Annex 1.SF.1.

A1. Estimating the price elasticity of global oil and gas investment

The following regression is used to estimate the (cumulative) elasticity of upstream oil and gas capital expenditures (i.e., CAPEX) with respect to global oil and gas prices

$$CAPEX_{j,t} = \gamma_{j,0} + \sum_{l=0}^{l=2} \gamma_{j,l}\, p_{t-l} + \sum_{k=0}^{k=1} \gamma_{j,3+k} Deflator_{t-k} + \boldsymbol{\beta_j X_t} \qquad (1)$$

where $CAPEX_{j,t}$ represents global annual capital expenditures (in log-differences) in the upstream oil and gas sector for firm type *j* (national oil companies, private, public, and total) in year *t*, p_{t-l} is a weighted average of oil and gas prices (in log-differences) in year *t-l*, $Deflator_t$ is the log-difference of the deflator for the oil and gas sector, and $\boldsymbol{X_t}$ contains a set of controls (including the 10-year US Treasury yield in logs and world real GDP growth in log-differences).[1] The regression is estimated separately for each of the 4 firm types.

To obtain the cumulative effect $\Gamma_{j,t}$ of a 1 percentage point change in oil and gas prices on CAPEX– as charted in Figure 1.SF.4 -- we sum over all the regression coefficients up to time *t*, that is, $\Gamma_{j,t} = \sum_{s=0}^{s=t} \gamma_{j,s}$, for *t=0,1,2*. Our sample covers the period 1971-2020. The deflator for the oil and gas industry is an expenditure weighted-average of the equipment and structures deflators for the US oil and gas drilling sector (US NIPA). The oil and gas price represents a weighted average of the WTI benchmark (in \$/TJ) and the Henry Hub natural gas price (in \$/TJ).

Annex Table 1.SF.1. Oil and Gas Price Effects on Global CAPEX

	NOC	Public	Private	Sum
	(1)	(2)	(3)	(4)
Oil and Gas Price	0.243**	0.314***	0.387***	0.296***
	(0.0872)	(0.0457)	(0.0659)	(0.0522)
Oil and Gas Price $_{t-1}$	-0.0340	0.259**	0.140	0.103
	(0.0972)	(0.0745)	(0.0870)	(0.0713)
Oil and Gas Price $_{t-2}$	0.0500	0.134*	0.0497	0.0816
	(0.0532)	(0.0605)	(0.0692)	(0.0446)
US NIPA Deflator	1.232***	0.695***	1.092***	1.029***
	(0.267)	(0.167)	(0.212)	(0.177)
US NIPA Deflator $_{t-1}$	-0.181	-0.442*	-0.485*	-0.343
	(0.220)	(0.192)	(0.222)	(0.181)
Constant	-0.00968	0.0247	-0.00981	0.00234
	(0.0181)	(0.0178)	(0.0185)	(0.0139)
Number of Observations	48	48	48	48
R^2	0.61	0.75	0.73	0.76
Adjusted R^2	0.56	0.72	0.69	0.74
Price Elasticity $_0$	0.243	0.314	0.387	0.296
Price Elasticity $_{0+L1}$	0.209	0.573	0.526	0.399
Price Elasticity $_{0+L1+L2}$	0.259	0.706	0.576	0.481
Model	OLS	OLS	OLS	OLS

Sources: Rystad Energy; U.S. Bureau of Economic Analysis; and IMF staff calculations.
Note: Robust standard errors in parentheses. All variables are in log-differences. CAPEX = capital expenditure; NIPA = national income and product accounts; NOC = national oil company; OLS = ordinary least squares.
Significance levels: *** p<0.001, ** p<0.01, * p<0.05.

[1] Data on upstream oil and gas expenditure are from Rystad.

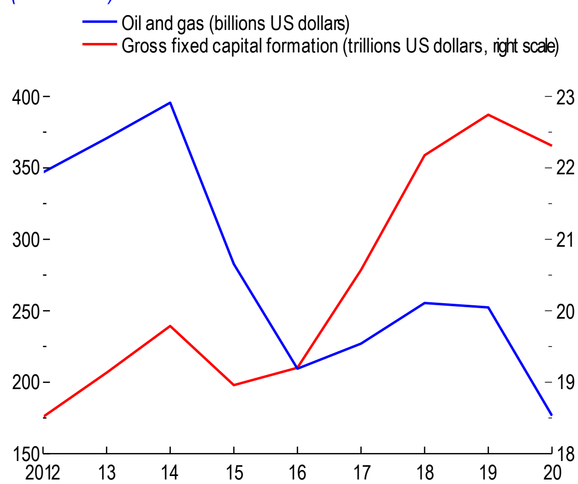
A2. Firm level analysis of oil and gas capital investment

We estimate a linear regression based on a difference-in-difference[2] specifications where capital investment in the oil and gas firms are contrasted with investment in a selection of sectors in the rest of the economy.

$$y_{ist} = a + \lambda D_s + (\beta_1 C_t + \beta_2 P_{oil,t}) D_s + \gamma X_{ist} + \varepsilon_{ist} \quad (2)$$

where y_{ist} is the log capex in firm *i*, group *s*, year *t*, *a* is a constant, $D_s = 1$ for all oil and gas firms and 0 for all other sectors, λ are group fixed effect, X includes log total assets, debt to equity ratio, asset turnover, Altman distance to default, region, industry and year fixed effects. Finally, C_t represents either a post-2015 time dummy or one of the climate change indices illustrated above. The post-2015 dummy aims at capturing the potential regime change for the oil and gas sector induced by the Paris Agreement[3] resulting in a reduced oil and gas investment relative to the rest of the economy. Brent oil prices $P_{oil,t}$ are also introduced interacted with the treatment dummy as they probably affect differentially the two groups. Annex 1. SF. Figure 1. shows that total capital investment in the oil and gas sector and in the rest of the world economy (net of oil and gas) has followed a similar declining trend through 2016 (providing suggestive evidence of *parallel trends*), while parting ways afterwards as the brown energy sector has lagged behind.[2]

Annex Figure 1.SF.1. Global Oil Gas CAPEX versus Global Gross Fixed Capital Formation
(US dollars)



Sources: Rystad; World Bank; and IMF staff calculations.

The analysis uses annual data between 2012 and 2020 from Compustat with global coverage for publicly traded firms in the oil and gas sector (SIC code = 1311, 1381) and in non-energy sectors for the control group (i.e., construction, manufacturing, transportation, communications, services). The estimation stops in 2019 to exclude the confounding effects of the pandemic.[4]

Results are shown in Annex 1. SF. Table 2. (Columns 1-6). The coefficient of the interaction between the oil sector dummy and C_t indicates that capex in oil/gas firms between 2016 and 2019 was 35% lower than in firms in the rest of the economy, i.e., had the regime change not

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[2] As a robustness check, we estimated alternative versions of equation (2) in first differences. First, we took first differences at lag 4 of each year after 2015 and compared the differences across treatment groups only. Second, we took standard one lag first differences and compared them across groups (specifications 2-7) and time (specification 1). Results of the baseline specification are mostly confirmed.

[3] The Paris Agreement is a legally binding international treaty on climate change. It was adopted by 196 Parties at COP 21 in Paris, on 12 December 2015 and entered into force on 4 November 2016. Its goal is to limit global warming to well below 2, preferably to 1.5 degrees Celsius, compared to pre-industrial levels.

[4] Firms with a total asset value below USD 49M are dropped.

taken place and net of the effect of oil prices (column 1). Further, every 1 percentage point increase in public awareness on the energy transition and on sustainable investments is accompanied by a 1% (column 2 – energy transition awareness) and 0.6% (column 3 – sustainable investment awareness) reduction in capex in oil and gas firms *vis a vis* non-energy firms. Results are robust to using a broader definition of the oil and gas sector (column 7). None of the effects of the three "hard" proxies is significant, signaling little influence of enacted climate policies (GHG coverage and CO2 prices) and portfolio choices (sustainable funds net inflows).

Based on the specification in column 2, we perform a scenario analysis by fixing the value of the energy transition awareness proxy at its 2014 level and tracing out the average level of investment in oil and gas firms. Results reported in Figure 1.SF.6 show that capex in oil and gas firms would have been 38% higher in 2020 had public awareness on energy transition not taken off. Similarly, holding oil prices or sustainable portfolio choices at the levels of 2014, oil and gas capex would have been, respectively, 67% and 29% higher on average in 2020. Considering that all our proxies include few data points and are highly correlated, it is hard to separate out the effect of each of them.

Annex Table 1.SF.2. Effects of Energy Transition on CAPEX

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_s	-1.085**	-2.180***	-2.521***	-2.600***	-2.402***	-2.425***	-2.205***
	(0.553)	(0.485)	(0.430)	(0.429)	(0.832)	(0.470)	(0.416)
D_sC_t	-0.351***	-0.010**	-0.006*	-0.233	-0.012	-0.097	-0.010***
	(0.079)	(0.004)	(0.003)	(0.202)	(0.023)	(0.063)	(0.004)
$D_s*P_{oil.t}$	0.371***	0.625***	0.675***	0.688***	0.668***	0.669***	0.571***
	(0.122)	(0.103)	(0.097)	(0.097)	(0.142)	(0.100)	(0.089)
Distance to Default	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Log Total Assets	1.054***	1.054***	1.054***	1.054***	1.054***	1.054***	1.053***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log Asset Turnover	0.174***	0.173***	0.173***	0.173***	0.173***	0.173***	0.150***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Leverage	-0.164*	-0.165*	-0.165*	-0.165*	-0.165*	-0.165*	-0.162*
	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.088)	(0.083)
Constant	-4.333***	-4.187***	-4.304***	-4.334***	-3.986***	-4.167***	-4.199***
	(0.115)	(0.116)	(0.115)	(0.115)	(0.120)	(0.117)	(0.116)
Number of Observations	40,378	40,378	40,378	40,378	40,378	40,378	41,149

Sources: Compustat; Google Trends; World Bank; and IMF staff calculations.

Note: All specifications include region, industry and year fixed effects. D_s is 1 for firms in the oil and gas scetor and 0 otherwise. Columns 1–3 refer to eq. 1 with C_t in the role of the post-2015 time dummy, the energy transition wareness proxy and the sustainable funds awareness proxy, respectively. In columns 4–6, C_t is the share of sustainable funds net inflows on global gross fixed capital formation, the share of GHG covered by regulations and the average global price of CO_2, respectively. Column 7 refers to the same specification as column 2, but with a wider definition for the oil and gas sector. Significance levels: *** p <0.01; ** p <0.05; * p <0.1.

[2] In a more formal test of the parallel trend assumption, we replace C_t with a full set of year dummies (omitting only 2012). All pre-2015 (including 2015) interaction coefficient are statistically insignificant, while the post-2015 coefficients are all significant and average to the interaction coefficient of column 1 in Annex 1. SF. Table 2.

A3. Data and Methodology for the Structural Oil Price Scenarios

A3.1 Data

We use historical annual data for global real GDP, global oil production and the real oil price. We construct a series for global real GDP by using data for 1840 to 2007 from Stuermer and Schwerhoff (2015), who build on Maddison (2010). We expand the data to 2021 based on growth rates of global real GDP from the IMF's World Economic Outlook database.

We employ global oil production data from the database of the International Energy Agency for the period 1973 to 2021. These data include the production of crude oil, natural gas liquids and feedstocks. We convert the data from EJ to BBL/d using 23.88 (EJ to M toe) *7.33/365 as a conversion factor (see IEA, 2021c, p. 352).

Annual price data are sourced from British Petroleum (2021) for 1973 to 2020. We apply the annual growth rate of the IMF's oil price in its Commodity Prices System to derive the respective value for 2021. The growth rate is based on the average between 2020 and 2021 up until November 17. The price refers to Arabian Light posted at Ras Tanura until 1983 and to Brent thereafter. We use the U.S. all urban consumers price index to adjust prices for inflation.

The IEA (2021c) provides oil production scenarios IEA (2021a) for the Net-Zero Emissions (NZE) Scenario. The scenario is based on the premise that global temperature increases can be limited to 1.5°C in 2050. The total production of oil would decline roughly 60 percent.

A3.2 Econometric Model

We set up separate VAR models with three endogenous variables $y_t = (REA_t, \Delta Q_t, P_t)'$, namely the log of global real GDP, REA_t, the percentage change of global oil production ΔQ_t, and the log of the real price of crude oil P_t:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + \Pi\, D_t + u_t \tag{3}$$

with a lag length of $p = 4$, where A_i are the reduced-form VAR coefficients and u_t the reduced-form forecast errors. These errors have no economic interpretation. The matrix of deterministic terms D_t consists of a constant.

The reduced-form VAR in equation (3) can be expressed in a structural form given by

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + \Gamma\, D_t + \varepsilon_t \tag{4}$$

In equation (4), ε_t are independent structural shocks with an economic interpretation. These are related to the reduced-form errors via the linear transformation $u_t = B_0^{-1}\varepsilon_t$. Thus, B_0^{-1} contains the impact effects of the structural shocks on the three endogenous variables in y_t. By assuming a unit variance for the uncorrelated structural shocks, i.e., $E(\varepsilon_t \varepsilon_t') = I_n$ (an identity matrix), the reduced-form covariance matrix Σ_u is related to the structural impact multiplier matrix as $\Sigma_u = E(u_t u_t') = B_0^{-1} E(\varepsilon_t \varepsilon_t') B_0^{-1\prime} = B_0^{-1} B_0^{-1\prime}$.

A3.3 Identification

Annex Table 1.SF.3. Sign Restrictions on Impact Effects

	Global Real GDP	Global Oil Production	Real Oil Price
Aggregate Demand Shock	+	+	+
Oil Supply Shock	+	+	-
Oil Specific Demand Shock	-	+	+

We apply conventional sign restrictions (e.g., Faust,1998, Canova and Nicolo, 2002, and Uhlig, 2005) on the elements in B_0^{-1}, i.e., we assume that the structural shocks have either a positive or negative effect on the endogenous variables on impact. We base these impact restrictions on economic intuition (see Annex 1 SF Table 3).

We interpret the first shock as an aggregate demand shock that is related to the global business cycle and thereby affects the demand for all commodities. A positive shock increases global economic activity, global oil production and its real price.

We label the second shock as an oil supply shock, capturing, for example, production outages, or a stronger than expected increase in production. A positive shock that increases global oil production is assumed to up global economic activity and to lower the real oil price on impact.

We interpret the third shock as an oil-specific demand shock that characterizes most closely the energy transition in our structural scenario analysis. This shock represents a shift in the demand curve due to factors that affect the demand for only oil. Note that this shock may also capture precautionary demand shocks, namely shifts in the demand for above-ground inventory due to forward-looking behavior. This is important because the energy transition may also affect oil markets through this anticipation channel. We assume that a positive shock increases the production and oil price. It decreases global economic output on impact because of the oil price increase (see also e.g., Faust,1998, Canova and Nicolo, 2002, and Uhlig, 2005). This assumes that the energy transition is a negative cost shock that makes parts of the capital stock obsolete and sees workers reallocate to renewable energy and electric automobile sectors.

Narrative sign restrictions (Antolin-Diaz and Rubio-Ramirez, 2018) help us to sharpen the identification of the different structural shocks. We assume that the aggregate commodity demand shock was the most important downward driver of crude oil price during the Great Recession in 2009.

A3.4 Structural scenario analysis

We conduct structural scenario analysis for the real price of crude oil following the framework of Antolin-Diaz et al. (2021). Compared to traditional conditional forecasts, this methodology has the advantage that it attributes the future path of endogenous variables to the path of a specific structural shock.

Our object of interest is a conditional forecast $y_{T+1,T+h}$ over the next $h = 9$ years for the endogenous variables, where T denotes the year 2021. The conditional forecast restricts some of the variables in $y_{T+1,T+h}$ and a subset of the future shocks $\varepsilon_{T+1,T+h}$, thereby linking the path of future variables directly to certain shocks. We take the oil production scenario as given, thus pre-specifying the oil quantities in the conditional forecasts $y_{T+1,T+h}$. We set global oil production equal to global oil consumption in the scenario, assuming no short-term changes in inventories.

Concerning the paths of future shocks, we first constrain the aggregate demand shock and the oil supply shock to their unconditional distributions and leave the oil-specific demand shock unrestricted. The algorithm then finds a series of oil-specific demand shocks that incentivizes the oil production path needed for the energy transition. We then derive the implied price path. In the alternative baseline we constrain the aggregated demand shock and the oil-specific demand shock to their unconditional distribution. We leave the oil supply shock unspecified.

A3.5 Estimation and Inference

Estimation and inference are based on standard Bayesian techniques laid out in Waggoner and Zha (1999), Rubio-Ramirez et al. (2010), and Antolin-Diaz et al. (2021). The algorithm uses a Gibbs sampler procedure that iterates between draws from the conditional distributions of the structural parameters and the conditional forecast

Hence, we pick a random draw of structural parameters out of 25,000 potential draws that relies both on the actual data and on a structural forecast. We use the structural parameters from this randomly picked draw to then draw the scenario paths of the price series and real GDP for the structural scenario that fits the specified oil production path. The next 25,000 draws for structural parameters rely on the original data and the data from the drawn structural scenario.

We use a Minnesota-type prior with standard shrinkage parameters (see Giannone et al., 2015) in combination with a sum-of-coefficients prior (Doan et. al., 1984) and a dummy-initial-observation prior (Sims, 1993) to estimation and the conditional forecasts. Our prior specification assumes that oil production growth is independent and identically distributed, while the log of real GDP and the logs of the price levels follow a random walk.

Identification via sign restrictions does not yield point estimates but instead sets of possible parameter intervals for the different elements in B_0^{-1}. For each model we obtain a set of 1,000 admissible draws, where each draw consists of a conditional forecast, future shocks, and an associated B_0^{-1} matrix that satisfies the identifying restrictions. These draws are also used for inference, i.e., they yield an indication of the uncertainty around the pointwise median estimates. Following Antolin-Diaz and Rubio-Ramirez, 2018 and Antolin-Diaz et al., 2021, we report pointwise median and percentiles of impulse responses for set-identified structural VAR models, as it is common in the literature.

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