Factor Structure in Commodity Futures Return and Volatility*

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Abstract

We uncover stylized facts of commodity futures price and volatility dynamics in the post-financialization period and find a factor structure in daily commodity volatility that is much stronger than the factor structure in returns. The common factor in commodity volatility relates to stock market volatility as well as to the business cycle. Model-free realized commodity betas with the stock market were high during 2008-2010 but have since returned to the pre-crisis level close to zero. We conclude that, while commodity markets appear segmented from the equity market when considering only returns, commodity volatility indicates a nontrivial degree of market integration.

Keywords: Commodity futures, realized volatility, realized correlation, factor structure, realized beta, systematic risk, high-frequency returns, financialization

JEL Classifications: G13, Q02.

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1 Introduction

The deregulation of commodity markets in the early 2000s, and the subsequent large inflows of investment capital to commodity futures and related securities, has sparked a heated debate in the popular press as well as in academia. A large part of the discussion of this so-called "financialization" of commodity markets has focused on bubbles in commodity prices and increases in commodity price volatility supposedly caused by futures market trading.[1] The relationship between commodity futures and other asset markets, and in particular risk sharing across markets, has received substantial attention in academia. Cheng & Xiong (2014) provide an excellent overview of existing work on the financialization of commodity futures markets. Our objective is to use the rich information available in intraday transaction-level data on highly liquid commodity futures contracts to cast new light on the factor structure and integration properties of the commodity futures market.

We use close to a billion commodity futures transactions to construct daily realized volatility for fifteen commodities during the 2004-2014 period. To our knowledge, we are the first to construct realized covariances for each commodity with the stock market which we use to develop time-varying but model-free stock market betas as well as systematic risk contributions for each commodity. We use these measures along with daily futures returns to address the following research questions:

First, what are the stylized facts of commodity futures volatility post financialization? Second, is there a factor structure in commodity futures volatility? Third, have commodity future correlations undergone structural shifts? Fourth, is the common component of commodity futures volatility driven by stock market volatility or by other observable economic factors? Finally, do commodity stock market betas and systematic risk in commodity futures returns vary significantly over time?

The stylized facts that we uncover are:

Fact 1: *Daily realized commodity futures volatility has high persistence.*

Fact 2: *The logarithm of realized commodity futures volatility is close to normally distributed.*

[1]"Financialization" refers throughout to the large inflows of investment capital to commodity futures from investors with no apparent commercial interest in the underlying commodity.

Fact 3: *The factor structure in daily commodity futures volatility is much stronger than the factor structure in returns.*

Fact 4: *Whereas the average return correlations have returned to their lower pre-crisis levels, the average volatility correlations have remained at the new higher level attained during the crisis.*

Fact 5: *There is little evidence of a time-trend in the degree of integration within commodity futures markets during the 2004-2014 period.*

Fact 6: *Commodity volatility is strongly related with volatility in other markets, it is higher in recessions, and when the stock market is declining. There is some evidence that commodity volatility is high when commodity carry returns are low.*

Fact 7: *The strong common factor in commodity volatility is strongly related to stock market volatility.*

Fact 8: *Commodity betas with the stock market were high during 2008-2010 but have since returned to a level close to zero.*

Most authors, including Baker (2016), Baker & Routledge (2017), and Hamilton & Wu (2015), date the financialization to take effect sometime in the 2004-2005 period. We follow these papers and begin our study in January 2004. Our analysis is based on close to one billion trades in commodity futures contracts observed from January 2004 through December 2014. We choose the three most heavily traded commodities in the energy, metals, grains, softs, and livestock categories for a total of 15 futures contracts. Our work builds heavily on recent advances in model-free volatility and covariance measurement using high-frequency data. See for example Andersen, Bollerslev, Christoffersen & Diebold (2013), Barndorff-Nielsen & Shephard (2007), and Hansen & Lunde (2011) for recent surveys.

Bakshi, Gao & Rossi (2017) develop a three-factor commodity pricing model, using the average commodity return, a basis spread factor, and a momentum factor. They find that the model captures both the cross-sectional and time-series variation in commodity returns. Szymanowska, De Roon, Nijman & Van Den Goorbergh (2014) also find that the basis spread factor explains the cross-section of commodity returns. Daskalaki, Kostakis & Skiadopoulos (2014) also explore common factors in the cross-section of commodity futures returns. They test various asset pricing models motivated either by the traditional empirical equity market studies, or by available commodity pricing theories. They find that none of the models they investigate are successful and conclude that commodity markets are heterogeneous and segmented from the equity market. From the apparent conflict in these recent studies we conclude that the factor structure of commodity returns needs to be studied further.

Evidence on the integration of commodity and equity markets is also mixed. For early evidence on segmentation, see Bessembinder (1992), Bessembinder & Chan (1992), and Gorton & Rouwenhorst (2006). For recent evidence on integration, see Tang & Xiong (2012), Henderson, Pearson & Wang (2015), Basak & Pavlova (2016), and Singleton (2014). We contribute to this discussion by constructing daily model-free realized volatilities and market betas from high-frequency returns on commodity futures and market index futures. These realized risk measures are highly informative about the factor structure and integration properties of the commodity futures market.

In recent work focusing on the U.S. equity market, Chen & Petkova (2012), Duarte, Kamara, Siegel & Sun (2014), and Herskovic, Kelly, Lustig & Van Nieuwerburgh (2016) find ample evidence of a factor structure in idiosyncratic volatility. Herskovic et al. (2016) use daily data to compute annual firm-specific realized volatilities on a large number of stocks. They find strong commonality in the volatility of individual equities. The commonality in equity volatility is strong even after the market factor is removed. This work is important because it has the potential to explain the so-called low-risk anomaly documented in Ang, Hodrick, Xing & Zhang (2006) and Ang, Hodrick, Xing & Zhang (2009) showing that stocks with low volatility this quarter have high returns next month and vice versa. Inspired by this equity market literature, we investigate the factor structure of individual commodity volatility. We find strong evidence of a common factor in daily commodity futures volatility computed from intraday returns.

When investigating contemporaneous correlations between innovations to the principal components in commodity future volatility and other economic variables the following results emerge: First, the principal components in commodity futures volatility appear to be strongly related to volatility in other asset markets including the U.S. equity market. Second, commodity volatility is high when macroeconomic activity indicators are low and funding liquidity risk indicators are high. Third, commodity volatility is correlated with some common cross-sectional equity return factors including the value factor. Fourth, we find some evidence of a negative relationship between commodity carry returns and commodity volatility. Finally, and somewhat surprisingly, we do not find much evidence of a robust relationship between commodity volatility and commodity futures market liquidity as measured using Amihud (2002).

Our study complements Tang & Xiong (2012) who focus on the connection between the large inflow of commodity index investments and the large increase in commodity price co-movements. They find that prices of non-energy commodity futures in the United States have become increasingly correlated with oil prices after 2004. They also find that the correlation between commodity returns and the MSCI Emerging Markets Index has been rising in recent years. Substantial increases in return correlation between commodities and stocks are also found in Büyüksahin, Haigh & Robe (2010) using the Dynamic Conditional Correlation (DCC) model of Engle (2002). In recent work, Boons, Roon & Szymanowska (2015) find that stocks that have high betas with a commodity index earned a relatively low average return in the pre-financialization period and a relatively high return in the post-financialization period. We investigate the dynamic relationship between commodities and the stock market using model-free realized betas. Our time-varying betas can be viewed as dynamic measures of integration with the stock market. Our work is therefore related to the research on time-varying integration of emerging markets, see for example Carrieri, Errunza & Hogan (2007) and Bekaert, Harvey, Lundblad & Siegel (2011).

The remainder of the paper is structured as follows. In Section 2 we describe the data and the methodology for computing returns and realized volatility. Section 3 investigates the factor structure in commodity futures returns and volatility. Section 4 investigates various economic drivers of volatility in the commodity futures market including the stock market, and Section 5 investigates the evolution of realized betas computed from high-frequency returns. Section 6 concludes. Supplementary figures and tables are placed in the appendix.

2 Constructing Returns and Realized Volatility

We obtain intraday trade data on commodity futures from TickData Inc. Our dataset includes intraday transactions and quotes for all maturities on more than 60 commodities traded across the world. From TickData we also obtain data on the highly liquid S&P 500 E-Mini futures, which is used as a proxy for the stock market index, as well as futures on the Nikkei 225 Index, MSCI Emerging Markets Index, MSCI EAFE Index, Eurodollar, US 2-year and 10-year Treasury Notes, which we use as observable factors in later sections. While we are thus considering equity index futures rather than the underlying cash index, note that Hasbrouck (2003) shows that the E-Mini futures dominate price discovery in the S&P 500 index.[2]

2.1 Commodity Categories

We study the post-financialization period from January 1, 2004 to December 31, 2014, and focus on commodities that are traded either in Chicago or New York during the entire sample period. Gorton, Hayashi & Rouwenhorst (2013) classify commodities into five categories: metals, softs, grains, energy, and livestock. We use this classification and focus on the three most actively traded commodities in each category. This leaves $K = 15$ commodities for our analysis, namely light crude, natural gas, heating oil; gold, silver, copper; soybeans, corn, wheat; sugar, coffee, cotton; live cattle, lean hogs, and feeder cattle.[3] See Table 1 for details on our fifteen commodities and other assets used in later sections. The normalized closing prices of the commodities and S&P 500 E-Mini are shown in Figure 1.

Not surprisingly, light crude is by far the most heavily traded commodity futures with more than 250 million transactions as evident from the last column of Table 1. Each transaction consists of at least one futures contract being traded on 1,000 barrels of crude oil. Table 1 illustrates the massive size of the crude oil futures market compared

[2]Hasbrouck (2003) compares different types of futures and ETF contracts and discusses a previous literature that finds that futures contracts generally dominate the cash index in price discovery. See his Section I.A and footnote 2.

[3]Other commodities traded in Chicago or New York include palladium, lumber, cocoa, orange juice, oats, soybean meal, soybean oil, platinum, ethanol, and rough rice. The last three were introduced after our sample started, and similarly pork bellies only traded until July 2011.

with other commodities. Gold is second, natural gas third, corn fourth, soybeans fifth, and feeder cattle is the least traded among the fifteen commodities with less than 2.5 million transactions in the most active futures contract during our sample period. Figure 2 illustrates the development in the daily average transactions, volume, and dollar volume per year. Trading in all commodities has increased remarkably since 2006. The availability of large amounts of transactions data forms the basis of our analysis on realized commodity futures volatility below.

2.2 Transaction Data Cleaning

The raw daily transactions data for all futures series in Table 1 are cleaned first using the TickData validation process and subsequently using the algorithm in Barndorff-Nielsen, Hansen, Lunde & Shephard (2009).[4] For the univariate realized variance analysis, the widest feasible estimation window within the trading day is used, and for the bivariate realized covariance analysis the window for each commodity is defined by its trading span overlap with the S&P 500 future as illustrated in Figure 3 and discussed further in Section 5.1 below. For most commodities, electronic trading is available 24 hours a day, only paused by short breaks.

2.3 Modeling the Futures Roll and Computing Daily Returns

For each of the fifteen commodities, a continuous price series is constructed from the nearest-to-maturity contracts in the sample period. Rollover to the subsequent contract occurs on days when the daily, day-session tick volume of the back-month contract exceeds the daily tick volume of the current month contract.[5] This procedure is intended to mimic the behavior of the majority of market participants. Rollover is always done

[4]From www.tickdata.com: *"Algorithmic data filters are employed to identify bad prints, decimal errors, transposition errors, and other data irregularities. These filters take advantage of the fact that since we are not producing data in real-time, we have the ability to look at the tick following a suspected bad tick before we decide whether or not the tick is valid. We have developed a number of filters that identify a suspect tick and hold it until the following tick confirms its validity. The filters are proprietary, and are based upon recent tick volatility, moving standard deviation windows, and time of day."* Following Barndorff-Nielsen, Hansen, Lunde & Shephard (2009), we use the median price if multiple transactions have the same time stamp and we delete entries for which the transaction price is more than five mean absolute deviations from a rolling centered median of the 25 preceding and the 25 subsequent observations.

[5]We implemented this using the "AutoRoll" algorithm in the TickWrite 7 software provided by TickData Inc. The data in our analysis is therefore straightforward to reproduce.

during the afternoon trading break illustrated in Figure 3.

In the univariate analysis, the first observed price for a commodity on day t is defined as the opening price, F_t^o, and the closing price, F_t^c, is defined as the last observed price before the afternoon trading break. This is illustrated for the S&P 500 futures in the top line in Figure 3. Commodities and other observable factors are treated similarly.[6]

The autocorrelation functions for the first 60 lags do not show any strong systematic evidence for daily return dynamics except for a weekly seasonal in natural gas.[7] Altogether we conclude that daily returns show little evidence of predictability based on sample autocorrelations which are generally economically small even if sometimes statistically significant in our large sample. We therefore do not model expected daily return dynamics below.

2.4 Constructing Realized Volatilities

Within the trading span highlighted in Figure 3, a 1-minute time-grid is constructed using previous-tick interpolation for each futures contract.[8] This results in $(n+1)$1-minute prices where the first price in the grid is F_t^o. From these prices, n 1-minute log returns on day t are calculated as

$$r_{t_j} = \log\left(F_{t_j}\right) - \log\left(F_{t_{j-1}}\right),$$

where $t_j - t_{j-1}$ equals one minute. We can then define $(n-4)$ 5-minute returns using

$$\tilde{r}_{t_k} = \sum_{k=j}^{j+4} r_{t_k},$$

which is a sum of overlapping 5-minute returns.

[6]Daily log returns of the closing prices, $r_t = \log\left(F_t^c\right) - \log\left(F_{t-1}^c\right)$, are plotted in Figure A.1 in the appendix.

[7]The autocorrelation functions have been relegated to Figure A.2 in the appendix.

[8]Previous-tick interpolation makes use of the most recent tick to form an evenly-spaced one-minute time-grid of prices. A tick is used if it falls exactly on the one-minute grid, otherwise the nearest previous tick is used.

The 5-minute realized open-to-close variance with 1-minute subsampling is then

$$RV_t^{oc} = \frac{n}{5 \cdot (n-4)} \cdot \sum_{k=1}^{n-4} \left(\tilde{r}_{t_k}\right)^2,$$

where the scaling factor ensures that the realized variance estimate is unbiased. The subsampling technique uses 5-minute returns to minimize the effect of market microstructure noise on our volatility estimate and the subsampled 5-minute returns are then averaged to increase the efficiency of the estimator. This estimator is a simplified version of the class of estimators advocated by Zhang et al. (2005).

Finally, variance and covariance measures are matched to close-to-close returns following Hansen & Lunde (2005). That is, the realized variance for the whole day based on intermittent high-frequency data is given by

$$RV_t = \hat{\omega}_1 \left(r_t^{co}\right)^2 + \hat{\omega}_2 RV_t^{oc}, \tag{1}$$

where $\hat{\omega}_1$ and $\hat{\omega}_2$ are estimated weights provided in the appendix,[9] and where r_t^{co} is the realized close-to-open return, i.e. $r_t^{co} = \log\left(F_t^o\right) - \log\left(F_{t-1}^c\right)$. The $RVol_t$ measure is then computed as the square root of RV_t.[10]

Note that the realized variances as stated would be subject to roll effects through possibly different contracts being the most active at day $t-1$ and t. This would impact the close-to-open and close-to-close returns as the change happens in the afternoon trading break. We therefore adjust the $t-1$ close price to that of the contract used for opening price and intraday information at time t to eliminate such roll effects.

2.5 Properties of Realized Commodity Volatility

Table 2.a reports various sample statistics for the daily realized volatilities, $RVol_t$. As expected, $RVol_t$ has high positive skewness, as well as positive excess kurtosis, but more importantly, $RVol_t$ is very persistent. The first-order autocorrelation is large and significant for all 15 commodities and the Ljung-Box test is highly significant across both 5 and 21 lags.

[9] See the notes to Table A.1.

[10] The time series of $RVol_t$ for the 15 commodities are shown in Figure A.3 in the appendix.

Table 2.b reports the same sample statistics as Table 2.a but for the natural logarithm of $RVol_t$. Note again the high persistence evident by the ACF(1), Q(5), and Q(21) statistics. Figure 4 plots the autocorrelation functions for the first 60 lags for $\log(RVol_t)$. The level of first-order autocorrelation varies a bit across commodities but the strong persistence is evident across our15 commodities and we can write our first stylized fact:

Fact 1: *Daily realized commodity futures volatility has high persistence.*

Comparing Table 2.b with Table 2.a we also see that $\log(RVol_t)$ is much closer to normally distributed than is $RVol_t$ itself; skewness is close to zero and kurtosis is close to 3. Figure 5 reports quantile-quantile plots of $\log(RVol_t)$ which visualizes its normality. The lognormal feature of $RVol_t$ is well-known in other asset markets, see for example Andersen, Bollerslev, Diebold & Labys (2001) for foreign exchange and Andersen, Bollerslev, Diebold & Ebens (2001) for equities. To our knowledge, we are the first to document that:

Fact 2: *The logarithm of realized commodity futures volatility is close to normally distributed.*

Given the approximately normal distribution of log realized volatility, we model the expected $\log(RVol_t)$ and use an ARMA(1,1) specification, defined by

$$\log(RVol_t) = \phi_0 + \phi_1 \log(RVol_{t-1}) + \theta_1 e_{t-1} + e_t. \tag{2}$$

We choose an ARMA(1,1) specification to capture the strong persistence in $\log(RVol_t)$ and also to capture the unavoidable measurement error in the realized variance measure defined in equation 1 above.[11] Figure 6 contains time series plots of the expected one-day ahead $\log(RVol_t)$ computed as

$$E_{t-1}[\log(RVol_t)] = \phi_0 + \phi_1 \log(RVol_{t-1}) + \theta_1 e_{t-1}. \tag{3}$$

For comparison, we also plot the realized stock market volatility (in grey) using the S&P 500 E-Mini futures contract.[12] Note that the commodity $\log(RVol_t)$ - unlike the

[11]Table A.2.a in the appendix contains the ARMA-coefficient estimates. Using a fractionally integrated ARFIMA$(1, d, 1)$ model to capture the long memory in volatility does not change any of our conclusions nor does recursive estimation the ARMA(1,1) model.

[12]Figure A.4 in the appendix contains time series plots of the raw $\log(RVol_t)$ series.

$RVol_t$ levels - are fairly well-behaved over time and in some cases shows a slightly decreasing trend over time. The concern of increased commodity market volatility post financialization often raised in the popular press does therefore not appear to be warranted.

Kamara (1984), Anderson (1985) and Bessembinder et al. (1996) have found evidence that futures volatility is affected by the time to delivery. In Figure 7 we therefore scatter plot $\log(RVol_t)$ for the most active futures contract against the number of days until the roll over to the next-maturity contract.[13] The slope from regressing $\log(RVol_t)$ on the days-to-roll is always very close to zero but sometimes significant (positive or negative) due to the large number of observations. In addition, the R^2 is always $< 1\%$ except for corn (2.7%), cotton (5.1%) and soybeans (1.2%). When reporting the expected $\log(RVol_t)$ as we often do below, any maturity effect will get partly captured by the lagged log realized volatility in the ARMA model in equation 3 above.

It is well known that certain commodities, in particular agriculturals, have annual seasonal patterns in returns, see for example Kamara (1982) and Gorton et al. (2013). We therefore investigate if commodity realized variances display seasonal patterns as well. To this end we regress the daily realized variance in levels for each commodity on monthly dummy variables as well as on twenty lags of the realized variance in order to pick up the strong persistence in volatility. Table 3 shows that apart from natural gas, the seasonal dummy variables are rarely significant. We acknowledge that the lack of significance could be driven by our relatively simplistic model for seasonality as well as our relatively short sample period covering 11 years.

[13] In 2011, the March and May contracts for cotton were never traded more than the December contract, which is evident in Figure 7. Similarly, the July contract for corn in 2004 was never the most traded. Also, recall that not all calendar months are used as delivery months and that the distance in months between the delivery months therefore varies. This sometimes leaves more observations with few days to roll than with many days to roll, which is evident in the figure for soybeans and sugar for instance.

3 Factor Structure in Commodity Returns and Volatility

In this section we investigate the multivariate properties of commodity returns and volatility. We pay particular attention to the factor structure in the cross-section of commodities. Bakshi, Gao & Rossi (2017) and Szymanowska, De Roon, Nijman & Van Den Goorbergh (2014) find evidence of a factor structure in commodity futures returns whereas Daskalaki, Kostakis & Skiadopoulos (2014) conclude that commodity futures returns are largely heterogeneous. The apparent conflict in these recent studies serve as an important motivation for our analysis in this section.

3.1 A Common Factor in Commodity Returns?

To get a quick first glance at the cross-commodity return dependence, the upper triangle of the matrix in Table 4 reports the sample correlations for daily futures returns. Note the high correlations for energy and metals, the somewhat lower correlations for grains and softs, and the close-to-zero correlations for livestock. The average correlation with all other commodities is highest for light crude at 35.3% and lowest for lean hogs at 16.5%. The within-commodity-market diversification benefits thus vary greatly across commodities. The average correlation across all pairs of commodity returns is 26.5%.

We now look for evidence of a common factor in our 15 commodity returns. Using the sample correlations in the upper triangle of Table 4, we compute the principal components (PCs) for the 15 return series and in Figure 8.a we plot the cumulative return for the first four PCs. The first four PCs explain 31.4%, 15.7%, 10.4%, and 7.8% respectively, for a total of 65.3% of the cross-sectional variation in the 15 commodity futures returns. Comparing the top-left panel in Figure 8.a with the top-left panel in Figure 1 we see that the first PC appears to capture the 2007-08 run up, and subsequent crash in oil prices and several other commodities. We conclude that there is some, but relatively weak, evidence of a factor structure in daily commodity future returns.

3.2 A Common Factor in Commodity Volatility?

In recent work focusing on the U.S. equity market, Chen & Petkova (2012), Duarte, Kamara, Siegel & Sun (2014), and Herskovic, Kelly, Lustig & Van Nieuwerburgh (2016) find ample evidence of a factor structure in idiosyncratic volatility that is arguably even stronger than the factor structure found in equity returns themselves. We now confirm that the same holds true in the commodity futures market.

Our daily realized volatility measures computed from intraday returns allow us to view volatility as an observed time series albeit measured with error. We therefore now investigate the multivariate properties of our commodity $\log\left(RVol_t\right)$. The bottom triangle of the matrix in Table 4 contains the sample correlations for $\log\left(RVol_t\right)$ and shows that the correlations for log volatility is higher than for returns for all the 15 commodities. This is particularly the case for livestock, where the average return correlation for live cattle, lean hogs, and feeder cattle is 24%, 17%, and 17% respectively, whereas their average $\log\left(RVol_t\right)$ correlations are 52%, 46%, and 48%. The average correlation across all pairs of commodity volatilities is 46% compared with 27% for returns.

The first four PCs corresponding to the ARMA(1,1) filtered $\log\left(RVol_t\right)$ are reported in Figure 8.b. They capture 54%, 11%, 8%, and 6% respectively, for a total of 79% of the total variation. Note again that the first PC for expected $\log\left(RVol_t\right)$ in the top left panel of Figure 8.b resembles quite closely the time series of expected $\log\left(RVol_t\right)$ for light crude in the top left panel of Figure 6. Note also that the first PC from the realized commodity volatilities is clearly related with the realized volatility of the S&P 500 depicted in grey in Figure 8.b.

Table 5.a reports the regressions of each expected $\log\left(RVol_t\right)$ on the first four PCs. For each commodity, we again run a separate PC analysis based only on the other 14 commodities to avoid endogeneity issues in these regressions. Note that all 15 commodities load positively on the first factor. Table 5.a also reports the regression fit, R^2, of each commodity. They show that the first four PCs capture a substantial share of the variation for all commodities except perhaps coffee. The average R^2 is 55% for volatility compared with 24% for returns. Compared with the commonality in returns, the commonality in volatility is much greater. We conclude:

Fact 3: *The factor structure in daily commodity futures volatility is much stronger than the factor structure in returns.*

One may reasonably wonder about the stability of the correlations in Table 4 in particular during the turbulent sample period (2004-2014) that we analyze. In the appendix we therefore conduct a subsample analysis.[14] In Figure 9.a we plot the average return correlation with other commodities and in Figure 9.b the average log volatility correlations. Each line in the figure corresponds to a subsample period. Figure 9.a shows that the pre-crisis and post-crisis commodity return correlations are very similar for each commodity whereas during the crisis the average return correlations increased for all commodities except gold. The increase in return correlation from pre-crisis to crisis is on average 11.5 percentage points. Figure 9.b shows that the increase in the volatility correlation was even higher than for returns at 22.4 percentage points on average. The average volatility correlations increased for all commodities except soybeans. The striking difference between Figure 9.a and Figure 9.b is that

Fact 4: *Whereas the average return correlations have returned to their lower pre-crisis levels, the average volatility correlations have remained at the new higher level attained during the crisis.*

Figure 9.a illustrates the need for time-varying return correlations, which has been known since Engle (2002) at least. We will allow for this below. Figure 9.b illustrates the need for time-varying volatility correlations. This is a much less explored area although Engle & Figlewski (2015) model dynamic correlations in option-implied volatilities for large cap stocks. We will allow for time-varying volatility correlations below as well.

3.3 Time-Varying Commodity Market Integration

It is natural to ask if the principal component analysis in Table 5.a is stable over time. In a study of international equity markets by Pukthuanthong & Roll (2009), they introduce

[14] In the supplementary Tables A.3-A.5 in the appendix we split the sample into a pre-crisis sample (January 2004 to June 2008) in Table A.3, a during-crisis sample (July 2007 to December 2011) in Table A.4, and a post-crisis sample (July 2010 to December 2014) in Table A.5.

a measure of time-varying market integration that is based on a time-varying principal component analysis. Following their approach we regress the return for each commodity on the first 10 PCs computed separately for each year and computed using only the other 14 commodities.[15] Using only daily returns within a given calendar year, the measure of time-varying market integration of Pukthuanthong & Roll (2009) consists of the time series of the annual adjusted R^2 from these return regressions. While Pukthuanthong & Roll (2009) only carry out the integration analysis on returns, we conduct their analysis first for returns and then for expected log realized volatility.

Our results are reported in Figure 10. The adjusted R^2 from the return regressions are shown with a black line and the adjusted R^2 from the volatility regressions are shown in grey. Three important conclusions are obtained from Figure 10. First, the evidence for commodity market integration is generally stronger when based on volatility than when based on returns. This is especially true for softs and livestock. Second, the degree of market integration varies greatly by commodity. It is strongest for oil and metals. Third, there is no obvious evidence of a time-trend in the degree of market integration during our 2004-2014 sample period. Indeed, the Pukthuanthong & Roll (2009) market integration measure for returns decreased in 2013 for all commodities except gold and silver. Note further that for several commodities the market appears to be less integrated in 2014 than in 2004 by this measure. We conclude:

Fact 5: *There is little evidence of a time-trend in the degree of integration within commodity futures markets during the 2004-2014 period.*

4 Economic Factors and Commodity Volatility

In this section we study the extent to which the PCs in commodity volatility are related to observable economic and financial factors. We pay particular attention to how commodity volatilities might be integrated with equity market volatility. We use intraday trades on the S&P 500 E-Mini futures contract to compute realized stock market volatility as described in Section 2 above.

[15]Our results are robust when changing the number of PCs used.

4.1 Economic Factors and Principal Components in Commodity Volatility

We have identified a strong factor structure in realized commodity volatility and we now investigate if observed financial and economic factors help explain the time-series variation in the commodity volatility PCs. To this end we run regressions of the following form for the i'th PC

$$PC_{i,t} = \alpha + \beta_1 PC_{i,t-1} + \beta_2 X_t + \varepsilon_t,\ i = 1,2,3,4, \tag{4}$$

where we have included the lagged PC as regressor to avoid spurious regression problems when estimating the coefficient of interest, β_2, on the economic variable, X_t.

We consider five sets of economic and financial factors as candidate variables for X_t in Tables 6-10: equity and bond volatility factors, macro factors, equity factor returns, commodity carry returns, and finally commodity liquidity measures. The factors are all available at a daily frequency.

In Table 6 we investigate equity and bond volatility factors, represented by the log of the CBOE SPX Volatility Index (VIX), as well as the log of realized volatility for the S&P 500, Nikkei 225, for MSCI indices for Europe, Australasia, and the Far East (MSCI-EAFE), as well as emerging markets (MSCI-EM) all obtained from TickData. We also include the log of realized interest rate volatility using futures on the 2-year and 10-year T-Note futures, respectively. Daily data for VIX are obtained from Bloomberg and high-frequency data for all other factors are available from TickData.

Panel a of Table 6 shows that all seven volatility factors are significantly positively related with the first commodity volatility PC at the 1% level. The factor structure in volatility we found above within the commodity futures markets thus appears to be strongly related to volatility in other markets. The factor structure in commodity futures volatility indeed appears to extend across other key asset markets. Panels b-d of Table 6 shows some evidence of equity and bond volatility impacting the second to fourth commodity volatility PC as well. Interestingly, Panel c shows that all coefficients are negative for the third PC although they are of course not always significant.

In Table 7 we analyze a number of daily macro factors often used in financial economics. They are the Aruoba et al. (2009) ADS business conditions index, the log of the index of credit spreads on the North American investment grade index (CDX), the Fed five-year break-even inflation rate (BE-Infl), the light crude oil price, the 3-month and 10-year constant maturity US Treasury rates (USGG3M and USGG10YR), the term slope (10-year less 3-month), and the TED spread (TED). Daily data for ADS are from the Philadelphia Fed and all other macro factors are available from Bloomberg.

Panel a of Table 7 shows that PC1 is high when ADS is low matching the findings of Bloom (2014) that volatility is generally higher in recessions. According to Merton (1974), CDX should be high when asset and equity volatility is high which coincides with PC1 being high as we found in Table 6. Following, for example, Boysen et al. (2010), we use the TED spread as a proxy for funding liquidity risk which is also generally high when volatility is high. PC1 is high when break-even inflation and long bond rates are relatively high but recall that inflation and rates have been relatively low during our sample period from 2004 to 2014. As our sample periods is relatively short and contain few cycles we must not over-interpret the coefficients on macro variables.

In Table 8 we study the impact of various equity return factors on commodity volatility. The total return on S&P 500 (SPXT), the betting-against-beta (BAB) factor of Frazzini & Pedersen (2014) for the US and the rest of the world (BAB-US and BAB-RoW), the quality-minus-junk (QMJ) factor of Asness, Frazzini & Pedersen (2013) for the US and the rest of the world (QMJ-US and QMJ-RoW), and the high-minus low book-to-market factor of Asness, Moskowitz & Pedersen (2013) for the US and the rest of the world (HML-US and HML-RoW). Frazzini & Pedersen (2014) argue that the betting-against-beta factor is created by leverage-constrained investors who bid up the prices of high-beta stocks in order to obtain leverage via the stocks' market exposure. Asness, Frazzini & Pedersen (2013) construct a quality-minus-junk factor and find that stocks low risk stocks with high profitability outperform high-risk stocks with low profitability.[16] The book-to-market (value) factor dates to at least Fama & French (1992) and has been found to hold in various markets in Asness, Moskowitz & Pedersen (2013) among others.[17] Daily data for SPXT are available from Bloomberg, and we use

[16]The quality-minus-junk portfolio construction is based on various corporate indicators capturing profitability levels, growth, pay-outs to shareholders, and low risk measured by equity beta and return volatility.

[17]The book value is defined as the 5-year lag of the market value when no book value is available.

daily close-to close log returns, and all other factors are available from the AQR Data Library.[18]

Panel a of Table 8 shows that PC1 commodity volatility is high when the S&P 500 index is low which corresponds to high equity volatility via the so-called leverage effect. We find a strong positive relationship between the QMJ returns and PC1 volatility. PC1 volatility thus appears to be related to a large spread in the returns to quality stocks over junk stocks. It is likely that the cross-sectional dispersion in equity volatility is high when the time-series level of volatility is high as well. Note from Panel d of Table 8 that the QMJ factor returns are related to commodity volatility PC4 also. The relatively strong relationship between the commodity PCs and the equity QMJ factor returns might seem surprising at first. But note that the QMJ factor is partly defined from the return volatility of the stocks and so the strong correlation between commodity and equity volatility could well be generating this relationship.

In Table 9 we compute a commodity carry return factor for each commodity and then average the carry return across the commodities within each of the commodity groups used above. We define carry using spot and futures prices as follows,

$$Carry_t = \frac{S_t - F_t}{F_t} \approx \frac{F_{1m,t} - F_{2m,t}}{F_{2m,t}}, \tag{5}$$

where we have used the one-month futures price as a proxy for the spot price. Carry has been studied in a pure commodity context by Gorton et al. (2013) among others. Koijen et al. (2017) find that assets with relatively large carry values (e.g. high dividend yields for stocks) tend to earn relatively high returns on average not only in commodity markets.

Panel a of Table 9 reveals a negative (but not always significant) relationship between commodity carry returns and PC1 commodity volatility for each of our five commodity groups. For commodities, carry will be large when convenience yields are large or when interest rates and storage costs are low. Convenience yields are large when the physical commodity is scarce for example corresponding to economic expansions when volatility is low as shown in Bloom (2014). Panel c in Table 9 shows that PC3 also generally has

[18] Available at aqr.com/library/data-sets.

a negative relationship with carry returns. The exception is for meats which we have found to be unusual in other respects as well.

Finally, in Table 10 we assess the relationship between commodity futures illiquidity and commodity volatility. For each commodity we construct the illiquidity measure of Amihud (2002) and average them across the commodities in each group. Amihud's measure is defined by combining absolute futures returns and trading volume via

$$Amihud_t = \frac{|r_t|}{Volume_t},$$

somewhat to our surprise we do not find a strong relationship between the principal components of volatility and Amihud's measure of illiquidity. This is surprising because the absolute return in the numerator in Amihud's measure above is a noisy but relatively unbiased proxy for return volatility. However, the volume measure in the denominator is positively related to volatility as well and so the net effect is not clear a priori.

Overall, we conclude:

Fact 6: *Commodity volatility is strongly related with volatility in other markets, it is higher in recessions, and when the stock market is declining. There is some evidence that commodity volatility is high when commodity carry returns are low.*

4.2 S&P 500 Volatility as a Factor for Commodity Volatility

Motivated by the findings in 4.1 we now explore further the role of S&P 500 volatility as a factor for commodity volatility.

The second to last line in Table 4 shows the sample correlation between S&P 500 returns and the return of each commodity. The correlations range from 7% for lean hogs to 44% for copper. The average correlation with S&P 500 returns is 19%. The last line in Table 4 shows the correlation between S&P 500 volatility and the volatility of each commodity. The correlations are generally high at an average of 48%. They are highest for light crude (63%) and the three metals. It is lowest for coffee and natural gas which are outliers in this regard. The S&P 500 volatilities are plotted in grey along with each commodity volatility in Figure 6.

We want to assess the ability of S&P 500 volatility to serve as an observed factor for commodity volatility. To this end we first regress each commodity volatility PC on S&P 500 volatility to obtain a S&P-orthogonalized PC series from the residuals. We then regress the volatility for each commodity on the S&P 500 volatility as well as on the four orthogonalized principal components. Again, the PCs used for each commodity are constructed from the remaining 14 commodities only. Table 5.b contains the regression results. The average R^2 is 55%.

Consider finally the sample correlation between S&P 500 volatility and the first four commodity volatility PCs plotted in Figure 8.b. The four correlations are 69%, −7%, −21%, and 10% respectively. This shows that the commodity volatility PC1 is highly correlated with stock market volatility, and we can write:

Fact 7: *The strong common factor in commodity volatility is strongly related to stock market volatility.*

5 Realized Commodity Betas

Our next task is to compute daily realized covariance measures for each commodity with S&P 500. The ultimate goal is to compute stock market betas for each commodity that vary daily without imposing a particular dynamic model a priori. Existing evidence on the integration of commodity and equity markets is mixed. For early evidence on segmentation, see Bessembinder (1992), Bessembinder & Chan (1992), and Gorton & Rouwenhorst (2006). For recent evidence on integration, see Tang & Xiong (2012), Henderson, Pearson & Wang (2015), Basak & Pavlova (2016), and Singleton (2014). Our dynamic, model-free, realized betas computed from high-frequency returns below shed new light on this debate.

5.1 Constructing Realized Covariance Measures

For the bivariate analysis with S&P 500, overlapping trading spans between commodity i and S&P 500 is required to avoid a bias towards zero in the realized covariances. Therefore, opening and closing prices are now redefined as the most recently observed price before the start and end of the overlapping trading span between commodity i and

S&P 500, respectively. S&P 500 E-Minis trade Monday to Friday from 18.00 Eastern Time the previous day to 17.15 in the full sample period, but for commodities the futures trading spans have changed several times. Therefore, the overlapping trade spans vary across commodities and over time.[19]

The construction of realized covariances is similar to the construction of the realized variances above. Within overlapping trade spans, a synchronized 1-minute time-grid between the commodities and S&P 500 is constructed. From the synchronized prices, 1-minute log returns on day t are calculated. Then, using overlapping 5-minute returns as in Section 2.4, the realized covariance with 1-minute subsampling is for commodity i calculated as,

$$RCov_{i,t}^{oc} = \frac{n_i}{n_i - 4} \cdot \frac{1}{5} \sum_{k=1}^{n_i - 4} \tilde{r}_{i,t_k} \tilde{r}_{S\&P\,500,t_k},$$

where we again use rescaling to make sure the realized covariance estimate is unbiased. The subsampling technique is used to eliminate bias from market microstructure noise and non-synchronous trades within the overlapping trading span, see for example Barndorff-Nielsen & Shephard (2004).

Finally, realized variance and covariance measures are matched to close-to-close returns following Hansen & Lunde (2005). That is, the realized covariance matrix for the whole day based on intermittent high-frequency data is given by

$$RCov_{i,t} = \hat{\omega}_1 r_{i,t}^{co} r_{S\&P\,500,t}^{co} + \hat{\omega}_2 RCov_{i,t}^{oc}, \tag{6}$$

where $r_{i,t}^{co}$ and $r_{S\&P\,500,t}^{co}$ is the realized close-to-open return, e.g. $r_{i,t}^{co} = \log\left(F_{i,t}^{o}\right) - \log\left(F_{i,t-1}^{c}\right)$, for commodity i and S&P 500 respectively, and $\hat{\omega}_1$ and $\hat{\omega}_2$ are again estimated weights similar to the ones reported for the univariate case in the appendix.

5.2 Realized S&P 500 Betas for Commodities

We now investigate the ability of the stock market to explain the variation in returns on the 15 commodity futures contracts. Recognizing that the relationship between each

[19] See Table A.6 in the appendix for details.

commodity and the stock market is likely changing over time, we follow Andersen, Bollerslev, Diebold & Wu (2005) and Patton & Verardo (2012) who use intraday data to compute a daily model-free realized beta for each asset defined by

$$R\beta_{i,t} = \frac{RCov_{i,t}}{RV_{S\&P\,500,t}}. \tag{7}$$

The realized covariance, $RCov_{i,t}$, is calculated on the cross-product of the intraday commodity and stock market return using the estimator in equation 6.

In order to filter the realized betas in equation 7 we estimate an ARMA(1,1) model on each realized beta series. The time series of the filtered betas are plotted in Figure 11.[20]

We plot the beta series along with bootstrapped 75% and 90% confidence intervals around zero constructed by resampling with replacement from the ARMA residuals. The confidence intervals are based on 10,000 bootstrap samples.

Figure 11 shows that the realized betas were close to zero until 2008, then rose dramatically in many cases to and even beyond one. The decrease in commodity betas since 2010 are equally interesting. By the end of 2013 all the realized betas were back to zero, the level at which they began at the onset of financialization in 2004. The betas were highest for energy and metals. The remarkable rise and fall of the commodity betas are shared by all except for lean hogs and feeder cattle which stayed close to zero throughout the period.[21] We assert:

Fact 8: *Commodity betas with the stock market were high during 2008-2010 but have since returned to a level close to zero.*

The beta of an asset does not tell us how much of the variance in the asset's return is driven by the market factor. To this end we define the Systematic Risk Ratio (SRR) for commodity i by

$$SRR_{i,t} = \frac{R\beta_{i,t}^2 \cdot RV_{S\&P\,500,t}}{RV_{i,t}}. \tag{8}$$

[20]The ARMA coefficients are reported in Table A.2.b in the appendix. The appendix also contains a plot of the raw realized betas in Figure A.5.

[21]We do note the uptick in oil betas at the very end of 2014 which marks the end of our sample. It is unfortunately too early to assess if this increase is more than just a temporary phenomenon.

The SRR can thus be interpreted as the fraction of commodity i variance that is explained by market variance. Clearly, $0 \leq SRR_{i,t} \leq 1$. Our use of high-frequency data enables us to compute a systematic risk ratio for each commodity on each day. We again estimate an ARMA(1,1) model on the raw SRR to filter the series.[22] Figure 12 plots the time series of the filtered SRR along with the average SRR over the sample period with bootstrapped 75% and 90% confidence intervals for the ARMA residuals. Note how the SRR was close to zero for all commodities before 2008, it then rose to substantial levels - in particular for energy and metals - before returning to zero at the end of 2014, thus roughly matching the evolution of the realized betas above.

6 Conclusion

We have addressed the following questions: First, what are the stylized facts of commodity futures volatility post financialization? Second, is there a factor structure in commodity futures volatility? Third, have commodity future correlations undergone structural shifts? Fourth, is the common component of commodity futures volatility driven by stock market volatility and/or by other observable economic factors? Finally, do commodity stock market betas and systematic risk in commodity futures returns vary significantly over time?

Analyzing almost a billion trades on 15 commodity futures contracts for the 2004-2014 period, we have uncovered the following:

Fact 1: *Daily realized commodity futures volatility has high persistence.*

Fact 2: *The logarithm of realized commodity futures volatility is close to normally distributed.*

Fact 3: *The factor structure in daily commodity futures volatility is much stronger than the factor structure in returns.*

Fact 4: *Whereas the average return correlations have returned to their lower pre-crisis levels, the average volatility correlations have remained at the new higher level attained during the crisis.*

[22] The ARMA coefficients and the raw SRR series are provided in the appendix.

Fact 5: *There is little evidence of a time-trend in the degree of integration within commodity futures markets during the 2004-2014 period.*

Fact 6: *Commodity volatility is strongly related with volatility in other markets, it is higher in recessions, and when the stock market is declining. There is some evidence that commodity volatility is high when commodity carry returns are low.*

Fact 7: *The strong common factor in commodity volatility is strongly related to stock market volatility.*

Fact 8: *Commodity betas with the stock market were high during 2008-2010 but have since returned to a level close to zero.*

An appropriate option valuation model or portfolio risk model for commodity futures needs to incorporate these features. We have deliberately taken a model-free approach in this paper.

Our results also show that the fear of increased volatility in the commodity markets as a consequence of financialization is largely overblown. Commodity volatility has not trended up nor has commodity return covariance with the stock market trended up. Commodity returns are not riskier now than a decade ago and commodities do not appear to have lost their ability to diversify equity market exposure.

Finally, our results have important implications for understanding the cross-section of commodity futures returns. In recent work focusing on the U.S. equity market, Chen & Petkova (2012), Duarte, Kamara, Siegel & Sun (2014), and Herskovic, Kelly, Lustig & Van Nieuwerburgh (2016) find very strong evidence of factor structure in idiosyncratic volatility. We find the same to be true in commodity futures volatility. Developing an asset pricing framework that can capture this feature presents an important challenge for future work.

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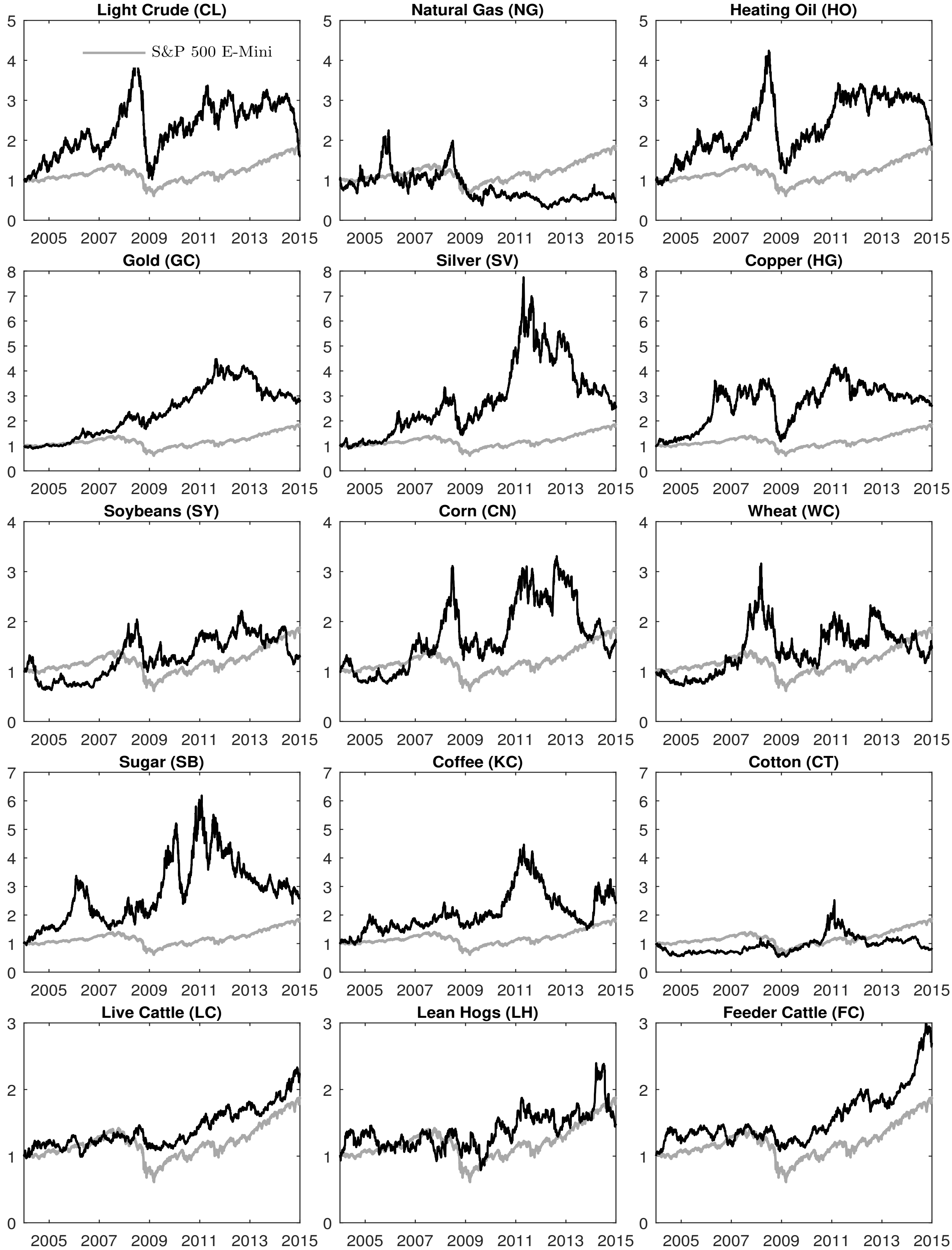
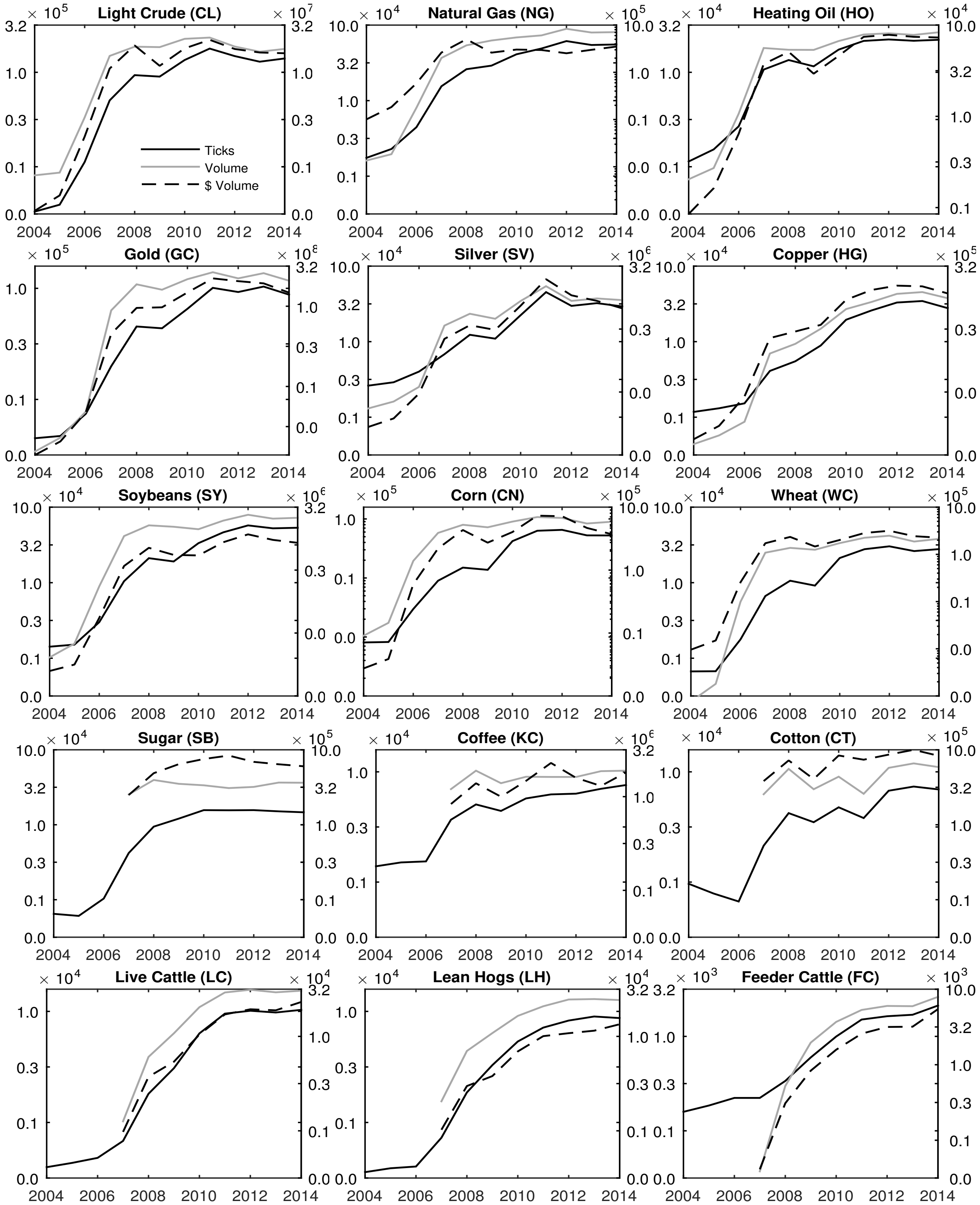
Figure 1: Daily Closing Prices for 15 Commodities and S&P 500.



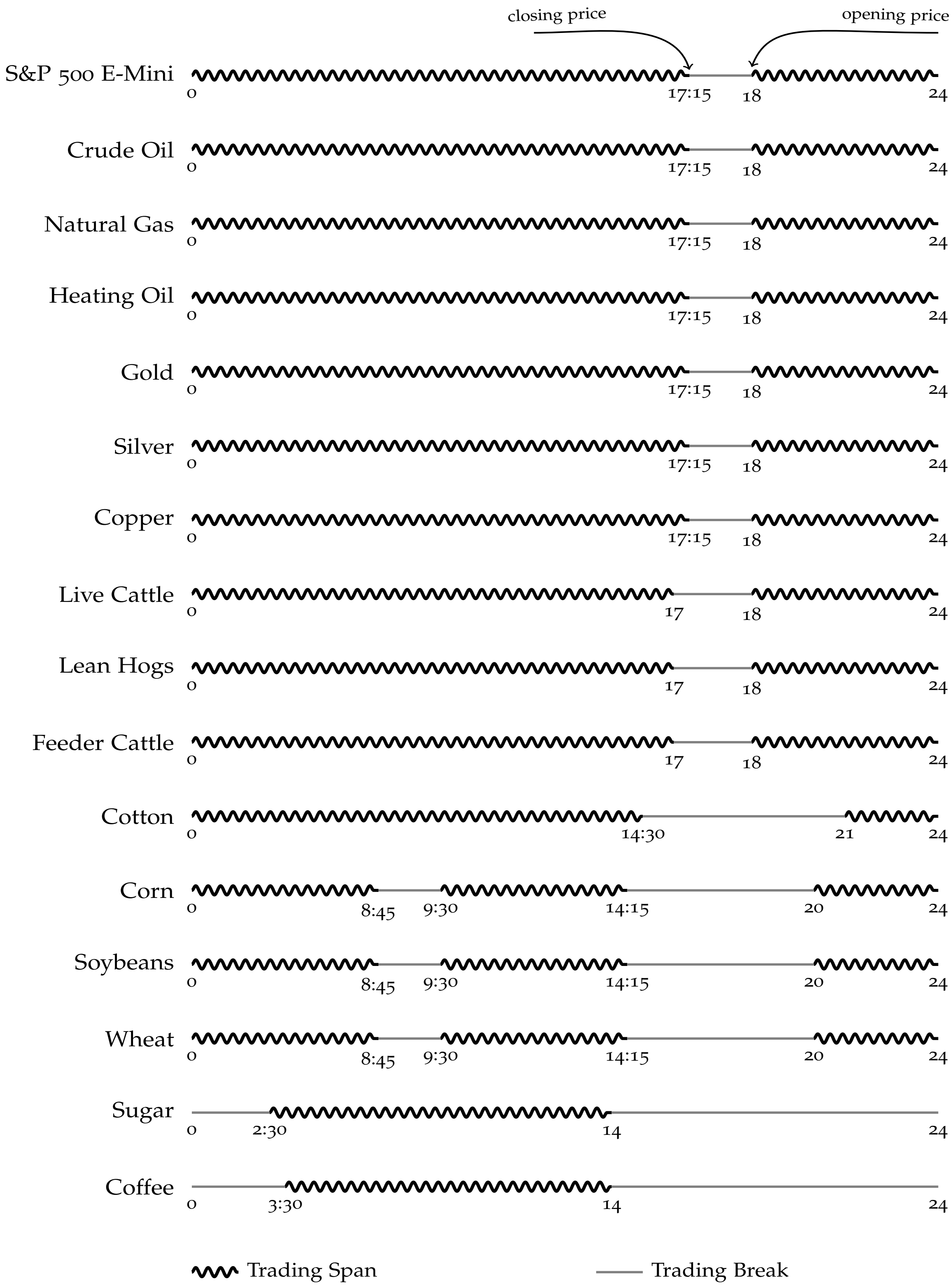
Notes: The figure shows normalized daily closing prices for 15 commodity futures during the 2004-2014 sample period. Closing prices for the S&P 500 E-Mini futures contract, used as stock market proxy, is shown in grey. All prices are for the most active contract on a given day (see Section 2.3).

Figure 2: Ticks, Volume, and Dollar Volume for 15 Commodities. Annual Averages.



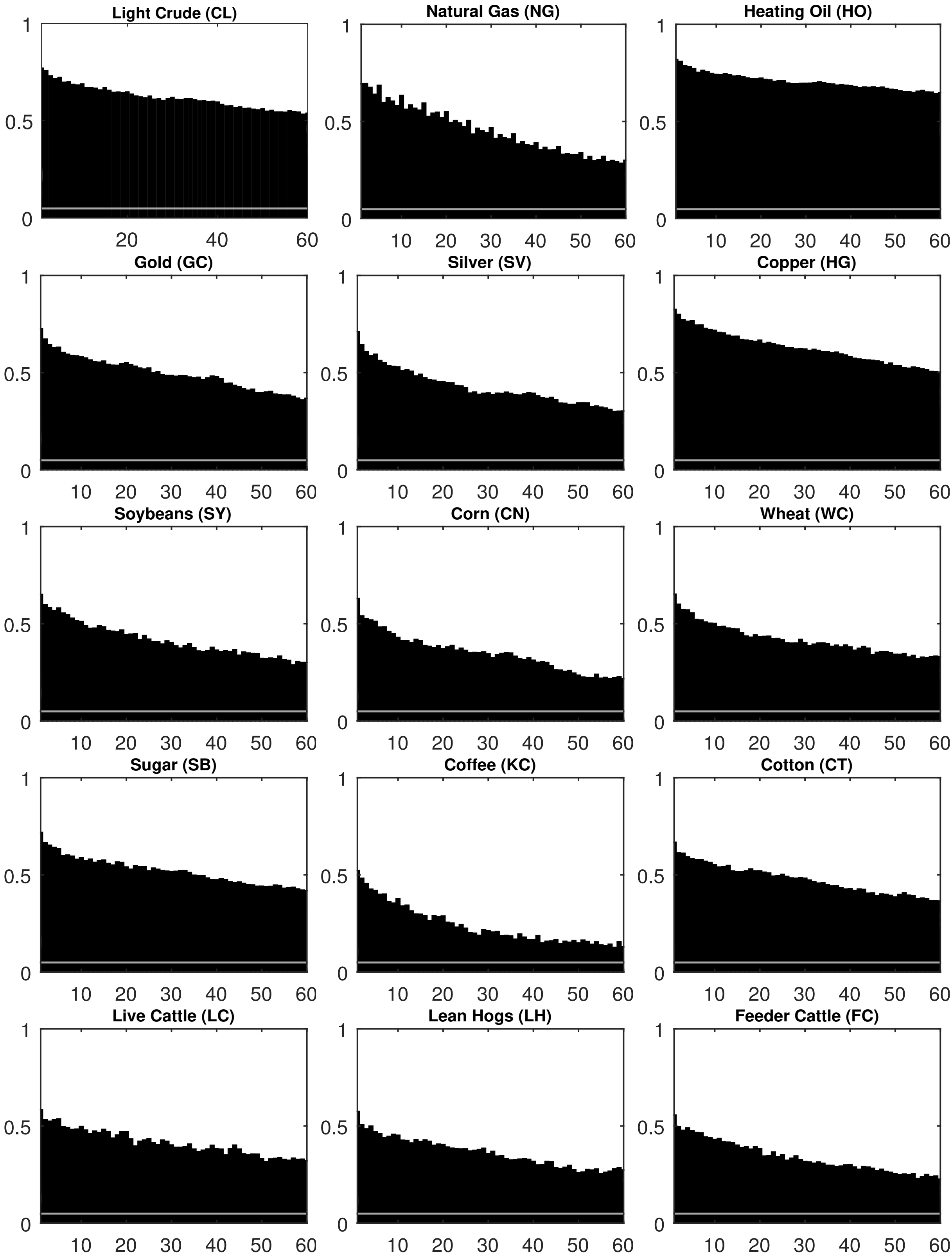
Notes: The figure shows annual averages of ticks, volume, and dollar volume during the 2004-2014 sample period. All averages are for taken over daily values for the most active futures contract each day (see Section 2.3). Ticks (left axis) denote the number of transactions, which may consist of one or more futures contracts (pit and electronic), volume (left axis) denotes the number of futures contracts traded (electronic only), dollar volume (right axis) denotes the dollar value of the futures contracts traded using the closing price each day (electronic only).

Figure 3: Daily Trading Hours for 15 Commodities and S&P 500 E-Mini.



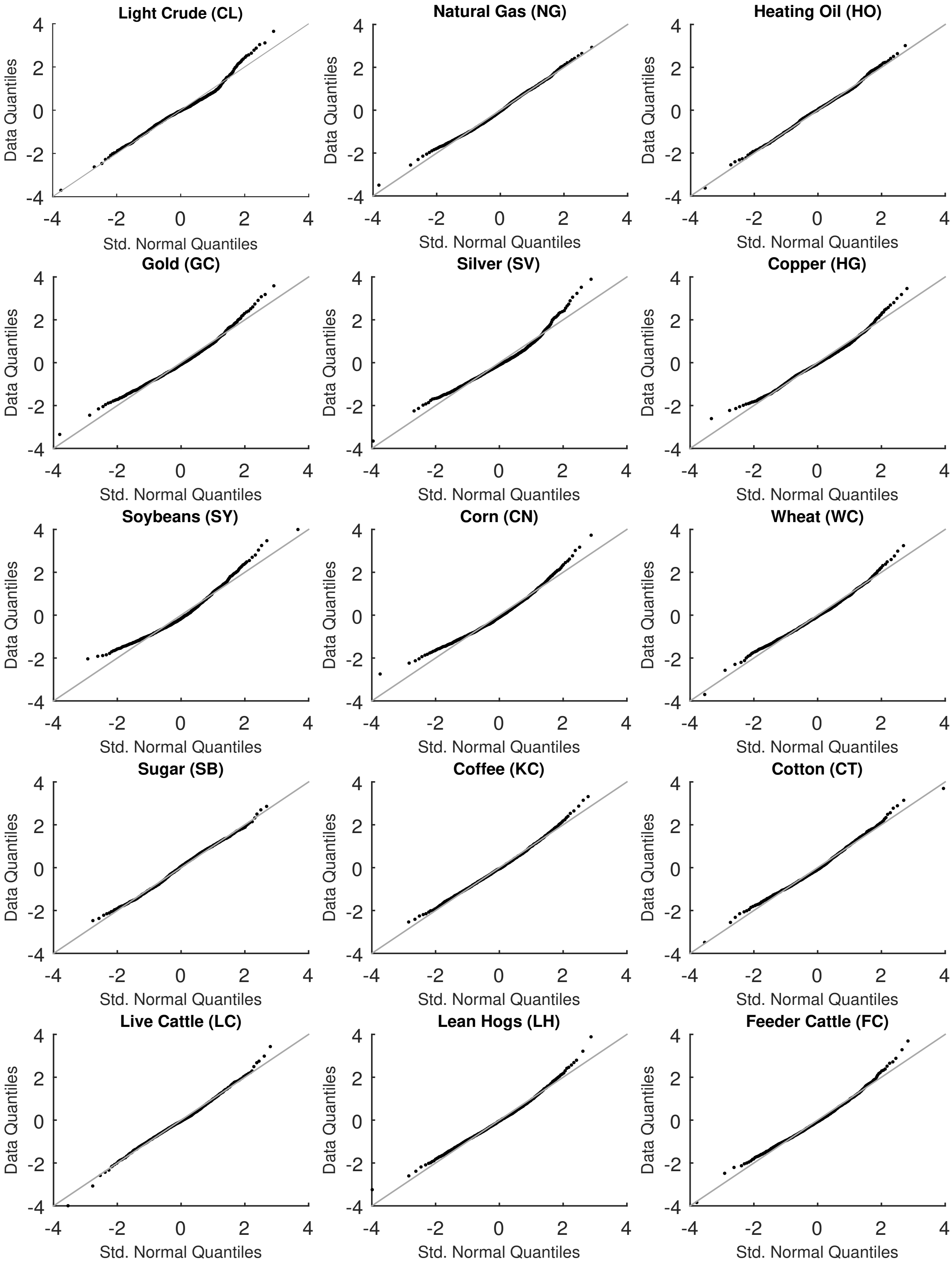
Notes: The figure shows windows of trading as of the last day in the 2004-2014 sample period for the S&P 500 E-Mini futures contract and 15 commodity futures. The figure also illustrates how closing and opening prices are recorded around the afternoon trading break in which any roll in contract would also take place.

Figure 4: Empirical Autocorrelation of Daily Log Realized Commodity Volatility.



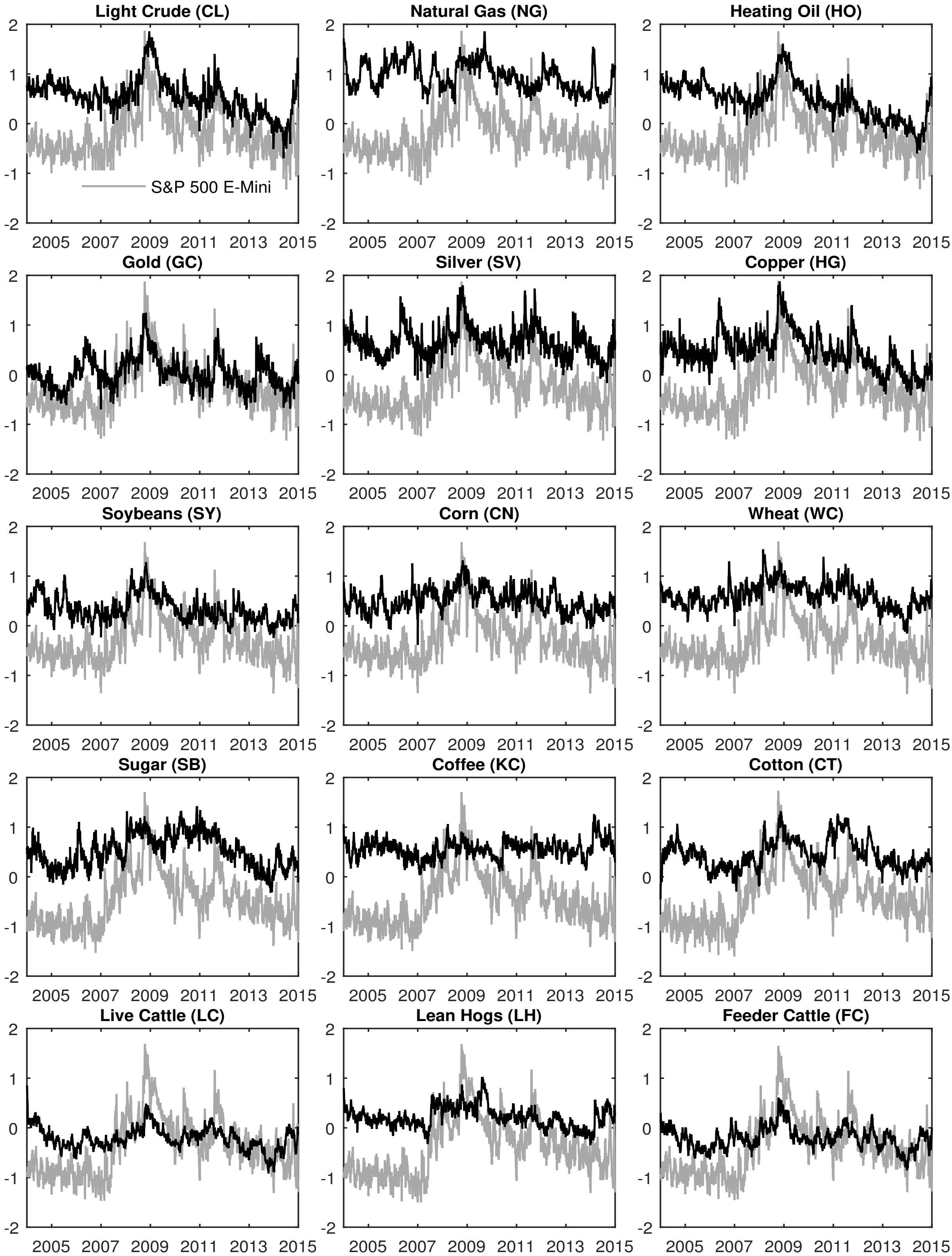
Notes: The figure shows the empirical autocorrelation of log realized volatility for 15 commodity futures during the 2004-2014 sample period. All volatilities are for the most active futures contract on a given day. Grey lines indicate 99% confidence bounds assuming that the series are Gaussian white noise. The horizontal axis indicates the lag order in days.

Figure 5: Quantile-Quantile Plots of Daily Log Realized Commodity Volatility.



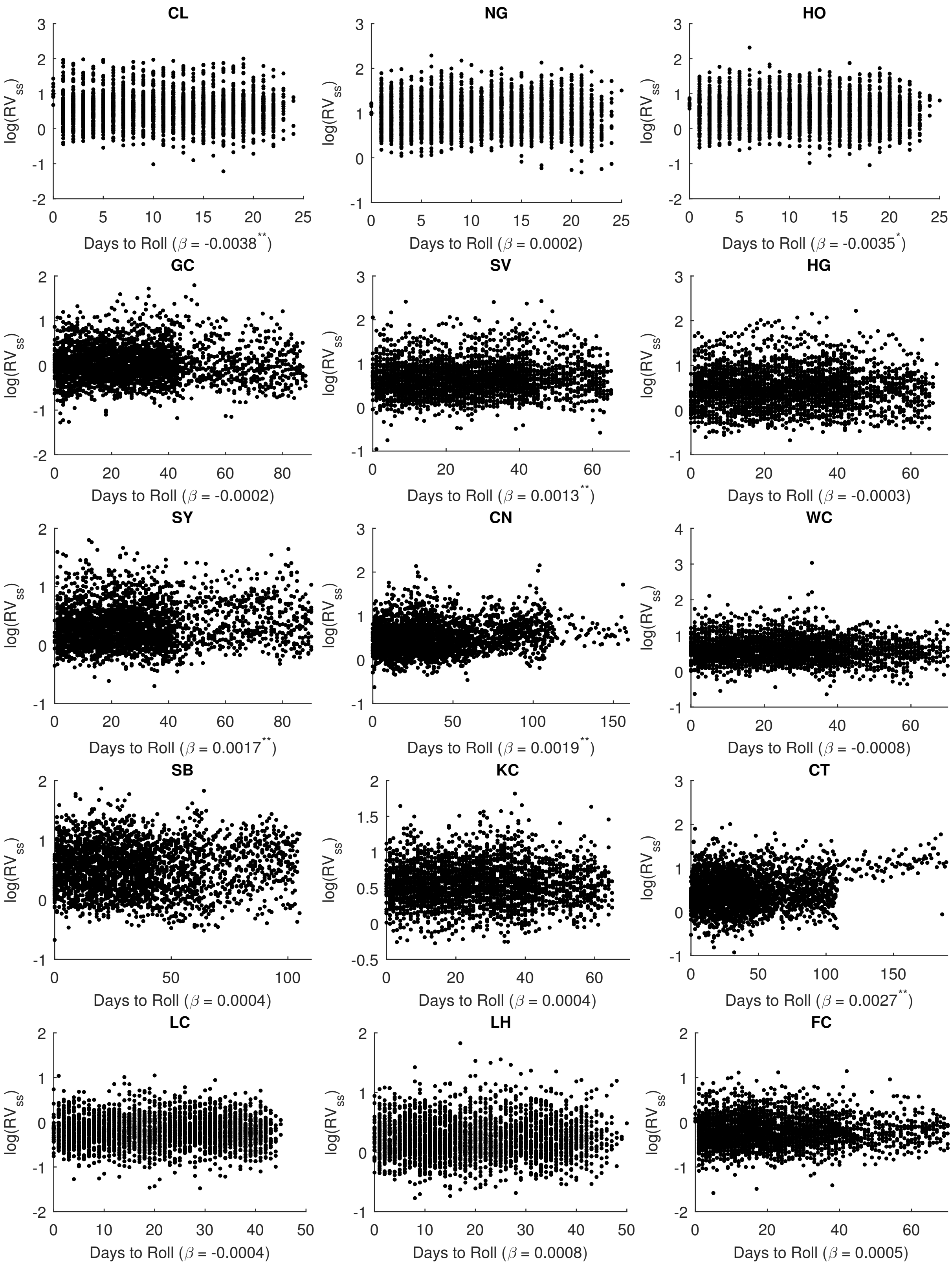
Notes: The figure shows the empirical quantile-quantile plots of daily log realized volatility for 15 commodity futures during the 2004-2014 sample period. All volatilities are for the most active futures contract on a given day.

Figure 6: Daily Expected Log Realized Commodity Volatility.



Notes: The figure shows expected one-day ahead log realized volatility for 15 commodity futures during the 2004-2014 sample period. The S&P 500 E-Mini futures contract, used as stock market proxy, is shown in grey. All volatilities are for the most active contract on a given day (see Section 2.3).

Figure 7: Daily Log Realized Volatility versus Days to Roll.



Notes: The figure shows log realized volatility (y-axis) against days to next roll (x-axis) for 15 commodity futures during the 2004-2014 sample period. All volatilities are for the most active contract on a given day (see Section 2.3). One asterisk indicates significance at the 95% level and two asterisks at the 99%.

Figure 8.a: Principal Components of Commodity Log Returns. Cumulative Sum.

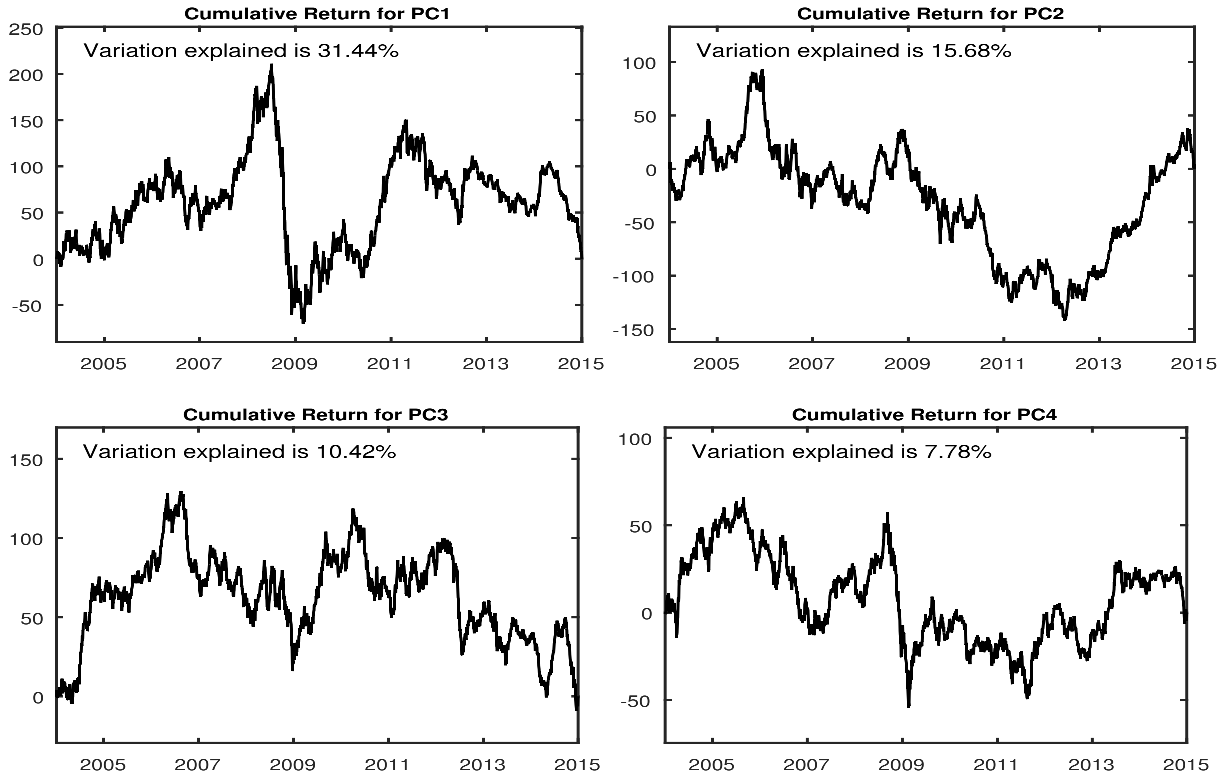
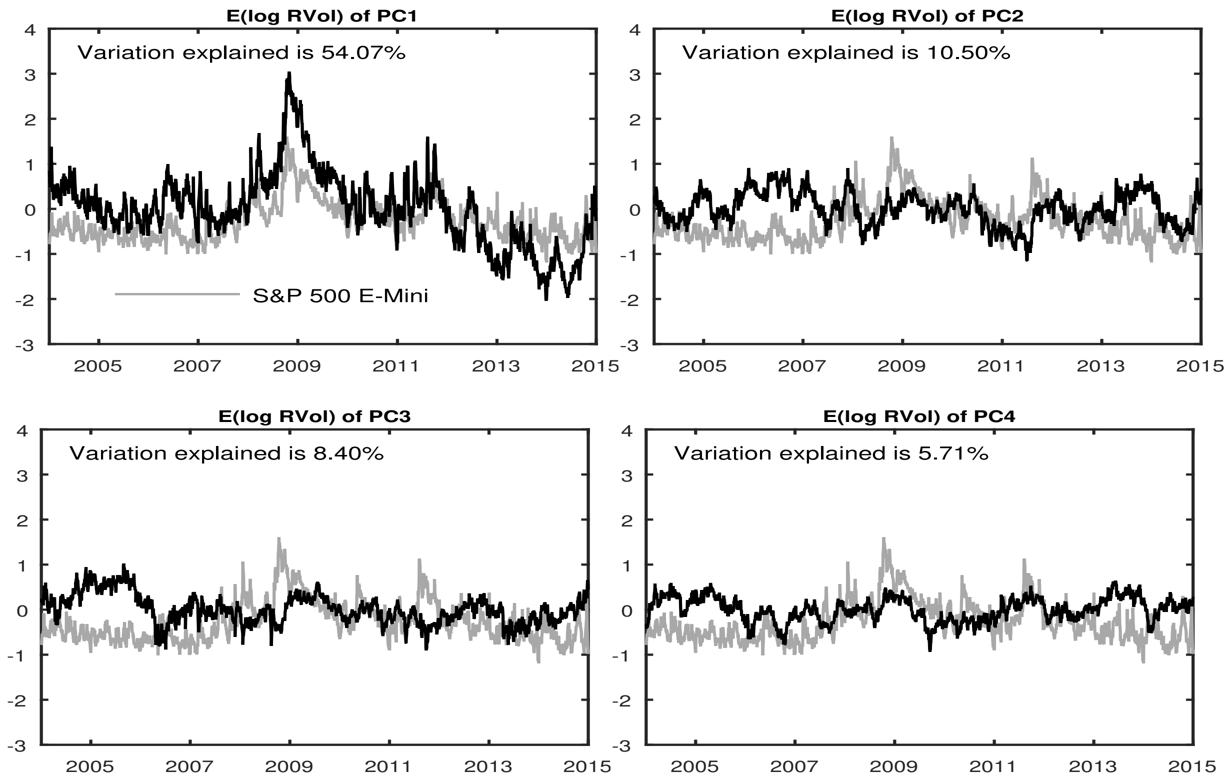


Figure 8.b: Principal Components of Log Realized Commodity Volatility.



Notes: The figure shows principal components of daily returns and log realized volatility for 15 commodity futures contracts during the 2004-2014 sample period. Log realized volatility of the S&P 500 E-Mini futures contract, used as stock market proxy, is shown in grey in the lower panel. All returns and volatilities are for the most active contract on a given day (see Section 2.3).

Figure 9: Average Correlation by Commodity.

Figure 9.a: Average Return Correlation by Commodity

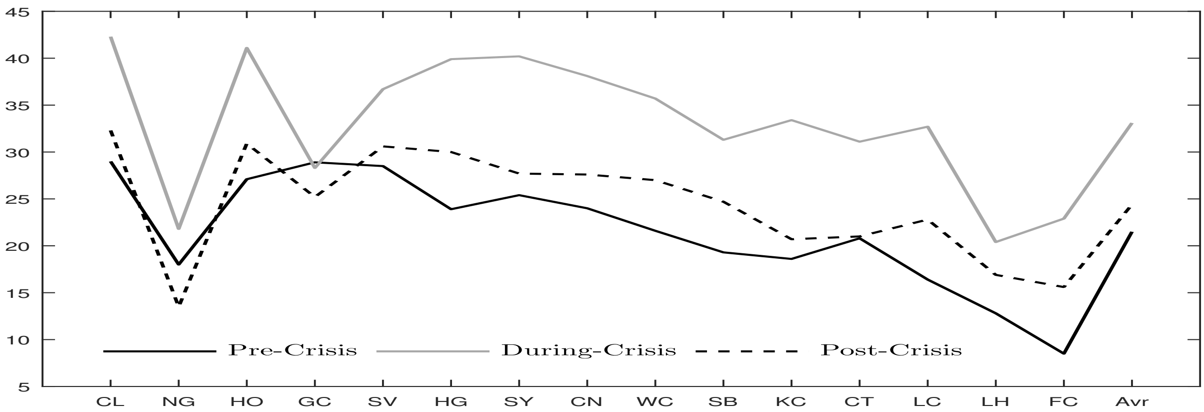
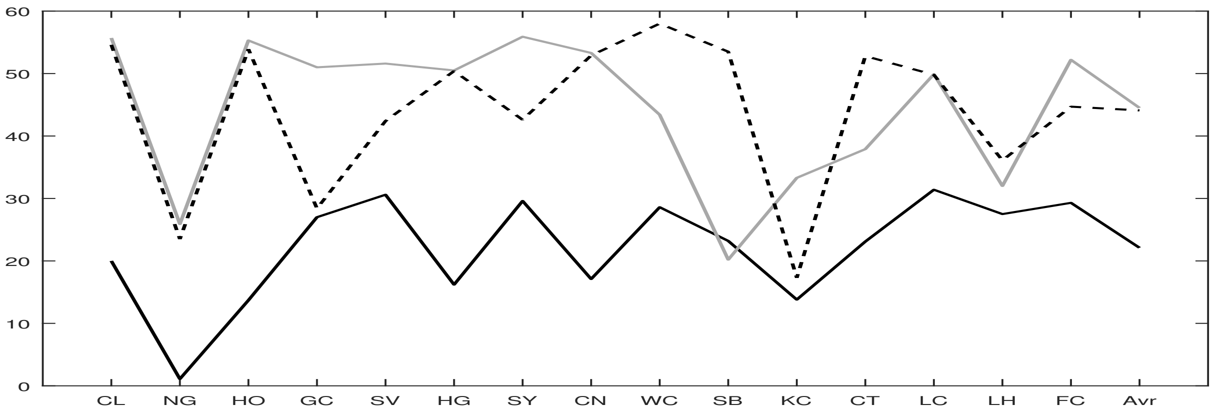
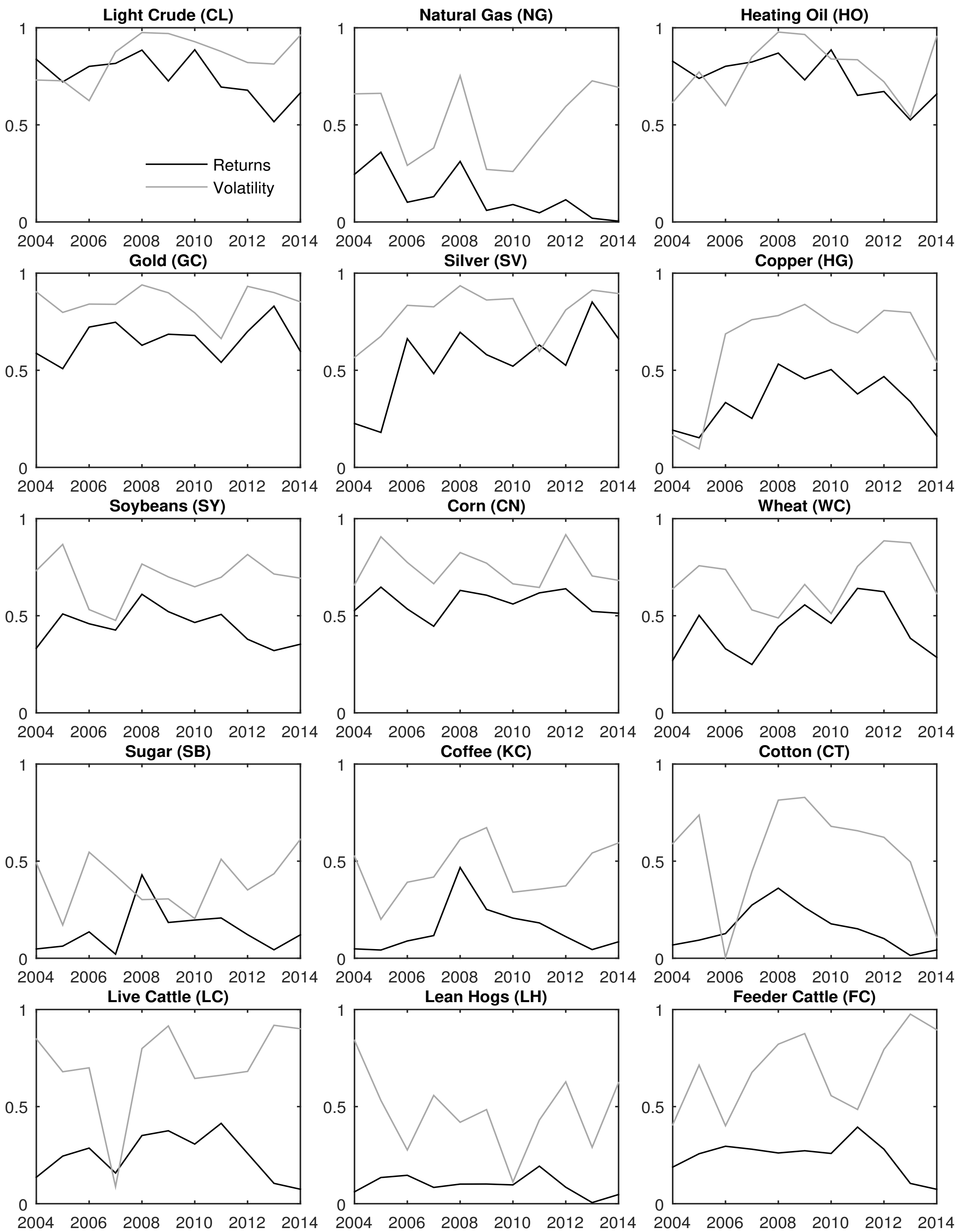


Figure 9.b: Average Volatility Correlation by Commodity



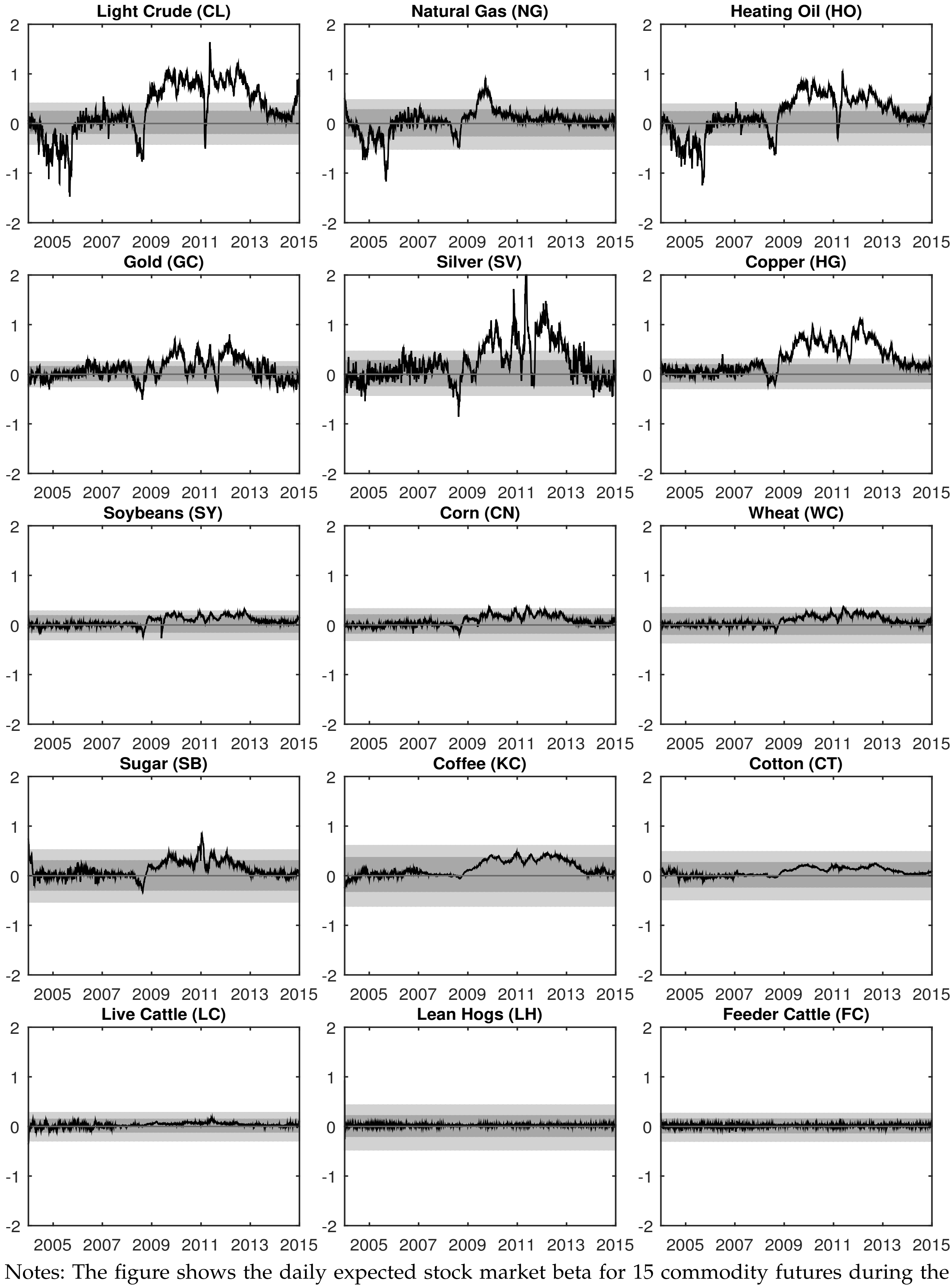
Notes: The figures show unconditional correlations for daily returns (upper panel) and log realized volatility (lower panel) for 15 commodity futures during the sub-periods of the 2004-2014 sample period. All observations are for the most active futures contract on a given day. Average correlations across the 15 commodities in the respective sub-periods are shown as the rightmost data point.

Figure 10: Time-Varying Market Integration in Returns and Volatility.



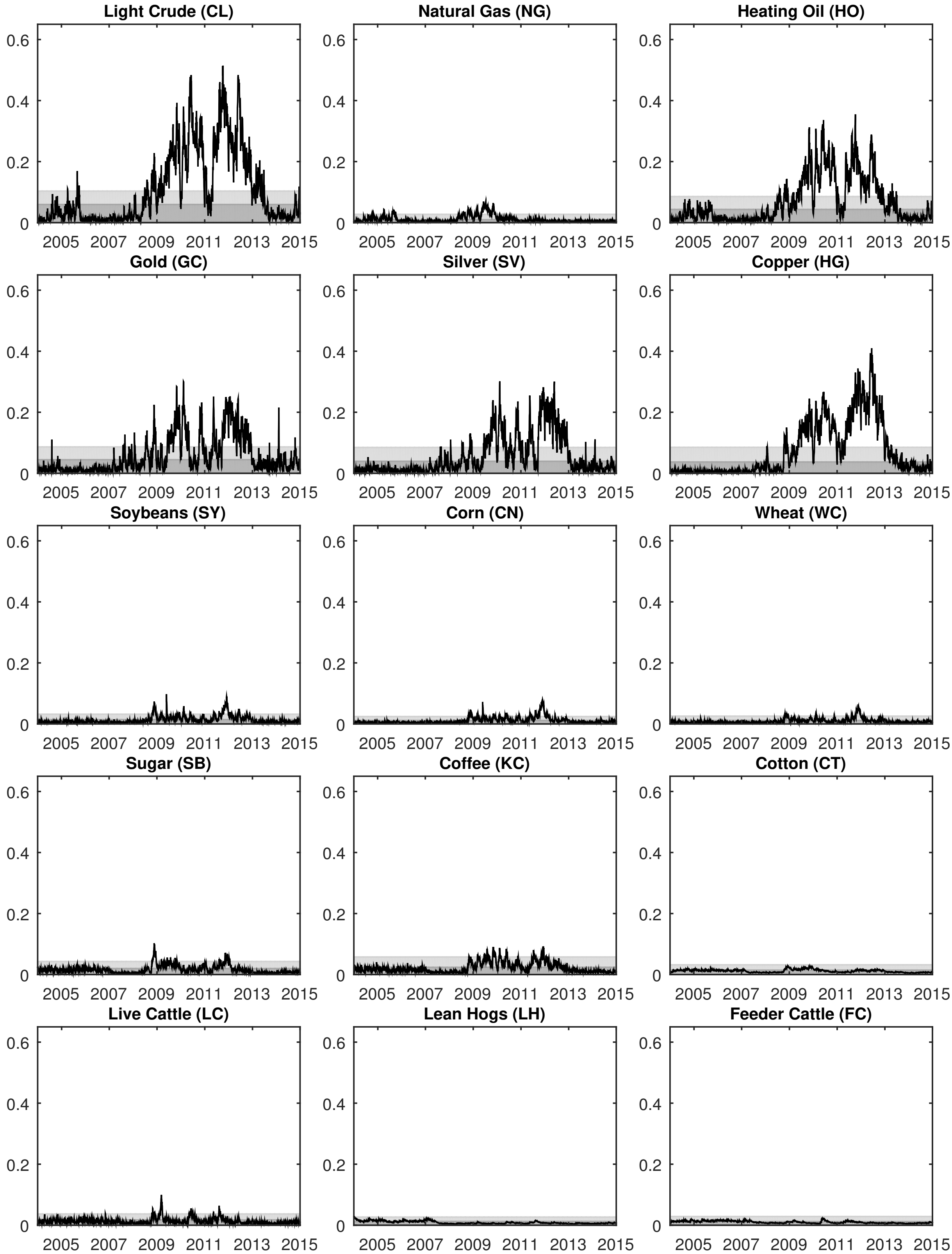
Notes: The figure shows daily time-varying market integration of Pukthuanthong & Roll (2009) for returns (black) and volatility (grey) for 15 commodity futures during the 2004-2014 sample period. For returns and expected log realized volatility each commodity is regressed annually on the first 10 principal components for the remaining 14 commodities. The figure displays the adjusted R^2 of the annual regressions for each commodity. All volatilities are for the most active contract on a given day (see Section 2.3).

Figure 11: Expected Daily Commodity Beta with the Stock Market.



Notes: The figure shows the daily expected stock market beta for 15 commodity futures during the 2004-2014 sample period. The calculation follows equation 7 where all co-volatilities used are for the most active futures contract on a given day. The shaded areas denote 75% (dark grey) and 90% (light grey) bootstrapped confidence intervals for the stock market betas.

Figure 12: Expected Stock Market Systematic Risk Ratio for 15 Commodities.



Notes: The figure shows the daily expected realized stock market systematic risk ratio for 15 commodity futures during the 2004-2014 sample period. The calculation follows equation 8 where co-volatilities used are for the most active futures contract on a given day. The shaded areas denote 75% (dark grey) and 90% (light grey) bootstrapped confidence intervals for the systematic risk ratio.

Table 1: The 15 Selected Commodities and 7 Other Assets.

Category	Asset	Exchange	Time Zone	Transactions
Energy Futures:	Light Crude (CL)	NYMEX/CME	New York	253,872,929
	Natural Gas (NG)	NYMEX/CME	New York	87,835,845
	Heating Oil (HO)	NYMEX/CME	New York	37,633,186
Metals Futures:	Gold (GC)	COMEX/CME	New York	148,537,170
	Silver (SV)	COMEX/CME	New York	51,209,261
	Copper (HG)	COMEX/CME	New York	42,004,247
Grains Futures:	Soybeans (SY)	CBOT/CME	Chicago	75,497,017
	Corn (CN)	CBOT/CME	Chicago	80,165,009
	Wheat (WC)	CBOT/CME	Chicago	41,042,846
Softs Futures:	Sugar #1 (SB)	ICE	New York	26,361,596
	Coffee "C" (KC)	ICE	New York	12,711,409
	Cotton #2 (CT)	ICE	New York	10,543,301
Livestock Futures:	Live Cattle (LC)	CME	Chicago	13,362,636
	Lean Hogs (LH)	CME	Chicago	11,469,432
	Feeder Cattle (FC)	CME	Chicago	2,440,045
Equity Futures:	S&P 500 E-Mini (ES)	CME	Chicago	793,290,475
	Nikkei 225 (NK)	CME	Chicago	11,922,113
	MSCI EM Mini (EI)	NYSE	New York	6,099,224
	MSCI EAFE Mini (MG)	NYSE	New York	4,064,036
Interest Rate Futures:	Eurodollar (ED)	CME	Chicago	42,691,119
	US 2-Year T-Note (TU)	CBOT/CME	Chicago	46,150,610
	US 10-Year T-Note (TY)	CBOT/CME	Chicago	203,282,945

Notes: The table shows for each category the selected commodities and additional assets used in our analysis. For each asset we report the total number of transactions in the most active futures contract each day (see Section 2.3) available during our 2004-2014 sample period. We also report the exchange and exchange time-zone. In the intraday analysis, time stamps are synchronized across time-zones (see Section 5.1).

Table 2.a: Sample Statistics for Daily Realized Commodity Volatility.

	Light Crude	Natural Gas	Heating Oil	Gold	Silver	Copper	Soy-beans	Corn	Wheat	Sugar	Coffee	Cotton	Live Cattle	Lean Hogs	Feeder Cattle	S&P 500 E-Mini
Mean	1.986	2.876	1.841	1.159	2.162	1.837	1.541	1.827	2.009	1.935	1.895	1.812	0.893	1.383	0.914	1.031
Std. Dev.	1.152	1.156	0.877	0.571	1.136	0.988	0.662	0.769	0.883	0.815	0.600	0.826	0.317	0.510	0.361	0.893
Min	0.350	0.741	0.351	0.274	0.458	0.519	0.576	0.639	0.525	0.570	0.761	0.403	0.231	0.465	0.233	0.167
Max	23.857	18.765	12.371	6.486	19.559	12.013	6.143	8.677	21.215	10.168	6.177	7.461	3.515	6.779	5.513	13.148
Skewness	5.068	2.072	2.270	2.676	3.883	2.673	2.040	2.369	5.760	1.479	1.512	1.792	1.796	2.533	2.603	5.181
Kurtosis	63.907	17.612	16.005	15.465	34.035	15.240	9.096	13.541	93.590	8.719	7.364	8.254	9.613	17.111	18.887	45.822
$ACF(1)$	0.610*	0.643*	0.726*	0.708*	0.636*	0.759*	0.598*	0.530*	0.557*	0.670*	0.496*	0.627*	0.539*	0.501*	0.498*	0.634*
$Q(5)$	4972*	5326*	7097*	5568*	4127*	7318*	4098*	2692*	2787*	4765*	2504*	4809*	3342*	2653*	2758*	4878 *
$Q(21)$	18247*	16187*	26456*	18787*	11783*	24957*	12960*	7459*	8116*	14976*	6447*	16806*	11296*	8388*	8389*	15267 *

Table 2.b: Sample Statistics for Log Daily Realized Commodity Volatility.

	Light Crude	Natural Gas	Heating Oil	Gold	Silver	Copper	Soy-beans	Corn	Wheat	Sugar	Coffee	Cotton	Live Cattle	Lean Hogs	Feeder Cattle	S&P 500 E-Mini
Mean	0.579	0.987	0.515	0.058	0.680	0.501	0.360	0.534	0.633	0.579	0.595	0.508	−0.168	0.270	−0.151	−0.154
Std. Dev.	0.440	0.368	0.431	0.405	0.400	0.444	0.364	0.358	0.345	0.402	0.293	0.406	0.325	0.319	0.340	0.548
Min	−1.051	−0.300	−1.048	−1.296	−0.782	−0.656	−0.551	−0.448	−0.643	−0.563	−0.273	−0.909	−1.466	−0.765	−1.455	−1.789
Max	3.172	2.932	2.515	1.870	2.973	2.486	1.815	2.161	3.055	2.319	1.821	2.010	1.257	1.914	1.707	2.576
Skewness	0.512	0.229	0.138	0.603	0.810	0.491	0.713	0.616	0.629	0.042	0.309	0.356	0.239	0.519	0.510	0.999
Kurtosis	4.581	3.054	3.235	3.847	4.658	3.630	3.464	3.665	4.822	2.765	3.413	3.099	3.787	4.072	3.933	4.749
$ACF(1)$	0.772*	0.694*	0.819*	0.726*	0.711*	0.825*	0.651*	0.630*	0.652*	0.719*	0.522*	0.667*	0.583*	0.574*	0.556*	0.764*
$Q(5)$	7746*	6486*	8891*	6164*	5605*	8704*	4937*	4155*	4847*	6084*	2957*	5213*	4074*	3581*	3462*	7319 *
$Q(21)$	27994*	21152*	33480*	20554*	16880*	30558*	15607*	11909*	14887*	20586*	7656*	18156*	13986*	11696*	11105*	23871*

Notes: The table shows sample statistics for daily realized volatility in levels and in logs for 15 commodity futures during the 2004-2014 sample period. All volatilities are for the most active futures contract on a given day. ACF(1) denotes the first-order autocorrelation. $Q(L)$ is the Ljung-Box test of zero autocorrelation in lags 1 through L. An asterisk indicates rejection at the 1% level.

Table 3: Seasonal Regression Dummies for Realized Variance.

	Light Crude	Natural Gas	Heating Oil	Gold	Silver	Copper	Soy-beans	Corn	Wheat	Sugar	Coffee	Cotton	Live Cattle	Lean Hogs	Feeder Cattle
C	1.202	2.645**	0.082	0.179	0.893**	0.587*	0.388	0.979*	1.576*	1.068*	0.564**	0.326	0.138**	0.407**	0.232**
AR(1)	0.049	0.177**	0.100**	0.296**	0.282	0.200**	0.237**	0.230**	0.280	0.363**	0.240**	0.170**	0.160**	0.158**	0.145**
AR(2)	0.020	0.124*	0.089**	0.051	0.044	0.134*	0.099**	0.052*	−0.025	0.039	0.174**	0.103**	0.152*	0.066**	0.091*
AR(3)	0.068	0.094*	0.075**	0.073*	0.039	0.096*	0.082*	0.048**	0.024	0.038	0.040	0.096**	0.026	0.075**	0.052*
AR(4)	0.044	0.051	0.092**	0.026	0.046	0.094*	0.044	0.062**	0.030*	0.069	0.024	0.091**	0.043	0.076**	0.076*
AR(5)	0.089	0.097	0.053*	0.049	0.061	0.066	0.070*	0.066**	0.013	0.078*	0.023	0.032	0.047	0.026	0.096*
AR(6)	0.015	−0.003	−0.002	0.017	−0.000	0.043	0.075*	0.037	0.030**	−0.007	0.053	0.105*	0.020	0.040*	0.044
AR(7)	0.048**	0.025	0.051*	0.030	0.029	0.038	0.067*	0.074**	0.006	0.047*	0.072**	0.020	0.021	0.037	0.032
AR(8)	0.016	0.014	0.042	0.063	0.024	0.024	0.044	0.024	0.048**	0.041	0.042	0.026	−0.002	0.030	−0.001
AR(9)	0.058**	−0.008	0.017	0.026	0.016	0.049	0.041	0.031*	−0.012	−0.034*	0.046	0.046	−0.005	0.035	0.014
AR(10)	0.042**	0.042	0.031	0.058	0.060**	0.070	0.041	0.006	0.064	0.066**	0.085**	0.022	0.052	0.045	0.021
AR(11)	0.050**	−0.001	0.023	−0.010	−0.019	0.011	−0.022	−0.008	0.103	−0.000	−0.015	0.045	0.029	0.008	0.046
AR(12)	0.060**	0.040**	0.045	0.037	0.035	0.030	−0.021	0.016	−0.035	0.023	0.040	−0.022	0.048	0.023	0.090
AR(13)	0.029	−0.004	0.027	0.046	0.004	−0.013	−0.001	−0.007	0.069	0.032	−0.019	0.060	0.029	0.000	0.008
AR(14)	0.014	0.059*	0.037*	0.018	−0.005	−0.018	0.072*	0.038*	−0.020	−0.026	−0.049	−0.024	0.027	0.024	0.023
AR(15)	0.042	0.084**	0.038*	0.055	0.114**	0.030	0.017	0.019	0.031**	0.089**	0.007	−0.012	0.048	0.037*	−0.003
AR(16)	0.014	−0.028	0.010	−0.019	−0.003	−0.009	−0.012	0.025	0.029*	0.003	0.001	−0.008	0.080**	0.023	−0.018
AR(17)	0.024	0.009	0.026	0.018	0.008	0.046	−0.018	0.002	0.001	−0.012	−0.020	0.072	0.019	0.052*	0.041
AR(18)	0.022	0.038	−0.007	−0.015	0.038**	0.007	0.014	0.019	0.019*	0.077	0.038	0.062	−0.012	0.009	0.020
AR(19)	0.120**	0.010	0.195*	0.024	−0.013	−0.021	0.054*	0.041*	0.012	0.015	0.019	−0.014	0.062	0.022	0.032
AR(20)	−0.007	0.015	−0.016	0.072	0.037	0.036	−0.004	0.026*	0.013	−0.040*	0.024	0.035	0.052	0.028	0.020
Feb	−0.399	−1.877**	0.066	−0.099	−0.124	−0.263	−0.035	−0.643	1.701	−0.459	0.316	0.237	−0.115*	−0.083	−0.104
Mar	−0.842	−2.104**	0.130	−0.080	0.052	−0.456	0.372	0.278	−0.313	−0.284	0.085	0.251	0.020	0.282	−0.037
Apr	−0.492	−1.735**	−0.163	0.030	1.199	0.010	−0.545*	−0.676	−0.618	−0.744	0.199	−0.217	−0.021	−0.178	−0.110
May	−0.610	−1.356*	0.268	−0.110	0.275	0.047	−0.006	−0.187	−0.111	−0.502	−0.037	−0.013	−0.092	−0.293*	−0.106
Jun	−0.381	−1.286*	0.170	−0.060	−0.248	−0.227	0.274	0.804	0.371	−0.423	0.240	0.412	0.115	0.381	0.051
Jul	−0.747	−0.936	0.102	−0.101	−0.169	−0.724**	−0.131	−0.778	−0.586	−0.726	−0.049	−0.219	−0.193**	−0.139	−0.110
Aug	0.703	0.992	0.660	0.035	1.148	−0.180	−0.156	−0.286	0.018	−0.362	0.135	0.040	−0.072	0.171	−0.163**
Sep	−0.602	−0.754	0.308	0.308	1.147	−0.102	−0.058	0.019	0.105	−0.123	0.298	0.087	−0.057	0.168	−0.074
Oct	−0.122	−1.768**	0.104	−0.085	0.595	0.613	0.126	0.094	0.306	−0.579	0.066	0.217	0.020	0.007	0.011
Nov	−0.198	−1.031	0.294	−0.152	−0.195	−0.472	−0.217	−0.553	−0.425	−0.407	0.183	0.077	−0.109	−0.257	−0.046
Dec	1.002	−1.067	0.698	−0.169	−0.106	−0.646	−0.266	−0.650	−0.731	−0.805	−0.072	−0.404	−0.077	−0.143	−0.091

Notes: The table shows parameter estimates for an AR(20) model for (1-minute sub-sampled) 5-minute realized variance for 15 commodities with monthly dummies during the 2004-2014 sample period. One asterisk indicates significance at the 95% level and two asterisks at the 99%.

Table 4: Unconditional Correlations for Daily Commodity Returns (upper diagonal) and Log Volatility (lower diagonal).

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*	
Light Crude		30.0	86.5	29.6	36.1	46.8	31.7	27.5	25.0	26.2	22.3	23.5	18.9	12.2	13.3	
Natural Gas	45.2		33.7	8.7	11.0	13.1	13.6	13.5	10.4	11.4	9.8	7.7	7.5	1.1	6.1	
Heating Oil	94.1	52.5		27.3	32.4	40.7	30.8	25.5	22.4	23.4	21.2	22.9	13.9	9.7	8.8	
Gold	55.3	32.5	49.1		79.8	38.6	21.1	21.7	18.4	14.7	16.9	16.1	5.4	4.2	−0.1	
Silver	58.1	29.7	50.8	86.9		46.8	28.6	27.4	23.3	20.0	21.8	21.1	12.2	7.5	5.9	
Copper	74.6	42.4	72.5	71.3	70.6		30.5	25.3	23.7	26.1	23.1	25.1	18.7	10.2	12.9	
Soybeans	61.3	23.6	61.5	38.3	42.4	50.3		63.1	49.5	25.6	21.7	31.9	12.3	7.8	−3.1	
Corn	51.3	22.7	44.4	43.8	44.7	57.0	68.6		65.1	26.9	21.5	29.1	15.0	7.5	−11.4	
Wheat	50.3	21.8	43.9	42.7	46.1	54.3	60.2	79.4		25.3	22.6	27.0	14.7	10.1	−4.4	
Sugar	43.4	27.3	40.1	38.7	42.0	46.8	36.5	52.9	64.3		25.7	22.9	12.8	5.0	6.4	
Coffee	3.4	2.9	2.4	−6.4	0.3	−12.4	16.8	0.4	12.5	−0.2		19.2	11.6	7.5	6.8	
Cotton	49.8	6.8	41.8	20.8	39.9	35.2	51.7	48.2	54.5	47.7	24.6		12.2	5.2	5.3	
Live Cattle	59.5	18.4	56.0	38.0	46.9	54.6	52.7	47.3	56.4	49.1	14.2	58.0		32.7	75.7	
Lean Hogs	49.6	37.0	51.2	28.4	29.3	46.8	57.1	46.7	55.0	41.6	16.3	36.5	53.6		26.3	
Feeder Cattle	56.3	11.4	48.1	40.0	43.0	47.0	52.5	51.2	57.2	44.5	5.7	46.1	80.8	44.3		
Average Correlations																*Average*
For Returns	35.3	18.5	33.3	26.8	31.6	32.1	31.0	30.5	28.9	24.8	23.5	24.6	24.2	16.5	16.6	26.5
For $E(\log RVol)$	56.8	31.6	53.9	45.3	48.7	54.1	51.6	50.6	53.2	45.0	12.0	44.1	52.4	46.2	48.5	46.3
Average Correlations																*Average*
With S&P 500 Returns	37.2	6.8	30.2	6.3	20.2	43.5	17.1	16.3	14.9	16.5	15.7	20.5	20.7	7.1	18.6	19.4
With S&P 500 $E(\log RVol)$	63.0	17.1	47.9	62.5	57.1	59.8	44.1	53.8	57.0	55.1	10.5	51.3	43.6	48.6	51.8	48.2

Notes: The table shows unconditional correlations for daily returns (upper diagonal) and log realized volatility (lower diagonal) for 15 commodity futures during the 2004-2014 sample period. All observations are for the most active futures contract on a given day. Average correlations with the S&P 500 E-Mini futures contract are shown in the lower panel for all commodities.

Table 5.a: Regression of Daily Expected Log Realized Volatility on Principal Components.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*	*S&P 500*
*PC*1	0.408	0.154	0.389	0.260	0.266	0.409	0.223	0.203	0.210	0.223	0.009	0.201	0.191	0.152	0.176	0.390
*PC*2	0.091	0.153	0.106	0.133	0.095	0.226	−0.155	−0.180	−0.240	−0.164	−0.109	−0.321	−0.176	−0.093	−0.166	−0.409
*PC*3	0.331	0.151	0.479	−0.468	−0.363	−0.200	0.111	−0.109	0.167	−0.129	0.072	0.134	0.024	0.103	−0.022	0.365
*PC*4	0.283	−0.250	0.349	0.334	0.238	0.006	0.071	−0.080	0.177	−0.215	0.034	0.139	0.094	−0.109	0.099	0.418
R^2	0.843	0.294	0.836	0.705	0.674	0.722	0.526	0.541	0.657	0.405	0.068	0.442	0.566	0.413	0.482	0.538
R^2_{pre}	0.401	0.217	0.472	0.772	0.715	0.421	0.571	0.454	0.541	0.334	0.356	0.447	0.431	0.260	0.311	0.362
R^2_{post}	0.723	0.096	0.745	0.686	0.758	0.677	0.332	0.540	0.781	0.687	0.098	0.658	0.671	0.450	0.537	0.532
R^2_{crisis}	0.888	0.450	0.874	0.777	0.699	0.736	0.710	0.675	0.479	0.165	0.311	0.452	0.676	0.453	0.648	0.721

Table 5.b: Regression of Daily Expected Log Realized Volatility on Principal Components.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*
Constant	0.630*	0.952*	0.496*	0.096*	0.683*	0.529*	0.344*	0.538*	0.645*	0.604*	0.609*	0.548*	−0.179*	0.268*	−0.153*
S&P 500	0.167*	−0.141*	−0.082*	0.138*	0.012	0.112*	−0.066	0.009	0.043	0.090	0.049	0.147*	−0.029	0.018	−0.006
*PC*1	0.341*	0.205*	0.422*	0.208*	0.261*	0.362*	0.249*	0.202*	0.196*	0.191*	−0.010	0.148*	0.200*	0.142*	0.179*
*PC*2	0.095*	0.150*	0.096*	0.148*	0.091	0.234*	−0.163*	−0.175*	−0.229*	−0.150*	−0.106*	−0.265*	−0.174*	−0.084*	−0.162*
*PC*3	0.390*	0.118*	0.468*	−0.441*	−0.363*	−0.170*	0.101*	−0.111*	0.162*	−0.106	0.086*	−0.217*	0.019	0.110*	−0.023
*PC*4	0.267*	−0.231*	0.341*	0.298*	0.237*	−0.008	0.083	−0.081	0.180*	−0.229*	0.025	0.113	0.101*	−0.106	0.101
R^2	0.860	0.309	0.838	0.718	0.676	0.726	0.532	0.541	0.658	0.411	0.076	0.462	0.558	0.399	0.480

Notes: The upper table shows parameter estimates of expected log realized volatility regressed on principal components of 15 commodity futures during the 2004-2014 sample period. The same regression for the S&P 500 E-Mini futures contract, used as stock market proxy, is shown in the rightmost column. For the lower panel, the S&P 500 contract is included as a regressor. All volatilities are for the most active contract on a given day (see Section 2.3).

Table 6: Contemporary Principal Component Regressions on Volatility Factors

Table 6.a: $PC_{1,t} = \alpha + \beta_1 PC_{1,t-1} + \beta_2 X_t + \epsilon_t$

	VIX	*S&P 500*	*Nikkei 225*	*MSCI-EAFE*	*MSCI-EM*	*2y-T-Note*	*10y-T-Note*
α	-1.410^{**}	0.125^{**}	-0.041^{**}	-0.003	-0.001	1.053^{**}	0.609^{**}
β_1	0.707^{**}	0.695^{**}	0.747^{**}	0.616^{**}	0.544^{**}	0.720^{**}	0.726^{**}
β_2	0.488^{**}	0.466^{**}	0.308^{**}	0.591^{**}	0.645^{**}	0.416^{**}	0.542^{**}
R^2	0.711	0.753	0.689	0.672	0.554	0.727	0.730

Table 6.b: $PC_{2,t} = \alpha + \beta_1 PC_{2,t-1} + \beta_2 X_t + \epsilon_t$

	VIX	*S&P 500*	*Nikkei 225*	*MSCI-EAFE*	*MSCI-EM*	*2y-T-Note*	*10y-T-Note*
α	-0.012	0.012	-0.009	-0.001	0.001	0.059	0.027
β_1	0.677^{**}	0.677^{**}	0.676^{**}	0.514^{**}	0.565^{**}	0.675^{**}	0.676^{**}
β_2	0.004	0.043^{**}	0.069^{**}	0.053^{**}	-0.213^{**}	0.023	0.024
R^2	0.458	0.461	0.476	0.274	0.388	0.455	0.456

Table 6.c: $PC_{3,t} = \alpha + \beta_1 PC_{3,t-1} + \beta_2 X_t + \epsilon_t$

	VIX	*S&P 500*	*Nikkei 225*	*MSCI-EAFE*	*MSCI-EM*	*2y-T-Note*	*10y-T-Note*
α	0.088	-0.011	0.008	0.000	0.001	-0.008	-0.084^{**}
β_1	0.733^{**}	0.727^{**}	0.729^{**}	0.564^{**}	0.458^{**}	0.735^{**}	0.732^{**}
β_2	-0.030	-0.042^{**}	-0.057^{**}	-0.030	-0.020	-0.003	-0.075^{**}
R^2	0.541	0.542	0.556	0.318	0.212	0.539	0.545

Table 6.d: $PC_{4,t} = \alpha + \beta_1 PC_{4,t-1} + \beta_2 X_t + \epsilon_t$

	VIX	*S&P 500*	*Nikkei 225*	*MSCI-EAFE*	*MSCI-EM*	*2y-T-Note*	*10y-T-Note*
α	-0.027	0.004	-0.006	-0.000	0.000	0.012	0.061^{**}
β_1	0.597^{**}	0.543^{**}	0.603^{**}	0.539^{**}	0.415^{**}	0.574^{**}	0.571^{**}
β_2	0.009	0.014	0.046^{**}	-0.008	0.023	0.005	0.055^{**}
R^2	0.357	0.297	0.377	0.291	0.173	0.330	0.334

Notes: The table shows output from regression of the first four principal components of commodity log volatility on its lag and different volatility factors. "VIX" is based on the log of the daily CBOE SPX Volatility Index and the other six data series are constructed as the log of realized volatilities, $RVol_t$, described in Section 2.4 for the S&P 500 E-Mini Futures, the Nikkei 225 Futures CME, MSCI EAFE Mini Futures, MSCI Emerging Markets Mini Futures, US 2-Year T-Note Futures, and the US 10-Year T-Note Futures, respectively. The principal components are constructed as the matrix of the (demeaned) log volatility for all 15 commodities multiplied by the eigenvectors of the covariance matrix. The sample period covers 2004-2014 except for MSCI-EM, which was not available before June 2010. Two asterisks indicates rejection of the null of zero coefficients at the 1% level and one asterisk at the 5% level.

Table 7: Contemporary Principal Component Regressions on Macro Factors

Table 7.a: $PC_{1,t} = \alpha + \beta_1 PC_{1,t-1} + \beta_2 X_t + \epsilon_t$

	ADS	CDX	$BE-Infl$	$OilPrice$	$USGG3M$	$USGG10YR$	$Slope$	TED
α	-0.050^{**}	-0.758^{**}	-0.431^{**}	0.749^{**}	-0.008	-0.126^{**}	-0.028^{*}	-0.118^{**}
β_1	0.752^{**}	0.795^{**}	0.818^{**}	0.813^{**}	0.829^{**}	0.820^{**}	0.828^{**}	0.764^{**}
β_2	-0.158^{**}	0.175^{**}	0.160^{**}	-0.173^{**}	0.006	0.037^{**}	0.014	0.003^{**}
R^2	0.702	0.695	0.690	0.691	0.689	0.690	0.689	0.701

Table 7.b: $PC_{2,t} = \alpha + \beta_1 PC_{2,t-1} + \beta_2 X_t + \epsilon_t$

	ADS	CDX	$BE-Infl$	$OilPrice$	$USGG3M$	$USGG10YR$	$Slope$	TED
α	-0.002	0.209^{*}	0.223^{*}	0.330^{**}	-0.031^{*}	-0.078^{*}	0.072^{**}	-0.014
β_1	0.677^{**}	0.670^{**}	0.671^{**}	0.670^{**}	0.657^{**}	0.670^{**}	0.655^{**}	0.674^{**}
β_2	-0.008	-0.048^{*}	-0.083^{*}	-0.076^{**}	0.022^{**}	0.023^{*}	-0.036^{**}	0.000
R^2	0.459	0.461	0.460	0.461	0.465	0.461	0.466	0.459

Table 7.c: $PC_{3,t} = \alpha + \beta_1 PC_{3,t-1} + \beta_2 X_t + \epsilon_t$

	ADS	CDX	$BE-Infl$	$OilPrice$	$USGG3M$	$USGG10YR$	$Slope$	TED
α	-0.001	0.164^{*}	0.079	1.255^{**}	-0.019^{*}	-0.101^{**}	0.020	0.006
β_1	0.735^{**}	0.728^{**}	0.735^{**}	0.613^{**}	0.722^{**}	0.715^{**}	0.732^{**}	0.735^{**}
β_2	-0.003	-0.038^{*}	-0.029	-0.290^{**}	0.013^{**}	0.030^{**}	-0.010^{*}	-0.000
R^2	0.541	0.543	0.541	0.573	0.544	0.546	0.542	0.541

Table 7.d: $PC_{4,t} = \alpha + \beta_1 PC_{4,t-1} + \beta_2 X_t + \epsilon_t$

	ADS	CDX	$BE-Infl$	$OilPrice$	$USGG3M$	$USGG10YR$	$Slope$	TED
α	-0.005	-0.093	0.136	0.219^{*}	0.021^{*}	0.086^{**}	-0.035^{*}	-0.007
β_1	0.594^{**}	0.595^{**}	0.594^{**}	0.593^{**}	0.582^{**}	0.584^{**}	0.589^{**}	0.596^{**}
β_2	-0.016^{*}	0.021	-0.051	-0.051^{*}	-0.015^{**}	-0.025^{**}	0.018^{*}	0.000
R^2	0.358	0.357	0.358	0.358	0.362	0.362	0.360	0.357

Notes: The table shows output from regression of the first four principal components of commodity log volatility on its lag and different macro factors. "ADS" is the business conditions index of Philadelphia Fed, "CDX" is the index of credit spreads on the North American investment grade index (in logs), "BE-Infl" is the Fed five-year break-even inflation rate, "Oil Price" the light crude oil price, "USGG3M" and "USGG10YR" are the 3-month and 10-year constant maturity US Treasury rates, "Slope" is the (10-year less 3-month) term slope, and "TED" is the TED spread. The principal components are constructed as the matrix of (demeaned) log volatility for all 15 commodities multiplied by the eigenvectors of the covariance matrix. The sample period covers 2004-2014. Two asterisks indicates rejection of the null of zero coefficients at the 1% level and one asterisk at the 5% level.

Table 8: Contemporary Principal Component Regressions on Equity Factors

Table 8.a: $PC_{1,t} = \alpha + \beta_1 PC_{1,t-1} + \beta_2 X_t + \epsilon_t$

	$SPXT$	$BAB-RoW$	$BAB-US$	$QMJ-RoW$	$QMJ-US$	$HML-RoW$	$HML-US$
α	0.001	-0.002	0.000	-0.006	-0.003	-0.001	-0.000
β_1	0.828**	0.836**	0.834**	0.832**	0.833**	0.834**	0.835**
β_2	-5.167**	3.182	-1.970	20.909**	13.623**	2.389	-2.320
R^2	0.693	0.697	0.697	0.703	0.704	0.697	0.697

Table 8.b: $PC_{2,t} = \alpha + \beta_1 PC_{2,t-1} + \beta_2 X_t + \epsilon_t$

	$SPXT$	$BAB-RoW$	$BAB-US$	$QMJ-RoW$	$QMJ-US$	$HML-RoW$	$HML-US$
α	-0.000	0.001	0.000	-0.000	-0.000	-0.000	-0.000
β_1	0.677**	0.675**	0.675**	0.675**	0.675**	0.675**	0.675**
β_2	0.048	-2.295*	-0.848	0.157	1.009	2.773	0.976
R^2	0.456	0.456	0.456	0.458	0.456	0.456	0.456

Table 8.c: $PC_{3,t} = \alpha + \beta_1 PC_{3,t-1} + \beta_2 X_t + \epsilon_t$

	$SPXT$	$BAB-RoW$	$BAB-US$	$QMJ-RoW$	$QMJ-US$	$HML-RoW$	$HML-US$
α	-0.000	-0.000	-0.000	0.001	0.000	0.000	0.000
β_1	0.735**	0.735**	0.735**	0.732**	0.734**	0.735**	0.736**
β_2	0.599	0.193	0.572	-3.791**	-1.633	-0.965	-1.445
R^2	0.541	0.540	0.540	0.541	0.541	0.540	0.541

Table 8.d: $PC_{4,t} = \alpha + \beta_1 PC_{4,t-1} + \beta_2 X_t + \epsilon_t$

	$SPXT$	$BAB-RoW$	$BAB-US$	$QMJ-RoW$	$QMJ-US$	$HML-RoW$	$HML-US$
α	0.000	-0.001	-0.000	-0.002	-0.001	0.000	0.000
β_1	0.596**	0.575**	0.575**	0.573**	0.574**	0.574**	0.575**
β_2	-0.843*	1.802*	-0.006	5.367**	3.399**	-4.251*	-1.090
R^2	0.357	0.331	0.331	0.333	0.334	0.332	0.331

Notes: The table shows output from regression of the first four principal components of commodity log volatility on its lag and different equity factors. "SPXT" is the total return on S&P 500, "BAB" the betting-against-beta factor of Frazzini & Pedersen (2014) for the US (BAB-US) and the rest of the world (BAB_RoW), "QMJ" the quality-minus-junk QMJ factor of Asness, Frazzini & Pedersen (2013) for the US (QMJ-US) and the rest of the world (QMJ-RoW), and "HML" is the high-minus low book-to-market factor of Asness, Moskowitz & Pedersen (2013) for the US (HML-US) and the rest of the world (HML-RoW). The principal components are constructed as the matrix of (demeaned) log volatility for all 15 commodities multiplied by the eigenvectors of the covariance matrix. The sample period covers 2004-2014. Two asterisks indicates rejection of the null of zero coefficients at the 1% level and one asterisk at the 5% level.

Table 9: Contemporary Principal Component Regressions on Commodity Carry

Table 9.a: $PC_{1,t} = \alpha + \beta_1 PC_{1,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	-0.027^{*}	-0.013	-0.000	-0.018	-0.013
β_1	0.819^{**}	0.830^{**}	0.835^{**}	0.829^{**}	0.829^{**}
β_2	-2.844^{**}	-2.115^{**}	-0.075	-3.303^{**}	-2.411^{**}
R^2	0.700	0.698	0.697	0.698	0.698

Table 9.b: $PC_{2,t} = \alpha + \beta_1 PC_{2,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	-0.010	-0.005	-0.001	-0.018	-0.008
β_1	0.671^{**}	0.673^{**}	0.675^{**}	0.660^{**}	0.669^{**}
β_2	-1.012^{*}	-0.891	-0.487	-3.463^{**}	-1.596^{*}
R^2	0.458	0.456	0.456	0.461	0.458

Table 9.c: $PC_{3,t} = \alpha + \beta_1 PC_{3,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	-0.010	0.008	-0.001	-0.014^{*}	-0.007
β_1	0.727^{**}	0.727^{**}	0.734^{**}	0.722^{**}	0.727^{**}
β_2	-1.067^{**}	1.404^{**}	-0.810^{*}	-2.580^{**}	-1.459^{**}
R^2	0.542	0.542	0.540	0.544	0.542

Table 9.d: $PC_{4,t} = \alpha + \beta_1 PC_{4,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	0.025^{**}	0.002	-0.001	0.000	0.014
β_1	0.534^{**}	0.575^{**}	0.575^{**}	0.575^{**}	0.552^{**}
β_2	2.620^{**}	0.383	-0.625	0.034	2.695^{**}
R^2	0.348	0.331	0.331	0.331	0.341

Notes: The table shows output from regression of the first four principal components of commodity log volatility on its lag and commodity carry defined in equation 5. The commodity category carry for day t is the simple arithmetic average of the day t carry for the individual commodities in the respective categories following Table 1. The principal components are constructed as the matrix of (demeaned) log volatility for all 15 commodities multiplied by the eigenvectors of the covariance matrix. The sample period covers 2004-2014. Two asterisks indicates rejection of the null of zero coefficients at the 1% level and one asterisk at the 5% level.

Table 10: Contemporary Principal Component Regressions on Commodity Liquidity

Table 10.a: $PC_{1,t} = \alpha + \beta_1 PC_{1,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	0.002	-0.002	-0.005	-0.003	-0.005
β_1	0.835^{**}	0.834^{**}	0.835^{**}	0.835^{**}	0.835^{**}
β_2	-0.001	-0.021	1.751^{**}	-0.013	2.782
R^2	0.697	0.697	0.697	0.697	0.697

Table 10.b: $PC_{2,t} = \alpha + \beta_1 PC_{2,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	-0.000	0.000	-0.004	-0.009	-0.002
β_1	0.675^{**}	0.675^{**}	0.676^{**}	0.670^{**}	0.675^{**}
β_2	0.000	0.007	1.465^{**}	-0.036^{*}	0.999
R^2	0.456	0.456	0.457	0.458	0.456

Table 10.c: $PC_{3,t} = \alpha + \beta_1 PC_{3,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	-0.001	-0.001	-0.004	-0.016	-0.010
β_1	0.735^{**}	0.733^{**}	0.730^{**}	0.710^{**}	0.713^{**}
β_2	0.001	-0.015	1.531^{*}	-0.065^{**}	6.322^{**}
R^2	0.541	0.540	0.542	0.549	0.544

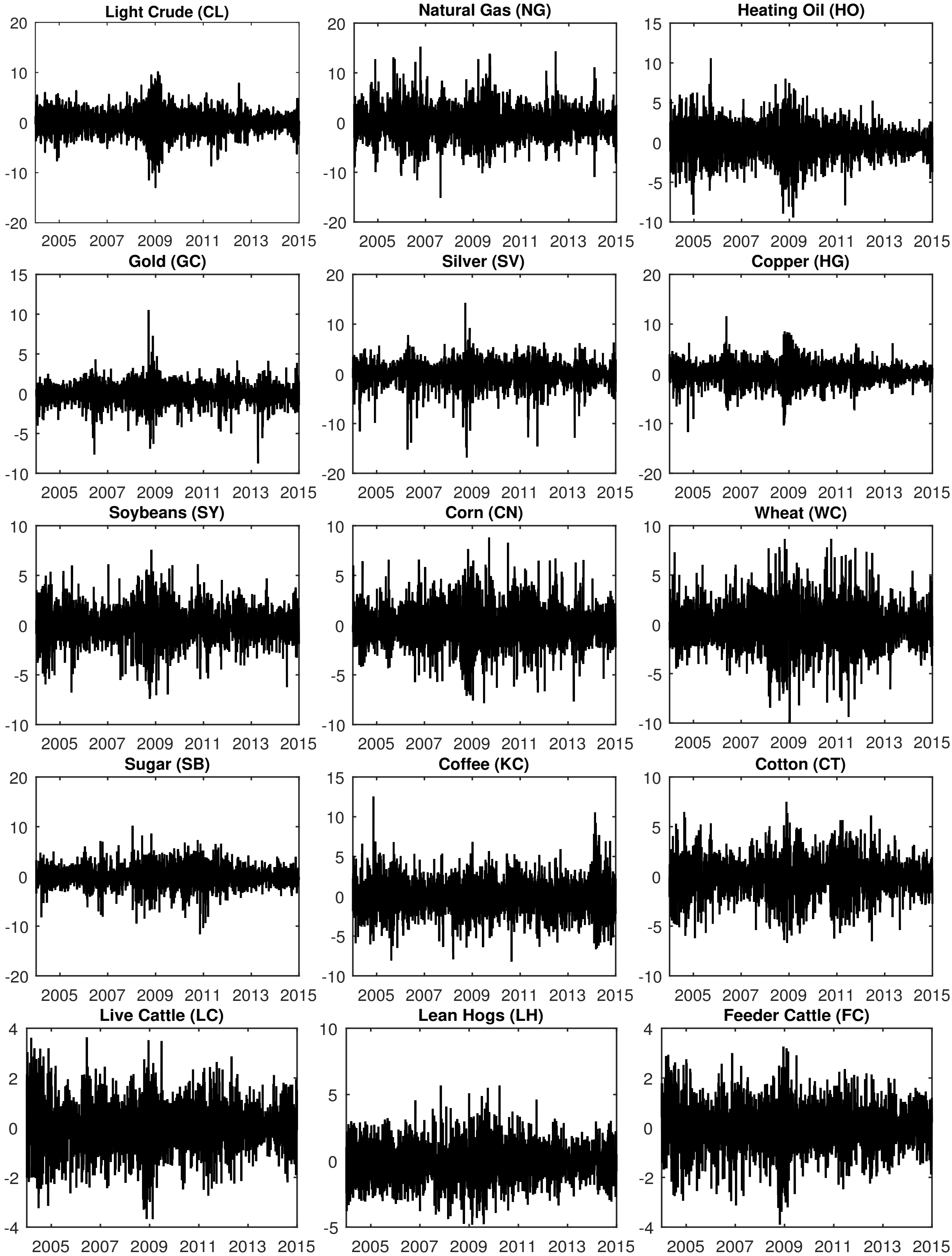
Table 10.d: $PC_{4,t} = \alpha + \beta_1 PC_{4,t-1} + \beta_2 X_t + \epsilon_t$

	Energy	*Meats*	*Metals*	*Softs*	*Grains*
α	0.000	-0.003	-0.002	-0.001	-0.009
β_1	0.575^{**}	0.565^{**}	0.573^{**}	0.575^{**}	0.562^{**}
β_2	-0.000	-0.045^{*}	0.674	-0.004	5.650^{**}
R^2	0.331	0.333	0.331	0.331	0.335

Notes: The table shows output from regression of the first four principal components of commodity log volatility on its lag and commodity liquidity. Commodity liquidity is calculated by the Amihud liquidity measure. The principal components are constructed as the matrix of (demeaned) log volatility for all 15 commodities multiplied by the eigenvectors of the covariance matrix. The sample period covers 2004-2014. Two asterisks indicates rejection of the null of zero coefficients at the 1% level and one asterisk at the 5% level.

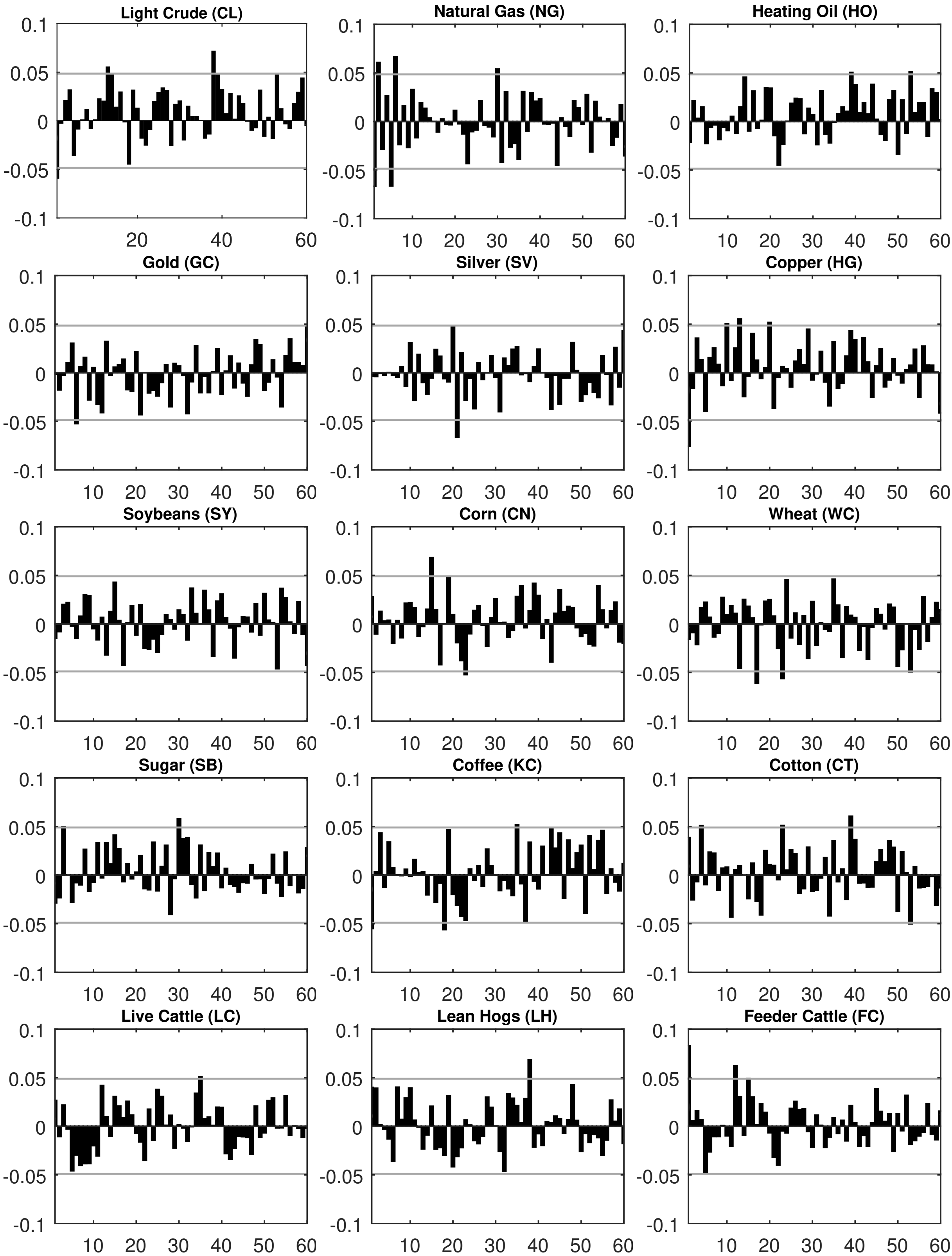
7 Appendix

Figure A.1: Daily Log Returns of Commodity Futures.



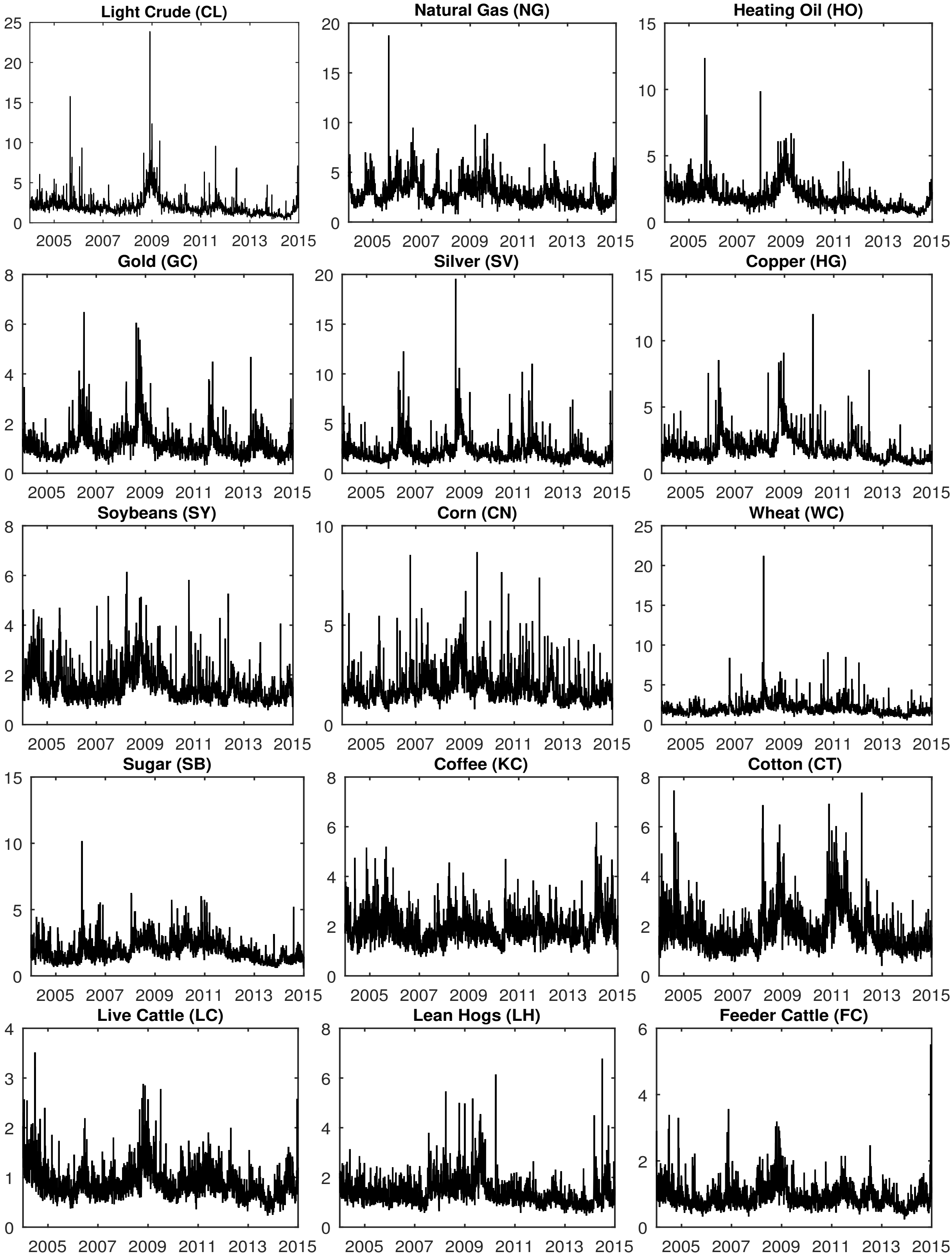
Notes: The figure shows the daily log returns of closing prices for 15 commodity futures during the 2004-2014 sample period. All returns are for the most active futures contract on a given day.

Figure A.2: Empirical Autocorrelation of Daily Commodity Futures Returns.



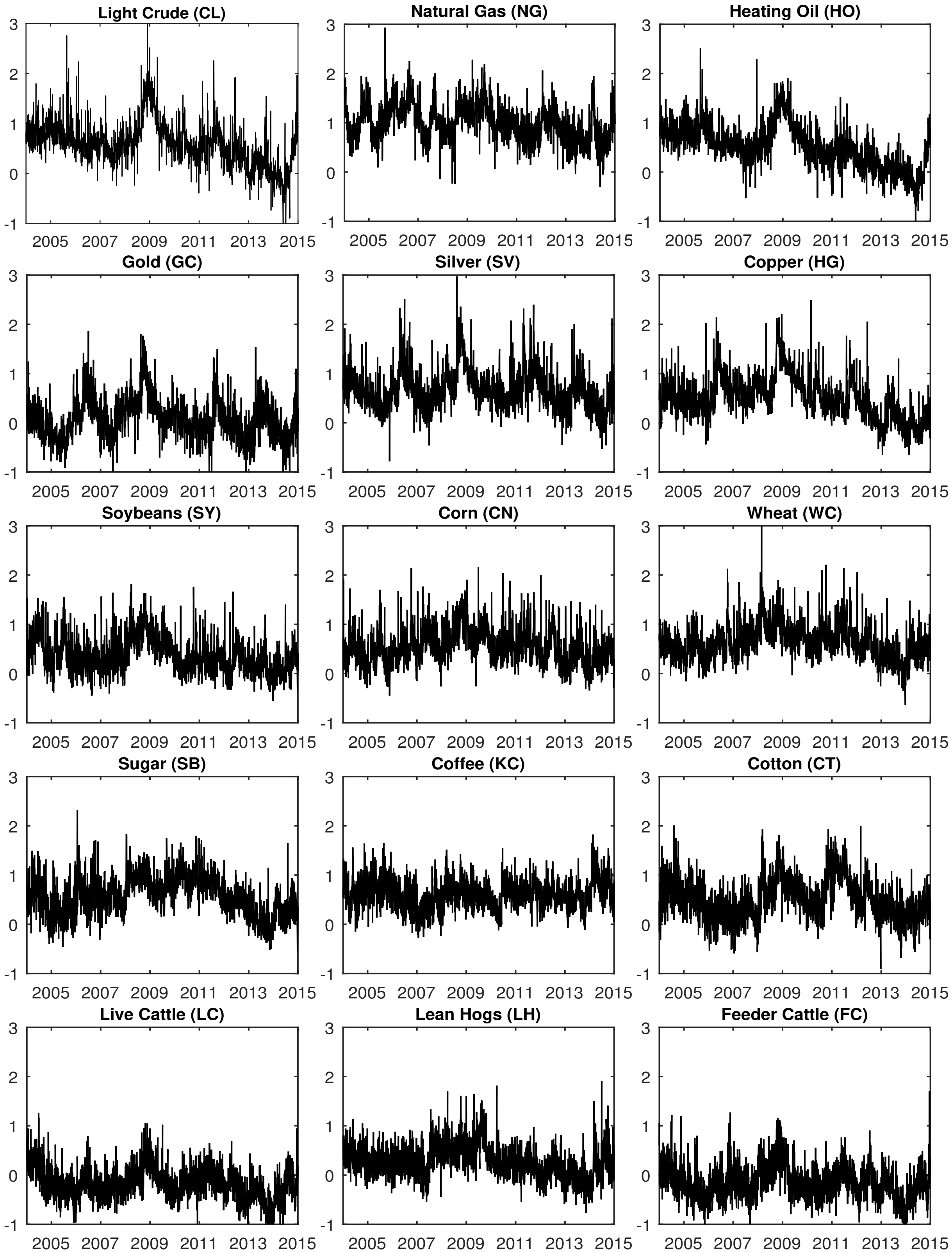
Notes: The figure shows the empirical autocorrelation of log returns for 15 commodity futures during the 2004-2014 sample period. All returns are for the most active futures contract on a given day. Grey lines indicate 99% confidence bounds assuming that the series are Gaussian white noise. The horizontal axis indicates the lag order in days.

Figure A.3: Daily Realized Commodity Volatility.



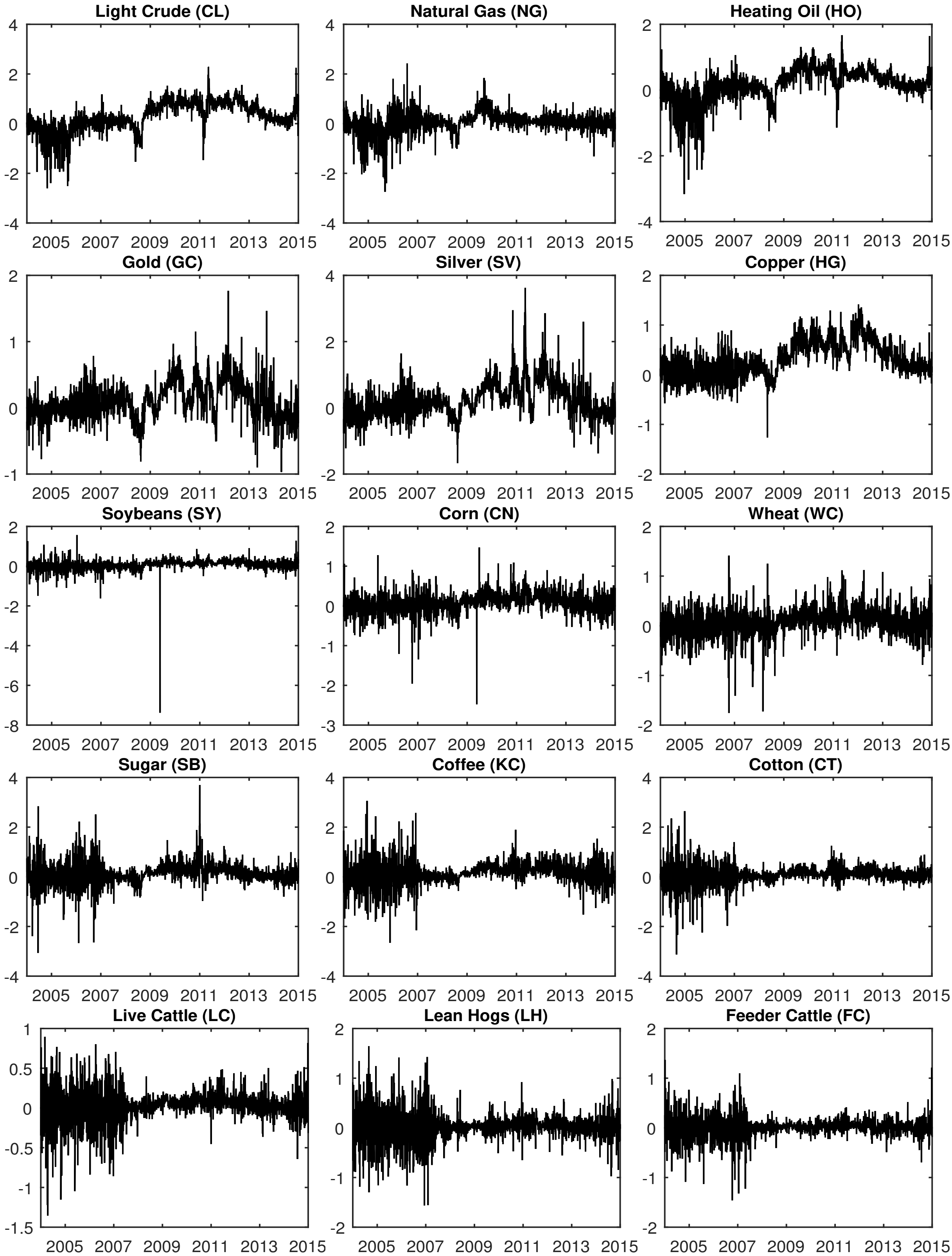
Notes: The figure shows the daily realized volatility for 15 commodity futures during the 2004-2014 sample period. All volatilities are for the most active futures contract on a given day.

Figure A.4: Daily Log Realized Commodity Volatility.



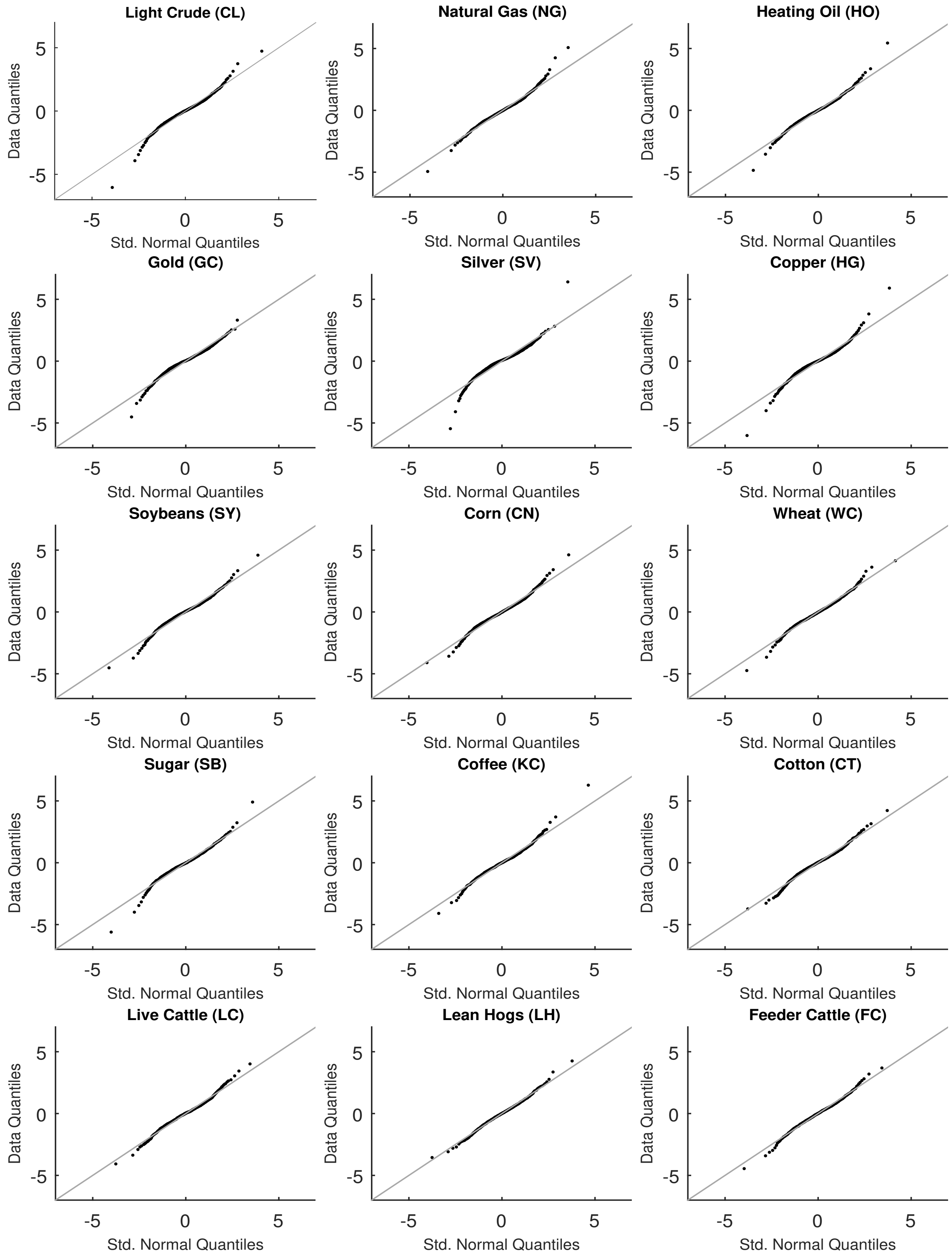
Notes: The figure shows the daily log realized volatility for 15 commodity futures during the 2004-2014 sample period. All volatilities are for the most active futures contract on a given day.

Figure A.5: Realized Stock Market Beta for 15 Commodities.



Notes: The figure shows the daily realized stock market beta for 15 commodity futures during the 2004-2014 sample period. The calculation follows equation 7 with all co-volatilities used are for the most active futures contract on a given day.

Figure A.6: Quantile-Quantile Plots of Daily Commodity Futures Returns.



Notes: The figure shows the empirical quantile-quantile plots of daily log return for 15 commodity futures during the 2004-2014 sample period. All prices are for the most active futures contract on a given day.

Table A.1: Optimal Weights on Open-to-Close Realized Volatility and Overnight Returns.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*S&P 500 E-Mini*
$\hat{E}\left[\left(r_{i,t}^{co}\right)^2 + RV_{i,t}\right]$	4.340	8.958	3.779	1.472	5.079	3.819	2.601	3.631	4.249	4.097	3.764	3.637	0.841	2.004	0.882
$\hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]$	0.024	0.264	0.036	0.009	0.026	0.031	0.100	0.152	0.116	0.259	0.202	0.228	0.052	0.129	0.062
$\hat{E}\left[RV_{i,t}\right]$	4.316	8.694	3.744	1.463	5.053	3.787	2.501	3.480	4.133	3.838	3.562	3.409	0.790	1.874	0.820
$\frac{\hat{E}\left[RV_{i,t}\right]}{\hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]}$	179.302	32.923	105.022	168.295	196.034	120.503	25.009	22.929	35.690	14.832	17.630	14.953	15.331	14.517	13.153
$\hat{E}\left[\left(\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right)^2\right]$	0.005	0.738	0.008	0.001	0.004	0.006	0.081	0.191	0.086	0.261	0.185	0.293	0.018	0.076	0.019
$\hat{E}\left[\left(RV_{i,t} - \hat{E}\left[RV_{i,t}\right]\right)^2\right]$	23.313	44.820	12.139	2.091	28.068	18.293	5.105	8.944	9.729	9.896	4.966	9.725	0.296	1.793	0.383
$\frac{\hat{E}\left[\left(RV_{i,t} - \hat{E}\left[RV_{i,t}\right]\right)^2\right]}{\hat{E}\left[\left(\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right)^2\right]}$	4813.945	60.717	1542.648	3357.871	6468.419	3090.076	62.908	46.894	113.169	37.973	26.775	33.240	16.560	23.677	19.874
$\frac{\hat{E}\left[RV_{i,t}\left(\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right)\right]}{\hat{E}\left[\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right] \cdot \hat{E}\left[RV_{i,t} - \hat{E}\left[RV_{i,t}\right]\right]}$	0.095	0.057	0.198	0.120	0.151	0.279	0.187	0.208	0.172	0.083	0.124	0.185	0.094	0.014	0.091
$\hat{\varphi}$	0.895	0.959	0.934	0.925	0.898	0.912	0.958	0.972	0.962	0.875	0.951	0.923	0.955	0.902	0.920
$\hat{\omega}_1^\star$	18.917	1.404	7.020	12.620	20.063	10.683	1.097	0.672	1.399	1.981	0.913	1.227	0.728	1.513	1.128
$\hat{\omega}_2^\star$	0.900	0.988	0.943	0.931	0.903	0.920	0.996	1.014	0.989	0.934	1.005	0.985	1.018	0.965	0.990

Notes: Table A.1 is similar to Table 2 in Hansen & Lunde (2005) and contains weighting parameters as per Hansen & Lunde (2005) that are used to compute the optimal measure of daily volatility for 15 commodities and the S&P E-Mini futures contract during the 2004-2014 sample period. The 1% largest squared overnight returns and the 0.5% largest realized covariances were omitted from the estimation. The estimated weights in equation 1 are given by

$$\hat{\varphi} \equiv \frac{\hat{E}\left[RV_{i,t}\right]^2 \hat{E}\left[\left(\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right)^2\right] - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\hat{E}\left[RV_{i,t}\right]\hat{E}\left[RV_{i,t}\left(\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right)\right]}{\hat{E}\left[RV_{i,t}\right]^2 \hat{E}\left[\left(\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right)^2\right] + \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]^2 \hat{E}\left[\left(RV_{i,t} - \hat{E}\left[RV_{i,t}\right]\right)^2\right] - 2\hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\hat{E}\left[RV_{i,t}\right]\hat{E}\left[RV_{i,t}\left(\left(r_{i,t}^{co}\right)^2 - \hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]\right)\right]}$$

$$\hat{\omega}_1^\star \equiv (1-\hat{\varphi})\frac{\hat{E}\left[\left(r_{i,t}^{co}\right)^2 + RV_{i,t}\right]}{\hat{E}\left[\left(r_{i,t}^{co}\right)^2\right]}, \qquad \hat{\omega}_2^\star \equiv \hat{\varphi}\frac{\hat{E}\left[\left(r_{i,t}^{co}\right)^2 + RV_{i,t}\right]}{\hat{E}\left[RV_{i,t}\right]}.$$

Table A.2.a: ARMA(1,1) on Log Realized Volatility.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*
ϕ_0	0.007	0.017	0.005	0.001	0.026	0.008	0.008	0.020	0.018	0.012	0.025	0.008	−0.003	0.005	−0.003
ϕ_1	0.988	0.983	0.991	0.975	0.961	0.984	0.977	0.963	0.971	0.979	0.959	0.985	0.986	0.980	0.979
θ_1	−0.752	−0.753	−0.753	−0.695	−0.641	−0.675	−0.748	−0.704	−0.722	−0.726	−0.734	−0.790	−0.837	−0.804	−0.802
R^2	0.699	0.619	0.760	0.608	0.574	0.750	0.533	0.478	0.526	0.608	0.384	0.560	0.483	0.442	0.436
σ_e	0.242	0.227	0.211	0.253	0.261	0.222	0.249	0.258	0.237	0.252	0.230	0.270	0.234	0.238	0.255
$ACF_e(1)$	0.046	−0.008	0.050*	0.087*	0.081*	0.060*	0.066*	0.090*	0.065*	0.083*	0.033	0.086*	0.070*	0.095*	0.067*
$Q_e(5)$	23.576*	63.908*	19.957*	44.738*	55.528*	39.032*	26.410*	46.752*	19.911*	28.903*	7.510	31.974*	21.025*	36.415*	21.889*
$Q_e(21)$	60.936*	306.840*	70.399*	77.970*	75.821*	66.974*	48.710*	67.759*	44.328*	84.175*	39.614*	52.883*	68.405*	63.456*	36.936*

Table A.2.b: ARMA(1,1) on Realized Beta.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*
ϕ_0	0.002	0.000	0.001	0.002	0.004	0.001	0.001	0.001	0.000	0.001	0.000	0.000	0.001	0.030	0.012
ϕ_1	0.993	0.991	0.994	0.984	0.984	0.996	0.991	0.993	0.994	0.989	0.998	0.997	0.963	−0.312	0.165
θ_1	−0.783	−0.891	−0.844	−0.759	−0.739	−0.845	−0.940	−0.940	−0.953	−0.927	−0.975	−0.979	−0.905	0.341	−0.073
R^2	0.773	0.366	0.667	0.624	0.664	0.726	0.120	0.179	0.137	0.148	0.122	0.050	0.027	0.006	0.009
σ_e	0.273	0.321	0.268	0.163	0.292	0.180	0.241	0.214	0.229	0.375	0.408	0.340	0.176	0.263	0.184
$ACF_e(1)$	0.029	0.013	−0.001	0.014	0.021	0.043	0.014	0.014	0.002	0.011	0.026	0.019	0.006	0.006	−0.000
$Q_e(5)$	18.720*	6.084	6.731	1.264	2.329	9.251	0.890	5.293	10.907	12.209	8.000	10.887	5.728	10.241	4.842
$Q_e(21)$	109.795*	41.201*	59.946*	42.179*	40.464*	43.229*	8.384	16.096	35.237	29.491	36.771	78.505*	37.451	38.391	31.147

Table A.2.c: ARMA(1,1) on Realized Systematic Risk Ratio.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*
ϕ_0	0.001	0.000	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.000	0.000
ϕ_1	0.991	0.985	0.987	0.975	0.982	0.993	0.974	0.982	0.981	0.979	0.977	0.993	0.959	0.994	0.991
θ_1	−0.704	−0.861	−0.739	−0.693	−0.703	−0.760	−0.843	−0.883	−0.880	−0.861	−0.856	−0.959	−0.816	−0.965	−0.960
R^2	0.817	0.332	0.713	0.617	0.681	0.789	0.253	0.214	0.221	0.245	0.242	0.071	0.202	0.070	0.047
σ_e	0.057	0.015	0.047	0.047	0.044	0.046	0.021	0.019	0.013	0.022	0.029	0.016	0.019	0.014	0.016
$ACF_e(1)$	0.042	0.009	0.024	0.076*	0.090*	0.110*	0.027	0.043	−0.004	0.065*	0.053*	0.018	0.025	−0.021	0.027
$Q_e(5)$	13.110	20.348*	22.631*	38.648*	49.604*	78.039*	5.198	9.402	3.096	18.695*	8.542	3.508	9.728	1.958	4.541
$Q_e(21)$	95.991*	69.401*	136.054*	85.403*	175.769*	221.140*	35.648	22.981	20.712	74.763*	35.961	17.709	30.951	21.781	33.654

Notes: The sample period covers 5 January 2004 to 31 December 2014.

Table A.3: Unconditional Correlations for Daily Returns (upper diagonal) and Log Volatility (lower). "Pre-crisis" sample.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*
Light Crude		42.7	88.7	33.5	29.5	24.4	23.3	19.9	14.7	18.3	14.2	17.0	4.1	7.9	−3.6
Natural Gas	0.4		45.0	14.1	11.5	9.4	12.8	8.1	1.8	8.0	5.6	5.7	1.9	0.3	2.5
Heating Oil	82.6	11.7		28.8	25.0	20.3	21.2	18.6	13.3	16.2	14.2	15.9	0.5	5.6	−6.0
Gold	−9.0	25.3	−13.7		80.3	50.3	22.0	23.5	18.3	18.7	18.5	20.6	4.6	2.5	−1.9
Silver	5.4	19.8	−0.3	83.0		49.2	24.3	23.3	17.9	18.9	18.4	20.2	6.7	2.6	0.1
Copper	−15.9	5.2	−26.4	63.1	61.5		16.3	13.3	13.2	19.4	14.1	15.4	6.7	5.8	0.5
Soybeans	28.4	−35.6	21.4	0.0	13.0	−5.6		60.0	41.7	19.4	16.3	32.3	1.2	4.3	−14.3
Corn	−20.1	−19.4	−35.8	16.2	7.7	23.7	45.4		55.6	19.3	15.3	28.7	1.0	−0.6	−25.7
Wheat	−4.1	−18.0	−25.2	39.9	27.7	27.2	43.0	68.5		18.7	15.6	20.2	3.1	4.0	−13.6
Sugar	−11.9	−7.5	−20.1	46.8	31.8	15.0	25.2	42.1	52.3		18.2	19.7	1.8	−1.5	−5.8
Coffee	41.0	6.1	48.1	−11.3	1.6	−35.2	28.1	−25.3	−1.6	−10.7		17.2	5.9	4.5	1.2
Cotton	36.3	−32.8	28.7	−17.6	4.2	−9.6	62.2	13.8	27.0	9.7	41.4		3.8	−0.2	−5.1
Live Cattle	21.3	−16.8	20.9	26.9	44.4	16.5	44.5	7.1	19.3	23.4	9.2	38.3		31.3	74.0
Lean Hogs	17.9	1.4	2.6	28.1	29.8	7.0	35.2	6.5	37.1	14.9	19.1	29.4	49.3		25.8
Feeder Cattle	27.2	−23.0	11.1	27.5	29.1	16.5	38.3	25.9	36.3	36.4	−3.1	15.1	67.4	34.1	
Average Correlation															
For Returns	29.0	18.0	27.1	28.9	28.5	23.9	25.4	24.0	21.6	19.3	18.6	20.8	16.4	12.8	8.5
For $E(\log RVol)$	20.0	1.1	13.7	27.0	30.6	16.2	29.6	17.1	28.6	23.2	13.8	23.1	31.4	27.5	29.3
Average Correlation															
With SP 500 Returns	0.1	−0.1	−4.4	8.6	12.5	20.0	3.6	6.9	3.5	−0.3	8.7	4.5	1.4	2.2	−2.9
With SP 500 $E(\log RVol)$	5.6	−24.3	−15.2	43.7	31.3	33.6	25.8	23.9	49.4	48.6	−1.9	19.5	21.8	62.4	31.1

Notes: The table shows unconditional correlations for daily returns (upper diagonal) and log realized volatility (lower diagonal) for 15 commodity futures during the 2004-2008 ("pre-ciris") sample period. All observations are are for the most active futures contract on a given day. Average correlations with the S&P 500 E-Mini futures contract are shown in the lower panel for all commodities.

Table A.4: Unconditional Correlations for Daily Returns (upper diagonal) and Log Volatility (lower). "During-crisis" sample.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*
Light Crude		28.1	88.5	31.2	42.8	59.7	43.3	38.3	34.2	32.6	34.0	29.0	32.3	16.4	24.4
Natural Gas	39.1		29.6	9.5	14.8	18.6	19.3	17.7	15.0	18.9	18.6	13.5	13.3	0.1	10.2
Heating Oil	95.7	49.5		30.8	41.1	56.1	44.9	36.9	31.1	30.8	32.7	30.1	28.5	14.4	21.3
Gold	74.1	21.6	68.4		78.0	32.7	27.2	27.2	23.2	16.2	21.5	17.1	6.5	6.3	−2.4
Silver	65.2	11.2	57.3	82.1		45.9	38.1	35.8	31.7	24.6	31.3	25.6	18.8	12.3	9.0
Copper	80.7	45.6	79.2	72.3	63.6		44.4	36.7	32.9	31.9	37.3	33.2	30.8	15.5	22.2
Soybeans	59.0	41.9	66.8	61.6	54.8	59.8		67.2	54.7	35.0	38.7	41.1	26.6	14.9	8.1
Corn	54.3	38.7	57.6	43.3	48.9	47.3	76.2		64.9	35.1	34.5	37.4	28.2	12.7	−1.1
Wheat	33.0	3.7	34.3	39.2	45.6	28.4	63.0	67.1		31.3	34.7	35.6	25.8	16.3	4.7
Sugar	8.7	−10.9	6.7	15.0	23.3	−0.7	17.7	26.6	22.4		35.9	30.2	23.4	9.9	14.0
Coffee	23.7	−5.8	19.7	27.9	36.9	20.6	38.2	39.3	50.4	21.0		31.9	23.1	11.8	15.8
Cotton	34.2	−6.0	29.0	22.5	47.7	15.8	37.1	45.6	42.8	35.7	47.2		21.8	9.2	11.5
Live Cattle	68.4	5.0	61.9	47.3	55.2	53.2	48.9	54.3	42.7	19.1	37.3	59.3		35.4	76.3
Lean Hogs	31.4	55.0	40.4	26.9	18.7	38.2	56.7	47.0	29.3	−5.1	9.4	5.9	9.4		30.0
Feeder Cattle	67.9	−0.5	62.7	63.3	63.2	53.6	56.4	53.6	49.7	23.6	34.0	51.1	87.1	17.4	
Average Correlation															
For Returns	42.3	21.8	41.1	28.3	36.7	39.9	40.2	38.1	35.7	31.3	33.4	31.1	32.7	20.4	22.9
For $E(\log RVol)$	55.7	25.9	55.3	51.0	51.6	50.5	55.9	53.3	43.4	20.2	33.3	37.9	49.9	32.0	52.2
Average Correlation															
With SP 500 Returns	46.9	11.3	43.4	4.7	24.2	54.2	23.0	21.7	20.3	21.6	27.4	25.3	32.6	9.9	31.3
With SP 500 $E(\log RVol)$	81.8	28.5	76.2	76.6	65.5	80.2	47.7	46.7	33.5	0.2	21.7	25.1	60.8	34.5	68.5

Notes: The table shows unconditional correlations for daily returns (upper diagonal) and log realized volatility (lower diagonal) for 15 commodity futures during the 2007-2011 ("during crisis") sample period. All observations are are for the most active futures contract on a given day. Average correlations with the S&P 500 E-Mini futures contract are shown in the lower panel for all commodities.

Table A.5: Unconditional Correlations for Daily Returns (upper diagonal) and Log Volatility (lower). "Post-crisis" sample.

	Light Crude	*Natural Gas*	*Heating Oil*	*Gold*	*Silver*	*Copper*	*Soy-beans*	*Corn*	*Wheat*	*Sugar*	*Coffee*	*Cotton*	*Live Cattle*	*Lean Hogs*	*Feeder Cattle*
Light Crude		12.2	81.9	28.6	40.8	51.5	24.7	18.9	20.2	25.4	18.4	19.9	15.0	11.9	14.7
Natural Gas	28.2		11.8	3.5	7.4	5.6	6.4	13.1	12.8	6.9	8.6	1.1	5.2	4.3	2.9
Heating Oil	94.5	31.8		28.0	39.3	45.1	26.1	19.1	20.8	22.9	17.4	22.5	9.8	10.0	9.3
Gold	52.7	3.2	47.4		80.7	34.9	18.2	14.6	14.1	11.2	14.6	12.6	8.3	3.6	5.5
Silver	67.6	11.6	64.8	82.5		48.8	24.0	20.0	19.3	16.4	19.4	18.3	10.2	7.2	6.7
Copper	71.0	18.5	68.3	64.8	75.1		29.4	18.8	20.6	22.9	21.6	22.6	11.2	7.4	10.0
Soybeans	47.6	24.9	44.3	16.6	29.9	37.3		60.5	49.5	26.1	15.7	23.4	11.0	7.2	−6.8
Corn	56.2	17.7	56.2	27.8	43.1	54.0	73.0		68.3	27.9	16.2	23.9	15.9	9.8	−13.7
Wheat	61.9	26.0	63.9	12.7	37.2	57.1	56.7	79.0		25.3	18.5	24.1	13.7	7.8	−9.6
Sugar	58.0	33.6	62.6	12.0	37.7	55.9	39.0	53.9	77.2		26.5	21.7	16.2	12.0	8.4
Coffee	−3.1	15.2	−5.1	−11.2	−7.9	4.1	16.4	19.0	28.5	24.9		11.1	8.8	8.5	5.2
Cotton	58.4	23.2	61.7	21.0	47.7	54.3	41.3	62.0	71.5	79.0	3.9		8.1	3.4	2.3
Live Cattle	49.4	12.2	48.6	5.4	25.9	45.9	33.5	54.8	73.2	65.8	23.9	67.9		34.7	74.4
Lean Hogs	29.6	1.2	26.2	−12.4	−0.9	15.5	37.4	43.3	58.8	52.0	43.6	40.6	56.6		25.1
Feeder Cattle	47.8	5.9	43.9	3.1	22.2	34.8	41.1	52.9	66.0	51.4	7.9	59.7	83.2	50.1	
Average Correlation															
For Returns	32.3	13.5	30.9	25.2	30.6	30.0	27.7	27.6	27.0	24.7	20.7	21.0	22.8	16.9	15.6
For $E(\log RVol)$	54.6	23.5	53.9	28.4	42.4	50.4	42.6	52.9	58.0	53.5	17.3	52.8	49.8	36.1	44.7
Average Correlation															
With SP 500 *Returns*	49.0	0.5	41.8	6.3	20.4	52.9	18.9	14.2	15.4	20.4	9.4	21.1	14.3	8.2	15.8
With SP 500 $E(\log RVol)$	72.6	19.4	67.9	53.6	56.3	68.2	33.2	49.1	55.4	53.8	15.4	48.2	43.8	26.6	38.7

Notes: The table shows unconditional correlations for daily returns (upper diagonal) and log realized volatility (lower diagonal) for 15 commodity futures during the 2010-2014 ("post-crisis") sample period. All observations are are for the most active futures contract on a given day. Average correlations with the S&P 500 E-Mini futures contract are shown in the lower panel for all commodities.

Table A.6: Intervals of Trading for 15 Commodities.

Commodity	Period	Trading Interval(s)
Crude Oil, Natural Gas, and Heating Oil	5/1-2004 to 9/6-2006	00.00 - 14.30
		15.15 - 12.00
	12/6-2006 to 31/12-2014	00.00 - 17.15
		18.00 - 12.00
Gold, Silver	5/1-2004 to 28/5-2004	00.00 - 13.30
		15.15 - 12.00
	1/6/2004 to 1/12-2006	00.00 - 13.30
		14.00 - 12.00
	4/12-2006 to 31/12-2014	00.00 - 17.15
		18.00 - 12.00
Copper	5/1-2004 to 4/6-2004	00.00 - 13.00
		15.15 - 12.00
	7/6-2004 to 1/12-2006	00.00 - 13.00
		14.00 - 12.00
	4/12-2006 to 31/12-2014	00.00 - 17.15
		18.00 - 12.00
Live Cattle, Lean Hogs, and Feeder Cattle	5/1-2004 to 1/6-2007	10.05 - 14.00
	4/6-2007 to 31/12-2014	00.00 - 17.00
		18.00 - 12.00
Corn, Soybeans, and Wheat	5/1-2004 to 7/10-2005	00.00 - 7.00
		10.30 - 14.15
		20.30 - 12.00
	10/10-2005 to 11/1-2008	00.00 - 7.00
		10.30 - 14.15
		19.30 - 12.00
	11/1-2008 to 30/6-2009	00.00 - 7.00
		10.30 - 14.15
		19.00 - 12.00
	1/7-2009 to 18/5-2012	00.00 - 8.15
		10.30 - 14.15
		19.00 - 12.00
	21/5-2012 to 5/4-2013	00.00 - 15.00
		18.00 - 12.00
	8/4-2013 to 31/12-2014	00.00 - 8.45
		9.30 - 14.15
		20.00 - 12.00
Sugar	5/1-2004 to 1/2-2007	9.00 - 00.00
	2/2-2007 to 31/12-2014	2.30 - 14.00*
Coffee	5/1-2004 to 1/2-2007	9.15 - 12.30
	2/2-2007 to 31/12-2014	3.30 - 14.00*
Cotton	5/1-2004 to 1/2-2007	10.30 - 14.15
	2/2-2007 to 27/3-2009	3.30 - 14.45
	30/3-2009 to 31/12-2014	00.00 - 14.30*
		21.00 - 12.00

Notes: All times are Eastern. The list indicates for each commodity the intraday trading intervals available in our dataset in the sample period.
* Minor changes in trading interval occurred during this period.