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Economic Consequences of Climate Change Impacts: The Case of Atlantic Canada

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Abstract

As recent literature has shown climate change impacts result in negative consequences for regional economies. In this study, we test this conclusion for the region of Atlantic Canada. In order to do and present our case study research, we designed economic and statistical models to describe the relationship between economic performance measure, which is regional value added, and two sets of control variables - economic and climate. Statistical model represents a linear multiple regression set in terms of panel data for five regional transportation hubs with autoregressive term for our dependent variable and two sets of control variables. The results obtained from the model estimation show statistically significant negative effect of rising temperature on regional value added: an increase in annual temperature by one degree Celsius causes a decrease in regional value added by 1.74%. In addition, the rise of the sea level by one meter would reduce regional value added by approximately 10% implying that coastal sub-region in Atlantic Canada is highly vulnerable to climate change impacts.

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Introduction

It is a fact reported in recent literature and accepted by majority of climate scientists that climate change is happening, and it is being caused by human activity. Increasing temperature, changing precipitation patterns, rising sea level, increasing frequency of large weather events are among fundamental features of ongoing climate change. According to the 5th Annual Report of the Intergovernmental Panel on Climate Change [1], these impacts negatively affect ecosystems, economies, human health, and infrastructure. Moreover, these impacts are highly dependent on geographical, political, and economic characteristics of the area under study. Therefore, evaluation of climate change impacts at regional level is currently identified as the most important problem.

Climate change is a sophisticated dynamic process that cannot be easily reversed in the short-run. Consequently, the focus of policy makers is on the development of long lasting adaptation mechanisms and mitigation measures. In this regard, economic evaluation of climate change consequences of climate change impacts has become necessary to justify funding for implementation of adaptation measuresat regional level.

In this study, we analyzed climate change impacts and their economic consequences for the two largest Atlantic Canada provinces – New Brunswick and Nova Scotia. Both provinces issued Climate Change Action Plans in which "…enhanced adaptation to the effects of climate change" was specified as one of the major goals. This study contributes to the knowledge about climate change impacts in the Atlantic Canada region and discovers channels through which they affects economic performance inthe region. Therefore, the major objective of this study was to evaluate how climate change impacts affect performance of regional economy in Atlantic Canada through relationship between economic performance measures and the so-called climate variables

Literature Review

Analysis of the existing models has shown that the most comprehensive models to study climate change impacts currently are the so-called Integrated Assessment Models (IAMs). These models combine information about human behavior and climate systems to make predictions about future climate change and its consequences. IAMs typically include four broad components: (i) a model projecting the path for greenhouse gas (GHG) emissions; (ii) a model mapping GHG emissions onto climatic change; (iii) a damage function that calculates the economic costs of climatic change, and; (iv) a social welfare function for aggregating damages over time and potentially across space.

According to the goalof our study, we are mostly interested in the third component of the IAMs, the so-called "damage function", which specifies how climate variables affect economic activity. Different IAMs model climate damage function in different ways. For example, the DICE/RICE models use a Cobb–Douglas aggregate production function with capital and labor as inputs, multiplied by total factor productivity (TFP), which grows at a constant, exogenously specified rate. Output is then reduced by the damage function. For example, in the DICE model, the damage function is

$$D(T) = \frac{1}{1 + \pi_1 T + \pi_2 T^2} \tag{1}$$

where T is this period's temperature and π's are parameters. Economic output is then modeled as

$$Y_t = D(T_t) \times A_t \times F(K_t, L_t) \tag{2}$$

where $F_t = A_t(K_t, L_t)$ denotes economic aggregate production function in period t in the absence of warming (e.g., a Cobb–Douglas aggregate production function augmented by TFP). This specification of the damage function implies a negative relationship between temperature T and total output Y, however, the relationship is postulated and not explained.

The PAGE model similarly specifies aggregate, nonlinear climate damage function that pre-multiplies economic output. However,

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PAGE uses separate damage functions for different regions. PAGE also separately calculates regional-specific damages for sea level impacts and extreme climatic changes [2].

In the FUND model, damage from climate changeis calculated at region as well as at sectorial level and then aggregated up. It means that actually FUND includes separate models for agriculture, forestry, energy consumption, and health while also considering water resources, extreme storm damage, sea level rise, and the value for ecosystems with potentially separate regional parameters for each of these models [3,4].

In recent review of IAMs, Pindyck [5]) makes the following conclusion: "…The bottom line here is that the damage functions used in most IAMs are completely made up, with no theoretical or empirical foundation".

There is another weakness of the existing IAMs identified by Dell, Jones, and Olken [6]:"For models that seek to construct aggregate damages by aggregating up sectorial effects, such as the FUND model, the question is which sectors to include and how those sectors interact in terms of climate change impacts".

Furthermore, damage function D(T)used in IAMs represents an approximate snap shot of climate change impact on economy which is not justified by the existing dynamics of climate variables. In reality, climate change represents a continuous cumulative long-run dynamic process and as such should be modeled with autoregressive or lag distributed models. In fact, labor productivity At in aggregate production function presented above is subject to the following process:

$$LnA_t = LnA_{t-1} + \Delta T \tag{3}$$

where ΔT is a dynamic long-run process associated with temperature change [6]. According to Pindyck [5], "while it is hard to know definitively the correct functional form for the damage function, even small impacts on productivity growth could, over time, swamp effects on the level of output". Therefore, relationship between total economic output and climate variables presented in IAMs is not based on rigorous empirics and does not reflect real dynamic process.

That is why we now turn our attention to the analysis of empirical studies dedicated to this issue. Two major statistical approaches have been originally used to address it: (i) cross-sectional analysis, and (ii) panel data analysis. Classic cross-sectional approach emphasizes spatial variation at a point in time and a linearized version of such model can be presented as follows

$$y_i = a + bc_i + cX_i + e_i \tag{4}$$

Where subscript i indexes different geographic areas, e.g., countries or subnational entities like counties, provinces, states as dictated by the question of interest and sources of data; *y* is economic performance measure, *C* is a vector of climate variables, and *X* is a vector of other exogenous variables used as controls. Economic performance variable *y* and explanatory variables in *C* and *X* are typically measured either in levels or logs. The error process e is typically modeled using robust standard errors, possibly allowing for spatial correlation in the covariance matrix by clustering at a larger spatial resolution or allowing correlation to decay smoothly with distance [7].

Applying cross-sectional analysis, Nordhaus [8] used a global database of economic activity with a resolution of 1° latitude by 1° longitude. Controlling for a country's fixed effects, he found that 20% of the income differences between Africa and the world's richest industrial regions can be explained by climate and geographical variables such as temperature, precipitation, elevation, soil quality, and distance from the coast.

Dell, Jones, and Olken [6] used municipallevel data for twelve countries in the Americas and found statistically significant negative relationship between average temperature and income within countriesand even within states (provinces) within countries. They found that a 1°C increase in temperature decreases income in the range of 1-8.5% in different regions. The authors also found little or no impact of average precipitation levels on economic performance measure. Overall, according to the presented above study, climate and geographic variation explains a remarkable 61% of the variation in income at the municipal level across 7,684 municipalities in 12 countries. In general, the cross-sectional approach justifies a strong, negative relationship between temperature and economic activity, with less clear evidence with respect to precipitation.

In turn, panel data analysis usually takes on the following form:

$$y_{it} = bc_{it} + cX_{it} + a_i + d_{rt} + e_{it} \tag{5}$$

Where subscript *t* indexes time (e.g., years, days, months, seasons, decades), a_i captures spatial effects of different geographical areas, d_{rt} captures time trends within different geographical areas, and eit is error term with some standard statistical properties.

In general, panel studies exploit the exogeneity of cross-time weather variation allowing for causality. For example, Dell, Jones, and Olken [6] examined how annual variation in temperature and precipitation affected per capita income in a sample of countries over 1950-2003 period. They showed that a 1°C increase in temperature reduces per capita income by 1.4% but only in poor countries. Estimating long-difference models, the above mentioned authors found that over 10–15 year time periods, temperature shocks have similar effects to annual shocks, although statistical precision decreases. Variation in mean precipitation levels was not found to affect per capita income. Temperature shocks appear to have little effect in rich countries, although estimates for rich countries are not statistically significant.

Bansal and Ochoa [9] examined the empirical relationship between a country's economic growth and worldwide average temperature shocks, as opposed to a country's particular temperature shock. They found that on average a 1°C global temperature increase reduces growth by about 0.9% with the largest effects for the countries located near the equator. Hsiang [10] showed similar findings using annual variation in a sample of twenty-eight Caribbean basin countries over the 1970–2006 period. According to his study, national output falls 2.5%per 1°C warming. This study further examined output effects by the time of year and showed that positive temperature shocks have negative effects on income only when they occur during the hottest season. Mean rainfall variation was controlled for in this study but results were not reported.

Barrios, Bertinelli, and Strobl [11] focused on sub-Saharan Africa over the 1960–1990 period, using a subsample of twentytwo African and thirtyeight non-African countries and weather variation occurring across five-year periods. The authors found that higher rainfall was associated with faster growth in sub-Saharan African countries but not elsewhere. They estimated that worsening rainfall conditions in Africa since the 1960s could explain 15–40% of the per capita income gap between sub-Saharan Africa and the rest of the

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developing world by the year of 2000. Unlike the majority of studies, which consider the effect of precipitation and temperature levels, this study used weather anomalies in the form of changes from country means, normalized by country standard deviations. On the other hand, Dell, Jones, and Olken [12] found that anomalies based analyses tend to provide broadly similar results to the levelsbased analyses.

Miguel, Satyanath, and Sergenti [13] studied fortyone African countries overthe 1981–1999 period. They showed that annual per capita income growth is positively predicted by current and lagged rainfall growth while not controlling for temperature. However, this relationship becomes weaker after 2000 [13].

Bruckner and Ciccone [14] also found that negative rainfall shocks lowered income in sub-Saharan Africa. Finally, Burke and Leigh [15] used precipitation and temperature as instruments for per capita income growth studying a large sample of 121 countries over the 1963–2001 period. In their analysis, temperature appeared to be a strong predictor of income while precipitation was weak.

The above mentioned studies can be classified as macroeconomic. It is so because in those studies the economic performance variable y implied national income or GDP as well as their growth rates. Similar statistical approaches have been applied at microeconomic level. In those studies, the outcome variable y implies industrial output like output in agriculture, mining, forestry, tourism, and other economic sectors usually expressed via value added. Within cross-sectional approach, frequently called the production function approach, the relationship between climate variables and industrial output is specified to estimate the impacts of changing climate. For example, this approach is popular to analyze climate change impacts on agricultural output [16,17].

In turn, Hsiang [10], and Dell, Jones, and Olken [12] examined the effect of weather fluctuations on aggregate industrial output for large samples of countries, using panel data specifications. Hsiang [10] measured the effects of temperature and cyclones in twentyeight Caribbean countries over the 1970–2006 period while also controlling for precipitation. He found that periods of unusually high heat waves have large negative effects in three of six non-agricultural sectors where non-agricultural output declined 2.4% per 1°C. Two of the three affected sectors were service oriented which provided the majority of output in these Caribbean economies while the other affected sectors were industrial - mining and utilities. Hsiang did not find statistically significant impact of temperature on manufacturing output. Cyclones did have negative effects on mining and utilities.

Dell, Jones, and Olken [12] studied annual industrial value added output within a sample of 125 countries over the 1950–2003 period. They found that industrial output falls by 2% per 1°C increase in temperature but only in poor countries. Magnitudes of these estimated temperature effects are similar to those reported in Hsiang [10]. Moreover, like Hsiang [10], this study controlled for mean rainfall but no effect of mean precipitation levels was found.

It is also necessary to mention that some studies estimated climate change impacts on output at a factory level [18] while some other studies used labor productivity at industry level as relevant economic performance measure [19].

All these studies provide rigorous econometric evidence that climate change impacts such as increase in temperature, change in precipitation patterns, extreme weather events and others have significant effects on economic activity. They also give us some statistical tools for the analysis. On the other hand, they show drawbacks of these tools which calls for the design of more sophisticated approaches and techniques. In our opinion, one major drawback of all these studies is their short-run or short memory analysis. In econometric terms, the above two approaches used in empirical studies – cross-sectional and panel – require stationarity of all variables involved. Climate change impacts are long memory processes that require appropriate statistical tools to address them, and in general, they are non-stationary at least in levels.

According to Dell, Jones, and Olken [20], cross-sectional models of climate change impacts produce biased parameter estimates that cannot be used for the long-run forecast. With respect to panel models, the authors claim that even though these models "correctly identify the causal effect of weather shocks on contemporaneous economic outcomes, they may not estimate the structural equation of interest for understanding the likely effects of future global climate change". Moreover, the authors state that the panel estimates are neither an upper bound nor a lower bound for the effect of climate change. Among some reasons for their conclusions the authors mention inter-temporal adaptation to and intensification of climate change as well as general equilibrium effects.

Based on the outcomes of the above described literature, we decided to do a case study research with respect to the region of Atlantic Canada. Mainland Atlantic Canada includes two provinces – New Brunswick and Nova Scotia which were our major target. In our study, we tried to address the drawbacks we mentioned in our literature review in consistent wayand below we present our methodology.

Methodology

In order to understand the climate change impact on regional economic activity, we introduced the following general relationship:

$$Y = F(C, X) \tag{6}$$

Where Y is an economic performance measure; C is a vector of climate variables, and X is a vector of economic controls that are correlated with climate variables.

In this study, our region of two Atlantic Canada provinces – Nova Scotia and New Brunswick – was divided into five regional transportation hubs. It was done due to the following two reasons: (i) these hubs are identified as distinct in all provincial economic development plans, and (ii) these hubs are quite different in terms of climate change dynamics. Value added generated by each regional transportation hub was chosen as our economic performance measure. Following our previous statistical analysis of dynamics of climate change in Atlantic Canada, we included temperature, precipitation, and sea level in vector C. However, some challenges arose with respect to the vector of economic controls X.

We were interested in variables that affect economic activity expressed through the value added at five regional transportation hubs. Statistics Canada publishes data at national and provincial levels only. Our five transportation hubs are located in two Atlantic Provinces which means that the hub specific data was hard to obtain. For our methodology, it was crucial to include the regional specific characteristics as well as hub specific data to capture time-invariant cross-sectional variation between transportation hubs. As a result, we identified four region specific variables – total output (aggregate provincial GDP), the Consumer Price Index (CPI), transportation price index and oil price – common for all hubs and three hub specific variables – number of people employed, income and gasoline prices.

Furthermore, we chose the longitudinal data for our analysis because we wanted to isolate the impacts of climate variables in our model from other factors. While emphasizing the variation of our variables over time within a given transportation hub, panel data method permits to focus on the effect of climate variation on the explanatory variable accounting for heterogeneity across transportation hubs and for dynamic effects that are not visible in cross-section analysis.

This choice is consistent with the existing literature that suggests that panel data method prevail over others for several reasons: First, it allows to combine both a cross-sectional data with time dimension as well as to control for time-constant unobserved spatial specific characteristics; second, it increases precision of estimation via increased number of observations. That is why this method is extremely useful to evaluate the impact of climate change on the regional economy.

In addition, since climate change is a long memory process, we addressed this point via inclusion of a lagged dependent variable. It is a well-known fact in econometrics that inclusion of a lagged dependent variable makes a short-run relationship work as a long-run relationship.

So, mathematically our model can be summarized as

$$VA_{it} = F(VA_{i(t-1)}, X1_t, X2_{it}, C_{it}) \tag{7}$$

where VA_{it} is the value added generated by the *i*-th regional transportation hub in year *t*; $VA_{i(t-1)}$) is the lagged value of the dependent variable; $X1_t$ is a subset of regional economic variables common for all transportation hubs in year *t*; $X2_{it}$ is a subset of economic variables associated with the *i*-th transportation hub in year *t*; C_{it} is the vector of climate variables associated with the *i*-th transportation hub in year *t*.

Since the number of crosssections in our study is relatively small, Least Squares Dummy Variables (LSDV) method is used. We include a dummy variable for eachcross sectional unit to bring unobserved time invariant effects explicitly into the model. This approach is equivalent to the within-groups method and gives the same estimates of the vector of parameters that could be obtained from the regression on time-dependent data. For the balanced panel we are using, there are $T - I - 1$ degrees of freedom since we included one dummy variable that takes the value of *i* from 1 to 5 for each transportation hub respectively. This is one of the advantages of LSDV specification:It properly computes the degrees of freedom directly.

For the panels with sufficiently large T, the timeseries properties of the data become an important consideration. In particular, test for stationarity of time series, which is an integral part of single timeseries analyses, becomes an important step in long panel data settings as well. Our panel contains observations over twenty-four years on five crosssectional units.

Recent literature suggests that panelbased unit root tests have higher power than unit root tests based on individual time series. While these tests are commonly termed "panel unit root" tests, theoretically, they are simply multiple series unit root tests that have been applied to panel data structures.

In this study, we applied simple Dickey-Fuller unit root test [21] for each variable as well as Levin, Lin and Chu [22] test and Im, Pesaran and Shin [23] test for panel unit root. In addition, we applied some other diagnostic tests. The results of the diagnostic tests and model estimation are presented in the next section.

Data Description and Estimation Results

In this study, we have used two sets of data: (i) economic control variables, vector X, and (ii) climate related variables, vector C. As follows from our methodological part, vector of economic control variables X includes two types of variables: (i) region specific, and (ii) transportation hub specific. Region specific data was obtained from Canadian Socio-Economic Information Management System (CANSIM). Hub specific data was derived from provincial input-output tables. Climate data which included temperature precipitation and sea level was obtained from Environment Canada.

For the purposes of our analysis, we applied natural logarithm transformation to all of our economic time series contained in vector *X*. This approach is justified from statistical and economic point of view. The former is based on the fact that for series with exponential growth and variance that grows with the level of the series-all our economic variables fall into this category-a natural logarithmic transformation can help linearize and stabilize the series. Economic interpretation is even more important: a regression coefficient of the log-transformed data represents elasticity. With logarithmic transformation, the parameters in our model are interpreted as a percentage change in dependent variable due to a percentage change in independent variable. Evaluating economic impacts, we are more interested in capturing the changes in growth rates rather than absolute changes in our variables.

On the other hand, we used levels for all variables included in the vector of climate variables *C* because it makes the interpretation of regression coefficients easier and more useful for the purpose of our analysis. According to our literature review, we expect a one degree increase in temperature to have a negative percentage effect on regional value added. Presumably, the metric change in a sea level would exhibit significant negative impact on the value added for transportation hubs located near the coastline such as Halifax, Saint John, and Moncton.

We have examined our time series for the presence of a unit root process. First, for this purpose, the Dickey-Fuller test was applied to each series individually. Dickey-Fuller unit root test showed that all our economic time series exhibit unit root process - random walk with drift - and therefore, they all are differencestationary. Further, following our methodology, we examined our variables with panel unit root tests checking for common and individual unit roots. The results of Levin, Lin & Chu [22] test showed that three out of seven economic variables are stationary: transportation price index, provincial GDP, and number of people employed. However, according to Im, Pesaran and Shin [23] panel unit root test, unit root is present in all economic variables except GDP that is stationary at 10% level.

The inclusion of non-stationary time series in regression might lead to spurious results as regression might capture the common unit root process among variables rather than explaining the true relationships among them. However, contrary to the standard procedure, we did not apply first differencing before including our variables into the model because it would completely eliminate the long-memory process present in the data. It would significantly limit the scope of questions we want to address and answer in this study. Consequently, taking into account the main goal of this analysis, the costs of first differencing are deemed to be much higher compared to a possible spurious regression. As future steps, this issues could be addressed using more advanced time series techniques such as co-integration and error correction model. In the meantime, facing the data limitations, this problem is solved by incorporating deterministic linear trend and cross-sectional dummy variables to capture potential common trends among variables and to allow the changes in intercept as well as slope of the regression line.

Based on our methodology, we estimated the climate change impacts on regional economic performance using panel model. The analysis started with estimation of a panel model for five transportation hubs -Halifax, Fredericton, Moncton, Saint John, Edmundston–located in two provinces–Nova Scotia and New Brunswick-including all relevant explanatory variables without lagged dependent variable. As a result of this estimation, we found that temperature has a negative impact as expected: a one degree Celsius increase in temperature reduces regional value added by 5.7%. This result is significant at 10% level. Diagnostics of residuals series obtained from this model revealed the presence of autocorrelation and heteroscedasticity. Therefore, we obtained statistical evidence in favor of dynamic nature of our process and the need for a lagged dependent variable.

Next, the dynamic panel model for five transportation hubs with lagged dependent variable was estimated using least squares dummy variable (LSDV) regression technique. Northern New Brunswick hub represented by Edmundston was identified as outlier and was excluded from the model. As our next step, the model with four transportation hubs-Halifax, Fredericton, Moncton, Saint John– and lagged dependent variable was estimated. Temperature became significant at 1% level with negative sign as expected: an increase in annual temperature by one degree Celsius decreases regional value added by 1.74%. Total precipitation has a small yet still significant at 10% level positive impact on the regional value added. Parameters of the other factors are also statistically significant with adjusted R-squared for regression equal to 0.95. Diagnostic tests showed that residuals are stationary andthe normality assumption is supported at 5% and 1% significance levels.

Finally, the panel model for coastal sub-region that includes Halifax, Moncton and Saint John was estimated. Temperature was still significant at 5% level with sea level rise significant at 1%. These results show that a one degree Celsius increase in temperature decreases regional value added by 1.25% while a one meter rise in sea level decreases regional value added by 9.9%. These results underlined the fact that this region is particularly susceptible to climate change impacts with significant negative joint impacts of sea level rise and temperature on value added generated by these hubs.

Conclusion

In our case study research, we have tested the hypothesis that climate change impacts cause negative economic consequences for a regional economy. Our target region consisted of two Maritime Provinces in Atlantic Canada–New Brunswick and Nova Scotia. In order to identify the economic consequences of climate change impacts, we have used panel data analysis framework. We identified five regional hubs-Halifax, Fredericton, Saint John, Moncton, Edmundston-located in the above mentioned Atlantic Canada provinces and collected annual economic and climate data for the period of twenty four years from 1991 to 2014.

Using standard panel methods, we combined cross-sectional data with time series in our models. It allowed us to account for time invariant spatial specific characteristic of each regional hub and capture dynamics of climate variation. As outlined in our literature review, the main criticism of current studies evaluating climate change impacts on economy is associated with the short memory nature of analysis and lack of attention to region specific effects. To address these issues in our analysis, we modified our models by:

- including a lagged dependent variable, regional value added, to account for long memory of climate change process;
- including a deterministic linear trend to capture potential common trends among variables;
- including a dummy variable for eachcross sectional unit to bring unobserved time-invariant effects explicitly in the model;
- including both region specific and hub specific factors.

We applied our methodology to estimate three panel data models: (i) model with all five transportation hubs, (ii) model with four regional hubs with similar dynamics, and (iii) model with coastal hubs. Obtained results confirmed our hypothesis of negative consequences of climate change for regional economic performance. Climate change expressed through the rise of annual temperature by one degree Celsius produced a 1.74% reduction in regional valued added.

At the same time, sea level rise by one meter can cause a significant 9.9% decrease in value added generated by the coastal sub-region. This is another proof that climate change impacts cause particular concern for Atlantic Canada, where major part of households is situated along the coastline, and much of the infrastructure is built in the areas with high risk of flooding. For New Brunswick and Nova Scotia provinces, particularly vulnerable areas include: the south coast of Nova Scotia and most of the Gulf of St. Lawrence coast of New Brunswick. Climate models predict that by the end of this century Atlantic Canada's average annual temperature will increase by 2 to 4°C. Forecast for the sea level rise ranges from 0.7 to over 1.0 meter depending on the area.

The above presented results can be used as a guideto evaluate the risks associated with climate change in Atlantic Canada. Currently observed weather variation and change in climate patterns induce the necessity to identify and quantify those risks Therefore, arranging sufficient funding for development and implementation of mitigation actions and adaptation plans on regional levels is the task of utmost importance.

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