The economic drivers of time-varying commodity market volatility*

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Abstract

In this paper, we investigate the relationship between economic uncertainty and commodity return volatility. We analyze volatility for the aggregate commodity market and for various commodity groups and 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. Moreover, dispersion of beliefs provides additional information to that contained in volatilities of current macroeconomic 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 pricing and risk management.

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1. Introduction

It is well known that asset return volatility is not constant. However, less is known about the economic sources of its variations. Starting with the seminal paper of Schwert (1989), a large number of studies have analyzed 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 variation in economic fundamentals.

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 provide useful input for regulators and economic 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 volatility 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 priced in the cross-section of stock returns and, as such, should be taken into account in asset pricing models (Boons et al., 2012).

We contribute to extant literature in several 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 employ an extensive dataset of professional forecasts for core macroeconomic variables to empirically test the impact of differences in beliefs on volatility of commodity returns. We argue that this has important asset pricing implications, since dispersion of beliefs becomes an additional risk factor that should be priced in commodity returns. Third, although it is of great interest to study the causal effect of various economic factors on volatility of commodity returns, potential causality of the opposite direction, from commodity to macroeconomic volatility, is also important from an economic policy perspective. To this end, we analyze feedback effects between macroeconomic uncertainty and commodity return volatility. Fourth, most previous studies are based on traded commodity indices, such as the GSCI or the DJUBS to construct commodity return volatility proxies. Nevertheless, many 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 fundamentals-based analysis. Instead, our evidence is based upon equally weighted commodity futures indices in a similar spirit to Gorton and Rouwenhorst (2006). Lastly, our analysis moves beyond aggregate commodity market volatility and studies the behavior of volatility across different commodity groups. Given the heterogenous nature of commodities, this comprehensive analysis can shed more light on the determinants of differences in behavior of particular commodity groups.

Our investigation leads to many interesting findings. Overall, the empirical analysis suggests that uncertainty about economic fundamentals has an important effect on commodity return volatility. Inflation uncertainty exhibits a consistently positive and strongly significant causal link with commodity return volatility. This result holds for the majority of sectoral commodity portfolios and over the various sub-periods considered. Moreover, we document some cross-sectional differences across commodity portfolios. We also find that variables associated with credit risk, funding liquidity and money market stress, such as the default return, the TED spread and the VIX offer significant explanatory power for subsequent commodity return volatility in many cases. In economic terms, the latter finding is consistent with the implications of Brunnermeier and Pedersen (2009) that lower funding liquidity signaled by a higher TED spread is associated with higher financial market volatility. Also the VIX can be regarded as a general proxy of economic uncertainty (Connolly et al., 2005) and thus is expected to bear information about other risky assets.

Interestingly, we document a weakening importance of macroeconomic fundamentals during the more recent sample period and especially after

2000. This finding paired with the strong significance of some financial risk factors, during the same period, provides indirect support for the view of "financialization" in commodity markets. For example, Tang and Xiong (2012) report spillovers from financial to commodity markets as a result of the increased participation of intsitutional investors in commodity markets. Thus, our results are supportive for their findings. Controlling for variables motivated by commodity pricing theories, such as the commodity futures basis and hedging pressure, we find that for some commodity groups these variables add significant explanatory power. In particular, futures basis leads to lower volatility, while hedging pressure exhibits the opposite effect. This result suggests that even though commodity markets have become more integrated with financial markets, they are still segmented to some extent.

We further 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 the majority of sub-samples. However, during the post '90s period, there is stronger evidence that commodity volatility causes inflation volatility than the other way around. This result has very important implications since commodities are widely used as tools for inflation forecasting (Chen et al., 2011). Furthermore, our analysis shows that commodity return volatility helps predict volatility of real economic activity and exchange rates.

We construct macroeconomic uncertainty proxies based on the differences in beliefs of professional forecasters and test their impact on time variation of commodity return volatility. The empirical results suggest that disagreement among market participants regarding future economic conditions has a profound effect on near term commodity market volatility. We move on to test the impact of dispersion of beliefs on commodity return volatility controlling for volatilities of macroeconomic aggregates. Our evidence suggests that macroeconomic uncertainty proxies contain information beyond that embedded in volatilities of macroeconomic factors.

Many studies have examined the variation of equity return volatility with respect to macroeconomic conditions. Schwert (1989) finds little evidence that economic volatility can help explain episodes of high equity and bond market volatility posing a “volatility puzzle”. Evidence that financial volatility has explanatory power for macroeconomic volatility is slightly stronger. Subsequent studies suggest alternative methodologies aiming to better accommodate the empirical behavior of the economic data. Beltratti and Morana (2006) document a bi-directional link between macroeconomic and equity volatility after accounting for structural breaks and long-memory in economic time series. Engle et al. (2008) find that PPI inflation and industrial production predict aggregate S&P500 volatility using mixed frequency volatility models. Diebold and Yilmaz (2008) document a positive link between macroeconomic and equity volatility in an a broad set of international equity markets. Recently, Paye (2012) tests the in- and out-of-sample predictive ability of various macroeconomic and financial variables for aggregate stock market volatility. The author provides encouraging evidence regarding several individual predictors although the overall predictive power of the models augmented with economic variables is rather limited, especially out-of-sample.

Most of the existing research on the determinants of commodity price volatility, 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) or the net positions of hedgers (e.g., Bessembinder, 1992; De Roon et al., 2000). Furthermore, studies that involve influences of economic variables are mainly concentrated on commodity returns (Bailey and Chan, 1992; Hong and Yogo, 2012). Little effort has been made to explicitly relate commodity return volatility to systematic risk factors common to all assets. Recently, Christiansen et al. (2012) employ 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.

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

2. Data and variables

2.1 Commodity futures returns

We construct equally weighted and fully-collateralized portfolios of commodity futures following a methodology similar to Gorton and Rouwenhorst (2006). To do this, we collect daily closing prices on nearest to maturity futures contracts for a large number of commodities traded in the US 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 period is from July, 1959 to December, 2011. Where missing values occur, 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). 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 commodity indices, we first take the price of the nearest 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

[1] We also experimented with other interpolation methods, in particular spline and cubic approaches. The resulting return series were not seriously affected by the interpolation method employed.

St Louis.

The above 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 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 (usually 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, 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] We apply the above procedure to construct equally weighted portfolios for each one of the four commodity sectors.

Figure 1 illustrates the evolution of the equally weighted aggregate commodity futures index for the full sample period from July, 1959 to December, 2011. From the figure one can easily observe the increase in commodity prices that gradually started 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., see Singleton, 2013, for the oil market). As a robustness check 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) as a commodity market portfolio. However, the fact that this index

[2]For more 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.

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.

2.2 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 10-year government bond yield and the return of the trade-weighted US dollar index against major currencies. The first three variables are available at monthly, whereas the rest at daily frequency. All data were obtained from the economic data service of the Federal Reserve Bank at St Louis (FRED).

2. Financial variables

In addition to the macroeconomic variables above, we also consider a number of financial variables.[4] First, we compute daily returns on the S&P500 index, using daily closing 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 is a performance index of all bonds rated as Aaa (Baa) by Moody's Investors Service. We also consider four variables related to credit risk, namely: (i) the default spread defined as the difference between 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 obtained as the difference between the 3-month LIBOR rate and the 3-month T-bill yield. The last four variables are monthly. The corporate and

[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 or the yield on 10-year government bonds.

government bond returns are obtained from the online appendix of Goyal and Welch (2008). The rest are from FRED. Monthly yields always 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 out-of-the-money call and put options (for further details see CBOE website). Moreover, VIX is generally regarded as a proxy for economic uncertainty (Connolly et al., 2005) or investors' sentiment (Baker and Wurgler, 2007).

3. Commodity-specific variables

We construct aggregate measures of variables that are central to fundamental commodity pricing theories, such as 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 investors, respectively.

Regarding the aggregate futures basis, we use monthly observations on the nearest and second nearest futures contracts. The former (latter) is treaded as spot (futures) price. This is a standard approach in the literature due to the absence of reliable spot data (Gorton et al., 2012). 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 nearest 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 sector. These series serve as basis measures for each commodity sector. Finally, to obtain a proxy for the adjusted basis of the whole commodity market, we take the average basis across all four sectors (agricultural, livestock, energy and metals).

For the open interest variable, similar to Hong and Yogo (2012), we collect monthly physical spot price data for all commodities from the CRB. Next, we obtain end-of-month data on the open interest in futures from the Commodity Futures Trading Commission (CFTC). The dataset covers the period from January, 1986 to December, 2011. To construct the open interest variable we closely follow the procedure described in Hong and Yogo (2012). We 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 open interest for the whole commodity market is obtained as the median across the four commodity sectors. As pointed out by Hong and Yogo (2012), the open interest proxies are very noisy. Therefore, following this 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 provides support for the notion that risk premia vary with the net positions of hedgers (Bessembinder, 1992; De Roon et al., 2000). Moreover, 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 hedging pressure variable 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 are treated as speculators. Using these data we compute the hedging

[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.

pressure for each one of the four commodity sector as follows:

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

where: $HP_{j,t}$ is the hedging pressure of commodity sector j and $Short_{ij,t}$ ($Long_{ij,t}$) is the number of short (long) positions in commodity i belonging to sector j. The above definition of hedging pressure is simply 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). Finally, 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 excess returns, 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 proxy is widely known as *realized volatility*. We also use this volatility estimator for the four sectoral portfolios.

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 from high-frequency data 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). 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 the realized volatility estimates of the series (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 less sensitive to outliers.

[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.

On the other hand, the fitted values from the second step represent 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 model 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 Aaa corporate bond yield.[7]

The second step of the above 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) and Paye (2012). It is necessary to point out here that for the VIX as well as for the credit risk variables, namely the term spread, the default spread, the default return spread and the TED spread we directly work with levels, as these variables can be directly considered to measure uncertainty.

3.1 Statistical analysis of volatility estimates

Figure 2 illustrates kernel density plots of realized volatility estimates for the equally-weighted commodity index and the 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 used the logarithm of annualized commodity return volatility, defined

[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.

as: $\tilde{RV}_t = \log(\sqrt{12RV_t})$. 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 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 close to 0.8 or higher in most cases. The t-statistics reject the null hypothesis that the autoregressive coefficients sum up to one. Therefore, the hypothesis of non-stationary (integrated) variance is rejected in all cases suggesting a 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 fails to reject the null hypothesis of no autocorrelation in model residuals in almost all cases, 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 predicted volatilities of the equally weighted commodity index against each macroeconomic volatility series obtained from the two-step procedure described above. 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 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. From the table we see 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 volatility. 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 prominent 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 test the ability of each individual economic variable to offer explanatory power beyond that contained in lagged volatility. Third, we extend the analysis to a multivariate framework that incorporates multiple factors. After this, we explore the impact of differences in beliefs of professional forecasters about future economic fundamentals on commodity return volatility. Finally, we analyze causal links between macroeconomic uncertainty and commodity market volatility in a VAR analysis.

4.1 Commodity market volatility during recessions

Commodity 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, their 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 logarithm of realized volatility of the equally weighted index and the GSCI(Eq) index, respectively, against NBER recession months (shaded areas). Inspection of this plot provides some indication that commodity market volatility tends to 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, commodity volatility hardly changed. Second, although volatility of commodity returns is generally higher during recessions, in many cases volatility is not substantially higher compared to volatile episodes not associated with recessions. This fact highlights the role of non-systematic (idiosyncratic) risk factors that affect the supply and demand of commodities, e.g. geopolitical events.

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

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

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 6 lags of realized volatility in the right hand-side of Equation (7) to account for persistence in volatility. A positive and significant business cycle dummy means that volatility is higher on average during recessions compared to expansions. 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 for this particular analysis, since its price history is too short (1983–2011). 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 this is also true 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 for most series. Furthermore, S&P500 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. The latter result for bond yields is in line with the evidence of Schwert (1989).

These results support 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 time 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 part of the information in current volatility. Therefore, for a variable to be characterized as a significant indicator of future volatility, it should provide information beyond that already embedded in volatility lags.

We estimate the above set of regressions using as dependent each one of the following six variables: the logarithm of realized volatility of the equally weighted commodity market index, its four equally weighted sub-indices, and the realized volatility of the GSCI(Eq) index. 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 the GSCI index begins in 1970. Therefore, we focus our analysis on the period from January, 1970 to December, 2011. 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 AR(6) specification used as benchmark.

Tables 6 to 11 summarize estimation results for the above six sets of regressions. All variables (explanatory and dependent) are standardized prior to the estimations by subtracting the sample mean and dividing with the sample standard deviation to facilitate comparability across coefficients. A first look on the results across sub-samples and commodity sectors reveals that some variables consistently enter with significant coefficients. Overall, inflation volatility appears to be the most significant individual predictor in statistical and economic terms. Factors related to credit risk, funding liquidity and market stress such as the default spread, the TED spread and the VIX, offer significant explanatory power for many commodity sectors and sub-periods. Controlling for commodity-specific factors, i.e. the basis

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

and hedging pressure, we observe that these are significant determinants of commodity return volatility in several cases, while their signs are consistent with theoretical predictions.

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 full sample period (1970–2011). Its sign suggests a positive impact on near term commodity market volatility. This positive effect may be related to the higher trading activity in commodities during periods of high inflation uncertainty, since commodity assets are widely perceived as good hedges against inflation (Edwards and Park, 1996). During the 2001–2011 sub-period, which includes the recent commodity price boom, the size and significance of inflation volatility seem to decrease. In contrast, factors related to financial market conditions, such as the default spread, TED spread and the VIX become more important during the same period. This finding provides indirect support for the argument of "financialization" in commodities, according to which commodity markets have gradually become more integrated with traditional financial markets due to the increased participation of new index investors (e.g. hedge funds, pension funds). As a consequence of this financialization process, the dependence of commodity prices and volatility on financial factors, previously specific to stock and bond markets, has increased (Tang and Xiong, 2012; Silvennoinen and Thorp, 2013).

Moreover, 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 of VIX can be understood if one thinks that it represents a proxy for investors' risk attitude and thus provides signals about volatility of other risky assets, like commodities. On the other hand, the TED spread is a proxy for funding illiquidity (Brunnermeier et al., 2008). Hence, the dry up in liquidity during the recent financial crisis pushed volatility higher. This may also be associated with the increased reallocation of funds from equity to commodity markets after the outburst of the credit crisis. The above findings suggest that TED spread and the VIX have the same effect (positive) on commodity return volatility. This is not totally unexpected in the light of the evidence of Brunnermeier et al. (2008) who find that these two variables have the same effect on return of carry trade positions.

Concerning variables specific to commodity markets, we observe that the aggregate commodity futures basis, although insignificant in the entire sample period, enters with a highly significant and large coefficient equal to -0.23 in the second half of the sample (1991–2011). This means that a one standard deviation increase in the aggregate basis increases commodity market volatility by 0.23%. This negative basis-volatility relationship is consistent with the predictions of the theory of storage (Ng and Pirrong, 1994; Geman and Nguyen, 2005; Gorton et al., 2012). Furthermore, the effect of hedging pressure variable on aggregate commodity market volatility is generally significant at the 5% level. Its positive sign suggests that higher hedging demand leads to higher volatility of commodity returns. This complements the evidence of Hong and Yogo (2012) for commodity returns. Speculative pressure, on the other hand, is important only in the period after 2000s. This highlights the potential role of speculation in the recent increase in commodity prices during 2008, which was accompanied by increased price volatility (see, Haniotis and Baffes, 2010). Our main conclusions remain very similar and in many cases identical for the GSCI(Eq) index, enhancing the robustness of our evidence.

Our results suggest some cross-sectional differences in the significance and explanatory power of the various predictors across commodity sectors. For instance, a look at the results of agricultural portfolio volatility shows that in 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 significant, i.e. equity return volatility, the default spread, the term spread, the VIX, etc. In contrast, considering metals the only common driving factor during the 1991–2011 period is inflation volatility. For energy portfolio volatility, on the other hand, TED spread, interest rate volatility and the futures basis seem to be the most important determinants. These differences are to some extent expected due to the heterogeneous nature of commodity assets. For example, different commodities are fundamentally different assets. Some of them are primary consumable goods (e.g. grains), some others are inputs in the production process (e.g. lumber), or are more like financial assets, e.g. gold.

As already mentioned above, a way to assess the incremental explanatory power offered by individual variables is through the increase in the adjusted R^2 of the model augmented by the particular predictor compared to the benchmark. The benchmark model is the AR(6) specification that includes only volatility lags. 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 in economic terms is relatively modest.

In sum, our results suggest that certain macroeconomic and financial variables contain information for explaining commodity market volatility. These variables include: inflation volatility, option implied volatility (VIX), credit and liquidity risk variables, such as the default spread, term and TED spread, etc. In addition, commodity-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 have become increasingly important over the most recent past, a finding that supports the evidence of recent studies in commodity markets (e.g., Tang and Xiong, 2012; Silvennoinen and Thorp, 2013).

4.3 Evidence from multivariate estimations

In the previous section, we analyzed the ability of individual economic factors to explain variation in commodity return volatility. Despite its usefulness, this 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 all are included in the same model. Information contained in the various factors is not necessarily orthogonal to each other and hence some of them might be redundant. On top of that, estimations that separately employ macroeconomic versus financial and commodity-specific predictors can lead to useful conclusions regarding which group of variables, if any, is more important for explaining changes in commodity market volatility over time. Also, from an econometric perspective, a univariate analysis is more likely to suffer from omitted variables bias.

For the reasons illustrated above, we proceed with investigating the impact of the 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. 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

We begin by regressing the logarithm of realized commodity volatility on lagged one period 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 returns. As previously, we include six lags of realized volatility in the estimations. The series of US dollar index begins in 1974 and therefore it is omitted from the full sample estimation, as well as from the estimation of the first sub-sample, 1970–1990. Similar to the case of univariate regressions we estimate the models using as dependent variable the volatility of the aggregate commodity market index and also the volatilities of the sectoral commodity return indices.

The 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 appears to be stable over the various sub-periods. T-bill volatility is also significant and positive for livestock and metal volatility in the full sample estimation.

The improvement in the explanatory power of the model that includes the full set of macroeconomic variables is relatively modest and lower than 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 period of 2001–2011. For illustration, the adjusted R-squared ($\bar{R}^2$) increase of agricultural return volatility is 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 the default spread from our analysis since it is highly correlated with the default return, the term spread and the VIX.

Table 13 shows the estimation results. Looking at the results for the entire sample period, we observe that credit risk variables such as the term spread and the default spread are significant for the aggregate commodity market (equally weighted index and GSCI(Eq)) and also for the agricultural and livestock indices in some cases. Equity market volatility is also significant at the 5% level for the agricultural and livestock indices 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 full sample period. In contrast, two variables, namely S&P500 volatility and the term spread, help to predict agricultural

[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).

return volatility. 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 AR(6) benchmark. Adding VIX and hedging pressure in our specifications in the second half of the sample (after '90s), we see that the former has a positive and strongly significant impact on volatility of all commodity portfolios except for the agricultural. Furthermore, variables specific to commodity markets offer significant explanatory power in many cases provideng support for the "segmentation hypothesis" of commodity markets (Bessembinder, 1992). For example, the adjusted futures basis is highly significant at the 1% level for the aggregate commodity portfolio and for the sub-indices of energy and livestock. Moreover, hedging pressure has a strong positive impact on aggregate commodity market volatility. For the 1991–2011 period the coefficient of the hedging pressure variable is equal to 0.13, which means that a one standard deviation increase in hedging pressure results to a 0.23% increase in aggregate commodity market volatility.

The increase in $\bar{R}^2$ is substantially higher in the second half of the sample and especially after 2000s. For example, the adjusted futures basis and the VIX add a 6.2% to the overall explanatory power over the 1991–2011 sub-period. Moreover, the increase in the $\bar{R}^2$ 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, contribute to a 5.2% increase in the 2001–2011 sub-period.

4.3.3 Full set of factors

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 predictors. 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 spread is highly correlated with variables like T-bill volatility and the VIX. Therefore, we exclude it from the estimations as well.

Table 14 contains the estimation results. As far as the results for the entire sample are concerned, we see that inflation volatility and to a lesser extent default return are the 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 further insights. 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 sub-sample (1991–2011), 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 and livestock portfolios. 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, extracted from option prices, signal higher volatility of commodity returns. This can be understood given that VIX is regarded as a proxy for investor sentiment, and as such, is expected to convey information about other risky assets. Commodity specific factors, especially hedging pressure, show up as important determinants of commodity return volatility supporting the implications of commodity pricing theories. This may suggest that commodity markets are still relatively segmented from other asset markets (Daskalaki et al., 2012).

The overall explanatory power offered of these variables becomes stronger after the '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 during 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 agricultural index are near 4%. As previously, heterogeneity seems to play a non-negligible 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, volatility of agriculturals and metals seems to be driven by roughly the same factors, whereas with only exception the inflation volatility, energy portfolio volatility is determined by a totally different set of factors. Moreover, these differences are also reflected in the $\bar{R}^2$ changes of the sectoral commodity indices.

4.4 Investigating causal relationships

Thus far, we investigated whether variation in commodity return volatility can be explained by economic volatility. However, there is also the possibility that volatility of commodity returns has explanatory power for economic uncertainty. 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 volatility and commodity market volatility by performing pairwise 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 realized volatility of commodity returns and the realized volatility of the variable we want to test for causality.[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 volatility series in question, i.e. the realized volatility of commodity returns and volatility of each 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 12×2 and 2×2 matrices of parameters, respectively. The above specification is the bivariate version of Equation (6) used to obtain volatility predictions. Estimations using higher lags (e.g. p = 12) led to very similar conclusions.

Table 15 presents the test results. Looking first at the column labeled "Full sample", 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. Most importantly, the results over sub-samples show that causality from commodity return volatility to inflation volatility is remarkably stable over time. In contrast, evidence that commodity market volatility 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

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

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 more volatile commodity prices affect the value of the embedded option in inventory (Pindyck, 2004). This, will eventually have an effect on prices of final goods and therefore on demand for exports which is a major determinant of exchange rates.

4.5 The role of dispersion of beliefs for commodity return volatility

In the preceding analysis we used information contained in historical data to construct proxies of economic uncertainty. In this section, we employ survey data to construct measures of macroeconomic uncertainty based on the differences in beliefs among professional economic forecasters regarding future economic fundamentals. Several 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 variance risk premia in currency markets. Buraschi and Whelan (2011) use survey data and show that heterogeneity of beliefs bears strong predictive power for bond returns and volatilities.

Our empirical evidence is based on the Bluechip Economic Indicators (BCEI) survey. This survey exhibits some clear advantages over other economic 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) or semi-annually (WSJ, LVS). Second, forecasts are made for the current as well as for the next year allowing for a richer set of information on economic agents' expectations about future economic conditions. Third, the survey covers a larger set of economic variables compared to other surveys.

Getting into the details of the dataset, BCEI 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. The survey includes around 50 forecasts on average.

Forecasts for the majority of indicators without missing observations 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]

We construct measures of dispersion of beliefs by taking the cross-sectional standard deviation across all forecasters as in Pasquariello and Vega (2007). We rely on next year forecasts for the construction of our proxies since our main focus is on explaining short-term commodity return volatility. 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 disagreement 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

[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.

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 dispersion of beliefs 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 determined 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 the 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 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 notable 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.

Further, we explore the incremental information content of macroeconomic disagreement. Specifically, we test whether dispersion of beliefs of professional economic agents provides information beyond that 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 provides information that is orthogonal to that already embedded in the historical volatility series. In particular, adding the set of macroeconomic uncertainty measures to 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 dispersion measures, not only inflation volatility remains significant but also the $\bar{R}^2$ increases by almost 3%. Another example is agricultural portfolio volatility, for which the explanatory power in the 1991–2011 period increases from 2.6% to 6.4% after including the survey based measures. Interestingly, the impact of survey-based proxies is in many cases greater in magnitude than that of macroeconomic volatility proxies. This may indicate that dispersion of beliefs measures contain more information about future economic conditions than time series based proxies.

In sum, disagreement 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 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 commodity and macroeconomic volatility proxies, we employ alternative methods to construct these proxies and then re-perform all estimations. In particular:

(i) Except for Schwert's two-step method, another non-parametric method for obtaining conditional volatility estimates from monthly data, 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 Equation (5). For variables sampled daily, we replace the absolute errors by the realized volatility computed as in Equation (4). We use L = 3 and 12, respectively.

(ii) In the presence of autocorrelation, the estimator in Equation (4) is biased. For this reason, we consider the autocorrelation-adjusted volatility estimator of French et al. (1987). This estimator is given by:

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

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 Equation (4) and the second component is a correction term for the autocorrelation bias.

Performing the analysis 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 and in many cases even more significant.

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, term spread and TED spread appear to be important drivers of commodity return 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 evidence that even though commodity markets have become more integrated with traditional asset markets in the past few years, they are still relatively segmented.

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 in general the statistical and economic significance of the economic variables varies across commodity sectors. This is possibly associated with the heterogenous nature of commodity assets.

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 predictive power for the volatility of real economic activity and exchange rates, which has important economic policy implications, since commodities are used as monetary policy tools.

Finally, we exploit the information from a unique dataset of professional forecasters about economic fundamentals to construct empirical proxies of macroeconomic uncertainty. We show that dispersion of beliefs among professional economic agents is informative about future commodity return volatility. Moreover, information embedded in dispersion measures appears to be orthogonal to that in volatilities of macroeconomic fundamentals. The survey-based proxies seem to have a stronger impact to financial volatility relative to proxies based on macroeconomic aggregates.

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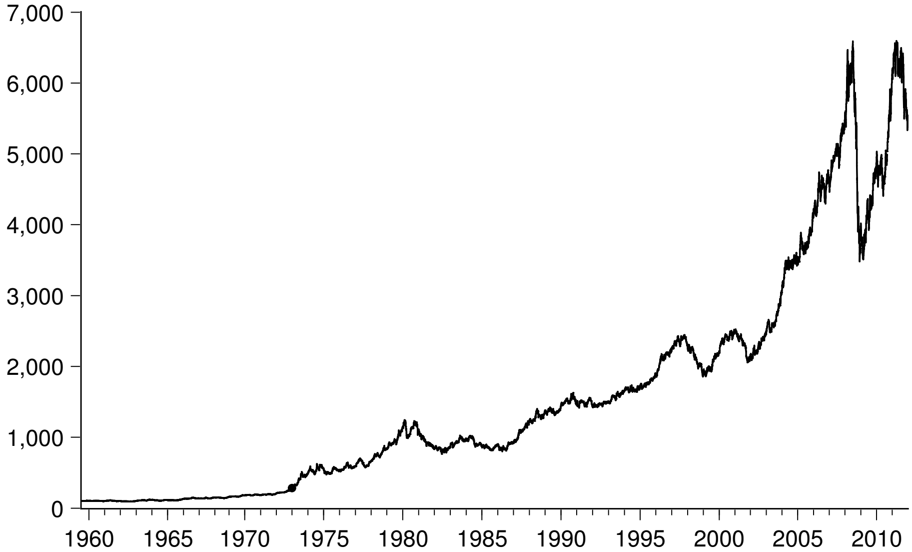

Figure 1: **Fully-collateralized commodity futures index**

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.

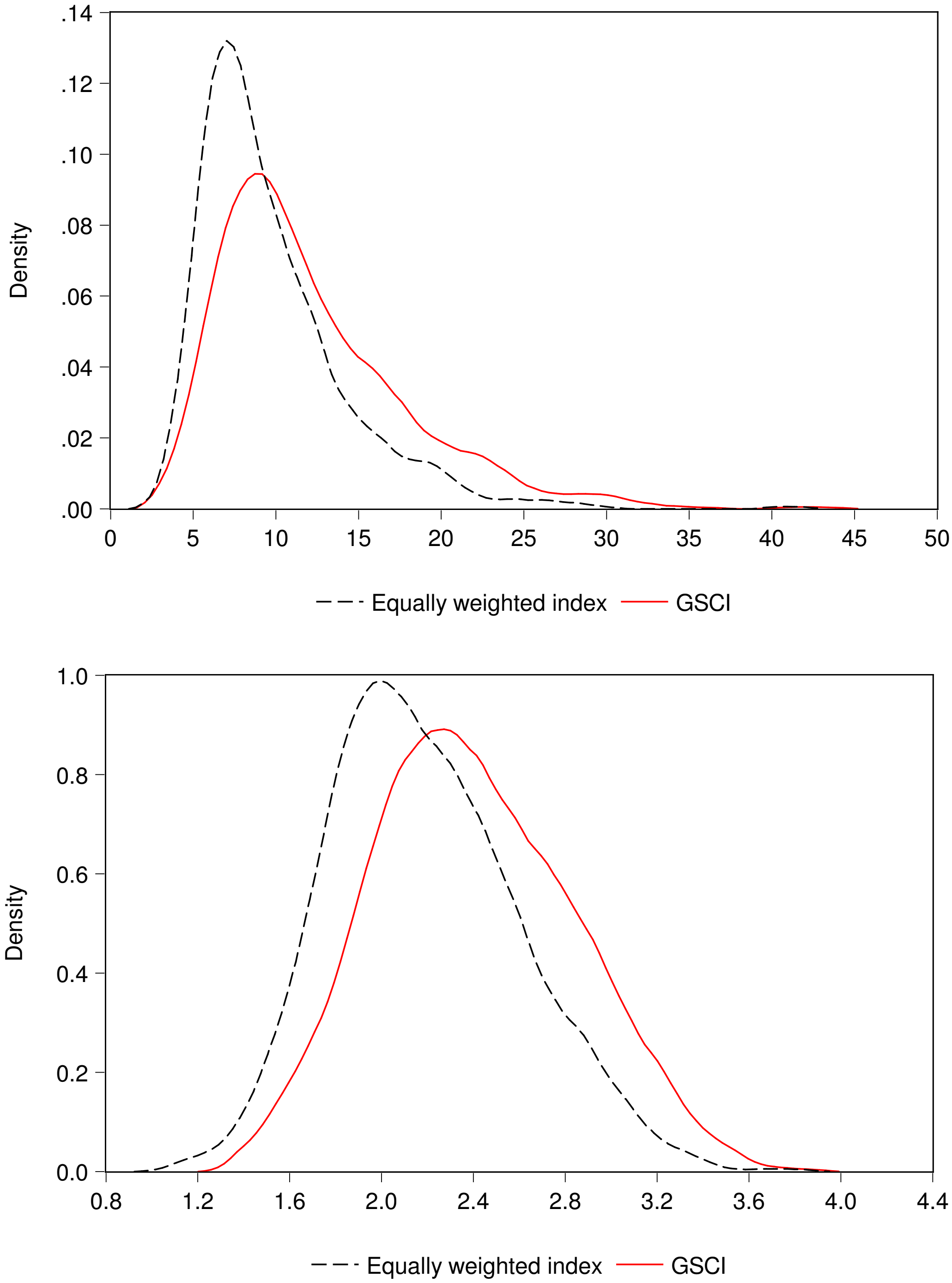

Figure 2: **Kernel density plots**

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.

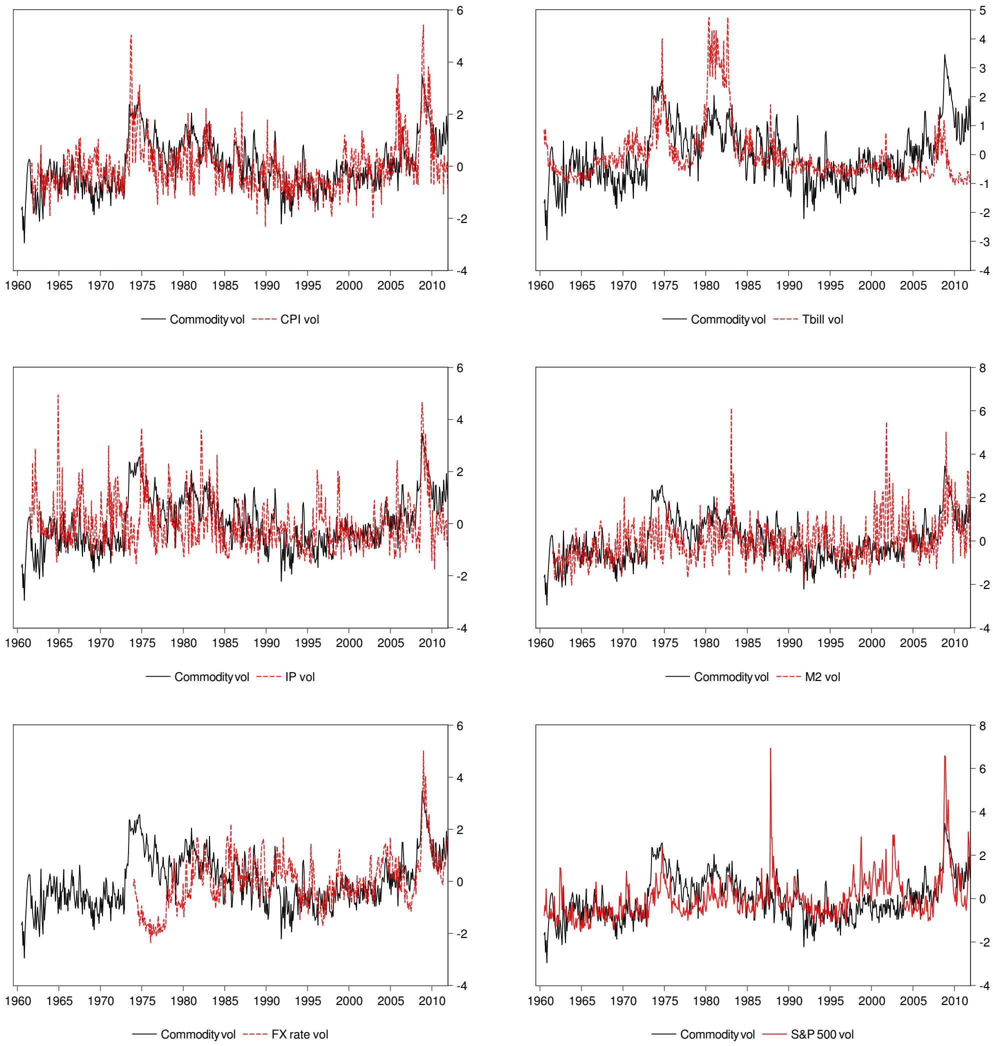

Figure 3: **Predictions of monthly volatilities of equally weighted commodity market index against predicted macroeconomic volatilities.**

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.

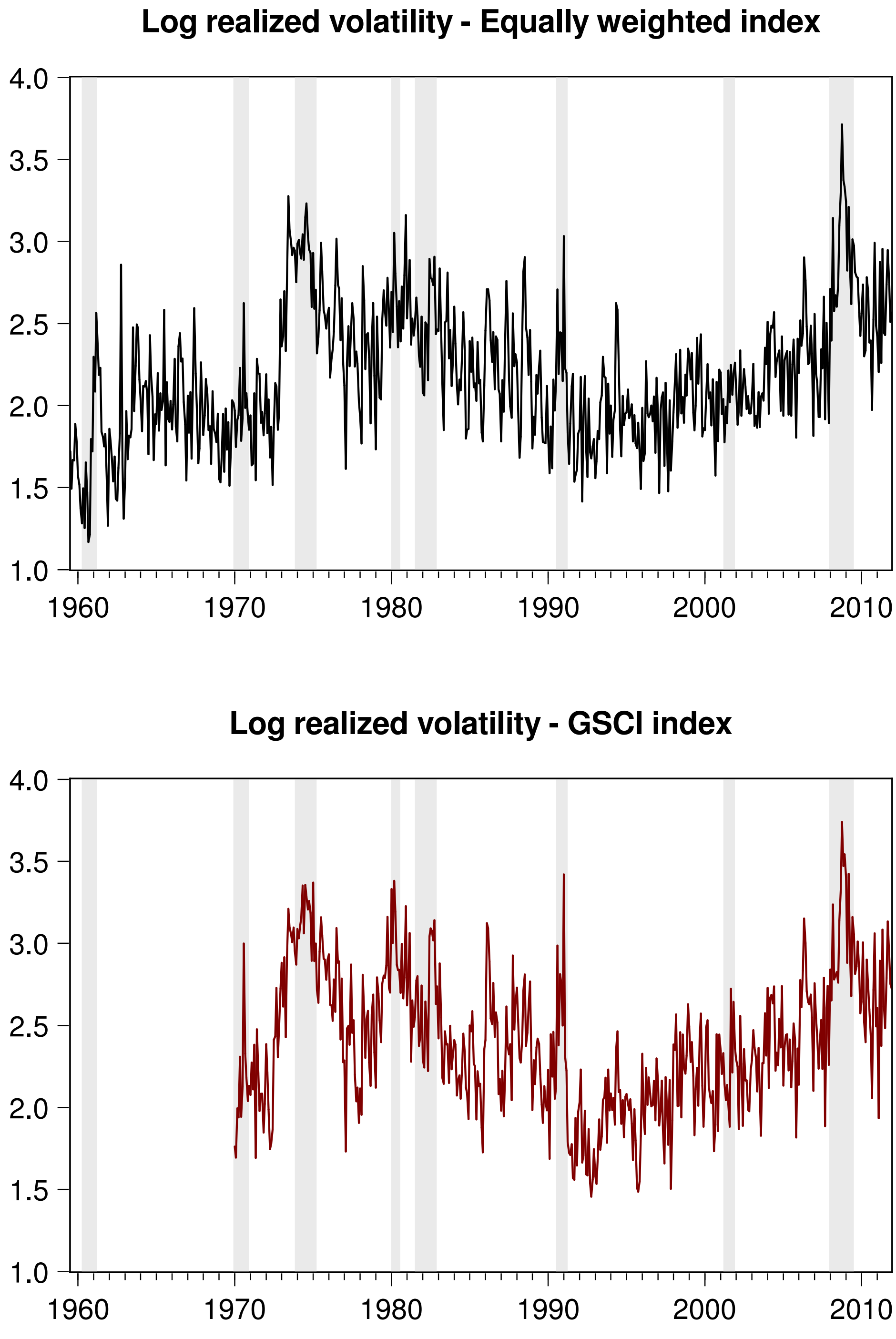

Figure 4: **Aggregate commodity volatility during recessions**

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).

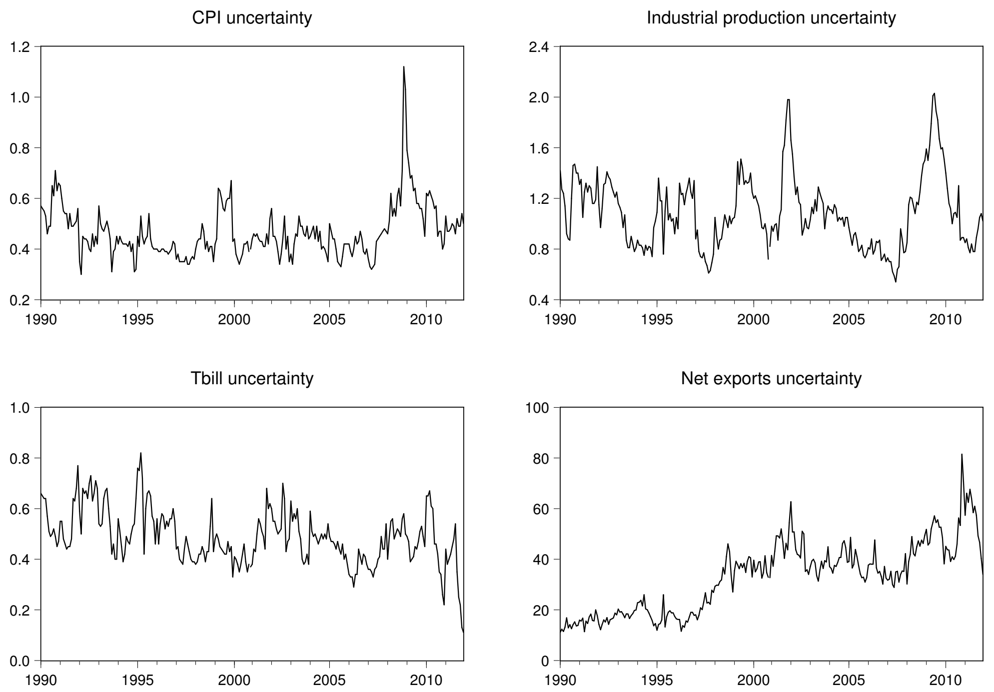

Figure 5: **Time series plots of dispersion of beliefs**

This figure displays time series plots of dispersion of beliefs of professional forecasters for the following economic series: Tbill, CPI, Industrial Production and Net Exports. The dispersion series is obtained as the cross-sectional standard deviation across individual forecasters for 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:

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

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									
	–									
T-bill 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	-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 and economic volatility over 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	23.10
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 spread	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	-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
Hedging pres.	-	-	-	-	-	-	0.09***	2.59	0.70	0.07**	2.05	0.14
Speculative pres.	-	-	-	-	-	-	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 spread	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	-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
Hedging pres.	-	-	-	-	-	-	0.05	1.21	0.03	0.10	1.63	0.59
Speculative pres.	-	-	-	-	-	-	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 spread	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	-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
Hedging pres.	-	-	-	-	-	-	-0.14***	-2.58	1.63	-0.04	-0.53	-0.47
Speculative pres.	-	-	-	-	-	-	-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 spread	-	-	-	-	-	-	0.07	1.39	0.11	0.09	1.22	-0.02
Default return	-	-	-	-	-	-	-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
Hedging pres.	-	-	-	-	-	-	0.02	0.44	-0.18	0.02	0.22	-0.51
Speculative pres.	-	-	-	-	-	-	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 spread	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	-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
Hedging pres.	0.12***	3.74	2.50	0.22***	2.83	-1.57	0.11***	2.97	0.90	0.07	1.21	0.10
Speculative pres.	-	-	-	-	-	-	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(Eq) 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 spread	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	-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
Hedging pressure	0.09***	3.25	0.77	0.11***	3.01	1.36	0.09**	2.37	0.66	0.08**	2.02	0.14
Speculative pres.	-	-	-	-	-	-	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	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	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	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	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 Disp.	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 Disp.	-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 Disp.	-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 Disp.	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 Disp.	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 Disp.	-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 Disp.	-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 Disp.	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*