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Oil Price Shocks and Bond Risk Premia: Evidence from a Panel of 15 Countries*

Leonardo Iania[†] Marco Lyrio[‡] Liana Nersisyan[§]

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Abstract

We study the effect of oil price shocks on bond risk premia. Based on Baumeister and Hamilton (2019), we identify the different sources of oil price shocks using a structural vector autoregressive (SVAR) model of the global market for crude oil. These structural factors are then used as unspanned factors in an affine term structure model based on the representation of Joslin et al. (2014). This is done for a total of 15 countries. Bond risk premia of net oil-exporting countries show a reaction to the structural shocks which is often statistically significant and in line with the expectation. For oil-importing developed countries, mainly the reaction to economic activity shocks is statistically significant and with the expected sign. The results for oil-importing developing countries are most of the time not statistically significant or run counter what one would expect. Among the unspanned factors, global economic activity explains most of the variability in bond risk premia. Finally, a historical decomposition around the outbreak of the COVID-19 crisis shows a variety of patterns in the evolution of bond risk premia.

JEL codes: C11, E43, E44, Q43.

Keywords: oil prices shocks; affine term structure models; bond risk premia.

*The authors are responsible for any errors and for the views expressed in this paper.

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1 Introduction

Crude oil is probably the most important commodity for the global economy. Its impact on aggregate economic activity was first pointed out by Hamilton (1983). Since then, a number of studies has analyzed its effect on various macroeconomic and financial market variables.[1] Due to the size of the global bond market[2], and the importance of the term structure of interest rates for investors and central bankers, among others,[3] this paper assesses the contribution of the different sources of oil price shocks to movements in bond risk premia.

For fixed income investors, bond risk premia (expected excess returns) indicate the reward risk averse agents require to hold riskier long-maturity bonds for a short period of time rather than riskless bonds for the same time period. For central bankers, in turn, bond premia are key drivers of the transmission mechanism linking changes in short-term rates (a central bank's primary monetary policy instrument) with changes in the entire yield curve. This is particularly the case for its long end, which has an important effect, for example, on aggregate demand. In both cases it is thus crucial to understand the primary sources of fluctuations in yield risk premia.

In this respect, we base our study in two well-established results in the literature. First, the rejection of the expectations hypothesis of interest rates. According to this theory, bond risk premia are constant (weak form) or zero (strong form).[4] In our setting, bond premia are time varying and a function of two types of risk factors (described below). Second, the empirical evidence linking macroeconomic variables to the term structure of interest rates. Some studies show that macroeconomic variables account for a large part of the variation in bond yields.[5] Others find that macro variables are able to predict bond holding period returns.[6] We use a set of structural shocks to the global

[1]For example, see the studies related to economic activity, Azad and Serletis (2022), inflation and interest rates, Cologni and Manera (2008), unemployment, Kocaaslan (2019), economic activity and exchange rates, Śmiech et al. (2021), the stock market, Park and Ratti (2008) and Clements et al. (2019), and the yield curve, Ioannidis and Ka (2018) and Cepni et al. (2022).

[2]According to Cepni et al. (2022), the global bond market exceeds USD100 trillion, in comparison to USD65 trillion for the global equity market.

[3]See Piazzesi (2010) for a description of the agents interested in the yield curve dynamics.

[4]Studies rejecting the expectations hypothesis include Fama and Bliss (1987), Stambaugh (1988), Campbell and Shiller (1991), Bekaert and Hodrick (2001), Cochrane and Piazzesi (2005), and Sarno et al. (2007).

[5]See Ang and Piazzesi (2003), Dewachter et al. (2006), Hördahl et al. (2006), Bekaert et al. (2010), and Bikbov and Chernov (2010), among others.

[6]For example, Cooper and Priestley (2009), Ludvigson and Ng (2009), and Bikbov and

oil market as our macroeconomic variables.

Beyond these premises, the approach adopted in this paper involves two important methodological issues. First, the correct identification strategy of the underlying sources driving oil price shocks. We discuss briefly two possibilities and the ongoing debate in the literature.[7] Second, the appropriate model for the yield curve. The debate here is centered around the spanning hypothesis implied by a generation of yield curve models.

Regarding the identification strategy of the structural shocks, the first method is due to the seminal contribution of Kilian (2009).[8] He applies a Cholesky identification strategy to a structural model of the global crude oil market. His three-equation system includes measures of global crude oil production, global real economic activity, and the real price of oil. This identification scheme has strong implications for the estimation of some of the structural parameters. For example, it implies that global oil supply has no contemporaneous response to the price of oil. On the other hand, it imposes no restrictions regarding the response of global oil demand to changes in the oil price.

According to Baumeister and Hamilton (2019), this approach can be viewed as a special case of Bayesian inference with very strong prior beliefs. Using our illustration above, it implies that the econometrician knows with certainty that oil supply has no immediate response to changes in the oil price. But it also means that the econometrician has absolutely no useful information regarding the response of oil demand to the price of oil. This is what they call the "all or nothing" characteristic of the prior information used in structural models.

Baumeister and Hamilton (2019), therefore, propose a method of identification that tries to find a middle ground between those extremes. The authors suggest the use of a Bayesian approach, allowing the econometrician to express the degree of uncertainty regarding each of the structural parameters.[9]

One common message between Kilian (2009) and Baumeister and Hamilton (2019) is the fact that different structural shocks to the oil market have

Chernov (2010). Interestingly, Sarno et al. (2016) show that even a model that jointly fits bond yields and bond excess returns cannot outperform the expectations hypothesis out-of-sample in terms of economic value.

[7] Ready (2018) proposes an alternative method of classifying changes in oil prices as demand or supply driven at daily frequency. This technique has been applied, for example, by Demirer et al. (2020) and Umar et al. (2022).

[8] This method is applied by Lee et al. (2017), Ioannidis and Ka (2018), and Filippidis et al. (2020), among others.

[9] The debate about these two methods of identification is expressed in Baumeister and Hamilton (2020), Kilian (2022), and Kilian and Zhou (2019).

different impacts on the real price of oil. Nevertheless, these authors disagree on the relative importance of such shocks. For example, Kilian finds that oil supply disruptions have a small and transitory increase in the price of oil. The results from Baumeister and Hamilton, however, give more importance to this type of shock when they consider the historical movements in the oil price.

In this paper, we adopt the identification methodology of Baumeister and Hamilton (2019) applied to a structural system composed of: (*i*) a global oil supply curve; (*ii*) an equation describing the global economic activity; (*iii*) an oil-specific global demand equation; and (*iv*) an equation describing global inventory demand. Their methodology avoids the hard restrictions on the set of parameter estimates mentioned before and gives more flexibility in the use of prior information regarding each structural parameter. We believe this might lead to a better estimation of the bond risk premium dynamics.

The second methodological issue relates to the specification of the appropriate model for the term structure of interest rates. Such model should satisfy a number of requirements, i.e. it should: (*i*) explain both the cross-section and the time series dimension of the yield curve; (*ii*) guarantee the absence of arbitrage opportunities; (*iii*) be econometrically and numerically tractable; and (*iv*) allow for considerable flexibility in the data generating process of the state variables. The class of affine term structure models satisfies all these requirements.[10] Ideally, however, such models should also be able to identify the economic forces behind yield curve movements. An important contribution in this direction is given by Ang and Piazzesi (2003).

A number of models followed the same direction incorporating macroeconomic and financial variables as possible drivers of bond yields.[11] Most of these models, though, implicitly assume that such risk factors can be expressed as a linear combination of, i.e. are spanned by, bond yields. This is the so-called spanning hypothesis. It also implies that the current yield curve contains all the relevant information necessary to predict future interest rates.

In an important contribution, however, Joslin et al. (2014) reject the spanning hypothesis. They regress bond returns on various macroeconomic variables controlling for information in the yield curve. They find that macro variables contain additional predictive power to forecast bond returns. Based on these results, these authors introduce macroeconomic variables as unspanned factors in otherwise standard affine models. They adopt the rep-

[10]The framework for (latent) affine term structure models is set out in Duffie and Kan (1996).

[11]See Gürkaynak and Wright (2012) for a review of such models, and Dewachter and Iania (2011) for a model with financial variables as risk factors.

resentation proposed by Joslin et al. (2011), which uses a small number of observable yield portfolios (spanned factors) to model the cross-section of the yield curve. In this way, although unspanned factors do not impact directly on bond yields, they may still have predictive content for bond excess returns beyond the information contained in bond yields.

That appeared to be an optimal solution, allowing one to keep the desirable features of affine yield models with the necessary flexibility to model the dynamics of risk premia. A candidate for a consensus model seemed in sight. Bauer and Hamilton (2018), nevertheless, contest this result. They propose a number of robust tests and challenge the previous rejection of the spanning hypothesis. Bauer and Rudebusch (2017) also support the original spanned models. They show that simply by incorporating small yield measurement errors one could (inappropriately) conclude in favor of the presence of unspanned macroeconomic information in the data.

Finally, a recent study by Bekaert et al. (2021) brings once more evidence against the spanning hypothesis, keeping the debate alive. They show that macroeconomic factors are significant predictors of bond excess returns, even after controlling for yield curve factors. Furthermore, these results are obtained using the robust tests proposed by Bauer and Hamilton (2018).

In this study, we follow Joslin et al. (2014) and adopt the class of macro-finance term structure models (MTSMs) with both spanned and unspanned factors. Our unspanned factors are obtained from the structural vector autoregressive (SVAR) model of the global market for oil of Baumeister and Hamilton (2019). The spanned factors are represented by the level, slope, and curvature of the yield curve.[12]

We apply our framework to monthly data for 15 countries with different profiles. This allows us to evaluate how the response of bond risk premia depends on: (*i*) the type of shock hitting the global economy (demand or supply, mainly); (*ii*) the country's economic situation (developing or developed); (*iii*) the country's position on the oil market (net oil-exporter or net oil-importer); and (*iv*) the maturity of the bond. We cover the period from 2007 to 2022, and include a wide range of maturities, from three months to 10 years.

We contribute to the literature in two dimensions. Our first contribution is methodological. As just mentioned, we combine the methodology of Baumeister and Hamilton (2019), which allows us to identify the sources of oil price shocks, with the yield curve representation proposed by Joslin et al. (2014), which allows us to use the oil factors as unspanned factors in the

[12] In this respect, we differ from Joslin et al. (2011), who propose the use of the first three principal components of the yield data as the spanned factors.

term structure model. Our second contribution is empirical. We analyze the effect of each oil factor on the risk premia of bonds from 15 countries, with different positions in the oil market and levels of development, and with a wide range of maturities.

Our model specification is able to fit the yield curve for the 15 countries rather well. Since we use three spanned factors, and based on the seminal work of Litterman and Scheinkman (1991), this is actually not surprising.[13] More importantly, the fit of the realized excess returns is also satisfactory.

Our results demonstrate that bond risk premia of net oil-exporting countries show a reaction to the structural shocks which is often statistically significant and in line with the expectation. For oil-importing developed countries, mainly the reaction to economic activity shocks is statistically significant and with the expected sign. The results for oil-importing developing countries are most of the time not statistically significant or run counter what one would expect.

From a variance decomposition, we see that the spanned factors explain most of the variability in bond risk premia. Among the unspanned factors, however, the economic activity factor plays the most important role in explaining the variance in bond premia. Finally, a historical decomposition around the outbreak of the COVID-19 crisis shows a variety of patterns in the evolution of the bond risk premia.

The remainder of the paper is organized as follows. Section 2 describes the model specification, including the standard term structure setting, the structure model for the global oil market, and the representation making use of both spanned and unspanned factors. Section 3 presents the estimation procedure and the data for the 15 countries in our sample. Section 4 presents the results of the paper and is divided in two parts. The first part presents a model evaluation while the second part analyzes the relative importance of each structural shock for the dynamics of bond risk premia of the different groups of countries. This is done by means of impulse response functions (IRFs), variance decompositions, and a historical decomposition. Concluding remarks are presented in Section 5.

2 The model

As mentioned before, our modelling specification has two key ingredients: (i) the SVAR model, which allows the identification of four global oil price factors, in the spirit of Baumeister and Hamilton (2019); and (ii) the term

[13] Litterman and Scheinkman (1991) show that three factors (labelled level, slope and curvature) are able to capture most of the variation in US bond yields.

structure specification, modelling bond prices, which is based on the class of MTSMs with both spanned and unspanned factors, as in Joslin et al. (2014).

For each country, the cross-section of yields is an affine function of a set of spanned risk factors. These factors are labelled *spanned* since they are represented by a linear combination of bond yields – the so-called yield portfolios. The factor loadings on each bond is obtained from no-arbitrage restrictions (see Ang and Piazzesi (2003), among others). The dynamics of the yield portfolios (under the historical measure), however, is represented by means of a SVAR model, including both the yield curve portfolios (spanned factors) and the four global oil price factors (unspanned factors).

Although the model is estimated separately for each country, the global unspanned factors are the same in all cases (the common factors among the 15 countries). Based on the affine yield curve representation and the SVAR dynamics, we assess the relative contribution of each macroeconomic variable (global oil factor) in the yield curve dynamics of each country.

2.1 The basic affine term structure setting

To fix notation, we denote by $y_t^{(n)}$ the zero-coupon yield of the n-period bond of a certain country. We call Y_t the vector collecting the yields for N maturities at time t. We employ a Gaussian affine no-arbitrage setting to price the government bonds, which is equivalent to expressing Y_t as an affine function of the risk factors $\mathbf{Z}_t$, identified in Section 2.2.

We impose that (i) the one-period zero-coupon rate, $y_t^{(1)}$, is an affine function of $\mathbf{Z}_t$; and (ii) the risk factors have affine Gaussian dynamics under both the risk-neutral and historical probability measures, $\mathbb{Q}$ and $\mathbb{P}$, respectively:

$$y_t^{(1)} = \rho_0 + \boldsymbol{\rho}_1' \mathbf{Z}_t, \tag{1}$$

$$\mathbf{Z}_t = \boldsymbol{\mu}^i + \boldsymbol{\Phi}^i\ \mathbf{Z}_{t-1} + \boldsymbol{\Sigma}\boldsymbol{\varepsilon}_t^i, \quad \boldsymbol{\varepsilon}_t^i \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I}) \text{ and } i = \mathbb{Q}, \mathbb{P}, \tag{2}$$

where ρ_0, $\boldsymbol{\rho}_1$, $\boldsymbol{\mu}^{\mathbb{Q}}$, $\boldsymbol{\mu}^{\mathbb{P}}$, $\boldsymbol{\Phi}^{\mathbb{Q}}$, $\boldsymbol{\Phi}^{\mathbb{P}}$, and $\boldsymbol{\Sigma}$ are model parameters, while $\boldsymbol{I}$ is an identity matrix of conformable dimension. The parameters of equation (2) under $\mathbb{Q}$ determine the pricing of the cross-section of yields, while the parameters under $\mathbb{P}$ are key for the risk premium dynamics. The link between the two probability measures is obtained (i) by assuming essentially affine market prices of risk, $\boldsymbol{\Lambda}_t$, and (ii) by expressing the stochastic discount factor, M_t, as an exponentially affine function of $y_t^{(1)}$, $\boldsymbol{\Lambda}_t$ and the system's shocks, $\boldsymbol{\varepsilon}_t^{\mathbb{P}}$, weighted by $\boldsymbol{\Sigma}$:

$$\boldsymbol{\Lambda}_t = \boldsymbol{\Sigma}^{-1}\left(\boldsymbol{\lambda}_0 + \boldsymbol{\lambda_1}\mathbf{Z}_t\right), \quad \boldsymbol{\mu}^{\mathbb{Q}} = \boldsymbol{\mu}^{\mathbb{P}} - \boldsymbol{\lambda}_0, \quad \boldsymbol{\Phi}^{\mathbb{Q}} = \boldsymbol{\Phi}^{\mathbb{P}} - \boldsymbol{\lambda_1}, \tag{3}$$

$$M_t = \exp(-y_t^{(1)} - \frac{1}{2}\boldsymbol{\Lambda}_t'\boldsymbol{\Lambda}_t - \boldsymbol{\Lambda}_t'\boldsymbol{\Sigma}\boldsymbol{\varepsilon}_t^{\mathbb{P}}). \tag{4}$$

Under these assumptions, it is possible to express $y_t^{(n)}$ as an affine function of the risk factors, $\mathbf{Z}_t$:

$$y_t^{(n)} = a_n + \boldsymbol{b}_n\mathbf{Z}_t, \tag{5}$$

whereby the weights of (5) derive from standard Riccati equations (see Ang and Piazzesi (2003)). Specifically, $a_n = -n^{-1}\mathrm{a}_n$ and $\boldsymbol{b}_n = -n^{-1}\mathrm{b}_n$

$$\mathrm{a}_n = \mathrm{a}_{n-1} + \mathrm{b}_{n-1}\boldsymbol{\mu}^{\mathbb{Q}} + \frac{1}{2}(\mathrm{b}_{n-1})'\boldsymbol{\Sigma}\boldsymbol{\Sigma}'\mathrm{b}_{n-1} - \rho_0, \tag{6}$$

$$\mathrm{b}_n = (\boldsymbol{\Phi}^{\mathbb{Q}})'\mathrm{b}_{n-1} - \boldsymbol{\rho}_1. \tag{7}$$

The next two sections define (i) equation (2) under both measures and (ii) identify the restrictions governing the change of measure and hence the risk premium dynamics.

2.2 Oil shocks and yield curve factors

We follow Baumeister and Hamilton (2019) and identify four structural shocks to the global oil market – shocks to oil supply, economic activity, oil-specific demand and inventory demand – via a SVAR model with four variables: (i) the monthly growth rate of oil production, q_t; (ii) a measure of real economic activity, g_t; (iii) the real price of oil, p_t; and (iv) the change in world crude oil inventories as a fraction of previous month's world production, $\Delta i_t = \Delta I_t/Q_{t-1}$, where Q_{t-1} is the oil production at t–1 and ΔI_t is the monthly change in global inventories. Staking the four variables in the vector $\mathbf{m_t} = [q_t, g_t, p_t, \Delta i_t]'$ and denoting its lagged values in the 12 preceding months by $\mathbf{m}^L_{1:12} = [\mathbf{m}'_{\mathbf{t-1}}, ..., \mathbf{m}'_{\mathbf{t-12}}]'$, we can express the structural model for the global oil market as follows:[14]

[14] We use 12 lags for the macroeconomic variables in the structural system as in Baumeister and Hamilton (2019) and Ioannidis and Ka (2018).

$$q_t = a_q + \alpha_{qp} p_t + \mathbf{b_1'} \mathbf{m}^L_{1:12} + \varepsilon^{\mathbb{P}}_{1t}, \tag{8}$$

$$g_t = a_g + \alpha_{gp} p_t + \mathbf{b_2'} \mathbf{m}^L_{1:12} + \varepsilon^{\mathbb{P}}_{2t}, \tag{9}$$

$$q_t - \chi \Delta i_t = a_d + \alpha_{dg} g_t + \alpha_{dp} p_t + \mathbf{b_3'} \mathbf{m}^L_{1:12} + \varepsilon^{\mathbb{P}}_{3t}, \tag{10}$$

$$\chi \Delta i_t = a_i + \alpha_{ip} p_t + \alpha_{iq} q_t + \mathbf{b_4'} \mathbf{m}^L_{1:12} + \varepsilon^{\mathbb{P}}_{4t}. \tag{11}$$

Equation (8) represents the oil supply curve, whereby oil production (q_t) depends on the real oil price (p_t) and on the lagged (12 months) values of all variables, $\mathbf{m}^L_{1:12}$. Equation (9) models world economic activity in function of the current real price of oil and the lagged values of $\mathbf{m_t}$. Equation (10) models the growth of world's oil consumption demand (net of the relative changes in oil inventories) as a function of real oil prices, world economic activity, and $\mathbf{m}^L_{1:12}$. Finally, Equation (11) models the relative growth in oil inventories in function of oil production, real oil price and the lagged values of all variables.

We assume that yield curve movements for a certain country can be summarized by linear combinations of three yield curve portfolios (factors), $\mathcal{L}_t$, $\mathcal{S}_t$, and $\mathcal{C}_t$, which are referred to as level, slope, and curvature, respectively, and represented by $\mathcal{F}_t = (\mathcal{L}_t, \mathcal{S}_t, \mathcal{C}_t)'$. These factors are computed as follows. For each point in time, the level factor is the average of the yields for all the maturities available. The slope factor is computed as the 10-year bond yield minus the three-month bond yield. Finally, the curvature factor is equal to the 10-year bond yield plus the three-month bond yield minus two times the five-year bond yield.[15] These three yield curve factors evolve according to the following system:

$$\mathcal{L}_t = a_{\scriptscriptstyle\mathcal{L}} + \alpha_{\scriptscriptstyle\mathcal{L}o} \mathbf{m}_t + \mathbf{b}'_{\scriptscriptstyle\mathcal{L}} \mathcal{F}_{t-1} + \mathbf{b}'_5 \mathbf{m}^L_{1:12} + \varepsilon^{\mathbb{P}}_{\scriptscriptstyle\mathcal{L}t}, \tag{12}$$

$$\mathcal{S}_t = a_{\scriptscriptstyle\mathcal{S}} + \alpha_{\scriptscriptstyle\mathcal{S}o} \mathbf{m}_t + \alpha_{\scriptscriptstyle\mathcal{S}\mathcal{L}} \mathcal{L}_t + \mathbf{b}'_{\scriptscriptstyle\mathcal{S}} \mathcal{F}_{t-1} + \mathbf{b}'_6 \mathbf{m}^L_{1:12} + \varepsilon^{\mathbb{P}}_{\scriptscriptstyle\mathcal{S}t}, \tag{13}$$

$$\mathcal{C}_t = a_{\scriptscriptstyle\mathcal{C}} + \alpha_{\scriptscriptstyle\mathcal{C}o} \mathbf{m}_t + \alpha_{\scriptscriptstyle\mathcal{C}\mathcal{L}} \mathcal{L}_t + \alpha_{\scriptscriptstyle\mathcal{C}\mathcal{S}} \mathcal{S}_t + \mathbf{b}'_{\scriptscriptstyle\mathcal{C}} \mathcal{F}_{t-1} + \mathbf{b}'_7 \mathbf{m}^L_{1:12} + \varepsilon^{\mathbb{P}}_{\scriptscriptstyle\mathcal{C}t}. \tag{14}$$

As it is standard in the term structure literature, equations (12) to (14) impose that the level factor is the most exogenous yield curve factor, followed by the slope and curvature factors. Comparing equations (12) to (14) with equations (8) to (11), two points standout. First, oil factors are not influenced by term structure factors and shocks. This is equivalent to saying that country-specific nominal interest rates do not have real impact on oil demand and supply beyond the impact on the global series summarized

[15] See Bekaert et al. (2010) for similar definitions.

by Baumeister and Hamilton (2019). Second, oil factors can influence term structure movements, and hence its shape, contemporaneously via $\alpha_{\epsilon o}$, α_{so}, and α_{co}, and with a lag via $\mathbf{b}_5$, $\mathbf{b}_6$, and $\mathbf{b}_7$.

Equations (8) to (14) can be expressed more compactly by grouping the parameters governing the contemporaneous (lagged) interaction between oil factors, between yield curve factors, and between oil factors and yield curve factors into $\mathbf{A}^m$ $(\mathbf{B}^m)$, $\mathbf{A}^{\mathcal{F}}$ $(\mathbf{B}^{\mathcal{F}})$, and $\mathbf{A}^{m\mathcal{F}}$ $(\mathbf{B}^{m\mathcal{F}})$ and the intercepts in the equations of the oil (yield curve) factors in $\mathbf{a}^m$ $(\mathbf{a}^{\mathcal{F}})$:

$$\begin{bmatrix}\mathbf{m}_t\\ \mathcal{F}_t\end{bmatrix} = \begin{bmatrix}\mathbf{a}^m\\ \mathbf{a}^{\mathcal{F}}\end{bmatrix} + \begin{bmatrix}\mathbf{A}^m & \mathbf{0}\\ \mathbf{A}^{m\mathcal{F}} & \mathbf{A}^{\mathcal{F}}\end{bmatrix}\begin{bmatrix}\mathbf{m}_t\\ \mathcal{F}_t\end{bmatrix} + \begin{bmatrix}\mathbf{B}^m & \mathbf{0}\\ \mathbf{B}^{m\mathcal{F}} & \mathbf{B}^{\mathcal{F}}\end{bmatrix}\begin{bmatrix}\mathbf{m}^L_{1:12}\\ \mathcal{F}_{t-1}\end{bmatrix} + \begin{bmatrix}\boldsymbol{\varepsilon}^{\mathbb{P},m}_t\\ \boldsymbol{\varepsilon}^{\mathbb{P},\mathcal{F}}_t\end{bmatrix}. \tag{15}$$

Equation (15) can be written in a standard compact dynamic structural form by defining $\mathbf{Z}_t = [\mathbf{m}_t', \mathcal{F}_t']'$, $\mathbf{Z}^L_{1:12} = [\mathbf{m}^{L'}_{1:12}, \mathcal{F}_{t-1}']'$, and staking the $\mathbf{a}'$s, $\mathbf{A}'$s, $\mathbf{B}'$s, and $\boldsymbol{\varepsilon}^{\mathbb{P}'}_t$s in $\mathbf{a}$, $\mathbf{A}$, $\mathbf{B}$, and $\boldsymbol{\varepsilon}^{\mathbb{P}}_t$, respectively:

$$(\mathrm{I} - \mathbf{A})\mathbf{Z}_t = \mathbf{a} + \mathbf{B}\mathbf{Z}^L_{1:12} + \boldsymbol{\varepsilon}^{\mathbb{P}}_t, \tag{16}$$

which can also be written as in equation (2):

$$\mathbf{Z}_t = \boldsymbol{\mu}^{\mathbb{P}} + \boldsymbol{\Phi}^{\mathbb{P}}\mathbf{Z}^L_{1:12} + \boldsymbol{\Sigma}\boldsymbol{\varepsilon}^{\mathbb{P}}_t, \tag{17}$$

with $\boldsymbol{\mu}^{\mathbb{P}} = (\mathrm{I} - \mathbf{A})^{-1}\mathbf{a}$, $\boldsymbol{\Phi}^{\mathbb{P}} = (\mathrm{I} - \mathbf{A})^{-1}\mathbf{B}$ and $\boldsymbol{\Sigma} = (\mathrm{I} - \mathbf{A})^{-1}$.

2.3 Canonical representation

We adopt the normalization of Joslin et al. (2011), which dramatically reduces the number of parameters of equation (2) under $\mathbb{Q}$ via two sets of restrictions. First, it imposes the so-called spanning restrictions, which means that under the risk-neutral measure $\mathbb{Q}$ only a few linear combinations of the yields in Y_t, i.e. $\mathcal{F}_t$, span the cross-section of Y_t over time:

$$\mathbb{E}^{\mathbb{Q}}_t[y^{(n)}_{t+j}|Z_t] = \mathbb{E}^{\mathbb{Q}}_t[y^{(n)}_{t+j}|\mathcal{F}_t]. \tag{18}$$

To satisfy condition (18), we impose that, under the risk-neutral dynamics, equations (1) and (2) depend only on $\mathcal{F}_t$:

$$y^{(1)}_t = \rho_0 + (\boldsymbol{\rho}^{\mathcal{F}}_1)'\mathcal{F}_t, \tag{19}$$

$$\mathcal{F}_t = \boldsymbol{\mu}^{\mathbb{Q},\mathcal{F}} + \boldsymbol{\Phi}^{\mathbb{Q},\mathcal{F}}\,\mathcal{F}_{t-1} + \boldsymbol{\Sigma}^{\mathcal{F}}\boldsymbol{\varepsilon}^{\mathbb{Q},\mathcal{F}}_t, \quad \boldsymbol{\varepsilon}^{\mathbb{Q},\mathcal{F}}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I}), \tag{20}$$

where the 3×1 vectors $\boldsymbol{\rho}_1^{\mathcal{F}}$ and $\boldsymbol{\mu}^{\mathbb{Q},\mathcal{F}}$ and the 3×3 matrices $\boldsymbol{\Phi}^{\mathbb{Q},\mathcal{F}}$ and $\boldsymbol{\Sigma}^{\mathcal{F}}$ are the non-zero components of $\boldsymbol{\rho}_1'$, $\boldsymbol{\mu}^{\mathbb{Q}}$, $\boldsymbol{\Phi}^{\mathbb{Q}}$ and $\boldsymbol{\Sigma}$ in equation (2) corresponding to $\mathcal{F}_t$. From equations (19) and (20), it follows that Y_t is an affine function of $\mathcal{F}_t$, hence equation (5) simplifies to:

$$y_t^{(n)} = a_n^{\mathcal{F}} + \boldsymbol{b}_n^{\mathcal{F}} \mathcal{F}_t, \tag{21}$$

where the loadings are obtained in a similar fashion as in equations (6) and (7), namely, $a_n^{\mathcal{F}} = -n^{-1} a_n^{\mathcal{F}}$ and $\boldsymbol{b}_n^{\mathcal{F}} = -n^{-1} \boldsymbol{b}_n^{\mathcal{F}}$ with:

$$a_n^{\mathcal{F}} = a_{n-1}^{\mathcal{F}} + b_{n-1}^{\mathcal{F}} \boldsymbol{\mu}^{\mathbb{Q},\mathcal{F}} + \frac{1}{2} (b_{n-1}^{\mathcal{F}})' \boldsymbol{\Sigma}^{\mathcal{F}} (\boldsymbol{\Sigma}^{\mathcal{F}})' b_{n-1}^{\mathcal{F}} - \rho_0, \tag{22}$$

$$b_n^{\mathcal{F}} = (\boldsymbol{\Phi}^{\mathbb{Q},\mathcal{F}})' b_{n-1}^{\mathcal{F}} - \boldsymbol{\rho}_1^{\mathcal{F}}. \tag{23}$$

Inspecting equations (19), (20), and (21), we notice that the spanning condition (18) is trivially satisfied as, under $\mathbb{Q}$, Y_t depends only on $\mathcal{F}_t$, which in turn depends only on its lagged values.

The spanning assumption results in the following set of zero restrictions on the prices of risks and stochastic discount factor, cfr. equations (3) and (4):

$$\boldsymbol{\Lambda}_t^{\mathcal{F}} = (\boldsymbol{\Sigma}^{\mathcal{F}})^{-1} \left(\boldsymbol{\lambda}_0^{\mathcal{F}} + \boldsymbol{\lambda}_1^{\mathcal{F}} \mathbf{Z}_t \right), \tag{24}$$

$$\boldsymbol{\lambda}_0^{\mathcal{F}} = \boldsymbol{D}_{\mathcal{F}} \boldsymbol{\mu}^{\mathbb{P}} - \boldsymbol{\mu}^{\mathbb{Q},\mathcal{F}}, \tag{25}$$

$$\boldsymbol{\lambda}_1^{\mathcal{F}} = \boldsymbol{D}_{\mathcal{F}} \boldsymbol{\Phi}^{\mathbb{P}} - [\mathcal{O} \; \boldsymbol{\Phi}^{\mathbb{Q},\mathcal{F}}], \tag{26}$$

$$M_t = \exp(-y_t^{(1)} - \frac{1}{2} (\boldsymbol{\Lambda}_t^{\mathcal{F}})' \boldsymbol{\Lambda}_t^{\mathcal{F}} - (\boldsymbol{\Lambda}_t^{\mathcal{F}})' \boldsymbol{\Sigma}^{\mathcal{F}} \boldsymbol{\varepsilon}_t^{\mathbb{P},\mathcal{F}}). \tag{27}$$

with $\mathcal{O}$ a zero matrix of conformable dimension and $\boldsymbol{D}_{\mathcal{F}} = [\mathcal{O} \; \boldsymbol{I}_{3\times 3}]$ a matrix selecting the last three rows of $\boldsymbol{\mu}^{\mathbb{P}}$ and $\boldsymbol{\Phi}^{\mathbb{P}}$, i.e. the parts related to $\mathcal{F}_t$.

In a nutshell, as the cross-section of bond rates is summarized by $\mathcal{F}_t$, only shocks to those principal components are priced; see equation (27). However, via equation (24), unspanned factors play a role in the pricing of those shocks, which are weighted by the 3×1 prices of risk vector $\boldsymbol{\Lambda}_t^{\mathcal{F}}$, that in turn is linked to all the variables of the dynamic system (17) via the matrix $\boldsymbol{\lambda}_1^{\mathcal{F}}$ of equation (24).

To identify the risk-neutral parameters, we follow Joslin et al. (2011) and impose a second set of identifying restrictions on the $\mathbb{Q}$-dynamics, so that the real-world dynamics can be estimated without restrictions. We assume

$N = 3$ latent factors $\mathcal{X}_t$ and impose the following restrictions on their $\mathbb{Q}$-dynamics:

$$y_t^{(1)} = \iota \mathcal{X}_t, \quad \boldsymbol{\mu}^{\mathcal{X}} = \begin{bmatrix} \boldsymbol{\kappa}^{\mathcal{X}} \\ 0 \\ 0 \end{bmatrix}, \quad \boldsymbol{\Phi}^{\mathcal{X}} = \begin{bmatrix} \boldsymbol{\lambda}_1^{\mathcal{X}} & & \\ & \boldsymbol{\lambda}_2^{\mathcal{X}} & \\ & & \boldsymbol{\lambda}_3^{\mathcal{X}} \end{bmatrix}, \tag{28}$$

where ι is 1×3 vector of ones and the $\boldsymbol{\lambda}^{\mathcal{X}}$s are assumed to be less than one in absolute value. Subsequently, we obtain the term structure loadings related to $\mathcal{X}_t$, $A_{\mathcal{X}}$ and $B_{\mathcal{X}}$, and use the definition of $\mathcal{F}_t = W^{\mathcal{F}} Y_t$ to obtain the loadings for $\mathcal{F}_t$ in function of the parameters in (28):

$$Y_t = (I - B_{\mathcal{X}}(W^{\mathcal{F}} B_{\mathcal{X}})^{-1} W^{\mathcal{F}}) A_{\mathcal{X}} + B_{\mathcal{X}}(W^{\mathcal{F}} B_{\mathcal{X}})^{-1} \mathcal{F}_t, \tag{29}$$

where $A_{\mathcal{X}}$ and $B_{\mathcal{X}}$ are the affine yield loadings on $\mathcal{X}_t$ and $W^{\mathcal{F}} = [\mathrm{w}_l', \ \mathrm{w}_s', \ \mathrm{w}_c']'$.

3 Econometric framework

3.1 Estimation

We estimate the model using a penalized likelihood approach, a widely-used methodology in high-dimensional statistics, see Hastie et al. (2001), among others. The three-equation system from which we derive the likelihood function is the following:

$$\mathbf{Z}_t = \boldsymbol{\mu}^{\mathbb{P}} + \boldsymbol{\Phi}^{\mathbb{P}} \mathbf{Z}_{1:12}^{L} + \boldsymbol{\Sigma} \boldsymbol{\varepsilon}_t^{\mathbb{P}}, \tag{30}$$

$$Y_t = A^{\mathcal{F}}(\boldsymbol{\Theta}^{\mathbb{Q}}, \boldsymbol{\Sigma}^{\mathcal{F}}) + B^{\mathcal{F}}(\boldsymbol{\Theta}^{\mathbb{Q}}, \boldsymbol{\Sigma}^{\mathcal{F}}) \mathcal{F}_t + \boldsymbol{\xi}_t, \tag{31}$$

where equation (31) is a compact form of equation (29), with $\boldsymbol{\epsilon}_t$ being i.d.d. Gaussian fitting errors and $\boldsymbol{\Theta}^{\mathbb{Q}} = \{\boldsymbol{\lambda}_1^{\mathcal{X}}, \boldsymbol{\lambda}_2^{\mathcal{X}}, \boldsymbol{\lambda}_3^{\mathcal{X}}, \boldsymbol{\kappa}^{\mathcal{X}}\}$ the risk-neutral parameters. The penalized log-likelihood is composed of two groups, l_t^Z and l_t^Y:

$$l_t \propto \overbrace{\underbrace{-\ln|\boldsymbol{E}_2| - \tilde{\boldsymbol{\varepsilon}}_t^{\mathbb{P}\prime} \boldsymbol{E}_2^{-1} \tilde{\boldsymbol{\varepsilon}}_t^{\mathbb{P}}}_{\text{Eq.(30)}} + \underbrace{p(\boldsymbol{\Phi}^{\mathbb{P}}) + p(\boldsymbol{\Sigma})}_{\text{Penalties}}}^{l_t^Z = \text{macro and yield's PCs likelihood}} \quad \overbrace{\underbrace{-\ln|\Xi| - \tilde{\boldsymbol{\xi}}_t' \Xi^{-1} \tilde{\boldsymbol{\xi}}_t}_{\text{Eq.(31)}}}^{l_t^Y = \text{term structure likelihood}} . \tag{32}$$

In the first group, $\tilde{\boldsymbol{\varepsilon}}_t^{\mathbb{P}}$ indicates the fitting errors from equation (30), $\boldsymbol{E}_2 = \boldsymbol{\Sigma}\boldsymbol{\Sigma}'$, and the two penalties parts (i) identify oil shocks as in Baumeister and Hamilton (2019) and (ii) shrink to zero higher-lag parameters. In the second group, $\tilde{\boldsymbol{\xi}}_t$ are the fitting errors from equation (31) and Ξ is a diagonal matrix containing the variances of $\tilde{\boldsymbol{\xi}}_t$. As indicated by equations (30) and (31), the likelihood of the macro and yields factors hinges upon the historical parameters while the fitting of the yield curve is related to the risk neutral parameters. The only parameters that belong to both likelihood is $\boldsymbol{\Sigma}^{\mathcal{F}}$.

Since l_t^Z is independent of $\boldsymbol{\Theta}^{\mathbb{Q}}$, we split the maximization of equation (32) in two steps. In the first step, we fit equation (30), which we write in an expanded version to elicit the components of the likelihood and the penalty functions:

$$\begin{bmatrix}\mathbf{m}_t\\ \mathcal{F}_t\end{bmatrix} = \begin{bmatrix}\boldsymbol{\mu}^m\\ \boldsymbol{\mu}^{\mathcal{F}}\end{bmatrix} + \begin{bmatrix}\boldsymbol{\Phi}^m & \mathbf{0}\\ \boldsymbol{\Phi}^{m\mathcal{F}} & \boldsymbol{\Phi}^{\mathcal{F}}\end{bmatrix}\begin{bmatrix}\mathbf{m}^L_{1:12}\\ \mathcal{F}_{t-1}\end{bmatrix} + \begin{bmatrix}\boldsymbol{\Sigma}^m & \mathbf{0}\\ \boldsymbol{\Sigma}^{m\mathcal{F}} & \boldsymbol{\Sigma}^{\mathcal{F}}\end{bmatrix}\begin{bmatrix}\boldsymbol{\varepsilon}_t^{\mathbb{P},m}\\ \boldsymbol{\varepsilon}_t^{\mathbb{P},\mathcal{F}}\end{bmatrix}. \tag{33}$$

Noticeably, equation (33) highlights that the oil block's equation related to $\mathbf{m}_t$ is independent of the country-specific yield curve factors. This observation, combined with the fact that all series are observed, allows us to estimate $\boldsymbol{\mu}^m$, $\boldsymbol{\Phi}^m$, and $\boldsymbol{\Sigma}^m$ separately from $\boldsymbol{\mu}^{\mathcal{F}}$, $\boldsymbol{\Phi}^{m,\mathcal{F}}$, $\boldsymbol{\Phi}^{\mathcal{F}}$, $\boldsymbol{\Sigma}^{m,\mathcal{F}}$, and $\boldsymbol{\Sigma}^{\mathcal{F}}$:

$$\begin{aligned} l_t^Z \propto\ & \overbrace{\underbrace{-\ln|\boldsymbol{E}^m| - \tilde{\boldsymbol{\varepsilon}}_t^{\mathbb{P},m'}\boldsymbol{E}^{m^{-1}}\tilde{\boldsymbol{\varepsilon}}_t^{\mathbb{P},m}}_{\text{Eq.(33): fitting of } \mathbf{m}_t} + \underbrace{p(\boldsymbol{\Sigma}^m)}_{\text{Oil shocks identification}}}^{l_t^m = \text{Oil penalized likelihood}} \\ & \overbrace{\underbrace{-\ln|\boldsymbol{E}^{\mathcal{F}}| - \tilde{\boldsymbol{\varepsilon}}_t^{\mathbb{P},\mathcal{F}'}\boldsymbol{E}^{\mathcal{F}^{-1}}\tilde{\boldsymbol{\varepsilon}}_t^{\mathbb{P},\mathcal{F}}}_{\text{Eq.(33): fitting of } \mathcal{F}_t} + \underbrace{p(\boldsymbol{\Phi}^{m,\mathcal{F}})}_{\text{Penalization for lags in oil factors}}}^{l_t^{\mathcal{F}} = \text{Yield's factor penalized likelihood}}. \end{aligned} \tag{34}$$

The functional form of the penalization terms related to $p(\boldsymbol{\Sigma}^m)$ is derived as follows. First, we denote by $\tilde{\boldsymbol{A}}^m$ the part of $\boldsymbol{I}-\boldsymbol{A}$ related to the oil variables in equation (17), implying that

$$\boldsymbol{\Sigma}^{\boldsymbol{m}} = \frac{1}{\det \tilde{\boldsymbol{A}}^m}\mathrm{adj}(\boldsymbol{A}^m).$$

Subsequently, following Baumeister and Hamilton (2019), we parameterize $\tilde{\boldsymbol{A}}^m$ as

$$\tilde{\boldsymbol{A}}^m = \begin{bmatrix} 1 & 0 & -\alpha_{qp} & 0\\ 0 & 1 & -\alpha_{gp} & 0\\ 0 & -\alpha_{dg} & -\alpha_{dp} & -1\\ -\alpha_{iq} & 0 & -\alpha_{ip} & \chi \end{bmatrix}, \tag{35}$$

with the penalty function for each parameter given by

$$p(\alpha_j) \propto -4 \ln \left[1 + \frac{(\bar{\alpha}_j - \mu_j)^2}{9\sigma_j^2}\right] \qquad \{\bar{\alpha}_j, \mu_j, \sigma_j\} = \begin{cases} \{\alpha_{qp}^{+}, .1, .2\} \\ \{\alpha_{gp}^{-}, -.05, .1\} \\ \{\alpha_{qg}^{+}, .7, .2\} \\ \{\alpha_{dp}^{-}, -.1, .2\} \\ \{\alpha_{iq}, 0, .5\} \\ \{\alpha_{ip}, 0, .5\} \end{cases} . \tag{36}$$

3.2 Data

Our analysis covers 15 countries, selected based on data availability and the size of the country (in terms of GDP). We divide the countries in three groups: (i) net oil exporters, i.e. Brazil, Canada, Mexico, Norway and Russia; (ii) developing countries which are net oil importers, i.e. China, India, Indonesia, South-Africa, and Turkey; and (iii) developed countries which are net oil importers, i.e. Germany, Japan, South-Korea, UK, and USA.[16]

For all countries, yield curve data are retrieved from Bloomberg. We use end-of-the-month zero-coupon yields with maturities of 3, 6, 12, 24, 36, 48, 60, 72, 84, 96, and 120 months (a total of 11 maturities).[17]

Oil-related data are from Baumeister and Hamilton (2019), and are available at their websites. Monthly global crude oil production comes from the weekly Oil and Gas Journal for the period January 1958 to December 1972, and from the U.S. Energy Information Administration's (EIA) Monthly Energy Review for the period January 1973 to June 2019.

The measure of global economic activity is the industrial production index for OECD countries and six major non-member economies (Brazil, China, India, Indonesia, the Russian Federation and South Africa), all retrieved from the OECD.

The nominal price of oil (spot) for West Texas Intermediate (WTI) is retrieved from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis[18] and is deflated by the U.S. consumer price index[19], also obtained from the FRED database.

Finally, monthly U.S. crude oil stocks in millions of barrels are available from the EIA. The estimate for global stocks is obtained by multiplying the

[16] A classification based on the country's net trade position in crude oil is provided by the International Energy Agency (IEA), https://www.iea.org.

[17] Table 1 shows the period used for each country.

[18] FRED mnemonic: OILPRICE.

[19] FRED mnemonic: CPIAUCSL (consumer price index for all urban consumers: all items, index 1982-1984 = 100).

U.S. crude oil inventories by the ratio of OECD inventories of crude petroleum and petroleum products to U.S. inventories of petroleum and petroleum products.

4 Results

The results are presented in two parts. Section 4.1 presents the overall model validation. We start by commenting on the performance of the model with respect to the fit of the yield curve for the 15 countries analyzed. We then analyze whether the model-implied risk premia is able to explain the realized excess returns.

Section 4.2 presents the main results of the paper. We analyze the effect of each macroeconomic shock on the bond risk premia of each country. This is done with the use of IRFs, variance decompositions, and a historical decomposition.

4.1 Model validation

4.1.1 Fit of the term structure

Since we analyze 15 countries and include 11 maturities for each country, we fit a total of 165 bonds. For all countries, the model is able to fit the term structure rather well. The maximum standard deviation of the fitting error among the 165 cases equals 32 basis points. The average of these 165 standard deviations is equal to 21 basis points.[20]

This result is not surprising since we include three spanned factors in our yield curve model. There is a vast literature starting with Litterman and Scheinkman (1991) showing that three factors are sufficient to capture most of the variation in US bond yields.[21] The crucial issue is how well our model is able to fit realized excess returns. We turn to this question in the next item.

4.1.2 Realized versus expected excess return

Although we use bonds with maturities ranging from 3 months to 10 years, we illustrate the relation between model-implied risk premia and realized excess returns for bonds with maturities of 2 and 10 years. We show results for holding periods of three and 12 months. This can be seen in Figures 1 to 6.

[20] All the results are available upon request

[21] See also de Jong (2000) and a number of studies that followed.

Above each graph in these figures, we also report the correlation between the series.

Visually, we observe that in many cases the two series follow a similar pattern. The best results are obtained for the group of oil-exporting countries. Particularly, the correlation between the series is the highest for 10-year bonds with a holding period of 12 months (average correlation among the five oil-exporting countries of 63%, with an average R^2 around 40%). The average correlation among the 60 cases presented (15 countries, 2 maturities, and 2 holding periods) is equal to 45%, with an average R^2 of 23%.

4.2 Effect of oil shocks on bond risk premia

4.2.1 Impulse-response functions

We analyze the dynamics of bond risk premia by means of IRFs. This allows us to visualize the response of the risk premium to a one-standard deviation shock to each variable in our structural model (8)-(11). We focus, however, on the first three shocks of our system, i.e. global oil supply, global economic activity, and global oil demand shocks. According to Baumeister and Hamilton (2019), changes in global inventory demand play a minor role in oil price movements.

We divide the 15 countries in our sample in three groups: (*i*) oil-exporting; (*ii*) oil-importing developing, and (*iii*) oil-importing developed countries.[22] Cepni et al. (2022), for example, show how the yield curve of oil-exporting and oil-importing countries respond differently to oil price shocks. For each group of countries, we show IRFs for a holding period of three and 12 months.

The IRFs are presented in Figures 7 to 12 and show the response of the risk premium for a horizon up to 12 months after the shock. Each graph shows two lines. Although we use bonds with maturities ranging from 3 months to 10 years, we illustrate the dynamics of the IRFs for bonds with maturities of 2 and 10 years. The lines, therefore, represent the median response of each bond risk premium to a specific structural shock. Finally, the color of the markers in each line represents the statistical significance of each point: white (less than 67%); grey (between 67% and 95%); and black (above 95%).

Before we analyze the results of each structural shock separately, we make a number of general observations. First, except for shocks to the global economic activity, we expect a different reaction of bond risk premia to the other two structural shocks depending on the country's position on the oil

[22] A classification based on the country's net trade position in crude oil is provided by the International Energy Agency (IEA), https://www.iea.org.

market (net oil-exporter or net oil-importer) and on the pass-through to inflation. Second, as expected, we observe that the risk premia on 10-year bonds are more responsive to all structural shocks than those for 2-year bonds. Third, in 80% of the cases (72 out of the 90 graphs we present), we observe a statistically significant reaction of the risk premium at the 5% level at some forecasting horizon (between 0 and 12 months).

Global oil supply shock: We follow Baumeister and Hamilton (2019) and impose a negative oil supply shock. We expect supply shocks to move oil production and prices in opposite directions. Therefore, we expect a negative oil supply shock to have an instantaneous negative impact on oil production and a positive impact on oil prices. This would benefit oil-exporting countries due to the increase in export revenues and possibly decrease the risk premium on its bonds. We expect the contrary to happen in oil-importing countries.

Korhonen and Ledyaeva (2010), however, point to the presence of indirect effects. Since a jump in oil prices slows down economic growth, oil-importing countries import less from oil-exporting countries. Therefore, the gain in growth from an oil-exporting country is not as large as one could expect.

We find that for net oil-exporting countries (Fig. 7 and 8, first column of graphs), oil supply shocks tend indeed to decrease bond risk premia. When we look at a short holding period (3 months, Fig. 7), we see that this is the case for all countries on impact, except Russia, being significant for Brazil and Norway. Overall, however, the effects are short lived.

Russia seems to be a special case. Oil supply disruptions increase risk premia significantly on impact. This could be a negative reaction to a possible increase in inflation or the consequence of the mentioned indirect effects. Although Korhonen and Ledyaeva (2010) find that Russia benefits from positive oil price shocks, through an increase in GDP, the indirect effects are negative for this country. In any case, three months after the shock, the effect on risk premia is as expected (negative) and statistically significant. We observe a similar pattern for a longer holding period (12 months, Fig. 8).

For oil-importing developing countries (Fig. 9 and 10), most of the statistically significant reactions of the risk premia are negative, running counter to what one would expect. This is the case for Indonesia and South Africa. Turkey presents mixed negative and positive risk premia reactions.

One possible explanation could be the fact that the increase in oil prices are associated with a reduction in short-term interest rates, i.e. a loosening in the monetary policy to counteract the negative impact on economic growth. Such reaction is documented by Ioannidis and Ka (2018) for a group of industrialized countries. They show that oil supply disruptions have a short-lived impact on the slope factor (decrease in the short-term interest rate). This is also observed by Cepni et al. (2022).

Finally, in the case of oil-importing developed countries, for both holding periods (short and long, Fig. 11 and 12, respectively), the reaction of the risk premium is in most cases not statistically significant. Nevertheless, when it is statistically significant it has the expected positive sign. This is the case for Germany, the UK, and the USA. Altogether, the results are in line with Baumeister et al. (2010) who observe very different effects across countries of oil supply shocks.

Global economic activity shock: As mentioned before, we expect a decrease in the risk premia for all countries after a positive shock in the economic activity. For net oil-exporting countries (Fig. 7 and 8, middle column of graphs), this is mostly what we find. For all countries, and again with the exception of Russia, we observe statistically significant negative risk premia on impact and after a few months in some cases. The statistically significant increase in risk premia in the case of Russia is hard to explain.

For net oil-importing developing countries (Fig. 9 and 10), responses to global economic activity shocks are in most cases not significant. We only observe the expected significant negative response of risk premia on impact for India. South Africa presents the expected sign one month after the shock being significant for the 10-year bond. Indonesia, South Africa and Turkey present positive and significant risk premia on impact, which is also hard to rationalize.

Finally, for oil-importing developed economies (Fig. 11 and 12), we observe the expected negative risk premia on impact and after a few months in all cases following an increase in global economic activity. In the case of Japan, however, after 8 months in the case of a three-month holding period and after three months in the case of a 12-month holding period, the effect on risk premia becomes positive.

Global oil demand shock: In the case of net oil-exporting countries (Fig. 7 and 8, right column of graphs), we expect a decrease in bond risk premia following an increase in global oil demand. On impact, this reaction is significant and as expected for Brazil, Mexico, and Norway. It has the wrong sign for Canada and it is not significant for Russia. In the case of Mexico, this reaction becomes positive and significant seven months after the shock for a 12-month holding period.

For net oil-importing developing countries (Fig. 9 and 10), only Indonesia and Turkey present a significant positive bond risk premia on impact (for three-month holding period). In Turkey, nevertheless, the reaction of bond risk premia is mostly negative, in contrast to what we would expect. In general, therefore, the evidence is mixed.

Finally, for net oil-importing developed economies, we expect an increase in bond risk premia following a global oil demand shock. For developed countries (Fig. 11 and 12), the reaction of bond risk premia, nevertheless, are mostly not significant. Only Japan presents a significant expected positive reaction on impact.

In summary: Regarding oil supply shocks, oil-exporting countries exhibit the expected reaction of bond risk premia, i.e. decrease, with Russia as the exception on impact. Oil-importing developing countries mainly exhibit a reaction counter to the expected. And for oil-importing developed countries, the reaction is mainly not statistically significant, but with the expected sign when it is.

With respect to global economic activity shocks, we have somehow a similar story. Oil-exporting countries exhibit the expected reaction of bond risk premia (i.e. decrease), again with the exception of Russia. Oil-importing developing countries present mixed results, with few cases being significant and with the expected sign. Oil-importing developed countries also present the expected negative reaction of bond premia, this time with the exception of Japan with a positive reaction a few months after the shock.

Finally, for global oil demand shocks, in the case of oil-exporting countries we get the expected negative reaction on impact in three out of the five cases. Only for Mexico we get a positive and significant reaction seven months after impact. For oil-importing developing countries bond premia reaction is also mostly not significant, with a few exceptions. Indonesia and Turkey present the expected and significant reaction on impact, and Turkey the opposite sign most of the time. And for oil-importing developed economies the reaction of bond premia are mostly not significant.

4.2.2 Variance decompositions

We now assess the contribution of each shock to the dynamics of bond risk premia making use of variance decompositions. The results are shown in Figures 13 and 14 for a holding period of three and twelve months, respectively. In each of these figures, there are three columns of graphs. The left column includes the oil-exporting countries, the middle column the oil-importing developing countries, and the right column the oil-importing developed countries. Each graph shows the forecasting horizon on the horizontal axis and the variance contribution on the vertical axis. Furthermore, each graph shows three groups of bars for bonds with different maturities. The left group (first three bars) represents the variance decomposition for six-month bonds, the middle group two-year bonds, and the right group 10-year bonds.

For the three-month holding period (Fig. 13), we illustrate a total of 135 cases (15 countries, 3 bonds, and 3 forecasting horizons). In 30% of these cases, the level factor explains most of the variability in bond risk premia, with the slope factor being the most important in 25% of the cases. Including the curvature factor, we have that in 64% of the cases, one of the spanned factor explains most of the variance in bond premia.

For the 12-month holding period (Fig. 14), we show a total of 90 cases (15 countries, 2 bonds, and 3 forecasting horizons). We cannot include six-month bonds since its maturity is shorter than the holding period. In this case, the explanatory power of the spanned factors is even higher. In 94% of the 135 cases shown, one of the spanned factors is the most important factor.

We now focus on the relative importance of the unspanned factors. For the three-month holding period, when one of the unspanned factors is the most important factor, in 40% of the times it is the economic activity factor, with the oil supply factor responsible for 19% of the cases. We have a similar result for the 12-month holding period. When one of the unspanned factors is the most important factor, in 46% of the times it is the economic activity factor, with oil supply and consumption demand accounting each for 11% of the cases.

In summary: In general, the spanned factors explain most of the variability in bond risk premia. Among the unspanned factors, economic activity is the most important in explaining the variance in bond premia.

4.2.3 Historical decomposition

As an illustration of the contribution over time of each structural shock to the total bond risk premia, we perform a historical decomposition of bond risk premia over the initial period of the COVID-19 crisis, from November 2019 to May 2020. We focus on bonds with maturities of 2 and 10 years. We also analyze the effect on bond premia for a holding period of 3 and 12 months. The graphs are presented in Figures 15 to 17.

In each graph we show the following. The long-dashed line represents the total model-implied risk premium. The bars show the contribution of the four different shocks (global oil supply, global economic activity, global oil demand shocks, and global inventory shocks). Finally, the short-dashed line with dots represents the sum of the three structural shocks. The difference between the dots in the short-dashed line and the long-dashed line is due to the shocks to the spanned factors (level, slope and curvature). Note that for each graph we show the evolution of the risk premium starting from zero at the beginning of the period analyzed.

The period analyzed is characterized by a drop of around 70% in the crude oil price. In general, we expect oil price decreases to be detrimental to net oil-exporting countries with an increase in bond premia. In turn, it should benefit net oil-importing countries with a decrease in bond risk premia.

This is exactly what we observe for the group of oil-exporting countries (Fig. 15), except for Russia. In general, it calls the attention the importance of the economic activity factor, in line with the results from our variance decomposition. The results for oil-importing countries, both developing (Fig. 16) and developed (Fig. 17) are less definite. In some cases we observe a clear decrease in bond premia (e.g. Turkey, 10-year bond, 3-month holding period). In other cases, however, we observe a variety of patterns in the dynamics of bond risk premia.

5 Conclusions

We present a methodology to analyze the effect of oil price shocks on bond risk premia. The approach combines the strategy proposed by Baumeister and Hamilton (2019) to identify the different sources of oil price shocks with an affine yield curve model including both spanned and unspanned factors, as in Joslin et al. (2014). The structural factors modelling the global market for crude oil are used as the unspanned factors in the yield curve model. The spanned factors are the usual level, slope and curvature factors.

The model is applied to a total of 15 countries divided in three groups: (*i*) oil-exporting; (*ii*) oil-importing developing; and (*iii*) oil-importing developed countries. We cover the period from 2007 to 2022 and include bond data with maturities ranging from three months to 10 years.

As expected, our specification fits the yield curve of all countries very well. More importantly, our model-implied bond risk premia also explain the realized excess returns satisfactorily.

IRFs show that oil-exporting countries exhibit mostly the expected reaction of bond risk premia to oil supply, global economic activity, and global oil demand shocks. The main exception is Russia for the first two shocks. For oil-importing developed countries, the reaction to economic activity shocks is mainly significant and with the expected sign. The reaction to the other two structural shocks is mostly not statistically significant. Finally, oil-importing developing countries, with a few exceptions, exhibit a reaction of bond risk premia which is either not statistically significant or counter to the expected for the three structural shocks.

In general, the spanned factors explain most of the variability in bond risk premia. Among the unspanned factors, economic activity is the most important factor in explaining the variance in bond premia. Finally, a historical decomposition of the initial COVID-19 crisis shows a variety of patterns in the evolution of the bond risk premia.

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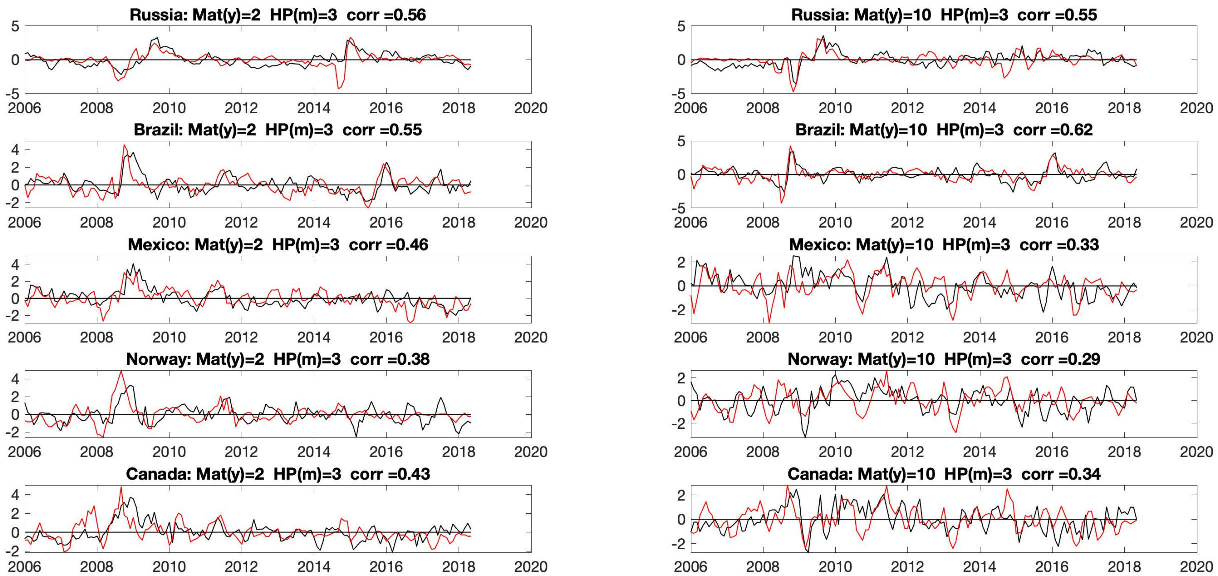
Table 1: Date range for each country

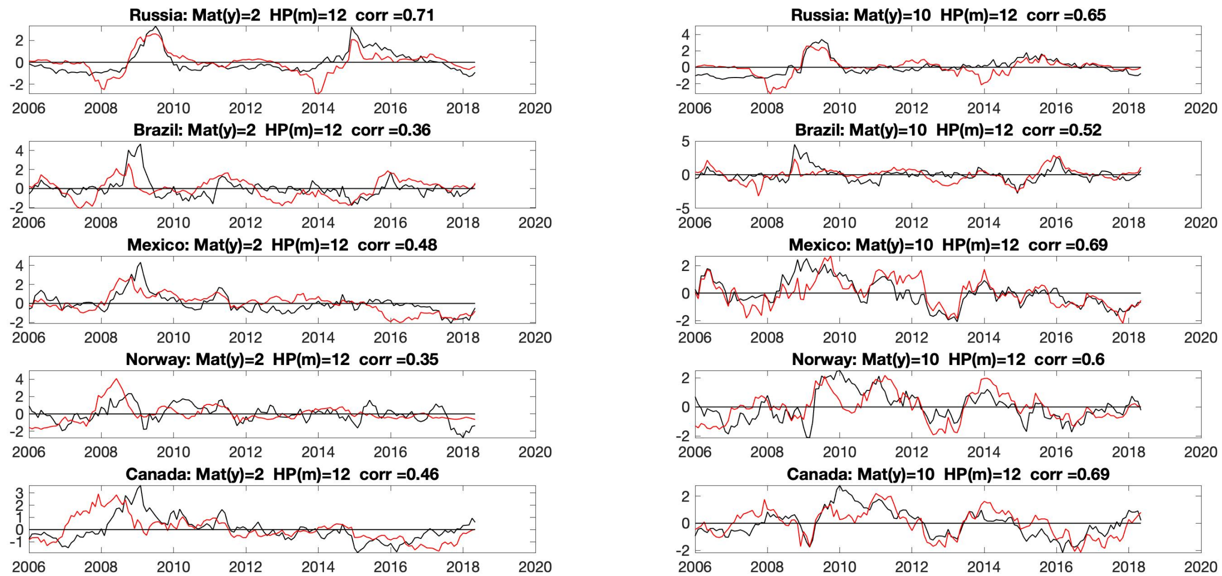
	Start date	End date
Exporting countries		
Brazil	Mar-2007	Apr-2022
Canada	Dec-1994	Apr-2022
Mexico	Sep-2002	Apr-2022
Norway	Jul-1998	Apr-2022
Russia	Jan-2007	Apr-2022
Importing developing countries		
China	Sep-2003	Apr-2022
India	Nov-1998	Apr-2022
Indonesia	Feb-2003	Apr-2022
South Africa	Dec-1994	Apr-2022
Turkey	Apr-2005	Apr-2022
Importing developed countries		
Germany	Oct-1991	Apr-2022
Japan	Apr-1991	Apr-2022
South Korea	Sep-1999	Apr-2022
UK	Dec-1994	Apr-2022
US	Dec-1994	Apr-2022

Figure 1: Realized vs. expected excess returns - Oil-exporting countries, 3-month holding period



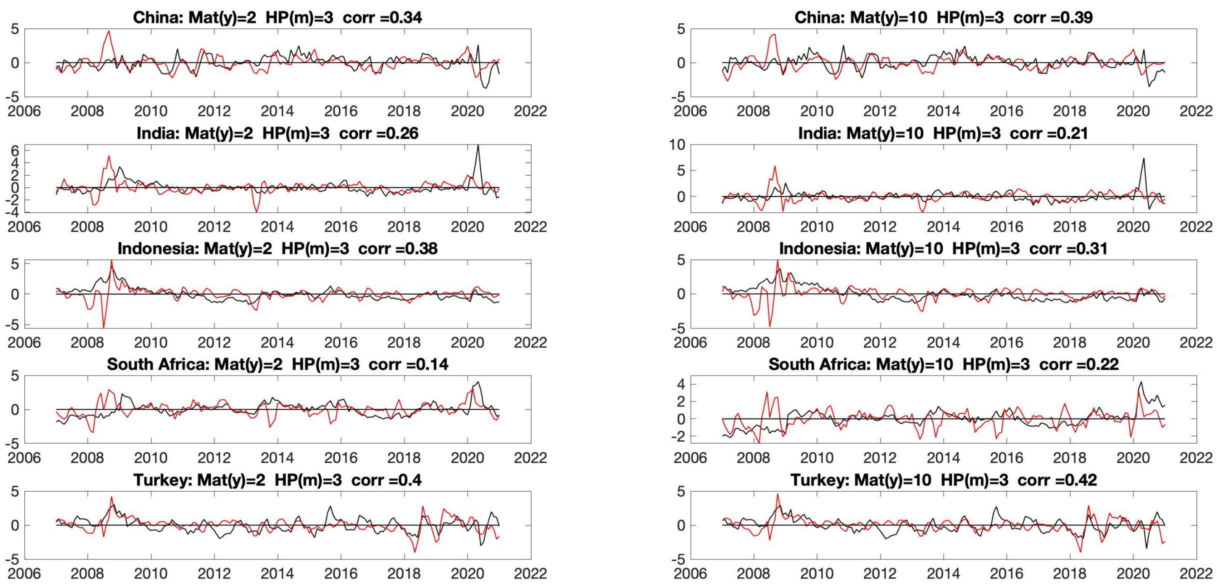
Note: The figure shows the realized (red lines) and expected excess returns (black lines) on 2-year bonds (left column of graphs) and 10-year bonds (right column of graphs) for oil-exporting countries with a holding period of three months.

Figure 2: Realized vs. expected excess returns - Oil-exporting countries, 12-month holding period



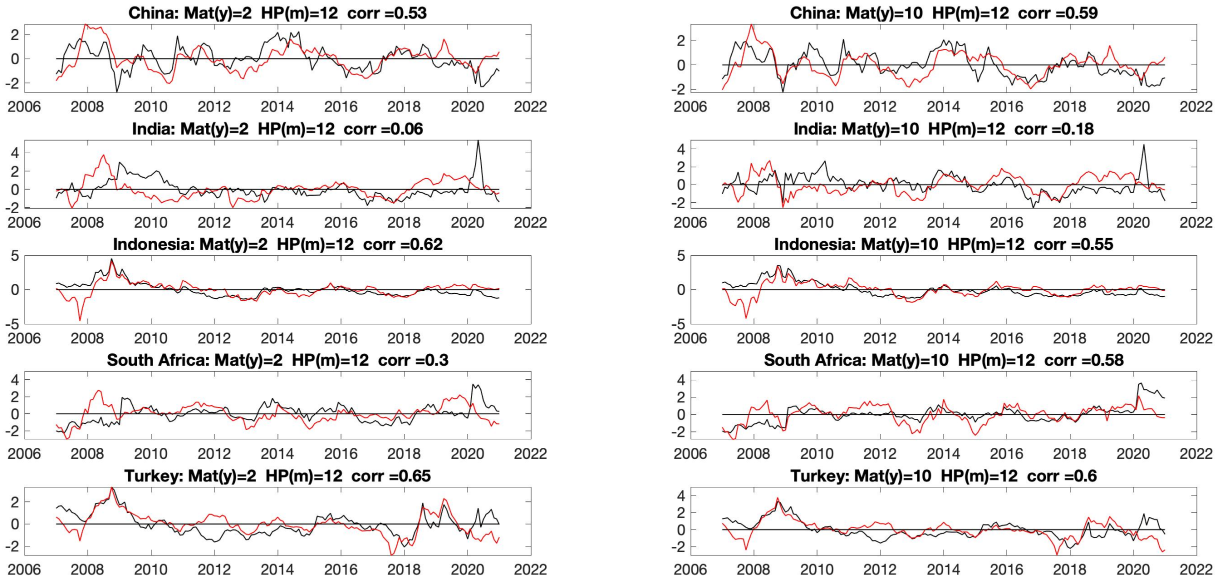
Note: The figure shows the realized (red lines) and expected excess returns (black lines) on 2-year bonds (left column of graphs) and 10-year bonds (right column of graphs) for oil-exporting countries with a holding period of twelve months.

Figure 3: Realized vs. expected excess returns - Oil-importing developing countries, 3-month holding period



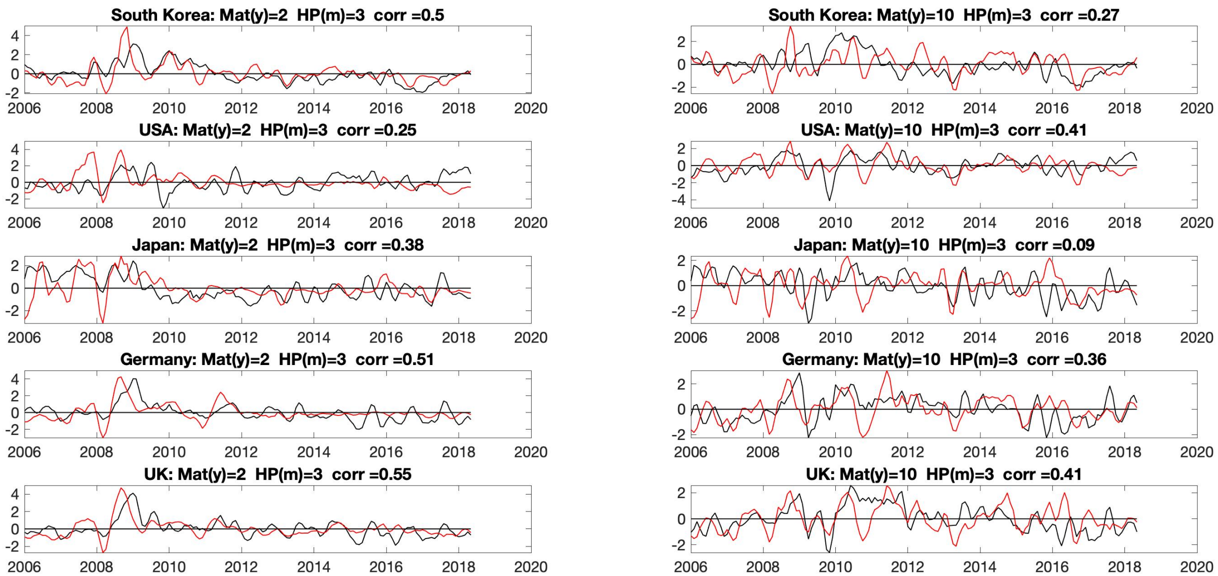
Note: The figure shows the realized (red lines) and expected excess returns (black lines) on 2-year bonds (left column of graphs) and 10-year bonds (right column of graphs) for oil-importing developing countries with a holding period of three months.

Figure 4: Realized vs. expected excess returns - Oil-importing developing countries, 12-month holding period



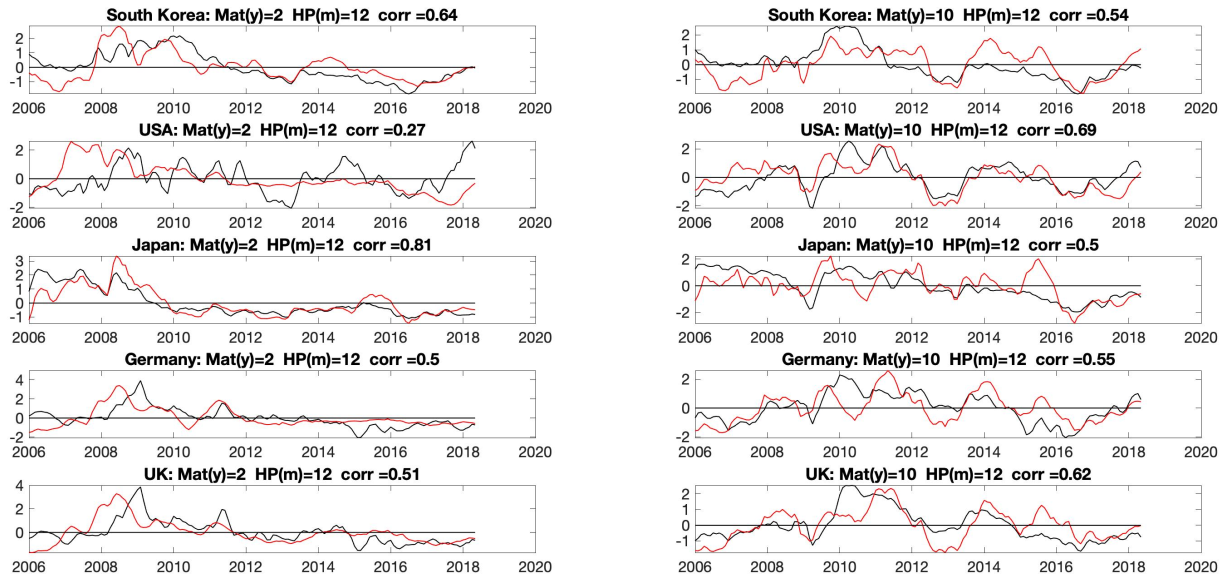
Note: The figure shows the realized (red lines) and expected excess returns (black lines) on 2-year bonds (left column of graphs) and 10-year bonds (right column of graphs) for oil-importing developing countries with a holding period of twelve months.

Figure 5: Realized vs. expected excess returns - Oil-importing developed countries, 3-month holding period



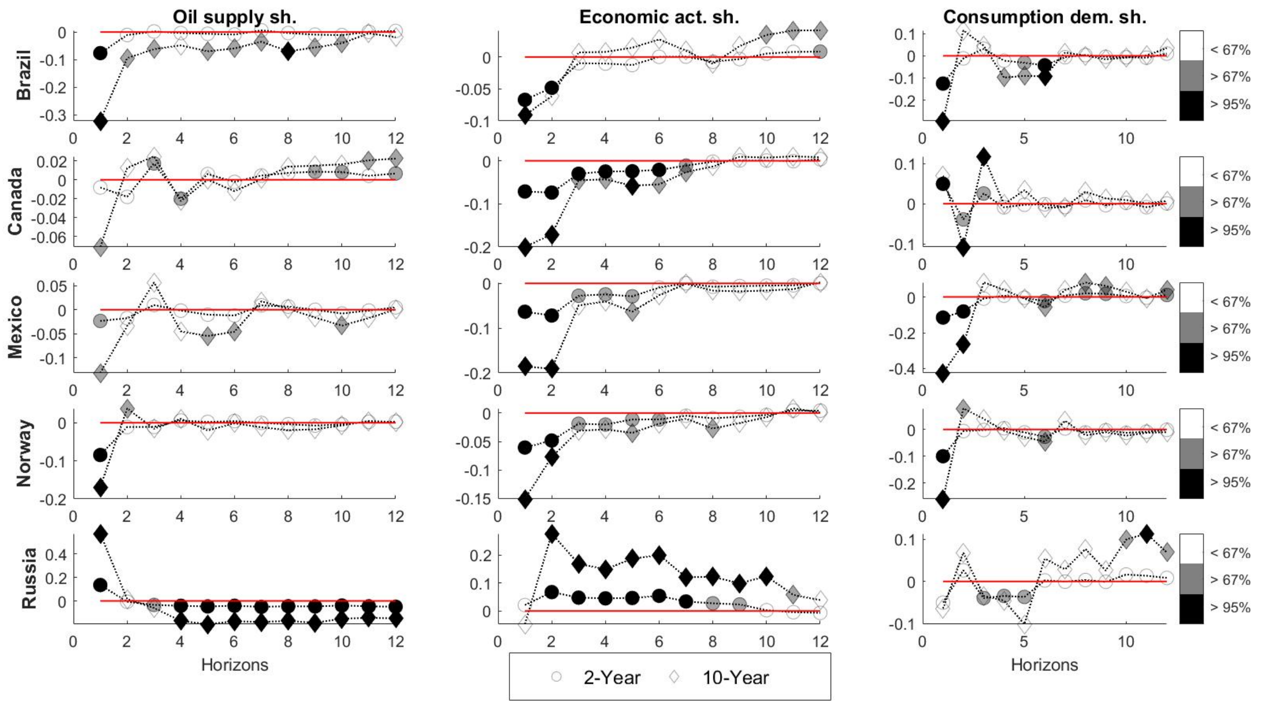
Note: The figure shows the realized (red lines) and expected excess returns (black lines) on 2-year bonds (left column of graphs) and 10-year bonds (right column of graphs) for oil-importing developed countries with a holding period of three months.

Figure 6: Realized vs. expected excess returns - Oil-importing developed countries, 12-month holding period



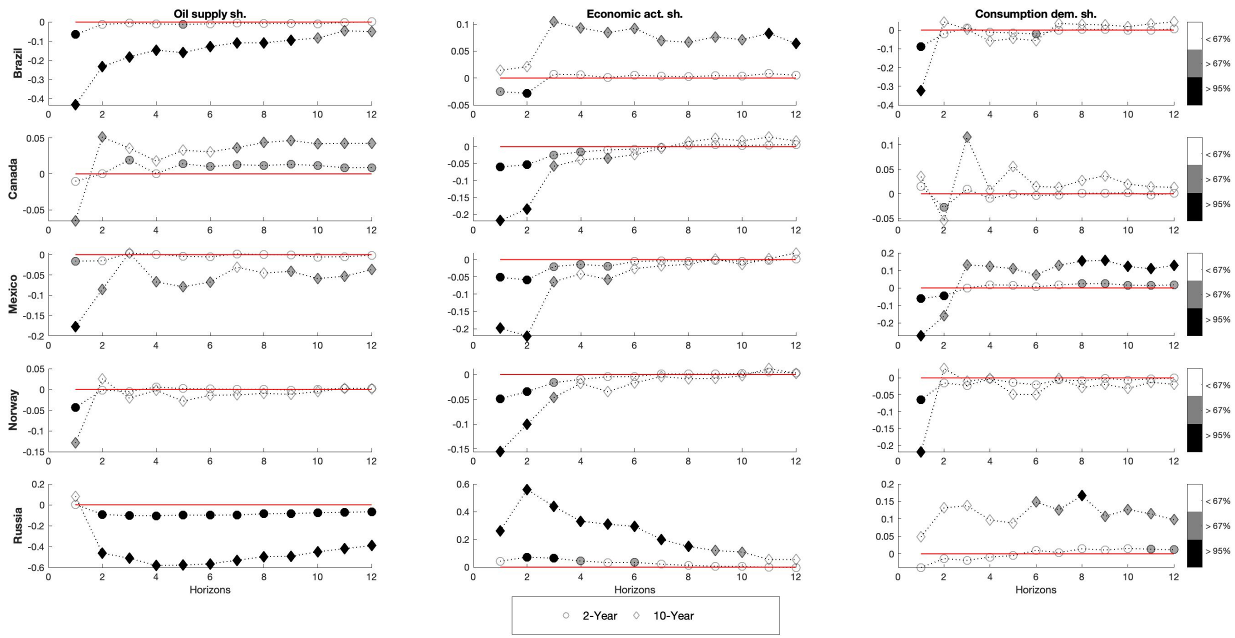
Note: The figure shows the realized (red lines) and expected excess returns (black lines) on 2-year bonds (left column of graphs) and 10-year bonds (right column of graphs) for oil-importing developed countries with a holding period of twelve months.

Figure 7: IRF - Oil-exporting countries, 3-month holding period



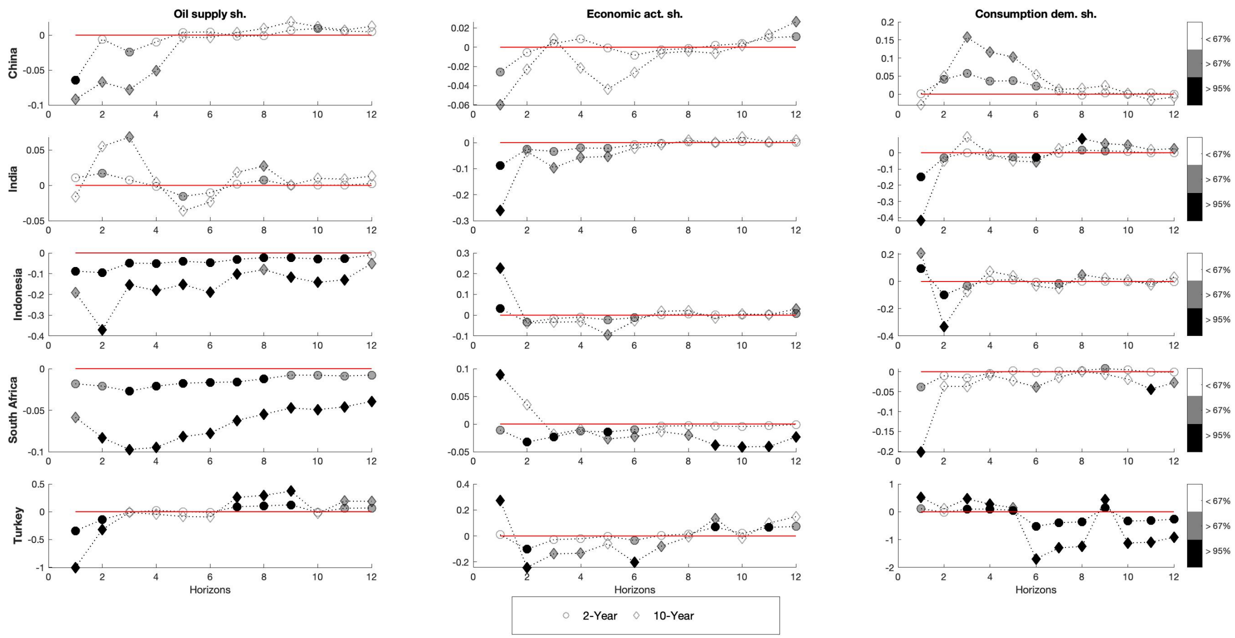
Note: The figure shows the 3-month impulse responses of expected excess return of 2-year bonds (lines with circles) and 10-year bonds (lines with diamonds) on one standard deviation oil supply shock on the left, one standard deviation Economic activity shock in the center and one standard deviation consumption demand shock on the right. The darkness of circles and diamonds shows the significance of the shocks: black represents more than 95% significance, grey is more than 67% and white is less than 67% significance. In the figure, the results are for oil-exporting countries (Brazil, Canada, Mexico, Norway and Russia)

Figure 8: IRF - Oil-exporting countries, 12-month holding period



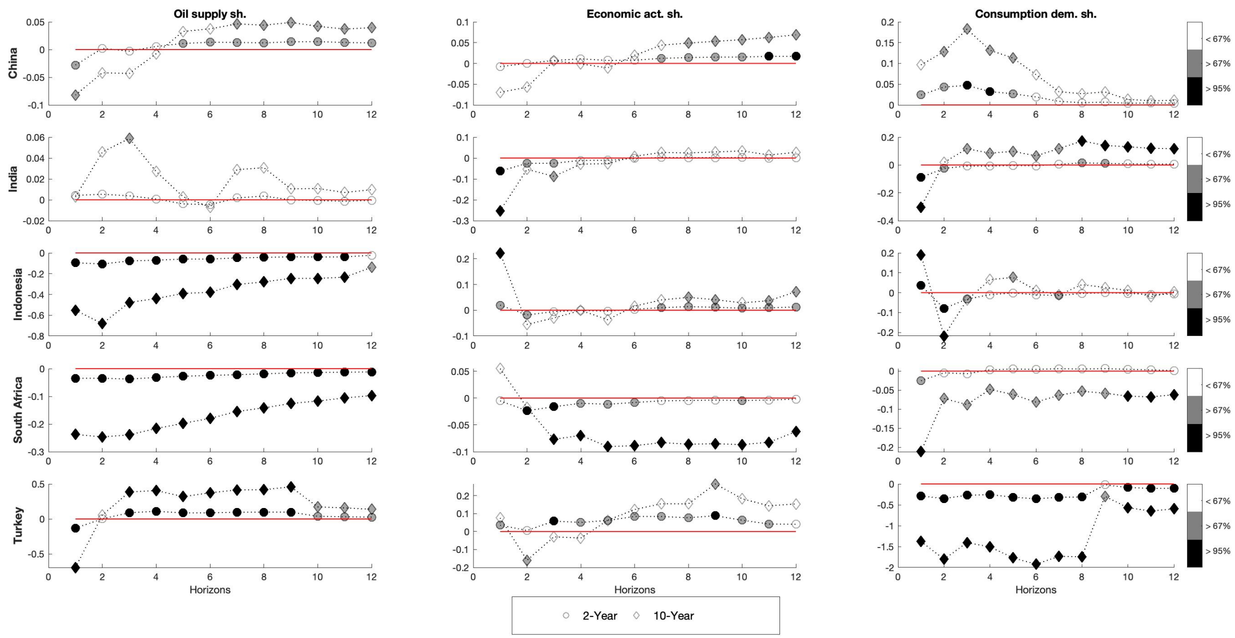
Note: The figure shows the 12-month impulse responses of expected excess return of 2-year bonds (lines with circles) and 10-year bonds (lines with diamonds) on one standard deviation oil supply shock on the left, one standard deviation Economic activity shock in the center and one standard deviation consumption demand shock on the right. The darkness of circles and diamonds shows the significance of the shocks: black represents more than 95% significance, grey is more than 67% and white is less than 67% significance. In the figure, the results are for oil-exporting countries (Brazil, Canada, Mexico, Norway and Russia)

Figure 9: IRF - Oil-importing developing countries, 3-month holding period



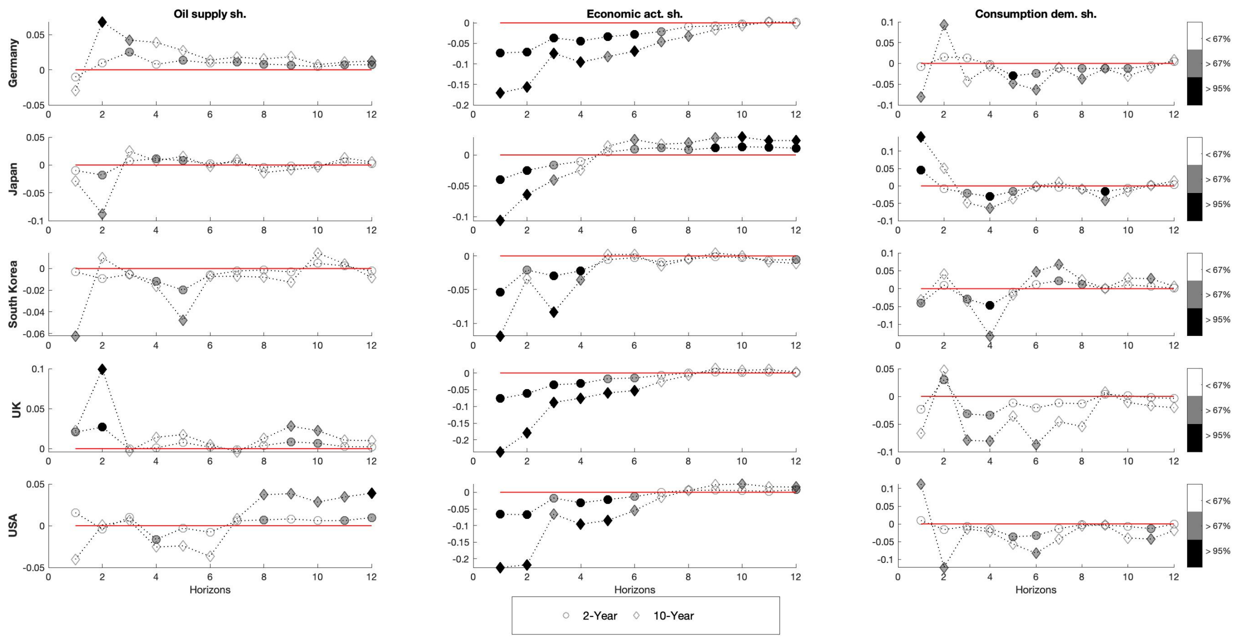
Note: The figure shows the 3-month impulse responses of expected excess return of 2-year bonds (lines with circles) and 10-year bonds (lines with diamonds) on one standard deviation oil supply shock on the left, one standard deviation Economic activity shock in the center and one standard deviation consumption demand shock on the right. The darkness of circles and diamonds shows the significance of the shocks: black represents more than 95% significance, grey is more than 67% and white is less than 67% significance. In the figure, the results are for oil-importing developing countries (China, India, Indonesia, South Africa and Turkey)

Figure 10: IRF - Oil-importing developing countries, 12-month holding period



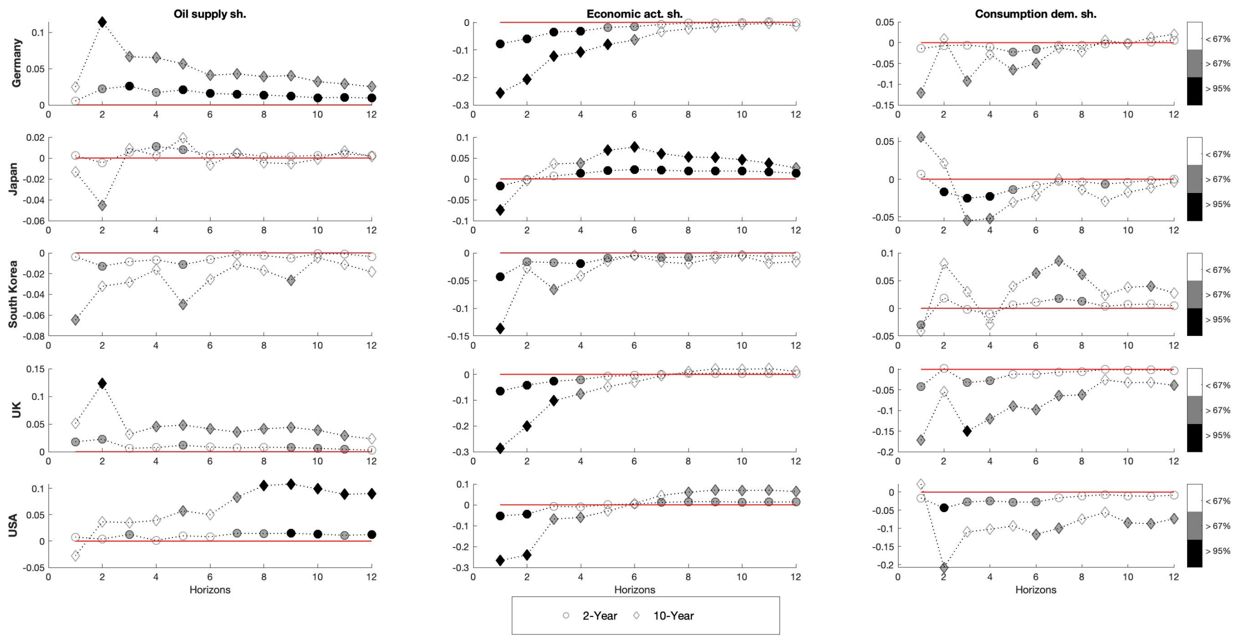
Note: The figure shows the 3-month impulse responses of expected excess return of 2-year bonds (lines with circles) and 10-year bonds (lines with diamonds) on one standard deviation oil supply shock on the left, one standard deviation Economic activity shock in the center and one standard deviation consumption demand shock on the right. The darkness of circles and diamonds shows the significance of the shocks: black represents more than 95% significance, grey is more than 67% and white is less than 67% significance. In the figure, the results are for oil-importing developing countries (China, India, Indonesia, South Africa and Turkey)

Figure 11: IRF - Oil-importing developed countries, 3-month holding period



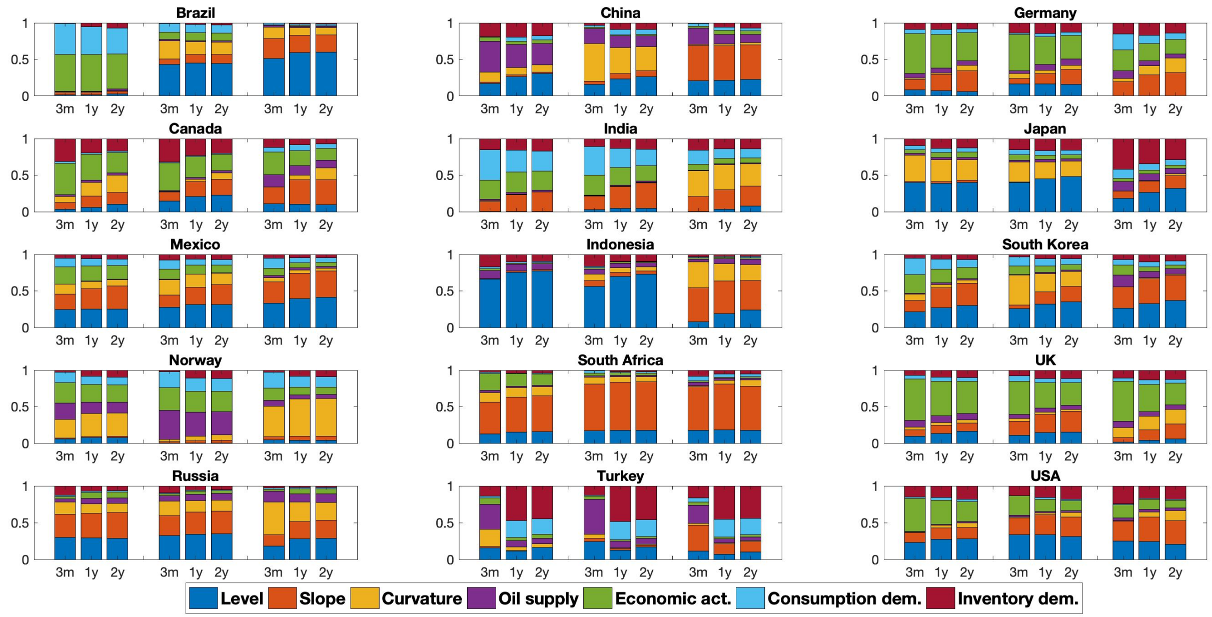
Note: The figure shows the 3-month impulse responses of expected excess return of 2-year bonds (lines with circles) and 10-year bonds (lines with diamonds) on one standard deviation oil supply shock on the left, one standard deviation Economic activity shock in the center and one standard deviation consumption demand shock on the right. The darkness of circles and diamonds shows the significance of the shocks: black represents more than 95% significance, grey is more than 67% and white is less than 67% significance. In the figure, the results are for oil-importing developed countries (Germany, Japan, South Korea, UK and US)

Figure 12: IRF - Oil-importing developed countries, 12-month holding period



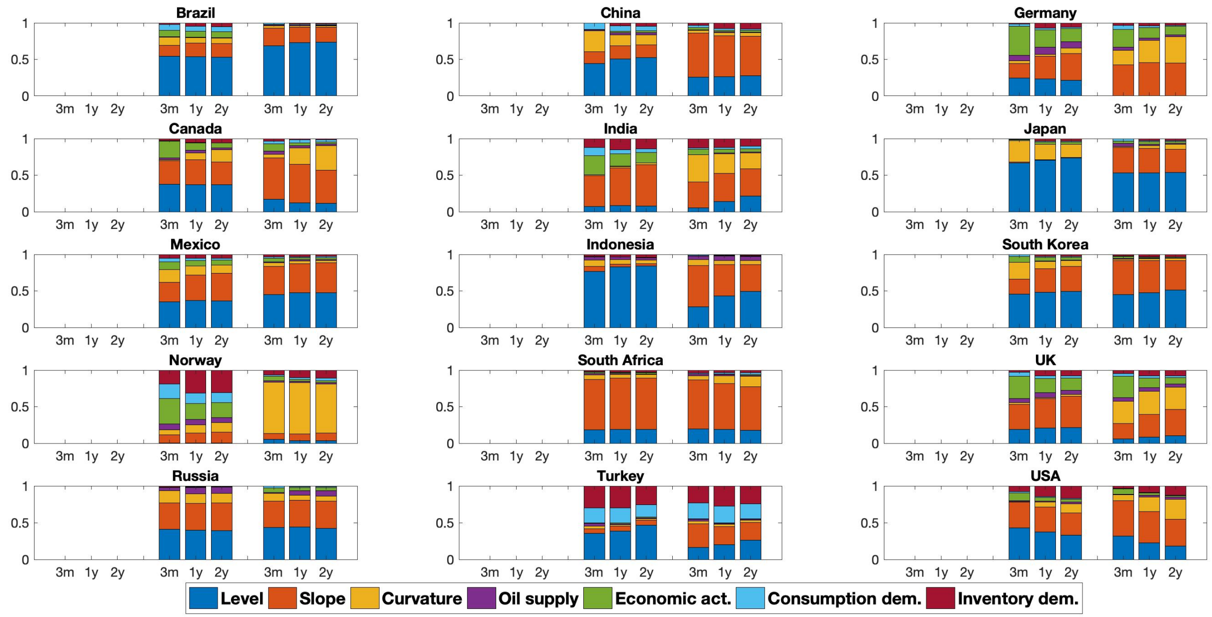
Note: The figure shows the 12-month impulse responses of expected excess return of 2-year bonds (lines with circles) and 10-year bonds (lines with diamonds) on one standard deviation oil supply shock on the left, one standard deviation Economic activity shock in the center and one standard deviation consumption demand shock on the right. The darkness of circles and diamonds shows the significance of the shocks: black represents more than 95% significance, grey is more than 67% and white is less than 67% significance. In the figure, the results are for oil-importing developed countries (Germany, Japan, South Korea, UK and US)

Figure 13: Variance decomposition - 3-month holding period



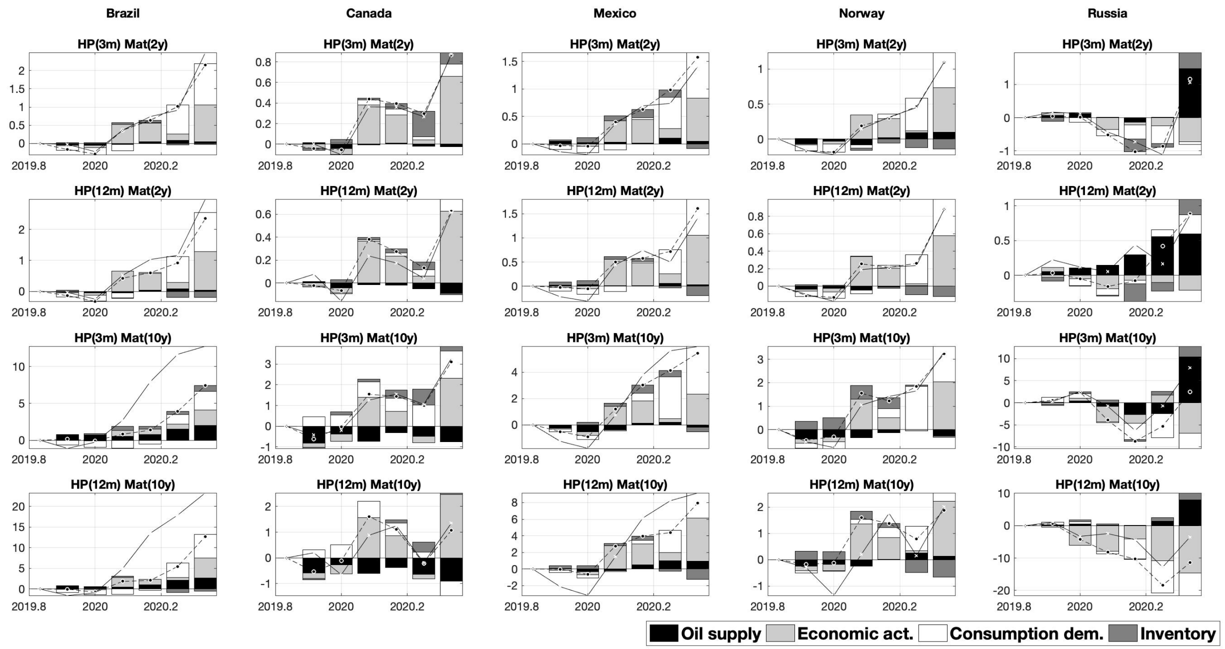
Note: The figure shows the variance decomposition of bond risk premia with 3-month holding period. Each graph shows the forecasting horizon on the horizontal axis and the variance contribution on the vertical axis. Each graph shows three groups of bars for bonds with different maturities. The left group (first three bars) represents the variance decomposition for six-month bonds, the middle group two-year bonds, and the right group 10-year bonds.

Figure 14: Variance decomposition - 12-month holding period



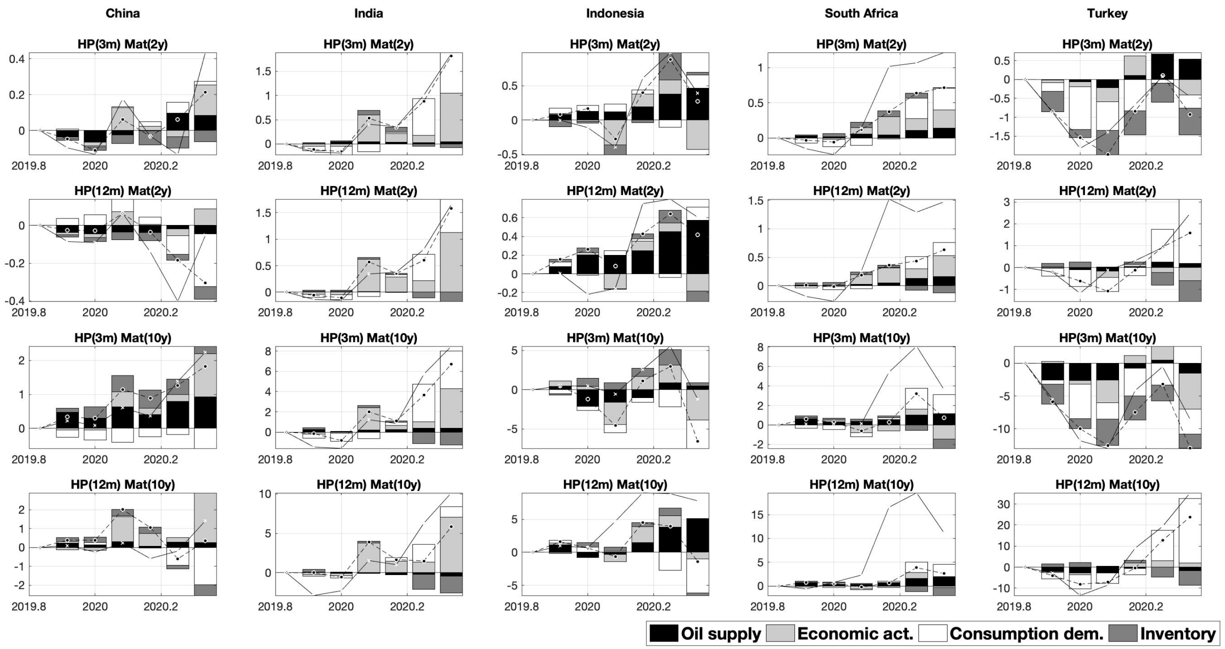
Note: The figure shows the variance decomposition of bond risk premia with 3-month holding period. Each graph shows the forecasting horizon on the horizontal axis and the variance contribution on the vertical axis. Each graph shows three groups of bars for bonds with different maturities. The left group (first three bars) represents the variance decomposition for six-month bonds, the middle group two-year bonds, and the right group 10-year bonds.

Figure 15: Historical Decomposition: Oil-exporting countries



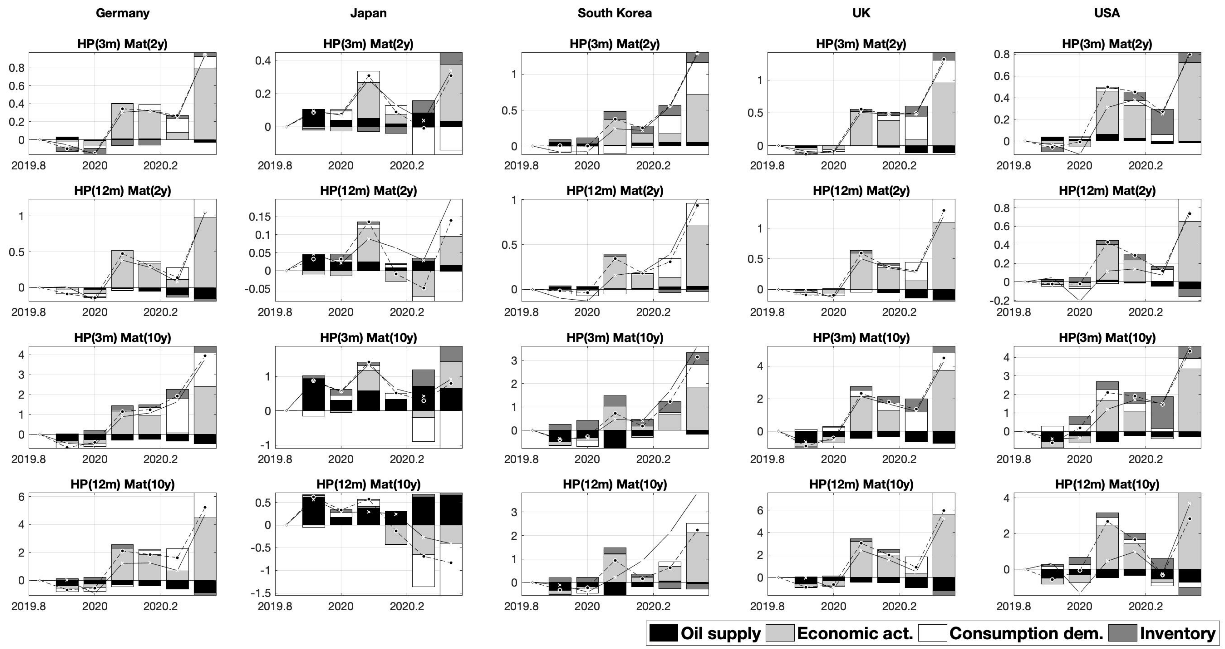
Note: The figure shows the historical decomposition of the bond risk premia of oil-exporting countries for the period between November 2019 and May 2020. The decomposition is done for bonds with maturities of 2 and 10 years and for a holding period of 3 and 12 months. The long-dashed line represents the total model-implied risk premium. The bars show the contribution of the four different shocks (global oil supply, global economic activity, global oil demand, and global inventory demand shocks). Finally, the short-dashed line with dots represents the sum of the three structural shocks. The difference between the dots in the short-dashed line and the long-dashed line is due to the shocks to the spanned factors (level, slope and curvature).

Figure 16: Historical Decomposition: Oil-importing developing countries



Note: The figure shows the historical decomposition of the bond risk premia of oil-importing developing countries for the period between November 2019 and May 2020. The decomposition is done for bonds with maturities of 2 and 10 years and for a holding period of 3 and 12 months. The long-dashed line represents the total model-implied risk premium. The bars show the contribution of the four different shocks (global oil supply, global economic activity, global oil demand, and global inventory demand shocks). Finally, the short-dashed line with dots represents the sum of the three structural shocks. The difference between the dots in the short-dashed line and the long-dashed line is due to the shocks to the spanned factors (level, slope and curvature).

Figure 17: Historical Decomposition: Oil-importing developed countries



Note: The figure shows the historical decomposition of the bond risk premia of oil-importing developed countries for the period between November 2019 and May 2020. The decomposition is done for bonds with maturities of 2 and 10 years and for a holding period of 3 and 12 months. The long-dashed line represents the total model-implied risk premium. The bars show the contribution of the four different shocks (global oil supply, global economic activity, global oil demand, and global inventory demand shocks). Finally, the short-dashed line with dots represents the sum of the three structural shocks. The difference between the dots in the short-dashed line and the long-dashed line is due to the shocks to the spanned factors (level, slope and curvature).