The economic drivers of time-varying commodity market volatility*

Marcel Prokopczuk[†,‡] and Lazaros Symeonidis[†,‡]

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Abstract

In this paper, we investigate the relationship between economic uncertainty and commodity return volatility. Analyzing volatility for the aggregate commodity market and for various commodity groups we find that factors associated with macroeconomic and financial market uncertainty explain subsequent volatility of commodity returns. Variables motivated by commodity pricing theories, such as the futures basis and hedging pressure, are also significant. Economic uncertainty measures based on differences in beliefs of economic agents extracted from survey data provide additional information to that contained in volatility series of current economic fundamentals. Finally, we find evidence of a strong bi-directional causal link between inflation uncertainty and commodity return volatility. Our results have important implications for economic policy making, asset allocation and risk management.

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†Zeppelin University, Am Seemooser Horn 20, 88045, Friedrichshafen, Germany

‡ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, UK.

1. Introduction

It is well known that asset return volatility is not constant. However, less is known about the economic drivers of its variations. Starting with the seminal paper of Schwert (1989), a large number of studies has challenged this issue for equity and bond markets using a wide range of different variables and techniques. In spite of their economic importance, commodity markets have attracted much less attention in the literature. In this paper, we fill this gap by investigating the links between time variation in commodity return volatility and economic uncertainty.

There are numerous reasons for studying the economic drivers of commodity price volatility. Unlike stocks and bonds, commodities are consumption assets and input factors for the production process. Thus, any evidence from equities should not be naively extrapolated to commodities. Moreover, prices of commodities are important determinants of core macroeconomic concepts, such as inflation, and therefore offer useful information to regulators and policy makers. Understanding the forces that drive volatility of commodity returns can also help investors improve their asset allocation decisions. In fact, the impact of macroeconomic forces on commodity prices and their volatilities is an issue of crucial importance for long term investors such as pension funds. Furthermore, from an asset pricing perspective, recent findings suggest that commodity risk is a priced factor in the cross-section of equity returns and, as such, should be taken into account in asset pricing models (DeRoon and Szymanowska, 2011).

We contribute to extant literature in multiple ways. To begin with, to the best of our knowledge, we are the first to comprehensively study the fundamental relationship between macroeconomic uncertainty and commodity return volatility. Second, our study is the first to use survey expectations data to quantify the impact of macroeconomic uncertainty on volatility of commodity returns. We argue that this has important commodity pricing implications. Third, although it is very important to test the causal effect of the various economic variables on the volatility of commodity returns, the possibility of causality going in the opposite direction, from commodity markets to macroeconomic volatility, is also of great relevance for economic policy makers. To this end, we analyze feedback effects between macroeconomic uncertainty and commodity return volatility. Fourth, previous studies are mainly based on indices, such as the GSCI or DJUBS to construct commodity volatility proxies. However, most of these indices are dominated by a particular group of commodities (e.g. energy in the case of the GSCI) and therefore do not represent a well-diversified commodity portfolio that is more appropriate for a fundamental analysis. Instead, our evidence is based on an equally weighted and fully-collateralized commodity futures index in the spirit of Gorton and Rouwenhorst (2006). Lastly, our analysis moves beyond aggregate commodity volatility and assesses the behavior of different commodity groups. Given the heterogenous nature of commodity assets, this more detailed analysis can shed light on differences in behavior of particular commodity groups (Erb and Harvey, 2006).

Our investigation leads to many interesting findings. Overall, our empirical analysis suggests that macroeconomic uncertainty has an important effect on commodity return volatility. Inflation uncertainty exhibits a consistently positive and significant causal link with commodity return volatility. This result holds for the majority of sectoral commodity portfolios and over the various sub-samples considered. Additionally, we find that variables associated with credit risk and money market stress, such as the default spread, TED spread and the VIX are significantly related to subsequent commodity return volatility in many cases. The latter observation is connected to the fact that lower funding liquidity and greater equity market uncertainty implied by VIX lead to higher volatility in financial markets (Brunnermeier and Pedersen, 2009).

Interestingly, we also find some evidence of a weakening role of fundamentals during the later part of our sample and especially after 2001. This effect paired with the strong importance of financial risk factors, such as those mentioned above, provides some indirect support for the view of "financialization" in commodity markets. Tang and Xiong (2012) report spillovers from financial to commodity markets as a result of the increased participation of new institutional investors in commodity markets. Thus, our results seem to corroborate their findings. Controlling for variables motivated by commodity pricing theories, such as the interest-adjusted futures basis and hedging pressure, we find that for some commodity groups these variables bear significant explanatory power. In particular, futures basis leads to lower volatility, while hedging pressure exhibits the opposite effect. This result can be regarded as evidence that even though commodity markets have become more integrated with financial markets, they are still segmented to some extent.

We also conduct a feedback analysis, which reveals a strong bi-directional link between inflation uncertainty and commodity return volatility. This bi-directional link is present over most sub-samples. Nevertheless, during the recent period after the '90s there is more evidence that commodity volatility causes inflation volatility than the other way around. Furthermore, our analysis shows that commodity return volatility helps to predict volatility of real economic activity and exchange rates.

Constructing proxies of macroeconomic uncertainty based on the BlueChip Economic Indicators survey, we obtain further evidence on the role of macroeconomic uncertainty. Differences in beliefs of professionals regarding short-term economic fundamentals have a strong effect on aggregate commodity market volatility. Moreover, the macroeconomic uncertainty measures based on survey expectations contain information additional to that already contained in macroeconomic volatility estimates from historical macroeconomic data.

Many researchers have examined the time variation in stock returns with respect to macroeconomic conditions. The seminal paper by Schwert (1989) analyzes the relationship between aggregate stock market volatility and macroeconomic volatility and finds more evidence that equity volatility causes macroeconomic volatility than the opposite. Subsequent studies have suggested alternative methodologies aiming to better accommodate the empirical behavior of the data. For example, Beltratti and Morana (2006) document a bi-directional link between macroeconomic and equity volatility by modelling structural breaks and long-memory of the volatility processes. Engle et al. (2008) find that inflation and industrial production predict aggregate S&P 500 volatility in the context of a new class of models called Mixed Data Sampling (MIDAS)-GARCH, which make it feasible to incorporate macroeconomic information in standard conditional volatility models. Recently, Paye (2006, 2012) tests the in- and out-of-sample predictive ability of various macroeconomic and financial factors for aggregate stock market volatility. The author provides encouraging evidence regarding several individual predictors although the overall performance of the models that include economic variables is rather limited.

Most of the existing research on volatility of commodity prices, has focused on factors specific to commodities, such as the value of the embedded option in inventory (e.g., Deaton and Laroque, 1992; Ng and Pirrong, 1996; Geman and Nguyen, 2005; Gorton et al., 2012, and many others) or the net positions of investors (e.g., Bessembinder, 1992; De Roon et al., 2000). Furthermore, studies that involve influences by economic variables are mainly concentrated on commodity returns (Bailey and Chan, 1992; Hong and Yogo, 2012). However, little effort has been made to explicitly relate commodity return volatility to systematic risk. Recently, Christiansen et al. (2012) employed the Bayesian Model Averaging approach to test the predictive ability of a large number of variables on realized volatility of different asset classes including the GSCI index for commodities. Our study focuses on the fundamental role of economic uncertainty and its implications for volatility of commodity returns rather than on finding the best predictors of future volatility in a large panel of economic variables.

The remaining of this paper is organized as follows. Section 2 describes the data and variables employed for our analysis. Section 3 analyzes volatility measurement issues and the statistical properties of volatility estimates. Section 4 presents empirical results. Section 5 discusses various robustness checks and finally Section 6 concludes.

2. Data and variables

2.1 Commodity futures returns

We construct an equally weighted and fully-collateralized commodity futures index following a methodology similar to Gorton and Rouwenhorst (2006). To do this, we collect daily closing prices on first nearby futures contracts for a large number of commodities traded in the US market and the London Metal Exchange. Our data source is the Commodity Research Bureau (CRB). We employ the entire history of daily prices available for each commodity futures contract. The longest sample covers the period from July, 1959 to December, 2011. Where missing values are observed we apply a linear interpolation.[1] The 33 commodities included in our index can be classified in four different categories: (i) Agricultural (grains and soft commodities), (ii) Livestock, (iii) Energy and (iv) Metals (industrial and precious metals). Table 1 lists the commodity contracts included in the index along with the exchange where they are traded and their introduction date to the index.

To construct the index we first take the price of the first nearby futures contract for each commodity, assuming it expires on the first day of the delivery month (rollover date). We assume that the position in futures is fully-collateralized, which means that for each dollar invested into futures an equal amount is invested in the risk-free asset. Therefore the so called "total return" on each individual futures contract is computed as:

$$r_{i,t} = \frac{F_{i,t,T} R_{f,t}}{F_{i,t-1,T}} - 1 \tag{1}$$

where: $F_{i,t,T}$ is the day t price of the futures contract on commodity i, maturing at T, and $R_{f,t}$ is the gross daily return on the risk-free asset. As risk-free rate we use the yield on the 3-month T-bill obtained from the Federal Reserve at St Louis.

The return corresponds to a rollover strategy according to which we keep a position on the nearest to maturity contract until the first day of the delivery

[1] We also experimented with other interpolation methods, in particular spline and cubic approaches. The resulting index was not affected by the particular interpolation method.

month when the position is changed to the next to maturity contract. Prior to the rollover day, the return on the position comes exclusively from the day-to-day changes in the futures price (also termed spot return) plus the return on the collateral (T-bill). On the rollover day, the previous position is closed by selling the expiring contract and immediately buying the next to maturity contract. This leads to an additional return, known as "roll return", which is positive when the term structure is downward sloping ("backwardation") and negative when it is upward sloping ("contango"). Therefore, the return on the rollover day is the sum of the spot return, the roll return and the return on the collateral.[2] Finally, we construct the aggregate commodity index as an equally weighted average of the daily returns across all available commodities on a particular day.[3]

Figure 1 illustrates the evolution of the equally weighted aggregate commodity futures index for the entire sample period from July, 1959 to December, 2011. From the figure one can easily observe the increase in commodity prices that started gradually in 2003 and peaked during 2006-2008. This period of steep increase in prices of most commodities from 2006 to 2008 is usually referred to as the "commodity price boom period" (Haniotis and Baffes, 2010). The driving factors of this escalation in commodity prices during the aforementioned period is an open research question (e.g., Singleton, 2013, for the oil market). As a robustness check and in order to ensure that our analysis is not sensitive to the use of the particular commodity futures index constructed above, we also include the exchange traded Goldman Sachs Commodity Index (GSCI) to represent the aggregate commodity market. However, the fact that this index is dominated by energy commodities may obscure our fundamental analysis and therefore we compute daily returns of this index as the equally weighted average of returns across its sub-indices. We denote this index by GSCI(Eq) to distinguish it from the standard GSCI index.

[2]For more technical details on the construction of the index and on potential issues with survivorship biases the interested reader can refer to Gorton and Rouwenhorst (2006).

[3]Note that the number of commodities included in the index changes over time depending on the availability of price data. Therefore, the index starts with 9 commodities in 1959 and ends up with 33 in 2011.

2.2 Explanatory variables

1. Macroeconomic variables

We collect a set of economic series to construct proxies of macroeconomic uncertainty. These series include: CPI inflation, industrial production growth, M2 money supply growth, 3-month T-bill yield, the yield on 10-year government bond and the return of the trade-weighted US dollar index against major currencies. The first three variables are available at monthly frequency, whereas the other three are sampled daily. All data were obtained from the Federal Reserve Bank of St Louis (FRED).

2. Financial variables

In addition to the previous macroeconomic variables we consider a number of financial variables.[4] First, we compute daily returns on the S&P 500 using daily prices collected from Bloomberg. Second, we obtain monthly average yields on Moody's Aaa and Baa-rated corporate bonds from FRED. Moody's Aaa (Baa) corporate bond yield represents an index of the performance of all bonds rated as Aaa (Baa) by Moody's Investors Service. Additionally, we consider four variables related to debt market risk, namely: (i) the default spread defined as the difference between the Moody's Baa and Aaa corporate bond yields, (ii) the term spread defined as the long term government bond yield minus the T-bill yield, (iii) the default return spread, defined as the difference between the long term corporate and the long term government bond returns, and (iv) the TED spread defined as the difference between the 3-month LIBOR rate and the 3-month T-bill. All four variables above are monthly. The data are from FRED except for the corporate and government bond returns that are obtained from the online appendix of Goyal and Welch (2008). Monthly yields correspond to averages from daily values.

Finally, we consider the end-of-month level of the VIX, which represents investors' expectations on the 30-day ahead volatility extracted from

[4] We should point out here that some of the variables in the macroeconomic group, could have also been classified as financial variables, e.g. the T-bill yield, the yield on the 10 year bond.

out-of-the-money call and put options (for further details see CBOE website). Moreover, VIX is often regarded as a proxy of general economic uncertainty (Connolly et al., 2005) or investor's sentiment (Baker and Wurgler, 2007).

3. Commodity-specific variables

We construct aggregate measures of variables that are central to fundamental commodity pricing theories, namely the *theory of storage* and the *theory of normal backwardation*. Specifically, we focus on aggregate measures of: (i) the commodity futures basis, (ii) the growth of open interest in commodity futures and (iii) the hedging pressure of commercial and non-commercial traders, respectively.

Regarding the aggregate futures basis, we use monthly observations on the first and second nearby contracts. The former (latter) is treaded as spot (futures) price. The source is the CRB as above. We first calculate the monthly interest-adjusted basis for each commodity i as follows:

$$b_{i,t} = \frac{F_{i,t,T_2} - F_{i,t,T_1}}{F_{i,t,T_1}} - r_{f,t} \tag{2}$$

where: F_{i,t,T_2} is the price in month t of a futures contract on commodity i maturing at T_2, F_{i,t,T_1} is the price in month t of the first nearby futures contract maturing at T_2 ($T_2 > T_1$) and $r_{f,t}$ is the monthly T-bill rate serving as a proxy for the risk-free rate. Based on the *cost-of-carry* relationship it follows that the above measure of the commodity futures basis represents storage costs and convenience yields (Ng and Pirrong, 1994). Next, we compute the median of the basis (less sensitive to outliers compared to the mean) across all commodities within a specific sub-index. These series serve as the basis measures for each commodity sector. Finally, to obtain a proxy for the adjusted basis of the aggregate commodity market, we take the average basis across all four sectors (agricultural, animal, energy and metals).

For the open interest variable, we first collect monthly spot price data for all commodities in our equally weighted portfolio from the CRB. Next, we obtain end-of-month data on the open interest in futures from the webpage of the Commodity Futures Trading Commission (CFTC). The dataset covers the period from January, 1986 to December, 2011. We should point out that certain commodities in our index are not covered by the CFTC dataset, such as, for example, the metals traded at the LME.

To construct the open interest variable we closely follow the procedure described in Hong and Yogo (2012). In particular, we first compute the open interest in monetary terms for each commodity as the product of spot price times the end-of-month open interest. Then, for each of the four sub-indices considered, we add up the dollar open interest across all commodities in the particular sub-sector and compute its logarithmic growth. Finally, the aggregate open interest measure for the whole market is obtained by taking the median across all commodity sub-indices. As pointed out by Hong and Yogo (2012), the open interest proxies are very noisy. Therefore, similar to the aforementioned study, we smooth the final open interest series by taking a 12-month geometric average.[5]

A prominent stream of the literature in commodity futures pricing supports the notion that risk premia vary with the net positions of hedgers (Bessembinder, 1992; De Roon et al., 2000). Also, recent studies provide evidence that positions of particular types of traders (e.g. hedge funds) have a significant impact on commodity price volatility (Buyuksahin and Robe, 2010). Motivated by these considerations, we include a measure of aggregate hedging pressure in the commodity market in our analysis. The CFTC reports contain the short and long positions of commercial and non-commercial traders for each month. Commercial traders are widely regarded as hedgers (De Roon et al., 2000) while non-commercial traders as speculators. Using these data we compute the hedging pressure for each commodity sector and over each month as follows:

$$HP_t = \frac{\sum_{i=1}^{N}(Short_{i,t} - Long_{i,t})}{\sum_{i=1}^{N}(Short_{i,t} + Long_{i,t})} \tag{3}$$

[5]To cross-check our constructed proxies, we download the relevant series from the online appendix of Hong and Yogo (2012). The final series look very similar even though the commodities included in our and their indices are not exactly the same.

The above definition simply refers to a ratio of the sum of short minus long positions within a particular sector over the total number of positions (in US dollars) for all commodities in each particular sector (agricultural, energy, livestock, metals). Finally, a measure of hedging pressure for the whole commodity market is obtained as the average hedging pressure across the four sectors (similar to Hong and Yogo, 2012). Furthermore, following exactly the same steps we create a measure of speculative pressure defined as the negative (long minus short) of the above variable and employing the positions of non-commercial traders.

3. Measuring volatility

Following French et al. (1987) and Schwert (1989) a proxy for commodity market volatility of month t is computed as the square root of the sum of daily squared returns. This measure is represented as follows:

$$RV_t = \sqrt{\sum_{j=1}^{N_t} r_{j,t}^2} \tag{4}$$

where: $r_{j,t}$ is the return on day j of month t in excess of the mean return of this month and N_t the number of daily return observations in month t. This measure is widely known as *realized volatility*. We also use this volatility proxy for the returns of the sectoral indices of the equally-weighted index.

The above method of computing volatility exhibits several advantages. First, it is model-free and easy to compute. Second, as pointed out in Andersen et al. (2003) and Barndorff-Nielsen and Shephard (2002), under appropriate conditions realized volatility is an unbiased estimator of the true volatility process. We also compute realized volatility for those macroeconomic and financial series that are sampled at daily frequency, namely: S&P 500 returns, T-bill yields, 10 year government bond yields and the returns on the US dollar trade-weighted exchange rate index.

Nonetheless, many of the macroeconomic series are available only at monthly frequency. Therefore, in these cases, we cannot rely on the above estimator to obtain realized volatility. Methodologies to obtain volatility estimates for low frequency data can be distinguished between parametric (e.g. multivariate/univariate GARCH models) and non-parametric (e.g., Schwert, 1989; Bansal et al., 2005). In our study, we follow the non-parametric two-step method of Schwert (1989). The first step of the method involves estimation of a 12th order autoregressive model (AR(12)) on the logarithmic difference of the series, including dummy variables to allow for different monthly intercepts, as follows:

$$R_t = \sum_{i=1}^{12} a_i M_i + \sum_{i=1}^{12} b_i R_{t-i} + e_t \tag{5}$$

where: R_t is the first order difference between the natural logarithm of the series (or simply the yield for interest rate instruments) and M_i are monthly dummy variables. In the second step, an AR(12) model is fitted on the absolute values of the residuals from the first step, including again dummy variables to allow for different monthly intercepts:

$$|e_t| = \sum_{j=1}^{12} \gamma_j M_j + \sum_{j=1}^{12} \delta_i |e_{t-i}| + a_t \tag{6}$$

The absolute values of the residuals from Equation (5) correspond to realized volatility estimates of the series (or equivalently unconditional volatility).[6] Relative to the squared residuals, for example in a GARCH model, the absolute value has the advantage that it is less skewed and also less sensitive to outliers.

On the other hand, the fitted values from the second step represent realized volatility predictions of month t conditional on information available up to month *t-1*. In other words, these predictions are conditional volatility estimates given information available at *t-1*. This is based on a similar idea to the GARCH models of Engle (1982) and Bollerslev (1986). For a detailed discussion on volatility measurement methods see Andersen et al. (2002). The two-step algorithm above is applied to the following series: CPI inflation, industrial production growth (IP), M2 money supply growth and Moody's

[6] Similar to Schwert (1989), the absolute values of the residuals from the first step are multiplied by $\sqrt{\pi/2}$ since the expectation of the absolute value is smaller than the expectation of the normal distribution that the error term is assumed to follow.

Aaa corporate bond yield.[7]

The second step of Schwert's method is also estimated for variables sampled daily in order to obtain conditional volatility series for those as well. In this case, we simply replace the absolute errors in the second step with the realized volatility series obtained from Equation (4). In our subsequent empirical analysis, we always employ these conditional volatility series (volatility predictions) as economic uncertainty proxies (explanatory variables) similar to (Schwert, 1989; Paye, 2012). It is necessary to point out here that for the VIX as well as for the debt market variables, namely the term spread, the default spread, the default return spread and the TED spread we directly work with these series rather than volatilities since they already express risk.

3.1 Statistical analysis of volatility estimates

Figure 2 illustrates kernel density plots of realized volatility estimates for the equally-weighted commodity index and GSCI(Eq) index, respectively. Looking at the top panel of this figure, which refers to the level of realized volatility, we see that the series of realized volatilities of both indices are positively skewed and highly leptokurtic. These non-Gaussian characteristics of the empirical distribution of volatility estimates may lead to non-normal errors in the linear regression models employed for our analysis. To this end, we choose to work with the logarithm of annualized realized commodity return volatility, defined as: $\tilde{RV}_t = \log(\sqrt{12 RV_t})$. Andersen et al. (2003) point out that although the distribution of raw volatility estimates is rightly-skewed, the logarithmic volatility distribution is close to normal. The bottom panel of Figure 2 that illustrates the kernel density plots of logarithmic realized commodity market volatility confirms this conjecture.

Table 2 presents diagnostic statistics for the regressions of Equation (6) used to obtain conditional volatility estimates. As already mentioned above the dependent variable in Equation (6) corresponds to realized volatilities

[7] The Moody's Aaa corporate bond yield is also available daily from FRED. However, the daily series begins only in 1983, which is a too short period for our study. Therefore, we choose to proceed with the monthly series.

computed by Equation (4) for variables sampled daily and by Equation (5) for variables sampled monthly. In the third column of the table we report the sum of the autoregressive coefficients that capture the persistence of the realized volatility process together with the t-statistic for the hypothesis that this sum is equal to unity (integrated volatility). Except for inflation volatility, all other series of volatility estimates exhibit a high degree of persistence, since the sum of autoregressive coefficients is higher close to 0.8 or higher in most cases. Therefore, the hypothesis of non-stationary (integrated) variance is rejected in all cases suggesting mean-reverting volatility processes. The fourth and fifth columns contain F-statistics with their associated p-values from the following two tests: i) all seasonal dummies are equal, and ii) all autoregressive coefficients are jointly zero. The F-test indicates rejection of the null hypothesis in all cases. Therefore, the selected approach of obtaining volatility proxies appears appropriate. Finally, the table reports the Ljung-Box statistic for serial correlation up to 24 lags, which evaluates the adequacy of the model. The statistic suggests rejection of the null hypothesis of autocorrelation in model residuals, which shows that the AR(12) model adequately captures the persistence of the volatility series and also removes most of the autocorrelation in the series.

In Figure 3 we plot the time series of conditional volatility series of the equally weighted commodity index against each conditional macroeconomic volatility series. To make the plots easier to read, we standardize all volatility series. These graphs reveal some interesting patterns concerning the relationship between macroeconomic and commodity return volatility. First, commodity market volatility is much higher compared to macroeconomic volatility. Second, there is a clear co-movement between commodity and macroeconomic volatility during the period that coincides with the financial crisis and the commodity price boom period. Furthermore, among the macroeconomic volatility series, inflation seems to be the most highly correlated with commodity return volatility.

Table 3 displays Spearman's rank order correlations between predictions of aggregate commodity market volatility and predicted volatilites of macroeconomic variables and financial variables. We report correlations for the period 1970-2011, which corresponds to the full sample period employed for our subsequent estimations, and for the sub-period, 1991–2011. We see that most correlation coefficients are positive and significant at the 5% level. This suggests that higher volatility of commodity returns is associated with higher macroeconomic and financial market volatility and vice versa. Overall, inflation volatility exhibits the highest correlation with commodity market volatility, around 50%, while correlation between commodity and equity return volatility is around 30%. Correlation of aggregate commodity return volatility with the other macroeconomic volatility series is generally low for both the full sample period and the sub-period considered. A notable exception is the correlation with the US exchange rate index volatility for the period 1991-2011, which is equal to 45%.

3.2 Summary statistics of explanatory variables

Table 4 reports summary statistics for the variables used in our empirical analysis that follows. Commodity-specific variables are not reported due to space limitations. Inspection of the table shows that historical equity market volatility and option implied volatility (VIX), are by far the most volatile series, followed by long term bond return volatility and US dollar index volatility. This observation is consistent with previous studies which showed that financial volatility is generally much higher than macroeconomic volatility (Schwert, 1989; Beltratti and Morana, 2006). The first order autocorrelation coefficients are positive and large for most series especially for those associated with interest rates and bond yields, such as the default spread or the T-bill yield. The twelfth order autorocorrelation coefficients are also large in many cases although much lower than the corresponding first order coefficients. This slow decay in autocorrelations suggests relatively high persistence of the series. To ensure that this high persistence is not related to non-stationary series that could potentially cause inference problems in our estimations, we perform Phillips-Perron (Phillips and Perron, 1988) unit root tests for each series. The test statistics and their associated p-values (MacKinnon, 1994) reject the null hypothesis of a unit-root at the 1% significance level for all series. Therefore, in the first place, we do not need to employ alternative econometric procedures (e.g., Integrated Moving Average processes).

4. Empirical results

In our empirical analysis, we investigate the links between time variation in commodity return volatility and macroeconomic and financial market uncertainty. To this end, we consider a number of economic and financial variables to test whether they explain subsequent return volatility of the aggregate commodity market and of various commodity sectors. Given the role of idiosyncratic risk in commodity markets, we also control for commodity-specific factors, such as the futures basis and the positions of hedgers/speculators. First, we analyze the behaviour of commodity market volatility over the business cycle. Second, in a univariate regression context, we analyze the ability of each individual variable to offer explanatory power beyond that contained in lags of volatility. Third, we extend the analysis to a multivariate framework that incorporates multiple factors. After this, we explore the impact of heterogeneity in beliefs about term economic conditions of professional forecasters on commodity return volatility. Finally, we investigate causality between macroeconomic uncertainty and commodity market volatility with a VAR analysis.

4.1 Commodity market volatility during recessions

Commodity futures prices vary across the business cycle. Fama and French (1988) analyze this issue for metals, while Gorton and Rouwenhorst (2006) document that commodity assets exhibit a slightly different exposure to business cycle conditions relative to stocks and bonds. In particular, they report that commodity returns tend to be higher on the onset of a recession whereas they become negative during later stages of a recession when stock and bond markets begin to recover. Below, we investigate the behaviour of commodity return volatility over the business cycle. Our longest sample period (1959-2011) covers seven recession periods according to the NBER classification.

Figure 4 plots the natural logarithm of realized volatility of the equally weighted index and the GSCI(Eq) index, respectively. Super-imposed on the graph are the NBER recession months. Inspection of this plot shows that commodity market volatility tends be higher during recessions. However, some additional remarks apply. First, the increase in volatility is not systematically documented during all recessions. For instance, during the recession of 2001, following the dot.com bubble, the volatility hardly changed. Second, although volatility of commodity returns tends to be higher during recessions, in many cases the volatility is not substantially higher compared to highly volatile episodes not associated with recessions. This fact highlights the role of non-systematic (idiosyncratic) risk factors that affect the supply and demand of commodity prices, e.g. geopolitical events.

To formally test the behaviour of commodity return volatility over the business cycle more formally, we estimate the following regression:

$$RV_{i,t} = a + \sum_{i=1}^{6} b_i RV_{i,t-i} + \gamma \cdot I_{NBER,t} + u_t \tag{7}$$

where: $RV_{i,t}$ is the realized volatility of commodity return index i in month t and $I_{NBER,t}$ is a dummy variable that takes the value of 1 for NBER recession months and 0 otherwise. We include six lags of realized volatility in the right side of Eq. (7) to account for persistence in volatility and avoid spurious inference (Paye, 2006). If the coefficient of the business cycle dummy is significantly different from zero means that the volatility of the series is higher on average during recessions. The regression is estimated for the equally weighed commodity index and its four sub-indices as well as for the GSCI index (equally weighted). The energy portfolio is excluded from the estimations since its price history is too short (1983-2011) for this analysis. In addition, we also estimate the above regression for the macroeconomic and financial volatility series.

Table 5 reports the estimation results. The coefficient of the recession dummy is positive and strongly significant for both the equally weighted index and for the GSCI(Eq) index. This result suggests that during recessions aggregate commodity market volatility is higher on average. Inspecting the individual commodity groups, we observe that volatility is significantly higher for metals, but not for agricultural and livestock portfolios. The last column of the table reports the percentage increase in volatility during recessions compared to expansions. These volatility increases are quite large in most cases. Furthermore, S&P 500 returns, inflation, industrial production and money supply exhibit substantial increase in volatility during recessions. There is relatively weaker evidence for interest rates, FX rates and corporate bond yields.

These results supports the view that volatility of commodity returns is strongly affected by real economic conditions. An interpretation for this is that shifts in investors' risk aversion during recessions may induce time-varying patterns in expected returns and therefore rime variation in return volatility.

4.2 Evidence from univariate estimations

We begin by estimating the following specification on the logarithm of commodity return volatility:

$$\tilde{RV}_t = a + \gamma X_{i,t-1} + \sum_{j=1}^{6} \beta_j \tilde{RV}_{t-j} + u_t \quad (8)$$

where: $\tilde{RV}_t$ is the natural logarithm of realized commodity return volatility in month t and $X_{i,t-1}$ is the scalar value of variable i in month $t-1$. The above specification refers to one-by-one regressions against each variable. Newey-West (1987) standard errors (with 12 lags) are employed for the estimations.[8] Given the persistent nature of volatility, its own lags already capture a rich set of information about current volatility. Therefore, for a variable to be characterized as a significant indicator of future volatility, it should provide information additional to that already contained in lagged volatility.

[8]Experimentation with higher lags (15 and 18 respectively) yield very similar t-statistics.

We estimate the above set of regressions for six different dependent variables: the logarithm of realized volatility of the equally weighted commodity futures return index, its four equally weighted sub-indices, and the realized volatility of the GSCI index adjusted for equal weights. Prior to 1970, our index consists only of few commodities (around 10), most of them agricultural. As a consequence, the index is not well-diversified since it is dominated by a single sector. Moreover, our price history for GSCI index begins in 1970. Therefore, we chose to start our analysis from January 1970 although for the previous business cycle analysis we employed the full history of data. Our estimations are performed on the entire sample spanning 1970-2011 and also on various sub-periods of this sample. One way to assess the economic significance of a specific variable is through the increase in the adjusted R^2 after adding the variable in the plain AR(6) specification (also called the benchmark).

Tables 6 to 11 summarize the results of estimating the above six sets of regressions. All variables, including the dependent, are standardized prior to the estimations by subtracting the sample mean and dividing with the sample standard deviation to facilitate better comparability across coefficients. A first look on the results across sub-samples and sectoral commodity indices, reveals that some variables consistently enter with significant coefficients. Inflation volatility appears to be the most significant individual predictor in economic and statistical terms. Moreover, factors related to financial market conditions, such as the default return spread, the term spread or the VIX offer explanatory power for many portfolios and sub-periods. Controlling for commodity-specific factors, we observe that these are significant determinants of commodity return volatility in many cases, while their signs are consistent with theoretical predictions.

We observe some evidence of time variation in the response of commodity return volatility to the various economic factors across the different commodity groups. This is, to some extent, expected due to the heterogeneous nature of commodity assets. For example, some of them are primary consumable goods (e.g. grains), some others are inputs in the production process, e.g. lumber, or behave more like financial assets, e.g. gold.

Looking at the results of the aggregate commodity market indices (Tables 6 and 11, respectively), we see that inflation volatility is highly significant at the 1% level for the whole sample period of 1970–2011. Its sign suggests a positive impact on short term volatility of commodity returns. This positive effect may be related to the higher trading activity in commodities during periods of high inflation uncertainty since they are widely considered as good a hedge against inflation (Edwards and Park, 1996). In the 2001–2011 sub-period, which includes the recent commodity price boom, the significance and the magnitude of the impact of inflation uncertainty seems to weaken.

In contrast, the importance of some financial factors, such as the default return spread, TED spread and VIX becomes greater in the sub-sample after 2000. This may provide some indirect support for the argument of "financialization" according to which commodity markets are becoming more integrated with traditional financial markets due to the participation of new investors (e.g. hedge funds). As a consequence of the financialization process the dependence of commodity prices on factors specific to stocks or bonds has increased (Silvennoinen and Thorp, 2010). The coefficients of both the VIX and TED spread are positive suggesting that greater values for these variables are associated with more volatile commodity returns. This positive effect for the VIX can be understood if one thinks that it represents investors' attitude to risk and as such it also provides signals about other risky assets, like commodities. On the other hand, the TED spread is a proxy for funding liquidity (Brunnermeier et al., 2008) and higher values of this variable are linked to higher illiquidity. Hence, the dry up in liquidity during the recent financial crisis pushed volatility higher. This shows that the VIX and TED spread have the same effect on commodity return volatility. Brunnermeier et al. (2008) reach a similar conclusion for currency returns.

Concerning the variables motivated by commodity pricing theories, we observe that the measure of aggregate commodity futures basis, although insignificant in the entire sample period, enters with a highly significant and large in absolute value coefficient in the second half of the sample

(1991–2011). Its sign is negative and consistent with the predictions of the theory of storage (Ng and Pirrong, 1994; Gorton et al., 2012). Furthermore, the effect of aggregate hedging pressure is positive for aggregate commodity market volatility and significant at the 5% level, while its sign suggests that volatility increases with higher hedging demand. This is in line with evidence of other studies which examine the impact of hedgers' positions on volatility of commodity returns (Buyuksahin and Robe, 2010; Silvennoinen and Thorp, 2010). Speculative pressure, on the other hand, is important only in the period after 2000. This, however, highlights the potential role of speculation in the recent commodity price boom during 2008, which was also accompanied by increased price volatility (see Figure 4). The conclusions are very similar and in many cases identical for the GSCI(Eq) index, enhancing the robustness of our evidence.

As already mentioned above, the estimation results suggest cross-sectional differences in the explanatory power afforded by the various variables. For instance, a look on the results of agricultural volatility shows that for the first half of the sample (1970–1990) only inflation volatility and the futures basis enter with significant coefficients. However, in the second half of the sample (1990–2011) several other variables become important, such as equity return volatility, the default spread, the term spread, the VIX, etc. In contrast, for metals the only common important factor during the 1991–2011 sub-period is inflation volatility, whereas from the rest of variables hedging and speculative pressure exhibit significant coefficients at the 1% level. Default return spread, the futures basis and interest rate volatility seem to matter as explanatory factors for energy price volatility.

As mentioned above, a way to assess the incremental explanatory power of individual variables is through the increase in the adjusted R^2 of the model augmented by the particular predictor compared to benchmark AR(6) specification. Consistent with previous studies for equity markets (e.g., Paye, 2006) we find that although many variables appear to cause commodity return volatility, their predictive power is relatively modest.

In sum, our results suggest that macroeconomic and financial variables contain information for explaining commodity market volatility. These variables include: inflation volatility, option implied volatility, debt market risk proxies, such as the default return spread and the term spread, etc. In addition, commodity market specific factors, like the futures basis and hedging pressure bear significant predictive power for subsequent commodity return volatility. Finally, our results suggest that financial predictors become increasingly important over time, a conclusion that is also supported by other studies.

4.3 Evidence from multivariate estimations

In the previous section, we analyzed the ability of individual economic uncertainty factors to explain the time variation in commodity return volatility. Despite its usefulness, the univariate analysis cannot be employed to investigate a number of important issues. For example, in a univariate context, we cannot identify the relative explanatory power of an individual variable with respect to other variables when several are included in the same model. Information contained in the various factors is not necessarily orthogonal and hence some of them might be redundant. On top of that, estimations that use the full set of macroeconomic versus financial or commodity market predictors can lead to conclusions regarding which group of variables, if any, is more important for explaining changes in commodity market volatility. Also, from an econometric perspective, a univariate analysis is more likely to suffer from omitted variables bias.

For the these reasons, we further investigate the impact of the various economic and financial factors on commodity return volatility in a multivariate regression framework. In particular, we first regress realized commodity return volatility, separately, on the full set of macroeconomic versus financial and commodity-specific factors. Then we repeat the estimations including all variables together in the same specification, an approach usually referred to as "kitchen sink regressions" (e.g., Goyal and Welch, 2008). The estimations are performed on the full sample (1970–2011), as well as on the three sub-samples analyzed in the previous section.

4.3.1 Macroeconomic factors

In the first set of estimations we regress the logarithm of realized commodity volatility on volatilities of the following five macroeconomic series: CPI inflation, industrial production growth (IP), M2 money supply growth, 3-month T-bill yield and trade-weighted US dollar index return. The price series of the US dollar index begins in 1974 and therefore it is omitted from the full sample estimation as well as the estimation of the first sub-sample (1970–1990). Similar to the case of univariate regressions we estimate the models using the return volatility of each commodity considered above as dependent variable.

Estimation results are presented in Table 12. Each column refers to a different commodity index as dependent variable. A first look at the results for the entire sample seems to confirm our previous evidence that inflation volatility is a consistently important driving factor of commodity return volatility across most sub-periods and commodity sectors. Its sign suggests a positive effect on commodity return volatility. Furthermore, the size of its coefficient is quite stable over the various sub-periods. T-bill volatility is also significantly positive for livestock and metals in the full sample.

The improvement in explanatory power of the model by including the full set of macroeconomic variables is relatively small and lower that 3% in most cases. Also, in line with the evidence from univariate estimations, we see that the in-sample forecasting ability of the models becomes much weaker in the recent sample period of 2001–2011. For example, in the case of agricultural volatility the increase in the adjusted R-squared ($\bar{R}^2$) was 2.7% during the period 1991–2011, whereas it falls to -0.5% in the sub-sample of 2001–2011.

4.3.2 Financial and commodity-specific factors

Next, we perform the same set of estimations against the group of financial and commodity specific variables. Before discussing the results, it is important to note some points. First, because data on open interest and positions of traders are not available prior to 1986 from the CFTC, we include these variables only in the estimations of the second sub-period (1991–2011).[9] Second, after the '90s we replace the historical proxy of equity market volatility with VIX. Since these two are highly correlated inclusion of both would raise serious multicollinearity concerns. In the same spirit we omit default spread from our analysis since it is highly correlated with default return spread, term spread and the VIX.

Table 13 shows the estimation results. Looking at the results for the entire sample period, we observe that debt market variables such as term spread and default return spread are significant for the agricultural and livestock indices in some cases, and also for the aggregate commodity market (equally weighted index and GSCI(Eq)). Equity market volatility is also strongly significant at the 5% level for the agricultural and livestock portfolios and weakly significant at the 10% level for the GSCI(Eq) index. Cross-sectional differences among the different commodity indices are also observed. For instance, none of the variables can explain metal volatility in the whole sample period. We also see that the in-sample predictive performance afforded by financial variables is rather limited as changes in the $\bar{R}^2$ of the benchmark AR(6) model augmented with financial variables is less than 1% in all cases for the entire sample period.

In the first half of the sample (1970–1990), the explanatory power offered by financial variables is quite low both in terms of the significance of individual coefficients and the increase in the $\bar{R}^2$ compared to the benchmark. Adding VIX and hedging pressure in our models in the second half of the sample, we see that it has a positive and strongly significant impact on volatility of all commodity portfolios except for the agricultural. Another notable fact is the significant explanatory power of commodity-specific variables in many cases. For example, the adjusted futures basis is highly significant at the 1% level for the aggregate commodity index and for the sub-indices of energy and livestock. Moreover, commercial hedging pressure has a strong positive effect on future aggregate commodity market volatility.

[9] Hong and Yogo (2012) used a more extensive dataset that starts since 1967, and is available from their online appendix. However, their datasets have gaps during some periods before 1986 when our own dataset begins. Therefore we choose to work with the original dataset we obtained from the source (CFTC).

The increase in $\bar{R}^2$ is substantially higher in the second half of the sample and especially after 2000. For example, adusted futures basis and the VIX add a substantial 6.2% to the explanatory power over the 1991–2011 sub-period. Moreover, the in $\bar{R}^2$ is double as high for the majority of commodity groups in the 2001–2011 sub-period. The same three variables that explain an additional 3% of return volatility of the GSCI(Eq) index in the 1991–2011 sub-sample, lead to an increase of 5.2% in the 2001–2011 sub-sample.

4.3.3 "Kitchen sink" regressions

Thus far, we have assessed the explanatory power of macroeconomic and financial/commodity variables in isolation. Below, we present the results from estimations that include the full set of variables. This analysis is similar to the so-called "kitchen sink" regressions. However, we make sure not to include regressors that are highly correlated to alleviate concerns about multicollinearity. Thus, given that government bond yield volatility, high grade corporate bond yield (Moody's Aaa) volatility and T-bill volatility are all highly correlated we only include T-bill volatility. In addition, default yield is highly correlated with some variables, such as T-bill volatility and the VIX. Therefore, we exclude it from the estimations as well.

Table 14 contains the estimation results. Regarding the results for the entire sample, we see that inflation volatility and to a lesser extent default return are most important determinants of commodity return volatility. Futures basis also appears to be strongly significant at the 1% level for the agricultural portfolio and the GSCI(Eq) index. The sign of inflation volatility suggests a positive impact on short-term volatility of commodity returns. The overall in-sample predictive performance in terms of the $\bar{R}^2$ increase of the benchmark is relatively low for most indices. An exception is the agricultural index with an increase in the $\bar{R}^2$ of 3.5%.

The analysis in sub-samples provides useful findings. In the first half of the sample variation in commodity market volatility is mainly driven by inflation volatility. The overall explanatory power of the models is relatively limited. The increase in $\bar{R}^2$ is often less than 2%. However, in the second half of the sample (1991–2011 subsample), the explanatory power of these variables becomes much stronger. Combined with the results from financial variables in Table 13, it can be seen that inflation volatility drives out the explanatory power of the futures basis in the case of the aggregate commodity market and livestock volatility. In contrast, the coefficient of hedging pressure is still positive and highly significant for aggregate commodity return volatility and for volatilities of most sectoral commodity indices.

In addition, equity implied volatility enters with positive and significant coefficients at the 5% level, which means that higher expectations about short-term equity market volatility is followed by higher volatility of commodity returns. This can be understood on the grounds of VIX being interpreted as a proxy of investors' sentiment and as such it should also convey information about other risky assets. Commodity specific factors (hedging pressure in particular) show up as important determinants of commodity return volatility supporting the implications of commodity pricing theories. This suggests that commodity markets are still relatively segmented from other asset markets (Daskalaki et al., 2012).

The overall explanatory power offered by these variables becomes stronger after '90s and is even greater in the 2001–2011 period. For example, adding the set of variables in the model leads to a 8.5% improvement in the case of the energy index. The economic significance of explanatory power over the 2001–2011 period is notable for most indices. The increases in $\bar{R}^2$ for the GSCI(Eq), livestock and energy indices are approximately 6%. The corresponding improvements for the aggregate index and the index of agricultural commodities are 4%. As previously, heterogeneity seems to play a dominant role on the impact of the various factors on return volatility of the different commodity sectors. For example, over the second half of the sample, return volatility of agriculturals and metals seems to be driven by almost the same factors, whereas with the only exception of inflation uncertainty, energy volatility is determined by a totally different set of factors. Moreover, these differences are also observed across the $\bar{R}^2$ changes of the sectoral commodity indices.

4.4 Investigating causal relationships

Thus far, we investigated whether uncertainty regarding fundamental economic factors can explain volatility of commodity returns. However, there is also the possibility that volatility of commodity returns explains subsequent variations in economic activity. For instance, Fornari and Mele (2009) find that financial volatility explains a large part of real economic activity and also helps to predict business cycles. Moreover, one of the main findings of Schwert (1989) is that although evidence of causality from macroeconomic to equity volatility was weak, evidence for causality of the opposite direction was stronger.

We look at the bi-directional links between economic uncertainty and commodity market volatility by performing Granger causality tests. We solely focus on the two indices representing the aggregate commodity market, namely the equally weighted commodity index and the GSCI(Eq) to keep the presentation manageable. Our tests are based on bivariate Vector Autoregressive models (VAR), which include the log realized volatility of commodity returns and the realized volatility series of the variable we want to test.[10] We include twelve monthly dummies in each equation to account for different monthly intercepts. This VAR specification has the following form:

$$Y_t = A \cdot D_t + B_1 \cdot Y_{t-1} + B_2 \cdot Y_{t-2} + ... + B_p \cdot Y_{t-p} + e_t \tag{9}$$

where: Y_t is a 2-by-1 vector that contains the two series in question, i.e. the realized volatility of commodity returns and volatility of one of the following variables, respectively: CPI inflation, industrial production growth, M2 money supply growth, 3-month T-bill yield and trade-weighted US dollar index returns. We select $p = 6$ lags for the estimation based on the Akaike Information Criterion. D_t is a matrix of 12 dummy variables to allow for different monthly intercepts (Schwert, 1989). A and B_j (j=1,2,...,p) are 12×6 and 6×6 matrices of parameters, respectively. The above specification is the bivariate version of Eq. (6) used to obtain volatility predictions. Estimations

[10]We also examine causal links in a higher dimensional VAR model that includes multiple variables together. The conclusions were qualitatively similar.

using higher lags (e.g. 12) led to very similar conclusions.

Table 15 presents the test results. Looking at the column labeled "Full sample" first, we see that from the macroeconomic series only inflation volatility predicts commodity return volatility. This finding is robust for both commodity indices. Regarding causality from commodity to macroeconomic volatility, we see that commodity return volatility helps to predict volatility of inflation, industrial production and high grade (Aaa) corporate bond yield. The results over sub-samples show that the causality from commodity return volatility to inflation volatility is remarkably stable over time. In contrast, evidence that volatility of commodity returns helps to predict industrial production volatility appears to depend on the specific sub-sample considered. Specifically, it is strongly significant over the full sample and during the 2001–2011 period but totally absent for the remaining sub-periods.

Furthermore, including exchange rate volatility in our analysis, we observe that the null of no Granger causality from commodity return volatility to exchange rate volatility is rejected at the 5% level for all sub-samples and for both commodity market indices employed. One potential interpretation for this is that volatile commodity prices affect the value of the embedded option in inventory (Pindyck, 2004). This, will have an impact on prices of final goods and therefore on the demand for exports which is a major determinant of exchange rates.

4.5 The role of heterogeneous beliefs for commodity return volatility

In the preceding analysis we used information contained in historical data to construct proxies of economic uncertainty. This section employs survey data to construct measures of macroeconomic uncertainty based on agents' expectations about future macroeconomic fundamentals. A large number of studies have used survey data to represent beliefs about the economy. For example, Beber et al. (2010) find that differences in beliefs have a strong impact on returns, implied volatility and the variance risk premia in currency markets.

We draw our evidence based on the Bluechip Economic Indicators survey. This survey exhibits some clear advantages over other professionsl forecasting surveys, such as the Survey of Professional Forecasters (SPF), the Livingston Survey (LVS), the Wall Street Journal (WSJ) or the ECB SPF. First, in contrast to the other surveys, it is published on a monthly basis rather than quarterly (SPF, LVS) or semi-annually (WSJ). Second, forecasts are made for the current as well as the next year allowing for a distinction between short- and long-run expectations about the economy. Third, the survey covers a larger set of economic variables compared to other surveys.

Getting into the details of the dataset, BlueChip Economic Indicators contains a set of short- and long-run predictions based on a monthly survey across a group of professional forecasters including insurance companies, leading financial institutions, consulting firms, etc. The participants are asked to provide current and next year forecasts for a wide range of economic variables that include: Real GDP, the GDP Deflator, Nominal GDP, Personal consumption expenditure, CPI inflation, Industrial production, Personal disposable income, Non-residential investment, Corporate profits, Unemployment rate, 3-month Treasury bill rate, 10-year Treasury bond yield, Automobile sales and Housing starts.

Forecasts for the majority of indicators without many missing values are available since the mid '80s. Hence, for the purpose of our analysis, we focus on the twenty year period from January, 1991 to December, 2011. The repeated forecasts against a fixed date induce a seasonal pattern in the expectation data. For this reason we seasonally adjust the series using the ARIMA X-12 method employed by the US Census Bureau. We try to focus on those series that match with our historical macroeconomic volatility proxies above. Therefore we consider the following series: CPI inflation, Industrial production, T-bill and Net exports.[11]

Survey based macroeconomic uncertainty proxies are constructed by taking the cross-sectional standard deviation across all forecasters as in Frankel and

[11]Note that, some series of forecasts are highly correlated pair-wise since they refer to closely related economic concepts, such as GDP and industrial production. Therefore, inclusion of both could potentially introduce spurious regression concerns.

Froot (1990). We rely on the short-term forecasts for the construction of our proxies since our focus is on explaining short-term volatility of commodity returns. Figure 5 illustrates the evolution of the four dispersion series and shows some meaningful time-variation. Inspection of the plots provides evidence that the obtained economic uncertainty proxies closely follow real economic conditions. Consider, for example, the time series of dispersion of forecasts concerning industrial production. This empirical proxy almost always increases during times associated with important events, such as the Gulf Wars (1991, 2003), the dot.com bubble (2000), or during the recent financial crisis.

We investigate the impact of survey-based macroeconomic uncertainty on commodity return volatility by estimating the following regression:

$$\tilde{RV}_t = \phi_0 + \phi_1\sigma_{t-1}^{CPI} + \phi_2\sigma_{t-1}^{IP} + \phi_3\sigma_{t-1}^{TBILL} + \phi_4\sigma_{t-1}^{NEXP} + \sum_{i=1}^{6}\phi_i\tilde{RV}_{t-i} + u_t \quad (10)$$

where: $\tilde{RV}_t$ is the logarithm of realized commodity return volatility of month t, and σ_{t-1}^{J}, where $J = \{CPI,\ IP,\ TBILL,\ NEXP\}$, are the macroeconomic uncertainty series of month *t-1*. We estimate the above set of regressions for each commodity return index. The equations are estimated for two periods: 1991–2011 and 2001–2011. We standardize all variables before the estimations, using the first two moments of the sample to facilitate comparisons across coefficients.

Panel A of Table 16 contains the estimation results. Overall, the results reinforce that macroeconomic uncertainty is important for commodity market volatility. This result is mainly driven by uncertainty about inflation and net exports. Coefficients of inflation uncertainty are positive, suggesting that higher disagreement about future inflation is followed by higher volatility in commodity returns. This is possibly related to higher trading activity in commodity futures during periods of higher uncertainty about future inflation since commodities are regarded as a good hedge against high inflation.

Uncertainty about net exports also has a positive impact on volatility of the aggregate commodity market and of most sub-indices. One possible explanation for this finding is that many commodities are used to produce export goods and therefore their prices and volatility heavily depend on net export demand. Regarding the second estimation period of 2001–2011, we see that inflation uncertainty remains strongly significant at the 1% level, whereas the impact of net export uncertainty gets relatively weaker. The explanatory power varies across the different commodity portfolios. The $\bar{R}^2$ improvement is remarkable for some portfolios, such as for instance the 5% increase for the agricultural portfolio in the 1991–2011 period or the 5% increase for the energy portfolio in the 2001–2011 sub-period.

Finally, we explore the incremental information content of macroeconomic uncertainty relative to volatility of current fundamentals. In other words, we test whether heterogeneity in agents' expectations provides information additional to that already contained in historical volatility proxies. To this end, we estimate the following regression:

$$\tilde{RV}_t = a + \sum_{i=1}^{5} \beta_i X_{i,t-1} + \sigma_{t-1}^{CPI} + \gamma_2 \sigma_{t-1}^{IP} + \gamma_3 \sigma_{t-1}^{TBILL} + \gamma_4 \sigma_{t-1}^{NEXP} + \sum_{j=1}^{6} \phi_j \tilde{RV}_{t-j} + \epsilon_t \tag{11}$$

where: $X_{i,t-1}$ is the vector of macroeconomic volatility series, $i = \{$*CPI, IP, T-bill, M2, FX index*$\}$ and σ^J represents the survey-based macroeconomic uncertainty variables as in Equation (10), with $J = \{$*CPI, IP, TBILL, NEXP*$\}$, measured by the standard deviation across forecasts.

The results are reported in Panel B of Table 16. These results indicate that macroeconomic uncertainty is important and also provide information that are orthogonal to that already contained in the historical volatility series. In particular, adding the set of macroeconomic uncertainty measures in the models, we see that they remain significant and also increase the overall explanatory power of the regressions in most cases. Consider, for example, the aggregate commodity index. In Table 12, which reports the results for regressions against macroeconomic volatilities, only CPI volatility is statistically significant in the 1991–2011 period with a weak improvement in the $\bar{R}^2$ of the model. Including the survey-based macroeconomic uncertainty measures, inflation volatility remains significant and the $\bar{R}^2$ increases by almost 3%. Another example is the case of agricultural volatility, where the explanatory power of the model in the 1991–2011 period increases from 2.6% to 6.4%.

In sum, uncertainty about macroeconomic fundamentals extracted from survey expectations is a significant source of information for explaining variations in commodity return volatility. The evidence above suggests that these uncertainty measures enlarge the set of information contained in volatility of current fundamentals.

5. Robustness tests

To ensure that our evidence is not sensitive to the use of a specific method to obtain macroeconomic volatility proxies, we employ alternative methods to construct these proxies and then re-perform all estimations. These methods include:

(i) Except for Schwert's two-step method, another non-parametric method for obtaining conditional volatility estimates employed in many empirical studies (e.g., Bansal et al., 2005) is the following:

$$\tilde{\sigma_t} = log(\sum_{i=1}^{L} |e_{t-i|}) \tag{12}$$

This estimator is the logarithm of the sum of past L-period realized volatilities obtained as the absolute value of the residuals from an AR(12) regression as in Eq. (5). For variables sampled daily, we replace the absolute errors by the realized volatility computed as in Eq. (4). We use L = 3 and 12, respectively.

(ii) In addition, we consider the estimator of French et al. (1987) that accounts for autocorrelation bias in squared daily returns to obtain realized volatility proxies for commodity returns. This estimator is given as:

$$\sigma_t = \sqrt{\sum_{j=1}^{N_t} r_{j,t}^2 + 2\sum_{j=1}^{N_t-1} r_{j,t} r_{j+1,t}} \tag{13}$$

where: $r_{j,t}$ is the daily return on commodity i in month t and N_t the number of daily returns in month t. The first component of the sum above corresponds to the realized variance estimator of Eq. (4) and the second component is a correction term for autocorrelation bias.

Performing the analyses using the two alternative estimators of realized volatility has very little impact. Overall, our results remain qualitatively similar.

In addition to the above methods we also re-estimate the models employing the level rather than the logarithm of realized commodity market volatility. The results are very similar in terms of significance and in many cases in even exhibit lower p-values. All robustness checks are available on request.

6. Conclusions

This paper examines the relationship between economic uncertainty and commodity return volatility. In particular, we attempt to shed more light on the economic sources of variations in volatility of commodity returns. We perform a comprehensive analysis that involves several commodity indices, economic variables and sub-samples. Our empirical investigation leads to a number of interesting results. First, performing an extensive regression analysis we find that certain variables are consistently significant explanatory factors of short term commodity return volatility. Inflation volatility exhibits a strongly positive and significant causal effect on commodity return volatility across sub-samples and commodity sectors. Also, variables associated with liquidity risk and market stress conditions, such as the VIX, the default return spread and the TED spread appear to be important drivers of commodity volatility.

Second, we document a weakening role of economic fundamental factors in favour of financial market factors in the later part of our sample. This result has some important implications in the light of the accelerating financialization process in commodity markets documented in several recent studies. Controlling for variables motivated by commodity pricing theories, we find that these are important drivers of return volatility for some periods and commodity portfolios as well. This can be regarded as indirect evidence that even though commodity markets have become more integrated with traditional asset markets in the past few years, they are still relatively segmented from those markets.

Third, we assess the economic significance of the various explanatory factors based on the increase in the explanatory power by adding these variables in a specification that includes only volatility lags. Our evidence shows that the statistical and economic significance of the variables varies across commodity sectors. This can be explained by the heterogenous nature of commodities.

Fourth, a VAR analysis reveals strong bi-directional causal links between inflation volatility and commodity market volatility. In addition, this feedback analysis suggests that commodity return volatility has some predictive power for the volatility of real economic activity and exchange rates, which has important implications for economic policy.

Finally, we exploit the information from a unique dataset of survey expectations about economic fundamentals to construct empirical proxies of macroeconomic uncertainty. Our evidence shows that dispersion of beliefs among professional economic agents provides essential information for commodity return volatility. Furthermore, this information appears to be orthogonal to that already contained in current economic fundamentals.

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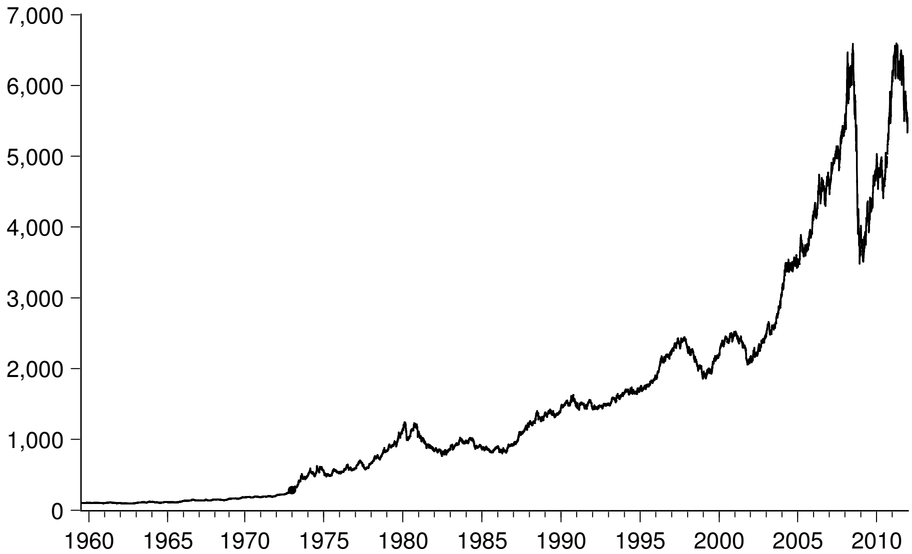

Figure 1: **Commodity futures return index**

This figure displays the time series of daily prices of the equally weighted fully-collateralized commodity futures index for the period from 6/7/1959 to 31/12/2011.

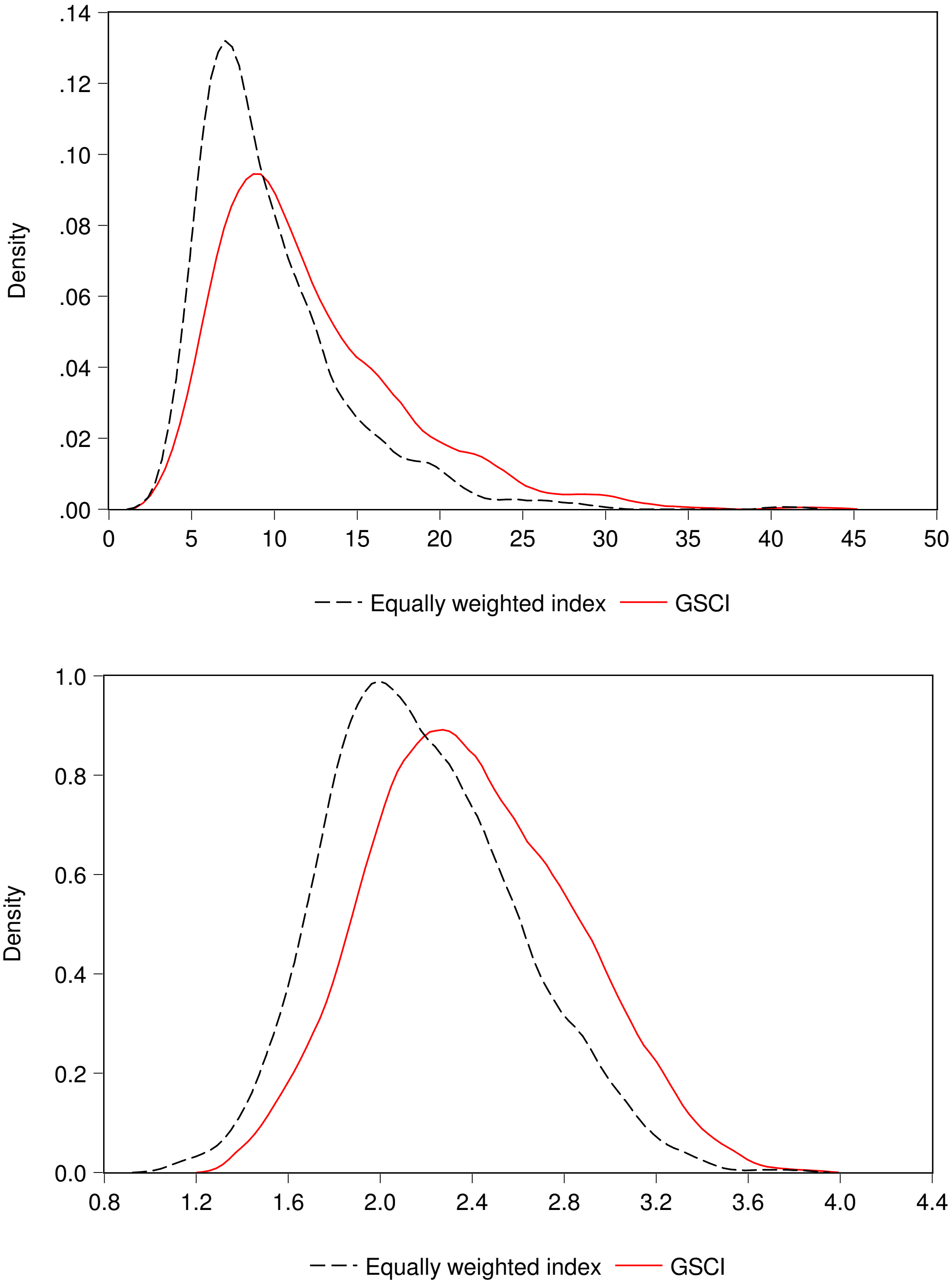

Figure 2: **Kernel density plots**

This figure illustrates kernel density plots for realized volatility estimates of the equally weighted commodity futures index (dashed line) and the equally weighted GSCI(Eq) index (solid line), respectively. The top panel refers to the level of realized volatility, while the bottom to its logarithm.

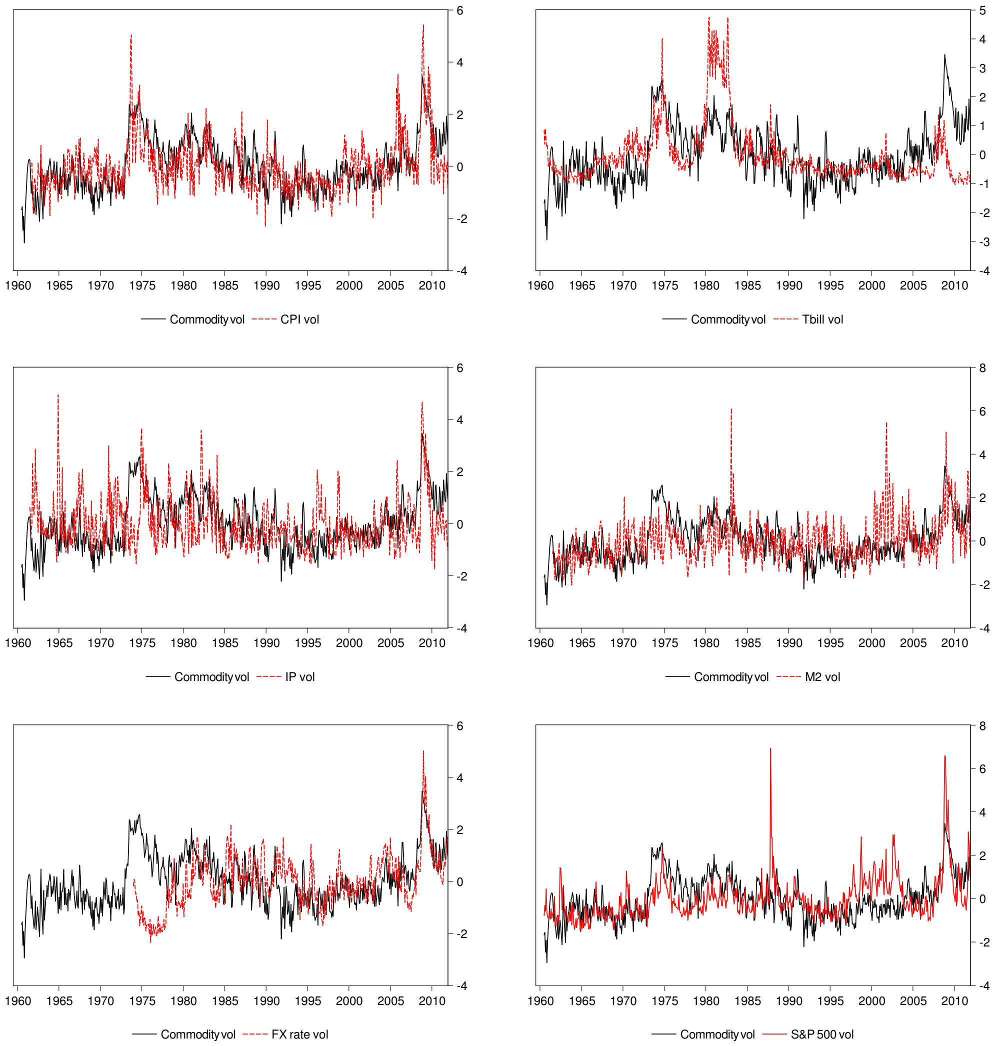

Figure 3: **Predictions of monthly volatilities for the equally weighted commodity index and macroeconomic variables.**

This figure displays predicted monthly volatilities of equally weighted commodity futures index against predicted volatilities of: CPI inflation, 3-month Tbill, Industrial production, M2 money supply, trade-weighted US dollar index and S&P 500 returns. All volatility series are standardized to facilitate comparisons. The period is July, 1959 to December, 2011.

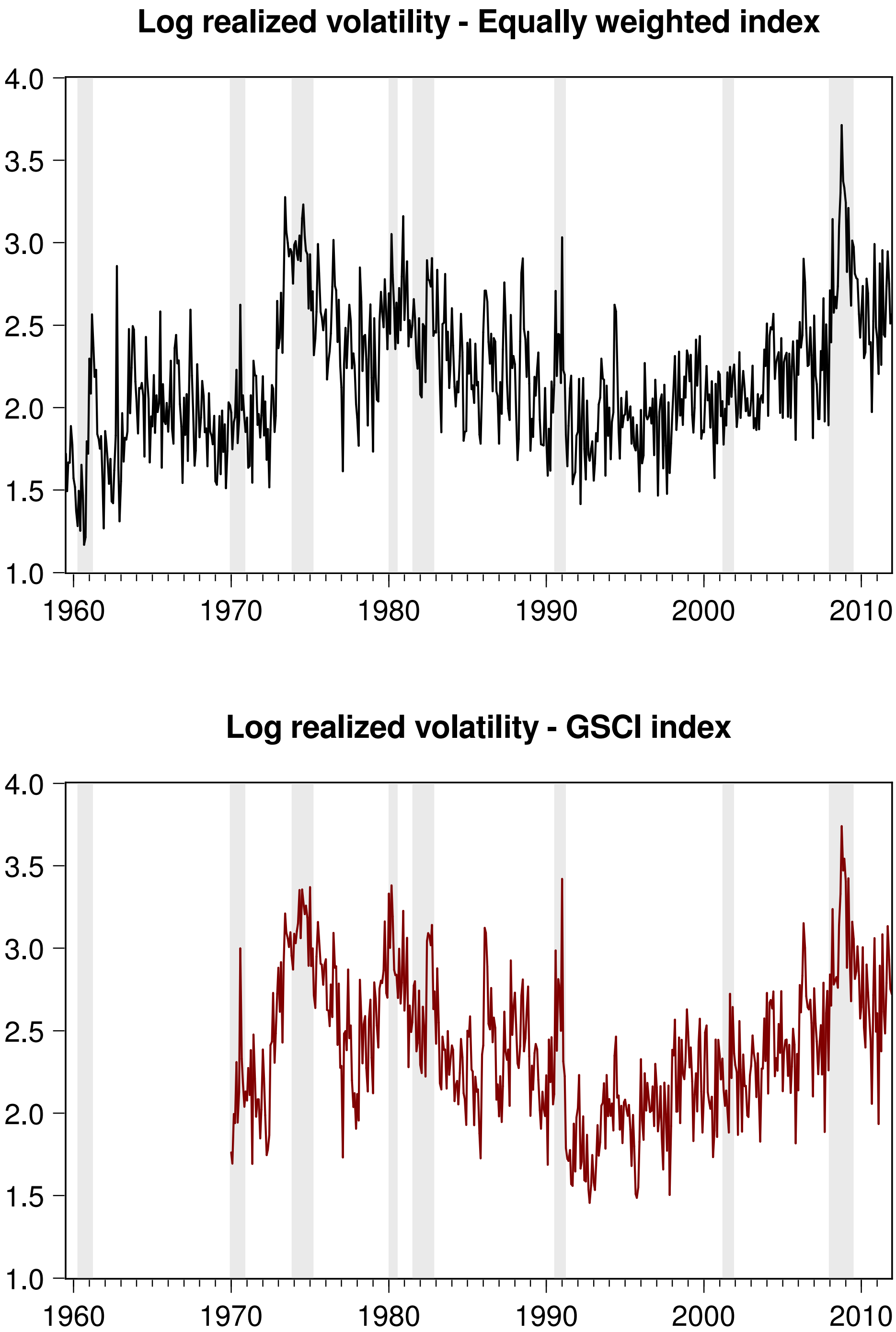

Figure 4: **Aggregate commodity volatility during recessions**

This figure displays time series plots of the logarithm of realized volatility for the equally weighted commodity index (upper panel) and the GSCI(Eq) index (lower panel) for the period July 1959 to December 2011. Superimposed on the graphs are NBER recession months (shaded areas).

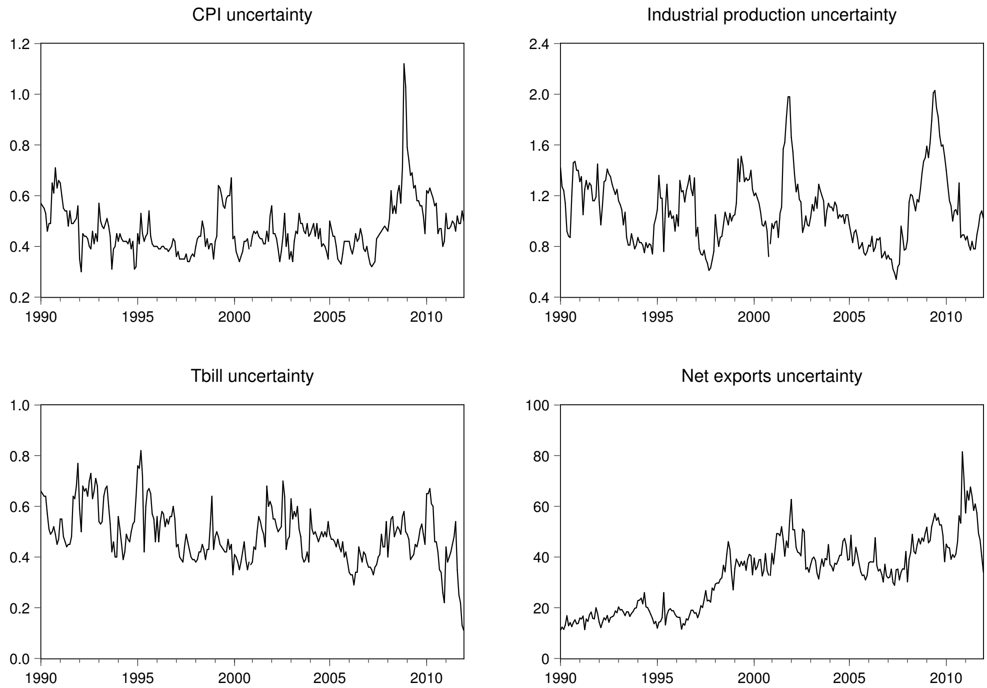

Figure 5: **Time series plots of dispersion of beliefs**

This figure displays the time series plots of short-term dispersion of beliefs of professional forecasters regarding the following economic series: Tbill, CPI, Industrial Production and Net Exports. The dispersion series is obtained as the cross-sectional standard deviation across expectations of individual forecasters over each month. The period under consideration is 1991-2011.

Table 1: **Commodity contracts used for index construction**

This table contains the commodity futures contracts used for the construction of the equally weighted and fully-collateralized commodity futures index and its corresponding sub-indices. All futures data were obtained from the Commodity Research Bureau (CRB). CME: Chicago Mercantile Exchange, NYMEX: New York Mercantile Exchange, ICE: Intercontinental Exchange, COMEX: Commodity Exchange and LME: London Metal Exchange.

Group	Commodity	Starting date	Exchange
Agricultural			
	Cocoa	06/07/1959	ICE
	Coffee	17/08/1972	ICE
	Corn	06/07/1959	CBOT
	Cotton	06/07/1959	ICE
	Lumber	02/10/1969	CME
	Oats	06/07/1959	CBOT
	Orange juice	02/02/1967	ICE
	Rough rice	06/07/1987	CBOT
	Soybean meal	06/07/1959	CBOT
	Soybean oil	06/07/1959	CBOT
	Soybeans	06/07/1959	CBOT
	Sugar	04/01/1961	ICE
	Wheat	06/07/1959	CBOT
Livestock			
	Feeder cattle	01/12/1971	CME
	Lean hogs	01/03/1966	CME
	Live cattle	01/12/1964	CME
	Milk	12/01/1996	CME
	Pork bellies	19/09/1961	CME
Energy			
	Coal	13/07/2001	NYMEX
	Crude oil (WTI)	31/03/1983	NYMEX
	Heating oil	05/09/1979	NYMEX
	Natural gas	05/04/1990	NYMEX
	Propane	24/08/1987	NYMEX
Metals			
	Aluminium	27/06/1994	LME
	Copper	06/07/1959	COMEX
	Gold	02/01/1975	COMEX
	Lead	27/06/1994	LME
	Nickel	27/06/1994	LME
	Palladium	04/01/1977	COMEX
	Platinum	05/03/1968	COMEX
	Silver	05/01/1965	COMEX
	Tin	27/06/1994	LME
	Zinc	27/06/1994	LME

Table 2: **Summary statistics of regressions for volatility prediction**

This table summarizes the results of regressions for volatility prediction. The estimated equation is:

$$RV_t = \sum_{i=1}^{12} \gamma_i D_i + \sum_{i=1}^{12} \phi_i |e_{t-i}| + a_t$$

where: RV_t stands for realized volatility and D_i are dummy variables to allow for different monthly intercepts. In those cases where daily observations are available, realized volatility (dependent variable) corresponds to the square root of the sum of squared daily returns (or growth rates in general) within each month as described in Eq. (4). For variables sampled monthly (e.g. CPI, IP, etc) realized volatilities are absolute values of residuals from an AR(12) regression with monthly dummies (Equation (5)). The third column reports the sum of the twelve AR coefficients which represents the persistence of the volatility process. Below the coefficients we report the t-statistics for the null hypothesis that the sum of AR coefficients is equal to unity (integrated variance), $\phi_1 + \phi_2 + ... + \phi_{12} = 1$. The fourth column reports results from an F-test for equality of the twelve monthly dummies (p-values in brackets), $\gamma_1 = \gamma_2 = ... = \gamma_{12}$. The fifth column contains results from testing the hypothesis that all AR coefficients are jointly equal to zero ($\phi_1 = \phi_2 = ... = \phi_{12} = 0$) with the corresponding p-values in brackets. The F-statistic follows a $\chi^2_{(12)}$ distribution. Q(24) denotes the Ljung-Box statistic (Ljung and Box, 1978) for serial correlation up to 24 lags with the associated p-values in brackets. The last column represent the R-squared of the regressions.

Volatility series	**Starting point**	**sum of AR coefs. (t-stat vs unity)**	**F-test equal monthly intercepts**	**F-test joint signif.of AR coefs**	**Q(24)**	**R-sq.**
Equally weighted index	Jul 59	0.89	1.73	72.89	8.12	60.00%
		(2.91)	(0.06)	(0.00)	(0.78)	
GSCI(Eq) index	Jan 71	0.86	1.72	67.61	7.34	61.60%
		(3.17)	(0.07)	(0.00)	(0.83)	
T-bill	Jul 59	0.60	1.42	41.25	31.34	55.40%
		(1.85)	(0.16)	(0.00)	(0.02)	
CPI	Jul 59	0.25	0.98	5.79	10.37	12.10%
		(4.28)	(0.46)	(0.00)	(0.58)	
IP	Jul 59	0.84	2.55	2.34	5.27	11.80%
		(7.45)	(0.00)	(0.00)	(0.95)	
M2	Jul 59	0.81	2.31	4.27	18.43	12.60%
		(4.54)	(0.01)	(0.00)	(0.10)	
FX index	Jan 75	0.86	1.87	24.82	18.1	49.10%
		(3.08)	(0.04)	(0.00)	(0.11)	
S&P 500	Jul 59	0.76	2.43	59.95	19.48	49.60%
		(2.98)	(0.01)	(0.00)	(0.08)	
Govt. bond yield	Jan 61	0.63	1.58	28.67	16.73	42.80%
		(2.72)	(0.10)	(0.00)	(0.16)	
Aaa bond yield	Jul 59	0.88	0.65	17.56	17.64	28.80%
		(-2.78)	(0.78)	(0.00)	(0.13)	

Table 3: **Correlations between aggregate commodity return volatility and macroeconomic volatility**

This table reports Spearman's rank order correlation coefficients between predicted volatility of the equally weighted commodity futures index and predicted macroeconomic volatilities for the periods: 1970–1990 and 1991-2011.

Series (symbol)	cmdvol	tbillvol	cpivol	ipvol	m2vol	fxvol	spvol	gvtvol	aaavol	vix
					1970-2011					
Eq. weighted index vol (cmdvol)	1.00									
	–									
T-bill vol (tbillvol)	0.31	1.00								
	(0.00)	–								
CPI vol (cpivol)	0.49	0.18	1.00							
	(0.00)	(0.00)	–							
IP vol (ipvol)	0.12	0.17	0.18	1.00						
	(0.01)	(0.00)	(0.00)	–						
M2 vol (m2vol)	0.19	0.04	0.23	0.05	1.00					
	(0.00)	(0.40)	(0.00)	(0.24)	–					
FX index vol (fxvol)	0.11	-0.05	0.07	0.05	0.18	1.00				
	(0.02)	(0.33)	(0.13)	(0.25)	(0.00)	–				
S&P 500 vol (spvol)	0.33	0.16	0.28	0.13	0.15	0.21	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	–			
Govt. bond yield vol (gvtvol)	0.13	0.34	0.08	0.11	0.19	0.33	0.24	1.00		
	(0.00)	(0.00)	(0.09)	(0.01)	(0.00)	(0.00)	(0.00)	–		
Aaa yield vol (aaavol)	0.16	0.21	0.10	0.00	0.16	0.19	0.22	0.61	1.00	
	(0.00)	(0.00)	(0.02)	(0.93)	(0.00)	(0.00)	(0.00)	(0.00)	–	
					1991-2011					
Commodity index vol (cmdvol)	1.00									
	–									
Tbill vol (tbillvol)	-0.09	1.00								
	(0.13)	–								
CPI vol (cpivol)	0.54	0.06	1.00							
	(0.00)	(0.36)	–							
IP growth vol (ipvol)	0.14	0.14	0.17	1.00						
	(0.02)	(0.03)	(0.01)	–						
M2 vol (m2vol)	0.28	-0.02	0.29	0.03	1.00					
	(0.00)	(0.73)	(0.00)	(0.62)	–					
FX index vol (fxvol)	0.46	0.01	0.26	0.22	0.28	1.00				
	(0.00)	(0.93)	(0.00)	(0.00)	(0.00)	–				
S&P 500 vol (spvol)	0.32	0.26	0.29	0.21	0.23	0.22	1.00			
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	–			
Govt. bond yield vol (gvtvol)	0.16	0.15	0.10	0.24	0.34	0.27	0.41	1.00		
	(0.01)	(0.02)	(0.10)	(0.00)	(0.00)	(0.00)	(0.00)	–		
Aaa yield vol (aaavol)	0.11	-0.06	0.06	0.02	0.15	-0.05	0.23	0.21	1.00	
	(0.09)	(0.34)	(0.34)	(0.77)	(0.02)	(0.41)	(0.00)	(0.00)	–	
VIX	0.22	0.10	0.17	0.16	0.17	0.15	0.82	0.29	0.26	1.00
	(0.00)	(0.11)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	–

Table 4: **Summary statistics of explanatory variables**

This table presents summary statistics for the explanatory variables. The period under consideration is 1970.01 - 2011.12. The first four central moments are reported for each series along with the autocorrelation coefficients of orders 1 and 12 (denoted ρ_1 and ρ_{12}, respectively) and the Ljung-Box Q statistic for autocorrelation up to 24 lags, denoted Q(24). Also, the table contains Phillips-Perron (1998) unit-root test statistics ($Z(t)$) with the associated p-values (MacKinnnon, 1994). Realized volatilities of variables sampled at daily frequency are computed as the square root of the sum of squared daily returns within each month. For the monthly sampled variables we applied the two step algorithm of Schwert (1989) described by Eq. (5) and (6). All volatility proxies are annualized and expressed as a percentage (multiplied by 100). The period for most macroeconomic variables is July, 1959 to December, 2011.

								Phillips - Perron test		
Variable	Mean	Std. Dev.	Skew	Kurt.	ρ_1	ρ_{12}	Q(24)	Z(t)	prob.	Obs.
A. *Macroeconomic*										
T-bill vol	1.08	0.99	2.71	11.51	0.90	0.63	3044.40	-7.27	0.00	492
CPI vol	0.71	0.26	1.59	7.40	0.61	0.30	1165.30	-12.68	0.00	492
IP vol	2.25	0.72	1.46	5.89	0.58	0.01	410.61	-11.35	0.00	492
M2 vol	0.88	0.31	1.59	8.03	0.47	0.30	557.49	-16.03	0.00	492
FX index vol	6.08	1.78	0.60	4.91	0.82	0.42	2286.30	-6.99	0.00	456
B. *Financial*										
S&P 500 vol	14.50	6.06	2.64	14.46	0.79	0.26	1386.70	-7.47	0.00	492
Govt bond yield vol	1.90	0.84	1.78	6.72	0.83	0.59	4343.50	-7.46	0.00	492
Aaa yield vol	0.68	0.35	1.57	5.67	0.86	0.57	4179.60	-5.58	0.00	492
VIX	20.54	7.91	1.53	6.66	0.85	0.38	1127.10	-4.38	0.00	264
Term spread	2.05	1.52	-0.64	3.25	0.95	0.47	3398.30	-3.63	0.00	492
Default spread	1.11	0.47	1.70	6.58	0.96	0.44	3513.00	-3.71	0.00	492
Default return spread	-0.02	1.46	-0.46	11.10	-0.04	-0.01	31.04	-23.28	0.00	492
TED spread	0.50	0.48	2.75	12.84	0.87	0.32	566.41	-3.18	0.02	140

Table 5: **Commodity volatility and the business cycle**

This table reports results from regressing realized volatilities of commodity returns and economic variables on a NBER recession dummy:

$$RV_t = a + \sum_{i=1}^{6} b_i RV_{t-i} + \gamma I_{NBER,t} + u_t \tag{14}$$

where: $I_{NBER,t}$ is an indicator variable that equals one for NBER recession months and zero otherwise. The last column ($\Delta\sigma(\%)$) contains the percentage increase in volatility during recessions compared to expansions. *, **, *** indicate significance at the 10%, 5% and 1%, respectively. Newey-West (1987) corrected standard errors were used for the estimations with 12 lags.

Dependent	**Sample**	**Obs.**	γ	t_γ	$\boldsymbol{\Delta\sigma}$**(%)**
Eq. weight. index vol.	07/1959-12/2011	624	0.11**	2.46	49.11
GSCI(Eq) vol	01/1970-12/2011	461	0.23***	3.05	47.02
Agricultural vol	07/1959-12/2011	624	0.08	1.52	27.33
Livestock vol	01/1966-12/2011	546	0.06	1.38	23.1
Metals vol	01/1968-12/201	522	0.24***	2.58	57.38
CPI vol	07/1959-12/2011	612	0.03***	2.85	72.46
IP vol	07/1959-12/2011	612	0.02**	2.09	42.01
T-bill vol	07/1959-12/2011	624	0.03	0.78	159.95
M2 vol	07/1959-12/2011	612	0.03**	2.49	57.56
FX rate vol	01/1975-12/2011	462	0.05	1.45	22.92
S&P 500 vol	07/1959-12/2013	624	0.20**	2.17	58.09
Govt. bond vol	01/1963-12/2011	594	0.04**	2.15	70.73
Aaa yield vol	07/1959-12/2011	612	0.01	1.64	69.15

Table 6: **Predictive regressions for volatility of the equally weighted commodity index**

This table presents results from in-sample regressions of log realized volatility of the equally weighted commodity futures index on various macroeconomic, financial and commodity-specific variables. The estimated model is:

$$\tilde{RV}_t = a + \gamma X_{i,t-1} + \sum_{j=1}^{6} b_j \tilde{RV}_{t-j} + e_t$$

where $\tilde{RV}_t$ is the logarithm of realized volatility (computed by Equation (4)) of an equally weighted index of all major commodities traded in the US market, $X_{i,t-1}$ is the scalar value of predictor i in month $t-1$ obtained by Eq. (6) for volatility variables. We include 6 lags on the right side of the equation to account for the persistence of the realized volatility process. The equations refer to one-by-one estimations against each variable. Columns (2) to (4) contain the results for the full sample period spanning 1970.01 to 2011.12. The remaining columns of the table report estimation results for sub-samples of the entire sample period. All variables are standardized prior to the estimations using the sample mean and standard deviation. We report for each forecasting variable the estimated coefficient (γ) for each explanatory variable along with the change in the adjusted R-square (denoted $\Delta\bar{R}^2$) relative to an AR(6) specification that serves as a benchmark. Newey-West (1987) corrected standard errors were employed for the estimations (with 12 lags). *, **, and *** indicate significance at the 10%, 5% and 10% level, respectively.

	Entire sample 1970-2011			*Sub-sample 1* 1970-1990			*Sub-sample 2* 1991-2011			*Sub-sample 3* 2001-2011		
Variable	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$
S&P 500 vol	0.04	1.17	0.02	0.01	0.28	-0.21	0.08*	1.85	0.27	0.04	0.57	-0.26
T-bill vol	0.03	1.45	0.00	0.04	0.88	-0.11	0.06	0.81	0.12	0.11	1.38	0.86
Govt bond yield vol	0.00	0.17	-0.09	-0.03	-0.62	-0.14	0.09**	2.05	0.49	0.03	0.59	-0.29
Aaa yield vol	-0.01	-0.20	-0.09	-0.01	-0.17	-0.21	0.00	-0.02	-0.18	-0.03	-0.36	-0.28
FX index vol	-	-	-	-	-	-	0.02	0.45	-0.16	0.03	0.41	-0.32
CPI vol	0.15***	4.30	1.50	0.17***	3.12	1.96	0.14***	3.15	0.97	0.08*	1.88	0.10
IP vol	0.01	0.25	-0.09	-0.05	-1.12	0.03	0.05	1.20	0.05	0.07	1.04	-0.02
M2 vol	0.03	1.16	-0.02	0.01	0.16	-0.22	0.06*	1.78	0.14	0.03	0.67	-0.27
Term spread	-0.02	-0.87	-0.04	-0.07*	-1.95	0.20	0.03	0.87	-0.11	0.02	0.47	-0.31
Default spr.	0.02	0.48	-0.07	-0.03	-0.53	-0.14	0.04	0.84	-0.09	-0.01	-0.09	-0.37
Default return spr.	-0.05**	-1.99	0.24	-0.07**	-2.00	0.33	-0.06	-1.29	0.21	-0.12**	-2.05	0.99
TED spread	-	-	-	-	-	-	0.07	1.34	0.30	0.17***	2.84	1.93
VIX	-	-	-	-	-	-	0.13**	2.39	1.17	0.17**	1.99	2.11
IP growth	0.00	-0.08	-0.09	0.05	1.20	0.00	-0.10*	-1.85	0.64	-0.13*	-1.84	1.05
OI	-	-	-	-	-	-	0.09**	2.50	0.63	0.10**	2.01	0.53
HP (hedgers)	-	-	-	-	-	-	0.09***	2.59	0.70	0.07**	2.05	0.14
HP (specul.)	-	-	-	-	-	-	0.05	1.35	0.06	0.09**	2.29	0.36
Basis	-0.05	-0.86	-0.01	0.04	0.54	-0.14	-0.23***	-3.13	0.90	-0.26***	-3.25	1.38

Table 7: **Predictive regressions for the realized volatility of agricultural sub-index**

This table reports results from regressions of realized return volatility of an equally weighted index of agricultural commodities on various macroeconomic, financial and commodity-specific variables. The estimated regression is given by Eq. (8). Realized commodity volatility of each month is computed as the square root of the sum of squared daily returns within each month. The logarithm of commodity return volatility is considered for the estimations. We include 6 lags on the right side of the equation to model the persistence of the realized volatility process. This number of lags is also sufficient to eliminate the autocorrelation in regression residuals. The equations refer to one-by-one estimations against each variable. The estimations are performed on the full sample period (1970.01 to 2011.12) as well as on various sub-samples. All variables are standardized before the estimations. We report for each explanatory variable the estimated coefficient (γ) together with its t-statistic and the change in the adjusted R-square ($\Delta\bar{R}^2$) relative to an AR(6) specification that serves as a benchmark. Newey-West (1987) corrected standard errors were employed for the estimations (with 12 lags). *, **, and *** indicate significance at the 10%, 5% and 10% level, respectively.

	Entire sample 1970-2011			*Sub-sample 1* 1970-1990			*Sub-sample 2* 1991-2011			*Sub-sample 3* 2001-2011		
Variable	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$
S&P 500 vol	0.07**	2.26	0.32	0.01	0.21	-0.23	0.13***	3.13	1.05	0.09*	1.78	0.28
T-bill vol	0.01	0.35	-0.11	0.01	0.30	-0.23	0.02	0.22	-0.21	0.06	0.67	-0.04
Govt bond yield vol	-0.02	-0.80	-0.07	-0.06	-1.58	0.17	0.10**	2.18	0.74	0.06	1.03	-0.16
Aaa yield vol	-0.01	-0.30	-0.11	-0.03	-0.66	-0.16	0.04	0.92	-0.11	0.04	0.48	-0.30
FX index vol	-	-	-	-	-	-	0.12**	2.30	0.78	0.15	1.63	0.71
CPI vol	0.18***	4.93	2.53	0.16***	3.58	2.13	0.21***	3.16	2.75	0.08	1.13	0.12
IP vol	0.01	0.29	-0.11	-0.02	-0.45	-0.19	0.05	1.05	-0.04	0.04	0.55	-0.32
M2 vol	0.08***	2.83	0.51	0.03	0.82	-0.13	0.12***	2.96	1.12	0.08	1.27	0.14
Term spread	0.01	0.37	-0.11	-0.04	-1.16	-0.11	0.06**	2.00	0.16	0.05	1.19	-0.24
Default spr.	0.03	0.82	-0.05	-0.04	-0.93	-0.08	0.15**	2.50	1.07	0.08	1.10	-0.06
Default return spr.	-0.04	-1.36	0.09	-0.04	-1.01	-0.04	-0.06	-1.11	0.10	-0.14**	-2.04	1.59
TED spread	-	-	-	-	-	-	0.05	0.82	-0.04	0.13**	2.11	1.05
VIX	-	-	-	-	-	-	0.10*	1.87	0.59	0.13*	1.82	1.19
IP growth	0.00	0.08	-0.12	0.05	1.17	0.04	-0.08	-1.27	0.34	-0.12	-1.36	0.89
OI	-	-	-	-	-	-	0.02	0.42	-0.21	0.00	0.00	-0.45
HP (hedgers)	-	-	-	-	-	-	0.05	1.21	0.03	0.10	1.63	0.59
HP (specul.)	-	-	-	-	-	-	0.05	1.07	-0.04	0.12**	2.04	0.72
Basis	-0.06*	-1.76	0.42	-0.12***	-2.81	1.51	-0.15***	-2.58	0.85	0.05	0.98	-0.16

Table 8: **Predictive regressions for the realized volatility of livestock sub-index**

This table reports results from in-sample regressions of realized return volatility of an equally weighted index of animal commodities on various macroeconomic, financial and commodity-specific variables. The estimated regression is given by Eq. (8). Realized commodity volatility of each month is computed as the square root of the sum of squared daily returns within each month. The logarithm of commodity return volatility is considered for the estimations. We include 6 lags on the right side of the equation to model the persistence of the realized volatility process. Ex post, this number of lags proves to eliminates the autocorrelation in regression residuals. The equations refer to one-by-one estimations against each variable. The estimations are performed on the full sample period (1970.01 to 2011.12) as well as on various sub-samples. All variables are standardized before the estimations. We report for each explanatory variable the estimated coefficient (γ) together with its t-statistic and the change in the adjusted R-square ($\Delta\bar{R}^2$) relative to an AR(6) specification that serves as a benchmark. Newey-West (1987) corrected standard errors were employed for the estimations (with 12 lags). *, **, and *** indicate significance at the 10%, 5% and 10% level, respectively.

	Entire sample 1970-2011			*Sub-sample 1* 1970-1990			*Sub-sample 2* 1991-2011			*Sub-sample 3* 2001-2011		
Variable	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$
S&P 500 vol	0.04*	1.76	0.06	0.04	1.51	-0.04	0.10**	2.48	0.69	0.12	1.46	0.87
T-bill vol	0.06***	2.59	0.18	0.03	1.09	-0.11	0.02	0.36	-0.26	0.04	0.42	-0.54
Govt bond yield vol	0.02	0.74	-0.06	0.00	-0.07	-0.19	0.09*	1.66	0.41	0.14*	1.83	1.37
Aaa yield vol	0.00	-0.02	-0.10	-0.01	-0.32	-0.18	0.00	-0.01	-0.29	0.04	0.86	-0.50
FX index vol	-	-	-	-	-	-	0.10**	2.34	0.57	0.16*	1.95	1.34
CPI vol	0.09***	2.91	0.72	0.14***	4.05	1.49	0.07	1.42	0.23	0.05	0.60	-0.39
IP vol	0.00	0.12	-0.10	-0.07	-1.63	0.26	0.10***	2.68	0.77	0.17***	3.01	2.47
M2 vol	0.01	0.38	-0.09	0.01	0.37	-0.18	0.04	0.50	-0.16	0.11	1.20	0.65
Term spread	-0.05	-1.61	0.16	-0.07*	-1.83	0.36	0.02	0.33	-0.25	0.18**	1.99	1.81
Default spr.	0.03	0.81	-0.04	-0.02	-0.46	-0.15	0.07*	1.82	0.21	0.12**	2.10	0.83
Default return spr.	-0.02	-0.47	-0.08	0.04	0.73	-0.05	-0.07	-1.47	0.20	-0.16**	-2.20	2.12
TED spread	-	-	-	-	-	-	0.04	0.76	-0.15	0.04	0.48	-0.52
VIX	-	-	-	-	-	-	0.14***	2.71	1.51	0.16*	1.94	2.33
IP growth	-0.07**	-2.06	0.32	0.00	0.10	-0.19	-0.18***	-4.03	2.98	-0.17*	-1.74	2.78
OI	-	-	-	-	-	-	-0.04	-0.71	-0.13	-0.06	-0.68	-0.30
HP (hedgers)	-	-	-	-	-	-	-0.14***	-2.58	1.63	-0.04	-0.53	-0.47
HP (specul.)	-	-	-	-	-	-	-0.17***	-2.97	2.50	-0.16*	-1.81	2.19
Basis	0.00	0.09	-0.10	0.04	0.76	-0.06	-0.02	-0.31	-0.25	-0.17**	-2.04	2.83

Table 9: **Predictive regressions for the realized volatility of energy sub-index**

This table reports results from in-sample regressions of realized return volatility of an equally weighted portfolio of energy commodities on various macroeconomic, financial and commodity-specific variables. Results are not reported for the first two sample periods because prices for most energy commodities become available after '80s, time that corresponds to their date of inclusion in the index (see table 1). Realized commodity volatility of each month is computed as the square root of the sum of squared daily returns within each month. The logarithm of commodity return volatility is considered for the estimations. We include 6 lags on the right side of the equation to model the persistence of the realized volatility process. Ex-post this number of lags is adequate to eliminate the autocorrelation in regression residuals. The equations refer to one-by-one estimations against each variable. The estimations are performed on the full sample period (1970.01 to 2011.12) as well as on various sub-samples. All variables are standardized before the estimations. We report for each explanatory variable the estimated coefficient (γ) together with its t-statistic and the change in the adjusted R-square ($\Delta\bar{R}^2$) relative to an AR(6) specification that serves as a benchmark. Newey-West (1987) corrected standard errors were employed for the estimations (with 12 lags). *, **, and *** indicate significance at the 10%, 5% and 10% level, respectively.

	Entire sample *1970-2011*			*Sub-sample 1* *1970-1990*			*Sub-sample 2* *1991-2011*			*Sub-sample 3* *2001-2011*		
Variable	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$
S&P 500 vol	-	-	-	-	-	-	0.10*	1.87	0.58	0.10	1.34	0.40
T-bill vol	-	-	-	-	-	-	0.09*	1.74	0.75	0.20**	2.13	3.32
Govt bond yield vol	-	-	-	-	-	-	0.05	1.17	0.05	0.11***	2.79	0.51
Aaa yield vol	-	-	-	-	-	-	0.01	0.23	-0.22	0.01	0.26	-0.52
FX index vol	-	-	-	-	-	-	-0.01	-0.25	-0.21	0.00	0.03	-0.53
CPI vol	-	-	-	-	-	-	0.07	0.96	0.12	0.05	0.56	-0.35
IP vol	-	-	-	-	-	-	0.06	1.23	0.17	0.09	1.08	0.21
M2 vol	-	-	-	-	-	-	0.06	1.08	0.07	0.06	0.80	-0.18
Term spread	-	-	-	-	-	-	-0.04	-1.07	-0.03	0.04	0.71	-0.38
Default spr.	-	-	-	-	-	-	0.07	1.39	0.11	0.09	1.22	-0.02
Default return spr.	-	-	-	-	-	-	-0.10***	-2.98	0.82	-0.15***	-2.84	1.44
TED spread	-	-	-	-	-	-	0.08	1.35	0.38	0.16*	1.89	1.78
VIX	-	-	-	-	-	-	0.18***	3.10	2.77	0.17**	2.05	2.15
IP growth	-	-	-	-	-	-	-0.06	-1.45	0.15	-0.12*	-1.95	0.71
OI	-	-	-	-	-	-	0.06*	1.71	0.13	0.05	0.74	-0.38
HP (hedgers)	-	-	-	-	-	-	0.02	0.44	-0.18	0.02	0.22	-0.51
HP (specul.)	-	-	-	-	-	-	0.00	0.10	-0.22	0.02	0.32	-0.51
Basis	-	-	-	-	-	-	-0.16***	-2.67	2.07	-0.04	-0.62	-0.29

Table 10: **Predictive regressions for the realized volatility of metals**

This table reports results from in-sample regressions of realized return volatility of an equally weighted portfolio of metals on various macroeconomic, financial and commodity-specific variables. The estimated regression is given by Eq. (8). Realized commodity volatility of each month is computed as the square root of the sum of squared daily returns within each month. The logarithm of commodity return volatility is considered for the estimations. We include 6 lags on the right side of the equation to model the persistence of the realized volatility process. Ex-post this number of lags turns out to be adequate to eliminate the autocorrelation in regression residuals. The equations refer to one-by-one estimations against each variable. The estimations are performed on the full sample period (1970.01 to 2011.12) as well as on various sub-samples. All variables are standardized before the estimations. We report for each explanatory variable the estimated coefficient (γ) together with its t-statistic and the change in the adjusted R-square ($\Delta\bar{R}^2$) relative to an AR(6) specification that serves as a benchmark. Newey-West (1987) corrected standard errors were employed for the estimations (with 12 lags). *, **, and *** indicate significance at the 10%, 5% and 10% level, respectively.

	Entire sample 1970-2011			*Sub-sample 1* 1970-1990			*Sub-sample 2* 1991-2011			*Sub-sample 3* 2001-2011		
Variable	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$
S&P 500 vol	0.01	0.32	-0.08	0.02	0.59	-0.19	0.03	0.65	-0.10	0.02	0.37	-0.30
T-bill vol	0.07**	2.16	0.23	0.12**	2.06	0.63	0.05	0.95	0.08	0.07	1.14	0.20
Govt bond yield vol	0.02	0.58	-0.05	0.03	0.50	-0.16	0.04	0.90	-0.04	0.02	0.31	-0.32
Aaa yield vol	-0.01	-0.24	-0.08	0.03	0.49	-0.16	-0.04	-1.01	-0.01	-0.08	-1.31	0.22
FX index vol	-	-	-	-	-	-	0.02	0.44	-0.14	0.04	0.91	-0.20
CPI vol	0.08***	2.94	0.39	0.06	1.23	0.05	0.13***	3.49	1.00	0.11***	3.07	0.74
IP vol	-0.01	-0.21	-0.08	-0.08	-1.56	0.40	0.06*	1.76	0.22	0.11**	2.45	0.80
M2 vol	0.02	0.68	-0.05	-0.05	-1.10	-0.01	0.09*	1.93	0.59	0.06	0.97	0.00
Term spread	-0.03	-1.15	0.02	-0.09*	-1.91	0.50	0.03	0.80	-0.07	-0.01	-0.22	-0.33
Default spr.	0.02	0.46	-0.06	-0.01	-0.09	-0.23	0.03	1.02	-0.10	-0.01	-0.14	-0.34
Default return spr.	-0.04	-1.13	0.04	0.00	0.07	-0.23	-0.08	-1.58	0.39	-0.10	-1.61	0.67
TED spread	-	-	-	-	-	-	0.03	0.57	-0.11	0.07*	1.68	0.12
VIX	-	-	-	-	-	-	0.07	1.41	0.32	0.11*	1.74	0.97
IP growth	-0.03	-0.79	-0.01	-0.01	-0.14	-0.23	-0.08	-1.64	0.41	-0.07	-1.01	0.16
OI	0.08***	3.21	2.00	0.12***	3.50	-0.77	0.09***	2.83	0.66	0.07**	1.99	0.22
HP (hedgers)	0.12***	3.74	2.50	0.22***	2.83	-1.57	0.11***	2.97	0.90	0.07	1.21	0.10
HP (specul.)	-	-	-	-	-	-	0.10***	2.58	0.52	0.08	1.31	0.10
Basis	0.04**	2.18	0.06	0.06**	2.06	0.05	0.02	0.56	-0.13	0.06	1.38	0.05

Table 11: **Predictive regressions for the volatility of the GSCI index**

This table presents results from regressions of the logarithm of realized return volatility of the Goldman Sachs Commodity Index (GSCI) against macroeconomic financial and commodity-specific variables. The results correspond to univariate regressions against each individual predictor. Instead of using the returns of the standard GSCI index which is dominated by energy commodities, we consider an equally-weighted variant of it by taking the average daily return across all its sub-indices comprised of agricultural, livestock, energy commodities and metals. The estimations are performed for the full sample period 1970.01 - 2011.12 as well as for various sub-periods. All variables are standardized before the estimation. We report for each explanatory variable the estimated coefficient (γ) together with its t-statistic and the change in the adjusted R-square ($\Delta\bar{R}^2$) relative to an AR(6) specification that serves as a benchmark. Newey-West (1987) corrected standard errors were employed for the estimations (with 12 lags). *, **, and *** indicate significance at the 10%, 5% and 10% level, respectively.

	Entire sample 1970-2011			*Sub-sample 1 1970-1990*			*Sub-sample 2 1991-2011*			*Sub-sample 3 2001-2011*		
Variable	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$	γ	t_γ	$\Delta\bar{R}^2$
S&P 500 vol	0.04	1.34	0.04	0.04	1.27	-0.03	0.07	1.63	0.18	0.08	0.97	0.05
T-bill vol	0.03	1.03	-0.02	0.02	0.34	-0.18	0.03	0.55	-0.05	0.10	1.19	0.58
Govt bond yield vol	-0.01	-0.41	-0.07	-0.05	-1.26	0.06	0.06	1.34	0.15	0.03	0.51	-0.36
Aaa yield vol	-0.02	-0.82	-0.03	-0.03	-0.79	-0.08	-0.02	-0.48	-0.13	-0.04	-0.53	-0.30
FX index vol	-	-	-	-	-	-	-0.01	-0.21	-0.16	0.03	0.37	-0.41
CPI vol	0.13***	3.99	1.02	0.14***	2.80	1.42	0.13***	2.95	0.91	0.13*	1.97	0.79
IP vol	0.00	-0.11	-0.08	-0.06	-1.20	0.12	0.04	0.84	-0.04	0.10	1.27	0.46
M2 vol	0.01	0.49	-0.07	-0.02	-0.59	-0.15	0.05	1.62	0.09	0.04	0.90	-0.29
Term spread	-0.05**	-2.06	0.18	-0.09**	-2.28	0.59	-0.01	-0.41	-0.15	-0.01	-0.12	-0.44
Default spr.	0.00	-0.04	-0.08	-0.05	-0.89	0.02	0.02	0.64	-0.14	0.02	0.24	-0.43
Default return spr.	-0.06**	-2.39	0.30	-0.07*	-1.79	0.25	-0.07*	-1.82	0.39	-0.15***	-2.65	1.83
TED spread	-	-	-	-	-	-	0.05	0.91	0.03	0.18***	2.59	2.00
VIX	-	-	-	-	-	-	0.14***	3.09	1.55	0.19**	2.31	3.03
IP growth	-0.01	-0.20	-0.08	0.04	1.24	-0.01	-0.08*	-1.85	0.47	-0.13*	-1.93	1.27
OI	0.09***	3.70	1.41	0.08**	2.02	1.94	0.10***	2.64	0.84	0.10*	1.91	0.51
HP (hedgers)	0.09***	3.25	0.77	0.11***	3.01	1.36	0.09**	2.37	0.66	0.08**	2.02	0.14
HP (specul.)	-	-	-	-	-	-	0.05	1.25	0.12	0.10**	2.24	0.54
Basis	-0.02	-0.40	-0.07	0.05	0.78	-0.08	-0.13*	-1.76	0.22	-0.19**	-1.98	0.54

Table 12: **Estimates of the relationship between commodity return volatility and macroeconomic variables**

This table reports results from regressions where the logarithm of realized commodity return volatility is regressed on lagged macroeconomic volatility proxies. Columns (2) and (7) report estimation results for the volatilities of the equally-weighted commodity index and GSCI index, respectively. Columns (3) to (6) display results for the realized volatilities of the equally-weighted sectoral commodity indices. The estimations are performed for the full sample period 1970.01 - 2011.12 and over three sub-samples: 1970.01-1990.12, 1991.01-2011.12 and 2001.01-2011.12. The row denoted $\Delta\bar{R}^2$ contains the percentage change in the adjusted R^2 of an AR(6) model after including the macroeconomic volatility proxies. The Newey-West corrected t-statistics (with 12 lags) are reported in brackets below each coefficient. *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variable	**Eq. weighted**	**Agricultural**	**Livestock**	**Energy**	**Metals**	**GSCI(Eq)**
			1970-2011			
T-bill vol	0.04*	-0.01	0.05**	-	0.08**	0.04
	(1.89)	(-0.38)	(2.31)	-	(2.45)	(1.48)
CPI vol	0.16***	0.18***	0.10***	-	0.09***	0.14***
	(4.38)	(4.61)	(3.15)	-	(2.95)	(4.06)
IP vol	-0.02	-0.03	-0.02	-	-0.03	-0.03
	(-0.78)	(-0.89)	(-0.79)	-	(-1.00)	(-1.05)
M2 vol	0.01	0.05	-0.01	-	0.01	-0.01
	(0.34)	(1.46)	(-0.35)	-	(0.27)	(-0.20)
$\Delta\bar{R}^2$	*1.40*	*2.50*	*0.70*		*0.60*	*0.90*
			1970-1990			
T-bill vol	0.04	-0.02	0.02	-	0.14**	0.03
	(1.13)	(-0.59)	(0.59)	-	(2.41)	(0.57)
CPI vol	0.18***	0.17***	0.15***	-	0.07	0.16***
	(3.25)	(3.42)	(4.62)	-	(1.60)	(3.02)
IP vol	-0.07	-0.04	-0.08*	-	-0.10**	-0.07
	(-1.65)	(-0.83)	(-1.88)	-	(-1.99)	(-1.52)
M2 vol	-0.02	0.01	-0.01	-	-0.05	-0.04
	(-0.49)	(0.17)	(-0.19)	-	(-1.04)	(-1.08)
$\Delta\bar{R}^2$	*1.90*	*1.70*	*1.50*		*1.50*	*1.50*
			1991-2011			
T-bill vol	0.04	-0.03	-0.01	0.09*	0.02	0.02
	(0.57)	(-0.32)	(-0.27)	(1.91)	(0.47)	(0.33)
CPI vol	0.13**	0.18***	0.02	0.14**	0.10**	0.13**
	(2.53)	(2.84)	(0.32)	(1.99)	(2.06)	(2.54)
IP vol	0.02	-0.00	0.08*	0.04	0.03	0.01
	(0.42)	(-0.02)	(1.73)	(0.69)	(0.86)	(0.21)
M2 vol	0.04	0.08*	-0.00	0.03	0.07	0.04
	(0.98)	(1.85)	(-0.00)	(0.48)	(1.33)	(1.04)
FX index vol	-0.01	0.05	0.06	-0.05	-0.04	-0.05
	(-0.12)	(0.79)	(0.91)	(-0.90)	(-0.77)	(-0.97)
$\Delta\bar{R}^2$	*0.70*	*2.70*	*0.00*	*2.00*	*1.00*	*0.50*
			2001-2011			
T-bill vol	0.10	0.04	-0.03	0.20**	0.04	0.08
	(1.31)	(0.44)	(-0.37)	(2.33)	(0.73)	(0.90)
CPI vol	0.05	0.05	-0.07	0.08	0.07	0.09
	(0.85)	(0.68)	(-0.82)	(0.81)	(1.25)	(1.31)
IP vol	0.03	-0.01	0.17**	0.06	0.08	0.06
	(0.47)	(-0.20)	(2.03)	(0.57)	(1.39)	(0.70)
M2 vol	0.01	0.04	0.07	0.05	0.04	0.03
	(0.25)	(0.58)	(0.73)	(0.58)	(0.62)	(0.51)
FX index vol	0.03	0.12	0.09	0.04	-0.03	-0.01
	(0.29)	(1.08)	(0.84)	(0.39)	(-0.38)	(-0.11)
$\Delta\bar{R}^2$	*-0.10*	*-0.50*	*1.10*	*3.30*	*0.30*	*0.10*

Table 13: **Estimates of regressions between commodity return volatility and financial/commodity-specific variables**

This table reports results from regressions where the logarithm of realized commodity return volatility is regressed on lagged financial and commodity specific variables. The row denoted $\Delta\bar{R}^2$ contains the percentage change in the adjusted R^2 of an AR(6) model after including the macroeconomic volatility proxies. The Newey-West corrected t-statistics (with 12 lags) are reported in brackets below each coefficient. *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variable	**Eq. weighted**	**Agricultural**	**Livestock**	**Energy**	**Metals**	**GSCI(Eq)**
			1970-2011			
S&P 500 vol	0.04	0.09**	0.06**	-	0.02	0.05*
	(1.49)	(2.54)	(2.15)	-	(0.58)	(1.94)
Aaa vol	-0.01	0.00	-0.01	-	-0.02	-0.03
	(-0.22)	(0.03)	(-0.28)	-	(-0.44)	(-0.91)
Term spread	-0.03	0.02	-0.06*	-	-0.02	-0.06**
	(-0.99)	(0.55)	(-1.70)	-	(-0.74)	(-2.34)
Default return	-0.06**	-0.04	-0.00	-	-0.03	-0.05**
	(-2.04)	(-1.34)	(-0.13)	-	(-1.02)	(-2.10)
Basis	-0.04	-0.10**	-0.05	-	0.05	-0.03
	(-0.92)	(-2.44)	(-1.64)	-	(1.48)	(-0.70)
$\Delta\bar{R}^2$	*0.00*	*1.00*	*0.30*	-	*0.00*	*0.40*
			1970-1990			
S&P 500 vol	0.01	0.02	0.04	-	0.03	0.07*
	(0.16)	(0.47)	(1.45)	-	(1.04)	(1.97)
Aaa vol	0.02	0.03	-0.02	-	0.04	-0.04
	(0.57)	(0.63)	(-0.42)	-	(0.69)	(-0.77)
Term spread	-0.05	-0.02	-0.09*	-	-0.09*	-0.10**
	(-1.35)	(-0.59)	(-1.92)	-	(-1.68)	(-2.38)
Default return	-0.09*	-0.03	0.05	-	0.02	-0.06**
	(-2.45)	(-0.78)	(0.87)	-	(0.37)	(-2.25)
Basis	-0.03	-0.14***	-0.04	-	0.07	-0.03
	(-0.46)	(-2.89)	(-0.74)	-	(1.30)	(-0.48)
$\Delta\bar{R}^2$	*-0.10*	*0.60*	*0.50*	-	*0.20*	*0.70*
			1991-2011			
VIX	0.18**	0.10*	0.13**	0.26***	0.11**	0.21***
	(2.56)	(1.70)	(2.30)	(4.03)	(1.99)	(3.75)
Aaa vol	-0.05	0.02	-0.03	-0.04	-0.05	-0.08**
	(-1.08)	(0.46)	(-0.33)	(-0.74)	(-1.26)	(-2.01)
Term spread	-0.03	0.05	0.06	-0.06	0.00	-0.09***
	(-0.90)	(1.20)	(0.98)	(-1.35)	(0.00)	(-2.66)
Default return	-0.03	-0.05	-0.04	-0.02	-0.06	-0.03
	(-0.71)	(-1.04)	(-0.98)	(-0.61)	(-1.41)	(-0.86)
Basis	-0.02	-0.03	-0.15***	-0.16***	-0.03	0.01
	(-0.44)	(-0.62)	(-3.19)	(-4.13)	(-0.78)	(0.15)
HP (hedg.)	0.13**	0.05	-0.06	0.01	0.13***	0.16***
	(2.59)	(1.03)	(-1.08)	(0.29)	(2.60)	(3.46)
$\Delta\bar{R}^2$	*1.80*	0.41	*2.60*	*6.20*	*1.70*	*2.90*
			2001-2011			
VIX	0.22**	0.08	0.10	0.22**	0.23***	0.26***
	(2.16)	(0.90)	(0.89)	(2.51)	(3.79)	(3.10)
AAA vol	-0.06	0.05	-0.01	-0.05	-0.11*	-0.07
	(-0.72)	(0.64)	(-0.08)	(-0.80)	(-1.96)	(-1.05)
Term spread	-0.09	0.02	0.23**	0.00	-0.09	-0.14**
	(-1.61)	(0.53)	(2.29)	(0.03)	(-1.48)	(-2.43)
Default return	-0.05	-0.13**	-0.14**	-0.06	-0.02	-0.06
	(-1.13)	(-2.14)	(-2.11)	(-1.43)	(-0.43)	(-1.64)
Basis	-0.11*	0.01	-0.14*	-0.09**	-0.00	-0.08
	(-1.95)	(0.15)	(-1.87)	(-2.12)	(-0.06)	(-1.29)
HP (hedg.)	0.11	0.10*	-0.14*	0.03	0.17**	0.15**
	(1.47)	(1.67)	(-1.87)	(0.55)	(2.14)	(2.01)
$\Delta\bar{R}^2$	*3.50*	1.63	*6.10*	*2.70*	*3.10*	*5.20*

Table 14: **Estimates of multivariate regressions of commodity return volatility against all predictors**

This table reports results from regressions where the natural logarithm of realized commodity return volatility is regressed on a set of lagged economic, financial and commodity-specific variables. The row denoted $\Delta\bar{R}^2$ displays the percentage change in the $\bar{R}^2$ after including the set of explanatory variables in a benchmark AR(6) model. The Newey-West corrected t-statistics (with 12 lags) are reported in brackets below each coefficient. *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variable	**Eq. weighted**	**Agricultural**	**Livestock**	**Energy**	**Metals**	**GSCI(Eq)**
			1970-2011			
T-bill vol	0.04	-0.00	0.03	-	0.06	0.02
	(1.62)	(-0.10)	(1.22)	-	(1.28)	(0.65)
CPI vol	0.16***	0.18***	0.09***	-	0.09***	0.13***
	(4.20)	(4.53)	(2.73)	-	(2.63)	(3.65)
IP vol	-0.02	-0.03	-0.03	-	-0.03	-0.03
	(-0.82)	(-0.89)	(-0.92)	-	(-0.90)	(-1.03)
M2 vol	0.01	0.05	-0.01	-	0.02	0.01
	(0.44)	(1.58)	(-0.25)	-	(0.53)	(0.29)
S&P500 vol	0.02	0.05	0.03	-	-0.01	0.03
	(0.73)	(1.64)	(1.00)	-	(-0.45)	(1.26)
Term spread	-0.00	0.02	-0.04	-	-0.00	-0.05
	(-0.10)	(0.77)	(-0.89)	-	(-0.06)	(-1.46)
Default return	-0.06**	-0.05*	-0.01	-	-0.04	-0.05**
	(-2.04)	(-1.73)	(-0.24)	-	(-1.15)	(-2.07)
Basis	-0.04	-0.11***	-0.05	-	0.03	-0.03
	(-1.12)	(-3.23)	(-1.63)	-	(0.80)	(-0.95)
$\Delta\bar{R}^2$	*1.50*	*3.50*	*0.70*	-	*0.40*	*1.30*
			1970-1990			
T-bill vol	0.03	0.03	0.01	-	0.10	-0.01
	(0.59)	(0.53)	(0.18)	-	(1.08)	(-0.08)
CPI vol	0.17***	0.14**	0.14***	-	0.05	0.14**
	(2.93)	(2.38)	(3.70)	-	(1.05)	(2.51)
IP vol	-0.06	-0.03	-0.11**	-	-0.10**	-0.06
	(-1.47)	(-0.56)	(-2.53)	-	(-2.05)	(-1.35)
M2 vol	-0.01	0.01	0.00	-	-0.04	-0.03
	(-0.35)	(0.29)	(0.01)	-	(-0.82)	(-0.77)
S&P500 vol	0.01	0.00	0.03	-	0.02	0.06**
	(0.26)	(0.05)	(0.73)	-	(0.71)	(2.01)
Term spread	-0.04	-0.00	-0.10*	-	-0.05	-0.09*
	(-0.91)	(-0.04)	(-1.94)	-	(-0.68)	(-1.83)
Default return	-0.06	-0.03	0.00	-	0.02	-0.04
	(-1.45)	(-0.59)	(0.08)	-	(0.43)	(-1.17)
Basis	-0.03	-0.11**	-0.04	-	0.05	-0.03
	(-0.35)	(-2.17)	(-0.92)	-	(0.94)	(-0.38)
$\Delta\bar{R}^2$	*1.60*	*1.70*	*1.60*	-	*0.90*	*1.80*

Table 14-continued

Variable	Eq. qeighted	Agricultural	Livestock	Energy	Metals	GSCI(Eq)
			1991-2011			
T-bill vol	0.04	-0.01	-0.06	0.06	0.03	0.01
	(0.79)	(-0.17)	(-1.56)	(1.41)	(0.71)	(0.19)
CPI vol	0.17***	0.26***	-0.03	0.17**	0.10**	0.15***
	(3.37)	(4.37)	(-0.45)	(2.14)	(2.32)	(2.99)
IP vol	-0.02	-0.03	0.08*	-0.02	0.03	-0.03
	(-0.49)	(-0.58)	(1.76)	(-0.38)	(0.77)	(-0.81)
M2 vol	0.02	0.06	-0.03	0.03	0.06	0.03
	(0.50)	(1.35)	(-0.36)	(0.55)	(1.18)	(0.71)
FX index vol	0.00	0.06	0.02	-0.01	-0.04	-0.02
	(0.04)	(0.89)	(0.29)	(-0.16)	(-0.79)	(-0.37)
VIX	0.15***	0.07	0.12**	0.24***	0.04	0.18***
	(2.78)	(1.47)	(2.37)	(3.84)	(0.94)	(3.73)
Term spread	-0.01	0.02	0.05	-0.06	0.02	-0.08*
	(-0.31)	(0.48)	(0.74)	(-0.93)	(0.34)	(-1.72)
Default return	-0.04	-0.09**	-0.05	-0.02	-0.08**	-0.04
	(-1.03)	(-2.52)	(-1.11)	(-0.51)	(-2.27)	(-1.28)
Basis	-0.02	-0.10**	-0.06	-0.22***	-0.04	0.00
	(-0.52)	(-2.09)	(-1.08)	(-4.28)	(-0.87)	(0.03)
HP (hedg.)	0.15***	0.11**	-0.17***	0.02	0.11**	0.16***
	(2.74)	(2.07)	(-3.19)	(0.46)	(2.22)	(3.42)
$\Delta\bar{R}^2$	*2.60*	*2.40*	*2.30*	*8.50*	*1.90*	*3.70*
			2001-2011			
T-bill vol	0.12*	0.07	-0.06	0.20**	0.01	0.06
	(1.75)	(0.80)	(-0.69)	(2.18)	(0.11)	(0.91)
CPI vol	0.16***	0.19**	-0.04	0.15	0.06	0.19***
	(2.85)	(2.46)	(-0.43)	(1.41)	(1.28)	(2.66)
IP vol	-0.03	-0.03	0.17**	0.05	0.05	-0.02
	(-0.43)	(-0.37)	(2.07)	(0.52)	(0.84)	(-0.20)
M2 vol	0.04	0.05	0.02	0.04	0.08	0.08
	(0.84)	(0.81)	(0.16)	(0.36)	(1.05)	(1.29)
FX index vol	-0.03	0.19*	-0.00	-0.02	-0.02	-0.04
	(-0.35)	(1.74)	(-0.04)	(-0.19)	(-0.23)	(-0.40)
VIX	0.15**	-0.02	0.05	0.08	0.13	0.19**
	(2.01)	(-0.29)	(0.48)	(0.90)	(1.57)	(2.06)
Term spread	-0.05	0.02	0.24**	0.10	-0.11	-0.13*
	(-0.78)	(0.41)	(2.03)	(1.25)	(-1.30)	(-1.73)
Default return	-0.07	-0.17***	-0.16**	-0.06	-0.07	-0.10**
	(-1.46)	(-3.43)	(-2.34)	(-1.26)	(-1.47)	(-2.41)
Basis	-0.14**	-0.07	-0.12*	-0.14**	0.00	-0.09
	(-2.49)	(-1.36)	(-1.82)	(-2.28)	(0.06)	(-1.46)
HP (hedg.)	0.20***	0.23***	-0.14*	0.08	0.18**	0.23***
	(2.82)	(3.62)	(-1.92)	(1.07)	(2.02)	(3.72)
$\Delta\bar{R}^2$	*4.40*	*4.20*	*5.80*	*6.10*	*1.90*	*5.90*

Table 15: **Causality between aggregate commodity volatility and macroeconomic volatilities.**

This table presents Granger causality test results between macroeconomic and commodity volatility. We consider volatilities of the following variables: Aggregate commodity returns (cmdvol), CPI inflation (infvol), industrial production (ipvol), Tbill (tbillvol), M2 money growth (m2vol), US dollar index against major currencies (fxvol), S&P500 returns (spvol), government bond yield (ltyvol), and aaa corporate bond yield (aaavol). The tests are based on a 2-by-2 VAR model with 12 lags and dummy variables to account for different monthly intercepts. We report the χ^2 for the null hypothesis of no Granger causality. We perform the tests on the whole sample and on various sub-samples. *, **, and *** indicate rejection of the null of no causality at the 10%, 5% and 1% level, respectively.

	Full sample 1970-2011	*Sub-sample 1 1970-1990*	*Sub-sample 2 1991-2011*	*Sub-sample 3 1980-2000*	*Sub-sample 4 2001-2011*
			Panel A. Equally weighted index		
Null hypothesis (Ho:)					
infvol $\nrightarrow$ cmdvol	24.74**	19.14*	12.65*	24.83**	10.80
cmdvol $\nrightarrow$ infvol	48.17***	24.20**	30.47***	6.29*	36.36***
ipvol $\nrightarrow$ cmdvol	5.93	11.58	13.39	11.77	13.52
cmdvol $\nrightarrow$ ipvol	23.21**	13.96	20.76*	13.28	23.01**
m2vol $\nrightarrow$ cmdvol	7.82	7.02	14.91	12.96	14.52
cmdvol $\nrightarrow$ m2vol	16.49	16.21	16.03	19.93*	13.92
fxvol $\nrightarrow$ cmdvol	-	-	11.14	6.12	9.70
cmdvol $\nrightarrow$ fxvol	-	-	32.58***	14.51**	24.76**
tbillvol $\nrightarrow$ cmdvol	6.09	2.60	18.42	13.20	13.09
cmdvol $\nrightarrow$ tbillvol	11.64	16.57	10.65	19.68*	8.61
spvol $\nrightarrow$ cmdvol	11.62	7.89	7.20	5.51	12.40
cmdvol $\nrightarrow$ spvol	14.65	21.92**	5.86	14.68	14.63
ltyvol $\nrightarrow$ cmdvol	11.70	10.59	5.50	25.89**	6.72
cmdvol $\nrightarrow$ ltyvol	8.68	5.74	14.97	15.20	15.33
aaavol $\nrightarrow$ cmdvol	19.28	18.18	10.47	33.55***	8.21
cmdvol $\nrightarrow$ aaavol	21.46**	11.70	29.62***	18.12	24.06**
			Panel B. GSCI(Eq) index		
Null hypothesis (Ho:)					
infvol $\nrightarrow$ cmdvol	23.31**	11.46*	23.44**	13.45**	14.25
cmdvol $\nrightarrow$ infvol	48.18***	15.42**	42.80***	10.41*	29.55***
ipvol $\nrightarrow$ cmdvol	8.18	14.75	14.73	5.76	17.19
cmdvol $\nrightarrow$ ipvol	24.98**	18.61	16.47	10.54	21.22*
m2vol $\nrightarrow$ cmdvol	13.80	6.13	12.33	7.62	11.93*
cmdvol $\nrightarrow$ m2vol	14.06	15.15	10.47	15.73	5.38
fxvol $\nrightarrow$ cmdvol	-	-	7.88	6.86	11.32
cmdvol $\nrightarrow$ fxvol	-	-	23.80***	20.89***	18.78*
tbillvol $\nrightarrow$ cmdvol	2.58	16.88	16.70	8.16	11.02
cmdvol $\nrightarrow$ tbillvol	14.07	15.97	10.08	29.51***	10.57
spvol $\nrightarrow$ cmdvol	9.21	2.97	5.74	1.67	11.91
cmdvol $\nrightarrow$ spvol	8.84	11.24	7.93	3.70	15.49
ltyvol $\nrightarrow$ cmdvol	7.97	10.84	2.47	14.16	7.54
cmdvol $\nrightarrow$ ltyvol	20.53*	10.57	16.46**	27.87**	11.53
aaavol $\nrightarrow$ cmdvol	13.62	12.20	7.29	22.00**	5.72
cmdvol $\nrightarrow$ aaavol	29.97***	20.50*	17.12**	25.20**	19.87*

Table 16: **Dispersion of beliefs and commodity return volatility**

This table reports results from regressions between commodity return volatility and macroeconomic uncertainty and volatility measures. Macroeconomic uncertainty is obtained as the cross-sectional standard deviation across forecasts of professional in a given month. Macroeconomic volatility proxies are obtained from the two-step procedure described by eq. (5) and (6). Panel A presents results from regressions of commodity volatility on macroeconomic uncertainty proxies only. Panel B displays results from regressing commodity volatility on macroeconomic uncertainty and volatility proxies. The Newey-West corrected t-statistics (with 12 lags) are reported in brackets below each coefficient. *, **, and *** indicate significance at the 10%, 5% and 1% level, respectively.

Variable	**Eq. weighted**	**Agricultural**	**Livestock**	**Energy**	**Metals**	**GSCI(Eq)**	**Eq. weighted**	**Agricultural**	**Livestock**	**Energy**	**Metals**	**GSCI(Eq)**
			1991-2011						*2001-2011*			
Panel A. Macroeconomic uncertainty												
CPI uncert	0.17***	0.22***	0.01	0.20**	0.07	0.10**	0.31***	0.28***	0.01	0.36***	0.13*	0.29***
	(3.05)	(4.17)	(0.14)	(2.37)	(1.26)	(1.99)	(3.85)	(2.80)	(0.14)	(2.75)	(1.66)	(3.67)
Tbill uncert	-0.04	-0.10	0.04	-0.10*	0.00	-0.04	-0.11*	-0.06	0.06	0.00	-0.09	-0.12*
	(-0.77)	(-1.64)	(0.61)	(-1.71)	(-0.02)	(-0.78)	(-1.76)	(-0.88)	(0.59)	(-0.06)	(-1.55)	(-1.76)
IP uncert	-0.07	-0.07	-0.01	-0.04	-0.03	-0.06	-0.06	-0.11	0.11	-0.01	0.00	-0.03
	(-1.58)	(-1.13)	(-0.08)	(-0.45)	(-0.65)	(-1.27)	(-1.03)	(-1.28)	(1.18)	(-0.12)	(0.00)	(-0.41)
NEXP uncert	0.16***	0.21***	0.14**	-0.04	0.08*	0.16***	0.07	0.14**	-0.02	0.09*	0.00	0.02
	(3.07)	(3.68)	(2.01)	(-0.73)	(1.86)	(2.63)	(1.29)	(2.28)	(-0.31)	(1.73)	(0.02)	(0.28)
$\Delta\bar{R}^2$	*1.95*	*5.08*	*0.15*	*3.39*	*0.09*	*1.41*	*2.34*	*3.11*	*-0.85*	*4.99*	*-0.19*	*2.01*
Panel B. Macroeconomic uncertainty and volatility												
CPI uncert	0.14**	0.15**	-0.06	0.22**	0.04	0.07	0.26***	0.18*	-0.16	0.27**	0.06	0.26***
	(2.44)	(2.51)	(-0.80)	(2.11)	(0.69)	(1.46)	(3.01)	(1.70)	(-1.34)	(2.00)	(0.59)	(2.92)
Tbill uncert	-0.04	-0.09*	0.06	-0.11*	0.00	-0.04	-0.13**	-0.06	0.14	0.03	-0.10	-0.14**
	(-0.92)	(-1.78)	(0.85)	(-1.81)	(-0.08)	(-0.80)	(-2.25)	(-0.90)	(1.42)	(0.41)	(-1.54)	(-2.02)
IP uncert	-0.09**	-0.11	-0.02	0.16**	-0.06	-0.07*	-0.09	-0.19*	0.08	0.03	-0.04	-0.05
	(-2.01)	(-1.61)	(-0.24)	(2.07)	(-1.23)	(-1.69)	(-1.41)	(-1.94)	(0.78)	(0.27)	(-0.59)	(-0.76)
NEXP uncert	0.16**	0.18***	0.14**	-0.05	0.04	0.16***	0.09	0.17**	-0.08	-0.09	0.01	0.04
	(2.74)	(2.86)	(2.01)	(-0.49)	(0.95)	(2.71)	(1.48)	(2.52)	(-0.75)	(-1.58)	(0.22)	(0.55)
CPI vol	0.12**	0.14**	0.02	0.07	0.10*	0.14***	0.07	0.06	-0.09	0.07	0.08	0.10
	(2.50)	(2.36)	(0.25)	(1.07)	(1.80)	(2.63)	(1.07)	(0.76)	(-0.83)	(0.75)	(1.20)	(1.22)
Tbill vol	0.05	-0.01	0.00	0.16**	0.03	0.04	0.10	0.07	-0.06	0.13	0.05	0.06
	(0.86)	(-0.15)	(0.01)	(2.55)	(0.64)	(0.68)	(1.16)	(0.68)	(-0.48)	(1.29)	(0.88)	(0.66)
IP vol	0.02	0.02	0.09	0.03	0.03	0.01	0.00	-0.03	0.23**	0.08	0.06	0.02
	(0.43)	(0.38)	(1.41)	(0.31)	(0.76)	(0.21)	(0.06)	(-0.34)	(2.36)	(0.79)	(0.89)	(0.25)
M2 vol	0.04	0.08	-0.04	-0.02	0.08	0.02	0.04	0.05	0.03	-0.03	0.08	0.06
	(0.70)	(1.64)	(-0.43)	(-0.33)	(1.24)	(0.50)	(0.66)	(0.79)	(0.31)	(-0.36)	(1.01)	(0.80)
FX ind vol	0.00	0.05	0.08	-0.06	-0.04	-0.04	0.00	0.18	0.23*	0.05	-0.03	-0.07
	(0.07)	(0.73)	(1.05)	(-1.10)	(-0.61)	(-0.78)	(0.04)	(1.45)	(1.94)	(0.49)	(-0.33)	(-0.69)
$\Delta\bar{R}^2$	*2.60*	*6.37*	*0.09*	*4.62*	*0.75*	*2.08*	*1.96*	*2.60*	*1.98*	*6.40*	*-0.04*	*1.36*