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Estimating state and sub-state economic effects of a carbon dioxide tax policy: An application of a new multi-region energy-economy econometric model*

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Abstract. This paper discusses an innovative econometric approach for modelling how national or state-level energy policies can affect state and sub-state economic outcomes using the new Indiana scalable energy-economy model (IN-SEEM). This model – which can be modified and scaled to investigate other states and sub-state regions – is used to analyse the economic effects of a carbon dioxide (CO_2) tax on the state of Indiana and two of its most populous regions. Results of this analysis offer a proof-of-concept for an econometric approach that allows for sub-state analysis of energy policies. Further, the policy analysis finds that without a mechanism for recycling CO_2 tax revenues back into the economy, a CO_2 tax of between \$15 and \$45 per ton will have a significant negative effect on the state economy and the two regions examined. While we find the tax to be an effective means of reducing energy consumption and thus CO_2 emissions, total employment and gross state product *per capita* are forecast to decline 4.0 and 3.2 per cent, respectively, for the state given a \$15 per ton CO_2 tax in the year 2025.

JEL classification: C150, C300, C530, R150, Q430, Q480, Q540

Key words: Energy policy analysis, carbon dioxide tax, state-level modeling, sub-state-level modeling

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1 Introduction

While a wealth of research accounts for the dynamics between economy and energy markets at the national level, few studies have been able to effectively model energy policies at both the state and local level. This oversight is not for lack of importance: most US energy policies over the past 20 years have been adopted at the sub-national level and the economic effects of policies vary markedly across states and municipalities (Wiser et al. 2000; Rabe 2008; Wei et al. 2010; Carley 2011). Understanding the interplay of energy-economy markets at the state and sub-state level are crucial to help stakeholders frame debates and policy-makers construct effective and economically efficient policies.

This paper discusses an innovative econometric approach for modelling how national or state energy policies can affect state and sub-state economic outcomes using the new Indiana scalable energy-economy model (IN-SEEM). As opposed to most computable general equilibrium (CGE) and econometric models that generate analyses at the national or state level, IN-SEEM allows the researcher to examine the effects of policy scenarios on economic activity and energy consumption at multiple geographic scales, thus revealing disparate spatial impacts. The recursive model also captures how the economic impacts of energy policies – in turn – affect energy consumption and subsequent environmental impacts. This model improves upon previous work by generating energy consumption values for three energy types and four end-uses at the sub-state level; in other models, these impacts are generally only estimated at the national and state levels.

To illustrate the nature of the model, IN-SEEM is used to analyse the effect of carbon dioxide (CO_2) taxes on the state of Indiana's economy, as well as two sub-state regions within Indiana. We analyse CO_2 taxes because of their salience in national debates and the wide-reaching effects they are likely to have on the broader economy. In this modelling scenario analysis, we assess the effects of a CO_2 tax on gross state product (GSP) *per capita*, employment, earnings, energy consumption and CO_2 emissions. These effects are then compared across three geographic units and ten economic sectors. Such policy analysis offers a challenging test of our multi-region econometric modelling approach.

What follows is an examination of the existing literature on the economic influence of CO_2 taxes at various geographic levels, an explanation of our data and methods for improving upon such examinations and the results of the CO_2 tax policy analysis followed by a discussion and conclusions.

2 Literature on the economic impacts of CO_2 taxes

Energy prices play a crucial role in national, state and local economic trends. Because a CO_2 tax will necessarily affect energy prices, it is important to evaluate the economic effects of such policies. Some expect a CO_2 tax to depress GDP, employment and earnings due to higher energy costs, whereas others argue a CO_2 tax can offset other taxes and reduce emissions with little or no adverse economic impacts. Fortunately, the literature offers some empirical insight on the nature and magnitude of these impacts.

While carbon pricing is widely suspected of slowing economic growth, few studies have modelled the theoretical influence of such taxes on the US economy. Jorgenson and Wilcoxen (1993) evaluated the economic impact of reducing carbon 20 per cent below 1990 levels over 20 years on 35 disaggregated industrial sectors. They found that it increased electricity costs, decreased demand for electricity and coal, dampened productivity growth, reallocated labour to low-wage industries and decreased GDP. Ho et al. (2008) and Aldy and Pizer (2011) also find a CO_2 tax-induced slowdown in economic productivity, competitiveness and profits – especially in carbon-intensive industries – due to a \$10–\$15 per ton[1] carbon tax. The former employs the 2002 Department of Commerce

[1] In this paper, 'tons' refers to short tons.

input-output tables to construct a series of partial and general equilibrium frameworks, while the latter uses regression analysis to estimate the supply and demand elasticities for energy with estimates that are highly disaggregated by industry (400+ sectors).

The existing models for evaluating economic impacts of energy policies are useful for answering different questions. Using the inter-temporal general equilibrium model (IGEM) – a model describing economic change on the basis of population growth, technological change and capital accumulation based on a 'perfect foresight' model – Jorgenson et al. (2008) predicted that constraining emissions to 2000 levels using a market-based climate permitting policy would create reductions in real GDP of 1.2 per cent by 2040. In an evaluation of the macroeconomic impacts of the American Power Act of 2010 through the national energy modeling system (NEMS), the Energy Information Administration (EIA 2010) estimated the cumulative real impacts from a cap-and-trade system with an estimated permit value rising from $25/ton in 2013 to $76 in 2035 (in constant 2008 dollars) at 0.1 per cent to 1 per cent of GDP, depending on a number of assumptions about pricing and alternatives.

Paul, Beasley and Palmer (2013) use the Haiku model – a partial equilibrium model that solves for operation and investment of the electricity system in 22 linked regions – to estimate the effects of a variety of carbon prices introduced through a carbon tax in the years 2013 to 2035. The examined scenarios cover a wide variety of carbon prices: $31 to $252 per ton of CO_2 by 2050 (in 2009 dollars). By 2020, they predict that carbon taxation would induce energy price increases that range from 7 per cent to 50 per cent and energy consumption reductions that range from 3 per cent to almost 20 per cent. Differences between regions in the Haiku model are remarkable under the high-level tax scenarios, where several states experience a greater than 100 per cent growth in prices by 2020. In comparison, under the low tax scenario, no state sees an increase of greater than 15 per cent by 2020.

Some analysts have focused on particular industrial sectors or economic actors. Rausch et al. (2011) – using a variant of the MIT US regional energy policy model, incorporating more than 15,000 households as autonomous agents – model a $20 per ton carbon tax on the US economy and find a heterogeneous impact on US households: specifically, greater variability in welfare effects among lower income deciles and the largest welfare losses associated with houses in regions with high a percentage of energy generated by coal. Schneider and McCarl (2005) employed a price-endogenous agriculture sector model of a range of carbon prices – from $0 to $500 per ton – and found positive impacts on farm income in the intermediate run.

While the effects of CO_2 policies vary from study-to-study based on differences in policy scenario details, one meta-analysis of 14 studies estimated that a 20 per cent carbon reduction would yield a 0.9 to 1.7 per cent decrease in 2010 GDP (Gaskins and Weyant 1993). Several studies try to explain the wide range of estimates for the gross economic impact of CO_2 pricing. Fischer and Morgenstern (2006) find that, in studies to date, marginal costs of compliance varied by a factor of five. They attribute this variation to crucial modelling assumptions, such as level of free trade and the degree to which analysts disaggregate their data. Others have pointed to the importance of existing tax distortions (Parry et al. 1999; Parry and Williams 2011) or the assumption of uniform marginal cost of compliance across sectors: as implemented, a carbon tax may be applied unevenly, with lower standards for politically sensitive industries (Babiker et al. 2000).

While these studies generally suggest that a CO_2 tax would result in a reduction in GDP relative to business-as-usual (BAU) conditions, it is difficult to extend these results to sub-national jurisdictions, across which economic and energy trends can vary significantly. It is also difficult to draw inferences from these results that are specific to different economic sectors or types of energy markets. These limitations are primarily attributable to the lack of sub-national modelling frameworks that realistically track energy and economic relationships within a specific region.

The vast majority of contemporary energy and climate models are aggregated at the state level or higher. There exist remarkably few models that disaggregate the interplay of energy and economy among sub-state regions. Exceptions include Rubin (1981) and Soloman and Rubin (1985), both of which estimated sub-state economic effects from energy policies. With respect to carbon pricing impacts, we are aware of only a handful of state and local estimates. Two studies have focused on the impact of carbon taxes on the Susquehanna River Basin: one modelled the total economic effect of a \$16.96 per ton tax (Kamat et al. 1999) and the second evaluated the distributional impact of a \$25 per ton tax (Oladosu and Rose 2007). Bae (2005) investigated the 'double-dividend' hypothesis in the state of Pennsylvania, finding that the substitution of a \$5 per ton carbon tax for a labour income tax did yield a double dividend, as well as a reduction in fossil fuel consumption overall. The tax also, however, increased natural gas consumption. In addition, some studies have focused on the relative regional distribution of national impacts. Using input-output tables from the Bureau of Economic Analysis (BEA), Hassett et al. (2007) analysed the lifetime incidence of a \$15 tax per ton of CO_2 and found little systematic variation in the burden of such a system across BEA regions in the US Their finding that regional differences in commodity exploitation determine little of the regional difference, which contradicts previous research, may be due to the fact that the study's focus on lifetime and ultimate incidence rather than direct incidence homogenizes the burden of the tax across all regions. Carbone et al. (2013) used a newly created dynamic general-equilibrium, overlapping-generations model to estimate the geographic and distributional impact of CO_2 taxes with different revenue recycling measures. The impact on GDP varied from net social costs of around zero (for the replacement of capital taxes) to a GDP loss of 3.5 per cent by 2035 (for lump-sum refunds, which had the most progressive incidence). Carbone et al. also found a relatively small difference between regions in comparison with the varied impact on different income groups; they argue this difference comes from the fact that the largest category of energy spending for households is on petrol, which does not exhibit the same variation between regions as other energy prices.

3 Data and methods

In the present analysis, we aim to add to the understanding of how energy and climate policies affect economic activity at a finer geographic scale than has been reported in the literature to date. We focus our efforts on the state of Indiana because of its status as a coal-intensive – and thus carbon-intensive – state with a relatively high manufacturing base. Thus, changes in energy prices in Indiana may have a greater economic effect than in states with broader energy portfolios or more diverse economic sectors. Further, a large number of contiguous counties within the state tend to have very similar economic profiles, which simplifies county-based regional aggregation. While these factors make the analysis particularly appealing for similar states in the Midwest and Northeast, the results may not be generalizable to other parts of the country. The methodological approach and modelling strategy however are generally applicable for any sub-national geographic scale at which appropriate data are available. Indeed, all data used in this analysis are available for each of the 50 states from national public data sources, with the exception of gross product at the regional level.

3.1 Data

The data for IN-SEEM are drawn from a variety of sources. The US Bureau of Economic Analysis (BEA 2013) provides data on employment and earnings by economic sector, non-wage income, gross state product (GSP), gross domestic product (GDP) and population. The Bureau of Labour Statistics (BLS 2013) provides data on unemployment, labour force participation and consumer price indices. Data on energy prices and consumption at the state level are available from the Energy Information Administration (EIA 2013a). Climatological data for both state and sub-state divisions are available from National Oceanic and Atmospheric Administration (NOAA 2013). And gross regional product (GRP) data for Indiana are compiled from county-level data provided by the Indiana Business Research Center (2014). The annual data for the model span the period from 1979 to 2011, the last year for which the data were available at the time of model construction.

To characterize the sub-state components of the econometric model, it is necessary to restrict data sources to those for which data are available at both the state and county levels. For instance, while detailed government finance data exist at the state level, similarly detailed data are not available at the county level. One exception is NOAA's climatic data, for which the most disaggregated level of collection is multi-county divisions. In this case, counties are associated with the climate data from the division within which they fall. Another exception is energy, for which we can find no comprehensive, longitudinal source of county prices or consumption. This analysis assumes, however, that average statewide energy prices do not differ meaningfully from sub-state energy prices because of the amount of influence state policies and agencies have over energy prices within their borders.

Energy consumption data are also not available at the sub-state level, so we developed a novel method of estimating sub-state energy consumption by means of a regression-based allocation method using a set of exogenous variables that are available at both the state and county levels, for example, expenditures on inputs to farm production such as livestock purchases.[2] These regional estimates are then used in the full IN-SEEM system of equations as both dependent and explanatory variables.

3.2 Modelling approach

Armed with a rich, multiyear data set broken down by sector and region, simultaneous econometric estimation in this case presents a more attractive route than CGE modelling, which usually relies on calibration. The benefits of CGE and our econometric approach largely overlap: both account for inter-industry relationships, can allow for a flow of goods and services across sectors and regions and incorporate industry responses to shifts in demand and price. But CGE models make hefty, sometimes untenable assumptions and they do so with data that, however fertile, are comparatively limited.[3]

CGE models are routinely underspecified, having been calibrated using data from a benchmark year that is chosen arbitrarily. CGE modellers must therefore rely on third-party sources for some of their parameters, which, when drawn from elsewhere in the literature, may not accord with the particular CGE model they are meant to supplement (Jorgensen 1984; Lau 1984; Jorgensen et al. 1992; Shoven and Whalley 1984; Diewert and Lawrence 1994; Hansen and Heckman 1996; McKitrick 1998; Partridge and Rickman 1998). There exist some practical remedies to such shortcomings, but they are 'in the spirit of econometric estimation' (Partridge and Rickman 1998, p. 229; McKitrick 1998). Such estimations, which provide the backbone of the IN-SEEM model, can be integrated with CGE models, but the CGE approach is further hampered by its extensive theoretical assumptions.

[2] See Wendling et al. (2014) for a detailed description of the allocation methodology used for this analysis.
[3] For an extended discussion of econometric and CGE approaches to policy investigations of the sort provided in this paper, see McKitrick (1998), Partridge and Rickman (1998) and West (1995).

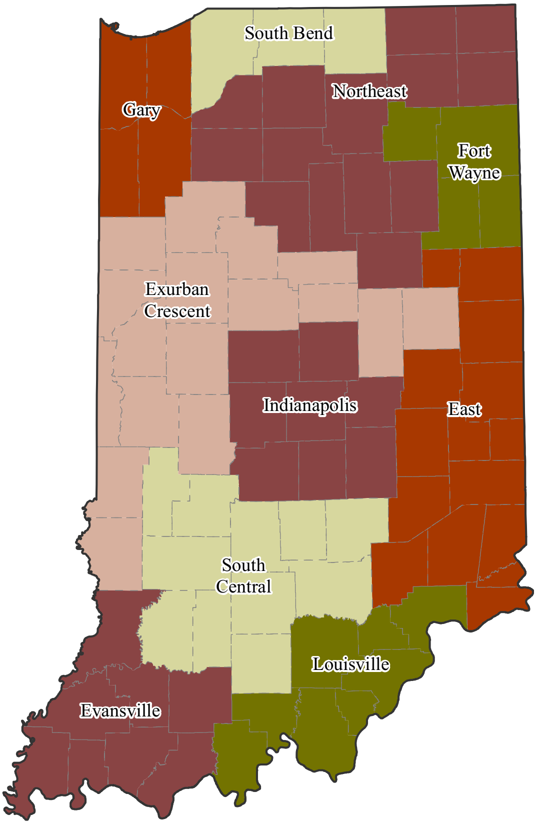

Fig. 1. The ten Indiana regions

At the very least, CGE modellers take as a given that their data describe a state of economic equilibrium. Their job is to conjecture and specify a deterministic model that might have led to that equilibrium. These models rest to varying degrees on neoclassical assumptions, such as zero economic profits, market clearing prices, profit-maximizing firms, labour market closures and other traditional suppositions. While we check our individual econometric models against standard economic theory (as will be described below), we neither presume that our data exemplifies an equilibrium, nor do we force our data to conform to neoclassical assumptions, as is inevitably done when CGE models adopt a functional form with which to calibrate their model.

The functional form eventually chosen for CGE calibration – again, an informed but somewhat arbitrary decision – has important implications for the findings and policy recommendations that result from the model. CGE outcomes are sensitive to alternative parameterizations (McKitrick 1998) and past sensitivity analyses have been overly optimistic about the robustness of CGE findings (Wigle 1991). In the end, it is difficult to report the degree of confidence to invest in CGE results (Partridge and Rickman 1998). Our econometric approach allows us to specify several models for each relationship of interest, compare these alternative specifications and objectively report statistical confidence.

To address the sub-state impacts we identified 10 regions within Indiana. Figure 1 displays the boundaries that define the sub-state regions. These regions are aggregations of Indiana's 92 counties, the finest scale at which relevant data are available. The number and boundaries of regions, however, can be altered to fit researchers' goals. From the outset,

Table 1. Indiana econometric model endogenous and exogenous variables

Employment and earnings-per-employee by sector	
Construction	Mining
Farming	Retail trade
Finance, insurance, and real estate	Services
Government	Transportation and utilities
Manufacturing	Wholesale trade
Energy variables	
Commercial electricity consumption	Commercial electricity price (exogenous)
Industrial electricity consumption	Industrial electricity price (exogenous)
Residential electricity consumption	Residential electricity price (exogenous)
Commercial natural gas consumption	Commercial natural gas price (exogenous)
Industrial natural gas consumption	Industrial natural gas price (exogenous)
Residential natural gas consumption	Residential natural gas price (exogenous)
Motor gasoline consumption	Motor gasoline price (exogenous)
Economic variables	
Gross State Product, *per capita*	Gross Domestic Product, *per capita* (exogenous)
State non-wage income, *per capita*	National non-wage income, *per capita* (exogenous)
State unemployment rate	National unemployment rate (exogenous)
Climate variables	
Annual cooling degree days (exogenous)	Annual heating degree days (exogenous)
Dummy variables	
Post-1990 dummy (exogenous)	Post-2001 dummy (exogenous)
Post-1997 dummy (exogenous)	

we wanted a model broadly applicable to questions of energy, the economy and political impacts and defined our sub-state regions accordingly. Statistical analysis of key economic indicators uncovered the underlying economic structures linking Indiana counties to one another. On top of this structure we outlined contiguous borders. The ten regions so derived were then subjected to the expert opinion of scholars familiar with the relationship between Indiana's energy, economic and geographic characteristics. Thus, each region is roughly homogenous, at least so far as we expect each sub-state equation to be generally true throughout each region and to show relationships that are distinct from other regions.

This paper reports on two of the ten regions – Indianapolis and a near-northwest region that we refer to as the Exurban Crescent – while also generating results for the state as a whole. The Exurban Crescent and Indianapolis were chosen as the first regions to model because of their status as the two largest regions by population and gross regional product and because of their different economic makeup: Indianapolis is an economically dynamic region analogous to many midsize US metropolitan areas, while the Exurban Crescent is home to less diverse suburban and rural economic activity and a substantial agricultural sector.

To develop the model we estimate separate econometric equations for each of 30 variables of interest and at two geographic scales: first, at the state level and second at the multi-county regional level. Each equation features a dependent variable endogenous within the system of equations, including employment and earnings in ten economic sectors, energy consumption for three energy types (electricity, natural gas and motor gasoline) across four end-uses (residential, commercial, industrial and transportation) and other traditional economic measures, including GSP *per capita*, non-wage income *per capita* and the unemployment rate. Table 1 contains a complete enumeration of the endogenous and exogenous variables included in the model. In total, the IN-SEEM model used in this study runs a system of 90 simultaneous equations.[4]

Once regions are established, all thirty dependent variables are estimated for the state and for each multi-county region using ordinary least squares.[5] For each of the 90 dependent variables in this version of IN-SEEM, we constructed a unique econometric model based upon historic data. Unlike other modelling procedures that rely on deterministic relationships, these econometric models provide accuracy and flexibility in satisfying a number of criteria for overall model performance. In selecting the specification for any given model, we sought to maximize theoretical plausibility, predictive power, goodness of fit and overall model stability. Predictive power and goodness of fit are measured with three values: parameter estimates ideally have *p*-values of less than 0.05, models are satisfactory if the adjusted-R^2 is greater than 0.95 and the entire system of equations should produce predicted values of the dependent variable over the sample period that have a mean absolute per cent error (MAPE) of less than 5 per cent. Model stability is established through satisfaction of the rank and order conditions and by careful selection of model specifications that do not give outsized influence to endogenous explanatory variables, which can be judged according to relative standardized parameter estimates. Final specifications are thus stable, statistically robust and theoretically sound. These final specifications are then run simultaneously for each region, allowing estimates of the endogenous variables to feed back into other equations. Estimates at the state level are also allowed to feed into region-level equations. One limitation of the current analysis, in which only two regions are simulated, is that the link between the state and the regions only goes in one direction: from the state to the regions. Thus, the model is currently simultaneous within regions and recursive between regions and the state. While there is no direct interaction between the regions, the nature of a simultaneous model allows for the indirect interaction between regions whenever a state level endogenous variable is included in the model. This is generally sufficient to provide a degree of interaction, particularly since multi-regional models that allow for flows between regions are scarce due to the inherent complexity of interactions that might arise. Moreover, such direct interactions would significantly enhance the risk that the model will have too much endogeneity and thus not converge.

3.3 Running IN-SEEM

Figure 2 shows the simultaneous character of IN-SEEM, with a significant number of linkages between the endogenous variables as they exist at the state and sub-state levels. We also account for relevant variables exogenous to Indiana and its regions; the most interesting for our purposes are energy prices for natural gas, motor gas and electricity. Whenever theoretically and empirically justifiable, we include energy price and consumption variables among the explanatory variables of our equations to account for the relationship between energy and the economy.

As shown in Figure 2, we start with an energy policy. In IN-SEEM, energy policies may be operationalized through changes to either energy price or energy consumption. In this case,

[4] When the model is fully developed it will be comprised of 300 variables, 30 for each of the 10 regions. The state-level model will be dropped, as the 10 regions will be aggregated to cover the economy of the entire state.

[5] Much of this work has grown out of earlier endeavours to model the interaction of climate change, energy development policy, and economic performance in the American Midwest (Rubin and Hilton 1996; Rubin et al. 1997). These studies and others conducted during the 1980s found that ordinary least squares often gives better results in replicating sample period endogenous variable values than simultaneous equation estimation techniques. This appears to be due to the increased degree of measurement errors on a sub-state regional scale, and the tendency of simultaneous equation methods to transmit these errors throughout the model.

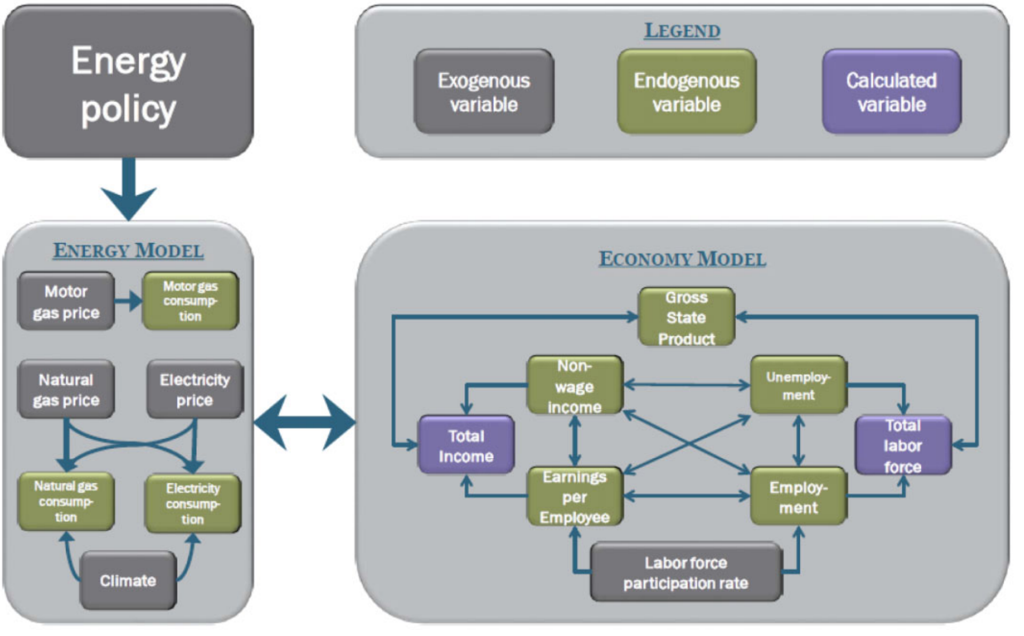

Fig. 2. This diagram illustrates the simultaneous nature of the IN-SEEM model
Note: Calculated variables are sums of econometric variables

a CO_2 tax affects energy price, which in turn affects energy consumption and so forth. Notice that natural gas prices or electricity prices may affect natural gas and/or electricity consumption due to own-price or cross-price responses. Climate variables – particularly heating degree and/or cooling degree days – also affect energy consumption. The endogenous consumption variables and the exogenous price and climate variables represent the energy portion of the IN-SEEM model. The economy component of the model is made up of the endogenous employment, earnings, unemployment, GSP and non-wage income variables, as well as the exogenous labour force participation rate. Total income (the sum of non-wage income and earnings) and total labour force (the unemployed plus employed) represent two calculated variables within the economy portion of IN-SEEM. As indicated by the two-way arrow connecting the energy and economy components, any variable within either module can affect any other endogenous variable. So, for instance, employment in manufacturing – estimated within the economy model – may help predict industrial natural gas consumption – estimated in the energy model.

Running IN-SEEM – for which we use PROC MODEL within SAS (SAS Institute Inc., Cary, NC, USA) – involves estimating the 90 equations simultaneously over a chosen period. Running the simulation over the sample period produces a set of predicted values for all endogenous variables in all years, which can be compared to their actual values over the sample period. This comparison, which is further detailed in subsection 4.2, allows the researcher to observe how well the model predicts the endogenous variables, which, in turn, provides a sense of its forecasting potential for years beyond the sample period.

4 CO_2 tax policy scenario analysis

We use the IN-SEEM model to generate a baseline forecast and four policy forecasts from 2015 through 2025, where 2015 is assumed to be the earliest possible year in which a CO_2 tax could

Table 2. Calculation of CO_2 tax across policy scenarios, energy types and end uses

Energy Type	End Use	Estimated emissions ratio [ton CO_2 /MMBTU][a]	Benchmark emissions ratio [ton CO_2 /MMBTU]	Tax [\$/MMBTU][b]			
				\$15 per ton CO_2	\$25 per ton CO_2	\$35 per ton CO_2	\$45 per ton CO_2
Electricity	Commercial	0.212	0.220[c]	3.18	5.31	7.43	9.55
	Industrial	0.213		3.19	5.32	7.45	9.57
	Residential	0.212		3.18	5.31	7.43	9.55
Natural Gas	Commercial	0.058	0.058[d]	0.87	1.46	2.04	2.62
	Industrial	0.056		0.83	1.39	1.95	2.50
	Residential	0.058		0.87	1.46	2.04	2.62
Petrol	Transportation	0.077	0.079[e]	1.16	1.93	2.70	3.47

Notes: [a] Calculated as an average from EIA data on emissions and consumption over the period 1990–2009. [b] All figures in 2011\$. [c] EPA Emissions & Generation Resource Integrated Database (2014), 2010 estimate for subregion Reliability First Corporation West. [d] EIA Voluntary Reporting of Greenhouse Gases Program (2014), weighted national average (1029 Btu/scf). [e] EIA Voluntary Reporting of Greenhouse Gases Program (2014).

be implemented given current policy debates. The baseline forecast represents business-as-usual and assumes no price on CO_2, while the policy forecasts use four estimates of the price of carbon suggested by the literature and current policy discussions. The difference in values between the policy and baseline forecasts represents the estimated effect of the CO_2 pricing policy.

4.1 Incorporating CO_2 taxes into the model

To simulate the effect of a CO_2 tax in IN-SEEM, each of the policy scenarios is run with baseline price forecasts for each fuel type increased by the amount of the tax multiplied by the ratio of CO_2 emissions per unit of energy. To derive this ratio, we rely on historic estimates from the EIA of CO_2 emissions generated in the commercial, industrial and residential end-use sectors for natural gas and electricity, along with emissions generated in the transportation sector from motor gasoline consumption (EIA 2011). Over the span of the emissions data, 1990 to 2009, the ratio of emissions of CO_2 per unit of energy is fairly stable; therefore, we use the average emissions ratio for each of the seven combinations of energy type and end use.

This last step introduces several assumptions for the sake of simplicity. First, we assume that natural gas consumed in Indiana will have a heating value consistent with past experience. Second, we assume that the composition of the fuel mix used in the generation of electricity will not change; and third, we assume that the efficiency of generation technology will not change. Our average historic values are comparable to estimates from the EIA and the EPA (see Table 2).

The policy scenarios that we estimate use a range of CO_2 taxes: \$15, \$25, \$35 and \$45 tax per ton of CO_2. This range reflects commonly used values in the literature (Carbone et al. 2013; Morris and Munnings 2013) and a realistic range for a CO_2 tax in the event that one is adopted in the United States in the future. We consider the \$15 and \$35 prices to be most relevant for our policy analysis, as these are the endpoints of CO_2 prices proposed in bills from the 113th US Congress (Morris and Munnings 2013). The per-MMBTU taxes are added to the forecast prices of natural gas, electricity and petrol for the applicable end-use sectors during the 2015–2025 time period in the four policy forecasts, except where such prices appear on the right-hand side of the mining employment and mining earnings per employee equations. This is to ensure that the

Table 3. *Per capita* gross production equation estimates for the state, Exurban Crescent and Indianapolis

		β Coefficient	*p*-value
Gross state product, Indiana			
Adj-R^2	Industrial electricity consumption	0.600	<0.001
0.980	Commercial electricity consumption; 1-year lag	0.402	<0.001
MAPE	Petrol consumption; 1-year lag	–0.193	<0.001
1.70	Earnings per employee, finance, insurance, and real estate	–0.218	0.018
Gross regional product, Exurban Crescent			
Adj-R^2	Commercial electricity price; 1-year lag	–0.213	0.031
0.969	Industrial electricity price	–0.312	0.009
MAPE	Non-wage income *per capita*; 1-year lag	0.400	0.017
2.62	Employment, manufacturing	0.100	0.080
Gross regional product, Indianapolis			
Adj-R^2	Industrial electricity price; 1-year lag	–0.144	<0.001
0.991	Petrol price; 1-year lag	–0.145	<0.001
MAPE	Commercial electricity consumption; 1-year lag	0.407	<0.001
1.23	Employment, services	0.346	<0.001

mining sector – which could be considered an energy producer – does not expand from a tax that they have no way of collecting through our model. The same decision was considered for the transportation and utilities equations; however, utilities comprise no more than 20 per cent of the utilities and transportation sector. Thus, we treat the sector as a consumer of energy, not a producer.

It is important to note that the current IN-SEEM model does not have a government revenue component, meaning the monetary outlays brought about by the tax cannot recycle within the model. Thus, estimates of the economic impacts of CO_2 taxes presented in this paper represent only a partial effect, where a full effect would also account for the manner in which the tax revenues are recycled back into the economy. However, since carbon dioxide taxes are likely to be assessed by the federal government, it is difficult to predict how the taxes would be reintroduced into the state economy, if at all. One could classify these estimates, therefore, as a 'worst-case' scenario, but we argue that it is important to understand first the negative economic consequences of such a tax before considering the manner in which revenues can be redistributed. To provide insight, we consider the negative effects that the emissions tax has on the state economy and compare that to the magnitude of the tax revenue, which provides an estimate of deadweight loss and excess burden of taxation. We also approximate how revenue recycling may reduce the negative economic impacts of a CO_2 tax by using a government expenditure multiplier.

4.2 Performance over the sample period

Our sample period covers the years 1979–2011, the interval over which data are available for all of the variables used in the IN-SEEM model. Accounting for the lagged variables in the system of equations, IN-SEEM estimates historic values over the period 1980–2011. Table 3 summarizes the equations for GSP *per capita* and GRP *per capita*. These equations show satisfactory goodness of fit and predictive power, with highly significant parameter estimates, high adjusted-R^2 and low MAPEs. Figure 3 provides a visual representation of how these IN-SEEM predictions closely trace the historical data. These equations also illustrate how IN-SEEM uses energy-economy relationships, as all three contain energy price or consumption among the explanatory variables.

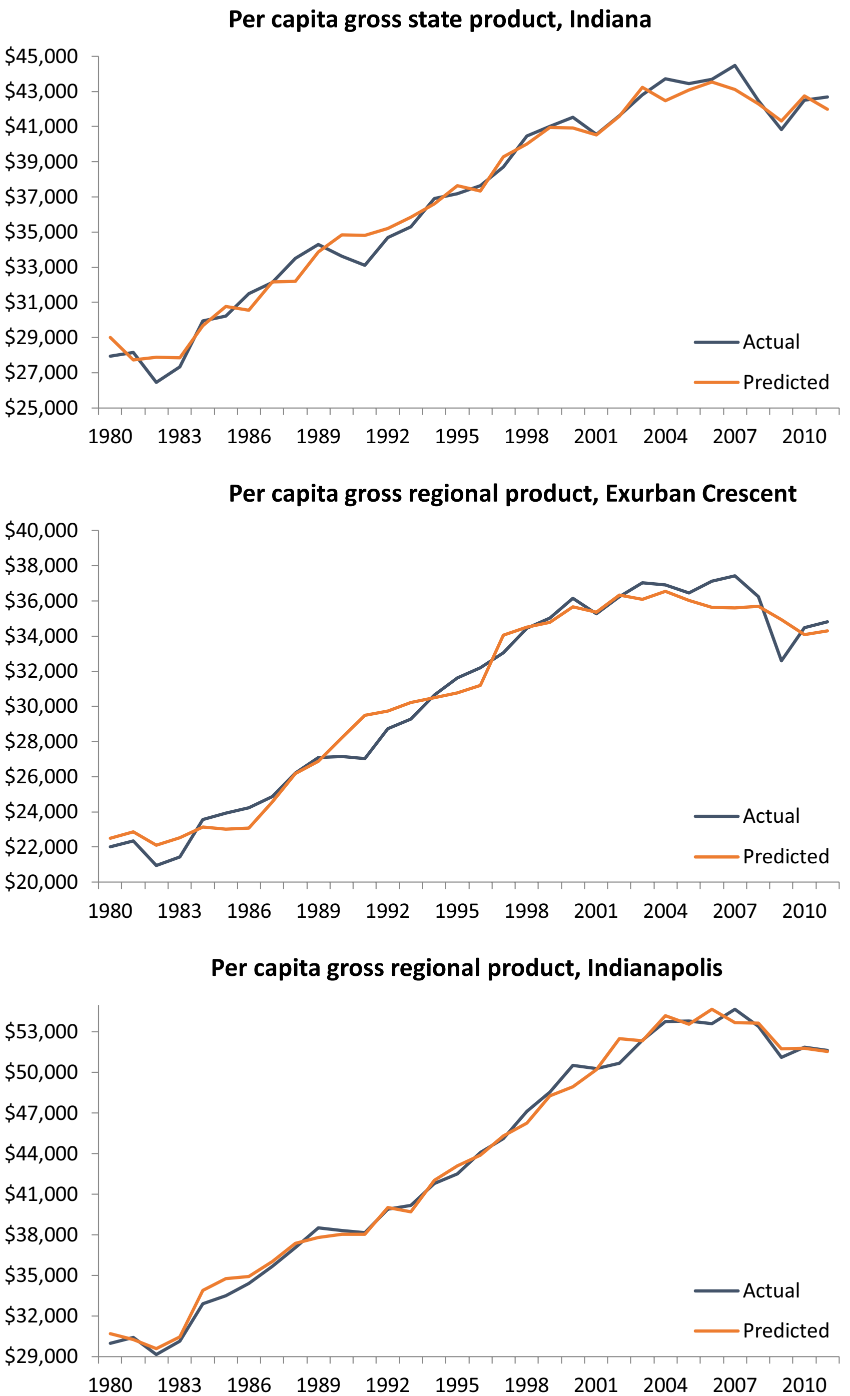

Fig. 3. Actual versus predicted gross product *per capita* (2011$) for Indiana and two regions, 1980–2011

5 Results of the policy scenario analysis

The baseline forecast to which the four policy forecasts are compared paints a relatively pessimistic picture of the state's economy between the years 2015 and 2025. Total employment

Table 4. General economic impacts of the four CO_2 tax policies, percentage difference from baseline in 2025

	\$15 policy (%)	\$25 policy (%)	\$35 policy (%)	\$45 policy (%)
State				
Total employment	–4.0	–6.7	–9.4	–12.1
Income *per capita*	–4.0	–6.7	–9.3	–11.9
Average earnings per employee	–2.2	–3.7	–5.2	–6.8
Gross state product *per capita*	–3.2	–5.4	–7.5	–9.7
Unemployment rate, state	0.2	0.3	0.4	0.5
Exurban Crescent				
Total employment	–3.7	–6.2	–8.7	–11.2
Income *per capita*	–1.0	–1.6	–2.2	–2.8
Average earnings per employee	–1.0	–1.7	–2.3	–2.9
Gross regional product *per capita*	–5.0	–8.4	–11.7	–15.1
Unemployment rate	–0.3	–0.5	–0.7	–0.8
Indianapolis				
Total employment	–4.1	–6.9	–9.6	–12.4
Income *per capita*	–5.7	–9.5	–13.2	–16.8
Average earnings per employee	–2.3	–3.9	–5.4	–7.0
Gross regional product *per capita*	–4.7	–7.8	–10.9	–14.0
Unemployment rate	0.6	1.1	1.5	1.9

is projected to decline about 10 per cent during that period, with a 5 per cent decline in total GSP (in inflation-adjusted 2011 dollars). The largest job losses in percentage terms are anticipated in construction (–31%), retail (–25%), manufacturing (–22%) and wholesale (–17%), with modest increases expected in mining (11%), farming (7%) and government (1%). The average earnings-per-employee, in 2011 dollars, is forecast to decline about 4 per cent between 2015 and 2025, with the largest reductions in mining and finance, insurance and real estate (both –15%) and the largest gains in farming (8 per cent) and transportation and utilities (1%).

The results of the baseline forecast, while interesting in their own right, are not the primary objective of this analysis. The value of the baseline forecast comes in its comparison to the policy forecasts. Because the baseline and policy forecasts use identical data and models – except for the energy price data – the differences between the policy forecasts and the baseline represent the changes expected from a CO_2 tax. These changes – not the absolute values – are of primary interest.

Table 4 presents the general economic results for all four policy scenarios in terms of percentage difference from the baseline forecast in the year 2025; Figure 4 illustrates such results over the entire 10-year period side-by-side with the baseline case. As economic theory would lead to us to expect, CO_2 taxes have a deleterious effect on state and regional economic trends.[6] In the absence of a mechanism for recycling the CO_2 tax revenue, gross production *per capita*, income, employment and wages are all expected to decline versus the baseline; the unemployment rate is projected to rise. As the size of the tax increases, the magnitudes of these effects also increase. While these results accord with theoretical expectations, this analysis contributes to our understanding of the policy impacts by estimating the magnitude of these impacts. And the magnitudes are relatively large. Though most studies vary in terms of the time periods and tax amounts used, the economic effects presented here – even for the lowest tax of \$15 – exceed those found in the studies discussed earlier in the paper. The relatively large

[6] We use the term 'economic trends' here in the narrow sense conveyed by our variables of interest: GSP, earnings, employment, and other traditional measures of financial fitness. A true economic accounting of a CO_2 tax would include the benefits of reduced carbon output. We are able to predict the effects of a CO_2 tax on carbon output, but extrapolating the economic externalities of such a reduction – which stand to be sizeable – are beyond the scope of this paper.

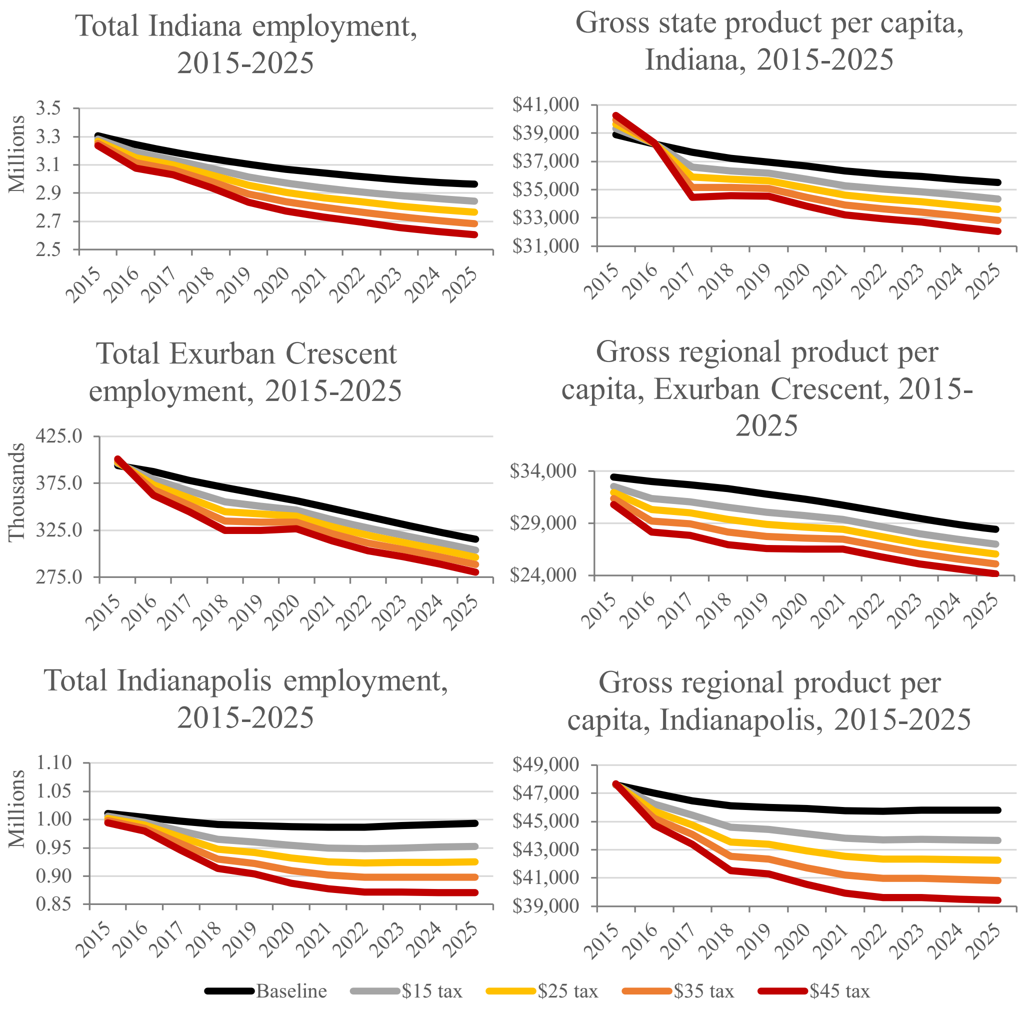

Fig. 4. Model forecasts of total employment and gross product for the baseline and policy scenarios for the state, Exurban Crescent and Indianapolis from 2015 to 2025

impacts may reflect the overall importance of energy in the Indiana state economy: in 2011, Indiana ranked as the 11th most energy intensive state in terms of energy use per dollar of GSP (EIA 2013b).

Even with a relatively low tax of $15 per ton, the 4 per cent decline in employment at the state level translates to almost 120,000 fewer jobs in the year 2025. And the 3.2 per cent decline in GSP *per capita* represents a $7.9 billion reduction in GSP versus the baseline (or, under the $45 tax, a reduction in GSP of $23.6 billion) (all figures in 2011$).

These general economic impacts are roughly equal across the state and the two regions estimated, though the Exurban Crescent is projected to fare somewhat better, actually reducing its unemployment rate – possibly due to a declining labour force participation rate – by 0.3 percentage points with a $15 per ton CO_2 tax. Considering the large proportion of the state economy that is covered by these two regions, this consistency is not unexpected; however, impacts may vary considerably among the smaller and more economically distinct regions not modelled here.

Table 5. Employment and earnings per employee impacts of a $15 per ton CO_2 tax by industry and geography in the year 2025

	State (%)	Exurban Crescent (%)	Indianapolis (%)
Employment			
Construction	–8.9	–13.3	–6.8
F arming	0.4	6.0	–7.4
Finance, insurance, and real estate	–2.1	–0.6	–1.2
Government	–1.0	–1.1	0.5
Manufacturing	–6.0	–15.3	–5.2
Mining	2.7	0.0	0.9
Retail	–11.3	–20.3	–9.7
Services	–3.8	–1.5	–5.2
Transportation and utilities	–1.6	3.9	–0.5
Wholesale trade	–4.4	1.6	–5.3
Earnings per employee			
Construction	–1.1	–2.6	–3.1
Farming	–3.6	6.5	0.0
Finance, insurance, and real estate	–15.0	–11.3	–15.3
Government	–1.6	–0.5	–0.5
Manufacturing	–0.8	–1.3	–0.9
Mining	–6.7	–2.9	12.2
Retail	–0.3	0.5	–3.2
Services	–2.6	0.0	–1.5
Transportation and utilities	1.6	1.3	2.0
Wholesale trade	–2.8	0.7	–3.2

5.1 Economic impacts by economic sector

While the general economic outcomes predicted for the state and the two regions are fairly uniform, substantial variation exists across the ten economic sectors. Table 5 contains percentage differences from the baseline in the year 2025 by industry and geography for employment and earnings-per-employee, our proxy for mean wages.

We predict per cent declines in jobs at the state level to be greatest in large sectors such as construction, manufacturing and retail trade. Farming and mining, though small in size, are expected to see an increase in jobs compared to the baseline forecast by 2025. Table 3 also illustrates the economic heterogeneity of the regions. Our model shows the more diversified Indianapolis region, for instance, experiences relatively muted job losses compared to the Exurban Crescent, where we predict double-digit percentage declines in construction, manufacturing and retail trade.

In terms of earnings-per-employee, we expect to see the largest declines in finance, insurance and real estate, with modest reductions in most other sectors. We predict earnings-per-employee in the transportation and utilities will rise. Again, sub-state regional variation is apparent. Whereas we expect higher energy prices to increase transportation and utilities earnings-per-employee in both regions, the Exurban Crescent and Indianapolis face differing prospects for employee earnings in the farming, mining, retail trade, services and wholesale trade sectors.

5.2 Impacts on energy consumption

Because a CO_2 tax will increase the price of energy, it is no surprise that the IN-SEEM model predicts reductions in energy consumption across the seven end-use sectors. We present these projections in Table 6 for two policy scenarios: the $15 and $35 per ton CO_2 taxes.

Table 6. Percentage change in energy consumption versus the baseline projection for 2025

	$15 per ton of CO_2			$35 per ton of CO_2		
	State (%)	Exurtoan Crescent (%)	Indianapolis (%)	State (%)	Exurban Crescent (%)	Indianapolis (%)
Commercial natural gas	−6.2	*−6.5*	−7.0	−14.4	−15.1	−16.4
Industrial natural gas	−13.2	−7.1	−2.7	−30.3	−16.5	−6.4
Residential natural gas	−4.5	−1.9	−6.9	−10.4	−4.3	−16.0
Commercial electricity	−5.2	−5.5.	−5.6	−12.2.	−12.9	−13.1
Industrial electricity	−6.7	−4.0	−7.1	−15.5.	−9.3	−16.5
Residential electricity	−3.6	1.4	−3.0	−8.4	3.4	−7.0
Petrol	−3.2	−8.0	−2.0	−7.4	−18.7	−4.7

The curious exception to our expectations is residential electricity consumption in the Exurban Crescent, wherein we predict slight increase under both a $15 and $35 per ton CO_2 tax. This slight increase may be due to a substitution effect brought about by higher natural gas prices. Or this may stem from the positive relationship in our model between residential electricity consumption and non-wage income *per capita*. If non-wage income *per capita* increases because of government transfers brought about by higher energy prices, residential consumers might use more electricity. The largest predicted consumption changes at the state and sub-state regions appear in the industrial end-use sector for natural gas and electricity, though we also anticipate Indianapolis to experience rather large reductions in the commercial sector. The model also predicts, unsurprisingly, that a larger CO_2 tax will yield larger energy consumption reductions, with a $35 tax generating double-digit declines for most energy types in most end-use sectors across the state and two regions.

5.3 Potential revenues from a CO_2 tax

While the IN-SEEM model does not contain a government revenue component, the policy analysis estimates allow us to calculate the potential tax revenue Indiana could collect from a state CO_2 tax. We multiply the projected energy consumption across energy types and end-use sectors by the equivalent tax for that energy type and end-use sector in each year.

Figure 5 displays the results of these calculations for the four CO_2 tax scenarios examined in the policy analysis. Over the decade-long period, revenues decline annually – although always remain positive – as consumers adapt to higher prices by reducing consumption. The levelling off of revenues – as opposed to a steeper decline – is consistent with the idea that CO_2 taxes may benefit from a relatively low tax elasticity of fossil fuel consumption (Bohm 1996). By 2025, a $15 tax would mean about $1.5 billion in annual tax revenues. A tax of $45 per ton of CO_2, the largest tax examined in this study, would result in annual revenues of about $4 billion.

As mentioned earlier, the current version of the IN-SEEM model does not recycle these monetary outlays back into the economic system. The $1.5 billion in revenue from a $15 per ton CO_2 tax could be used to offset other distortionary taxes – for instance, those on labour – that could soften the estimated negative economic impacts (Parry 1995).

In the absence of such offsetting actions, the policy analysis and our calculations suggest the excess burden of the tax will be large. As evident in Table 7, even the $15 CO_2 tax results in an average deadweight loss per year – the difference between the absolute amount of the GSP

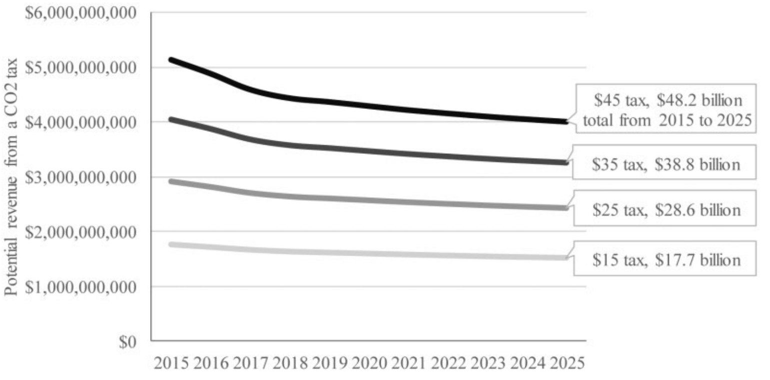

Fig. 5. Potential tax revenue at the state level by year from a per-ton CO_2 tax
Note: All amounts are in year 2011 dollars

Table 7. The estimated deadweight loss and excess burden of a CO_2 tax at four different tax levels

Tax level	Cumulative 2015–2025 tax revenue (billion)	Cumulative 2015–2025 GSP loss (billion)	Cumulative 2015–2025 deadweight loss (billion)	Average deadweight loss per year, 2015–2025 (billion)	Excess burden as percent of revenue (%)
$15/ton	$17.7	$58.5	$40.5	$3.6	228.8
$25/ton	$28.6	$97.5	$68.5	$6.2	239.5
$35/ton	$38.8	$136.5	$97.5	$8.9	251.3
$45/ton	$48.2	$175.5	$127.5	$11.6	264.5
Dollars are in 2011$					

reduction and the revenues generated by the tax – of about $3.6 billion. This corresponds to an excess burden of 229 per cent of revenue (annual deadweight loss divided by annual revenue, multiplied by 100). The burden rises to 265 per cent on an average annual deadweight loss of $11.6 billion for a $45/ton CO_2 tax. A burden in excess of 100 per cent is considered high by any estimate.

It is possible, however, to approximate how revenue recycling may soften the blow of the CO_2 tax by multiplying the estimated tax revenues by the Indiana state government expenditure multiplier of 1.8 (IMPLAN 2014), which thereby reduces the anticipated GSP loss (Table 8). This approximation also assumes the state rather than the federal government imposes and collects (and in turn spends) the CO_2 tax dollars. By incorporating these assumptions, excess burden falls significantly to between 48 per cent and 85 per cent for tax rates between $15 and $45 per ton, with respective average annual deadweight losses of between $0.78 and $3.7 billion. While still high, the excess burden of the $15 tax begins to fall within a more normal range when this multiplier approach is used to approximate the effect of revenue recycling.

5.4 *Estimated emissions reductions from a CO_2 tax*

Emissions reductions can also be estimated using results from our policy analysis in conjunction with the aforementioned EIA data on the ratio of emissions per unit of energy by type and end-use sector. The reduction values are then summed across the seven combinations of energy

Table 8. The estimated deadweight loss and excess burden of a CO_2 tax at four different levels assuming a government expenditure multiplier of 1.8

Tax level	Cumulative 2015–2025 tax revenue	Cumulative 2015–2025 GSP loss, incorporating mulitplier	Cumulative 2015–2025 deadweight loss	Average deadweight loss per year, 2015–2025	Excess burden as percent of revenue (%)
\$15/ton	\$18 billion	\$26.6 billion	\$8.6 billion	\$780 million	47.8
\$25/ton	\$29 billion	\$45.5 billion	\$16.5 billion	\$1.5 billion	56.9
\$35/ton	\$39 billion	\$66.8 billion	\$27.6 billion	\$2.5 billion	70.8
\$45/ton	\$48 billion	\$88.6 billion	\$40.6 billion	\$3.7 billion	84.6

Dollars are in 2011$

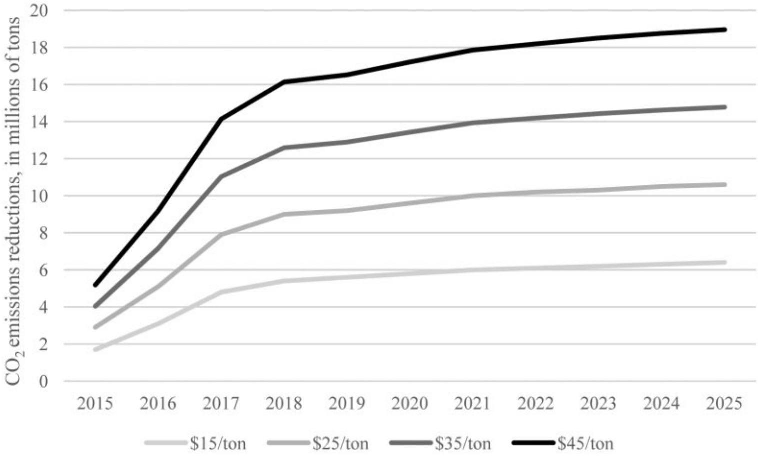

Fig. 6. Emissions reductions for the state of Indiana in millions of tons for each CO_2 tax scenario from 2015 to 2025

types and end-use sectors to produce an estimate of total CO_2 emissions reductions in each year between 2015 and 2025, displayed in Figure 6.

The analysis finds modest reductions in CO_2 emissions from the various tax rates, roughly in line with the per cent reductions estimated by the EIA (2010, 2013) in analyses that examined \$10, \$15 and \$25 per ton CO_2 policies. We expect a \$15 per ton carbon tax to yield reductions of 57.4 million tons of CO_2 over the 2015 to 2025 period, a difference of 4.5 per cent from the baseline forecast. Per cent reductions reach 13.3 per cent with a \$45 tax. Emissions reductions increase over time, although at a decreasing rate, with 5.7 per cent to 17.1 per cent reductions from the baseline case expected in 2025.

6 Discussion and conclusion

The results generated by the IN-SEEM model are important for several reasons. First, the results highlight one of the primary and unique features of the IN-SEEM model: the ability to analyse energy policies at both state and sub-state levels. Because of the nature of the econometric multi-equation framework and the inclusion of sub-state energy consumption data, estimates generated at the state level were able to simultaneously feed through to the two county-based regions. As IN-SEEM is further developed, analyses using all ten regions will provide impact estimates using a two-way linkage between the regions and the state, providing a level of granularity previously unattainable in energy-economy analyses.

Second, the policy analysis revealed heterogeneous economic impacts. While broad economic indicators like employment, earnings and gross production *per capita* are expected to decline at similar rates within the state and the two regions, disparate impacts are evident by sector across these geographies. This variability has implications for state and local economic development agencies given the substantial geographic differences in economic specializations and activity even in a small state like Indiana. For example, our results show a $15 tax will reduce manufacturing employment by 6 per cent in 2025 for the state as whole, but this state result masks regional variation. While we predict the Exurban Crescent will experience a 15.3 per cent decline in manufacturing employment from this tax, the decrease in the Indianapolis region will be only 5.2 per cent.

Third, the results confirm that CO_2 taxes reduce both energy consumption and CO_2 emissions. A $15 tax leads to reductions in energy consumption generally ranging from 2 to 7 per cent, depending upon the type of energy, the end-use and the region in question. This same tax level results in a 57.4 million ton reduction in CO_2 emissions over the 2015 to 2025 period, a difference of 4.5 per cent from the baseline model. These reductions reach 170.7 million tons – or 13.3 per cent – with a $45 tax.

Finally, the analysis suggests the potential for substantial revenues accruing from a CO_2 tax. These revenues – which range from around $1.5 billion annually from a $15 tax to $4 billion per year from a $45 tax – could be used to reduce taxes in other areas of the economy. Doing so could potentially mitigate the negative economic impacts brought about by higher energy prices. As previously discussed, this analysis offers only a partial, 'worst-case' look at the financial effects of a CO_2 tax due to the inability of IN-SEEM to recycle tax revenues back into the economy. The predicted negative impacts on most economic sectors suggest that any efforts to enact a CO_2 tax must pay careful attention to how tax revenues are managed.

These findings, in turn, suggest two important general takeaways, one regarding energy-economy modelling and the other for CO_2 taxes. First, results from IN-SEEM suggest models that are only capable of running policy analyses at the national or state level are likely obscuring important variations in the effects of energy policies at the sub-state level. This is of crucial importance due to the metropolitan nature of the nation's economy. Given the diversity of economic activities across such regions, knowing how the effects of energy policies may vary geographically is valuable information for decision-makers at multiple levels. Analysis at the sub-state level can help state and national policy-makers make better-informed decisions on energy policies while local governments and economic development agencies can better prepare for the consequences of such policies.

Second, the analysis supports claims of both proponents and opponents of CO_2 taxes. At the state and regional levels, the policy analysis suggests the energy price increases caused by a CO_2 tax will indeed significantly reduce consumption and hence emissions. But our analysis shows these reductions will not come about without similarly significant economic consequences, though these consequences should be considered a worst case scenario. Applying a state government expenditure multiplier to the results in order to approximate recycling of tax revenues softens the blow to GSP but does not eliminate the excess burden. Thus, this analysis does not find evidence of a double-dividend, nor is it currently designed to explore that issue in detail. Future development of IN-SEEM will include building a government finance component allowing for the ability to more realistically cycle CO_2 tax revenues back into the economy and examine the consequences of various tax schemes, such as reducing taxes on labour and/or capital given increased revenue from a CO_2 tax.

References

Aldy JE, Pizer WA (2011) *The competitiveness impacts of climate change mitigation policies*. HKS Faculty Research Working Paper Series RWP11-047. John F. Kennedy School of Government, Harvard University

Babiker MHM, Bautista M, Jacoby HD, Reilly JM (2000) Effects of differentiating climate policy by sector: A United States example. Report Number 61. MIT Joint Program on the Science and Policy of Global Change

Bae JH (2005) The welfare consequences of carbon tax reform in open economies: The application of computable general equilibrium model for Pennsylvania. The Pennsylvania State University

Bohm P (1996) Environmental taxation and the double dividend: Fact or fallacy? Centre for Social and Economic Research on the Global Environment. Working Paper GEC 96-01

Bureau of Economic Analysis (BEA) (2013) Regional economic accounts. URL: http://www.bea.gov/regional

Bureau of Labour Statistics (BLS) (2013) Local area unemployment statistics. URL: http://www.bls.gov/lau

Carbone JC, Morgenstern RD, Williams RC III, Burtraw D (2013) Deficit reduction and carbon taxes: Budgetary, economic and distributional impacts. RFF Report. Washington DC, Resources for the Future

Carley S (2011) The era of state energy policy innovation: A review of policy instruments. *Review of Policy Research* 28: 265–294

Diewert WE, Lawrence D (1994) The marginal costs of taxation in New Zealand. Report prepared for the New Zealand Business Round Table by Swan Consultants Pty Ltd. Canberra

Energy Information Administration (EIA) (2010) Energy market and economic impacts of the American Power Act of 2010. Report #SR-OIAF/2010-01

Energy Information Administration (EIA) (2011) Emissions of greenhouse gases in the US. URL: http://www.eia.gov/environment/emissions/ghg_report/ghg_carbon.cfm

Energy Information Administration (EIA) (2013a) State energy data system. URL: http://www.eia.gov/state/seds/

Energy Information Administration (EIA) (2013b) Annual energy outlook 2013. Report DOE/EIA-0383

Fischer C, Morgenstern RD (2006) Carbon abatement costs: Why the wide range of estimates? *Energy Journal* 27: 73–86

Gaskins DW, Weyant JP (1993) Model comparisons of the costs of reducing CO_2 emissions. *The American Economic Review* 83: 318–323

Hansen LP, Heckman JJ (1996) The empirical foundations of calibration. *Journal of Economic Perspectives* 10: 87–104

Hassett KA, Mathur A, Metcalf GE (2007) *The incidence of a US carbon tax: A lifetime and regional analysis*. National Bureau of Economic Research Working Paper Number 13554

Ho MR, Morgenstern RD, Shih J-S (2008) Impact of carbon price policies on US Industry. Resources for the Future Discussion Paper 08-37

IMPLAN (2014) IMPLAN system (data and software). URL: http://www.IMPLAN.com

Indiana Business Research Center (IBRC) (2014) Indiana Business Research Center. URL: http://www.ibrc.indiana.edu

Jorgenson DW (1984) Econometric methods for applied general equilibrium. In: Scarf H, Shoven J (eds) *Applied general equilibrium analysis*. Cambridge University Press, New York

Jorgenson DW, Goettle RJ, Wilcoxen PL, Ho MS, Jin H, Schoennagel PA (2008) The economic costs of a market-based climate policy. DW Jorgenson Associates for Pew Center on Global Climate Change, Arlington

Jorgenson DW, Slesnick DT, Wilcoxen PJ (1992) Carbon taxes and economic welfare. Harvard Institute of Economic Research Discussion Paper 1589

Jorgenson DW, Wilcoxen PJ (1993) US carbon emissions: An econometric general equilibrium assessment. *Resource and Energy Economics* 15: 7–25

Kamat R, Rose A, Abler D (1999) The impact of a carbon tax on the Susquehanna River Basin economy. *Energy Economics* 21: 363–384

Lau L (1984) Comments on Mansur and Whalley's numerical specification of applied general equilibrium models. In: Scarf H, Shoven J (eds) *Applied general equilibrium analysis*. Cambridge University Press, New York

McKitrick RR (1998) The econometric critique of computable general equilibrium modelling: The role of functional forms. *Economic Modelling* 15: 543–573

Morris DF, Munnings C (2013) Progression to a fair carbon tax: Policy design options and impacts to households. Issue Brief 13-03. Resources for the Future: Washington, DC

National Oceanic and Atmospheric Administration (NOAA) (2013) National Climatic Data Center. URL: http://www.ncdc.noaa.gov

Oladosu G, Rose A (2007) Income distribution impacts of climate change mitigation policy in the Susquehanna River Basin economy. *Energy Economics* 29: 520–544.

Parry IWH (1995) Pollution taxes and revenue recycling. *Journal of Environmental Economics and management* 29: S64–S77

Parry I, Williams R (2011) Moving US climate policy forward: Are carbon taxes the only good alternative? Resources for the Future Discussion Paper 11-02

Parry IWH, Williams RC, Goulder LH (1999) When can carbon abatement policies increase welfare? The fundamental role of distorted factor markets. *Journal of Environmental Economics and Management* 37: 52–84

Partridge MD, Rickman DS (1998) Regional computable general equilibrium modelling: A survey and critical appraisal. *International Regional Science Review* 21: 205–248

Paul A, Beasley B, Palmer K (2013) *Taxing electricity sector carbon emissions at social cost. Discussion paper 13-23*. Washington DC, Resources for the Future

Rabe BG (2008) States on steroids: The intergovernmental odyssey of American climate policy. *Review of Policy Research* 25: 105–128

Rausch S, Metcalf GE, Reilly JM (2011) Distributional impacts of carbon pricing: A general equilibrium approach with micro-data for households. *Energy Economics* 33: S20–S33

Rubin BM (1981) Econometric models for metropolitan planning. *Journal of the American Planning Association* 47: 408–420

Rubin BM, Hilton MD (1996) Identifying the local economic development impacts of global climate change. *Economic Development Quarterly* 10: 262–279

Rubin BM, Gailmard S, Marsh D, Septoff A (1997) Assessing the state-level consequences of global warming: Socioeconomic and energy demand impacts. *World Resource Review* 9: 379–387

Schneider UA, McCarl BA (2005) Implications of a carbon-based energy tax for US agriculture. *Agricultural and Resource Economics Review* 34: 265–279

Shoven JB, Whalley J (1984) Applied general equilibrium models of taxation and international trade: An introduction and survey.*Journal of Economic Literature* 23: 1007–1051

Soloman BD, Rubin BM (1985) Environmental linkages in regional econometric models: An analysis of coal development in Western Kentucky. *Land Economics* 61: 43–57

U.S. Energy Information Administration (2014) Voluntary Reporting of Greenhouse Gases Program. URL: http://www.eia.gov/oiaf/1605/

U.S. Environmental Protection Agency (EPA) (2014) EPA Emissions and Generation Resource Integrated Database (eGRID). URL: http://developer.epa.gov/emission__generation_resource_integrated_database_egrid/

Wei M, Patadia S, Kammen DM (2010) Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the US? *Energy Policy* 38: 919–931

Wendling Z, Warren D, Rubin B, Richards KR, Carley S (2014) A method for estimating sub-state consumption of delivered energy. Social Science Research Network. URL: http://ssrn.com/abstract=2431356

West GR (1995) Comparison of input-output, input-output + econometric and computable general equilibrium impact models at the regional level. *Economic Systems Research* 7: 209–227

Wigle RM (1991) The Pagan-Shannon approximation: Unconditional systematic sensitivity analysis in minutes. *Empirical Economics* 16: 35–49

Wiser R, Porter K, Clemmer S (2000) Emerging markets for renewable energy: The role of state policies during restructuring. *The Electricity Journal* 13: 13–24

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Resumen. Este artículo debate un enfoque econométrico innovador para el modelado de la forma en que las políticas energéticas nacionales, o las de escala estatal, pueden afectar a los resultados económicos estatales y subestatales, mediante el empleo del nuevo modelo energético-económico redimensionable Indiana (IN-SEEM, por sus siglas en inglés). Este modelo, que se puede modificar y redimensionar para investigar otros estados y regiones subestatales, se usa para analizar los efectos económicos de un impuesto sobre dióxido de carbono (CO_2) en el estado de Indiana y en dos de sus regiones más pobladas. Los resultados de este análisis ofrecen una prueba de concepto de un enfoque econométrico que permite el análisis subestatal de las políticas energéticas. Además, el análisis de políticas considera que sin un mecanismo para el reciclaje de los ingresos fiscales por CO_2 de vuelta a la economía, un impuesto sobre el CO_2 entre 15 USD y 45 USD por tonelada tendrá un efecto negativo significativo en la economía estatal y en la de las dos regiones examinadas. Si bien encontramos que el impuesto es un medio eficaz para reducir el consumo de energía y por lo tanto las emisiones de CO_2, se pronostica que el empleo total y el producto estatal bruto *per capita* disminuirán en un 4,0 y 3,2 por ciento respectivamente para el estado, dado un impuesto de 15 USD por tonelada de CO_2 en el año 2025.

要約: 本論文では、国または州レベルのエネルギー政策が、州と州の地域レベルの経済にどのような影響を与えるかをモデル化するイノベーティブな計量経済的アプローチを、新しいIndiana Scalable Energy-Economy Model (IN-SEEM) を用いて考察する。このモデルは、他の州とその州の地域を分析するのに補正および拡張が可能である。このモデルを用いて、炭素税がインディアナ州全体と、同州で人口の多い2つの地域に与える経済効果を分析する。本分析結果は、州下レベルの地域のエネルギー政策分析を考慮した計量経済学的アプローチの概念を実証するものである。さらに、本政策分析によれば、炭素税の税収を経済に還元するシステムがない場合、1トン当たり15ドルから45ドルまでの炭素税は、分析の対象となったインディアナ州およびその州下の2つの地域に大きなマイナスの影響を与える。炭素税は、エネルギーの消費量とそれに応じた二酸化炭素の排出量を削減する上で効果的な手段であるが、2025年に1トン当たり15ドルの炭素税を課した場合、同州の総雇用率と一人当たりの州内総生産はそれぞれ、4.0%、3.2%減少することが予想される。