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Conference Paper

Financialization in Commodity Markets: Disentangling the Crisis from the Style Effect

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2013: Wettbewerbspolitik und
Regulierung in einer globalen Wirtschaftsordnung - Session: Crisis, No. C19-V2

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: Adams, Zeno; Glück, Thorsten (2013) : Financialization in Commodity
Markets: Disentangling the Crisis from the Style Effect, Beiträge zur Jahrestagung des Vereins
für Socialpolitik 2013: Wettbewerbspolitik und Regulierung in einer globalen Wirtschaftsordnung
- Session: Crisis, No. C19-V2, ZBW - Deutsche Zentralbibliothek für Wirtschaftswissenschaften,
Leibniz-Informationszentrum Wirtschaft, Kiel und Hamburg

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Financialization in Commodity Markets: Disentangling the Crisis from the Style Effect

Abstract

In this paper, we show that large inflows into commodity investments, a recent phenomenon known as financialization, has changed the behavior and dependence structure between commodities and the general stock market. The common perception is that the increase in comovements is the result of distressed investors selling both assets during the 2007-2009 financial crisis. We show that financial distress alone cannot explain the size and persistence of comovements. Instead, we argue that commodities have become an investment style for institutional investors. Given that institutional investors continue to target funds into commodities, we predict spillovers between commodities and the stock market to remain high in the future.

Keywords: Financialization; commodities; risk spillovers; style investing; state-dependent sensitivity VaR

JEL-Classification: G01, G13, Q02

1. Introduction

The past decade witnessed a fundamental change in the composition of commodity futures market participants. Traditionally, the market was dominated by specialized investors who would earn a risk premium by providing insurance to short hedging commodity producers and long hedging commodity processors (Keynes, 1930; Hicks, 1939; Hirshleifer, 1988). Starting in the early 2000s, however, flows into commodities investments began to grow at an unprecedented rate and are reported to have increased from \$ 15 billion in 2003 to at least \$ 200 billion in 2008 (CFTC staff report, 2008). These vast inflows are mainly attributable to institutional investors that have historically never been engaged in commodity investments of such a large scale (Domanski and Heath, 2007). Conservative estimates show that from 2000 to 2010 the number of commodity index traders, i.e. long-only investors such as pension funds and insurance companies, more than quadrupled and the number of hedge funds more than tripled. In contrast, during the same time period, the amount of traders engaged in futures markets to hedge commodity price risk less than doubled (Cheng, Kirilenko, and Xiong, 2012).

Investment incentives of these new types of investors differ from those of traditional investors. For instance, Commodity Index Traders intensify their investment in commodities to improve portfolio diversification (Norrish, 2010) while trading decisions of hedge funds are driven by past increases in spot prices and high roll returns (Domanski and Heath, 2007). The appearance of these new types of investors had therefore important consequences for the behavior of commodities in financial markets, and the way commodities are linked to other assets. For instance, Tang and Xiong (2012) argue that these vast inflows led to a process of integration of commodity futures markets with other financial markets in which portfolio rebalancing of index investors can cause volatility spillovers from outside to commodity markets. This process, commonly referred to as the financialization of commodity markets, has been observed with concern among policy makers who made commodity index traders responsible for the unwarranted increase in energy and food prices.¹ The shift in the behavior of commodities has also sparked the interest of the academic literature and marks an important change from the traditional description of commodities as an asset class that

¹ See for instance the U.S. Senate Permanent Subcommittee on Investigations (2009). More generally, financialization is defined as the increasing dominance of the finance industry and the expanding role of financial motives in the overall economy (Casey, 2011)

reliably delivers returns with low correlation to the stock market (Bessembinder, 1992, Bessembinder and Chan, 1992, Gorton and Rouwenhorst, 2006).²

Previous studies note that the behavior of commodities appears to have changed somewhere between 2004 and the 2007-2009 financial crisis (Tang and Xiong, 2012; Daskalaki and Skiadopoulos, 2011).³ We will be more specific and use a statistical framework to determine the exact date associated with a fundamental change in the relation between commodities and stocks. This will prove useful when we explore the changes in commodity behavior before and after the identified break. As measure for this relation we use the returns correlation. However, we do not follow the existing literature to identify changes in correlation by means of a parametric model with time-varying correlations, i.e. a multivariate GARCH (Engle, Granger, and Kraft, 1984). When it comes to the implementation of these models, the researcher is confronted with a multitude of competing MGARCH specifications, each of them implying a different pattern of correlation dynamics (Kroner and Ng, 1998, Bauwens, Laurent, and Rombouts, 2006). As a consequence, the results from these models can be highly misleading (Füss, Glück, and Mutl, 2012). For this reason, we identify a change in correlation using a simple yet efficient algorithm for correlation change-point inference (Galeano and Wied, 2012). We thereby circumvent a possibly miss-specified parametric model.

Identification of a structural change in the correlations between commodities and the stock market allows us to split the sample into a pre- and a post-financialization period. We quantify the impact of the structural change by estimating the transmission of a shock in the stock market to the commodity market during both periods. We thereby apply an empirical approach based on risk spillovers (Adams, Füss, and Gropp, 2012). In contrast to correlations, this approach allows us to measure the direction of the impact and, given the model is properly specified, provides a causal interpretation of the spillovers.

We show that risk spillovers from stocks to commodities were nonexistent before 2008 but have increased significantly since then. It would seem reasonable to explain the sudden appearance of risk spillovers by the impact of the financial crisis which had its full

² A number of studies focus on different aspects of financialization in commodity futures markets. For instance, Irwin and Sanders (2012) investigate whether CIT's trading behavior explains the recent changes in the dynamics of commodity futures prices. Gao and Liu (2012) and Chan et al. (2013) focus on the methodological aspect of identifying comovements appropriately. For an excellent overview, see Irwin and Sanders (2011).

³ Among many others, Caballero, Farhi, and Gourinchas (2008) argue that a commodity price bubble emerged around June 2007. Empirical evidence for this argument is provided by Phillips and Yu (2010).

scale impact on markets following the weeks after the Lehman default (Bartram and Bodnar, 2009): in the months following the Lehman collapse in September 2008, the prices of most tradable assets experienced simultaneous sharp declines within the same days. A prominent model for the explanation of this phenomenon is the Brunnermeier and Pedersen (2009) liquidity and loss spiral which has been adopted by many studies investigating comovements and spillovers among asset classes and financial institutions (see, e.g., Adrian and Brunnermeier, 2011; Acharya et al., 2010; Shleifer and Vishny, 2011, and the reference therein). Indeed, our empirical results show that risk spillovers from stocks to commodities reach their peak during the market distress period of 2008. However, we also make an observation that appears to stand in contrast with the idea that risk spillovers from the stock market to commodities are essentially a phenomenon of the financial crisis. We show that while the period of high volatility ended around July 2009, spillovers remain persistently high until the end of 2012. One important finding in our paper is therefore that the risk spillovers from stocks to commodities are more persistent than what could be explained by the impact of the financial crisis alone. The financial crisis may have uncovered and even amplified the dependence structure caused by financialization, but financialization seems to have a strong influence on spillovers even without the general environment of contagion that was present during the financial crisis.

In this paper, we argue that this previously unobserved factor, which is mainly responsible for creating the transmission channel from stocks to commodities is essentially a style effect: the dominant presence of financial investors caused certain commodities to effectively become an “investment style”, a financial opportunity that has attracted liquidity from institutional investors in a time when other assets seemed too risky or too unprofitable. The large inflows has thereby turned commodity investments into a self-fulfilling success, which in turn attracts even more financial investors, resulting in even higher spillovers from stock markets. The result of this ongoing process is persistently high spillovers even during moderate or tranquil market periods. Although investment styles have traditionally been associated with stocks and mutual funds, styles can materialize for any asset. It is not the economic fundamental, but the perceived characteristics of an asset that are responsible for creating a style (Barberis and Shleifer, 2003). For instance, Barberis, Shleifer, and Wurgler (2005) show that the comovement between a stock and its index increases when a stock is added to the S&P 500 Index and Boyer (2011) finds that economically meaningless fund labels have explanatory power for the returns comovements of index constituents. More recently, Wahal and Yavuz (2012) show that in the past, the coefficient on a style factor for

stocks was not significantly different from zero but started to show explanatory power beginning in 1988, which coincides with increased use of size and value categorization in mutual funds.⁴ Lee and Swaminathan (2000) furthermore show that it is common for stocks to undergo a momentum life-cycle in which they move through periods of attention and neglect. In short, the appearance and disappearance of investment styles is a common phenomenon in stock markets and can be driven by simple factors that are detached from economic fundamentals.

The recent exposure of certain commodities to stock market risk shows many signs which together could make a case for an investment style. Our main argument, however, one that we can also test empirically, is that style investing has been shown to generate comovement of the asset with its style (Barberis and Shleifer, 2003; Barberis Shleifer and Wurgler, 2005; Greenwood, 2008; Boyer, 2011).⁵ For instance, Wahal and Yavuz (2012) disentangle the comovement, which can be generated by style investing but also by common shocks, by identifying an event that influences style investment but does not act as a common shock. In a similar way, we will compare a set of hypothetical spillovers that would be expected if they had been generated by common shocks during the financial crisis with the actually observed spillovers to expose the impact of the style factor.⁶ Our empirical findings suggest that common shocks have played an important role during the financial crisis of 2007-2009, but that during the more tranquil period from 2009-2012, the majority of observed spillovers can be attributed to style investing. Our results highlight the changing role of commodity investments in the broader context of portfolio diversification and have important implications for the risk management decisions of commodity speculators and institutional investors. Finally, our findings may guide policy makers and regulators in the ongoing debate concerning recent run-ups in energy and food prices.

Our paper is related to Tang and Xiong (2012) who provide evidence that financialization caused commodities in investable indices such as the GSCI to show larger responses to shocks during the financial crisis than similar commodities that are not in the

⁴ Indeed, Cooper, Gulen, and Rau (2005) show that some mutual funds have been reported to strategically change their names to “hot” styles in order to attract more inflows.

⁵ An advantage of using comovement is that it can be measured with precision, whereas other measures of investor sentiment and behavioral biases are more difficult to quantify (Baker and Wurgler, 2007).

⁶ The literature mentions a number of common shocks during the 2007-2009 financial crisis, the most important one being selling pressure of liquid assets such as stocks and commodities in order to meet margin calls. See Brunnermeier (2008) for an excellent overview.

indices. However, we focus on spillover effects between commodities and the stock market, rather than the impact of financialization on the comovement within the commodity class. Furthermore, Tang and Xiong briefly touch the issue of index investors but do not further investigate their importance for explaining increased spillovers after 2009.

The remained of the paper is structured as follows. In the next section we describe the methodology used to identify the break in correlations and to measure the risk spillovers. We present our empirical results regarding the exposure of commodities to risk spillovers in section 3. In Section 4 we expand our discussion of the determinants behind the recent increase in spillovers. Section 5 draws our conclusions.

2. Methodology

This section outlines our empirical approach that we use to quantify the impact of financialization on the dependence structure between commodities and stocks. It involves the following two steps: First, we locate the time-frame associated with a structural change in the correlation between the returns of stocks and commodities. The importance of this step becomes clear in the empirical part of this paper where we show that the interconnectedness between commodities and stocks shifted dramatically in September 2008. This is accomplished with the statistical procedure that we describe in the following subsection. In a second step, we show that the structural change is associated with an increase in risk spillovers. Our measure for risk spillovers is subject to the second subsection.

2.1 Locating Structural Changes in Correlation

To identify and locate the structural change in correlation we implement a simple and effective algorithm provided Galeano and Wied (2012). This algorithm involves the following steps: Given is a sample of T observations of the returns vector $(r_{1,t} r_{2,t})'$. Let ρ_t denote the time t unconditional correlation between $r_{1,t}$ and $r_{2,t}$. The algorithm starts with testing the null hypothesis of constant correlations against the alternative hypothesis of a change-point t^c , i.e.

$$H_0 : \rho_t = \rho \quad \text{for all } t \in \{1, \dots, T\} \quad (1)$$

versus

$$H_1 : \exists t^c \in \{1, \dots, T-1\} \quad \text{such that } \rho_{t^c} \neq \rho_{t^c+1}. \quad (2)$$

This is accomplished using the model-free fluctuation-type test originally proposed by Wied, Kraemer, and Dehling (2012). The test statistic is defined as

$$Q_T := \hat{D} \max_{2 \leq t \leq T} \frac{t}{\sqrt{T}} |\hat{\rho}_t - \hat{\rho}_T|, \quad (3)$$

where $\hat{\rho}_t$ is the sample correlation of the first t observations and \hat{D} is a scalar coefficient as defined in Appendix A. Under the null hypothesis and several reasonable moment and dependency restrictions, the test statistic Q_T is asymptotically Kolmogorov distributed (Wied, Kraemer, and Dehling, 2012, Theorem 1).⁷ If Q_T stays below the upper critical value the null hypothesis is not rejected and the algorithm stops. Otherwise H_0 is rejected and there is at least one change-point t^c within the sample period. The estimator for the single change-point is given by

$$t^c = \arg \max_t \hat{D} \frac{t}{\sqrt{T}} |\hat{\rho}_t - \hat{\rho}_T|. \quad (4)$$

To identify further change-points, the sample is split into the two subsamples $[1, \dots, \hat{t}^c]$ and $[\hat{t}^c + 1, \dots, T]$. These subsamples are then both tested individually. This procedure is repeated until no further change-points are detected. The last step of the algorithm consists of refining the vector of the n detected change-points $\theta = [\hat{t}_1^c, \dots, \hat{t}_n^c]$ where $\hat{t}_1^c \leq \dots \leq \hat{t}_n^c$. Define $\hat{t}_0^c = 1$ and $\hat{t}_{n+1}^c = T$ and form the subsamples $[\hat{t}_i^c, \dots, \hat{t}_{i+1}^c]$ for $i = 0, \dots, n$. Each subsample thus contains one change-point. Again, these subsamples are tested individually. If the null hypothesis is not rejected the change-point contained in the subsample is removed from θ . As shown in Galeano and Wied (2012), this procedure detects the correct number of correlation change-points.

2.2 Quantifying Risk Spillovers

Once we have identified the structural change in correlation, we quantify and compare the size of risk spillovers from the stock market to commodities for the periods before and after the break. The change point in the previous section was detected using correlations because the available statistical methodology is designed for correlation breaks. However, we proceed in this section using risk spillovers instead of correlations. Risk spillovers have the advantage of measuring the direction and the size of the impact. We can therefore obtain additional economically important information from switching to risk spillovers. From a statistical standpoint the challenge is to find an adequate measure of spillovers from stocks to

⁷ See Wied, Krämer, and Dehling (2012, A.1 to A.5). In particular, it is assumed that $\{(r_{1,t}, r_{2,t})'\}$ is *near-epoch* dependent. For an extensive discussion see Davidson (1994, Ch. 17).

the commodity market. In the empirical literature, a common approach is to measure spillovers among the returns of financial assets or firms.⁸ One drawback of measuring spillovers in returns, however, is that the largest spillovers typically occur in an environment of high uncertainty and financial distress. During this period, returns typically show an alternating pattern of large positive and negative returns as market participants struggle to process incoming information. As a consequence, a significant fraction of spillovers are not observable in returns but can be detected in some form of risk. Recent work has therefore proposed methodologies that measure spillovers in risk, often with emphasis on the tails of the risk distribution.⁹

The empirical approach in this paper is based on the state-dependent sensitivity value-at-risk (SDSVaR) model of Adams, Füss, and Gropp (2012). This approach is an extension of the common value-at-risk model in that it explicitly accounts for spillovers from other relevant markets.¹⁰ In other words, while the common VaR considers financial assets in isolation, the SDSVaR explicitly models their linkages to account for the systemic nature of risk during a crisis. Capturing the systemic part of shocks can be considered as the methodological key for adequate spillover measurement. Financial institutions have been shown to be particularly vulnerable to bad market news when a shock occurs in an environment of high volatility (see in particular Adrian and Brunnermeier, 2011 and Adams, Füss and Gropp, 2012). As will be shown in the empirical section of this paper, the spillovers from stock markets to commodities are considerably higher when the shock receiving commodity is trading at a high volatility.

The SDSVaR follows a two-step process of computing a commodity's common VaR in a first step, $\widehat{VaR}_m = \hat{\mu}_{m,t} + z\hat{\sigma}_{m,t}$, and estimating the risk spillovers from stock markets to commodities in a second step.¹¹ In the second step, \widehat{VaR}_m is now the dependent variable and

⁸ See for instance Billio, Getmansky, Lo, and Pelizzon (2012) for return spillovers among financial institution or Büyüksahin, Haigh, and Robe (2010) for return comovements of commodities with the stock market.

⁹ See for instance Brownlees and Engle (2011), Acharya et al. (2010), Boyson, Stahel, and Stulz (2010), and Adrian and Brunnermeier (2011). Billio et al. (2012) also propose a nonlinear spillover measure to overcome the shortcomings of measuring spillovers in returns.

¹⁰ The value-at-risk is a linear function of volatility so that the empirical results in this paper are very similar using a measure of volatility directly. The appeal of VaR comes from its direct and intuitive interpretation, a feature that is lacking with volatility despite its widespread use.

¹¹ Following the usual notation, $\hat{\mu}_{m,t}$ is the mean return of commodity m , $\hat{\sigma}_{m,t}$ is the standard deviation of commodity m , modeled with an EGARCH model (Nelson 1991), and z is the 5% quantile of the standard normal

is modeled by the VaR of the stock market and some control variables. The vector of control variables includes the lag of the dependent variable, the VaR of the S&P GSCI commodity index excluding the commodity that acts as the dependent variable, and the MSCI emerging market equity index.¹² The purpose of the lag is to capture the strong autoregressive structure of the VaR. The commodity index acts as a control variable and ensures that measured spillovers coming from the stock market are not biased by the presence of spillovers between different types of commodities. Finally, the emerging market equity index controls for price variation that is generated by the demand in emerging economies. If correctly specified, our risk spillovers can therefore be interpreted in a causal way (and not just in a Granger causal sense).

$$\widehat{VaR}_{i,t,\theta} = \alpha_{\theta} + \beta_{1,\theta} \widehat{VaR}_{i,t-1} + \beta_{2,\theta} \widehat{VaR}_{stocks,t} + \beta_{3,\theta} \widehat{VaR}_{Commod,t} + \beta_{4,\theta} \widehat{VaR}_{Emerg.Mkt.,t} + \varepsilon_t. \quad (5)$$

Our main interest lies in the spillover coefficient $\beta_{2,\theta}$ which quantifies the degree to which shocks in the stock market affect the value-at-risk of commodity i .¹³ As we have emphasized before, the model in Equation (5) requires additional flexibility that allows the dependent variable to respond differently to shocks when uncertainty and volatility are high. We therefore estimate the parameters in Equation (5) as a function of commodity i 's value-at-risk distribution. In particular, we use quantile regression to measure risk spillovers $\beta_{2,\theta}$ for low quantiles, θ , of the VaR distribution (when commodity i is trading at a high volatility), and for the median (when the volatility of commodity i is trading at normal levels). We thereby choose the 12.5% quantile for the high volatility state and the 50% quantile for the normal market state.¹⁴ Our empirical results indicate that distinguishing between both states has a large impact on the size of the spillover coefficient.

distribution. For a more detailed discussion of the model the interested reader is referred to Adams, Füss and Gropp (2012).

¹² The Goldman Sachs Commodity Index (GSCI) is an industry-benchmark with index constituent weights determined by world production rates.

¹³ We thereby assume that commodity i is not sufficiently large to have a feedback effect on the overall stock market.

¹⁴ Our choice of 12.5% for the low quantile is to some extent arbitrary but reflects the trade-off between obtaining estimates that are dominated by a few observations with very large weights (too far into the left tail of the distribution) and estimates that reflect only moderate risk (not far enough into the left tail of the distribution). The exact choice for the lower quantile has no material impact on our main results but we believe it should be somewhere between 5% and 20%.

3. Quantifying the Impact of Financialization

3.1 Data and Descriptive Statistics

Our empirical results are based on daily returns and risk spillovers from the stock market to commodities over the period 9/15/1994 to 12/31/2012 (4773 observations). Returns are measured as log returns $r_t = \log(P_t / P_{t-1}) \cdot 100$ and risk is measured as the daily value at risk $\widehat{VaR}_m = \hat{\mu}_{m,t} + z\hat{\sigma}_{m,t}$. We follow the convention to use the S&P 500 as a measure of the stock market (e.g., Tang and Xiong, 2012) but also use the MSCI Emerging Market Equity Index to control for stock market movements in economies with a growing consumption of commodities.¹⁵ Due to the heterogeneity of the commodity subsectors, defining a representative set of commodities is somewhat more involved (Erb and Harvey, 2006). For our study, we consider the S&P Goldman Sachs Commodity Index (GSCI) excess return indices of corn and wheat (agricultural), crude oil and heating oil (energy), copper and aluminum (base metals), gold (precious metals) and cattle (livestock).¹⁶ As shown in Table 1, these eight commodities are the main constituents of the respective subsector and account for a combined weight of 79 percent of the GSCI.

<< Table 1 about here >>

In Table 2 we provide some descriptive statistics. The sample mean returns shown in Panel A lie in a range that is commonly observed in stock and commodity futures markets, e.g. positive returns for stocks and energy commodities but negative returns for agriculturals (Gorton, Hayashi, and Rouwenhorst, 2013). None of the sample means are statistically significant. We find significant first order autocorrelation coefficients for corn, heating oil, copper, cattle, and the S&P 500. Although the log returns of these assets do not satisfy the martingale property, autocorrelations are at most 0.052 in absolute values and can be safely neglected. In Panel B of Table 2 we report the sample correlation matrix of the log-returns. Correlations are all positive and statistically significant. The only exception is gold which has a significant negative correlation with stocks. Positive correlations across commodity returns are a stylized fact: commodities have been found to be closely related to each other within

¹⁵ Many emerging market economies are also important producers of commodities. To the extent that production shocks impact their national stock market, this effect will also be captured by the MSCI Emerging Market Equity index.

¹⁶ The GSCI sub-indices are based on the usual nearby or second nearby futures contract. The strategy of rolling futures contracts is similar to that implemented in related studies, e.g., Gorton, Hayashi, and Rouwenhorst (2013). For further information see the index provider's web site: <http://us.spindices.com/index-family/commodities/sp-gsci>. The commodity indices are from Datastream.

commodity subsectors (Erb and Harvey, 2006; Marshall, Nguyen, and Visaltanachoti, 2013). More recently, Tang and Xiong (2012) find that the correlation among commodities has further increased as a result of Commodity Index Traders simultaneously trading in and out of commodities. Perhaps unexpected, however, are the observed significant positive correlations between the returns of stocks and commodities. Earlier studies have stressed the segmentation between stock and commodity futures markets (Dusak, 1973; Bessembinder, 1992) and cross-market correlations have been found to be insignificant or significantly negative (Gorton and Rouwenhorst, 2006).

<< Table 2 about here >>

3.2 A Shift in Correlations

In Table 3 we test all bivariate stock/commodity combinations for a structural change in correlations. The second column of Table 3 reports the Wied, Krämer, and Dehling (2012) statistic Q_T as defined in Equation (3). The test statistics range from 2.245 in the case of gold to 5.621 for copper and are well above the 1% critical value of 1.63. We thus reject the null hypothesis of constant returns correlations for all stock-commodity combinations. Cheng, Kirilenko, and Xiong (2012) note that because of higher volatility, one may find changing correlations during the period of the crisis even when the underlying correlation structure remains stable. For this reason, we repeat the test procedure on returns standardized by their EGARCH(1,1) conditional volatilities. As shown in the third column of Table 3, controlling for volatility does not qualitatively change the results. Again, the test statistics are all above the critical value at the 1 percent significance level.¹⁷

<< Table 3 about here >>

Under the alternative hypothesis, there is at least one change-point t^c such that $\rho_{t^c} \neq \rho_{t^c+1}$. Table 4 reports the change-points that have been identified using the algorithm of Galeano and Wied (2012) (see section 2.1). As shown in column 2, there has been a fundamental shift in correlation at the end of fall 2008: all stock-commodity combinations indicate a change-point between August 29, 2008 and October 15, 2008. These change-points are associated with a tremendous increase in correlations (Table 4, column 3). At the same time, no further change-points are detected after 2008. This indicates that changes in correlations are permanent and cannot be explained by temporary shocks such as fire sales of

¹⁷ Controlling for volatility using GARCH standardized residuals is a common approach in the applied literature (Bollerslev, 1990; Tse and Tsui, 1999)

liquid risky assets during the crisis period. In the following section we show that the structural break detected in 2008 has important implications for the transmission of shocks from stocks to commodity markets.

<< Table 4 about here >>

3.3 Quantifying Risk Spillovers

The correlation change-point tests suggest a major shift in the behavior of commodities during September 2008. The single most important economic event during this month was the bankruptcy of Lehman brothers on September, 15, 2008. Although our empirical results do not depend on the choice of an exact day during this month, we decided to split our sample into a pre-Lehman period (09/15/1994 – 09/15/2008, 3653 obs.) and a post-Lehman period (9/15/2008 – 12/31/2012, 1121 obs.). Table 5 shows the estimated spillover coefficients from Equation (5) together with the accompanying control variables during both time intervals. Over the 14 year period from 1994 to September 2008 shocks in the stock market did not impact risk in commodities. The spillover coefficients for the lower tail indicate that this feature even holds in times of high volatility as risk spillovers are estimated to be close to zero and economically insignificant. The remarkable resilience of commodity returns has been empirically confirmed a number of times and has earned commodities the reputation of providing diversification benefits “when they are needed most” (Gorton and Rouwenhorst, 2006).¹⁸ The control variables behave as expected: the autoregressive structure of the value-at-risk estimates leads to large and statistically significant first order lags. When significant, the composite commodity index was included to control for spillovers from other commodities. Except for crude oil and heating oil which both show a moderate reaction to risk changes in the overall commodity index, spillovers between commodity types seem to be rare. From Panel A of Table 2 we can safely say that in the years before the crisis, shocks coming from the stock markets did not impact the risk in commodity markets in any economically important way.

Our conclusion changes in important ways if we look at the risk spillovers during the post-Lehman subsample. Panel B of Table 5 indicates that shocks in the stock market lead to substantial spillover to commodities, especially when the shock receiving commodity is

¹⁸ Because our dependent variable itself is the result of an estimation problem the usual robust standard errors do not adequately reflect the additional model and parameter uncertainty incorporated in the dependent variable. The parameter covariance matrix is therefore estimated with the Markov chain marginal bootstrap of Kocherginsky, He, and Mu (2005) and 200 replicates.

trading at a high volatility. For instance, a 1% increase in the VaR of the stock market leads to a 0.0455% higher VaR in crude oil during normal market times. The same shock, however, leads to a response in the order of 0.0985% during a highly volatile period.¹⁹ The results from the post-Lehman subsample show a very different picture. Commodities, historically praised for their diversification potential and low correlation with the stock markets no longer seem to be shielded from distress in the stock market. Indeed, it seems that with the beginning of the Lehman default, a new transmission channel has opened that transmits risk spillovers from stocks to the commodity market, in particular when commodities are trading at high volatility.

<< Table 5 about here >>

The spillover size varies over commodity types. Whereas corn, crude oil, and copper show considerable reactions to stock market shocks, the behavior of other commodities such as wheat or aluminum seems to have remained unchanged.

In Figure 1 we take a closer inspection of the spillover coefficients of corn, crude oil, and copper to reveal another salient feature of the more recent dependence structure between stocks and the certain commodities. We compare the spillover size for the entire quantile range during the first sample period (left column) to the spillovers during the second sample period (right column). The striking feature of the recent spillovers is that they are not only substantially higher than before, but that commodities are particularly exposed to shocks if the commodity is trading in a highly volatile market. This seems to be especially true for crude oil, which is substantially more vulnerable to shocks in the lower tails of its VaR distribution.

<< Figure 1 about here >>

To put the spillover estimates in economic perspective we perform the following simulation. Two equally weighted portfolios consisting of the S&P 500 stock index, and the three commodities corn, copper, and crude oil are formed. The portfolios are of equal size—

¹⁹ While a spillover coefficient of 0.0985 may not seem particularly large, this is only the response on the same day. The coefficients for lagged values are close to unity indicating a high persistence in the response. Over a few trading days, the cumulative response can therefore be a multiple of the initial coefficient. Further, note that the financial distress period is represented by the 12.5% quantile of the VaR distribution. The choice for this quantile is to some extent arbitrary. For instance, the spillover coefficient of 0.0985 would increase to 0.107 if we had selected the 5% quantile, and it would decrease to 0.0894 for the 20% quantile. However, the coefficient estimates do not change dramatically and the exact choice of a low quantile has no material impact on our main results.

\$100 million each—and receive the same one standard deviation shock at day 10.²⁰ In our treatment portfolio, the commodity investments in the portfolio react to the shock according to the estimated spillover coefficients from Table 5. In contrast, the control portfolio is based on the historical view that a shock to the stock market does not affect the commodity investments. Figure 2 shows how the variation in portfolio returns changes as a consequence of financialization. In the case of the treatment portfolio, the sensitivity of the commodities to a stock market shock leads to a substantially higher variation in the return series. The high persistence in the VaR of the commodities furthermore means that the fluctuation remain in the portfolio for much longer than was the case of the control portfolio.

<< Figure 2 about here >>

The findings suggest that some commodities have lost their formerly praised diversification benefits and, more importantly, that adding commodities to a traditional stock market portfolio today provides substantially less loss protection than during the years before the events of 2008.

3.4 Risk Spillovers: The Crisis and the Style Effect

A common perception in the recent literature on risk spillovers is that the increased interrelationship among assets and financial institutions is a phenomenon of the 2007-2009 financial crisis alone. The main model providing convincing explanations for the spillover mechanism is the liquidity and loss spiral of Brunnermeier and Pedersen (2009). The argument, by which margin calls lead to selling pressure of other assets in a struggle to raise liquidity, has become widely accepted in the finance industry. Indeed recent studies argue that this was the main driver of comovements between stocks and certain commodities during the 2007-2009 financial crisis (Büyükkahin, Haigh, and Robe, 2010; Tang and Xiong, 2012). The loss spiral argument provides an intuitive and attractive explanation for the observed change in commodity behavior during the 2007-2009 financial crisis. An important implication of that argument is that commodities are expected to revert to their pre-crisis behavior after 2009. In this section, we show that risk spillovers from stocks to commodities remain high through the four year period from 2008 to 2012, casting doubt on the loss spiral argument as the only explanation for risk spillovers. Instead, we argue that the unprecedented inflow of institutional investor money into commodity investments has led to a “style shift” in

²⁰ In both cases, the shock occurs in the stock returns of the S&P 500 with the size of the shock being determined by the daily standard deviation of the stock returns for the period after the structural break from 9/15/2008–12/31/2012.

commodities, a permanent change in the way commodities behave in a portfolio of stocks. This style shift is likely to last until the funds invested into commodities decline to their pre-crisis levels. To support our claim empirically, Figure 3 shows risk spillovers from stocks to commodities in a 3 year rolling window over our entire sample period from 1997 to 2012.²¹ Figure 3 shows that after the identified break in September 2008, spillovers increased markedly, especially during times of high volatility. These findings support our conclusion from the static results in Table 5. A new feature of risk spillovers that was not visible in the static table, however, is that contrary to expectations, risk spillovers did not decline after the impact of the crisis on financial markets subsided. Instead spillovers stayed high in the following years, especially during times of high volatility.²²

<< Figure 3 about here >>

One way to illustrate the argument of a permanent shift in spillover behavior is to simulate a value-at-risk series for crude oil that follows the original series at first, but returns to its pre-crisis behavior at the end of the financial crisis. The simulated VaR begins to deviate from the original series on 8/31/2009 after which the time-series exhibits the same mean, variance, and degree of autocorrelation as before 2007 but is driven by pure random shocks.²³ In other words, we try to disentangle the impact of the financial crisis and the impact of another factor that reflects the style shift. Panel A of Figure 4 shows both, the actual and simulated VaR series for crude oil. Note that the deviation does not become noticeable until the VaR has recovered from the distress period at the end of 2009. If the increased linkages between stocks and crude oil are the result of a liquidity and loss spiral during the financial crisis, we would expect these linkages to disappear once markets have returned to a normal behavior. Since spillovers could not be observed prior to the financial crisis, a simulated VaR driven by random shocks can be used to describe a pre-crisis behavior. We compare the risk spillovers based on the actual data with the spillovers from the simulated VaR in Panel B. Because our estimates are based on a 750 day rolling window, the theoretical spillovers do not drop to zero immediately after August 2009 but rather decrease slowly until the sample

²¹ Since a foregoing 750 day observation window is necessary to obtain an estimate of the first spillover, the graphs begin in late 1996 instead of 1994.

²² For the purpose of illustration, the time-varying coefficients in Figure 3 are estimated without the emerging market equity index which is often insignificant and causes a higher variation in the spillover coefficients. This noise is likely due to high multicollinearity that was found to be at times above 90% between the emerging market and the S&P 500 stock index.

²³ According to the NBER, the recession in the U.S. officially ended in June 2009. The period of high volatility of the S&P 500 returns and other financial series seems to have ended sometime in mid-2009.

window is dominated by random shocks.²⁴ We can draw important conclusions from the difference of both spillover series. First, spillovers are higher than what we would expect under the assumption of a loss spiral as the only determinant. Second, and more importantly, the sensitivity to risk spillovers does not return to its pre-crisis level but remains high. This suggests that spillovers cannot be explained by the crisis alone but that a more permanent change has taken place. In fact, the comparison of actual and expected risk spillovers suggest that (i) the style effect has added to the existing impact of the financial crisis, amplifying the overall spillover size, and that (ii) the style effect has recently become the dominant driver of risk spillovers, replacing the initial crisis effect since 2010. Although the spillover coefficients of the other commodities copper, corn, and gold are somewhat lower in 2012 compared to their peak during the crisis, there seems to be no general tendency to decline in the future. An update of our analysis as new data becomes available will show whether the shift in risk spillovers is permanent or if they decline to pre-crisis levels. Our empirical investigation in the following section indicates that risk spillovers will be a continuing issue as long as financial investors remain active participants in commodity futures markets.

<< Figure 4 about here >>

4. The Determinants of Risk Spillovers

In the previous section we have demonstrated that risk spillovers from stocks to commodities is a recent phenomenon. However, we have yet to provide empirical evidence that points to the cause of these important economic changes. We have shown that the obvious candidate for an explanation—the financial crisis of 2007-2009—cannot by itself explain the size and persistence in risk spillovers that we observe after 2009. In this section we will empirically test the hypothesis that certain commodity investments have effectively become an investment style for stock investors. In other words, the presence of financial investors and their distinctive trading strategies are responsible for the recent spillovers between stocks and commodities. Under this hypothesis, the amount of funds flowing into commodity investments from financial investors has to be able to explain the variation in spillovers over time. As a measure of the amount of funds invested into commodities we use the total assets under management by commodity ETFs. Compared to other investment vehicles such as commodity options or futures, ETFs have become a convenient and popular

²⁴ We obtain similar but more erratic spillover series using a 500 or 250 observation window. To focus on the underlying trend, the spillover series in Figure 4 are smoothed with a Hodrick-Prescott filter.

investment instrument for gaining long-only commodity exposure. This is reflected in the remarkable increases in the amount of total assets under management since 2006.

In Datastream, 203 funds are classified as commodity ETFs.²⁵ In 117 cases, Bloomberg provides the “total funds managed” for these ETFs for the relevant period after 2008. The majority of all funds are invested in general composite ETFs which in turn distribute the funds on different commodity classes using either the S&P-GSCI or the UBS-Dow Jones weights. To obtain the amount of funds that are invested in a certain commodity therefore requires (i) measuring the funds invested in ETFs that are specialized on that commodity, and (ii) adding the funds being invested indirectly over composite funds. For instance, we obtain the amounts of assets flowing into copper by observing the funds managed by two specialized copper funds (ETFS copper, and ETFS leveraged copper), adding the funds invested into a specialized industrial metals certificate (ETFS FIND) multiplied by the fraction of copper in the industrial metals index, and adding the fraction of copper investments of the 8 largest composite ETFs using the weights given in the prospectus of the respective ETF.²⁶ For a more detailed description of the ETF data we refer the interested reader to the appendix of the paper. Our dependent variable is the risk spillover coefficients from equation (5) for the commodities that have responded to shocks in the stock market (corn, copper, crude oil, and gold). To introduce time variation in the dependent variable the spillovers are estimated in a 3 year rolling window that is based on daily data but rolled forward in quarterly steps resulting in quarterly spillovers from 2008Q3 to 2012Q4 (18 quarters).²⁷ We estimate the spillovers for normal and volatile market states to obtain 36 observations per commodity or 144 observations in total. Our first model contains commodity and time fixed effects as control variables and measures the impact of an increase in ETF assets on the size of risk spillovers:

$$Spillover_{i,t,\theta} = \mu_i + \lambda_t + c_1 + c_2 I_{\{\theta=0.5\}} + \left(\gamma_1 I_{\{\theta=0.125\}} + \gamma_2 I_{\{\theta=0.5\}} \right) Assets_{i,t} + \varepsilon_t \quad (6)$$

²⁵ It appears that some of these ETFs are actually certificates. Although an issuer of certificates may not be invested in the underlying commodity, he is likely to hedge the commodity price risk with a swap agreement. If the swap dealer generates the demand for that commodity, it has the same aggregate effect than a direct investment. We therefore also treat commodity certificates as a commodity investment. On the other hand, we exclude equity funds that invest in natural resource companies.

²⁶ The 8 largest composite ETFs make up 99.47% of all funds invested into composite ETFs.

²⁷ The long 3 year window reduces the noise in the risk spillover estimates and leads to a better model fit compared to shorter window sizes

where $Spillover_{i,t,0.5}$ is the time t spillover from stocks to commodity i during normal market times. Likewise, $Spillover_{i,t,0.125}$ corresponds to the spillover from the same shock during a period of financial distress or high volatility. Our main interest lies in the coefficients measuring the impact of fund inflows γ_1 and γ_2 . The results of our first model are shown in the second column of Table 6. The coefficient for spillovers in volatile states (0.00363) measures the impact of a \$100 million increase in commodity investments on the size of the spillover coefficient. For instance, a one standard deviation increase in total ETF assets (\$780 million), is estimated to increase risk spillovers coming from stock markets during volatile times by 0.028. Given our range of estimated risk spillovers from 0.0228 for gold to 0.0985 for crude oil, the size of the coefficient is economically important.²⁸ The same one standard deviation increase in total assets is estimated to increase risk spillovers during normal times by only 0.016. This impact is only about half the size of the impact during volatile times indicating that inflows in commodities not only increase spillovers in general, but more importantly, lead to a latent spillover risk that could suddenly surface when commodity price volatility is high.

<< Table 6 about here >>

To account for the high persistence that can be observed for most spillover coefficients, the t -statistics shown in parenthesis are based on Newey-West standard errors. An alternative way to model the autocorrelation in spillovers directly is to include lags of the dependent variable. In our case, this leads to downward biased coefficients cause by the presence of a lagged dependent variable in combination with autocorrelated residuals (Hsiao, 2004). We reestimate our results under this specification as a kind of control group that provides a conservative lower bound for the range of coefficients that can be expected:

$$Spillover_{i,t,\theta} = \mu_i + \lambda_t + c_1 + c_2 I_{\{\theta=0.5\}} + \beta \cdot Spillover_{i,t-1,\theta} + (\gamma_1 I_{\{\theta=0.125\}} + \gamma_2 I_{\{\theta=0.5\}}) Assets_{i,t} + \varepsilon_t \quad (7)$$

The results for this model are shown in column three of Table 6. Although still statistically significant, the coefficient size for the impact of an increase in ETF total assets is reduced by roughly one fourth. A one standard deviation increase in commodity ETF's assets under management is now estimated to increase spillovers by 0.008 and 0.005 for a volatile and a normal market state, respectively. If the investment flows into crude oil would continue to increase by the average annual growth rate of the last four years (21%), spillovers from the

²⁸ Estimating the impact of one or two quarter lags of funds total assets leads to statistically significant but smaller coefficients, with an overall reduced goodness of fit.

stock market on crude oil would increase by \$540.23 million times 0.008 or 0.043. This constitutes an economically relevant increase in spillover size from currently 0.0985 to 0.1417. Although investment flows into commodity ETFs have recently become smaller (annual growth rate in 2012 was 9.6% vs almost 200% over the entire 4 year period from 2008 to 2012) the consequences of a continued increase in commodity investments are likely to have substantial consequences for portfolio diversification and risk management even under these very conservative estimates.

Finally, we provide a model specification based on dynamic panel methods (Arellano and Bover, 1995) that is designed to include a lagged dependent variable but uses instruments to avoid the downward bias in coefficients. The last column in Table 6 shows that the results are somewhere between the downward biased OLS specification (model II) and the specification that excluded the lagged dependent variable (model I). From our empirical results of all three models we conclude that an exact impact of commodity investments on risk spillovers is hard to quantify, but that the impact is likely to be large economically. Our findings are in line with the hypothesis that risk spillovers from stocks into commodity markets were not solely driven by the aftermath of the global financial crisis but that the increased participation of financial traders in commodity markets play a major role in explaining the persistently high spillovers. Recent findings in the literature on style shifts and style investing (Wahal and Yavuz, 2012; Boyer, 2011; Barberis, Shleifer, and Wurgler, 2005) suggest that something very similar might have taken place in commodity markets, i.e. commodity investments have become an investment style for stock investors. A direct testable implication of an investment style is that it should lead to comovements between stocks and the new style (commodities), a second implication that follows directly from the first is that increased inflows of funds into commodity investments should also lead to higher spillovers. We test both implications and find empirical evidence that is in favor with the investment style hypothesis. Our results cannot definitely reject other stock market or commodity market specific explanations for the increases in spillovers. For instance, the unusual persistence in spillovers could be simply due to extended investor nervousness that has sometimes occurred after a financial crisis (Gulko, 2012, Feldstein, 1999). However, such an explanation would not explain why investment flows constitute important determinants of spillover size.

5. Conclusion

Over the last decade, financial traders strongly increased their participation in commodity futures markets. The dominant presence of these new types of investors started a

continuing process of financialization in which the behavior of commodities has changed in important ways. In this paper, we investigate the impact of financialization on commodity futures markets. We make use of recent methodological advancements for detecting change-points in a correlation structure and identify a shift in the dependence structure between commodities and the stock market in 2008. In line with other studies on financialization in commodity markets (e.g. Cheng, Kirilenko, and Xiong, 2012, and Henderson, Pearson, and Wang 2012) we find that shocks in the stock market did not transmit to commodity markets prior to 2008, but that substantial risk spillovers can be observed after September 2008. These spillovers appear to be particularly relevant in markets of high volatility. In other words, if uncertainty among investors causes a commodity to trade at a high volatility this commodity shows an increased exposure to risk spillovers from shocks to the stock market. A common perception is that risk spillovers from the stock market to commodities is a transitory phenomenon that occurred during the 2007-2009 financial crisis in a market environment of general increased interdependencies among financial institutions. In contrast, our empirical results suggest that the financial crisis may have initiated and amplified the occurrence of risk spillovers, but that a second factor which we identify as a style effect, has replaced the crisis effect. This style effect reflects the investment behavior of financial investors who tend to sell stocks and commodities simultaneously or in quick succession as a reaction to changes in their portfolio values. Thus, the problem of risk spillovers is not confined to the years of the financial crisis but continues to affect portfolio risk until today. Our results therefore have important implications for the hedging strategies of commodity producers, investment strategies of speculators, and, more generally, for the energy and food policy of countries.

A natural question that arises from our analysis is whether the shift in risk spillovers is permanent or whether commodity prices will return to their pre-crisis behavior. The literature on style investing finds that style investors move prices away from fundamental value which generates reversals in the long run (Jegadeesh and Titman, 1993; Barberis and Shleifer, 2003). Our empirical results however suggest that a reversal should only be expected when financial investors reverse their active role in commodity futures markets.

Appendix A: The Scalar \hat{D} for the test statistic of Wied, Kraemer and Dehling (2012)

We briefly describe the construction of the scalar \hat{D} as used in our paper. For a general and in-depth treatment we refer to Wied, Krämer, and Dehling (2012, Appendix A.1). Let $\{(x_{1,t}, x_{2,t})'\}$ be the bivariate time-series with $E((x_{1,t}, x_{2,t})') = 0$. Given is a sample of size T . For $i = 1, 2$, denote $\bar{x}_i = T^{-1} \sum_{t=1}^T x_{i,t}$, $\overline{x_i^2} = T^{-1} \sum_{t=1}^T x_{i,t}^2$ and $\hat{\sigma}_{x_i} = \sqrt{\overline{x_i^2} - \bar{x}_i^2}$. Further, denote $\overline{x_1 x_2} = T^{-1} \sum_{t=1}^T x_{1,t} x_{2,t}$ and $\hat{\sigma}_{x_1 x_2} = \overline{x_1 x_2} - \bar{x}_1 \cdot \bar{x}_2$. Let $k(\cdot)$ be the Bartlett kernel function. The scalar \hat{D} is then given by

$$\hat{D} = \sqrt{\hat{D}_3 \hat{D}_2 \hat{D}_1 \hat{D}_2' \hat{D}_3'}, \quad (\text{A.1})$$

where

$$\hat{D}_1 = \sum_{t=1}^T \sum_{u=1}^T k\left(\frac{t-u}{\lfloor \log T \rfloor}\right) V_t V_u', \quad (\text{A.2})$$

with $V_t = T^{-1/2} (x_{1,t}^2 - \overline{x_1^2}, x_{2,t}^2 - \overline{x_2^2}, x_{1,t} - \bar{x}_1, x_{2,t} - \bar{x}_2, x_1 x_2 - \overline{x_1 x_2})'$,

$$\hat{D}_2 = \begin{pmatrix} 1 & 0 & -2\bar{x}_1 & 0 & 0 \\ 0 & 1 & 0 & -2\bar{x}_1 & 0 \\ 0 & 0 & -\bar{x}_2 & -\bar{x}_1 & 1 \end{pmatrix}, \quad (\text{A.3})$$

and

$$\hat{D}_3 = \begin{pmatrix} -\frac{1}{2} \frac{\hat{\sigma}_{x_1 x_2}}{\hat{\sigma}_{x_2}} \hat{\sigma}_{x_1}^{-3} & -\frac{1}{2} \frac{\hat{\sigma}_{x_1 x_2}}{\hat{\sigma}_{x_1}} \hat{\sigma}_{x_2}^{-3} & \frac{1}{\hat{\sigma}_{x_1 x_2}} \end{pmatrix}. \quad (\text{A.4})$$

The purpose of the scalar \hat{D} is to appropriately rescale the cumulated sum of empirical correlation coefficients in such a way that convergence of Q_T to the asymptotic null distribution is achieved.

Appendix B: Descriptive Statistics of Commodity Exchange Traded Funds

The process of financialization has led to tremendous inflows of investments into commodity exchange traded funds. The total assets managed by commodity ETFs is therefore a key variable in this study. According to Datastream, 203 funds are classified as commodity ETFs. After removing funds that either (i) replicate short positions, (ii) invest into stocks of natural resource companies, or (iii) have an insufficient data history, 83 funds remain. Panel A of Table B1 gives an overview of the funds that were used in this study. A striking feature that all commodity sectors seem to share is the tremendous growth in assets under management that occurred since commodity behavior shifted in September 2008. The majority of investor money is directed towards composite ETFs, indicating that investors generally prefer exposure to the asset class “commodities” rather than speculating on the price movement of any particular commodity sector.

Table B1: Descriptive Statistics of Commodity Exchange Traded Funds

	No. of ETFs	AUM in 2008Q3 ^b	AUM in 2012Q4	Growth 08Q3–12Q4
Panel A				
Corn	2	250	653	161%
Wheat	2	271	667	146%
Crude Oil	7 ^a	869	2,573	196%
Heating Oil	4	330	925	180%
Copper	2	151	766	405%
Alu	3	155	469	200%
Gold	2	366	1,040	184%
Cattle	2	49	79	62%
Composite	11	4,197	12,430	196%
Panel B:				
Power Shares DB Commodity Index Tracking Trust		1,795	6,608	268%
iShares S&P GSCI Commodity- Indexed Trust		671	1,167	74%
iShares Dow Jones-AIG Commodity Swap		116	708	513%

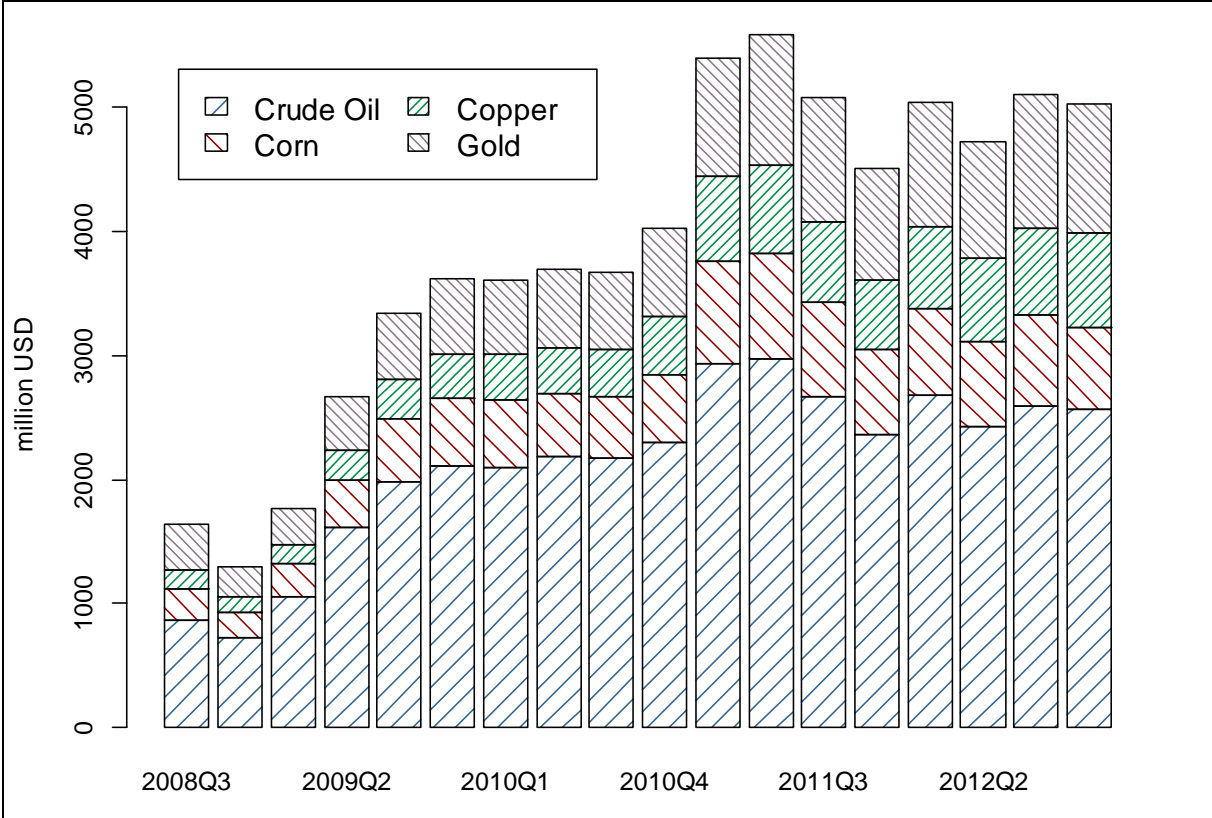
^a includes 4 WTI and 3 Brent ETFs

^b in million USD. Includes estimates of indirect investment through composite indices

It should be noted that an unusual large fraction of total ETF investments is concentrated among 3 composite funds, the largest one being the Power Shares DB Commodity Index

Tracking Trust. Taken together, these three large ETFs hold almost 67% of all investments into the commodity ETF industry. Since ETFs represent passive investments, however, this high concentration should not raise any issues regarding representativeness. Figure B1 below shows the absolute value of total assets over time for the 4 commodity sectors with the highest exposure to stock market shocks (see Table 5). The variation in total assets for these four commodity sectors are used as the explanatory variable in Equations (6) and (7)

Figure B1: Total Assets in the Commodity ETF industry



The majority of funds seem to flow into crude oil investments. This commodity also shows the largest exposure to risk spillovers. Although other sectors like copper exhibit much smaller inflows, they have also recorded higher growth rates over time. With a lower market volume in these sectors even relatively small inflows can lead to large risk spillovers.

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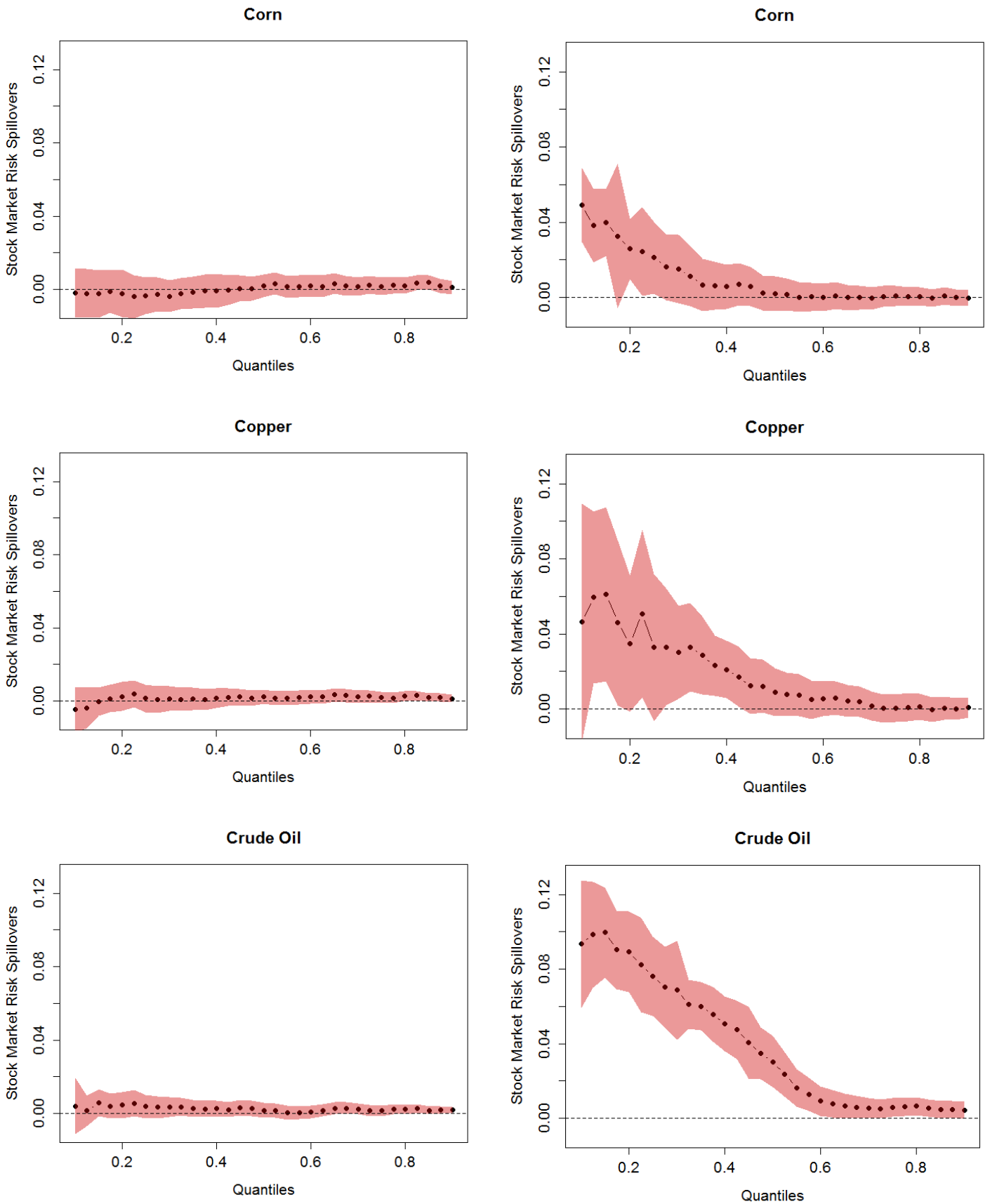
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Figure 1: Risk Spillovers for Various Quantiles

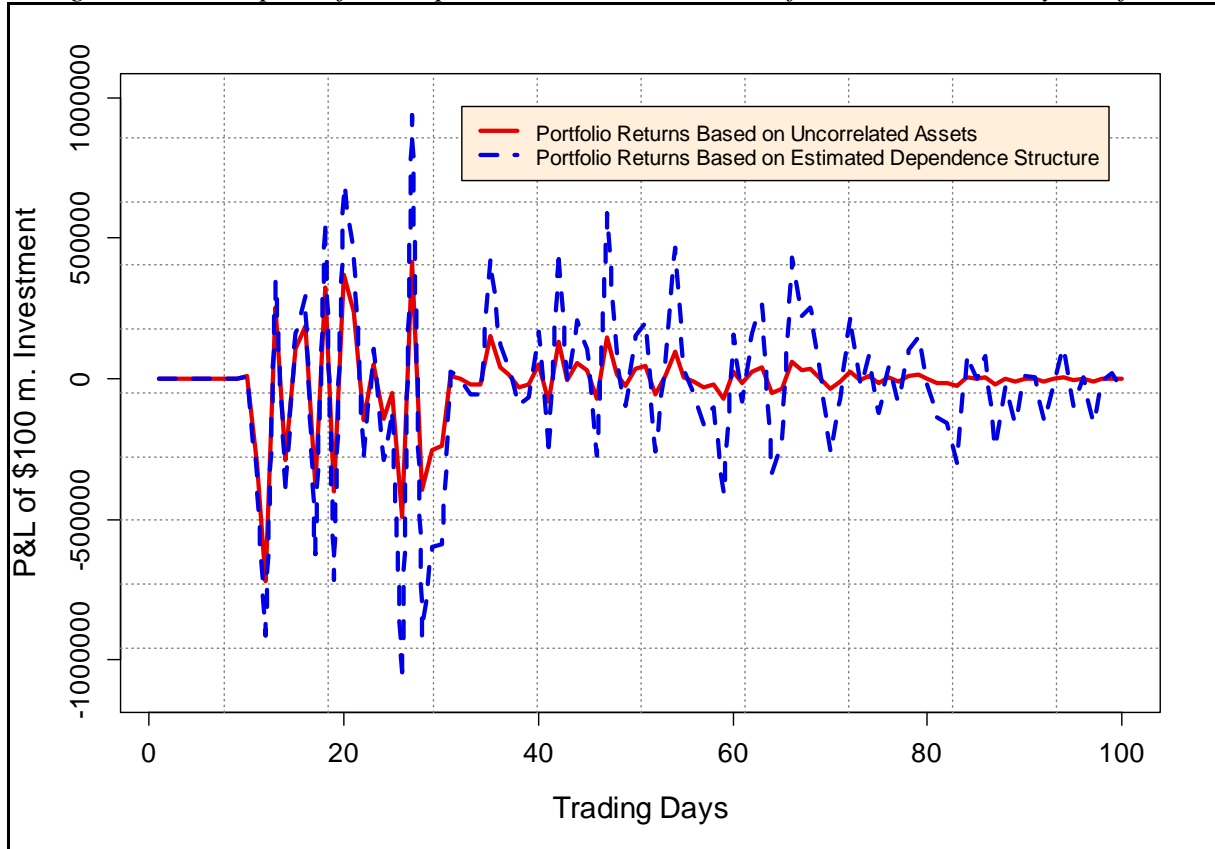
Sample Period 1: 9/15/1994 – 9/15/2008

Sample Period 2: 9/15/2008 – 12/31/2012



This Figure shows the estimated risk spillover coefficients for crude oil, corn, and copper. Spillovers are nonexistent before September 2008 (sample period 1) but are predominant in the tails after the break (sample period 2).

Figure 2: *The Impact of Risk Spillovers on the Variation of a Stock/Commodity Portfolio*



Note: This Figure compares the returns of two hypothetical portfolios experiencing a shock in one of its constituents (the S&P 500). The control Portfolio (solid line) is based on the traditional finding that stocks and commodities are uncorrelated. The treatment portfolio (dashed line) is based on the estimated dependence structure from Table 2 and therefore takes into account, that a shock in the stock market affects the risk in commodity markets.

Figure 3: Dynamics in Risk Spillover Estimates

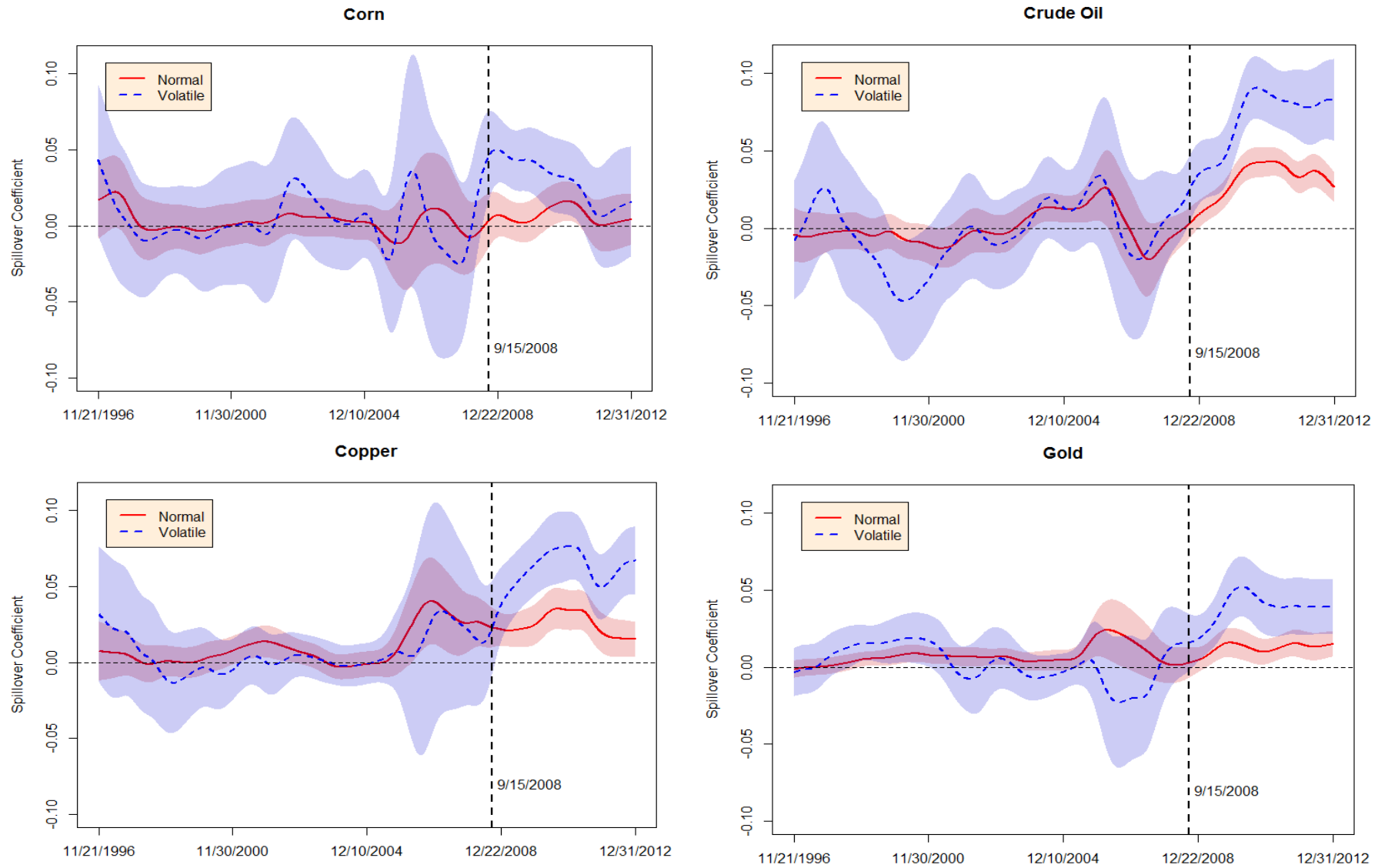
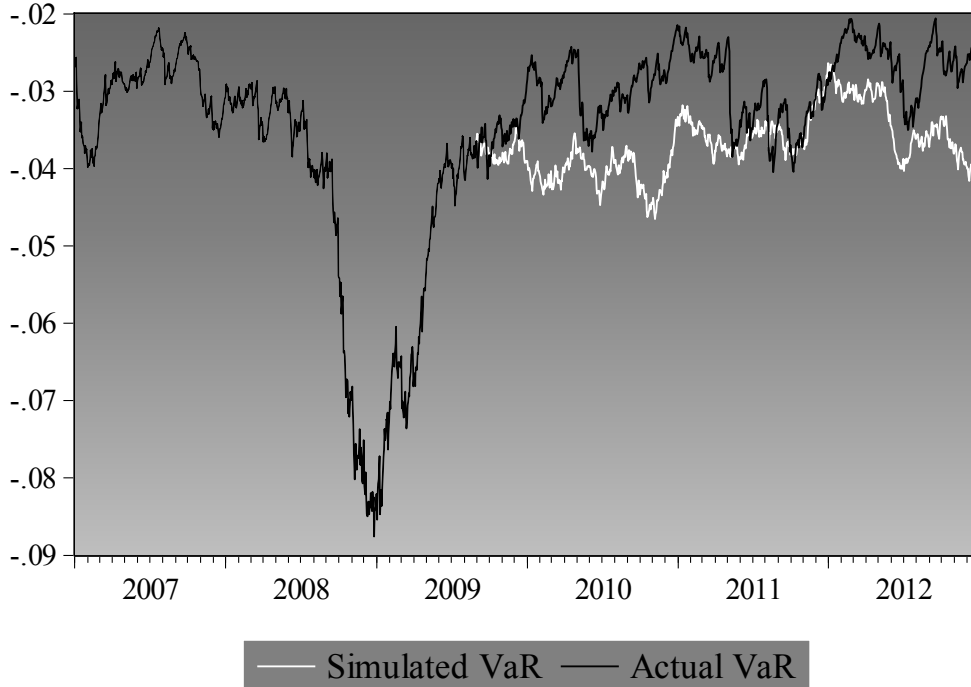
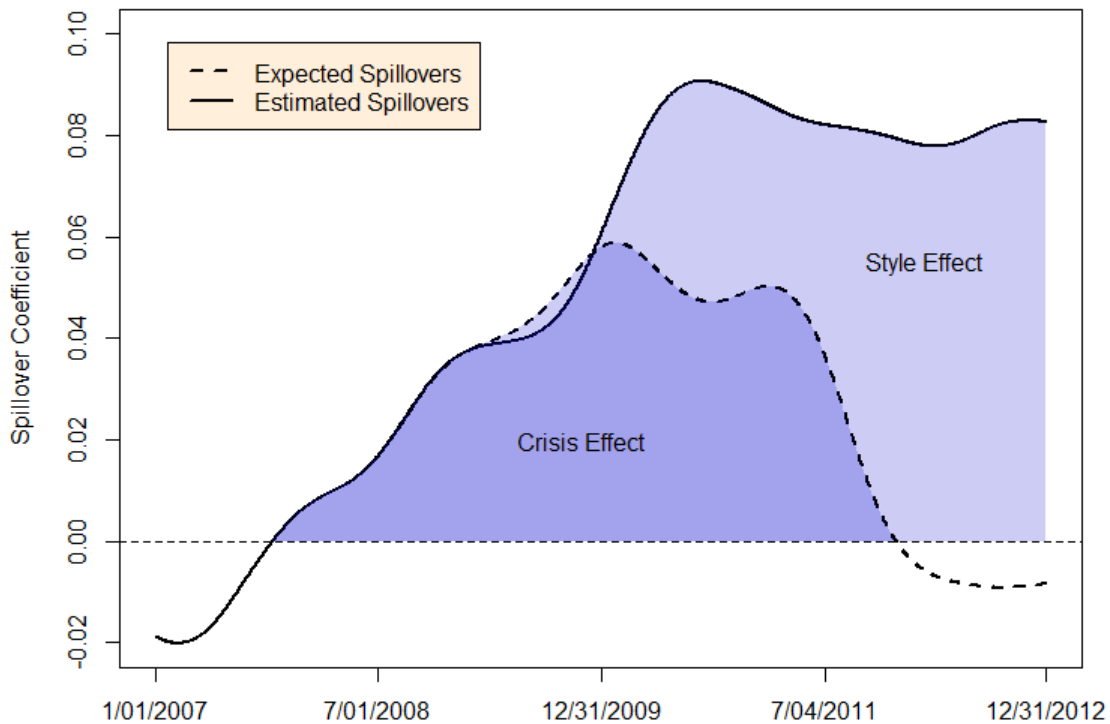


Figure 4: Expected vs Estimated Risk Spillovers for Crude Oil

Panel A: Simulated and Actual Crude Oil VaR



Panel B: Estimated Spillover and Expected Spillover



This Figure shows the development of risk spillovers for crude oil estimated from a 750 day rolling window and compares this estimate with a hypothetical spillover that would be observed when the VaR of crude oil were to return to its pre-crisis behavior at the end of August 2009. The simulated crude oil VaR after August 2009 has the same mean, variance, and degree of autocorrelation as before the crisis but consists of random shocks.

Table 1: S&P GSCI Constituent Weights for Selected Commodities

	Full Index Weight	Subsector Weight
<i>Agricultural</i>		
<i>Corn</i>	5.0	32.1
<i>Wheat</i>	4.4	28.2
		$\Sigma = 60.3$
<i>Energy</i>		
<i>Crude Oil</i>	48.4	70.1
<i>Heating Oil</i>	5.2	7.7
		$\Sigma = 77.8$
<i>Base Metals</i>		
<i>Copper</i>	3.3	47.8
<i>Aluminum</i>	2.1	30.4
		$\Sigma = 78.2$
<i>Precious Metals</i>		
<i>Gold</i>	3.1	86.1
<i>Livestock</i>		
<i>Cattle</i>	3.5	70.0
Σ	79.0	

This table shows GSCI constituent weights as of December 31, 2012. Full Index Weight refers to overall index weights assigned to the commodities. Subsector Weights refers to weights assigned within a particular commodity subsector. For example, precious metals consists of gold with an overall index weight of 3.1 percent and of silver with an overall index weight of 0.5 percent. The precious metals subsector weight of gold is thus $3.1 / (3.1 + 0.5) \cdot 100 = 86.1$ percent. The full list of index constituents and corresponding constituent weights can be obtained from the index provider's website: <http://us.spindices.com/index-family/commodities/sp-gsci>.

Table 2: Descriptive Statistics of Log Returns

	S&P 500	Corn	Wheat	Crude Oil	Heat. Oil	Copper	Alu	Gold	Cattle
Panel A: Summary Statistics									
Mean	0.022	-0.028	-0.037	0.031	0.023	0.037	-0.008	0.018	-0.012
Std.dev	1.296	1.638	1.774	2.096	2.054	1.665	1.300	1.038	0.881
Auto.Cor	-0.07***	0.052***	0.006	-0.020	-0.024*	-0.042***	-0.017	0.006	0.027*
Panel B: Sample Correlations									
S&P 500	1								
Corn	0.113***	1							
Wheat	0.108***	0.633***	1						
Crude Oil	0.165***	0.218***	0.202	1					
Heat.Oil	0.135***	0.193***	0.177***	0.908***	1				
Copper	0.231***	0.191***	0.191***	0.279***	0.244***	1			
Alu.	0.192***	0.179***	0.164***	0.234***	0.211***	0.675***	1		
Gold	-0.024***	0.177***	0.161***	0.229***	0.214***	0.297***	0.260***	1	
Cattle	0.100*	0.110***	0.104***	0.122***	0.094***	0.112***	0.099***	0.043***	1

Panel A of this table shows means, standard deviations and first order autocorrelations of a sample of daily log returns. Panel B shows corresponding cross-correlations. The sample period ranges from 09/15/1994 to 12/31/2012.

Table 3: Wied, Krämer, and Dehling (2012) Test for Structural Changes in Correlation

	Untransformed Returns	Standardized Returns
Corn	3.999	3.401
Wheat	3.964	3.577
Crude Oil	5.448	5.400
Heating Oil	5.236	5.227
Copper	5.621	5.210
Aluminum	5.121	4.956
Gold	2.245	2.705
Cattle	3.393	3.100

This table shows the test statistic Q_t as defined in Equation (3) and based on either the untransformed log returns (second column) or log returns standardized by their EGARCH(1,1) conditional volatilities. Under the null hypothesis of no change in correlation Q_t converges in distribution to a Kolmogorov distribution. Critical values are: 10%: 1.22, 5%: 1.36, and 1%: 1.63. The sample period ranges from 09/15/1994 to 12/31/2012.

Table 4: Correlation Change-Point Inference

	<i>Change-Points</i>	$\Delta\hat{\rho}$
Corn	09/25/2008	0.242
Wheat	09/17/2008	0.261
Crude Oil	09/19/2008	0.539
Heating Oil	08/28/2008	0.520
Copper	06/24/1999	0.128
	08/29/2008	0.278
Aluminum	04/10/2000	0.179
	01/03/2004	-0.048
	11/21/2007	-0.232
	09/05/2008	0.463
Gold	10/15/2008	0.192
Cattle	09/17/2008	0.252

This table shows the correlation change-points as estimated with the algorithm of Galeano and Wied (2012) where the null hypothesis of constant correlations is rejected if the Wied, Krämer, and Dehling (2012) test statistic exceeds the critical value at the 1 percent significance level. We also report $\Delta\hat{\rho}$ which is the change in sample correlation between two consecutive subsamples determined by the change-points. For example, $\Delta\hat{\rho}$ for Corn is given by the correlation of the subsample ranging from 09/26/08 to 12/31/2012 minus the correlation of the subsample ranging from 09/15/1994 to 09/25/2008.

Table 5: Risk Spillovers from U.S: Stocks to Commodities

Panel A: Sample Period before Lehman Bankruptcy: 9/15/1994 – 9/15/2008								
	Corn	Wheat	Crude	Heating	Copper	Alu	Gold	Cattle
	<i>Normal Period: 50% Quantile</i>							
Spillover	0.0019	0.0015	0.0017	-0.0043	0.0024	5.00E-04	0.0026	-6.00E-04
Lag	0.9773*	0.9736*	0.979*	0.9606*	0.9879*	0.9818*	0.9828*	0.9767*
Commodities	-	-	0.0462*	0.0668*	-	-	-	-
Emerg. Mkt.	-	-	-	-0.0012	0.0027	-	-	-
	<i>Volatile Period: 12.5% Quantile</i>							
Spillover	-0.0022	0.0097	0.0014	0.0067	-0.0038	-0.0088	-0.0033	-0.0024
Lag	1.0394*	1.0353*	1.0084*	0.957*	1.0263*	1.0111*	1.029*	1.0153*
Commodities	-	-	0.0394*	0.1231*	-	-	0.0121*	-
Emerg. Mkt.	-	-	-	-0.0109*	0.0046	0.013*	0.0115*	-
Panel B: Sample Period After Lehman Bankruptcy: 9/15/2008 – 3/30/2012								
	Corn	Wheat	Crude	Heating	Copper	Alu	Gold	Cattle
	<i>Normal Period: 50% Quantile</i>							
Spillover	0.002	0.0022	0.0455*	0.0028	0.0065	-0.0032	0.0076*	0.0025*
Lag	0.9627*	0.9738*	0.9374*	0.9507*	0.9489*	0.9761*	0.9672*	0.9654*
Commodities	-	-	0.098*	0.0511*	0.0173*	-	-	-
Emerg. Mkt.	-	-	-0.0176*	-0.0031	0.0172*	0.0102	-	-

	<i>Volatile Period: 12.5% Quantile</i>							
Spillover	0.0381*	0.0015	0.0985*	0.0214	0.0594*	0.0086	0.0228*	0.0179*
Lag	1.0104*	0.9982*	0.8759*	0.8363*	0.9183*	0.9806*	0.9877*	0.9574*
Commodities	-	-	0.3362*	0.2639*	-	-	-	-
Emerg. Mkt.	-	-	-	-0.0443*	0.0959*	0.0174	-	-

This Table Shows the risk spillover coefficients $\beta_{1,\theta}$ from Equation (5) before, and after the identified break in the time-series of correlations between stocks and commodities. Within each sample period, the spillover coefficients are estimated for the median and the left tail of the value-at-risk distribution of selected commodities which corresponds to periods of normal (50% quantile) and high (12.5% quantile) commodity return volatility. Standard errors are based on 200 Markov chain marginal bootstrap replicates. The Commodity index is the GSCI S&P Composite excess return index excluding the commodity for which the stock market relationship is being investigated. Emerg.Mkt is the MSCI emerging market equity index. * indicates statistical significance at the 5% level or higher.

Table 6: Determinants of Risk Spillover Size

	Model I	Model II	Model III
$Spillover_{t-1}$	-	0.656 (15.516)	0.607 (14.830)
^a $Assets_t I_{\{\theta=0.125\}}$	0.00363 (8.401)	0.00102 (3.094)	0.00155 (2.721)
$Assets_t I_{\{\theta=0.5\}}$	0.00204 (4.085)	0.00058 (2.613)	0.00211 (2.608)
$I_{\{\theta=0.5\}}$	-0.00568 (-0.774)	-0.00451 (-2.212)	-
<i>Individual FE</i>	Yes	Yes	Orthogonal
<i>Time FE</i>	Yes	Yes	Yes
<i>Number Obs.</i>	144	136	128
<i>Adj.R-squared</i>	0.72	0.93	-
<i>Estimation Type</i>	OLS	OLS	GMM ^b

Note: This table shows the impact of total funds invested in commodity ETFs (copper, corn, crude oil, and gold) on their risk exposure to spillovers from the stock market. The dependent variable is defined as the daily spillover coefficient from equation (5) estimated in a 3 year rolling window. The number of time-series observations is 18 quarters (2008Q3 – 2012Q4). The number of observations in the cross-section is 4 commodities times 2 market states (normal and volatile). t -statistics are shown in parenthesis. OLS t -statistics are based on HAC standard errors. The GMM t -statistics are based on White period standard errors adjusting for heteroscedasticity in the cross-section serial correlation in the residuals.

a: total assets measured in levels. Panel PP test rejects null hypothesis of unit root

b: Arellano-Bover (1995) Dynamic Panel GMM.