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Gold, oil, and stocks: Dynamic correlations☆

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ABSTRACT

We employ a wavelet approach and conduct a time-frequency analysis of dynamic correlations between pairs of key traded assets (gold, oil, and stocks) covering the period from 1987 to 2012. The analysis is performed on both intra-day and daily data. We show that heterogeneity in correlations across a number of investment horizons between pairs of assets is a dominant feature during times of economic downturn and financial turbulence for all three pairs of the assets under research. Heterogeneity prevails in correlations between gold and stocks. After the 2008 crisis, correlations among all three assets increase and become homogenous: the timing differs for the three pairs but coincides with the structural breaks that are identified in specific correlation dynamics. A strong implication emerges: during the period under research, and from a different-investment-horizons perspective, all three assets could be used in a well-diversified portfolio only during relatively short periods.

1. Introduction

Given the extent of the global financial market, co-movements in asset prices receive considerable attention due to their relevance to market integration, portfolio diversification, cross–hedging, and cross-speculation.[1] However, a majority of the empirical analyses that investigate dynamic co-movements employ a time-domain approach that is limited to dynamic links while the frequency analysis of investment horizons is omitted (Ramsey, 2002). Yet, dynamic correlations among assets have been documented to have specific characteristics for particular investment horizons (Conlon, Cotter, & Gençay, 2015), which may be instructive both for policy-makers (financial stability measures) and market participants (predictions of price changes). To better understand the co-movements in asset prices a combined time and frequency analysis is needed. In this paper we take a comprehensive approach to

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[1] The literature on co-movements is vast and a full review is beyond the scope of our study. There was a wave of publications on co-movements in top-tier journals in the mid-1990s. More recent contributions include Forbes and Rigobon (2002), Greenwood (2008), Bekaert et al. (2009), Green and Hwang (2009), and Bekaert et al. (2010) with a focus on co-movement factors. Later in this section we introduce studies that are more directly related to our analysis.

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enrich the literature. We perform a time-frequency wavelet analysis of three important assets that have unique economic and financial characteristics: gold, oil, and stocks. For comparison, we also employ standard techniques as well as include a cointegration analysis. By covering a long time span (1987–2012) at both intra-day and daily frequencies and using an array of investment horizons, we deliver a comprehensive study of the dynamic correlations among different classes of major assets.[2] To the best of our knowledge our paper is the first to address the issue of the heterogeneity in correlations among several highly financialized assets over various investment horizons and it brings new insights into their dynamics.

A knowledge of the correlations among assets at different investment horizons is significant for several reasons that are underpinned by the fact that homogenous correlations between assets across investment horizons preclude effective risk diversification in time. First, the importance of various investment horizons for portfolio selection was already recognized by Samuelson (1989). In this respect, Marshall (1994) showed that investors' preference for risk is inversely related to time and different investment horizons have direct implications for portfolio selection.[3] Second, there exist a variety of investors with markedly different investment horizons and transmissions of shocks through market transactions may vary according to time scale (Reboredo & Rivera-Castro, 2014a). Long-term investors base their strategy on fundamental analysis and trade at monthly or yearly horizons. Weekly or daily investors operate on much shorter horizons and base their strategies more on technical analysis. The shortest investment horizons are the domain of speculative traders that operate on an intra-day basis. In such an environment, market activity is necessarily far from homogeneous. Still, the dynamics of the market would be subject to interactions across all trading classes at different investment horizons (Gençay, Gradojevic, Selçuk, & Whitcher, 2010). Third, heterogeneity of market behavior coupled with interactions among assets might result in dynamic correlations among assets that would exhibit less-than-obvious patterns.

We aim to analyze those patterns simultaneously in the time and frequency domains by employing wavelet analysis. Gençay, Selçuk, and Whitcher (2001) and Ramsey (2002) provide ample exposition on the use and versatility of wavelet techniques in economics and finance. During the past decade the methodology gained currency and relevant applications of wavelets include analyses of stocks (Fernandez, 2006, 2008; In & Kim, 2006; Rua & Nunes, 2009), commodities (Graham, Kiviaho, & Nikkinen, 2013; Reboredo & Rivera-Castro, 2014a; Vacha & Barunik, 2012), exchange rates (Karuppiah & Los, 2005; Nekhili, Altay-Salih, & Gençay, 2002; Nikkinen, Pynnönen, Ranta, & Vähämaa, 2011), and other financial and economic variables or their interactions (Aguiar-Conraria & Soares, 2011; Aguiar-Conraria, Martins, & Soares, 2012; Faÿ, Moulines, Roueff, & Taqqu, 2009; Gallegati, Gallegati, Ramsey, & Semmler, 2011 Kim & In, 2005, 2007; Reboredo & Rivera-Castro, 2014b; Rua, 2010).

By using wavelets we are able to test the hypothesis on the existence of homogeneity in dynamic correlations across various investment horizons among assets, an issue that so far has been largely overlooked in the literature. In this way we are able to explore the following related questions: To what extent do the assets co-move at different investment horizons? Do correlations among the assets at various investment horizons vary a lot or a little, and are they subject to dramatic changes? Do they share a long-term equilibrium relationship?

For our empirical analysis we chose three assets: gold, oil, and stocks (proxied by the S&P 500). This selection is based on the following reasons: (i) gold and oil represent the most actively traded commodities in the world and the S&P 500 is one of the most actively traded and comprehensive stock indices[4]; (ii) all three assets exhibit marked differences in leverage, which makes them highly interesting from a financial perspective; (iii) there is a motivation for the existence of links among the three assets but empirical evidence is limited to a time-domain approach. Below we review some key facts that further underpin the above reasoning along with some of the literature covering co-movements among the assets under research.

In terms of individual assets, first, gold is traditionally perceived as a store of wealth, especially with respect to periods of political and economic insecurity (Aggarwal & Lucey, 2007). However, gold is a commodity as well as a monetary asset. In this respect Batten, Ciner, and Lucey (2010) find monetary variables to explain gold volatility. The behavior of gold prices is covered by Lucey, Larkin, and O'Connor (2013). Second, the key importance of oil comes from an industrial perspective and its importance for our society can be documented by the almost 90 million barrels of daily global consumption.[5] As oil is a vital input of production, its price is driven by distinct demand and supply shocks. Lombardi and Van Robays (2011) find that a short run destabilization in the oil price may be caused by financial investors. However, they argue that while financial activity boosted volatility in the oil market over the recent 2007–2008 crisis, shocks to oil demand and supply remain the main drivers of oil price swings. Over the years, oil also became heavily financialized, as documented in Büyükşahin and Robe (2013). Third, from an economic perspective, stocks reflect the economic and financial development of firms, and market perceptions of a company's standing. They also represent investment opportunities, as well as a link to perceptions of aggregate economic development. Further, stock prices provide helpful information on financial stability and can serve as an indicator of crisis (Gadanecz & Jayaram, 2009). Hence, a wide market index can be used to convey messages on the status and stability of the economy.

From the above account, one may sense that the channels through which the links and co-movements among the assets under research may propagate are not limited only to differences among investors and their investment horizons.[6] For example, the relationship between gold and oil is closely linked to inflation. An inflation channel can well explain the theoretical underpinnings between

[2] The literature on asset co-movements is fragmented in terms of the assets used, time spans, data frequencies, and the techniques employed. Further, correlation analyses usually investigate behavior within a specific class of assets and often disregard the existence of structural shifts.

[3] A parallel can be drawn from the classical term structure theory of interest rates where different maturities are, in a sense, investment horizons as well.

[4] According to the CME Group Leading Products Resource, S&P 500 futures are traded with the highest average volume among equity indices, gold among metals, and oil among energy commodities (http://www.cmegroup.com/education/featured-reports/cme-group-leading-products.html).

[5] The corresponding consumption figures in millions of barrels daily are 29 for Asia, 18.5 for the U.S.A., and 14.4 for Europe (2012 World Oil Consumption in millions of barrels per day, U.S. Energy Information Administration, assessed on March 1, 2014, http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=5&pid=5&aid=2).

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the two assets: rising oil prices usually influence the aggregate price level (Hunt, 2006) and generate inflationary pressures that prompt hedging against inflation in the form of investments in gold (Narayan, Narayan, & Zheng, 2010). Using a long span of annual data (1960–2005), Baffes (2007) shows that the prices of precious metals, including gold, strongly respond to the price of oil. A similar result is produced by Zhang and Wei (2010), who, based on daily data (2000–2008), find that a rising oil price drives up the price of gold, but they do not find a reverse link.

The above results hint at the potential existence of a long-term equilibrium relationship between gold and oil. Hence, the Efficient Market Hypothesis (EMH) is the basis that motivates an analysis of cointegration among the assets under research. Zhang and Wei (2010) identify a cointegration link between two assets on daily data. Narayan et al. (2010) improve on the cointegration approach and analyze the long-run relationship between gold and oil futures prices over the period 1963–2008 at different levels of maturity in order to gauge differences in hedging behavior. The results indicate that the gold and oil markets are cointegrated, which is presented as evidence of joint market inefficiency. The fact that annual data are employed for the analysis precludes the more detailed and comprehensive results that could be inferred from data of higher frequencies. Studies analyzing the impact of oil prices on stocks across the market show that stock prices rise when the oil price falls and vice versa (Faff & Brailsford, 1999; Huang, Masulis, & Stoll, 1996; Sadorsky, 1999). Later studies that analyze the prices of stocks in related (oil, gas) industries show a positive link between those stock prices and the price of oil (El-Sharif, Brown, Burton, Nixon, & Russell, 2005; Sadorsky, 2001). Fratzscher, Schneider, and Van Robays (2013) show that oil was not correlated with stocks until 2001, but as oil started to be used as a financial asset, the link between oil and other assets strengthened.

Our key empirical results can be summarized as follows: (i) Correlations between the three assets are low or even negative at the beginning of our sample but following the financial crisis (2007–2009), they dramatically increase. The change in the pattern becomes most pronounced after decisive structural breaks take place (breaks occur during the 2006–2009 period at different dates for specific asset pairs). (ii) Correlations before and after the crisis are homogenous at different investment horizons. (iii) Around the crisis, the heterogeneity in correlations is quite prominent. (iv) Pronounced post-crisis homogeneity in correlations indicates vanishing room for risk diversification based on these assets: until the end of our sample gold, oil, and stocks cannot be used together for risk diversification. (v) In terms of the long-term equilibrium relationship we account for structural breaks and show that the assets under research do not exhibit cointegration.

The paper is organized as follows. In Section 2, we introduce the theoretical framework of the methodologies we use to perform our analysis. Our large data set is described in detail in Section 3 with a number of relevant commentaries. We bring forth our empirical results in Section 4, in which we present detailed inferences on dynamic correlations as well as long-term relationships among the assets under study. Section 5 concludes.

2. Theoretical framework of the employed methodologies

In our study, we employ both standard techniques as well as wavelets. In this section we first provide a brief account and then formalize the techniques. The time domain tools to measure correlations are the nonparametric realized volatility and parametric DCC GARCH methods. While these two approaches are fundamentally different, they both average the relationships over the entire range of possible frequencies and suffer from limited application when dealing with non-stationary time series. When studying market prices with time-series approaches, we have to first-difference the prices to obtain stationary data. This step has economic intuition as first-differenced logarithmic prices are market returns. Still, by this transformation, we lose information about long-term behavior. When analyzing dependencies between asset markets, this may be a crucial loss of information. Wavelets, on the other hand, allow us to analyze time series in the time-frequency domain. Moreover, the wavelet time-frequency domain framework allows for various forms of localization. Thus, when dealing with non-stationary time series, wavelet analysis is better because it is more flexible. Wavelets allow us to simply work with prices and thus study the dynamics of the dependencies not only in time, but also at various investment horizons or frequencies at the same moment. In this way, we may obtain short- as well as long-term dependence structures.

In the following sections we briefly introduce the set of methodologies used for estimating dynamic correlations. We begin with a benchmark parametric DCC GARCH approach, we continue with non-parametric realized measures, and finally introduce an innovative time-frequency approach of wavelet analysis.

2.1. Time-varying correlations: the DCC GARCH methodology

Early work on the estimation of time-varying covariances between returns was done by Bollerslev (1990) in his constant correlation model, where the volatilities of each asset were allowed to vary through time but the correlations were time invariant. In a subsequent work, Engle (2002) allowed for dynamics in correlations as well in the now well-established multivariate concept of the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC GARCH) model. In this section, we provide a very basic overview of the model.

[6] Investment horizons are associated with various types of investors, trading tools, and strategies that correspond to different trading frequencies (Gençay et al., 2010).

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In Bollerslev's model, correlation matrix R is constant: $H_t = D_t R D_t$, where $D_t = diag\{\sqrt{h_{i,t}}\}$ and $h_{i,t}$ represents the i-th univariate (G)ARCH(p,q) process, and $i = 1, \ldots, n$ where n is a number of assets at time $t = 1, \ldots, T$. Engle (2002) allowed R to vary in time t thus:

$$H_t = D_t R_t D_t. \tag{1}$$

The correlation matrix is then given by the transformation

$$R_t = diag\left(\sqrt{q_{11,t}}, \ldots, \sqrt{q_{nn,t}}\right) Q_t diag\left(\sqrt{q_{11,t}}, \ldots, \sqrt{q_{nn,t}}\right), \tag{2}$$

where $Q_t = (q_{ij,t})$, which is

$$Q_t = (1-\alpha-\beta)Q + \alpha\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1}, \tag{3}$$

where $\eta_t = \varepsilon_{i,t}/\sqrt{h_{i,t}}$ are the standardized residuals from the (G)ARCH model, $Q = T^{-1}\sum \eta_t \eta'_t$ is a $n \times n$ unconditional covariance matrix of η_t, and α and β are non-negative scalars such that $\alpha + \beta < 1$.

To estimate DCC GARCH, we use the standard quasi-maximum likelihood (QML) procedure proposed by Engle (2002) assuming that the innovations are Gaussian. As shown by Engle (2002) and Engle and Sheppard (2001), the DCC model can be estimated consistently by estimating the univariate GARCH models in the first stage and the conditional correlation matrix in the second stage. Parameters are also estimated in stages. This two-step approach avoids the dimensionality problem of most multivariate GARCH models.[7] The above DCC model is parsimonious and ensures that time-varying correlation matrices between stock exchange returns are positive definite.

2.2. Time-varying correlations: the realized volatility approach

While DCC GARCH estimates the time-varying dynamics of correlations in a parametric way, a simple non-parametric way of estimating the covariance matrix has been developed using high-frequency data. Andersen, Bollerslev, Diebold, and Labys (2003) and Barndorff-Nielsen and Shephard (2004) suggest estimating the covariance matrix analogously to the realized variation by taking the outer product of the observed high-frequency return over the period. The realized covariance over $[t-h, t]$ for $0 \le h \le t \le T$ is defined as

$$RC_{t,h} = \sum_{i=1}^{M} \mathbf{r}_{t-h+\left(\frac{i}{M}\right)h} \mathbf{r}'_{t-h+\left(\frac{i}{M}\right)h}, \tag{4}$$

where M is the number of observations in $[t-h, t]$. Details can be found in Andersen et al. (2003) and Barndorff-Nielsen and Shephard (2004), who show that the *ex-post* realized covariance $RC_{t,h}$ is an unbiased estimator of the *ex-ante* expected covariation. Moreover, with increasing sampling frequency the realized covariance is a consistent estimator of the covariation over any fixed time interval $h > 0$ as $M \to \infty$. In practice, we observe only discrete prices, thus bias from discretization is unavoidable. Much more damage is caused by market microstructure effects such as price discreteness, bid-ask spread, and bid-ask bounce. Hence, when using this estimator in practice, one is left with the advice not to sample too often. While the optimal sampling frequency resulting from the vast research on the noise-to-signal ratio[8] can be used, this approach still causes a large amount of available data to be discarded. The best trade-off between reducing bias and losing information is to use the standard 5-min sampling frequency as suggested by Andersen and Benzoni (2007). We follow their approach and use 5-min data for the calculation of realized covariances. One last important assumption about the process is that the data are assumed to be synchronized: this means that the prices of the assets have to be collected at the same time. This is not an issue here as in our analysis all three assets under research are paired under equal-stamps matching.

2.3. Time-frequency dynamics in correlations: the wavelet approach

While both DCC GARCH and realized volatility approaches allow us to study the covariance matrix solely in the time domain, we are interested in studying its time-frequency dynamics. In other words, we are interested to see how the correlations vary over time and over different investment horizons.

Wavelets offer a decomposition of the economic relationship into time-frequency components. In wavelet analysis, scale is often used instead of frequency, because scale usually represents broader frequency bands. The set of scales represents investment horizons (resolution levels) at which we can study the relationships separately, i.e., on a scale-by-scale basis (Gallegati et al., 2011). Each scale therefore describes the time development of the economic relationship at a particular scale but also dynamically in time. The wavelet decomposition usually provides a broader picture when compared to the time domain approach that in fact aggregates all investment

[7] In this respect, Bauwens and Laurent (2005) show that both the one-step and two-step methods provide very similar estimates.

[8] The literature is well surveyed by Hansen and Lunde (2006), Bandi and Russell (2006), McAleer (2008), and Andersen and Benzoni (2007).

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horizons together. Hence, if we expect that economic relationships follow different patterns at various investment horizons, then the wavelet decomposition can reveal interesting characteristics of the data that would otherwise remain hidden.

In our analysis we use a discrete version of wavelet transform called maximal overlap discrete wavelet transformation (MODWT). This transform is a translation-invariant type of discrete wavelet transformation, i.e., it is not sensitive to the choice of the starting point of the examined process. Furthermore, the MODWT does not use a downsampling procedure, therefore the wavelet and scaling coefficient vectors, which are the outcomes of the decomposition, have equal length at all scales similar to the number of observations of the decomposed time series. As a consequence, the MODWT is not restricted to sample sizes that are powers of two.

To obtain the MODWT wavelet and scaling coefficients from time series $x(t)$, we use the pyramid algorithm (Percival & Walden, 2000). A vector of wavelet coefficients is denoted as $W_x(j,s)$,where j denotes the scale and parameter s represents the position that corresponds to the time position of the decomposed time series $x(t)$. For time series $x(t)$, $t=1,2,\ldots,N$, we obtain $j=1,\ldots,J$ vectors of wavelet coefficients, where $J \leq log_2(N)$ represents the maximum level of the wavelet decomposition. Generally, the j-th level wavelet coefficients in vector $W_x(j,s)$ represent a frequency band $f \in [1/2^{j+1}, 1/2^j]$, whereas the j-th level scaling coefficients in vector $V_x(J,s)$ represents frequency band $f \in [0, 1/2^{j+1}]$. Hence, as we increase the number of scales only, the scaling coefficients vector represents a small portion of the spectra. For example, at the first scale $j = 1$, representing the lowest scale (highest frequency), we obtain vector $W_x(1,s)$; in case we have 5-min data, the first scale represents activity at investment horizons of 10–20 min. The second scale coefficients, $W_x(2,s)$, represent investment horizons of 20–40 min. The full wavelet decomposition of time series $x(t)$ results in a set of vectors of wavelet and scaling coefficients: $W_x(1,s), W_x(2,s), \ldots, W_x(J,s), V_x(J,s)$. Since the MODWT is an energy preserving transform, the variance of the decomposed time series $x(t)$, $t=1,2,\ldots,N$ is completely encompassed in the wavelet scaling coefficients:

$$\|x\|^2 = \sum_{j=1}^{J} \sum_{s=1}^{N} \|W_x(j,s)\|^2 + \sum_{s=1}^{N} \|V_x(J,s)\|^2. \tag{5}$$

For a more detailed introduction to wavelets, see Daubechies (1988); Percival (1995), and Percival and Walden (2000).

Finally, wavelet correlation allows for an alternative study of dependence between two time series. As wavelets decompose the time series on a scale-by-scale basis, we can estimate correlations for various time horizons represented by scales.

As a first step, a wavelet transform is performed on the examined time series, i.e., the prices of gold, oil, and stocks. As an output from the wavelet transform we obtain vectors of wavelet and scaling coefficients. Since we use the maximal overlap discrete wavelet transform (MODWT), all vectors of wavelet coefficients have the same length.

Following Whitcher, Guttorp, and Percival (2000), we define wavelet correlation $\rho_{xy}(j)$ between time series x and y at scale j as:

$$\rho_{xy}(j) = \frac{cov\left(W_x(j,s), W_y(j,s)\right)}{\left[var(W_x(j,s))var\left(W_y(j,s)\right)\right]^{\frac{1}{2}}} \equiv \frac{\gamma_{xy}(j)}{\nu_x(j)\nu_y(j)} \quad , \tag{6}$$

where $W_x(j,s)$ and $W_y(j,s)$ are vectors of the MODWT wavelet coefficients for time series $x(t)$ and $y(t)$ at scale j. For instance, using 5-min data, the wavelet correlation at scale j describes the correlation at an investment horizon of 10–20 min. We provide the details about the wavelet variance $\nu_x^2(j)$ d wavelet covariance $\gamma_{xy}(j)$ in Appendix A and Appendix B. Using the definition of the wavelet correlation (6) we can write an estimator of the wavelet correlation in the form:

$$\rho_{xy}(j) \equiv \frac{\gamma_{xy}(j)}{\nu_x(j)\nu_y(j)}, \tag{7}$$

where $\gamma_{xy}(j)$ is the estimator of wavelet covariance at scale j and $\nu_x(j)^2$ and $\nu_y(j)^2$ are estimators of wavelet variance and covariance, respectively. The central limit theorem for estimator (7) was established by Whitcher, Guttorp, and Percival (1999). Approximate confidence intervals for the MODWT wavelet correlations are constructed based on Whitcher et al. (1999); empirical values are reported in Section 4.1.

3. Data

For our analysis, we use the prices of gold, oil, and the broad U.S. stock market index S&P 500. The data set consists of the tick prices of gold, oil, and S&P 500 futures traded on the platforms of the Chicago Mercantile Exchange (CME) and obtained from Tick Data, Inc. More specifically, oil (Light Crude) is traded on the New York Mercantile Exchange (NYMEX) platform, gold is traded on the Commodity Exchange, Inc. (COMEX), a division of NYMEX, and finally S&P 500 is traded at the CME in Chicago. We use the most active rolling contracts from the pit (floor traded) session. The prices of all futures are expressed in U.S. dollars.

The sample period spans from January 2, 1987 until December 31, 2012. We acknowledge the fact that the CME introduced the Globex(R) electronic trading platform on Monday, December 18, 2006, and began to offer nearly continuous trading. However, we restrict the analysis of intraday 5-min returns within the business hours of the New York Stock Exchange (NYSE) as most of the liquidity of S&P 500 futures comes from the period when U.S. markets are open. The time synchronization of our data is achieved in such a way that gold and oil prices are paired with S&P 500 by the same Greenwich Mean Time (GMT) stamp. We eliminate transactions

Table 1
Descriptive Statistics for high-frequency and daily gold, oil and, stock (S&P 500) returns over the sample period extending from January 2, 1987 until December 31, 2012.

	High-frequency data			Daily data		
	Gold	Oil	Stocks	Gold	Oil	Stocks
Mean	1.0E-06	3.2E-06	−2.5E-06	2.2E-04	2.4E-04	2.7E-04
St. dev.	0.001	0.002	0.001	0.010	0.023	0.012
Skewness	−0.714	1.065	0.326	−0.147	−1.063	−0.392
Kurtosis	47.627	104.561	32.515	10.689	19.050	11.474
Minimum	−0.042	−0.045	−0.024	−0.077	−0.384	−0.098
Maximum	0.023	0.163	0.037	0.103	0.136	0.107

executed on Saturdays and Sundays, U.S. federal holidays, December 24 to 26, and December 31 to January 2, because of the low activity on these days, which could lead to estimation bias. Hence, in our analysis we work with data from 6472 trading days. In Table 1 we present the descriptive statistics of the returns of the data that constitute our sample. The distributions of intra-day as well as daily returns are standard, although a very high excess kurtosis of 104.561 for oil can be noted. This is caused by a single maximum value of a 16.3% return on January 19, 1991, the day when the worst intentional environmental damage ever was caused by the late Iraqi leader Saddam Hussein ordering a large amount of oil to be spilled into the Persian Gulf (for an assessment see Khordagui & Al-Ajmi, 1993). We show the development of the prices of the three assets in Fig. 1.

4. Empirical analysis of gold, oil, and stocks relationships

4.1. Time-varying correlations

We present dynamic correlations for each pair of assets graphically in Figs. 2–4. Each figure contains two panels that plot correlations obtained by the three methods described in Section 2. In the upper panel, the figures report realized volatility-based correlations computed on 5-min returns for each day and daily correlations from the DCC GARCH(1,1) estimates. The lower panels contain time-frequency correlations computed using wavelet decomposition of 5-min data.[9] We depict only four investment horizons as examples: 10 min, 40 min, 160 min and 1.6 days.

There are several key features we can infer from the plots. Correlations for asset pairs exhibit stable and similar patterns—correlations are low (and even negative on a few occasions)—until 2005 between gold and oil, until 2001 between gold and stocks, and until 2004 between oil and stocks. After these years the pattern of correlations between assets radically changes. Dynamic correlations between pairs of variables exhibit the same patterns but their plots differ in the extent of detail depending on what method is used. Correlations based on realized volatility provide very rough evidence. More contoured correlation patterns are inferred from the DCC-GARCH method. The wavelet approach shows its advantage over the two other methods as it offers individual correlation patterns for a number of investment horizons. Thus, it provides true time-frequency research output.[10]

We now turn to more detailed inferences. Intraday correlations for the gold-oil pair are remarkably low during the period 1992–2005 at short (10-min) as well as longer horizons (this result is more accessible from Table 2, presented in the next section). Higher correlations during the period 1990–1991 correspond to the spike visible in graphical form (Fig. 2) that is associated with the economic recession in the U.S. (July 1990 to March 1991). A significant increase in correlation begins in 2006. Contrary to only a temporary increase in correlation during 1990–1991, the correlation structure between gold and oil has changed from the recent financial crisis until the end of our sample. This is an interesting result that indicates the existence of a decisive structural break in the correlation structure between the two assets. The result is actually corroborated by the evidence of the structural break on September 8, 2006 reported in Section 4.3.

The presence of negative correlations is a feature that is common to the gold-stocks and oil-stocks pairs (Figs. 3 and 4). For the gold-stocks pair (Fig. 3), the period 1991–1992 is characterized by negative correlations, especially at longer horizons. The negative link might have its root in the fact that gold is traditionally perceived as a store of wealth during periods of political and economic insecurity (Aggarwal & Lucey, 2007) and when stock markets decline, the price of gold often rises. The economic tradeoff in which gold acts as a financial variable important for the investors on stock markets thus might produce a negative correlation, as in Fig. 3.[11] Our finding is also in accord with that of Ciner et al. (2013; p. 206) who claim that “a clear negative relation is detected between gold and equities.” Later, from 2001, the gold-stocks pair exhibits very rich correlation dynamics: the correlations reached their minima during 2002–2003, then a steady increase followed. From 2006 this pair has significantly high correlation, except for two short periods in 2008 and 2009. Contrary to the other two pairs, in 2012 there was a very significant increase in the correlation between

[9] For improved clarity of the time-frequency plot, we report aggregated monthly correlations.
[10] Despite the fact that the wavelet approach is superior to the other two methods in terms of dynamic correlation analysis, we employ the other methods for the purpose of comparison and completeness of analysis as these are benchmark methods.
[11] This financial link (extended to investors on the forex market) is similar to that between gold and the U.S. dollar. Specifically, using a wavelet analysis, Reboredo and Rivera-Castro (2014b) show that gold and U.S. dollar depreciation have a positive dependence (eg. a negative correlation between the value of gold and the U.S. dollar) that is robust across different time scales.

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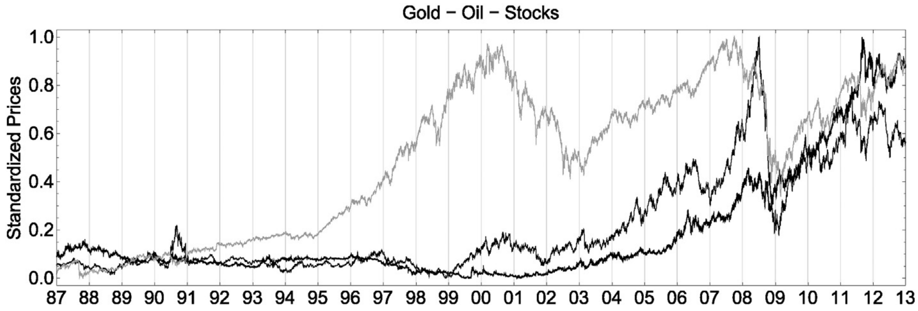

Fig. 1. Normalized prices of gold (thin black), oil (black), and stocks (gray).

gold and stocks at all scales. We can observe an increase in the magnitude that is three times larger relative to the previous year. Future research will show whether 2012 was only an anomalous year or whether we are witnessing a more profound change in the correlation structure.

The oil-stocks pair also exhibits a negative correlation in the early part of the sample (Fig. 4). An economic reasoning for this finding comes from the fact that the response of stock markets to oil price shocks differs according to the origin of such a shock (Hamilton, 1996). Specifically, a supply-side shock negatively impacts stock market returns and leads to negative correlation in the oil-stocks pair. An increase in oil prices—a supply-side shock—might result from an abrupt reduction of output by major producers (eg. OPEC countries) or a major political event such as the 1990–1991 Gulf War. In accord with the above reasoning and our findings, Filis, Degiannis, and Floros (2011) shows that during the period 1990–1991 precautionary demand for crude oil caused a negative correlation between oil prices and stock market returns. The same effect is also documented in Table 4, presented in the next section.

The oil-stocks pair records markedly increased correlations after the onset of the financial crisis. However, unlike the other two pairs, the correlation between oil and stocks before the crisis was significantly lower than after the crisis. This indicates that the correlation structure of this pair was strongly influenced by developments in 2008. From 2009 on, the oil-stocks pair has the highest correlation of the three examined pairs. Moreover, often we observe highly similar correlation on all scales.

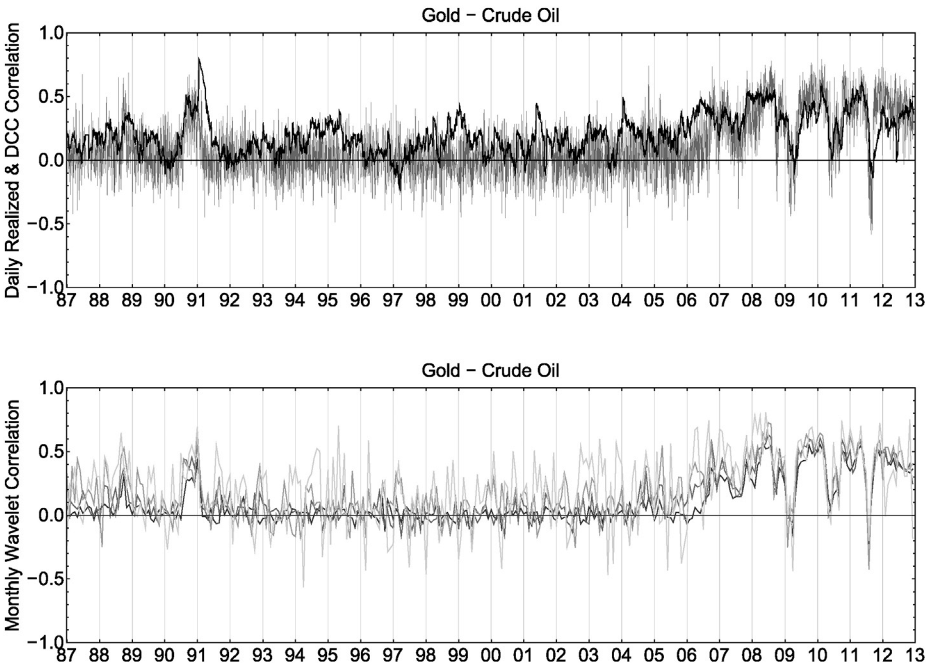

Fig. 2. Dynamics in gold-oil correlations. The upper panel contains the realized correlation for each day of the sample (gray line) and daily correlations estimated from the DCC GARCH model (black line). The lower panel contains time-frequency correlations based on the wavelet correlation estimates from high-frequency data for each month separately. We report correlation dynamics at 10-min, 40-min, 2.66 h (approximate), and 1.6-day (approximate) horizons depicted by the thick black to thin black lines.

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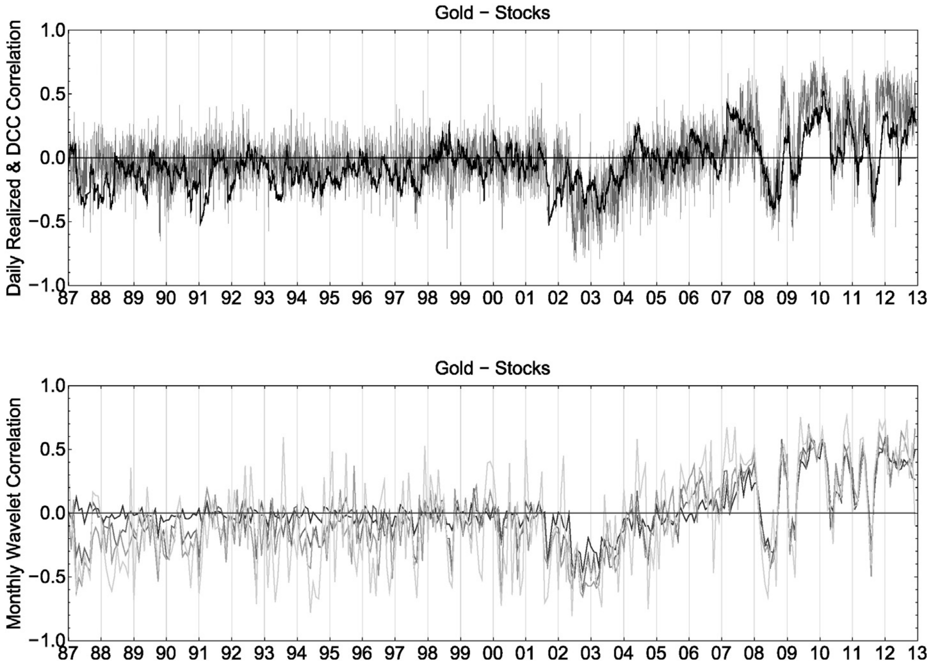

Fig. 3. Dynamics in gold – stocks correlations. The upper panel contains the realized correlation for each day of the sample (gray line) and daily correlations estimated from the DCC GARCH model (black line). The lower panel contains time-frequency correlations based on the wavelet correlation estimates from high-frequency data for each month separately. We report correlation dynamics at 10-min, 40-min, 2.66 h (approximate), and 1.6-day (approximate) horizons depicted by the thick black to thin black lines.

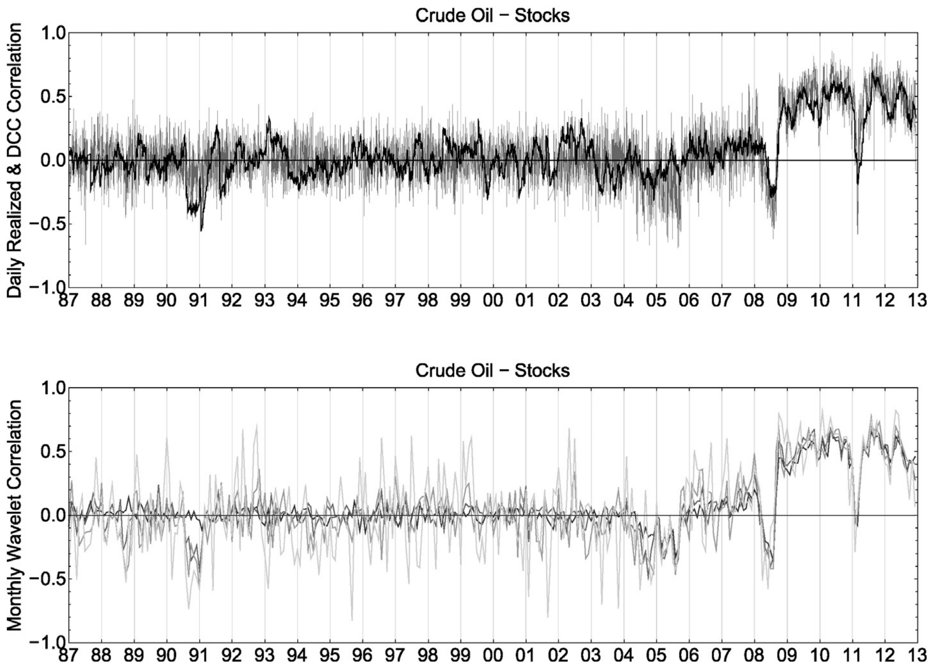

Fig. 4. Dynamics in oil – stocks correlations. The upper panel contains the realized correlation for each day of the sample (gray line) and daily correlations estimated from the DCC GARCH model (black line). The lower panel contains time-frequency correlations based on the wavelet correlation estimates from high-frequency data for each month separately. We report correlation dynamics at 10-min, 40-min, 2.66 h (approximate), and 1.6-day (approximate) horizons depicted by the thick black to thin black lines.

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Table 2
Time-frequency correlation estimates for the gold – oil pair. The high-frequency set contains wavelet correlation estimates based on high-frequency data. The daily set contains wavelet correlation estimates based on daily data. Gray background represents years where the hypothesis of homogeneous correlations is rejected. Correlations statistically different from zero are denoted by asterisks (* 10%, ** 5%, *** 1%).

	Gold–Oil										
	High–frequency data					Daily data					
	10 min	20 min	40 min	80 min	160 min–year	2 days	4 days	8 days	16 days	32 days	64 d. – year
1987	0.02	0.03	0.08***	0.15***	0.8***	0.12	0.00	0.14	0.07	−0.13	0.77***
1988	0.11***	0.19***	0.19***	0.23***	0.42***	0.23***	0.25*	0.32*	0.38	0.55	0.93***
1989	0.02*	0.03*	0.06***	0.06*	0.53***	0.02	0.11	0.05	0.09	0.74*	−0.14**
1990	0.16***	0.27***	0.3***	0.29***	0.43***	0.51***	0.47***	0.4***	0.33	0.76***	0.69***
1991	0.21***	0.32***	0.31***	0.32***	0.63***	0.01	0.00	0.47***	0.48*	−0.31	−0.47***
1992	0.02	0.08***	0.03	0.01	−0.56***	0.06	0.01	−0.18	0.25	−0.05	−0.41***
1993	0.00	0.01	0.04	0.02	0.6***	0.12	0.04	0.20	0.30	−0.26	−0.77***
1994	0.02	0.02	0.03	0.03	−0.13***	0.16*	0.37***	0.22	−0.09	−0.28	0.33***
1995	0.01	0.00	0.03	0.07	0.05***	0.23***	0.17	0.07	−0.02	0.16	0.39***
1996	0.01	0.02	0.00	0.04	−0.62***	−0.09	−0.03	0.13	−0.34	−0.31	−0.68***
1997	0.00	−0.01	0.00	0.06	0.33***	0.00	−0.22*	0.04	−0.13	0.09	0.57***
1998	0.00	−0.02	−0.01	−0.01	0.65***	0.14	0.28***	0.4***	0.21	0.65	0.18***
1999	0.01	0.01	−0.01	0.02	−0.58***	−0.02	0.12	0.31*	−0.17	0.17	−0.8***
2000	0.00	0.00	0.01	0.07*	−0.68***	0.16*	0.03	0.32*	−0.12	0.01	0.44***
2001	0.00	0.01	0.01	0.02	−0.83***	0.23***	0.04	0.11	−0.25	−0.10	0.10
2002	−0.01	−0.01	0.04	0.07*	0.62***	0.10	0.03	−0.17	0.08	−0.64	0.86***
2003	0.01	0.02	0.04	0.06	0.68***	0.24***	0.05	−0.08	0.12	0.47	0.54***
2004	0.04***	0.08***	0.10***	0.11***	0.4***	0.17*	0.38***	0.23	0.13	−0.58	−0.74***
2005	0.01	0.07***	0.09***	0.11***	−0.42***	0.08	0.07	0.22	0.42	0.27	0.4***
2006	0.11***	0.17***	0.3***	0.35***	0.74***	0.37***	0.53***	0.47***	0.58***	0.57	0.92***
2007	0.26***	0.3***	0.33***	0.35***	0.29***	0.49***	0.38***	0.07	0.41	0.42	0.48***
2008	0.32***	0.35***	0.39***	0.39***	0.74***	0.44***	0.45***	0.55***	0.67***	0.41	0.27***
2009	0.19***	0.21***	0.22***	0.22***	−0.21***	0.19***	0.20	0.53***	−0.03	−0.12	0.45***
2010	0.33***	0.34***	0.36***	0.37***	−0.3***	0.29***	0.35***	0.48***	0.57***	0.07	−0.37***
2011	0.26***	0.27***	0.31***	0.29***	0.22***	0.2***	0.18	0.20	0.37	0.62	0.72***
2012	0.4***	0.42***	0.42***	0.41***	−0.36***	0.37***	0.4***	0.63***	0.43	−0.19	0.71***

Table 3
Time-frequency correlation estimates for the gold – stocks pair. The high-frequency set contains wavelet correlation estimates based on high-frequency data. The daily set contains wavelet correlation estimates based on daily data. Gray background represents years where the hypothesis of homogeneous correlations is rejected. Correlations statistically different from zero are denoted by asterisks (* 10%, ** 5%, *** 1%).

	Gold–Stocks										
	High–frequency data					Daily data					
	10 min	20 min	40 min	80 min	160 min–year	2 days	4 days	8 days	16 days	32 days	64 d. – year
1987	0.05***	−0.04***	−0.11***	−0.22***	−0.54***	−0.22***	−0.22*	−0.24	−0.39	−0.58	0.64***
1988	−0.02	−0.05***	−0.14***	−0.22***	−0.21***	−0.25***	0.08	−0.06	−0.17	−0.12	−0.54***
1989	−0.03***	−0.1	−0.19***	−0.15***	−0.59***	0.03	−0.26***	−0.23	0.06	−0.67	−0.92***
1990	−0.04***	−0.15***	−0.20***	−0.25***	−0.77***	−0.32***	−0.33***	−0.28	−0.10	−0.36	−0.84***
1991	−0.01	−0.07***	−0.10***	−0.09***	−0.55***	−0.16*	−0.14	0.11	0.18	0.14	−0.59***
1992	−0.03*	−0.04*	−0.03	−0.10***	0.52***	0.01	−0.01	−0.21	−0.28	0.37	0.21***
1993	−0.02*	−0.06***	−0.10***	−0.13***	0.49***	−0.24***	−0.15	−0.23	0.03	−0.12	0.43***
1994	−0.02	−0.10***	−0.17***	−0.21***	0.41***	−0.26***	−0.18	0.05	0.00	0.38	0.31***
1995	−0.01	−0.04*	0.01	−0.04	−0.37***	−0.17*	−0.06	−0.02	0.01	−0.39	0.71***
1996	−0.04***	−0.12***	−0.08***	−0.13***	−0.26***	−0.20***	−0.27***	−0.24	0.47*	0.57	−0.77***
1997	−0.03***	−0.06***	−0.07***	−0.11***	−0.49***	−0.15*	−0.17	−0.26	−0.05	0.03	−0.93***
1998	−0.05***	−0.07***	−0.13***	−0.11***	0.80***	−0.03	0.17	0.28	−0.05	0.49	0.43***
1999	−0.01	−0.01	−0.04	0.01	0.54***	−0.03	0.10	0.05	0.15	0.45	−0.75***
2000	−0.03***	−0.07***	−0.10***	−0.20***	0.54***	−0.03	0.00	0.24	0.32	−0.25	−0.80***
2001	−0.01	−0.01	0.00	0.01	−0.49***	−0.24*	−0.11	0.07	0.04	0.16	0.43***
2002	−0.27***	−0.34***	−0.38***	−0.37***	−0.58***	−0.21***	−0.24*	−0.37***	−0.28	−0.34	−0.66***
2003	−0.26***	−0.35***	−0.38***	−0.42***	0.46***	−0.42***	−0.12	−0.07	−0.51*	−0.49	0.18***
2004	−0.07***	−0.09***	−0.08***	−0.09***	0.65***	0.03	0.14	0.38***	0.14	0.17	0.29***
2005	−0.02	−0.02	0.02	0.00	0.08***	−0.08	0.11	0.09	−0.02	0.40	0.13**
2006	0.05***	0.11***	0.17***	0.20***	0.30***	0.10	−0.01	0.20	0.34	0.65	0.16**
2007	0.20***	0.26***	0.29***	0.27***	−0.18***	0.39***	0.28***	0.42***	0.42	0.85***	0.39***
2008	0.11***	0.14***	0.10***	0.09***	0.87***	−0.03	−0.16	−0.09	−0.16	−0.68*	−0.89***
2009	0.14***	0.13***	0.15***	0.17***	−0.17***	0.01	−0.05	0.28	0.31	−0.05	−0.38***
2010	0.25***	0.25***	0.28***	0.29***	0.06***	0.14	0.29***	0.46***	0.38	−0.08	−0.20**
2011	0.13***	0.14***	0.18***	0.13***	−0.40***	−0.17*	−0.18	−0.08	−0.04	0.20	0.49***
2012	0.40***	0.39***	0.37***	0.38***	0.67***	0.42***	0.26***	0.62***	0.58***	0.06	0.05

Table 4
Time-frequency correlation estimates for the oil – stocks pair. The high-frequency set contains wavelet correlation estimates based on high-frequency data. The daily set contains wavelet correlation estimates based on daily data. Gray background represents years where the hypothesis of homogeneous correlations is rejected. Correlations statistically different from zero are denoted by asterisks (* 10%, ** 5%, *** 1%).

	Oil-Stocks										
	High-frequency data					Daily data					
	10 min	20 min	40 min	80 min	160 min-year	2 days	4 days	8 days	16 days	32 days	64 d. - year
1987	0.03*	0.01	0.05***	0.04	−0.64***	−0.11	0.21	−0.07	−0.09	−0.03	0.66***
1988	0.03***	−0.03*	−0.05***	−0.11***	0.30***	−0.06	0.13	−0.09	−0.15	−0.30	−0.74***
1989	0.01	0.00	0.03	−0.02	0.13***	−0.08	0.12	−0.06	−0.10	−0.74*	0.06
1990	−0.02	−0.12***	−0.18***	−0.20***	−0.54***	−0.38***	−0.46***	−0.62***	−0.25	0.04	−0.84***
1991	−0.04***	−0.10***	−0.17***	−0.19***	−0.49***	−0.06	−0.06	0.38***	0.34	−0.51	0.58***
1992	0.03	0.01	0.04	−0.02	−0.51***	0.08	0.04	0.20	−0.20	−0.52	0.50***
1993	0.00	0.00	−0.01	−0.02	0.73***	−0.05	−0.11	0.24	0.42	0.10	−0.63***
1994	0.00	0.01	−0.03	−0.04	−0.77***	−0.23***	−0.05	0.01	0.13	−0.47	−0.58***
1995	−0.02	0.01	0.02	0.00	−0.47***	−0.05	0.04	0.06	0.37	−0.14	−0.20***
1996	0.00	0.00	0.00	−0.03	−0.02	−0.02	0.05	−0.18	−0.15	−0.38	0.56***
1997	0.00	0.00	0.07***	0.08***	−0.61***	−0.15	0.00	0.02	0.08	0.19	−0.50***
1998	0.00	−0.02	0.02	0.02	0.64***	0.04	0.13	0.15	0.21	0.52	−0.79***
1999	−0.01	0.02	0.03	0.00	−0.94***	−0.03	0.01	0.09	0.17	0.73*	0.99***
2000	0.02	−0.01	−0.02	−0.05	−0.18***	−0.11	−0.09	0.07	−0.11	−0.53	−0.24***
2001	0.01	0.04***	0.03	−0.05	0.51***	−0.12	−0.04	0.08	0.03	0.84***	0.81***
2002	−0.01	−0.01	−0.02	−0.03	−0.70***	0.17*	0.19	0.41***	0.24	0.36	−0.53***
2003	−0.01	−0.03	−0.04	−0.05	0.57***	−0.24***	0.08	−0.49***	−0.36	−0.58	−0.54***
2004	−0.07***	−0.15***	−0.18***	−0.25***	0.13***	−0.13	0.01	0.05	−0.08	−0.68***	−0.71***
2005	−0.16***	−0.19***	−0.17***	−0.18***	0.00	−0.09	0.14	0.04	−0.46*	−0.20	0.32***
2006	0.04***	0.07***	0.09***	0.10***	−0.08***	0.07	0.07	0.08	0.24	0.46	−0.12*
2007	0.09***	0.13***	0.13***	0.12***	−0.63***	0.17*	0.07	−0.04	0.04	0.18	0.74***
2008	0.26***	0.27***	0.31***	0.33***	0.70***	0.42***	0.32***	0.09	0.05	0.12	−0.47***
2009	0.42***	0.46***	0.48***	0.50***	0.92***	0.53***	0.28***	0.61***	0.10	−0.05	0.51***
2010	0.57***	0.59***	0.58***	0.62***	0.69***	0.70***	0.71***	0.51***	0.58***	0.91***	0.86***
2011	0.50***	0.53***	0.53***	0.56***	0.32***	0.53***	0.57***	0.62***	0.53***	−0.03	0.74***
2012	0.49***	0.48***	0.47***	0.46***	0.26***	0.52***	0.54***	0.74***	0.53***	0.12	0.30***

4.2. Homogenous vs. heterogeneous correlations

Figs. 2–4 provide important insights into the correlation dynamics but cannot offer more precise inferences. Therefore, we proceed with a detailed test of our hypothesis of homogeneous correlations across investment horizons (within each year). Formally we can write the hypothesis as H_0: $\rho_{xy}(j) = \rho_{xy}(i)$ for $i, j \in \{1,2,3,4\}$, where j and i are wavelet scales representing investment horizons, and $i \neq j$. We test this hypothesis on high-frequency data for each year. The hypothesis allows testing whether there is heterogeneity in correlations that is theoretically underpinned by differences in investors, their beliefs, investment strategies, and market links among assets.

We summarize our results in Tables 2–4. First, for each pair of variables, we present an individual table containing the summarized correlations over the period of one year. Each table contains two sets of results where correlations are computed on various investment horizons obtained by the wavelet decomposition for each year. The first set of correlations is based on high-frequency intraday data for different investment horizons ranging from 10 min ($j = 1$) to 80 min ($j = 4$. The second set contains daily correlations with investment horizons ranging from 2 days ($j = 1$) to 32 days ($j = 5$). For both data resolutions, we also offer a low-frequency component (about one year; columns labeled 160 min-year and 64 day-year). In order to support the interpretation of our results we test whether the correlations, for each year and for each investment horizon, are statistically different from zero. The statistical significance of correlations at standard significance levels is reported in Tables 2–4 and denoted by the usual asterisks. Finally, the assumption of homogeneous vs. heterogeneous correlation is assessed through a hypothesis test. The years in which the hypothesis of homogeneous correlations across scales (investment horizons) is rejected within the 95% confidence interval are emphasized by a gray background (Tables 2–4).

Our key finding on the intraday frequency is that in a uniform way we are able to reject the hypothesis of homogeneity in correlations for all three pairs during specific periods that are common to all three pairs. With some minor gaps in years we reject the hypothesis during the early years of our sample (1987–1991), and then immediately prior to and during the financial crisis (2006–2009). Hence, periods of heterogeneity in correlations for all three pairs are present around prominently troubled times: first, the 1987 market crash slowly turning into the early 1990s recession, and second, the financial crisis in 2007–2008. During the rest of our data span the correlations are quite homogenous for the gold-oil and oil-stocks pairs, while the gold-stocks pair exhibits substantial heterogeneity in correlations over time.

Daily correlations offer a more complex pattern. The correlations change their values at various investment horizons more often than the intraday-based correlations. Further, both periods of increased correlations, in the early 1990s and around the financial crisis, are present but they do not stand out so sharply because during other years correlations at specific investment horizons are also quite high. Finally, daily correlations are homogenous across the chosen horizons since the hypothesis could not be rejected. Correlations seem to be higher at longer investment horizons of about one month, while they are very low at short investment horizons measured in days. From 2006 the pattern changes, though. First, correlations alter their magnitudes quite often and these changes are unparalleled in the past. Second, markets become quite homogeneous in the perception of time. Correlations at shorter and longer investment horizons become less diversified. This indicates that differences in short and long investment horizons diminish. A greater homogeneity in the perception of these differences among investors may reflect a heightened uncertainty on markets as well as questionable economic performance in many developed countries following the crisis.

Intraday-based correlations provide further insights (Tables 3–4). First, the results show an overwhelming evidence of heterogeneity in correlations between gold and stocks (Table 3). With some gaps for individual years, we are able to reject the hypothesis of homogeneous correlations for most of the sample from 1987 to 2007. Second, in terms of heterogeneity, the results of the oil-stocks pair (Table 4) resemble the outcome for the gold-oil pair (Table 2). In the early years of our sample we also witness a prevailing heterogeneity in the correlations across horizons during troubled times (1988, 1990–1991). Another period of heterogeneity is visible during the crisis period (2008–2009); in this sense we find heterogeneity in correlations later than in the case of the gold-oil pair.

Further, an interesting pattern emerges in the heterogeneity of correlations at investment horizons before the correlations radically change pattern. This is visible in Figs. 2–4 in the form of structural breaks (more details on structural breaks in assets are presented in Section 4.3).[12] For example, the gold-oil pair shows a significant increase in the overall correlation inferred from the DCC GARCH estimates during the periods 1994–1996 and 1998–2000; in line with this finding Turhan, Sensoy, Ozturk, and Hacihasanoglu (2014) cover the 1983–2013 period and document a strong positive trend towards higher correlations for the crude oil and gold pair. While DCC GARCH in fact shows the averaged correlation over the various investment horizons, wavelet correlations further reveal that this increase might be induced specifically by the long term correlations because correlations on short horizons are zero. We further observe that before the structural break, correlations between gold and stocks were very heterogeneous across various investment horizons implying a potential for risk diversification related to different investment horizons. However, after the structural break we can notice that correlations became very homogeneous in terms of their patterns (gold-oil, gold-stocks), which implies that gold, oil, and stocks could not be used effectively in one portfolio at the same time for risk diversification. This finding goes against the results of Baur and Lucey (2010), who find gold to be a good hedge against stocks and moreover a safe haven in extreme stock market conditions. In general, however, our result resonates well with the argument of Bartram and Bodnar (2009) that diversification provided little help to investors during the financial crisis. Further, our findings of increased correlations and their homogeneity during the post-crisis period are also in line with the results of the wavelet analysis of Reboredo and Rivera-Castro (2014a; p.149) who provide "evidence of both contagion and increased (positive) interdependence between oil and (European and US) stock markets in

[12] We formally tested for structural breaks in correlations by employing the supF test (Andrews, 1993; Andrews and Ploberger, 1994; Hansen, 1992) with p-values computed based on Hansen (1997).

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Table 5
Johansen's cointegration results. The table reports trace test statistics together with *p*-values in parentheses. The break dates dividing the period into pre-break and post-break are September 8, 2006, May 5, 2009, and September 26, 2008 for the gold-oil, gold-stocks and oil-stocks pairs, respectively. The full period covers January 2, 1987 to December 31, 2012.

	gold-oil		gold-stocks		oil-stocks	
pre-break	10.07	(0.31)	6.70	(0.64)	7.87	(0.52)
post-break	9.75	(0.34)	7.66	(0.55)	6.94	(0.62)
full period	4.66	(0.84)	10.64	(0.25)	11.19	(0.20)

the period after the onset of the global financial crisis." Further, Turhan et al. (2014) show very fast increase in positive correlations between the crude oil-stocks pair after the 2008 global financial crisis. Our results also indirectly support findings of Ewing and Malik (2013) pointing at the idea of cross-market hedging and sharing of common information by financial market participants trading gold and oil futures.

The pattern described above can also be attributed to changes in investors' beliefs, which become homogeneous across investment horizons after the structural break.[13] This can be partially caused by broader uncertainty on financial markets; the influence of time-varying uncertainty on price formation and the diversification benefits is shown by Connolly, Stivers, and Sun (2007) during 1992–2002 across a number of major stock markets. Another good reason for more homogeneous correlations across investment horizons could be the movement of investors away from passive investment strategies to more aggressive ones. Finally, after the introduction of full electronic trading on exchange platforms in 2005, the volume of automatic trading increased rapidly, a feature that may have increased homogeneity in correlations as well.

Thanks to the ability of wavelet analysis to provide results at different investment horizons, we are able to generalize inferences related to risk diversification. When correlations differ in their magnitudes at different investment horizons, risk diversification is possible. Low, negligible, or even no differences in correlation magnitudes at different investment horizons on the other hand preclude effective risk diversification in time. With the assets under research, risk diversification seems to be successful until 1991 for all three pairs. Later on differences emerge: (i) the diversification potential continues for the gold-stocks pair until the financial crisis eruption in 2007; (ii) diversification is limited from 1991 until the crisis for the gold-oil and oil-stocks pairs as correlations are largely homogenous; finally, (iii) no pair allows for diversification during the post-crisis period as correlations become homogenous.

4.3. Structural changes and long-term equilibrium links: cointegration

Finally, we test for the existence of structural changes and when accounting for them, we test for long-term equilibrium relationships among assets. There exist reasons why gold and oil might share a cointegration relationship. Both assets are sensitive to strong economic and political events (Aggarwal & Lucey, 2007). The simple fact that both assets in our data set are quoted in U.S. dollars creates a potential link as well because volatile movements in the U.S. dollar would affect both assets in the same direction. Plus, Tully and Lucey (2007) show that the U.S. dollar is a key variable that exhibits a strong link towards gold and Zhang, Fan, Tsai, and Wei (2008) show the same for oil. Further, gold is quite resistant with respect to inflation while increases in oil prices usually affect the aggregate price level and lead to an increase in inflation, which makes investment in gold more attractive. Finally, when major oil deliveries are paid during periods of higher oil prices, producers might use excess proceeds to buy gold whose price would increase due to higher demand (Zhang & Wei, 2010).

We have tested three pairs of assets for structural breaks and cointegration in the following way. First, we employed the sup*F* test (Andrews, 1993; Andrews & Ploberger, 1994; Hansen, 1992), with *p*-values computed based on Hansen (1997), and applied it to derived correlations between pairs of assets to endogenously search for the presence of structural breaks.[14] Hence, the endogenously detected break in the correlation series for a specific pair of assets is taken as a break to divide the sample of data to test for cointegration between the same pair of assets. Second, based on the results of the break test we divided the data into individual pre-break and post-break sub-samples that differ in their spans depending on the date of the identified break. For the asset pairs, the break dates were identified as follows: September 8, 2006 for gold-oil; May 5, 2009 for gold-stocks; and September 26, 2008 for oil-stocks. Finally we tested for cointegration between pairs of assets by employing the standard Johansen's procedure with appropriately chosen numbers of lags.[15] The cointegration results are presented in Table 5 for three periods: the pre-break period, the post-break period, and the full period (1987–2012).

For all three periods and all pairs of assets the result is unique: no cointegration was found. This finding is not entirely unexpected, though. Our result resonates well with that of Zhang and Li (2014) who show no cointegration relationship between the Chinese and U.S. stock markets even when allowing for structural change. Further, Egert and Kočenda (2007) show that cointegration is often missing among less developed emerging markets in Europe. Finally, the lack of cointegration is in line with a lack of economic linkages

[13] The importance of investors' beliefs and how they act on them has been recently shown by Ben-David and Hirshleifer (2012). Further, Chen et al. (2013) show that heterogeneous beliefs cause excess volatility and dispersion in investors' beliefs well explains stock market mispricing.

[14] To conserve space, we do not report the test statistics for the detection of structural breaks. The results are available upon request.

[15] This result is robust with respect to lag selection as it does not change for any tested lag from 0 to 5. The results are available upon request.

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among these assets in terms of production, substitution, and complementary relationships as voiced by Casassus, Liu, and Tang (2013).

5. Conclusions

In this paper we analyze dynamic correlations between pairs of key traded assets by employing a time-frequency approach with a wavelet methodology; the realized volatility and DCC GARCH approaches serve for comparison. In terms of the dynamic method the wavelet-based correlation analysis enables analyzing co-movements among assets not only from a time series perspective but also from the investment horizon perspective. Hence, we are able to provide unique evidence on how correlations between major assets vary over time and different investment horizons. We analyze the dynamic correlations of the prices of gold, oil, and the broad U.S. stock market index S&P 500 over 26 years from January 2, 1987 until December 31, 2012. The analysis is performed on both intraday and daily data.

Our findings suggest a superior performance of wavelet analysis over standard benchmark approaches: wavelet analysis offers rich evidence of the heterogenous patterns in linkages among assets over time and across number of investment horizns. We show that heterogeneity in correlations across a number of investment horizons and between pairs of assets is a dominant feature during times of economic downturn and financial turbulence for all three pairs of asset under research. Moreover, heterogeneity prevails for most of the pre-crisis period in correlations between gold and stocks. The period when correlations between assets across investment horizons are homogenous run from the early 1990s until the financial crisis in 2008 (gold-oil, oil-stocks).

The post-crisis development is marked by a dramatically increased extent of correlations among all three assets and homogenous correlations as well. The timing of these changes differs for the three pairs. However, increases in correlations and their homogeneity occur after the structural breaks that have been identified in specific correlation series. After the breaks, the correlations for all pairs increased on average, but their magnitudes exhibited large swings up and down. Despite this strongly varying behavior, the correlations between pairs of assets became homogeneous and did not differ at distinct investment horizons. A strong implication emerges. During the period under research, and from different investment horizons perspectives, all three assets could be used in a well-diversified portfolio less often than common perception would have it.

Appendix A. Wavelet variance

For a real-valued covariance stationary stochastic process $x(t)$, $t = 1, 2, \ldots, N$, with mean zero, the sequence of the MODWT wavelet coefficients $W_x(j,s)$, for all $j, s > 0$ unaffected by the boundary conditions, obtained by the wavelet decomposition at scale j is also a stationary process with mean zero. The wavelet variance at scale j is the variance of wavelet coefficients at scale j, i.e.,

$$\nu_x(j)^2 = var(W_x(j,s)). \tag{A1}$$

For process $x(t)$, the estimator of the wavelet variance at level j is defined as

$$\nu_x(j)^2 = \frac{1}{M_j} \sum_{s=L_j-1}^{N-1} W_x(j,s)^2, \tag{A2}$$

where $M_j = N - L_j + 1 > 0$ is the number of j-th level MODWT coefficients that are unaffected by boundary conditions and L_j denotes length of a wavelet filter at scale j (Serroukh, Walden, & Percival, 2000). While the variance of a covariance stationary process $x(t)$ is equal to the integral of the spectral density function $S_x(.)$, the wavelet variance at a particular level j is the variance of the wavelet coefficients $W_x(j,s)$ with spectral density function $S_x(j)(.)$:

$$\nu_x(j)^2 = \int_{-1/2}^{1/2} S_x(j)(f)df = \int_{-1/2}^{1/2} \mathscr{H}_j(f) S_x(j)(f)df, \tag{A3}$$

where $\mathscr{H}_j(f)$ is the squared gain function of the wavelet filter h_j (Percival & Walden, 2000). Since the variance of a process $x(t)$ is the sum of the contributions of the variances at all scales we can write:

$$var(x) = \sum_{j=1}^{\infty} (\nu_x(j)^2. \tag{A4}$$

However, for a finite number of scales we have:

$$var(x) = \int_{-1/2}^{1/2} S_x(f)df = \sum_{j=1}^{J} \nu_x(j)^2 + var(V_x(J,s)). \tag{A5}$$

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Appendix B. Wavelet covariance

Let $x(t)$ and $y(t)$ be covariance stationary processes with the square integrable spectral density functions $S_x(.), S_y(.)$, and cross spectra $S_{xy}(.)$. Since we use an LA8 wavelet with length $L = 8$, we can use a generally non-stationary process, that is, it is stationary after the d-th difference, where $d \leq L/2$. The wavelet covariance of $x(t)$ and $y(t)$ at level j is then defined as:

$$\gamma_{xy}(j) = Cov\Big(W_x(j,s), W_y(j,s)\Big). \tag{B1}$$

For a particular level of decomposition $J \leq log_2(N)$, the covariance of $x(t)$ and $y(t)$ is the sum of the covariances of the MODWT wavelet coefficients $\gamma_{xy}(j)$ at all scales $j = 1, 2, \ldots, J$ and the covariance of the scaling coefficients $V_x(J,s)$ at scale J:

$$Cov(x_t, y_t) = Cov\Big(V_x(J,s), V_y(J,s)\Big) + \sum_{j=1}^{J} \gamma_{xy}(j). \tag{B2}$$

For the processes $x(t)$ and $y(t)$ defined above, the estimator of the wavelet covariance at level j is defined as

$$\gamma_{xy}(j) = \frac{1}{M_j} \sum_{s=L_j-1}^{N-1} W_x(j,s) W_y(j,s), \tag{B3}$$

where $M_j = N - L_j + 1 > 0$ is the number of j-th level MODWT coefficients for both processes that are unaffected by boundary conditions and L_j denotes the length of the wavelet filter at scale j. Whitcher et al. (1999) prove that for Gaussian processes $x(t)$ and $y(t)$, the MODWT estimator of wavelet covariance is unbiased and asymptotically normally distributed.

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