Technology shocks and crude oil market connection: The role of climate change

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Abstract

We study the connection between global technology shocks (TS) and the crude oil market from 1880 to 2018. Our study utilizes newly constructed global TS datasets that cover OECD countries and 164 countries, while also considering the role of climate change using temperature anomalies. We use the GARCH-MIDAS framework to account for mixed data frequencies and statistical properties of the variables. Our findings show that the link between TS and oil return volatility is episodic, with the relationship becoming apparent after the great depression of the 1930s. Technological innovations appear to moderate oil return volatility. We also estimate the effect of climate change-augmented TS on oil volatility and find that it reduces the potential of technology shocks to lessen oil return volatility. We also find that the out-of-sample forecast gains are realized from observing TS and climate change in the predictability of oil return volatility. Nonetheless, a more general definition of global TS (with 164 countries) offers higher forecast gains than a more restricted global TS (with OECD countries only). Finally, we document the implications of our findings for policy and practice.

Keywords: Technology shocks; Crude oil market; Climate change; Predictability; GARCH-MIDAS
JEL Codes: C53; N7; Q47; Q54; Q55

1. Introduction

The oil market has grown considerably over the years, becoming the world's largest commodity market as it transitioned from a largely physical to a highly sophisticated and complicated financial market (Turdo & Anghel, 2021).[7] With the financialization of the crude oil market, higher financial stress has been shown to transmit to higher oil-market volatility, particularly in the aftermath of the 2007/2008 global financial crisis (see Bampinas & Panagiotidis, 2015; Bonato, 2019), whereby hedge funds, pension funds, and

[7] The literature on the crude oil market is huge, and we do not intend to review all the relevant papers here for want of space. However, it is important to highlight that the market has been found to respond to global shocks/uncertainties from different sources, such as energy shocks (Akram and Haider, 2022), the COVID-19 pandemic (Devpura and Narayan, 2020; Narayan, 2020; Kartal, 2021; Yilmazkuday, 2021); policy uncertainty (Wang and Lee, 2022); and climate uncertainty (Chen et al., 2019; Salisu et al., 2022a); as much as it also influences other important macroeconomic variables such as stock market (Narayan and Gupta, 2015; Smyth and Narayan, 2018; Yıldırım et al., 2018; Wen et al., 2019); and exchange rate (Narayan, 2013; Narayan et al., 2013; Salisu et al., 2021), among others. By and large, the oil market has increasingly become an important subject among policymakers and practitioners, and we further advance the discourse in a more topical area that connects the market to technology shocks and climate-induced technology shocks.

insurance companies increased their participation in the market. Oil price volatility has also posed a significant economic effect on oil import and oil export-dependent countries (see Tumala et al., 2022). Concerned about strategies to avert risks associated with oil price volatility[8], investors, policymakers, academics, and financial analysts are increasingly interested in accurate prediction of oil returns volatility (see Hou and Suardi, 2012; Ma et al., 2019; Naeem et al., 2020; Chen et al., 2020; Alanya-Beltran, 2022, Liu, et al. 2022).

Significant technological innovations have been improved over the years, which are expected to play an important role in shaping the behaviour of different economic and financial factors. Despite Kogan and Papanikolaou's (2014) establishment that technology shock has a differential effect on the value of assets in place and the value of growth opportunities, previous research on the economic effects of technological developments has mostly concentrated on the growth process (see Kung and Schmid, 2015). In other words, the effect of technology shock has been rarely explored, particularly on the predictability of financial markets (see, for example, Hou and Suardi, 2012; Ma et al., 2019; Alanya-Beltran, 2022, Liu et al., 2022). Recently, however, Sharma and Narayan (2022) investigate the predictability of stock returns volatility by technology shock, with evidence that global technology shock is a time-varying predictor of stock returns.

This study builds on the work of Sharma and Narayan (2022) to examine the role of climate change in the connection between technology shock and oil market behaviour. This innovation was motivated by technological advancements towards reducing greenhouse gas emissions, which will inevitably affect the oil demand and, eventually, oil price. According to Lin and Raza (2020), the process of oil consumption produces a lot of pollutants, such as carbon dioxide (CO2), which is the principal source of global warming and, as a result, climate change (see also Jia et al., 2020; Mensal et al., 2019;

[8] The extreme fluctuation of the oil price has a negative impact on productivity, employment, wages, capacity utilization rates, and real economic activity (Hamilton, 2003; Mo et al., 2019; Nonejad, 2021).

Munir et al., 2020; Smith et al., 2021). Also, Li et al. (2022) explained that crude oil price volatility plays a major role in environmental deterioration. Inspired by this dynamic link between oil price and climate change induced-technological progress, this study is an effort to offer comprehensive empirical evidence on the connection between technological advancement and oil return volatility.

The theoretical relationship between technology shock and oil return volatility in this study is based on firm value theory by Fama and French (1993), where firm value is decomposed into the value of assets in place and the value of growth opportunities (see Kogan and Papanikolaou, 2014). In this theory, an increase in growth opportunities (due to technological advancement) will increase the value of assets. In this study, technological advancement represents an increase in global production of more sophisticated equipment that uses oil, leading to an increase in oil demand and oil price and causing a reduction in oil return volatility. However, when increased consciousness about global warming which makes technological innovation to consumption of less oil than more oil, climate change-induced technology shock may tend to increase oil returns volatility. Thus, we hypothesize that climate change will play a moderating role in determining the significance of technology shock as a predictor of oil return volatility.

Given the foregoing, the contributions of this study to the literature are threefold. First, countries and firms have continued to view technological progress, particularly green innovations, as a potential means of reducing high oil dependence and dealing with price shocks. However, Sharma and Narayan's (2022) recent discovery of technology shock as a novel predictor of financial assets was validated primarily in the context of traditional financial assets, specifically stock prices, whereas there has been increasing evidence in the finance literature that crude oil can be classified as both a commodity and a financial asset (see Kolodziej, 2014). In other words, fundamentals such as demand and supply activities, speculative trading, and economic outlooks in terms of shocks, crises, and uncertainties about policy and economic events that have been widely identified as sources of volatility in traditional financial asset returns have been shown to cause volatility in crude oil price returns (see Liu et al., 2016; Amendola et al., 2017; Kim, 2018; Le et al., 2023). More so, crude oil prices typically fluctuate continuously and are likely to be more volatile than traditional financial assets, thus fueling our motivation that the underlying sources of volatility in the crude oil market are far from exhaustive. As a result, the first contribution of this study is to reduce the unexplained component of oil price dynamics with technological innovations projected as a novel predictor of the crude oil market.

Second, technical advancements are widely recognized as one of the most important pathways for mitigating climate change without jeopardizing the growth process. However, for this to happen, the correct incentives for developing and diffusing climate-friendly technologies are required, which is why efforts to manage climate change are predicted to facilitate technological innovations (Chen & Lee, 2020). In other words, technology shock can also be climate change induced, and therefore, it will be an interesting exercise to see how climate change moderates the connection between technology shocks and the crude oil market. This consideration is quite plausible since the crude oil market is one of the largest emitters of emissions, and therefore, some of the new technologies deployed in the market may have been largely induced by the need to mitigate the increasing emissions from crude oil production. However, the few related extant studies separately discuss the link between energy prices and technological innovation (Corff, 2018; Korotayev et al., 2018; Kong et al., 2020; Waheed et al., 2020); and between technological innovations and climate change (De Dreu & van Dijk, 2018; Matos et al., 2022). Thus, we extend the Sharma and Narayan (2022) bivariate approach to modelling technology shocks predictive of financial market returns to a multivariate predictor setup. The essence is to enable us to account for the role of climate change in the forecasting power of technological innovations in the predictability of the crude oil market.

Third, technological innovations in the context of crude oil markets are mostly described in the form of green innovation; however, restricting the technological innovation prediction of the crude oil market to green innovation is likely to undermine the financialization component of the crude oil market, which is vulnerable to other dimensions of technological advancement. Consequently, we give preference to a measure of all-encompassing technology shock by adopting the new data set on technology developed by Sharma and Narayan (2022) using patents granted to residents across 164 countries. In addition to the global spread of the data, what further motivates our preference for the dataset is its historical nature, which makes it align with other historical variables of interest under consideration. One of the main advantages of such a historical dataset, which dates to 1890, is that it allows us to understand the empirical relationship over a long period, particularly for countries (and perhaps variables) that may have transformed dramatically over this period (see Madsen and Ang, 2016) where the crude oil market serves as a good market (see Narayan and Gupta, 2015) transiting from being a commodity to a financial asset.

However, unlike Sharma and Narayan (2022), the historical data used in this study is a mix of annual and monthly frequencies (where technology shock is annual and oil price is monthly over a long range of period), resulting in our preference for the GARCH-MIDAS model as the most appropriate estimation technique for the study. However, in addition to our acknowledgement of the increasing prominence of the application of the GARCH-MIDAS model in the literature (see Pan et al., 2017; Salisu et al., 2020; Salisu et al., 2022b, 2022c, among others), the outcome of our preliminary analysis (see Table 1) further establishes its appropriateness in the context of this study. The table includes preliminary evidence of conditional heteroscedasticity and serial correlation, which support our preference for GARCH-MIDAS. Beyond its suitability to accommodate variables with mixed data frequencies when modelling volatility, the GARCH-MIDAS has been proven adequate to capture these inherent statistical features (Salisu et al., 2022d; Chuang & Yang, 2022; Yaya, 2022).

Empirically, our novel findings are threefold. First, we show that the impact of TS on oil volatility did not become noticeable until after the Great Depression of the 1930s. Second, we show that the TS's potential to reduce oil volatility is moderated by climate change. Third, we demonstrate the importance of technology in the crude oil market with evidence of improved out-of-sample forecasts courtesy of TS and/or climate-induced TS as predictors of volatility in the crude oil market. The remaining sections of the paper are structured as follows. Section 2 provides some preliminary analyses; Section 3 presents the methodology; Section 4 discusses the results, and Section 5 concludes the paper.

2. Data and Preliminary Results

2.1 Data description and source

The historical annual technology shock (TS) data used in this study ranges from 1876 to 2018 for the OECD countries and 1890 to 2018 for the 164 countries. Thus, we restrict the start period for all the analyses to 1890, and we obtain the data from Sharma and Narayan (2018), whose method of computing the data is consistent with the idea proposed by Hsu (2009). This idea suggests obtaining TS by detrending patent growth (see Sharma & Narayan, 2022). This approach to measuring TS has two distinct advantages: (i) it is free of look-ahead bias, and (ii) it makes the weakest assumptions on model parameters. Following the Sharma & Narayan (2022) procedure, the TS is estimated as follows:

$$TS_{t-1} = \ln(PAT_{t-1}) - \frac{1}{5}\sum_{h=1}^{5} \ln\left(PAT_{t-h-1}\right) \quad (1)$$

where PAT represents the number of patents granted to residents.[9] Using equation (1), TS in the context of this study is measured from a global perspective, defined as "global technology shocks" (GTS), using the sum of patents from 12 OECD countries (GTS-OECD) and 164 countries (GTS-164), for which data are available, respectively. Historical monthly WTI oil price returns are considered for the crude oil market, while the climate change variable is measured as monthly temperature (TMP) anomalies. The data on oil

[9] See Sharma & Narayan (2022) for detail on the construction of the TS.

prices are obtained from Global Financial Data[10] while those for the latter are obtained from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Studies (GISS).[11]

Table 1: Summary Statistics and Preliminary Results

	WTI	GTS_OECD	GTS_164	TEMP
Summary statistics				
Mean	0.25	0.05	0.07	0.05
Standard deviation	6.28	0.14	0.16	0.36
Skewness	0.13	0.72	-0.40	0.67
Kurtosis	11.82	4.85	3.65	2.95
No. Observation	1548	129		1548
Frequency	Monthly	Annually		Monthly
Start	January 1890	1890		January 1890
End	December 2018	2018		December 2018
Conditional Heteroscedasticity & Autocorrelation				
ARCH(6)	32.33***	3.46***	11.88***	971.81***
ARCH(12)	16.96***	1.58	5.67***	510.35***
ARCH(24)	8.75***	0.89	2.28***	262.96***
Q(6)	225.00***	115.44***	94.63***	7644.4***
Q(12)	238.24***	120.90***	147.60***	1449.0***
Q(24)	270.01***	132.02***	210.36***	2681.0***
$Q^2(6)$	270.92***	27.84***	145.70***	5680.1***
$Q^2(12)$	313.26***	31.02***	102.71***	1011.0***
$Q^2(24)$	328.34***	42.14**	113.41***	1702.0***

Note: WTI is the West Texas Intermediate crude oil price returns; GTS_OECD is the Technology Shocks for the OECD countries; GTS_164 is the Technology Shocks for the 164 countries; and TEMP is the temperature anomaly, and it is the proxy for climate change in this study. The Q –stat. and Q^2-stat. are associated with the Ljung-Box serial correlation test, while for the conditional heteroscedasticity test, we used the ARCH test and reported the F-statistic associated with it. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM test is that there is no conditional heteroscedasticity. *** indicates significance at 1%.

2.2 Preliminary results

Our preliminary analysis starts with descriptive statistics, with statistics of interest including the mean, standard deviation, skewness, and kurtosis of our key variables. A cursory look at Table 1 shows that the average monthly returns in the crude oil market

[10] https://globalfinancialdata.com/.
[11] https://data.giss.nasa.gov/gistemp

are positive for the period under consideration. However, while the global technological shock also has positive mean values in terms of GTS-OECD and GTS-164, respectively, the magnitude of the average annual technology shocks appears to be relatively higher in the latter case. Regarding the climate change variable, the fact that the mean value is positive is an indication that the observed temperature is, on average warmer than the baseline for the period under consideration.

Turning to the standard deviation statistics, we find the value relatively higher for WTI compared to other variables of interest, thus suggesting that the crude oil market is the most volatile while GTS-OECD is the least volatile. Except for GTS-64, all variables are positively skewed, whereas the kurtosis statistic is predominantly leptokurtic, with TMP being the sole exception. We extend the table to include additional information, such as conditional heteroscedasticity and autocorrelation. The formal tests employed in this regard are the autoregressive conditional heteroscedasticity (ARCH) test and the Ljung-Box autocorrelation test (Q and Q2 statistics). Even though these tests were performed at varying lags, we still find consistent evidence of the ARCH effect and autocorrelation in all of the series, regardless of the choice of lag. This, among other things, further ascertains the appropriateness of the choice of our estimation technique in the following immediate section.

We further complement our preliminary analysis with possible co-movement among the variables of interest. Figure 1a depicts historical trends in crude oil prices and technology shock returns. It is quite obvious that there is potential for possible co-movement, given that the series appears to be trending in the same direction for most of the sample. However, the illustration in Figure 2 implies that the likelihood of co-movement is only evident in the later part of the sample. However, because the illustration in the preceding figures, particularly Figure 1b, lacks any evidence of a formal test, we further subjected it to a more rigorous and technical testing procedure in the empirical section of the study using a time-varying Granger causality test. The essence is to statistically validate climate change's potential as a technological innovation driver.

Fig. 1: Trends in oil returns, technology shocks, and climate change

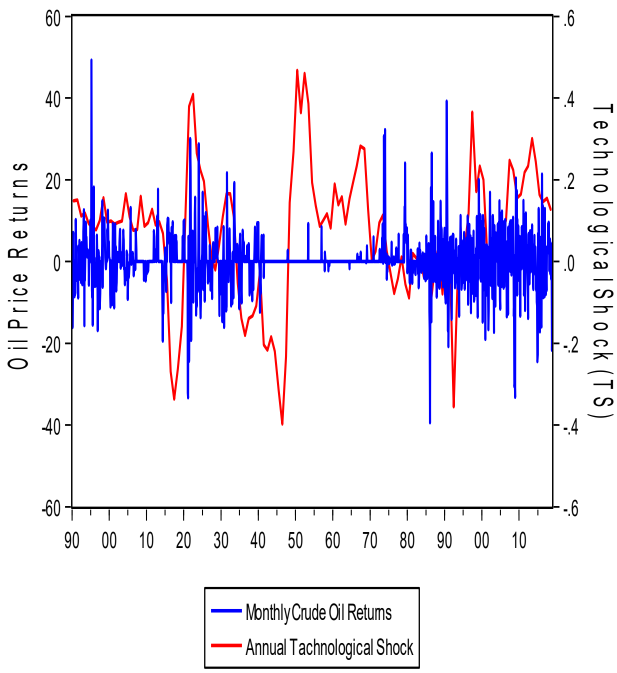

Fig. 1a: Crude Oil Returns & Technology Shocks

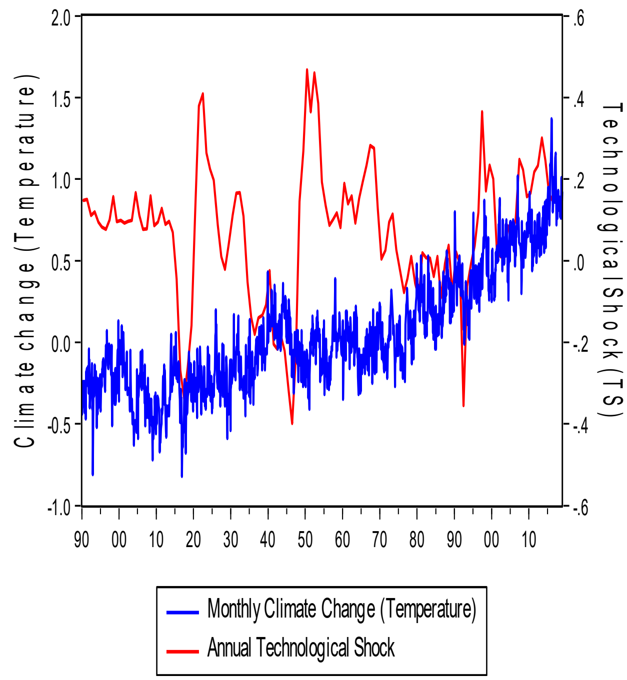

Fig. 1b: Climate Change & Technology Shocks

3. Methodology

Our preference for the GARCH-MIDAS model as the most appropriate for analyzing the crude oil market and the technology shock connection is motivated by the mixed frequencies of the variables of interest. More importantly, the choice of GARCH-MIDAS enables us to accommodate data in their natural frequency and overcome the likelihood of information loss often associated with data aggregation into a uniform frequency (i.e. data splicing). Thus, with GARCH-MIDAS, we are able to retain the natural features of our variables of interest, such that our dependent variable (WTI), which is a measure for the crude oil market, has a higher (monthly) frequency, while the exogenous factor in this case, TS, related to the primary objective of this study, has a lower (annual) frequency. Moving forward, we construct a GARCH-MIDAS-X model of the crude oil market measured in terms of WTI oil price returns as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}}\, \varepsilon_{i,t}, \quad \varepsilon_{i,t} \mid \Phi_{i-1,t} : \ N(0,1), \quad \forall i = 1, \ldots, N_t \tag{2}$$

$$h_{i,t} = (1-\alpha-\beta) + \frac{(r_{i-1,t}-\mu)^2}{\tau_i} + \beta h_{i-1,t} \tag{3}$$

$$\tau_i^{(r\omega)} = m^{(r\omega)} + \theta^{(r\omega)} \sum_{k=1}^{K} \phi_k(\omega_{1,} \omega_{1,}) X_{i-k}^{(r\omega)} \tag{4}$$

While equation (2) defines our mean equation, equations (3) and (4), on the other hand, are the conditional variance of our GARCH-MIDAS model for short –and long-run components, respectively. Regarding the parameters associated with each of the equations, μ in equation (1) captures the unconditional mean of the return series while the short-run component of the variable with high-frequency data in equation (2) is h_{it} following a GARCH (1,1) process where α and β are ARCH and GARCH terms, respectively, which are conditioned to be positive and/or at least zero $(\alpha > 0 \text{ and } \beta \geq 0)$ and summing to less than unit $(\alpha + \beta < 1)$. The term τ_t captures the long-run component that incorporates the exogenous series (or realized volatility where there is no exogenous series) and involves repeating the annual value through the months in that year. Implementing a rolling-window framework, which enables the secular long-run component to vary monthly, is denoted by subscript $(r\omega)$ in equation (3), while m represents the long-run component intercept. Quite of interest and a focal point of our analysis in the MIDAS slope coefficient (θ), which incorporates the predicting power of technology shocks or the exogenous predictor X_{i-k} in the predictability of oil price returns, where $\phi_k(\omega_1, \omega_2) \geq 0, k = 1, \ldots, K,$ is the weighting scheme that must sum to one for the parameters of the model to be identified.[12]

[12] Since we are isolating Technology shock among other predictors of oil return volatility, it is only appropriate to test if there is an endogeneity issue to resolve due to the exclusion of other predictors. Thus,

4. Empirical Results

In line with the various objectives of this study, the empirical results in this section are divided into four parts. Using the full sample of our dataset, the first part of our empirical analysis presents and discusses our main results on the nexus between the crude oil market and technological innovation. In the second part, we adjust the start date of our sample to 1950 to validate the hypothesis that the increased technological advancement in the aftermath of the 1930s great depression heightened the effect of technological shock on the crude oil market. In the third part, we subject our results and findings to a robustness check using a number of alternative measures of technological shocks. We present additional results in the final part using an ex-ante approach.

4.1 Crude oil –technology shock nexus: the role of climate change (TEMP)

In addition to utilizing historical data dated back to 1890 to examine the extent to which technological shocks matter in the crude oil market's volatility dynamics, one of this study's main innovations is the hypothesis that the technological shock is climate change-induced. Rather than assuming climate change arbitrarily in the crude oil marker-technological shock nexus, we begin our empirical study with verifiable evidence linking technological shocks and climate change. Considering the highly historical time-series dynamics of the variables of interest, we depart from the usual VAR modelling approach to causality testing and instead rely on the time-varying VAR model proposed by Shin et al. (2018, 2019). Estimated using the recursive (RE) window, the optimal lag order of the VAR model is chosen using SIC, which recommends p = 1 lag. In what appears to conform to our hypothesis that technological shock is climate change-induced, a cursory look at Figure 2 shows significant evidence of the climate change Granger causing TS, irrespective of whether the TS is of absolute global dimension (Figure 2b) or limited global dimension in the form of OCED (Figure 2a).

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we perform an endogeneity test following the procedure presented in Table A1 in the appendix, and our results indicate that there is no evidence of any significant endogeneity issue that may bias the outcome of our analyses (see Table A1 in the appendix for the endogeneity test results).

Figure 2: Time-varying causality test for TS granger caused by climate change

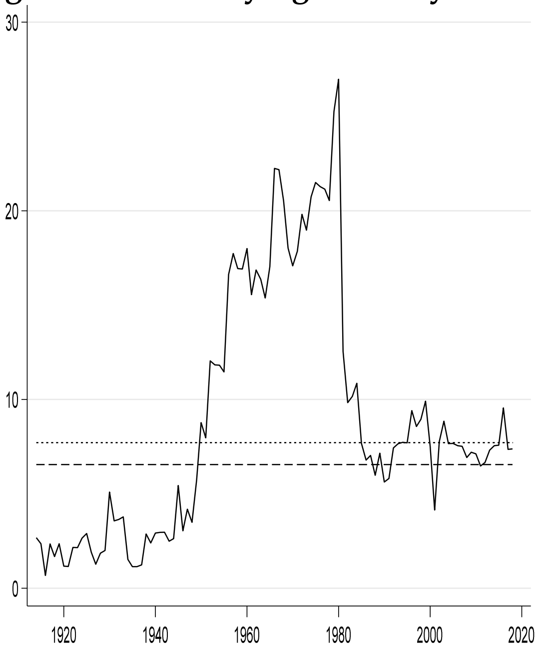

Figure 2a: Global TS_OECD

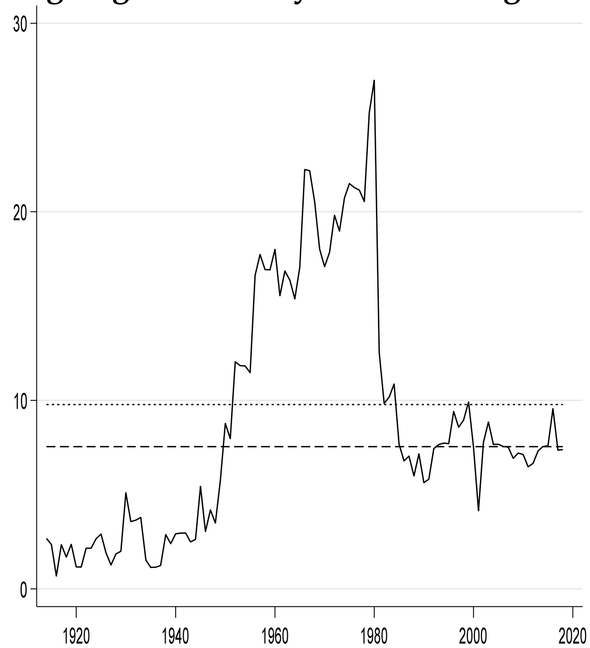

Figure 2b: Global TS_164

Note: TS is Technology Shocks; TS_OECD is the Technology Shocks for the OECD Countries; TS_164 is the Technology Shocks for the 164 countries. The Figures are the outcomes of causality testing based on the time-varying VAR model of Shin et al. (2018, 2019).

Following our finding of a significant linkage between technological shock and climate change, we conducted predictability tests to determine the viability of climate change as the underlying source of technological shock's predictability of volatility in the crude oil market. To construct the climate-induced technology shocks, we create a dummy variable for climate change (where we assign 1 to positive (high) temperature anomaly and zero otherwise) and then interact it with TS. This new predictor is used in place of TS, and the results are presented in Table 3. Surprisingly, a look at the predictive regression shows that the non-rejection of the null hypothesis of no predictability manifests not only when technological shock is the sole predictor in the regression but even when we controlled for climate change as the underlying source of technological innovations in the regression. For instance, it is expected that technological innovation will help to harness volatility in the crude oil market. However, we find the slope coefficient (θ) for technological shock in the predictive regression to be statistically insignificant. This portends that the technological shock does not contain predictive content for volatility in the crude oil market. In other words, the GARCH-MIDAS model framework with realized volatility can be considered sufficient for predicting the long-term volatility of the crude oil market. This notwithstanding, the fact that the sum of the ARCH (α) and GARCH (β) terms is close to one irrespective of the variants of the GARCH-MIDAS model that is under consideration tends to confirm the persistence of shocks in the crude oil market.

Table 3: Predictability testing results

	μ	α	β	θ	w	m
RV	0.0012*	0.4533***	0.5064***	0.4504**	3.6676***	0.0014*
	[0.0006]	[0.0260]	[0.0125]	[0.2293]	[0.5147]	[0.0008]
GTS_164	0.0010*	0.2096***	0.7882***	-0.7045	48.517	0.0130
	[0.0006]	[0.0073]	[0.0069]	[0.5627]	[706.28]	[0.0106]
TEMP_TS_GTS_164	0.0011*	0.2125***	0.7852***	0.6702	1.1739	0.0129
	[0.0006]	[0.0072]	[0.0068]	[0.7169]	[2.1826]	[0.0098]

Note: RV is the Realized Volatility; GTS_164 is the Technology Shocks for the 164 countries; TEMP_TS_GTS_164 is the climate change-augmented technology shocks, and TEMP is the temperature anomaly, and it is the proxy for climate change. μ - unconditional mean of oil price returns, α - ARCH term, β- GARCH term, -θ slope coefficient, w –the adjusted beta polynomial weight, and m – long run constant term. The values in square brackets are the standard errors of the parameter estimates, while the ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively.

4.2 The post-Great Depression perspective

An interesting observation from the causality results in Figure 2 is the overwhelming evidence of technological innovations possibly caused by the quest to mitigate climate change in the aftermath of the Great Depression. Compared to the period before and during the Great Depression, the recovery phase of the aftermath of the Great Depression tends to be characterized by technological improvements (Watanabe, 2016). Thus, our earlier finding of a lack of significant evidence of a link between crude markets and technological shocks may be due to the episodic dynamic of technological innovations. To test the validity or otherwise of this latter position, we adjust the start date of our sample to 1950, which corresponds practically with the periods that defined the post-Great Depression sample. Thus, the predictive regression results presented in Table 4 were obtained when the data sample was adjusted to accommodate some historical trends in the dynamics of technological innovations. Compared to our previous finding, where the realized volatility seemed sufficient for the prediction of the long-term volatility of the global crude oil market, the rejection of the null hypothesis of no predictability at the 1% level of significance in Table 4 is an indication that technology shocks may yet matter in the volatility dynamics of the crude oil market.

Essentially, we find the slope coefficient (θ) for both technological shock and technological shock induced by climate change to be statistically significant after adjusting our sample to reflect mainly the post-Great Depression period. This, among other things, is an empirical confirmation of our assertion that the predicting power of technological shocks on the volatility of the crude oil market is episodic. Saying it differently, we find the volatility reduction effect of technological shocks in the crude oil market mainly evident in the period that coincides with a record of unprecedented improvement in technological progress. More importantly, we find the volatility reduction effect to be relatively higher when the technological shock is reflected as the sole exogenous predictor of volatility in the crude oil market compared to when it is reflected as induced by climate change. This portends that technological innovations induced by conventional fundamentals tend to reduce volatility in the crude oil market much more than those triggered by climate change. This, in particular, conforms to the assertion that while increased consciousness about global warming makes technological innovation contribute to the consumption of less oil than more oil, climate change-induced technology shock may tend to increase oil return volatility.

Table 4: Predictability testing results (Post-Great Depression)

	μ	α	β	θ	w	m
RV	0.0019	0.2684***	0.6462***	0.1870***	44.746	0.0005***
	[0.0015]	[0.0378]	[0.0415]	[0.0480]	[126.21]	[0.0002]
GTS_164	0.0034***	0.1176***	0.8622***	-0.0630***	7.3786***	0.0004***
	[0.0005]	[0.0031]	[0.0033]	[0.0051]	[2.2541]	[3.31E-05]
TEMP_TS_GTS_164	0.0027***	0.0637***	0.9054***	-0.0445***	4.9992***	0.0002***
	[0.0007]	[0.0016]	[0.0026]	[0.0018]	[0.3417]	[1.26E-05]

Note: RV is the Realized Volatility; GTS_164 is the Technology Shocks for the 164 countries; TEMP_TS_GTS_164 is the climate change-augmented technology shocks for the 164 countries, and TEMP is the temperature anomaly, and it is the proxy for climate change. μ - unconditional mean of oil price returns, α - ARCH term, β- GARCH term, -θ slope coefficient, w –the adjusted beta polynomial weight, and m – long run constant term. The values in square brackets are the standard errors of the parameter estimates, while the ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively.

4.3 Robustness check results: an alternative measure of technology shock

To test the robustness of our finding, we consider an alternative measure of global technology shock. Following the Sharma and Narayan (2022) approach, our alternative measure of technology shock is in terms of the aggregation of patents for OECD countries, which we then named GTS_OECD. Although the aggregated patents, in this case, are not as huge as those in GTS_164, it is instructive that the OECD member countries collectively account for 62.2% of the world economy, 61.2% of world mechanism imports, and 17.5% of the world population. More importantly, a look at the parameter estimates in Table 5, both for the full-sample and post-Great Depression periods, shows that our result is robust to alternative measures of technology shock. For instance, irrespective of whether GTS_164 or GTS_OECD defines the global technology shock, the extent to which the technology shock matters in the volatility dynamics of the crude oil market is episodic. This time-varying behaviour of the technology-oil nexus is also valid whether the technological innovation is climate change-induced or spurred by other fundamentals.

Table 5: Predictability testing results (GTS_OECD)

	μ	α	β	θ	w	m
Full-sample						
RV	0.0012*	0.4533***	0.5064***	0.4504**	3.6676***	0.0014*
	[0.0006]	[0.0260]	[0.0125]	[0.2293]	[0.5147]	[0.0008]
GTS_OECD	0.0010*	0.2088***	0.7889***	-0.5065	3.3986	0.0123
	[0.0006]	[0.0073]	[0.0069]	[0.3955]	[4.6840]	[0.0094]
TEMP_TS_GTS_OECD	0.0011*	0.2128***	0.7850***	1.7408	1.6596**	0.0126
	[0.0006]	[0.0072]	[0.0069]	[1.4155]	[0.6968]	[0.0097]
Post-Great Depression						
RV	0.0019	0.2684***	0.6462***	0.1870***	44.746	0.0005***
	[0.0015]	[0.0378]	[0.0415]	[0.0480]	[126.21]	[0.0002]
GTS_OECD	4.07E-05	0.1961***	0.7883***	-0.2628***	7.8882***	0.0019***
	[0.0005]	[0.0082]	[0.0086]	[0.0290]	[0.0900]	[0.0002]
TEMP_TS_GTS_OECD	5.82E-05	0.1509***	0.8274***	-0.1301***	8.5863***	0.0009***
	[0.0003]	[0.0058]	[0.0061]	[0.0170]	[0.4168]	[0.0001]

Note: RV is the Realized Volatility; GTS_OECD is the Technology Shocks for the OECD countries; TEMP_TS_GTS_OECD is the climate change-augmented technology shocks for the OECD countries, and TEMP is the temperature anomaly, and it is the proxy for climate change. μ - unconditional mean of oil price returns, α - ARCH term, β - GARCH term, - θ slope coefficient, w – the adjusted beta polynomial weight, and m – long run constant term. The values in square brackets are the standard errors of the parameter estimates, while the ***, **, and * represent statistical significance at 1%, 5%, and 10%, respectively.

4.4 Additional results: Forecast evaluation

Here, we compare the relative out-of-sample forecast performance of the alternative GST-based GARCH-MIDAS with that of the benchmark predictive GARCH-MIDAS that mainly involved realized volatility (GARCH-MIDAS-RV). In addition to considering the out-of-sample forecast performance evaluation for the full sample and then a sub-sample period tagged as post-Great depression, we also consider it along alternative measures of technology shock and across multiple forecast horizons (h = 30, 60, 90). Using the Harvey et al. (1997) test, we find that the GARCH-MIDAS-X, which includes the role of a technology shock, is more suitable for forecasting the volatility dynamics of the crude oil price market than the traditional GARCH-MIDAS. This finding also holds for the GARCH-MIDAS-X, which includes the role of climate change regardless of the choice of forecast horizons.

Table 6: Out-of-Sample Forecast Evaluation

Crude oil predictor		Full sample			Post-Great Depression		
		h=30	h=60	h=90	h=30	h=60	h=90
GST_OECD	RV vs GTS_OECD	-5.0679***	-4.5317***	-4.4977**	-4.3987***	-3.8278***	-3.9588***
	RV vs TEMP-TS-GTS_OECD	-4.9521***	-4.4017***	-4.4422***	-3.5569***	-3.2242***	-3.4831***
GTS_164	RV vs GTS-164	-5.1365***	-4.5537***	-4.5128***	-4.4063***	-3.8022***	-3.9240***
	RV vs TEMP-TS-GTS_164	-5.0354***	-4.4796***	-4.4677***	-3.7514***	-3.3810***	-3.5744***

Note: The reported values in the table are the test statistic as per Harvey, Leybourne, and Newbold (1997). If the value of the statistic is negative and statistically significant, then the GARCH-MIDAS-X (with the exogenous factor, whether GST_OECD, TEMP-TS-GTS_OECD, GTS_164, or TEMP-TS-GTS_164) is considered the most accurate to forecasting crude oil price returns volatility, while GARCH-MIDAS-RV is chosen if otherwise. If the test statistic is insignificant, then the implication is a non-rejection of the null hypothesis, meaning the forecast performance of the two competing models is identical (see Salisu et al. 2020). Finally, the syntax **** indicates statistical significance at 1%.

5. Conclusion

In this study, we evaluate the role of technological innovations in the crude oil market from a long-term perspective covering centuries of data from 1880 to 2018. We are particularly motivated by the new datasets on technology shocks (TS) by Sharma and Narayan (2022), which distinctly estimate global TS for the OECD countries and 164 countries in addition to country-specific TS for the advanced economies. We note that the frequencies for the two variables differ, and rather than forcing the data to be of uniform frequency, we employ the GARCH-MIDAS framework that accommodates variables at their "natural" mixed frequencies. The literature on the application of the GARCH-MIDAS variant of the models with mixed data frequencies is fast growing (see, for example, Pan et al., 2017; Salisu et al., 2020; Salisu et al., 2022b, 2022c, among others) and it is considered suitable for volatility modelling. Since the predicted variable is of high frequency with evidence of salient features such as conditional heteroscedasticity and serial correlation, using the GARCH-MIDAS model for volatility modelling when confronted with mixed data frequencies is justified.

We pursue four objectives in this study. First, we examine the connection between TS and oil volatility using the full sample of the long-range data to see whether the connection has a long history that needs to be documented. We employ the time-varying causality test of Shi et al. (2018, 2020) and show a significant linkage between technological innovations and climate change. Given the conformity of such linkage to the view that technological advancement towards reducing carbon emissions will inevitably affect oil demand and, by extension, oil price, our second objective involves testing the impact of climate-induced TS on oil volatility. This additional predictor is computed by creating a dummy variable for climate change (where we assign 1 for a positive (high) temperature anomaly and zero otherwise) and interacting it with TS. Third, we consider a shorter long-range dataset from 1950 following the evidence of Watanabe (2016), which finds that technological improvements in the recovery were so rapid that, over the whole Great Depression period, technology growth was highest among pre-WWII decades. In other words, we replicate the analyses in objectives 1 and 2 for a shorter long-range dataset from 1950 to 2018. Fourth, we evaluate the out-of-sample forecast gains of observing TS and climate change in the predictability of oil volatility. The availability of datasets for technological shocks governs our data scope.

Our findings can be summarized as follows. One, the impact of TS on oil volatility does not become noticeable until after the great depression of the 1930s. This outcome aligns with the work of Watanabe (2016), which underscores significant improvements in technological innovations post-great depression. Second, while TS reduces oil volatility, this feature is moderated by climate change. In other words, climate change may have heightened oil volatility which further justifies the need for technological innovations to mitigate the environmental hazards associated with oil production. Third, we show improved out-of-sample forecast gains when the realized volatility (which is the traditional predictor in the GARCH-MIDAS framework in the absence of any explicit exogenous factor) is replaced with either TS or climate-induced TS, which is an indication of the significant role technology plays in the crude oil market. Finally, we test the robustness of our results using alternative measures of TS (involving OECD and 164 countries), and our conclusions remain valid regardless of the choice of TS measure. Notwithstanding, a broader definition of global TS (with 164 countries) offers higher forecast gains than a more restricted global TS (with OECD countries only).

By way of policy implications, technological advancements can help moderate the pressure on the crude oil market, and therefore increased investments in technology need to be encouraged. More importantly, improvements in technology should be done in a way as to help mitigate climate change since high oil volatility is linked to high-temperature anomalies. With the growing concern on climate change and how it connects with technology and, by extension crude oil market, more studies are required to broaden our understanding of other related markets such as the stock market, foreign exchange market, real estate markets, and other commodity markets.

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Appendix Section

Table A1: Endogeneity Test for Oil return volatility and Technology Shock

Endogeneity coefficient	**Full Sample [1890 -2018]**		**Post-Great Depression [1950 -2018]**	
	GTS_OECD	**GTS_164**	**GTS_OECD**	**GTS_164**
δ	-1.170413	0.596087	-0.573884	0.166998

Note: The endogeneity test involves three steps: the first step involves regressing oil return volatility (using the return realized variance) on the technology shock (TS) proxy $Oilrv_t = \alpha + \beta TS_{t-1} + \varepsilon_t$ and saving the resulting residuals (i.e. $\hat{\varepsilon}_t$); the second step requires regressing the TS proxy on its first lag and constant $TS_t = \rho_0 + \rho_1 TS_{t-1} + \upsilon_t$, and saving the resulting residuals (i.e. $\hat{\upsilon}_t$); and the third step combines the results from the first and second steps by regressing the residuals from the former (i.e. $\hat{\varepsilon}_t$) on the residuals of the latter, (i.e. $\hat{\upsilon}_t$), $\hat{\varepsilon}_t = \delta\hat{\upsilon}_t + \mu_t$ where μ_t is the remainder disturbance term with zero mean and constant variance. Note that the endogeneity between oil return volatility and TS is measured by δ. The endogeneity exists if δ it is statistically significant. Otherwise, it does not exist. Thus, we report in the table the t statistic of the endogeneity coefficient, δ