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The Zero Lower Bound and Market Spillovers: Evidence from the G7 and Norway

BY

Evangelos Kyritsis AND **Apostolos Serletis**

Norges Handelshøyskole

NORWEGIAN SCHOOL OF ECONOMICS

The Zero Lower Bound and Market Spillovers: Evidence from the G7 and Norway

Evangelos Kyritsis
Department of Business and Management Science
Norwegian School of Economics
Bergen, Norway
and
Apostolos Serletis*
Department of Economics
University of Calgary
Calgary, Alberta, T2N 1N4
Canada

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*Corresponding author. Phone: (403) 220-4092; Fax: (403) 282-5262; E-mail: Serletis@ucalgary.ca; Web: http://econ.ucalgary.ca/serletis.htm.

ABSTRACT

This paper investigates mean and volatility spillovers between the crude oil market and three financial markets, namely the debt, stock, and foreign exchange markets, while providing international evidence from each of the seven major advanced economies (G7), and the small open oil-exporting economy of Norway. Using monthly data for the period from May 1987 to March 2016, and a four-variable VARMA-GARCH model with a BEKK variance specification, we find significant spillovers and interactions among the markets, but also absence of a hierarchy of influence from one specific market to the others. We further incorporate a structural break to examine the possible effects of the prolonged episode of zero lower bound in the aftermath of the global financial crisis, and provide evidence of strengthened linkages from all the eight international economies.

JEL classification: C32, E32, E52, G15.

Keywords: Crude oil, Financial markets, Mean and volatility spillovers, Structural breaks, VARMA-BEKK model.

1 Introduction

Crude oil constitutes one of the world's most important primary energy commodities, and arguably affects the global economy through several different channels or transmission mechanisms. Some notable studies that investigate the effects of crude oil prices on different aspects of the economy are Hamilton (1983), Mork (1989), Lee *et al.* (1995), Elder and Serletis (2010), and Jo (2014). Oil prices were traditionally determined by oil-market distinct demand and supply forces whereas Kilian (2009), in an impressive study, disentangles the determinants of oil price fluctuations, and underlines the importance of global economic activity triggered by the state of the global business cycle. Another strand of the literature, however, attributes the recent dramatic oil price fluctuations to the financialization of commodity markets and speculative activities, which induce oil prices to depart from their fundamental values. See, for example, Singleton (2014) and Juvenal and Petrela (2015). Motivated by these developments and the recent increase of oil price volatility, the aim of this paper is to explore for spillovers and interactions among the crude oil market and the three most important financial markets, namely the bond, stock, and foreign exchange markets. Moreover, in the aftermath of the global financial crisis, we examine the effects of unconventional monetary policy, when the Federal Reserve and other central banks of the G7 countries as well as Norges Bank (the Norwegian Central Bank), cut their policy rates to their effective zero lower bound.

There is a substantial body of literature investigating crude oil price fluctuations, as well as the transmission channels through which they affect different macroeconomic measures, as for instance the GDP — see Hamilton (2003). In recent years, however, a new strand of research has emerged studying and trying to explain the determinants of the price of oil by the financialization of the crude oil market, rather than solely by changes in economic fundamentals. Dramatic oil price fluctuations, for instance from \$140/barrel in the summer of 2008 to \$60/barrel by the end of 2008, support the view that the oil price might not be only determined though its primary supply and demand mechanism, and raise the question of whether oil has itself become a financial asset with its price reacting to and influencing other assets in financial markets. Indeed, since the early 2000s the financialization of commodity markets, and more particularly the oil market, started taking place with financial investors and portfolio managers using energy assets as a means to diversify their portfolios and hedge their exposure against uncertainty risk — see, for example, Ta and Xiong (2012) and Hamilton and Wu (2014). In fact, Alquist and Kilian (2010) comment on the financialization of the oil market, and based on data from the Commodity Futures Trading Commission argue for an unprecedented increase in speculative activities after 2003. Specifically, it is estimated that the total value of assets allocated to commodity index trading strategies increased from \$15 billion at the end of 2003 to \$260 in mid-2008 [see Creti and Nguyen (2015)], while Daskalaki and Skiadopoulos (2011) attribute the financialization of energy markets to different return behavior and low correlation with stock and bond returns.

In this regard, Fattouh *et al.* (2013) examine whether the drastic changes in oil prices during the period from 2003 to 2008 can be viewed as a result of the increased financialization of the oil market, but find evidence that supports the view of economic fundamentals as the main determinant of the oil price. However, this view has been challenged by Juvenal and Petrela (2015), who argue that speculation constituted a major factor in the oil price increase between 2004 and 2008, as well as its subsequent collapse. It is worth noting that several studies investigate the role of speculation in the oil market through different channels. Hamilton (2009) suggests that speculation may occur through the supply side of the market, by speculators purchasing a high number of futures contracts and thereby signalling higher expected prices. In contrast, Kilian and Murphy (2014) look at speculation from the demand side, and more particularly through the demand for oil inventories that are driven by shifts in expectations, not captured by demand and supply factors. Although there is no consensus among academic researchers about how much crude oil financialization and speculative activities are responsible for oil price fluctuations during the past decade, they all agree that participation of financial investors in the oil market has rendered crude oil a financial asset with new stylized facts, as for instance increased price volatility.

The effects of oil price changes on stock prices have been investigated extensively by numerous research papers. Kilian and Park (2009), in an interesting and influential study, treat the price of oil as endogenous, and examine the impact of oil price changes on stock market returns in the United States, by disentangling the supply and demand factors of the oil market. Their empirical results suggest that stock markets react more strongly to changes in global aggregate demand. Recently, and from a similar point of view, Ahmadi *et al.* (2016) investigate the impact of the global oil market on the U.S. stock market taking into account determinant factors from both the crude oil and stock markets. Their findings corroborate the view that a positive global demand shock increases the market return, while a shock to speculative demand for crude oil depreciates the stock market. They also argue that omission of the stock market determinants overestimates the contribution of the oil price shocks in stock market variation. Some more interesting studies on the relationship between oil prices and stock prices using different types of econometric tools are Kling (1985), Jones and Kaul (1996), Sadorsky (1999, 2001, 2012), Cong *et al.* (2008), Park and Ratti (2008), Lee *et al.* (2012), Li *et al.* (2012), Ding *et al.* (2016), and Joo and Park (2017).

Another very interesting relationship with a less extensive yet still growing literature is between oil prices and exchange rates. Oil price changes affect a country's exchange rate primarily through two separate transmission channels, while the impact differs between oil-importing and oil-exporting countries. The first one was initially introduced by Golub (1983) and Krugman (1983), and refers to the wealth effect channel, according to which an oil price increase is related to a wealth transfer from an oil-importing to an oil exporting country, which in turn induces a real depreciation of the exchange rate of the former country, and vice versa. For an empirical application, see Kilian *et al.* (2009). The second transmission mechanism is within the context of the trade balance, based on which higher oil prices result in an improved trade balance of the oil-exporting country, and thereby to a local currency appreciation (vice versa for an oil-importing country). Related empirical evidence is provided by Amano and van Norden (1998), while Buetzer *et al.* (2012) underline the danger of oil price increases to eventually steer the economies of oil-exporting countries towards the Dutch disease. This view, however, has recently been challenged by Bjørland and Thorsrud (2016), who use Australia and Norway as representative cases studies, and argue that booming resource sectors may have significant productivity spillovers to non-resource sectors, while commodity price growth related to global demand is also favourable. In the same study, it is noted that commodity price growth which is unrelated to global activity is less favourable, due to the significant real exchange rate appreciation and reduced competitiveness. In this regard, Basher *et al.* (2016) build upon their previous work and find evidence of nonlinear interaction between oil prices and exchange rates in both oil exporting and importing economies, after they first separate the underlying sources of the oil price movements, according to Kilian's (2009) approach, to an oil supply shock, an oil-market specific demand shock, and a global economic demand shock. Specifically, they find evidence for substantial currency appreciation in oil exporting countries after oil demand shocks whereas global economic demand shocks are found to influence both oil exporting and importing countries, though there is no systematic pattern of appreciating and depreciating exchange rates. Some other interesting studies on this link are Sadorsky (2000), Chen and Chen (2007), and Chen *et al.* (2010).

Moreover, there is an extended literature analyzing the relationship between oil prices and interest rates; a relationship in which the conducted monetary policy, through changes in interest rates and monetary aggregates, plays an important role. In this regard, Krichene (2006) analyzes the link between monetary policy and oil prices, and finds evidence of a two-way relationship contingent on the type of oil shock. Specifically, he finds that during a supply shock, oil price increases cause interest rates to rise whereas falling interest rates cause oil prices to increase during a demand shock. Moreover, the fact that both oil prices and interest rates have increased prior to the majority of postwar U.S. recessions, triggered the intensive interest of literature to explore this relationship in regard to economic activity. Bernanke *et al.* (1997, 2004) try to answer the question of whether those recessions were caused by oil price increases, or by contractionary monetary policy. Using Hamilton's (1996) measure of oil price shocks, they argue that oil price and interest rate increases contribute to the recessions to the same extent, while Hamilton and Herrera (2004) find that oil price shocks have a greater impact on the economy, and that tightening monetary policy does not have such a great effect as implied by Bernanke *et al.* (1997). Hammoudeh and Choi (2006), in contrast, study the impact of oil price and interest rate on the Gulf Cooperation Council's (GCC) stock markets, and provide evidence that only the short-term interest rate has an important, but mixed, effect on the GCC markets. More recently, and within the framework of a dynamic stochastic general equilibrium model, Kormilitsina (2011) shows that tightening monetary policy amplifies the negative effects of the oil price shock.

In the aftermath of the global financial crisis and Great Recession, many central banks, such as the Federal Reserve, the Bank of Japan, the European Central Bank, the Bank of England, the Bank of Canada, and the Norges Bank lowered their policy rates towards, or slightly above, the zero lower bound in order to provide additional monetary stimulus to their economies. Since the monetary policy rate has been used as the primary operating instrument during the last decades and zero was by that time considered the lowest bound, central banks lost their usual ability to signal policy changes via changes in interest rate policy instruments, and attempted further monetary easing by resorting to unconventional measures, such as forward guidance, asset purchase programs, and credit easing. Filardo and Hofmann (2014) investigate the effectiveness of forward guidance by four major central banks, namely, the Federal Reserve, the Bank of Japan, the European Central Bank, and the Bank of England, and conclude that although it has reduced the volatility of near-term expectations about the future path of policy interest rates, the evidence for its impact on expected interest rates has varied significantly, thus making it difficult to draw firm conclusions about their overall effectiveness in reliably stimulating further actual economies. Some more interesting studies on the effectiveness of unconventional monetary policies are Hamilton (2012) and Gambacorta *et al.* (2014). Furthermore, Serletis and Istiak (2016) investigate the relationship between economic activity and Divisia money supply shocks and argue, based on evidence of a symmetric relationship, in favor of monetary aggregates as appropriate policy instruments, since they are measurable, controllable, and have predictable effects on goal variables.

Motivated by the aforementioned discussions, we investigate mean and volatility spillovers between the crude oil market and the three most important financial markets, the bond, stock, and foreign exchange markets, using a multivariate volatility model. This model was first proposed by Bollerslev *et al.* (1998) and has become much more widely used in economics and finance, since it allows for shocks to the variance of one of the variables to 'spill-over' to the others. A recent example is the work by Gilenko and Fedorova (2014) who use a four-dimensional BEKK-GARCH-in-mean model to investigate the spillover effects between the stock markets of BRIC countries (Brazil, Russia, India, and China). In fact, as Bauwens *et al.* (2006, p. 79) put it, "is the volatility of a market leading the volatility of other markets? Is the volatility of an asset transmitted to another asset directly (through its conditional variance) or indirectly (through its conditional covariances)? Does a shock on a market increase the volatility on another market, and by how much? Is the impact the same for negative and positive shocks on the same amplitude?" It is worth mentioning that although there is a substantial body of literature exploring the interactions among the four markets, most of them study each relationship separately rather than in a systems context. Some related studies that investigate up to three markets together are Nadha and Hammoudeh (2007), Akram (2009), Basher *et al.* (2012), and Diaz *et al.* (2016). Here, we follow Serletis and Xu (2018) and examine the possible effects of monetary policy at the zero lower bound in the aftermath of the global financial crisis, while providing international evidence from each of the seven major advanced economies (G7) and the small open oil-exporting economy of Norway. The main argument behind this is that spillovers and interactions among the four markets might vary across different international economies, since the latter exhibit different characteristics, such as oil dependency or conducted monetary policy.

The rest of the paper is structured as follows. In Section 2, we describe the data and investigate their time series properties. In Section 3, we present the VARMA-GARCH model with a BEKK representation and structural break, while in sections 4 and 5 the empirical evidence is presented, discussed, and summarized. Some concluding remarks are given in section 6.

2 Data and Basic Properties

We use monthly data for each of the G7 countries, namely Canada, France, Germany, Italy, Japan, the U.K., and the U.S., as well as for the significantly smaller and oil-exporting country of Norway, for the period from May 1987 to March 2016. Other papers also use monthly data to study the interaction between the crude oil and stock market [see Park and Ratti (2008), Miller and Ratti (2009), and Ahmadi *et al.* (2016)], and the relationship between oil prices and exchange rates [see Chen and Chen (2007), and Atems *et al.* (2015)].

For the oil price series (o_t), we use the world's most commonly referenced crude oil price benchmark, the spot British price of oil (Brent) published by the U.S. Energy Information Administration. The main argument behind this is the fact that around two-thirds of the global physical oil-trading uses the Brent as a reference price, primarily due to the "light" and "sweet" properties of Brent oil which render it ideal for transportation to distant locations.[1] In order to take fluctuations of exchange rates and inflation into account, we follow Güntner (2014) and accordingly construct the national real oil price of each country. In doing so, we convert the Brent oil price from U.S dollars to national currency using the corresponding bilateral exchange rate as reported by the St. Louis Federal Reserve Economic Database (FRED), and then deflate it using the domestic consumer price index (CPI), available from OECD. In the case of the euro area countries, namely France, Germany, and Italy, we also use the irreversible parity rates with the euro, obtained from the exchanging national cash archives of the European Central Bank, in order to convert to national currency for the period after the introduction of the euro in January 2002.

For the interest rate series, i_t, we use the short-term interest rate from IMF International Financial Statistics and OECD.[2] Moreover, we employ the monthly average share price indices from OECD for the stock price series, s_t, after deflating them using the corresponding CPI. Last, the bilateral exchange rates between the U.S dollar and the different national

[1] These properties refer to the low sulfur concentration of crude oil (less than 0.5%).

[2] These refer either to three month interbank offer rate or the rate associated with Treasury Bills, Certificates of Deposit or comparable instruments, each with a three month maturity.

currencies are used for the exchange rate series, e_t, while for the case of the U.S. we use the nominal effective exchange rate, available from the IMF International Financial Statistics. Tables 1-8 present summary statistics of each individual series of each of the eight countries, namely the log levels, $\ln o_t$, $\ln i_t$, $\ln s_t$, and $\ln e_t$, and logarithmic first differences, $\Delta \ln o_t$, $\Delta \ln i_t$, $\Delta \ln s_t$, and $\Delta \ln e_t$. It is worth noting that in the cases of negative short-term interest rate such as in France and Italy, the levels, rather than the logarithms of the short-term interest rate are examined, while from a similar point of view in the case of Germany and Japan we employ the levels, and not the logarithms, of all the series. In general, the p-values for skewness and kurtosis underline significant deviations from symmetry and normality with both the logged series and the first differences of the logs. Moreover, the Jarque-Bera (1980) test statistic, distributed as $x^2(2)$ under the null hypothesis of normality, rejects the null hypothesis with nearly all the series. It is to be noted that all series are scaled up by a factor of 100, except for the case of Japan where the stock price series and exchange rate are scaled down by a factor of 0.01, and the oil price by a factor of 0.001; the main reason for doing so is to make all four series be in the same range.

In the first step of volatility modeling, we test for the presence of a unit root (a stochastic trend) in the autoregressive representation of each individual series of each of the eight countries. Panel A of Tables 9-11 reports the results of unit root and stationary tests in log levels, $\ln o_t$, $\ln i_t$, $\ln s_t$, and $\ln e_t$, and logarithmic first differences, $\Delta \ln o_t$, $\Delta \ln i_t$, $\Delta \ln s_t$, and $\Delta \ln e_t$. Specifically, we use the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller (1981)] and the Dickey-Fuller GLS (DF-GLS) test [see Elliot *et al.* (1996)] which evaluate the null hypothesis of a unit root against an alternative of stationarity, assuming both a constant and trend. We select the optimal lag length based on the parsimonious Bayesian information criterion (BIC) assuming a maximum lag length of four for each series. In addition, the KPSS test [see Kwiatkowski *et al.* (1992)] is used in order to test the null hypothesis of stationarity around a trend. As shown in Panel A of Tables 9-11, the null hypothesis of a unit root cannot in general be rejected for most of the series at conventional significance levels by both the ADF and DF-GLS test statistics. Furthermore, the null hypothesis of trend stationarity can be rejected at conventional significance levels by the KPSS test. Accordingly, we conclude that each of the four series in all countries is non-stationary, or integrated of order one, $I(1)$. We repeat the unit root and stationary tests in Panel B of Tables 9-11 using the first differences of the series. The null hypotheses of the ADF and DF-GLS tests are in general rejected at conventional significance levels, while the null hypothesis of the KPSS test cannot be rejected. Hence, we can safely argue that the first differences of the series are integrated of order zero, $I(0)$.

Most of the literature perceives this property of 'difference stationary' [see Nelson and Plosser (1982)] as a suggestion for using first differences as the appropriate representation of the data in the model. However, in the case of Canada and Japan, evidence of cointegration among the four series is found based on Johansen's (1988) maximum likelihood method. Such a cointegrated system with $I(1)$ variables normally encourages the use of vector error correction (VEC) models, since the latter allow for the explicit investigation of the cointegrating relations. However a VAR in levels is also adequate provided that the cointegrating relations are not the primary goal of study, as in our case. In fact, Lütkepohl (2004) demonstrates that VAR and VEC models are equivalent. Therefore, in the case of Canada and Japan we estimate the model using the series in levels. Finally, motivated by all previous discussions, we proceed to the next section which describes our econometric model.

3 The Econometric Model

In this section, we estimate a four-variable VARMA-GARCH model with a Baba, Engle, Kraft, and Kroner (BEKK) representation [see Baba *et al.* (1991) and Engle and Kroner (1995) for more details], which models in a systems context the levels and volatilities of the crude oil price, interest rate, stock price, and exchange rate in each of the G7 countries and Norway. The main reason for selecting a VARMA framework is the fact that it allows us to capture the features of the data generating process in a parsimonious way, without the need for additional number of parameters. In fact, Inoue and Kilian (2002, p.322) argue that "the existence of finite-lag order VAR models is highly implausible in practice and often inconsistent with the assumptions of the macroeconomic model underlying the empirical analysis."

It is also noteworthy that in contrast to a large part of the literature, we abandon the assumption of normally distributed errors, and instead assume a student-t distribution with the shape parameter being estimated together with the other parameters. The main argument behind this is the fact that financial series have empirical distributions that exhibit fatter tails than the normal distribution. See Jansen and de Vries (1991), Koedijk *et al.* (1992), Koedijk and Kool (1994), Loretan and Phillips (1994), Kearns and Pagan (1997), Corsi (2009), and Huisman *et al.* (1998). The latter is of high importance since underestimation of fat tails could lead to an erroneous assessment of the extreme events. Moreover, Aghababa and Barnett (2016) assess the dynamic structure of the spot price of crude oil and find evidence of nonlinear dependence, which is however moderated by time aggregation, as for instance in monthly observations that we actually use here.

We follow Serletis and Xu (2018) and for the mean equation, we use a VARMA(1,1) model specification with a break to capture the possible effects of monetary policy at the zero lower bound

$$z_t = \Phi + (\Gamma + \tilde{\Gamma} \times D)z_{t-1} + (\Psi + \tilde{\Psi} \times D)\epsilon_{t-1} + \epsilon_t$$

where

$$\epsilon_t|\Omega_{t-1} \sim t_v(0, H_t); \qquad H_t = \begin{bmatrix} h_{oo,t} & h_{oi,t} & h_{os,t} & h_{oe,t} \\ h_{io,t} & h_{ii,t} & h_{is,t} & h_{ie,t} \\ h_{so,t} & h_{si,t} & h_{ss,t} & h_{se,t} \\ h_{eo,t} & h_{ei,t} & h_{es,t} & h_{ee,t} \end{bmatrix}$$

and

$$z_t = \begin{bmatrix} ln : o_t \\ ln : i_t \\ ln : s_t \\ ln : e_t \end{bmatrix}; \epsilon_t = \begin{bmatrix} \epsilon_{o,t} \\ \epsilon_{i,t} \\ \epsilon_{s,t} \\ \epsilon_{e,t} \end{bmatrix}; \Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} \end{bmatrix}; \tilde{\Gamma} = \begin{bmatrix} \tilde{\gamma}_{11} & \tilde{\gamma}_{12} & \tilde{\gamma}_{13} & \tilde{\gamma}_{14} \\ \tilde{\gamma}_{21} & \tilde{\gamma}_{22} & \tilde{\gamma}_{23} & \tilde{\gamma}_{24} \\ \tilde{\gamma}_{31} & \tilde{\gamma}_{32} & \tilde{\gamma}_{33} & \tilde{\gamma}_{34} \\ \tilde{\gamma}_{41} & \tilde{\gamma}_{42} & \tilde{\gamma}_{43} & \tilde{\gamma}_{44} \end{bmatrix};$$

$$\Psi = \begin{bmatrix} \psi_{11} & \psi_{12} & \psi_{13} & \psi_{14} \\ \psi_{21} & \psi_{22} & \psi_{23} & \psi_{24} \\ \psi_{31} & \psi_{32} & \psi_{33} & \psi_{34} \\ \psi_{41} & \psi_{42} & \psi_{43} & \psi_{44} \end{bmatrix}; \tilde{\Psi} = \begin{bmatrix} \tilde{\psi}_{11} & \tilde{\psi}_{12} & \tilde{\psi}_{13} & \tilde{\psi}_{14} \\ \tilde{\psi}_{21} & \tilde{\psi}_{22} & \tilde{\psi}_{23} & \tilde{\psi}_{24} \\ \tilde{\psi}_{31} & \tilde{\psi}_{32} & \tilde{\psi}_{33} & \tilde{\psi}_{34} \\ \tilde{\psi}_{41} & \tilde{\psi}_{42} & \tilde{\psi}_{43} & \tilde{\psi}_{44} \end{bmatrix},$$

where D is a dummy variable being always equal to zero, except for the time that the policy rate in the United States hits the zero lower bound and takes the value of one; Ω_{t-1} is the information set available in period $t-1$, and v a parameter that characterizes the shape of the student-t distribution. The last parameter, also called shape parameter, describes the level of the tail fatness in the error distribution and equals the number of existing moments. Actually, the lower the value of the shape parameter is, the fatter the tails of the error distribution become.

For the variance equation, the BEKK model specification is preferred for a number of reasons over other models, such as the dynamic conditional correlation (DCC) model or the asymmetric dynamic conditional correlation (ADCC) model, developed by Engle (2002) and Cappiello *et al.* (2004), respectively. First, the BEKK model forces all the parameters to enter the model via quadratic forms, ensuring that all the conditional variances are positive, while the positive definiteness of the conditional variance-covariance matrix H_t is guaranteed, by construction, without imposing any restrictions on the parameters. Secondly, the parameter estimation of the BEKK model is more accurate than that provided by the DCC model [see Huang *et al.* (2010)], whereas it allows for more rich dynamics in the variance-covariance structure of time series. For instance, a shortcoming of the DCC model is that imposes a common dynamic structure (persistence) on all conditional correlations. Finally, grounded on the fact that the crucial decision in MGARCH modelling is between flexibility and parsimony, we prefer the BEKK model specification that is flexible enough to provide a realistic representation, while also being parsimonious for such a system of four elements (Bauwens *et al.* 2006).

More precisely, we use the BEKK (1,1,1) specification which can be regarded a multivariate generalization of GARCH(1,1) model. The resulting variance equation with a dummy variable is

$$\begin{aligned} H_t = C'C &+ (B + \tilde{B} \times D)' H_{t-1} (B + \tilde{B} \times D) \\ &+ (A + \tilde{A} \times D)' \epsilon_{t-1} \epsilon'_{t-1} (A + \tilde{A} \times D) \end{aligned}$$

where

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}; \tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \tilde{a}_{13} & \tilde{a}_{14} \\ \tilde{a}_{21} & \tilde{a}_{22} & \tilde{a}_{23} & \tilde{a}_{24} \\ \tilde{a}_{31} & \tilde{a}_{32} & \tilde{a}_{33} & \tilde{a}_{34} \\ \tilde{a}_{41} & \tilde{a}_{42} & \tilde{a}_{43} & \tilde{a}_{44} \end{bmatrix};$$

$$B = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix}; \tilde{B} = \begin{bmatrix} \tilde{\beta}_{11} & \tilde{\beta}_{12} & \tilde{\beta}_{13} & \tilde{\beta}_{14} \\ \tilde{\beta}_{21} & \tilde{\beta}_{22} & \tilde{\beta}_{23} & \tilde{\beta}_{24} \\ \tilde{\beta}_{31} & \tilde{\beta}_{32} & \tilde{\beta}_{33} & \tilde{\beta}_{34} \\ \tilde{\beta}_{41} & \tilde{\beta}_{42} & \tilde{\beta}_{43} & \tilde{\beta}_{44} \end{bmatrix}$$

where $C'C$, B, $\tilde{B}$, A and $\tilde{A}$ are 4×4 matrices with C being a triangular matrix to ensure positive definiteness of H_t. The variance equation allows every conditional variance and covariance to be a function of all lagged conditional variances and covariances, as well as of all lagged squared residuals and cross-products of residuals. Assuming that the H matrix is symmetric, the model produces ten unique equations modeling the dynamic variances of oil, interest rate, stock price, and exchange rate, as well as the covariances between them. We forgo employing additional explanatory variables, since our model already contains 68 mean equation parameters, 74 variance equation parameters, and the distribution shape parameter v, for a total 143 parameters. Last, the following restriction is imposed on our model $\tilde{\gamma}_{11} = \tilde{\psi}_{11} = \tilde{\alpha}_{11} = \tilde{\beta}_{11} = 0$, thus not allowing the crude oil price to be affected by the zero lower bound constraint.

4 Individual country estimates

The four-variable VARMA(1,1)-BEKK(1,1,1) model with a structural break described above is estimated individually for each country in Estima RATS 9.0 using the Maximum Likelihood method. In doing so, we use the BFGS (Broyden, Fletcher, Goldfarb, & Shanno) estimation algorithm, which is recommended for GARCH models, along with the derivative-free Simplex pre-estimation method. Tables 12-19 report the estimated coefficients (with significance levels in parentheses), as well as the student-t distribution shape parameter estimate, v, and the key diagnostics for the standardized residuals

$$\hat{z}_{jt} = \frac{\hat{e}_{jt}}{\sqrt{\hat{h}_{jt}}}$$

for $j = \ln o_t$, $\ln i_t$, $\ln s_t$, and $\ln e_t$. In fact, Panel B of Tables 12-19 reports some descriptive statistics for the standardized residuals, as well as the p-values of the Ljung-Box Q test for residual autocorrelation, and the McLeod-Li Q^2 test for squared residual autocorrelation. Both tests evaluate the null hypothesis of independently distributed data against an alternative of autocorrelation.

In order to answer our research question, we need to capture and discuss the dynamics of the system, given by the Γ, Ψ, A, and B coefficient matrices for the period before the zero lower bound was reached, and by $\Gamma + \tilde{\Gamma}$, $\Psi + \tilde{\Psi}$, $A + \tilde{A}$, and $B + \tilde{B}$ for the time that the zero lower bound constraint is binding. It is to be noted that we focus only on the estimation results that are statistically significant at the 95% level, as well as that our discussion takes place in terms of predictability and not as implying an underlying structural economic relationship. Moreover, we do not identify the source of shocks since this is not within the scope of this paper, and present the estimation results for each country individually. Finally, the conditional correlation coefficients can be easily computed from the BEKK model, as follows:

$$\rho_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t} \; h_{22,t}}}$$

Figures 1 and 2 depict the development of the conditional correlation coefficients between the crude oil market and each of the three financial markets, in each of the G7 countries and Norway. The evolution of the market interactions is illustrated, for the period before and after the zero lower bound was reached, while differences across countries are detected and discussed in the following sections.

4.1 Canada

As can be seen in Table 12, in the oil-dependent Canadian economy, we find that the autoregressive coefficients along the main diagonal in the Γ matrix are all significant and close to one. That is to say, for each of the four markets, today's performance is a good predictor of tomorrow's performance. Moreover, the off-diagonal elements of the Γ matrix suggest significant spillover effects affecting the crude oil, bond, and foreign exchange markets, but not the stock market. Specifically, the current price of crude oil is affected by last period's interest rate, stock price, and exchange rate; a higher interest rate leads to a decrease in the price of oil ($\gamma_{12} = -0.046$ with a p-value of 0.000), whereas a higher stock market index leads to an increase in the price of oil ($\gamma_{13} = 0.102$ with a p-value of 0.000), and an appreciation of the U.S. dollar relative to the Canadian dollar leads to a decline in the price of oil ($\gamma_{14} = -0.248$ with a p-value of 0.000). Last, we find evidence of spillovers from the crude oil market to the debt and foreign exchange markets, since $\gamma_{21} = -0.018$ (with a p-value of 0.014) and $\gamma_{41} = -0.011$ (with a p-value of 0.008).

However, some spillover effects change or new ones occur when the zero bound is reached in the U.S. policy rate, as is indicated by the $\tilde{\Gamma}$ matrix. In particular, we find that an increase in the price of oil today will lead to a higher stock price tomorrow, since $\tilde{\gamma}_{31} = 0.056$ (with a p-value of 0.000). Moreover, the intertemporal correlation between the oil price and the interest rate changes when the zero lower bound constraint is binding, since in that case an increase in the interest rate leads to a higher oil price (as $\gamma_{12}+\tilde{\gamma}_{12} = -0.046+0.080 = 0.034$). Overall, we find that some new spillovers are created across the markets, while some intertemporal relationships change after the zero lower bound occurs.

On the other hand, the moving average coefficients along the diagonal of the Ψ matrix are moderate and significant, except for the case of the stock price, implying that each of the crude oil price, interest rate, and exchange rate series is consistent with a typical ARMA process. In addition, a single spillover effect in the moving average terms, otherwise called shock spillover, is found propagating from the stock market towards the debt market, while affecting it in a negative way ($\gamma_{23} = -0.137$ with a p-value of 0.008). Furthermore, new shock spillovers are found for the case of the crude oil market when the zero lower bound occurs. In particular, negative shock spillovers occur from the debt and foreign exchange markets towards the crude oil market, since $\tilde{\gamma}_{12} = -0.379$ (with a p-value of 0.000), and $\tilde{\gamma}_{14} = -1.342$ (with a p-value of 0.009).

Regarding volatility spillovers, all the 'own-market' coefficients in the A and B matrices are found statistically significant whereas the estimates suggest a high degree of persistence. There is no evidence for spillover ARCH effects from the oil market to any of the three financial markets, but we find statistically significant spillover ARCH effects when the zero lower bound is reached. In particular, an unexpected shock in the crude oil market increases the volatility of the debt market when the zero lower bound occurs, since $\tilde{a}_{12} = 0.151$ with a p-value of 0.001. On the other hand, an unexpected shock in the stock market increases the volatility in the crude oil market (as $a_{31} = 0.634$ with a p-value of 0.001), and this spillover ARCH effect is strengthened further when the zero lower bound constraint on the policy rate is binding, since $\tilde{a}_{31} = 1.405$ (with a p-value of 0.000), implying an ARCH effect of $(0.634 + 1.405)^2$. Moreover, a new significant spillover ARCH effect propagates from the foreign exchange market to the crude oil market when the zero lower bound occurs (as $\tilde{a}_{41} = 1.668$ with a p-value of 0.021).

Furthermore, statistically significant spillover GARCH effects occur between the four markets. In particular, we find volatility spillovers running from the crude oil market to the stock market (as $\beta_{13} = 0.254$ with a p-value of 0.000), as well as from the debt and stock markets to the crude oil market, since $\beta_{21} = -0.384$ (with a p-value of 0.035) and $\beta_{31} = -1.435$ (with a p-value of 0.000). Moreover, we find that the spillover GARCH effect from the oil market on the stock market increases when the zero lower bound is reached, since $\tilde{\beta}_{13} = -0.269$ (with a p-value of 0.000), implying a GARCH effect of $(0.254+0.269)^2$. Overall, we find that monetary policy at the zero lower bound strengthens already existing volatility spillovers, or even creates some new ones between the crude oil and financial markets.

4.2 France

In the case of France (see Table 13), which is the 6th largest export economy in the world and the 9th largest oil-importing economy (IEA, 2016), we find that the autoregressive coefficients of debt and stock markets along the main diagonal in the Γ matrix are moderate and statistically significant, suggesting that for both of them, today's performance could be a useful predictor of tomorrow's performance. Regarding spillover effects between the oil and financial markets, there is empirical evidence only for the case of crude oil and stock markets. In particular, we find that the current price of oil is affected by last period's stock price in a positive way ($\gamma_{13} = 1.083$ with a p-value of 0.000) whereas a higher oil price leads to an increase in the stock price ($\gamma_{31} = 0.356$ with a p-value of 0.000). Moreover, we do not find significant interactions between the three financial markets, except for the spillover effect propagating from the debt and foreign exchange markets to the stock market. Hence, we find that a higher interest rate leads to a lower stock price, since $\gamma_{32} = -0.035$ (with a p-value of 0.044), while a stronger U.S. dollar relative to the French franc leads also to a decline in stock prices, since $\gamma_{34} = -0.265$ (with a p-value of 0.032).

However, the spillover effects change after the zero lower bound constraint is binding, as indicated by the $\tilde{\Gamma}$ matrix. Specifically, we find that an increase in the price of oil could affect negatively the interest rate, since $\tilde{\gamma}_{21} = -0.848$ (with a p-value of 0.043), and ambiguously the stock market, since $\gamma_{31} = 0.356$ (with a p-value of 0.000) and $\tilde{\gamma}_{31} = -0.373$ (with a p-value of 0.000). Moreover, a new spillover effect is found from the crude oil market to the foreign exchange market, since $\tilde{\gamma}_{41} = 0.462$ (with a p-value of 0.000). On the other hand, the intertemporal correlation between the stock price and the oil price changes when the zero lower bound is reached, since an increase in stock market price could lead to a decline in the price of oil (as $\gamma_{13} + \tilde{\gamma}_{13} = 1.083 - 91.567 = -90.484$). Last, the debt and foreign exchange markets are found to affect the stock price in an uncertain way when the zero lower bound occurs, since $\gamma_{32} = -0.035$ and $\tilde{\gamma}_{32} = 0.047$ (with a p-value of 0.044 and 0.008, respectively), whereas $\gamma_{34} = -0.265$ and $\tilde{\gamma}_{34} = 0.234$ (with a p-value of 0.032 and 0.038, respectively). Overall, we find that spillover effects between the crude oil market and the financial markets are mainly strengthened when the zero lower bound constraint is binding, while the financial markets interact with each other in an ambiguous way.

Regarding volatility linkages, we find significant spillover ARCH effects from the oil market to the debt and foreign exchange market (as $\alpha_{12} = -0.305$ with a p-value of 0.002 and $\alpha_{14} = -0.090$ with a p-value of 0.004) whereas these are further strengthened after the zero lower bound occurs, since $\tilde{\alpha}_{12} = 0.278$ (with a p-value of 0.013) and $\tilde{\alpha}_{14} = 0.275$ (with a p-value of 0.000), implying ARCH effects of $(0.305 + 0.278)^2$ and $(0.090 + 0.275)^2$, respectively. Moreover, a new spillover ARCH effect is found from the crude oil market to the stock market when the zero lower bound is reached. In particular, an unexpected shock in the crude oil price increases the volatility of the stock price when the zero lower bound constraint is binding, since $\tilde{\alpha}_{13} = 0.204$ (with a p-value of 0.009).

In addition, we find that all the 'own-market' coefficients in the B matrix are statistically significant and the estimates suggest a high degree of persistence. There are also volatility spillovers from the crude oil market to the foreign exchange market, with $\beta_{14} = -0.113$ (with a p-value of 0.000), as well as from the stock and foreign exchange markets to the crude oil market, since $\beta_{31} = -0.923$ (with a p-value of 0.000) and $\beta_{41} = 1.377$ (with a p-value of

0.000). We also find a new volatility spillover propagating from the debt market to the crude oil market, as $\tilde{\beta}_{21} = 0.273$ (with a p-value of 0.000).

4.3 Germany

In the case of Germany, as can be seen in Table 14, we find that all the autoregressive coefficients in the Γ matrix, except that for the foreign exchange market, are moderate and significant along the main diagonal. Hence, for each of the three markets, today's performance is a good predictor of tomorrow's performance. Moreover, we find significant spillover effects propagating from the stock and foreign exchange markets to the crude oil market, since $\gamma_{13} = 0.131$ (with a p-value of 0.009) and $\gamma_{14} = 43.545$ (with a p-value of 0.048). On the other hand, there is also evidence of spillovers from the crude oil market to the debt and foreign exchange markets, since $\gamma_{21} = 0.009$ (with a p-value of 0.000) and $\gamma_{41} = 0.002$ (with a p-value of 0.000).

In addition, we find that spillover effects change after the policy rate hits the zero lower bound, as indicated in the $\tilde{\Gamma}$ matrix. In particular, we find that a higher stock price today leads to an even larger increase in the price of oil tomorrow (as $\tilde{\gamma}_{13} = 1.756$ with a p-value of 0.000), while the intertemporal correlation between the foreign exchange market and the crude oil market changes when the zero lower bound constraint is binding (as $\gamma_{14} + \tilde{\gamma}_{14} = 43.545 - 92.506 = -48.961$). Moreover, there is evidence of a strengthened spillover effect from the crude oil market to the debt market (as $\tilde{\gamma}_{21} = 0.011$ with a p-value of 0.000), as well as of a new spillover effect running from the crude oil market to the stock market, since $\tilde{\gamma}_{31} = -0.270$ (with a p-value of 0.000).

The moving average coefficients along the diagonal of the Ψ matrix are moderate and significant, implying that each of the four markets are consistent with a typical ARMA process, while the off-diagonal elements indicate the spillover effects across the four markets. Regarding the oil price equation, we find that stock market shocks affect the crude oil market negatively at normal times (as $\psi_{13} = -0.299$ with a p-value of 0.000), and even stronger when the zero lower bound is reached (as $\tilde{\psi}_{13} = -1.514$ with a p-value of 0.000). Moreover, we find evidence of shock spillovers running from the crude oil market to all the financial markets, and influencing them in a negative way, since $\psi_{21} = -0.009$ (with a p-value of 0.000), $\psi_{31} = -0.133$ (with a p-value of 0.000), and $\psi_{41} = -0.002$ (with a p-value of 0.000). In addition, we find a new shock spillover propagating from the debt market towards the crude oil market, and affecting it in a positive way when the zero lower bound occurs (as $\tilde{\psi}_{12} = 40.184$ with a p-value of 0.000).

Furthermore, we find statistically significant spillover ARCH effects from the crude oil market to the debt and stock markets, implying that an unexpected shock in the crude oil market increases the volatility of the bond and stock markets, since $\alpha_{12} = -0.003$ (with a p-value of 0.002) and $\alpha_{13} = -0.131$ (with a p-value of 0.030). In addition, there is evidence of a new spillover ARCH effect propagating from the debt market to the crude oil market when the zero lower bound is reached. In particular, an unexpected shock in the debt market increases the volatility of the crude oil market when the zero lower bound occurs, since $\tilde{\alpha}_{21} = -146.568$ (with a p-value of 0.000). Moreover, the spillover ARCH effect from the foreign exchange market to the crude oil market increases when the zero lower constraint is binding, since $\tilde{\alpha}_{41} = 373.555$ (with a p-value of 0.000), implying an ARCH effect of $(39.401 + 373.555)^2$.

Regarding volatility linkages, all the 'own-market' coefficients in the B and $\tilde{B}$ matrices are statistically significant, except that for the crude oil market, while the estimates imply a high degree of persistence. Moreover, we find statistically significant spillover GARCH effects running from the crude oil market to the stock market ($\beta_{13} = 0.734$ with a p-value of 0.000), as well as a new one from the crude oil market to the bond market after the zero lower bound is reached, since $\tilde{\beta}_{12} = 0.005$ (with a p-value of 0.001). Overall, we find that unconventional monetary policy at the zero lower bound establishes stronger first- and second- moment linkages between the markets.

4.4 Italy

In the case of Italy (see Table 15), we find that all the autoregressive coefficients in the Γ matrix, except that for the foreign exchange market, are moderate and significant along the main diagonal. This indicates that, for each of the three markets, today's performance provides high predictive power for tomorrow's performance. Furthermore, we find significant spillover effects from the crude oil market to the bond and stock markets, and vice versa, while there is no evidence of interaction between the crude oil and the foreign exchange markets. In particular, a higher interest rate leads to an increase in the price of oil (as $\alpha_{12} = 0.066$ with a p-value of 0.029) whereas a higher stock price leads also to an increase of the crude oil price (as $\alpha_{13} = 1.137$ with a p-value of 0.005). On the other hand, a higher oil price leads to an increase of the interest rate ($\alpha_{21} = 0.908$ with a p-value of 0.004) and the stock price ($\alpha_{31} = 0.221$ with a p-value of 0.008). However, the intertemporal correlation between the crude oil market and the debt market changes after the zero lower bound occurs. In particular, a higher oil price leads to a decrease of the interest rate when the zero lower bound is reached, since $\tilde{\alpha}_{21} = -1.106$ (with a p-value of 0.002).

On the other hand, the moving-average coefficients along the diagonal of the Ψ matrix are moderate and significant, suggesting that the dynamics of all markets are consistent with a typical ARMA process. Another interesting result is that there are also shock spillovers across the markets. In particular, there is a significant impact of a surprise change in the oil price on the interest rate, stock price, and foreign exchange market in the next period. For instance, an unexpected increase in the oil price will affect the interest rate and the stock market in a negative way ($\psi_{21} = -0.930$ with a p-value of 0.003 and $\psi_{31} = -0.921$ with a p-value of 0.008), while it will increase the foreign exchange of the U.S. dollar to Italian lira (as $\psi_{41} = 0.103$ with a p-value of 0.020). Moreover, we find shock spillovers running from the bond market towards the crude oil market, since $\psi_{12} = -0.056$ (with a p-value of 0.023), whereas this is further strengthened when the zero lower bound constraint is binding as $\tilde{\psi}_{12} = -0.302$ (with a p-value of 0.005).

The estimates for the variance equation show moderate and significant ARCH coefficients along the main diagonal of the A matrix, for the case of the crude oil and bond market (since $\alpha_{11} = -0.315$ and $\alpha_{22} = 0.789$, both with a p-value of 0.000), suggesting that volatility is persistent in both these markets. Moreover, we find statistically significant spillover ARCH effects from the crude oil market to the bond market (as $\alpha_{12} = -0.237$ with a p-value of 0.005), which is further strengthened when the zero lower bound occurs (since $\tilde{\alpha}_{12} = 0.235$ with a p-value of 0.007). Moreover, there is evidence of new spillover ARCH effects, for instance propagating from the crude oil market towards the foreign exchange market. Hence, an unexpected shock in the price of oil will increase the volatility of the foreign exchange rate of U.S. dollar to Italian lira, since $\tilde{\alpha}_{14} = 0.094$ with a p-value of 0.006.

Finally, the main diagonal coefficients of the B matrix indicate that there are statistically significant GARCH effects for the crude oil and debt markets, since $\beta_{11} = 0.555$ (with a p-value of 0.000) and $\beta_{22} = 0.706$ (with a p-value of 0.000). Moreover, there are significant spillover GARCH effects across the four markets. For instance, there is evidence for volatility spillovers from all three financial markets towards the crude oil market, since $\beta_{21} = -0.035$ (with a p-value of 0.008), $\beta_{31} = -1.256$ (with a p-value of 0.000), and $\beta_{41} = 0.977$ (with a p-value of 0.042), while the latter two spillover GARCH effects are further strengthened after the zero lower bound is reached, since $\tilde{\beta}_{31} = 0.767$ (with a p-value of 0.000) and $\tilde{\beta}_{41} = -2.715$ (with a p-value of 0.000). Hence, we find evidence of strengthened volatility spillovers across markets when the zero lower bound occurs.

4.5 Japan

In the case of Japan (see Table 16), we find all the autoregressive coefficients in the Γ matrix to be statistically significant and close to one along the main diagonal, suggesting that today's performance is a useful predictor of tomorrow's performance. In addition, we find evidence of significant spillover effects to the crude oil and stock markets, but not to the debt and foreign exchange markets. For instance, the current price of crude oil is affected by last period's interest rate and stock price; a higher interest rate leads to a decline in the price of oil ($\gamma_{12} = -0.029$ with a p-value of 0.023) whereas a higher stock price leads to an increase in the price of oil ($\gamma_{13} = 0.076$ with a p-value of 0.049). In addition, an appreciation of the U.S. dollar relative to the Japanese yen leads to an increase in the price of the stock market, since $\gamma_{34} = 0.163$ (with a p-value of 0.000). Last, we find that although the interactions between the crude oil and the three financial markets do not change when the zero lower bound occurs, spillovers across the financial markets become stronger. In fact, there is evidence of an increased spillover effect propagating from the foreign exchange market towards the stock market, since $\tilde{\gamma}_{34} = 0.540$ (with a p-value of 0.000), as well as from the stock market to the bond market as $\tilde{\gamma}_{23} = -0.093$ (with a p-value of 0.000).

The moving average coefficients along the diagonal of the Ψ matrix are moderate and statistically significant, except for the case of the debt market, implying that each of the crude oil price, stock price, and exchange rate series is consistent with a typical ARMA process. The off-diagonal elements of the Ψ matrix indicate the spillover effects across the four markets. There is no evidence of shock spillovers from each of the financial markets towards the crude oil market, except for the case of the debt market and when the zero lower bound is reached, since $\tilde{\psi}_{12} = 13.127$ (with a p-value of 0.000). On the other hand, oil price shocks affect the stock market positively when the zero lower bound occurs, since $\tilde{\psi}_{31} = 0.028$ (with a p-value of 0.012).

Moreover, we find statistically significant spillover ARCH effects running from the crude oil market to the debt and stock markets, since $\alpha_{12} = 0.087$ (with a p-value of 0.033) and $\alpha_{13} = -0.104$ (with a p-value of 0.048). In fact, the latter spillover ARCH effect is found to be strengthened after the zero lower bound is reached, since $\tilde{\alpha}_{13} = 0.227$ (with a p-value of 0.042), implying an ARCH effect of $(0.104 + 0.227)^2$. Although we do not find significant spillover ARCH effects propagating from the financial markets towards the crude oil market at normal times, there is evidence for new spillover ARCH effects running separately from the debt and foreign exchange markets to the crude oil market, when the zero lower bound occurs ($\tilde{\alpha}_{21} = 43.201$ with a p-value of 0.041 and $\tilde{\alpha}_{41} = 67.791$ with a p-value of 0.039).

Regarding volatility linkages, all the 'own-market' coefficients in the B and $\tilde{B}$ matrices are statistically significant and the estimate coefficients suggest a high degree of persistence. Moreover, we find significant spillover GARCH effects across the markets when the zero lower bound occurs. In particular, there is evidence for volatility spillovers from the crude oil market to the stock and foreign exchange markets, with $\tilde{\beta}_{13} = 0.038$ (with a p-value of 0.000) and $\tilde{\beta}_{14} = 0.015$ (with a p-value of 0.000). Last, the past volatility of the interest rate has a positive effect on the volatility of the crude oil price, since $\tilde{\beta}_{21} = 7.764$ (with a p-value of 0.006).

4.6 Norway

The Norwegian economy is a small and open economy highly dependent on oil-exports, and thereby on the price of oil. In Table 17, we find that all the autoregressive coefficients in the Γ matrix, except those for the crude oil and foreign exchange markets, are moderate and significant along the main diagonal. This indicates that, for both the debt and stock markets, today's performance provides high predictive power for tomorrow's performance. Moreover, we find significant spillover effects to the crude oil, debt, and stock markets, but there is no evidence of spillovers from the crude oil, debt, and stock markets to the foreign exchange market. In fact, the current price of crude oil is affected by last period's interest rate and stock price. Specifically, a higher value of each of the interest rate and stock price leads to an increase in the price of oil, since $\gamma_{12} = 0.662$ (with a p-value of 0.000) and $\gamma_{13} = 1.206$

(with a p-value of 0.000), respectively.

However, the spillover effects across the markets are found to change after the zero lower bound occurs. Hence, we find that the intertemporal correlation between the crude oil market and each of the debt and stock markets change after the zero lower bound is reached, since in those cases a higher interest rate leads to a decline in the price of oil ($\gamma_{12} + \tilde{\gamma}_{12} = 0.662 - 1.572 = -0.910$), while a higher stock price also leads to a decline in the price of oil ($\gamma_{13} + \tilde{\gamma}_{13} = 1.206 - 2.094 = -0.888$).

On the other hand, the moving-average coefficients along the diagonal of the Ψ matrix are all moderate and significant, except for the case of the bond market, suggesting that each of the crude oil price, stock price, and exchange rate series is consistent with a typical ARMA process. The off-diagonal elements of the Ψ matrix capture the shock spillovers across the four markets, and suggest negative and significant shock spillovers from the debt and stock markets to the crude oil market ($\psi_{12} = -0.785$ with a p-value of 0.000 and $\psi_{13} = -1.269$ with a p-value of 0.000), and vice versa ($\psi_{21} = -0.669$ with a p-value of 0.000 and $\psi_{31} = -0.085$ with a p-value of 0.029). Furthermore, we find evidence of new shock spillovers, such as from the stock market to the foreign exchange market (as $\tilde{\psi}_{43} = -0.262$ with a p-vale of 0.011), as well as strengthened spillover effects, for instance from the crude oil market to the stock market (as $\psi_{31} + \tilde{\psi}_{31} = -0.085 - 0.250 = -0.335$) when the zero lower bound is reached.

Furthermore, we find significant spillover ARCH effects propagating from the crude oil market to the stock market at normal times ($\alpha_{13} = 0.288$ with a p-value of 0.000), and even further increased when the zero lower bound occurs ($\tilde{\alpha}_{13} = -0.853$ with a p-value of 0.000), implying an ARCH effect of $(0.288 + 0.853)^2$. Moreover, the spillover ARCH effect from the stock market on the crude oil market is statistically significant, and increases further when the zero lower bound is reached, since $\tilde{\alpha}_{31} = 1.020$ (with a p-value of 0.000), implying ARCH effects of $(0.488 + 1.020)^2$. In addition, there is evidence for a new spillover ARCH effect running from the foreign exchange market to the crude oil market. In particular, an unexpected change in the bilateral exchange rate between the U.S. dollar and the Norwegian krone will increase the volatility of the crude oil price, since $\tilde{\alpha}_{41} = -2.866$ (with a p-value of 0.000)

Finally, all the main diagonal coefficients of the B matrix, except that for the foreign exchange market, are statistically significant suggesting GARCH effects in all three markets. Furthermore, there are significant spillover GARCH effects from the crude oil market to all the financial markets, implying that past oil price volatility has a positive effect on the volatility of the interest rate (as $\beta_{12} = 0.127$ with a p-value of 0.002), the stock price (as $\beta_{13} = 0.484$ with a p-value of 0.000), and the bilateral exchange rate between the U.S. dollar and the Norwegian krone (as $\beta_{14} = 0.084$ with a p-value of 0.026), respectively. Last, there is evidence for increased spillover GARCH effects from the crude oil market on the stock and foreign exchange markets, since $\tilde{\beta}_{13} = -0.191$ (with a p-value of 0.017) and $\tilde{\beta}_{14} = -0.155$ (with a p-value of 0.000), implying spillover GARCH effects of $(0.484 + 0.191)^2$ and $(0.084 + 0.155)^2$, respectively.

4.7 United Kingdom

In the case of the U.K. (see Table 18), we find the autoregressive coefficients of the stock and foreign exchange markets in the Γ matrix significant and close to one along the main diagonal, suggesting that for both of them, today's performance is a useful predictor of tomorrow's performance. In addition, all four markets experience significant spillover effects from each other. In fact, the current price of crude oil is affected by last period's stock price and exchange rate; a higher stock price leads to an increase in the price of oil ($\gamma_{13} = 1.226$ with a p-value of 0.000) whereas a stronger U.S. dollar relative to the British pound leads to a decline in the price of oil ($\gamma_{14} = -1.395$ with a p-value of 0.007). Moreover, we find that at normal times the performance of all the financial markets is influenced by last period's oil price, suggesting that a higher oil price could lead to an increase in the interest rate and stock price, respectively, since $\gamma_{21} = 0.681$ (with a p-value of 0.002) and $\gamma_{31} = 0.998$ (with a p-value of 0.000), as well as to an appreciation of the U.S. dollar compared to the British pound, since $\gamma_{41} = 0.421$ (with a p-value of 0.000).

However, the spillover effects change after the zero lower bound is reached. For instance, we find that the intertemporal correlation between the crude oil market and the three financial markets changes when the zero lower bound constraint on the policy rate is binding; an increase in the crude oil price could lead to a decrease of the interest rate and stock price, respectively, since $\tilde{\gamma}_{21} = -0.975$ (with a p-value of 0.002) and $\tilde{\gamma}_{31} = -1.501$ (with a p-value of 0.000), as well as to a depreciation of the U.S. dollar compared to the British pound ($\tilde{\gamma}_{31} = -0.993$ with a p-value of 0.000).

Furthermore, the moving average coefficients along the main diagonal of the Ψ matrix are all singificant, except for the case of the oil market, implying that each of the interest rate, stock price, and exchange rate series is consistent with a typical ARMA process. Another interesting result is that there are shock spillovers from both the stock and foreign exchange markets towards the crude oil market, since $\psi_{13} = -1.378$ (with a p-value of 0.000) and $\psi_{14} = 1.384$ (with a p-value of 0.006), and vice versa (as $\psi_{31} = -1.062$ with a p-value of 0.000 and $\psi_{41} = -0.421$ with a p-value of 0.000). We also find evidence of a new shock spillover propagating from the debt market towards the crude oil market when the zero lower bound occurs, since $\tilde{\psi}_{12} = -0.464$ (with a p-value of 0.023).

Moreover, the estimates for the variance equation show significant ARCH coefficients along the main diagonal of the A matrix, except that for the crude oil market, suggesting that volatility is persistent in all three markets. The off-diagonal elements of the A matrix also indicate significant spillover ARCH effects across the four markets. For example, an unexpected shock in the crude oil market increases the volatility of the exchange rate between the U.S. dollar and the British pound at normal times (as $\alpha_{14} = -0.049$ with a p-value of 0.016), while this effect becomes stronger when the zero lower bound occurs, since $\tilde{\alpha}_{14} = 0.085$ (with a p-value of 0.003), implying an ARCH effect of $(0.049 + 0.085)^2$.

Finally, all the 'own-market' coefficients in the B matrix are statistically significant and the estimates suggest a high degree of persistence. There is also evidence for volatility spillovers from the crude oil market to the debt and foreign exchange markets, with $\beta_{12} = -0.168$ (with a p-value of 0.000) and $\beta_{14} = 0.080$ (with a p-value of 0.000). In addition, we find that some spillover GARCH effects become stronger when the zero lower bound occurs; past volatility of the crude oil price has a bigger effect on the volatility of the interest rate and exchange rate series when the zero lower bound occurs, since $\tilde{\beta}_{12} = 0.095$ (with a p-value of 0.009) and $\tilde{\beta}_{14} = -0.133$ (with a p-value of 0.000).

4.8 United States

As can be seen in Table 19, the autoregressive coefficients in the Γ matrix suggest spillover effects from the stock and foreign exchange markets to the crude oil market. In particular, the current price of crude oil is affected by last period's stock price and exchange rate; a higher stock price leads to an increase in the price of oil ($\gamma_{13} = 2.357$ with a p-value of 0.000), while a stronger U.S. dollar leads to a decline in the price of oil ($\gamma_{14} = -1.912$ with a p-value of 0.033). Moreover, there is no evidence of significant spillovers to the three financial markets at normal times; however, new spillover effects run across the financial markets when the zero lower bound is reached. Hence, we find that a higher stock price could lead to an increase in the interest rate, since $\tilde{\gamma}_{23} = 11.241$ (with a p-value of 0.000), whereas a stronger U.S. dollar could affect the interest rate in a negative way, since $\tilde{\gamma}_{24} = -15.660$ (with a p-value of 0.000).

On the other hand, the moving average coefficients along the main diagonal of the Ψ matrix are all significant, except that for the crude oil market, suggesting that each of the interest rate, stock price, and exchange rate series is consistent with a typical ARMA process. The off-diagonal elements of the Ψ matrix indicate the spillover effects across the four markets. For instance, there is evidence of shock spillovers propagating from the stock market towards the crude oil market, since $\psi_{13} = -2.483$ (with a p-value of 0.000), as well as from the debt market towards the stock market, since $\psi_{32} = 0.086$ (with a p-value of 0.049). However, all financial markets shocks affect the crude oil market significantly after the zero lower bound constraint is binding. Hence, an unexpected shock in each of the bond and stock markets is associated with an increase in the price of oil (as $\tilde{\psi}_{12} = 0.589$ with a p-value of 0.007 and $\psi_{13} + \tilde{\psi}_{13} = -2.483 + 6.561 = 4.078$), while an unexpected appreciation of the U.S. dollar influences the crude oil market negatively, since $\tilde{\psi}_{14} = -5.711$ (with a p-value of 0.001).

The estimates for the variance equation show significant ARCH coefficients along the main diagonal of the A matrix, except that for the foreign exchange market, suggesting that volatility is persistent in all three markets. Moreover, we find significant spillover ARCH effects running from the crude oil market towards the stock and foreign exchange markets, since $\alpha_{13} = 0.119$ (with a p-value of 0.000) and $\alpha_{14} = -0.036$ (with a p-value of 0.005). In particular, the spillover ARCH effect from the oil market on the stock market increases when the zero lower bound is reached, since $\tilde{\alpha}_{13} = -0.430$ (with a p-value of 0.000), implying an ARCH effect of $(0.119 + 0.430)^2$. Furthermore, a new spillover ARCH effect is found from the foreign exchange market to the oil market when the zero lower bound is reached, since $\tilde{\alpha}_{41} = -4.639$ (with a p-value of 0.000). Hence, an unexpected appreciation of the U.S. dollar will increase the volatility of the crude oil market.

Finally, the main diagonal coefficients of the B matrix, except that for the stock market, indicate that there are statistically significant GARCH effects in all three markets. Moreover, there are significant spillover GARCH effects from the crude oil market towards all the financial markets, since $\beta_{12} = 0.148$ (with a p-value of 0.014), $\beta_{13} = -0.222$ (with a p-value of 0.000), and $\beta_{14} = 0.050$ (with a p-value of 0.003). Moreover, all these spillovers are further strengthened when the zero lower bound constraint on the policy rate is binding, since $\tilde{\beta}_{12} = -0.738$ (with a p-value of 0.000), $\tilde{\beta}_{13} = 0.470$ (with a p-value of 0.000), and $\tilde{\beta}_{14} = -0.130$ (with a p-value of 0.000). Overall, we find that the volatility spillovers across the markets increase when the zero lower bound is reached.

5 Summary of Key Results

In this section we summarize the results paying special attention to systematic patterns of market spillovers across countries. In this regard, for each of the eight countries, we find a significant spillover effect propagating from the stock market towards the crude oil market; a higher stock price leads to an increase in the price of oil during normal times. On the contrary, when the zero lower bound constraint on the U.S. policy rate is binding, we find that the same spillover effect is strengthened further in Germany and the United Kingdom, whereas it becomes negative in France, Norway, and the United States, and weakens slightly in the case of Canada. With respect to spillovers between the financial markets, we find evidence that in Canada, Germany, Italy, and Norway, a higher stock price leads to an increase of the interest rate at normal times, and a decline of the interest rate when the zero lower bound is reached.

However, a surprise change in the stock market affects the debt market in the opposite way. We find that in Canada, Germany, Italy, and Norway, an unexpected increase in the stock market is associated with a decline of the interest rate at normal times, and an increase of it when the zero lower bound occurs. Moreover, we notice that an unexpected increase in the price of oil affects the stock price in a negative way during normal times, in France, Germany, Italy, Norway, and United Kingdom, and in a positive way in France, Germany, and the United Kingdom when the zero lower bound is reached. It is worth noting that, when the zero lower bound occurs, a new positive shock spillover is running from the crude oil market to the stock market in Japan, while in Norway the previously negative shock spillover between the two markets is further increased.

Finally, with respect to second-moment linkages, we find that in France, Germany, and

Italy, there is a significant spillover ARCH effect running from the foreign exchange market to the crude oil market, suggesting that an unexpected shock in the foreign exchange market increases the volatility of the crude oil price, while this effect increases further in these countries and starts running in the rest of them when the zero lower bound is reached. In addition, we find at normal times a significant spillover ARCH effect propagating from the crude oil market towards the debt market in all three eurozone countries, namely, France, Germany, and Italy, as well as in Japan and the United Kingdom. Furthermore, there is evidence that this spillover ARCH effect increases further in France and Italy, and start occurring in Canada, the United States, and Norway, when the zero lower bound is reached. Finally, we find a statistically significant spillover GARCH effect running at normal times from the crude oil market towards the stock market in Canada, Germany, Norway, and the United States, while increasing further in all these countries and starts running in Italy and Japan, when the zero lower bound is reached. Last, based on the estimated cross-market conditional correlations, we do not find any evidence to support the view of a different underlying structure in the spillover mechanism, in each of the studied Eurozone countries, France, Germany, and Italy, in the two periods, before and after the introduction of the Euro. The employment of a more parsimonious model, however, would provide the opportunity to investigate the two periods, separately, and extract more information about any possible change in the interaction mechanism.

6 Concluding Remarks

Motivated by the financialization of the crude oil market over the past decade, and the speculative activities that induce oil prices to depart from their fundamental values due to several financial factors, in this paper we explore for mean and volatility spillovers among the crude oil market and the three most important financial markets, namely, the debt, stock, and foreign exchange markets, in each of the seven major advanced economies (G7), and the small open oil-exporting economy of Norway. Using monthly data that span from the first Brent oil price in May 1987 up to March 2016, and a four-variable VARMA-GARCH model with a BEKK variance specification, we find that in all the G7 countries, as well as in Norway, significant spillovers occur among the four markets, both in terms of volatility and mean estimates. Moreover, we find evidence for strengthened market relationships after the zero lower bound is reached and unconventional monetary measures are employed. Yet, a few individual country results are worth highlighting; with respect to the spillovers between the crude oil market and each of the financial markets, we can notice that these are more tightened in the oil-dependent economies of Norway and Germany, while they are significantly weaker in the case of Japan.

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Table 1: Summary Statistics for Canada

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
lno_t	3.918	0.235	0.044	0.000	0.000
lni_t	1.201	0.758	0.000	0.076	0.000
lns_t	4.271	0.131	0.043	0.000	0.000
lne_t	0.217	0.019	0.707	0.000	0.000
			B. First differences		
Δlno_t	0.000	0.007	0.876	0.000	0.000
Δlni_t	-0.007	0.006	0.003	0.000	0.000
Δlns_t	0.002	0.002	0.000	0.000	0.000
Δlne_t	0.000	0.000	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 2: Summary Statistics for France

Series	Mean	Variance	*p*-values Skewness	Kurtosis	Normality
A. Levels					
lno_t	5.382	0.296	0.106	0.000	0.000
i_t	4.255	10.559	0.000	0.009	0.000
lns_t	4.504	0.130	0.322	0.001	0.002
lne_t	1.708	0.017	0.000	0.729	0.001
B. First differences					
Δlno_t	0.001	0.008	0.315	0.000	0.000
Δi_t	-0.024	0.101	0.313	0.000	0.000
Δlns_t	0.002	0.003	0.000	0.000	0.000
Δlne_t	0.000	0.001	0.464	0.567	0.645

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 3: Summary Statistics for Germany

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
o_t	75.093	1753.321	0.000	0.026	0.000
i_t	3.688	7.001	0.000	0.400	0.000
s_t	97.314	926.107	0.001	0.004	0.000
e_t	0.616	0.006	0.083	0.233	0.107
			B. First differences		
Δo_t	0.029	43.007	0.000	0.000	0.000
Δi_t	-0.012	0.040	0.122	0.000	0.000
Δs_t	0.193	25.126	0.000	0.000	0.000
Δe_t	0.000	0.000	0.305	0.018	0.033

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 4: Summary Statistics for Italy

Series	Mean	Variance	*p*-values Skewness	Kurtosis	Normality
			A. Levels		
lno_t	11.091	0.271	0.050	0.000	0.000
i_t	5.433	19.853	0.000	0.000	0.000
lns_t	4.748	0.117	0.005	0.001	0.000
lne_t	7.340	0.025	0.002	0.731	0.009
			B. First differences		
Δlno_t	0.001	0.008	0.352	0.000	0.000
Δi_t	-0.031	0.152	0.000	0.000	0.000
Δlns_t	-0.001	0.003	0.001	0.000	0.000
Δlne_t	0.001	0.001	0.013	0.007	0.001

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 5: Summary Statistics for Japan

Series	Mean	Variance	*p*-values Skewness	Kurtosis	Normality
			A. Levels		
o_t	4677.788	9269802.685	0.000	0.090	0.000
i_t	1.008	2.339	0.000	0.000	0.000
s_t	160.058	3189.314	0.000	0.000	0.000
e_t	113.050	298.191	0.624	0.269	0.475
			B. First differences		
Δo_t	3.644	241490.380	0.000	0.000	0.000
Δi_t	-0.007	0.018	0.013	0.000	0.000
Δs_t	-0.351	66.214	0.000	0.000	0.000
Δe_t	-0.080	9.243	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 6: Summary Statistics for Norway

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
A. Levels					
lno_t	5.627	0.266	0.083	0.000	0.000
lni_t	1.528	0.480	0.284	0.000	0.000
lns_t	3.974	0.470	0.786	0.000	0.000
lne_t	1.906	0.018	0.000	0.714	0.000
B. First differences					
Δlno_t	0.001	0.007	0.903	0.000	0.000
Δlni_t	-0.008	0.004	0.000	0.000	0.000
Δlns_t	0.006	0.004	0.000	0.000	0.000
Δlne_t	0.001	0.001	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 7: Summary Statistics for UK

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
lno_t	3.223	0.316	0.006	0.000	0.000
lni_t	1.317	1.103	0.000	0.023	0.000
lns_t	4.553	0.061	0.091	0.002	0.002
lne_t	-0.498	0.008	0.000	0.171	0.000
			B. First differences		
Δlno_t	0.000	0.008	0.731	0.000	0.000
Δlni_t	-0.008	0.003	0.000	0.000	0.000
Δlns_t	0.001	0.002	0.000	0.000	0.000
Δlne_t	0.000	0.001	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 8: Summary Statistics for US

Series	Mean	Variance	*p*-values Skewness	Kurtosis	Normality
			A. Levels		
lno_t	3.747	0.308	0.003	0.000	0.000
lni_t	0.746	1.848	0.000	0.014	0.000
lns_t	4.448	0.156	0.000	0.000	0.000
lne_t	4.595	0.032	0.000	0.001	0.000
			B. First differences		
Δlno_t	0.000	0.008	0.380	0.000	0.000
Δlni_t	-0.007	0.011	0.000	0.000	0.000
Δlns_t	0.003	0.001	0.000	0.000	0.000
Δlne_t	0.002	0.000	0.008	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table 9: Unit Root and Stationary Tests

Series	Canada			France			Germany		
	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
				A. Levels					
lno_t	-3.477	-2.157	0.521	-3.021	-2.035	0.627	-2.803	-2.077	0.627
lni_t	-3.768	-3.065	0.179	-2.695	-2.218	0.519	-2.680	-1.630	0.228
lns_t	-3.032	-2.333	0.433	-2.167	-2.332	0.796	-2.676	-2.661	0.339
lne_t	-1.494	-1.738	1.047	-2.509	-2.340	0.492	-2.637	-2.478	0.478
				B. First differences					
Δlno_t	-14.590	-8.687	0.071	-14.712	-8.130	0.076	-13.971	-8.306	0.085
Δlni_t	-7.553	-6.086	0.036	-13.869	-6.878	0.052	-11.801	-5.626	0.133
Δlns_t	-14.843	-7.580	0.056	-15.216	-4.742	0.049	-13.451	-6.951	0.042
Δlne_t	-13.329	-6.215	0.158	-13.497	-6.920	0.060	-13.441	-7.232	0.055

Note: Sample period, monthly observations, 1987:5-2016:3. The 1% (and 5%) critical values for the ADF, DF-GLS, and KPSS tests are -3.989, -3.484, and 0.216 (-3.425, -2.891, and 0.146), respectively.

Table 10: Unit Root and Stationary Tests

Series	Italy			Japan			Norway		
	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
				A. Levels					
lno_t	-3.342	-2.163	0.520	-3.318	-2.378	0.664	-3.262	-2.028	0.624
i_t	-2.827	-2.467	0.687	-1.643	-1.639	0.911	-3.171	-2.900	0.190
lns_t	-1.901	-1.907	0.894	-2.413	-2.035	0.658	-3.118	-3.041	0.142
lne_t	-1.904	-1.880	1.050	-2.820	-2.346	0.244	-2.300	-2.114	0.622
				B. First differences					
Δlno_t	-14.548	-8.119	0.070	-12.847	-8.158	0.065	-14.816	-8.394	0.073
Δi_t	-10.317	-5.230	0.055	-5.251	-5.252	0.155	-12.015	-6.259	0.053
Δlns_t	-14.792	-6.443	0.090	-13.959	-6.331	0.033	-14.818	-7.618	0.031
Δlne_t	-12.293	-6.956	0.073	-13.666	-5.987	0.040	-12.572	-7.808	0.087

Note: Sample period, monthly observations, 1987:5-2016:3. The 1% (and 5%) critical values for the ADF, DF-GLS, and KPSS tests are -3.989, -3.484, and 0.216 (-3.425, -2.891, and 0.146), respectively.

Table 11: Unit Root and Stationary Tests

	United Kingdom			United States		
Series	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
			A. Levels			
lno_t	-2.726	-1.817	0.737	-2.688	-1.951	0.745
lni_t	-2.363	-2.286	0.835	-2.039	-1.960	0.790
lns_t	-2.042	-1.914	0.988	-2.104	-2.089	1.037
lne_t	-3.285	-3.311	0.354	-2.187	-0.801	1.463
			B. First differences			
$\Delta ln o_t$	-15.090	-7.631	0.092	-14.081	-8.142	0.090
$\Delta ln i_t$	-8.727	-5.069	0.062	-11.691	-5.923	0.098
$\Delta ln s_t$	-13.708	-5.014	0.056	-14.000	-5.812	0.052
$\Delta ln e_t$	-13.592	-6.350	0.034	-11.638	-5.616	0.169

Note: Sample period, monthly observations, 1987:5-2016:3. The 1% (and 5%) critical values for the ADF, DF-GLS, and KPSS tests are -3.989, -3.484, and 0.216 (-3.425, -2.891, and 0.146), respectively.

Table 12: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Canada

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.857(0.000) & -0.046(0.000) & 0.102(0.000) & -0.248(0.000) \\ -0.018(0.014) & 0.991(0.000) & 0.025(0.000) & -0.031(0.331) \\ -0.005(0.261) & -0.005(0.282) & 0.994(0.000) & -0.020(0.317) \\ -0.011(0.008) & -0.006(0.003) & 0.007(0.113) & 0.971(0.000) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & 0.080(0.000) & -0.015(0.005) & 0.048(0.599) \\ 0.045(0.000) & -0.116(0.000) & -0.047(0.000) & 0.054(0.118) \\ 0.056(0.000) & -0.002(0.849) & -0.059(0.000) & 0.231(0.000) \\ 0.016(0.097) & 0.008(0.286) & -0.017(0.094) & -0.038(0.273) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.279(0.000) & 0.103(0.170) & -0.136(0.352) & 0.079(0.829) \\ -0.001(0.980) & 0.422(0.000) & -0.137(0.008) & 0.196(0.254) \\ -0.006(0.797) & -0.039(0.296) & 0.050(0.402) & 0.049(0.747) \\ 0.000(0.981) & -0.012(0.380) & -0.041(0.061) & 0.213(0.001) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.379(0.000) & -0.233(0.403) & -1.342(0.009) \\ 0.002(0.938) & -0.148(0.064) & 0.164(0.019) & -0.022(0.911) \\ 0.001(0.983) & 0.067(0.124) & -0.036(0.723) & -0.835(0.000) \\ -0.013(0.585) & 0.020(0.349) & 0.045(0.407) & 0.288(0.014) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.047	0.879	0.070	0.483
z_{i_t}	-0.158	1.088	0.000	0.962
z_{s_t}	-0.052	0.976	0.028	0.548
z_{e_t}	0.083	0.856	0.103	0.530

C. Student's t distribution shape

$v = 6.812(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.177(0.019) & -0.008(0.825) & 0.055(0.454) & -0.002(0.890) \\ 0.134(0.090) & 0.491(0.000) & -0.043(0.233) & -0.013(0.361) \\ 0.634(0.001) & 0.074(0.174) & 0.191(0.006) & -0.009(0.587) \\ 0.199(0.642) & -0.865(0.000) & 0.125(0.478) & -0.153(0.000) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.151(0.001) & -0.078(0.480) & -0.048(0.261) \\ -0.071(0.552) & 0.247(0.085) & -0.105(0.114) & 0.161(0.000) \\ 1.405(0.000) & -0.412(0.000) & -0.066(0.673) & -0.133(0.135) \\ 1.668(0.021) & 0.644(0.005) & 0.153(0.701) & 0.334(0.102) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.637(0.000) & -0.094(0.083) & 0.254(0.000) & 0.000(0.998) \\ -0.384(0.035) & -0.824(0.000) & 0.089(0.327) & 0.054(0.191) \\ -1.435(0.000) & 0.166(0.200) & 0.653(0.000) & 0.008(0.759) \\ -1.118(0.057) & 0.484(0.325) & -0.288(0.226) & 0.985(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.110(0.095) & -0.269(0.000) & -0.015(0.566) \\ 0.234(0.258) & 0.155(0.028) & -0.032(0.763) & -0.064(0.277) \\ 0.631(0.069) & -0.140(0.340) & -0.988(0.000) & 0.430(0.000) \\ 0.113(0.866) & -0.665(0.210) & -1.111(0.000) & 0.037(0.708) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Table 13: The four-variable VARMA(1,1)-BEKK(1,1,1) model for France

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.212(0.074) & 0.024(0.532) & 1.083(0.000) & 0.118(0.743) \\ 0.236(0.311) & 0.762(0.000) & -0.082(0.764) & -0.726(0.197) \\ 0.356(0.000) & -0.035(0.044) & 0.412(0.000) & -0.265(0.032) \\ -0.073(0.160) & -0.021(0.081) & 0.014(0.886) & -0.113(0.284) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & 0.790(0.096) & -91.567(0.000) & -4.080(0.310) \\ -0.848(0.043) & 0.331(0.061) & -38.899(0.000) & -2.297(0.172) \\ -0.373(0.000) & 0.047(0.008) & -1.020(0.000) & 0.234(0.038) \\ 0.462(0.000) & 0.057(0.001) & 0.171(0.515) & 0.261(0.058) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.318(0.012) & -0.014(0.699) & -1.150(0.000) & 0.124(0.642) \\ -0.128(0.606) & -0.460(0.000) & 0.507(0.126) & 1.340(0.047) \\ -0.445(0.000) & 0.047(0.007) & -0.206(0.059) & 0.389(0.000) \\ 0.080(0.113) & 0.016(0.145) & 0.017(0.861) & 0.568(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.893(0.069) & 91.548(0.000) & 4.034(0.309) \\ 0.834(0.050) & -0.034(0.877) & 38.132(0.000) & 1.797(0.306) \\ 0.466(0.000) & -0.053(0.002) & 0.814(0.000) & -0.361(0.000) \\ -0.519(0.000) & -0.052(0.028) & -0.271(0.313) & -0.674(0.000) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.078	0.752	0.317	0.639
z_{i_t}	0.008	1.550	0.195	0.987
z_{s_t}	-0.054	0.843	0.317	0.001
z_{e_t}	-0.018	0.777	0.735	0.722

C. Student's t distribution shape

$v = 3.983(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} -0.426(0.000) & -0.305(0.002) & 0.030(0.554) & -0.090(0.004) \\ -0.015(0.370) & 0.612(0.000) & -0.002(0.823) & -0.006(0.223) \\ 0.377(0.004) & -0.732(0.000) & 0.051(0.456) & 0.115(0.001) \\ 0.753(0.008) & 0.162(0.690) & 0.580(0.000) & -0.099(0.180) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.278(0.013) & 0.204(0.009) & 0.275(0.000) \\ 0.356(0.014) & -0.638(0.000) & 0.546(0.000) & -0.101(0.026) \\ -0.286(0.121) & 0.535(0.019) & -0.678(0.000) & 0.026(0.659) \\ 1.837(0.001) & 0.267(0.607) & 0.538(0.158) & -0.289(0.069) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.656(0.000) & -0.055(0.297) & 0.073(0.104) & -0.113(0.000) \\ 0.001(0.941) & 0.813(0.000) & -0.002(0.686) & 0.003(0.336) \\ -0.923(0.000) & 0.166(0.057) & 0.701(0.000) & -0.015(0.809) \\ 1.377(0.000) & -0.261(0.132) & 0.459(0.020) & 0.932(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.045(0.454) & -0.113(0.061) & 0.090(0.000) \\ 0.273(0.000) & 0.017(0.737) & -0.003(0.961) & -0.011(0.427) \\ 0.766(0.000) & 0.010(0.939) & -0.282(0.042) & 0.014(0.835) \\ -0.146(0.671) & 0.219(0.303) & -0.165(0.485) & -0.180(0.037) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Table 14: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Germany

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.177(0.000) & -0.281(0.921) & 0.131(0.009) & 43.545(0.048) \\ 0.009(0.000) & 0.725(0.000) & 0.015(0.000) & 2.851(0.000) \\ 0.035(0.082) & 4.077(0.016) & 0.471(0.000) & 16.796(0.477) \\ 0.002(0.000) & 0.005(0.670) & 0.001(0.018) & 0.023(0.821) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -8.635(0.136) & 1.756(0.000) & -92.506(0.000) \\ 0.011(0.000) & 0.124(0.000) & -0.036(0.000) & -10.643(0.000) \\ -0.270(0.000) & 2.831(0.246) & 0.147(0.000) & -6.779(0.828) \\ 0.000(0.455) & -0.002(0.888) & -0.001(0.000) & -0.520(0.001) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.456(0.000) & 0.621(0.817) & -0.299(0.000) & -28.656(0.152) \\ -0.009(0.000) & -0.468(0.000) & -0.015(0.000) & -4.012(0.000) \\ -0.133(0.000) & -6.357(0.001) & -0.235(0.000) & -62.564(0.025) \\ -0.002(0.000) & -0.006(0.570) & -0.001(0.023) & 0.391(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 40.184(0.000) & -1.514(0.000) & 150.582(0.000) \\ -0.011(0.000) & 0.442(0.000) & 0.035(0.000) & 11.902(0.000) \\ 0.512(0.000) & 20.976(0.000) & -0.362(0.000) & 77.346(0.023) \\ 0.000(0.000) & 0.029(0.095) & 0.001(0.000) & 0.319(0.024) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.005	0.926	0.282	0.693
z_{i_t}	-0.004	0.981	0.349	0.240
z_{s_t}	-0.036	0.929	0.235	0.032
z_{e_t}	0.060	0.886	0.793	0.144

C. Student's t distribution shape

$v = 6.490(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.416(0.000) & -0.003(0.002) & -0.131(0.030) & 0.000(0.750) \\ 2.061(0.100) & 0.406(0.000) & 2.569(0.047) & -0.030(0.000) \\ -0.043(0.556) & -0.003(0.040) & -0.411(0.000) & 0.001(0.001) \\ 39.401(0.024) & 0.243(0.621) & -33.554(0.040) & 0.087(0.366) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.000(0.887) & -0.130(0.117) & 0.001(0.013) \\ -146.568(0.000) & -0.494(0.001) & -136.227(0.000) & -0.091(0.034) \\ 0.277(0.103) & -0.002(0.383) & 0.648(0.000) & 0.000(0.451) \\ 373.555(0.000) & 0.199(0.746) & 323.245(0.000) & -0.300(0.061) \end{bmatrix};$$

$$B = \begin{bmatrix} -0.091(0.071) & -0.003(0.063) & 0.734(0.000) & 0.000(0.099) \\ -3.110(0.071) & -0.900(0.000) & 1.123(0.407) & -0.004(0.361) \\ -1.084(0.000) & 0.001(0.443) & -0.204(0.000) & -0.000(0.863) \\ -116.547(0.000) & 1.053(0.015) & 22.984(0.443) & -0.455(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.005(0.001) & -0.709(0.000) & 0.000(0.352) \\ 73.597(0.000) & 1.426(0.000) & 1.575(0.793) & 0.044(0.053) \\ 0.573(0.000) & 0.000(0.808) & 0.562(0.000) & 0.000(0.302) \\ -25.313(0.657) & -0.479(0.459) & -156.196(0.000) & 0.444(0.004) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Table 15: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Italy

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.264(0.018) & 0.066(0.029) & 1.137(0.005) & 0.250(0.541) \\ 0.908(0.004) & 0.322(0.000) & 2.299(0.001) & -0.741(0.331) \\ 0.221(0.008) & 0.011(0.424) & 0.408(0.002) & -0.137(0.481) \\ -0.082(0.065) & -0.019(0.019) & -0.172(0.124) & 0.063(0.564) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -0.007(0.921) & -0.835(0.060) & 1.088(0.402) \\ -1.106(0.002) & 0.560(0.000) & -2.452(0.001) & -0.783(0.382) \\ 0.151(0.540) & -0.043(0.540) & -0.148(0.534) & 4.106(0.000) \\ -0.055(0.335) & 0.036(0.017) & 0.183(0.117) & 0.026(0.903) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.494(0.000) & -0.056(0.023) & -1.174(0.002) & -0.197(0.595) \\ -0.930(0.003) & 0.282(0.001) & -2.183(0.002) & 1.407(0.071) \\ -0.291(0.002) & -0.029(0.039) & -0.292(0.028) & 0.408(0.103) \\ 0.103(0.020) & 0.007(0.291) & 0.131(0.234) & 0.388(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.302(0.005) & 0.779(0.072) & -1.791(0.160) \\ 1.149(0.001) & -0.596(0.000) & 2.322(0.001) & 0.131(0.886) \\ 0.113(0.638) & -0.034(0.705) & 0.334(0.155) & -4.957(0.000) \\ 0.016(0.788) & 0.018(0.371) & -0.251(0.035) & -0.424(0.050) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.049	0.772	0.494	0.671
z_{i_t}	0.035	1.216	0.215	0.956
z_{s_t}	-0.125	0.872	0.343	0.649
z_{e_t}	-0.056	0.853	0.630	0.489

C. Student's t distribution shape

$v = 5.034(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} -0.315(0.000) & -0.237(0.005) & 0.060(0.093) & -0.016(0.463) \\ -0.029(0.026) & 0.789(0.000) & -0.028(0.001) & -0.019(0.000) \\ -0.502(0.000) & -1.276(0.000) & -0.062(0.360) & -0.085(0.017) \\ 0.656(0.028) & -1.004(0.009) & -0.137(0.382) & -0.070(0.333) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.235(0.007) & -0.040(0.622) & 0.094(0.006) \\ 0.020(0.901) & -2.079(0.000) & -0.720(0.000) & 0.107(0.017) \\ 0.648(0.000) & 1.163(0.000) & 0.713(0.000) & 0.302(0.000) \\ 2.142(0.000) & 0.732(0.064) & 0.577(0.067) & 0.500(0.003) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.555(0.000) & -0.055(0.434) & 0.051(0.430) & 0.198(0.000) \\ -0.035(0.008) & 0.706(0.000) & 0.001(0.896) & 0.004(0.470) \\ -1.256(0.000) & 0.164(0.217) & 0.284(0.077) & 0.241(0.000) \\ 0.977(0.042) & -0.248(0.562) & 1.467(0.000) & -0.106(0.610) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.000(0.999) & 0.244(0.004) & -0.244(0.000) \\ -0.089(0.203) & -0.159(0.008) & -0.173(0.010) & -0.047(0.137) \\ 0.767(0.000) & -0.047(0.726) & -0.229(0.288) & -0.441(0.000) \\ -2.715(0.000) & 0.191(0.660) & -1.752(0.000) & 0.407(0.089) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Table 16: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Japan

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.957(0.000) & -0.029(0.023) & 0.076(0.049) & -0.014(0.907) \\ 0.001(0.059) & 1.000(0.000) & 0.000(0.858) & -0.010(0.057) \\ 0.002(0.436) & -0.006(0.288) & 1.014(0.000) & 0.163(0.000) \\ 0.000(0.876) & -0.001(0.431) & 0.007(0.090) & 0.944(0.000) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -1.374(0.391) & -0.888(0.227) & 1.406(0.169) \\ -0.001(0.077) & -0.229(0.000) & -0.093(0.000) & 0.133(0.000) \\ 0.001(0.843) & -0.434(0.002) & -0.385(0.000) & 0.540(0.000) \\ -0.001(0.678) & 0.006(0.920) & 0.107(0.000) & -0.140(0.000) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.379(0.000) & -0.015(0.776) & -0.164(0.187) & 0.039(0.918) \\ 0.002(0.560) & 0.055(0.220) & -0.003(0.641) & 0.021(0.366) \\ -0.004(0.720) & -0.069(0.029) & 0.298(0.000) & 0.038(0.803) \\ 0.001(0.883) & -0.010(0.367) & -0.006(0.777) & 0.233(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 13.127(0.000) & -1.582(0.157) & 4.219(0.108) \\ -0.003(0.356) & -0.548(0.000) & 0.193(0.000) & -0.390(0.000) \\ 0.028(0.012) & 1.445(0.000) & -0.298(0.010) & 0.830(0.002) \\ 0.006(0.202) & 0.358(0.000) & -0.216(0.000) & 0.642(0.000) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	0.033	0.096	0.074	0.811
z_{i_t}	-0.144	4.680	0.811	0.996
z_{s_t}	-0.016	0.114	0.201	0.424
z_{e_t}	0.000	0.112	0.239	0.002

C. Student's t distribution shape

$v = 2.123(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} -0.853(0.020) & 0.087(0.033) & -0.104(0.048) & -0.026(0.139) \\ -0.131(0.753) & 1.149(0.015) & -0.348(0.112) & -0.040(0.485) \\ -0.927(0.101) & 0.070(0.189) & 0.467(0.094) & -0.058(0.413) \\ -1.310(0.225) & -0.554(0.045) & -0.928(0.079) & 0.036(0.849) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & -0.041(0.100) & 0.227(0.042) & 0.057(0.085) \\ 43.201(0.041) & -1.705(0.022) & 7.157(0.029) & 2.584(0.033) \\ -20.498(0.051) & -0.428(0.050) & -1.439(0.146) & -0.248(0.340) \\ 67.791(0.039) & -1.419(0.053) & 4.946(0.063) & 1.142(0.159) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.963(0.000) & -0.001(0.797) & -0.004(0.093) & -0.001(0.357) \\ 0.172(0.755) & -0.615(0.000) & 0.379(0.082) & -0.006(0.938) \\ 0.026(0.554) & 0.019(0.180) & 0.967(0.000) & -0.022(0.016) \\ 0.103(0.587) & 0.005(0.879) & 0.035(0.446) & 0.914(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.000(0.951) & 0.038(0.000) & 0.015(0.000) \\ 7.764(0.006) & 1.103(0.000) & 1.117(0.002) & 0.239(0.068) \\ -1.249(0.225) & -0.045(0.037) & -0.480(0.000) & -0.033(0.566) \\ -2.027(0.528) & 0.024(0.659) & -0.179(0.589) & -0.451(0.015) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Table 17: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Norway

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.089(0.219) & 0.662(0.000) & 1.206(0.000) & 0.207(0.520) \\ 0.668(0.000) & 0.589(0.000) & 0.581(0.000) & -0.459(0.109) \\ 0.022(0.609) & -0.172(0.033) & -0.183(0.013) & -0.242(0.075) \\ -0.035(0.334) & -0.064(0.199) & 0.116(0.070) & -0.178(0.129) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -1.572(0.000) & -2.094(0.000) & -0.402(0.398) \\ -0.310(0.067) & -0.305(0.061) & -1.810(0.000) & -1.241(0.010) \\ 0.188(0.000) & -0.196(0.139) & -0.433(0.000) & 0.849(0.002) \\ -0.179(0.001) & 0.049(0.389) & 0.231(0.046) & 0.491(0.003) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.190(0.005) & -0.785(0.000) & -1.269(0.000) & -0.108(0.737) \\ -0.669(0.000) & -0.159(0.155) & -0.547(0.000) & 0.485(0.085) \\ -0.085(0.029) & -0.024(0.730) & 0.364(0.000) & 0.290(0.016) \\ 0.046(0.219) & 0.020(0.680) & -0.094(0.118) & 0.529(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 1.330(0.000) & 2.230(0.000) & -0.447(0.316) \\ 0.433(0.011) & 0.236(0.185) & 1.548(0.000) & 1.638(0.001) \\ -0.250(0.000) & 0.218(0.067) & 0.545(0.000) & -1.467(0.000) \\ 0.128(0.034) & 0.124(0.044) & -0.262(0.011) & -0.522(0.001) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.011	0.973	0.081	0.469
z_{i_t}	-0.049	1.043	0.281	0.938
z_{s_t}	0.009	0.965	0.558	0.350
z_{e_t}	0.088	0.913	0.661	0.021

C. Student's t distribution shape

$v = 10.497(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.055(0.406) & 0.029(0.505) & 0.288(0.000) & -0.052(0.027) \\ -0.299(0.009) & 0.657(0.000) & -0.395(0.000) & -0.073(0.024) \\ -0.488(0.000) & -0.024(0.684) & -0.466(0.000) & 0.134(0.000) \\ 0.083(0.692) & 0.110(0.401) & -0.248(0.157) & -0.105(0.128) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.309(0.000) & -0.853(0.000) & -0.041(0.519) \\ 0.095(0.545) & -0.599(0.000) & 0.328(0.016) & -0.093(0.272) \\ 1.020(0.000) & -0.925(0.000) & 0.731(0.000) & -0.277(0.003) \\ -2.866(0.000) & -0.839(0.000) & -1.089(0.001) & 0.345(0.049) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.443(0.000) & 0.127(0.002) & 0.484(0.000) & 0.084(0.026) \\ -0.524(0.000) & 0.601(0.000) & 0.093(0.441) & 0.055(0.077) \\ -0.334(0.039) & -0.299(0.000) & 0.435(0.000) & 0.016(0.697) \\ -2.987(0.000) & 0.133(0.432) & -0.128(0.582) & 0.128(0.226) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.015(0.821) & -0.191(0.017) & -0.155(0.000) \\ 0.308(0.070) & -1.191(0.000) & -0.019(0.908) & 0.015(0.819) \\ 0.225(0.160) & 0.235(0.031) & -0.248(0.086) & 0.006(0.921) \\ 2.647(0.000) & 0.190(0.378) & 0.522(0.094) & 0.021(0.910) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Table 18: The four-variable VARMA(1,1)-BEKK(1,1,1) model for United Kingdom

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.177(0.192) & 0.127(0.426) & 1.226(0.000) & -1.395(0.007) \\ 0.681(0.002) & -0.091(0.601) & 1.413(0.000) & -1.188(0.020) \\ 0.998(0.000) & -0.618(0.000) & 0.772(0.000) & -1.547(0.000) \\ 0.421(0.000) & -0.324(0.000) & 0.508(0.000) & -1.099(0.000) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & 0.130(0.442) & 1.141(0.000) & 1.067(0.131) \\ -0.975(0.002) & 1.039(0.000) & -0.214(0.654) & -0.182(0.728) \\ -1.501(0.000) & 0.710(0.000) & 1.252(0.000) & 0.599(0.000) \\ -0.993(0.000) & 0.422(0.000) & 0.939(0.000) & 0.326(0.064) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} -0.086(0.525) & -0.005(0.977) & -1.378(0.000) & 1.384(0.006) \\ -0.636(0.003) & 0.662(0.000) & -1.334(0.000) & 0.976(0.053) \\ -1.062(0.000) & 0.635(0.000) & -0.583(0.000) & 1.719(0.000) \\ -0.421(0.000) & 0.227(0.001) & -0.498(0.000) & 1.324(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.464(0.023) & -0.502(0.087) & -1.152(0.059) \\ 0.862(0.008) & -1.005(0.000) & 0.006(0.990) & 0.069(0.896) \\ 1.556(0.000) & -0.793(0.000) & -1.343(0.000) & -0.568(0.000) \\ 0.951(0.000) & -0.261(0.001) & -1.090(0.000) & -0.408(0.011) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.031	0.921	0.227	0.047
z_{i_t}	0.004	1.025	0.956	0.974
z_{s_t}	-0.153	0.970	0.982	0.255
z_{e_t}	0.019	0.929	0.461	0.511

C. Student's t distribution shape

$v = 7.442(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.048(0.563) & 0.086(0.006) & -0.020(0.587) & -0.049(0.016) \\ -0.347(0.077) & 0.650(0.000) & -0.121(0.162) & -0.181(0.000) \\ 0.093(0.562) & 0.042(0.432) & 0.363(0.000) & 0.010(0.774) \\ -0.292(0.315) & -0.395(0.000) & -0.283(0.017) & 0.390(0.000) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.025(0.671) & 0.229(0.000) & 0.085(0.003) \\ -0.560(0.028) & -0.035(0.778) & -0.100(0.422) & 0.166(0.003) \\ -1.681(0.000) & -0.355(0.014) & -0.547(0.000) & -0.229(0.001) \\ 1.377(0.011) & 0.431(0.060) & 1.510(0.000) & -1.097(0.000) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.721(0.000) & -0.168(0.000) & 0.039(0.344) & 0.080(0.000) \\ 0.086(0.732) & 0.377(0.001) & -0.041(0.609) & 0.302(0.000) \\ -1.179(0.000) & -0.202(0.005) & 0.732(0.000) & 0.073(0.102) \\ -0.033(0.910) & 0.481(0.000) & -0.045(0.577) & 0.713(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.095(0.009) & 0.069(0.288) & -0.133(0.000) \\ -0.499(0.100) & 0.192(0.157) & -0.510(0.000) & -0.262(0.000) \\ -0.366(0.365) & 0.109(0.512) & -1.270(0.000) & -0.132(0.076) \\ -0.357(0.458) & -1.263(0.000) & 0.143(0.565) & -0.112(0.223) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Table 19: The four-variable VARMA(1,1)-BEKK(1,1,1) model for United States

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.066(0.637) & 0.245(0.136) & 2.357(0.000) & -1.912(0.033) \\ 0.178(0.069) & 0.777(0.000) & 0.034(0.892) & -0.062(0.871) \\ -0.011(0.802) & -0.082(0.088) & -0.111(0.469) & 0.009(0.968) \\ 0.046(0.154) & -0.049(0.065) & 0.171(0.070) & 0.117(0.315) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -0.918(0.000) & -6.673(0.000) & 6.325(0.000) \\ -0.238(0.643) & 1.019(0.003) & 11.241(0.000) & -15.660(0.000) \\ 0.043(0.490) & -0.084(0.232) & -1.708(0.001) & 0.497(0.000) \\ -0.095(0.055) & 0.232(0.000) & 1.712(0.000) & -0.826(0.020) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.016(0.905) & -0.050(0.763) & -2.483(0.000) & 0.974(0.289) \\ -0.148(0.118) & -0.340(0.002) & 0.098(0.717) & 0.125(0.792) \\ -0.056(0.214) & 0.086(0.049) & 0.325(0.025) & 0.069(0.708) \\ -0.042(0.205) & 0.051(0.041) & -0.142(0.111) & 0.325(0.002) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 0.589(0.007) & 6.561(0.000) & -5.711(0.001) \\ 0.345(0.507) & -0.922(0.011) & -11.544(0.000) & 18.986(0.000) \\ 0.011(0.864) & 0.043(0.469) & 1.521(0.004) & -0.868(0.000) \\ 0.112(0.026) & -0.203(0.000) & -1.778(0.000) & 0.591(0.085) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.015	0.809	0.191	0.726
z_{i_t}	0.020	1.087	0.024	0.782
z_{s_t}	-0.088	0.876	0.996	0.751
z_{e_t}	-0.016	0.835	0.909	0.978

C. Student's t distribution shape

$v = 5.535(0.000)$

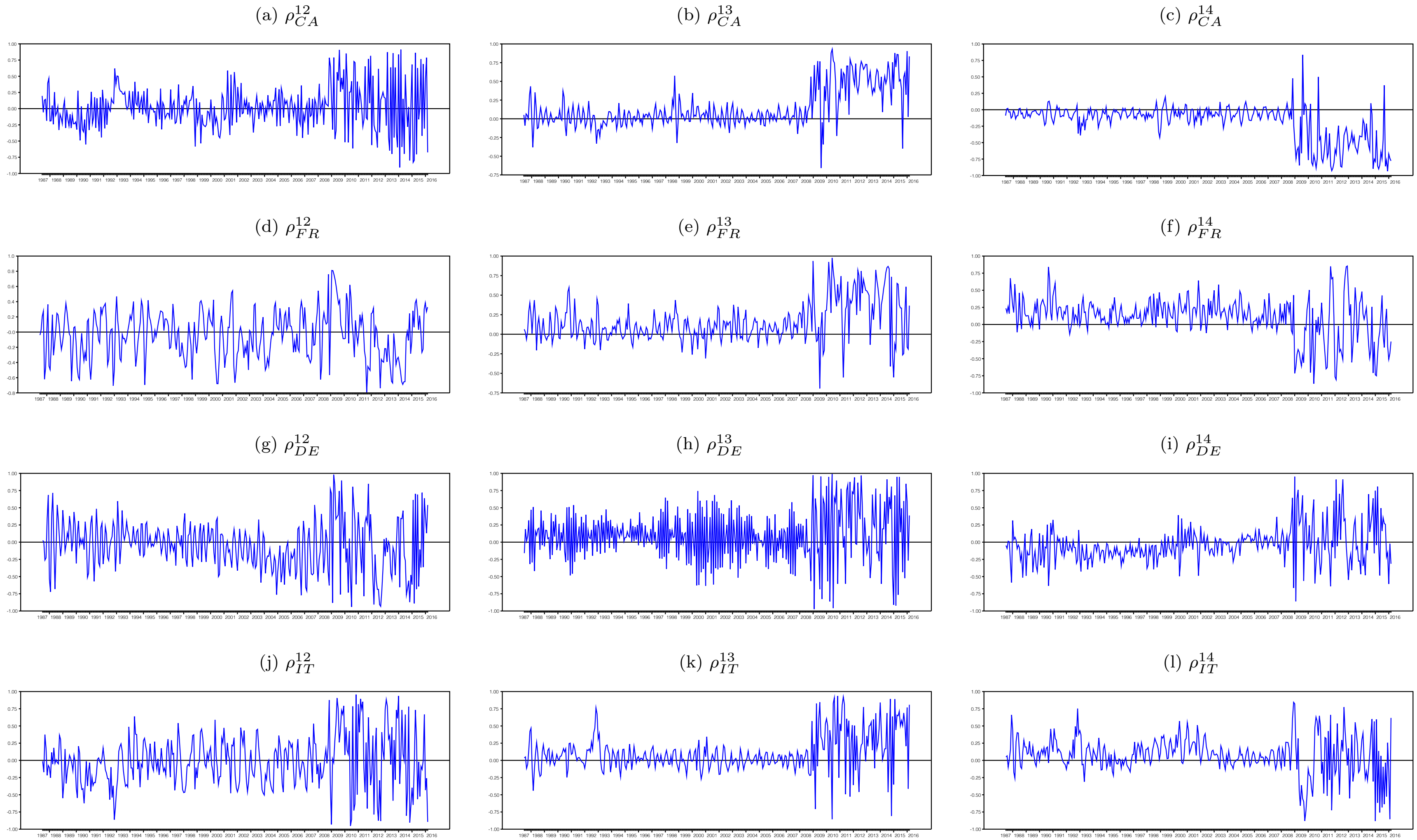
D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.341(0.000) & -0.009(0.779) & 0.119(0.000) & -0.036(0.005) \\ -0.159(0.055) & 0.304(0.000) & -0.169(0.000) & -0.003(0.878) \\ 0.036(0.851) & -0.055(0.561) & 0.497(0.000) & 0.026(0.432) \\ 0.191(0.720) & -0.020(0.921) & 0.437(0.095) & 0.061(0.550) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 2.304(0.000) & -0.430(0.000) & -0.023(0.397) \\ 0.055(0.625) & 1.108(0.000) & 0.089(0.071) & -0.020(0.408) \\ -0.465(0.132) & 1.785(0.000) & -0.330(0.015) & -0.157(0.006) \\ -4.639(0.000) & 15.714(0.000) & -1.120(0.034) & -0.035(0.867) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.639(0.000) & 0.148(0.014) & -0.222(0.000) & 0.050(0.003) \\ -0.546(0.026) & -0.531(0.001) & 0.312(0.000) & 0.189(0.000) \\ -1.100(0.000) & 0.649(0.000) & 0.120(0.425) & 0.184(0.000) \\ 2.855(0.001) & 2.315(0.000) & -0.001(0.997) & 0.397(0.040) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & -0.738(0.000) & 0.470(0.000) & -0.130(0.000) \\ 0.538(0.029) & 0.187(0.284) & -0.355(0.000) & -0.216(0.000) \\ 0.849(0.024) & -1.434(0.000) & -0.259(0.154) & -0.335(0.000) \\ -0.796(0.526) & -5.726(0.000) & 2.212(0.000) & -1.225(0.000) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

Figure 1: Cross-market conditional correlations in Canada, France, Germany, and Italy



(a) ρ^{12}_{CA} (b) ρ^{13}_{CA} (c) ρ^{14}_{CA}

(d) ρ^{12}_{FR} (e) ρ^{13}_{FR} (f) ρ^{14}_{FR}

(g) ρ^{12}_{DE} (h) ρ^{13}_{DE} (i) ρ^{14}_{DE}

(j) ρ^{12}_{IT} (k) ρ^{13}_{IT} (l) ρ^{14}_{IT}

Figure 2: Cross-market conditional correlations in Japan, Norway, United Kingdom, and United States