Inflation synchronization among the G7and China:
The important role of oil inflation

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Abstract

We investigate the interconnectedness and spillovers between oil price inflation and CPI inflation in the G7 countries and China over the available period 1987M6-2020M6. To this end, we employ the multivariate DECO-GARCH model and both time-domain and frequency-domain spillover methods to achieve the objectives. We find that there is a reasonably high degree of integration between the oil price inflation and the CPI inflation rates in those countries. This relationship is not only time-varying, but also has been rising over time and, remarkably so, during oil crises and financial stress episodes. We also show that the oil price inflation is a crucial transmitter of spillovers to the CPI inflation of the countries under consideration, particularly to the US inflation, which, in turn, has a weak to mild influence on the paths of inflation of other countries. Additionally, the largest gross directional spillovers to other CPI inflation rates accrue to the US, while the lowest accrue to China. Finally, the oil price inflation influences the CPI inflation over the short-end of the business cycle, but much less so over the medium- to long-ends.

Keywords: Oil price inflation, CPI inflation, G7 and China, DECO-GARCH model, spillovers.
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1. Introduction

Inflation is an important phenomenon because it resonates in advanced and fast-growing economies as well as developing countries, and affects many aspects of the economic, political and social livelihoods of the population. It also reverberates through the economy during booms and even in the slow growth phases of the business cycles. During booms, high inflation has a redistributive effect on real and financial assets and could force monetary authorities to restrain the economy and, in the process, it may lead to recessions. During slow growth, low inflation will contribute to having low interest rates, which may over time also heat up the overall economy.

Over the last few decades, globalization has acutely shaped the inflation dynamics. Not surprisingly, there is mounting empirical evidence suggesting that the global drivers play an increasingly important role in driving domestic inflation (Gamber and Hung, 2001; Bean, 2006; Borio and Filardo, 2007; Hakkio, 2010; Aastveit *et al.*, 2016), while domestic factors are becoming less prominent (Ciccarelli and Mojon, 2010; Eickmeier and Pijnenburg, 2013; Forbes, 2019). Thus, it is likely that inflation is more synchronized across countries now than it used to be in the past, a feature that not only poses key challenges for policymakers but also makes the empirical gauging and tracing of inflation spillovers more crucial (Tiwari *et al.*, 2015, 2016).

Among the several catalysts for changes in inflation, changes in oil prices in particular strike as extremely relevant, as most of the oil price swings are passed on to consumers in the form of higher prices of goods and services. Higher oil prices may increase the prices of all goods and services made of oil or use oil, ranging from refined products and petrochemicals to traveling. They may also depress the supply of some goods by increasing their production costs. High oil prices may also lead to stagflation (high unemployment and high inflation) as happened in the 1970s. By contrast, lower oil prices may lead to less investment in the energy sector, which may repress future oil production and fuel future oil prices. Production costs and, hence, the prices of goods and services produced may also fall due to lower oil prices.

Higher oil prices may also affect inflation in the short run but may or may not have an effect in the medium and long runs, an issue that is related to inflation persistence (Wang and Wen, 2007). For instance, inflation reached 4% in the US and 5% in Europe in 2008 but when the global financial crisis struck at the end of 2008, inflation dropped to negative levels in 2009. Additionally, higher oil prices may also not necessarily result in higher inflation over the long-term, because of the dominance of other factors that are related to inflation (Salisu *et al.*, 2017). This could happen if the drivers of higher oil prices are short-lived supply side factors, such as the interruption of oil supplies in major oil-exporting countries. In the late 1990s and early 2000s, those driving factors include the improvement in productivity and energy efficiency and more flexibility in the labor markets. It has happened in the current period because of the COVID-19 pandemic, which is also a mix of demand and supply shocks.

We are concerned about those issues because policymakers are eager to know whether to use monetary policy to deal with inflation overshoots before they flourish, and then it will be hard to combat inflation, as for example when the US had two back-to-back recessions in 1980-1982. Investors would also like to understand the extent to which higher oil prices may not lead to interest rate hikes (particularly, in the Inflation Protected Securities (TIPS)), because these can suppress growth and mitigate the oil price inflation (Coward, 2018).

This narrative has motivated us to study the relation between oil prices and CPI inflation. We start by considering changes in three major proxies for crude oil prices, i.e., the West Texas Intermediate (WTI), the Europe Brent (Brent), and the Crude Oil Dubai (Dubai) to represent oil inflation. We have also chosen the G7 countries (i.e. US, U.K., Japan, Canada, Germany, France and Italy) and China. On one hand, these countries are major players in the world economy and meet regularly to coordinate their economic and financial policies. They are transforming countries whether in terms of global economic growth or CPI inflation. They also have a strong influence on oil price inflation and global prices of goods and services. On the other hand, China is the "world factory" and can move global economic growth and inflation and also accounts for a large portion of the increase in global oil demand, and the G7 countries have large economies and are major consumers of crude oil. China is also the second largest global economy and accounts for half of the increase in the global oil demand. Thus, it has a substantial influence on oil inflation and stands as a good example for the transmission of oil inflation to global CPI inflation. Consequently, comparing the transmission of inflation in China and the G7 countries is relevant and could be timely, given the increase in global inflation expectations.

All in all, there is a policy channel that connects the policies of the G7 and China regarding to their economic growth, inflation, unemployment, exchange rates, …, etc. In addition, those countries trade significantly with each other, which implies that this channel also brings connectedness among them.

In this context, the objectives of this paper are fourfold. The first objective aims to study the strength of the oil price-CPI inflation relationship for the G7 countries and China. The study strives to assess if this relationship is positive over a relatively long period, namely, 1987M6-2020M6. Second, the paper attempts to understand whether the link between oil price inflation and CPI inflation a short-run phenomenon or it is going to persist over the medium and the long runs. This issue is relevant because it guides policymakers (particularly, monetary authorities) by pointing them to the need of fighting inflation if it is going to persist in the long run or letting the underlying dynamics vanish when they are perceived as temporary. Third, we examine the synchronization and spillover patterns of CPI inflation rates among the G7 countries and China, as well as how these are affected by oil price inflation. Finally, we identify the main transmitters/receivers of shocks to oil price inflation and CPI inflation and their dynamic transmissions.

Our main contributions to the existing literature are as follows:

(i) This is the first study that combines the synchronization of changes in oil prices and CPI inflation in the G7 countries and China. These countries are the largest industrialized economies that heavily depend on oil, while China is among the fastest-growing major developing economy with substantially expanding energy needs.

(ii) We use the ARMA(1,1)-DECO-GARCH(1,1) models proposed by Engle and Kelly (2012) to examine the different synthetizations. In particular, the multivariate DECO-GARCH model is an extreme case of the dynamic conditional correlation (DCC) model in which the correlations are equal across all pairs but the common equicorrelation changes over time. This econometric framework is particularly well-suited to jointly model the conditional volatility and the time-varying correlation between oil price inflation and CPI inflation in the G7 and China.

(iii) We assess the international co-movement and directional spillovers of oil price inflation and CPI inflation across the G7 countries and China. We do so by analyzing the time-domain spillovers using the methodology developed by Diebold and Yilmaz (DY, 2009, 2012, 2014). This methodology allows us to discern between the roles played by *local* and *global* factors in shaping the dynamics of inflation, namely, by distinguishing between *own* shocks and *spillovers* in the form of contributions *to* and *from* other countries' inflation rates. Additionally, we investigate whether this interconnectedness can last at different business cycle frequencies or not by relying on the frequency-domain spillovers approach of Barunik and Krehlik (BK, 2018). This framework highlights the relevance of cross-sectional correlation in the connectedness origins, which remains hidden when one only takes into consideration the time-domain measures. While the DY and BK methodologies have been applied in a wide

range of research areas including asset market returns and volatility (Diebold and Yilmaz, 2009, 2012), commodity market integration (Antonakakis *et al.*, 2014; Batten *et al.*, 2015), connectedness of the global business cycle (Diebold and Yilmaz, 2015) and macro-financial spillover dynamics and systemic risk (Barunik and Krehlik, 2018), to the best of our knowledge, only Tiwari *et al.* (2015, 2016, 2019a) rely on them to assess inflation spillovers. Yet, they can be useful to identify if a specific country is a net transmitter/receiver of inflation shocks and to investigate whether inflation co-movements materialize at the short-/long-end of the business cycle.

(iv) We employ the ForceAtlas2 algorithm developed by Jacomy *et al.* (2014) to network analysis with the aim of providing a visualization of the role played by oil price inflation in shaping the dynamics of CPI inflation.

The results of the DECO-GARCH model show that there is a reasonably high degree of integration between CPI inflation rates and oil price inflation in the G7 and China. This is not only time-varying but also has been rising over time, particularly during oil crisis episodes and periods of financial stress. In fact, inflation rates appear increasingly synchronized, possibly reflecting common shocks and similarities in international trade and monetary policy frameworks (Tiwari *et al.*, 2019a).

In what concerns interconnectedness, the *time-domain* spillover methods reveal that the oil price inflation is a crucial transmitter of spillovers to CPI inflation. Additionally, the US is responsible for the largest gross directional spillovers to the CPI inflation rates of the other countries included in our study. As for the *frequency-domain* frameworks, they point to a stronger influence of oil price inflation on CPI inflation over the short-end of the business cycle, but much less so over the medium- to long-ends.

(v) The network analysis shows that oil price inflation is a net transmitter of strong spillovers to the US inflation, which, in turn, has a weak to mild influence on the paths of inflation in several countries.

All results considered, our empirical evidence can prove helpful for investors engaging in asset allocation and risk management, who are eager to factor in the impact of oil crises and financial turmoil in their portfolio decisions at different horizons. It is also of paramount importance to policy makers as to whether to make changes to the monetary policy in order to curb the inflation rate and achieve price stability or leave it fading over time. This is timely as the central banks around the world are now following the impact of expansionary monetary policies and exploring their impacts on inflation expectations.

The remainder of the paper is organized as follows. Section 2 provides a brief review of the literature. Section 3 presents a description of the models employed in this study. Section 4 illustrates and discusses the empirical results. Finally, Section 5 concludes.

2. Literature review

It has been acknowledged in the literature that fluctuations in oil prices are a key to understanding the dynamics of consumer prices around the world (Hamilton, 1983, 1988; Mork, 1989; Hooker, 1996). This, in turn, has important implications for monetary policy implementation, as central banks design their policies to achieve price stability over the medium-term (Bernanke *et al.*, 2004; Hamilton and Herrera, 2004; Chen, 2009).

Yet, the strength of the linkages between oil price inflation and CPI inflation has evolved over time due to oil crisis episodes, financial turmoil events, and relevant institutional and technological structural changes (e.g., investments in renewable technologies and commodity financialization) (Nguyen *et al.*, 2020).

From a theoretical perspective, a rise in oil prices can lead to higher consumer prices (Alvarez *et al.*, 2011), as oil directly affects oil-derived products and oil typically is an input in the production processes of many goods and services (Hamilton, 1996). Changes in oil prices may also impact personal consumption expenditures (Wang, 2013), economic policy uncertainty (Kang and Ratti, 2013; Antonakakis *et al.*, 2014; Ma *et al.*, 2019), exchange rates (Chen and Chen, 2007; Ji *et al.*, 2019) and inflation expectations (Herrera and Pesavento, 2009). While oil supply disruptions appear to have a small effect on consumer prices (Kilian, 2009), oil demand shocks seem to generate CPI inflation (Kilian and Park, 2009).

At the same time, CPI inflation can also influence oil price inflation. For example, higher food prices may boost agricultural activity which uses fertilizers made of oil among other things, thus, translating into higher oil demand (Baumeister and Kilian, 2014). In the meantime, central banks may react to higher CPI inflation by hiking interest rates, which should lead to a fall in real economic activity and cause a lower oil demand, thus, effectively reducing oil prices.

On the empirical front, a number of studies assess the relationship between oil price inflation and CPI inflation. For instance, Hooker (2002) shows that while oil price shocks contributed substantially to the core CPI inflation until the early eighties, the oil price pass-through has declined since then due to the fall in the oil share in the US economy and to the less responsive monetary policy to oil shocks. By means of using the Structural Vector Auto-Regression (SVAR) techniques, including time-varying parameters and stochastic volatility or rolling-samples, Blanchard and Galí (2009) and Clark and Terry (2010) uncover a significant decline in the pass-through from oil price inflation to CPI inflation. A similar conclusion is reached by Tiwari *et al.* (2019b) who rely on a wavelet coherency analysis to examine this relation. Tiwari *et al.* (2015, 2016) use the VAR approaches to examine inflation spillovers. Panel frameworks also show that a rise in oil prices is associated with an increase in CPI inflation, albeit the effect has been fading over time (Chen, 2009; Cunado and Perez de Gracia, 2003; Cunado *et al.*, 2015; Choi *et al.*, 2018).

Additionally, a few papers look at the linkages between oil price inflation and CPI inflation through the lenses of specific time horizons. In this context, Wang and Wen (2007) stress the existence of worldwide 'persistent and lagged' inflation and report strong inflation synchronization in the short-term. Relying on panel ARDL models, Salisu *et al.* (2017) find that oil price inflation and CPI inflation are positively and significantly correlated in the long-term, but the evidence is mixed in the short-term. Additionally, the impact of oil price inflation is larger in net oil-importing countries than in net oil-exporting countries.

Finally, an important body of research has also analyzed inflation co-movement or synchronization across economies and geographical regions, revealing that the degree of oil price-pass through into inflation is varied (Chen, 2009). For example, Friedman and Schwartz (1980) find inflation convergence across continents and nations in the aftermath of war-specific episodes. In Europe, Hall *et al.* (1992) use a Kalman filter technique and show that the process of inflation convergence is slow and protracted. Relying on panel unit root tests, Kočenda and Papell (1997) and Lopez and Papell (1997) uncover inflation convergence in the European Union. By contrast, Holmes (2002) finds that inflation convergence among the original set of Eurozone member states was stronger in the eighties than in the nineties. For China, Osorio and Unsal (2013) argue that the economy is influenced by inflation spillovers both directly via import prices and indirectly through commodity prices. Similarly, Gong and Lin (2018) point to the fact that China’s output and inflation is sensitive to both oil supply and oil demand shocks. Nusair (2019) evaluates the impact of oil price fluctuations on inflation in the Gulf Cooperation Council (GCC) countries and finds evidence of asymmetry over the long-run: rising (fall) oil price has a significant positive (insignificant or negative) effect on inflation.

In the case of the ASEAN countries, Kisswani and Nusair (2014) present evidence of nonlinear convergence of inflation rates, relative to the US and Japan. Kang *et al.* (2020) assess pairwise causality of inflation rates across time and frequency, inflation synchronization and network causality structure among five ASEAN countries (i.e. Indonesia, Malaysia, Philippines, Singapore and Thailand). Using a similar set of methodologies that we apply in this paper, those authors find time-varying co-movement between inflation cycles. Finally, according to Tiwari *et al.* (2019a), inflation rates appear increasingly synchronized, possibly reflecting common shocks and similarities in international trade and the monetary policy frameworks.

Against this background, we investigate the interconnectedness between CPI inflation in the G7 countries and China and oil price inflation, relying initially on the multivariate DECO-GARCH model. We also construct both time-domain and frequency-domain spillover indices among oil price inflation and CPI inflation, using the Barunik and Krehlik (2018) method to study the inflation interconnectedness.

3. Econometric Methodology

We use three different models, as well as the network analysis, because those methods serve the different objectives of this study**.**

3.1 The DECO-GARCH model

To jointly model multivariate conditional volatility and the time-varying correlations between changes in consumer price indices (CPIs) and oil price inflation series, we start by considering the Dynamic Equicorrelation GARCH (DECO-GARCH) model proposed by Engle and Kelly (2012). By setting the average of the conditional correlations equal to the average of all pair correlations, this framework eases the handling of large-scale correlation matrices.[4]

Let us have a vector of n inflation series, $INFL_t = [INFL_{1,t}, \dots, INFL_{n,t}]'$, which follow an ARMA(1,1) process, that is:

$$INFL_t = c + \varphi INFL_{t-1} + \xi_t + \theta \xi_{t-1}, \quad \xi_t = u_t z_t, \tag{1}$$

where c is a vector of constant terms, $\xi_t = [\xi_{1,t}, \dots, \xi_{n,t}]'$is the vector of residuals, and u_t is an independently and identically distributed (i.i.d) process.

From the univariate GARCH(1,1) process, we can estimate the conditional volatilities, $z_{j,t}$, as:

$$z_{j,t} = \kappa_j + \alpha_i \xi_{j,t-1}^2 + \beta_j z_{j,t-1}, \tag{2}$$

where $\kappa_j > 0$, $\alpha_j \geq 0$, $\beta_j \geq 0$, and $\alpha_j + \beta_j < 1$.

The dynamic correlations between the variables of interest can be computed using the DCC formulation of Engle (2002). Thus, by assuming that $E_{t-1}[\xi_t] = 0$ and $E_{t-1}[\xi_t \xi_t'] = Z_t$, the conditional variance–covariance matrix, Z_t, can be written as:

$$Z_t = \mathrm{B}_\mathrm{t}^{1/2} R_t \mathrm{B}_\mathrm{t}^{1/2}, \tag{3}$$

where $E_t[\cdot]$ is the expectation conditional on the information set available at time t, $R_t = [\rho_{\mathrm{jk,t}}]$ is the conditional correlation matrix, and $B_t = \mathrm{diag}(z_{1,t}, \dots, z_{n,t})$ is the diagonal matrix of conditional variances.

The DCC-GARCH model proposed by Engle (2002) and extended by Aielli (2013) embeds the following dynamic correlation structure (c^{DCC}):

$$R_t = \{\Lambda_\mathrm{t}^*\}^{-1/2} \Lambda_t \{\Lambda_\mathrm{t}^*\}^{-1/2}, \tag{4}$$

$$\Lambda_t^* = diag[\Lambda_t], \tag{5}$$

[4] In fact, it overcomes the computational requirements and interpretation of the complexity (Abouara and Chevallier, 2014) of the Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model developed by Engle (2002).

$$\Lambda_t = [\Lambda_{jk,t}] = (1 - a - b)Q^* + a\left({\Lambda_{t-1}^*}^{1/2} u_{t-1} u_{t-1}^{'} {\Lambda_{t-1}^*}^{1/2}\right) + b\Lambda_{t-1}, \quad \textbf{(6)}$$

where Q^* is the unconditional covariance matrix of $\Lambda_t^{*1/2} u_t$, $u_t = [u_{1,t}, \ldots, u_{n,t}]'$ is the vector of standardized residuals, and a and b are non-negative scalars such that $(a + b) < 1$.

To improve the time efficiency in the estimation, Engle and Kelly (2012) model ρ_t using the c^{DCC} process to obtain the conditional correlation matrix Λ_t and taking the mean of its off-diagonal elements. Thus, using the scalar equicorrelation:

$$\rho_t^{DECO} = \frac{1}{n(n-1)}\left(D_n^{'} R_t^{c^{DCC}} D_n - n\right) = \frac{2}{n(n-1)} \sum_{j=1}^{n-1} \sum_{k=j+1}^{n} \frac{\Lambda_{jk,t}}{\sqrt{\Lambda_{jj,t}\Lambda_{kk,t}}}, \quad \textbf{(7)}$$

where $\Lambda_{jk,t} = \rho_t^{DECO} + a_{DECO}\left(u_{j,t-1}u_{k,t-1} - \rho_t^{DECO}\right) + b_{DECO}\left(\Lambda_{jk,t} - \rho_t^{DECO}\right)$ is the $(\mathrm{j,k})^{\mathrm{th}}$ element of the matrix Λ_t, one can estimate the conditional correlation matrix:

$$R_t^{DECO} = (1 - \rho_t) I_n + \rho_t D_n, \quad \textbf{(8)}$$

where $\mathrm{I_n}$ is the n-dimensional identity matrix and D_n is the $(\mathrm{n} \times \mathrm{n})$ matrix of ones.

Under the assumption of equicorrelation, the likelihood equation is given by:

$$L = -\frac{1}{T}\sum_{t=1}^{T}\left(ln(1-\rho_t)^{n-1}(1+(n-1)\rho_t)\right) + \frac{1}{1-\rho_t}\left(\sum_{j=1}^{n}\xi_{j,t}^2 - \frac{\rho_t}{1+(n-1)\rho_t}\left(\sum_{j=1}^{n}\xi_{j,t}^2\right)\right) \quad \textbf{(9)}$$

which is simpler and quicker to estimate, as one is able to avoid the inversion of matrix R_t, and ρ_t is a single dynamic correlation coefficient (Kang and Yoon, 2019) representing comovement.

3.2 Time-domain spillover indices

We construct *time-domain* spillover indices by estimating a VAR model consisting of a vector of endogenous (consumer price and oil price) inflation series, $INFL_t$, such that its moving-average representation is:

$$INFL_t = \sum_{j=0}^{\infty} \Gamma_j \xi_{t-j}, \quad \textbf{(10)}$$

where Γ_j are N×N coefficient matrices satisfying the condition $\Gamma_j = \Psi_1\Gamma_{j-1} + \cdots + \Psi_p\Gamma_{j-p}$, with $\Gamma_0 = \mathrm{I_n}$ and $\Gamma_\mathrm{j} = 0$ for *j <0*, and $\xi_t \sim N(0, \Omega)$ is a vector of independently and identically distributed (i.i.d.) disturbance terms with mean nil and variance-covariance matrix, Ω.

Next, we follow Koop *et al.* (1996) and Pesaran and Shin (1998), and compute the *H*-step-ahead generalized forecast error-variance decompositions (GFEVD), $\lambda_{jk}(H)$, for *H = 1, ..., h*, as:

$$\lambda_{jk}(H) = \frac{\sigma_{kk}^{-1}(H)\sum_{h=0}^{H-1}\left(\mathrm{a_j'\Gamma_h\Omega a_k}\right)^2}{\sum_{h=0}^{H-1}\left(\mathrm{a_j'\Gamma_h\Omega\Gamma_h' a_j}\right)}, \tag{11}$$

where σ_{kk} is the standard deviation of the disturbance term of the *k*th equation, and a_j is the selection vector consisting of one as the *j*th element and zeros otherwise.

Finally, we apply the methodology developed Diebold and Yilmaz (2009, 2012, 2014), such that spillovers (or cross variance shares) correspond to fractions of the *H*-step-ahead error variances in forecasting $INFL_j$ that are due to shocks to $INFL_k$, for *j, k = 1, . . . , N*, such that $j \neq k$, while the own variance shares are fractions of the *H*-step-ahead error variances in forecasting $INFL_j$ that are due to shocks to $INFL_k$, for *j = 1, . . . , N*.

In this context, we normalize each entry of the variance decomposition matrix by the row sum as $\breve{\lambda}_{jk}(H) = \lambda_{jk}(H)/\sum_{j=1}^{N}\lambda_{jk}(H)$, so the *total spillover* index can be expressed as:

$$S(H) = \frac{\sum_{\substack{j,k=1\\ j\neq k}}^{N}\breve{\lambda}_{jk}(H)}{\sum_{j,k=1}^{N}\breve{\lambda}_{jk}(H)}\cdot 100 = \frac{\sum_{\substack{j,k=1\\ j\neq k}}^{N}\breve{\lambda}_{jk}(H)}{N}\cdot 100, \tag{12}$$

which measures the contribution of spillovers of shocks to the total forecast error-variance.

The *directional spillovers* received by (consumer price and oil price) inflation measure *j from* all other (consumer price and oil price) inflation measures *k* are computed as:

$$S_{j.}(H) = \frac{\sum_{\substack{k=1\\ k\neq j}}^{N}\breve{\lambda}_{jk}(H)}{\sum_{j,k=1}^{N}\breve{\lambda}_{jk}(H)}\cdot 100 = \frac{\sum_{\substack{k=1\\ k\neq j}}^{N}\breve{\lambda}_{jk}(H)}{N}\cdot 100. \tag{13}$$

Similarly, the *directional spillovers* transmitted by (consumer price and oil price) inflation measure *j to* all other (consumer price and oil price) inflation measures *k* are:

$$S_{.j}(H) = \frac{\sum_{\substack{k=1 \\ k\neq j}}^{N} \breve{\lambda}_{kj}(H)}{\sum_{j,k=1}^{N} \breve{\lambda}_{kj}(H)} \cdot 100 = \frac{\sum_{\substack{k=1 \\ k\neq j}}^{N} \breve{\lambda}_{kj}(H)}{N} \cdot 100. \quad \textbf{(14)}$$

Net spillovers from (consumer price and oil price) inflation measure *j* to all other (consumer price and oil price) inflation measures *k* are defined as

$$S_j(H) = S_{.j}(H) - S_{j.}(H), \quad \textbf{(15)}$$

which tells us how much each (consumer price and oil price) inflation measure contributes to other (consumer price and oil price) inflation measures, in net terms.

Finally, *net pairwise spillovers* are measured as:

$$S_{jk}(H) = \left(\frac{\breve{\lambda}_{kj}(H)}{\sum_{j,k=1}^{N} \breve{\lambda}_{kj}(H)} - \frac{\breve{\lambda}_{jk}(H)}{\sum_{j,k=1}^{N} \breve{\lambda}_{jk}(H)}\right) \cdot 100 = \left(\frac{\breve{\lambda}_{kj}(H) - \breve{\lambda}_{jk}(H)}{N}\right) \cdot 100, \quad \textbf{(16)}$$

which is the difference between shocks transmitted from (consumer price and oil price) inflation measure *j* to (consumer price and oil price) inflation measure *k* and those transmitted from *k* to *j*.

In this framework, we set the *H*-step forecast horizon equal to 10 months to adequately capture the short- to medium-term comovement between CPI inflation and oil price inflation. Moreover, the lag length of the VAR model corresponds to the optimal lag length based on the Bayesian information criterion (BIC), that is, one month.

3.3 Frequency-domain spillover indices

We also consider the *frequency-domain* spillover indices computed using the methodology developed by Barunik and Krehlik (2018). In this context, given the frequency-response function, $\mathit{\Gamma}\left(e^{-i\gamma}\right) = \sum_h e^{-i\gamma h}\, \mathit{\Gamma}_h$, obtained from the Fourier transform of $\mathit{\Gamma}$ coefficients (with $i = \sqrt{-1}$), the fraction of the spectrum of the j^{th} variable at frequency ω due to shocks in the k^{th} variable is:

$$\left(f(\omega)\right)_{jk} \equiv \sigma_{kk}^{-1} \left|\left(\Gamma\left(e^{-i\gamma}\right)\Sigma\right)_{jk}\right|^2 \Big/ \left(\Gamma\left(e^{-i\gamma}\right)\Sigma\Gamma'\left(e^{+i\gamma}\right)\right)_{jj}, \quad \textbf{(17)}$$

where $\omega \in (-\pi, \pi)$.

If we weigh $\left(f(\omega)\right)_{jk}$ by the frequency share of the variance of the j^{th} variable, i.e.

$$\Gamma_j(\omega) = \left(\Gamma\left(e^{-i\gamma}\right)\Sigma\Gamma'\left(e^{+i\gamma}\right)\right)_{jj} \Big/ \frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Gamma\left(e^{-i\tau}\right)\Sigma\Gamma'\left(e^{+i\tau}\right)\right)_{jj} d\tau, \quad \textbf{(18)}$$

where the power of the j^{th} variable at a given frequency sums over frequencies to 2π, then, the generalized FEVD on frequency band d can be expressed as:

$$\lambda_{jk}(d) = \frac{1}{2\pi}\int_d \Gamma_j(\omega)\left(f(\omega)\right)_{jk} d\omega, \quad \textbf{(19)}$$

where $d = (r, s): r, s \in (-\pi, \pi), r < s$.

Normalizing each entry of the generalized FEVD on the frequency band d as $\breve{\lambda}_{jk}(d) = \lambda_{jk}(d)/\sum_k \lambda_{jk}(\infty)$, the spillover on the frequency band d can be represented by:

$$S_d^F = 100\left(\frac{\sum_{j\neq k}\breve{\lambda}_{jk}(d)}{\sum\breve{\lambda}_{jk}(\infty)} - \frac{\mathrm{Tr}\{\breve{\lambda}_d\}}{\sum\breve{\lambda}_{jk}(\infty)}\right), \quad \textbf{(20)}$$

where $Tr\{\cdot\}$ is the trace operator.

Finally, the overall spillover within the frequency band d is given by:

$$S_d^W = 100\left(1 - \frac{\mathrm{Tr}\{\breve{\lambda}_d\}}{\sum\breve{\lambda}_{jk}(\infty)}\right). \quad \textbf{(21)}$$

3.4 Network analysis

As an illustration of the interconnectedness among CPI and oil price inflations, we compute nodes and edges that describe the pairwise directional spillover indices by applying the ForceAtlas2 algorithm developed by Jacomy *et al.* (2014) in the visualization software Gephi.

In our VAR model with *N* variables, each variable has *N-1* edges, implying a total of k^2-k edges. Each pairwise directional spillover is illustrated by the edge size and the edge color.

4. Empirical Results

4.1 Data and preliminary analysis

We use Consumer Price Index (CPI) data at the monthly frequency for the G7 countries (i.e. United Kingdom (UK), United States (US), Japan (JP), Canada (CA), Germany (DE), France (FR) and Italy (IT)), to which we add China (CH).[5] We also gather monthly data for three different oil price indices, namely, the West Texas Intermediate (WTI), the Brent Blend (Brent), and the Dubai Crude Oil (Dubai). These oil price indices have shown somewhat different trajectories during periods of crises and turmoil. The continuously compounded monthly inflation rates and oil returns are calculated as the logs of the first-difference of the CPI and oil price indices, respectively. Finally, all variables are collected from Datastream and the sample period is June 1987 - June 2020, which is determined by the data availability.

Table 1 provides a summary of the descriptive statistics for all variables included in our study. As can be seen in the upper panel of this table, average inflation over the sample period was positive for all the countries, and it was particularly high (low) for China (Japan). The high inflation for China is due to having high economic growth, while the low inflation for Japan is due to the lost decades. The mean oil returns were also positive and similar across the three oil price indices. Both CPI inflation and oil price inflation were not normally distributed (as confirmed by the Jarque-Bera tests). The standard Phillips and Perron (1988) (i.e. PP) tests indicate that the variables are stationary at levels. The kurtosis coefficients are well above 3 for inflation in the UK, the US, Japan and Canada and the Dubai Crude Oil price inflation, which implies that they are leptokurtic.

[5] We note that India is the third largest oil importer in the world after China and the US and its current consumption of oil has reached the pre-COVID-19 level. While India may have an influence on oil inflation, the inclusion of India does not quantitatively and qualitatively change our main empirical findings. Moreover, the spillovers transmitted to other countries' inflation rates from India's CPI inflation, as well as those transmitted to India's CPI inflation from other countries' inflation rates, are negligible. For these reasons, we do not include India in the econometric analysis. Despite this, the empirical results are available from the authors upon request.

Table 1. Descriptive statistics for monthly inflation rates and oil returns.

	CH	**UK**	**US**	**JP**	**CA**	**DE**	**FR**	**IT**	**WTI**	**Dubai**	**Brent**
Mean	0.381	0.216	0.207	0.042	0.175	0.15	0.135	0.217	0.155	0.205	0.187
Std. Dev.	0.977	0.351	0.325	0.359	0.363	0.338	0.282	0.236	10.643	10.949	11.485
Maximum	4.333	2.515	1.213	2.058	2.591	1.729	1.019	0.925	38.862	46.287	44.669
Minimum	-2.338	-0.724	-1.932	-0.969	-1.012	-1.036	-0.953	-0.542	-49.487	-61.961	-57.601
Skewness	0.772***	0.798***	-0.947***	1.283***	0.613***	0.313**	-0.268**	-0.035	-0.621***	-1.073***	-0.730***
Kurtosis	1.685***	5.950***	5.323***	5.533***	4.796***	2.081***	0.780***	0.767**	2.422***	4.988***	3.387***
JB	86.169***	626.088***	526.728***	613.796***	404.364***	77.933***	14.781***	9.777***	122.227***	486.638***	224.458***
PP	-15.291***	-17.388***	-11.004***	-15.683***	-17.265***	-21.951***	-20.675***	-16.042***	-17.679***	-17.868***	-18.714***
Q(20)	251.117***	193.619***	147.579***	229.30***	37.757***	80.249***	96.502***	540.982***	17.359*	23.669***	16.052*
$Q^2(20)$	120.988***	27.054***	96.192***	20.05	10.968	23.103***	47.802***	259.403***	132.304***	12.141*	82.552***
LM(20)	112.969***	115.027***	49.747***	17.902	9.736	48.491***	121.833***	133.842***	87.475***	33.411**	77.598***
					Correlation Matrix						
CH	1										
UK	0.191	1									
US	0.157	0.24	1								
JP	0.177	0.445	0.298	1							
CA	-0.050	0.160	0.619	0.122	1						
DE	-0.017	0.223	0.204	0.020	0.177	1					
FR	0.053	0.536	0.424	0.292	0.327	0.443	1				
IT	0.197	0.279	0.407	0.168	0.294	0.315	0.429	1			
WTI	0.014	0.160	0.439	0.186	0.381	0.255	0.262	0.140	1		
Dubai	0.014	0.167	0.419	0.142	0.337	0.245	0.259	0.140	0.875	1	
Brent	0.025	0.160	0.421	0.152	0.344	0.265	0.251	0.125	0.921	0.935	1

Notes: This Table reports the descriptive statistics of the inflation rates for the G7 (i.e., United Kingdom (UK), United States (US), Japan (JP), Canada (CA), Germany (DE), France (FR) and Italy (IT)) and China (CH), and oil price inflation computed using the three oil price indices (namely, the West Texas Intermediate (WTI), the Brent Blend (Brent) and the Dubai Crude Oil (Dubai)). The sample period is 1987M6-2020M6. JB is the Jarque-Bera test for normality, PP is the Phillips-Perron unit root test. Q(20) and Q2(20) are the Ljung-Box statistic for serial correlation in the raw series and squared residuals, respectively. ARCH (20) is Engle's ARCH test up to 20 lags. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

The lower panel of Table 1 presents the unconditional correlations. As expected, the correlation among the CPI inflation rates displays some geographical clustering, being especially high (and positive) between the US and Canada and between France and Germany. The co-movement among the three measures of oil price inflation is also particularly strong, with correlations close to 0.90. Finally, while US inflation loads more significantly on the oil price inflation than on any other country (as the correlation between US inflation and the different measures of oil price inflation stands at around 0.40), CPI inflation in China is basically uncorrelated with oil price inflation, which could be due to excess capacity in this country.

4.2 The DECO-GARCH model

Table 2 presents the estimation results for the ARMA (1,1)-DECO-GARCH(1,1) model that aims at capturing the nexus between the CPI inflation rates in the G7 countries and China and each of the three measures of oil price inflation. It shows that the dynamic equicorrelation is always positive (ρ_{DECO}) with a value of around 0.20, indicating a reasonably high degree of integration between the inflation rates in the G7 countries and China and oil price inflation. The estimated DCC parameter a_{DECO} is also positive and significant for all models - albeit slightly larger in the model with the WTI oil price inflation, thus, underlying that the oil price shocks have an effect on equicorrelations. At the same time, the DCC parameter b_{DECO} is significant but substantially lower than unity – with the coefficient estimates ranging between 0.27 and 0.35, indicating that the equicorrelations are not strongly dependent on past correlations. Taken together, the significance of the parameters a_{DECO} and b_{DECO} justifies the appropriateness of the DECO-GARCH model.

Table 2. Estimation results of the ARMA(1,1)-DECO-GARCH(1,1) models.

	ρ_{DECO}	a_{DECO}	b_{DECO}	Student-df
Model 1 (WTI)	0.1972***	0.1804***	0.2746*	7.6241***
	(0.0212)	(0.0684)	(0.1425)	(0.84431)
Model 2 (Brent)	0.1979***	0.1491**	0.3453**	7.1825***
	(0.0211)	(0.0609)	(0.1760)	(0.7651)
Model 3 (Dubai)	0.1968***	0.1485**	0.2959**	6.7749***
	(0.0207)	(0.0648)	(0.1487)	(0.6864)

Notes: The three ARMA(1,1)-DECO-GARCH(1,1) models are estimated where each model includes a specific measure proxy for crude oil returns, i.e., West Texas Intermediate (WTI), Europe Brent (Brent), and Crude Oil Dubai (Dubai). The sample period is 1987M6-2020M6. The ρ coefficient indicates the dynamic equicorrelation coefficient for each model. Standard errors are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

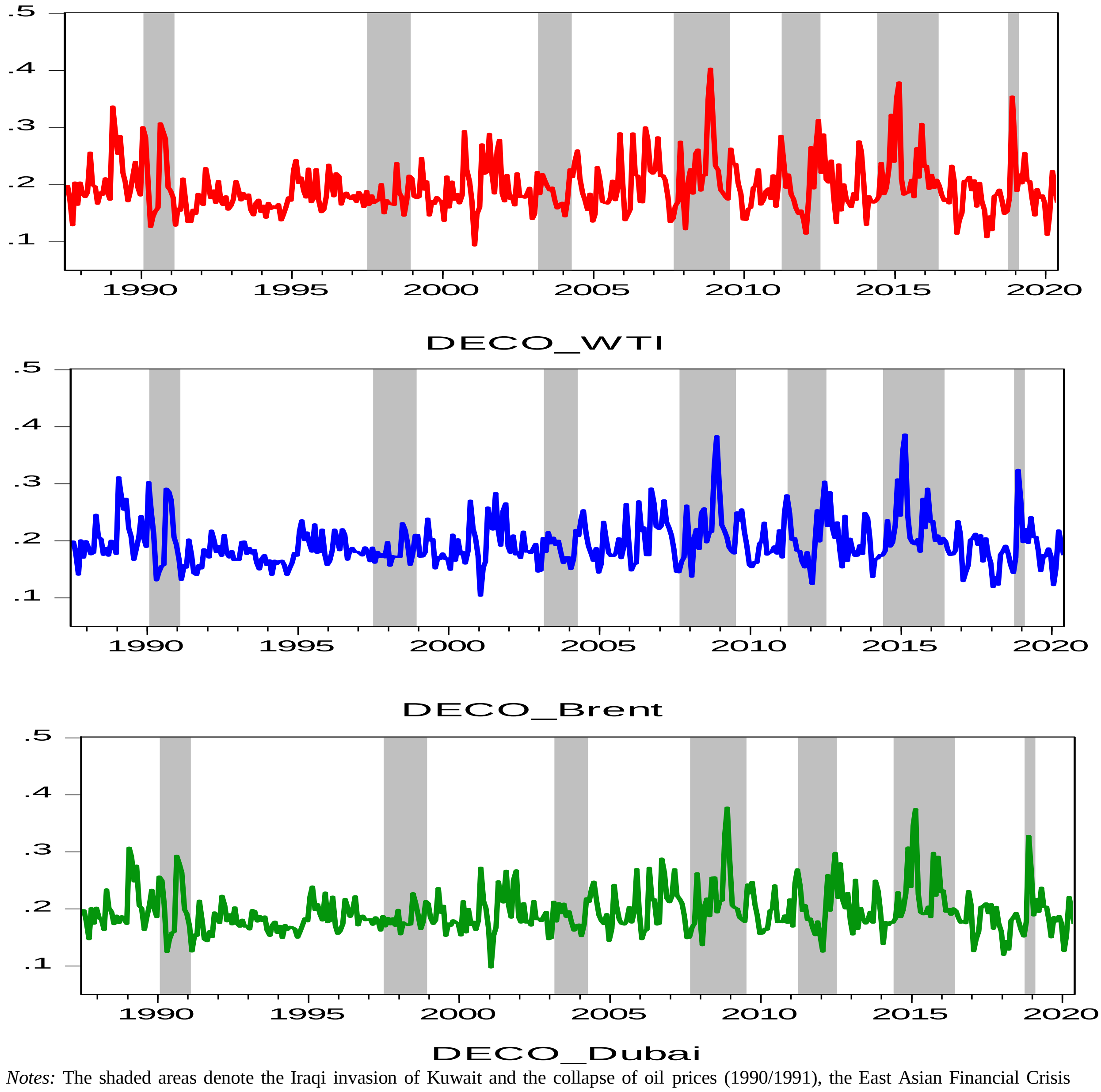
Figure 1 displays the dynamic equicorrelation between the CPI inflation rates and each measure of the oil price inflations. The shaded areas correspond to specific crisis episodes and major oil-related events, namely, the Iraqi invasion of Kuwait and collapse of oil prices (1990/1991), the East Asian financial crisis (1997/1998), the Iraq War (2003), the Global Financial Crisis and the oil price spike (2007/2008), the euro area sovereign debt crisis (2011-2012), the oil price crisis (2014/2016), and the collapse of oil prices (October 2018/January 2019).

As shown in this figure, we observe time-varying correlations over the sample period and, more importantly, a remarkable increase in the equicorrelation levels during the shaded periods. This implies that the links between CPI inflation and oil price inflation are stronger around such periods. As a result of this interconnectedness/integration, shocks to a particular oil price are significantly transmitted to consumer prices. This effect is particularly visible during the periods of oil price turmoil.[6] Finally, we note that regardless of the oil price inflation measure used, the empirical evidence is both quantitatively and qualitatively similar. Moreover, the unconditional correlations among the three measures of oil price inflation are also high (as reported in Table 1). For these reasons, we proceed with the connectedness and

[6] Sensoy *et al.* (2015) use a similar approach to uncover evidence of convergence for precious and industrial metal commodity futures since the mid-2000s.

spillover analysis, while focusing on a single oil price inflation measure, as proxied by the WTI.[7]

Figure 1. Dynamic equicorrelation across inflation rates and each of the oil prices (WTI, Brent, and Dubai) over the period June 1987 to June 2020.



Notes: The shaded areas denote the Iraqi invasion of Kuwait and the collapse of oil prices (1990/1991), the East Asian Financial Crisis (1997/1998), the Iraq War (2003), the Global Financial Crisis and the oil price spike (2007/2008), the European debt crisis (2011-2012), the Oil crisis (2014/2016), and the China-US trade war and collapse of oil prices (October 2018 to January 2019). The sample period is 1987M6-2020M6.

[7] We would like to thank an anonymous reviewer for highlighting this issue. When we conduct the connectedness and spillover analysis using the three oil price inflation measures, the empirical evidence is both quantitatively and qualitatively similar to that reported in the paper. The analysis is available from the authors upon request.

4.2 Connectedness and spillover analysis

4.2.1 Time-domain spillovers

We start by calculating the *time-domain* spillovers between CPI inflation and oil price inflation, using the methodology developed by Diebold and Yilmaz (2009, 2012, 2014).

As can be seen from Table 3, the total spillover index (TSI) shows that 40.5% of the forecast-error variance comes from the spillovers between CPI inflation and oil markets. This corroborates the idea of a very strong link between oil price inflation and CPI inflation.

Table 3. Time-domain static spillovers.

	CH	**UK**	**US**	**JP**	**CA**	**DE**	**FR**	**IT**	**WTI**	**FROM Others**
CH	84.77	3.00	1.99	3.12	3.05	0.17	0.48	3.00	0.41	15.23
UK	3.13	50.11	6.63	10.79	3.25	2.73	14.47	4.81	4.08	49.89
US	2.60	0.72	46.36	1.95	14.66	4.64	6.31	4.75	18.01	53.63
JP	3.63	12.83	7.29	64.21	0.98	0.89	6.21	0.75	3.20	35.79
CA	2.48	0.50	20.09	0.45	54.87	1.81	4.57	3.98	11.25	45.13
DE	0.72	2.53	3.40	1.08	2.59	68.57	10.52	5.22	5.38	31.43
FR	2.42	11.92	9.59	3.35	7.94	6.73	45.12	5.33	7.59	54.88
IT	6.76	2.48	8.65	0.59	4.27	6.35	5.79	60.10	5.04	39.93
WTI	0.02	1.90	13.72	1.69	8.16	4.52	6.62	1.77	61.60	38.39
TO Others	21.75	35.89	71.36	23.02	44.89	27.84	55.00	29.61	54.97	364.32
Net spillovers	6.52	-14.01	17.73	-12.77	-0.24	-3.60	0.11	-10.32	16.57	TSI = 40.48%

Notes: This Table summarizes the empirical results of the total, directional and pairwise spillovers from the DY static analysis. The sample period is 1987M6-2020M6. All the results are based on a VAR model of order 1 and the generalized variance decompositions of 10-month ahead forecast errors. 'TO' directional spillovers correspond to the off-diagonal column sums (labeled contributions TO others), i.e., spillovers from market *i* to all markets *j*. 'FROM' directional spillovers denote the off-diagonal row sums (labeled contributions FROM others), i.e. spillovers from all markets *j* to market *i*. Net spillovers ('NET') are simply the "from" minus "to" differences. The total spillover index, which appears in the lower right corner of the Table, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including the diagonals (or row sum including diagonals), expressed as a percentage.

The "To" row reveals that, among inflation rates, the largest gross directional spillovers to others accrue to the US (71.4%). France is the second largest transmitter of spillover effects (55%). By contrast, China (21.8%) and Japan (23%) are responsible for the lowest gross direction spillovers to others. Importantly, oil price inflation is a crucial transmitter of spillovers to CPI inflation (55%).

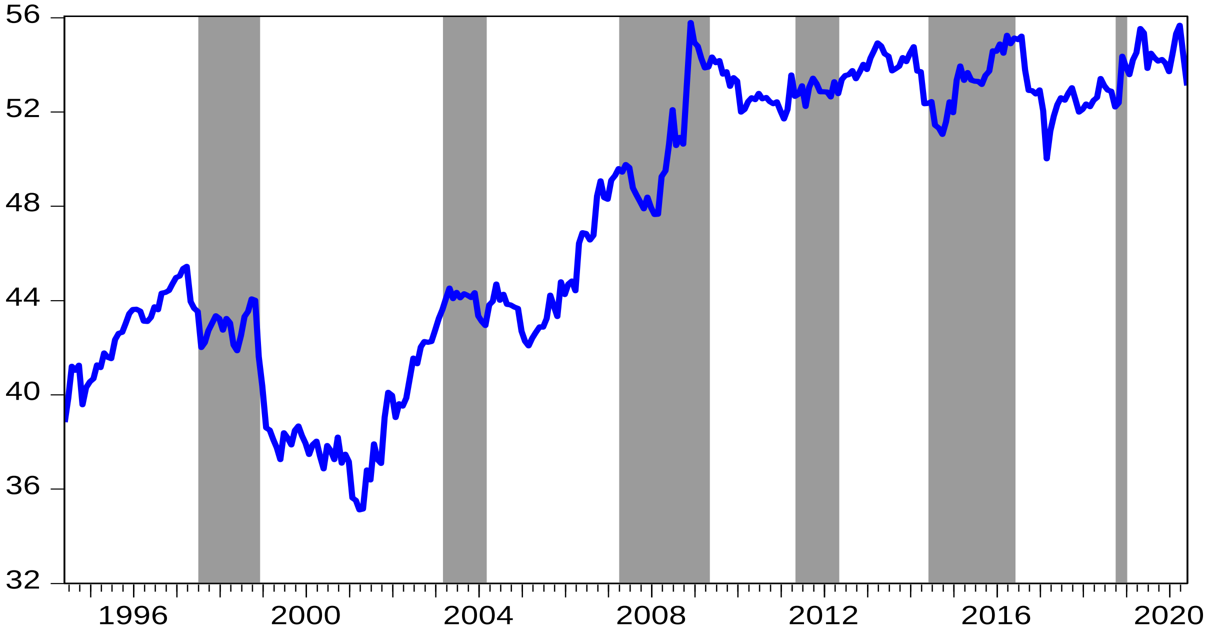
We also find from the ''directional FROM Others'' column that the gross directional spillovers from others are the largest for the US (53.6%) and France (54.9%) and the lowest for China (15.2%) and Germany (31.4%). Similarly, the spillovers that oil price inflation receives from others stand at 38.4%.

Finally, as for the net directional spillovers, the largest are from the US (17.7%) and China (6.5%) to others, while the lowest are associated with the UK (-14%), Japan (-12.8%) and Italy (-10.3%). Oil price inflation is also responsible for large and positive net directional spillovers (16.6%).

Given that the VAR model with fixed parameters may not capture well the joint dynamics of (consumer price and oil price) inflation measures over the entire sample, we also estimate the dynamic version of directional spillovers. Thus, in Figure 2, we present the time-varying total spillover index, which is estimated based on a monthly VAR model of order 1, with 10-month ahead forecasts and 100-month rolling windows. As before, the shaded areas denote specific crisis episodes and major oil-related events.

Three striking observations emerge. First, the spillovers have significantly risen since the early 2000s, from close to 35% to around 55%, probably due to increases in globalization and improvements in communications. This suggests that the dynamics of inflation rates among the G7 countries and China reflect the intensification of common (global) factors (Gamber and Hung, 2001; Bean, 2006; Borio and Filardo, 2007). Second, these spillovers have remained relatively high since the 2008-2009 global financial crisis (Yung, 2017). Third, the spillovers typically spike during turbulent times, such as financial crises and periods characterized by large oil price fluctuations.

Figure 2. Time-domain dynamic spillovers (total).

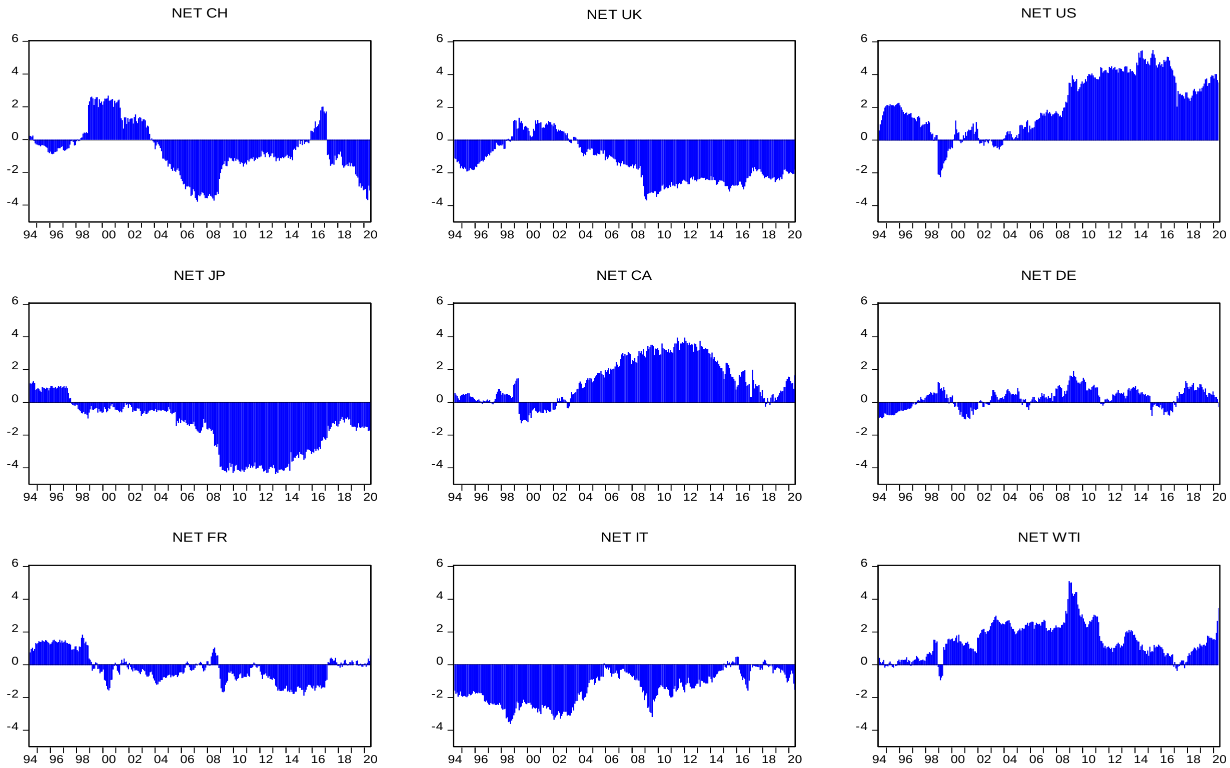


Notes: The time-varying total spillover index is estimated based on a monthly VAR model of order 1 with 10-step ahead forecasts and 100-month rolling windows. The shaded bars reflect turbulent episodes.

Figure 3 plots the time-varying net spillover index by country. As can be seen, the net spillovers from the oil price inflation have always been positive (transmitter of oil shocks), which reveals the importance of the oil price fluctuations in shaping the dynamics of inflation in the G7 countries and China. Moreover, they have been particularly large since the 2008-2009 Global Financial Crisis and until the end of the oil crisis of 2016.

Interestingly, the net spillovers from the US shifted from negative to positive around the time of the 2008 Great Recession, showing that shocks to the US inflation have become more of a source of shock transmission than shock absorption. By contrast, the negative net spillovers of inflation in China, the UK, France and Italy increased in absolute terms, thus, suggesting that their CPI inflation dynamics have become a receiver of shocks from elsewhere. This empirical evidence suggests that inflation has become an increasingly global phenomenon since the Global Financial Crisis of 2008-2009 (Jasová *et al.*, 2018).

Figure 3. Time-domain dynamic net directional spillovers (by country).



Notes: Time-varying net spillover indices are estimated based on a monthly VAR model of order 1, with 10-step ahead forecasts and 100-month rolling windows. The index is negative for receivers and positive for spillover transmitters.

4.2.2 Frequency-domain spillovers

Tables 4-6 report the total *frequency-domain* spillover indices constructed using the methodology proposed by Barunik and Krehlik (2018). We estimate the total static spillover index across the CPI inflation and oil price inflation and decompose it by directional spillover transmitters (‘to others’) and receivers (‘from others’). The net-pairwise directional spillovers are negative (for the net recipients) and positive (for the net transmitters). All results are based on a VAR model of order 1 and generalized variance decompositions of forecast-errors.

Additionally, we match the frequency-domain spillovers approach with the world macroeconomic background. Specifically, we consider three frequency intervals that are traditionally used in the macro literature, namely: (i) cycles of 1-24 months (i.e., the short-end of business cycles corresponding to bands 3.14 to 0.13); (ii) cycles of 24-48 months (i.e., the bulk of business cycle fluctuations corresponding to bands 0.13 to 0.07); and (iii) cycles longer than 48 months (i.e., the long-end of business cycles corresponding to bands 0.07 to 0). This characterization is closely aligned with the studies of Pancrazi (2015), Aguiar-Conraria *et al.* (2018) and Crowley and Hallett (2018).

Table 4 summarizes the *short-term* (i.e., 1 to 24 months) spillovers within the same frequency band (i.e., 3.14 to 0.13), which are generally small. Among the CPI inflation, the largest transmitter of gross directional spillovers to others is still the US (6.9%), being followed very closely by France (5.5%) and Canada (4.5%). China (2%), Japan (2.4%) and Italy (2.8%) transmit the smallest gross direction spillovers. Oil price inflation remains important, being responsible for the gross directional spillovers amounting to 5.2%.

Regarding gross directional spillovers from others (see the directional “FROM Others” column), they are the largest for France (5.5%), then the US (5.1%) and the UK (4.8%) and the lowest for China (1.6%), then Germany (3.2%) and Japan (3.4%). Oil price inflation receives spillovers from others of around 4%. As for the net directional spillovers, they are positive for the US (1.8%) and oil (1.1%) but negative for Japan (-1.1%). Other net directional spillovers stand at below 1% (in absolute terms). Finally, a large fraction (35.6%) of the forecast-error variance is explained by the spillovers between oil price inflation and CPI inflation.

Table 4. Frequency-domain short-term (1 to 24 months) spillovers.

	CH	**UK**	**US**	**JP**	**CA**	**DE**	**FR**	**IT**	**WTI**	**FROM Others**
CH	76.42	2.93	1.98	2.98	2.45	0.16	0.40	2.62	0.41	1.55
UK	2.46	46.73	5.43	9.57	2.81	2.46	12.99	3.83	3.18	4.75
US	2.02	0.64	40.89	1.80	12.97	3.97	5.49	3.89	15.24	5.11
JP	3.01	11.58	5.95	59.45	0.82	0.74	5.39	0.59	2.56	3.40
CA	2.41	0.44	17.61	0.41	51.22	1.50	4.01	3.28	9.59	4.36
DE	0.66	2.48	2.99	1.06	2.35	65.45	10.16	4.59	4.87	3.24
FR	2.08	11.29	8.30	3.18	7.20	6.11	42.89	4.58	6.46	5.47
IT	5.31	2.13	7.08	0.50	3.64	5.32	5.07	52.61	4.01	3.68
WTI	0.02	1.82	12.73	1.63	7.79	4.27	6.11	1.70	57.70	4.01
TO Others	2.00	3.70	6.90	2.35	4.45	2.72	5.51	2.79	5.15	
Net spillovers	0.45	-1.05	1.78	-1.06	0.9	-0.51	0.05	-0.89	1.14	TSI = 35.56%

Notes: This Table summarizes the empirical results of the total, directional and pairwise spillovers derived from the DY static analysis. The sample period is 1987M6-2020M6. All the results are based on a VAR model of order 1 and generalized variance decompositions of 10-month ahead forecast errors. ‘TO' directional spillovers correspond to the off-diagonal column sums (labeled contributions TO others), i.e., spillovers from market *i* to all markets *j*. 'FROM' directional spillovers denote the off-diagonal row sums (labeled contributions FROM others), i.e., spillovers from all markets *j* to market *i*. Net spillovers ('NET') are simply the "from" minus "to" differences. The total spillover index, which appears in the lower right corner of the Table, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including the diagonals (or row sum including diagonals), expressed as a percentage.

In Table 5, we present the *medium-term* (i.e., 24 to 48 months) spillovers within the same frequency band (i.e., 0.13 to 0.07). The largest transmitter of the gross directional spillovers to others is the US (0.4%), while Japan and the UK transmit the smallest spillovers (both, 0.1%). Oil price inflation is responsible for gross directional spillovers amounting to 0.4%. Similarly, the largest gross directional spillovers from others accrue to the US, the UK and Italy (all, 0.3%), while the smallest ones are recorded for China and Germany (both, 0.1%). The oil price inflation receives spillovers from others of 0.1%.

As for the net directional spillovers, they are typically negative for CPI inflation rates, and positive for oil price inflation. This suggests that oil price inflation influences CPI inflation over the medium-term. Over the medium-term, about 2% of the variation of the oil price inflation and CPI inflation in the G7 and China is explained by spillovers.

Table 5. Frequency-domain short-term (24 to 48 months) spillovers.

	CH	UK	US	JP	CA	DE	FR	IT	WTI	FROM Others
CH	3.33	0.03	0.00	0.06	0.23	0.00	0.03	0.15	0.00	0.06
UK	0.26	1.34	0.48	0.48	0.18	0.11	0.59	0.39	0.35	0.31
US	0.23	0.03	2.18	0.06	0.67	0.27	0.33	0.34	1.10	0.34
JP	0.24	0.50	0.53	1.90	0.07	0.06	0.33	0.06	0.25	0.23
CA	0.03	0.03	0.99	0.02	1.46	0.12	0.22	0.28	0.66	0.26
DE	0.02	0.02	0.17	0.01	0.10	1.24	0.14	0.25	0.20	0.10
FR	0.14	0.25	0.51	0.07	0.30	0.25	0.89	0.29	0.45	0.25
IT	0.57	0.14	0.62	0.04	0.25	0.40	0.29	2.95	0.41	0.30
WTI	0.00	0.03	0.40	0.02	0.15	0.10	0.20	0.03	1.56	0.10
TO Others	0.17	0.11	0.41	0.08	0.22	0.15	0.24	0.20	0.38	
Net spillovers	0.11	-0.20	0.07	-0.14	-0.04	0.05	-0.01	-0.10	0.28	TSI =1.95%

Notes: This Table summarizes the empirical results of the total, directional and pairwise spillovers from the DY static analysis. The sample period is 1987M6-2020M6. All the results are based on a VAR model of order 1 and generalized variance decompositions of the10-month ahead forecast errors. 'TO' directional spillovers correspond to the off-diagonal column sums (labeled contributions TO others), i.e., spillovers from market *i* to all markets *j*. 'FROM' directional spillovers denote the off-diagonal row sums (labeled contributions FROM others), i.e. spillovers from all markets *j* to market *i*. Net spillovers ('NET') are simply the "from" minus "to" differences. The total spillover index, which appears in the lower right corner of the Table, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including the diagonals (or row sum including diagonals), expressed as a percentage.

Finally, Table 6 reports the *long-term* (i.e., above 48 months) spillovers within the same frequency band (i.e., below 0.07). Albeit small, all gross directional spillovers to others are positive, and the largest transmitter being the US (0.6%) and the smallest being Japan (0.1%). Spillovers of oil price inflation to others stand at 0.6%. The largest gross directional spillovers from others are the US, the UK and Italy (all, 0.5%), while China is the smallest one (0.1%). China is not an open economy like the G7 countries. Oil price inflation receives spillovers of 0.2%.

Table 6. Frequency-domain short-term (over 48 months) spillovers.

	CH	UK	US	JP	CA	DE	FR	IT	WTI	FROM Others
CH	5.02	0.04	0.00	0.08	0.36	0.01	0.05	0.23	0.00	0.09
UK	0.41	2.03	0.73	0.73	0.27	0.16	0.90	0.59	0.54	0.48
US	0.35	0.05	3.30	0.09	1.01	0.40	0.49	0.52	1.67	0.51
JP	0.38	0.75	0.81	2.86	0.10	0.10	0.49	0.10	0.39	0.35
CA	0.04	0.04	1.50	0.03	2.19	0.19	0.34	0.43	1.00	0.40
DE	0.03	0.03	0.25	0.01	0.15	1.87	0.22	0.38	0.31	0.15
FR	0.21	0.38	0.78	0.10	0.45	0.38	1.34	0.45	0.69	0.38
IT	0.88	0.21	0.95	0.05	0.37	0.62	0.44	4.51	0.62	0.46
WTI	0.00	0.05	0.60	0.03	0.22	0.15	0.30	0.04	2.34	0.15
TO Others	0.25	0.17	0.62	0.13	0.33	0.22	0.36	0.30	0.58	
Net spillovers	0.17	-0.31	0.11	-0.22	-0.07	0.07	-0.02	-0.16	0.43	TSI =2.97%

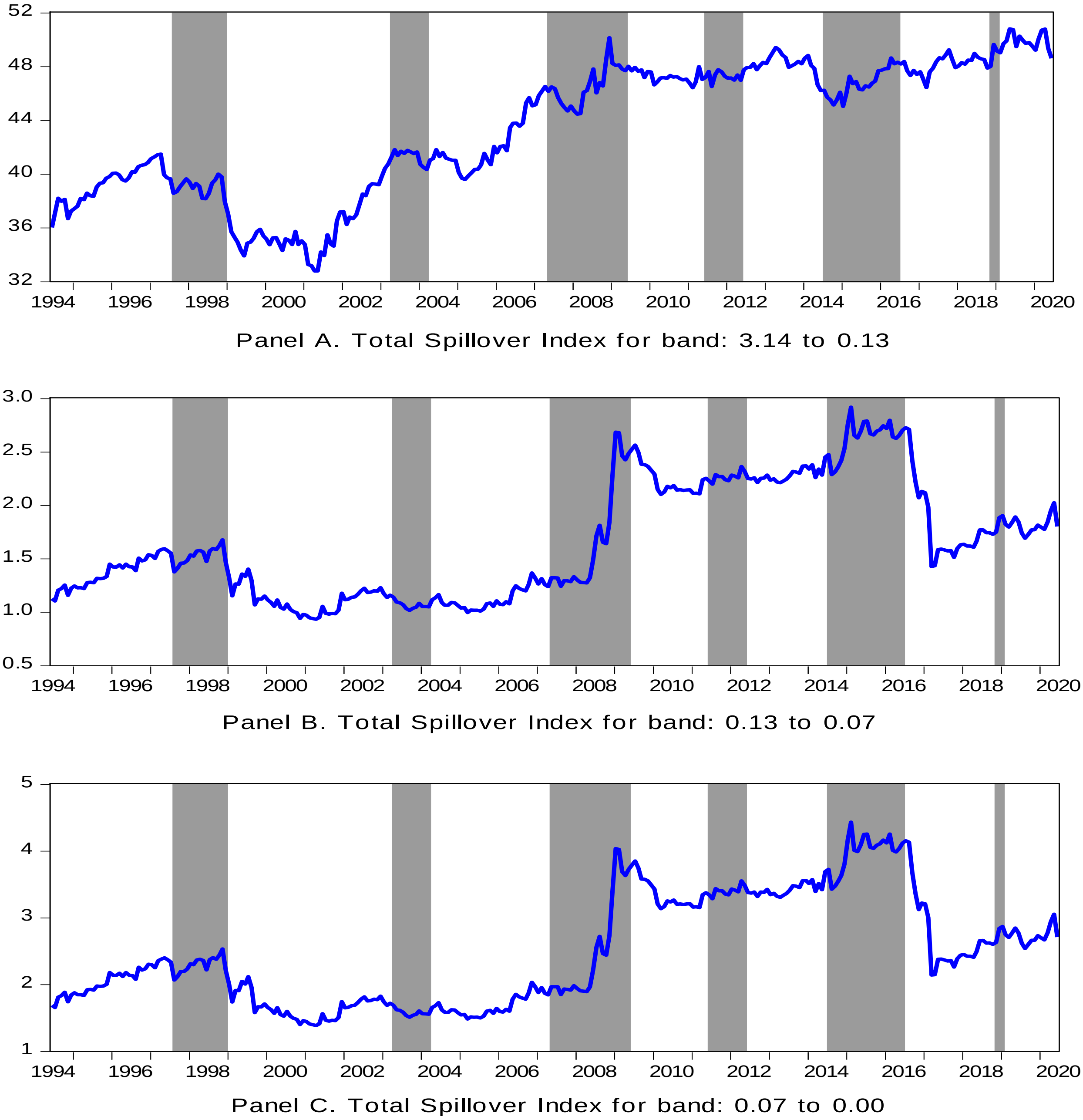
Notes: This Table summarizes the empirical results of the total, directional and pairwise spillovers from the DY static analysis. The sample period is 1987M6-2020M6. All the results are based on a VAR model of order 1 and generalized variance decompositions of the 10-month ahead forecast errors. ‘TO' directional spillovers correspond to the off-diagonal column sums (labeled contributions TO others), i.e. spillovers from market *i* to all markets *j*. 'FROM' directional spillovers denote the off-diagonal row sums (labeled contributions FROM others), i.e. spillovers from all markets *j* to market *i*. Net spillovers ('NET') are simply the "from" minus "to" differences. The total spillover index, which appears in the lower right corner of the Table, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including the diagonals (or row sum including diagonals), expressed as a percentage.

Net directional spillovers tend to be negative for CPI inflation - especially, in the UK (-0.3%) and Japan (-0.2%) - and positive for oil price inflation. Therefore, CPI inflation also loads on oil price inflation in the long-term. The total spillover index (TSI) shows that around 3% of the forecast-error variance decomposition can be attributed to spillovers between the oil price and CPI inflation.

The dynamic version of the *frequency-domain* directional spillovers is plotted in Figure 4, which is estimated based on a monthly VAR model of order 1, with 10-month ahead forecasts and 100-month rolling windows. Panels A, B and C of this figure depict the *short-term*, *medium-term* and *long-term* spillovers, respectively. The shaded areas denote specific crises and oil-related events (see Figure 1).

All the three spillover indices have increased over time, even though the short-term spillovers have remained much larger than the medium- and long-term spillovers. However, it is interesting to note that the short-term spillovers remained broadly elevated since the 2008-2009 Global Financial Crisis, which marks the end of the 2005-2008 commodity boom. On the other hand, the spillovers at the medium- and the long-term display an important spike during the2008-2009 Great Recession and show a sharp fall since the oil crisis of 2016.

Figure 4. Frequency-domain dynamic spillovers.



Notes: Panels A, B, and C show the dynamic spillover indices on bands (3.14 to 0.13), (0.13 to 0.07) and (0.07 to 0.00), which correspond to spillovers in the short-term (1 to 24 months), the medium-term (24 to 48 months), and the long-term (more than 48 months).The shaded areas denote the East Asian Financial Crisis (1997/1998), the Iraq War (2003), the Global Financial Crisis and the oil price spike (2007/2008), the European debt crisis (2011-2012), the Oil crisis (2014/2016), and the China-US trade war and collapse of oil prices (October 2018 to January 2019). The sample period is 1987M6-2020M6.

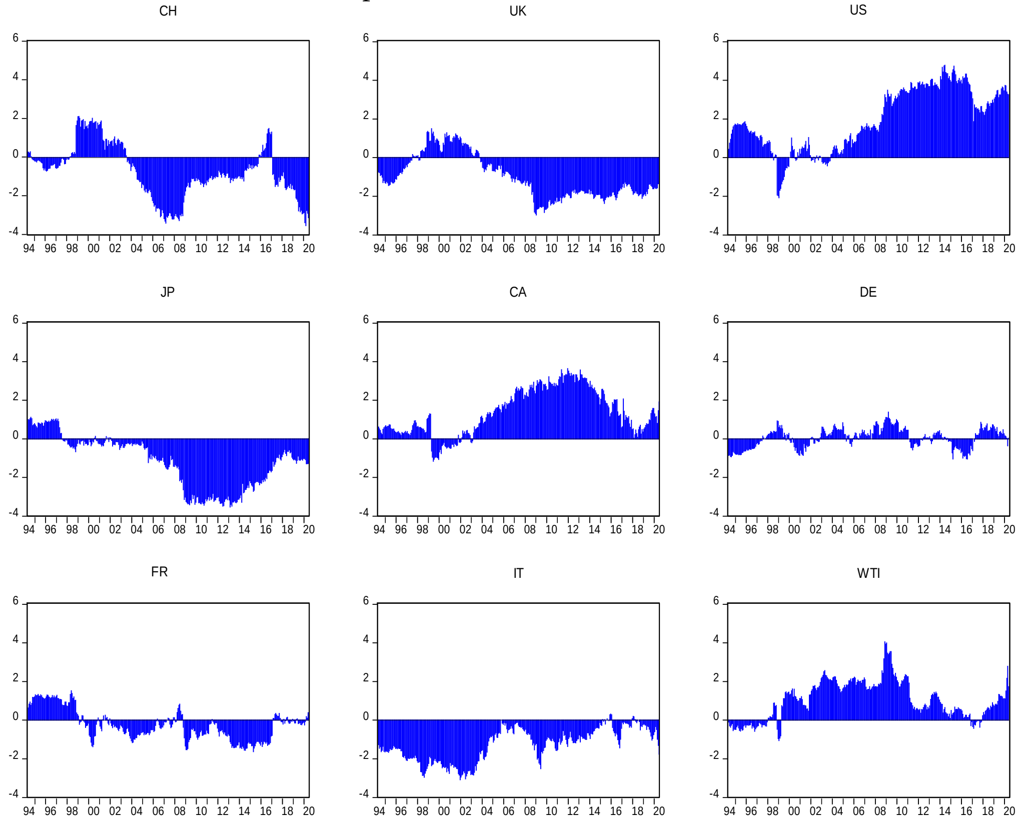
Panels A, B and C of Figure 5 plot the time-varying short-term, medium-term and long-term net spillover indices by country, respectively. The net spillovers from oil price inflation to CPI inflation rates have almost always been positive, reinforcing the view that they are a key trigger of the dynamics of CPI inflation in the G7 countries and China. Moreover, those net oil spillovers have been particularly large since the Global Financial Crisis of 2008-2009 and lasted until the end of the oil price crisis in 2016 after the OPEC+ countries agreed to substantially cut oil production.

The *frequency-domain* net spillovers from the US also shifted from negative to positive since the 2008 Great Recession. Over the medium-and the long-terms, the net spillovers of CPI inflation in the UK, Japan and Italy have generally been negative. In the short-term, the net spillovers of CPI inflation in China, France and Italy have also been negative. This may be due to the negative impact of higher oil prices on economic growth. However, they changed sign from positive to negative in the UK and Japan since the late nineties and early 2000s.

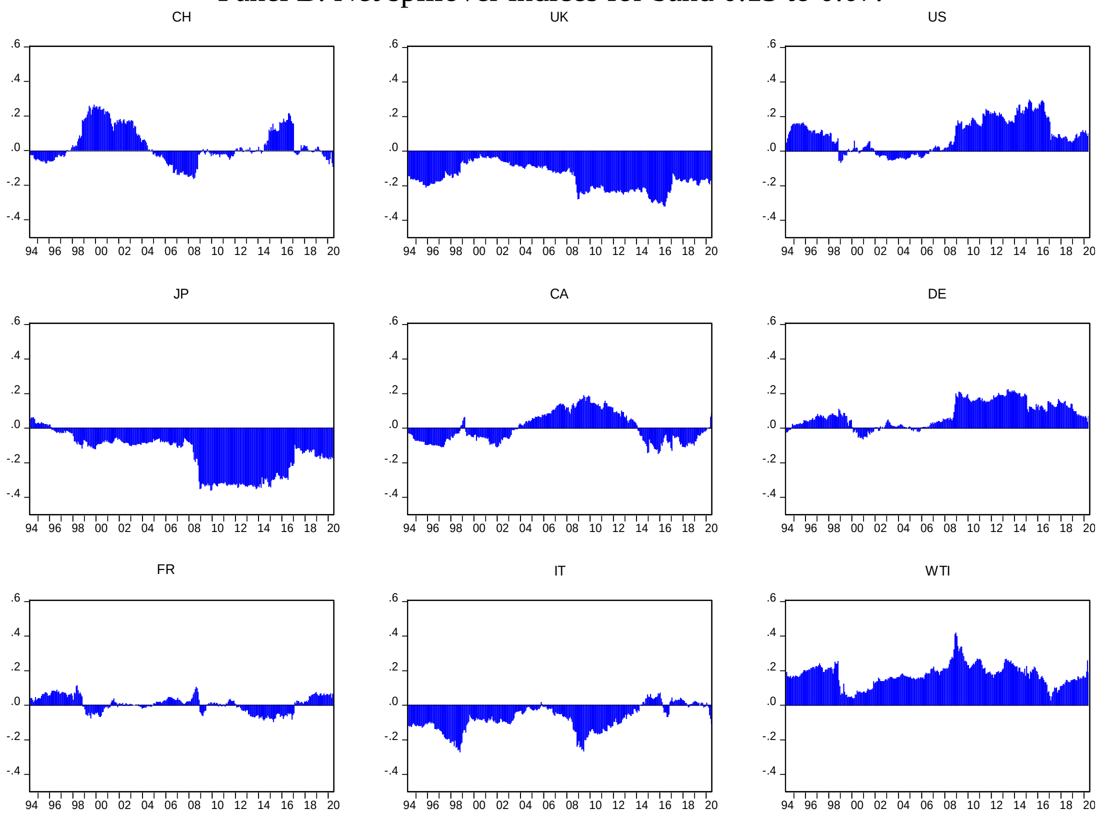
History shows that China received negative volatility in its economic growth from the 2008-2009 global financial crisis that started in the US. Consequently, it experienced a recession even though it quickly recovered from this crisis and later contributed to growth in other countries. However, in the medium and long run, the global factors are increasingly driving inflation (Gamber and Hung, 2001; Bean, 2006; Borio and Filardo, 2007; Hakkio, 2010; Aastveit *et al.*, 2016) and the role played by the domestic factors appears to be weakening (Ciccarelli and Mojon, 2010; Eickmeier and Pijnenburg, 2013; Forbes, 2019). Indeed, as highlighted by Jasová *et al.* (2018), while both global and domestic output gaps are key drivers of inflation, the effect of the domestic output gap in advanced economies and the effect of global output gap in emerging markets have declined since the Great Recession. Our empirical evidence corroborates these findings.

Figure 5. Frequency-domain dynamic short-term net directional spillovers (by country).

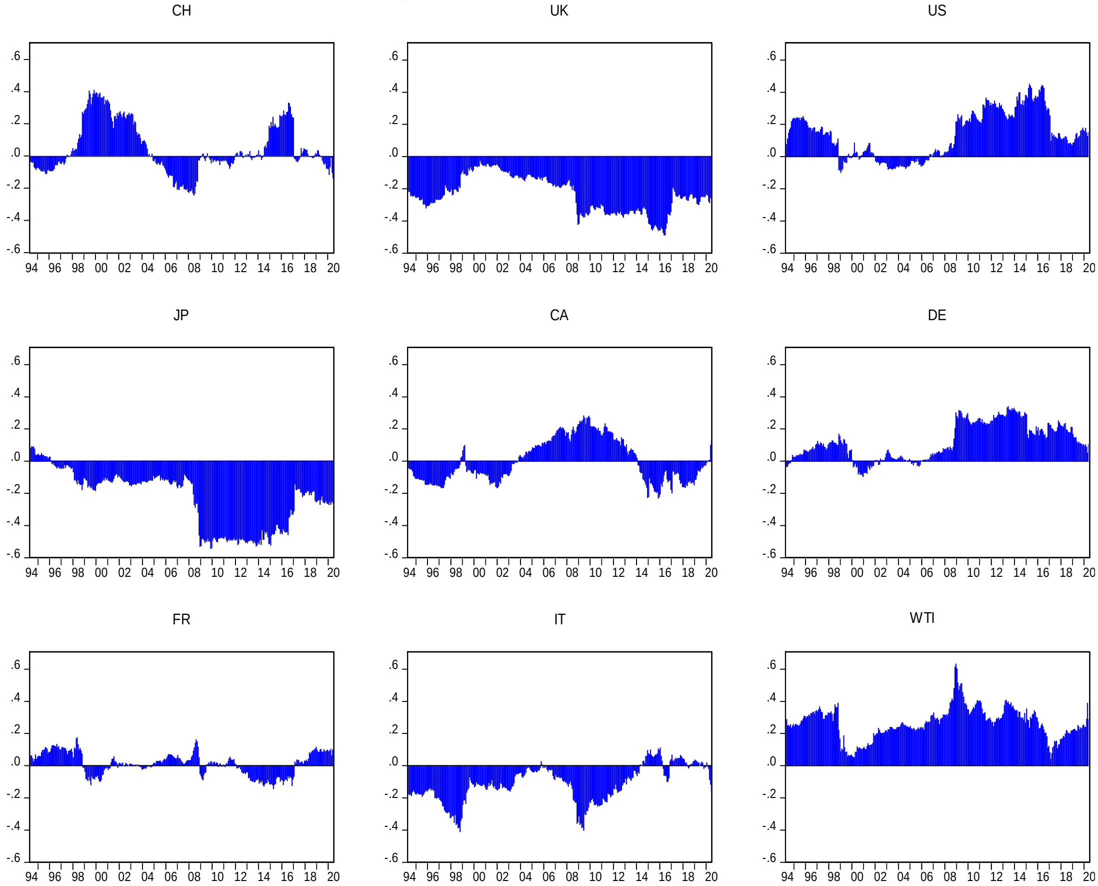
Panel A. Net spillover indices for band 3.14 to 0.13.



Panel B. Net spillover indices for band 0.13 to 0.07.



Panel C. Net spillover indices for band 0.07 to 0.00.



Notes: Panels A, B, and C show the net spillover indices on the bands (3.14 to 0.13), (0.13 to 0.07) and (0.07 to 0.00), which correspond to the net spillovers in the short-term (1 to 24 months), the medium-term (24 to 48 months), and the long-term (more than 48 months).

4.2.3 Network analysis

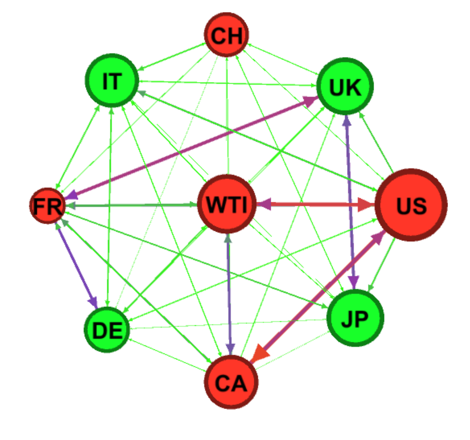
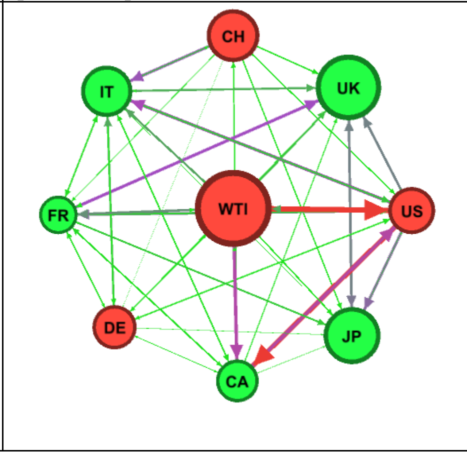
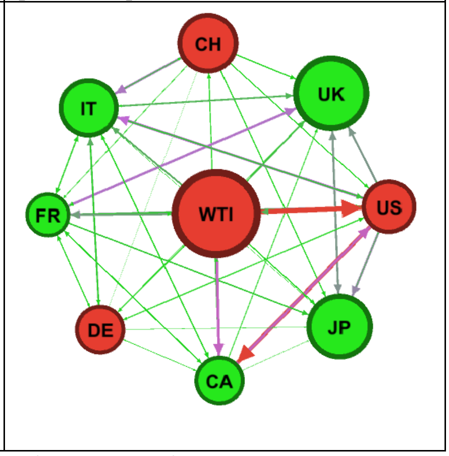
To further understand the results obtained from the computation of the *frequency-domain* spillovers, Figure 6 displays the network analysis derived from the previous tables. Specifically, Panels A, B, and C of this figure portray the average pairwise directional spillovers in the short-term (1 to 24 months), the medium-term (24 to 48 months) and the long-term (more than 48 months). The size of the node shows the magnitude of a net transmission/reception TO/FROM other markets, whereas a node's color identifies if a variable is a net transmitter (receiver) of shocks to (from) other variables. In particular, the red color indicates that the variable is a net transmitter of spillovers, while the green color denotes the case in which the variable is a net receiver of spillovers. Furthermore, the thickness and the color of the arrows represent the magnitude and strength of the average spillover from one node to another, respectively. In this case, the red color indicates strong spillovers, the purple color shows moderate spillovers, and the green color signifies weak spillovers. Distance is also a part of the algorithm but does not necessarily reflect the strength of interconnectedness among the nodes as other measures are valued more strongly. This is because the simulation depends on the initial conditions and the absence of a unique arrangement of the system (Jacomy *et al.*, 2014).

In the short-term, Panel A shows that oil price inflation is a net transmitter of spillovers, exerting/receiving strong spillovers to/from the US CPI inflation, probably due to efficiency and the increasing dominance of the service sector in the economy. CPI inflation spillovers in the US, Canada, China and France are also net transmitters of spillovers, reflecting their prominent role in shaping the dynamics of global inflation.

Panels B and C depict a similar description of the average pairwise directional spillovers in the medium-term and the long-term. Thus, they confirm that oil price inflation is a net transmitter of strong spillovers to the US inflation and mild spillovers to inflation in Canada. Additionally, inflations in the US, China and Germany are the only net transmitters of spillovers in the medium and the long term, showing that these economies dominate the developments of inflation at these horizons.

Finally, we note that inflation spillovers between the US and Canada, France and Germany, and France and the UK tend to be mild across all horizons considered, which reflects the important interdependence among their economies (Tiwari *et al.*, 2019a) and the high inflation synchronization among the Eurozone member states (Tiwari *et al.*, 2015).

Figure 6. Directional pairwise spillovers.

Panel A. Short-term directional pairwise spillovers.	Panel B. Medium-term directional pairwise spillovers.	Panel C. Long-term directional pairwise spillovers.
		

Notes: Panels A, B, and C portray the average pairwise directional spillovers among all possible pairs of the variables of bands (3.14 to 0.13), (0.13 to 0.07) and (0.07 to 0.00), which corresponds to the net spillovers in the short-term (1 to 24 months), the medium-term (24 to 48 months) and the long-term (more than 48 months). A node's color identifies if a variable is a net transmitter/receiver of shocks to/from other variables. The red (green) color indicates that the variable is a net transmitter (receiver) of spillovers. The size of the node shows the magnitude of a net transmission/reception TO/FROM other markets. Furthermore, the thickness and the color of the arrows represent the magnitude and strength of the average spillover between each pair, respectively. In this case, the red color of the arrows indicates strong spillovers, the purple color shows moderate spillovers, and the green color refers to weak spillovers. The sample period is 1987M6-2020M6.

5. Conclusion

We investigate the interconnectedness between CPI inflation in the G7 countries and China and oil price inflation over the period 1987M6-2020M6. To achieve this objective, we employ the multivariate DECO-GARCH model and both the time-domain and frequency-domain spillover methods of Diebold-Yilamz (2009, 2012, 2014) and Barunik and Krehlik (2018). These models serve different functions in the realm of the objectives of this research. We also apply the network analysis developed by Jacomy *et al.* (2014) to illustrate the interconnectedness between the variables in each country.

The DECO-GARCH model shows that there is a reasonably high degree of integration between the oil price inflation and the CPI inflation rates in the G7 countries and China. This integration is not only time-varying but also has been rising over time and, extraordinarily so, during oil crises and periods of financial turmoil.

Regarding the spillovers, the time-domain methods reveal that the oil price inflation is a crucial transmitter of spillovers to CPI inflation in those countries. The largest gross directional spillovers to CPI inflation rates accrue to the US, which consumes more than 20% of the global crude oil production. As for the frequency-domain methods, the results suggest that oil price inflation influences CPI inflation over the short-term, but much less in the medium- to long-terms.

Finally, the network analysis confirms that oil price inflation is a net transmitter of spillovers, in particular, to the US inflation, which, in turn, has a weak to mild influence on the path of inflation in several countries.

Our finding of positive spillovers for higher oil prices poses a problem for central banks in those countries since some of oil price shocks are supply-side shocks, which they cannot effectively control. On one hand, central banks are mandated to deal with price stability when the shocks come from the demand side. On the other hand, ignoring those supply shocks will generate higher inflation expectations and, in turn, increases nominal interest rates, which negatively affect the real side of the economy, especially investment, as well as the bond, stock and currency markets. However, dealing with those oil supply shocks by pursuing a restrictive monetary policy will shift the aggregate demand curve to the left and likely cause stagflation as happened in the seventies. If the ministries of finance/ treasury decide to impose price controls, this policy will trigger shortages and a pent-up demand. In the few past decades, central banks have been more committed to deal with inflation than to care about output. This shift in monetary policy has kept inflation expectations in check and prevented them from turning into actual inflation.

Despite providing valuable evidence about the role played by oil price inflation in the synchronization between CPI inflation in the G7 countries and China, it would be remiss if we did not indicate the limitations of this study. In particular, we do not account for transmission channels, such as the bilateral trade through which price inflation transmits from the oil-producing countries to the oil-consuming countries via the trade of oil. Indeed, bilateral trade is considered as an observed factor in other econometric frameworks (e.g., the global VAR (GVAR)), but it implicitly is an unobserved factor in our VAR model. This potential bias is somewhat minimized by the inclusion of a global variable (namely, the oil price inflation) in the system. Moreover, oil is traded between the producers and the consumer. Further, the methodology that we use is specific and relevant to quantify the spillovers between major countries and at different time horizons.

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