ECONOMIC CONSEQUENCES OF CLIMATE CHANGE IMPACTS:

THE CASE OF ATLANTIC CANADA

by

Iuliia Nesterova

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Supervisor: Yuri Yevdokimov, Ph.D., Economics Department

Examining Board: Elif Dalkir, Ph.D., Economics Departemnt, Chair
Mehmet Dalkir, Ph.D., Economics Department
Weiqiu Yu, Ph.D., Economics Department

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ABSTRACT

Climate change poses wide-reaching challenges for regional economy. We study economic consequences of climate change impacts for Atlantic Canada. Designed economic and statistical models describe relationship between economic performance measure, which is regional value added, and two sets of control variables: economic and climate. Statistical model represents linear multiple regression, set in terms of panel data for five regional transportation with autoregressive term for dependent variable. Obtained results showed the negative effect of rising temperature on regional economic performance: if average annual temperature increases by one degree Celsius, it decreases regional value added by 1.74%. Along with an increase in temperature, the rise of the sea level by 1 meter would reduce regional value added by more than 11% meaning that coastal sub-region in Atlantic Canada is highly vulnerable to weather variation and change in climate patterns.

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Chapter 1. Introduction

The majority of climate scientists agree that climate change is happening and is caused by human activity. The main observable features of climate change include: increasing temperature, changing precipitation patterns, rising sea level, increasing frequency of large weather events and others.

According to the Intergovernmental Panel on Climate Change, impacts refer to effects on lives, ecosystems, health, economies, cultures, and infrastructure due to the interaction of climate changes and the susceptibility of a system.

The impacts of climate change diverse globally and highly depend on geographical, political, and economic characteristics of the area. Diffuse estimates produced by Integrated Assessment Model - currently the most comprehensive models to study climate change impacts - induce the necessity in conducting region specific research.

Climate change is a sophisticated long run process that definitely could not be reversed in a short-run. Consequently, the focus of policy makers should be on development of adaptation mechanisms and mitigation actions. Hence, the important policy issue is how to evaluate the risks associated with climate change outcomes to be able to arrange sufficient funding for development and implementation of adaptation plans on regional levels.

Both New Brunswick and Nova Scotia provincial governments issued Climate Change Action Plans. One of their goals is formulated as follows: “enhanced adaptation to the effects of climate change.” This goal is realized through number of key action areas.

The purpose of this study is to evaluate climate change impacts on regional economic activity by describing relationship between economic performance measure and climate variables in Atlantic Canada. This report proceeds as follows. In Chapter 2, we discuss recent literature dedicated to the economic consequences of climate change impacts that helped us in our empirical work. Chapter 3 presents the methodology used in this study. In particular, we estimate the climate change impacts on regional economic performance using panel models with the lagged dependent variable for five regional hubs located in two Atlantic Canada provinces: New Brunswick and Nova Scotia. Chapter 4 contains information about the data, detailed estimation results, and residuals diagnostics of the models. Last Chapter offers concluding observations and suggests future directions.

Chapter 2. Literature Review

As mentioned in Introduction chapter, 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 used for economic policy analysis typically include four broad components: (i) a model projecting the path for greenhouse gas (GHG) emissions; (ii) a model mapping GHG emissions into 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. This study is concerned with the third component of the IAMs, the so-called "damage function", which specifies how climate variables affect economic activity. Different IAMs model the climate-damage function in somewhat different ways. For example, the DICE/RICE models use a Cobb–Douglas 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 climate-damage function. For example, in the DICE model, the damage function is

$$D(T)=1+\pi_1 T_1+\pi_2 T_2 \tag{2.1}$$

where T is this period's temperature anomaly and π's are parameters. Output is modeled as

$$Y_t = D(T_t) A_t F(K_t, L_t) \tag{2.2}$$

where $F_t = A_t F(K_t, L_t)$ denotes output in period t in the absence of warming (e.g., a Cobb–Douglas aggregate of capital and labor, augmented by TFP). The parameters of the loss function are calibrated in different ways.

The PAGE model similarly specifies an aggregate, nonlinear climate-damage function that multiplies GDP in the absence of climate change, but PAGE calibrates separate loss functions by region. PAGE also separately calculates regional-specific damages for sea level impacts and extreme climatic changes (Hope 2006).

In the FUND model, climate damages are calculated at the region-by-sector level and aggregated up. It means that 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 (Tol 2002; Anthoff, Hepburn, and Tol 2009).

In a recent review of IAMs, when discussing the calibration of the D(T) function, Pindyck (2013) concludes: "…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 drawback of IAMs identified by Dell, Jones, and Olken (2014). 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) in IAMs represents a snap shot or statistical version of climate change impact on economy. In reality, climate change represents a continuous cumulative long-run shock 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:

$$LnA_t = LnA_{t-1} + \Delta(T) \qquad (2.3)$$

where Δ(T) is a dynamic long-run process associated with climate variable T (see Dell, Jones, and Olken, 2014). According to Pindyck (2013), while it is hard to know definitively the correct functional form for the loss function, even small impacts on productivity growth could, over time, swamp effects on the level of output.

As intermediate conclusion, relationship between economic outcome and climate change variables presented in IAMs is not based on rigorous empirics and therefore does not reflect real processes. 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.

A classic cross-sectional approach emphasizes spatial variation at a point in time. A linearized version of such model is

$$y_i = a + bC_i + cX_i + e_i \qquad (2.4)$$

where 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 outcome variable, C is a vector of climate variables, and X is a vector of other exogenous variables used as controls. The outcome 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 (Conley 1999).

Within cross-sectional analysis, Nordhaus (2006) used a global database of economic activity with a resolution of 1° latitude by 1° longitude. Controlling for country fixed effects, this study found that 20 percent of the income differences between Africa and the world's rich industrial regions can be explained by geographic variables, which include temperature and precipitation as well as elevation, soil quality, and distance from the coast. Dell, Jones, and Olken (2009) used municipal-level data for twelve countries in the Americas and found that a statistically significant negative relationship between average temperature and income persists within countries—and even within states (provinces) within countries. The drop in per capita income per 1°C falls from 8.5 percent (across countries) to 1–2 percent (within countries or within states), and they found little or no impact of average precipitation levels either across or within countries. Overall, geographic variation (temperature, precipitation, elevation, slope and distance to coast) explains a remarkable 61 percent of the variation in incomes at the municipal level across the 7,684 municipalities studied in these 12 countries. In general, the cross-sectional evidence finds a strong, negative relationship between temperature and economic activity, with less clear evidence on precipitation.

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

$$y_{it}=bC_{it} +cX_{it} +a_i +d_{rt} +e_{it} \qquad (2.5)$$

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

In general, panel studies exploit the exogeneity of cross-time weather variation, allowing for causative identification. In a world sample from 1950 to 2003, Dell, Jones, and Olken

(2012) examined how annual variation in temperature and precipitation affected per capita income. They show that being 1°C warmer in a given year reduces per capita income by 1.4 percent, but only in poor countries. Moreover, estimating a model with lags of temperature, they find that this large effect is not reversed once the temperature shock is over, suggesting that temperature is affecting growth rates, not just income levels.

Estimating log-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 the path of per capita income. Temperature shocks appear to have little effect in rich countries, although estimates for rich countries are not statistically precise.

Bansal and Ochoa (2011) 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 1ºC global temperature increase reduces growth by about 0.9 percentage points, with effects largest for the countries located near the equator. Hsiang (2010) showed similar findings using annual variation in a sample of twenty-eight Caribbean-basin countries over the 1970–2006 period. According to the study, national output falls 2.5 percent per 1°C warming. This study further examined output effects by 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 (2010) focused on sub-Saharan Africa over the 1960–1990 period, using a subsample of twenty-two African and thirty-eight non-African countries and weather variation occurring across five-year periods. The authors found that higher rainfall was associated with faster growth in these sub-Saharan African countries but not elsewhere. They estimated that worsening rainfall conditions in Africa since the 1960s could explain 15–40 percent of the per capita income gap between sub-Saharan Africa and the rest of the developing world by the year 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 (2012) found that anomalies-based analyses tend to provide broadly similar results to levels-based analyses when predicting national income growth, but with weaker statistical precision.

Miguel, Satyanath, and Sergenti (2004), studied forty-one African countries from 1981–1999 and showed that annual per capita income growth is positively predicted by current and lagged rainfall growth, while not controlling for temperature. However, this relationship appears weaker after 2000 (Miguel and Satyanath 2011).

Bruckner and Ciccone (2011) also found that negative rainfall shocks lowered income in subSaharan Africa. Finally, Burke and Leigh (2010) used precipitation and temperature as instruments for per capita income growth studying a large sample with 121 countries over the 1963–2001 period. In their analyses, 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 outcome variable y implied national income or GDP as well as their growth rates. The very same statistical approached 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 denoted the production function approach, a relationship between climate 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 (see Adams 1989; Kaiser et al. 1993; Adams et al. 1995).

In turn, Hsiang (2010); Jones and Olken (2010); and Dell, Jones, and Olken (2012) all examined the effect of weather fluctuations on aggregate industrial output for large samples of countries, using panel specifications. Hsiang (2010) measured the effects of temperature and cyclones in twenty-eight Caribbean countries over the 1970–2006 period, while also controlling for precipitation. He founds that periods of unusually high heat have large negative effects for three of six nonagricultural sectors, where nonagricultural output declined 2.4 percent per 1°C. Output losses were driven by heat shocks during the hottest season. Two of the three affected sectors were service-oriented and provided the majority of output in these Caribbean economies, while the other affected sector was industrial (mining and utilities). Hsiang did not find a statistically significant impact of temperature on manufacturing output. Cyclones had negative output effects on mining and utilities, among other sectors in the economy, while having offsetting positive output effects for construction, leading to no net effects on economy wide output flows.

Dell, Jones, and Olken (2012) studied annual industrial value-added output within a global sample of 125 countries over the 1950–2003 period. They found that industrial losses are 2 percent per 1°C, but only in poor countries. The magnitudes of these estimated temperature effects are similar to Hsiang (2010). Further, like Hsiang (2010), this study controlled for mean rainfall but no effect of mean precipitation levels was found.

Jones and Olken (2010) reconsidered industrial output losses in the global sample using trade data. This data, collected in rich countries, helps avoid possible data quality issues in national accounts while also allowing examination of narrower product classes. Using two-digit product codes, this analysis found an average 2.4 percent decline in exports from a poor country per 1°C warming there. No robust effect of average precipitation appeared across specifications. Analyzed by sector, twenty of the sixty-six two-digit export categories showed statistically significant negative impacts of temperature. In addition to agriculture exports, negative temperature effects appeared for many manufactured goods.

It is also necessary to mention that some studies estimated climate change impacts on output at a factory level (see for example, Cachon, Gallino, and Olivares, 2012) while some other studies used labor productivity at industry level as relevant outcome variable (see for example, Seppanen, Fisk and Faulkner, 2003).

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 (2014), cross-sectional models of climate change impacts produce biased parameter estimates that cannot be used for the long-run forecasts. 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 these conclusions they mention intertemporal adaptation to and intensification of climate change as well as general equilibrium effects.

Dell, Jones, and Olken (2014) present the following classification of different approaches to capture long-run effects of climate change:

(i) different geographic areas have different baseline climates. An unusual weather shock in one area is often well within normal experience in another area, where adaptation has had the opportunity to occur. Comparing these areas by interacting weather shocks with the existing distribution of weather events can help assess the magnitude of adaptation.

(ii) one can examine long term differences; i.e., instead of looking at annual shocks, one can examine average impacts over longer time horizons, such as decades.

(iii) one can focus on particular permanent shocks and trace out their impacts over many years.

(iv) combining the previous two methods with short-run panel estimation, one can explicitly compare the same event at different time scales to assess the degree of adaptation.

Based on the literature review, we proceed to develop our methodology for this study based on the following basic principles:

- the model should reflect evolution of the relationship “economic outcome-climate change” over time;
- climate change impacts should be regarded as stochastic continuous shocks reflecting dynamics of climate variables;
- calibration of the model should be done on the basis of statistical work.

Chapter 3. Methodology

As mentioned in Introduction, this study is dedicated to the analysis of climate change impacts on regional transportation hubs. In order to understand the climate change impact on regional economic activity, we introduced the following general relationship:

$$Y=F(C,X) \tag{3.1}$$

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.

Value added generated by each regional transportation hub was chosen as our economic performance measure. Following 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 different levels namely regional and transportation hubs levels. Statistics Canada publishes data at national and provincial levels. Our model includes five transportation hubs located in two Atlantic Provinces – New Brunswick and Nova Scotia. It appeared to be that the regional specific data was hard to obtain due to relatively small areas and high level of detalization. For our methodology, it was crucial to include the regional specific characteristics to capture time-invariant cross-sectional variation between transportation hubs.

So, in this study, in order to construct vector X, we have used the following steps:

(i) define subset of general macroeconomic indicators such as the consumer price index (CPI), transportation price index, and oil price that is common for all transportation hubs;

(ii) sum up income-based GDP for Nova Scotia and New Brunswick;

(iii) collect data on population, income, number of people employed, and gasoline price specific for each of earlier defined five transportation hubs.

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 methods prevail over others for several reasons: First, they allow to combine both a cross-sectional data with time dimension as well as to control for time-constant unobserved spatial specific characteristics; second, they increase precision of estimation via increased number of observations.

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. Even though inclusion of the lagged dependent variable takes away a sufficiently great deal of variation in our dependent variable that may make the effect of all other factors less significant, not including it would lead to omitted variable bias.

Included lagged dependent variable – value added in our case - allows us to conclude that other explanatory variables still have an impact controlling for the value of the lagged dependent variable. Consequently, we consider the lagged dependent variable as an important part of the data generating process, and its inclusion in our model is methodologically necessary and theoretically important. On the one hand, the lagged value of value added is correlated with the error term and makes the coefficients of the regression biased, but on the other hand, with long enough panel data set, these biases are negligible and treated as a second-order (Bond, 2013). Recent literature suggests Arellano and Bond estimator and the generalized method of moments (GMM) procedure to estimate dynamic panel data models. Although, those methods effectively remove endogeneity and autocorrelation in a panel model, their procedure involves first-differencing and utilization of lagged variables as an instruments. Consequently, for application of such sophisticated methods, the bigger data set is required. Moreover, the issue of bias and inconsistency of within estimator is a greater concern for the typical labor panels where N is large and T is fixed. For the panels with T>N, some researchers still favor the Within estimator with an argument that this bias is not large. Kiviet (1995) proposed a corrected Within estimator that subtracts a consistent estimator of this bias form the original Within estimator. It performed well in simulation with other consistent instrumental variable or GMM estimators (Baltagi, 2005). Judson and Owen (1999) recommended this Within estimator as the best choice followed by GMM. By performing Monte Carlo experiments, they proved that the bias in the Within estimator can be sizeable.

Mathematically our model can be summarized as

$$VA_{it} = F(VA_{i(t-1)}, X1_{t} , X\,2_{it} ,C_{it}) \tag{3.2}$$

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; X1t 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 cross-section in our study is relatively small, N=5, Least Squares Dummy Variables (LSDV) method is used. We include a dummy variable for each-cross sectional unit to bring unobserved time-invariant effects explicitly in the model. This approach is equivalent to within-groups method and gives the same estimates of the vector β that could be obtained from the regression on time-demeaned data. For the balanced panel we are using, there are NT – K – 1 degrees of freedom since we included one dummy variable that takes the values from 1 to 5 for each transportation hub respectively. That's one of the advantages of LSDV specification – it properly computes the degrees of freedom directly while Within estimator replies on the programmed built-in fixed effect options of econometrics software packages.

For the panels with sufficiently large T, the time-series properties of the data become an important consideration. In particular, test for stationarity of data series, which is an integral part of single time-series analyses, becomes an important step in long panel data settings as well. Our panel contains observations over twenty-four years on five cross-sectional units. We expect our economic variables to have long memory meaning they contain a long-lasting impact of previous shocks. Hence, we begin our analysis from statistical tests for identification of nonstationarity in relevant variables in our model.

To test this hypothesis, we examined our time series for the presence of a unit root process. For this purpose, the Dickey-Fuller test was used. Intentionally, we did not apply the augmented Dickey-Fuller test, because it would remove all the structural autocorrelation in time series, and hence, would require a larger data set. According to the methodology described in Enders (2010), we applied the following approach to each time series:

(i) run $\Delta y_t = \alpha_0 + \gamma y_{t-1} + \varepsilon_t$,, where α_0 is a drift term and $\gamma = \alpha_1 - 1$; it is obtained by first-differencing the AR(1) process $y_t = \alpha_1 y_{t-1} + \varepsilon_t$;

(ii) under the H0: $\gamma = 0$, i.e. $\alpha_1 = 1$, series contains unit root;

(iii) check the corresponding t-statistics from the Dickey-Fuller table;

(iv) if the null-hypothesis is rejected, i.e. $|\alpha_1| < 1$, then we conclude that this is weakly dependent process called integrated of order zero or I(0), meaning that we can use such series in regression analysis without any additional manipulations;

(v) if the null-hypothesis is supported, the process is I(1), and the first difference of it is considered to be weakly dependent.

Recent literature suggests that panel-based 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.

Levin et al. (2002) argued that compared to performing a separate unit root test for each individual time series, the power of the panel-based unit root test is higher. They developed a procedure utilizing pooled cross-section time series data to test the null hypothesis that each individual time series contains a unit root against the alternative hypothesis that each time series is stationary. Levin, Lin and Chu test (LLC) is proved to be practically useful for panels of moderate size. It allows for individual-specific intercepts and time trends. However, the test depends crucially upon the assumption of common unit root ($\rho i = \rho$), i.e. all cross-section have or do not have a unit root. (Baltagi, 2005)

Even though we expect our cross-sectional units have similar dynamics, assuming them to be identical with respect to the presence or absence of a unit root is deemed to be restrictive assumption in our analysis. Consequently, we apply another Im, Pesaran and Shin test (IPS) to check whether the results are sensitive to the assumption of the homogeneous persistence parameter ρ. Similarly to LLC test, it combines individual unit root test to obtain a panel-specific result and has the same null-hypothesis of unit root presence in each series in the panel, i.e. H0: $\rho_i=0$, $\forall$ i. However, the alternative hypothesis allows for some of the individual series to have unit roots:

IPS test also allows the inclusion of individual constants, or individual constant and trend terms.

To further determine our model specification and estimation procedure, we run classical linear OLS regression including all the relevant variables and perform residuals diagnostics. Presence of serial correlation in linear panel data models biases the standard errors. To test the assumption of serially-uncorrelated residuals, we use Wooldridge test for autocorrelation for several reasons. First, this test exhibits good size and power properties with samples of moderate size. Second, it requires relatively few assumptions and is easy to implement. (Drukker, 2003). The test procedure begins from estimating the following equation: $\Delta y_{it} = \Delta X_{it}\beta_1 + \Delta\varepsilon_{it}$ - first differenced transformation of original model $y_{it} - y_{it-1} = (X_{it} - X_{it-1})\ \beta_1 + \varepsilon_{it} - \varepsilon_{it-1}$. As a second step, obtained residuals $\hat{e}_{it}$ are regressed on their lagged value. The test is based on Wooldridge observation that for residuals to be serial uncorrelated Corr($\Delta\varepsilon_{it}$, $\Delta\ \varepsilon_{it-1}$) should be equal to −0.5. Consequently, as the last step, it tests the hypothesis whether the coefficient for the êit-1 is equal to -0.5. If the test proves the presence of autocorrelation in residuals, apart from theoretical justification mentioned above, we will obtain statistical evidence for inclusion of lagged dependent variable in our model.

Next, we test the assumption of homoscedasticity, i.e. if the variance of unobserved errors constant across samples. For this purposes, the White Test for Heteroskedasticity is applied. This test regresses the squared residuals on the cross product of the original regressors and a constant. It is explicitly intended to test for forms of heteroscedasticity that invalidate the usual OLS standard errors and statistics. Under null hypothesis, nR^2 has a chi-squared distribution χ^2 (p), where p is the number of explanatory variables in the auxiliar regression minus one. The null-hypothesis is rejected if nR^2 is too large meaning that if the R^2 of the auxiliar regression were high, then we could explain the behavior of the squared residuals, providing evidence that they are not constant and homoscedasticity assumption fails. If the heteroscedasticity is present, the usual OLS t statistics are not valid. Hence, we should adjust our standard errors to obtain a heteroscedasticity robust t statistic. We specify a method for computing coefficient covariances that is robust to observation specific heteroscedasticity in the disturbances. In this case, the coefficient asymptotic variance is estimated as:

$$\left(\frac{N^*}{N^*-K^*}\right)\left(\sum_{i,\,t} X_{it}'X_{it}\right)^{-1}\left(\sum_{i,\,t} \hat{\epsilon}_{it}^2 X_{it}'X_{it}\right)\left(\sum_{i,\,t} X_{it}'X_{it}\right)^{-1}$$

where N* is a total number of stacked observations, K* is a total number of estimated parameters.

This method allows the unconditional variance matrix to be an unrestricted $E(\varepsilon\varepsilon') = \Lambda$ diagonal matrix, with the conditional variances $E(\varepsilon_{it}^2 \mid X_{it})$ depending on X_{it} in general fashion. This method allows to account for the presence of heteroscedasticity of unknown form, but not to correlation between residuals for different observations. We intentionally chose this method as we expect the serial correlation in disturbances to be removed by inclusion of lagged dependent variable in our model.

In a situation of data constrains we face, our methodology described in this section allows us to obtain consistent estimates of the impact of climate variables on economic performance at regional level. In the next chapter, we present empirical application of our methodology in order to evaluate the risks associated with climate change outcomes for regional hubs in Atlantic Canada.

Chapter 4. Data Description and Estimation

Based on our methodology, we estimated the climate change impacts on regional economic performance using panel models. The analysis starts with estimation of a panel model for five transportation hubs - Halifax, Fredericton, Moncton, Saint John, Edmundston - including all relevant explanatory regressors without lagged dependent variable. As a result of estimation, mean annual temperature has a negative yet insignificant at 10% level impact on regional value added. The diagnostic of residuals series obtained from this model revealed the presence of autocorrelation and heteroscedasticity. Therefore, apart from our theoretical justification outlined in the methodology chapter, we obtained statistical evidence in favour of dynamic nature of our process and the need for a lagged dependent variable.

Further, the dynamic panel model for five transportation hubs was estimated using least squares dummy variable regression technique which is equivalent to the within estimator. Northern New Brunswick hub represented by Edmundston was identified as outlier and was excluded from the model. As our next step, the model for four transportation hubs - Halifax, Fredericton, Moncton, Saint John - was estimated. Temperature and total precipitation showed significant impact on regional economic performance at 1% and 10% levels respectively.

Finally, the panel model for coastal sub-region that includes Halifax, Moncton, Saint John was estimated. The results underlined the fact that this region is particularly susceptible to climate change impacts with significant negative joint impact of sea level rise and temperature on value added generated by these hubs.

This chapter consists of three sections. First section contains information about the data: it outlines the main challenges associated with the data collection and describes approaches we developed to address the limited data availability problem. Estimation procedure in accordance with developed methodology is described in section two. This section also presents estimation results and residual diagnostics. Finally, last section offers summary of obtained results to give us general overview of estimation outcomes and their implications.

4.1 Data description

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. Below we describe our data according to this classification.

4.1.1. Region specific data

Regional value added, VA: The data for value added in the provinces of New Brunswick and Nova Scotia was obtained from CANSIM Table 3790025 and 3790030. The data for the period 19972014 is obtained from CANSIM Table 3790030 in 2007 constant dollars. The data for period 1991-1997 comes from CANSIM Table 3790025 in current dollars which were converted into 2007 constant dollars.

The weight of each hub in aggregate demand for transportation was used to split the value added collected for New Brunswick province among four transportation hubs: Fredericton, Saint John, Moncton, and Edmundson.

Transportation price index, PI_TRANSPORTATION: Data was obtained from Annual Reports by Transport Canada located at https://www.tc.gc.ca/eng/policy/anre-menu.htm

Gross domestic product, GDP: The data on provincial GDP in New Brunswick and Nova Scotia was obtained from Statistic Canada, table 384-0037. However, this table contained nominal values of GDP, and that is why they were converted into 2007 constant dollars on the basis of the consumer price index (CPI).

Consumer Price Index, CPI_GENERAL: The data was constructed based on table 326-002 "Consumer Price Index annual (2002 = 100)", Statistic Canada. In order to be consistent with other variables, the year 2007 was taken as the base year (2007=100%). Therefore, the table 326-002 "Consumer Price Index annual (2002=100)" was converted using the following approach:

$$CPI_t^{2007} = \frac{CPI_t}{CPI_{2007}} \times 100\%,$$

where CPI*t*2007 is the CPI in year t, based on 2007 year; CPIt is the CPI in year t, based on 2002 year, obtained from the table 326-002 "Consumer Price Index annual (2002=100)", Statistic Canada.

Price of oil, OIL_PRICE: The data was taken from Natural Resources Canada at http://www.nrcan.gc.ca/energy/fuel-prices/crude/4927 in terms of 2007 dollars.

4.1.2. Transportation hub specific data

Gasoline prices, GASOLINE_PRICE: The main source of the data was Statistic Canada (Natural Resources Canada branch). It contains monthly gasoline prices for our transportation hubs. Average annual gasoline prices were computed based on monthly data.

Unfortunately, we could not find complete set of data over the entire period 1991-2015, and therefore, in order to fill out the gap autoregressive model was used for the years 1991 and 1997 for Edmundston transportation hub.

Total income, TOTAL_INCOME: Statistic Canada conducts census every five years. Hence, we obtained precise information on average income for the following years: 1990, 1995, 2000, 2005, 2010. Statistical annual report for 1990 contains only average male and female income, thus, in order to get average income, the following approach was used:

Average income_{1990} = (average male's income + average female's income)·0,5.

There is no accurate data for other years, and we used autoregressive model to estimate average income based on CANSIM – gross domestic product, income-based, provincial and territorial annual (dollars x $1,000,000) – CANSIM, Table 384-0037. Since gross domestic product has similar dynamics as average income, we applied autoregressive AR(1) model obtained for GDP to approximate values of average income. Values of total income for Edmunston, Fredericton, Moncton, Saint John and Halifax were computed as a product of average income and population.

Number of employed, EMPLOYED: The data was provided by Statistics Canada. The annual data for the number of people employed for the period 1991-2000 was downloaded from Table 2820061 - Labor force survey estimates (LFS), employment by economic region and North American

Industry Classification System (NAICS). This table was terminated and replaced by Table 2820125 1 Labor force survey estimates (LFS), employment by economic region based on 2011 Census boundaries and North American Industry Classification System (NAICS). This revised table is the source of the data for 2000-2014 period in our analysis. The data was collected for economic regions that are defined as geographical units generally composed of several census divisions within a province. The following regions were chosen to represent the transportation hubs in our model:

Table 4.1. Regional transportation hubs and corresponding economic regions

Transportation hub	Economic region	Classification code
Fredericton	Fredericton-Oromocto	1340
Saint John	Saint John-St. Stephen	1330
Moncton	Moncton-Richibucto	1320
Edmundston	Edmundston-Woodstock	1350
Halifax	Halifax	1250

4.1.3. Climate data

Climate variables: Values of the climate variables such as temperature (TEMPERATURE), precipitation (TOTAL_PRECIP, RAIN, SNOW) and sea level (SEA_LEVEL) for each transportation hub were taken from Environment Canada website. The daily data was downloaded and further converted into annual format. The meteorological stations were chosen according to the geographical location of regional hubs in our model. The information about the meteorological stations is summarized in Table 4.2 below.

Table 4.2 List of meteorological stations

Station Name	Station ID	Province	Period
Halifax	8202250	NS	1991-2014

Fredericton	8101500	NB	1991-2014
Moncton	8103200	NB	1991-2014
Saint John	8104900	NB	1991-2014
Edmundston	810AL00	NB	1991-2014

As the results, we compiled the regional dataset that includes economic and climate variables of interest and contains all the necessary information for application of our methodology. Therefore, we proceed to the next step: model estimation.

4.2 Panel models estimation

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 log 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. Descriptive statistics of our dataset is presented in Table 4.3.

Table 4.3. Descriptive statistics of all variables

Variable name	Mean	Std. Dev.	CV %	Max.	Min.	Range	Obs
VA	7.54	0.70	9%	8.85	6.78	2.07	120
CPI_GENERAL	4.52	0.13	3%	4.72	4.31	0.41	120
PI_TRANSPORTATION	4.46	0.18	4%	4.72	4.13	0.59	120
GDP	10.15	0.16	2%	10.46	9.82	0.64	120
OIL_PRICE	8.73	0.57	7%	9.54	7.86	1.68	120
GASOLINE_PRICE	4.37	0.33	8%	4.88	3.86	1.02	120
TOTAL_INCOME	7.54	1.11	15%	9.67	5.40	4.27	120
EMPLOYED	4.37	0.55	13%	5.41	3.42	1.99	120
TEMPERATURE	5.60	1.33	24%	8.89	1.40	7.49	120
RAIN	955.59	235.73	25%	1,609.3	341.7	1,267.6	120
SNOW	243.38	76.80	32%	429.7	51.5	378.2	120
TOTAL_PRECIP	1,184.5	226.21	19%	1,814.2	433.9	1,380.3	120
SEA_LEVEL	2.11	1.68	80%	4.60	0.75	3.85	72

There is no data on sea level for Fredericton and Northern New Brunswick transportation hubs due to their geographical location. Sea level is measured by tide-gauges relatively to land. It explains why the ratio of the standard deviation σ to the mean μ is so high as regional hubs have different altitude elevation.

We expect our economic variables to have long memory meaning they contain a long-lasting impact of previous shocks. To test this hypothesis, we 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. The test procedure is outlined in the methodology part. 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 difference-stationary. 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 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 panel unit root test, unit root is present in all the economic variables except GDP that is stationary at 10% level.

The inclusion of I(1) 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 cointegration 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 in our model to capture potential common trends among variables and to allow the changes in intercept as well as slope of the regression line.

As outlined in methodology chapter, we use least squares dummy variable model since the number of cross-sections is small in our model, n=5. A panel data regression with one-way error component is defined by the following equation:

$$y_i = X_i\boldsymbol{\beta} + \mathbf{i}\alpha_i + \boldsymbol{\varepsilon_i}, \qquad (4.1)$$

where $\mathbf{i}$ is a T*1 column of ones, $\mathbf{i}\alpha_i + \boldsymbol{\varepsilon_i}$ is a composite error term with α_i being unobserved fixed spatial characteristics and ε_{it} being the associated T*1 vector of disturbances. Including the dummy variable for each cross-sectional unit, we assume that it captures unobserved time-invariant characteristics associated with each regional hub in our model, i.e.:

$$y_i = X_i\boldsymbol{\beta} + \mathrm{DUMMY}\alpha_i + \boldsymbol{\varepsilon_i}, \qquad (4.2)$$

Therefore, according to the model described in methodology, its econometric specification is:

$$VA_{it} = \alpha DUMMY_i + \rho VA_{i(t-1)} + \beta X_{it} + \gamma C_{ti} + \delta TIME + \varepsilon_{it} \qquad (4.3)$$

where VA_{it} is the value added at hub i in year t; ρ is autoregressive parameter; $DUMMY_i$ takes the values from 1 to 5 for each transportation hub respectively; X_{it} is the vector of economic control variables with β as the vector of corresponding parameters; C_{it} is the vector of climate variables with γ as the vector of corresponding coefficients, $TIME$ is a time trend variable, and ε_{it} representing other time-variant unobserved factors.

X consists of regional specific variables CPI_GENERAL, PI_TRANSPORTATION, GDP, OIL_PRICE (vector X1) plus hub specific variables GASOLINE_PRICE, TOTAL_INCOME, EMPLOYED (vector X2).

In turn, vector C includes TEMPERATURE, RAIN, SNOW, TOTAL_PRECIP, SEA_LEVEL..

First, we estimated panel data model for all five hubs without lagged dependent variable using *Eviews 8.1* statistical package. The estimation results are summarized in Tables 4.4.

Table 4.4. Panel Data Model for five transportation hubs

Sample: 1991 – 2014. Cross-sections included: 5. Total panel observations: 120			
Variable	**Coefficient**	**t-statistic**	**p-value**
DUMMY	0.412582	11.51819	0.0000
CPI_GENERAL	-4.723757	-6.556961	0.0000
PI_TRANSPORTATION	-2.184866	-3.459075	0.0008
GDP	2.645838	8.425309	0.0000
OIL_PRICE	-0.353197	-2.333614	0.0214
GASOLINE_PRICE	1.042580	3.184993	0.0019
EMPLOYED	2.804829	19.01719	0.0000
TOTAL_INCOME	-0.489861	-6.336530	0.0000
TEMPERATURE	-0.056717	-2.899075	0.0045
TIME	0.063501	5.982465	0.0000
R-squared	0.941980		

Adjusted Rsquared	0.937233

As we can see from the table, the temperature has a negative impact as expected, i.e. one degree Celsius increased in temperature reduces regional value added by 5.7%. However, in order to rely on the obtained results, residuals series should be tested for presence of autocorrelation and heteroskedasticity. For this purposes, we used Wooldridge test for autocorrelation in panel data and White's general test for heteroskedasticity. The results are presented in Table 4.5

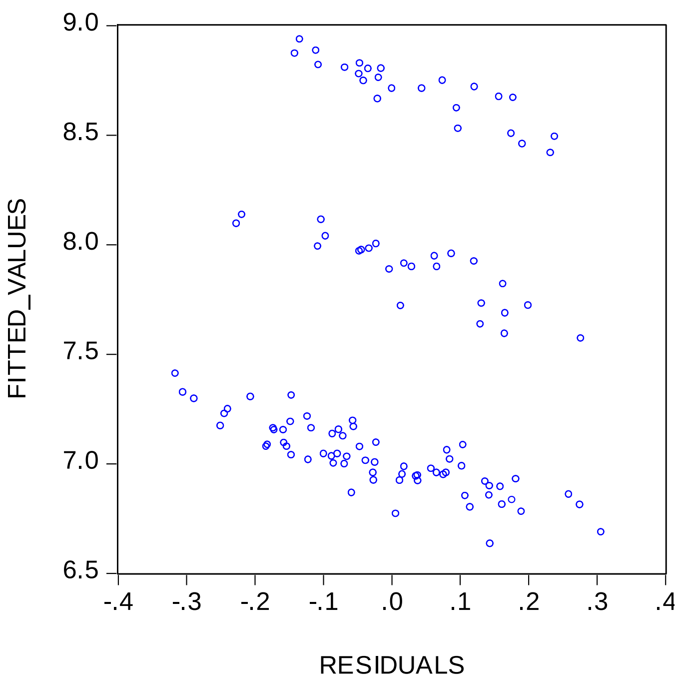
Table 4.5. Panel Data Model for five transportation hubs. Residuals diagnostics

Wooldridge test for autocorrelation in panel data		Heteroskedasticity	
F-statistic	136.029	F-statistic	2.412748
p-value	0.0003	p-value	0.0005

Under the null-hypothesis, Wooldridge test for autocorrelation in panel data assumes no first-order autocorrelation in the error term. From the table, we can see that there is enough statistical evidence to reject null-hypothesis. Hence, the residual series are serially correlated. It means that some degree of determinism is present in the error term and it can be modelled using statistical method. In general, the Box-Jenkins methodology should be applied to choose the appropriative specification of ARMA (Autoregressive moving average) model. However, with limited dataset we have, short time series in particular, we assume that the deterministic part can be described by AR(1) process. Therefore, apart from theoretical justification outlined in methodology part, we also obtained a statistical evidence for the inclusion of a lagged dependent variable in our model.

White's Heteroskedasticity test showed that the null-hypothesis of homoskedastic errors should be rejected as well. To examine this issue further, we plot fitted values generated by estimated model against the residual series. Figure 4.1 represents this graph.

Figure 4.1 Residuals vs fitted values plot



From Figure 4.1 we see that plot exhibits the presence of patterns between predicted values and residuals. Consequently, the homoscedasticity assumption is not supported. We cannot rely on our standard errors. Hence, we need to account for the presence of heteroscedasticity in our residuals. As outlined in our methodology, for this purpose we used a method for computing coefficient covariances that is robust to observation specific heteroskedasticity in the disturbances. It allows us to obtain a heteroscedasticity robust t statistic.

As a result, we estimated the panel model for five transportation hubs again. The results of the estimation are presented in Table 4.6

Table 4.6. Panel Data Model for five transportation hubs with lagged dependent variable

Sample: 1992 – 2014. Cross-sections included: 5. Total panel observations: 115			
Variable	**Coefficient**	**t-statistic**	**p-value**
DUMMY	0.039905	2.723002	0.0076
LAGGED VALUE ADDED	0.912826	34.36850	0.0000
CPI_GENERAL	-0.325401	-1.408662	0.1619
PI_TRANSPORTATION	-0.485731	-3.288631	0.0014
GDP	0.371644	3.617690	0.0005
OIL_PRICE	-0.167607	-3.947047	0.0001
GASOLINE_PRICE	0.235851	2.942232	0.0040
EMPLOYED	0.274094	3.202177	0.0018
TOTAL_INCOME	-0.064063	-2.600437	0.0107
TEMPERATURE	-0.007732	-1.573918	0.1185
TIME	0.013391	5.155311	0.0000
R-squared	0.995223		
Adjusted Rsquared	0.994764		

From our results we can conclude that regional value added is highly dependent on region specific economic control variables. Hub specific characteristics such as number of people employed and total income affect economic outcome in different directions. Since value added measures the value of goods and services produced in some area, the total income is a proxy for the cost of production which explains its negative influence on value added. Even though the coefficient for temperature is not statistically significant at 10% level, it has a negative sign as expected. This result is consistent with the existing literature.

We tested the residuals from this model for stationarity using the panel unit root tests described in Chapter 3. Also, we performed tests for normality of error term. Jarque-Bera statistic compares the difference of the skewness and kurtosis of the series with the values from the normal distribution. The reported probability is the probability that the Jarque-Bera statistic exceeds the observed value under the null of a normal distribution.

The residual diagnostics in the Table 4.7 shows residuals do not contain unit root and are normally distributed. Therefore, we accept this model.

Table 4.7. Panel Data Model for five transportation hubs. Residuals diagnostics

Levin, Lin & Chu t-stat unit root test (common unit root process)		Normality	
Statistic	-7.82490	Skewness	0.446441
p-value	0.0000	Kurtosis	3.264107
Im, Pesaran and Shin W-stat (individual unit root process)		Jarque-Berra statistic	4.154326
Statistic	-6.82645	p-value	0.125285
p-value	0.0000		

Statistically significant coefficients for dummy and time variables point out towards the fact that the transportation hubs in our model have individual dynamics which can be explained by their geographical location. First, Halifax hub is located in Nova Scotia in contrast to the remaining four hubs located in New Brunswick. Although Edmundson represents Northern New Brunswick hub, it is situated right on the border with Quebec province. We presume that the dynamics of its economic activity is highly influenced by its bordering location, and we treat it as an outlier among our transportation hubs. Therefore, we estimated another model excluding Edmundston hub to test our assumption. Our estimation results are presented in Table 4.8.

Table 4.8. Panel Data Model for four transportation hubs with lagged dependent variable

Sample: 1992 – 2014. Cross-sections included: 4. Total panel observations: 92			
Variable	**Coefficient**	**t-statistic**	**p-value**
DUMMY	0.070672	3.658923	0.0005
LAGGED VALUE ADDED	0.865171	20.08927	0.0000
CPI_GENERAL	-0.599830	-2.362203	0.0206
PI_TRANSPORTATION	-0.307346	-1.664112	0.1000
GDP	0.396132	2.620929	0.0105
OIL_PRICE	-0.209503	-3.718059	0.0004
GASOLINE_PRICE	0.287189	2.721006	0.0080
EMPLOYED	0.439052	3.322159	0.0013
TOTAL_INCOME	-0.079120	-3.193490	0.0020
TEMPERATURE	-0.017384	-3.018376	0.0034

TOTAL_PRECIP	4.97E-05	1.866917	0.0656
TIME	0.012506	3.200866	0.0020
R-squared	0.996045		
Adjusted Rsquared	0.995502		

Now we can see that the effect of temperature becomes significant at the 1% level, has negative sign as expected, and the magnitude of the effect increased. Specifically, if average annual temperature increases by one degree Celsius, it 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 have slightly changed in magnitude, but the direction of impacts did not change.

Table 4.9 shows the results of residuals testing. As we see from the p-values, the residuals are stationary. The normality assumption is supported at 5% and 1% significance levels, but not at 10%.

Table 4.9. Panel Data Model for four transportation hubs. Residuals diagnostics

Levin, Lin & Chu t-stat unit root test (common unit root process)		Normality	
Statistic	-5.76571	Skewness	0.515526
p-value	0.0000	Kurtosis	3.467009
Im, Pesaran and Shin W-stat (individual unit root process)		Jarque-Berra statistic	4.911142
Statistic	-5.62541	p-value	0.085814
p-value	0.0000		

Further, we focused on three transportation hubs located along the coastline. We included the sea level variable in our vector of climate variables. Obtained results confirmed our hypothesis: sea level rise has a significant negative impact at 1% level (see Table 4.10). Along with an increase in temperature, the rise of the sea level by 1 meter would reduce regional value added by more than 11%. This result confirms our assumption that coastal sub-region in Atlantic Canada that includes Halifax, Moncton, and Saint John is highly vulnerable to weather variation and change in climate patterns.

Table 4.10. Panel Data Model for coastal sub-region

Sample: 1992 – 2014. Cross-sections included: 3. Total panel observations: 69			
Variable	**Coefficient**	**t-statistic**	**p-value**
DUMMY	-0.004224	-0.049435	0.9607
LAGGED VALUE ADDED	0.578367	7.700275	0.0000
CPI_GENERAL	-0.027740	-0.080473	0.9361
PI_TRANSPORTATION	0.055498	0.339533	0.7355
GDP	0.232980	1.751145	0.0853
OIL_PRICE	-0.147361	-2.944095	0.0047
GASOLINE_PRICE	0.103042	0.994510	0.3242
EMPLOYED	0.373672	2.232599	0.0295
TOTAL_INCOME	0.025060	0.243774	0.8083
TEMPERATURE	-0.012542	-2.094354	0.0407
SEA_LEVEL	-0.099094	-2.802639	0.0069

TIME	-0.000715	-0.145964	0.8845
R-squared			0.996794
Adjusted Rsquared			0.996175

Residuals diagnostics represented in Table 4.11 show that the hypothesis of the unit root presence in residuals series is rejected and the assumption of normal distribution holds.

Table 4.11. Panel Data Model for coastal sub-region. Residuals diagnostics

Levin, Lin & Chu t-stat unit root test (common unit root process)		Normality	
Statistic	-5.40854	Skewness	0.443826
p-value	0.0000	Kurtosis	3.854898
Im, Pesaran and Shin W-stat (individual unit root process)		Jarque-Berra statistic	4.366481
Statistic	-4.50238	p-value	0.112676
p-value	0.0000		

4.3 Summary of estimation results

Empirical application of the methodology developed in Chapter 3 confirmed the hypothesis about the negative effects of climate change on regional economic performance. Estimation results are summarized in Table 4.12

Table 4.12 Panel models estimation summary

Model for four regional hubs		Model for coastal sub-region	
Variable	**Coefficient**	**Variable**	**Coefficient**
Temperature	-0.017384***	Temperature	-0.012542**
Total precipitation	0.00005*	Sea level rise	-0.099094***

***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively

Estimation of our model for all five regional transportation hubs showed that regional value added is highly dependent on region specific economic control variables. Hub specific variables are also significant and affect regional value added in different directions. Even though the coefficient for temperature came as not statistically significant at 10% level, it had a negative sign implying negative impact on regional value added. After Edmundson (Northern New Brunswick) hub was excluded from estimation as outlier, effect of temperature increase became significant at 1% level with a negative sign: if average annual temperature increases by one degree Celsius, it 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. Sea level rise has also a significant negative impact at 1% significance level: rise of the sea level by 1 meter decreases regional value added by 9.9%

meaning that coastal sub-region in Atlantic Canada is the most vulnerable to the climate change impacts.

Estimated climate change impacts on regional transportation hubs will be further included in the hybrid general equilibrium model of the regional road transportation network (RRTN). Also, obtained results can be used as a guiding information for developing mitigation actions and adaptation plans as a part of climate change provincial policy.

Chapter 5. Conclusions

In this study, we have analyzed the climate change impacts on economics performance in Atlantic Canada. To identify the economic consequences of climate change outcomes, we have used the panel data analysis framework. We identified five regional hubs located in two Atlantic Canada provinces: Halifax, Fredericton, Saint John, Moncton, Edmundston 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 dimension in our model. It allowed us to account for time-invariant spatial specific characteristic of each regional hub and capture dynamics of adjustment to climate variation. As outlined in a literature review, the main criticism of studies evaluating climate change impacts on economy is associated with short memory nature of analysis and lack of attention to region specific effects. To address these issues in our analysis, we modified our model by:

- including a lagged dependent variable 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 each-cross sectional unit to bring unobserved time-invariant effects explicitly in the model

We applied our methodology to three panel data models: model that includes all five transportation hubs, four regional hubs that assumed to have similar dynamics, and model that includes coastal sub-region hubs. Obtained results confirmed that hypothesis of adverse consequences of climate variation on regional economic performance. Climate change expressed through the rise of temperature by one degree on Celsius is associated with 1.74% reduction in regional valued added.

At the same time, sea level rise by 1 meter can cause the significant damage of 10% decrease in value added generated by coastal sub-region. That's is another proof that climate change outcomes cause particular concerns 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 the century Atlantic Canada's average temperatures will increase by around a further 2 to 4o C. The predictions for sea level rise range from 0.7 to 1.0 meter depending on the area.

Further work on extending the regional dataset and fine-tuning econometric model should be done. With sufficiently long time series, the serial correlation in residuals can be modeled according to Box-Jenkins methodology. It will allow to relax our assumption that all deterministic components are captured by autoregressive process of order one.

Furthermore, we expect the long memory process that underlines climate change impacts on economy to have different trend regimes. In our model, we assumed that they could be identified with one common linear trend that we included. One might fairly consider it a strong assumption. Data for longer period of time would allow to analyze the time series for the presence of structural breaks and model changing dynamics in economic and climate control variables more precisely.

Finally, the obtained results could be used as a guiding information for evaluation the risks associated with climate variability for 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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Curriculum Vitae

Iuliia Nesterova

East Ukrainian National University, BA, Master’s degree in Accounting and Audit

2007-2012

Conference Presentations:

Nesterova I. (2016, April) Evaluation of consequences of climate change impacts: The case of Atlantic Canada. 2016 The Atlantic Association of Applied Economists (AAAE) Student Panel

Kosenchuk S. Nesterova I. (2015, April). Estimation of precipitation and sea level dynamics in Atlantic Canada. The Graduate Research Conference. University of New Brunswick