Oil prices and the macroeconomy reconsideration for Germany: Using continuous wavelet

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1. Introduction

The oil prices and macroeconomy are one of the extensively studied topics in the literature. Studies have used a vast variety of statistical tools and techniques but focusing on, mainly, the US economy. For the US economy, the empirical evidence shows that until the mid-1980s oil prices were a significant determinant of the economic activity (for details, see Aguiar-Conraria and Soares, 2011; Aguiar-Conraria and Wen, 2007; Gisser and Goodwin, 1986; Hamilton, 1983, 1985) and after 1985 the correlation between oil prices and economic activity is not very clear (Hooker, 1996). However, in the present study we focus on the German economy, Germany is of special interest because of her position enjoyed in the world crude oil market, among others. Germany was ranked 5th in 2006 in the world in the demand for crude oil by consuming 2.638 million barrels of crude oil per day as per the US Energy Information Administration. Nonetheless, her crude oil consumption has continued to decline from a record high of 2.923 million barrels of crude oil per day in 1998 which has reduced to 2.4 million barrels of crude oil per day in 2011. Germany produced 123,200,36 thousand barrels of total oil per day in 2006, which was only 4.668% of total petroleum consumption. In 2004, Germany consumed 2.6 million barrels of oil per day, with imports supplying over 90% of these needs. To meet her demand, Germany imported 794,294,05 thousand barrels of refined petroleum products per day in 2006. According to the Oil and Gas Journal, Germany had 390 million barrels of proven oil reserves in 2005 which has fallen to, as of January 2006, an estimated 367 million barrels of proven oil reserves. However, because of her economic size and the lack of significant domestic oil production, Germany is one of the world’s largest oil importers. “To save energy cost and develop renewable energy technologies, Germany is the world largest producer of biodiesel and generator of electricity from wind and provided tax incentives to encourage consumers to blend biodiesel with conventional diesel fuel” (Hsing, 2007). Substitution policies away from oil to more secure domestic energy sources, although pursued effectively, have only resulted in gradual improvement because close to half of total oil demand is used in the transportation sector where alternatives remain very limited. Domestic German oil production meets only 5.874% of total oil needs as of 2011. In Fig. 1, we present total petroleum consumption, total imports of refined petroleum products and total oil supply/production measured in thousand barrels per day.

According to the conventional wisdom the relationship between the oil prices and both fundamental macroeconomic and financial market variables is much less clear as one would perhaps anticipate. A number of studies have addressed the issues of linearity versus non-linearity, symmetry versus asymmetry or stability versus instability while analyzing this issue. In this work we extend the context of oil prices and macroeconomy addressed in Gronwald (2009) in the framework of Aguiar-Conraria and Soares (2011). Gronwald (2009) has investigated for the German economy whether the extent of causality running...
from the oil price to both fundamental macroeconomic and financial market variables differs between frequency bands using Breitung and Candelon’s (2006) frequency-domain causality test, which is build on Geweke’s (1982) and Hosoya’s (1991) frequency-wise causality measures. Aguiar-Conraria and Soares (2011) addressed the issue of oil prices and macroeconomy for the US economy by utilizing the tools such as wavelet coherency of continuous wavelets approach. Tools used in Aguiar-Conraria and Soares (2011) to analyze the same issue as addressed in Gronwald (2009) are relatively superior (for superiority of the continuous wavelet tools over the discrete wavelet tool and the frequency-domain approach please see Section 2).

Our present contribution is built upon three pillars. In the first place, the much debated question of whether or not a causal relationship exists between the oil price and fundamental macroeconomic (that is industrial production, a proxy of macroeconomic activity, and inflation, measured by consumers price index) variables, calling upon the notion of causality based on the pioneering work of Granger. Secondly, within this causality debate, the relevance of frequency domain concepts is introduced as Granger and Lin (1995) documented that the extent and direction of causality can differ between frequency bands. Thirdly, we introduced time concept with frequency domain hence we analyzed time–frequency relationship as in the frequency-domain framework time information is lost. Hence, in our contribution we used continuous wavelet tools such as the wavelet power spectrum, wavelet coherency, and wavelet phase-difference to analyze the impact of oil price changes in two macroeconomic variables namely industrial production and CPI based in inflation. The wavelet power spectrum illustrates the evolution of the variance of a time-series at the different frequencies; the wavelet coherency demonstrates the correlation coefficient in the time–frequency space; and the information on the delay between the oscillations of two time-series i.e., lead–lag relationships provided by phase-difference.

The remainder of the paper is organized as follows: Section 2 briefly discusses the data and methodology. Section 3 presents and discusses the results, and Section 4 concludes.

2. Data and methodology

2.1. Data

For the empirical estimation, monthly data from 1958M1 to 2009M2, of industrial production and CPI was accessed from IFS CD-ROM of IMF 2010 and data of crude oil prices is the spot price: West Texas Intermediate (WTI) — Cushing Oklahoma (Source: U.S. Department of Energy: Energy Information Administration).

2.2. Motivation and introduction to methodology

In many studies, the analysis is exclusively done in the time-domain and the frequency domain is ignored. However, some appealing relations may exist at different frequencies: oil price may act like a supply shock at high and medium frequencies (see Section 2; Naccache, 2011), therefore, affecting industrial production, whereas, in the long run (i.e., at the lower frequencies) it is the industrial production, through a demand effect, that affects the oil price.

There has been a general practice to utilize Fourier analysis to expose relations at different frequencies between interest variables. However, the shortcomings of the use of Fourier transform for analysis has been well established. A big argument against the use of Fourier transform is the total loss of time information and thus making it difficult to discriminate ephemeral relations or to identify structural changes which is very much important for time series macroeconomic variables for policy purposes. Another strong argument against the use of Fourier transform is the reliability of the results. It is strongly recommended (i.e., it is based on assumptions such as) that this technique is appropriate only when time series is stationary, which is not so usual as in the case with macro-economic variables. The time series of macro-economic variables are mostly noisy, complex and rarely stationary.

To overcome such situation and have the time dimensions within Fourier transform, Gabor (1946) introduced a specific transformation of Fourier transform. It is known as the short time Fourier transformation. Within the short time Fourier transformation, a time series is broken into smaller sub-samples and then the Fourier transform is applied to each sub-sample. However, the short time Fourier transformation approach was also criticized on the basis of its efficiency as it takes...
equal frequency resolution across all dissimilar frequencies (see, for details, Raihan et al., 2005).

Hence, as solution to the above mentioned problems wavelet transform took birth. It offers a major advantage in terms of its ability to perform “natural local analysis of a time-series in the sense that the length of wavelets varies endogenously: it stretches into a long wavelet function to measure the low-frequency movements; and it compresses into a short wavelet function to measure the high-frequency movements” (Aguiar-Conraria and Soares, 2011, p. 646). Wavelet possesses interesting features of conduction analysis of a time series variable in spectral framework but as function of time. In other words, it shows the evolution of change in the time series over time and at different periodic components i.e., frequency bands. However, it is worthy to mention that the application of wavelet analysis in the economics and finance is mostly limited to the use of one or other variants of discrete wavelet transformation. There are various things to consider while applying discrete wavelet analysis such as up to what level we should decompose. Further, it is also difficult to understand the discrete wavelet transformation results appropriately. The variation in the time series data, what we may get by utilizing any method of discrete wavelet transformation at each scale, can be obtained and more easily with continuous transformation. For example, looking at Fig. 2c, one can immediately conclude the evolution of the variance of the return series of oil price and industrial production, and inflation at the several time scales and extract the conclusions with just a single diagram. Even if wavelets possess very interesting features, it has not become much popular among economists because of two important reasons as pointed out by Aguiar-Conraria et al. (2008). Aguiar-Conraria et al. (2008, p. 2865) pointed out that “first, in most economic applications the (discrete) wavelet transform has mainly been used as a low and high pass filter, it being hard to convince an economist that the same could not be learned from the data using the more traditional, in economics, band pass-filtering methods. The second reason is related to the difficulty of analyzing simultaneously two (or more) time series. In economics, these techniques have either been applied to analyze individual time series or used to individually analyze several time series (one each time), whose decompositions are then studied using traditional time-domain methods, such as correlation analysis or Granger causality.”

To overcome the problems and accommodate the analysis of time–frequency dependencies between two time series, Hugdins et al. (1993) and Torrence and Compo (1998) developed approaches of the cross-wavelet power, the cross-wavelet coherency, and the phase difference. We can directly study the interactions between two time series at different frequencies and how they evolve over time with the help of the cross-wavelet tools. Whereas, (single) wavelet power spectrum helps us understand the evolution of the variance of a time series at the different frequencies, with periods of large variance associated with periods of large power at the different scales. In brief, the cross-wavelet power of two time series illustrates the confined covariance between the time series. The wavelet coherency can be interpreted as correlation coefficient in the time–frequency space. The term “phase” implies the position in the pseudo-cycle of the series as a function of frequency. Consequently, the phase difference gives us information “on the delay, or synchronization, between oscillations of the two time series” (Aguiar-Conraria et al., 2008, p. 2867).

2.2.1. The Continuous Wavelet Transform (CWT)²

A wavelet is a function with zero mean and that is localized in both frequency and time. We can characterize a wavelet by how localized it is in time (Δt) and frequency (Δf or the bandwidth). The classical version of the Heisenberg uncertainty principle tells us that there is always a tradeoff between localization in time and frequency. Without properly defining Δt and Δf, we will note that there is a limit to how small the uncertainty product Δt · Δf can be. One particular wavelet, the Morlet, is defined as:

\[ \psi_0(\eta) = \pi^{-1/4} e^{i \omega_0 \eta} e^{-\eta^2 / 2}. \]  

(1)

where \( \omega_0 \) is dimensionless frequency and \( \eta \) is dimensionless time. When using wavelets for feature extraction purposes the Morlet wavelet (with \( \omega_0 = 6 \)) is a good choice, since it provides a good balance between time and frequency localization. We therefore restrict our further treatment to this wavelet. The idea behind the CWT is to apply the wavelet as a band pass filter to the time series. The wavelet is stretched in time by varying its scale \( s \), so that \( \eta = s^{-1} \tau \) and normalizing it to have unit energy. For the Morlet wavelet (with \( \omega_0 = 6 \)) the Fourier period \( (\Delta \omega) \) is almost equal to the scale \( (\lambda_n) = 1.03 \) s. The CWT of a time series \( \{x_n, n = 1, \ldots, N\} \) with uniform time steps \( \delta t \) is defined as the convolution of \( x_n \) with the scaled and normalized wavelet. We write

\[ W^X_s(s) = \sqrt{\frac{1}{s}} \sum_{n=1}^{N} x_n \psi_0 \left[ \frac{(n - \tau) \delta t}{s} \right]. \]  

(2)

We define the wavelet power as \( |W^X_s(s)|^2 \). The complex argument \( W^X_s(s) \) can be interpreted as the local phase. The CWT has edge artifacts because the wavelet is not completely localized in time. It is therefore useful to introduce a cone of influence (COI) in which edge effects cannot be ignored. Here we take the COI as the area in which the wavelet power caused by a discontinuity at the edge has dropped to \( e^{-2} \) of the value at the edge. The statistical significance of wavelet power can be assessed relative to the null hypothesis that the signal is generated by a stationary process with a given background power spectrum \( P_b \).

Torrence and Compo (1998) show how the statistical significance of wavelet power can be assessed against the null hypothesis that the data generating process is given by an AR (0) or AR (1) stationary process with a certain background power spectrum \( P_b \). More generally, processes one has to rely on Monte-Carlo simulations. However, in our case we assess the statistical significance of the wavelet power against the null hypotheses that each variable follows an ARMA \((p, q)\) process, with no pre-conditions on \( p \) and \( q \). The simulations are done using the amplitude adjusted Fourier-transformed surrogates proposed by Schreiber and Schmitz (1996).

2.2.2. The cross wavelet transform

The cross wavelet transform (XWT) of two time series \( x_n \) and \( y_n \) is defined as \( W^X = W^XW^y \), where \( \hat{W}^X \) and \( \hat{W}^y \) are the wavelet transforms of \( x \) and \( y \), respectively, \( * \) denotes complex conjugation. We further define the cross wavelet power as \( W^{XY} \). The complex argument \( \arg(W^{XY}) \) can be interpreted as the local relative phase between \( x_n \) and \( y_n \) in time frequency space. The theoretical distribution of the cross wavelet power of two time series with background power spectra \( P_b^x \) and \( P_b^y \) is given in Torrence and Compo (1998) as

\[ D \left( \frac{|W^{X}_{s}(s)|^2}{\sigma_{xy}^{2}} \right) < p \]  

(3)

where \( Z_{s}(p) \) is the confidence level associated with the probability \( p \) for a pdf defined by the square root of the product of two \( \chi^2 \) distributions.

2.2.3. Wavelet Coherency (WTC)

As in the Fourier spectral approaches, Wavelet Coherency (WTC) can be defined as the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local correlation, both in time and frequency, between two time series. Thus, WTC near one shows a high similarity between the time series, while coherency near zero shows no relationship. While the wavelet power spectrum depicts the variance of a time-series, with times of large variance
showing large power, the cross wavelet power of two time-series depicts the covariance between these time-series at each scale or frequency. Aguiar-Conraria et al. (2008, p. 2872) defines WTC as “the ratio of the cross-spectrum to the product of the spectrum of each series, and can be thought of as the local (both in time and frequency) correlation between two time-series”.

Following Torrence and Webster (1999) we define the WTC of two time series as

$$R_c^2(s) = \frac{|S(s^{-1}W_n^c(s))|^2}{S(s^{-1}|W_n^c(s)|) \cdot S(s^{-1}|W_n^c(s)|)},$$

(4)

where $S$ is a smoothing operator. Notice that this definition closely resembles that of a traditional correlation coefficient, and it is useful to think of the wavelet coherence as a localized correlation coefficient in time frequency space. Without smoothing coherence is identically 1 at all scales and times. We may further write the smoothing operator $S$ as a convolution in time and scale:

$$S(W) = S_{\text{scale}}(S_{\text{time}}(W_n(s)))$$

(5)

where $S_{\text{scale}}$ denotes smoothing along the wavelet scale axis and $S_{\text{time}}$ denotes smoothing in time. The time convolution is done with a Gaussian and the scale convolution is performed with a rectangular window (see, for more details, Torrence and Compo, 1998). For the Morlet wavelet a suitable smoothing operator is given by

$$S_{\text{time}}(W)|_t = \left( W_n(s) \ast c_3 e^{-2s^2} \right)|_t$$

(6)

$$S_{\text{scale}}(W)|_l = (W_n(s) \ast c_4 II(0, 6\delta))|_l$$

(7)

where $c_3$ and $c_4$ are normalization constants and $II$ is the rectangle function. The factor of 0.6 is the empirically determined scale de-correlation length for the Morlet wavelet (Torrence and Compo, 1998). In practice both convolutions are done discretely and therefore the normalization coefficients are determined numerically. Since theoretical distributions for wavelet coherence have not been derived yet, to assess the statistical significance of the estimated wavelet coherence, one has to rely on Monte Carlo simulation methods.

However, following Aguiar-Conraria and Soares (2011) we will focus on the WTC, instead of the wavelet cross spectrum. Aguiar-Conraria and Soares (2011, p. 649) gives two arguments for this: “(1) the wavelet coherency has the advantage of being normalized by the power spectrum of the two time-series, and (2) that the wavelets cross spectrum can show strong peaks even for the realization of independent processes suggesting the possibility of spurious significance tests”.

### 2.2.4. Cross wavelet phase angle

The phase for wavelets shows any lag or lead relationships between components, and is defined as

$$\phi_{xy} = \tan^{-1} \frac{I(W_n^x)}{R(W_n^y)} \quad \phi_{xy} \in [-\pi, \pi]$$

(8)

where $I$ and $R$ are the imaginary and real parts, respectively, of the smooth power spectrum.

Phase differences are useful to characterize phase relationships between two time series. A phase difference of zero indicates that the time series move together (analogous to positive covariance) at the specified frequency. If $\phi_{xy} = [0, \pi/2]$, then the series move in-phase, with the time-series y leading x. On the other hand, if $\phi_{xy} = [-\pi/2, 0]$ then x is leading. We have an anti-phase relation (analogous to negative covariance) if we have a phase difference of $\pi$ (or $-\pi$) meaning $\phi_{xy} \in [-\pi, -\pi/2]$.

### 3. Data analysis and empirical findings

In Fig. 2, we can see the estimated power spectrum for monthly time-series of the variables under consideration (i.e., oil prices (growth rate), Industrial Production Index (growth rate), and inflation (based on the Consumer Price Index)) for the German economy.

The results of wavelet analysis are summarized in Fig. 2. Fig. 2a displays the transient dynamics of the inflation (based on the Consumer Price Index), Industrial Production Index (growth rate), and oil prices (growth rate) for the German economy. Fig. 2b displays the classical Fourier spectrum (Chafftfield 1989) of these time-series. There are large peaks at a period of 20–25 and around 40 months. Although these periodic modes are present in the time series (Fig. 2a), the Fourier spectrum is not able to specify when these modes are present. Conversely, the wavelet power spectrum can quantify the time evolution of these oscillatory modes and show when they are dominant (Fig. 2c).

It is clear that the different time-series have different characteristics in the time–frequency domain. During 1958–1960, the inflation rate variance was quite high at medium scales and during the late-1963–65 and early-1967–1980 the inflation rate variance was quite high at higher scales. It decreased during 1981–85, and during 1991–1997, probably as a consequence of very active oil shocks, the variance of the inflation rate became higher, but in this case, the effect is clearer at short, medium and high scales, suggesting that we were facing short, medium and long term shocks to inflation. After 2001, the variance of the inflation rate is again higher but at very short scales, suggesting that we were facing very short term shocks to inflation. Overall from the figure we can conclude for the evidence of high powered region during 1958–1960, 1963–65 and early-1967–1980.

The power, at medium scales, of the industrial production was high throughout the study period but it was quite high during 1963–1977 and 1982–1995. After 1995 we observe that, the industrial production growth rate variance has been steadily decreasing, but at very short scale some significant island is observed. This suggests that the “Great Moderation” in Germany started after 1995.

We observe by looking at the power spectrum of the oil prices growth rate that until 1974 the variance of oil prices growth rate was very stable. During 1974, 1985–1986, and 1990–1992, the 12–50 month time-scale bands show high power. Hence, we conclude that after 1974 there is evidence of structural change in the oil price series due to which oil prices became much more volatile.

In Fig. 3, we estimate the coherency between the return series of oil price series and industrial production and between oil price returns and inflation. We also estimate the phase of the oscillations, as well as their phase-difference. Given that for oil price returns and inflation the most coherent regions are between the 20 and 60 month bands, we focus our phase difference analysis on two frequency bands: 20–30, and 34–60 months. For the same reasons, when analyzing the phases and phase-differences between return series of oil prices and industrial production the most coherent regions are between the 12–30 month bands, we focus our phase difference analysis on three frequency bands: 12–16, 16–24 and 28–35 months. For both cases and each band, we calculate the average phase and phase-difference.

In Fig. 3, we also see that the relationship between oil prices return and inflation is stronger and more stable. The phase differences reveal a fairly stable relation. At 20–30 month scales and for most of the time, the phase difference has consistently been between 0 and $\pi/2$. This suggests that both series move in phase and the Consumer Price Index based inflation leads the oil price returns. Of course, in 1969, 1974–75 and 1992–93 we have evidence when the phase difference has been between $\pi/2$ and $\pi$ indicating that there is an anti-phase relationship between oil price returns and inflation and oil price returns is the leading variable.
Now if we focus on the 34–60 month frequency bands, it is clear that during 1978–1990, 1991–1994 and 2004–2009 the phase difference has been between 0 and $-\pi/2$ indicating that there is a phase relationship between oil price returns and inflation and oil price returns is the leading variable. However, during 1994–2004 the phase difference has been between $-\pi/2$ and $-\pi$ indicating that there is an anti-phase relationship between oil price returns and inflation and inflation is the leading variable.

Looking at coherency some different patterns emerge. There is a structural change in 1958. In 1974 there is high coherency at both medium (12–14 month bands) and large scales (40–44 month bands). During 1979–83, we observe high coherency in the 48–64 month bands and also at the 22–28 month bands. After 1996 and before 2005, only at very high scales we observe strong coherency and after 2005 at medium frequencies strong coherency is observed. Some political economy major events that happened during these decades may explain this evolution.

Many interesting structural changes have occurred in the relationship between return series of oil prices and industrial production in the German economy. In 1958 and 1965, we have some coherency regions at business cycle frequencies (16 months and 25–28 months). During 1975–1980, the high coherency region shifted to the 29–35 month bands. During 1991–1995, the high coherency region is found in the 11–15 month bands. During 1998–2004, the high coherency region is found in the 18–25 month bands. During 2005–2009, the high coherency region is found in the 10–48 month bands.

The phase-difference gives us more details. Looking first at the 12–16 month frequency bands, we observe that there is an inconsistency between the phase-difference between $\pi$ and $-\pi$ and lead–lag relationship between the test variables. Looking first at the 16–24 month frequency bands, we observe that during 1962–1969 and 1971–1982 the phase-difference is on average between 0 and $-\pi/2$ indicating that there is a phase relationship between return series of oil price and industrial production and oil price returns is the leading variable. Further, evidence shows that during 1982–2009 the phase-differences are on average between 0 and $\pi/2$ indicating that both series move in phase and the industrial production return leads the oil price returns. Combining the findings of this frequency band, we found that oil price changes that have occurred after 1982 (i.e., specifically during 1982–2009) were demand-driven, while, during 1962–1969 and 1971–1982, oil-price increases led to increases in the industrial production, capturing the positive effects of oil price shocks.

However, looking first at the 28–35 month frequency bands, we observe that during 1963–1984 the phase-difference is on average between $\pi/2$ and $\pi$ indicating that there is an anti-phase relationship between the return series of oil price and industrial production and oil price increase is the leading variable. Further, evidence shows that during 1984–1989 the phase-difference is on average between $-\pi/2$ and $-\pi$ indicating that there is an anti-phase relationship between the return series of oil price and industrial production and industrial production increase is the leading variable. We also find that during 1994–2004 the phase-difference is on average between 0 and $-\pi/2$ indicating that there is a phase relationship between the return series of oil price and industrial production and oil price increase is the leading variable.

Combining the findings of this frequency band, we found that oil price changes that have occurred during 1984–1989 were demand-driven (but negative relationship is found), while, during 1963–1984, oil-price increases led to increases in the industrial production, capturing the negative effects of oil price shocks and during 1994–2004 oil-price increases led to increases in the industrial production, capturing the positive effects of oil price shocks.
4. Conclusions

We utilized the tools of the continuous wavelet to uncover the relationship between the oil price returns and inflation and the return series of oil price and industrial production and thereby expose the time–frequency patterns in the relationship as well as the structural breaks in the relationship.

We find at the 20–30 month scales that during most of the time, the phase difference has consistently been between 0 and $\pi/2$ implying phase relationship between inflation and oil price returns and inflation leads the oil price returns. However, for the 34–60 month frequency bands, it is clear that during 1978–1990, 1991–1994 and 2004–2009 the phase difference has been between 0 and $-\pi/2$ indicating that there is a phase relationship between oil price returns and inflation and inflation is the leading variable. This implies that tight monetary policy of Germany proved to be successful, with a decrease of the inflationary impact of oil price shocks for lower frequencies during study period however, for higher frequencies during 1978–1990, 1991–1994 and 2004–2009 the inflationary impacts of oil price returns were also very well contained.

We find that there is a huge inconsistency between the phase-difference, between $\pi$ and $-\pi$ and lead–lag relationship between the return series of oil price and industrial production at the 12–16 month frequency bands. However, at the 16–24 month frequency bands, we find that oil price changes that have occurred after 1982 (i.e., specifically during 1982–2009) were demand-driven, while, during 1962–1969 and 1971–1982, oil-price returns led to changes in the industrial production, capturing the positive effects of oil price shocks. Further, our results of 28–35 month frequency bands show that oil price changes that have occurred during 1984–1989 were demand-driven with negative correlation, while, during 1963–1984, oil-price returns led to changes in the

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**Fig. 3.** The cross-wavelet coherency and phase-differences. Note: On the top in the left and the right panel: (a) presents cross-wavelet coherency between oil and inflation and between oil and industrial production; and (b)–(c) and (b)–(d) present the phases and phase-difference between oil and inflation and between oil and industrial production; below (a), in the left panel, in (b)–(c) the green line represents the inflation phase, the blue line the oil phase and the red line the phase-difference between inflation and oil prices; below (a), in the right panel, in (b)–(d) the green line represents the industrial production phase, the blue line the oil phase and the red line the phase-difference between industrial production and oil prices; the black contour designates the 5% significance level based on an ARMA(1,1) null estimated by Monte Carlo simulations (5000 trials). Coherency ranges from blue (low coherency—close to zero) to red (high coherency—close to one).
industrial production, capturing the negative effects of oil price shocks and during 1994–2004 oil-price returns led to changes in the industrial production, capturing the positive effects of oil price shocks. Overall our results suggest that oil price changes that have occurred after 1994 were demand-driven. These results are broadly in line with those of Kilian (2006), Baumeister and Peersman (2008), and also with Aguiar-Conraria and Soares (2011) who concluded that, approximately since the Asian crisis, demand-driven oil price shocks have become more important than supply-side induced shocks. Putting all this information together, one concludes that demand driven oil price shocks became important in 1982, and became even more important after 1994.

References