Extreme Weather Events and Climate Change: the Case of the Province of New Brunswick in Atlantic Canad

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Abstract. *Extreme weather events such as snowstorms, heavy rainfalls and heat waves have recently started to affect the province of New Brunswick in a more pronounced way. Many researchers attribute these increasing impacts to the changing climate in the province. These stylized facts are tested in this study. Testing was based on the so-called damage functions defined at the so-called meso or regional level. First, it is shown statistically that the number of these extreme weather events in the province has been increasing over time, and second, that they have negative impact on regional economy in terms of provincial real GDP. The link between extreme weather events and climate change in the province of New Brunswick is also detected, however, it is rather weak according to the obtained results. The latter points at the need to extend this study using disaggregated microeconomic data.*

Keywords: *extreme weather events, climate change, provincial real GDP.*

1 Introduction

Historically, Maritime Provinces in Atlantic Canada (New Brunswick, Nova Scotia and Prince Edward Island) are vulnerable to extreme weather events such as flooding, snowstorms, heavy rainfalls, heat waves and some other. The destructive consequences of such events are significant, and according to the existing literature, frequencies of those events have been increasing over time. Many researchers attribute this fact to changing climate in the region.

As a result, the main goal of this study was to test this claim statistically particularly for the province of New Brunswick. The Canadian Disaster Database contains more than 100 extreme weather events occurred in Maritime Provinces during 1900–2014 period. The data is presented in Table 1.

As can be seen from the Table 1, the frequency of large weather events has been increasing over time. In total, 60 extreme weather events were reported during last 25 years or 2.4 events on average per year. In turn, 34 extreme weather events occurred during 1965–1989 or 1.36 on average per year, 18 events during 1940–1964 or 0.72 on average per year, and 16 events during 1900–1939 or 0.4 on average per year.

It is also important to note that flooding has been the most frequent event followed by snowstorms, hurricanes, heavy rainfalls and storm

Table 1 Extreme weather events in Canadian Maritime Provinces

Type of event	Quantity of events in different years							
	1990–2014		1965–1989		1940–1964		1900–1939	
	total quantity	quantity per year	total quantity	quantity per year	total quantity	quantity per year	total quantity	quantity per year
Floods	22	0.88	17	0.68	9	0.36	10	0.25
Snowstorms	15	0.6	2	0.08	2	0.08	1	0.025
Hurricanes and tropical storms	11	0.44	5	0.20	6	0.24	3	0.075
Heavy rainfalls	8	0.32	7	0.28	1	0.04	2	0.05
Storm surges	4	0.16	3	0.12	0	0	0	0
TOTAL	60	2.4	34	1.36	18	0.72	16	0.4

surges. Since in our previous studies we analyzed the link between climate change and inland floods in the province of New Brunswick, in this study, our focus was on the other three extreme weather events in this province namely snowstorms, heavy rainfalls and heat waves. We wanted to test the following two hypotheses:

1. Frequencies of the above-mentioned extreme weather events have been increasing over time.
2. The increasing frequencies are due to climate change.

In order to test the above hypotheses statistically, it was necessary to choose appropriate economic model. In this regard, we did extensive literature review, and our main findings are reported below.

2 Methodology

Jahn (2015) provides a comprehensive review and critical analysis of the models used for estimation of economic impact from extreme weather and climate events. According to his classification, all these models can be divided into three groups:

(i) Econometric models
(ii) Input-Output (I-O) models
(iii) Computable General Equilibrium Models (CGEM)

Main advantage of *econometric models* is that the effect of an extreme weather event on any regional economy can be computed without knowing the precise impact channels. These impacts over time can be captured easily using the existing time series of weather and climate variables. Major disadvantage is the lack of impact theory to understand in which way losses in different sectors depend on each other. These models are usually expressed in various forms but the most popular tool in climate related literature is the so-called *damage functions*.

The second important model class is the class of input-output (I-O) models. The core of these models is the input-output tables which represent interdependence of different sectors of a regional economy. One reason for the popularity of those models is their simplicity and their linear structure. Reconstructive dynamics after an extreme weather event occurred seems to be replicated by these models quite well. There is an easy, clear theory about how impacts propagate through the economy, and all direct and indirect losses are defined at a sectoral level. However, since price adjustments are often ignored, some medium-term impacts are not captured completely. In general, there is a lack of behavioral content. Long-term impacts are also difficult to assess with the help of these models, and some support from other model classes, first of all econometric models, is needed. Many authors (Okuyama, 2003; Hallegatte and Przyluski, 2010) find that I-O models are likely to overestimate indirect losses from extreme weather events because inputs are assumed not to be substitutable.

General equilibrium analysis in the context of economic impacts of extreme weather events has been used by several authors (see, for example, Freeman et al, 2002; Rose, 2004; Shibusawa and Miyata, 2011; Carrera, 2013 and others). Computable General Equilibrium Models (CGEM) consist of equations of supply and demand functions which are simultaneously solved to obtain equilibrium factor allocation and prices. Major advantage of the CGEMs is their flexibility: supply and demand function can take any form. Also, many dynamic CGEMs allow to capture medium-term and long-term impacts of extreme weather events. Another advantage is that CGEMs often work with a certain welfare measure arising from utility function of households. This implies that basically all indirect and higher-order losses can be captured by these models. The welfare measure makes it possible to analyze social and distributional impacts as well as changing decisions of households. Finally, it can help assess overall social costs and benefits of adaptation strategies associated with climate change and/or extreme weather events. Disadvantage of these models is large set of parameters that need to be calibrated, which is especially a problem at a regional level where decent microeconomic data is not always available. Furthermore, impacts might be underestimated as, in contrast to I-O models, some impacts are assumed to be substitutable.

Prahl, Rybski1, Boettle, and Kropp (2016) emphasized that there exists a variety of analytical tools to evaluate economic impact from extreme weather events. However, according to these authors, the main analytical tool in the new climate related economic literature is the so-called *damage functions* or what we previously defined as econometric model class.

In general, *damage function* is a relationship between value of the damage and factors that caused this damage. There are two most popular approaches to define damage functions that we found in the literature. The first one is called *empirical approach*. It uses real data collected after occurrences of the extreme weather events. The second one is known as *synthetic approach*. It uses data collected via inventories or interviews plus hypothetical analysis and expert opinion. Empirical approach to evaluate damage functions has broader support in the literature due to its better reflection of real events while synthetic approach is based on subjectivism coupled with much more efforts and time needed to conduct surveys and collect data.

Another existing classification of damage functions is associated with the choice of the so-called *economic performance measure* to capture the damage from extreme weather events. There exist monetary economic performance measures and non-monetary economic performance measures. Both are popular in the literature and depend on data availability in different geographical areas.

The level of analysis is also very important. For example, Messner and Meyer (2005) identified three levels of damage analysis:

(i) Macro-level analysis for national and even international studies

(ii) Meso-level analysis for regional studies

(iii) Micro-level analysis for local studies.

In this study, we used damage functions defined at meso (regional) level as our primary analytical tool with damage expressed in monetary form which is discussed further in more detail.

3 Results

In our analysis, we used monetary economic performance measure namely provincial real GDP. In order to estimate economic impacts from extreme weather events and climate change in the province of New Brunswick, we applied a 2-step procedure:

Step 1: Estimate aggregate production function for the province of New Brunswick as a relationship between provincial real GDP and quantity of labour and capital stock; save residuals of this regression.

Step 2: Regress weather and climate variables of interest on residuals obtained in step 1.

The above methodology is based on the concept of Solow residuals. In the literature on Solow residuals (see, for example, Raa and Shestalova, 2011), it is stated that residuals from step 1 estimation reflect all potential shocks in an economy including weather and climate change impacts.

Accordingly, the following model was specified for step 2:

$$RES_t = a_0 + a_1 M_i + a_2 YEAR_t + a_3 NS_{it} +$$
$$+ a_4 NR_{it} + a_5 NH_{it} + a_6 TEMP_t + a_7 GHG_t + e_{it} ,$$

where RES_t – residuals from OLS regression of capital stock and labor hours in the province of New Brunswick on real GDP;

NS_{it} – the number of days of extreme snow in month i of year t;

NR_{it} – the number of days of extreme rainfall in month i of year t;

NH_{it} – the number of days of extreme heat in month i of year t;

$YEAR_t$ – year of observation;

M_i – month of observation;

$TEMP_t$ – annual average temperature;

GHG_t – annual emissions of greenhouse gases.

In the above specification, *NS*, *NR* and *NH* are weather related variables while *TEMP* and *GHG* are climate related variables. Different regressions were estimated, and below we present the most important results.

In our first statistical model we included all weather and climate variables in one regression. The following table presents descriptive statistics of the data we used:

Below results of our regression are presented.

In the above regression, the number of days of extreme heat *NH* was omitted to avoid multi-collinearity. As can be seen from the results, the number of days of extreme rainfall is significant at 5% level while year is significant at 1%. The number of days of extreme snow *NS* and

Table 2 Descriptive statistics of the data

Variable	Obs	Mean	Std. Dev.	Min	Max
RES	28	0	.038	-.095	.072
YEAR	28	2003.5	8.226	1990	2017
NR	196	.958	1.122	0	6
NH	140	.958	1.122	0	6
NS	112	.033	.178	0	1
TEMP	28	5.187	.785	3.859	7.374
GHG	28	17995.59	2457.906	14162.01	22639.58
GDP	28	28064.32	3956.875	21445	32563
Capital stock	28	3817.929	894.707	2518	5642
Labor hours	28	139000	8645.453	122000	148000
Population	28	752000	5807.746	740000	767000

Table 3 All extreme weather events

RES	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
M	0.000	0.000	0.48	0.629	0.000	0.000	
NS	-0.004	0.003	-1.36	0.176	-0.009	0.002	
NR	-0.001	0.000	-2.31	0.021	-0.002	0.000	**
NH	0.000	.	.	.	.	.	
YEAR	0.005	0.000	73.47	0.000	0.005	0.005	***
TEMP	-0.001	0.001	-1.24	0.217	-0.002	0.000	
GHG	0.000	0.000	-0.84	0.402	0.000	0.000	
Constant	-0.059	0.005	-12.57	0.000	-0.069	-0.050	***
Mean dependent var	-0.000		SD dependent var			0.038	
R-squared	0.954		Number of obs			336.000	
F-test	1124.455		Prob > F			0.000	
Akaike crit. (AIC)	-2260.240		Bayesian crit. (BIC)			-2233.520	

*** *p < 0.01, *** *p < 0.05, * p < 0.1*

rainfall *NR* are negatively correlated with residuals while year is positively correlated with residuals. These results imply that the number of snowstorms and heavy rainfalls increases over time, and what is more important, these events negatively affect provincial GDP: one snowstorm reduces real GDP by $4,000 in real 2012 Canadian dollars while one heavy rainfall reduces real GDP by $1,000. Temperature is significant at 10% level, and it is negatively correlated with provincial GDP: an increase in average annual temperature by 1^0C decreases real GDP by $1,000.

Next, we estimated individual impacts from snowstorms, heavy rainfall, and heat waves separately.

As can be seen from Table 4, year is significant at 1% level and is positively corelated with residuals. The number of days of snowstorms and annual temperature are negatively correlated with residuals, and both are statistically significant at 10%. Monetary impacts of these variable are similar to what we had before in our unrestricted general regression.

The number of days of heavy rainfall is significant at 5% level, while year is significant at 1%. Temperature is significant at 15%. Year is positively corelated with residuals, while the number of days of heavy rainfall and annual temperature are negatively correlated with residuals. Monetary impacts of these variable are similar to what we had in our unrestricted general regression.

The number of days of extreme heat is significant at 5% level, while year is significant at 1%. Temperature is significant at 15%. Year is positively

Table 4 Snowstorms

RES	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
M	0.000	0.000	-0.11	0.913	0.000	0.000	
NS	-0.003	0.003	-1.10	0.274	-0.008	0.002	
YEAR	0.005	0.000	73.03	0.000	0.005	0.005	***
TEMP	-0.001	0.001	-1.58	0.115	-0.002	0.000	
GHG	0.000	0.000	-0.86	0.390	0.000	0.000	
Constant	-0.059	0.005	-12.36	0.000	-0.068	-0.049	***
Mean dependent var	-0.000		SD dependent var		0.038		
R-squared	0.953		Number of obs		336.000		
F-test	1330.717		Prob > F		0.000		
Akaike crit. (AIC)	-2256.816		Bayesian crit. (BIC)		-2233.914		

*** *pм< 0.01, *** *p < 0.05, * p <0.1*

corelated with residuals, while the number of days of extreme heat and annual temperature are negatively correlated with residuals. As can be seen from Table 6, one day of extreme heat reduces provincial real GDP by $1,000 in terms of 2012 Canadian dollars.

4 Conclusion

Based on our statistical estimations, the following conclusions can be made:

The number of extreme snowstorms, heavy rainfall, and heat waves in the province of New Brunswick in Atlantic Canada increases over time.

Extreme snowstorms, heavy rainfall and heat waves negatively affect real GDP in the province although individual impacts are not large in monetary terms.

Climate variable such as temperature plays some role in the increasing frequencies of extreme weather events and increased monetary damage, however the impact is not statistically significant.

Climate variable greenhouse gases has no impact statistically.

These conclusions point at the need of a more disaggregated model to better define the costs of all above discussed extreme weather events and their link to the climate change in the province of New Brunswick.

The paper examines the features of the ecological transformation of the economy in the Shanxi province, offers an analytical assessment of the practical use of the ecological and economic mechanism for the implementation of ET in the Shanxi province.

To improve the process of ecological transformation of the national economy in Shanxi province, it is necessary to take into account the following directions: improving the use of

Table 5 Heavy rainfall

RES	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
M	0.000	0.000	0.58	0.565	0.000	0.000	
NR	-0.001	0.000	-2.17	0.031	-0.002	0.000	**
YEAR	0.005	0.000	73.45	0.000	0.004	0.005	***
TEMP	-0.001	0.001	-1.15	0.249	-0.002	0.001	
GHG	0.000	0.000	-0.82	0.410	0.000	0.000	
Constant	-0.060	0.005	-12.70	0.000	-0.069	-0.051	***

Mean dependent var	-0.000	**SD dependent var**	0.038
R-squared	0.953	**Number of obs**	336.000
F-test	1345.555	**Prob > F**	0.000
Akaike crit. (AIC)	-2260.367	**Bayesian crit. (BIC)**	-2237.464

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

Table 6 Heat waves

RES	Coef.	St. Err.	t-value	p-value	[95% Conf	Interval]	Sig
M	0.000	0.000	0.58	0.565	0.000	0.000	
NH	-0.001	0.000	-2.17	0.031	-0.002	0.000	**
YEAR	0.005	0.000	73.45	0.000	0.004	0.005	***
TEMP	-0.001	0.001	-1.15	0.249	-0.002	0.001	
GHG	0.000	0.000	-0.82	0.410	0.000	0.000	
Constant	-0.060	0.005	-12.70	0.000	-0.069	-0.051	***

Mean dependent var	-0.000	**SD dependent var**	0.038
R-squared	0.953	**Number of obs**	336.000
F-test	1345.555	**Prob > F**	0.000
Akaike crit. (AIC)	-2260.367	**Bayesian crit. (BIC)**	-2237.464

**** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*

ecological and economic tools, active development of the national economy in the direction of increasing the degree of processing of raw materials, reducing production waste, increasing the level of recycling of materials, expanding the ecological sector of the economy, increasing investments in the field of scientific environmental research.

For the effective implementation of ET, it is recommended to comprehensively select environmental and economic tools for management influence. To substantiate management decisions, a system of analytical assessment of the priority of certain economic and organizational tools is proposed. As criteria for evaluating tools, the following are proposed: cost efficiency, reliability, simplicity of information requirements, feasibility of implementation, long-term action, flexibility, fairness and minimal uncertainty.

References

Carrera, L. (2013). Assessing direct and indirect economic impacts of a flood event through the integration of spatial and computable general equilibrium modelling, Research Papers Issue, RP0202, December 2013.

Freeman, P.K., Martin, L.A., Mechler, R., Warner, K., and Hausmann, P. (2002). Catastrophes and Development: Integrating Natural Catastrophes into Development Planning, *Working Paper Series No. 4*, World Bank.

Hallegatte, S., Przyluski, V. (2010). The Economics of Natural Disasters: Concepts and Methods, Policy Research Working Paper 5507, WorldBank.

Jahn, M. (2015). Economics of extreme weather events: Terminology and regional impact models, *Weather and Climate Extremes,* 10, 29-39.

Messner, F., Meyer, V. (2005). Flood damage, vulnerability and risk perception – challenges for flood damage research", UFZ Discussion Papers, UFZ – Umweltforschungszentrum Leipzig – Halle Department Ökonomie Permoserstr, 15D – 04318 Leipzig.

Okuyama Y. (2003). Economics of Natural Disasters: A Critical review, Research Paper, Regional Research Institute, West Virginia University 511 N. High Street Morgantown, WV 26506-6825 USA.

Prahl, B.F., Rybski, D., Boettle, M. Kropp, J.P. (2016). Damage functions for climate-related hazards: unification and uncertainty analysis, Research article, Potsdam Institute for Climate Impact Research (PIK), Potsdam, Germany.

Raa, T., Shestalova, V. (2011). The Solow residual, Domar aggregation, and inefficiency: a synthesis of TFP measures. *Journal of Productivity Analysis*, 36, 71–77.

Rose, A. (2004). Economic Principles, Issues, and Research Priorities in Hazard Loss Estimation, *Springer, NewYork*, pp. 13–36.

Shibusawa, H., and Miyata, Y. (2011). Evaluating the dynamic and spatial economic impacts of an earthquake: ACGE application to Japan, *Regional Sciences Inquiry Journal*, 3(2), 13–25.