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Gold Price Dynamics and the Role of Uncertainty*

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Abstract

This study adopts a copula wavelet approach to analyze dynamics of the gold price against bonds, stocks and exchange rates based on disaggregation of the underlying relationships across different frequencies. We also examine whether gold prices are directly affected by changes in uncertainty. Analyzing data for nine economies for a sample period starting in 1985, we find that the role of gold changes significantly after the collapse of Lehman Brothers in 2008. Gold is unable to serve as a hedge in the classical sense while the findings for the period prior to 2008 mostly suggest that gold is able to shield investors. Uncertainty measures display a surprising and time-varying relationship with the path of the gold price. While economic policy uncertainty is positively correlated with gold price developments, macroeconomic uncertainty and inflation uncertainty among forecasters are both negatively related to gold.

Keywords: bonds, exchange rates, gold, hedge, safe haven, stocks, uncertainty

JEL classification: G11, G15, C58

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1 Introduction

There is arguably no asset which mirrors the transformation of financial markets over the last decades more appropriately than gold. Under the fixed exchange rate arrangement of Bretton Woods, gold was originally supposed to operate as the main anchor due to its fixed rate against the US dollar of 35$ per troy ounce. However, private demand for gold increased significantly during the 1960s and contributed to the breakdown of Bretton Woods in 1973. While the gold market was mostly dominated by central banks prior to this point, private demand is now the main driver of gold price fluctuations. In line with the deepening of financial markets, both size and volatility of the gold markets have increased, leaving economists with the task of understanding the path of gold prices. After a comparably stable period during the eighties, the volatility of the gold price has increased significantly since the start of the Millennium due to the evolution of financial markets. As a result, the price of gold is one of the most studied topics in international finance. A well-established wisdom is that gold has the ability to serve as a hedge or safe haven against other assets (Baur and Lucey, 2010). Considering that this topic has been extensively examined, it is surprising that most results only focus on a particular selection of (either) sampling frequencies, investment horizons or assets. Another shortcoming in the quite extensive literature on the economics of gold is the narrow focus when it comes to the role of risk and uncertainty for the gold price. This is even more surprising considering that paths and turning points of the gold price remain some kind a mystery, with even Ben Bernanke stating that he does not fully understand the price of gold.[1]

Against this background, this paper provides an innovative and comprehensive perspective on the role of gold for investors and financial markets. The contribution of this paper is a systematic analysis of the hedge and safe haven function of gold against bonds, stocks and exchange rates as well as the link between gold and uncertainty. Instead of exclusively relying on the traditional definition of hedge and safe haven properties, we explicitly take different categories of macroeconomic uncertainty and policy uncertainty into account. These measures reflect uncertainty based on newspaper coverage, common unpredictable components in macroeconomic series as well as dispersion among the opinions of forecasters. As previous research has mostly focused on the correlation between gold and assets such as stocks or bonds when assessing hedge and safe haven properties, we argue that the explicit consideration of risk and uncertainty measures offers an additional perspective which provides novel insights on the role of gold. Different kinds of uncertainty potentially have different impacts on the price of gold. Previous research on hedge or safe haven properties implicitly assumes that the link between gold and other assets is different in times of uncertainty. It is therefore necessary to assess the

[1] "*Nobody really understands gold prices and I don't pretend to understand them either.*" Ben Bernanke, Congressional Testimony, July 18, 2013.

link between gold and uncertainty directly instead of looking at the relationship between other assets and gold as a potential transmission channel of uncertainty effects. Forward looking agents base their decision on present values of assets and portfolios. For this reason, a rise in uncertainty should result in an increasing demand for gold and, ceteris paribus, should therefore lead to a higher gold price if gold is considered to be of particular importance in times of stress and uncertainty. Besides distinguishing between economic policy and macroeconomic uncertainty, we also take inflation forecast uncertainty based on expectations of professionals into account.

Furthermore, we apply a wavelet analysis to decompose the assessed return series into its short-run and long-run trends. In doing so, we are able to analyze the properties of gold with respect to different time horizons and provide a thorough analysis of the safe haven properties of gold for different trends of the underlying assets. Additionally, we add to the analysis of linear dependence by taking joint extreme movements (i.e. tail dependence) into account. Therefore, we apply a flexible copula approach and assess the dependence between the returns of gold and other assets in calm and turmoil market times.

Based on these thoughts, we contribute to the literature by providing an extensive analysis regarding the relationship of gold relative to bonds, stocks, exchange rates and uncertainty indices for several economies. In addition, we emphasize the properties of gold with respect to market uncertainty by assessing competing uncertainty indexes. Based on this setting, we provide a broad analysis of gold price properties, mainly focusing on three issues: (1) Has the role of gold in financial markets undergone changes since the start of the Millennium? (2) Are gold prices directly affected by uncertainty? (3) Over which time horizons does a relationship between gold and other assets (i.e. stocks, bonds, and exchange rates) as well as risk and uncertainty measures exist?

Compared to previous research, our study is based on a broader range of countries and time periods. We analyze three different sub-sample periods and different time horizons as well as emerging and industrial economies. Furthermore, our analysis is based on the connection of copula and wavelet techniques which have not been used simultaneously in this context in previous studies. Our empirical strategy enables us to provide systematic results over different time horizons. This allows a critical assessment of hedge and safe haven properties for short-, medium- and long-run trends. Finally, we take into account different uncertainty measures to address both uncertainty related to macroeconomic indicators and also the future stance of economic policy.

The rest of this paper is organized as follows. The next section summarizes previous empirical findings. Section 3 describes our dataset and our empirical methodology. Section 4 summarizes our empirical results and Section 5 concludes.

2 Literature review

Considering that gold has attracted a wide field of research, we briefly summarize the overall research results which are related to our study.[2] From an economic perspective, our study is related to the role of gold in investment portfolios. There is a strong belief that gold is able to diversify portfolios. The safe haven assumption reflects the common view that investors invest in gold in times of financial stress or uncertainty. The existing literature usually compares the correlation between gold and other assets in normal times and periods of uncertainty. We also focus on an inverse relationship between the price of gold and uncertainty. More precisely, the main question we address is whether gold serves as a hedge or safe haven across different periods. Generally, a strong (weak) hedge is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio on average whereas a strong (weak) safe haven is defined as an asset that is negatively correlated (uncorrelated) with another asset or portfolio in times of market stress or turmoil (Baur and McDermott, 2010).

Before we turn to specific empirical findings, it is useful to reconsider previous empirical research on the role of gold as a hedge or a safe haven. The return of gold is usually analyzed relative to stock and/or bond returns testing the assumption that gold serves as a hedge or safe haven against both. Since gold is denominated in US dollar, another strand of the literature analyzes the price of gold relative to dollar exchange rates with the underlying idea that the price of gold is the same in different currencies according to the law of one prices. It is therefore argued that a currency depreciates against other currencies if the gold price denominated in the corresponding currency increases (Pukthuanthong and Roll, 2011). Table I presents a summary of a broad range of studies dealing with these properties for specific assets adopting different techniques. Stock prices and exchange rates are the most frequently considered assets relative to gold while bond prices have also attracted some attention recently. Hedge and safe haven properties have been analyzed using different frameworks. Overall, the results of these studies mainly provide evidence in favor of the hedge and safe haven function of gold. However, the findings differ with regard to the choice of the sample period, the country, the data frequency and the empirical approach. As outlined in the Introduction, the usual correlation/regression based test approach relying on the definition for a hedge and a safe haven does not directly relate to risk or uncertainty. This is problematic since a correlation between returns of gold and other assets is potentially driven by several factors in times of financial stress. One study which draws a direct link between gold prices and uncertainty is provided by Jones and Sackley (2016) who find that an increase in economic policy uncertainty contributes to an increase in the price of gold. However, they neither distinguish between different kinds of uncertainty nor

[2] See O'Connor *et al.* (2015) for a comprehensive overview of gold research.

take different time frequencies into account. Most importantly, they do not consider co-movements between gold prices and macroeconomic uncertainty. We aim to fill this gap by directly addressing the role of different uncertainty measures for different trends based on a copula wavelet approach.

The uncertainty measure provided by Jurado *et al.* (2015) focuses on predictability of the state of the economy. More precisely, uncertainty for a specific variable $y_{j,t}$ is given by

$$y_{j,t+k} - E_t(y_{j,t+k}|I_t), \tag{1}$$

where I_t denotes the information set of economic agents. The underlying idea of this uncertainty measure is to control for the systematic component $E_t(y_{j,t+k}|I_t)$ while dissecting forecastable variations and the unpredictable component. The aggregated uncertainty measure displays the common variation of uncertainty across many variables $y_{j,t}$ but is independent of the uncertainty about any particular variable (Jurado *et al.*, 2015).

The consideration of forecasters disagreement regrading CPI (consumer price index) inflation as an additional measure of uncertainty also provides a novel perspective in this context. One view is that higher inflation expectations will increase the demand for gold because investors use gold as a hedge or put a bet on an increase in the price of gold. On the other hand, Blose (2010) argues that the price of gold is not affected by changing inflation expectations since costs of carrying gold increase through changes in interest rates due to a rise in expected inflation. Considering that heterogeneous expectations of agents are also relevant when analyzing the gold market (Baur and Glover, 2014), examining the link between disagreement among inflation forecasters and the gold price is an interesting addition to studies on the gold-inflation nexus.

When it comes to the analysis of different time horizons, many studies have adopted cointegration techniques to disentangle long-run and short-run dynamics. Although these kinds of studies provided important contributions, their insights regarding the exact horizons for gold properties are limited. A typical analysis includes long-run estimates and an error correction analysis. The resulting degree of reversion to a long-run equilibrium depends on the chosen technique and is restricted by the frequency of the analyzed data (Beckmann and Czudaj, 2013). The average speed of long-run equilibrium adjustment over a full sample period is only able to account for a fraction of the short-run dynamics while long-run relations by definition do not account for structural breaks. The provided information therefore turns out to be insufficient for an investor who has a specified time horizon in mind when managing his portfolio. The applied wavelet approach we adopt is able to address hedge and safe haven properties through a dissection of these properties for different time spans at a specific point in time.

Studies relying on copula and wavelet approaches have recently been adopted to analyze gold price movements. From an econometric perspective, the closest contributions to our study are provided by Reboredo and Rivera-Castro (2014a,b) and Michis (2014). However, the latter two studies adopt wavelet approaches in a different context while the first study focuses exclusively on copulas when analyzing the price of gold. In addition, both studies do not address the issue of uncertainty, focus on one frequency and do not analyze stocks, bonds and exchange rates simultaneously. Thus, we add to the assessment of gold price movements by taking joint extreme movements of particular seasonalities into account.

*** Insert Table I about here ***

3 Data and empirical framework

3.1 Data

Gold prices denominated in different currencies, exchange rates against the US dollar as well as stock and 10-year bond indices for the US, Germany, Japan, the UK, Canada, India, China, South Africa, and Australia are obtained from Thomson Reuters Datastream. We have calculated returns of all these series. In addition, we base our analysis on three different uncertainty measures. As a proxy for macroeconomic uncertainty, we rely on the measure provided by Jurado *et al.* (2015) which relies on common volatility in the unforecastable component of 132 macroeconomic time series based on a large number of economic indicators.[3]

We see this as an advantage in the sense that this puts us in a position to compare intensities of the link between gold and other assets on the one hand and between gold prices and macroeconomic uncertainty on the other hand. In addition, we also account for the role of policymakers by considering the economic policy uncertainty index provided by Baker *et al.* (2016). This index is based on uncertainty coverage in newspapers based on text-searching of the 10 largest newspapers in the US: the USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, New York Times, and the Wall Street Journal.[4]

[3]We consider macroeconomic uncertainty over the next month owing to the fact that we analyze different time horizons based on our wavelet approach. This macroeconomic uncertainty measure provided by Jurado *et al.* (2015) is also available for 6 and 12 month horizons. The corresponding results for these two horizons are available by the authors upon request.

[4]The index is obtained based on articles containing the triple of: 'uncertainty' or 'uncertain'; 'economic' or 'economy';

Finally, the third index we consider is also provided by Baker *et al.* (2016) and reflects disagreement among consumer price index (CPI) forecasters. As outlined earlier, such a measure is important considering the proposed link between inflation and the price of gold. Expected inflation uncertainty should have a direct impact on the price of gold if the latter incorporates inflation expectations. For all three measures an increase reflects higher uncertainty.[5]

Our sample period runs from 1985 until 2014 and we analyze daily, weekly, and monthly data. Our sample is sub-divided in three sub-sample periods: 1985-2000, 2001-2008 and 2008-2014.[6] This distinction is motivated by the gold price cycle. The first sub-period is characterized by comparable small fluctuations in the gold price while the second sub-sample displays higher volatility and an upward trend in the price of gold. The collapse of Lehman Brothers in 2008:09 marks the starting point of the final period.

3.2 Empirical framework

3.2.1 Wavelet decomposition

As we aim at extracting both time-varying and frequency-varying properties of the underlying return series, wavelet analysis describes an adequate signal processing technique to assess an alternative presentation of a decomposed time series on a scale-by-scale basis.[7] In the remainder we will briefly state the applied wavelet setup and we refer to Percival and Walden (2000) and Gençay *et al.* (2001) for a thorough technical introduction to wavelets and to Crowley (2007) for an intuitive discussion on wavelets for economists.

In order to decompose financial return series into its different trends, we use the maximal overlap discrete wavelet transform (MODWT) as introduced by Percival and Walden (2000). The applied algorithm is based on the discrete wavelet transform (DWT), but in contradiction to this approach it overcomes DWT-specific shortcomings as it is described by so called shift invariance. That is, all decomposed trends comprise the same amount of observations and we are able to localize events at each scale.

However, as MODWT describes a natural extension of DWT, the choice of wavelet coefficients remains the balance point of this decomposition technique. Let $h_{j,l}$ be the DWT mother wavelet filter, with

and one of the following six policy terms: 'congress', 'deficit', 'Federal Reserve', 'legislation', 'regulation' or 'white house' (Baker *et al.*, 2016).

[5]We are aware that stock market developments are included in this approach.

[6]Bampinas and Panagiotidis (2015) used a break point in 2007:08 in a comparable context. However, our findings are not sensitive to this choice.

[7]Typically, the Fourier transformation describes the most common approach to decompose a signal into different frequencies. However, as the Fourier analysis does not allow us to locate events at different frequencies, we apply the wavelet technique.

$l = 0, \ldots, L-1$ describing the length of the filter and $j = 1, \ldots, J$ the level of decomposition, the DWT wavelet filter $h_{j,l}$ is characterized as a linear time invariant filter such that for all $n \neq 0$:

$$\sum_{l=0}^{L-1} h_{j,l} = 0, \qquad \sum_{l=0}^{L-1} h_{j,l}^2 = 1, \qquad \sum_{l=-\infty}^{+\infty} h_{j,l} h_{j,l+2n} = 0. \tag{2}$$

This means, that $h_{j,l}$ sums to zero, has norm 1 and is orthogonal to its even shifts. The respective scaling filter $g_{j,l}$ is then determined by the quadrature mirror relationship.[8]

Then, the relevant MODWT wavelet and scaling filter are obtained directly from the respective DWT filters by

$$\tilde{h}_{j,l} = h_{j,l}/2^{j/2}, \tag{3}$$

and

$$\tilde{g}_{j,l} = g_{j,l}/2^{j/2}. \tag{4}$$

To decompose a time series $y = \{y_t, t = 1, 2, ..., N\}$ into J frequencies, as presented by Percival and Walden (2000), the relevant wavelet coefficients of level j are achieved by the convolution of y and the MODWT filters:

$$\widetilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} y_{t-l \bmod N}, \tag{5}$$

and

$$\widetilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} y_{t-l \bmod N}. \tag{6}$$

with $L_j = (2^j - 1)(L-1) + 1$. Due to the setup of MODWT, wavelet coefficients at all scales are described by the same amount of observations as the original time series and can be expressed in matrix notation:

$$\widetilde{W}_{\mathbf{j}} = \tilde{\omega}_j y \tag{7}$$

and

$$\widetilde{V}_{\mathbf{j}} = \tilde{v}_j y. \tag{8}$$

Specifically, both $\tilde{\omega}$ and $\tilde{v}$ describe $N \times N$ matrices and the relevant detail coefficients are then achieved by $\widetilde{D}_j = \tilde{\omega}_j^T \widetilde{W}_j$ and the smoothed version of the return series is given by $\tilde{S}_J = \tilde{v}_j^T \widetilde{V}_J$.

Therefore, the relevant property of wavelet decomposition is given by the fact that a time series y

[8] More precisely, $g_{j,l} = (-1)^{l+1} h_{j,L-1-l}$ for $l = 0, ..., L-1$. We refer to Percival and Walden (2000) for a detailed proof.

can be decomposed into a set of $j = 1, 2, \ldots, J$ components that describe short-term noise, long-run trends and a smoothed version at scale J of the underlying series:

$$y = y(\widetilde{D}_1) + y(\widetilde{D}_2) + \ldots + y(\widetilde{D}_J) + y(\widetilde{S}_J). \tag{9}$$

In this setup $y(\widetilde{D}_j)$ describes the local details of the time series at decomposition level j and $y(\tilde{S}_J)$ provides the smoothed version of the underlying time series.[9] Specifically, $y(\widetilde{D}_1)$ describes high frequency components whereas as j increases the frequency decreases.[10] In order to take account for an adequate filter length and to ensure robustness of our results, we follow Gallegati (2012) and Gençay *et al.* (2001) and apply competing filters.[11]

3.2.2 Dependency measurement

The setup of the decomposed return series (as presented in Eq. (9)) enables us to analyze dependence of particular trends ($\widetilde{D}_j$) and we apply copulas to scrutinize dependence patterns between short-term changes and long-run trends of the underlying return series. The copula approach is based on Sklar's theorem (1959) and separates dependence modeling from the choice of marginal distributions.

In our analysis, we assess either the original return series of asset i (y_i) or its decomposed version ($y(\widetilde{D}_j)_i$) at level j. Moreover, if the univariate marginal distributions are known, the copula dependence (C) can be estimated. Thus, to fit the copula parameters to our data, we transform the original and the details of the underlying data to the copula scale by using a kernel estimator of the cumulative distribution functions.

Moreover, as the t copula presents a solid middle way between the intuitive interpretation of the linear correlation coefficient and the capability of more sophisticated Archimedean copulas that capture joint extreme movements (so called tail dependence), we focus on dependence between different frequencies of gold returns modeled via the t copula.[12]

Let u_i denote the transformed series of the original or decomposed return series of asset i, then, the

[9] It is worth to note that we apply the MODWT-specific notation to avoid any confusion with DWT-specific notation.

[10] We provide an economic interpretation of the different scales in Section 4.

[11] We apply the Haar filter with $L = 2$ as well as the least asymmetric (LA) wavelet filter with different lengths $L = 4$, $L = 6$ $L = 8$ as introduced by Daubechies (1992). Due to the fact that the results led to qualitatively similar conclusions, in the remainder we exclusively present results based on the Haar filter, to indicate the relevance of our results for potential out-of-sample applications.

[12] It is to note, that we also applied linear correlation coefficients, Gaussian copulas, DCC-Gaussian copulas, DCC-t copulas as well as Archimedean copulas (Clayton, Gumbel) to check for the robustness of our results. These generally support our main findings but provide a weaker fit according to the AIC. All results are available upon request to the authors.

setup of the t copula is given by

$$C^t(u_1, \ldots, u_n) = t_{\rho,v}(t_v^{-1}(u_1), \ldots, t_v^{-1}(u_n)), \tag{10}$$

with t_v^{-1} presenting the inverse of the univariate t distribution and v indicating symmetric tail dependence. $t_{\rho,v}$ stands for the multivariate t distribution with correlation matrix ρ and v degrees of freedom (d.o.f.). The parameters of the t copula are estimated via a two-step maximum likelihood procedure as presented in Joe (1996) and also applied by Beckmann *et al.* (2016) in a different context.

4 Empirical results

In the following our framework provides results for the original returns and five different time-scales according to Eq. (9) based on three data frequencies (i.e. daily, weekly and monthly) for three different sub-sample periods (i.e. 1985-2000, 2001-2008 and 2008-2014) and nine different markets (i.e. the US, Germany, Japan, the UK, Canada, India, China, South Africa, and Australia). This section summarizes the findings for gold against stocks, bonds, exchange rates and uncertainty measures. We consider different time horizons and different copulas. For the sake of brevity, all results described in the following are based on the t copula. As we aim at the assessment of the dependence between decomposed time series, the results of the t copula are, from our point of view, the most important and most intuitive. As dependence is expressed analogous to the linear correlation coefficient in a range between -1 and 1 its interpretation is straightforward. But in contrast, a low number of degrees of freedom highlights that tail dependence (i.e. dependence between the extreme events of the returns of both assets) is an important feature of the underlying data. The overall findings are independent of the choice of a particular copula with results for alternative copulas available upon request. The results in Section 4.1 for stocks, bonds and exchange rates are solely provided for daily and monthly data while our findings for weekly data are available upon request in order to save space.

*** Insert Table II about here ***

As presented in Table II the n-th wavelet decomposition corresponds to a trend (time scale) of $2^5 = 32$ which leaves 32 observations as the maximum time span we consider. Due to a lack of data availability, the results for gold against our uncertainty measures are provided for monthly data only.[13] Figure I

[13]The newspaper-based index of Baker *et al.* (2016) is also available on a daily frequency. However, this is not the case for the macroeconomic risk measure of Jurado *et al.* (2015) and the disagreement among CPI forecasters. Daily data results for the newspaper-based measure are also available upon request.

illustrates the decomposition of monthly gold returns from 1985 to 2014 over the different time scales. By definition, the first scale displays a great degree of volatility while the fifth scale captures the long-term movement with remarkable less variation. This distinction needs to be kept in mind for the following interpretations.

*** Insert Figure I about here ***

4.1 Gold against stocks, bonds and exchange rates

Our framework provides two perspectives on the underlying dynamics. One the one hand, a comparison between daily and monthly results illustrates how the sampling frequency affects our findings. In addition, the different decomposed trends provided by our wavelet approach dissect dependence over seasonalities. Although both perspectives are related, since higher wavelet frequencies for daily data in a sense correspond to monthly developments, they are not equivalent with the higher monthly wavelet frequencies.[14] However, in the remainder of this survey, we present the analysis of both daily and monthly sampling frequencies to provide a complete picture of the underlying dynamics.[15]

Has the relationship changed over time?

(a) Stocks

First, we start by assessing the dependence between gold and stock returns. Therefore, we analyze the differences between the sampling frequency (daily and monthly) and we assess the dependence between stocks and gold for different sub-samples (1985-2000, 2001-2008 and 2008-2014).

*** Insert Table III about here ***

Table III presents the relevant dependence parameters that describe the relationship between stocks and gold and the corresponding degrees of freedom (d.o.f.). Obviously, stock returns do not display any remarkable dependence with gold returns at a daily frequency in all three sub-samples. Albeit monthly dependence turns out to be slightly stronger, it remains weak (within a range of -0.2 and 0.2)

[14] The fact that return series are measured periodically (daily/weekly/monthly) does not rule out seasonalities and long-run trends for the return series.

[15] The results for weekly data are available upon request.

for almost all markets while both positive and negative co-movements are observed. Interestingly, the findings indicate different dependence regimes over time. For instance, the dependence between gold and US stocks decreases in the second (2001-2008) compared to the first period (1985-2000) for monthly returns but slightly increases for daily observations. On the other hand, for Japan both daily and monthly stock returns are described by a stronger dependence to gold in the second compared to the first period. Both US and Japanese stocks are described by a slightly positive dependence to gold in the third sample period (2008-2014). Furthermore, based on monthly returns, India, South Africa and Australia are characterized by remarkable changes in the dependence between gold and stocks throughout the assessed sub-samples. In the 2001-2008 period monthly dependence between stocks and gold is positive (0.24) for South Africa and turns into negative (-0.18) for the period from 2008-2014. As well, stronger changes of co-movements are mostly observed for the third sample period whereas, (slightly) negative dependence is evident for Germany, India, South Africa and Australia. This indicates that gold has turned out to be a better hedge in many economies while a positive dependence for the US, South Africa, and Japan suggests that gold has been unable to shield investors in these markets. It is important to keep in mind that the relationship between gold and specific assets is affected by a variety of factors which are not explicitly considered in our study. Up to this point, our results provide little reason to believe that the link between gold and different assets can be characterized by a simple relationship.

The changing pattern for the United States deserves specific attention. The dependencies between the long-run trends ($y(\widetilde{D}_5)$) of daily and monthly observations of 0.11 and 0.20 suggest that gold has been unable to serve investors as a full hedge or safe haven after the financial crisis. Although the underlying driver of changing gold price dynamics are somehow beyond the scope of our paper, unconventional monetary policy and the zero lower bound of interest rates in the aftermath of the crisis have affected global financial markets. A positive dependence might for example be driven by the overall increase of the gold price and the simultaneous recovery of stock prices in 2010 and 2011 which coincides with the emergence of unconventional monetary policy and a strong increase in global liquidity. It is important to keep in mind that our third sample period (2008-2014) includes both a decrease and a recovery of global markets.

(b) Bonds

Turning the focus on the relationship between gold and bond returns, mixed evidence can be reported. Table IV provides the estimated dependence parameters and degrees of freedom. Generally, the dependence increases from the mid 80s to 2014, whereas the magnitude differs by sampling frequency.

Unsurprisingly and analogous to the dependence between stocks and gold, the dependence between monthly returns of gold and bonds is remarkably stronger than observed at a daily frequency.

*** Insert Table IV about here ***

In contradiction to the stock-gold dependence, the daily bond-gold dependence for India, China, South Africa and Australia is less affected by the outbreak of the financial crisis in 2008, whereas Germany and the UK describe the strongest changes over the sample from 1985 to 2014. However, for all markets (with available data) the dependence between bonds and gold increases from negative to positive throughout the investigated subsamples for both, daily and monthly data, implying that gold has displayed stronger co-movements with bonds and has been unable to serve as a hedge in the latest period.

One has to keep in mind that the changing stance of monetary policy at the zero lower bound had partly different impacts on stocks and bonds. Stocks prices essentially follow a random walk behavior and have recovered after the financial crisis. On the opposite, yields on the analyzed 10-year government bonds have experienced a downward trend over recent years due to the effect of unconventional monetary policy which has increased the demand for bonds. One aim of the conducted policies was to lower risk expectations and interest on government bonds for specific economies. Lower bond prices reduce the opportunity costs of holding gold, resulting in potential co-movements.

Our findings also show the importance of cross-country differences, for example when comparing the opposite results for Japan and Germany over the recent period. German bonds are an important safe haven asset and highly correlated with the gold price while German stocks display a negative relationship with gold. The opposite holds for most time horizons in Japan. The positive relationship with German bonds therefore simply reflects a positive correlation of two safe haven assets. This again suggests that a direct measure of uncertainty is potentially more appropriate when assessing hedge and safe haven properties of gold. The relationship between gold and specific assets is driven by a variety of factors and it is possible that an asset price is not (or even positively) affected by negative financial shocks. In such a case, a positive correlation of gold with such an asset does not necessarily imply that gold is not useful as a hedge. It just reflects that gold was not required to act as a hedge during this period since the other asset was not negatively affected by negative shocks.

(c) Foreign exchange (FX) rates

Table V gives the copula parameters for the dependence between the returns of gold and the investigated exchange rates against the US dollar. In contradiction to stocks and bonds, daily returns are characterized by stronger dependence regimes than monthly returns. The particularly low degrees of freedom reflect that this strong relationship exists in the extreme tails of both distributions. Therefore, extremely high (low) gold returns coincide with extremely high (low) exchange rate returns. Moreover, different dynamics between FX-rates and gold can be observed for the different sub-sample periods. For instance, between 1985 and 2000 the German DM/USD rate is characterized by a relatively strong dependence to gold (daily = 0.49 and monthly = 0.39), which turned out to be much weaker after the introduction of the euro (daily = 0.06 and monthly = 0.13) in the period from 2001-2008 and stronger again in the last period from 2008-2014 (daily = 0.21 and monthly = 0.30). A similar pattern can be observed for the Japanese yen. However, mixed evidence can be reported for daily and monthly returns of some currencies, whereas for all currencies dependence between FX-rates and gold is per se lower in the period from 2008 to 2014 compared to the period from 1985-2000. The financial crisis and the changing stance of monetary policy has not systematically affected exchange rates as relative asset prices but has changed the cycle of the gold price. The different findings compared to stocks and bonds also reflect that exchange rates are linked to the price of gold via the law of one price. This explains the stronger dependence for daily observations but also implies that cross-country dynamics are more important compared to stocks and bonds.

*** Insert Table V about here ***

Is the ability of gold to act as a hedge or safe haven against stocks, bonds and exchange rates different over particular trends?

Turning to the different time-scales provided by our wavelet approach, the results for daily data show an almost linear relationship between the time-scale frequency and the intensity of the relationship which is in line with the higher dependence for the monthly data. The different time-scales for the monthly frequency provide further insights in the sense that co-movements mainly increase up to the third scale and decrease afterwards. This might be due to the fact that the higher (i.e. long-run) frequencies are less volatile. As presented in Tables III, IV and V, differences between daily and monthly data are less pronounced for co-movements between bond and gold returns although the intensity is also mostly stronger for monthly data. For both daily and monthly data, the intensity of the relationship mostly increases for higher scale frequencies without a reversed pattern for the monthly data as observed for stocks.

The findings for exchange rates display a different pattern. As already mentioned, the co-movements of exchange rate returns with gold returns are mainly higher for daily frequencies. As described above, this is simply due to the fact that exchange rates, unlike stocks and bonds, are linked to the gold price via the law one price. Hence, short-run changes are necessary to eliminate risk-less arbitrage opportunities which would contradict market efficiency. In the present case, the positive dependence mirrors the law of one price: An increasing gold price in the domestic currency is positively related to domestic depreciations against the US dollar. The findings for different trends provide an ambiguous pattern for both the monthly and the daily frequency in the sense that both increasing and decreasing dependencies are observed.

Overall, the findings shows that gold is a weak hedge for stocks, i.e. is uncorrelated with stocks over the very short-run (i.e. low frequency scales) but not necessarily over the medium- and the long-run (i.e. higher frequency scales). Changes in the relationship over the considered sub-sample periods will be addressed in the next section but at a first glance the findings for different time frequencies show that gold is often negatively correlated with stocks, which points to a strong hedge function. The magnitude of the relationship also changes for a specific series over frequencies. This pattern is in line with the ambiguous empirical record summarized in Section 2 which shows that the corresponding evidence varies across sample periods, frequencies and countries. The findings for bond returns provide less evidence for a weak hedge over the very short-run but more evidence for a strong hedge over the medium- and the long-run while changes across frequencies are less frequently observed. Finally, the link to exchange rates provides a different pattern. The results are relatively robust over the different frequency scales and reflect the established wisdom that gold prices and the dollar exchange rates are inversely related.

4.2 Gold and uncertainty

Having illustrated the country-specific role of gold against stocks, bonds and exchange rates, we turn to a direct link between the price for gold and uncertainty in the following. Table VI presents the copula dependence parameters between the assessed uncertainty indices and gold.[16] We start our assessment with the relationship between gold returns and economic policy uncertainty (EPU) which turns out to be rather weak for the first two periods. The results even display a slightly negative

[16] For the sake of page constraints, we skip the presentation of the d.o.f., however, all figures are available upon request.

relationship between gold returns and policy uncertainty for Germany and the UK. This pattern intensifies for longer trends identified through our wavelet approach. The second period between 2001 and 2008 is also characterized by a minor degree of co-movement since nearly all coefficients turned out to be small and negative. As outlined in the previous subsection, the relationship again increases for higher time-scales. Interestingly, the start of the subprime crisis results in a remarkable turnaround since the relationship increases in absolute terms and becomes positive for all economies except for Japan where the relationship remains weak. The fact that policy uncertainty and the gold price are positively related after 2008 suggest that market participants consider gold to be a safe haven asset relying on uncertainty about the stance of economic policy.

*** Insert Table VI about here***

A quite interesting finding is that the link between CPI forecasters disagreement (CPIU) and gold returns also increases for the second and third sample period and changes remarkably with the start of the third sample period. In contrast to the newspaper-based economic policy uncertainty measure, the relationship switches from positive to negative. This suggests that an increasing gold price is positively related with inflation uncertainty before the subprime crisis while the opposite holds after 2008. Once again, the worldwide drop of interest rates and unconventional monetary policy offer a possible explanation for this finding. The role of gold as a hedge against inflation only materializes if an increase in prices is expected. However, the aftermath of the crisis has resulted in substantial deflation fears and low inflation expectations which are part of the observed disagreement between inflation forecasters. Historically, the price of gold also increased during the last global period of deflation in the 1930s after being pegged. Nevertheless, our findings suggest that inflation uncertainty which incorporates deflation fears rather decreases the gold price. A deeper understanding of those linkages is beyond the scope of this paper and should explicitly include expectations related to monetary policy decisions which are unavailable over the full sample period under investigation.

The final measure we consider is the macroeconomic uncertainty (MU) index proposed by Jurado *et al.* (2015). This measure is based on the conditional volatility of the unforecastable component for a large number of series. While the results hardly differ between the first and the second sample period and mostly display a slightly negative or not existing dependence, the link also intensifies for the last period, still displaying a negative relationship in most cases. An interesting exception is the fourth and fifth wavelet scale for the US where a positive relationship is observed. Taking the findings above into consideration, market participants do not always seem to increase the gold demand in case of higher uncertainty. This could also be interpreted as evidence for the price of gold being not necessarily expected to increase in case of uncertainty.

5 Conclusion

This study has analyzed co-movements of the gold price against stocks, bonds and exchange rates and different uncertainty measures for several economies and time horizons based on a copula wavelet approach. In line with previous findings, we find quite different patterns across gold markets. We also find that the role of gold in financial markets has undergone significant changes over the last decades, in particular after the collapse of Lehman Brothers in 2008. On the one hand, the relationship between gold and stocks, bonds and exchange rates has mainly intensified. On the other hand, gold mostly displays a positive dependence to stocks and bonds after 2008 and is therefore unable to serve as a hedge in the classical sense while the findings for the period prior to 2008 mostly suggest that gold was able to shield investors prior to the financial crisis.

We have argued that bilateral considerations of gold and a specific asset might be misleading in terms of hedge or safe haven functions. The observed positive relationship between German bonds and gold for example displays a positive relationship of two safe haven assets. In such a case, gold is still able to serve as a hedge or safe haven on global markets. For this reason, we proposed a direct assessment of the link between gold returns and uncertainty. This relationship has also intensified after 2008. In addition, different kinds of uncertainty and risk measures have different effects on the path of the gold price. While economic policy uncertainty is positively correlated with gold price developments, macroeconomic uncertainty and inflation uncertainty among forecasters both display a negative dependence to gold. In particular the result regarding inflation disagreement is potentially driven by the low interest rate environment and the change of the stance in monetary policy. The different findings can be traced back to different definitions of uncertainty: Economic policy uncertainty is based on newspaper coverage while macroeconomic uncertainty is based on the common unpredictable variation of macroeconomic aggregates. The link to economic policy uncertainty therefore potentially reflects market decisions in the sense that the demand for gold increases if uncertainty is brought to attention in newspapers. On the opposite, the link to macroeconomic uncertainty shows that an increase in the unpredictable component across macroeconomic aggregates coincides with a reduction in the price of gold. This finding could be considered as a de-facto measure of the link between uncertainty and gold in the sense that gold is not able to offer a protection against unpredictability in the state of the economy and financial markets. Finally, it is also somehow surprising that most linkages except exchange rates increasingly materialize over longer horizons. A simple explanation is that asset specific short-run volatilities are not observed at higher wavelet frequencies.

Overall, we identify several avenues for further research. Our results essentially suggest that the classical view on hedge and safe haven functions can be quite misleading and that it is useful to analyze the direct link between gold and uncertainty. Besides considering explicit loss functions for forecasters and investors, the link between gold and uncertainty could be analyzed from a more historical perspective, for example covering a full century which includes a greater number of crises periods. Another interesting extension for further research is a more detailed analysis of the relationship between expectations and the gold price in the spirit of the analyzed link to inflation uncertainty. Such an approach could provide useful insights related to professional market expectations regarding gold. Finally, the role of unconventional monetary policy for the price of gold has yet to be analyzed in greater detail.

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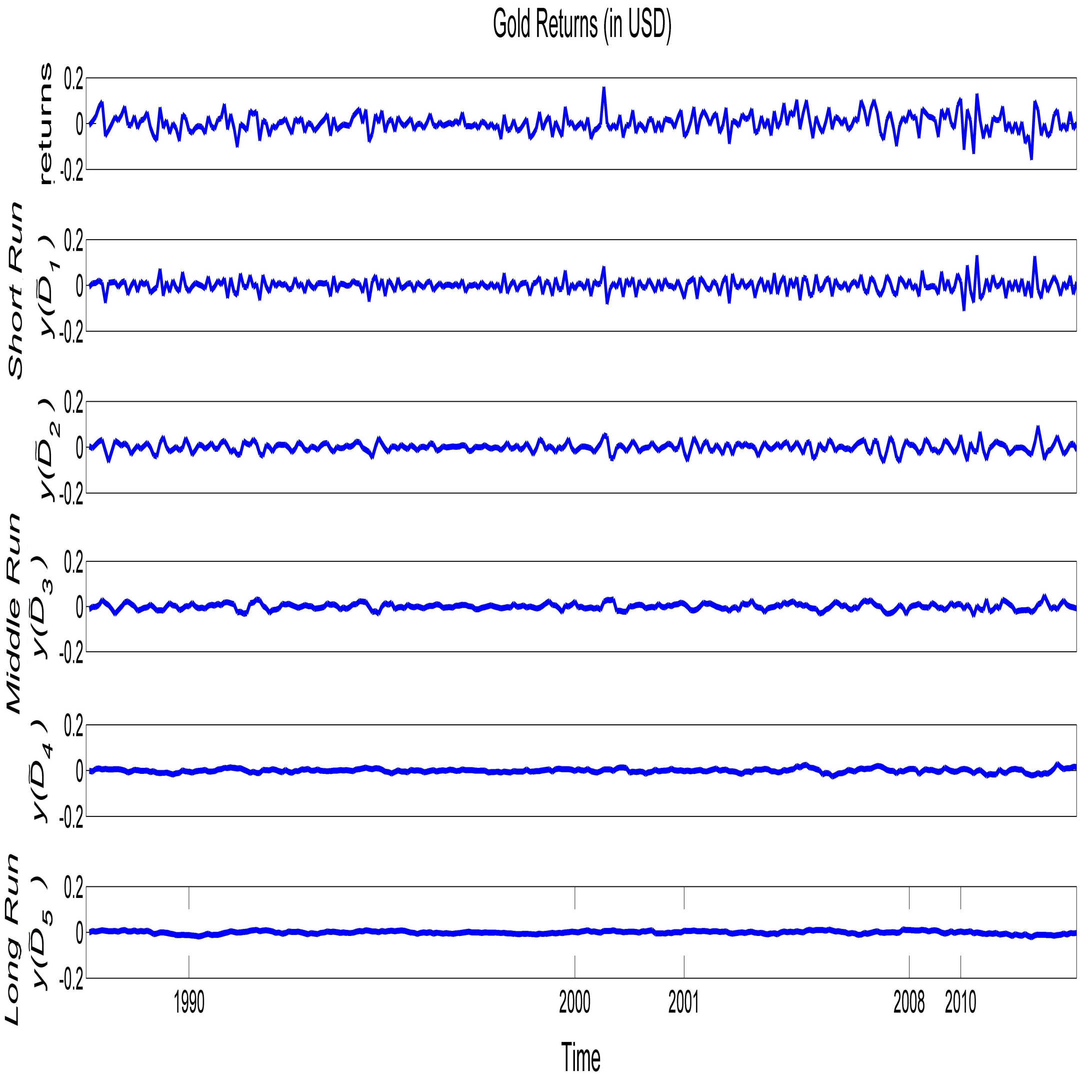
Figures

Figure I–Monthly gold returns and their decomposition (in USD) 1985-2014



Tables

Table I–Previous empirical findings

Market	Study	Sample period	Frequency	Countries	Methodology	Main result
stocks, bonds	Baur and Lucey (2010)	1995 to 2005	daily	US, UK, Germany	regression with dummy variables for lower quantiles	hedge (US, UK) & safe haven for stocks, no hedge (US, UK) & no safe haven for bonds
stocks	Baur and McDermott (2010)	1979 to 2009	daily, weekly, monthly	G7, BRIC countries, Australia, Switzerland	regression with dummy variables for lower quantiles	hedge & safe haven (EMU, US), no hedge & no safe haven (Australia, Canada, Japan, BRIC)
stocks	Hood and Malik (2013)	1995 to 2010	daily	US	regression with dummy variables for lower quantiles	hedge & weak safe haven for stocks
stocks, bonds, FX, (oil)	Ciner *et al.* (2013)	1990 to 2010	daily	US, UK	DCC-GARCH, regression with dummy variables for lower quantiles	hedge & safe haven for FX and bonds, no safe haven for stocks
stocks, bonds	Michis (2014)	1991 to 2012	monthly	US, UK, Germany	Wavelet analysis	hedge for stocks & bonds in the long-run
stocks	Gürgün and Ünalmis (2014)	1980 to 2013	daily	28 countries (emerging markets)	regression with dummy variables for lower quantiles	hedge & safe haven for stocks
stocks	Arouri *et al.* (2015)	2004 to 2011	daily	China	VAR-GARCH, multivariate GARCH	hedge & safe haven for stocks
stocks	Beckmann *et al.* (2015a)	1970 to 2012	monthly	18 countries (G7, emerging markets)	Smooth transition regression	hedge & safe haven for stocks, but market-specific
bonds	Agyei-Ampomah *et al.* (2014)	1993 to 2012	daily	US, UK, EMU (10 countries)	regression with dummy variables for lower quantiles	copper provides a better hedge & safe haven function than gold
FX	Beckmann *et al.* (2015b)	1979 to 2013	daily	US, UK, EMU, Japan, India	SVAR-GARCH	hedge for FX
FX	Capie *et al.* (2005)	1971 to 2004	weekly	US, UK, Japan	ARDL model	hedge for FX
FX	Pukthuanthong and Roll (2011)	1971 to 2009	daily	US, UK, EMU, Japan	DCC-GARCH	hedge for FX
FX	Joy (2011)	1986 to 2008	weekly	16 countries (G7, emerging markets)	DCC-GARCH	hedge, but no safe haven for FX
FX	Reboredo (2013)	2000 to 2012	weekly	Australia, Canada, EMU, UK, Japan, Norway, Switzerland	Copula	hedge & safe haven for FX
FX	Reboredo and Rivera-Castro (2014a)	2000 to 2012	weekly	Australia, Canada, EMU, UK, Japan, Norway, Switzerland	Likelihood ratio test	hedge & weak safe haven for FX
FX	Reboredo and Rivera-Castro (2014b)	2000 to 2013	daily	Australia, Canada, EMU, UK, Japan, Norway, Switzerland	Wavelet analysis, correlation	hedge for FX
FX	Pierdzioch *et al.* (2016)	1999 to 2015	weekly	Australia, Canada, EMU, UK, Japan	Bayesian additive regression trees	hedge for FX

Note: This table presents a comprehensive literature overview relevant for this study.

Table II–Frequency interpretation of decomposed wavelet levels

Scales	Daily	Weekly	Monthly
$y(\widetilde{D}_1)$	1-2 days	1-2 weeks	1-2 months
$y(\widetilde{D}_2)$	2-4 days	2-4 weeks	2-4 months
$y(\widetilde{D}_3)$	4-8 days	4-8 weeks	4-8 months
$y(\widetilde{D}_4)$	8-16 days	8-16 weeks	8-16 months
$y(\widetilde{D}_5)$	16-32 days	16-32 weeks	16-32 months

Note: This table presents an intuitive interpretation of the decomposed return series ($y(\widetilde{D}_1)$,$y(\widetilde{D}_2)$,$y(\widetilde{D}_3)$,$y(\widetilde{D}_4)$,$y(\widetilde{D}_5)$).

Table III–Stocks: t Copula Parameters for Monthly and Daily Data

Daily

Stocks	USA	GER	JAP	UK	CAN	IND	C	SA	AUS
1985-2000									
returns	-0.06	0.04	-0.02	0.02	-0.01				-0.04
$y(\widetilde{D}_1)$	-0.01	0.01	-0.01	0.01	0.00				-0.04
$y(\widetilde{D}_2)$	-0.10	0.04	-0.03	0.01	-0.01				-0.04
$y(\widetilde{D}_3)$	-0.09	0.08	-0.07	0.07	0.02				-0.03
$y(\widetilde{D}_4)$	-0.07	0.05	-0.04	0.03	0.02				0.00
$y(\widetilde{D}_5)$	-0.12	0.05	-0.03	0.03	0.00				-0.06
d.o.f.									
returns	8.66	6.58	9.99	8.14	16.30				11.44
$y(\widetilde{D}_1)$	8.50	9.76	11.02	9.35	20.95				15.59
$y(\widetilde{D}_2)$	9.21	8.39	9.62	13.44	22.25				11.49
$y(\widetilde{D}_3)$	10.18	8.47	9.25	16.63	15.03				21.41
$y(\widetilde{D}_4)$	14.01	8.48	11.59	16.23	11.23				26.43
$y(\widetilde{D}_5)$	19.14	6.32	16.66	9.51	100.00				98.18
2001-2008	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.07	0.02	0.11	0.02	0.04	-0.02	0.10	0.21	-0.01
$y(\widetilde{D}_1)$	-0.09	0.02	0.12	0.01	0.02	-0.02	0.10	0.17	0.01
$y(\widetilde{D}_2)$	-0.07	0.05	0.10	0.05	0.08	0.01	0.14	0.25	-0.05
$y(\widetilde{D}_3)$	-0.04	0.01	0.10	0.05	0.08	0.00	0.10	0.27	-0.05
$y(\widetilde{D}_4)$	-0.07	-0.03	0.07	0.00	0.05	-0.03	0.10	0.25	-0.06
$y(\widetilde{D}_5)$	-0.13	-0.03	0.07	0.01	0.03	0.00	0.21	0.30	-0.09
d.o.f.									
returns	12.39	100.00	9.31	11.79	7.11	7.53	8.34	5.74	6.74
$y(\widetilde{D}_1)$	18.76	42.38	9.75	13.98	10.00	8.90	10.10	7.38	6.56
$y(\widetilde{D}_2)$	16.11	65.89	13.57	10.52	7.00	4.64	8.20	6.11	5.61
$y(\widetilde{D}_3)$	28.70	15.25	7.14	6.20	7.24	4.67	5.82	7.59	4.60
$y(\widetilde{D}_4)$	72.48	100.00	7.77	25.38	7.35	6.63	7.93	8.27	6.28
$y(\widetilde{D}_5)$	100.00	100.00	10.62	21.28	9.75	4.08	14.22	19.51	7.33
2008-2014	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.08	-0.07	0.19	0.05	0.02	-0.07	0.16	-0.09	-0.14
$y(\widetilde{D}_1)$	0.07	-0.09	0.12	0.06	0.02	-0.06	0.15	-0.07	-0.08
$y(\widetilde{D}_2)$	0.10	-0.07	0.22	0.02	0.01	-0.07	0.16	-0.05	-0.18
$y(\widetilde{D}_3)$	0.17	-0.05	0.30	0.04	0.06	-0.10	0.19	-0.12	-0.20
$y(\widetilde{D}_4)$	0.21	-0.03	0.31	0.07	0.07	-0.06	0.25	-0.12	-0.20
$y(\widetilde{D}_5)$	0.20	-0.06	0.25	0.08	0.04	-0.02	0.31	-0.14	-0.33
d.o.f.									
returns	3.35	3.79	5.16	3.31	4.05	3.86	4.55	3.97	3.75
$y(\widetilde{D}_1)$	3.44	3.99	5.08	3.24	3.55	3.59	3.42	3.45	3.59
$y(\widetilde{D}_2)$	3.03	3.89	4.31	3.98	3.30	3.78	3.41	3.78	3.48
$y(\widetilde{D}_3)$	3.25	3.32	4.83	3.17	3.55	5.12	3.51	4.46	4.07
$y(\widetilde{D}_4)$	4.24	5.30	5.50	4.47	4.27	7.57	4.07	5.61	4.53
$y(\widetilde{D}_5)$	4.93	4.96	4.73	5.72	3.47	8.28	6.68	5.30	5.48

Monthly

1985-2000	USA	GER	JAP	UK	CAN	IND	C	SA	AUS
returns	-0.20	0.10	-0.04	0.05	-0.11				-0.10
$y(\widetilde{D}_1)$	-0.12	-0.07	0.04	0.02	-0.08				-0.08
$y(\widetilde{D}_2)$	-0.30	0.03	-0.17	0.04	-0.10				-0.25
$y(\widetilde{D}_3)$	-0.16	0.29	0.02	0.17	-0.17				-0.30
$y(\widetilde{D}_4)$	-0.17	0.35	0.27	0.29	-0.12				-0.07
$y(\widetilde{D}_5)$	-0.12	-0.01	0.06	0.39	0.02				0.33
d.o.f.									
returns	9.99	4.81	94.18	6.41	100.00				31.09
$y(\widetilde{D}_1)$	14.78	10.00	4.99	10.00	100.00				100.00
$y(\widetilde{D}_2)$	24.68	30.87	100.00	8.29	100.00				12.54
$y(\widetilde{D}_3)$	4.72	100.00	34.05	5.97	97.37				99.92
$y(\widetilde{D}_4)$	4.36	66.70	97.75	100.00	5.45				5.77
$y(\widetilde{D}_5)$	8.77	100.00	100.00	99.42	100.00				2.67
2001-2008	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.05	0.01	0.25	-0.06	0.15	0.00	0.27	0.24	-0.02
$y(\widetilde{D}_1)$	0.04	-0.01	0.23	0.03	0.15	-0.12	0.28	0.23	0.05
$y(\widetilde{D}_2)$	-0.17	-0.24	0.23	-0.06	0.01	-0.17	0.02	0.06	-0.08
$y(\widetilde{D}_3)$	-0.01	0.06	0.18	0.08	0.09	0.32	0.28	0.18	-0.05
$y(\widetilde{D}_4)$	-0.04	0.25	0.29	0.09	-0.05	0.27	0.34	0.19	-0.24
$y(\widetilde{D}_5)$	-0.08	0.26	0.45	-0.03	0.10	0.37	0.16	0.56	0.16
d.o.f.									
returns	9.99	10.00	5.64	89.05	2.77	3.96	2.25	4.20	3.15
$y(\widetilde{D}_1)$	100.00	100.00	100.00	2.94	100.00	53.55	5.54	88.60	100.00
$y(\widetilde{D}_2)$	2.10	3.25	3.56	2.42	3.37	2.10	2.73	5.47	3.11
$y(\widetilde{D}_3)$	100.00	100.00	100.00	10.01	5.09	100.00	6.13	10.01	19.05
$y(\widetilde{D}_4)$	100.00	100.00	2.80	100.00	4.27	100.00	100.00	5.67	100.00
$y(\widetilde{D}_5)$	100.00	100.00	10.01	100.00	100.00	100.00	100.00	100.00	100.00
2008-2014	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.10	-0.18	0.13	0.04	0.19	-0.21	0.19	-0.18	-0.27
$y(\widetilde{D}_1)$	0.19	-0.19	0.07	0.03	0.25	-0.08	0.31	-0.20	-0.31
$y(\widetilde{D}_2)$	0.08	-0.23	0.12	-0.06	0.10	-0.13	0.37	-0.20	-0.21
$y(\widetilde{D}_3)$	-0.05	-0.16	0.24	-0.07	0.10	-0.10	0.32	-0.05	-0.34
$y(\widetilde{D}_4)$	-0.35	-0.51	-0.07	-0.41	-0.16	-0.34	-0.02	-0.29	-0.63
$y(\widetilde{D}_5)$	0.11	-0.18	0.00	0.01	-0.22	-0.32	-0.10	-0.37	-0.66
d.o.f.									
returns	3.85	3.24	10.00	6.16	5.57	3.60	2.10	3.24	3.04
$y(\widetilde{D}_1)$	6.99	5.40	10.01	9.99	4.75	100.00	10.00	2.10	2.70
$y(\widetilde{D}_2)$	10.00	5.08	3.05	10.00	10.00	42.13	3.45	100.00	2.82
$y(\widetilde{D}_3)$	100.00	2.81	100.00	4.96	10.00	100.00	100.00	100.00	2.55
$y(\widetilde{D}_4)$	100.00	100.00	6.06	100.00	10.00	100.00	100.00	10.01	100.00
$y(\widetilde{D}_5)$	100.00	100.00	100.00	100.00	100.00	2.16	5.24	100.00	100.00

Note: This table presents the copula dependence parameters of the applied t copula based on returns and decomposed return series on the different scales ($y(\widetilde{D}_1)$,$y(\widetilde{D}_2)$,$y(\widetilde{D}_3)$,$y(\widetilde{D}_4)$,$y(\widetilde{D}_5)$). Dependence is assessed between gold and: USA = MSCI US, GER = MSCI Germany, JAP = MSCI Japan, UK = MSCI UK, CAN = MSCI Canada, IND = MSCI India, C = MSCI China, SA = MSCI South Africa, AUS = MSCI Australia. d.o.f. stands for the degrees of freedom parameter v mentioned in Section 3.2.2. The left panel reports results for daily and the right panel for monthly data.

Table IV–Bonds: t Copula Parameters for Monthly and Daily Data

Daily

Bonds	USA	GER	JAP	UK	CAN	IND	C	SA	AUS
1985-2000	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.07	-0.08	-0.05	-0.11	-0.09				
$y(\widetilde{D}_1)$	-0.05	-0.06	-0.01	-0.10	-0.05				
$y(\widetilde{D}_2)$	-0.10	-0.09	-0.04	-0.13	-0.11				
$y(\widetilde{D}_3)$	-0.10	-0.11	-0.13	-0.12	-0.13				
$y(\widetilde{D}_4)$	-0.09	-0.09	-0.13	-0.13	-0.16				
$y(\widetilde{D}_5)$	-0.10	-0.10	-0.10	-0.14	-0.16				
d.o.f.									
returns	13.09	11.44	14.42	10.71	18.30				
$y(\widetilde{D}_1)$	13.15	15.66	12.18	15.14	17.93				
$y(\widetilde{D}_2)$	27.93	19.33	11.39	21.25	16.07				
$y(\widetilde{D}_3)$	17.40	27.40	17.70	34.66	31.93				
$y(\widetilde{D}_4)$	31.45	99.72	15.33	100.00	26.15				
$y(\widetilde{D}_5)$	44.87	18.84	7.48	14.22	10.71				
2001-2008	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.09	-0.01	0.00	0.07	0.00	0.02	0.07	-0.24	0.16
$y(\widetilde{D}_1)$	0.05	-0.03	0.04	0.07	-0.04	-0.02	0.03	-0.19	0.12
$y(\widetilde{D}_2)$	0.11	-0.02	0.02	0.07	-0.05	-0.02	0.11	-0.23	0.19
$y(\widetilde{D}_3)$	0.12	0.02	-0.03	0.06	0.06	0.06	0.11	-0.28	0.23
$y(\widetilde{D}_4)$	0.18	0.07	-0.06	0.09	0.21	0.16	0.17	-0.20	0.32
$y(\widetilde{D}_5)$	0.19	0.05	-0.11	0.12	0.23	0.21	0.17	-0.28	0.26
d.o.f.									
returns	18.66	44.15	19.49	31.54	44.63	100.00	21.80	8.40	17.61
$y(\widetilde{D}_1)$	50.32	100.00	12.53	22.69	37.95	62.88	25.11	9.31	12.54
$y(\widetilde{D}_2)$	44.16	100.00	15.50	79.29	88.45	100.00	37.76	11.92	54.85
$y(\widetilde{D}_3)$	100.00	85.01	15.52	37.16	40.50	29.15	43.85	16.53	37.77
$y(\widetilde{D}_4)$	100.00	100.00	97.45	100.00	100.00	100.00	100.00	85.83	75.14
$y(\widetilde{D}_5)$	95.45	26.97	73.24	15.20	21.55	100.00	84.56	14.73	21.17
2008-2014	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.04	0.20	-0.05	0.20	-0.03	-0.06	0.03	-0.18	0.23
$y(\widetilde{D}_1)$	0.01	0.18	0.00	0.19	-0.03	-0.07	0.02	-0.16	0.21
$y(\widetilde{D}_2)$	0.07	0.22	-0.07	0.22	-0.21	-0.11	0.06	-0.16	0.29
$y(\widetilde{D}_3)$	0.06	0.20	-0.09	0.21	-0.03	-0.03	0.03	-0.14	0.28
$y(\widetilde{D}_4)$	0.09	0.26	-0.08	0.26	0.16	-0.05	0.04	-0.22	0.38
$y(\widetilde{D}_5)$	0.16	0.25	-0.04	0.29	0.32	0.00	0.10	-0.23	0.39
d.o.f.									
returns	4.74	4.74	10.92	4.75	10.52	4.73	6.39	5.03	4.63
$y(\widetilde{D}_1)$	6.16	6.52	8.45	6.63	12.95	4.63	7.43	5.23	5.44
$y(\widetilde{D}_2)$	4.13	6.03	14.56	5.61	10.77	3.95	6.10	4.72	9.31
$y(\widetilde{D}_3)$	4.49	5.73	10.75	6.15	6.71	6.75	6.57	6.89	6.24
$y(\widetilde{D}_4)$	4.89	5.82	9.99	5.99	9.56	4.96	7.79	6.37	8.10
$y(\widetilde{D}_5)$	5.97	11.04	100.00	8.44	5.86	4.04	7.20	7.61	7.98

Monthly

	USA	GER	JAP	UK	CAN	IND	C	SA	AUS
1985-2000	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.12	-0.11	-0.16	-0.06	-0.13				
$y(\widetilde{D}_1)$	-0.17	-0.13	-0.14	-0.10	-0.15				
$y(\widetilde{D}_2)$	-0.12	-0.22	-0.18	-0.14	-0.13				
$y(\widetilde{D}_3)$	0.02	-0.15	-0.36	-0.20	-0.09				
$y(\widetilde{D}_4)$	-0.12	0.00	-0.13	-0.01	-0.13				
$y(\widetilde{D}_5)$	-0.15	-0.09	-0.27	-0.05	-0.16				
d.o.f.									
returns	10.00	4.11	5.37	4.02	30.62				
$y(\widetilde{D}_1)$	100.00	95.57	3.56	10.00	100.00				
$y(\widetilde{D}_2)$	100.00	29.43	7.06	11.80	22.00				
$y(\widetilde{D}_3)$	100.00	11.48	2.68	4.09	100.00				
$y(\widetilde{D}_4)$	100.00	32.85	5.17	100.00	100.00				
$y(\widetilde{D}_5)$	100.00	3.23	12.99	6.47	100.00				
	USA	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.02	-0.04	-0.04	0.14	0.01			-0.18	0.08
$y(\widetilde{D}_1)$	0.00	0.02	0.06	0.03	0.05			-0.14	0.19
$y(\widetilde{D}_2)$	0.16	0.16	-0.08	0.14	0.15			-0.07	0.16
$y(\widetilde{D}_3)$	0.03	-0.06	0.03	0.18	-0.03			-0.24	-0.07
$y(\widetilde{D}_4)$	-0.22	-0.42	-0.36	0.17	-0.04			-0.49	-0.06
$y(\widetilde{D}_5)$	-0.13	-0.13	-0.09	0.41	-0.39			-0.43	-0.02
d.o.f.									
returns	4.42	43.52	100.00	100.00	10.00			5.02	100.00
$y(\widetilde{D}_1)$	4.22	9.99	100.00	10.00	4.57			4.04	100.00
$y(\widetilde{D}_2)$	100.00	3.73	100.00	26.54	100.00			99.01	4.72
$y(\widetilde{D}_3)$	2.10	2.10	100.00	2.10	2.63			4.35	100.00
$y(\widetilde{D}_4)$	3.48	3.64	3.41	6.86	2.10			100.00	100.00
$y(\widetilde{D}_5)$	100.00	100.00	100.00	100.00	100.00			7.06	100.00
	USA	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.11	0.32	0.03	0.14	0.32	-0.15	-0.10	-0.19	0.39
$y(\widetilde{D}_1)$	0.06	0.22	-0.08	0.04	0.31	0.04	0.02	-0.25	0.45
$y(\widetilde{D}_2)$	0.23	0.39	0.04	0.33	0.52	-0.01	-0.12	-0.31	0.34
$y(\widetilde{D}_3)$	0.23	0.35	-0.07	0.18	0.40	-0.23	-0.25	-0.05	0.23
$y(\widetilde{D}_4)$	0.46	0.71	0.11	0.46	0.68	-0.07	0.01	0.49	0.61
$y(\widetilde{D}_5)$	0.50	0.61	0.28	0.61	0.71	-0.19	0.06	0.49	0.67
d.o.f.									
returns	2.47	5.74	100.00	2.69	2.74	2.10	100.00	2.10	10.00
$y(\widetilde{D}_1)$	4.31	3.67	92.22	10.00	6.15	2.75	9.99	3.79	3.83
$y(\widetilde{D}_2)$	48.45	9.99	4.29	100.00	100.00	2.10	4.23	10.00	9.99
$y(\widetilde{D}_3)$	100.00	100.00	3.18	100.00	10.00	3.03	9.99	100.00	4.45
$y(\widetilde{D}_4)$	27.35	100.00	100.00	100.00	100.00	10.00	100.00	100.00	100.00
$y(\widetilde{D}_5)$	100.00	100.00	100.00	100.00	100.00	4.48	76.58	6.15	100.00

Note: This table presents the copula dependence parameters of the applied t copula based on returns and decomposed return series on the different scales ($y(\widetilde{D}_1)$,$y(\widetilde{D}_2)$,$y(\widetilde{D}_3)$,$y(\widetilde{D}_4)$,$y(\widetilde{D}_5)$). Dependence is assessed between gold and the corresponding bond prices: USA = US, GER = Germany, JAP = Japan, UK = UK, CAN = Canada, IND = India, C = China, SA = South Africa, AUS = Australia. d.o.f. stands for the degrees of freedom parameter v mentioned in Section 3.2.2. The left panel reports results for daily and the right panel for monthly data.

Table V–FX: t Copula Parameters for Monthly and Daily Data

Daily

FX	GER	JAP	UK	CAN	IND	C	SA	AUS
1985-2000								
returns	0.49	0.56	0.49	0.28			0.35	0.43
$y(\widetilde{D}_1)$	0.44	0.52	0.43	0.23			0.28	0.37
$y(\widetilde{D}_2)$	0.50	0.55	0.50	0.26			0.38	0.44
$y(\widetilde{D}_3)$	0.52	0.57	0.52	0.28			0.37	0.47
$y(\widetilde{D}_4)$	0.53	0.60	0.54	0.32			0.44	0.46
$y(\widetilde{D}_5)$	0.56	0.64	0.56	0.30			0.49	0.45
d.o.f.								
returns	3.70	3.72	3.93	6.26			2.78	4.07
$y(\widetilde{D}_1)$	4.51	4.60	4.51	7.99			3.12	5.10
$y(\widetilde{D}_2)$	5.02	5.27	5.04	10.39			2.81	4.88
$y(\widetilde{D}_3)$	6.22	5.10	6.46	9.17			2.45	5.81
$y(\widetilde{D}_4)$	6.38	6.35	6.48	8.12			2.87	5.03
$y(\widetilde{D}_5)$	5.93	8.62	5.41	8.07			3.68	5.39
2001-2008	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.06	0.30	0.11	0.20	0.06	-0.05	0.59	0.21
$y(\widetilde{D}_1)$	0.06	0.31	0.10	0.21	0.06	0.00	0.57	0.21
$y(\widetilde{D}_2)$	0.03	0.29	0.10	0.17	0.05	-0.08	0.58	0.21
$y(\widetilde{D}_3)$	-0.01	0.24	0.05	0.10	0.04	-0.13	0.59	0.14
$y(\widetilde{D}_4)$	-0.09	0.17	-0.06	0.06	0.01	-0.13	0.54	0.13
$y(\widetilde{D}_5)$	-0.07	0.24	0.02	0.06	0.10	-0.14	0.58	0.10
d.o.f.								
returns	9.39	6.29	8.02	7.98	7.41	6.07	3.40	5.79
$y(\widetilde{D}_1)$	12.99	8.29	13.14	11.58	6.97	5.93	5.24	8.81
$y(\widetilde{D}_2)$	15.44	6.51	10.88	9.43	7.09	5.70	4.45	9.69
$y(\widetilde{D}_3)$	17.01	7.26	15.64	8.76	8.08	4.37	6.07	11.70
$y(\widetilde{D}_4)$	100.00	14.01	100.00	100.00	5.93	8.58	13.09	23.03
$y(\widetilde{D}_5)$	10.80	7.42	10.01	21.82	4.85	6.22	6.28	11.03
2008-2014	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.21	0.38	0.25	0.24	0.12	-0.07	0.52	0.36
$y(\widetilde{D}_1)$	0.16	0.35	0.21	0.22	0.10	-0.03	0.46	0.30
$y(\widetilde{D}_2)$	0.16	0.33	0.22	0.19	0.11	-0.10	0.48	0.32
$y(\widetilde{D}_3)$	0.21	0.36	0.22	0.17	0.05	-0.15	0.49	0.34
$y(\widetilde{D}_4)$	0.12	0.36	0.14	0.13	0.06	-0.16	0.47	0.27
$y(\widetilde{D}_5)$	0.17	0.32	0.15	0.13	0.13	-0.06	0.49	0.32
d.o.f.								
returns	3.60	3.90	3.29	3.59	4.68	70.93	3.32	2.66
$y(\widetilde{D}_1)$	4.60	5.87	4.37	3.85	5.79	23.20	3.19	2.87
$y(\widetilde{D}_2)$	4.98	5.35	5.23	5.75	5.00	93.20	5.63	4.03
$y(\widetilde{D}_3)$	7.39	4.61	4.11	4.94	8.33	14.48	4.22	3.64
$y(\widetilde{D}_4)$	4.32	5.95	3.71	5.62	5.49	99.80	4.90	3.70
$y(\widetilde{D}_5)$	5.76	12.30	7.23	6.45	5.72	100.00	9.73	3.88

Monthly

	GER	JAP	UK	CAN	IND	C	SA	AUS
1985-2000								
returns	0.39	0.35	0.35	0.17			0.32	0.35
$y(\widetilde{D}_1)$	0.31	0.31	0.26	0.12			0.24	0.22
$y(\widetilde{D}_2)$	0.38	0.45	0.41	0.21			0.25	0.42
$y(\widetilde{D}_3)$	0.49	0.48	0.45	0.22			0.50	0.46
$y(\widetilde{D}_4)$	0.64	0.72	0.72	0.35			0.70	0.69
$y(\widetilde{D}_5)$	0.55	0.64	0.57	0.35			0.61	0.62
d.o.f.	d.o.f.							
returns	100.00	5.13	100.00	100.00			10.00	26.23
$y(\widetilde{D}_1)$	11.87	22.63	98.27	100.00			99.70	99.16
$y(\widetilde{D}_2)$	4.92	6.19	4.72	100.00			4.02	9.99
$y(\widetilde{D}_3)$	18.02	6.54	5.43	100.00			10.00	4.22
$y(\widetilde{D}_4)$	100.00	30.71	24.17	99.86			100.00	100.00
$y(\widetilde{D}_5)$	15.30	17.50	100.00	100.00			100.00	100.00
	GER	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.13	0.04	0.21	0.19	0.31	-0.21	0.47	0.18
$y(\widetilde{D}_1)$	0.04	0.10	0.08	0.09	0.29	-0.22	0.39	0.08
$y(\widetilde{D}_2)$	-0.02	0.02	0.23	0.26	0.38	-0.08	0.44	0.08
$y(\widetilde{D}_3)$	0.24	0.00	0.36	0.49	0.29	-0.27	0.62	0.51
$y(\widetilde{D}_4)$	0.25	0.16	0.54	0.33	0.62	-0.11	0.58	0.60
$y(\widetilde{D}_5)$	0.65	0.66	0.64	0.29	0.68	-0.34	0.79	0.68
d.o.f.								
returns	4.19	10.00	100.00	4.06	3.46	4.46	4.70	100.00
$y(\widetilde{D}_1)$	100.00	2.93	100.00	100.00	98.34	100.00	6.14	100.00
$y(\widetilde{D}_2)$	2.47	100.00	99.38	100.00	100.00	2.78	100.00	100.00
$y(\widetilde{D}_3)$	100.00	100.00	100.00	100.00	10.01	100.00	100.00	100.00
$y(\widetilde{D}_4)$	100.00	100.00	100.00	100.00	100.00	100.00	4.75	100.00
$y(\widetilde{D}_5)$	100.00	100.00	25.71	100.00	99.13	100.00	100.00	100.00
	GER	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.30	0.08	0.07	-0.14	0.08	0.03	0.36	0.04
$y(\widetilde{D}_1)$	0.34	0.19	0.05	-0.11	-0.03	-0.15	0.31	0.03
$y(\widetilde{D}_2)$	0.02	0.04	0.22	0.20	0.20	0.09	0.39	0.28
$y(\widetilde{D}_3)$	0.19	0.21	0.06	0.13	0.32	0.04	0.35	0.21
$y(\widetilde{D}_4)$	0.57	0.06	0.38	0.26	0.22	0.25	0.53	0.30
$y(\widetilde{D}_5)$	0.60	-0.24	0.25	-0.02	0.16	-0.46	0.43	-0.24
d.o.f.								
returns	9.99	2.86	3.80	6.12	3.13	100.00	2.62	9.99
$y(\widetilde{D}_1)$	14.33	3.87	5.82	100.00	2.10	10.01	2.25	5.27
$y(\widetilde{D}_2)$	3.51	100.00	2.88	100.00	3.52	100.00	2.49	2.28
$y(\widetilde{D}_3)$	3.50	100.00	10.00	100.00	2.10	10.01	2.10	6.21
$y(\widetilde{D}_4)$	99.80	5.43	5.38	100.00	100.00	3.91	3.04	2.42
$y(\widetilde{D}_5)$	100.00	6.88	99.26	10.00	100.00	100.00	100.00	100.00

Note: This table presents the copula dependence parameters of the applied t copula based on returns and decomposed return series on the different scales $(y(\widetilde{D}_1),y(\widetilde{D}_2),y(\widetilde{D}_3),y(\widetilde{D}_4),y(\widetilde{D}_5))$. Dependence is assessed between gold and the corresponding bilateral US dollar exchange rates: GER = Germany, JAP = Japan, UK = UK, CAN = Canada, IND = India, C = China, SA = South Africa, AUS = Australia. d.o.f. stands for the degrees of freedom parameter v mentioned in Section 3.2.2. The left panel reports results for daily and the right panel for monthly data.

Table VI–Uncertainty: t Copula Parameters for Monthly Data

Monthly									
EPU									
1985-2000	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.03	-0.05	0.03	-0.06	0.11	0.04	0.02	0.12	0.15
$y(\widetilde{D}_1)$	0.04	0.04	0.06	0.02	0.08	0.02	0.01	0.14	0.08
$y(\widetilde{D}_2)$	-0.05	-0.12	-0.05	-0.13	0.09	0.00	-0.05	0.09	0.18
$y(\widetilde{D}_3)$	0.08	-0.21	0.03	-0.21	0.14	0.17	0.04	0.04	0.19
$y(\widetilde{D}_4)$	0.07	-0.20	-0.01	-0.19	0.25	0.13	-0.02	0.12	0.24
$y(\widetilde{D}_5)$	-0.01	-0.31	0.19	-0.23	0.12	0.05	0.03	-0.03	0.28
2001-2008	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.19	-0.07	-0.16	0.00	-0.11	-0.15	-0.18	0.12	0.10
$y(\widetilde{D}_1)$	-0.25	-0.19	-0.18	-0.05	-0.27	-0.19	-0.23	-0.05	-0.07
$y(\widetilde{D}_2)$	-0.15	-0.15	-0.18	-0.04	0.04	-0.10	-0.14	-0.02	0.16
$y(\widetilde{D}_3)$	0.17	0.30	0.29	0.25	0.18	0.29	0.21	0.25	0.35
$y(\widetilde{D}_4)$	0.01	0.06	0.06	0.03	0.08	0.01	0.00	-0.07	0.35
$y(\widetilde{D}_5)$	-0.09	-0.02	-0.10	0.19	0.06	-0.04	-0.17	0.27	0.14
2008-2014	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.13	0.25	0.06	0.14	0.21	0.34	0.18	0.24	0.30
$y(\widetilde{D}_1)$	0.15	0.28	0.17	0.11	0.19	0.32	0.17	0.24	0.24
$y(\widetilde{D}_2)$	0.08	0.16	0.05	0.07	0.07	0.19	0.10	0.13	0.09
$y(\widetilde{D}_3)$	0.32	0.38	0.03	0.31	0.39	0.52	0.36	0.33	0.47
$y(\widetilde{D}_4)$	0.24	0.48	0.02	0.36	0.32	0.37	0.27	0.48	0.49
$y(\widetilde{D}_5)$	0.38	0.50	-0.05	0.47	0.40	0.41	0.41	0.44	0.53
CPIU									
1985-2000	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.02	0.00	-0.07	-0.02	-0.04	-0.05	0.01	-0.01	-0.04
$y(\widetilde{D}_1)$	-0.05	-0.01	-0.05	-0.03	-0.03	-0.08	0.04	0.07	-0.03
$y(\widetilde{D}_2)$	0.02	0.03	-0.05	0.03	-0.06	0.06	0.06	-0.07	-0.08
$y(\widetilde{D}_3)$	0.07	-0.01	-0.05	-0.08	0.00	0.10	-0.01	-0.14	-0.19
$y(\widetilde{D}_4)$	-0.10	-0.24	-0.15	-0.31	-0.11	-0.30	-0.03	-0.20	-0.22
$y(\widetilde{D}_5)$	-0.07	-0.05	-0.16	-0.16	-0.17	-0.33	-0.16	-0.24	-0.21
2001-2008	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	0.02	0.08	0.00	0.12	0.07	0.01	-0.03	0.06	0.06
$y(\widetilde{D}_1)$	-0.02	-0.14	-0.08	-0.06	-0.03	-0.08	-0.05	-0.06	-0.13
$y(\widetilde{D}_2)$	0.18	0.12	0.15	0.15	0.11	0.10	0.14	-0.09	0.09
$y(\widetilde{D}_3)$	0.10	0.00	-0.01	0.05	-0.18	0.03	0.07	0.06	-0.10
$y(\widetilde{D}_4)$	0.50	0.59	0.33	0.50	0.20	0.37	0.49	0.31	0.27
$y(\widetilde{D}_5)$	0.36	0.02	0.08	0.25	0.03	0.27	0.33	-0.16	-0.10
2008-2014	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.33	-0.34	-0.35	-0.43	-0.31	-0.25	-0.33	-0.22	-0.32
$y(\widetilde{D}_1)$	-0.37	-0.40	-0.36	-0.42	-0.34	-0.35	-0.37	-0.35	-0.34
$y(\widetilde{D}_2)$	-0.25	-0.20	-0.21	-0.26	-0.17	-0.11	-0.27	0.00	-0.06
$y(\widetilde{D}_3)$	-0.44	-0.34	-0.37	-0.33	-0.25	-0.18	-0.44	-0.12	-0.16
$y(\widetilde{D}_4)$	-0.32	-0.39	-0.40	-0.44	-0.25	-0.19	-0.37	-0.45	-0.34
$y(\widetilde{D}_5)$	0.05	-0.16	-0.23	-0.10	0.07	-0.11	-0.01	0.00	0.17
MU									
1985-2000	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.04	-0.13	-0.04	-0.11	-0.02	-0.06	0.00	-0.10	0.05
$y(\widetilde{D}_1)$	-0.03	-0.17	-0.11	-0.13	-0.04	0.02	0.05	-0.14	-0.05
$y(\widetilde{D}_2)$	-0.05	-0.17	-0.09	-0.13	-0.01	-0.08	0.00	0.00	0.03
$y(\widetilde{D}_3)$	0.13	-0.11	0.10	-0.01	0.16	0.07	0.09	-0.09	0.18
$y(\widetilde{D}_4)$	0.04	-0.23	0.06	-0.10	0.30	-0.11	0.18	-0.07	0.27
$y(\widetilde{D}_5)$	-0.04	-0.37	0.05	0.04	0.13	-0.23	0.14	0.01	0.27
2001-2008	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.14	-0.09	-0.11	-0.06	-0.05	-0.08	-0.17	-0.04	0.05
$y(\widetilde{D}_1)$	-0.02	-0.12	-0.04	-0.16	0.09	0.02	-0.02	0.02	0.11
$y(\widetilde{D}_2)$	-0.02	0.08	0.04	0.02	0.12	0.00	-0.04	0.00	0.12
$y(\widetilde{D}_3)$	-0.15	-0.08	-0.10	-0.08	-0.17	-0.13	-0.19	-0.28	-0.04
$y(\widetilde{D}_4)$	-0.23	-0.14	-0.05	0.10	-0.06	-0.02	-0.28	-0.12	0.06
$y(\widetilde{D}_5)$	-0.23	0.01	-0.17	0.28	-0.40	-0.20	-0.29	-0.21	-0.11
2008-2014	**USA**	**GER**	**JAP**	**UK**	**CAN**	**IND**	**C**	**SA**	**AUS**
returns	-0.22	-0.28	-0.15	-0.27	-0.28	-0.27	-0.26	-0.28	-0.30
$y(\widetilde{D}_1)$	-0.27	-0.29	-0.19	-0.36	-0.30	-0.26	-0.30	-0.33	-0.39
$y(\widetilde{D}_2)$	-0.26	-0.19	-0.16	-0.20	-0.30	-0.22	-0.29	-0.20	-0.18
$y(\widetilde{D}_3)$	0.01	0.06	0.21	0.04	-0.07	-0.13	-0.03	-0.01	-0.04
$y(\widetilde{D}_4)$	0.39	0.23	0.29	0.36	0.29	0.12	0.37	0.36	0.31
$y(\widetilde{D}_5)$	-0.03	-0.08	-0.17	-0.03	0.18	0.13	-0.10	0.46	0.36

Note: This table presents the copula dependence parameters of the applied t copula based on returns and decomposed return series on the different scales ($y(\widetilde{D}_1)$,$y(\widetilde{D}_2)$,$y(\widetilde{D}_3)$,$y(\widetilde{D}_4)$,$y(\widetilde{D}_5)$). Dependence is assessed between gold and the corresponding uncertainty measures: the newspaper-based economic policy uncertainty (EPU) index provided by Baker *et al.* (2016), the macroeconomic uncertainty measure (MU) by Jurado *et al.* (2015) and the disagreement among CPI forecasters (CPIU).