.106***	8.28%
		(-23.017)	(-3.010)	
Heating oil	227	0.306***	-0.227**	4.90%
		(-26.184)	(-2.301)	
Natural gas	227	-0.001	-0.101	0.83%
		(-0.080)	(-0.963)	
Crude oil	227	0.314***	-0.620***	6.26%
		(-21.663)	(-2.960)	
Aluminium	171	0.003	-0.001	2.21%
		(-1.364)	(-0.529)	
Copper	227	0.176***	-0.032***	9.32%
		(-10.487)	(-3.056)	
Gold	227	0.075***	0.001	0.05%
		(-3.415)	(-0.128)	
Silver	227	0.268***	0.004	2.96%
		(-17.121)	(-0.130)	
Tin	171	-0.002	-0.004**	3.71%
		(-0.844)	(-2.112)	

Table 6: **Inventory and volatility: the effect of market states**

This table reports commodity-by-commodity regressions to control for different impact of basis on price volatility during contango and backwardation states of the market:

$$\sigma_{i,\tau} = \phi_0 + \phi_1 I_{\{b_{i,\tau-1}>0\}} b_{i,\tau-1} + \phi_2(1 - I_{\{b_{i,\tau-1}>0\}})b_{i,\tau-1} + e_{i,\tau} \tag{8}$$

$\sigma_{i,\tau}$ is the nearby futures or adjusted basis volatility, respectively, of commodity i in month τ and I an indicator function that takes the value of 1 if the 2-month adjusted basis of month $\tau - 1$ is positive and 0 otherwise. $b_{i,\tau-1}$ is the adjusted basis of commodity i at the end of month $\tau - 1$. Columns 2 and 3 report the number of contango and backwardation months respectively. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels. t-statistics are reported in parentheses below each coefficient. Newey and West (1987) HAC standard errors and covariances were employed in the estimations.

			spot volatility		basis volatility	
Commodity	**contango**	**backwardation**	ϕ_1	ϕ_2	ϕ_1	ϕ_2
Corn	202	23	-0.370	-0.478**	-0.523***	-1.194***
			(-0.668)	(-2.505)	(-3.052)	(-6.220)
Oats	166	59	-0.771*	-0.770***	-1.272***	-1.442***
			(-1.806)	(-3.521)	(-4.287)	(-5.380)
Soybeans	147	75	-1.522	-1.159***	-0.929*	-2.130***
			(-1.611)	(-2.753)	(-1.807)	(-2.732)
Soybean oil	179	41	-0.534	-0.173	-0.512*	-1.847***
			(-0.442)	(-0.224)	(-1.918)	(-3.358)
Wheat	192	31	-0.109	-0.851*	-0.984***	-1.094***
			(-0.175)	(-1.911)	(-3.618)	(-3.763)
Cocoa	171	48	-0.596	-2.371***	0.317	-0.845
			(-1.056)	(-3.057)	(-1.002)	(-1.404)
Coffee	168	55	0.426	-1.520**	0.312	-1.883***
			(-0.604)	(-2.099)	(-0.628)	(-4.086)
Cotton	166	57	0.460	-0.615*	-0.220	-1.035**
			(-1.034)	(-1.693)	(-0.444)	(-2.494)
Lumber	157	67	-0.771***	-0.136	0.321*	-1.521***
			(-3.586)	(-0.657)	(-1.911)	(-4.207)
Orange juice	160	59	1.224*	0.331	-0.265	-0.387
			(-1.836)	(-0.568)	(-0.613)	(-0.855)
Cattle	131	93	0.006	-0.200	0.159	-0.341*
			(-0.047)	(-0.957)	(-0.923)	(-1.955)
Hogs	122	102	0.459***	-0.561***	0.573**	-0.052**
			(-2.611)	(-3.519)	(-2.017)	(-2.109)
Pork bellies	81	135	0.092	0.393	-0.109	-0.721
			(-0.868)	(-0.804)	(-1.264)	(-1.055)
Heating oil	140	80	1.215	-1.276**	0.293	-3.234***
			(-1.018)	(-2.467)	(-0.440)	(-7.230)
Natural gas	148	73	0.881***	-2.486***	3.378***	-5.196***
			(-4.139)	(-5.857)	(-8.246)	(-10.782)
Crude oil	101	121	8.059***	-2.098**	5.267***	-3.355***
			(-4.815)	(-2.413)	(-4.359)	(-6.027)
Aluminium	103	60	0.220	-0.004	3.728	-3.875***
			(-1.157)	(-0.033)	(-1.303)	(-3.059)
Copper	124	95	-3.623	0.137	-2.258***	-1.428***
			(-1.364)	(-0.193)	(-3.743)	(-3.984)
Gold	218	5	-	-	-	-
			-	-	-	-
Silver	214	10	-	-	-	-
			-	-	-	-
Tin	42	119	-0.908	0.003	-3.099**	-2.072***
			(-1.171)	(-0.020)	(-2.513)	(-7.151)

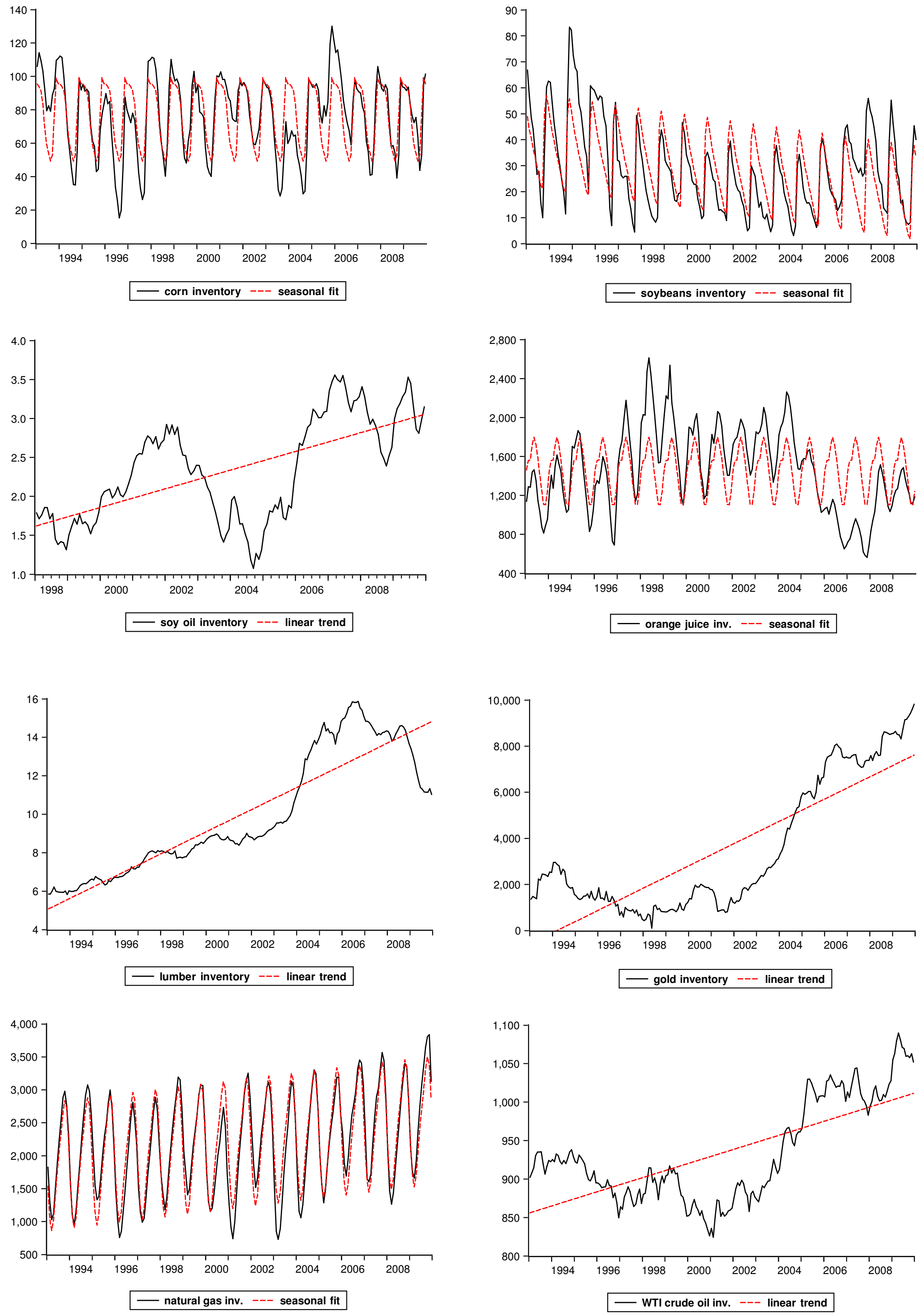

Figure 1: **Inventory Series for selected commodities**

This figure plots end-of-month inventory series for a selected group of commodities. The horizontal axis represents time (in months) while the vertical inventory units. Superimposed on the graphs are seasonal fits and linear trends (dotted lines). Seasonal fits are functions of monthly dummy variables.