



# Oil price shocks and green bonds: An empirical evidence

Dina Azhgaliyeva<sup>a,\*</sup>, Zhanna Kapsalyamova<sup>b</sup>, Ranjeeta Mishra<sup>c</sup>

<sup>a</sup> Asian Development Bank Institute, Kasumigaseki Building 8F, 3-2-5, Kasumigaseki, Chiyoda-ku, Tokyo 100-6008, Japan

<sup>b</sup> Department of Economics, Nazarbayev University, 53 Kabanbay Batir Ave., Nur-Sultan 010000, Kazakhstan

<sup>c</sup> Reserve Bank of India, Central Office, Shahid Bhagat Singh Road, Fort, Mumbai, Maharashtra - 400001, India

## ARTICLE INFO

### Keywords:

Green bonds  
Sovereign bonds  
Green finance  
Oil shock  
Crude oil price

## ABSTRACT

This paper contributes to the existing literature by investigating the impacts of crude oil price shocks on financial markets through an examination of the effect of oil price shocks on the issuance of corporate green bonds. Green bond issuance has been growing fast over the past several years; despite this, the share of green bonds in the total bonds remains less than 1%. Using the multilevel models, this study investigates the effect of flow oil-supply, flow oil-demand, and speculative oil-demand shocks on (1) probability of the corporate green bond issuance and (2) the share of corporate green bond issuance. We find that flow supply shocks, flow demand shocks and the issuance of sovereign green bonds have a positive and significant effect on the probability of the issuance of corporate green bonds, but shocks have no significant impact on the share of the corporate green bond issuance. The results are robust to alternative specifications of our models.

## 1. Introduction

There is mounting evidence that a growing frequency of extreme events such as heat waves, drought, heavy rainfall events, storms, and hurricanes is linked to human-caused climate change (IPCC, 2021). Limiting global warming to 1.5 °C requires total annual investments of 2.1–4.4 trillion USD2010 on average in energy supply and demand up to 2050 (IPCC, 2018). Financing climate change mitigation and adaptation has been at the forefront of the 2021 United Nations Climate Change Conference (COP26) in Glasgow. Financial instruments, such as green bonds, could play a significant role in confronting climate change. Despite the universal attempts of the governments to create a large green bond market, there are challenges associated with upscaling the green bond market development, such as global oil market shocks due to global events, such as the COVID-19 crisis, technological advancement, war conflicts, etc. (Narayan, 2020). The effects of such shocks on green financial instruments are understudied.

This paper explores the links between crude oil prices and the issuance of corporate green bonds. We build this paper on the ‘CR Model’, the price model by Kanamura (2020) based on the supply and demand of green bond and crude oil and the correlation model, using ‘a structural type model’ framework. If a green bond has value as an environmental asset, then according to the CR Model, a correlation between green bond and crude oil prices should be positive. It is likely that an increase in oil

prices will stimulate renewable energy investment, as there is a tendency to substitute away from crude oil to alternative energy, which should lead to the growth in the issuance of green bonds, especially in oil-importing economies. In turn, a decrease in oil prices should diminish the issuance of green bonds as there is a reduced incentive to promote renewable energy resources and instead continue reliance on available fossil fuels. However, the effect of oil prices on the issuance is an empirical question and it is important to study it from the standpoints of tracing the effects of volatility in oil prices on financial markets, such as green bonds, expanding the market of energy finance, and addressing global environmental challenges. Furthermore, volatility in the oil market could affect investment in green technologies, undermining further the issuance of green bonds.

The literature scrutinizes the implications of crude oil price fluctuations through the lenses of shocks to real prices of oil distinguishing between demand and supply shocks (Clements et al., 2019; Kolodziej and Kaufmann, 2014; Kilian, 2009; Kilian and Murphy, 2014; Kilian and Park, 2009). Given these findings, expanding the analysis to examine the relationship between oil prices and other financial markets is instrumental. Studies on how oil price shocks ripple through the green bonds market are particularly relevant from the perspective of the effects of oil prices on the broader economy and tackling climate change mitigation and adaptation, which require sound investment and financial resources. Green bonds, a recent innovation in sustainable finance, are a

\* Corresponding author.

E-mail addresses: [dazhgaliyeva@adbi.org](mailto:dazhgaliyeva@adbi.org) (D. Azhgaliyeva), [zhanna.kapsalyamova@nu.edu.kz](mailto:zhanna.kapsalyamova@nu.edu.kz) (Z. Kapsalyamova), [ranjeetamishra@rbi.org.in](mailto:ranjeetamishra@rbi.org.in) (R. Mishra).

<https://doi.org/10.1016/j.eneeco.2022.106108>

Received 5 November 2020; Received in revised form 18 April 2022; Accepted 25 May 2022

Available online 31 May 2022

0140-9883/© 2022 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

prominent financial instrument designed to raise capital for green projects. The first green bond was issued by the European Investment Bank (EIB) in 2007, and since then, global capitalization of green bonds reached \$258 billion in 2019, \$282 billion in 2020, and \$611 billion in 2021 (Bloomberg, 2022). However, the green bond market is still in the nascent stage of development, especially in developing countries, with the People's Republic of China, the United States, Germany, France, and the United Kingdom accounting for 50% of the global issuance in 2021 (Bloomberg, 2022).

Following Kilian and Murphy (2014), this study distinguishes between three types of oil shocks such as flow supply shocks, flow demand shocks, and speculative demand shocks. It provides a discussion of the effects of these shocks on the issuance of corporate green bonds using monthly data from 41 green bond-issuing economies across eight sectors from January 2010 to April 2021. The dataset covers both developed and developing economies, both net exporters and net importers of crude oil.

The results suggest that crude oil shock is an important determinant of the probability of the corporate green bond issuance. We find that crude oil flow supply shocks and flow demand shocks have a positive and statistically significant impact on the corporate green bond issuance probability. This result supports the CR Model findings by Kanamura (2020) by demonstrating a positive relationship between crude oil and green bonds. That indicates that green bonds possess the characteristics of environmental assets.

We contribute to the literature by examining the relationship between green bonds and oil price shocks. Previous studies have tackled the effects of oil price shocks on bonds' returns and stock market valuation (Demirer et al., 2020; Reboredo, 2018; Reboredo, Juan and Ugoilini, 2020); however, the studies on the effects of oil price shocks on the issuance of corporate green bonds are limited. To our best knowledge, this paper is the first empirical study to explore the role of oil price shocks on corporate green bond issuance. Our findings hold under two robustness tests: (a) alternate specifications of two independent variables and (b) alternate specifications of the regression model by removing sector-control variables.

The structure of the rest of the paper is as follows. Section 2 reviews the studies on oil price shocks and green investment. Section 3 describes the data. Section 4 explains the methodology. Section 5 discusses the results. Section 6 provides conclusions and policy recommendations.

## 2. Literature review: Oil price shocks

A host of literature studies the effect of oil prices on economic activity and financial markets through the lenses of the response of the variables to exogenous variation in oil prices. Properly defined, such approaches accommodate for reverse causality from macroeconomic variables to oil prices and identify the distinct demand and supply shocks (Kilian, 2009). Kilian (2009) invalidates the assumption of the exogenous nature of the crude oil price and instead attributes a significant role to the sources of oil price fluctuations.

Although there seems to be a consensus on the smaller role of oil supply shocks versus demand shocks (Baumeister and Kilian, 2016), the literature disagrees on the magnitude of the effect of oil supply shocks. Baumeister and Hamilton (2019) prompted to revisit the way prior information is used in structural VAR models of the world oil markets and presented estimates of the effect of oil supply shocks that are substantially larger than in other studies (Kilian, 2009; Kilian and Murphy, 2014). A study by Kolodziej and Kaufmann (2014) tests these outcomes of Kilian (2009) using robustness tests and finds that the results are not robust to alternative specifications. Hamilton (2021) criticizes the study by Kilian (2009) for using the index based on shipping costs as a measure of world real economic activity and proposes an index of global industrial production as a better measure of world economic activity than the Kilian index (Kolodziej and Kaufmann, 2014).

Herrera and Rangaraju (2020) re-estimated the key seminal

structural VAR models for the global oil market (Baumeister and Hamilton, 2019; Baumeister and Peersman, 2013; Kilian, 2009; Kilian and Murphy, 2012, 2014; Lippi and Nobili, 2012) and found that if priors are conditioned on the basis of microeconomic evidence, the response of the real oil prices is closer to the original findings of Kilian (2009) and Kilian and Murphy (2014). Similarly, Kim and Vera (2019) revisit Kilian's (2009) findings by expanding the dataset to include the period through 2015. They also find that aggregate demand shocks and oil-market specific demand shocks have the most significant impact on the U.S. output and prices as compared to oil supply shocks. Kilian and Zhou (2020b) confirm the findings of Kilian and Murphy (2014) by modeling shocks to the U.S. Strategic Petroleum Reserve.

Baumeister and Hamilton (2022) question the approach that relies on estimated elasticities in sign-restricted vector autoregressions used by different studies, such as Basher et al. (2018), Herrera and Rangaraju (2020), Kilian and Murphy (2014), and Zhou (2020). The disagreement stems from the values of the short-run oil supply elasticity used in their studies. Kilian and Murphy (2014) use a cutoff for short-run oil supply elasticity of 0.0258. Zhou (2020) assumes 0.04 as an upper bound for the oil supply elasticity, while Baumeister and Hamilton (2020) do not impose a strict upper bound. Instead they apply a continuous distribution that assigns a lower probability to a larger value of the elasticity. In general, the studies agree that oil demand shocks are the dominant shocks, though Baumeister and Hamilton (2020) attribute a somewhat larger role to the supply shocks compared to other studies. The most recent study by Zhou (2020) demonstrates that the revisions and extensions of the model do not qualitatively change the conclusions of Kilian and Murphy (2014). Kilian (2022) reviews the approaches used to derive oil supply and oil demand elasticities used in structural VAR models of the global oil market and explains why some of these approaches lead to controversial estimates. Kilian (2022) confirms earlier findings that a one-month oil supply elasticity is close to zero and hence oil demand shocks are the primary driver of the real price of oil.

Despite the ongoing controversy in the literature, Kilian and Murphy's (2014) structural vector autoregressive (SVAR) model of the global oil market remains the workhorse model largely due to the introduction of the role of expectations via modeling storage demand (Zhou, 2020). Expectations about the future oil supply or news about oil discoveries are not observed in the historical data rendering traditional VAR models invalid to capture these effects. While expectations of a future oil supply shortfall relative to the future oil demand could be modeled through the changes in the demand for above-ground oil inventories and the real price of oil. The shock is deemed as a speculative demand shock for crude oil. Given the structural nature of Kilian and Murphy's (2014) model, we can use it to generate oil-market shocks.

A study by Ready (2018) proposes another decomposition method to classify changes in oil prices into three shocks, such as supply, demand, and risk shocks based on the VIX index. He finds that most of the variation is due to the supply shocks that account for 78% of the variation and demand shocks that account for 21%. Clements et al. (2019) examine three variations of the identification scheme of Ready (2018) and find that Ready's (2018) definition of VIX-based risk shocks leads to biased results for the aggregate demand-driven oil shocks in the model. The decomposition scheme of Ready (2018) tends to overestimate the supply shocks as a major source of variation in oil prices. Clements et al. (2019) find that including precautionary demand shock in the model significantly reduces variation in oil prices due to the supply shock and increases the role of demand shocks. Overall, they point towards a higher significance of the aggregate demand shocks as compared to what was previously defined.

The studies that look at the implications of oil price shocks on bonds and green investment are not extensive. Pertinent studies examine the connectedness of green investments, renewable energy consumption, bonds, and oil price shocks (Kang et al., 2014; Apergis and Payne, 2015; Shah et al., 2018; Dutta et al., 2020; Kanamura, 2020). Dutta et al. (2020), in their study on green investments, find that oil market

volatility affects green assets more than fluctuations in oil prices. [Shah et al. \(2018\)](#) find a positive and significant effect of oil price shocks on renewable energy investment in the U.S. and Norway and a negative and small effect in the UK. [Apergis and Payne \(2015\)](#) determine that real oil prices have a positive effect on renewable energy consumption using data for 11 South American countries from 1980 to 2010.

[Kang et al. \(2014\)](#) conclude that oil-related demand and supply shocks jointly contribute 30.6% of the variation in the US bond index real returns in the long run. Demand shocks play a significant role in the long-run variation of the Treasury bill returns. An oil price increase due to the uptake in the global aggregate demand reduces the bond market returns over 24 months. [Kanamura's \(2020\)](#) recent study investigates the dynamic correlations between green bond prices and oil prices. It finds positive correlations between green bond returns and crude oil price returns, suggesting green bonds have greenness features. However, to the best of our knowledge, it is the only study to have investigated the relationship between green bond returns and oil prices. No studies so far have considered the effects of oil price shocks on corporate green bond issuance, though the former are likely to influence the latter. Our study contributes to this strand of the literature by examining the impact of three oil shocks — flow supply, flow demand, and speculative demand shocks — on the issuance of corporate green bonds.

### 3. Data

We use monthly data from 41 green bond-issuing economies across eight sectors over the period January 2010 to April 2021 ([Table 1](#)). We do not cover the period before 2010 since the annual issuance of green bonds was below US \$1 billion with only three issuers ([Fig. 1](#)). The data are collected mainly from the Bloomberg terminal, the World Bank, and the International Energy Agency (IEA). We adopt the sector classification from the Bloomberg Industry Classification System for Fixed Income (BICS), which includes the following corporate green bond issuing sectors: financials, utilities, industrials, consumer discretionary and staples, energy, materials, technology, and communications ([Fig. 2](#)). Nearly 80% of green bonds are issued by two sectors, financials (48%) and utilities (29%) ([Fig. 2](#)). [Tables A1, A3](#) in [Appendix A](#) present the summary statistics and correlation matrix.

**Table 1**  
Variables.

Variables	Country-level (i)	Sector level (j)	Month-level (t)	Notation
Corporate green bond issuance, share in total corporate bonds	✓	✓	✓	$\frac{B_{ijt}^{GP}}{B_{ijt}}$
Sovereign green bond issuance, share in total sovereign bonds	✓		✓	$\frac{B_{it}^{GS}}{B_{it}^S}$
Sovereign conventional bonds, log	✓		✓	$B_{it}^{CS}$
Index of industrial production	✓		✓	$IIP_{it}$
Inflation	✓		✓	$CPI_{it}$
Flow supply shock			✓	$\epsilon_t^{flow\ supply}$
Flow demand shock			✓	$\epsilon_t^{flow\ demand}$
Speculative demand shock			✓	$\epsilon_t^{speculative\ demand}$
Exporter	✓			$X_i$
Developed	✓			$D_i$

Source: Authors' elaboration.

The bonds are considered 'green' if they use the proceeds for green projects ([CBI, 2016](#)). Specifically, we use a definition of green bonds by [Bloomberg \(2022\)](#), which expresses green bonds as "instruments for which the proceeds are exclusively applied (either by specifying use of proceeds, direct project exposure, or securitization) towards new and existing green projects, defined as projects and activities that promote climate or other environmental sustainability purposes".

#### 3.1. Crude oil market shocks

To identify oil price shocks, we use monthly data from January 1974 to October 2021. Following [Kilian and Murphy \(2014\)](#), global crude oil production is extracted from the *Monthly Energy Review* by the Energy Information Agency. Crude oil production is expressed in percent changes. The real price of oil is measured as demeaned log difference between the U.S. crude oil imported acquisition cost by refiners and the U.S. consumer price index (CPI). Data for CPI are obtained from the U.S. Bureau of Labor Statistics database. We use an updated index of global real economic activity proposed by [Kilian \(2019\)](#), which represents a proxy for the volume of shipping in global industrial commodity markets. Data for the Kilian index are sourced from the Federal Reserve Bank of Dallas database. Following [Kilian and Murphy \(2014\)](#), we calculate the inventory proxy as a product of the U.S. crude oil inventories by the ratio of OECD to the U.S. petroleum stocks. This ratio ranges from 2.22 to 2.61, which is similar to [Baumeister and Hamilton \(2019\)](#), [Herrera and Rangaraju \(2020\)](#), [Kilian and Murphy \(2014\)](#). The resulting proxy is expressed in changes.

### 4. Methodology

We apply a two-stage approach developed by [Kilian \(2009\)](#) while using the structural model of the global oil market, following [Kilian and Murphy \(2014\)](#), to identify the oil-market shocks in the first stage. In the second stage, we estimate the impact of shocks on the issuance of corporate green bonds using multilevel methods. Alternatively, a structural VAR (SVAR) model of the oil market could have been extended to include the green bonds issuance data. However, as green bonds issuance data are available for a shorter period, mainly starting from 2010 we rely on the SVAR approach to identify the oil price shocks, which are further used to estimate their impact on the issuance of green bonds. [Kilian and Zhou \(2020a\)](#) support the application of the two-stage regression model when the variable of interest is not available for the entire estimation period. In such cases, it is feasible to recover the oil market shocks from the SVAR model that use long-time series data and estimate the impacts of the shocks on the variables of interest using a shorter sample. Estimating a structural model of the oil market requires long time series ([Kilian and Zhou, 2020a](#)), such as the dataset we use for our analysis, which spans from 1974 to 2021.

#### 4.1. SVAR model

SVAR model is specified as follows:

$$B_0 y_t = B(L) y_{t-1} + \epsilon_t, \quad (1)$$

where  $y_t$  is a vector of four variables, such as global oil production (in percent changes), Kilian index, demeaned real price of oil, and changes in global oil inventories.  $\epsilon_t$  is a vector of orthogonal structural innovations. The first shock is the 'flow supply shock' that arises due to the oil supply disruptions as a result of political events in oil-rich countries; the second shock is the 'flow demand shock' due to the global business cycle fluctuations; the third shock is the 'speculative demand shock' due

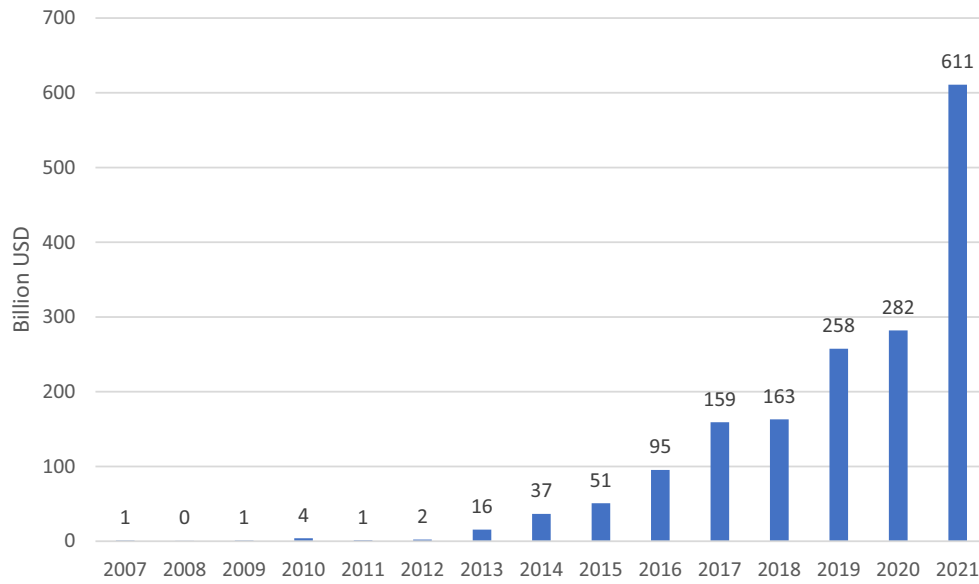


Fig. 1. Annual issuance of green bonds (not accumulated). Source: own elaboration using data from Bloomberg (2022).

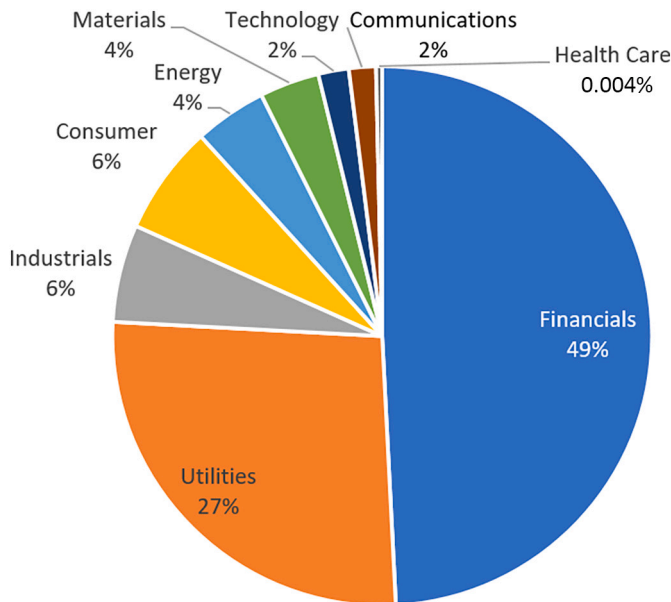


Fig. 2. Issuance of green bonds by sector (excluding government) over the period 2010–2021. Source: own elaboration using data from Bloomberg (2022). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

to the shift in the above-ground oil inventories demand; and final, the fourth shock is the residual idiosyncratic demand shock due to changes in weather, technology, preferences (Kilian and Murphy, 2014).

The reduced-form VAR model is:

$$y_t = B_0^{-1}B(L)y_{t-1} + e_t. \quad (2)$$

The identifying sign restrictions are imposed following Kilian and Murphy (2014):

$$e_t = \begin{pmatrix} e_t^{\text{oil production}} \\ e_t^{\text{real activity}} \\ e_t^{\text{real price of oil}} \\ e_t^{\text{inventories}} \end{pmatrix} = \begin{bmatrix} - & + & + & b_{14}^0 \\ - & + & - & b_{24}^0 \\ + & + & + & b_{34}^0 \\ & & + & b_{44}^0 \end{bmatrix} \begin{pmatrix} e_t^{\text{flow supply}} \\ e_t^{\text{flow demand}} \\ e_t^{\text{speculative demand}} \\ e_t^{\text{residual}} \end{pmatrix} \quad (3)$$

In addition to the sign restrictions, following Kilian and Murphy (2014) the bounds of 0.025, and -0.8 are imposed on the impact price elasticity of oil supply and impact price elasticity of oil demand, respectively. Another restriction is related to the dynamic response of the real price of oil to a negative flow supply shock that is bound to be positive for at least 12 months. Structural impulse responses are estimated using Bayesian methods. Gaussian-inverse Wishart prior distribution for the reduced-form VAR parameters and a Haar distribution for the rotation matrix are adopted. The model is retained if all implied impulse response functions satisfy the identifying restrictions; while the model is discarded if a set of a priori restrictions on the implied impulse response functions are not satisfied.

#### 4.2. Multilevel models

Corporate green bonds are not necessarily issued every month in every sector, therefore the data tend to contain many zero values. Also corporate green bond issuance varies considerably across sectors. To exploit the unique nature of the data we create a dependent variable as a binary variable that takes a value of zero if no corporate green bonds are issued in a given month, and it is set equal to one if the outcome of the dependent variable is above zero. Further, we apply the multilevel probit model to accommodate for a sector-wise clustered nature of the dependent variable. To estimate robust standard errors, we allow for intragroup correlation at the sectoral level. We specify the probit model as the following:

$$P(d_{ijt} = 1) = \alpha + \beta_1 e_t^{\text{flow supply shock}} + \beta_2 e_t^{\text{flow demand shock}} + \beta_3 e_t^{\text{speculative demand shock}} + \beta' Z_{ijt} + \nu_j + \omega_{ijt},$$



$$d_{b_{ijt}} = \begin{cases} 1 & \text{if } B_{ijt}^{GP} > 0 \\ 0 & \text{if } B_{ijt}^{GP} = 0 \end{cases} \quad (4)$$

where,  $d_{b_{ijt}}$  represents a binary variable that takes the value of one if  $B_{ijt}^{GP}$ , corporate green bond issuance per month across sectors and countries is positive and zero otherwise.  $i = 1, \dots, 41$  indexes economies,  $j = 1, \dots, 8$  indexes sectors, and  $t = \text{Jan 2010}, \dots, \text{Apr 2021}$ <sup>1</sup>.  $Z_{ijt}$  represent a set of control variables explained in Table 1 and below.  $v_j$  is the random intercept for sector  $j$ , and  $\omega_{ijt}$  is a random error term.

Second, we adopt a multilevel model (Laird and Fitzmaurice, 2013) to study the effects of oil-market shocks on the issuance of corporate green bonds using a sub-sample of the dataset for which the issuance of green bonds is different from zero. The multilevel model also accounts for cross-sector and longitudinal effects (Skrondal and Rabe-Hesketh, 2008). The baseline random-intercept model has the following specification:

$$\frac{B_{ijt}^{GP}}{B_{ijt}} = \alpha + \beta_1 e_t^{\text{flow supply shock}} + \beta_2 e_t^{\text{flow demand shock}} + \beta_3 e_t^{\text{speculative demand shock}} + \beta' Z_{ijt} + \phi_j + \varepsilon_{ijt}. \quad (5)$$

Explanatory variables are the same as in equation (4) and explained below.  $\phi_j$  is the random intercept for sector  $j$ . The error terms,  $\phi_j$  and  $\varepsilon_{ijt}$  are assumed to have zero means and are mutually uncorrelated (Skrondal and Rabe-Hesketh, 2008),  $\phi_j \sim N(0, \sigma_\phi^2)$ , and  $\varepsilon_{ijt} \sim N(0, \sigma_\varepsilon^2)$ .

The structural oil-market shocks follow orthogonality conditions by construction (Kilian and Murphy, 2014). However, whether they are orthogonal to the green bond issuance depends on how VAR is specified (Basher et al., 2018). In Kilian and Murphy's (2014) model, the main three shocks are explicitly identified, and the idiosyncratic shocks are implicitly identified since they account for all residual influences. Basher et al. (2018) in their study of the effects of the oil-market shocks on stock returns state that the estimates from the second-stage regression are consistent "as long as the shocks are at least predetermined variables with respect to unexpected changes in stock returns, so that there is no feedback from excess stock returns to the shocks within the month". We follow the standard convention, according to which oil-market shocks are predetermined to other macroeconomic and financial variables (Basher et al., 2018; Kilian, 2009). Hence, we allow green bond issuance to respond contemporaneously to structural oil-market shocks. We can do it as it is unlikely that the shocks to green bonds issuance would affect global oil production, global real economic activity, global speculative oil demand, and global real oil prices within a month because bond issuance and labeling bonds 'green' takes some time. Also, given that the shocks from the first-stage regression are generated regressors, estimates of the standard errors of the coefficients may be inconsistent; however, that is largely dependent on the model specification (Basher et al., 2018). Since our second-stage regression does not include lags of the shocks, following Basher et al. (2018), the standard errors should be consistent (Pagan, 1984).

Other than oil shocks, the list of explanatory variables includes the issuance of sovereign green bonds, issuance of sovereign conventional bonds, consumer price index, index of industrial production, dummy variables related to exporting of crude oil and macroeconomic development level, and sector and country control binary variables.

We measure the issuance of *sovereign green bonds*, the value of green bonds that governments issue monthly across economies, as a share in government-issued total (green and non-green, i.e. conventional) bonds. Sovereign green bonds include bonds that governments issue and have the label "green." We could treat the government issuance of green

bonds as a government measure for supporting green bond issuance by corporates. The government issuance of green bonds provides liquidity and initial market product pipelines (Azhgaliyeva et al., 2020). This variable captures the conducive policy environment favoring green bonds.

The issuance of *sovereign conventional bonds* is measured as a log of value of the monthly issuance of conventional bonds by governments across economies. We use it as a measure of the size of the bond market.

The *index of industrial production* (IIP) is an index that shows the growth rates in different industry groups of the economy, calculated monthly. IIP measures changes in industrial production and is widely used for observation and analysis of the current economic activity. This data is collected from the World Bank's Global Economic Monitor portal. As our dependent variable is at a monthly frequency, IIP as an indicator of economic activities suits the model better than GDP, released quarterly. In the model, we included the log transformation of actual IIP.

*Inflation* is measured as a consumer price index (CPI) from the World Bank's Global Economic Monitor portal that accounts for the general price movements in the economies. This variable is also collected on a monthly frequency. Including CPI in the model controls for the overall macroeconomic environment in the economies.

The *exporter* is a binary variable that equals one if the country's net crude oil exports are positive and zero otherwise. We also controlled for the development level of a country with a binary variable *developed* that equals one if the country is developed and zero otherwise. These variables control for differences between different types of economies. Most of the major green bond issuing economies are developed (Fig. 3). Although Demirer et al. (2020) show no difference in the impact of oil shocks on financial markets in importing/exporting and advanced/emerging countries, such countries might have different attitudes, risks, and costs for issuing green bonds. The issuance of green bonds in developed or oil net-importing economies might be more attractive due to greater support for green projects, more stable currency exchange rates, more issuers with a higher Moody's risk rating, the greater value of reputation as a responsible investor, or experience in issuing green bonds.

As our panel data have a clustered nature, i.e., green bonds issued by different sectors within different economies, we apply the random-intercept models to allow the overall level of response to vary

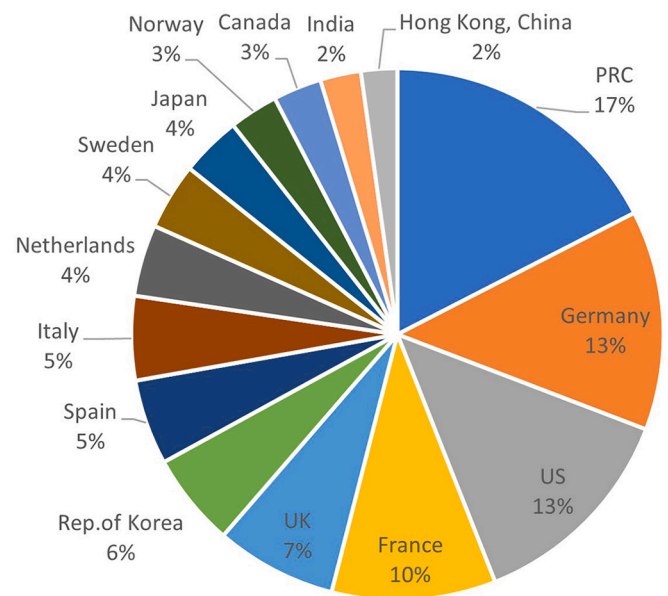


Fig. 3. Top 15 green bond issuing economies in 2021. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

<sup>1</sup> Since the healthcare sector in our dataset issues only sovereign green bonds and no corporate green bonds, we don't include it as a sectoral control variable in the model. The model includes only 8 sectors in the analysis.

**Table 2**

Test results.

Test	Null hypothesis (H0)	Alternative hypothesis (H1)	$\chi^2$	Prob > $\chi^2$	Result
Likelihood-ratio test	RI1	RI2	715.57***	0.00	RI2
Likelihood-ratio test	RI2	RIRC UC	0.59	0.74	RI2

Note: RI—random intercept; RIRC—random intercept and random coefficient; UC—unstructured covariance. Source: Authors' own elaboration.

between clusters or levels after controlling for explanatory variables (Skrondal and Rabe-Hesketh, 2008). It may also be the case that the slope coefficients (covariates) may vary between levels. Random intercept and random coefficient models allow the effects of explanatory variables to differ between levels (Skrondal and Rabe-Hesketh, 2008). We investigate that by including a random coefficient of country's net oil exporting status. As we do not assume any structure of the covariance matrix between random effects, we use the parsimonious form, i.e., unstructured covariance matrix. We test three multilevel models: two random intercept models (RI1 and RI2), and random intercept and random coefficients with unstructured covariance (RIRC UC) using the likelihood ratio (LR) test (see Table 2 for the test results).  $LR = -2(L_r - L_u)$ , where  $L_r$  and  $L_u$  are the maximized log-likelihood values from the restricted and unrestricted models, respectively (Green, 2012). First, we test the random intercept models, RI1 and RI2, for the presence of the sector/country controls. We reject RI1 model in favor of the RI2 model, which includes the dummy controls. Secondly, we test whether the

random slope is needed in addition to the random intercept. Based on the results of the test, RIRC UC model is rejected in favor of the RI2 model (Table 2).

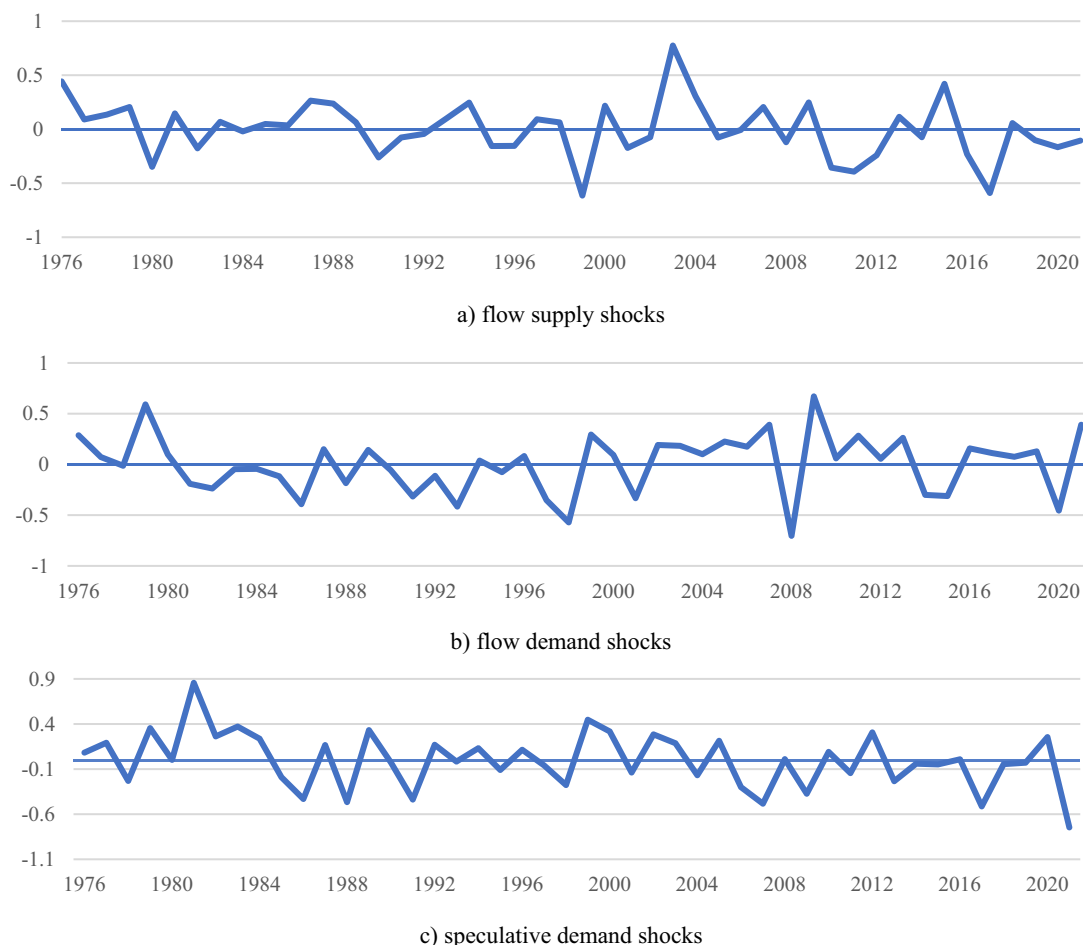
## 5. Empirical results and discussion

### 5.1. Crude oil shocks

Table A2 presents summary statistics of the variables used in the SVAR model and the flow supply, flow demand, and speculative demand shocks. Shocks have zero mean and the same standard deviation. Fig. 4 plots structural shocks of the crude oil market from February 1976 – to October 2021. The values are presented at an annual frequency as annual averages of the monthly structural shocks for each particular year.

Fig. 5 shows the response of the real price of oil to the shocks. Following Kilian and Murphy (2014), all shocks are normalized to represent an increase in the real price of oil. In general, the results are consistent with the findings of Kilian and Murphy (2014). The real price of oil increases in response to the flow supply shock. However, after one year real price of oil subsides below its starting level. The response of the real price of oil to the flow demand shock is considerably larger as compared to the other shocks. Similar to Kilian and Murphy (2014), the flow demand shock generates a persistent rise in the real price of oil. However, a speculative demand shock does not generate overshooting in the real price of oil, though it leads to a persistent increase in the price of oil.

Like in Kilian and Murphy (2014), the cumulative contribution of the flow demand shock on the real price of oil is larger compared to the

**Fig. 4.** Structural crude oil market shocks.

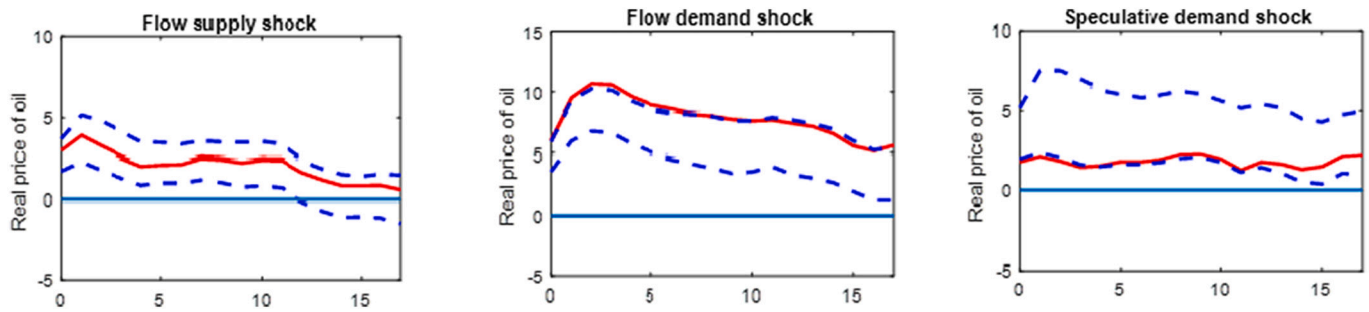


Fig. 5. Structural impulse responses of the real price of oil. Notes: Solid lines indicate the impulse response estimates. Dashed lines indicate the pointwise 68% posterior error bands.

contribution of the cumulative effect of flow supply shock and speculative demand shock.

## 5.2. Main results

We present the results for the multilevel models in Table 3 and Table 4. The dependent variable in the probit model (Table 3) is the probability of issuing corporate green bonds (a binary variable that equals one if green bonds are issued and zero otherwise). The dependent variable in the multilevel model (Table 4) is the market share of corporate green bonds, i.e., share of corporate green bonds in total corporate bonds. The main results of the random-intercept model, which

Table 3  
Multilevel probit model results.

Dependent variable: corporate green bond issuance (0 or 1)	Probit model
Sovereign green bond issuance, share in total sovereign bonds	0.031*** (0.006)
Sovereign conventional bond issuance, log	0.022 (0.016)
Consumer price index	0.005*** (0.0009)
Index of industrial production, log	0.328*** (0.034)
Sector (Reference: financial)	
• utility	−0.302*** (0.002)
• industrial	−0.716*** (0.007)
• consumer	−0.970*** (0.006)
• energy	−0.930*** (0.006)
• material	−1.280*** (0.009)
• technology	−1.721*** (0.015)
• communication	−1.929*** (0.019)
Oil exporter	0.002 (0.078)
Developed country	0.498*** (0.165)
Flow supply shock	0.025*** (0.007)
Flow demand shock	0.019* (0.011)
Speculative demand shock	0.013 (0.012)
Constant	−10.486*** (0.590)
Observations	38,624
Number of sectors	8

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Robust standard errors in parentheses.

the tests in Section 4.2 identified as the preferred model, are presented in column (2) of Table 4. For a robustness check, Table 4 also contains the results from other models: random intercept with no country/sector controls (column 1) and random intercept and random coefficient with unstructured covariance (column 3).

Our results suggest that flow supply and flow demand shocks are essential determinants of the probability of corporate green bond issuance (Table 3), mainly due to changes in oil production and changes in real economic activity. However, neither flow supply nor flow demand shocks are significant determinants of the market size of corporate green bonds (Table 4).

Table 4  
Multilevel model results.

Dependent variable: corporate green bond issuance, share in total corporate bonds	RI1 (1)	RI2 (2)	RIRC UC (3)
Sovereign green bond issuance, share in total sovereign bonds	−0.07 (0.08)	−0.02 (0.06)	−0.02 (0.06)
Sovereign conventional bond issuance, log	−2.89*** (0.19)	−3.84*** (0.21)	−3.85*** (0.21)
Index of industrial production, log	1.54*** (0.32)	−1.44 (2.28)	−1.38 (2.28)
Developed country	1.84*** (0.53)	6.83** (2.70)	6.93** (2.70)
Oil exporter	1.92*** (0.51)	19.07** (8.01)	18.95** (8.01)
Flow supply shock	−0.04 (0.16)	0.03 (0.12)	0.03 (0.12)
Flow demand shock	0.04 (0.16)	0.14 (0.12)	0.14 (0.12)
Speculative demand shock	0.11 (0.20)	0.18 (0.15)	0.18 (0.15)
Sector (reference: financial)			
• utility		1.39*** (0.39)	1.41*** (0.39)
• industrial		0.14 (0.51)	0.14 (0.51)
• consumer		−0.06 (0.64)	−0.05 (0.64)
• energy		−0.22 (0.59)	−0.22 (0.59)
• material		0.56 (0.88)	0.53 (0.88)
• technology		1.55 (1.44)	1.52 (1.44)
• communication		1.80 (2.02)	1.83 (2.02)
Countries	No	Yes	Yes
Constant	33.96*** (4.81)	119.23** (52.95)	118.12** (52.91)
Observations	1098	1098	1098
Number of sectors	8	8	8

Note: \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Standard errors in parentheses. RI—random intercept, RIRC—random intercept random coefficient, UC—unstructured covariance.

### 5.2.1. Crude oil flow supply shock

We find that crude oil flow supply shocks have a positive and statistically significant, at a 1% level of significance, impact on the probability of the corporate green bond issuance (Table 3). Although, to our best knowledge the literature has not assessed the impact of supply shocks on green bonds, it shows the positive impact of crude oil supply shocks on the stock returns of clean energy corporations (Zhao, 2020), and the positive impact of oil price shocks on renewable energy investment in net-oil importing economies (Shah et al., 2018). Disruption in crude oil supply that leads to the rise in the crude oil price stimulates adoption of clean energy and hence has a positive effect on stock returns of clean energy corporations (Zhao, 2020). That in turn might increase the issuance of corporate green bonds. On the other hand, the literature that does not separate the impact on the green financial market (Cunado and Perez de Gracia, 2014; Demirer et al., 2020) shows mainly the negative impact of the oil supply shock on stock returns. The literature suggests that the impact of an oil supply shock on the green market is opposite to the impact of an oil supply shock on the non-green financial market. The majority of the economies that we included in the sample are net oil-importing nations, and hence the positive impact of oil supply shocks on the probability of the corporate green bond issuance is not surprising.

### 5.2.2. Crude oil flow demand shock

We observe that crude oil flow demand shocks have a positive and statistically significant, at a 10% level of significance, impact on the probability of the corporate green bond issuance (Table 3). The pertinent studies on the financial markets predict a positive impact on stock market returns (Kilian and Park, 2009; Wang et al., 2013; Zhu et al., 2017; Basher et al., 2018; Ready, 2018; Demirer et al., 2020), a positive impact on clean energy stock returns of oil demand shock due to the increase in the aggregate economic activity (Zhao, 2020); mainly a negative impact of oil demand shocks on bond returns 'due to substitution effects as rising oil prices caused by global aggregate demand shocks drive positive sentiment and risk appetite in financial markets, thus leading to fund outflows from the bond market into riskier equities' (Demirer et al., 2020:7); with some insignificant impact of oil demand shocks on bond returns in a few countries (Demirer et al., 2020:7).

### 5.2.3. Sovereign green bonds

Examining the role of policy support in green bond issuance, we observe that the market share of sovereign green bonds, i.e., the percentage of issuance of sovereign green bonds in total sovereign bonds, has a positive and significant effect, at a 1% level of significance, on the probability of the green bond issuance by corporates (Table 3). This result is consistent with Dittmar (2008), who showed that sovereign bonds promote the corporate bond market in emerging economies. This result is expected because the issuance of green bonds promotes the demand for green bonds by engaging investors and educating them about green bonds (Azhgaliyeva et al., 2020). The public issuance of green bonds sets an example, acts as a benchmark, and guides the other sectors to issue green bonds. Though, the market share of sovereign green bonds increases the probability of corporate green bond issuance, we find that it is not a significant determinant of the market share of corporate green bonds (Table 4).

### 5.2.4. Oil exporter

We find that net exporting countries of crude oil have no statistically significant difference in the probability of corporate green bond issuance with net oil importing economies (Table 3). Demirer et al. (2020) also show that the impact on sovereign bonds of crude oil shocks does not depend on whether a country is an importer or exporter of crude oil. Crude oil prices encompass expectations regarding global growth and do not merely reflect imported/exported fuel (Demirer et al., 2020).

### 5.2.5. Developed

We find that developed economies are more likely to issue green bonds, at a 1% level of statistical significance, (Table 3) and are more likely to have a greater market share of green bonds, at a 5% level of statistical significance (column 2 of Table 4), than developing economies.

### 5.2.6. Sector

We included sector binary variables to control for sector-specific effects that could affect green bond issuance, such as policies supporting green projects for specific sectors (i.e., feed-in tariffs for renewable energy generators), experience with green projects, and other relevant knowledge and information. The results show that industry-specific factors are important determinants of the probability of the corporate green bond issuance (Table 3) and the market share of green bonds (Table 4).

The financial sector is more likely to issue green bonds than the rest of the sectors (excluding the government), at a 1% level of significance (Table 3). The sector is the most significant predictor of the green bond issuance probability. This result is not surprising because the financial sector is the largest green bond issuer in most economies (Fig. 6). Nearly 1/3 of green bonds are issued by the financial sector (31% in 2020 and 33% in 2021), and similarly nearly 1/3 of green bonds are issued by the government (33% in 2020 and 2021), followed by utilities – nearly 1/5 of green bonds (20% in 2020 and 16% in 2021) (Fig. 6).

Utilities have a larger market share of green bonds than other sectors at a 1% level of significance (Table 4). This result is also not surprising. Although utilities issue less green bonds than financial or government sectors, utilities have the largest share of green bonds in total bonds issued by utilities. 9-15% of all bonds issued by utilities are green, i.e., 9.01% in 2020 and 14.81% in 2021 (Fig. 7). For comparison, the global share of green bond issuance in total bonds is less than 1% (0.42% in 2019 and 0.52% in 2020).

### 5.3. Robustness checks

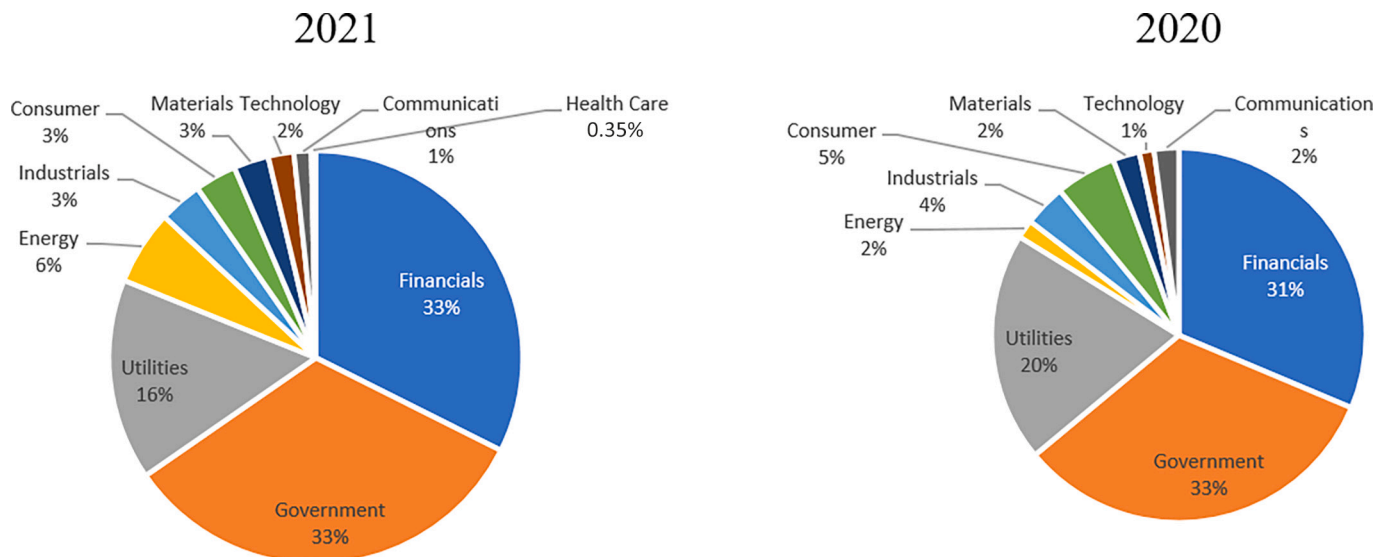
This section tests the robustness of our key results. We test whether the findings regarding oil price shocks' effect on corporate green bond issuance are robust to (a) alternate specifications of two independent variables and (b) alternate specifications of the regression model by removing sector control variables. We check the robustness of our results by replacing two independent variables: (i) the share of sovereign green bonds in total sovereign bonds with the ratio of sovereign green bonds to sovereign conventional bonds; and (ii) sovereign conventional bond issuance with sovereign total bond issuance. Table B1 in Appendix B reports the results obtained using (a) alternative measures of two independent variables and (b) alternate specifications of the regression model by removing sector control variables are consistent with our main results. The models provide coefficients of most variables with the same significance and sign.

## 6. Conclusion and policy recommendations

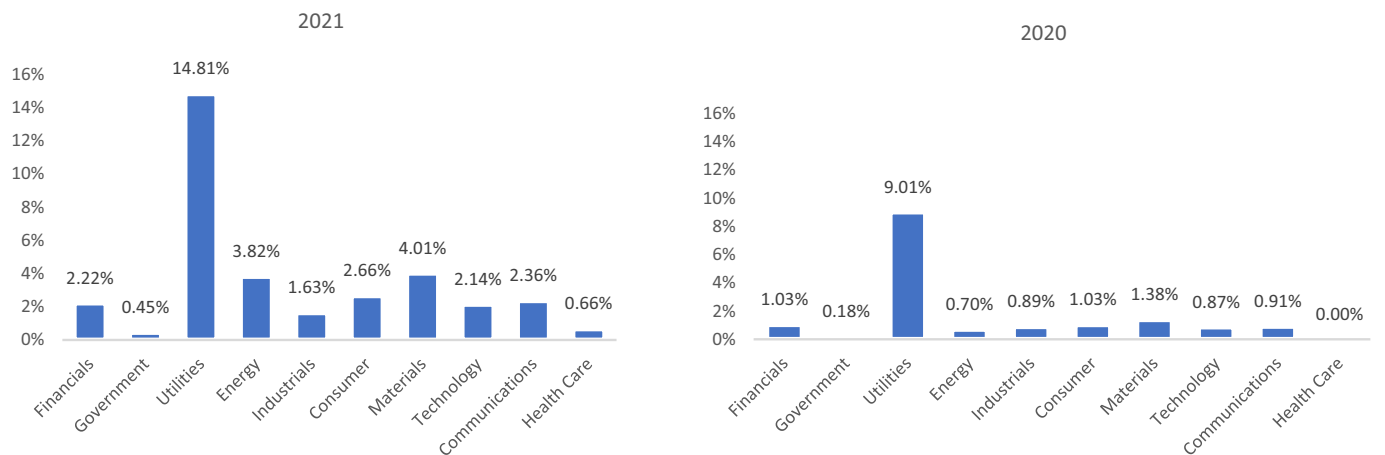
Using monthly data from 41 green bond-issuing economies across eight sectors over the period January 2010 to April 2021 and oil market shocks following Kilian and Murphy (2014), this study utilizes multi-level models to estimate the impact of crude oil shocks and sovereign green bond issuance on corporate green bond issuance. We reach the following three conclusions.

Firstly, our results suggest that flow supply and flow demand shocks are important determinants of the probability of corporate green bond issuance. However, neither of the shocks is a significant determinant of the market size of corporate green bonds. The impact of an oil supply shock on the green market is opposite to the impact on the non-green financial market. This positive impact of the flow supply shock and flow demand shock on green bonds demonstrates that green bonds





**Fig. 6.** Issuance of green bonds by sector. Source: own elaboration using data from Bloomberg (2022). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).



**Fig. 7.** Issuance of green bonds as a share in total bonds by sector. Source: own elaboration using data from Bloomberg (2022). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

possess the characteristics of the environmental assets.

Secondly, we observe that the market share of sovereign green bonds, i.e., the share of issuance of sovereign green bonds in total sovereign bonds, has a positive impact on the probability of green bond issuance by corporates. The public issuance of green bonds demonstrates the existence of the demand for green bonds and increases liquidity by expanding the supply of green bonds. The market share of sovereign green bonds is not a significant determinant of the market share of corporate green bonds. The issuance of green bonds by governments can incentivize other sectors to issue green bonds, although it is not a good predictor for the market share of green bonds, but rather a predictor for the probability of green bond issuance by corporates. This shows the importance of government support and the need for policies that reduce the costs and risks of green bond issuance, especially for first-time issuers.

Thirdly, the results show that industry-specific factors are important determinants of both the probability of the green bond issuance and the market share of green bonds. The financial sector is more likely to issue green bonds than the other sectors. This result is not surprising because the financial sector is the largest green bond issuing sector (excluding the government) in most economies. Utilities have a larger market share

of green bonds than other sectors. Although utilities issue fewer green bonds than financial or government sectors, utilities have the largest share of green bonds in total bonds.

#### CRediT authorship contribution statement

**Dina Azhgaliyeva:** Conceptualization, Methodology, Data curation, Visualization, Supervision, Formal analysis, Writing – original draft, Writing – review & editing, Project administration. **Zhanna Kapsalyanova:** Conceptualization, Methodology, Data curation, Visualization, Formal analysis, Writing – original draft, Writing – review & editing. **Ranjeeta Mishra:** Conceptualization, Methodology, Data curation, Validation, Formal analysis, Writing – original draft, Writing – review & editing.

#### Disclaimer

The views and opinions expressed in this article are those of the authors and do not necessarily reflect the views of the organisations they represent.

## Acknowledgements

We thank Somnath Sharma of Reserve Bank of India, for his technical support in this paper. We are grateful to the guest editor Paresh Kumar Narayan, Marek Weretka from the University of Wisconsin-Madison,

three anonymous reviewers, and conference participants at the BELT & ROAD FORUM: The 5th International Energy & Finance Conference 2020 on 26 September 2020 for their valuable comments and suggestions.

## Appendix A

**Table A1**

Summary statistics.

Variable	Obs	Mean	Std. dev.	Min	Max
Corporate green bond issuance, share in total corporate bonds	38.624	0.027	0.163	0	1
Sovereign green bond issuance, share in total sovereign bonds	38.624	0.127	1.575	0	66.167
Sovereign conventional bond issuance, log	38.624	22.847	2.262	9.408	28.957
Sovereign green bonds to sovereign conventional bonds ratio, in %	38.624	0.174	3.240	0	195.568
Sovereign total bond issuance, log	38.624	22.848	2.263	9.408	28.957
Consumer price index	38.624	116.081	24.295	96.994	279.209
Index of industrial production, log	38.624	23.330	1.388	19.685	27.093
Oil exporter	38.624	0.246	0.430	0	1
Developed country	38.624	0.540	0.498	0	1
Flow supply shock	38.624	-0.143	1.071	-6.633	3.124
Flow demand shock	38.624	0.024	1.098	-3.139	3.505
Speculative demand shock	38.624	-0.032	0.981	-2.422	2.573

**Table A2**

Summary statistics for generating crude oil price shocks.

Variable	Obs	Mean	Std. Dev.	Min	Max
Change in global production of oil	585	0.08	1.60	-13.56	6.71
Kilian index	585	1.00	55.40	-162.30	188.70
Log real price of oil	573	-0.04	48.39	-127.53	104.11
OECD crude oil inventories	585	3.17	24.63	-80.83	98.99
Flow supply shock	549	0.00	0.91	-6.63	3.13
Flow demand shock	549	0.00	0.91	-4.88	3.51
Speculative demand shock	549	0.00	0.91	-2.42	3.09
Residual shock	549	0.00	0.91	-3.09	3.83

**Table A3**

Correlation matrix.

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Corporate green bond issuance, share in total corporate bonds	[1]	1											
Sovereign green bond issuance, share in total sovereign bonds	[2]	0.042	1										
Sovereign conventional bond issuance, log	[3]	0.134	0.030	1									
Sovereign green bonds to sovereign conventional bonds ratio, in %	[4]	0.022	0.918	0.016	1								
Sovereign total bond issuance, log	[5]	0.135	0.039	1.000	0.025	1							
Consumer price index	[6]	-0.009	0.006	-0.087	0.004	-0.087	1						
Index of industrial production, log	[7]	0.162	0.038	0.693	0.018	0.693	-0.011	1					
Oil exporter	[8]	0.052	-0.025	0.148	-0.020	0.147	0.016	0.356	1				
Developed country	[9]	0.065	0.037	0.104	0.027	0.104	-0.383	0.020	-0.111	1			
Flow supply shock	[10]	0.009	-0.004	0.000	-0.009	-0.001	0.015	0.002	-0.001	0.004	1		
Flow demand shock	[11]	0.003	-0.005	0.001	-0.001	0.000	-0.013	0.000	0.006	-0.002	-0.121	1	
Speculative demand shock	[12]	-0.002	-0.004	0.026	-0.004	0.026	-0.019	-0.018	-0.005	0.004	-0.264	-0.111	1

## Appendix B

This appendix reports the results of the robustness tests. We test the consistency of the results with: (a) alternate specifications of two independent variables and (b) alternate specifications of the regression model by removing sector-control variables.

**Table B1**  
Robustness tests.

Variables	Probit	RI	Probit	RI
Sovereign green bonds to sovereign conventional bonds ratio, in %	0.008*** (0.002)	0.017 (0.049)	0.008*** (0.002)	0.014 (0.049)
Sovereign total bonds, log	0.021 (0.015)	−3.835*** (0.213)	0.021 (0.015)	−3.817*** (0.214)
Index of industrial production, log	0.330*** (0.034)	−1.440 (2.282)	0.330*** (0.034)	−1.497 (2.287)
Oil exporter	−0.005 (0.079)	19.072** (8.013)	−0.005 (0.079)	19.231** (8.030)
Developed country	0.502*** (0.164)	6.827** (2.701)	0.502*** (0.164)	6.664** (2.707)
Flow supply shock	0.025*** (0.007)	0.030 (0.119)	0.025*** (0.007)	0.034 (0.119)
Flow demand shock	0.018* (0.011)	0.136 (0.116)	0.018* (0.011)	0.137 (0.116)
Speculative demand shock	0.013 (0.012)	0.184 (0.152)	0.013 (0.012)	0.189 (0.152)
Consumer Price Index	0.005*** (0.001)		0.005*** (0.001)	
Constant	−10.517*** (0.592)	119.217** (52.954)	−11.483*** (0.581)	120.677** (53.083)
Countries	No	Yes	No	Yes
Sectors	Yes	Yes	No	No
Observations	38,624	1,098	38,624	1,098
Number of sectors	8	8	8	8

Note: Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

## Appendix C. Supplementary data

The estimated values of shocks are generated using Matlab codes from Kilian and Murphy (2014)<sup>2</sup>. Stata codes that we used for generating our results are submitted here.

## References

- Apergis, N., Payne, J.E., 2015. Renewable energy, output, carbon dioxide emissions, and oil prices: evidence from South America. *Energy Sources, Part B: Economics, Planning, and Policy* 10 (3), 281–287. <https://doi.org/10.1080/15567249.2013.853713>.
- Azhgaliyeva, D., Kapoor, A., Liu, Y., 2020. Green bonds for financing renewable energy and energy efficiency in South-East Asia: a review of policies. *J. Sustain. Finance Invest.* 10 (2), 113–140. <https://doi.org/10.1080/20430795.2019.1704160>.
- Basher, S.A., Haug, A.A., Sadorsky, P., 2018. The impact of oil-market shocks on stock returns in major oil-exporting countries. *J. Int. Money Financ.* 86, 264–280. <https://doi.org/10.1016/j.jimonfin.2018.05.003>.
- Baumeister, C., Hamilton, J.D., 2019. Structural interpretation of vector autoregressions with incomplete identification: revisiting the role of oil supply and demand shocks. *Am. Econ. Rev.* 109 (5), 1873–1910. <https://doi.org/10.1257/aer.20151569>.
- Baumeister, C., Hamilton, J.D., 2020. Drawing conclusions from structural vector autoregressions identified on the basis of sign restrictions. *J. Int. Money Financ.* 109 <https://doi.org/10.1016/j.jimonfin.2020.102250>.
- Baumeister, C., Hamilton, J.D., 2022. Advances in Using Vector Autoregressions to Estimate Structural Magnitudes. <https://econweb.ucsd.edu/~jhamilto/BH7.pdf>.
- Baumeister, C., Kilian, L., 2016. Forty years of oil price fluctuations: why the price of oil may still surprise us. *J. Econ. Perspect.* 30 (1), 139–160. <https://doi.org/10.1257/jep.30.1.139>.
- Baumeister, C., Peersman, G., 2013. Time-varying effects of oil supply shocks on the US economy. *Am. Econ. J. Macroecon.* 5 (4), 1–28. <https://doi.org/10.1257/mac.5.4.1>.
- Bloomberg, 2022. Fixed Income Securities. Bloomberg terminal.
- CBI, 2016. Bonds and Climate Change: The State of the Market in 2016. Climate Bonds Initiative in association with HSBC Climate Change Centre of Excellence. <https://www.climatebonds.net/resources/publications/bonds-climate-change-2016>.
- Clements, A., Shield, C., Thiele, S., 2019. Which oil shocks really matter in equity markets? *Energy Econ.* 81, 134–141. <https://doi.org/10.1016/j.eneco.2019.03.026>.
- Cunado, J., Perez de Gracia, F., 2014. Oil price shocks and stock market returns: evidence for some European countries. *Energy Econ.* 42, 365–377. <https://doi.org/10.1016/j.eneco.2013.10.017>.
- Demirer, R., Ferrer, R., Shahzad, S.J.H., 2020. Oil price shocks, global financial markets and their connectedness. *Energy Econ.* 88, 104771 <https://doi.org/10.1016/j.eneco.2020.104771>.
- Dittmar, R., 2008. Do sovereign bonds benefit corporate bonds in emerging markets? *Rev. Financ. Stud.* 21, 1983–2014. <https://doi.org/10.1093/rfs/hhn015>.
- Dutta, A., Jana, R.K., Das, D., 2020. Do green investments react to oil price shocks? Implications for sustainable development. *J. Clean. Prod.* 266, 121956 <https://doi.org/10.1016/j.jclepro.2020.121956>.
- Green, W.H., 2012. *Econometric Analysis*, 7th ed. Pearson.
- Hamilton, J.D., 2021. Measuring global economic activity. *J. Appl. Econ.* 36 (3), 293–303. <https://doi.org/10.1002/jae.2740>.
- Herrera, A.M., Rangaraju, S.K., 2020. The effect of oil supply shocks on US economic activity: what have we learned? *J. Appl. Econ.* 35 (2), 141–159. <https://doi.org/10.1002/jae.2735>.
- IPCC, 2018. Summary for Policymakers. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA, pp. 3–24. <https://doi.org/10.1017/9781009157940.001>.
- IPCC, 2021. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. <https://www.ipcc.ch/report/ar6/wg1/#FullReport>.
- Kanamura, T., 2020. Are green bonds environmentally friendly and good performing assets? *Energy Econ.* 88, 104767 <https://doi.org/10.1016/j.eneco.2020.104767>.
- Kang, W., Ratti, R.A., Yoon, K.H., 2014. The impact of oil price shocks on U.S. bond market returns. *Energy Econ.* 44, 248–258. <https://doi.org/10.1016/j.eneco.2014.04.009>.
- Kilian, L., 2009. Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *Am. Econ. Rev.* 99 (3), 1053–1069. <https://doi.org/10.1257/aer.99.3.1053>.
- Kilian, L., 2019. Measuring global real economic activity: do recent critiques hold up to scrutiny? *Econ. Lett.* 178, 106–110. <https://doi.org/10.1016/j.econlet.2019.03.001>.
- Kilian, L., 2022. Understanding the estimation of oil demand and oil supply elasticities. *Energy Econ.* 107, 105844 <https://doi.org/10.1016/j.eneco.2022.105844>.
- Kilian, L., Murphy, D.P., 2012. Why agnostic sign restrictions are not enough: understanding the dynamics of oil market var models. *J. Eur. Econ. Assoc.* 10 (5), 1166–1188. <http://www.jstor.org/stable/23251216>.
- Kilian, L., Murphy, D.P., 2014. The role of inventories and speculative trading in the global market for crude oil. *J. Appl. Econ.* 29 (3), 454–478. <https://doi.org/10.1002/jae.2322>.

<sup>2</sup> Matlab codes are accessed from <http://qed.econ.queensu.ca/jae/datasets/kilian003/> on February 25, 2022.

- Kilian, L., Park, C., 2009. The impact of oil price shocks on the U.S. stock market. *Int. Econ. Rev.* 50 (4), 1267–1287. <https://doi.org/10.1111/j.1468-2354.2009.00568.x>.
- Kilian, L., Zhou, X., 2020a. *The Econometrics of Oil Market VAR Models* (No. 2006; Research Department Working Papers). <https://doi.org/10.24149/wp2006>.
- Kilian, L., Zhou, X., 2020b. Does drawing down the US strategic petroleum reserve help stabilize oil prices? *J. Appl. Econ.* 35 (6), 673–691. <https://doi.org/10.1002/jae.2798>.
- Kim, G., Vera, D., 2019. Recent drivers of the real oil price: revisiting and extending Kilian's (2009) findings. *Energy Econ.* 82, 201–210. <https://doi.org/10.1016/j.eneco.2017.12.020>.
- Kolodziej, M., Kaufmann, R.K., 2014. Oil demand shocks reconsidered: a cointegrated vector autoregression. *Energy Econ.* 41, 33–40. <https://doi.org/10.1016/j.eneco.2013.10.009>.
- Laird, N., Fitzmaurice, G., 2013. *The SAGE Handbook of Multilevel Modeling*. SAGE Publications Ltd. <https://doi.org/10.4135/9781446247600>.
- Lippi, F., Nobili, A., 2012. Oil and the macroeconomy: a quantitative structural analysis. *J. Eur. Econ. Assoc.* 10 (5), 1059–1083. <https://doi.org/10.1111/j.1542-4774.2012.01079.x>.
- Narayan, Paresh Kumar, 2020. Oil price news and COVID-19—Is there any connection? *Energy Res. Lett.* 1 (1) <https://doi.org/10.46557/001c.13176>.
- Pagan, Adrian, 1984. Econometric issues in the analysis of regressions with generated regressors. *Int. Econ. Rev.* 25 (1), 221–247. <https://doi.org/10.2307/2648877>.
- Ready, R.C., 2018. Oil prices and the stock market. *Rev. Finance* 22 (1), 155–176. <https://doi.org/10.1093/rof/rfw071>.
- Reboredo C., Juan, 2018. Green bond and financial markets: Co-movement, diversification and price spillover effects. *Energy Econ.* 74, 38–50. <https://doi.org/10.1016/j.eneco.2018.05.030>.
- Reboredo, Juan, C., Ugolini, Andrea, 2020. Price connectedness between green bond and financial markets. *Econ. Modell.* 88, 25–38. <https://doi.org/10.1016/j.econmod.2019.09.004>.
- Shah, I.H., Hiles, C., Morley, B., 2018. How do oil prices, macroeconomic factors and policies affect the market for renewable energy? *Appl. Energy* 215, 87–97. <https://doi.org/10.1016/j.apenergy.2018.01.084>.
- Skrondal, A., Rabe-Hesketh, S., 2008. Multilevel and related models for longitudinal data. In: Leeuw, J., Meijer, E. (Eds.), *Handbook of Multilevel Analysis*. Springer, New York, NY. [https://link.springer.com/chapter/10.1007/978-0-387-73186-5\\_7#citeas](https://link.springer.com/chapter/10.1007/978-0-387-73186-5_7#citeas).
- Wang, Y., Wu, C., Yang, L., 2013. Oil price shocks and stock market activities: evidence from oil-importing and oil-exporting countries. *J. Comp. Econ.* 41 (4), 1220–1239. <https://doi.org/10.1016/j.jce.2012.12.004>.
- Zhao, X., 2020. Do the stock returns of clean energy corporations respond to oil price shocks and policy uncertainty? *J. Econ. Struct.* 9 (1), 53. <https://doi.org/10.1186/s40008-020-00229-x>.
- Zhou, X., 2020. Refining the workhorse oil market model. *J. Appl. Econ.* 35 (1), 130–140. <https://doi.org/10.1002/jae.2743>.
- Zhu, H., Su, X., You, W., Ren, Y., 2017. Asymmetric effects of oil price shocks on stock returns: evidence from a two-stage Markov regime-switching approach. *Appl. Econ.* 49 (25), 2491–2507. <https://doi.org/10.1080/00036846.2016.1240351>.