THE IMPACT OF EXTREME WEATHER EVENTS ON QUALITY OF LIFE IN SMALL ISLANDS DEVELOPING STATES WITH VARYING LEVELS OF EXPORT DIVERSIFICATION

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Abstract

The increasing frequency and severity of extreme weather events disproportionately impacts the world's most vulnerable populations, which makes understanding the relationship between a country's economic structure and the magnitude impact of these exogenous shocks imperative. The aim of this study is to examine the relationship between export diversification and the magnitude impact of extreme weather events on quality of life (QOL). The analysis of the relevant literature informs the creation of the hypothesis, which predicts that less diverse export structures will experience larger negative impacts compared to their more diverse counterparts. Small Island Developing States (SIDS), as defined by the UN, are used as the sample in this study. Four linear regressions are utilized to approach this question and they use GDP per Capita and GDP Growth Rate as the QOL indicators. The models predicting GDP per Capita yielded statistically significant results, which communicate that less diverse export structures experience increasingly positive effects as the number of extreme weather events increase. To demonstrate this, the expected percentage increase in GDP per Capita for each additional extreme weather event across three increasingly less diverse export categories are included here. An additional extreme weather event is expected to increase GDP per Capita by 0.7% in the most diverse of these three categories, 1.262% in the middle, and 1.765% in the least diverse, all compared to the most diverse category which serves as our reference level. However, the GDP Growth Rate models' results did not return statistically significant results. It is the hope of this paper that its findings will inform economic adaptation and mitigation measures as climate change worsens.

KEYWORDS: (Extreme Weather, Export Diversification, Quality of Life, Small Island Developing States)

JEL CODES: (Q54, F18, Q51)

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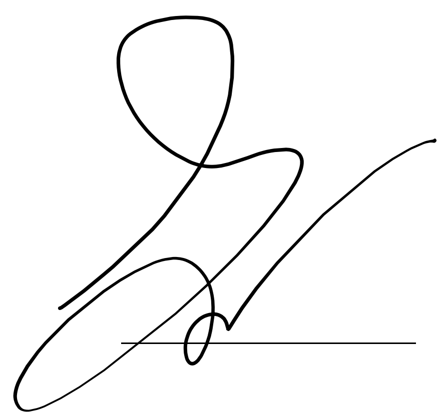

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Introduction

The frequency and severity of extreme weather events is increasing, and Small Island Developing States (SIDS) are being disproportionately impacted. In 2020, the United Nations Office for Disaster Risk Reduction (UNDRR) reported 7,348 major disaster events between the years 2000-2019. These events resulted in the loss of 1.23 million lives and cost the global economy 2.97 trillion USD. Of the 7,348 disaster events, 6,681 of them were categorized as climate related disasters. This is a dramatic increase from the previous twenty-year span (1980-1999) where only 3,656 of the 4,212 disaster events were identified as climate related disasters (CRED EM-DAT, 2020) This increase in occurrence and severity is not contended in the literature and the disproportionate effect on SIDS is acknowledged across the field (Rasmussen, 2004; Noy, 2008; Fomby et. al, 2009; Raddatz, 2009; Laframboise and Loko, 2012). These findings are reported in the literature review.

The increase in occurrence and severity of extreme weather events coupled with the disproportionate impact on a small subset of the global population presents the opportunity for this study. This study is motivated by an interest in both understanding the quality of life (QOL) impacts of extreme weather events on SIDS and their countries economic dependency on tourism. At the intersection between these two interests lies the question surrounding the effect that export diversification has on the magnitude impact of extreme weather events on QOL. The relationship being investigated is if a SIDS level of export diversification softens the impact of exogenous shocks–in this case extreme weather events–on QOL.

The level of export diversification will be calculated using the percentage of the SIDS exports that are attributed to tourism. These values will be translated into a scale based on the range their percentage value falls in. This score undergoes dummy coding and becomes a vector of dummy variables symbolizing different levels of export diversification in the models. The indicators selected for QOL are GDP per Capita and GDP Growth Rate. This is expanded on in the data section.

Utilizing common economic theory and the relevant literature, this study predicts that SIDS with a lower export diversification score, which signals less of a reliance on tourism, will experience a smaller QOL impact in the wake of weather disasters as compared to the impact felt by their less diverse counterparts.

Braynen (2019) exposes the gap in the literature surrounding SIDS and the impact that export diversification has on their economic growth. It is in this piece where Binger et al., 2002 and their work surrounding the difficulty that SIDS face in having diversified export structure is brought up. This serves, in conjunction with the disproportionate vulnerability to weather events that SIDS face, which is confirmed throughout the literature, as the call to action for this study. Some influential studies that align in terms of subject matter, but differ in approach, include McIntyre et al. (2018) and Coulson et al. (2020). McIntyre et al. (2018), as will be examined in the literature review section, studies the impact that export diversification has on output volatility and growth in small states. Their findings support the hypothesis of this paper. Coulson et al. (2020), uses regional housing prices to uncover the effect of natural disasters on the health of the regional economy. Their findings support the hypothesis that a diversified economy will better withstand the impacts caused by exogenous shocks, which in the case of this paper, are natural disasters.

The hypothesis of this study is explored through four linear regressions. These models and their variables are outlined in the following section. Regressions 1 and 2, which use GDP per Capita (*GDPPC*) as the dependent variable, yield statistically significant results, while Regressions 3 and 4, which use GDP Growth Rate (*GDPGR*) as the dependent variable, do not. As such, the results of Regressions 1 and 2 attract the most attention. The coefficients on the key variables communicate that the expected impact of an additional extreme weather event on a GDP per Capita is both positive and increasing as export structures become less diverse. To express these results more clearly, the expected increase in *GDPPC* for each additional extreme weather event across three of the export diversification categories are included here. For economies ranked 3 on the ten-point export diversification scale, an additional extreme weather event is expected to increase *GDPPC* 0.7% when using the first dataset. For countries ranked 5 on the ten-point export diversification scale, an additional extreme weather event is expected to increase *GDPPC* by 1.262% when using the first dataset. Finally, for countries ranked 8 on the ten-point export diversification scale, an additional extreme weather event is expected to increase *GDPPC* by 1.765% when using the first dataset. All of these are the expected percentage increase in *GDPPC* for each additional extreme weather event as compared to the countries ranked 1 on the ten-point scale. These results contradict the prediction of the hypothesis but reveal that the assumptions underlying this expectation may have been too generalized. A closer examination and more thorough explanation exist in the data and conclusion sections.

Section 2 of this paper is the literature review, where the relevant literature, including the pieces discussed above, will be introduced. The literature review examines work pertaining to the benefits of export diversification, the impacts of extreme weather events (economical and welfare), and touches on some tourism focused studies. Section 3 develops the theory backing this study and uses it to develop the model that is implemented into the linear regression. Section 5 speaks about the data, including where it was collected from, how it was organized, and how it was adapted to construct the variables included in the regression equations. Section 5 analyzes the data and the results obtained from running the regression equations introduced in Section 4. Section 6 showcases the key conclusions from these results and provides commentary on how to further develop this study in the future, as well as areas of opportunity for other studies.

Literature Review

Benefits of Export Diversification

Export diversification is an important economic concept that must be examined in order to lay the foundation for this paper's hypothesis. The relevant literature is reviewed here in an effort to introduce and emphasize the importance of this topic. A common pattern of conclusions will emerge through the reporting of different authors' findings, which adds strength to the hypothesis of this paper, as they argue in favor of diverse export structures.

The existence of a ‘nonlinear’ or ‘u-shaped’ relationship between economic growth and export diversification is consistent throughout the literature. However, each author's presentations of these findings differ slightly. These overlapping results are reported here. Markakkaran and Sridharan (2022) investigate the impact of export diversification on GDP per capita growth. They find that export concentration is negatively associated with GDP per capita growth. They develop this finding further by extending their analysis to compare results across countries' income levels. They find that lower income countries benefit from export diversification, while higher income countries benefit from export specialization. Trinh and Thuy (2021) also investigate the ‘non-linear’ relationship between export diversification and economic growth. Although their threshold regression approach is confusing, their high-level findings communicate that export diversification can reach a level where it no longer contributes positively to economic growth. It is beyond this level, where export specialization is preferred. Aditya and Acharyya (2011) examine the export-growth relationship and report similar results. They find that, as mentioned above, there is a critical level of export concentration. Above this level is where export specialization is favorable for economic growth, and below is where export diversification remains favorable for growth.

Naude and Rossouw (2010) align with the studies mentioned above and reinforce the results that were found by Markakkaran and Sridharan (2022) and those suggested by Trinh and Thuy (2021) and Aditya and Acharyya (2011). Naude and Rossouw (2010) look at the relationship between export diversity and economic performance in Brazil, China, India, and South Africa (BCIS). Their most relevant results include the findings that export diversification causes GDP per capita growth in Brazil, China, and South Africa, but not India, where the relationship is flipped. Additionally, South Africa is identified as the only country where export diversification has a ‘unambiguous’ positive impact on economic development. Export specialization is preferred in Brazil, China, and India, which aligns with the results of Markakkaran and Sridharan (2022) that were discussed above. Gnangnon (2022) adds to the emerging pattern within these findings in their investigation of the effect of services export diversification on economic growth. They find that services export diversification increases economic growth in developing countries, but that economic specialization is more favorable for growth in higher income countries. The pattern found throughout the literature is clear. In smaller, lower-income countries, export diversification has favorable effects on economic growth. However, in higher-income countries or above a certain value of diversification, specialization becomes the preferred export strategy. In the context of this paper, which focuses on SIDS, the hypothesis that a more diversified export structure will create a more resilient economy is strengthened by this observed pattern.

Despite the consistent pattern in the literature observed above, it is important to note that one article reported contradicting conclusions. Gözgör and Can (2017) examined the causal relationships between economic globalization, product diversification of exports, and economic growth. They find that the diversification of exports is positively associated with economic growth in upper-middle economies. This comes as a direct contradiction to the overwhelming consistency in the results above that communicated the favorability of export specialization for economic growth in more developed and higher income countries.

Two pieces of literature discussed the relationship between economic diversification and weather events. Ramcharan (2005) investigates the benefits of economic diversification by utilizing the unpredictable and exogenous characteristics of earthquakes. They find that more specialized economies undergo larger declines in consumption after the earthquake. This study helps validate the hypothesis of this paper, but also illustrates the room for further research that incorporates more than one type of weather event and focuses on QOL impacts too. Coulson et al. (2020) study the effect of natural disasters on regional housing markets. They use natural disasters in a similar fashion to how Ramcharan utilized earthquakes, as they capitalize on the exogeneity of weather events. They use the housing market as an indicator for the health of regional economies. Their research finds diversity 'dampens' the magnitude and duration of the effects of a disaster on the local real estate values (health of local economy). Again, this study demonstrates support for the guiding hypothesis of this paper and also the space for a broader study. As will be explored in the following section, SIDS are uniquely vulnerable to climate change and understanding this relationship is timely.

McIntyre et al. (2018) focuses on economic diversification by looking at exports in small states to assess economic performance. They find that more diversified economies with regards to their exports experienced lower output volatility and higher average growth. This means that a more diversified export structure helps create a stable economy, with stability being the keyword of interest. It will be interesting to investigate if these findings of stability remain consistent in SIDS who have experienced a natural disaster.

Extreme Weather Events: Economic Effects

Studying the macroeconomic effect of weather events raises questions regarding which time frame to investigate. Deciding to study short-run or long-run effects is a choice that authors need to make when creating their model. Despite differences in the time frames selected, the results and findings are similar from a high-level perspective.

Kim et al. (2022) utilizes a high-frequency approach, or in other terms, monthly data in their investigation of the macroeconomic impact of climatic disasters in Central American countries. The study focuses on the period 2000-2019 and uses dummy variables for storm and flood events that the sample countries experienced. Their findings communicate that a climatic disaster results in a 0.5-1 percentage point decrease in economic activity and leads to persistent effects on the level of GDP. In an extension of their work, they note that an increase in remittances is observed in the wake of a weather event. These remittances act as a shock absorber, which introduces them as a logical control variable to be added to the model suggested in this paper. Raddatz (2009) examines both the short-term and long-term impact of climatic disasters on a country's GDP. Aligning with the findings discussed above, but more explicitly reporting their results, Raddatz finds that climate related disasters reduce real GDP per capita by at least 0.6%. Out of the natural disasters that impacts were individually examined (windstorms, floods, droughts, and extreme temperatures), droughts were found to have the largest impact.

Ilan Noy is a widely cited author in this subject matter, whose 2008 paper on the macroeconomic consequences of natural disasters contributes greatly to this review. Noy (2008) examines the macroeconomic impact of natural disasters in the short run. They find that natural disasters have a statistically significant negative impact on a country's macro-economy in the short run. They also highlight that countries with higher literacy rates, better institutions, higher per capita income, higher degree of openness to trade, and higher levels of government spending are more resilient to the exogenous shock delivered by a natural disaster. This connects to their additional findings that smaller and developing states experience a larger, negative, impact than more developed countries during climate events of similar magnitude. This introduces an additional area of focus within this field of study that will be expanded on later.

Hochrainer (2009) identifies a gap in the literature and conducts a medium-term analysis, focusing on the macroeconomic impacts of natural disasters up to five years post disaster. They communicate that, on average, natural disasters can have negative effects on GDP. Laframboise and Loko (2012) in their IMF working paper cite Hochrainer and report that across the literature a significant negative impact on real GDP can be traced to natural disasters. Hochrainer continues and adds that greater aid and an increase in remittances, much like Kim et al. (2022), help to reduce the negative macroeconomic consequences that these events cause. Von Peter et al. (2012) conducts a large panel study that examines the macroeconomic consequences of natural disasters and how the transfer of risk to the insurance market can initiate economic recovery. Through the utilization of panel regressions for a cross-section of 203 countries during a 52-year period, they found that growth falls by 0.65% on impact of a median disaster and 1% for the mean disaster. They estimate that cumulative output loss is 1.7% for the median disaster and 2.6% for the mean. The main result is that major natural disasters have large and immediate negative effects on economic activity that also extend over the long run.

Interestingly Fomby et al. (2009) challenges the seemingly consistent results found in the literature regarding the negative macroeconomic effects of natural disasters. They find that natural disasters differ in the growth response that they initiate. This result is not unfamiliar as we have already recognized that different types of events have different magnitude effects, this was encountered primarily in Raddatz (2009). What differs here is that Fomby et al. (2009) reports that some events can result in benefits for economic growth. Despite this, Fomby et al. (2009) reinforces the additional literature with their second finding that ‘severe’ disasters never have positive effects on the macroeconomy.

The IMF Policy Paper from 2016 titled ‘Small States’ Resilience to Natural Disasters and Climate Change-Role for the IMF’ was one of the most influential resources in identifying important authors and the contributions their papers made to this field of study. Additionally, and since SIDS are the sample size of interest in this paper, this IMF publication allowed for the identification of the unique vulnerability of SIDS to extreme weather events. In conjunction with this, many of the papers and studies discussed above also included findings regarding the disproportionate vulnerability of small and developing states to extreme weather and its impacts compared to their larger and more developed counterparts.

Raddatz (2009) included the finding that small states are more vulnerable to the negative macroeconomic impacts of windstorms but have a similar response when it comes to other types of disasters. They also found that the stronger response to natural disasters by low-income countries is a result of their response to droughts, which across the study, was found to be the climate event traced to the most negative impact. Laframboise and Loko (2012) report on the data and showcase that natural disasters occur more frequently and affect more people in developing countries. Noy (2008), who introduced us to this disproportionate effect on developing countries, concludes that developing countries face larger declines in output in the wake of weather events. Rasmussen (2004) is the most influential study in this section of the review, as their work is widely cited across other sources and provides insightful results that align with the scope of this paper. They find and report that the relative costs of natural disasters are far higher in developing countries, with small island states being the most vulnerable. They arrive at these findings by focusing on Eastern Caribbean nations and investigating the macroeconomic impact of natural disasters. Aside from identifying the vulnerability of developing states, they overall report that natural disasters have negative macroeconomic impacts that include effects on fiscal and external balances. Fomby et al. (2009) also confirms the disproportionate relationship on developing countries and reports that the effects of natural disasters are stronger (not necessarily worse in all cases) on developing countries as opposed to rich ones.

This will be touched on later in the development of the model, but it is important to note that much of the literature gathers their disaster data from the EM-DAT database. This helps validate the decision to use this database in the data collection process.

Extreme Weather Events: Welfare Effects

Although the model employed in this study utilized GDP per capita and GDP growth rate as indicators of QOL, it is still important to include a discussion on the welfare impacts of extreme weather events. This will help generate an understanding of the negative effects caused by these events that are hidden when we approach it from a solely economical perspective.

Ahmadiani and Ferreira (2020) studied the well-being effects of extreme weather events in the United States. They accomplished this by matching thirty-one individual billion-dollar disasters with individual survey data from the behavioral risk factor surveillance system. This allowed them to estimate the effect of extreme weather events on the subjective well-being of United States residents. Their relevant findings report that natural disasters have a negative and robust effect on the subjective well-being of people affected by the disaster. They also find that, on average, the impact peaks 6 months after the event. Additionally, it is found that emotional and social support helps to mitigate the well-being effect of these disasters, which introduces an opportunity to investigate unique response strategies in the future. Von Mollendorff and Hirschfield (2015) use a life satisfaction approach when studying the impacts of extreme weather events on human welfare. Their study utilized self-reported life satisfaction measures and focused on storm, hail, and flood events in Germany between 2000-2011. They found that all three types of weather events resulted in a negative impact on life satisfaction. More specifically, life satisfaction was reduced by 0.020-0.027 on the 11-point scale. Arouri et al. (2015) studied the effect of natural disasters on welfare and poverty in Vietnam, specifically rural households. They found that storms, floods, and droughts all have negative effects on household income and expenditure. Additionally, they found that households in communes with higher levels of mean expenditure and a more equal expenditure distribution are more resilient to these events. They also comment on the strengthening effect that access to microcredit, internal remittances, and social allowances can have on household resilience.

Gray et al. (2023) studied the effect of weather shocks on employment outcomes in South Africa. This extends the definition of welfare to also include employment opportunities. They find that the increase in drought reduces overall employment, with the loss being found mainly amongst workers in provinces that rely heavily on tourism. This introduces a relationship that is in line with the motivation of this paper. Mainly, the effect that a reliance on tourism (less export diversity) can have when coupled with extreme weather events on the QOL (which may be calculated economically but includes human welfare) of a country's citizens. In the case of this study, their results coincide with the underlying hypothesis of this study, which is rooted in the theory of economic diversification, which is that countries with more export diversification will experience a smaller QOL impact than less diversified economies.

You cannot speak of the impact of extreme weather events on human welfare and omit the literature that discusses health impacts. Wang et al. (2009) study the health impacts of extreme weather events in Sub-Saharan Africa. They approached this study with the goal of quantifying the impact of extreme rainfall and temperature on diarrhea, malnutrition, and mortality in young children. They found that both weather occurrences significantly increased the occurrence of diarrhea and weight-for-height malnutrition among children under the age of 3. They found it to have little impact on long term health indicators. Interestingly, they calculated the economic impact of these results and found that the health cost of an increase in diarrhea caused by climate change in 2020 is equivalent to 0.2-0.5 percent of GDP in Africa. This study is an interesting addition to the literature review as it extends the impact of the weather events to include the corresponding health costs. This signals that some of the earlier papers may have been under estimating the negative effect on GDP following an extreme weather event.

Tourism Dynamics

Tourism is an essential component of the model utilized in this paper. The export diversification variable is based on the percentage of a country's exports that are attributed to tourism. This will be developed later in section, but briefly introducing it here makes the importance of examining the relevant literature clear. More specifically, the interplay between tourism, climate change, and its economic importance for SIDS will be examined.

Gaki and Koufodontis (2022) studied tourism resilience of regions through tourism employment and focused on measuring the potential for the tourism industry to rebound from the pandemic (Covid-19). Their findings were interesting, as they noted that estimated resiliency does not always mean recovery. Additionally, they reported that regions who have a strong tourism sector appear to have a stronger resilience than regions with other industries. This communicates to them that the tourism industry has potential to help develop a region. It is important to note that this conclusion contact with those of Gray et al. (2023), where it was reported that provinces in South Africa with a higher reliance on tourism face the worst employment impacts caused by extreme weather events. An important distinction between the two is that Covid-19 was not an extreme weather event, although its effect on tourism (sharp decline) could mimic those caused by a climate event. It is also important to recognize that the two conclusions do not contradict each other, as Gray et al. (2023) does not provide commentary on the recovery ability of those regions and the tourism industry. However, it is critical to see that the findings of Gray et al. (2023) supported the hypothesis of this paper, while Gaki and Koufodontis (2022) are reporting findings that weaken the hypothesis of this paper. Again, remembering that Covid-19 is not a weather event and caused no immediate and physical destruction to locations can help rationalize the difference in conclusions here.

The La Palma Volcano eruption, explored by Leoni and Boto-Garcia (2022), provides a good case study for the effect of natural disasters on tourism demand, supply, and labor markets. What is important about this study in relation to this paper, is that La Palma is an island economy which relies heavily on its large tourism sector. The study found that asymmetrical drops in international demand, number of hotels, and hospitality workers came as a result during and after the eruption. This case study begins to create a thorough line between the contradictions and connections drawn above. However, it is still important to recognize that Gray et al. (2023) finds that heavily reliant tourism communities are most adversely affected by natural disasters in terms of welfare, but that Gaki and Koufodontis (2022) find that these areas are also the quickest to rebound from an exogenous shock (Covid-19). It is hard to fully decipher what this means for the hypothesis of this paper based on the reasoning provided above regarding the nature of Covid-19 shutdowns and the unsatisfied demand for tourism that built up during that time.

Cevik and Ghazanchyan (2021) examined the long-term impact of climate change on the tourism industry in relation to a destination's vulnerability to climate change. As has already been uncovered, SIDS are especially vulnerable to climate change (Rasmussen, 2004) which is important to keep in mind when considering the findings of this study since the sample consisted of thirteen Caribbean countries. Cevik and Ghazanchyan (2021) found that climate vulnerability has a statistically significant impact on tourism revenue, communicating the existence of a key relationship between at-risk destinations and economic success.

Methodology

The econometric method employed in this paper is a linear regression. This is the selected methodology because it allows for an investigation into the role that export diversification plays in softening the impact of extreme weather events on QOL indicators across SIDS. The guiding hypothesis and its accompanying regression equations is that SIDS with more diverse export structures will experience smaller QOL impacts following extreme weather events. Two dependent variables, GDP per Capita (*GDPPC*) and GDP Growth Rate (*GDPGR*) are designated as the QOL indicators. The goal of the below equations is to help control fluctuations across these indicators by utilizing six control variables. Controlling for normal fluctuations allows for the investigation into the magnitude impact of extreme weather events and how export diversification plays a role in either dampening or expounding their effects. The regression equations of choice are presented below, followed by an explanation of their variables.

Regression Equations

$$log(GDPPC_{\mathrm{ct}}) = \alpha + EWE_{\mathrm{ct}} + \boldsymbol{EDS}_{\mathrm{ct}} + EGDP_{\mathrm{ct}} + IGDP_{\mathrm{ct}} + POP_{\mathrm{ct}} + LFPR_{\mathrm{ct}} + HSGDP_{\mathrm{ct}} + FDIGDP_{\mathrm{ct}} + EWE\_EDS_{\mathrm{ct}} + \varepsilon_{\mathrm{ct}} \quad (1)$$

$$log(GDPPC_{\mathrm{ct}}) = \alpha + EWE_{\mathrm{ct}} + \boldsymbol{EDS}_{\mathrm{ct}} + EGDP_{\mathrm{ct}} + IGDP_{\mathrm{ct}} + POP_{\mathrm{ct}} + HSGDP_{\mathrm{ct}} + FDIGDP_{\mathrm{ct}} + EWE\_EDS_{\mathrm{ct}} + \varepsilon_{\mathrm{ct}} \quad (2)$$

$$GDPGR_{\mathrm{ct}} = \alpha + EWE_{\mathrm{ct}} + \boldsymbol{EDS}_{\mathrm{ct}} + EGDP_{\mathrm{ct}} + IGDP_{\mathrm{ct}} + POP_{\mathrm{ct}} + LFPR_{\mathrm{ct}} + HSGDP_{\mathrm{ct}} + FDIGDP_{\mathrm{ct}} + EWE\_EDS_{\mathrm{ct}} + \varepsilon_{\mathrm{ct}} \quad (3)$$

$$GDPGR = \alpha + EWE_{\mathrm{ct}} + \boldsymbol{EDS}_{\mathrm{ct}} + EGDP_{\mathrm{ct}} + IGDP_{\mathrm{ct}} + POP_{\mathrm{ct}} + HSGDP_{\mathrm{ct}} + FDIGDP_{\mathrm{ct}} + EWE\_EDS_{\mathrm{ct}} + \varepsilon_{\mathrm{ct}} \quad (4)$$

The above equations are used for regressions across two dependent variables which include GDP per Capita (*GDPPC*) (regression 1 and 2) and GDP Growth Rate (*GDPGR*) (regression 3 and 4) in country (c) and year (t). The log of *GDPPC* is taken but is not taken for *GDPGR* due to some of its values being negative. Alpha signifies the intercept of our equation and ε_{ct} is the error term that captures everything left out of the model.

The first variable, EWE_{ct}, is a constructed variable that equals the number of extreme weather events experienced in a given country for a specific year and follows the same level of analysis as the dependent variables, as do all the variables in the equation. This is one of the most important variables in the equation, as it is expected to have a significant impact on the annual QOL indicators that serve as the dependent variables. More information on the construction and collection of this data is explained in the following section.

EDS_{ct} stands for the annual export diversification score of a SID. This variable is crucial for identifying the effect that the differing export diversification structures have on determining the QOL impacts caused by extreme weather events, which is the key relationship of interest in this paper. This variable is first turned into a ten-level categorical variable, which is then translated into 10 dummy variables corresponding to each of the levels. The bolded *EDS* in each regression equation symbolizes a vector of 9 of the dummy variables, the first categorization denoted by *EDS1* serves as the reference level and is left out. This explanation is developed further in the data section.

The rest of the variables in the equation are control variables, implemented with the intention of isolating *EWE* and *EDS* as the determinants of the observed magnitude impact of extreme weather events on QOL in SIDS. Both $EGDP_{ct}$ and $IGDP_{ct}$ are the SIDS annual exports and imports, respectively, as percentages of GDP. The inclusion of these as control variables is intentional, as the level at which a country is exporting and importing is a key determinant of their GDP. As a country exports, they earn money and their GDP increases alongside it, the inverse relationship exists for imports. Accounting for this relationship is important when attempting to isolate the fluctuations in the dependent variables to extreme weather events.

POP_{ct} is the reported population of the SID for any given year. Again, population plays a role in determining the level of a country's GDP, specifically GDP per Capita, making it clear that it should be included as a control variable. $LFPR_{ct}$ is the labor force participation rate for a SID in any given year. A 2017 report from the Federal Reserve Bank of Philadelphia found that a shrinking labor force participation rate can slow GDP growth (Federal Reserve of St. Louis, 2023), which helps to validate including it in the model. $HSGDP_{ct}$ is healthcare spending as a percentage of GDP for each SID in any given year. Raghupathi and Raghupathi (2020) find that an increase in health expenditure is attributed to a higher GDP and helps confirm that *HSGDP* is a necessary control variable for this model. $FDIGDP_{ct}$ is foreign direct investment as a percentage of GDP for each SID in any given year. In support of the addition of *FDIGDP* as a control variable, Borensztein et al, (1995) finds that foreign direct investment has positive effects on economic growth. However, these results need to be cautioned as this positive effect only exists when the level of education is above a certain threshold, which could have implications when remembering that the sample countries for this paper are SIDS.

This methodology and the nature of the export diversification score variable allow for the hypothesis to be approached both effectively and uniquely. Additionally, the implementation of the above listed control variables into the regression equation allows for them to be held constant when analyzing results. This effectively isolates the magnitude impact differences observed across SIDS to variations in the diversity of their export structures.

A slew of other approaches and variables were considered during the creation of this model when determining how to approach this study. These alternative directions remain as opportunities for future research, contingent on the significance of the results obtained here.

The original idea for this study was to examine how the export diversification of a country, measured through their reliance on tourism, impacts the duration of time it takes for the economy to rebound to its pre-disaster level. The motivation here was to examine the speed at which small, tourist-reliant, economies are able to recover from natural disasters as compared to their more diversified counterparts. The hypothesis in this case would be that more tourism-heavy economies would recover faster due to the consistency of demand, if the natural disaster fell below a certain level of severity. Beyond this level of severity, it would be predicted that the natural environment and infrastructure would be damaged for an extended period of time, in which case the tourism industry would take longer to recover, leading to the conclusion that the more diverse economy would have a faster rebound. The main cause for concern with this approach is that a variable for the duration of recovery (years, months, or days) would need to be constructed. Although this is doable, the nature of the block plan and only having a limited number of days to complete this thesis resulted in the decision to save this idea for another time where it can be completed successfully.

A secondary idea that originated from an academic class last semester and is related to the methodology selected in this paper is DEA analysis. Linear regression is the correct choice for achieving the desired goals of this study. However, Data Envelopment Analysis (DEA) has become increasingly interesting to me, due to its ability to produce efficiency scores based on given inputs and outputs for similar decision-making units (DMUs). Efficiency is an important topic when it comes to analyzing economies and it would be interesting to find a way to implement DEA into an investigation on how efficiently economies recover from natural disasters. In relation to the alternative approach discussed above, one could use recovery duration across multiple indicators (GDP growth rate, GDP per Capita, happiness index, etc.) as outputs and select inputs they were interested in and utilize a DEA approach. This would return efficiency scores that identify which SIDS were the most efficient at turning the selected inputs into shorter recovery periods. This could result in powerful insights that inform countries on what the most favorable levels of the selected inputs should be. One major shortcoming of DEA analysis is that the efficiency scores are calculated using only the inputs and outputs that you provide it with. This makes the variable selection process rigorous and complex, which would be hard to accomplish in the timeframe that the block allows for.

Another alternative approach that has come to mind for this study is to study singular events that impact a region of countries. For example, individual hurricanes impact on countries in the Caribbean could be the selected event and region. This would help to control the severity of the events, as the same event hits each country. This would also allow for the variation of countries' economic structures to be examined in a more isolated setting and unveil what causes some countries to experience smaller impacts vs, their neighbors.

Returning to the model selected in the paper, it is important to discuss additional variables that could be added to the equations in future iterations in an effort to make it more accurate. As was mentioned above, the accelerated schedule of this thesis restricts the ability to obtain every variable of interest and there is room to add more to this model in the future. As discussed in the literature review, Kim et al. (2022) found that remittances acted as a shock absorber for the macroeconomic impacts of climatic disasters. Additionally, Hochrainer (2009) found similar results and also added that greater aid also reduced the negative macroeconomic outcomes of extreme weather events. Unfortunately, data on remittances could not be implemented into this model and should be a variable that is considered in the future. However, foreign direct investment data could be found within the timeframe and was implemented as an indicator of aid.

Data

The two dependent variables of interest in this study are GDP per Capita (*GDPPC*) and GDP Growth Rate (*GDPGR*) in country (c) and year (t). The two key explanatory variables are a categorical variable that is transformed into ten dummy variables and denoted by the bolded *EDS* vector variable and a discrete continuous variable that records the number of extreme weather events experienced by a country in a given year. The model includes six control variables in the first round of analysis and five in the second. These include exports as a percentage of GDP (*EGDP*), imports as a percentage of GDP (*IGDP*), population (*POP*), labor force participation rate (*LFPR*), healthcare spending as a percentage of GDP (*HSGDP*), and foreign direct investment as a percentage of GDP (*FDIGDP*). In Regressions 2 and 4 *LFPR* is removed from the model to incorporate more observations from other countries.

Data was intended to be collected for all 39 SIDS from the years 2000-2020. However, after aggregating all the necessary data, only 18 SIDS were found to have years with complete data in the 2000-2020 timeframe. Additionally, 5 more SIDS were found to have complete data when *LFPR* is omitted from the model, which is the dataset used in regressions 2 and 4. The remaining 16 SIDS were either missing data for the dependent variables or for more than one control variable. After removing observations that lacked the necessary data the complete dataset was left with 287 unique observations to work with, and the secondary dataset that omits *LFPR* had 356 unique observations to run on. It is important to remember that Regressions 1 and 3 are run on the dataset with *LFPR* that has 287 observations, while Regressions 2 and 4 are run on the dataset without *LFPR* that has 356 observations.

Gross Domestic Product (*GDPPC* and *GDPGR*) Data

As mentioned above, the two key dependent variables in this study are GDP per Capita (*GDPPC*) and GDP Growth Rate (*GDPGR*). The reasoning behind using these as QOL of indicators is addressed in the above methodology section. *GDPPC* data is recorded in USD and *GDPGR* is recorded as a percentage. The values of both these variables were collected through Macrotrends which pulled its data from the WorldBank. Initially, observations were collected for all available years and then shrunk down to years where all variables had data. However, this collection approach changed to only collecting the years 2000-2020 after realizing the storm data in this range was the most reliable. This change also resulted in a more efficient data collection process. Additionally, it is important to be reminded that the *GDPPC* variable is transformed into its natural log form in both rounds of regressions, while *GDPGR* remains in its raw format.

Extreme Weather Event (*EWE*) Data

The extreme weather event data is pulled from the EM-DAT database, which is a widely recognized and utilized data resource for disasters. The primary disasters of interest in this paper are naturally occurring climate disasters. The “Natural” filter was applied to the dataset, which includes events falling under the subcategories of Biological, Climatological, Geophysical, Hydrological, and Meteorological disasters. The Biological filter includes disasters such as epidemics, infestations, and animal incidents. The Climatological filter captures droughts, wildfires, and glacial lake outbursts. The Geophysical filter captures events such as earthquakes, avalanches, landslides, and volcanic activity. The Hydrological filter mainly returns floods and includes similar events to the Geophysical filter. The Meteorological filter includes extreme temperature, fog, and storms including hurricanes, tornados, cyclones, and even snowstorms. The Extra-Terrestrial filter also falls under the larger “Natural” filter, but no events appeared under this designation for the desired years and countries. In the case that they did, they would be omitted due to lack of relevance. Data on weather disasters that fall into these subcategories was pulled for the 18 SIDS that have complete data and the additional 5 that were missing *LFPR* data. In total, data was pulled for 23 SIDS across the years 2000-2020 resulting in the aggregation of 388 weather disaster observations. It is important to comment on how the EM-DAT database categorizes its data before explaining how this data was translated into the discrete continuous variable *EWE*.

One of the following four criteria must be satisfied in order for a weather event to be considered a “disaster” by the database. The criteria are the event resulting in 10 casualties, affecting 100 people, the declaration of a state of emergency, or a call for international assistance (EM-DAT). This criterion helps alleviate the need to control for weather events of differing magnitudes, as they all hit one of the above criteria. However, this lack of control measures will be brought up again in the conclusion section of this paper to offer suggestions for future improvements to this study’s methodology.

The translation of the EM-DATs raw data into a discrete continuous variable was relatively seamless. The EWE_{ct} variable takes the value of the number of extreme weather events experienced by that country in a given year. In order to do this effectively, the EM-DAT data was organized by country and then a numerical value matching the number of events that country experienced in a given year was added to the full model’s dataset if that year had complete data across the control variables (or was missing *LFPR*). It is important to note that not all the 356 unique observations (specific years for selected countries) had an accompanying data point in the filtered EM-DAT data. Therefore, some observations obtained values of 0 for *EWE*, while others had values as high as 9. Again, the value of *EWE* is the number of weather disasters that the selected country experienced in a given year.

Export Diversification (*EDS*) Data

The export diversification variable is initially a ten-level categorical variable that is then transformed into ten dummy variables in an effort to better serve the hypothesis and model in this paper. These dummy variables are denoted by the bolded *EDS* variable in each equation, which symbolizes a vector containing them. The intent of this study is to examine the impact of extreme weather events on QOL and how export diversification plays a role in the magnitude of that impact. The percentage of a country's exports that were attributed to tourism was selected as an indicator of how diverse their export structure was. This data was also collected from Macrotrends, which utilizes data from the WorldBank and UN. In order to scale this data effectively, a grading method was implemented to translate the percentages into values ranging from 1-10. These values are the data points for the *EDS* variable. The scale is intuitive, where a country with 0-10% of their exports coming from tourism receives a score of 1. This pattern follows all the way up to the 90-100% level, which would receive a 10. The complete scale and the accompanying percentages are as follows, 0-10% equals 1, 10-20% equals 2, 20-30% equals 3, 30-40% equals 4, 40-50% equals 5, 50-60% equals 6, 60-70% equals 7, 70-80% equals 8, 80-90% equals 9, 90-100% equals 10. The scale is intended to pair more diverse export structures with lower values and less diverse export structures with higher values to align the dataset with the hypothesis of this study.

Once the *EDS* variable is created, ten dummy variables denoted as *EDS1*, *EDS2*, *EDS3*, *EDS4*, *EDS5*, *EDS6*, *EDS7*, *EDS8*, *EDS9*, and *EDS10* are constructed. These dummy variables take a value of 1 if the number in their name corresponds to that country's *EDS* value for a given year. For example, if a country has an *EDS* value of 2 in year X, their *EDS2* dummy variable would be given a value of 1, while the remaining nine levels received a value of 0. The dummy coding of the ten-level categorical *EDS* variable allows for countries with different *EDS* values to be compared to one another in the analysis. This allows for an effective investigation into the role that export diversification plays in the magnitude of *EWEs* impact on QOL. In the regressions, the bolded *EDS* vector variable symbolizes the *EDS2-EDS9* dummy variables. *EDS1* is intentionally left out in order to serve as the reference level across the analyses. *EDS10* is omitted by the computer, as no data points in either dataset corresponded to a country with 90-100% of their exports coming from tourism.

***EWE* and *EDS* Interaction Term (*EWE_EDS*)**

The interaction term *EWE_EDS*, which is present in all four of the regression equations will help make the decision to dummy code the categorical *EDS* variable clearer. As has been mentioned throughout the paper, it is the intent of this study to investigate how differences across the diversity of export structures impact the resiliency of a country's QOL in the wake of extreme weather events. Without the ten dummy variables and this interaction term, the regression results would be analyzed in a way that is not aligned with the intent of this paper. These variables must be included in order to understand how countries with different levels of export diversification are impacted by extreme weather events.

The *EWE_EDS* interaction term is created by multiplying the number of extreme weather events in a given country and year by the value of their *EDS* variable. This is not to be confused with the value of their dummy *EDS (1-10)* variables, but rather the original ten-level categorical variable that is labeled *EDS*. When the regression is run with both the dummy *EDS (2-9)* variables and the interaction term (*EWE_EDS*) along with *EWE* and the rest of the control variables, it allows the results to be analyzed in a favorable manner. More specifically, it allows us to understand the increase or decrease that is expected in our dependent variable for each additional *EWE* at a given level of *EDS* compared to the reference level of *EDS1*. To make this clearer, the coefficient on any of the *EDS* dummy variables plus the coefficient on the interaction term will give us this expected impact. These values can then be compared across the ten levels, which will unveil the relationship of interest and either confirm or deny this study's hypothesis.

Control Variable Data

The rest of the control variables include exports as a percentage of GDP (*EGDP*), imports as a percentage of GDP (*IGDP*), population (*POP*), labor force participation rate (*LFPR*), healthcare spending as a percentage of GDP (*HSGDP*), and foreign direct investment as a percentage of GDP (*FDIGDP*). All of these variables were collected through Macrotrends, which utilizes data from the WorldBank and UN. No adaptations were performed on any of these variables, and all of them take the form of percentages aside from *POP*. *POP* takes the numerical value of a given country's population in a given year.

EGDP, *IGDP*, *POP*, *HSGDP*, and *FDIGDP* are exactly what the variable name implies and *LFPR* is the only control variable that requires additional explanation. *LFPR*, according to Macrotrends, is the percentage of 15–24-year-olds who are in the workforce for a given country (c) in year (t).

Limitations

The limitations of the data collection process were minimal, but still notable. The main concern comes with the time frame of the thesis schedule. This has been mentioned before, but the quickness of the block plan has significant impacts on the ability to collect or consider all the data that might be available to use. As a result, the models employed in this paper are likely smaller than they would have been if more time existed. Smaller in both the number of observations that were found and the number of variables that were used. However, this is no cause for concern and rather suggests an opportunity for future improvements to this methodology.

Results

As was explained in both the methodology and data sections, the analysis of this study relies on two datasets. The first dataset has 287 observations and includes *LFPR* as a control variable, the second omits *LFPR* from the model which increases the observation count to 356. The first data set is used for regressions 1 and 3, while the second data set is used for regressions 2 and 4. Regressions 1 and 2 use *log_GDPPC* from their respective datasets as the dependent variable and regressions 3 and 4 use *GDPGR* from their respective datasets as the dependent variable. As a result, we see very similar results between equations 1 and 2 and between 3 and 4 since these pairings have the same dependent variable and only differ in their inclusion or exclusion of *LFPR* as a control. Despite the redundancy, all four regression results will be analyzed and both the consistency between the results and the key takeaways will be highlighted.

The summaries of all the variables in both datasets that were utilized for regressions 1 and 3 and regressions 2 and 4 can be found in Table 1 and Table 2, respectively, below. *EDS10* is the only variable that needs to be discussed across both datasets, as it does not exist in either, meaning that none of the 287 observations or the additional 69 added to the second dataset included a country whose tourism industry accounted for 90-100% of their exports. This was previously mentioned in the above sections, and the Max value on the *EDS* and *EDS10* variables both confirm this to be true. The summary statistics also showcase the nature of the constructed *EWE_EDS* interaction term, which will be instrumental in understanding the relationship of interest in this paper.

Table 1. Summary Statistics (Regressions 1 and 3)

Descriptive Statistics (Regressions 1 and 3)

Variable	Obs	Mean	Std. Dev.	Min	Max
log gdppc	287	8.401	1.113	6.356	11.11
gdpgr	287	0.025	0.048	-0.335	0.152
ewe	287	1.021	1.470	0	9
eds	287	4.749	2.217	1	9
eds1	287	0.125	0.332	0	1
eds2	287	0.073	0.261	0	1
eds3	287	0.066	0.249	0	1
eds4	287	0.146	0.354	0	1
eds5	287	0.206	0.405	0	1
eds6	287	0.171	0.377	0	1
eds7	287	0.108	0.311	0	1
eds8	287	0.056	0.230	0	1
eds9	287	0.049	0.216	0	1
eds10	287	0	0	0	0
egdp	287	0.466	0.439	0.057	2.290
igdp	287	0.577	0.342	0.187	2.083
pop	287	2163557	3213783.4	104951	11012421
lfpr	287	0.434	0.131	0.137	0.739
hsgdp	287	0.048	0.014	0.024	0.113
fdigdp	287	0.052	0.056	-0.084	0.298
ewe eds	287	4.606	6.323	0	36

Note: This table shows the summary statistics for the dataset used in regressions 1 and 3. Data was collected from MacroTrends for all variables except EWE. EWE data was collected from the EM-DAT database. The EDS dummy variables were constructed through dummy coding of the EDS categorical variable. EWE is a constructed discrete continuous variable that tracks the number of extreme weather events experienced in a given country and year.

Table 2. Summary Statistics (Regressions 2 and 4)

Descriptive Statistics (Regressions 2 and 4)

Variable	Obs	Mean	Std. Dev.	Min	Max
log gdppc	356	8.454	1.066	6.356	11.11
gdpgr	356	0.023	0.048	-0.335	0.152
ewe	356	0.874	1.367	0	9
eds	356	4.638	2.276	1	9
eds1	356	0.121	0.326	0	1
eds2	356	0.118	0.323	0	1
eds3	356	0.059	0.236	0	1
eds4	356	0.140	0.348	0	1
eds5	356	0.205	0.404	0	1
eds6	356	0.149	0.356	0	1
eds7	356	0.090	0.286	0	1
eds8	356	0.067	0.251	0	1
eds9	356	0.051	0.219	0	1
eds10	356	0	0	0	0
egdp	356	0.479	0.415	0.057	2.290
igdp	356	0.632	0.338	0.187	2.083
pop	356	1759653.5	3000245.3	45989	11012421
hsgdp	356	0.055	0.028	0.024	0.203
fdigdp	356	0.055	0.063	-0.084	0.563
ewe eds	356	3.919	5.926	0	36

Note: This table shows the summary statistics for the dataset used on regressions 2 and 4 (LFPR omitted). Data was collected from MacroTrends for all variables except EWE. EWE data was collected from the EM-DAT database. The EDS dummy variables were constructed through dummy coding of the EDS categorical variable. EWE is a constructed discrete continuous variable that tracks the number of extreme weather events experienced in a given country and year.

Table 3, below, contains the regression results for equation 1, 2, 3, and 4. It is logical to see that *EDS10* does not appear in this table, as it is omitted due to its lack of existence in either data set.

Taking the natural log of *GDPPC* and using dummy variables for each of the ten levels of the *EDS* categorical variable complicates the analysis of the coefficients in the regression results. These coefficients are explained along with their level of statistical significance and contextual interpretation under Table 3. Table 3 also shows the key difference between equations 1 and 2, as well as equations 3 and 4, which, again, is the omission of *LFPR* from the model.

Table 3. Regression Results (Equations 1-4)

	(1)	(2)	(3)	(4)
	log_gdppc	log_gdppc2	gdpgr	gdpgr2
ewe	-0.128	-0.137	-0.001	-0.003
	(0.096)	(0.084)	(0.006)	(0.006)
eds2	0.483*	0.356*	-0.010	0.005
	(0.253)	(0.183)	(0.016)	(0.012)
eds3	0.700***	0.516**	0.012	0.013
	(0.266)	(0.213)	(0.017)	(0.014)
eds4	1.391***	1.690***	0.009	0.010
	(0.227)	(0.177)	(0.015)	(0.012)
eds5	1.262***	0.983***	0.009	0.006
	(0.242)	(0.181)	(0.016)	(0.012)
eds6	1.326***	1.116***	0.015	0.013
	(0.237)	(0.193)	(0.015)	(0.013)
eds7	1.835***	1.550***	-0.003	0.001
	(0.252)	(0.212)	(0.016)	(0.014)
eds8	1.765***	1.545***	-0.019	-0.016
	(0.273)	(0.216)	(0.018)	(0.015)
eds9	0.626**	0.860***	0.048***	0.037**
	(0.275)	(0.224)	(0.018)	(0.015)
egdp	3.697***	3.013***	0.016	-0.014
	(0.422)	(0.279)	(0.027)	(0.019)
igdp	-1.969***	-1.427***	-0.018	0.035*
	(0.491)	(0.299)	(0.032)	(0.020)
pop	3.74e-09	-5.16e-10	2.10e-09*	2.81e-09**
	(1.97e-08)	(1.73e-08)	(1.27e-09)	(1.17e-09)
lfpr	0.193	Omitted	0.024	Omitted
	(0.419)		(0.027)	
hsgdp	21.145***	11.879***	-0.919***	-0.284**
	(3.579)	(1.853)	(0.230)	(0.125)
fdigdp	0.794	1.235	0.069	0.017
	(1.262)	(0.821)	(0.081)	(0.055)
ewe_eds	0.020	0.017	-0.001	-0.0002917
	(0.021)	(0.018)	(0.001)	(0.0012262)
_cons	5.599***	6.352***	0.052*	0.015
	(0.437)	(0.244)	(0.028)	(0.016)
Observations	287	356	287	356
R-Squared	0.616	0.611	0.146	0.107

Standard errors are in parentheses

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

Note: This table shows the results of the four regressions utilized in this paper. Data comes from the two datasets described above, which used data from Macrotrends and the EM-DAT database. Again, regressions 1 and 3 use the dataset summarized in Table 1, while regressions 2 and 4 use the dataset summarized in Table 2.

Taking the natural log of the dependent variable shifts the interpretation of the coefficients in an important way that is highlighted through the example below. In the case of *GDPPC,* we would say that the coefficient is the expected increase or decrease in *GDPPC* expressed in USD for every one unit increase in the independent variable. However, when we take the natural log of *GDPPC* and create *log_GDPPC* we now interpret the coefficient as the percentage change in *GDPPC* that is expected as a result of a one unit increase in the independent variable. This interpretation is used for Regressions 1 and 2. The interpretation of the regressions that use *GDPGR* as the dependent variable (3 and 4) follows the normal approach described above since no logarithmic transformation was done to that variable. *GDPGR* remained in its normal format due to it having negative values for some observations. Interestingly, since *GDPGR* is reported as a percentage the interpretation of the results will sound similar to how the *log_GDPPC* results are being communicated. The regression results are interpreted individually and are organized by equation.

Before beginning each individual analysis, it is important to note that the intercepts of each regression will not be analyzed. This is a result of them having no realistic interpretation despite serving as the starting point for the data. An example is included here to showcase the intercepts' lack of utility. For Regression 1, the intercept value of 5.599 is the *log_GDPPC* of countries in the *EDS1* category that have 0 *EGDP*, *IGDP*, *POP*, *LFPR*, *HSGDP*, *FDIGDP*. It is clear that this does not provide useful information to the analysis that needs to be conducted in this paper.

Regression 1

Regression 1 uses *log_GDPPC* as its dependent variable and includes the *EDS* dummy variables (*EDS2-EDS9*), all six control variables, and the interactions term *EWE_EDS* as the explanatory variables.

The coefficient on *EWE* is -0.128, which suggests an expected 0.128% decrease in *GDPPC* for every additional extreme weather event experienced in the given country and year when all else is held constant. This coefficient makes logical sense and aligns with the prediction of this paper and the findings in the literature. It is important to note that *EWE* was not statistically significant, so although this coefficient is promising it cannot be accepted with confidence due to its high p-value.

The coefficients on the *EDS* dummy variables (*EDS2-EDS9*) communicate the percentage difference in *GDPPC* that is expected at each level compared to that of *EDS1* (countries with 0-10% of their exports coming from the tourism industry). Therefore, the results can be interpreted as follows. Countries in the *EDS2* category (10-20% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 0.483% higher than *EDS1* countries when all else is held constant. *EDS3* countries (20-30% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 0.7% higher than *EDS1* countries when all else is held constant. *EDS4* countries (30-40% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 1.391% higher than *EDS1* countries when all else is held constant. *EDS5* countries (40-50% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 1.262% higher than *EDS1* countries when all else is held constant. *EDS6* countries (50-60% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 1.326% higher than *EDS1* countries when all else is held constant. *EDS7* countries (60-70% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 1.835% higher than *EDS1* countries when all else is held constant. *EDS8* countries (70-80% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 1.765% higher than *EDS1* countries when all else is held constant. Finally, *EDS9* countries (80-90% of their exports coming from the tourism industry) are expected to have *GDPPC* levels that are 0.626% higher than *EDS1* countries when all else is held constant. As was mentioned above, *EDS10* is omitted and does not have an interpretation due to not having any data points in the dataset. It is important to note that all of the remaining *EDS* dummy variables (*EDS2-EDS9*) are statistically significant, which allows for these results to be accepted with high levels of confidence. *EDS2* is significant at the 90% level, *EDS3-EDS8* is significant at the 99% level, and *EDS9* is significant at the 95% level.

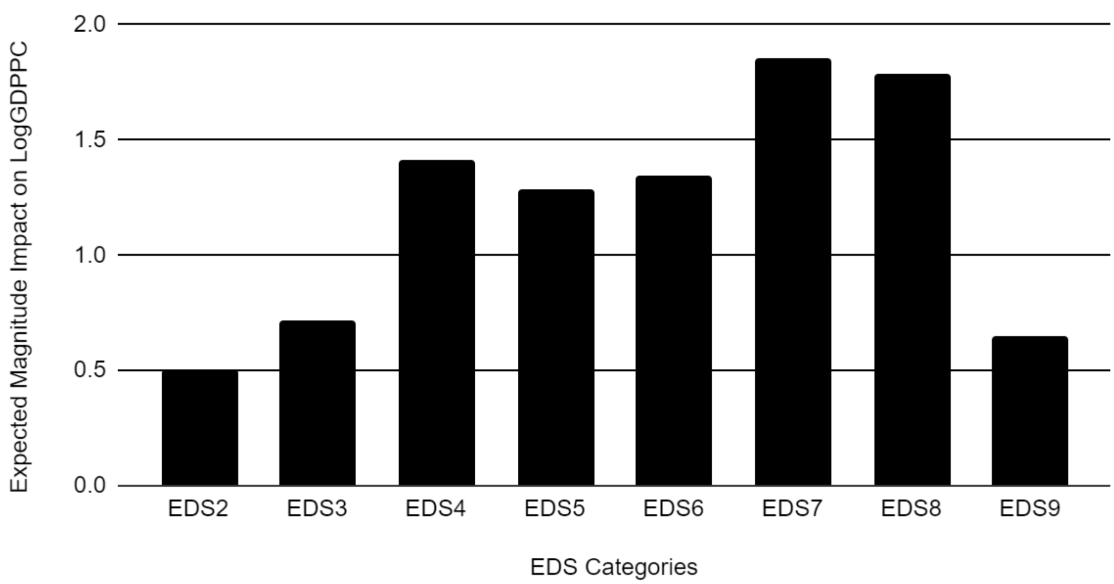
EGDP, *IGDP*, and *HSGDP* are also all statistically significant at the 99% level and their coefficients have the following contextual interpretation. For each unit increase in *EGDP*, which is reported as a percentage, *GDPPC* is expected to increase by 3.697% when all else is held constant. For each unit increase in *IGDP*, which is also reported as a percentage, *GDPPC* is expected to decrease by 1.969% when all else is held constant. For each unit increase in *HSGDP*, which, again, is reported as a percentage, *GDPPC* is expected to increase by 21.145% when all else is held constant. The magnitude of this effect is prominent and draws attention despite not being an important part of the key relationship in this study. The magnitude of this impact is likely tied to the tight spread of this variable which has a minimum value of 0.024 and a maximum value 0.113 in dataset one. This could potentially explain why a unit increase in *HSGDP* results in such a large expected impact on *log_GDPPC*.

POP, *LFPR*, and *FDIGDP* are the remaining three control variables in regression 1, and none of them report having a statistically significant effect on *log_GDPPC*. Despite the lack of statistical significance, their expected impact is contextually explained here. A unit increase in *POP*, which is reported as the true total population, is expected to increase *GDPPC* by 3.74e-09% when all else is held constant. This value is so small that STATA often reports it as a zero in the results tables. For each unit increase in *LFPR*, which is reported as percentage, *GDPPC* is expected to increase by 0.193% when all else is held constant. A unit increase in *FDIGDP*, which is also reported as a percentage, is expected to increase *GDPPC* by 0.794% when all else is held constant.

The interaction term is arguably the most important variable in each of the regressions equations as a result of what the coefficient communicates individually and what it communicates when added to the coefficients on the *EDS* (*EDS2-EDS9*) dummy variables. When analyzing the coefficient on its own the value and sign tell similar stories, with the interpretation of the sign providing the more general of the two. The coefficient on *EWE_EDS* for regression 1 is .02, which is a positive coefficient. It suggests that *GDPPC* is expected to increase by 0.02% for every unit increase in both *EWE* and *EDS*. The positive coefficient communicates a similar story, that is the impact of an additional extreme weather event on *log_GDPPC* becomes more positive as the level of export diversification decreases. This is a surprising result as it contradicts what the hypothesis of this paper predicted. However, it is also important to note that

EWE_EDS is not a statistically significant variable in Regression 1 and since its magnitude is so close to zero it is hard to fully accept this result. The other way to utilize the coefficient on the interaction term is to add it to the coefficients on each of the dummy variables. This sum gives the expected percentage increase in *GDPPC* for each additional extreme weather event for countries falling in the categories *EDS2-EDS9* as compared to *EDS1*. Figure 1 shows these magnitudes and serves as a visual aid for the analysis of the *EWE_EDS* coefficient described above. It clearly shows an upwards trend as the *EDS* categories increase, signaling groupings of countries with less diverse export structures experience larger percentage increases in *GDPPC* per unit increase in extreme weather events. As a side note, these sums were calculated using the unrounded coefficients in the raw regression results, this remains true for Figures 2, 3 and 4 as well.

Figure 1. Expected Percent Change in GDPPC for each Additional EWE across EDS Categories Compared to that of EDS1 (Regression 1)



Note: This chart was created by summing the coefficients of the interaction term with the coefficients on each level of the EDS dummy variable in regression 1. These coefficients can be found in the first column of Table 3.

The upward trend here is undeniable and the argument for an inverse of the predicted relationship has gotten stronger through the interpretation of the interaction terms coefficients and the reinforcing effect that this visual has on its conclusions. It is important to note the decrease in effect size for the *EDS9* categorization, we believe this exists due to lack of observations in this category. The low mean of this variable in Table 1 shows this. To confirm this, each dummy variable was summed to see which categories had the most observations. Unsurprisingly, *EDS9* had the smallest amount at 14 in dataset 1. However, a favorable finding to report is that the spread of observations across categories is not heavily skewed to the lower or higher end. This bolsters the strength of these conclusions. Both *log_GDPPC* regressions (Regressions 1 and 2) contain the most exciting results, as will become clear over the next sections. These conclusions will be discussed again at the end of this section and serve as the jumping off point for the conclusion section.

Regression 2

The coefficient on *EWE* for regression 2 communicates that *GDPPC* is expected to decrease by 0.137% for each additional extreme weather event. This variable is not statistically significant, so the interpretation of its coefficient cannot be accepted with any level of confidence.

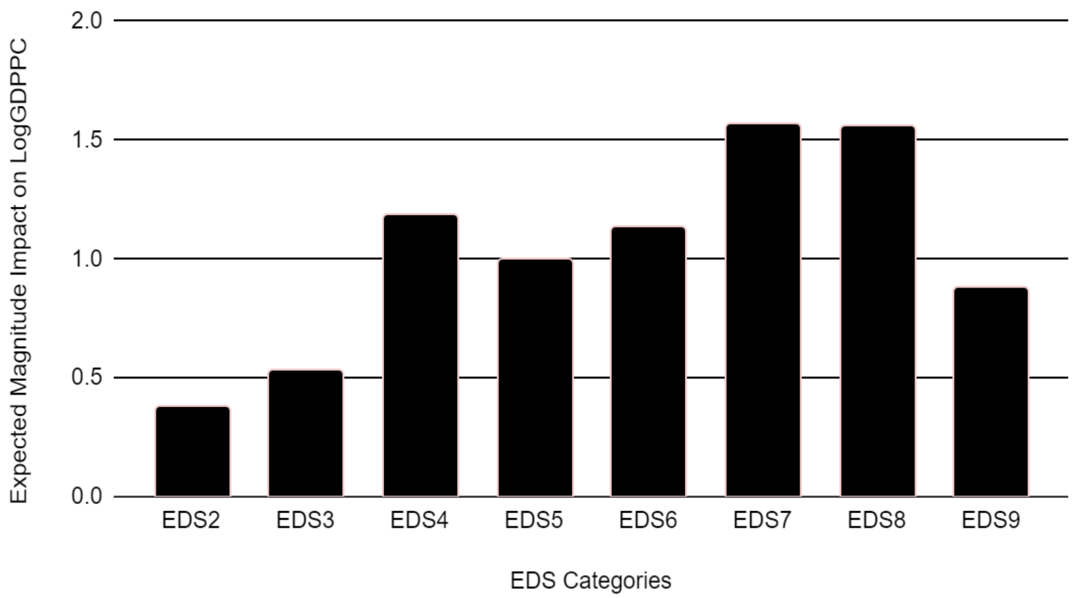
The interpretation of the coefficients on the dummy variables (*EDS2*-*EDS9*) is given below. Countries that fall under the *EDS2* categorization are expected to have a *GDPPC* that is 0.356% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS3* categorization are expected to have a *GDPPC* that is 0.516% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS4* categorization are expected to have a *GDPPC* that is 1.169% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS5* categorization are expected to have a *GDPPC* that is 0.983% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS6* categorization are expected to have a *GDPPC* that is 1.116% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS7* categorization are expected to have a *GDPPC* that is 1.55% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS8* categorization are expected to have a *GDPPC* that is 1.545% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. Finally, countries that fall under the *EDS9* categorization are expected to have a *GDPPC* that is 0.86% higher as compared to countries that fall under the *EDS1* categorization when all else is held constant. All of the dummy variables are statistically significant, so we can accept their interpretations with varying levels of confidence. *EDS2* is statistically significant at the 90% level, *EDS3* is statistically significant at the 95% level, and *EDS4-EDS9* is statistically significant at the 99% level.

The interpretation of the model's control variables are as follows. A unit increase in *EGDP*, which is reported as a percentage, is expected to increase *GDPPC* by 3.013% when all else is held constant. A unit increase in *IGDP*, which is also reported as a percentage, is expected to decrease *GDPPC* by 1.427% when all else is held constant.

Both these variables are significant at the 99% level, meaning the interpretation of their coefficients can be accepted with a high level of confidence. The *POP* variable behaves similarly to how it did in Regression 1, where its expected per unit impact on *GDPPC* is small. For every unit increase in *POP*, *log_GDPPC* is expected to decrease by -5.16e-10% when all else is held constant. A unit increase in *HSGDP*, which is reported as a percentage, is expected to increase *GDPPC* by 11.879% when all else is held constant. Again, a large magnitude and statistically significant increase in *GDPPC* is tied to *HSGDP*. Finally, a unit increase in *FDIGDP*, which is reported as a percentage, is expected to increase *GDPPC* by 1.235% when all else is held constant. However, this variable is not statistically significant, which means, again, that we cannot accept the interpretation of results with confidence.

The interaction term is utilized in the same way as it was in Regression 1. Similarly to the interpretation done in the above analysis, the positive sign attached to the coefficient on *EWE_EDS* in Regression 2 suggests an additional extreme weather event in countries with less export diversification (higher *EDS* categories) will have a larger positive impact on the percent change in *GDPPC*. More specifically, a unit increase in *EWE* and *EDS* is expected to increase *GDPPC* by 0.17%. This result is confirmed by Figure 2, which shows the effect that one additional extreme weather event has on *log_GDPPC* for each *EDS* categorization compared to *EDS1* countries.

Figure 2. Expected Percent Change in GDPPC for each Additional EWE across EDS Categories Compared to that of EDS1 (Regression 2)



Note: This chart was created by summing the coefficients of the interaction term with the coefficients on each level of the EDS dummy variable in regression 2. These coefficients can be found in the second column of Table 3.

In Figure 2, we see the same exact pattern that was identified for this relationship in Figure 1. This makes sense, as the omission of *LFPR* would not disrupt the relationship being observed here. We see the decrease in the *EDS9* category, which can be attributed, again, to the lack of observations in this category. This was confirmed again by summing each dummy variable and finding that *EDS9* had the lowest number of observations at 18. The spread across dummy variables was similar to that of dataset one, where it was generally even aside from a spike across *EDS4-EDS6* that exists in both. Again, these results contradict the hypothesis of this paper, which predicted that an additional extreme weather event would have a larger negative impact in countries with less export diversification as compared to their more diverse counterparts. However, after examining and thinking about these results, they might not be as surprising as previously thought. These thoughts will be further explored in the conclusion section that follows the analysis of Regression 3 and 4.

Regression 3

Regression 3 uses GDP Growth Rate (*GDPGR*) as the dependent variable and the explanatory variables and includes *LFPR* as a control variable. The summary statistics for the variables in this model can be found in Table 1 and the results of the regression can be found in Table 3. The results of this regression are not as statistically significant as the models that use *log_GDPPC* as a dependent variable, and as a result, the reporting of the coefficients is done faster. However, it is still important to see if the signs on the coefficients make sense despite the lack of statistical significance and to highlight some interesting effects.

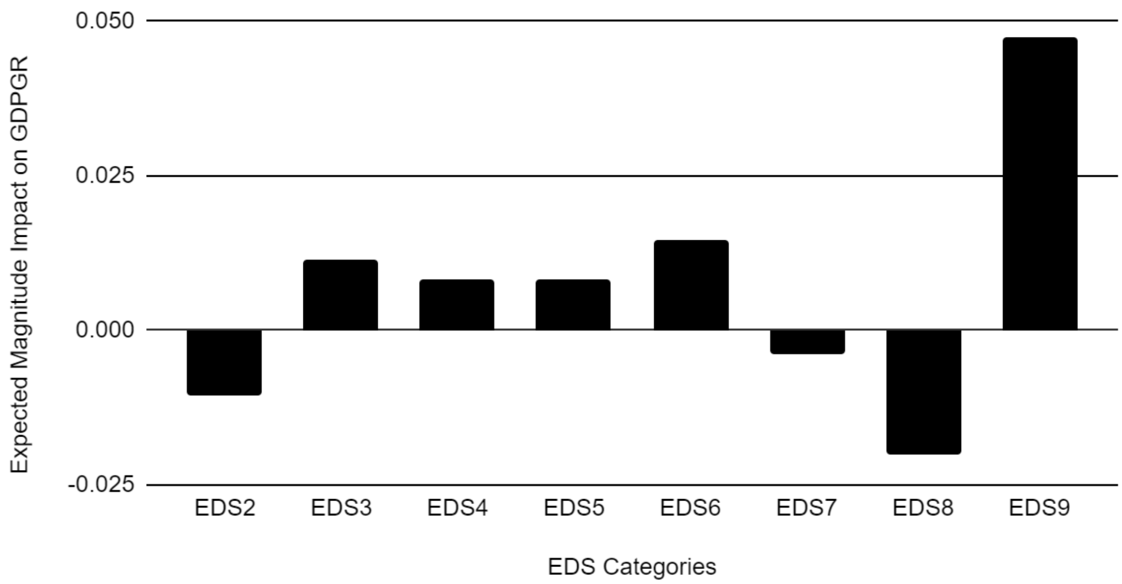
EWE has a coefficient of -0.001, which communicates that a 0.001 percentage point decrease in *GDPGR* is expected for each additional extreme weather event when all else is held constant. This variable is not statistically significant and we cannot accept it with any level of confidence. However, it is notable that the sign on the variable does make logical sense and aligns with the hypothesis of this paper, as well as, the findings in the literature.

The *EDS* dummy variables all lack statistical significance aside from the *EDS9* variable which is significant at the 99% level. The interpretation of these variables is given below. Countries that fall under the *EDS2* categorization are expected to have a *GDPGR* that is 0.01 percentage points lower as compared to that of countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS3* categorization are expected to have a *GDPGR* that is 0.012 percentage points higher as compared to that of countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS4* or the *EDS5* categorization are expected to have a *GDPGR* that is 0.009 percentage points higher as compared to that of countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS6* categorization are expected to have a *GDPGR* that is 0.015 percentage points higher as compared to that of countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS7* categorization are expected to have a *GDPGR* that is 0.003 percentage points lower as compared to that of countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS8* categorization are expected to have a *GDPGR* that is 0.019 percentage points lower as compared to that of countries falling under the *EDS1* categorization when all else is held constant. Finally, countries that fall under the *EDS9* categorization are expected to have a *GDPGR* that is 0.048 percentage points higher as compared to that of countries falling under the *EDS1* categorization when all else is held constant. *EDS10* is omitted again due to it not existing in the dataset. *EDS9* is the only dummy variable that is statistically significant, meaning we can only accept its interpretation with confidence at the 99% level. It is interesting to note that *EDS9* had the largest magnitude of any of the coefficients and due to its statistical significance could lead to the prediction that this model behaves similarly to the *log_GDPPC* regressions (1 and 2).

The coefficients for the control variables and their interpretations are reported here. The *GDPGR* of a country is expected to be 0.016 percentage points higher for each additional unit increase in *EGDP*, which is reported as a percentage, when all else is held constant. Additionally, the *GDPGR* of a country is expected to be 0.018 lower for each additional unit increase in *IGDP*, which is reported as a percentage, when all else is held constant. The impact of a unit increase in *POP* is expected to increase *GDPGR* by 2.10e-09 percentage points. *POP* is statistically significant at the 90% level, so we can accept this interpretation with confidence. *GDPGR* is expected to be 0.024 percentage points higher for each additional unit increase in *LFPR*, which is reported as a percentage, when all else is held constant. For each additional unit increase in *HSGDP*, the *GDPGR* of the country is expected to be 0.919 percentage points lower when all else is held constant. *HSGDP* is statistically significant at the 99% level, so these results can be accepted with a high level of confidence. Finally, a unit increase in *FDIGDP*, which is reported as a percentage, is expected to decrease *GDPGR* by 0.069 percentage points when all else is held constant. It is important to note that only *HSGDP* had any statistical significance across all the control variables, which means that we cannot accept any of the other coefficients with any level of confidence.

The interaction term, again, is the most important variable in the models both for its individual contributions and the joint contributions it has when summed with the coefficients on the dummy variables. When analyzing the interaction term individually, we are only concerned with the sign on the variable and the magnitude of the coefficient. Unlike Regression 1 and 2, the interaction term now has a negative sign on it which changes its interpretation. The negative sign suggests that the impact of an additional extreme weather event on *GDPGR* becomes more negative as export diversification decreases. In this case, a unit increase in *EWE* and *EDS* is expected to decrease *GDPGR* by 0.001 percentage points. This interpretation supports the hypothesis of the paper, as it argues that extreme weather events have a greater negative impact on more tourist reliant economies. However, this variable is not statistically significant, so it cannot be accepted with a high level of confidence. The same approach for Regression 1 and 2 is utilized here to show the impact of an additional extreme weather event on *GDPGR* for countries in each *EDS* category compared to *EDS1*. These results are communicated visually below in Figure 3.

Figure 3. Expected Percent Change in GDPPC for each Additional EWE across EDS Categories Compared to that of EDS1 (Regression 3)



Note: This chart was created by summing the coefficients of the interaction term with the coefficients on each level of the EDS dummy variable in regression 3. These coefficients can be found in the third column of Table 3.

Unsurprisingly, these results are less visually appealing and conclusive than the results found for this relationship in Regression 1 and 2 that were displayed in Figure 1 and 2 respectively. This can be traced back to the fact that most of this model was not statistically significant, while most of model 1 and 2 was. Due to the lack of statistical significance, the results in Figure 3 cannot be accepted with a high level of confidence.

Regression 4 is analyzed next, which uses *GDPGR* as the dependent variable and omits *LFPR* as a control variable.

Regression 4

Regression 4 uses *GDPGR* as the dependent variable and is much like Regression 3, with the only difference being the omission of *LFPR*. These two regressions follow the same patterns in a similar fashion to how Regression 1 and 2 were aligned. The results of this regression are reported here.

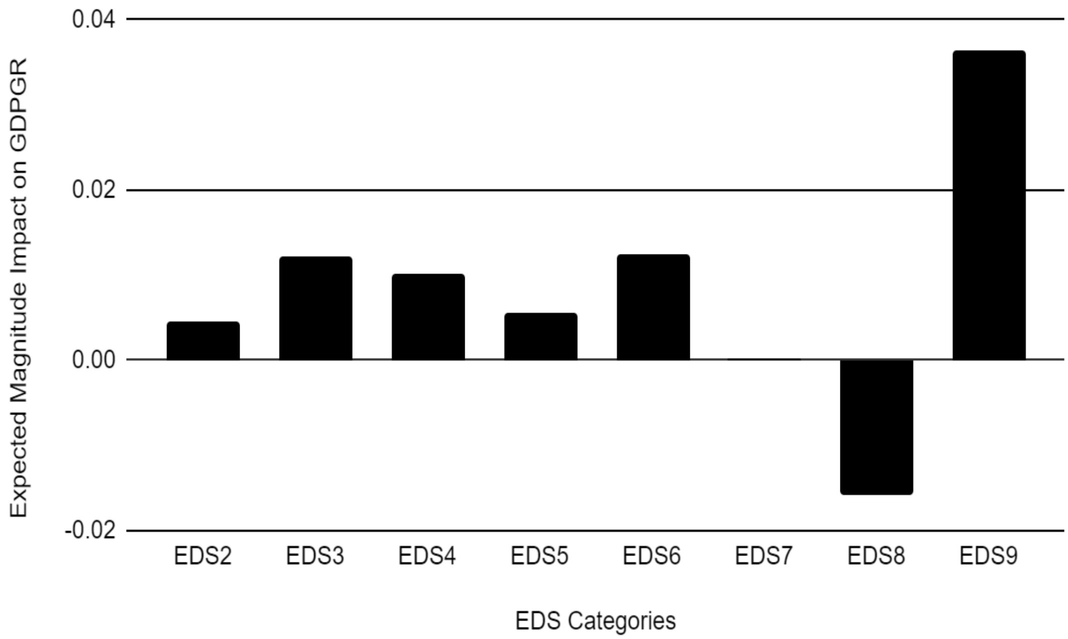
The coefficient on *EWE* is -0.003, which communicates that an additional extreme weather event is expected to decrease *GDPGR* by 0.003 percentage points when all else is held constant. This variable is not statistically significant and therefore the interpretation cannot be accepted with any level of confidence. However, like Regression 3, the sign on this coefficient makes logical sense. It is expected that an increased number of extreme weather events experienced in a year would have a negative impact on *GDPGR*.

In line with the analysis done for Regression 3, the only dummy variable with statistical significance in this model is *EDS9*, which is significant at the 95% level. However, the interpretation of each dummy variables' coefficients is reported below. Countries that fall under the *EDS2* categorization are expected to have a *GDPGR* that is 0.005 percentage points higher than countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS3* categorization are expected to have a *GDPGR* that is 0.013 percentage points higher than countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS4* categorization are expected to have a *GDPGR* that is 0.01 percentage points higher than countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS5* categorization are expected to have a *GDPGR* that is 0.006 percentage points higher than countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS6* categorization are expected to have a *GDPGR* that is 0.013 percentage points higher than countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS7* categorization are expected to have a *GDPGR* that is 0.001 percentage points higher than countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS8* categorization are expected to have a *GDPGR* that is 0.016 percentage points lower than countries falling under the *EDS1* categorization when all else is held constant. Countries that fall under the *EDS9* categorization are expected to have a *GDPGR* that is 0.037 percentage points higher than countries falling under the *EDS1* categorization when all else is held constant. Again, *EDS9* is the only statistically significant dummy variable, and we can be confident in the accompanying interpretation to the 95% level.

The interpretation of the five control variables is given here. It is important to note that *IGDP*, *POP*, and *HSGDP* are statistically significant variables in this regression. The coefficient on *EGDP* is -0.014, which communicates that *GDPGR* is expected to decrease by 0.014 percentage points for every unit increase in *EGDP*, which is reported as a percentage. For every unit increase in *IGDP*, which is reported as percentage, *GDPGR* is expected to increase by 0.035 percentage points. *IGDP* is statistically significant at the 90% level, meaning that this interpretation can be accepted at that 90% confidence level. The coefficient on *POP* is small, but statistically significant. *GDPGR* is expected to increase by 2.81e-09 percentage points for every unit increase in population. *POP* is also statistically significant at the 95% level, so this interpretation can be accepted with a high level of confidence. *GDPGR* is expected to decrease by 0.284 percentage points for every unit increase in *HSGDP*, which is reported as a percentage. Again, *HSGDP* has the largest magnitude impact on *GDPGR* out of all the variables in the regression. It is also statistically significant at the 95% level, meaning we can accept this interpretation with a high level of confidence. Finally, *GDPGR* is expected to increase by 0.017 percentage points for every unit increase in *FDIGDP*, which is reported as a percentage.

As has been discussed in the previous subsections, the interaction term is integral to the conclusions of this paper. Again, both the sign and magnitude are important indicators of what is occurring between the two variables, as well as the sum of the coefficients with each of the *EDS* dummy variables' coefficients. These sums are presented in Figure 4 and show the impact of an additional extreme weather event on *GDPGR* across export diversification levels, just as Figures 1, 2, and 3 did for their respective models. The coefficient on *EWE_EDS* communicates the impact on *GDPGR* for a unit increase in *EWE* and *EDS*. The value of the coefficient is -0.0002917, which communicates that *GDPGR* is expected to be 0.0002917 percentage points lower for every unit increase in both *EWE* and *EDS*. The negative sign on the interaction term confirms this interpretation more generally. It communicates that the impact of an additional extreme weather event on *GDPR* becomes more negative as a country's export structure becomes less diverse (higher *EDS* category). Figure 4 shows the expected impact of an additional storm on *GDPGR* for each of the *EDS* categories present in the regression as compared to *EDS1* countries. There is no conclusive trend in Figure 4, which matches the conclusion obtained from analyzing Figure 3. This can, again, be traced to the lack of statistical significance in the model.

Figure 4: Expected Percent Change in GDPPC for each Additional EWE across EDS Categories Compared to that of EDS1 (Regression 4)



Note: This chart was created by summing the coefficients of the interaction term with the coefficients on each level of the EDS dummy variable in regression 4. These coefficients can be found in the fourth column of Table 3.

The overall results of the four regressions are surprising. The results of Regression 3 and 4 cannot be taken with any level of confidence, while the results of Regression 1 and 2 can be taken with a high level of confidence. This divide occurs when the model switches dependent variables and the results are minimally impacted by the omission of *LFPR*. The main takeaway is that the impact of an additional extreme weather event is expected to have a more positive impact on *log_GDPPC* as export diversification decreases. This relationship is clearly present in both Figure 1 and 2. However, this conclusion contradicts the original hypothesis of this study, which raises questions regarding what incited this prediction. These questions will be addressed in the conclusion section of the paper, as well as room for improvement in future iterations of this study and the impact of these findings in general.

Conclusion

Extreme weather events are increasing in both severity and frequency. It is undeniable that this increase will lead to larger and more frequent negative effects on citizens of countries across the world. The extended findings that confirm the disproportionate impact of these events on SIDS is staggering and elevates the need for investigations like this. Understanding how a country's economic structure, in this case, export diversification, either mitigates or expounds the impact of these events allows for important and relevant results. It is the hope of this study that the results found here and in similar investigations will be utilized to generate insights for country leaders.

The results across the literature confirmed two main points that informed the construction of this paper's hypothesis. The first is that export diversification has negative economic impacts and the second being that extreme weather events have negative impacts on quality of life. These conclusions led to the formation of the hypothesis, which predicts that countries with higher *EDS* scores (a more tourism reliant export structure) will experience greater negative QOL impacts from extreme weather events. The results of the regressions communicate an inverse effect but unveil aspects of this relationship that may have been previously overlooked.

Regressions 1 and 2 yielded statistically significant results surrounding the impact of an extreme weather event on GDP per Capita (*GDPPC*) across export diversification levels. Regressions 3 and 4 did not yield statistically significant results for the same relationship's impact on GDP Growth Rate (*GDPGR*). For this reason, the results of equations 1 and 2 are the primary focus. Figures 1 and 2 depict the percent change in *GDPPC* that is expected for each additional extreme weather event. Both of these charts were characterized by upward trends, which is the inverse relationship predicted by the hypothesis. Initially this result is surprising, as it contradicts the hypothesis that was guided by the literature. However, this result begins to make logical sense when it is interpreted outside the context of the hypothesis. It is likely that rebuilding, government spending, insurance payouts, and foreign aid are all positively correlated with the number and severity of natural disasters experienced in a given year. These increases could result in a positive boost to the economy and are why the results do not show a negative impact on *GDPPC* for each additional weather event. This helps explain why the impact is positive across all categories. However, the reasoning behind this positive effect growing as export structures become less diverse is still unexplained. One potential explanation is that countries with a larger dependency on tourism have a higher demand for tourism, which allows them to rebound quicker than the less coveted destinations. It can also follow that with more demand for tourism comes more aid and urgency to rebuild, which could help explain the larger positive impact as export structures become less diverse. These thoughts provide a good opportunity for studies in the future, and some additional suggestions built from the limitations of this paper are below.

As was discussed in the methodology section, there is significant room for this study to be extended on and developed in the future. The improvements range from collecting more data, being more thorough and intentional with data, and shifting the relationship of interest. These areas of improvement are discussed here to help guide future iterations of this study.

One concern with the analysis done in this paper is the lack of data that existed for all 39 SIDS. Sixteen SIDS were not included in the analysis of this paper, which is a significant proportion of all SIDS. In future studies, and where more time is available, ensuring that more SIDS can be included is an important step to make. An alternative approach, that was discussed when talking about the work of Rasmussen (2004) in the literature review section presents an opportunity for future work. The approach they took focused on a specific geographic region, in their case it was eastern Caribbean Island countries. This sampling approach has a few positive differences when compared to the sampling choices made in this paper. These differences are discussed below. However, deciding to look at all SIDS should not be discouraged, as this will likely allow for more overall observations and results that are applicable to a more diverse set of nations.

The guidance to be more intentional with the data is motivated by concerns surrounding the extreme weather event data collected through the EM-DAT database. One shortcoming of this paper's methodology was the decision to collect EM-DAT data by using the "Natural" filter. While this was the easiest way to collect data that was relevant to this project, it also encapsulated some non-relevant data. This non-relevant data refers to the observations captured under the "Biological" secondary filter. In the future, there should be a more intentional effort to filter out any events that would not be considered an extreme weather event. This shortcoming came as a result of limited time and the speed at which the data collection process occurred. A second concern with extreme weather event data is the controls for severity. Rasmussen's (2004) approach is unique as it indirectly controls for weather event severity across countries, as the same events impact the entire region. When looking at all 39 SIDS that are geographically scattered, this built-in control is lost. Another reason for concern is the four criteria that decide whether an event is included in the EM-DAT database. Recalling earlier sections, an event has to hit only one of those criteria to be included. Additionally, the criteria have low barriers of entry, meaning events that were treated the same could have had extremely different magnitudes of impact. For example, tropical storm Dorian is reported to have killed 356 people in the Bahamas, while a lot of the other events have 0 reported casualties but still are included in the database because they hit another criterion. Hopefully this illustrates the need for better controls for the severity of weather events when conducting this study or a similar one in the future.

Alternative approaches to the study as a whole were discussed in the methodology section and an additional idea is suggested here. It was the intent of this study to examine how the diversity of a SIDS export structure impacted the magnitude effect that extreme weather events had on QOL in SIDS. Building off the need to be more intentional with data, I think there is a need to re-examine what dependent variables to use, for example using the happiness index as an indicator of QOL. Moving forward, I think using an extreme weather event variable as an explanatory variable in a regression that includes controls for a scale like the happiness index would be favorable. Again, the idea of this study was to observe impacts on quality of life. While *GDPPC* and *GDPGR* are indicators of that, it would be interesting to use alternative measurements. This may require creating an original scale, that is guided by suggestions from the literature, for the sole intention of being used in that paper. Again, it is the hope of this paper, that the conclusions found here will be used to inform mitigation and adaptation decision making and motivate further research into how differing economic structures interact with the impacts of extreme weather events.

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