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Research Article

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Posted Date: December 10th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-877031/v1

Evaluating Technological Innovation Impact. An Empirical Analysis of the Offshore Wind sector.

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Abstract.

This study analyses the drivers that impact innovation on offshore wind energy for a select group of countries, applying the quantile and GMM approaches for a period between 2010-2019. The OLS results from the quantile analysis say the log of trademark, Carbon emissions, offshore wind capacity, and electricity from renewable energy are significant and impact on innovation regarding offshore wind energy. Generally, the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity test reveals the variables have a constant variance, confirming the robustness of the findings. The quantile regression depicts that at 25th and 75th quantiles levels, the log of trademark, the log of trade flows, the log of scientific and technical journals quantile coefficients is significantly different from zero and exhibit varied effects on the explained variable patent.

Similarly, the analysis applied the IV-GMM estimation in *ivreg2* to identify the over restrictions, the Hansen J statistic, and give the robust moment of conditions analysis. The findings are consistent with prior analysis with the log of trademark, the log of offshore wind capacity, the log of carbon emissions, Scientific and technology journals, the log of patent, electricity from renewables to be significant and impact on innovation.

The robustness was done on the GMM models, by applying the Huber-White-Sandwich estimator of the variance of the GMM linear models approximators. The *ivreg2* robust analysis revealed that the estimates are efficient for homoskedasticity and Statistics robust to heteroskedasticity.

Ultimately, the interaction term ‘’cross’’ came out significant in the analysis. Signifying the importance of the interaction variables in scaling innovation.

This study will sever as a reference document for policy formulators regarding scaling up innovation for offshore wind energy.

Keywords: **Innovation**, **GMM**, **Offshore Wind, Quantile regression, carbon dioxide emissions, climate change, energy transition.**

1.0 Introduction

Energy innovation is vital for fighting the menace of climate change, ensuring energy security and energy access, especially in the emerging countries where electrification is at its lowest levels yet(Alemzero et al., 2021)(Hu, 2017). The energy sector emits nearly 80 percent of carbon dioxide emissions that cause climate change(Irena, 2021). Offshore Wind is the panacea to abating climate change and delivering cost-effective electricity to the populace. However, this important aim can be only achieved based on sound technological innovation in offshore wind energy deployment and other negative emission technologies at scale.

Similarly, whereas innovation is cumbersome to estimate, other parts correlated to important keys-ins and outputs can still be measured(Vidican-Sgouridis et al., 2011). Hence, estimating innovation is vital for a nascent sector such as the offshore wind sector, which attracts huge expenditure across the private and public sectors for commercial upscaling(Vidican-Sgouridis et al., 2011). In recent times, research has been focused on data mining on the key-ins to the innovation process, not much has been done to measure the outcomes and productivity of renewable energy innovation. Thus, we apply variables such as the patent data from the study unit, Gross domestic product(GDP), foreign investment,(FDI) the capacity factor(CF), Trademark, Carbon emissions, trade flows, offshore capacity, installation costs, offshore wind installations, and Science and technical journals to analyze innovation or support for offshore wind energy. These indicators would make room for a thorough relative assessment of innovation performance for technologies(Vidican-Sgouridis et al., 2011).

Further, renewables energy innovation, such as offshore wind energy, research, research development, and demonstration play a key role in this front. This will act to spur on the global energy transition. Since the transition is gathering momentum and there are renewed commitments from governments, place innovation at the heart of the debate.

Innovation support is the integration of varied approaches such as RD&D investment from public and private sources, market policies, and regulatory policies(Irena, 2021)(Jamasb & Köhler, 2007). Overall, these steps result in promoting innovation activities. Thus, these supports mechanisms are considered as key-ins in the innovation procedure, that will result in outputs, such as improved negative emissions technologies and transformations of the energy systems. Nevertheless, innovation entails times differences and vagueness amongst producing knowledge as well as

,beating down costs and scaling up the deployment of these technologies. Coupling the effects of the key-ins of the innovation advancement on RE innovation and comprehension could be cumbersome. Nonetheless, grasping these impacts are necessary for previous years support and measures in scaling up funding, in addition, to underpin future policy crafting process on offshore wind deployment(Green & Vasilakos, 2020)(Vidican-Sgouridis et al., 2011)(Irena, 2021).

The novelty of this research is that; it applies a quantile and GMM method to empirically analyze the impact of innovation within the offshore sector of the drivers of offshore wind capacity in the world. The analysis equally proved that the interaction of patent, R&D and installation costs will encourage offshore wind energy innovation. Furthermore, we demonstrated that scientific publications, trademarks, and carbon emissions are meaningful in scaling up innovation. Ultimately, the study applied the *ivreg2* robust analysis to analyze econometrically and obtained significant results. This adds to growing literature on innovation in the offshore sector.

The rest of the paper is structured as follows: Chapter two reviews literature concerning innovation in the offshore sector. Chapter three deals with the methodology used in the analysis the research and Chapter four presents results and discussions. Whiles chapter five wraps up with conclusion

2.0 Literature Review

Offshore wind presents an opportunity for countries to scale up sustainable energy consumption as it emits zero carbon emissions**.** The increase in the growth of offshore wind energy will reduce carbon intensity greatly. Reaching the deployment of 30GW by 2030 in the UK will significantly reduce the system carbon intensity as the additional wind energy displaces the future of combined cycle gas turbines (CCGTs) (Aurora**,** 2018). The World Bank energy sector management program together(ESMAP) with the International finance corporation(IFC) has committed $5 million to unlock finances of 20 million pounds from the United Kingdom government to help emerging markets scale up projects on the development and deployment of offshore wind energy. (ESMAP 2019). The sector has seen 23gigawatts of energy installed since 2018 and represents $26 billion of investment or 8% of total global investment in clean energy. The sector is projected to spend over $500 billion by 2030(ESMAP, 2019)(Green & Vasilakos, 2020). The key areas of focus for the World Bank and its Energy sector Management program are knowledge generation, destination and information exchange in scaling up, and the adoption of offshore wind energy.

By the end of 2020, global cumulative installed offshore Wind energy capacity was above 34 gigawatts, an increment of 6GW from the previous year, and nearly 11 times within 2010, when the capacity was just 3 GW(IRENA, 2021). In addition, more than 70percetn of newly installed additions were located in Europe, and in 2020, China added over 3 gigawatts of new capacity additions, more than any country(IRENA, 2021)(Green & Vasilakos, 2020)

Juniger(2004) using the learning curve methodology in his work concluded that investment costs and the cost of electricity from offshore wind are likely to be lowered by 39% in 2020. This assertion was based on the fast pace of the development of technologies and the attractiveness of offshore wind energy over conventional forms of energy. It is not exhaustible, too.

There is this debate regarding the transition to a low economy by technology development and mass development of technology for offshore wind development in the UK in particular. They hold the view that it is not the mass deployment of technologies that matters in transiting to a low carbon future, but that the market is already mature and may not drive down costs in the renewable energy sector. They contend there is the need to develop new technologies (Helm (2010) and Moore (2011). According to (Lee & Zhao, 2021) global wind installations add up to an aggregate of 93 gigawatts, offshore wind making up 86.9 GW a 59 percent increase relative to 2019 installations.

A divergent view is being held by (Sagar et al 2006) argue that there is historical antecedence regarding the pattern of learning by doing and R&D in related technologies. The difference is well noticeable regarding the latter. A work done in the UK by Crown Estate(2012) contends that a 40% reduction in the levelised cost of electricity from offshore wind is achievable by 2020 through learning by doing in the supply chain. The cynics have said they are overly optimistic by the prospects of the industry in meeting this target against other forms of renewable energies.

A paper that was reviewed the economics of offshore wind energy in Europe by (Green & Vasilakos, 2020) conclude offshore wind energy is associated with high installation and connections costs, making governments' support essential. They say policy drivers by governments such as feed-in tariffs in certain European are key to reducing costs and promoting the development of offshore wind energy. The siting up of interconnections of transmission infrastructure among European countries will drive down costs.

In the USA, for instance, offshore wind could generate 28 Gigawatts from 2021 to 2022, thanks to the Bureau of Ocean Energy Management(BOEM) leases, generating about 1.2 billion in treasury earnings(Zhang, 2020). The technical offshore Wind energy potential of the USA is 2,450GW, China is 2,240 GW(Irena, 2021) Also, auctions in lease territories within the Gulf Maine and parts of California in 2022 possible could generate an extra $800 million in earrings to the United States Treasury(Zhang, 2020). Furthermore, significant financing would be invested in the economy of the US to back offshore wind energy projects. The cumulative investments will be around $17 billion by 2025, $ 108B by 2030, and $166B by 2035(Zhang, 2020). Indeed, it is projected that jobs from the offshore sector would reach around 19.0000-45,0000 in 2025 as well as 45,000-80,000 in 2030(AWEA, 2020). The multiplier effect of the offshore sector in the US economy is forecasted between $5.5B -14.2 billion by 2025, and $ 45B and $ 83B by 2030(AWEA, 2020).

Furthermore, global total installation costs plummeted by 28 percent from 2015 to 2019, nonetheless, costs rigidity persist in the immature markets, coupled with LCOE plummeting to 32% around USD 0.169/ kilowatts per hour in 2010 to USD 0.115 kilowatts per hour in 2019. The drivers of these reductions were research and development, learning-by-doing, and the scale of economies(Irena, 2021)(Jafari et al., 2020). Additionally, the capacity grew by 18 percent, attaining 44 percent in 2019. (Irena, 2021)(Alemzero et al., 2021). Similarly, Vietnam has the potential to generate about 30 percent of it is electricity from offshore Wind by 2050(Enslow, 2020). Additionally, Chile is another country that in South America that has a good potential for offshore wind generation, with a fixed offshore Wind technical potential of 131 GW as well as floating offshore Wind potential of 826, cumulatively making 937 GW technical of offshore Wind energy(ESMAP, 2020). Interestingly, the G-20 members account for about 99.3 percent of offshore Wind installed generation capacity and about all installed generation capacity(IRENA, 2021).

3.0 Methodology

3.1 Data and Variables

This study analyses the impact of innovation on renewables deployment with a focus on offshore wind energy. That is the study empirically analyses the drivers of innovation on offshore Wind energy. The data was derived from the International Renewable Energy Agency (IRENA) and the World Bank development indicators(WDI) for the period 2010-2019. The study applies the quantile regression approach and the generalized method Moment(GMM) approach, in doing the analysis. In all, the study applied ten countries that have the potential for offshore wind energy and currently drive offshore capacities in the world. These are Brazil, China, Chile, Denmark, The Philippines, India, South Africa, United States, The United Kingdom, and Vietnam. The patent variable is the explained variable used for innovation.

Innovation

Here, innovation is the explained variable that is measured by patent as in (Manzoor Ahmad, 2021), is one of the main instruments of the energy transition. Technological innovation is very key at the heart of these, nonetheless, there are other innovations too. There is a need for innovation in markets designs, policies, as well as innovative financing models. Innovations indicators that serve as key-ins are research demonstration and development. Market formation and commercial diffusion, would contribute to knowledge, strengthen partnership, and advance technological performances at the different stages of the innovation cycles(Irena, 2021)(Jafari et al., 2020). A patent application has been growing for these countries across all the technology types. Patents are very important for evaluating technological variations as a result of the granularity of information they provide via innovation, invention, country, the location the patent is registered(Jafari et al., 2020)(Vidican-Sgouridis et al., 2011), vital for country crosswise analysis.

Foreign Direct Investment

There has been a plethora of research on foreign direct investment (FDI) and innovation. This variable would shed on light its relevance in technological developments. A study by (Amendolagine et al., 2021) found green foreign direct investment attains a direct meaningful effect on green patent development such as offshore wind technology. On the other hand, (Amendolagine et al., 2021) discovered FDI to have a negative impact on renewable development. Thus, this study would delve into the veracity of this claim.

Trademark

A trademark is defined as a unique sign, which identifies, particular goods and services like those provided by those individuals or firms, according to the World Intellectual Property Organization(WIPO)(Mendonça et al., 2004) Trademark equals patents regarding ease of access, however, patents provide more detailed information(Mendonça et al., 2004). Offshore Wind energy has been acknowledged as a game-changer and this is boosting its deployment in the energy transition. Around 2010-2015, the number of trademarks for offshore wind energy grew from seventy-three to one hundred and ninety-three, thereafter, plunged to eighty-six in 2019. Additionally, a good number of the holders, of trademarks shows the sector is getting to maturity and scale-up. Whiles few firms hold the trademark signifies an amalgamation strategy being

pursued by the bigger firms (Alemzero et al., 2021)(Hao et al., 2021)(Irena, 2021). In addition, trademark, we believe has not been widely applied as an indicator to estimate innovation and so, will empirical analysis to see how it impacts innovation within the offshore sector.

GDP

The gross domestic product of any country determines the level of development the country has achieved. Thus, countries that have greater GDP can invest part of it to scale up innovation. Several studies tend to say that developed countries have the wherewithal to invest a part of their GDP in energy consumption, renewables in particular (Ehsanullah et al., 2021)(Petrović-Ranđelović et al., 2020). For instance, (Li & Leung, 2021) found that renewable energy adds to a robust economic output. This study will empirically assess this narrative.

Carbon dioxide emission.

Carbon dioxide pollution has become the major cause of climate change. Some of the study countries have are the major emitters in the globe. Globally, the United States and China are leading emitters of CO2. Given the negative ramifications of Climate change, there is the to transition to a low carbon economy. Many studies believe that innovation and changes in the energy systems are some of the ways to abate pollution and therefore avoid the menace of climate(Munir Ahmad et al., 2020; Al-mulali, 2011; Kang et al., 2019; Korkut Pata, 2021; Mehmood et al., 2020; Wu et al., 2020)

Trade flows

The deployment of offshore wind energy to move to a greener economy has an economy-wide impact. The fast development of the offshore wind sector has increased trade in parts and equipment. There is significant growth in trade in wind turbines across the globe, gear and gearing boxes(Irena, 2021). Trade figures from 2005-2015 have grown for both component types, particularly, for gearing and gear, nearly double(Irena, 2021). China, the USA, Germany, Japan, Demark are the leading manufacturers of blades, while China, Germany, the USA, and Japan are the leading exporters of gears(Irena, 2021).

Capacity Factor(CP)

The capacity factor explains the ratio of the mean produced power to the potential maximum output(Boccard, 2009). The capacity factor is not static but increases as time goes on. For instance, the UK around 2010-2019 saw an increase of the capacity factor of 46%, 2015 -2019 grew by 22%. Denmark's capacity factor grew between 2010-2019 equally grew by 12percent. Whereas the capacity factor of Japan and China didn't experience any changes on their capacity factors in 2015-2019(Irena, 2021)(Boccard, 2009)(Adefarati & Obikoya, 2019).

Offshore Wind Capacity.

Offshore Wind capacity globally gas been increasing. In 2019, 28 GW capacity was installed, of which nine-tenths were commissioned and operational in the North sea as well as the Atlantic, Denmark, Germany, and the UK ae the pacesetters in the Offshore industry, however, China, America, and the Korea Republic are gradually taking their rightful in the sector(Irena, 2021)(Lacal-Arántegui et al., 2018). According to the (GWEC, 2020), offshore wind has grown from 1percent of global installations since 2009 to 10 per in 2019.

Installation Costs

Installations costs have been falling amongst the renewable energy sources, however, that of offshore wind energy continues to be costly relative to the others. This is a result of the multifaceted nature of offshore wind technology, controlling project costs and other logistical needs, impacting the costs of the sector(Lacal-Arántegui et al., 2018). Offshore wind is a market that is mature nonetheless, it is still growing in certain areas of the globe. Hence, the need to empirically estimate its growth patterns as a result of innovation. Again, (Lacal-Arántegui et al., 2018) say installations cost of generating electricity from offshore wind can attain 75 percent, depending on the parameters taken into account by 2024(Lacal-Arántegui et al., 2018). Generally, installations costs have plummeted across the geographies, with weighted mean falling by 28 percent in 2015 and 2019, around UDS 5 260 Kw to 3, 800/ kw. (Irena, 2021)(Lacal-Arántegui et al., 2018). The study will analyze to ascertain the correlation of costs among the study countries empirically.

Percentage of Electricity from Renewables.

The proportion of electricity from renewables is growing among some of the countries. In the US, Wind generated about 8.3 percent of cumulative electricity generation in 2020(*DOE*, 2021).(Yao

et al., 2021) found when government grows the quantum of renewables generations in the power systems, costs fall, mirroring in the reductions in the prices of energy. Again, (Ameyaw et al., 2021) demonstrated renewable energy generation in China and the US will grow under the business as usual approach in 2030 and proffered policy incentives to boost generation levels.

Scientific and Technical Journals

Capturing and spreading knowledge from onshore wind energy technology has been increasing with increased scientific publications on offshore Wind energy. Between 2010 and 2019, over 12,300 technology correlated papers were published, with the yearly figure growing from 756 in 2010 to 1777 in 2019. The topics that were published were varied and included technology, energy, engineering, and material science(Irena, 2021). This variable will scientifically be analyzed to determine the correlation to the push of innovation in the study countries.

Research and Development(RD&D).

Research and development form the bedrock of innovation. This forms the foundation for the diffusion of knowledge across sectors and nations. The study will analyze the percentage of the gross domestic product is spent on research development activities. Interestingly, (Ragwitz & Miola, 2005) found public investment in RES sources attracts private investment that ultimately increases research and a direct correlation between R&D and GDP growth.

3.2 Model.

To enable us to analyze the impact of innovation on offshore Wind energy sector deployment of the study countries, we applied a dual-pronged approach in the analysis. The initial analysis begins with the impacts of innovation on offshore wind energy analysis. To carry out the evaluation, we applied the longitudinal quantile regression model. The rationale for using the quantile regression is to enable elucidate the distribution of the dependent variables, Patent. The ordinary least square analyses the relationship between the multiple or single exploratory variables denoted as x, in addition to the conditional mean of the explained variable patent. A quantile regression analysis provides an all-encompassing effect of the exploratory variables on the explained variable. Thus, the equation is formulated below:

$$\mathbb{Q}Patent_{it}(\tau_K/a_i, x_{it}) = \alpha_i + \beta_1 + \beta_2 FDI_{it} + \beta_3 TRDMK_{it} + \beta_4 GDPGRT_{it} + \beta_5 COe_{it} + \beta_6 TRDFL_{it} + \beta_7 CPF_{it} + \beta_8 OWCAP_{it} + \beta_9 RELECT_{it} + \beta_{10} INSTACSTS_{it} + \beta_{11} STJNLS_{it} + \beta_{12} R\&D_{it} \quad (1)$$

From equation (1), i and t connote country and year correspondingly, a_i stands for unobservable effects. τ is the quantum of the quantile of the conditional distribution, as well as $(PATENT\ FDI, TRDMK, GDPGRT, COE, TRDFL, CPF, OWCAP, REELECT, INSTACSTS, STJNLS, R\&D)$ are the parameters that are to be used in the analysis, represented by a vector x. Additionally, to estimate the coefficients of the $\tau\, th$ quantile of the conditional distribution, equation (2) is formulated below.

$$\hat{\beta}_\tau = argmin \sum_{i=1}^{n} \rho_\tau(y_i = x_i^\tau \beta) \quad (2)$$

From the equation, $\rho_\tau \mu = \mu\big(\tau - I(\mu < 0)\big), I(\mu < 0) = \begin{cases} I, \mu < 0 \\ 0, \mu > 0 \end{cases}$ represent the check function and $I(.)$ Represents the indicator function.

Given the allotment of variant weights τ and $\tau - I$ are characterized the negative and positive noise, equation (2) denote the quantile regression that is the kind of a weighted estimation. This approach does not account for the individual variances among the study countries. Hence, the applies a different estimation approach that was mooted by(Koenker, 2004)(Habib et al., 2020)(Katchova, 2013) where the unseen individual heterogeneity effect α_i to be one of regressed estimators. Differently, (Koenker, 2004) presented a separate approach put $\{a_j\}_{i=1}^{n}$ to be a variable to be concurrent regressed alongside with β_τ as q varied quantiles.

He then proffered the penalized model in equation three.

$$\big(\hat{\beta}\ \ (\tau_q \lambda), \{a_i(\lambda)n\}_{i=1}^{M}\big) \equiv argmin \sum_{q=1}^{q} \sum_{t=1}^{T} \sum_{m=1}^{m} w_p \rho_{\tau q}(y_{it} = \beta x_{it}^\tau)\ ) + \lambda \sum_{i=1}^{M} |\ a_i| \quad (3)$$

From equation (3), w_p represents the weight of the weight qth quantile, λ is the tuning parameter of the individual impact(Koenker, 2004). Concerning this paper, the same weight$\big(w_p = 1/Q\ \big)$ is applied as in(Alexander et al., 2011) (Habib et al., 2020)(Alexander et al., 2011).Likewise, this study sets $(\lambda = 1\ )$, see (Damette & Delacote, 2012)(Habib et al., 2020).

The subsequent approach to measuring the impact of innovation is the approximation si the application of the GMM panel estimation approach where the past variable can serve as instruments, and the number of instruments grows before the end of the study period. This is called sequential moment conditions(Hayakawa, 2019). The study applies the Generalized Method of Moments (GMM) to estimate the subsequent equations four and five. The Generalised method of moments has been widely used in the analysis of panel data models and varied relationships amongst some parameters. GMM centered approximation is an approach for instrumental parameter estimation and attains merits over traditional estimator 2SLS. This estimation approach is optimal for checking for heterogeneity(Habib et al., 2020)(Katchova, 2013).

$$lnPatent_{it} = \varphi + \theta_1 + \theta_2 lnFDI_{it} + \theta_3 lnTRDMK_{it} + \theta_4 lnGDPGRT_{it} + \theta_5 lnCOe_{it} + \theta_6 lnTRDFL_{it} + \theta_7 lnCPF_{it} + \theta_8 lnOWCAP_{it} + \theta_9 lnRELECT_{it} + \theta_{10} lnINSTACSTS_{it} + \theta_{11} lnSTJNLS_{it} + \theta_{12} lnR\&D_{it} + \varepsilon_{it} \quad (4)$$

$$lnCoe_{it} = \emptyset + \varphi_1 + \varphi_2 lnFDI_{it} + \varphi_3 lnTRDMK_{it} + \varphi_4 lnGDPGRT_{it} + \varphi_5 lnPatent_{it} + \varphi_6 lnTRDFL_{it} + \varphi_7 lnCPF_{it} + \varphi_8 lnOWCAP_{it} + \varphi_9 lnRELECT_{it} + \varphi_{10} lnINSTACSTS_{it} + \varphi_{11} lnSTJNLS_{it} + \varphi_{12} lnR\&D_{it} + \varepsilon_{it} \quad (5)$$

Interaction Effects.

Explains the situation when two or more variables are associated to see their effect on the explained variable. In linear regression, it is commonly constructed by cross-product terms(Xin Yan and Xiao-Gang Su, 1980). Considering the multiple regression equation as the Patent as the explained variable, the interaction model is created without considering the i subscript for the observations,

$$Patent = \alpha + \beta_1 + \beta_2 FDI + \beta_3 TRDMK + \beta_4 GDPGRT + \beta_5 COe + \beta_6 TRDFL + \beta_7 CPF + \beta_8 OWCAP + \beta_9 RELECT + \beta_{10} INSTACSTS + \beta_{11} STJNLS + \beta_{12} R\&D + \varepsilon_{it}$$

$$Patent = \alpha + \beta_1 + \beta_2 FDI + \beta_3 TRDMK + \beta_4 GDPGRT + \beta_5 COe + \beta_6 TRDFL + \beta_7 CPF + \beta_8 OWCAP + \beta_9 RELECT + \beta_{10} INSTACSTS + \beta_{11} STJNLS + \beta_{12} R\&D * Patent * \beta_{10} INSTACSTS + \varepsilon_{it} \quad (6)$$

Thus, equation six presents a three -stage interaction term comprising of patent, R&D as well as installation costs. This is done to ascertain the effects of these covariates on innovation on offshore wind energy deployment.

4. Results and Discussions

Table one depicts the descriptive statistics of the regressors. The patent application has the highest mean figure of 119382.46 and the maximum figure of 1393815. This explains the growth trajectory of innovation in these economies. Trademark equally has a high mean figure of 1555905 explaining the business sector of the offshore wind energy sectors growing around the work, with increased manufacturers of turbines and parts(Alemzero et al., 2021). Carbon dioxide emissions have a high mean value among the regressors, this is no surprise because both the first and the

second emitters of carbon dioxide globally are found among these countries, China and the USA(Li & Leung, 2021). Its minimum value is zero and the maximum value is 10609150. Another noticeable variable that attains a high mean figure is Scientific and technical journals, recently, more scholarly works have been published in the area of energy, material emerging, China and the USA lead the world regarding academic publications(Irena, 2021)(Vidican-Sgouridis et al., 2011).

Of courses, the variable with the least means value is a capacity factor of the shore wind energy. This variable has been growing but at a reduced rate due to advancements in technology and good wind resources in some areas. The USA has significant offshore wind capacity factor than China(GWEC, 2020). Conspicuously, the percent of GDP that is spent on research and development equally has the least mean value. This explains that these countries spent much of their GDP on R&D which is vital to accelerate innovation globally. Installations costs are having the least mean, explaining costs are falling but not at a faster rate relative to onshore wind energy.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Patent	100	119382.46	292481.81	162	1393815
Fdi	100	2.901	2.659	-4.998	12.06
Trdmark	100	155905.46	334547.59	0	1997058
Gdp	100	3.954	2.774	-3.546	10.636
Coe	100	1770772	3043786.4	0	10609150
Tradeflows	100	54.151	40.746	17.812	197.64
Cpf	100	.84	4.31	.2	43.5
Offswcap	100	9.923	20.475	0	103.83

Reelect	100	36.31	19.86	2.2	83.3
Instalcstow	100	.372	.189	.015	.66
Stjornls	100	99141.326	152778.83	0	528263.25
Rd	100	.634	.975	0	3.085

Source Author's calculations

From the correlation matrix, the overall variables correlate strongly. A correlation typically shows the association between two variables**.** The range of figures is between zero and one. One depicts a stronger correlation between the two variables. It is clear that from table 2 that the association between scientific and technical journals is strong with a value of 0.954**.** Clearly, these two variables correlate strongly together with the majority of the regressors. This elucidates the significance of these variables in influencing innovation in the offshore wind energy sector. As these variables take keep increasing, the better for the offshore wind sector to grow faster. The subsequent variables that correlate strongly are trademark and patent. Their coefficient value is 0.928. Clearly, the big elephant in the room, the log of carbon dioxide emissions obtained the strongest correlation alongside the log of the trademark with the value of 0.985. Carbon emissions pollute the global economy causing climate change, hence the imperative to innovate for negative emissions technologies such as offshore Wind energy to abate emissions and transition the global economy to a low carbon future, that is just and equitable. Interestingly, the log of trade flows correlates feebly with most with the regressors, this explains the limited trade activities taking place within the global economy concerning offshore wind energy chain products. As it is known, the offshore wind energy trade activity is limited to China, the USA, Germany, Japan and a few others(AWEA, 2020)(IEA, 2019). For the sector to be a global market and permeates all aspects of the global economy, it has to enjoy economies of scale.

Table 2. Matrix of Correlation

Variables	1	2	3	4	5	6	7	8	9	10	11	12
(1) lnpatent	1											
(2) lnfdi	0.555	1										
(3) lntrdmark	0.928	0.578	1									
(4) lnGDP	0.514	0.523	0.744	1								

(5) lncoe	0.951	0.559	0.985	0.65	1							
(6) lntradeflows	-0.542	-0.156	-0.495	-0.007	-0.606	1						
(7) lncpf	-0.249	-0.355	-0.521	-0.806	-0.452	-0.018	1					
(8) lnoffswcap	-0.598	-0.188	-0.509	-0.153	-0.59	0.646	-0.033	1				
(9) lnreelect	-0.472	-0.28	-0.446	0.013	-0.557	0.773	0.122	0.369	1			
(10) lninstalcstow	0.455	0.308	0.276	0.009	0.365	-0.51	0.077	-0.274	-0.379	1		
(11) lnstjornls	0.954	0.51	0.823	0.349	0.875	-0.592	-0.142	-0.496	-0.545	0.637	1	
(12) lnrd	0.357	0.079	0.02	-0.299	0.083	-0.041	0.442	-0.244	0.108	0.565	0.494	1

Source Author's calculations

From table 3, is the explained variable of patent and the distribution mean of the exploratory variables. It is clear that the overall mean effect of the exploratory variables increases as the category of the mean variables increase. An observation from the six quantiles shows that the mean effects have been increasing from table 3A 5.69, table 3B's mean increases to 6.285, and that of table3C increases to 7.04. Table 3F is the mean of the last table, table 3F has the mean figure of 13.202. This demonstrates the incremental trends of the mean of the six quantiles, depicting the overall mean effects of the exploratory variables on the explained variables in promoting innovation concerning the offshore wind energy sector. Generally speaking, the impacts are varied nonetheless they are direct impacts, except that of carbon emission that has an adverse impact on the global economy. However, its adverse impacts make it vital for the world to craft policy frameworks to mitigate its impacts would come in the form of sustained policy implementation and the right financing model.

Table 3 Summary statistics: N mean sd min max by(ycat)
6 quantiles of lnpatent: 1 Table3A

	N	mean	Sd	Min	max

Lnpatent	17	5.691	.292	5.088	6.006
Lnfdi	17	1.198	.916	-.666	2.463
lntrdmark	17	9.819	.38	9.089	10.369
LnGDP	17	1.582	.624	-.419	1.993
Lncoe	17	11.516	.256	11.152	11.915
lntradeflows	17	4.102	.43	3.764	5.012
Lncpf	17	-1	.167	-1.204	-.693
lnoffswcap	2	2.303	0	2.303	2.303
Lnreelect	17	3.543	.205	3.303	3.867
lninstalcstow	17	-1.245	.888	-3.101	-.431
Lnstjornls	17	7.582	.806	6.496	8.871
Lnrd	6	-1.49	.506	-2.143	-1.008

2 Table 3B

lnpatent	17	6.285	.157	6.052	6.488
lnfdi	17	1.241	.715	-.006	2.202
lntrdmark	17	10.141	.203	9.879	10.531
lngdp	17	1.082	1.016	-1.88	1.957
lncoe	15	12.156	.637	11.244	12.987
lntradeflows	17	4.402	.577	3.879	5.278
lncpf	17	-.852	.17	-1.109	-.511
lnoffswcap	6	-.618	.941	-1.833	-.01
lnreelect	17	3.097	1.05	.788	3.94
lninstalcstow	17	-.791	.637	-2.996	-.416
lnstjornls	14	8.436	.649	7.546	9.473
lnrd	4	-.632	.372	-.969	-.309

3 Table 3C

lnpatent	16	7.04	.321	6.557	7.394
lnfdi	13	.188	.942	-1.619	1.817
lntrdmark	16	8.875	1.12	7.78	10.684
lngdp	16	.501	.824	-1.485	1.948
lncoe	14	11.406	1.218	10.414	13.013
lntradeflows	16	4.139	.31	3.915	5.286
lncpf	16	-.709	.109	-.916	-.511
lnoffswcap	10	2.275	.831	-.01	2.834
lnreelect	16	3.329	1.009	.788	4.127
lninstalcstow	16	-1.347	1.129	-4.2	-.431
lnstjornls	14	9.4	.178	8.936	9.571
lnrd	6	.87	.576	-.305	1.127

4 Table 3D

lnpatent	17	8.812	.405	8.349	9.44
lnfdi	17	.8	.946	-2.538	1.42
lntrdmark	17	11.918	.309	11.139	12.432
lngdp	15	1.161	.865	-.685	2.14
lncoe	15	13.597	.742	12.894	14.581
lntradeflows	17	3.254	.359	2.88	3.762
lncpf	17	-1.176	.239	-1.609	-.693
lnoffswcap	7	2.713	.874	2.303	4.643
lnreelect	17	3.92	.602	3.114	4.422
lninstalcstow	17	-1.243	.738	-2.996	-.431
lnstjornls	15	11.035	.28	10.637	11.531
lnrd	5	.087	.161	-.196	.212

5 Table 3E

lnpatent	17	10.284	1.254	9.462	12.561

lnfdi	17	.72	.569	.015	2.49
lntrdmark	17	11.559	.971	10.197	12.743
lngdp	17	.937	.583	.225	2.111
lncoe	16	13.887	1.146	12.791	15.501
lntradeflows	17	3.489	.266	3.033	3.802
lncpf	17	-.547	1.122	-1.022	3.773
lnoffswcap	17	2.303	2.16	-1.238	4.602
lnreelect	17	3.218	.387	2.61	3.798
lninstalcstow	17	-1.033	.581	-3.072	-.511
lnstjornls	15	11.83	.589	11.449	12.977
lnrd	8	.699	.254	.484	1.016

6 Table3F

lnpatent	16	13.202	.647	12.561	14.148
lnfdi	16	.756	.359	.271	1.387
lntrdmark	11	13.338	.836	12.507	14.507
lngdp	16	1.566	.637	.537	2.364
lncoe	15	15.869	.333	15.387	16.177
lntradeflows	16	3.432	.336	2.978	3.889
lncpf	16	-.951	.222	-1.204	-.511
lnoffswcap	16	.811	1.871	-1.238	4.083
lnreelect	16	3.299	.273	2.821	3.704
lninstalcstow	16	-1.795	.973	-3.507	-.558
lnstjornls	15	12.912	.145	12.652	13.177
lnrd	11	.674	.127	.547	1.003

Source Author's calculations

Table 4. depicts the ordinary least square regression model of the variables. Trademark is significant in scaling up innovation within the offshore sector. Trademark significant and attains a direct correct with lnpatent which is the proxy variable for innovation. This is result is in line with (Mendonça et al., 2004) that corroborated that trademark is vital for encapsulating vital parts of innovation phenomena as well as the process of industrial transformation. As was expected, Carbon emissions is significant and has an indirect correlation to lnpatent. This is rightly so because an increase in carbon emissions increases global economy temperatures and its consequences on the globe. Hence the need to innovate to abate emissions from the sector. So, the more innovation in the offshore sector, the more the world can reduce Coe emissions(Sun et al., 2020)(Korkut Pata, 2021). Equally significant from the analysis is offshore wind capacity. Yes, offshore capacity has been for a decade. This implies that the world needs more patents on the offshore sector to abate the issue of pollution and generate clean electricity from there. For instance, in 2010, offshore Wind capacity was 3GW and quickly grew to 23GW in 2018, giving a 30% per year increment more than any other source, except for solar PV(IEA, 2019)(Lindman & Söderholm, 2012). Also, electricity from renewables source is significant but has an indirect correlation. This conforms with (Manzoor Ahmad, 2021)(Manish et al., 2006) that said renewables

electricity generation has grown globally. From the analysis, the rest of the variables are not significant, according to this model. The model, however, reports a very strong R-squared, depicting the high explaining power of the model. The R-squared is 99 percent.

Table 4. Linear regression

Lnpatent	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
Lnfdi	-.057	.067	-0.85	.423	-.215	.101	
Lntrdmark	2.298	.44	5.22	.001	1.257	3.34	***
LnGDP	-.006	.214	-0.03	.98	-.511	.5	
Lncoe	-2.161	.783	-2.76	.028	-4.012	-.311	**
Lntradeflows	.621	.361	1.72	.129	-.233	1.474	
Lncpf	.531	.537	0.99	.355	-.738	1.8	
Lnoffswcap	-.405	.168	-2.42	.046	-.802	-.009	**
Lnreelect	-1.446	.424	-3.41	.011	-2.449	-.443	**
Lninstalcstow	-.116	.13	-0.89	.401	-.423	.191	
Lnstjornls	.9	.545	1.65	.143	-.389	2.189	
Lnrd	.465	.536	0.87	.414	-.802	1.733	
Constant	6.942	3.983	1.74	.125	-2.478	16.361	

Mean dependent var	10.254	SD dependent var	2.604
R-squared	0.999	Number of obs	19.000
F-test	635.885	Prob > F	0.000
Akaike crit. (AIC)	-17.990	Bayesian crit. (BIC)	-6.657

**** p<.01, ** p<.05, * p<.1*

Source Author's calculations

Table 5. presents the regression analysis for the 25th and 75th quantiles of the model. Quantiles models estimate the variations in a specified quantile of the explained variable patent, is caused by a unit variation in the exploratory variable. At the 25th quantile level, the coefficient lnfdi is not significantly different from zero, and explains that it will not impact on patent by [-0.93]. As is expected at the 25th quantile level, the coefficient of ln trademark is highly significant, more than zero. This explains that trademark is [2.66] likely to impact on patent which is a proxy for innovation. This is evident in the two percentile levels on table five. This analysis is backed by(Mendonça et al., 2004), that said trademark impacts on innovation practices and industrial development. Similarly, the log of GDP coefficient is [-.149], meaning the coefficient will not impact innovation at the 25th and the 75th quantiles levels, as shown in table six. This is curious as counties that have higher GDP can invest a significant amount of GDP in innovation. Clearly, at 25th quantiles as well as the 75th the log of trade flows, the log capacity factor, in addition to the scientific and technical journal will likely impact on innovation, as their coefficients are greater than zero. These findings confirm with(Irena, 2021)(Wiser et al., 2016)(Boccard, 2009). The advancements of technology have enabled the manufacturing of turbines that have more swept

areas and greater sizes to produce electricity. The capacity is not static but evolves as time goes. The USA has offshore wind capacity above 40% (Irena, 2021. For instance, California's capacity factor grew from 13% in 1985 to 24 percent in 2001(Boccard, 2009). On the contrary, the log of research and development as a percent of GDP has mixed results for both the 25th and 75th quantiles. The coefficient is negative at the 25th quantile but positive at the 75th quantile level. Meaning it impacts innovation only at the 75th percentile level.

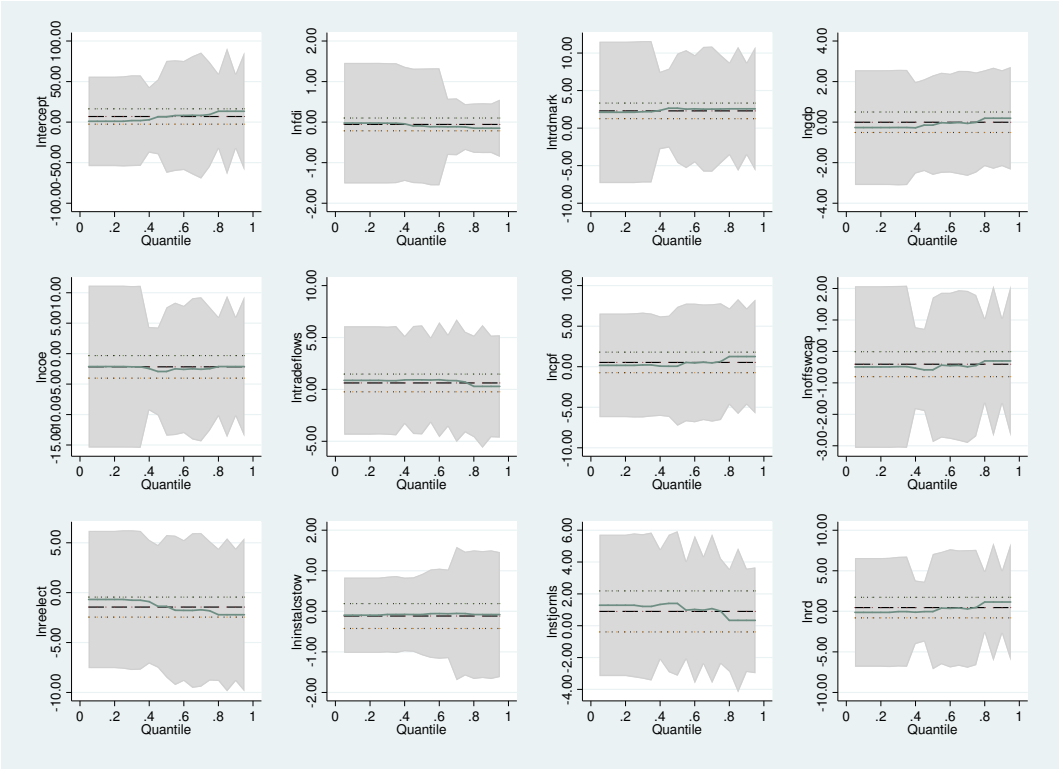
Table 5. Quantile regressions for 25th and 75th quantiles regression

Patent	25th Quantiles Coef.	75th Quantiles Coef.
lnfdi	-0.093	-0.121
lntrdmark	2.661	2.544
lngdp	-0.149	-0.013
lncoe	-2.922	-2.469
lntradeflows	0.915	0.707
lncpf	0.063	0.633
lnoffswcap	-0.584	-0.448
lnreelect	-1.365	-1.818
lninstalcstow	-0.079	-0.056
lnstjornls	1.404	0.919
lnrd	-0.035	0.481
Constant	6.545	9.396

Source Author's calculation

Figure 1. Plot coefficients for each regressor by quantiles

The graph depicts the impact of the drivers of innovation within the offshore wind energy sector, using patent as the proxy variable for offshore wind energy innovation, in addition to how the scales of the impacts differ at varied quantiles from the ordinary least squares coefficients, the confidence interval around them. Quantiles that have their coefficients lie outside the confidence interval is the ideal situation. Such as the log of electricity from renewable sources, the log of trademark scientific and technical journals etc.



Source Author's calculations

Table 6 Testing the Exploratory variables for heteroskedasticity

In to test for heteroscedasticity, the Breusch- Pagan Cook -Weiisberg was deployed.

It is deployed to analyze the linear function of the null hypothesis that the error term variances are equal against the alternative that the error is term is at variance or multiplicative function one or

more variances. From the analysis, the analysis accepts the Null that the variables have a constant variance. This gives a robust and consistent estimate.

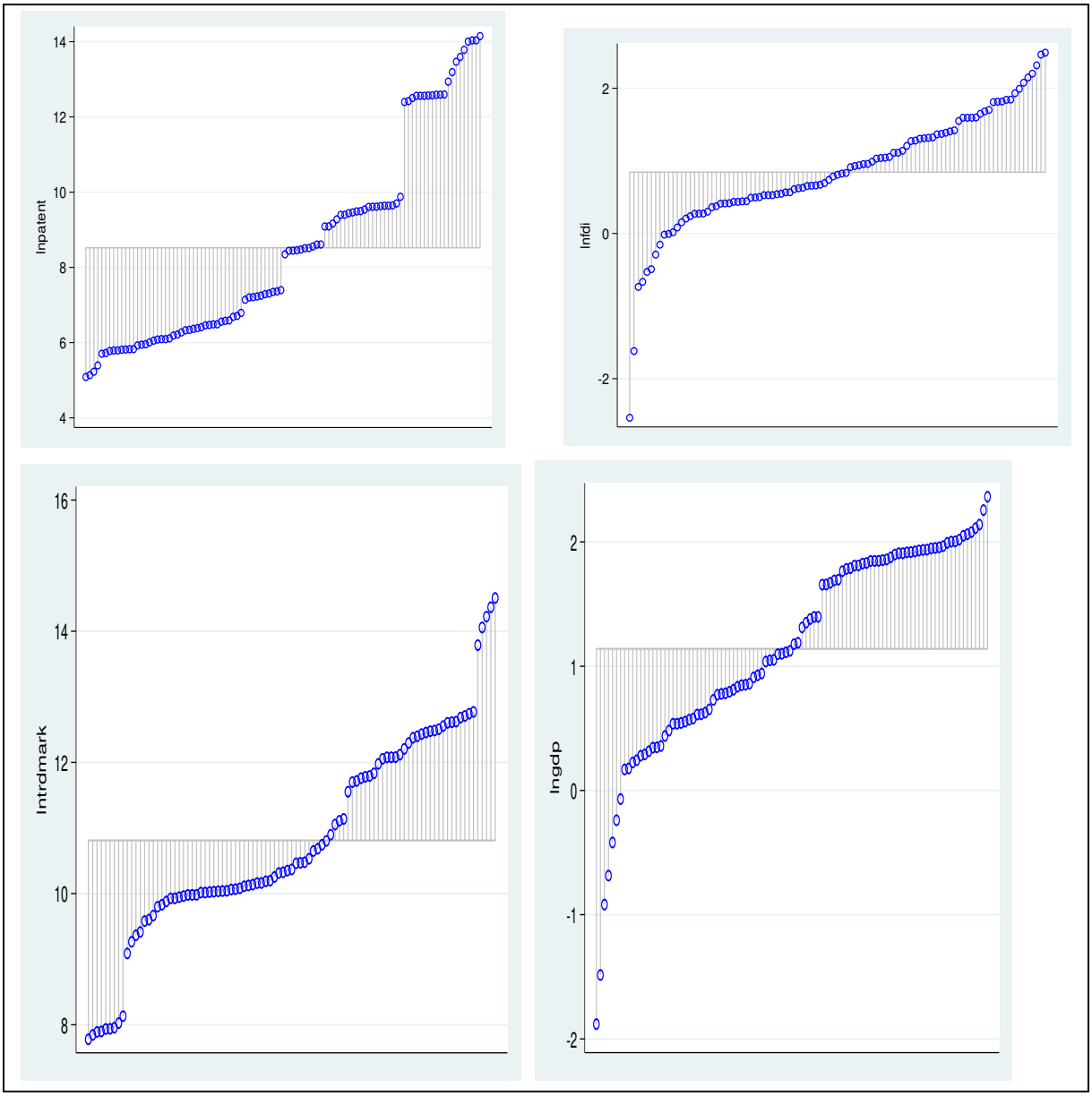
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: lnfdi lntrdmark lngdp lncoe lntradeflows lncpf lnoffswcap lnreelect lninstalcstow lnstjornls lnrd
chi2(11) = 7.18
Prob > chi2 = 0.7846

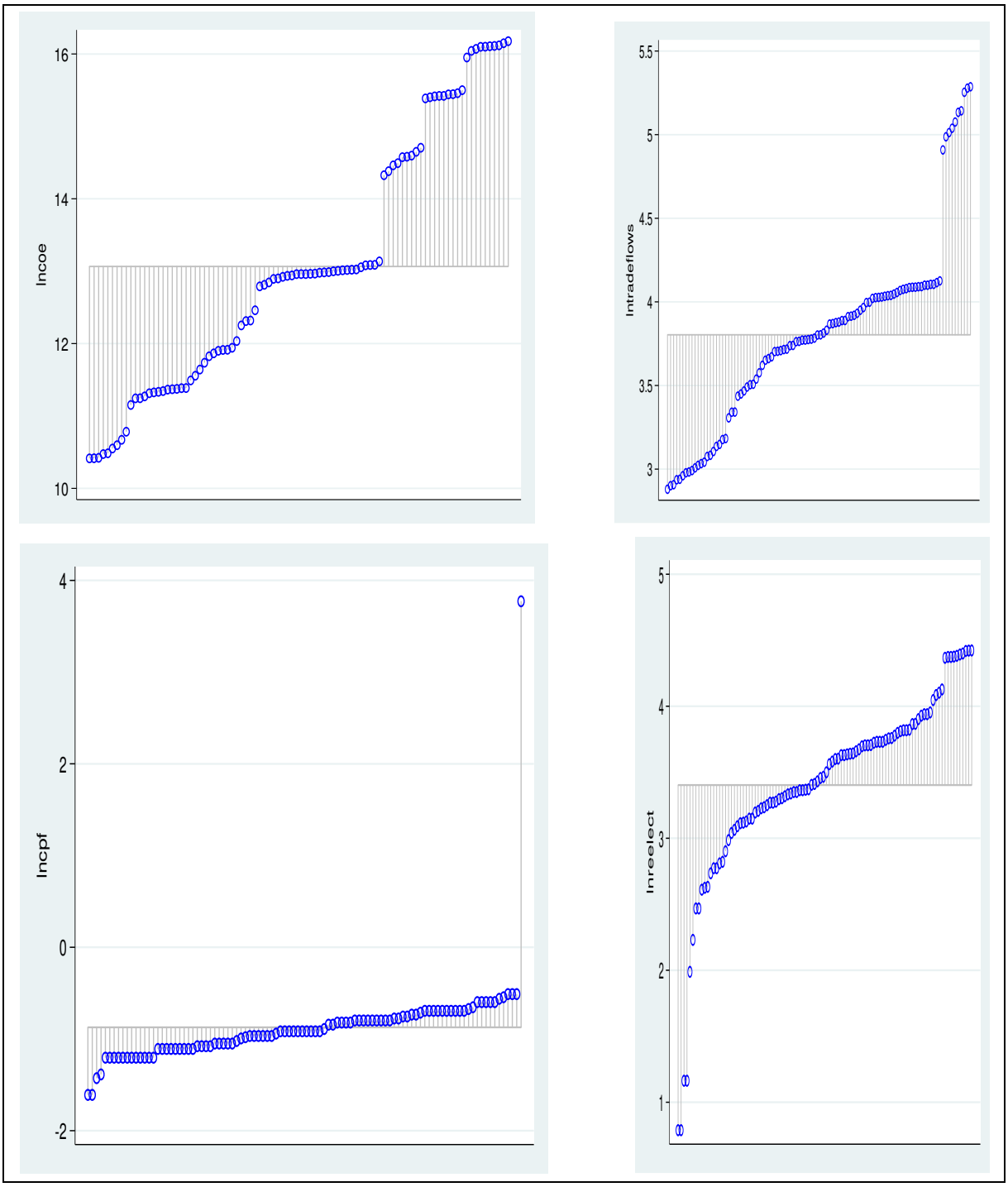
Source Author's calculations

Figure 2 Devnplot of the regressors.

Devnplots are originally written to highlight data synopsis of results of anova patterns. However, they have been increasingly been used in quantiles analysis, to depict a set of quantiles. As you can see from the figure each regressor is represented with a devnplot , showing the impact of each variable on innovation. Looking closely, you would see that lntadreflows is growing with a significant figure above 55, showing that trade in the offshore Wind sector is growing and is a booster to the innovation of the sector. Equally, emission is on an increasing trajectory, giving an impetus to decarbonize and move the global economy to a low carbon one. Several studies

concurred to this finding(Naveed Anwar et al., 2021)(Korkut Pata, 2021)(Le Quéré et al., 2019) .In addition, the log of the percentage of GDP spent in research and development is very significant and grows at a steady pace. The log of offshore wind capacity is also increasing but at a slow pace as the log of the capacity factory, installation costs, GDP. The vertical axis shows the rate of the impact or rate of movement of each variable. This calls for the enactment of policies to increase these important variables necessary to scale up innovation concerning offshore Wind energy.




lncoe
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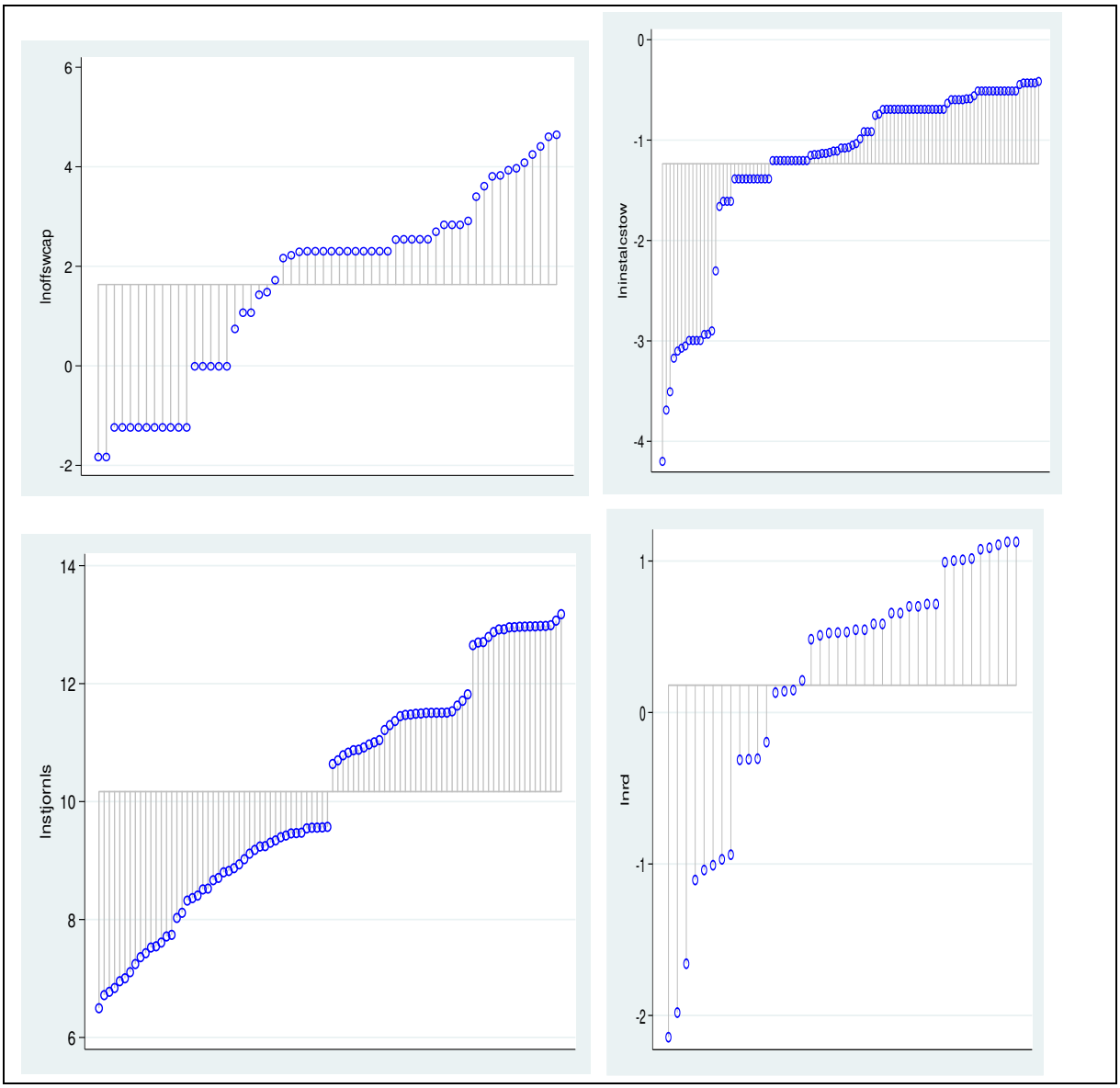

Source Author's calculations

GMM Results

A test of overidentifying restrictions estimates the residual from an independent variable or a two-stage of all variables. The analysis applied the IV-GMM estimation in *ivreg2* to identify the over restrictions is the Hansen J statistic and give the robust moment of conditions analysis, the GMM criterion function. J is identically zero for any precisely overly identified equation, it is direct for any over-identified equation. The Sargan-Hansen test is done so that to identify restrictions since the IV was employed to obtain robust results. Thus, the analysis obtained the most consistent results. Table 7. The results show that the two-equation are efficient and consistent for homoskedasticity. This is in line with the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity. From the ordinary least square analysis of the sequential equations below, the log of a trademark is significant and has a direct impact on the log of patent on equation 4, where the patent is the dependent variable. A unit increase in patent will grow trademark by nearly 23%.(Malmberg, 2005) used trademark as a measure of innovation in their study. Also, (Flikkema et al., 2015) confirmed the use of trademark to measure innovation in their analysis. In equation four, Carbon emissions is also perfectly significant but attain an indirect correlation to the link of a patent which is a proxy for innovation. The increased releases of carbon dioxide make the world want to innovate to abate the pollution, particularly, regarding offshore wind energy. Offshore Wind capacity is significant as well as electricity from renewable sources, and Scientific and technical journals. They have diverse magnitudes to the explained variable. Their significance shows the importance to innovation for offshore wind energy consumption, according to(Dechezleprêtre & Glachant, 2013; Hsu et al., 2021; IRENA, 2014; Khan et al., 2021;

Olanrewaju et al., 2019; Yan et al., 2020). On the contrary, on equation 5. The study used carbon emissions to be the explained variable, and that the log of patent is perfectly significant to the log of emissions. The association is adverse. As patents for offshore wind increase, the log of Carbon emissions reduces by 24.13%. Likewise, (Alemzero et al., 2021)(Odam & Vries, 2020) corroborated this finding in their seminal studies. Similarly, the significance of the variables is the same within the two equations. However, the foreign direct investment came not significant in any of the models. The capacity factor was not equally significant within any of the models. This is quite surprising since it is what determines the quantum of megawatts to be generated

Table7. GMM estimates for the equations

Equation (4)				Equation (5)	
lnPatent	Coef.	P-value	lnCoe	Coef.	t-value
Lnfdi	-0569	0.161	lnpatent	-.2413	0.000
Lntrdmark	2.298	0.000	Lnfdi	-.0164	0.233
LnGDP	-.0057	0.965	lntrdmark	.791	0.000
Lncoe	-2.161	0.000	LnGDP	-.0431	0.307
lntradeflows	.620	0.500	Lncpf	-.116	0.306
Lncpf	.513	0.103	lnoffswcap	-.1905	0.000
Lnoffswcap	-.405	0.000	lnreelect	-.374	0.001
Lnreelect	-1.446	0.000	lninstalcs~w	-.042	0.104
lninstalcstow	-.116	0.141			
Lnstjornls	.900	0.007	lnstjornls	.484	0.000
			Lnrd	-.108	0.334
Lnrd	.465	0.153	Lntradeflows	-‘201	0.004
Constant	6.941	0.004	Constant	2.382	0.003

Source Author’s calculations

Robustness Check of the GMM Models

We demonstrate the robust analysis of the GMM models, by applying the Huber-White-Sandwich estimator of the variance of the GMM linear models approximators, available on Stata approximation command as a robust option(Baum, 2011). Thus, following the analysis, the process reported robust standard errors as shown in table 8. The standard errors have been robust for both models. The coefficients have been efficient within the two models. The *ivreg2* robust analysis revealed that the estimates are efficient for homoskedasticity and Statistics robust to heteroskedasticity. From equation 4, the log of carbon emissions has more consistent coefficients and robust standard errors as well as the log of trademark. The log of scientific and technical journals is robust and consistent within equation 4. On the other hand, in equation 5, the log of trademark has a consistent coefficient but not a robust standard error. This shows the importance of these variables in encouraging innovation within the offshore wind energy sector.

Table 8 Robustness Check of GMM equations.

Equation (4)			Equation (5)		
Patent	Coef	Robust Std. Err.	Coe	Coef.	Std. Err.
Lnfdi	0.06	0.03	Lnpatent	0.24	0.04
Lntrdmark	2.30	0.27	Lnfdi	0.02	0.01
LnGDP	0.01	0.19	Lntrdmark	0.80	0.05
Lncoe	2.16	0.56	LnGDP	0.04	0.04
lntradeflows	0.62	0.24	Lntradeflows	0.21	0.08
lncpf	0.53	0.47	Lncpf	0.12	0.07
lnoffswcap	0.41	0.14	Lnoffswcap	0.19	0.01
lnreelect	1.45	0.31	lnreelect	0.37	0.07
lninstalcstow	0.12	0.07	lninstalcstow	0.04	0.03
lnstjornls	0.90	0.43	lnstjornls	0.48	0.05
Lnrd	0.47	0.44	lnrd	0.11	0.06
Constant	6.94	2.38	Constant	2.38	0.55

Source Author's calculations

Interaction Effects

An interaction term is performed to ascertain the impact of an independent parameter on the explained variable relies on the scale of another independent variable(Ai & Norton, 2003). The table presents the interaction effect of the variables. As shown in table 9, the log of trademark, carbon emissions, offshore wind capacity, electricity from renewables of sources, and scientific and technical journals are significant as in the previous models. Nevertheless, the variable of interest is the ‘’cross’’ variable that is an interaction of patent, research, and development percentage of gross domestic product and installation costs, which came out perfectly significant as shown in table 9. It equally has a direct magnitude. Meaning that as patent increases the interaction term increases. A unit increase in the patent variable increases the ‘’cross’’ by 50%. This signifies that when these variables are given the needed policy push, they can accelerate the deployment of offshore wind energy via innovation.

Table 9.

patent	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
fdi	-2939.469	4047.699	-0.73	.47	-10984.709	5105.771	
trdmark	-.211	.039	-5.36	0	-.289	-.132	***
gdp	-363.546	4466.935	-0.08	.935	-9242.063	8514.971	
coe	.081	.009	8.63	0	.062	.1	***
tradeflows	334.511	286.661	1.17	.246	-235.259	904.281	
cpf	-1900.307	2266.095	-0.84	.404	-6404.415	2603.802	
offswcap	584.492	485.561	1.20	.232	-380.613	1549.598	
reelect	1167.452	555.742	2.10	.039	62.854	2272.049	**
instalcstow	-81938.699	62757.06	-1.31	.195	-206675.15	42797.754	
stjornls	.065	.114	0.57	.571	-.161	.29	
rd	-20982.938	12418.74	-1.69	.095	-45666.528	3700.652	*
cross	.507	.127	3.99	0	.254	.759	***
Constant	-37530.394	46836.337	-0.80	.425	-130622.69	55561.898	

Mean dependent var	119382.460	SD dependent var	292481.806
R-squared	0.909	Number of obs	100.000
F-test	72.359	Prob > F	0.000
Akaike crit. (AIC)	2586.402	Bayesian crit. (BIC)	2620.269

**** p<.01, ** p<.05, * p<.1*

Source Author’s calculations

5.0 Conclusion

This study has analyzed the drivers of innovation in the offshore wind energy sector, using a dual approach of quantile regression and the GMM method between 2010-2019. This was done to deeply understand the variables that impact innovation on the offshore sectors, by utilizing patent, trademark, capacity factor, Installations cost, offshore wind capacity, percentage of GDP spent on research and development, electricity from renewable sources, trade flows, Carbon emissions, Scientific and technical journals, and FDI.

The findings revealed varied results. On the quantile, OLS regression, trademark, carbon emissions, and electricity from renewable sources are significant in incentivizing innovation within the offshore wind sector. On the 25th quantile regression, trademark will likely impact innovation in the offshore sector.

Further, on the 25th and 75th quantiles, scientific and technical journals, the capacity factor will likely impact on innovation with higher coefficients, while the log of trademark has a greater coefficient implying its significant impact on innovation. The implication is that these coefficients are significantly more than zero and show varied impacts around the distribution of the explained variable patent, a proxy for innovation. Generally, the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity test reveals the variables have a constant variance, confirming the robustness of the findings.

Additionally, the devnplot that depicted the set of quantiles explained showed all the variables increasing at an increased trajectory, some at a reduced pace as the vertical axis figures show.

Regarding the GMM results, the analysis applied the IV-GMM estimation in *ivreg2* to identify the over restrictions, the Hansen J statistic and obtained the robust moment of conditions analysis. The sequential order of ordinary least square shows that equation 4 has the log of trademark, carbon emissions, the log of offshore wind capacity, the log of electricity from renewable sources, and the log of scientific and technical journals are significant in impact innovation within the study countries, this is seen in the study countries progress in innovative negative emissions technologies deployment. Inversely, foreign direct investment and installation costs are not significant. Similarly, where carbon emissions is the explained variable, the log of patent is significant in encouraging innovation. Similar results are obtained.

A robustness check was done applying the Huber-White-Sandwich estimator of the variance of the GMM linear models approximators, available on the Stata approximation command as a robust option. The findings were robust and consistent. The *ivreg2* robust analysis revealed that the estimates are efficient for homoskedasticity and Statistics robust to heteroskedasticity.

Ultimately, the interaction effect produced interesting findings which were consistent with another model of analysis, with the log of trademark, the log of carbon emissions, the log of scientific and technology journals is significant. The interaction term ''cross'' is perfectly significant and has a direct magnitude. That means the interaction of patent, R& D, and installation is very key in commercializing innovation.

Overall, offshore wind energy is one the fastest growing renewable sources that has achieved costs reductions as well as policy support. The findings reveal that more policy support is needed to scale up innovation in the sector considering the factors analyzed such as the issue of increased emissions, the need to transition to a low carbon economy.

Author Contribution:

David Alemzero: Conceptualization, data curation, methodology, writing-original draft, software, Junguo Shi: Data curation, visualization, supervision, editing. Shanshan Dou: writing-review and editing. Xuhua Hu: writing, review and editing. Elvis Alhassan: review and supervision.

Project Fund.

This research piece is proud to be associated with the National Natural Science Funding, number: 72102090, China.

Compliance with ethical standards

Competing interests. The authors declare that they have no conflict of interest.

Data availability. The data that support the findings of this study are openly accessible on request.

Ethical approval and consent to participate

The authors declare that they have no known competing interests or personal relationships that could have appeared to influence the work reported in this paper. We declare that we don't have human participants, human data or human issue.

Consent for publication

We do not have any individual person's data in any form.

Reference.

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