Development of Reduced-Form Models to Evaluate Macroeconomic Impacts of Greenhouse Gas Mitigation

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Abstract: Since 2000, more than thirty-five states have or are developing comprehensive plans to mitigate greenhouse gas (GHG) emissions and to achieve related public policy goals. Most State Climate Action Plans include detailed micro-level analyses of the mitigation policy options focusing on the direct costs/savings associated with the implementation of the options. Estimation of the macroeconomic impacts of a policy on future employment and income typically requires the use of sophisticated modeling tools, whose application is often costly and time-consuming, and thus is often prohibitive at an early phase of the policy evaluation process. In this paper, we develop reduced form statistical models that can be used to quickly and relatively inexpensively predict the likely macroeconomic impacts of various climate mitigation options. The regression models are built based on the macroeconomic modeling results of 92 GHG mitigation policy options across four major states in the U.S.

Keywords: Climate action plans, GHG mitigation options, macroeconomic impacts, reduced-form model

1 Introduction

Given the lack of significant progress in comprehensive climate policy formation at the federal level, major climate initiatives have been undertaken at sub-national levels of government in the U.S. in the past decade. Since 2000, more than thirty-five states and several hundred municipalities have or are developing comprehensive plans to mitigate greenhouse gas (GHG) emissions and to achieve related

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public policy goals, such as health, energy, and economic improvement. Although the process used in formulating climate action plans (CAPs) varied to some extent from state to state, most engaged in a comprehensive, multi-objective, stakeholder-based planning process that developed and analyzed a range of sector-specific policy actions and mechanisms.

The analysis and evaluation of the GHG mitigation and sequestration policy options in the state CAPs are usually grouped into four broad sectoral categories: 1) Energy Supply (ES), which focuses on fossil fuel extraction, processing and transportation, and electricity generation, transmission, and distribution (major options include renewable portfolio standards, combined heat and power, power plant efficiency improvements); 2) Residential, Commercial, and Industrial (RCI), which focuses on emissions from stationary sources such as industrial processes and fuel and electricity use in residential and commercial buildings (major options include demand-side management, building codes, appliance standards, customer-sited renewable energy); 3) Transportation and Land Use (TLU), which focuses on mobile sources of GHG emissions and related drivers associated with land use (e.g., alternative fuel strategies, alternative vehicles, transit, land use); 4) Agriculture, Forestry and Waste Management (AFW) that examines emissions and carbon sequestration opportunities in AFW management (e.g., soil carbon management, on-farm energy efficiency and renewable, afforestation/reforestation).[1]

In most of the state CAPs, microeconomic impacts of individual policy options or bundles, such as GHG reduction potentials and direct net costs, are quantified in a Delphi-type process (expert elicitation) by a group of experts comprising a Technical Working Group (TWG) for each of the four sectoral groupings associated with mitigation as mentioned above. The analysis of the options are based on the policy-specific definition of the baseline, the technical policy design in terms of level of effort, timing, coverage of parties, and the choices of data sources, methods, key assumptions, and uncertainty techniques throughout the planning process that is led by the TWGs with high level engagement of stakeholders [1–4].

However, all of the micro-level analyses of these policy options focus on the direct (on-site) costs or savings associated with the implementation of the options. When policymakers and stakeholders consider the impacts of potential options to mitigate GHG emissions or sequester carbon, a major question often asked is: "how will these options affect the local, state, or national economy?" Calculation of the *microeconomic* (direct) costs or cost savings of policy options is a generally

[1] Other than the above widely adopted options, some were less commonly recommended but were carefully evaluated in some states depending on the economic structure, energy production and consumption mix, and other special features and policy priorities. Examples include carbon capture and sequestration, power distribution system upgrades, industrial process incentives, active transportation programs that encourage bike/walk trips, and others.

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straightforward application of accounting and cost-engineering. However, the analysis of the *macroeconomic* impacts of a policy—the effects of the policy on future employment and income, for example—typically requires the application of sophisticated modeling tools. Moreover, the cost and time involved in performing a full macroeconomic study is often prohibitive at an earlier phase of the policy evaluation process. The objective of this study is to develop reduced form statistical models that can be used to quickly and relatively inexpensively predict the likely macroeconomic impacts of various climate mitigation options. To the extent that most of these options are related to energy, the models can also be used to evaluate some major aspects of energy policy.

The models we have developed are based on multivariate analyses of the relationships between macroeconomic impacts and various microeconomic costs, structural linkages within the economy, and the characteristics of the mitigation options evaluated. We accomplish this by utilizing the results of the application of a macroeconomic modeling approach that has been widely used to analyze the broader economic impacts of CAPs. This is the Regional Economic Models, Inc. Policy Insight Plus (REMI PI+) Model [5]. We regress the results of the applications of the model in 4 major US states against several explanatory variables. This is not the typical application of regression analysis to explain variations in random processes. Rather, it is more of a curve-fitting approach to develop an expedient model that can provide rapid and inexpensive estimates of the macroeconomic impacts of various GHG mitigation options, in contrast to having to run a complicated and expensive model. The model will yield crude estimates of macroeconomic impacts, but does provide insight into their margin of error. The "reduced form" model is intended for use at the early scoping, or screening stages of the CAP process to identify individual mitigation options for further study with more advanced models. Note that the analysis is not intended as an assessment of the REMI model results themselves, or a vindication of the REMI model in general but simply to develop a quick turn-around and inexpensive tool to facilitate the Climate Action Planning process.

The REMI Model is well-documented [6–8] and widely used at the state and local level for policy analysis [9]. The reduced form modeling approach is well-documented for understanding, testing, and simplifying the results of large-scale economic models, including REMI [10–13].The paper is structured as follows. Section 2 introduces the basic data we use in the regression analyses. The development and summary results of regression models for GDP and employment impacts are described in Sections 3 and 4, respectively. Section 5 briefly summarizes the strengths and weaknesses of these regression models, describes how they might be applied to results of the evaluation of direct costs of mitigation options to prepare estimates of the macroeconomic impacts of those options, and identifies key "next steps" in the development of these "reduced form" macroeconomic modeling tools.

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2 Basic Data

The basic data utilized for the regression analyses are taken from a set of macroeconomic analyses undertaken by the authors in conjunction with the Center for Climate Strategies[2] for the states of Florida, Pennsylvania, Michigan, and New York. These state-based analyses evaluated the macroeconomic impacts of a comprehensive set of GHG emission mitigation options, the critical features of which were specified in each respective state's CAP [14–17]. Appendix A presents the list of major GHG mitigation and sequestration policy options that are recommended in the CAPs in the four states. The variables analyzed by the regression tool specified below are the estimated microeconomic and macroeconomic impacts of a pooled cross-section of mitigation options. The mitigation options were identified and the microeconomic impacts were analyzed by sets of sector-specific technical working groups (TWGs) in each state, with each group comprised of a broad set of stakeholders [1,15,18,19].The dependent variables to be explained by the statistical regression analyses are the Net Present Value (NPV) of Gross State Product (GSP) impacts (in million 2005$) and employment impacts (in thousand person-years) of each individual mitigation option. Estimates of these impacts are derived from the results generated by the REMI PI$^+$ macroeconometric model [5,7]. These results in turn are shaped by the values and interactions of many independent variables, the most relevant of which are carried over in the reduced form model [12]. Given the diversity of the four states from which modeling results were taken, there is also a great deal of variation in the macroeconomic impacts across the states. For this reason, the data analyzed here are "noisy," and some adjustments must be made in order for the analysis to attain the required inferential asymptotic qualities (i.e., to be able to provide mathematically reliable results). The planning horizon used for Florida and Michigan was 17 years (from 2009 to 2025), for New York 20 years (from 2011 to 2030) and for Pennsylvania 12 years (from 2009 to 2020). Given the differences in planning horizons, and nonlinearities presented in the macroeconomic impacts across years (e.g., some policy options may have relatively more long-run benefits), in the regression model for GSP impacts, our dependent variable considers GSP impacts on an annualized basis; i.e., the NPV of GSP impacts across a planning horizon is divided by the number of years of its planning horizon. In the regression model for employment impacts, the annualized employment impact is used. We first compute the total employment impact in terms of person-years of a policy option as the simple sum of each year's employment impacts over the planning horizon. The average employment impact is then computed by dividing the total employment impact by the number of years in each state's planning horizon.

[2] The Center for Climate Strategies (CCS) is a non-profit organization headquartered in Washington, DC. Since 2000, CCS has facilitated the comprehensive, multi-objective, stakeholder-based climate action planning process for 22 states.

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The two main explanatory variables are the NPV of the direct net cost ("*DNC*") of a GHG mitigation option over the entire planning horizon and the NPV of the investment requirements ("*INV*") over the same time period, which are obtained from the microeconomic analyses of the individual policy options in the respective state CAPs. Analogous to the dependent variable, the annualized direct net cost and investment requirements are calculated by dividing the NPVs of the direct net cost and investment requirements, respectively, by the number of years in the planning horizon. For the direct net cost variable, a positive value indicates that the option has been estimated to be cost incurring, and a negative value indicates that the direct effect of the option will be cost saving.

The regression model also includes eight binary ("categorical") variables to help explain the option-specific characteristics. The variables *ES*, *RCI*, *TLU*, and *AFW* indicate the sector in which the mitigation policy is implemented (Energy Supply; Residential, Commercial and Industrial; Transportation and Land Use; and Agriculture, Forestry and Waste Management Sectors, respectively). These variables have a value of 1 when the policy option is applied to the respective sector, and zero when the option is applied to other sectors. These sectoral dummy variables are also used in interaction terms in some regression models to assign the direct costs (or net savings) and the investment requirements of each option to the sector that implements the option. "Construction" (*CONST*) is a binary variable that indicates whether or not the mitigation option involves a capital investment in construction (e.g., building a new power plant). "Manufacturing" (*MFG*) is a binary variable that indicates that the option involves a capital investment in equipment or appliance manufacturing. "Government Subsidy" (*GS*) is a binary variable indicating whether or not the mitigation option receives state government aid. And finally, "Consumption Reallocation" (*CR*) indicates that the mitigation option results in a shift in the composition of consumer expenditures, such as reducing spending on electricity, gas, and other fuels, and increasing consumption in energy-efficient appliances and other consumption categories.

Table 1 provides the descriptive statistics of all of the independent variables used in our regression models. Here statistics for interaction terms, such as "*DNC** *TLU*" or "*INV***TLU*", describe the annualized NPV of the direct net cost (or investment requirement) of policy options in each sector. The references to Model 1 through 4 in Table 1 pertain to the different regression models discussed below.

3 Regression Model for GSP Impacts

The functional form of the regression model for the GSP impacts is given by equation 1. The first four terms of the model are the interaction terms of sectoral binary variables and the direct net cost of an option. These interaction terms describe the direct net cost impacts of the options applied to different sectors on GSP. The following four terms are the interaction terms of sectoral binary variables and the investment requirement associated with an option. These interaction terms

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Table 1 Descriptive Statistics

	Mean	**Standard Deviation**	**Minimum Value**	**Maximum Value**
D.V.: Annual Gross State Product Impact (y) (in Models 1 and 2)	-23.30	194.39	-886.00	532.74
D.V.: Annual Employment Impact (y)(in Models 3 and 4)	2.20	4.81	-5.57	22.59
Direct Net Cost (DNC)	60.13	165.53	-279.12	1,075.39
Investment Requirement (INV)	114.97	233.51	0.00	1,420.13
DNC × ES	-0.21	65.55	-528.23	259.59
DNC × RCI	-22.41	81.99	-488.34	79.46
DNC × TLU	-15.06	150.40	-886.00	532.74
DNC × AFW	14.39	61.23	-30.39	423.38
INV × ES	44.64	158.59	0.00	1,268.71
INV × RCI	26.42	151.41	0.00	1,420.13
INV × TLU	24.35	98.85	0.00	666.98
INV × AFW	19.55	79.58	0.00	541.28
ES	0.17	0.38	0	1
RCI	0.24	0.43	0	1
TLU	0.24	0.43	0	1
AFW	0.35	0.48	0	1
CONST	0.38	0.49	0	1
MFG	0.57	0.50	0	1
GS	0.22	0.41	0	1
CR	0.35	0.48	0	1

describe the impact of investment requirement of the options coming from different sectors on GSP. The next four terms describe sectoral impacts (we assume that options from different sectors have inherent differences in addition to the direct net cost and investment requirement impacts captured by the interaction terms) of the policy option on GSP. The final four terms describe the GSP impacts of the option related to whether or not the option involves construction investment, manufacturing investment, government subsidies, and consumption reallocation.

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$$\begin{aligned} y = {} & \beta_1 DNC * ES + \beta_2 DNC * RCI + \beta_3 DNC * TLU + \beta_4 DNC * AFW + \\ & \beta_5 INV * ES + \beta_6 INV * RCI + \beta_7 INV * TLU + \beta_8 INV * AFW + \\ & \beta_9 ES + \beta_{10} RCI + \beta_{11} TLU + \beta_{12} AFW + \beta_{13} CONST + \beta_{14} MFG + \beta_{15} GS + \beta_{16} CR + \varepsilon \end{aligned} \tag{1}$$

where

y:	Annualized NPV of the GSP impacts of a policy option
DNC:	Annualized NPV of the direct net cost of a policy option
INV:	Annualized NPV of investment requirement of a policy option
ES:	Energy Supply policy option binary variable
RCI:	Residential, Commercial, Industrial policy option binary variable
TLU:	Transportation and Land Use policy option binary variable
AFW:	Agriculture, Forestry, and Waste Management policy option binary variable
$CONST$:	Capital investment on building constructions, which has stimulus impacts to the construction sector (binary variable)
MFG:	Capital investment on equipment, which has stimulus impacts to the machinery and equipment manufacturing sectors (binary variable)
GS:	Policy option that receives state government subsidy (assuming government spending decreases by the same amount elsewhere) (binary variable)
CR:	Policy option that results in consumer consumption reallocation and increased purchasing power of the consumers (binary variable)
β_1 to β_{16}:	Regression coefficients
ε:	Stochastic error term

Tables 2 and 3 provide the results of our multivariate statistical analysis. We ran both a basic model (Model 1) and an interactive model (Model 2), which includes interaction terms to evaluate the individual sectoral impacts of the direct net costs and investment requirements associated with GHG mitigation policy options. The functional form of the regression model, as specified in equation 1, provides the full interactive model.

In each model the intercept term is suppressed. This is warranted on theoretical grounds, due to the fact that in the absence of a policy change there would be no incremental change in the GSP of a state economy. This also enables us to

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Table 2 Results of the Regression Analysis for GSP Impact – Model 1

	Coefficient	Robust Std. Error
Direct Net Cost (DNC)	–0.51***	0.15
Investment Requirement (INV)	0.31***	0.08
ES	–15.27	38.26
RCI	–18.64	45.62
TLU	–45.66	36.25
AFW	6.83	20.97
Construction Inv. (CONST)	40.91	30.38
Manufacturing Inv. (MFG)	25.13	25.34
Government Subsidy (GS)	21.59	34.99
Consumption Reallocation (CR)	–17.49	38.01
N	92	
R-squared	0.52	
F-Statistic	4.13***	

Ordinary Least Squares (OLS) Regression with White's Robust Standard Errors.
*** $p<0.01$, **$p<0.05$, *$p<0.1$.

explicitly display the effects of our four binary sectoral variables.[3] Our analysis also implicitly assumes that the extant economies, as described by the coefficients and equations in the REMI models for each state, are in equilibrium. To account for potential heteroskedasticity (a violation of one of the basic regression modeling assumptions, which requires that the modeling errors have a constant variance across the observations), we used the White's robust standard errors [20], which provides a correction that penalizes the model for any heteroskedasticity [21].

Both models 1 and 2 have strong fitness and summary statistics, as indicated by a statistically significant F-statistic and the R-squared values. These measures indicate that the model fits the data relatively strongly and that more than half (almost three fourths) of the error variance is explained by model 1 (and model 2). Given that the sample size is relatively small compared to other large sample analyses (N=92), the relatively strong fitness measures indicate that the sample is large enough to have predictive power and thus remain externally valid. We also conducted tests to ensure that the explanatory variables were not correlated (i.e., multicollinearity). These tests indicate that the only collinearity present in the models that would inflate the variance comes from sectoral indicator variables

[3] Inclusion of the intercept would force us to exclude one sectoral category from the regression model to use it as the reference sector for the other sectoral binary variables, and in such a case, the coefficients of the sectoral binary variables included in the regression model need to be interpreted as the differential impact of the modeled sector with respect to the reference sector).

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Table 3 Results of the Regression Analysis for GSP Impact – Model 2

	Coefficient	**Robust Std. Error**
DNC × ES	–1.35***	0.25
DNC × RCI	–0.42**	0.20
DNC × TLU	–0.32***	0.07
DNC × AFW	–0.56*	0.29
INV × ES	0.57***	0.09
INV × RCI	0.22***	0.07
INV × TLU	0.12*	0.05
INV × AFW	0.63*	0.36
ES	–67.18**	32.44
RCI	–10.09	44.22
TLU	–27.19	26.21
AFW	–19.65	21.14
Construction Inv. (CONST)	39.41	25.61
Manufacturing Inv. (MFG)	42.31	26.07
Government Subsidy (GS)	27.22	39.57
Consumption Reallocation (CR)	–9.34	32.11
N	92	
R-squared	0.71	
F-Statistic	11.07***	

Ordinary Least Squares (OLS) Regression with White's Robust Standard Errors.
*** *p<0.01*, ***p<0.05*, **p<0.1*.

(i.e., dummies), which does not present a problem, as policy options cannot simultaneously be in two sectors. Furthermore, a moderately high degree of collinearity exists between Government Subsidy and Manufacturing Investment (rho = -0.49). However, as only 2 of the 20 policy options that receive a government subsidy are in the manufacturing sector, we do not believe that the degree of collinearity is high enough to justify exclusion from the models.

Model 1 indicates that the direct costs of mitigation options constitute a significant determinant of the overall macroeconomic impacts on GSP. Based on the results of Model 1, when the other variables are held constant at their mean values, when the annualized direct net cost of an average mitigation option decreases by one million dollars, the annualized GSP impact is expected to increase by about $0.51 million.

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Looking at the sectoral decomposition of the direct cost effects, the coefficients of the interaction terms of direct net cost with the four sector dummy variables (in Model 2) are all negative, which indicates that options with higher direct net cost are expected to result in less favorable GSP impacts. All of the interaction terms with respect to direct net cost are statistically significant in Model 2. Based on the results of Model 2, when all the other variables are held constant at their mean values, a one million dollar decrease in direct net costs for average mitigation options in the ES, RCI, TLU, and AFW sectors is expected to increase the annualized GSP impact by $1.35, $0.42, $0.32, and $0.56 million, respectively.

Model 1 also indicates the statistically significant role of a policy option's investment requirement on GSP. If all of the other variables are held constant at their mean values, when the annualized investment requirement of an average mitigation option is increased by one million dollars, the annualized GSP impact is expected to increase by about $0.31 million. All of the interaction terms related to investment requirement are statistically significant in Model 2. If we hold all of the other variables constant at their mean values, a one million dollar increase in investment requirements for an average mitigation option in the ES, RCI, TLU, and AFW sectors is expected to increase the annualized GSP impact by $0.57, $0.22, $0.12, and $0.63 million, respectively.

The sectoral binary variables, which try to capture the inherent difference (other than direct net cost and investment requirements) of options from different sectors, however, lack statistical significance across the board in both Model 1 and Model 2, except for the Energy Supply sector. It is important to control for differences in each sector's mitigation options, but our models show there to be no statistically significant difference between sectors (other than the impacts of direct net cost and investment requirement that are captured in the interaction terms). The only exception is the ES sector. Holding all of the other variables constant at their mean, an average ES option tends to have a lower stimulus effect on GSP compared with an average option from the other sectors.

The coefficient estimate of the variable pertaining to the capital investment to the construction sector is positive and just shy of significant in Model 2. The positive sign of the coefficient means that those mitigation options that involve a capital investment expenditure in the construction sector (for example, investments in building industrial plants, electricity generation facilities, highways, or other infrastructure) have an overall positive impact on a state's macroeconomy. Based on the results of Model 2, holding all the other variables fixed at their mean values, if a mitigation option involves capital investment in construction (i.e., the value of the *CONST* dummy variable changes from zero to one), the overall impact on the annualized GSP is expected to be an increase of $39 million. Simulating the macroeconomic impact of construction capital investment increases in the REMI Model results in two types of effects: 1) increases in capital costs in the sectors that undertake the mitigation actions, and 2) increases in the final demand for goods and services in the construction sector. In general, the former yields negative impacts on

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the economy, while the latter yields positive impacts. The positive sign of the construction investment binary variable indicates that the positive effects are expected to exceed the negative effects in the four states to which the model was applied.

The coefficient estimate of the variable pertaining to the capital investment in the equipment manufacturing sector is positive as well, but just shy of significance due to the variability of impacts of those policy options. The positive sign of the coefficient means that at the mean, those mitigation options that involve investments in manufactured equipment also tend to have a strong positive influence on a state's overall macroeconomy. Based on the results of Model 2, holding all the other variables fixed, if a mitigation option involves capital investment in equipment and machinery (for example, energy-efficient appliances, vehicles, equipment, and other manufactured devices), that is, the value of the *MFG* dummy variable changes from zero to one, the overall average impact on the annualized GSP is expected to be an increase of $42 million.

Those options that include subsidies from a state government have an overall positive, but insignificant, effect on GSP. In REMI, the state government subsidy is simulated in two ways: 1) stimulus effects arise from increased spending by households or increased investment in sectors that receive the subsidies, 2) while dampening effects stem from the decrease of the same amount of government spending elsewhere. The positive sign of this variable indicates it is expected that the stimulus effects of directing government subsidies to mitigation options, in general, can more than offset the dampening effects associated with decreased government spending in other areas.

Mitigation options that include consumption reallocation have only a minimal influence on a state's GSP, on the average. Whereas some mitigation options that include a consumption reallocation have overall positive effects on a state's GSP and others have overall negative effects, based on the results of Model 2, an average mitigation option that includes a consumption reallocation has a $9 million lower positive effect on GSP if all the other variables are held constant at their mean values. Again, however, this relationship is not statistically significant.

4 Regression Model for Employment Impacts

We developed similar regression models to that shown in equation 1, to estimate the employment impacts of climate mitigation options. The dependent variable in this case is the annualized employment impact over the entire planning horizon in terms of person-years. All of the explanatory variables included in the employment impact regression models are the same as those included in the corresponding GSP impact regression models.

Tables 4 and 5 provide the results of the regression analyses for employment impacts. Similar to the modeling of GSP impacts, we ran both a basic model (Model 3) and an interactive model (Model 4). The former model includes one independent variable each pertaining to the direct net costs and investment

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Table 4 Results of the Regression Analysis for Employment Impact -- Model 3

	Coefficient	Robust Std. Error
Direct Net Cost (DNC)	–0.0080***	0.00
Investment Requirement (INV)	0.0126***	0.00
ES	–0.2187	1.17
RCI	–1.7634*	1.04
TLU	–2.4386***	0.80
AFW	0.2195	0.57
Construction Inv. (CONST)	1.7896**	0.79
Manufacturing Inv. (MFG)	0.5216	0.67
Government Subsidy (GS)	1.5744	1.10
Consumption Reallocation (CR)	0.6010	0.89
N	92	
R-squared	0.57	
F-Statistic	9.32***	

Ordinary Least Squares (OLS) Regression with White's Robust Standard Errors. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Additional decimal places provided for coefficients due to the magnitude of employment impacts.

requirements, respectively, associated with the implementation of the GHG mitigation options, while in the latter model we include interaction terms to evaluate the individual sectoral impacts of the direct net costs and of investment requirements associated with the options implemented in respective sectors.

The direct net cost of an option provides a significant determinant of the overall employment impact of this option. Based on the results of Model 3, holding all of the other variables constant at their mean values, decreasing the annualized direct net cost of an average mitigation option by one million dollars yields an annualized employment impact increase of about 8.0 person-years.

Model 4, which includes the interaction terms of direct net costs in each sector with sectoral dummy variables, provides a sectoral decomposition of the effects stemming from changes in direct net cost. The coefficients of the four interaction terms of direct net cost with the four sector dummies are all negative, which indicate that options with higher direct net cost are expected to result in less favorable employment impacts. According to Model 4, the coefficient estimates show that the most statistically significant variation across the direct cost variable occurs in the ES, RCI, and TLU sectors. Holding the non-sectoral binary variables constant at their mean values, a decrease of one million dollars in direct net cost of an average mitigation option in the ES, RCI, and TLU sector is expected to increase the annualized employment impacts by 6.9, 13.9, and 6.8 person-years, respectively.

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Table 5 Results of the Regression Analysis for Employment Impact – Model 4

	Coefficient	**Robust Std. Error**
DNC × ES	–0.0069*	0.00
DNC × RCI	–0.0139**	0.01
DNC × TLU	–0.0068***	0.00
DNC × AFW	–0.0004	0.01
INV × ES	0.0344***	0.00
INV × RCI	0.0065***	0.00
INV × TLU	0.0056***	0.00
INV × AFW	0.0312***	0.01
ES	–2.4217**	0.93
RCI	–0.1769	0.94
TLU	–0.2919	0.61
AFW	–0.1210	0.43
Construction Inv. (CONST)	1.0762*	0.60
Manufacturing Inv. (MFG)	0.3516	0.57
Government Subsidy (GS)	–0.2325	0.67
Consumption Reallocation (CR)	–0.2268	0.77
N	92	
R-squared	0.02	
F-Statistic	16.78***	

Ordinary Least Squares (OLS) Regression with White's Robust Standard Errors. ****p<0.01, **p<0.05, *p<0.1*. Additional decimal places provided for coefficients due to the magnitude of employment impacts.

Model 3 also indicates that the impact of a policy option's investment requirement on employment is statistically significant. If all the other variables are held constant at their mean values, when the annualized investment requirement of an average mitigation option is increased by one million dollars, the annualized employment impact is expected to increase by about 12.6 person-years. In Model 4, all of the sector-specific interaction terms for investment requirement are statistically significant at the significance level of 0.01. If we hold all the other variables constant at their means, an increase of one million dollars in the investment requirement for average mitigation options in each of the ES, RCI, TLU, and AFW sectors is expected to increase the annualized employment impacts by 34.3, 6.5, 5.6, and 31.2 person-years, respectively.

Based on the results of Model 4, the sectoral binary variables again lack statistical significance except for the ES sector. That means, across our sample, the

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sectoral impact has no statistically discernible difference (other than the impacts of direct net cost and investment requirement that are captured in the interaction terms) on employment impacts results except for the ES sector mitigation options. Holding all the other variables constant, an average ES option tends to have lower stimulus effects to the economy in terms of employment impact compared with an average option from other sectors.

The coefficient estimate of the variable pertaining to capital investment in mitigation options directed to the construction sector is positive and significant in both models. This means that, holding all the other variables constant at their mean values, those mitigation options that involve a capital investment expenditure in the construction sector are expected to result in more employment gains than those options that do not. The coefficient of the binary variable pertaining to the capital investment in equipment is also positive but not statistically significant. The positive sign of the coefficient means those mitigation options that involve investments in equipment are also expected to lead to a stronger positive effects on job creation. The higher value of the coefficient of *CONST* (the construction sector investment binary variable) than the coefficient of *MFG* (the equipment manufacturing sector investment binary variable) comes about for two reasons. First, in most states, the construction sector has a higher Regional Purchase Coefficient (RPC) than the equipment manufacturing sector. This indicates that, dollar for dollar, capital investments in the construction sector are more stimulating to the in-state job market than investments in equipment manufacturing, whose demand is satisfied by a greater proportion of imports of equipment and related items from out of state. Second, compared with the equipment manufacturing sectors, the construction sector is relatively more labor-intensive.

The coefficients of the binary variables pertaining to the state government subsidy and consumption reallocation are positive in Model 3, but negative in Model 4. These two variables, however, are not statistically significant in either model.

5 Model Applications and "Next Steps" in Model Development

In response to the need for an affordable and rapid use policy screening tool to evaluate the likely macroeconomic impacts of GHG mitigation policy options at an earlier phase of their design process, we developed reduced-form statistical models that can be used to quickly predict the likely GDP and employment impacts of these various climate mitigation options. The reduced-form models are developed based on microeconomic impact assessment results from state stakeholder processes and REMI macroeconometric modeling results of climate action plans for four states (Florida, Pennsylvania, Michigan, and New York), which include the analyses of 92 mitigation policy options across these states.

The reduced-form models presented above have been developed based on REMI modeling results of 92 individual GHG mitigation options at the state level. Therefore, the direct application of the regression models should be for individual

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options at the state level in order to appropriately capture the impacts of the dummy variables included in the models. If these regression models are applied to evaluate the likely macroeconomic impacts of policy options at different scales, such as policy bundles that aggregate options from one sector together, or mitigation options implemented at different geographical levels, the direct net cost and investment requirement values of the options need to be scaled-up or scaled-down to the individual option level, as well as to the appropriate geographic level, before applying the regression equations. For example, when we apply the models to evaluate the potential macroeconomic impacts of mitigation options at the national level, the estimated direct net cost and investment requirement of an option both need to be first divided by a factor of 25 to scale down from the national level to the state level before applying the regression models to the input data. (Note that a factor of 25 rather than a factor of 50—as in 50 states—is used for the national-state scale-down is because the four states from which microeconomic and macroeconomic results were used as the basis for the reduced-form regression models are larger, in terms of the size of their economies, than average states in the U.S.). Then the regression application results need to be multiplied by 25 to get back to the national level estimations of GDP and employment impacts. To the extent that the reduced-form model is applied to regions, states, or sub-state areas that have economies different in size from the average of the four states upon which model results are based, macroeconomic results pertaining to the average impacts of individual options may need to be scaled up or down to account for those size differences. Similarly, the macroeconomic impacts of options depend to some extent on the particular, locale-specific design of the option, including how aggressive the option's goals are, relative to those of the average option by sector among the 92 options now used as the basis for the reduced-form models. These issues of model scale and option design need to be considered when interpreting the results of the reduced-form model in particular applications.

The key next step to further refine the reduced-form modeling tool is to expand the underlying database as more REMI macroeconomic impact analyses on mitigation options for additional states and regions are performed. As the underlying database expands, specific regression models that are tailored to specific types of economies or are designed for specific sectors in the economy can be developed as well. We also plan to develop a documented, easily-applied spreadsheet-based version of the reduced-form model that is convenient for application in the early option screening phase. The function of the spreadsheet-based application would include functions such as scale-up/down factors based on state GSP/employment, and key drivers of policy stringency for at least some key policies.

Note also that the results pertain to conditions in which we assume that all investment in mitigation options does not displace investment in ordinary plant and equipment. This requires that additional investment funds become available by attracting investors from outside the state, attracting federal subsidies, or using in-region business retained earnings. State governments can take actions to

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promote the first two of these conditions, while the third is likely in times other than economic recession years. As such, the estimates yielded by our reduced form equations should be considered reasonable upper bounds in terms of the availability of additional investment funds to support the GHG mitigation actions.

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References

1. Florida Climate Action Team (FCAT). *Florida's Energy and Climate Change Action Plan*. http://www.naseo.org/Data/Sites/1/documents/stateenergyplans/FL_2008.pdf (2008).
2. Pennsylvania Department of Environmental Protection (PA DEP). *Pennsylvania Final Climate Change Action Plan*. http://www.elibrary.dep.state.pa.us/dsweb/View/Collection-10677 (2009).
3. Michigan Climate Action Council (MCAC). *Michigan Climate Action Plan MCAC Final Report*. http://www.michigan.gov/documents/deq/deq-miclimateactionplan-part1_276563_7.pdf (2009).
4. New York State Climate Action Council (NYSCAC). *Climate Action Plan Interim Report*. http://www.dec.ny.gov/docs/administration_pdf/irpart1.pdf (2010).
5. Regional Economic Models, Inc. (REMI). REMI Website: http://www.remi.com/ (2015)
6. G. Treyz, M.J. Greenwood, G.L. Hunt, and D.S. Rickman. Migration, regional equilibrium, and the estimation of compensating differentials. *Am. Econom. Rev.* **81** (5): 1382–1390 (1991).
7. G. Treyz. *Regional Economic Modeling: A Systematic Approach to Economic Forecasting and Policy Analysis*, Boston, Kluwer (1993).
8. W. Fan, F. Treyz, and G. Treyz. An evolutionary new economic geography model. *J. Reg. Sci.* **40** (4), 671–695 (2000).
9. F. Treyz, and G. Treyz. The Evaluation of Programs Aimed at Local and Regional Development: Methodology and Twenty Years' Experience Using REMI Policy Insight, *Evaluating Local Economic and Employment Development: How to Assess What Works Among Programmes and Policies*, (pp. 151–189). Paris, France: Organization for Economic Co-operation and Development, ISBN: 9264017089 (2004).

DOI: 10.7569/JSEE.2015.629503

10. P. Dixon, J. Giesecke, M. Rimmer, and A. Rose, The economic costs to the U.S. of closing its borders: A computable general equilibrium analysis. *Defen. Peace Econom.* **22** (1), 85–97 (2011).
11. P. Dixon and M. Rimmer. Validation in Computable General Equilibrium Modeling, in *Handbook of Computable General Equilibrium Modeling*, P.B. Dixon, D.W. Jorgenson, (Eds.), pp. 1271–1330, Amsterdam: North-Holland (2013).
12. A. Rose, D. Wei, and N. Dormady. Regional macroeconomic assessment of the pennsylvania climate action plan. *Reg. Sci. Policy Pract.* **3** (4), 357–379 (2011).
13. J.A. Giesecke and J.R. Madden. Regional Computable General Equilibrium Modeling, in *Handbook of Computable General Equilibrium Modeling*, P. D. , Vol. 1A, pp. 379–476, Amsterdam: North-Holland (2013).
14. A. Rose and D. Wei. Macroeconomic impacts of the florida energy and climate change action plan. *Clim. Policy* **12**(1), 50–69 (2012).
15. A. Rose, D. Wei, J. Wennberg, and T. Peterson. Climate change policy formation in Michigan: The case for integrated regional policies. *Intl. Reg. Sci. Rev.* **32** (4), 445–465 (2009).
16. S. Miller, D. Wei, and A. Rose. *The Macroeconomic Impact of the Michigan Climate Action Council Climate Action Plan on the State's Economy*. Report to Michigan Department of Environmental Quality. http://www.climatestrategies.us/ewebeditpro/items/O25F22416.pdf (2010).
17. D. Wei and A. Rose. *The Macroeconomic Impact of the New York Climate Action Plan: A Screening Analysis*. Report to New York State Energy Research and Development Authority (2011).
18. T. Peterson, R. McKinstry, and J. Dernbach. Developing a comprehensive approach to climate change policy in the United States that fully integrates levels of Government and economic sectors. *Virginia Environ. Law J.* **26** (219), 227-269 (2008).
19. M. Doria, E. Boyd, E.L. Tompkins, and W.N. Adger. Using expert elicitation to define successful adaptation to climate change. *Environ. Sci. Pol.* **12** (7), 810–819 (2009).
20. H. White. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* **48** (4), 817–838. (1980).
21. J.M. Woolridge. *Introductory Econometrics: A Modern Approach*. Cengage (2013).

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Appendix A. List of Major GHG Mitigation Policy Options

Table A1 lists the major GHG mitigation options that are recommended in the four state CAPs (those that are capable of reducing emissions by more than 1% of baseline in at least one of the four states analyzed). Overall they represent two-thirds of the options and around 93% of total emission reductions across the four states.

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Appendix Table A1. List of Policy Options Applying to More than 1% of GHG Emission Reduction in Various States

Policy Option	Policy Name	Florida		Pennsylvania		Michigan		New York	
		% GHG Reduction	Cost-Effectiveness	% GHG Reduction	Cost-Effectiveness	% GHG Reduction	Cost-Effectiveness	% GHG Reduction	Cost-Effectiveness
Energy Supply Options									
FL_ESD-5; MI_ES1, NY_PSD-2/6	Renewable Portfolio Standard (RPS)	7.45%	−$32.3	3.73%	$21.0	4.42%	$47.1	14.56%	$30.0
ESD-6, PA_E-10, MI_ES2	Nuclear Power	1.58%	$40.1	4.96%	$8.2	2.59%	$24.8		
FL_ESD-8, PA_E-9, MI_ES4, NY_RCI-2b,	Combined Heat and Power (CHP) Systems	0.47%	$5.6	1.47%	$9.8	0.17%	$5.1	0.43%	$2.3
FL_ESD-9, PA_E-6, MI_ES3	Power Plant Efficiency Improvements	1.92%	−$15.6	1.83%	−$16.1	0.85%	$3.1		
FL_ESD-11	Landfill Gas-To-Energy (LFGTE)	1.88%	$1.1						
PA_E-5	Carbon Capture and Sequestration			1.70%	$33.7				
Residential, Commercial, and Industrial Options									
FL_ESD-12, PA_RC-10/11/13, MI_RCI1, NY_RCI-2a	Demand-Side Management (DSM)	4.71%	−$47.9	4.45%	−$16.3	9.87%	−$31.4	6.70%	$0.0
FL_ESD-13a	Energy Efficiency in Existing Residential Buildings	1.17%	−$31.2						

(Continues)

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Appendix Table A1. (Continued)

Policy Option	Policy Name	Florida		Pennsylvania		Michigan		New York	
		% GHG Reduction	Cost-Effectiveness	% GHG Reduction	Cost-Effectiveness	% GHG Reduction	Cost-Effectiveness	% GHG Reduction	Cost-Effectiveness
PA_RC-6/8, MI_RCI2, NY_RCI-7	Appliance Standards			4.99%	–$40.3	8.75%	–$31.4	2.48%	–$30.9
PA_RC-9, NY_RCI-3a/3b/3c	Customer-Sited Renewable Energy			0.48%	$67.8			4.42%	$17.1
PA_Ind-2	Industrial NG & Electricity Best Management Practices			1.74%	–$41.7				
NY_RCI-11	Industrial Process Incentives							1.03%	–$108.9
Transportation and Land Use Options									
FL_TLU-1, MI_TLU4, NY_TLU-4	Alternative Fuel Strategies	2.72%	–$158.2			2.02%	$4.8	3.35%	$90.5
FL_TLU-4	Improving Transportation System Management (TSM)	1.51%	–$89.1						
PA_T-9, MI_TLU5, NY_TLU-7/10	Transit			0.40%	$61.0	0.15%	$117.9	2.13%	$286.9
NY_TLU-1	Vehicle Technology and Operations							6.70%	$71.1
Agriculture, Forestry, and Waste Management Options									
FL_AFW-1, PA_F1/3, NY_AFW-7a	Forest Protection/ Restoration	0.13%	$29.0	0.78%	$21.6			1.85%	$6.9
FL_AFW-2A1/2A2, PA_F-4, MI_AFW6, NY_AFW-7c	Afforestation/ Reforestation	3.17%	$5.6	1.35%	$25.0	0.32%	$52.1	0.95%	$41.3

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FL_AFW-2B, PA_F-7, MI_AFW7, NY_AFW-7b	Urban Forestry	1.88%	$11.1	1.01%	$95.4	1.04%	$210.0	0.79%	$160.4
FL_AFW-4, PA_F-8/9a/9b/W-1/5/6, NY AFW-6	Expanded Use of Agriculture, Forestry, and Waste Management (AFW) Biomass Feedstocks for Electricity, Heat, and Steam Production	8.63%	$23.4	0.60%	−$17.0			0.16%	$1.1
FL_AFW-6, NY_AFW-5	Reduce the Rate of Conversion of Agricultural Land and Open Green Space to Development	0.11%	$103.6					2.17%	$18.3
FL_AFW-7	In-State Liquid/Gaseous Biofuels Production	1.77%	-$8.9						
FL_AFW-9B	WWTP Biosolids Energy Production & Other Biomass Conversion Technologies	1.08%	$49.0						
PA_W-2, MI_AFW5, NY_AFW-3	Waste Recycling			1.84%	−$8.2	7.03%	$18.9	0.28%	$40.1

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