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Laura Spierdijk and Zaghum Umar

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Laura Spierdijk* Zaghum Umar†

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*Laura Spierdijk (corresponding author) is affiliated to University of Groningen and Netspar. Address: University of Groningen, Faculty of Economics & Business, Department of Economics, Econometrics and Finance, P.O. Box 800, NL-9700 AV Groningen, The Netherlands. Email: l.spierdijk@rug.nl. Phone: +31 50 363 5929. Fax: +31 50 363 7337.

†Zaghum Umar is affiliated to University of Groningen and Netspar. Address: University of Groningen, Faculty of Economics & Business, Department of Economics, Econometrics and Finance, P.O. Box 800, NL-9700 AV Groningen, The Netherlands. Email: z.umar@rug.nl. The authors are grateful to Laurens Swinkels and Peter Schotman for useful comments. We also thank the audiences at the Dutch Central Bank, the Netspar Pension Day in Utrecht, the Netspar International Pension Workshop in Amsterdam, and the WEAI conference in San Francisco. The usual disclaimer applies.

Are Commodity Futures a Good Hedge Against Inflation?

Abstract

This study assesses the hedging properties of commodity futures across three dimensions: market, investment horizon and time. Measured over the full sample period (1970 – 2011), commodity futures show significant ability to hedge US inflation, especially for investment horizons of at least one year. Particularly commodity futures in the markets energy, industrial metals, and live cattle have favorable hedging properties. However, the hedging capacity exhibits substantial variation over time. It has been increasing since the early 1980s and reaches an historical high towards the end of the sample period. Although we establish significant hedging ability for commodity futures indices, we observe a trade-off between the reduction in real return portfolio variance realized by adding commodity futures indices to the portfolio and the expected real portfolio return.

Keywords: inflation hedging; costs of hedging; commodity futures; investment horizon

JEL classification: G11, G15, E44

1 Introduction

The short-run effects of price increases may seem small and negligible, but the long-run erosive effects of inflation on real asset returns can be substantial. Long-term investors therefore prefer to invest in assets that provide some protection against increases in the general price level – especially pension funds, whose liabilities usually rise with inflation. Inflation hedging has become particularly relevant in light of the recent global economic crisis. To circumvent this financial catastrophe, regulators and policy makers have been experimenting with unconventional tools, such as quantitative easing and stimulus packages, which might help overcome the crisis but also are likely to instigate inflation.

A vast literature investigates the inflation-hedging behavior of various asset classes, including stocks, bonds, commodities, and real estate. The present study contributes to this literature by analyzing the inflation-hedging potential of commodity futures across three different dimensions: market, investment horizon and time.

Commodity futures differ from conventional assets such as stocks in bonds in many ways (Gorton & Rouwenhorst 2006). Commodity futures represent a bet on commodity prices, where the latter are the main drivers of inflation rates. Consequently, commodity futures are directly linked to the components of inflation, although Erb & Harvey (2006) observe that even a broad-based commodity futures index does not contain all components of the consumer price index. Because commodity futures prices embed expectations about future commodity spot prices, they are expected to rise and fall with unexpected inflation.

Most empirical studies tend to confirm the positive hedging ability of commodities and commodity futures (Gorton & Rouwenhorst 2006, Erb & Harvey 2006, Worthington & Pahlavani 2007, Hoevenaars et al. 2008, Bekaert & Wang 2010, Bruno & Chincarini 2010, Beckmann & Czudaj 2013). Where some of these studies focus solely on an aggregate commodity or commodity futures index, others analyze a specific commodity market such as gold. Erb & Harvey (2006) are a notable exception. They analyze commodity futures in different markets, for a 1-year investment horizon.

This study extends the existing literature by assessing the hedging properties of commodity futures indices for short-term, medium-term and long-term investors (with investment horizons between 1 month and 10 years). In addition to the aggregate commodity futures indices of S&P GSCI, Thomson Reuters/Jefferies, Dow Jones UBS, and Rogers, we also assess the hedging capacity of commodity futures across different markets (including agriculture, energy, industrial metals, live cattle, and precious metals). Rolling-window and subsample analyses are applied to assess how the hedging capacity of the commodity futures indices has changed over time.

To analyze the hedging ability of commodity futures, we use four different inflation-hedging measures: (1) the Fisher coefficient, which is based on the seminal work of Fama & Schwert (1977); (2) the Pearson correlation between inflation and nominal asset returns, as proposed by Bodie (1982) and used by e.g. Hoevenaars et al. (2008); (3) the hedge ratio and associated costs of hedging defined by Bodie (1976); and (4) the hedging demand considered by Schotman & Schweitzer (2000), which is closely related to the inflation tracking approach proposed by Lamont (2001) and applied by e.g. Bekaert & Wang (2010). The costs of hedging proposed by Bodie (1976) quantify the possible trade-off between the hedging capacity of an asset and its expected real return. These four hedging measures assess the hedging capacity of an asset on a stand-alone basis; i.e., using only asset returns and inflation rates. They have been used in the literature as a tool for doing a quick scan of an asset's hedging ability. Their popularity can be explained from their relative simplicity and modest data requirements.

We apply a vector autoregressive (VAR) model to specify the relation between inflation rates and commodity futures returns and to estimate the multi-period hedging measures. As noted by Hodrick (1992), the VAR approach provides a flexible means to assess the long-horizon properties of asset returns without using overlapping data. VAR models have been used widely in other studies (Schotman & Schweitzer 2000, Campbell & Viceira 1999, 2001, Campbell et al. 2003, Hoevenaars et al. 2008). Because of the heterogeneity of the sample period in terms of inflationary regimes (including several years prior to the Great Moderation) and commodity futures prices (Chinn & Coibion 2013), a rolling-window and subsample analysis is performed to deal with any structural change.

Long-horizon hedging measures are likely to be subject to substantial estimation uncertainty. But there is an additional reason to suspect estimation uncertainty, even for short investment horizons. Commodity futures returns exhibit substantially more volatility than the slowly moving process of inflation. The time-series properties of inflation rates and commodity futures returns thus differ completely (Schotman & Schweitzer 2000), which may induce a considerable amount of estimation uncertainty in the hedging measures. We use a bootstrap approach to obtain confidence intervals for the multi-period hedging measures. These confidence intervals explicitly quantify the amount of estimation uncertainty involved with the hedging measures and are used to assess the statistical significance of an asset's hedging capacity.

The main results of this study are as follows. Measured over the full sample period (1970 – 2011), commodity futures show significant ability to hedge US inflation (particularly commodity futures in the markets energy, industrial metals, and live cattle), especially for investment horizons of at least one year. However, the hedging capacity exhibits substantial variation over time. It has been increasing since the early 1980s and reaches an historical high towards the end of the sample period. We explain the increase in the hedging ability from the economic environment. In a relatively stable inflationary period such as the Great Moderation, low (expected) inflation rates are more likely to reflect negative demand shocks and vice versa. Under such conditions, low inflation rates tend to go hand in hand with low commodity futures returns (and vice versa). Although we establish significant hedging ability for commodity futures indices, we identify a trade-off between the reduction in real return variance realized by adding commodity futures indices to the portfolio and the expected real portfolio return. Whether or not investors are willing to sacrifice part of their expected return in exchange for (partial) immunization against inflation risk depends on their risk preferences.

The setup of the remainder of this paper is as follows. Section 2 reviews four common methods for quantifying the hedging potential of an asset, which we compare in Section 3. The empirical implementation of four of these hedging measures appears in Section 4. Sections 5 and 6 present and discuss the empirical results, focusing on the hedging properties of four commodity futures indices during the period 1970 – 2011. Finally, Section 7 concludes.

2 Definitions of inflation hedge

In this section, we detail four commonly applied methods to quantify the hedging potential of an asset. We start with some notation. We assume a k-period investment horizon and focus on simple k-period asset returns and inflation rates. We denote the nominal k-period asset returns from time

t to time $t+k$ as $R_t^{(k)}$. Real returns over the same interval are denoted by $r_t^{(k)}$. The k-period real return on a nominally riskless bond thus is $r_{b,t}^{(k)}$, and the corresponding nominal return is $R_{b,t}^{(k)}$. Similarly, the k-period real return on a portfolio is denoted by $r_{p,t}^{(k)}$. The inflation rate from time t to $t+k$ is $\pi_t^{(k)}$, which is based on the consumer price index. One-period inflation rates, nominal asset returns, and nominal bond yields are denoted by π_{t+1}, R_{t+1}, and $R_{b,t+1}$, respectively.

2.1 Fisher hypothesis

Following Fisher (1930), the ex ante nominal return on an asset is equal to the sum of the ex ante real return and the anticipated inflation rate for the same period. In an efficient market, all available information goes into calculating the anticipated returns and inflation, so conditional on market efficiency, we can write the Fisher hypothesis as

$$\mathbb{E}_t[R_t^{(k)}] = \mathbb{E}_t[r_t^{(k)}] + \mathbb{E}_t[\pi_t^{(k)}]. \tag{1}$$

According to Fisher (1930), the real and monetary sectors in an economy are largely independent, which means that expected real asset returns and expected inflation are unrelated. Consequently, Equation (1) is equivalent to saying that expected nominal returns on any asset move in parallel with expected inflation – often formulated by stating that expected real returns are statistically uncorrelated with expected inflation.

Fama & Schwert (1977) translated the Fisher hypothesis into an empirical test of the hedging potential of an asset. They started by regressing nominal asset returns on the expected rate of inflation:

$$R_t^{(k)} = \mu + \beta \mathbb{E}_t[\pi_t^{(k)}] + \varepsilon_t. \tag{2}$$

In this case, (ε_t) is a mean-zero error term with variance σ^2, uncorrelated with $\mathbb{E}_t[\pi_t^{(k)}]$. With some abuse of notation, we omit the investment horizon k in the notation of model coefficients and error terms. According to Fama & Schwert (1977), the asset is a perverse hedge for $\beta < 0$, a partial hedge for $0 < \beta < 1$, and a complete hedge for $\beta \geq 1$. The estimation of Equation (2) thus requires a suitable proxy for expected inflation, which is inherently unobserved. Because we may be also interested in the extent to which nominal asset returns reflect the unexpected component of inflation (the inflation risk premium), we can expand Equation (2) (Fama & Schwert 1977):

$$R_t^{(k)} = \mu + \beta \mathbb{E}_t[\pi_t^{(k)}] + \gamma\left(\pi_t^{(k)} - \mathbb{E}_t[\pi_t^{(k)}]\right) + \varepsilon_t, \tag{3}$$

where $\pi_t^{(k)} - \mathbb{E}_t[\pi_t^{(k)}]$ denotes unexpected inflation. Alternatively, we might regress nominal asset returns on ex post (realized) inflation rates (Jaffe & Mandelker 1976, Boudoukh & Richardson 1993, Bekaert & Wang 2010), yielding the regression model

$$R_t^{(k)} = \mu + \beta \pi_t^{(k)} + \varepsilon_t. \tag{4}$$

Whereas the Fisher coefficient in Equation (4) reflects the contemporaneous impact of inflation on expected asset returns, dynamic extensions are possible using VAR or Vector Error Correction (VEC) models (Ely & Robinson 1997, Anari & Kolari 2001, Worthington & Pahlavani 2007).

2.2 Optimal portfolio

Following Bodie (1976, 1982) and Schotman & Schweitzer (2000), we consider an investor who invests a fraction $w^{(k)}$ of his wealth in a risky asset and the remaining $1 - w^{(k)}$ in a k-period nominally riskless bond. At time t, the investor seeks to maximize the multi-period mean-variance criterion

$$\max_{w^{(k)}} \mathbb{E}_t[r_{p,t}^{(k)}] - \frac{\mathbb{V}\mathrm{ar}_t[r_{p,t}^{(k)}]}{2\gamma}, \tag{5}$$

where $r_{p,t}^{(k)} = w^{(k)} r_t^{(k)} + (1 - w^{(k)}) r_{b,t}^{(k)}$ equals the real portfolio return and γ is the investor's risk-aversion parameter. At time t, the mean-variance optimal portfolio weight $w^{(k)}$ is given by

$$w^{(k)} = \underbrace{\frac{\gamma \mathbb{E}_t[r_t^{(k)} - r_{b,t}^{(k)}]}{\mathbb{V}\mathrm{ar}_t[R_t^{(k)}]}}_{\textit{speculative demand}} + \underbrace{\frac{\mathbb{C}\mathrm{ov}_t[R_t^{(k)}, \pi_t^{(k)}]}{\mathbb{V}\mathrm{ar}_t[R_t^{(k)}]}}_{\textit{inflation-hedging demand}}. \tag{6}$$

Bodie (1982) explicitly distinguishes between the first and second term in Equation (6). The first term reflects the demand for the asset that results from the real risk premium on the asset (called the speculative demand). The second term is demand for the asset that arises from its covariance with inflation (called the inflation-hedging demand). The hedging demand is independent of an investor's risk preferences, so that an extremely risk averse investor (with a very small value of γ) would still invest at least this amount in the asset regardless of the asset's real risk premium. The hedging demand represents the fraction of the asset that has to be added to the nominal bonds in order to obtain the global minimum-variance (GMV) portfolio (Bodie 1982). This part of the demand is called hedging demand because it results in a decrease in the portfolio's real return variance, as will be pointed out in Section 2.2.3.

2.2.1 Hedging demand (Schotman & Schweitzer 2000)

Schotman & Schweitzer (2000) use the k-period hedging demand, denoted by Δ, as a measure of the hedging capacity of an asset. We can rewrite the hedging demand in Equation (6) as

$$\Delta = \rho \Big(\frac{\mathbb{V}\mathrm{ar}_t[\pi_t^{(k)}]}{\mathbb{V}\mathrm{ar}_t[R_t^{(k)}]} \Big)^{1/2}, \tag{7}$$

where $\rho = \mathbb{C}\mathrm{orr}_t[R_t^{(k)}, \pi_t^{(k)}]$ is the correlation between the k-period nominal asset return and the k-period inflation rate. Schotman & Schweitzer (2000) view assets with a higher hedging demand as better hedges against inflation.

2.2.2 Inflation-tracking portfolio (Lynch 2001)

We can also give an alternative interpretation to the hedging demand of Schotman & Schweitzer (2000). An economic tracking portfolio contains assets with returns that track an economic variable, such as inflation (Lynch 2001). The portfolio weights of such a portfolio can be obtained by regressing the inflation rate on nominal asset returns (and any relevant control variables), with the additional restriction that the regression coefficients sum to unity if multiple assets are involved. The hedging demand of Schotman & Schweitzer (2000) is a special case of an inflation-tracking portfolio, where the inflation rate is tracked by a single nominal return series. It is obtained by regressing the inflation rate on nominal asset returns, such that it boils down to the coefficient Δ in the regression

$$\pi_t^{(k)} = c + \Delta R_t^{(k)} + \eta_t. \tag{8}$$

This is the reversed regression of Equation (2).

2.2.3 Hedge ratio (Bodie 1976)

Instead of considering the hedging demand Δ itself, Bodie (1976) looks at the maximum possible decrease in real return variance realized by adding the risky asset to a portfolio consisting of nominal bonds only. Hence, Bodie (1976) hedge ratio, denoted by S, is defined as

$$S = \frac{k\text{-period real return variance of the GMV portfolio}}{k\text{-period real return variance of the nominally risk-free bond}}. \tag{9}$$

A risky asset is considered a better hedge against inflation when its hedge ratio is *lower*.

Because inflation is the only source of risk for the real return on the nominal bond, S measures the pure inflation hedging potential of the risky asset. If we use another benchmark asset instead of the nominally riskless bond, with a risky nominal return, the hedge ratio would also pick up the ability of the asset to reduce the risk associated with the nominal return on the benchmark asset.

Although the correlation is usually associated with normal distributions (for which the concepts of independence and uncorrelatedness are equivalent), the interpretation of the hedge ratio as the reduction in real-return variance does not require normally distributed asset returns and inflation rates. However, our assumption of mean-variance utility implicitly assumes that investor preferences are fully captured by the mean and variance of portfolio returns.

Because of the possible trade-off between the hedging capacity of an asset and its expected real return, Bodie (1976) also considers the costs of hedging C. Specifically, he calculates C as

$$\begin{aligned} C \quad = \quad & \text{expected } k\text{-period real return on the nominally risk-free bond} \\ & - \text{expected } k\text{-period real return on the GMV portfolio.} \end{aligned} \tag{10}$$

These costs reflect the minimum possible decrease in expected real return incurred by adding the risky asset to a portfolio consisting of nominal bonds only.[1]

2.3 Correlation coefficient

Bodie (1982) shows that $S = 1 - \rho^2$. For $\rho = 1$, we find $S = 0$. Hence, the variance of the GMV portfolio equals zero; the risky asset eliminates all inflation risk and acts as a perfect hedge against inflation. The same holds for $\rho = -1$, but this value corresponds to a short position in the risky asset. For $\rho = 0$, we get $S = 1$, which means that the risky asset does not have any inflation-hedging ability. In this case the hedging demand equals zero and the GMV portfolio consists of nominally risk-free bonds only. In general, higher values of $|\rho|$ result in a lower value of the correlation between the real return on the nominal bond and the real return on the risky asset. Hence, the diversification potential of the risky asset increases with $|\rho|$.

[1]To calculate the costs of hedging, we will use the following quadratic approximation to calculate the simple real return on an asset: $r_t^{(k)} = R_t^{(k)} - \pi_t^{(k)} - \mathbb{C}\mathrm{ov}[R_t^{(k)}, \pi_t^{(k)}] + \mathbb{V}\mathrm{ar}[\pi_t^{(k)}]$. This approximation is based on Îto's lemma and holds exactly in continuous time (Sercu 1981).

Bodie (1982) uses the correlation ρ as a measure of the effectiveness of an asset as a hedge against inflation. Indeed, instead of looking at the hedge ratio S, we can equivalently consider the correlation coefficient. The squared correlation coefficient reflects the maximum possible decrease in the k-period real-return variance of a portfolio consisting of k-period nominally risk-free bonds, realized by adding the risky asset to the nominal bonds. This results in the following definition: An asset is a better hedge against inflation when the absolute value of the correlation between nominal asset returns and the rate of inflation is higher.

3 Relation between hedging measures

This section investigates the properties of the various hedging measures and assesses the differences and similarities among the different definitions.

3.1 Relation with correlation

We note an important link among Bodie (1982) correlation between nominal asset returns and inflation, Fama & Schwert (1977) approach, and Schotman & Schweitzer (2000) method. To see it, note that the coefficient β in the regression

$$R_t^{(k)} = \mu + \beta \pi_t^{(k)} + \varepsilon_t, \tag{11}$$

is closely related to the correlation ρ:

$$\beta = \frac{\mathbb{C}\mathrm{ov}_t[R_t^{(k)}, \pi_t^{(k)}]}{\mathbb{V}\mathrm{ar}_t[\pi_t^{(k)}]} = \rho\Big(\frac{\mathbb{V}\mathrm{ar}_t[R_t^{(k)}]}{\mathbb{V}\mathrm{ar}_t[\pi_t^{(k)}]}\Big)^{1/2}. \tag{12}$$

Hence, the Fisher coefficient in Equation (11) boils down to a scaled version of the correlation. Intuitively, Equation (12) indicates that the influence of inflation on the expected return is determined by the correlation between returns and inflation, as well as a factor related to the scale difference between returns and inflation. Similarly, we can rewrite the hedging demand in Equation (7) as

$$\Delta = \rho\Big(\frac{\mathbb{V}\mathrm{ar}_t[\pi_t^{(k)}]}{\mathbb{V}\mathrm{ar}_t[R_t^{(k)}]}\Big)^{1/2}. \tag{13}$$

The hedging demand of Schotman & Schweitzer (2000) in turn is a scaled version of the correlation, and the scaling factor is exactly the reciprocal of the one in the Fisher coefficient. For a given correlation between nominal asset returns and inflation rates, the Fisher coefficient and the hedging demand have the same sign as the correlation. However, the magnitude of the three measures generally differs, according to the scale difference between nominal asset returns and inflation rates. The variance of asset returns is typically higher than the variance of inflation, causing the scaling factor in the Fisher coefficient to be relatively large. Consequently, if the correlation is high, the Fisher coefficient of a typical asset is also high. In contrast, the hedging demand is low in such a typical case.

3.2 Discussion

The Fisher coefficient is a marginal effect and reflects the impact on expected returns of a unit change in inflation. Because it is a marginal effect, it depends on the scale of both inflation and nominal asset returns. Ceteris paribus, the best hedge is the asset with the highest volatility in nominal returns. According to Schotman & Schweitzer (2000) hedging demand, which is also a marginal effect, the best hedge is the asset with the lowest volatility.

It is possible that an asset is a complete hedge against inflation according to the Fisher coefficient, although its correlation with inflation is low. Hence, adding such an asset to a portfolio of nominal bonds will not lead to a large reduction in the real return variance. Similarly, the hedging demand for an asset that is strongly correlated with inflation may be low. Such an asset is able to realize a substantial reduction in the portfolio's real return variance, although the hedging demand for the asset is low.

When different hedging measures lead to contradictory results on the hedging ability of an asset, we feel that the correlation coefficient should be leading. The interpretation of the (squared) correlation coefficient as an inflation-hedging measure is grounded in mean-variance investment theory; it is directly related to the reduction in real return variance that can be achieved by adding the risky asset to a portfolio of nominal bonds. Moreover, the correlation coefficient is scale-free and can be used to compare the hedging capacity across assets, sample periods, and investment horizons. The other hedging measures are scale dependent and do therefore not allow for a comparison of the hedging ability across different dimensions.

4 Methodology

To estimate the hedging measures from Section 2, we first model the relation between asset returns and inflation. Moreover, we quantify the uncertainty involved with the hedging measures by means of bootstrapped confidence intervals.

4.1 VAR model

Our data sample, containing more than 40 years of monthly data, contains too few non-overlapping long-horizon returns to reliably estimate 5-year and 10-year hedging measures. We therefore opt for a VAR-based approach to estimate the hedging measures. According to Hodrick (1992), VAR models are a convenient tool for long-horizon measurement and inference. Motivated by Wold's decomposition theorem, VAR models provide a flexible way to model the relation between inflation rates and asset returns and avoid the statistical difficulties related to using overlapping returns. VAR models have been used widely in other studies, such as Schotman & Schweitzer (2000) and Hoevenaars et al. (2008).

We thus use a reduced-form VAR(p, q) model to specify the dynamics between nominal one-period asset returns (R_{t+1}) and one-period inflation rates (π_{t+1}):

$$\pi_{t+1} = \mu_1 + \sum_{i=0}^{p} \beta_{1i} R_{t-i} + \sum_{j=0}^{q} \gamma_{1j} \pi_{t-j} + \varepsilon_{1,t+1};$$

$$R_{t+1} = \mu_2 + \sum_{i=0}^{p} \beta_{2i} R_{t-i} + \sum_{j=0}^{q} \gamma_{2j} \pi_{t-j} + \varepsilon_{2,t+1}. \quad (14)$$

Thus($\varepsilon_{1,t}$) and ($\varepsilon_{2,t}$) are mutually and serially uncorrelated error terms, with $\mathbb{E}[\varepsilon_{1,t}] = \mathbb{E}[\varepsilon_{2,t}] = 0$ and contemporaneous covariance matrix $\Sigma_t = \mathbb{E}[\varepsilon_{1,t}\varepsilon_{2,t}]$. We notice that consistent (OLS) estimation of the VAR model does not require any assumption about conditional heteroskedasticity. We will come back to this issue in Section 4.2.

Although it is possible to extend the VAR model with additional predictor variables to improve the goodness of fit, we confine the present analysis to the bivariate VAR model of Equation (14). We do this because the hedging measures under consideration are designed as stand-alone measures, using only commodity returns and inflation rates to assess the hedging capacity.

4.2 Hedging measures and confidence bounds

We use the estimated VAR model to calculate the (multi-period) hedging measures of Section 2 in the following way. We estimate a bivariate VAR model for monthly asset returns and inflation rates. Subsequently, we recursively simulate long series of monthly asset returns and inflation rates under specific distributional assumptions regarding the VAR errors (while maintaining the contemporaneous correlation between the errors of the return and inflation rate equations). We use the simulated series to construct non-overlapping multi-period asset returns and inflation rates. We then calculate the single-period and multi-period correlations between the returns and inflation rates, as well as the costs of hedging. Because we find similar results regardless of the (homoskedastic or heteroskedastic) distributional assumptions about the VAR residuals, we estimate the correlations under the assumption that the VAR errors follow the empirical distribution of the VAR residuals. Simulation is a convenient way to calculate the (multi-period) hedging measures, because the latter are highly non-linear functions of the model parameters.[2]

Because the simulated asset returns and inflation rates are based on an estimated VAR model, the resulting estimates of the single-period and multi-period correlations are subject to parameter uncertainty. They are also subject to sampling uncertainty, because we estimate the correlation using simulation (see above). We estimate 95% confidence intervals for parameter and sampling uncertainty for the single-period and multi-period correlations by means of a bootstrap. Each of the $B = 1,000$ bootstrap runs consists of the following steps. We generate VAR model residuals according to a wild bootstrap (Mammen 1993), which we use to recursively generate new series of monthly asset returns and inflation rates with the same series length as the original sample. Next, we estimate the VAR model by means of OLS per equation, using the newly generated asset returns and inflation rates. We use the estimated VAR model to calculate the single-period and multi-period correlations as described above. The wild bootstrap is robust against heteroskedasticity of unknown form, including conditional heteroskedasticity of the GARCH type (Gonçalves & Lutz 2004). Finally, we use the percentile method to obtain the 95% confidence intervals.

[2]For the square of the correlation coefficient to be interpreted as the reduction in real return variance realized by adding the asset to a portfolio of nominal bonds only, we have to use simple (instead of continuously compounded) asset returns and inflation rates. The gross multi-period asset returns and inflation rates are obtained as the product of the one-period gross returns and inflation rates. Because the multi-period returns arise as a product, they are non-linear functions of the model parameters.

The hedging measures of Section 2 are defined in terms of conditional expectations, variances, and covariances. In line with previous studies such as Hoevenaars et al. (2008), we calculate unconditional hedging measures, which does not change the essence of our analysis and facilitates comparisons with existing studies.

5 Empirical results

We start this section with a brief data description, then discuss the values of the various hedging measures for different investment horizons.

5.1 Data

To assess the hedging potential of commodities, we use monthly returns on the S&P GSCI Total Return Index, a composite index of commodity sector returns that represents a broadly diversified, unleveraged, and long-term investment in commodity futures. It measures a fully collateralized commodity futures investment rolled forward from the fifth to the ninth business day of each month. The GSCI index uses T-bills as collateral. Currently the S&P GSCI includes 24 commodity futures contracts, classified into five groups (energy, industrial metals, precious metals, agriculture, and livestock). This series has been used in prior studies assessing the hedging capacity of commodities such as Hoevenaars et al. (2008), which facilitates comparison. Investors can invest in the S&P GSCI index by means of exchange traded funds (ETFs) and/or exchange traded notes (ETNs). The monthly inflation rates reflects the US seasonally corrected all urban consumer price index (CPI), provided by the Bureau of Labor Statistics. The sample period starts in January 1970 and runs until May 2011 and has been chosen on the basis of the availability of the S&P GSCI Total Return Index in Thomson Reuters Datastream.

Table 1 provides sample statistics on nominal returns on the S&P GSCI Total Return Index and monthly inflation rates. The average monthly inflation rate is 0.4%, with a standard deviation of 0.3%. The average monthly nominal return on the S&P GSCI during this period is 1.0%, and volatility equals 5.8%. The monthly inflation rate is characterized by some excess kurtosis, which implies departures from normality. By contrast, the returns on the S&P GSCI Total Return Index have a kurtosis close to three.

For the sample period, augmented Dickey-Fuller and Philips-Perron unit root tests reject the null hypothesis that the log of the CPI has a unit root at a 10% significance level. If we run Johansen (1991) cointegration tests anyhow, these tests indicate no cointegration at the 5% level. These results legitimate our use of VAR models to capture the dynamics between commodity returns and inflation rates.

The sample correlation between the monthly return on the S&P GSCI index and the inflation rate is 0.14 (with asymptotic standard error 0.065), resulting in a Fisher coefficient of 2.4 (with White's heteroskedasticity robust standard error equal to 1.1) and a hedging demand of 0.008 (0.004). The VAR-based multi-period hedging measures will be derived in Section 5.3.

To calculate the costs of hedging, we need the average yields during the sample period on risk-free bills and bonds with maturities between 1 month and 10 years. For this purpose we use average T-bill rates (with 1-month and 6-month maturities) and average Treasury Constant Maturity rates (for maturities between one and 10 years).[3]

5.2 VAR model

On the basis of the Akaike criterion and the amount of residual autocorrelation, we select a lag length of four.[4] Table 2 displays the estimation results. As usual the adjusted R^2 is low for the return equation; it is much higher for the inflation equation. The difference in time-series properties between inflation rates and commodity returns becomes apparent when we consider the contemporaneous covariance matrix that corresponds to the model innovations in Equation (14). During the full sample period, the volatility of innovations in inflation equals 0.12%, whereas innovations in commodity returns reveal a much larger volatility of 5.7%. The contemporaneous correlation between the two innovations equals 0.09. Persistence in inflation is higher than in returns (0.74 versus 0.12).

[3]We take average yields from http://research.stlouisfed.org/fred2/categories/22. We use the series with mnemonics TB4WK, TB6MS, GS1, GS2, GS3, GS5, and GS10. The series GS2 and TB4WK are not available during the full sample period that starts in 1970. We therefore calculate the average yield for these two maturities during the available time period, which starts in 2001 (TB4WK) and 1976 (GS2), respectively. Moreover, the 4-year yield is obtained as the average of the 3-year and 5-year yields. This results in the following 'average' yield curve for the full sample period 1970 – 2011: 0.15% (1 month), 2.8% (6 months), 6.1% (1 year), 13.1% (2 years), 21.0% (3 years), 30.1 (4 years), 39.2% (5 years), 99.8% (10 years). These percentages have been obtained under the assumption that annual interest payments are reinvested against the average annual yield. The yield curves for the subsamples have been calculated in a similar fashion.

[4]We varied the lag length of the VAR model, but this did not have a significant impact on the results.

5.3 Estimated hedging measures

Following the approach outlined in Section 4, we estimate the four hedging measures for investment horizons between 1 month and 10 years. Because the hedge ratio S proposed by Bodie (1976) provides qualitatively the same information as the correlation coefficient, we do not report the estimates of the former hedging measure. Hence, we focus on the correlation, Fisher coefficient, hedging demand, and costs of hedging based on the total inflation rate and the returns on the commodity futures index.

The VAR-based hedging measures appear in Table 3. We see that the VAR-based values of the monthly hedging measures are very close to the sample values obtained in Section 5.1, confirming the robustness of our VAR-approach.

Table 3 also provides 95% bootstrap confidence intervals for the point estimates of the hedging measures. Throughout, we use the confidence intervals to assess the significance of the hedging measures. For example, if 0 lies in the confidence interval, then the hedging measure does not significantly differ from 0 at a 5% significance level.

Table 3 shows that the correlation coefficient is significant regardless of the investment horizon. Moreover, it increases with investment horizons up to four years, after which it slightly declines. With a 6-month investment horizon, the hedging capacity of the commodity index is much better than for a 1-month horizon. For longer investment horizons though, the differences in hedging ability become smaller. The best hedging capacity of commodity futures is achieved for a 4-year investment horizon. Given a correlation of 0.55, the hedge ratio equals $S = 0.7$, which means that at most 30% of the real return variance of the nominal bond can be eliminated by adding the commodity futures index.

Table 3 also reports the estimated costs of hedging (assuming the yield curve described in Section 5.1), expressed in percentage points. The costs of hedging are significant for investment horizons of twelve months and longer (although the amount of parameter uncertainty is substantial). Hence, adding commodity futures to the nominally risk-free bonds results at best in a 30% decline in the real return variance, but doing so significantly reduces the expected return of the portfolio with at least 15% over a 4-year investment period (which boils down to about 0.3% per month). Whether or not investors are willing to sacrifice part of their expected return in exchange for protection against inflation risk depends on their risk preferences.

The value of the Fisher coefficients in Table 3 may seem remarkably high, particularly for longer investment horizons. To understand this, it is important to realize that the value of Fisher coefficient depends on the scale of asset returns and inflation. Because the volatility of commodity returns rises faster with the investment horizon than the volatility of the inflation rate, the Fisher coefficient becomes relatively large for longer investment horizons. In contrast with the correlation, the Fisher coefficient increases monotonically with the investment horizon. According to the Fisher coefficient, the commodity index is a complete hedge against inflation for all investment horizons.

Schotman & Schweitzer (2000) hedging demand is low, but significantly positive for investment horizons exceeding 1 month. Because the scaling factor in the hedging demand is reciprocal to the one appearing in the Fisher coefficient, the low value of the hedging demand comes as no surprise. The hedging demand starts to decrease as of investment horizons of four years, which is caused by a decline in both the correlation coefficient and the scaling factor.

As expected, the confidence intervals' width tends to increase with the investment horizon for all hedging measures. This is particularly apparent for the Fisher coefficient and the costs of hedging. It emphasizes the importance of quantifying the estimation uncertainty for long investment horizons.

Finally, we compare our results to the existing literature. Although comparison across studies is difficult due to substantial differences in data, sample period, investment horizon, and methodology, several studies reveal a tendency for positive Fisher and correlation coefficients, particularly at longer investment horizons.[5] Hence, our estimation results confirm the positive hedging capacity of commodity futures. At the same time, however, we show that significant costs of hedging may arise, in the form of a lower expected real portfolio return.

Clearly, the real return on the nominally risk-free rate plays a crucial role in our calculation of the costs of hedging. The average yield on nominally risk-free bills and bonds shows a decreasing trend during the sample. This suggests that the costs of hedging vary over time, which we will explore in more detail in Section 6.3.

[5] See e.g. Bodie (1983), Irwin & Brorsen (1985), Irwin & Landa (1987), Elton et al. (1987), Edwards & Park (1996), Taylor (1998), Gorton & Rouwenhorst (2006), Worthington & Pahlavani (2007), Hoevenaars et al. (2008), Bekaert & Wang (2010), and Bruno & Chincarini (2010).

5.4 Hedging capacity of S&P GSCI subindices

The aggregate S&P GSCI Total Return Index currently consists of five subindices (energy, industrial metals, precious metals, agriculture, and livestock). Sample statistics for these subindices during the period 1983 – 2011 are displayed in Table 4. We start the sample in 1983 instead of 1970 because of more limited data availability of the subsector indices (in particular the energy subindex). Because the livestock subindex is only available as of January 2002, we have replaced it with the live cattle index. Table 4 reveals some differences in the risk-return characteristics of the five subsector indices, suggesting that we may also find differences in hedging ability.

Table 5 details the hedging measures and their associated confidence intervals for the five subsector indices during 1983 – 2011, for investment horizons ranging from 1 month to 10 years. With the discussion of Section 3.2 in mind (and to save space), we only report and discuss the estimated correlation coefficients and the costs of hedging. We emphasize that the point estimates and confidence bounds for the other hedging measures give comparable outcomes; they are available upon request. According to the correlation coefficient the energy, industrial metals, and live cattle subindices are the best inflation hedges. The largest hedging capacity is found for the energy subsector index, which has a maximum correlation of 0.66 (for a 1-year investment horizon). This means that up to more than 40% of the real return variance of the nominal bond can be eliminated by adding the energy subsector index. Agriculture and precious metals have no significant hedging potential. Although certain studies claim gold to act as a hedge against inflation (Bekaert & Wang (2010), Bruno & Chincarini (2010)), we do not find any evidence for a significant hedging ability of precious metals. Finally, the costs of hedging are particularly significant for the energy and live cattle subindices (at least 6% over a 10-year investment horizon).

For the sake of comparison, Table 6 reports the hedging measures for the aggregate S&P GSCI Total Return Index during the period 1983 – 2011. During the subperiod the correlation coefficient is substantially higher than during the full sample period (up to 0.75 instead of 0.55), corresponding to a maximum reduction in the portfolio's real return variance of more than 50% for a 3-year investment horizon. The difference in hedging capacity between the full sample and the subperiods suggests that the hedging capacity changes over time; an issue that we will discuss in more detail in Section 6.3.

6 Further empirical analysis

This section considers three alternative commodity indices and investigates if their hedging capacity is comparable with that of the S&P GSCI Total Return Index. Second, we analyze the influence of the collateral on the hedging capacity of the commodity indices. Third, we apply a rolling-window analysis to assess changes in the hedging capacity over time.

6.1 Alternative commodity futures indices

As a robustness check on the results obtained with the S&P GSCI index, we consider three alternative commodity futures total return indices: the indices of Dow Jones UBS, Thomson Reuters/Jefferies, and Rogers. These commodity indices are available as of February 1991 (Dow Jones UBS), February 1994 (Thomson Reuters/Jefferies), and August 1998 (Rogers), respectively. Like the S&P GSCI Total Return Index, the former commodity indices are investable through ETFs and/or ETNs. Table 1 displays sample statistics for these commodity futures indices, from which we see that the indices' risk-return characteristics differ from those of the S&P GSCI Total Return Index. We may therefore also expect differences in hedging capacity.

Table 7 displays the hedging measures and their associated confidence intervals for investment horizons ranging from 1 month to 10 years. Their correlations with inflation tend to be significantly positive and relatively high (up to almost 0.8). A correlation of 0.8 corresponds to a maximum reduction in the real return variance of more than 60%. The significance of the costs of hedging depends on the index and the investment horizon. For each of three alternative indices they are significant for investment horizons of three years and longer (at least 12.3% over a 10-year investment horizon).

The three alternative commodity indices become available in the nineties, whereas the S&P GSCI index is already available from the early seventies. To obtain fully comparable results, we recalculate the hedging measures for the S&P GSCI Total Return Index based on the samples that start on February 1991 (i.e., the starting date of the DJ UBS Total Return Index), February 1994 (Thomson Reuters/Jefferies CRB Total Return Index), and August 1998 (Rogers International Total Return Index), respectively. Table 6 details the hedging measures based on the S&P GSCI Total Return Index and the corresponding confidence intervals for investment horizons ranging from 1 month to 10 years. According to the correlation coefficient, the hedging capacity during the subperiods is higher than during the full sample period (up to almost 0.8 instead of about 0.55), but of the same magnitude as the other commodity futures indices during the same sample periods. Also here we establish significant costs of hedging (at least about 12% over a 10-year investment horizon), but the point estimates of the costs of hedging are substantially lower than for the full sample.

Again we establish differences in hedging properties between the full sample and certain subperiods, which we will explore in more detail later.

6.2 The hedging capacity of the collateral

The total return on a collateralized commodity futures index consists of three components: spot, roll, and collateral return. The spot return stems from the change in the spot price of the underlying commodity, the roll return is derived from selling an expiring commodity futures contract and rolling into another contract to continue the investment, and the collateral return is the return earned by investing any remaining cash during the term of the contract.

All four commodity futures indices considered in this paper have US T-bills as collateral. T-bills have been shown to be good inflation hedges in existing studies such as Hoevenaars et al. (2008). It is therefore important to investigate to what extent the positive hedging capacity of the total return indices stems from the collateral. For all four commodity indices we compare the hedging capacity of the total return index with that of the excess return index to assess the influence of the collateral on the hedging ability.

Table 8 shows that the S&P GSCI Excess Return Index has significant hedging capacity during the 1970 – 2011 period for all investment horizons, according to the correlation coefficient. The correlation based on excess returns is somewhat lower than the correlation based on total returns. In terms of the hedge ratio, a correlation of 0.55 (Total Return) results in a maximum 30% reduction in the real return variance, whereas a correlation of 0.4 (Excess Return) leads to at most a 16% reduction. Moreover, the costs of hedging are significant (at least 41.4% over a 10-year investment horizon).

To assess the robustness of these findings, we also consider the total return indices of Dow

Jones UBS, Thomson Reuters/Jefferies and Rogers and analyze the influence of the collateral on the hedging capacity of these indices. Table 9 displays the estimation results. For all three indices the correlations between the excess returns and the inflation rate are very comparable with correlations in Table 7. Again the costs of hedging tend to be significant.

As in Section 6.1, we recalculate the hedging measures for the S&P GSCI Excess Return Index for the subsamples starting on February 1983, February 1991, February 1994, and August 1998. From Table 10 it becomes clear that the S&P GSCI Excess Return Index has significant hedging capacity during the subperiods according to the correlation coefficient, which is of the same magnitude as the correlations for the total return index in Table 6. Also the magnitude and significance of the costs of hedging across investment horizons is similar to what we found for the total return index.

We conclude that the influence of the collateral on the hedging capacity of the total return index is limited.

6.3 Rolling-window estimates

The differences in hedging properties across subperiods suggest that the hedging capacity of commodity indices is subject to change, which comes as no surprise given that the analysis spans a 41-year period. We adopt a rolling-window approach to gain insight in the time-varying behavior of the hedging capacity. The rolling-window approach also allows for a comparison of the hedging capacity across different time periods. For example, US inflation rates stabilized after 1980 – a time period referred to as the Great Moderation (Benati & Surico 2009) and commodity prices started to rise as of the early 2000s (Chinn & Coibion 2013). The rolling window approach will make clear how these changes affected the hedging capacity of commodity futures.

Figure 1 displays rolling window estimates of the correlation between the inflation rate and the return on the S&P GSCI Total Return Index, for investment horizons ranging from 1 month to 10 years. The rolling window estimates are plotted against the mid-date of the rolling-window interval. The length of the rolling window width has been determined on the basis of 'eyeballing'. Too small a window results in very erratic patterns in the correlation over time, but too large a window yields too little variation over time. Eyeballing makes clear that a window width of 10 years works well.

We establish substantial time variation in the rolling window estimates of the correlation. Most of the time the correlation between inflation rates and commodity returns is positive, with an exception during the 10-year sample periods with starting years 1979 –1981 (in Figure 1 this corresponds to the mid-years 1984 – 1986). This period contains the second Oil Crisis, as well as Black Monday in 1987. Low commodity returns in combination with high inflation rates (and vice versa) resulted in negative correlations during this period.

The samples that have a starting year of 1981 or later show a remarkable rise in the correlation (in Figure 1 this period corresponds to the mid-years 1981 and later). In a relatively stable inflationary environment such as the Great Moderation, low expected inflation rates are more likely to reflect negative demand shocks (and vice versa). Under such conditions, low inflation rates tend to go hand in hand with low commodity futures returns (and vice versa), resulting in positive correlation. The observed increase in the correlation largely explains the differences in hedging capacity established in the subsample analyses of Sections 6.1 and 6.2.

The fall of Lehman Brothers in September 2008 was followed by several months of low commodity returns and low inflation rates (occasionally even deflation). The low commodity returns and low inflation rates were a direct consequence of the weakening of the global economy and the associated negative demand shock. The combination of low commodity returns and low inflation rates resulted in a further rise in the correlation as measured over 10-year rolling window intervals.

As of the early nineties, the correlation has been fairly high with values ranging between 0.3 and 0.85 for investment horizons exceeding 6 months. The latter values correspond to a maximum reduction in the portfolio's real return variance of, respectively, almost 9% and more than 70%. Since September 2008 the correlation has reached a historical high; even above 0.8 for the longest investment horizons. This value of the correlation corresponds to a maximum reduction in the portfolio's real return variance of more than 60%.

A similar plot for the costs of hedging (not displayed) shows that the decline in the risk-free yield over time resulted in a decrease in the costs of hedging over time. In the current period, with historically low risk-free yields, the costs of hedging as defined by Bodie (1976) are very low.

7 Conclusions

Inflation hedging has become particularly relevant in light of the recent global economic crisis. This study has investigated the inflation hedging properties of commodity futures across three dimensions: market, investment horizon and time.

We have shown that commodity futures indices had significant ability to hedge US inflation during the 1970 – 2011 period, in particular for investment horizons of at least one year. However, the hedging capacity exhibits substantial variation over time. It has been increasing since the early 1980s and reaches an historical high towards the end of the sample period. By analyzing subsector indices, we found that commodities futures in the markets energy, industrial metals, and live cattle are the best inflation hedges.

Although we established significant hedging ability for commodity futures, we identified a trade-off between the reduction in real return variance realized by adding commodity futures to the portfolio and the expected real portfolio return. In practice, this trade-off may turn out even worse for investors. The commodity futures indices analyzed in this study are investable via Exchange Trades Funds or Exchange Traded Notes, which are subject to fees. These fees will further increase the costs of hedging. Whether or not investors are willing to sacrifice part of their expected return in exchange for protection against inflation risk depends on their risk preferences.

The different time-series properties of inflation rates and asset returns make it difficult to accurately estimate the relation between these two variables. To reduce parameter uncertainty, it is therefore tempting to use long data series. However, the use of long samples increases the risk of structural change. We established substantial variation over time in the hedging ability of commodity futures. To accurately assess the hedging capacity of an asset, it is therefore crucial to capture the time-varying relation between inflation rates and asset returns. Our rolling-window and subsample analysis serves as a first step in this direction, but more advanced options are available. We leave this as a direction for future research.

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Table 1: **Sample statistics for commodity returns and inflation rates**

	S&P GSCI	**CPI**	**CRB**	**DJ-UBS**	**Rogers**
mean	1.0	0.4	0.9	0.6	1.1
std.dev.	5.8	0.3	4.7	4.2	5.7
skewness	0.1	0.0	-0.5	-0.5	-0.6
kurtosis	2.7	4.8	2.4	2.9	2.4
Q1%	-13.3	-0.5	-9.8	-9.8	-12.2
Q5%	-8.6	0.0	-6.3	-6.3	-7.4
Q10%	-6.0	0.1	-4.9	-4.7	-5.5
Q50%	1.0	0.3	1.4	0.8	1.6
Q90%	7.4	0.8	6.0	5.5	7.3
Q95%	9.6	1.0	8.3	7.4	8.9
Q99%	16.9	1.3	11.9	10.5	14.5
start sample	1/30/1970	1/30/1970	2/28/1994	2/28/1991	8/31/1998
# observ.	497	497	208	244	154

Notes: This table displays sample statistics for the nominal returns on the S&P GSCI Total Return Index and the inflation rate (in %). The sample statistics are based on monthly data, covering the period January 1970 – May 2011. The last three columns contain sample statistics for three alternative commodity futures indices: Thomson Reuters/Jefferies CRB Total Return Index (available from February 1991), Dow Jones UBS Total Return Index (February 1994), and Rogers Total Return Index (August 1998). The sample quantiles are denoted Q1% etc.

Table 2: **Estimation results for VAR model**

dep.var: π_t				
	coeff.	**std.dev.**	**t-value**	**p-value**
intercept	0.078	0.021	3.734	0.000
π_{t-1}	0.508	0.072	7.109	0.000
π_{t-2}	0.055	0.078	0.710	0.478
π_{t-3}	0.028	0.062	0.452	0.651
π_{t-4}	0.146	0.052	2.825	0.005
r_{t-1}	0.021	0.003	6.586	0.000
r_{t-2}	-0.004	0.002	-1.791	0.074
r_{t-3}	0.000	0.002	0.045	0.964
r_{t-4}	0.000	0.002	-0.044	0.965
adj. R^2	0.551			
dep.var: r_t				
	coeff.	**std.dev.**	**t-value**	**p-value**
intercept	0.646	0.446	1.447	0.148
π_{t-1}	-0.095	1.206	-0.079	0.937
π_{t-2}	0.562	1.421	0.396	0.693
π_{t-3}	0.798	1.458	0.547	0.585
π_{t-4}	-0.699	1.133	-0.617	0.537
r_{t-1}	0.159	0.059	2.699	0.007
r_{t-2}	0.007	0.063	0.110	0.912
r_{t-3}	0.018	0.054	0.329	0.742
r_{t-4}	-0.065	0.057	-1.137	0.256
adj. R^2	0.031			

Notes: This table displays the estimation results for Equation (14) applied to the returns of the S&P GSCI Total Return Index during the full sample period January 1970 – May 2011. Estimation of the VAR model relies on OLS per equation. The standard errors are based on White's heteroskedasticity robust covariance matrix.

Table 3: **Hedging measures applied to S&P GSCI Total Return Index**

	ρ	β	Δ	C
1 M	**0.14**	**2.36**	**0.01**	**-0.01**
L	0.05	0.96	0.00	-0.01
U	0.22	3.80	0.01	0.00
6 M	**0.40**	**4.46**	**0.04**	**0.17**
L	0.17	1.87	0.02	0.00
U	0.55	6.67	0.05	0.78
12 M	**0.47**	**4.45**	**0.05**	**1.06**
L	0.16	1.49	0.02	0.05
U	0.63	6.99	0.07	3.95
24 M	**0.53**	**4.81**	**0.06**	**4.48**
L	0.15	1.26	0.02	0.19
U	0.69	7.93	0.08	15.61
36 M	**0.54**	**5.21**	**0.06**	**9.24**
L	0.16	1.22	0.02	0.40
U	0.71	8.84	0.08	31.97
48 M	**0.55**	**5.73**	**0.05**	**14.91**
L	0.15	1.26	0.01	0.74
U	0.72	10.09	0.08	50.22
60 M	**0.53**	**6.04**	**0.05**	**20.08**
L	0.14	1.32	0.01	0.94
U	0.71	11.41	0.08	73.46
120 M	**0.51**	**9.06**	**0.03**	**66.12**
L	0.14	1.80	0.01	3.13
U	0.66	22.27	0.06	222.73

Notes: This table displays various hedging measures applied to the S&P GSCI Total Return Index (for investment horizons ranging from 1 month until 10 years, during the full sample period January 1970 – May 2011. The hedging measures include the Pearson correlation (ρ), the Fisher coefficient in the Fama & Schwert (1977) regression (β), the hedging demand (Δ) of Schotman & Schweitzer (2000) and the costs of hedging (C). The upper (U) and lower (L) bounds of the 95% confidence intervals for the hedging measures are provided. The confidence intervals are based on $B = 1,000$ bootstrap runs. The investment horizons is given in months.

Table 4: **Sample statistics for commodity subsector indices**

	AGR	**EN**	**IM**	**LC**	**PM**
mean	0.4	1.1	1.1	0.3	0.5
median	0.3	1.0	0.6	0.2	0.1
sd	5.3	9.2	6.8	4.7	4.7
skewness	0.2	0.4	0.8	-0.3	0.1
kurtosis	1.5	1.9	4.5	1.3	1.7
Q1%	-13.1	-19.4	-13.3	-11.1	-11.1
Q2.5%	-11.0	-15.5	-9.5	-7.9	-7.7
Q5%	-8.7	-13.0	-7.7	-7.0	-6.2
Q10%	-5.8	-9.5	-5.8	-5.2	-4.8
Q50%	0.3	1.0	0.6	0.2	0.1
Q90%	6.5	11.2	9.1	6.5	6.2
Q95%	8.3	16.0	11.8	7.8	8.3
Q97.5%	11.9	19.7	14.3	9.6	10.7
Q99%	16.5	28.9	22.1	11.0	13.3

Notes: This table displays sample statistics (in %) for the nominal returns on the S&P GSCI Total Return subsector indices during the period January 1983 – May 2011. AGR stands for agriculture, EN for energy, IM for industrial metals, LC for live cattle, and PM for precious metals. All sample statistics are on a monthly basis. The sample quantiles of the return distribution are denoted Q1% etc.

Table 5: **Hedging measures applied to the subsector indices of the S&P GSCI Total Return Index**

	AGR		EN		IM		LC		PM	
	ρ	C	ρ	C	ρ	C	ρ	C	ρ	C
1 M	**0.00**	**0.00**	**0.24**	**0.00**	**0.16**	**0.00**	**0.13**	**0.00**	**0.04**	**0.00**
L	-0.08	0.00	0.14	-0.01	0.08	-0.01	0.08	-0.01	-0.05	0.00
U	0.07	0.00	0.33	0.00	0.24	0.00	0.21	0.00	0.12	0.00
6 M	**0.21**	**0.04**	**0.63**	**0.19**	**0.42**	**0.06**	**0.39**	**0.09**	**-0.09**	**0.01**
L	-0.02	0.00	0.53	0.03	0.21	-0.04	0.24	0.00	-0.28	-0.01
U	0.44	0.22	0.75	0.46	0.59	0.28	0.56	0.31	0.10	0.09
12 M	**0.24**	**0.11**	**0.66**	**0.50**	**0.46**	**0.19**	**0.44**	**0.26**	**-0.14**	**0.03**
L	-0.05	-0.01	0.56	0.11	0.21	-0.06	0.26	0.02	-0.39	-0.02
U	0.53	0.70	0.78	1.15	0.65	0.81	0.63	0.98	0.11	0.31
24 M	**0.25**	**0.27**	**0.65**	**1.15**	**0.47**	**0.50**	**0.46**	**0.64**	**-0.16**	**0.08**
L	-0.06	-0.02	0.56	0.31	0.20	-0.07	0.26	0.06	-0.45	-0.04
U	0.56	1.79	0.78	2.63	0.66	2.06	0.66	2.49	0.13	0.84
36 M	**0.27**	**0.49**	**0.65**	**1.84**	**0.48**	**0.91**	**0.47**	**1.10**	**-0.17**	**0.14**
L	-0.08	-0.03	0.55	0.54	0.20	-0.06	0.27	0.13	-0.46	-0.07
U	0.57	3.07	0.76	4.14	0.65	3.33	0.67	4.19	0.13	1.54
48 M	**0.26**	**0.65**	**0.63**	**2.56**	**0.48**	**1.33**	**0.46**	**1.52**	**-0.16**	**0.16**
L	-0.08	-0.03	0.54	0.84	0.19	-0.03	0.27	0.22	-0.46	-0.12
U	0.56	4.31	0.74	5.70	0.63	4.45	0.67	6.13	0.13	2.09
60 M	**0.27**	**1.00**	**0.60**	**3.14**	**0.46**	**1.66**	**0.46**	**2.04**	**-0.16**	**0.22**
L	-0.08	-0.04	0.52	1.20	0.18	0.00	0.26	0.29	-0.48	-0.17
U	0.57	5.81	0.72	7.24	0.62	5.78	0.67	8.26	0.13	2.87
120 M	**0.27**	**2.63**	**0.54**	**7.45**	**0.41**	**4.17**	**0.48**	**6.03**	**-0.17**	**0.63**
L	-0.08	-0.10	0.43	3.00	0.16	0.28	0.25	1.02	-0.47	-0.50
U	0.55	14.34	0.65	15.12	0.57	12.70	0.66	21.60	0.13	7.28

Notes: This table displays various hedging measures applied to the subsector indices of the S&P GSCI Total Return Index, for investment horizons ranging from 1 month until 10 years. The sample period is January 1983 – May 2011. AGR stands for agriculture, EN for energy, IM for industrial metals, LC for live cattle, and PM for precious metals. The hedging measures include the Pearson correlation (ρ) and the costs of hedging (C). The upper (U) and lower (L) bounds of the 95% confidence intervals for the hedging measures are provided. The confidence intervals are based on $B = 1,000$ bootstrap runs.

Table 6: **Hedging measures applied to the S&P GSCI Total Return Index for four subperiods (total returns)**

	start: 1/31/1983		start: 2/28/1991		start: 2/28/1994		start: 8/31/1998	
	ρ	C	ρ	C	ρ	C	ρ	C
1 M	**0.27**	**0.00**	**0.30**	**0.00**	**0.32**	**0.00**	**0.34**	**0.00**
L	0.17	-0.01	0.19	-0.01	0.21	-0.01	0.21	-0.02
U	0.37	0.01	0.41	0.02	0.43	0.03	0.47	0.03
6 M	**0.70**	**0.26**	**0.74**	**0.34**	**0.76**	**0.39**	**0.77**	**0.52**
L	0.59	0.06	0.66	0.06	0.67	0.09	0.67	0.11
U	0.80	0.57	0.85	0.73	0.86	0.86	0.87	1.13
12 M	**0.74**	**0.69**	**0.78**	**0.85**	**0.79**	**0.95**	**0.81**	**1.25**
L	0.60	0.17	0.68	0.17	0.70	0.24	0.70	0.24
U	0.85	1.45	0.88	1.69	0.89	2.08	0.90	2.53
24 M	**0.75**	**1.64**	**0.79**	**1.87**	**0.80**	**2.12**	**0.81**	**2.77**
L	0.61	0.40	0.69	0.45	0.71	0.61	0.72	0.60
U	0.85	3.40	0.88	3.71	0.88	4.56	0.89	5.53
36 M	**0.75**	**2.67**	**0.78**	**3.02**	**0.80**	**3.38**	**0.80**	**4.34**
L	0.61	0.71	0.69	0.82	0.70	1.02	0.71	1.12
U	0.84	5.47	0.86	5.66	0.87	7.06	0.87	8.61
48 M	**0.74**	**3.81**	**0.78**	**4.29**	**0.78**	**4.71**	**0.78**	**6.01**
L	0.61	1.06	0.68	1.21	0.70	1.50	0.71	1.60
U	0.83	7.59	0.85	7.73	0.85	9.55	0.86	11.48
60 M	**0.73**	**5.00**	**0.77**	**5.43**	**0.78**	**5.93**	**0.74**	**7.13**
L	0.60	1.54	0.67	1.70	0.69	2.01	0.70	2.20
U	0.82	9.74	0.83	9.87	0.84	11.78	0.84	14.21
120 M	**0.70**	**12.66**	**0.68**	**11.37**	**0.69**	**12.33**	**0.68**	**16.40**
L	0.58	4.41	0.61	4.94	0.59	5.30	0.55	5.62
U	0.77	23.63	0.78	20.86	0.78	23.59	0.79	27.58

Notes: This table displays the Pearson correlation (ρ) and the costs of hedging (C) applied to the S&P GSCI Total Return Index for investment horizons ranging from 1 month until 10 years. The upper (U) and lower (L) bounds of the 95% confidence intervals for the hedging measures are provided. The confidence intervals are based on $B = 1,000$ bootstrap runs.

Table 7: **Hedging measures applied to the alternative commodity indices (total returns)**

	CRB		UBS		Rogers	
	ρ	C	ρ	C	ρ	C
1 M	**0.29**	**-0.01**	**0.24**	**0.00**	**0.32**	**-0.01**
L	0.18	-0.02	0.13	-0.01	0.18	-0.03
U	0.41	0.01	0.36	0.01	0.44	0.02
6 M	**0.72**	**0.25**	**0.69**	**0.26**	**0.72**	**0.33**
L	0.58	-0.02	0.55	0.00	0.57	-0.05
U	0.82	0.70	0.79	0.54	0.82	0.83
12 M	**0.77**	**0.71**	**0.74**	**0.70**	**0.77**	**0.90**
L	0.60	0.01	0.59	0.03	0.58	-0.07
U	0.87	1.70	0.86	1.34	0.87	1.94
24 M	**0.79**	**1.75**	**0.76**	**1.63**	**0.78**	**2.14**
L	0.61	0.15	0.60	0.15	0.58	-0.03
U	0.88	3.83	0.88	3.21	0.88	4.38
36 M	**0.79**	**2.93**	**0.76**	**2.75**	**0.77**	**3.41**
L	0.61	0.32	0.60	0.31	0.58	0.15
U	0.88	5.99	0.87	5.18	0.87	7.02
48 M	**0.79**	**4.27**	**0.76**	**3.89**	**0.77**	**5.10**
L	0.61	0.61	0.60	0.57	0.57	0.46
U	0.87	8.50	0.87	7.18	0.86	9.89
60 M	**0.79**	**5.52**	**0.75**	**5.08**	**0.74**	**6.16**
L	0.61	0.85	0.60	0.87	0.56	0.79
U	0.86	10.96	0.86	9.39	0.84	12.40
120 M	**0.75**	**13.64**	**0.72**	**12.30**	**0.69**	**15.36**
L	0.58	3.09	0.59	3.13	0.54	3.18
U	0.82	24.84	0.83	22.28	0.79	27.66

Notes: This table displays the Pearson correlation (ρ) and the costs of hedging (C) applied to the total return indices of Thomson Reuters/Jefferies, Dow Jones UBS, and Rogers, for investment horizons ranging from 1 month until 10 years. The upper (U) and lower (L) bounds of the 95% confidence intervals for the hedging measures are provided. The confidence intervals are based on $B = 1,000$ bootstrap runs. The sample periods end in May 2011 and start in February 1991 (Thomson Reuters/Jefferies CRB Total Return Index), February 1994 (Dow Jones UBS Total Return Index), and August 1998 (Rogers Total Return Index).

Table 8: **Hedging measures applied to S&P GSCI Excess Return Index**

	ρ	C
1 M	**0.11**	**0.00**
L	0.03	0.00
U	0.20	0.00
6 M	**0.32**	**0.22**
L	0.10	0.01
U	0.50	0.72
12 M	**0.36**	**0.93**
L	0.07	0.03
U	0.58	3.38
24 M	**0.39**	**3.24**
L	0.04	0.05
U	0.63	13.41
36 M	**0.41**	**6.27**
L	0.04	0.09
U	0.65	27.19
48 M	**0.41**	**9.81**
L	0.03	0.11
U	0.66	43.53
60 M	**0.40**	**12.96**
L	0.02	0.18
U	0.66	62.19
120 M	**0.39**	**41.40**
L	0.01	0.63
U	0.62	191.41

Notes: This table displays the Pearson correlation (ρ) and the costs of hedging (C) applied to the S&P GSCI Excess Return Index, for investment horizons ranging from 1 month until 10 years. The sample period covers the period January 1970 – May 2011. The upper (U) and lower (L) bounds of the 95% confidence intervals for the hedging measures are provided. The confidence intervals are based on $B = 1,000$ bootstrap runs.

Table 9: **Hedging measures applied to the alternative commodity indices (excess returns)**

	CRB		UBS		Rogers	
	ρ	C	ρ	C	ρ	C
1 M	**0.29**	**0.00**	**0.24**	**0.00**	**0.43**	**0.02**
L	0.18	-0.02	0.13	-0.01	0.21	-0.03
U	0.40	0.02	0.36	0.02	0.60	0.12
6 M	**0.72**	**0.34**	**0.68**	**0.35**	**0.79**	**1.18**
L	0.56	0.06	0.53	0.08	0.63	0.21
U	0.81	0.79	0.79	0.65	0.88	2.97
12 M	**0.77**	**0.90**	**0.73**	**0.91**	**0.82**	**2.88**
L	0.57	0.14	0.55	0.16	0.65	0.32
U	0.86	1.84	0.85	1.53	0.90	6.29
24 M	**0.78**	**2.11**	**0.75**	**2.05**	**0.82**	**6.27**
L	0.57	0.37	0.57	0.40	0.66	0.65
U	0.88	4.12	0.87	3.57	0.89	12.72
36 M	**0.79**	**3.45**	**0.75**	**3.37**	**0.81**	**9.63**
L	0.57	0.65	0.57	0.69	0.65	1.14
U	0.87	6.36	0.87	5.67	0.88	18.94
48 M	**0.78**	**4.92**	**0.75**	**4.74**	**0.78**	**12.93**
L	0.57	0.94	0.57	1.06	0.64	1.80
U	0.86	8.96	0.86	8.00	0.87	23.67
60 M	**0.78**	**6.28**	**0.74**	**6.12**	**0.76**	**15.95**
L	0.57	1.29	0.57	1.46	0.63	2.63
U	0.85	11.48	0.85	10.39	0.85	28.88
120 M	**0.74**	**14.72**	**0.71**	**14.36**	**0.69**	**32.28**
L	0.55	3.55	0.55	4.04	0.48	7.42
U	0.81	25.78	0.82	24.39	0.81	66.58

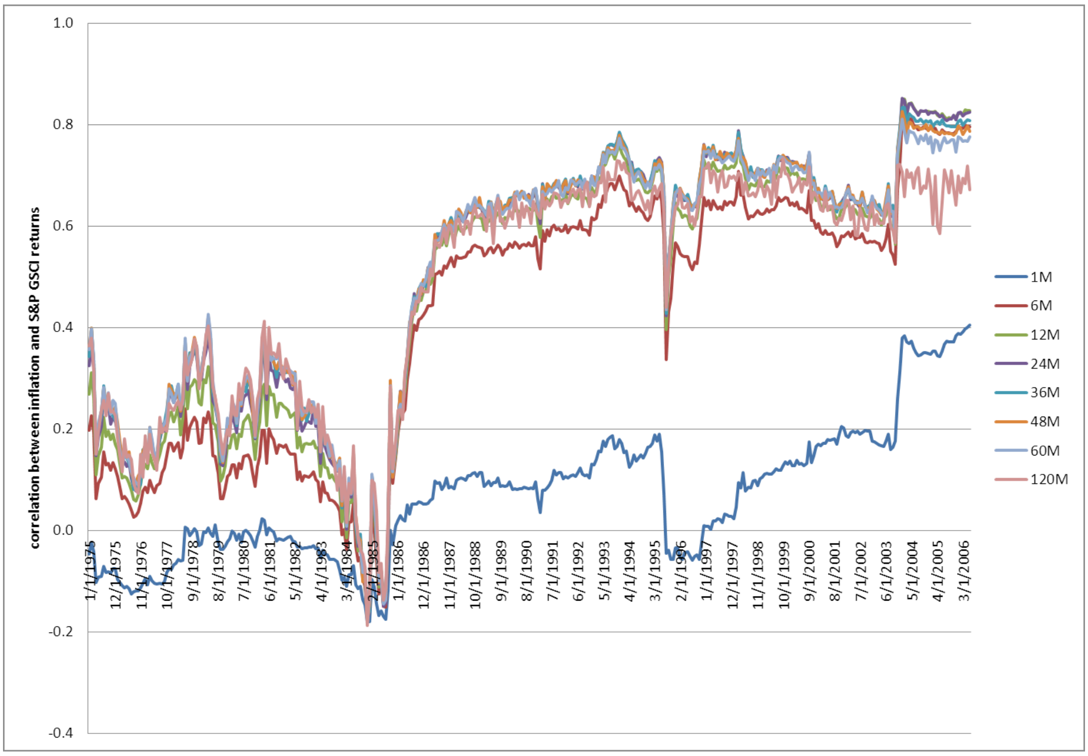
Notes: This table displays the Pearson correlation (ρ) and the costs of hedging applied to the excess return indices of Thomson Reuters/Jefferies, Dow Jones UBS, and Rogers, for investment horizons ranging from 1 month until 10 years. The upper (U) and lower (L) bounds of the 95% confidence intervals for the hedging measures are provided. The confidence intervals are based on $B = 1,000$ bootstrap runs. The sample periods end in May 2011 and start in February 1991 (Thomson Reuters/Jefferies CRB Total Return Index), February 1994 (Dow Jones UBS Total Return Index), and August 1998 (Rogers Total Return Index).

Table 10: **Hedging measures applied to the S&P GSCI Total Return Index for three subperiods (excess returns)**

	start: 1/31/1983		start: 2/28/1991		start: 2/28/1994		start: 8/31/1998	
	ρ	C	ρ	C	ρ	C	ρ	C
1 M	**0.27**	**0.00**	**0.29**	**0.01**	**0.32**	**0.01**	**0.34**	**0.01**
L	0.16	-0.01	0.19	-0.01	0.21	-0.01	0.21	-0.02
U	0.36	0.01	0.40	0.02	0.43	0.03	0.46	0.03
6 M	**0.68**	**0.33**	**0.73**	**0.40**	**0.75**	**0.44**	**0.77**	**0.56**
L	0.55	0.12	0.64	0.11	0.66	0.13	0.66	0.14
U	0.78	0.63	0.84	0.79	0.85	0.92	0.86	1.17
12 M	**0.72**	**0.81**	**0.78**	**0.95**	**0.79**	**1.05**	**0.80**	**1.33**
L	0.56	0.27	0.67	0.26	0.68	0.31	0.69	0.32
U	0.83	1.58	0.87	1.81	0.88	2.18	0.89	2.58
24 M	**0.73**	**1.88**	**0.78**	**2.08**	**0.79**	**2.32**	**0.80**	**2.91**
L	0.56	0.60	0.67	0.61	0.69	0.74	0.70	0.75
U	0.83	3.62	0.87	3.93	0.88	4.76	0.88	5.63
36 M	**0.73**	**3.01**	**0.78**	**3.33**	**0.79**	**3.66**	**0.79**	**4.53**
L	0.56	0.95	0.67	1.05	0.68	1.19	0.70	1.26
U	0.83	5.81	0.86	6.01	0.86	7.32	0.87	8.72
48 M	**0.72**	**4.24**	**0.77**	**4.72**	**0.78**	**5.07**	**0.78**	**6.23**
L	0.55	1.40	0.66	1.47	0.68	1.71	0.69	1.78
U	0.82	8.02	0.84	8.29	0.85	9.78	0.85	11.62
60 M	**0.72**	**5.54**	**0.76**	**5.93**	**0.77**	**6.36**	**0.74**	**7.36**
L	0.55	1.81	0.65	1.99	0.67	2.23	0.68	2.40
U	0.80	10.43	0.83	10.43	0.83	12.25	0.84	14.22
120 M	**0.68**	**13.55**	**0.68**	**12.24**	**0.69**	**12.93**	**0.67**	**16.61**
L	0.52	4.94	0.59	5.24	0.58	5.45	0.55	5.69
U	0.76	24.67	0.78	22.86	0.78	23.98	0.78	28.41

Notes: This table displays the Pearson correlation (ρ) and the costs of hedging (C) applied to the S&P GSCI Excess Return Index for investment horizons ranging from 1 month until 10 years. The upper (U) and lower (L) bounds of the 95% confidence intervals for the hedging measures are provided. The confidence intervals are based on $B = 1,000$ bootstrap runs.

Figure 1: **Rolling window estimates of correlation between the return on the S&P GSCI Total Return Index and the inflation rate**



Notes: This figure displays rolling window estimates of the correlation between the return on the S&P GSCI Total Return Index and the inflation rate, for investment horizons ranging from 1 month to 10 years. The rolling window width is equal to 10 years. An investment horizon of 1 month is abbreviated as 1M etc. The horizontal axis displays the mid-date of the 10-year rolling window interval. The first 10-year interval is 1970 – 1980 with mid-year 1975 and the last 10-year window is 2001 – 2011 with mid-year 2006.