***Abstract***

This paper empirically investigates a question based on Paris global climate deal (COP21): what is the effect of carbon emissions on sovereign risk? To answer this question, we use fixed effects model by using annual data from G7 advanced economies, which includes Canada, France, Germany, Italy, Japan, UK and USA, for the period from 1996 to 2014. We employ a novel extreme value theory to measure sovereign risk. The results indicate that climate change (carbon emissions) are likely to increase sovereign risk significantly. We also expand our analysis to some specific sectors, as some of the sectors emit more carbon than others. Specifically, we take top three polluting sectors namely: transportation, electricity and industry and show that they are more likely to increase the sovereign risk. Our results are robust to change in risk measures, estimation in differences and dynamic version of econometric models. Therefore, we have robust consideration that the results significantly explain the sovereign risk.

**JEL codes:** G15, C49, O50, Q54

**Keywords:** sovereign risk; multivariate extreme value theory; climate change; carbon emissions; G7

1. **Introduction**

With the participation of 196 sovereign nations in the Paris global climate deal (COP21) in 2015, the global plan of actions was seriously taken into account to impede the potential threats of an increase of Greenhouse gas (GHG) in the new era. The COP21 negotiations ended with a promise to reduce global climate change measures from 2020. Until COP25 in 2019, not much progress has been made to restrict two degree Celsius temperatures in comparison with the pre-industrial levels (Haber, 2016). COP25 was also defined as an ‘Ambitious COP’ as countries have to make concrete efforts from 2020. In COP25, progress was checked against outstanding rules, assessment of loss and damage was made as per Warsaw International Mechanism (WIM) and commitments were made toward financial support and capacity building. Despite the global efforts for a change, President Trump’s America decided to withdraw from the Paris accord (Rhodes, 2017). Many Democrat senators criticized this political decision because it might hurt America’s credibility (Blair, 2017). Following the commitments among parties in COP21, Nationally Determined Contributions (NDCs) also declared that there is a green bond market issued by sovereign issuers (Climate Bonds Initiative, 2018). Therefore, the Paris Agreement (COP21) action plan to tackle the climate challenges not only for economic growth but also for the financial system. The governor of the Bank of England, Mark Carney, also highlighted that climate change is a real risk and it can be an issue for financial stability (Carney, 2015). The possible damaging concerns of climate change and its implications for our economy and living standards are undesirable. Moreover, these concerns lead to irreversible environmental events, such as loss of land, species and major interruption of global oceanic circulation, which damages the global economy and causing sovereign risk (IPCC, 2001). As carbon emissions have a substantial impact on climate change and climate change is a great threat for financial stability, a natural question arises whether the carbon emissions have any impact on sovereign risk. This innovation of studying the impact of carbon emissions on sovereign risk will inform policy makers the devastating impact of carbon emissions and will help achieve the Nationally Determined Contributions (NDCs), as described in the COP21 and have continuously been reviewed until COP25.

There are different definitions and types of risk. However, there is no consensus in the literature about definition of risk and quite often the concepts of ‘risk and uncertainty’ are used interchangeably.[[1]](#footnote-1) In this paper, we use country equity index returns to measure sovereign risk, which is represented by repayment capacity of government through their bonds and considered as one of the key asset class for investors. However, environmental risks are generally not incorporated into estimating the sovereign risk. Currently, environmental risk and more specifically carbon emission risks are hardly considered by financial institutions when examining overall risks at the country level (UNPRI and UNEP-FI, [2011](https://www.tandfonline.com/doi/full/10.1080/20430795.2013.837810)). More precisely, environmental risks are not material into the country’s economic and financial performance in the short run (S&P, [2012](https://www.tandfonline.com/doi/full/10.1080/20430795.2013.837810)). Environmental factors recognised as ‘extra financial’ and are generally counted with social and governance factors. Therefore, environmental factors are usually not considered because of an established and recognised impact on financial performance but rather considered for ethical reasons (Clarvis et al., 2014).

For a country there are different types of risks including exchange risk, investment risk, political risk, legal risk and reputation risk. We focus on sovereign risk encapsulating all these types of risks that a country can potentially face. To measure sovereign risk, we employ extreme value theory (EVT) following Hartmann et al. (2004) and Straetmans et al. (2008) who measure the sovereign risk of G5 countries and USA respectively. EVT employs semi parametric estimation procedure and estimates marginal and joint probabilities of tail events without resorting to a parametric estimation procedure. It also carries the advantage of focusing on extreme events that occur with very low frequency and are long term in nature. This is important for our study as carbon emissions are not likely to have impact on the sovereign risk in the short term. Finally, the EVT focuses on the unconditional distribution of returns in compared to for example stochastic volatility models that produce time-varying measures of volatility and dependence and hence of long-term horizon. It is also important to note that economic growth has increased living standards recently in the most countries; however, it is also escalating CO2 emissions and deteriorating the natural resources. The CO2 emission is linked with social, economic and industrial factors ([Adom et al., 2012](https://www.sciencedirect.com/science/article/pii/S0048969718331930?via%3Dihub#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010#bb0010" \l "bb0010)). The main reason behind the emission of CO2 are burning of oil, coal, gas, petrol and deforestation ([Sanglimsuwan, 2011](https://www.sciencedirect.com/science/article/pii/S0048969718331930?via%3Dihub#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645#bb0645" \l "bb0645)). Mainly the earlier literature from the last two decades has been extensively concentrated on relationship among economic growth and energy use with substantial effect on the CO2 emissions (See Riti et al., 2017; Bildirici, 2017; Han et al., 2018; Song et al., 2018; Alam et al., 2016; He et al., 2017 and Chiu, 2017 among others). To explicitly examine the relationship between sovereign risk and climate change, this paper emphasize emphasizes the extreme events with high frequency and severe destruction (Kraemer and Negrila, 2014). First, the intuitive thinking for this channel is economic performance. For example, China lost a total of US$874,613 million by natural disasters (from 1985-2014) (around 8.3% GDP) (Han et al, 2016). Thus, the welfare inequality and economic growth under the climate change could lead to lower sovereign ratings in some countries. The relationship between economic growth and carbon emission has been researched extensively so far, with a database upwards of 4194 papers (Mardani et al., 2019). Second, the study of Kraemer and Negrila (2014) also indicates that government budgets would generate the future burden of national spending. National budgets might suffer bad fiscal performance when natural disaster happens and the government debt burden is one of criteria for assessing country's sovereign risk (Clarvis et al., 2014). For example, in the past, the Britain also suffered the event called Caribbean island of Montserrat.[[2]](#footnote-2) This island suffered violent volcanic eruption in July 1995 that influenced the fiscal performance in the country. These are only two example that climate change could cause the sovereign risk in one country. Balint et al. (2017) also introduced the climate risk and Clarvis et al. (2014) built the new framework to explain the environmental risk to sovereign credit risk. In addition, Kraemer and Negrila (2014) also find the positive correlation between the high score of environmentally vulnerable countries and low sovereign credit ratings. It confirms the link between the impacts of climate change on country risk; therefore, this paper attempts to explain the indirect channel from environmental issues to sovereign risk through economic growth and fiscal performance.

Source: Climate Transparency (2019).[[3]](#footnote-3)

**Figure 1: G7 GHG emissions per capita and share of global GHG emissions**

In Figure 1, we can observe that the environmental footprints of the G7 economies are quite heterogeneous. More precisely, the USA is an outlier which experiences high GHG emissions per capita as well as high share of global GHG emissions. Meanwhile, the US decided to withdraw from the Paris Agreement 2020. Of course, the United States is the largest economy and a producer, as well as a consumer of fossil fuel; therefore, the withdrawal of the leading country might cause serious implications and consequences among the strictly environmental compliance countries such as Germany or Japan. In addition, G7 economies are also the largest emitters of GHGs, including CO2 emissions. It is undeniable that the G7 economies are the most influential countries in terms of economic as well as political status. Therefore, it is vital to examine their impact as the typical case for the further implications.

Our paper contributes to the existing empirical studies of energy economics and wider economic and environmental literature in the following several novel ways. (i) We explore the role of innovation in managing the environmental challenges via examining the relationship of sovereign risk with carbon emission. Our paper uses a long sample period i.e. from 1996 to 2014 and use dataset of G7 countries. (ii) We provide an evidence on the statistical relationship between carbon emission and sovereign risk, which has only been mentioned as a theory as well as a framework in the prior studies (Carvis et al., 2014; Kraemer and Negrila, 2014). (iii) We employ extreme value theory to compute risk measures i.e. tail quantile and tail expected shortfall as it captures extreme risk deep into the left tail of the distribution and long term in nature. Long-term risk measure is more appropriate as carbon emissions are likely to affect the sovereign risk in the longer term. (iii) Rather than concentrating on traditional sovereign risk with systematic modelling with debt, we are interested in business models, which allow sovereign countries to minimise contagion exposure due to climate change. (iv) We provide evidence that carbon emissions are a determinant of sovereign risk at the country level as well as at the industry-level. We analyse the top 3 polluting sectors namely: Transportation, Electricity and Industry. They sectors are responsible for 29%, 28% and 22% of carbon emissions respectively.[[4]](#footnote-4)

We find that that climate change (carbon emissions) increase sovereign risk of G7 countries both economically and statistically. When we expand our analysis by sectors, we find that that they are more likely to increase the sovereign risk. Our results are robust to change in risk measures, estimation in differences and dynamic version of econometric models. Therefore, we have robust consideration that the results significantly explain the sovereign risk. Policy makers are looking for innovative ways to inform the debate on tackling climate challenges as indicated by the quotes from the Governor of the Bank of England., So policy makers are interested in mitigating climate risks and achieving COPs Nationally Determined Contributions (NDCs). Our paper also raises alarm as an increase in the sovereign risk will put off foreign investors as well as domestic investors. Many investors are keen to know about disclosures of carbon and climate risks in sovereign bonds and managing those risks. Carbon emissions are also likely to increase the risk of those businesses that contribute the most to the carbon emissions.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on the carbon emission as well as the sovereign risk. Section 3 provides the data with the empirical models and explains the econometric methodology used in the empirical analysis. Section 4 reports the empirical findings as well as discusses. Section 5 provides the conclusion and policy implications.

1. **Literature Review**
	1. *Global Warming and Carbon Emission*

The issue of global warming is a major concern that the whole world is facing. Based on existing literature, the ideal strategy to tackle the world-wide global warming is to reduce carbon emissions. It is also very important to understand that extensive majority of CO2 emissions originated from the human activities for instance combustion of fossil fuels. Therefore, monitoring and controlling of CO2 emissions is a significant concern for civilization. Globally, occurrence of frequent extreme weather events will lead higher insurance premiums and resulted the re-classification of uninsurable risks. In this respect, the United Nations took major steps through organising conventions and conferences under United Nations Framework Convention on Climate Change (UNFCCC) in recent years. The aim of organising the conferences is to control the CO2 emissions. During 2009, Copenhagen accord signed to ensure the implementation of Kyoto protocol and the world community accepted that climate change has major impact on people’s living standards (Nordhaus, 2010). The Conference of Parties (COP) organised in Durban-2011, all the participants agreed to emphasise on and adopt low carbon practices in the short period (Deleuil, 2012). According to Brenton (2013), Kyoto Protocol has been adopted for eight years to control the Greenhouse Gas (GHG). Finally, Intergovernmental Panel on Climate Change (IPCC) is under the auspices of the United Nations Environment Programme stated into the IPCC report, the nations were approved the maximum global warming bound to be 2°C temperature and agreed to decrease the GHG to zero level by 2020 (Friedlingstein et al., 2014). Moreover, recently many studies highlighted the importance of low carbon emission into different perspectives; for instance, the education industry (Liu et al., 2016), production and industrial firms (Wang and Wu, 2017).

* 1. *Nexus of Carbon Emission, Economic Growth and Financial Investment*

There has been substantial literature on nexus between CO2 emissions and economic growth (See Soytas and Sari, 2006; Lee, 2006; Shahbaz et al., 2011; Omri et al., 2014; Zhang and Da, 2015; and Arvin et al., 2015; Wu et al., 2016 and Nasir et al., 2019 among others). Specifically, He (2006) described the factor of Population Haven Hypothesis (PHH) for China. The results showed that 1 percent rise in the FDI leads to 0.098% in pollution. Al-mulali (2012) investigated the Middle East nations from 1990 to 2009. The results highlighted that energy consumption; FDI net inflows, GDP and trade are the main cause for rising CO2 emissions in the long run. Shahbaz et al. (2013b) illustrated the relationship between energy use, FDI, economic growth and CO2 emissions in Malaysia from 1971 to 2011. The results indicate that energy use and economic growth rising CO2 emissions while FDI reduced CO2 emissions. In another study, Shahbaz et al. (2013a) recognised the relationship between CO2 emissions, energy use and trade openness in Indonesia from the period of 1975 to 2011. The results of this study illustrated that FDI and trade openness, energy consumption and economic growth increased CO2 emissions; however, trade openness and financial development reduced CO2 emissions.

Alam and Paramati (2015) applied VECM to examine the relationship between FDI, economic growth, CO2 emissions, internationalization, oil consumption and trade openness from the period of 1980 to 2012 from 18 emerging economies. The results indicate the presence of significant long run relationship between oil consumption, economic growth, internationalization, CO2 emissions, trade openness and financial development. Omri et al. (2014) also examined the link between CO2 emissions, FDI, energy use and economic growth among 54 countries for the period of 1990-2011 by applying the methodology of Cobb Douglas production function dynamic simultaneous equation models. The outcome of the study found the determinants of CO2 emissions were output, energy and FDI. Further related studies on CO2 emission, economic growth and financial investment are examined by (Chiu and Chang, 2009; Apergis and Payne, 2010; Menyah and Wolde-Rufael, 2010; Zhu et al., 2016 and Hakimi and Hamdi, 2016).

Moreover, Central Banks globally have started to debate the consequences of climate change for monetary policy, for example; Bank of England elevating Central Bank’s response to considering the environmental changes into research priorities.

* 1. *Sovereign Risk and Environmental Risk*

Existing literature on the sovereign risk in the context of energy and environmental risk is very limited. Agliardi et al. (2012) applied 34 indicators into three key classifications i.e. political, economic, operational and social to develop risk index. Several other studies also focus on sovereign risk in the context of industrial environment for instance Miller (1992) developed the international environmental risk awareness model, which examined the investment risk of the host country constructed on three levels i.e. macro-environment, the industrial environment and the corporate micro-environment. Another study of Sanchez et al. (2014) applied nine different economic indicators to distinguish the sovereignty of 27 countries in the European Union. Brown et al. (2015) has chosen four different categories (political, economic, operational and social) to develop a more comprehensive risk index.

Further Chinese overseas investment was under a debate with natural resources and particularly this variable plays crucial part in illustrating China’s overseas investment behaviour. In this regard, Li et al. (2012) applied methodology of decomposition hybrid approach to forecast the sovereign risk of major crude oil exporting countries. Tan et al. (2013) examined the scope of Chinese foreign investment in the energy sector as well as its key risks. Sun et al. (2014) also explained the investment of the Chinese sovereign wealth fund in the energy sector. Recently, Conrad and Kostka (2017) and Liedtke (2017) examined activities in Chinese investment in the European energy sector which illustrate imbalanced competition and economic risk for a country.

Most of the other existing literature on sovereign risk examined with sovereign debt and consideration of financial crisis (See e.g., Manganelli and Wolswijk, 2007; Cecchetti et al., 2010; Fischer and Dötz, 2010; Schuknecht et al., 2010 and Aizenman et al., 2013). In addition, there are several studies to examine the relationship between the impact of environmental policies and firm value, credit risk, and the cost of capital (e.g.,Chava, 2014; Bauer and Hann, 2010, and Konar and Cohen, 2001). Interestingly, the study of Dietz et al. (2016) mentioned the existence of ‘climate value-at-risk’, which is of great impact itself on asset values. This study also contributes to the theoretical literature how climate change can affect the value of financial assets. Later, Dietz et al. (2018) introduce the term ‘climate beta’, which represents a kind of risk factor capturing the high discount rate on the expected benefits of emissions reductions. By doing so, the growing body of literature also needs to examine the role of carbon emission on sovereign risks, which is still fruitful avenue.

We have formulated the following two hypotheses to understand the potential effect of carbon emissions on sovereign risk:

Hypothesis 1. Carbon emissions are likely to increase the sovereign risk.

We extend our analysis towards specific sectors because some of the sectors have significant role in the carbon emission. We have selected the main three polluted sectors of the economy i.e. transportation, electricity and industry to measure more likely impact on sovereign risk. We therefore hypothesize that:

Hypothesis 2: The transportation, electricity and industrial sectors are more likely to increase the sovereign risk.

1. **Data and Methodology**

Our sample includes annual data of G7 countries from 1996 to 2014. These countries are Canada, France, Germany, Italy, Japan, the UK and the USA. As we use stock market data to calculate our risk measure, namely, tail quantile and tail expected shortfall, we restrict ourselves to only G7 countries as the stock markets are much developed, and risk measures will be more reliable for these countries. For calculation of tail risk measure, we download daily stock price index data from Datastream (dividend-corrected total return indices) for the G7 countries from 2nd January 1990 to 31st December 2014. We use six years data to calculate tail risk. For example, we use daily data from 2nd January 1990 to 31st December 1995 to calculate tail risk measure for 1996, 2nd January 1991 to 31st December 1996 to calculate tail risk measure for 1997 and so on to come up annual tail risk measure from 1996 to 2014. We fix 2nd January 1990 as a start date because we need at least 1000 observation to calculate tail risk. Because of this, we exclude high carbon emitting countries like China and Russia as the stock market data for these countries do not start from 2nd January 1990. Our data sample stops in 2014 as 2014 is the latest year for which the carbon emissions data are available from the World Bank. Moreover, G7 countries are among top 20 countries in terms of carbon emissions, so we cover most of the top emitters in our sample. As an additional robustness check, we substitute the country financial risk measures–*tail quantile* and (tail) *expected shortfall*–calculated using 5-year government bond data. We collect other data from multiple sources. Variable definition together with the data sources are provided in Table A1 of Appendix A.

* 1. *Measurement of Risk:*

Our measure of risk is identified by a sharp decline in the equity prices of banks. We use univariate extreme value theory (EVT) to measure equity tail risk. The univariate EVT comprises of the Generalised Extreme Value (GEV) distribution and that is the limit law for maxima of a stationary process. We opt for Peaks-Over-Threshold (POT) approach to determine the parameters of the GEV distribution. We do this in a semi-parametric way and fit the distributional excess losses over a given high threshold that converges to a Generalised Pareto Distribution (GPD)[[5]](#footnote-5).

We exploit the empirical stylised fact that equity returns of banks exhibit heavy tails and define as the loss distribution where stands for the dividend adjusted stock price of a bank. The heavy tail implies that the marginal tail probability for as a function of the corresponding quantile can be approximated by a power law (as we call tail quantile above):

 (1)

And with =1 and t>0, i.e., “slowly varying”.

Lower the *α*, the slower the decay to zero and a higher tail probability for a given *x* and vice versa. According to the regulation variation property, all distributional moments higher than *α* (), are unbounded. The distributional models like the Student-t, exhibit fat tails. We define the exceedance probability in equation (1) for given values of value at risk (VaR) level *x* or tail-VaR *x* it can also be calculated for a given value of the tail probability *p*.

VaR is an important risk measure for risk managers, regulators and investors even though it is not a coherent risk measure. Therefore, we also use expected shortfall, which is a conditional expected loss given a sharp fall in the equity capital (). Expected shortfall shows how bad things can go once loss exceeds the VaR boundary and it can be shown as follows:

 (2)

The above equation shows that the expected shortfall is a linear transformation of within the EVT framework.

We use the following semi-parametric estimator of De Haan et al. (1994) to estimate the quantile *x* for extremely low values of :

 (3)

where is the tail cut-off point and it is the *(n-m)*th ascending order statistics from a sample size *n* such that

We estimate the in the above tail quantile estimator in equation (3) with the help of the popular Hill (1975) estimator, which is as follows:

 (4)

The parameter *m* determines how many extreme returns are used in estimation. We use for our main analysis for country level analysis as well as for industry analysis. We do sensitivity analysis by changing and for country analysis and and for industry level analysis. We select m values by using the Hill (1975) estimator. We substitute the Hill statistic in equation (4) and tail quantile estimator in equation (3), to come up with expected shortfall estimator as follows:

 (5)

* 1. *Econometric Methodology*

The starting point of our empirical analysis is a baseline panel regression testing the effect of carbon dioxide (CO2) on country (national) level financial risk measures while controlling for exposure to the financial system. Following Hilscher and Nosbusch (2010) and Dieckmann and Plank (2012), we specify equation (6) as the fixed-effects model for assessing financial risk in the G7 economies:

|  | (6) |
| --- | --- |

where, is the dependent variable representing our risk measure of tail quantile and (tail) expected shortfall over time (*t*) for each country (*i*). is the constant term of the regression while - represent the slope coefficients with respect to each regressor. The exposure to the country’s financial system is accounted for using the following: debt to GDP ratio (*debtgdp*), terms of trade volatility (*totvol*), exchange rates (*exr*), and stock market volatility (*stmvol*). The country-fixed effects (FE) are captured by . The idiosyncratic error term , which captures regression disturbances, is assumed to independently and identically distributed (i.i.d.).

The baseline model (6) may appear underspecified and suffer from endogeneity due to omitted variables affecting country financial risk (Roberts and Whited, 2013; Ullah et al., 2018). As such, we additionally control for the exposure to the financial system using a proxy for international liquidity–i.e. total *reserves* (excluding gold). This results in augmenting the baseline model to equation (7).

|  | (7) |
| --- | --- |

The country risk analysis model is extended further to control for the effects of local and global financial shocks. The local and global financial shocks are captured by measuring the effect of the MSCI World Financial Index and domestic Stock Market Index returns on the Dow Jones Total Market (DJTM) Financial Index returns (*locfin*), the effect of Market Index on Financial Index returns domestically (*finmar*), the effect of MSCI World Financial Index on domestic Market Index returns (*marmsci*), the effect of MSCI World Financial Index on domestic Financial Index returns (*finmsci*), and the effect of Stoxx50 Index and S&P 500 Index returns on MSCI World Financial Index (*stoxx50*). Lastly, equation (8) controls for the yields spreads of corporations in the respective country. This is done by calculating two yield-spread variables: (i) yield spread between BB- and BBB-rated corporations (*hyyield*), and (ii) yield spread between BBB- and AA-rated corporations (*igyield*).

|  | (8) |
| --- | --- |

We check for robustness of the results from equations (6)-(8) by estimating them using the first difference of each variable. This allows us to investigate how the changes in carbon emissions affect the changes in country financial risk. The robustness of the estimated equations (6)-(8) can also be verified by estimating their dynamic panel versions. The dynamic versions of equations (6)-(8) are estimated by incorporating first-lag of each regressor in their respective models. This allows us to observe the dynamic–lagged–effect of the regressors on the country risk measures in respective models. In addition, it reduces endogeneity biases in the estimates that may arise due to reverse causation from country risk measures to carbon emissions and/or simultaneity (Roberts and Whited, 2013; Ullah et al., 2018). As an additional robustness check, we substitute the country financial risk measures–*tail quantile* and (tail) *expected shortfall*–calculated using 5-year government bond data and re-estimating equations (6)-(8).

Furthermore, we extend the national level analysis to three most-polluting sectors of the G7 economies: electricity, industry, and transport. This allows a more in-depth analysis by assessing how, if at all, the financial risk of these sectors is affected by the country’s CO2 emissions. The effect of carbon emissions on sector financial risk is examined by replacing the national level *tail quantile* and (tail) *expected shortfall* measures with that of each sector and re-estimating equations (6)-(8) for each sector.

* 1. *Descriptive Statistics*

Table 1 explains the descriptive statistics of G7 countries. Of the risk measures, the mean values are similar in magnitudes, with the (tail) *expected shortfall* of the transport sector registering the highest value, followed by *tail quantile* measure of the electricity sector. The financial risk measures for the transport sector appear to have higher means compared to the national level, as well as other sectors. Turning to the other variables, we find the highest value of mean for market capitalization (*marcap*), followed by international liquidity (*reserves*), yield spread between BBB- and AA-rated corporations (*igyield*), debt to GDP ratio (*debtgdp*), stock market volatility (*stmvol*), yield spread between BB- and BBB-rated corporations (*hyyield*), exchange rates (*exr*), and carbon emissions (CO2). The remaining variables have respective means that are close to zero (0) in magnitude.

The standard deviation is found to be the highest for *marcap* and *reserves*, followed by the measures for global financial shocks­–*marmsci* and *stoxx50*, *igyield*, local financial shocks–*finmsci* and *finmar*, *hyyield*, *debtgdp*, *exr*, and *stmvol*. The remaining variables have single-digit standard deviations. In addition, the country financial risk measures as well as the carbon emissions appear to have high standard deviations compared to their respective means. The minimum value is the lowest for *marmsci*, followed by *stoxx50*, *finmsci*, *finmar*, and local financials (*locfin*). The minimum values of the remainder of the variables are relatively high. For the financial risk measures, the *tail quantile* measures show higher minimum values relative to their *expected shortfall* counterparts. The maximum values are the largest for *marcap*, *reserves*, *marmsci*, *stoxx50*, *igyield*, *hyyield*, *debtgdp*, *finmar*, *finmsci*, *exr*, and *stmvol*. The maximum values in the other variables are less than 100 in magnitude. Here too, the country risk measures are relatively high in contrast to their mean and minimum values. The national level risk measures are higher than that of their sectoral counterparts.

**Table 1: Descriptive statistics**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variables | N | Mean | Std. Dev. | Min. | Max. |
| Tail Quantile (National level) | 133 | 7.707 | 2.944 | 3.331 | 18.26 |
| Expected Shortfall (National level) | 133 | 7.305 | 4.180 | 1.364 | 24.73 |
| Tail quantile (electricity) | 131 | 8.147 | 4.285 | 1.190 | 20.47 |
| Expected shortfall (electricity) | 131 | 7.620 | 4.925 | 0.275 | 23.65 |
| Tail quantile (industry) | 133 | 7.202 | 2.637 | 3.381 | 17.53 |
| Expected shortfall (industry) | 133 | 7.366 | 3.820 | 1.732 | 22.74 |
| Tail quantile (transport) | 133 | 7.643 | 2.746 | 3.522 | 15.34 |
| Expected shortfall (transport) | 133 | 8.439 | 4.728 | 2.184 | 23.35 |
| CO2 | 133 | 10.84 | 4.539 | 4.573 | 20.18 |
| debtgdp | 133 | 89.32 | 42.66 | 34.32 | 236.1 |
| totvol | 133 | 2.048 | 1.616 | 0.258 | 8.043 |
| exr | 133 | 16.15 | 37.88 | 0.500 | 130.9 |
| reserves | 133 | 1.545e+11 | 2.862e+11 | 1.782e+10 | 1.258e+12 |
| locfin | 124 | 0.525 | 0.510 | 0.0191 | 1.781 |
| stmvol | 133 | 27.62 | 25.54 | 0.877 | 117.6 |
| finmar | 132 | 1.98e-14 | 61.77 | -142.7 | 171.0 |
| marmsci | 132 | 1.05e-12 | 3,380 | -10,965 | 14,476 |
| marcap | 118 | 4.161e+12 | 5.554e+12 | 4.771e+11 | 2.633e+13 |
| finmsci | 133 | 2.94e-14 | 70.82 | -176.0 | 170.0 |
| stoxx50 | 112 | -2.73e-13 | 755.6 | -1,364 | 1,482 |
| hyyield | 102 | 24.70 | 53.65 | 1 | 320 |
| igyield | 128 | 126.8 | 221.8 | 1 | 1,286 |

Table A2 in Appendix A provides the pairwise correlation coefficients between the dependent variables–the financial risk measures–and each of the independent variables. As can be seen, the risk measures­–tail quantile and expected shortfall measures–are positively correlated with CO2 emissions at the national level as well as with that of the three sectors. The highest correlation coefficients are at the national level risk measures while the lowest values are observed for industrial sector. The *debtgdp* variable is found to be negatively correlated with financial risk variables for all four instances. Terms of trade volatility (*totvol*) and exchange rates are positively correlated with the risk measures with two exceptions–*totvol* and risk measures are negatively correlated for the industry sector. The *exr* values are negatively correlated with financial risk at the national level and in the industry sector, while it is positively correlated with the electricity and transport sectors.

The *locfin* is positively correlated with risk measures with one exception–the negative correlation between the former and tail quantile measure for electricity. *finmar* also has positive correlation coefficients for all four instances–nationally as well as in the three sectors. The *marmsci* coefficients are negative, except in the industrial sector. *marcap* is negatively correlated with financial risk measures with exception of expected shortfall nationally. The risk measures and *finmsci* are positively correlated except for the electricity sector’s *tail quantile* measure. The *stoxx50* and *hyyield* values are all negatively correlated with the financial risk variables in the national level as well as sectoral level data. Lastly, *igyield* has positive correlation coefficients with all the national and sectoral level financial risk measures.

1. **Results and Discussion**
	1. *National level Analysis*

Table 2 provides estimated results from equations (6)-(8) using national level risk data. The baseline model estimates can be found in columns (1)-(2). The coefficients on the carbon emissions (CO2) are positive and statistically significant for both *tail quantile* and (tail) *expected shortfall*. Moreover, the results of our study are aligned with the existing literature with environmental policies and firm value, credit risk, or the cost of capital (e.g., Chava, 2014; Bauer and Hann, 2010, and Konar and Cohen, 2001). The effect of carbon emissions on *expected shortfall* is found to be larger in magnitude in contrast to that of *tail quantile*. Stock market volatility is found to have negative and statistically significant effects on country risk in the baseline models (6). The values indicate that baseline models explain between 40.1% and 44.6% of the variations in the country financial risk measures. After augmenting the baseline models with international liquidity measure (*reserves*), the impact of carbon emissions on the risk measures appear to increase in magnitude (columns 3 & 4, Table 2). Similar to the baseline models, the coefficient on CO2, estimated using equation (7), is greater for *expected shortfall* than for *tail quantile*. Here, the stock market volatility is also found to have negative statistically significant coefficients. These two variants of equation (7) also indicate an improvement in goodness of fit: explaining 45.7% and 40.2% of the variations in the *tail quantile* and *expected shortfall* values, respectively.

Columns (5) & (6) of Table 2 provide the results from estimating model (8) using the *tail quantile* and (tail) *expected shortfall* measures. Equation (8) augments equation (7) by accounting for local and global financial shocks as well as incorporating the yield spreads of two groups (differentiated by their credit rating) of corporations. The coefficients on CO2 can be found to be positive and statistically significant, at the 10% and 1% levels of significance (related studies on CO2 emission, economic growth and financial investment are examined by Chiu and Chang, 2009; Apergis and Payne, 2010; Menyah and Wolde-Rufael, 2010; Zhu et al., 2016; and Hakimi and Hamdi, 2016, inter alia). However, the coefficient magnitudes are smaller than that of both the baseline model (6) and international liquidity augmented model (7). In addition, the effect of carbon emissions on *expected shortfall* is larger in value than on *tail quantile*. Stock market volatility no longer has statistically significant coefficient. Turning to the other regressors, *stoxx50* has positive and significant coefficients, at 10% level of significance, in both variants of model (8). In addition, *hyyield* has a positive and significant (at the 10% level) coefficient when equation (8) is estimated using *expected shortfall* as the dependent variable. The adjusted-*R*2 of both version of the model (8) can be found to improve substantially: explaining between 54.7% and 69.1% of the changes in the two measures for country financial risk. Consequently, carbon emissions can be found to increase financial risk in the G7 economies. The magnitude of results with expected shortfall as a risk measure is higher than the tail quantile as a risk measure. Expected shortfall is a superior risk measure as it shows how bad things can go once loss exceeds the VaR (tail quantile in our case) boundary. This reinforces our findings even more as we get higher positive and significant result with a superior risk measure.

**Table 2: Models (6)-(8) estimation, National level**

|  |  |
| --- | --- |
|  | Dependent variable |
|  | Tail Quantile | Expected Shortfall | Tail Quantile | Expected Shortfall | Tail Quantile | Expected Shortfall |
| Independent variables | (1) | (2) | (3) | (4) | (5) | (6) |
| CO2 | 1.962\*\*\* | 2.475\*\*\* | 2.313\*\*\* | 2.618\*\*\* | 0.824\* | 2.189\*\* |
|  | (0.385) | (0.459) | (0.571) | (0.702) | (0.384) | (0.884) |
| debtgdp | -0.0133 | -0.0241 | 0.0208 | -0.0102 | -0.0651 | -0.0739 |
|  | (0.0173) | (0.0154) | (0.0467) | (0.0508) | (0.0414) | (0.0597) |
| totvol | -0.185 | -0.291 | -0.118 | -0.263 | 0.0717 | 0.135 |
|  | (0.168) | (0.205) | (0.198) | (0.237) | (0.197) | (0.341) |
| exr | 0.0483 | 0.0650 | 0.0150 | 0.0514 | 0.0185 | 0.0537 |
|  | (0.0322) | (0.0339) | (0.0245) | (0.0272) | (0.0283) | (0.0544) |
| reserves |  |  | -5.32e-12 | -2.17e-12 | 8.50e-13 | -8.59e-14 |
|  |  |  | (5.47e-12) | (5.82e-12) | (3.30e-12) | (4.71e-12) |
| locfin |  |  |  |  | -0.815 | -1.135 |
|  |  |  |  |  | (1.488) | (3.594) |
| stmvol | -0.0290\*\* | -0.0442\*\* | -0.0280\*\* | -0.0438\*\* | -0.00772 | -0.00449 |
|  | (0.0110) | (0.0165) | (0.0111) | (0.0167) | (0.00924) | (0.0188) |
| finmar |  |  |  |  | 0.0112 | 0.00442 |
|  |  |  |  |  | (0.00721) | (0.0145) |
| marmsci |  |  |  |  | 6.87e-05 | 7.77e-06 |
|  |  |  |  |  | (7.24e-05) | (9.11e-05) |
| marcap |  |  |  |  | 1.22e-13 | 8.26e-14 |
|  |  |  |  |  | (9.82e-14) | (2.48e-13) |
| finmsci |  |  |  |  | -0.00847 | 0.000399 |
|  |  |  |  |  | (0.00559) | (0.00730) |
| stoxx50 |  |  |  |  | 0.000551\* | 0.00120\* |
|  |  |  |  |  | (0.000227) | (0.000542) |
| hyyield |  |  |  |  | -0.00243 | 0.0104\* |
|  |  |  |  |  | (0.00236) | (0.00528) |
| igyield |  |  |  |  | -0.00255 | 0.00211 |
|  |  |  |  |  | (0.00225) | (0.00588) |
| Constant | -11.97\* | -16.60\*\* | -17.62\* | -18.91 | 2.802 | -13.88 |
|  | (5.280) | (5.857) | (8.737) | (10.76) | (7.409) | (13.94) |
| Diagnostics |  |  |  |  |  |  |
| Observations | 133 | 133 | 133 | 133 | 73 | 73 |
|  (within) | 0.446 | 0.401 | 0.457 | 0.402 | 0.691 | 0.547 |
| Number of countries | 7 | 7 | 7 | 7 | 7 | 7 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** Parentheses provide robust standard errors. \*\*\*, \*\*, & \* denote statistical significance at 1%, 5%, & 10% levels of significance (), respectively.

Table 3 presents the model selection tests performed on the variants of equations (6)-(8). The first model selection test is the Hausman (1978) test for any systematic difference between panel fixed- and random-effects regressions. As can be seen, null of no systematic difference in the fixed and random effects coefficients estimates is rejected by the test statistics for all three models–equations (6) to (8)–at the 5% level of significance. Thus, the Hausman (1978) tests point in favour of fixed effects regression estimates providing better estimates compared to their random effects counterparts. The second test for model selection ascertains the necessity of country fixed effects. This is achieved by allowing the intercepts to vary across countries and testing them for joint significance. As such, we can determine whether pooled OLS estimates overlook unobserved heterogeneity–i.e. redundancy of the fixed effects estimates. The estimated -statistics reject, at 5% level, the null of joint insignificance of the fixed effects intercepts from all three specified models. This provides further evidence of unobserved heterogeneity in our G7 panel, and superiority of the fixed effects estimates over their pooled OLS counterparts. Accordingly, the use of the panel fixed effects regressions to estimate the country financial risk models (6)-(8) is appropriate.

**Table 3: Model selection tests, National level**

|  |  |  |  |
| --- | --- | --- | --- |
|  | Hausman (1978) test a |  | Fixed effects redundancy test b |
| Model | Test statistic () | *p*-value |  | Test statistic () | *p*-value |
| Equation (6) | 57.79\*\* | 0.0000 |  | 10.01\*\* | 0.0000 |
| Equation (7) | 45.69\*\* | 0.0000 |  | 10.42\*\* | 0.0000 |
| Equation (8) | 26.99\*\* | 0.0026 |  | 3.92\*\* | 0.0026 |

**Notes:** a : No systematic difference in the fixed and random effects coefficient estimates. b: Fixed effects intercept estimates are all equal to zero (0).

\*\* Denotes rejection of the respective null hypothesis when *p*-value < 0.0500.

* 1. *Robustness checks*

To test the whether our results are robust to a change in specification, we perform a number of checks. Following Hilscher and Nosbusch (2010) and Dieckmann and Plank (2012), we estimate models (6)-(8) using first difference of each variable. Table 4 provides the results from models (6)-(8) estimated using first difference of each variable. As can be seen, the impact of the change in carbon dioxide emissions is positive, and statistically significant, on the change in risk measures in the baseline models (columns 1-2), the baseline models extended by international reserves (column 3-4), and the full models (columns 5-6). In particular, the risk-augmenting effect of CO2 emissions is higher in the full models compared to the baseline models. The change in the exchange rate can also be seen to increase country financial risk in the baseline models (columns 2-4) but not in the full models (columns 5-6). For model (8) estimated with ∆ *expected shortfall* as the regressand, the significant effects of *finmar* and *marmsci* are negative while that of *stoxx50* and *hyyield* are positive.

**Table 4: Models (6)-(8) estimation in differences, National level**

|  |  |
| --- | --- |
|  | Dependent variable |
|  | ∆ Tail Quantile | ∆ Expected Shortfall | ∆ Tail Quantile | ∆ Expected Shortfall | ∆ Tail Quantile | ∆ Expected Shortfall |
| Independent variables | (1) | (2) | (3) | (4) | (5) | (6) |
| ∆CO2 | 0.776\*\* | 1.485\*\* | 0.765\*\* | 1.451\*\* | 1.636\*\* | 2.919\*\* |
|  | (0.262) | (0.482) | (0.257) | (0.485) | (0.540) | (0.858) |
| ∆debtgdp | -0.0294 | 0.0123 | -0.0323 | 0.00359 | -0.0242 | 0.0117 |
|  | (0.0379) | (0.0571) | (0.0388) | (0.0585) | (0.0640) | (0.127) |
| ∆totvol | 0.00417 | -0.00559 | -0.0130 | -0.0584 | -0.0562 | -0.198 |
|  | (0.107) | (0.142) | (0.102) | (0.120) | (0.0978) | (0.174) |
| ∆exr | 0.0200 | 0.0450\* | 0.0310\* | 0.0786\*\*\* | -0.105 | -0.103 |
|  | (0.0152) | (0.0212) | (0.0140) | (0.0193) | (0.0840) | (0.0999) |
| ∆reserves |  |  | 3.70e-12 | 1.14e-11\*\* | -5.56e-12 | -9.88e-12 |
|  |  |  | (2.28e-12) | (3.51e-12) | (5.12e-12) | (1.16e-11) |
| ∆locfin |  |  |  |  | -2.506 | -4.052 |
|  |  |  |  |  | (2.457) | (6.483) |
| ∆stmvol | -0.000898 | -0.00281 | -0.000555 | -0.00175 | -0.00409 | -0.00633 |
|  | (0.00598) | (0.0109) | (0.00600) | (0.0107) | (0.00597) | (0.0119) |
| ∆finmar |  |  |  |  | -0.00405 | -0.0198\*\* |
|  |  |  |  |  | (0.00516) | (0.00550) |
| ∆marmsci |  |  |  |  | -8.96e-05 | -0.000204\*\*\* |
|  |  |  |  |  | (5.57e-05) | (4.86e-05) |
| ∆marcap |  |  |  |  | 3.14e-14 | 4.76e-14 |
|  |  |  |  |  | (4.40e-14) | (9.28e-14) |
| ∆finmsci |  |  |  |  | 0.00338 | 0.0175 |
|  |  |  |  |  | (0.00831) | (0.0101) |
| ∆stoxx50 |  |  |  |  | 0.000495 | 0.00138\*\* |
|  |  |  |  |  | (0.000340) | (0.000509) |
| ∆hyyield |  |  |  |  | 0.000516 | 0.00697\* |
|  |  |  |  |  | (0.00171) | (0.00331) |
| ∆igyield |  |  |  |  | 0.000348 | 0.00533 |
|  |  |  |  |  | (0.00152) | (0.00403) |
| Constant | -0.284\*\* | -0.435\*\* | -0.314\*\* | -0.529\*\*\* | -0.125 | -0.254 |
|  | (0.0935) | (0.132) | (0.0905) | (0.133) | (0.140) | (0.220) |
| Diagnostics |  |  |  |  |  |  |
| Observations | 126 | 126 | 126 | 126 | 57 | 57 |
|  (within) | 0.057 | 0.050 | 0.060 | 0.062 | 0.530 | 0.480 |
| Number of countries | 7 | 7 | 7 | 7 | 7 | 7 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** Parentheses provide robust standard errors. \*\*\*, \*\*, & \* denote statistical significance at 1%, 5%, & 10% levels of significance (), respectively.

Next, we check the persistence of our econometric model by running the dynamic models. The dynamic versions of models (6) to (8) can be found in Table A3 in Appendix A. As can be seen, the country financial risk-augmenting effect of carbon emissions remain valid in the dynamic models. The coefficients on the CO2 variables are statistically significant in all versions of the country risk models, except when the baseline model (6) is estimated with tail quantile as the dependent variable (column 1, Table A3). The coefficients on carbon emissions are lower in the baseline models from the dynamic estimations (columns 1-4, Table A3, Appendix A) when compared to static estimates in Table 3 (columns 1-4). However, in the full versions of the country risk models, i.e. equation (8), this effect is roughly the same (in magnitude) in both the static and dynamic estimations. Stock market volatility (*stmvol*) can be seen to have a lagged negative effect on financial risk in the baseline models (columns 1-4, Table A3), while in the full models the negative effect is contemporaneous. In addition, *stoxx50* can be seen to increase country risk contemporaneously and at first lag in column 6 of Table A3. *hyyield* appears to reduce risk in level form and aggravate it in first lag form. In contrast, *marcap* in its first-lag form has a financial risk-reducing effect (columns 5 & 6, Table A3).

We demonstrate further robustness of the results in Table 3 by re-estimating models (6) to (8) using 5-year government bond data as the proxy for country financial risks; as opposed to using country equity index return in the previous estimations.[[6]](#footnote-6) Here too, we find that carbon emissions consistently aggravate the country bond risk measures. However, the estimated positive coefficients on the CO2 variable are, on average, substantially larger for the bond data than those in Table 3. Lastly, dynamic versions of equations (6)-(8) are also estimated using the country risk variables calculated from the bond data. Here too, the estimated results demonstrate the financial risk-augmenting effect of the carbon emissions. As such, we can confidently state that carbon emissions increase the (national level) financial risk of the G7 countries, and this finding is robust to specification of the risk model as well as the proxy for risk measures.

* 1. *Sectoral level Analysis*

The analysis is extended to the three largest polluting sectors of the G7 economies. Table 5 demonstrates the results from equations (6) & (8) with *expected shortfall* as the dependent variable, by electricity, industry and transport sectors, respectively. Generally, the effect of carbon emissions (CO2) has a positive impact on both (tail) *expected shortfall* in our six estimations, except from the last column. Most of the estimated coefficients on this variable are significant at the 1% and 5% level. Although the signs of coefficients in last column (for transportation sector with all control variables) are positive, they are insignificant; providing weak evidence to support the effect of carbon emission on sovereign risk in the transport sector. When it comes to exchange rate (*exr*) factor, only industrial sector holds the significance coefficient for both models (6) & (8). In other sectors, the exchange rate coefficients became insignificant after controlling the other variables. Regarding the goodness of fit (), it is observed that model (8)–which includes the full set of control variables–substantially improves the explanatory power of the baseline model (6): from 29.3% to 50.7% for electricity, 34.3% to 61.5% for industrial, and 34.9% to 42.4% for transport.

Looking at other independent variables, our models also validate that local financials (*locfin*) has positive effect on sovereign risk at the 10% significance level in the electricity sector only. In contrast, *finmsci* and *igyield* reduce the country risk at electricity and industrial sector. In summary, we consistently find carbon emissions to aggravate sovereign risk in all sectors, with the effect being the highest in the electricity sector.

Overall, there is a clear evidence that carbon emission is a determinant of sovereign risk in electricity, industry and transport sectors. This effect is robust in two sectors, electricity and industry, while the contribution of carbon emissions to financial risk in the transport sector is only found in the baseline model. The results of goodness-of-fit in the sectoral analysis are also akin to the results of the national level analysis. Finally, apart from carbon emissions, there are several factors, which affect country financial risk in our models, such as exchange rate, yield spread and so forth. It is also important to note that our sectoral results are virtually identical when the dependent variable is *tail quantile*.[[7]](#footnote-7)

**Table 5: Models (6) & (8) estimations, Sectoral level**

|  |  |
| --- | --- |
| Dependent variable: Expected Shortfall | Sector |
|  | Electricity | Electricity | Industrial | Industrial | Transport | Transport |
| Independent variables | (1) | (2) | (3) | (4) | (5) | (6) |
| CO2 | 2.756\*\*\* | 2.499\*\* | 2.138\*\*\* | 1.141\*\*\* | 2.236\*\* | 1.361 |
|  | (0.455) | (0.992) | (0.286) | (0.307) | (0.737) | (2.589) |
| debtgdp | 0.0236 | 0.0113 | -0.00649 | -0.0499 | -0.0167 | -0.151 |
|  | (0.0264) | (0.0944) | (0.0266) | (0.0405) | (0.0371) | (0.195) |
| totvol | 0.0391 | 0.0924 | -0.0213 | 0.394 | 0.461\* | -0.209 |
|  | (0.417) | (0.753) | (0.210) | (0.452) | (0.235) | (0.710) |
| exr | 0.156\*\* | 0.132 | 0.161\*\* | 0.144\*\* | 0.168\* | 0.0631 |
|  | (0.0532) | (0.0825) | (0.0546) | (0.0497) | (0.0860) | (0.0936) |
| reserves |  | 4.62e-12 |  | 5.89e-13 |  | 5.37e-12 |
|  |  | (1.03e-11) |  | (4.95e-12) |  | (1.57e-11) |
| locfin |  | 19.62\* |  | 1.688 |  | 6.756 |
|  |  | (9.250) |  | (5.516) |  | (5.510) |
| stmvol | -0.00546 | -0.00782 | -0.0363\*\* | -0.0218 | -0.0192 | -0.0172 |
|  | (0.0125) | (0.0221) | (0.0117) | (0.0170) | (0.0219) | (0.0351) |
| finmar |  | 0.0348\*\* |  | 0.0386\*\* |  | 0.0333 |
|  |  | (0.0101) |  | (0.0107) |  | (0.0375) |
| marmsci |  | 0.000272 |  | 0.000338\* |  | 0.000326 |
|  |  | (0.000178) |  | (0.000149) |  | (0.000395) |
| marcap |  | 3.99e-13 |  | 8.99e-14 |  | 3.30e-13 |
|  |  | (2.23e-13) |  | (1.51e-13) |  | (1.83e-13) |
| finmsci |  | -0.0559\*\*\* |  | -0.0414\*\*\* |  | -0.0392 |
|  |  | (0.0135) |  | (0.0105) |  | (0.0274) |
| stoxx50 |  | 0.000298 |  | -0.000230 |  | 0.00269\*\* |
|  |  | (0.000624) |  | (0.000608) |  | (0.000761) |
| hyyield |  | -0.00635 |  | -0.00191 |  | -0.0215\*\*\* |
|  |  | (0.00516) |  | (0.00389) |  | (0.00539) |
| igyield |  | -0.0140\*\* |  | -0.00302 |  | -0.00941\*\* |
|  |  | (0.00534) |  | (0.00320) |  | (0.00377) |
| Constant | -26.92\*\*\* | -32.83\* | -16.78\*\* | -5.729 | -17.43 | 0.949 |
|  | (4.543) | (15.51) | (5.009) | (4.211) | (11.23) | (44.91) |
| Diagnostics |  |  |  |  |  |  |
| Observations | 131 | 73 | 133 | 73 | 133 | 73 |
|  (within) | 0.293 | 0.507 | 0.343 | 0.615 | 0.349 | 0.424 |
| Number of countries | 7 | 7 | 7 | 7 | 7 | 7 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** Parentheses provide robust standard errors. \*\*\*, \*\*, & \* denote statistical significance at 1%, 5%, & 10% levels of significance (), respectively.

1. **Summary and Conclusion**

This paper studies the role of innovation on tackling environmental challenges via studying an innovative question whether climate change as proxied by carbon emissions determine the sovereign risk. To answer this question, we use annual data from G7 countries for the period from 1996 to 2014. We argue that carbon emissions are likely to increase economic cost of a country with high incidence of floods, draught and less healthy human capital; therefore, they are likely to increase the risk of a country. Following Hartmann et al. (2004) and Straetmans et al. (2008) we employ semi parametric extreme value theory (EVT) and estimates marginal and joint probabilities of tail events. It carries the advantage of focusing on extreme events that occur with very low frequency and are long term in nature. This is important for our study as carbon emissions are not likely to have impact on the sovereign risk in the short term. Our results show that climate change (carbon emissions) is likely to increase risk significantly at country level as well as at the sectoral level. At sectoral level, we conduct analyses on top 3 sectors of transportation, electricity and industry, which are responsible for 29%, 28% and 22% of total global carbon emissions. Our results indicate that they are more likely to increase the sovereign risk. We carry out a number of robustness checks. First, following Hilscher and Nosbusch (2010) and Dieckmann and Plank (2012), we estimate models (6)-(8) by using first difference of each variable. Second, we estimate the dynamic models to check the persistence of our econometric model and finally, we substitute the country financial risk measures tail quantile and (tail) expected shortfall measured by using 5-year government bond index data. Our results are robust to these changes in the econometric models and risk measures.

The findings of this paper point to new avenues for future research, two of which we outline here. First, we do not explore if there is any impact on portfolio returns for investors having portfolio in high carbon emission countries. An answer to this question will be of great value for investors in managing their portfolio. Second, there is no empirical evidence if industries with high carbon emissions are creating value or destroying value. Historically, there has been belief that they create value and contribute toward employment as well as economic growth. However, this issue is under debate these days. A look into this question can provide clear evidence toward favourable or damaging impact of high carbon emitting industries.

Our paper informs policy makers about the importance of carbon emissions reduction in order to tackle environmental challenges and Nationally Determined Contributions (NDCs) as determined in the COP21 and whose progress has been continuously monitored in all the subsequent COPs until COP25. It provides evidence to the country policy makers that not subscribing to the NDCs is likely to increase their sovereign risk, which will harm them in the long run in the form of lower investment and high risk for businesses. Local and foreign investors are interested to know about disclosures of carbon emissions as they are likely to increase sovereign risk, which is important for them to rebalance their portfolio. There are also policy implications for businesses as carbon emissions are also likely to increase their risk especially if they are from the sectors that contribute the most to the carbon emissions. Furthermore, countries also need to turn high carbon emitting industries green by switching away from fossil fuels.

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**Appendix A. Supplementary data**

Supplementary data to this article can be found online.

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**Appendix A. Supplementary data**

**Table A1: Variable definition and source**

|  |  |  |
| --- | --- | --- |
| Variable | Definition | Data source |
| Tail quantile | Estimated using equation (1); see Section 3.1 for details | Datastream |
| Expected shortfall | Estimated using equation (5); see Section 3.1 for details | Datastream |
| CO2 | Carbon dioxide (CO2) emissions (metric tons per capita) | World Bank |
| debtgdp | Gross debt (% of GDP) | IMF, Federal Reserve Economic Data |
| totvol | Terms of Trade (2010=100%) volatility; 3-year moving average standard deviation | OECD |
| exr | Exchange Rates, Domestic Currency per U.S. Dollar, Period Average, Rate; | IMF |
| reserves | International Liquidity, Total Reserves excluding Gold, US Dollars | IMF |
| locfin, Local financials | DJTM Financials Index return (intercept and residuals from a regression on MSCI World Financial index return and domestic Stock Market Index return) | Datastream |
| stmvol, Stock Market Volatility | 360 day rolling volatility of Stock Market Index | Bloomberg |
| finmar | Intercept and residuals from a regression of domestic Financial Index on Market Index | Bloomberg |
| marmsci | Intercept and residuals from a regression of Market Index on MSCI World Financial index | Bloomberg |
| marcap | Market capitalization of listed domestic companies (current US$) | World Bank |
| finmsci | Intercept and residuals from a regression of Financial Index on MSCI World Financial index | Datastream |
| stoxx50 | Intercept and residuals from a regression of MSCI World index on Stoxx 50 index and S&P 500 index | Datastream |
| hyyield | Yield spread between BB- and BBB- rated corporations of the respective countries | Bloomberg |
| igyield | Yield spread between BBB- and AA- rated corporations of the respective countries | Bloomberg |

**Table A2: Correlation coefficients between dependent variables and independent variables**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Tail quantile(national) | Expected shortfall(national) | Tail quantile(electricity) | Expected shortfall(electricity) | Tail quantile(industry) | Expected shortfall(industry) | Tail quantile(transport) | Expected shortfall(transport) |
| Tail quantile(national, sectoral) | 1.000 |  | 1.000 |  | 1.000 | 1.000 | 1.000 |
| Expected shortfall(national, sectoral) | 0.884 | 1.000 | 0.970 | 1.000 | 0.923 | 0.923 | 0.952 | 0.952 |
| CO2 | 0.338 | 0.257 | 0.212 | 0.109 | 0.016 | 0.016 | 0.033 | 0.033 |
| debtgdp | -0.296 | -0.194 | -0.101 | -0.123 | -0.277 | -0.277 | -0.185 | -0.185 |
| totvol | 0.058 | 0.032 | 0.160 | 0.123 | -0.053 | -0.053 | 0.002 | 0.002 |
| exr | 0.055 | 0.110 | 0.124 | 0.135 | 0.075 | 0.075 | 0.183 | 0.183 |
| reserves | -0.088 | -0.018 | 0.061 | 0.052 | -0.103 | -0.103 | 0.068 | 0.068 |
| locfin | 0.077 | 0.019 | -0.015 | 0.091 | 0.220 | 0.220 | 0.360 | 0.360 |
| stmvol | -0.007 | -0.059 | -0.207 | -0.114 | 0.073 | 0.073 | 0.235 | 0.235 |
| finmar | 0.570 | 0.535 | 0.118 | 0.142 | 0.365 | 0.365 | 0.370 | 0.370 |
| marmsci | -0.077 | -0.042 | -0.153 | -0.137 | 0.030 | 0.030 | -0.156 | -0.156 |
| marcap | -0.083 | 0.022 | -0.183 | -0.240 | -0.173 | -0.173 | -0.111 | -0.111 |
| finmsci | 0.439 | 0.462 | -0.003 | 0.032 | 0.266 | 0.266 | 0.269 | 0.269 |
| stoxx50 | -0.428 | -0.241 | -0.390 | -0.402 | -0.631 | -0.631 | -0.246 | -0.246 |
| hyyield | -0.170 | -0.005 | -0.207 | -0.248 | -0.285 | -0.285 | -0.232 | -0.232 |
| igyield | 0.121 | 0.115 | -0.024 | 0.025 | 0.042 | 0.042 | 0.377 | 0.377 |

**Table A3: Dynamic estimations of models (6)-(8), National level**

|  |  |
| --- | --- |
|  | Dependent Variable |
|  | Tail Quantile | Expected Shortfall | Tail Quantile | Expected Shortfall | Tail Quantile | Expected Shortfall |
| Independent Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| CO2 | 1.063 | 1.195\* | 1.033\* | 1.182\* | 1.057\*\*\* | 2.415\*\* |
|  | (0.569) | (0.490) | (0.519) | (0.500) | (0.278) | (0.872) |
| debtgdp | -0.0693 | -0.104 | -0.0687 | -0.106 | -0.000351 | 0.0611 |
|  | (0.0685) | (0.112) | (0.0702) | (0.115) | (0.123) | (0.328) |
| totvol | -0.0610 | -0.200 | -0.0379 | -0.200 | -0.154 | -0.261 |
|  | (0.134) | (0.182) | (0.147) | (0.177) | (0.208) | (0.440) |
| exr | 0.0148 | 0.0108 | -0.0267 | 0.00613 | 0.185 | -1.682 |
|  | (0.0302) | (0.0347) | (0.0454) | (0.0653) | (3.360) | (7.354) |
| reserves |  |  | -5.75e-12 | 2.84e-13 | -2.46e-11 | -3.74e-11 |
|  |  |  | (4.70e-12) | (8.84e-12) | (2.50e-11) | (5.48e-11) |
| locfin |  |  |  |  | 3.257 | 8.038 |
|  |  |  |  |  | (2.902) | (6.217) |
| stmvol | -0.00573 | -0.0105 | -0.00307 | -0.00987 | -0.0289\*\*\* | -0.0577\*\*\* |
|  | (0.00904) | (0.0168) | (0.00828) | (0.0175) | (0.00363) | (0.00867) |
| finmar |  |  |  |  | 0.0123 | 0.00200 |
|  |  |  |  |  | (0.0115) | (0.0200) |
| marmsci |  |  |  |  | 9.72e-05 | 8.90e-05 |
|  |  |  |  |  | (0.000128) | (0.000238) |
| marcap |  |  |  |  | 9.51e-14 | 2.94e-13 |
|  |  |  |  |  | (1.45e-13) | (2.58e-13) |
| finmsci |  |  |  |  | -0.0132 | -0.0102 |
|  |  |  |  |  | (0.0114) | (0.0205) |
| stoxx50 |  |  |  |  | 0.000911 | 0.00253\*\* |
|  |  |  |  |  | (0.000488) | (0.000891) |
| hyyield |  |  |  |  | -0.00757\*\*\* | -0.00698 |
|  |  |  |  |  | (0.00177) | (0.00453) |
| igyield |  |  |  |  | -0.00257 | -0.000147 |
|  |  |  |  |  | (0.00351) | (0.0102) |
| L.CO2 | 0.529 | 0.755 | 0.847 | 0.819 | -1.325 | -1.731 |
|  | (0.531) | (0.620) | (0.610) | (0.847) | (1.487) | (2.888) |
| L.debtgdp | 0.0484 | 0.0677 | 0.0767 | 0.0747 | -0.0845 | -0.207 |
|  | (0.0641) | (0.110) | (0.0763) | (0.133) | (0.106) | (0.278) |
| L.totvol | -0.238 | -0.335 | -0.201 | -0.318 | -0.213 | -0.307 |
|  | (0.167) | (0.192) | (0.185) | (0.262) | (0.305) | (0.641) |
| L.exr | 0.0143 | 0.0203 | 0.0215 | 0.0168 | -0.160 | 1.000 |
|  | (0.0250) | (0.0332) | (0.0218) | (0.0396) | (2.161) | (4.709) |
| L.reserves |  |  | 1.03e-12 | -1.20e-12 | -1.73e-11 | -1.77e-11 |
|  |  |  | (1.75e-12) | (6.62e-12) | (3.31e-11) | (7.21e-11) |
| L.locfin |  |  |  |  | -0.708 | -3.566 |
|  |  |  |  |  | (4.418) | (9.861) |
| L.stmvol | -0.0285\*\* | -0.0312\*\* | -0.0281\*\* | -0.0313\*\* | 0.00381 | 0.00738 |
|  | (0.00927) | (0.0108) | (0.00922) | (0.0114) | (0.0132) | (0.0296) |
| L.finmar |  |  |  |  | 0.00634 | 0.0219 |
|  |  |  |  |  | (0.0139) | (0.0360) |
| L.marmsci |  |  |  |  | 0.000136 | 0.000195 |
|  |  |  |  |  | (0.000135) | (0.000202) |
| L.marcap |  |  |  |  | -1.95e-13\* | -6.61e-13\*\* |
|  |  |  |  |  | (8.72e-14) | (2.13e-13) |
| L.finmsci |  |  |  |  | -0.00403 | -0.0135 |
|  |  |  |  |  | (0.00995) | (0.0235) |
| L.stoxx50 |  |  |  |  | 0.000598 | 0.000515 |
|  |  |  |  |  | (0.000791) | (0.00163) |
| L.hyyield |  |  |  |  | 0.00799 | 0.0261\* |
|  |  |  |  |  | (0.00546) | (0.0118) |
| L.igyield |  |  |  |  | -0.00256 | -0.00301 |
|  |  |  |  |  | (0.00213) | (0.00544) |
| Constant | -6.724 | -8.983 | -11.31 | -9.780 | 22.26 | 20.26 |
|  | (5.809) | (5.508) | (7.260) | (9.475) | (25.86) | (52.05) |
| Diagnostics |  |  |  |  |  |  |
| Observations | 126 | 126 | 126 | 126 | 57 | 57 |
|  (within) | 0.532 | 0.464 | 0.541 | 0.465 | 0.843 | 0.775 |
| Number of countries | 7 | 7 | 7 | 7 | 7 | 7 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The ‘L’ prefix defines the first lag of respective variables.

Parentheses provide robust standard errors. \*\*\*, \*\*, & \* denote statistical significance at 1%, 5%, & 10% levels of significance (), respectively.

1. See Ullah et al. (2019) for a systematic discussion on the definition and types of risks. [↑](#footnote-ref-1)
2. See more on ‘Ash to cash’: Montserrat gambles future on the volcano that nearly destroyed it (<https://www.theguardian.com/world/2016/jan/28/montserrat-volcano-british-territory-geothermal-energy-tourism-sand-mining>). [↑](#footnote-ref-2)
3. <https://www.climate-transparency.org/>. [↑](#footnote-ref-3)
4. See the link below for further detail on carbon emissions by sector (<https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions>). [↑](#footnote-ref-4)
5. See for example Jansen and de Vries (1991), Danielsson and de Vries (1997) and Straetmans and Chaudhry (2015) among others for semi-parametric tail estimation approaches. [↑](#footnote-ref-5)
6. Results estimated using the 5-year government bond data are not provided here but will be available upon request from the author(s). [↑](#footnote-ref-6)
7. These results will be available upon request from the author(s). [↑](#footnote-ref-7)