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Extending the Macroeconomic Impacts Forecasting Capabilities of the National Energy Modeling System

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Abstract

To comprehensively model the macroeconomic impacts that result from changes in long-term energy-economy forecasts, the United States Department of Energy's National Energy Technology Laboratory (NETL) partnered with West Virginia University's (WVU) Regional Research Institute to develop the NETL/WVU econometric input-output (ECIO) model. The NETL/WVU ECIO model is an impacts forecasting model that functions as an extension of the U.S. energy-economic models available from the United States (U.S.) Energy Information Administration's National Energy Modeling System (NEMS) and the U.S. Environmental Protection Agency's Market Allocation (MARKAL) model. The ECIO model integrates a macroeconomic econometric forecasting model and an input-output accounting framework along derived forecast scenarios detailing a baseline of the U.S. energy-economy and an alternative forecast on how power generation resources can meet future levels of energy demand to generate estimates of the impacts to gross domestic product, employment, and labor income. This manuscript provides an overview of the model design, assumptions, and standard outputs.

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1 Introduction

Decision makers involved in energy policy are facing unprecedented challenges arising from globalization, decarbonization, and the advent of new energy technologies. Since the early 1970s energy-economic forecasting models have been used to assess potential consequences of meeting these types of energy market challenges (Hoffman and Wood 1976; Nakata 2004; Bhattacharyya and Timilsina 2010). Forecasts generated by these models help to inform public energy system planning decisions and private energy sector investments. Available forecasts (e.g., the International Energy Association [IEA]'s World Energy Outlook [WEO] or the United States [U.S.] Energy Information Administration [EIA]'s Annual Energy Outlook [AEO]), however, do not include detailed estimates of the economic impacts associated with changes in long-term energy economic conditions at the industry-level.

Recognizing the need for a model that could generate comprehensive estimates of the macroeconomic impacts of changes in the U.S. energy system, the U.S. Department of Energy (DOE)'s National Energy Technology Laboratory (NETL) partnered with researchers at West Virginia University's (WVU) Regional Research Institute (RRI) to develop the WVU/NETL econometric input-output (ECIO) model. The NETL/WVU ECIO model (hereafter, the ECIO model) is an impacts forecasting model capable of generating industry-level estimates of changes in employment, labor income, and total output resulting from proposed shocks to the U.S. energy economy.[1]

This paper provides an overview of the ECIO model as of late 2019, including the model's design, assumptions, and standard model outputs. The ECIO model exists as a series of interrelated equations that characterize the interdependencies of industries, value added sectors, and components of final demand for the U.S. economy. Equations are connected across three primary modules and several sub-modules. Following a traditional input-output (IO) accounting framework, interactions between industries are represented by the sales and purchases of goods and services.

While not the only model available to estimate the employment and labor income impacts of a changing energy landscape,[2] the ECIO model makes at least three important contributions to the literature on energy-economic modeling. First, similar to the National Renewable Energy Laboratory (NREL)'s Jobs and Economic Development Impact (JEDI) models, the ECIO model can be used to estimate the economic impacts of constructing and operating new energy facilitates (e.g., a power plant) (Goldberg 2004). The ECIO model, however, can also be used to estimate the economic impacts of research, design, and development (RD&D) spending, the deployment of new energy technologies, and/or unplanned capacity retirements. Second, the ECIO model is able to respond to changes in energy sector prices, which influence production costs both directly and indirectly across industries. The effects of changes in energy prices are incorporated in the ECIO model using a variant of the IO price model described by Bazzazan and Batey (2003).[3] Third, unlike other static IO modeling frameworks (e.g., IMPLAN) the ECIO model is dynamic in nature to be consistent with both the U.S. EIA's National Energy Modeling System (NEMS) and the U.S. Environmental Protection Agency's U.S. Nine-Region (USEPA9r) version of the Market Allocation (MARKAL) model, and to allow for impacts forecasts over decadal time frames.

While not without skepticism (Pindyck 2013), both NEMS and the EPAUS9r version of MARKAL are used regularly to forecast the effects of shocks on energy-economic conditions for the U.S.[4] Model results

[1]Following the Bureau of Labor Statistics (BLS), the ECIO model defines employment as the number of nonfarm, payroll jobs in the U.S. economy. Employment includes the total number of persons on establishment payrolls either part-time or full-time and whether they received pay or not. Temporary and intermittent employees are also included, as well as those on sick or paid leave (BLS 2020).

[2]Other models used to estimate the employment and labor income impacts of economic shocks include but are not limited to the National Renewable Energy Laboratory (NREL)'s Jobs and Economic Development Impact (JEDI) models, the international JEDI (i-JEDI) model, the Impact Analysis for Planning (IMPLAN) model, the Regional Economic Models Inc. (REMI) models, and the UKENVI model. For a review of energy-economic forecasting models, see Hall and Cukley (2016), Hoffman and Wood (1976), Nakata (2004), or Bhattacharyya and Timilsina (2010).

[3]Although prices of all goods change, and IO coefficients change as a result, there is no endogenous intermediate quantity.

[4]NEMS and MARKAL have been used to evaluate energy-economic shocks including but not limited to implementation of strategies used to mitigate greenhouse gas (GHG) emissions (Palmer et al. 2010; Goulder 2010; Wilkerson 2014; Victor et al. 2018), utilization of renewable energy resources (Bernow et al. 1997; Deyette and Clemmer 2004; Chen et al. 2009), the connections between the natural gas boom and carbon mitigation (Nichols and Victor 2015; Gillingham and Huang 2019),

are delivered in the form of alternate outcome scenarios.[5] Scenarios include information on updates to the aggregated electricity generation, transmission, and distribution sector such as changes in the technology and/or resource mix used to meet demand. Annual use tables within the ECIO model's framework can be modified annually to reflect such changes.

The remainder of this paper is organized as follows. Section 2 discusses how the ECIO model fits within the continuum of impacts forecasting frameworks and provides a more in-depth overview of the ECIO model's design and general assumptions. Section 3 describes the standard results presentation using an example application of the ECIO model. Section 4 concludes and provides a brief discussion of future model extensions.

2 ECIO Model Design

Several organizations have developed economic impacts forecasting models, including Terry Barker at Cambridge Econometrics (CE) who has used these models in wide-ranging policy analysis contexts; Dick Conway who has used these models productively for decades in Washington and Hawaii among other areas; Geoffrey Hewings with models of Chicago, St. Louis, and the U.S. Midwest; RRI's Randall Jackson with models of Ohio and the U.S.; José Manuel Rueda-Cantuche and Kurt Kratena for the EU-27; Sergio Rey for various California regions; Clopper Almon, Douglas Meade, and others at the University of Maryland with the IN-FORUM model of the U.S. and many other countries; and Guy West, who has applied interindustry econometric models to policy issues in Australia and its regions using this type of model.[6,7]

Similar to these models, the ECIO model can be calibrated and parameterized to represent the existing structure of an economy, and to forecast, incorporate, and respond to changes in that structure. In the process, temporal changes in prices, interest rates, wage rates, output, employment, income and the like are determined, carrying clear implications for socioeconomic impacts across different groups in the economy. Depending on model design, some of these variables are specified exogenously, and most can be manipulated to reflect scenario specific changes.

As of late 2019, the ECIO model could serve as an extension to both U.S. EIA's NEMS and the U.S. Environmental Protection Agency's USEPA9r version of the MARKAL model. Both models are data-driven energy-economic optimization models used to project energy market conditions, subject to a set of market and technology constraints.[8] Results from NEMS and the USEPA9r version of MARKAL are presented as a series of alternate future scenarios that provide a range of alternative possible futures for the U.S. energy-economy (Nakata 2004). At minimum, two competing scenarios are generated: 1) a reference scenario (i.e., base case) and 2) a counterfactual scenario. The reference scenario depicts the current and future state of the energy economy with current laws and regulations in place. The counterfactual scenario depicts an alternative future state of the energy economy, where an underlying goal of a proposed policy or program has been met. The ECIO model is used to generate estimates of the economic impacts associated with departures from the reference scenario (base case).

The ECIO model consists of three modules and several sub-modules, connected through a series of inter-related equations that represent the interconnections between 32 major industrial sectors of the U.S. economy. The

the impact of government intervention in the biofuels industry (Saruca and Tyner 2013), cost-effectiveness of the clean energy standard (CES) (Mignone et al. 2012), the impact of renewable portfolio standards (RPS) on energy prices (Fisher 2010) and cross border energy infrastructure in North America (Siddigui et al. 2020).

[5] More information on how the scenarios produced from NEMS and the USEPA9r version of MARKAL are used by the ECIO is available in Section 2.1.

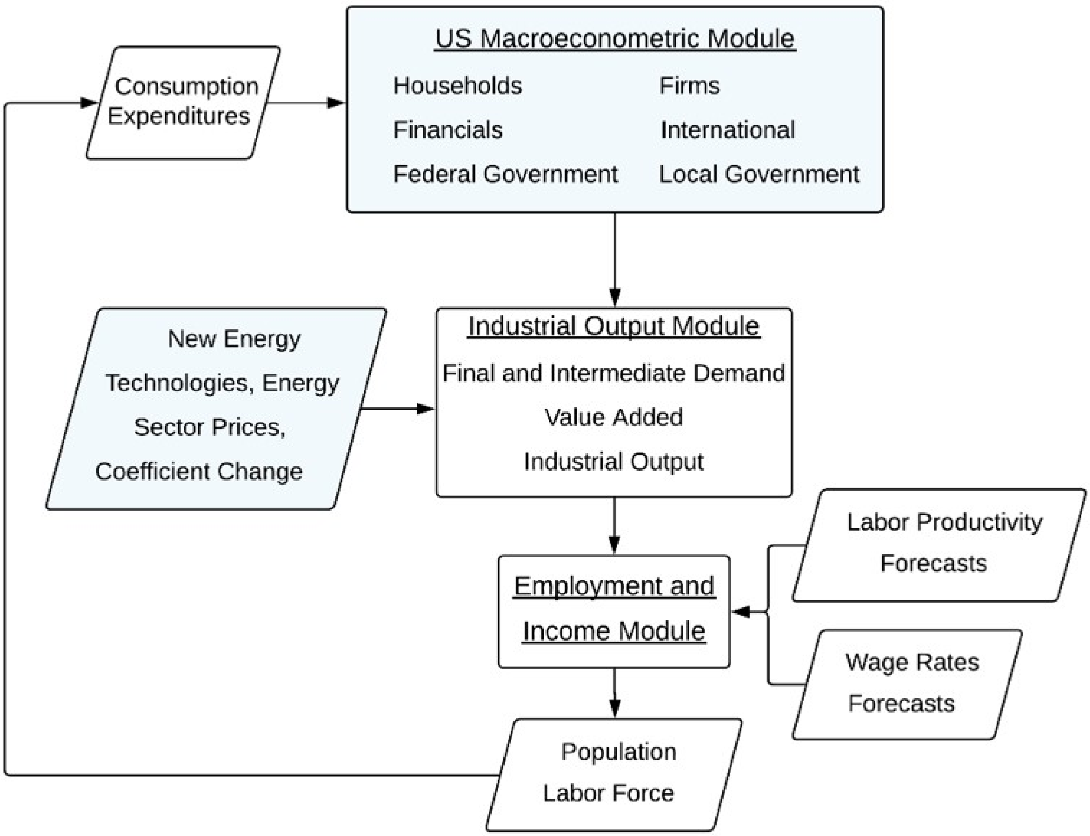
[6] CE's Terry Barker provides an excellent discussion paper accentuating the strengths of this family of models, which he referred to as space-time economic models, in the context of modeling the transition to sustainability (Barker, 2004).

[7] For a selection of related literature, see Conway, 1990; Donaghy et al., 2007; Israilevich et al., 1996; Israilevich et al., 1997; Kim et al., 2015; Kratena et al., 2013; Kratena and Temurshoev, 2017; Rey, 1997; Rey, 1998; Rey, 2000; Rey and Jackson, 1999; West, 1991; West and Jackson, 1998; and West and Jackson, 2014.

[8] MARKAL is data-driven, bottom-up, energy systems economic optimization model tailored by the input data to represent the evolution of a national, regional, state, or community energy system over a forecast period of 40 to 50 years. Each MARKAL model run identifies the cost minimizing combination of technologies needed to meet pre-specified energy demand (Loulou et al. 2004). NEMS is a computer-based energy-economic modeling system of the U.S. NEMS is used to project energy market conditions including the production, consumption, imports, and exports of energy resources subject to constraints on the energy system (e.g., resource availability and the cost and performance characteristics of energy technologies) (U.S. EIA 2019).

three primary modules include the U.S. macroeconometric module, the industrial output module, and the employment and income module. A configuration of the ECIO's primary modules is shown in Figure 1. Although the code for the macroenomic module is embedded in the ECIO algorithm, it can be considered to be exogenous, in effect, and is shaded blue to reflect this. Likewise, inputs from NEMS or Markal that describe scenario-specific data on new energy technologies, energy sector prices, and related variables are exogenous to the ECIO model.

Figure 1: ECIO Model Configuration including Primary Modules



Integration of the three primary modules provides a fully integrated approach to estimating economic activity at the national (and regional) level.

The U.S. macroeconomic module is an adaptation of the Fair model, a public domain macroeconomic econometric model developed by Ray Fair (Fair 2009). The role of this module is to generate forecasts of the components of final demand, which are used as inputs for the ECIO's industrial output module. The industrial output module provides projections of sectoral output for 32 sectors of the U.S. economy (see Table 1 in Appendix B for a complete description of the industrial aggregation scheme used within the ECIO's industrial output module).[9] The employment and income module uses the projections of industrial output from the industrial output module to compute employment for the 32 industries. Altogether, there are five

[9] At the time that the ECIO model was being developed, of main interest to those supporting the model were the economic impacts of technologies being designed and developed to support the U.S. energy system. As a result, estimating changes to employment, labor income, and total output for energy-related sectors was a priority. In an effort to reduce aggregation bias, efforts were made to retain as much detail as possible for energy-related sectors and group non-energy related sectors into reasonable categories based on the North American Industry Classification Scheme (NAICS) descriptions of economic sectors. Expanding the ECIO model to include more industries is computationally expensive, but not impossible. For each industry, an econometric output equation, a wage rate equation, and a productivity equation are required. Each new industry to be added corresponds to the need for $2n + 1$ parameters in the interindustry quadrant (where n is the number of sectors before expansion), three value-added parameters, and as many final demand parameters as there are final demand activities. The number of the iterations is between four and seven depending on the required accuracy of the convergence the relative size of the shock.

energy and 27 non-energy sectors within the industry classification scheme.[10]

There are two primary mechanisms that integrate the interindustry and the econometric subsystems. The first is the reliance of the IO production requirements solution on econometric final demand estimates. Final demand totals by major component are transformed using data from the national IO accounts. Commodity final demand distributions are then transformed into industry space to determine production levels that meet direct and indirect demands. The second integrating mechanism centers on income estimation. Because income is the primary source of consumption expenditures and because consumption expenditures are the dominant driving force and determinant of overall economic activity (i.e., GDP), income provides a powerful variable for integrating the two model systems.

Econometric time series equations provide the basis for forecast labor and non-labor income estimates, and production-based output estimates coupled with productivities and wage rates provide a second source for labor income estimates. The model uses a variable weighting parameter in which full or partial weight can be accorded to either the IO or econometric labor income estimate. By weighting the two equally, the econometric and IO sub-systems exert equal influence on the initial impacts solutions for each year. Because each model year is solved iteratively, the final weighting of econometric and IO labor income can deviate from the equal weighting, but the initial solution starting point for each year allows equal influence of econometric and IO estimates. Once weighted, the resulting labor income estimates are added to econometrically estimated non-labor income, then adjusted to disposable income, which then drives consumption.

2.1 *Macroeconomic Econometric Module*

The ECIO model's macroeconomic econometric (EC) module attempts to capture the interdependence and interactions among the six major components of the U.S. economy: households, firms, financial institutions, international trade, 5)federal governments, and state governments. It provides a consistent theoretical framework and reference for the impacts projections while maintaining a balance among interrelated economic variables and ensuring consistency at the macro level. [11]

The quarterly model covers 289 variables (147 endogenous and 142 exogenous variables) across 26 stochastic equations and 102 identities that describe the U.S. economy. Most of the stochastic equations are estimated via Two Stage Least Squares, and most estimated equations include a lagged dependent treatment variable to account for both partial adjustment and expectation effects. The key outputs of the model are forecasts of consumption, investment, imports, exports, and government expenditures. A bridge matrix based on the most recent benchmark IO tables published by the U.S. Bureau of Labor Statistics (BLS) is used to transform the forecasted aggregate components of final demand into demand by commodity. The following sub-sections detail the construction of each of the final demand components within the EC module's framework and the determination of GDP within the EC module.

2.1.1 *Consumption*

There are three consumption categories in the econometric module: durable goods, nondurable goods, and services. The key determinants of personal consumption expenditures on commodity group i, (C_i), are current disposable income (YD), past total net wealth (AA_{t-1}) and past consumption $(C_{i,t-1})$ included to

[10]Embedded within NEMS is a Macroeconomic Activity Module (MAM) that is used to provide projections of the economic variables needed to estimate energy supply and demand. Similar to the ECIO model, the MAM exists a system of interrelated equations, connected across a series of models including the IHS Markit Inc.'s model of the U.S. economy, EIA's industrial output and employment model, and EIA's regional model. In addition to providing estimates of energy supply and demand, NEMS's MAM can also be used to generate economic impact estimates of shocks to the domestic energy economy (U.S. EIA 2019). However, although NEMS is publicly available, the necessary modules to run the MAM are proprietary and access is restricted by software licensing.

[11]Because our intention is to rely heavily on the FAIR model for the macroeconomic module, we stay as true as possible to that model so as it continues to be enhanced and extended, continued use of it in future iterations of the ECIO model are possible. The FAIR model is a widely recognized and respected tool for macroeconomic forecasts; the American Economic Association retains an entry for the FAIR model within the Resources for Economists repository that they maintain. This section highlights the FAIR model's most important/salient features. Readers interested in additional detail on the FAIR model's structure, see the FAIR models reference documents at https://fairmodel.econ.yale.edu/mmm1.htm

account for partial adjustment and expectation effects,[12] the price deflator of consumption (PH), the interest rate (R), the age distribution of the population including the non-institutional population of men (AG_1) and women (AG_2) 25 to 54 years of age and all other over the age of 16 (AG_3), total population (POP), and a time trend (T). With the exception of the age distribution variables, these variables are determined endogenously. A representative form of consumption equation is shown in equation 1.

$$\left(\frac{C_i}{POP}\right) = f\left(AG_1, AG_2, AG_3\left(\frac{C_i}{POP}\right)_{t-1}, \left(\frac{AA}{POP}\right)_{t-1}, \left(\frac{YD}{POP \times PH}\right), R_i, T\right) \tag{1}$$

2.1.2 *Investment*

Private investment is composed of seven investment variables, three that account for residential investment (IHH, IHB, IHF), three that account for nonresidential fixed investment (IKH, IKB, IKF), and one for inventory investment (IVF).[13] These investment variables determine the flow of private investment from the households, firms, and financial sectors to the economy. IHH, IKF, and IVF are determined endogenously. The specifications of the three behavioral equations in the investment sub-module are as follows:

$$\Delta\frac{IHH}{POP} = f\left(DELH\left(\frac{KH}{POP}\right)_{t-1} - \left(\frac{IHH}{POP}\right)_{t-1}, \left(\frac{KH}{POP}\right)_{t-1}, \left(\frac{AA}{POP}\right)_{t-1}, \left(\frac{YD}{POP \times PH}\right), RMA_{t-1}\right) \tag{2}$$

$$IKF = KK - (1 - DELK)KK_{t-1} \tag{3}$$

$$IVF = V - V_{t-1} \tag{4}$$

where the variable KH is the housing stock, $DELH$ is the depreciation rate of the housing stock, KK is the stock of capital, $DELK$ is the physical depreciation rate of the stock of capital, IHH is the residential investment, RMA is the mortgage interest rate, V is the stock of inventory and IHH, AA, YD, and POP are defined as in the consumption equation. The stock of capital (equation 3) and stock of inventories (equation 4) are determined by identities. For further information on why equations (3) and (4) are not represented as changes see Fair (2016).

2.1.3 *Government Expenditures*

There are two types of government expenditures in the ECIO model: federal and state government (COG and COS) consumption and investment of goods purchased, and nonresidential fixed investment from the government sector (IKG). All three of these variables and their growth rates are exogenously determined.[14]

2.1.4 *Net Exports*

The exports (EX) and export growth rates are exogenous in the Fair model. Imports (IM) are determined endogenously as a function of consumption and investment spending, the domestic price level (PF), and the import price level (PIM). The general form of the imports function is specified in equation 5.

$$\frac{IM}{POP} = f\left(\left(\frac{IM}{POP}\right)_{t-1}, \left(\frac{PF}{PIM}\right), \left(\frac{(CS + CN + CD + IHH + IHB + IHF + IKH + IKB + IKF)}{POP}\right)\right) \tag{5}$$

[12] Following the Crowles Commission approach, in empirical approximations of current period consumption, we assume there are utility costs associated with large changes in consumption between two periods. More information on the Crowles Commission approach can be found (Fair 2009; Fair 2016).

[13] For additional information, see Appendix A, which contains a full list of variable names.

[14] Government transfers to industry in the form of subsidies can be exogenously specified within NEMS or the EPAUS9r version of MARKAL during scenario development. For more information, see Documentation of the National Energy Modeling System Modules (U.S. EIA 2019) or Database Documentation for the EPA U.S. Nine-Region MARKAL Database (Lenox et al. 2013).

2.1.5 *Determining Gross Domestic Product*(GDP)

GDP is equal to consumption plus investment plus government spending plus exports minus imports. The Fair model includes the six major components of the economy = (households [h], firms [b], financials [f], international [r], federal government [g], and state government [s]) and more than one category of consumption, investment, and government spending. As a result, the GDP has a more complex restatement. We define the Real GDP (GDPR) in the ECIO model as the sum of business production, production of the financial sector (capital consumption [CCB], + before tax profits, [$PIEB$]), and government sector production (federal civilian [$JG \times HG$], and military [$JM \times HM$], and state [$JS \times HS$]) compensation of civilian and military employees). JG, JM, and JS are the number of civilian, military, and state jobs respectively. HG, HM, and HS are the average number of hours paid per civilian, military, and state job respectively. The resulting econometric equation is shown below in equation 6.

$$GDPR = Y + PIEB + CCB + PSI13 \times (JG \times HG + JM \times HM + JS \times HS) + STATP \tag{6}$$

$PSI13$ is the ratio of gross product of federal and state government to total employee hours in federal and state government, and $STATP$ is a statistical discrepancy pertaining to the use of the chain weighted data in the derivation of the variables.

2.1.6 Total Private Production and Employment

The general form of the private production equation is given in (7) and is based on the assumption that the firms in the private sector set their prices and know their sales (X) for the current period, and the firms will select what and how much to produce for the period.

$$Y = f(Y_{t-1}, X, V_{t-1}) \tag{7}$$

In equation 7, Y is GDP, X is private production sales, and V is inventory stock. Total employment (E) is the sum of employment in the private sector (JF), public civilian employment in the federal (JG) and state (JS) governments, and military employment (JM) less moonlighters (LM, persons holding more than one job) as shown in equation 8.

$$E = JF + JG + JM + JS - LM \tag{8}$$

The variables JG and JM in equation 8 are exogenously determined, and the variables JF and LM are endogenous to the ECIO model. JF is determined by total production in the private sector, number of workers on hand at the end of the previous period JF_{t-1}, the ratio of JF_{t-1} to the minimum number required to produce the output of that period ($JHMIN_{t-1}$), given an estimate of the desired number of hours worked per worker in the previous period (HFS_{t-1}) as shown in its general form in equation 9.

$$\Delta JF = f\left(\left[\frac{JF}{(\frac{JHMIN}{HFS})}\right]_{t-1}, \Delta JF_{t-1}, \Delta Y\right) \tag{9}$$

The supply of labor from the household sector is determined by four equations that explain the labor force participation rate for four groups in the labor force: labor force-men 25-54 ($L1$), labor force-women 25-54 ($L2$), labor force-all others 16+ ($L3$), and the number of moonlighters (LM). The key variables that explain the labor force are the unemployment rate (UR) and the level of total net wealth (AA). These equations take the general form shown in equation 10, below:

$$\frac{L_x}{POP_x} = f\left(\left(\frac{L_x}{POP_x}\right)_{t-1}, \left(\frac{AA}{POP}\right)_{t-1}, UR\right) \tag{10}$$

Total non-institutional population (POP) over age 16 and above is the sum of non-institutional population of men ($POP1$) and women ($POP2$) 25-54 years of age and all others above 16 ($POP3$). Unemployment (U) is explained as the difference between total labor force and number of people employed as shown in equation 11.

$$U = L_1 + L_2 + L_3 - E \tag{11}$$

2.2 *Industrial Output Module*

The objective of the industrial output module is to create a projection of total output that accounts for the energy economic shock being considered (e.g., the penetration of a new energy technology), changes in the IO coefficients, and temporal changes in final demand. It also provides an accounting framework to ensure the supply side of the economy is consistent with the demand side. The general starting point of the industrial output module is the standard IO model output disposition equations shown in equations 12 and 13.

$$X = AX + F \tag{12}$$

$$F = B \times FD \tag{13}$$

where A is the $(n \times n)$ matrix of direct coefficients that represents the amounts of the inputs required from sector i per unit of output from sector j, X is an $(n \times 1$ vector of industrial gross outputs, and F is a vector $(n \times 1)$ of industrial final demand. B is the bridge matrix from the BLS benchmark IO tables, and FD is the estimated aggregate final demand from the EC module.

For a given direct coefficient matrix, it is possible to solve the set of simultaneous equations to find new sectoral production levels, X, that are required to satisfy industrial final demands F. By rearranging and converting to differences, this equation can be rewritten in impacts form as in equation 14:

$$\Delta X = (I - A)^{-1} \Delta F \tag{14}$$

where I is an $(n \times n)$ identity matrix and $(I - A)^{-1}$, also defined as the Leontief inverse matrix, describes the direct and indirect changes in the output of each sector in response to a change in the final demand of each sector. Also, ΔF includes all elements of final demand expenditure from all six major components of the economy considered in the model. With gross output by sector determined, (inverse) productivities by sector can be used to obtain sectoral employment demand.

The standard IO solution is static and does not account for changes in economic structure over time, implying that the interdependence among industries will be constant over the projected time horizon. In the ECIO model, however, structural change is modeled using a formulation for integrated IO econometric models developed by Dick Conway (Conway, 1990). Rather than forecasting changes for every IO coefficient, Conway's approach builds on foundations laid by Leontief (1965), Tilanus and Harkema (1966) and Carter (1967) in their early studies of changes in the structure of the American economy. Given the interindustrial input-output structure for an economy for time t along with final demands for time t and $t - n$, the industrial output and or factor input requirements by industry for each year can be estimated. Differences between expected (estimated) and observed values for year $t - n$ and are a measure of structural change from $t - n$ to t. Given a time series of final demands and IO accounts for a model calibration year, the relationships among observed and expected values can be modeled econometrically and incorporated within the ECIO to account for system-wide structural economic change.[15]

The procedure to project the gross output or total demand for each sector includes the following steps. First, we compile a series of historical final demand values in real dollars (i.e., values of consumption, investment, imports, exports, and government expenditures) for the industrial sectors in the model. Next, we calculate the forecasts of industrial output by pre-multiplying historical final demand by the Leontief inverse for the model base year. With the exception of the base year, in which the interindustry and final demand structures are contemporaneous, the predicted output will differ from observed actual output (X) as a result of structural change. To correct for these differences in the interindustry structure, we regress the actual output by industry on expected industry output as shown in equation 15:

$$X = f(Z, M) \tag{15}$$

where M, will include a set of related independent variables that help explain the influence of changes in IO coefficients and Z is forecasted industrial output. The regressions typically reveal that the actual output grows more slowly or quickly than the predicted output, on a sector-by-sector basis. As the model forecasts for each year progress, the output responses to final demand for each industry are likewise adjusted according to the relationships between actual and predicted output.

[15] For a summary of the procedure for estimating expected output, see Jackson and Jarosi (2020).

2.3 *Employment and Income Module*

The employment and income module utilizes the industrial output (X) projections from the industrial output module and sectoral (inverse) productivities in units of output per employee to compute employment for the 32 industries. Sectoral employment by industry and sectoral wage rates are combined to forecast labor income by industry. Both inverse productivities and wage rates are forecast econometrically. Sums of sectoral forecasts equal national totals. Total labor income is combined with non-labor income from the FAIR model to generate total income, which is then used to update disposable income (YD). This provides a primary integrating mechanism for the EC and industrial output modules.

3 Applications of the NETL/WVU ECIO Model

The ECIO model was designed to facilitate quantitative estimation of the economic impacts of energy technology development, deployment, and operation over a forecast period consistent with the U.S. EIA's NEMS model, providing a consistent and comprehensive method for quantifying NETL's programmatic impacts. The capabilities of the ECIO model, however, do extend beyond examining the economic impacts of NETL sponsored programs. It can be used to assess potential economic impacts that result from any changes in final demand.[16] A description of an example model application is included below to demonstrate the ECIO model output structure. The presentation of results from this application are included to highlight the type of results that are standard outputs of the ECIO model. These results are intended to be demonstrative in nature and do not constitute a formal policy analysis nor serve as a detailed interpretation of scenario-specific model results. While the model is capable of producing results for various sensitivity analyses considered by the user, sensitivity analyses are not included given the demonstrative nature of the example application.

3.1 *Example Model Application*

NETL carbon capture and storage (CCS) RD&D efforts seek to decrease the cost of capturing carbon dioxide (CO_2) from fossil fuel energy plants dramatically relative to technologies that are available commercially. NETL RD&D aims to decrease the cost of electricity (COE) and of CO_2 capture, and to increase base power plant efficiency, thus lowering the amount of CO_2 that needs to be captured and stored per kilowatt hour (kWh) of electricity generation. As a supplement to analyzing the potential of these impacts in terms of changes to electricity generation and capacity, the ECIO model can be used to provide estimates of the economic impacts of such RD&D efforts.

Specifically, as part of their CCS program effort NETL is interested in quantifying the economic impact of NETL RD&D in a scenario with CO_2 storage tax credits. A storage tax credit would provide a tax credit per ton of CO_2 used for enhanced oil recovery (EOR) or CO_2 sent to geologic storage for power generation and industrial CCS. Several scenarios were generated and converted into ECIO inputs using a version of the NEMS model modified by NETL to integrate CCS activities and markets, the NETL Capture, Transport, Utilization, and Storage NEMS (CTUS-NEMS) model. To demonstrate the operation and output of the ECIO model, a model run comparing a reference case to a program goals case is presented. The details of the two cases are below. Results should be interpreted at the national level.

Reference Case (RC): A scenario based on the 2016 AEO Reference Case (No Clean Power Plan) (EIA 2016); plus:

- 5% lower natural gas and oil resources and lower production technology improvements
- Lower EOR operation and maintenance (O&M) costs
- High macroeconomic growth (2.8%/year increase) and high electricity demand (2%/year increase)
- Very low-cost heat rate improvements
- Removes requirement to retire 14 gigawatts (GW) of planned coal retirements from 2017 onward

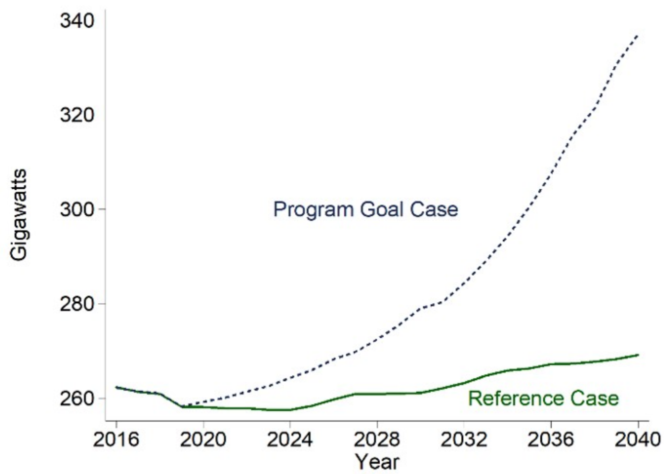
[16] Examples of changes in final demand include an increase in foreign exports, the substitution of imports from new products being developed domestically, or the construction and operation of a new facility (e.g., a new oil refinery).

Program Goal Case (PGC): Reference Case, plus:

- CO_2 storage tax credits that provide \$35/ton CO_2 for EOR and \$50/ton CO_2 sent to geologic storage for power generation and industrial CCS for 12 years
- CCS power plant Program Goals are included. These goals involve lowering the cost of capturing CO_2 from fossil fuel power plants dramatically compared to today's commercially available CCS technologies. Successful CCS RD&D program goals are assumed to lead to lower capital costs, earlier commercial deployment, and greater plant efficiency[17]

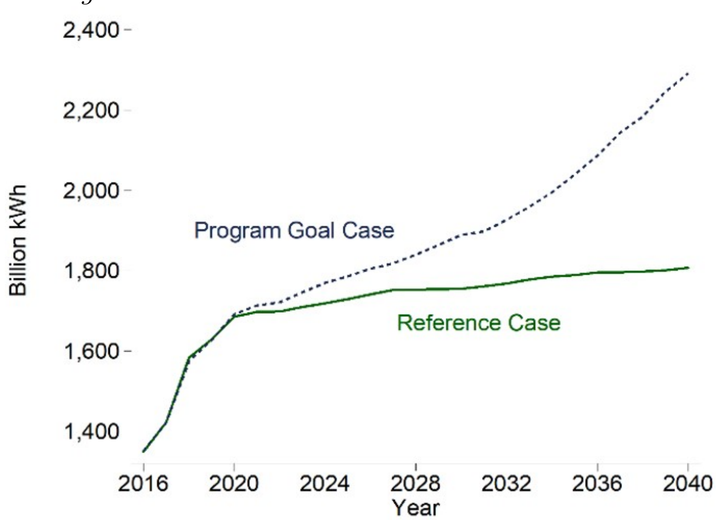
As shown in Figure 2, NETL CTUS-NEMS results show over the forecast period across the U.S. a total of 80 GW of coal fired capacity with CCS is built under the PGC, while only 13 GW of coal fired capacity with CCS is built under the reference case.

Figure 2: Total Coal-Fired Power Generation Capacity Additions



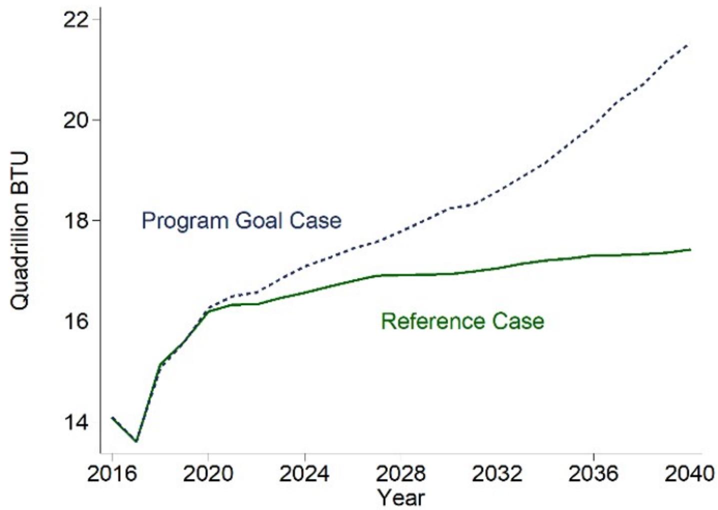
NETL CTUS-NEMS results show in response to coal-fired power generation capacity with CCS being added, power generation from coal and consumption of coal in the power generation sector increases, as shown in Figures 3 and 4. Coal consumption in the power generation sector and power generation from coal are higher under the PGC.

Figure 3: Total Coal-Fired Power Generation



[17]Assumptions for the storage tax credit of the PGC (reference case plus) are based the Internal Revenue Service (IRS) Section 45Q tax credit, a performance-based tax credit offered per ton of CO_2 sequestered (DOE 2019). CCS power plant Program goals are demonstrative in nature but meant provide an example of some of NETL's R&D goals related CCS.

Figure 4: Power Generation Coal Consumption



To quantify GDP, employment, and income impacts, results from the NETL CTUS-NEMS model were passed through a translation tool developed by NETL to create scenario-specific ECIO model inputs. The difference between the two scenarios is interpreted as the impact of both storage tax credits and NETL RD&D in a scenario with high oil and gas prices, lower EOR costs, and strong economic and electricity demand growth. The resulting cumulative national impacts include 3.5 million job years, $175.1 billion in income, and $315.6 billion in GDP.

Annual impacts, which represent differences in employment, labor income, and GDP relative to the base case are shown in Figure 5. Small negative impacts in early years reflect differences in the timing of capital expenditures across scenarios.[18]

Figure 5: Overall Economic Impacts

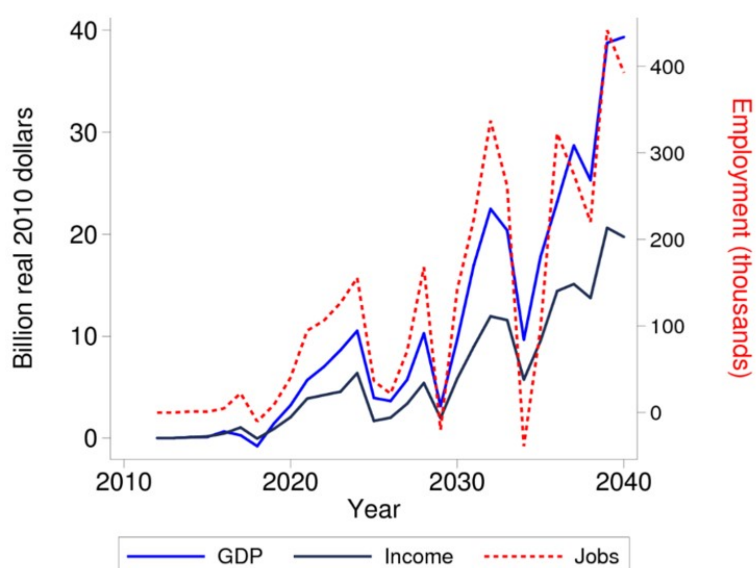


Figure 6 and Figure 7 show job and income impacts by industry. Employment impacts were largest in the Construction sector (Sector 9), the Educational services, healthcare, and social assistance sector (Sector 29), and Retail Trade (Sector 18), while income impacts were the largest in sectors 9, 29, and 26, the Professional,

[18] Figure C1 in Appendix C compares the estimated total output impacts produced by NEMS MAM and the ECIO model.

scientific, and technical services sector. The differences in job and income sectoral impact rankings reflect inter-sectoral differences in wage rates.

Figure 6: Employment Impacts by Industry

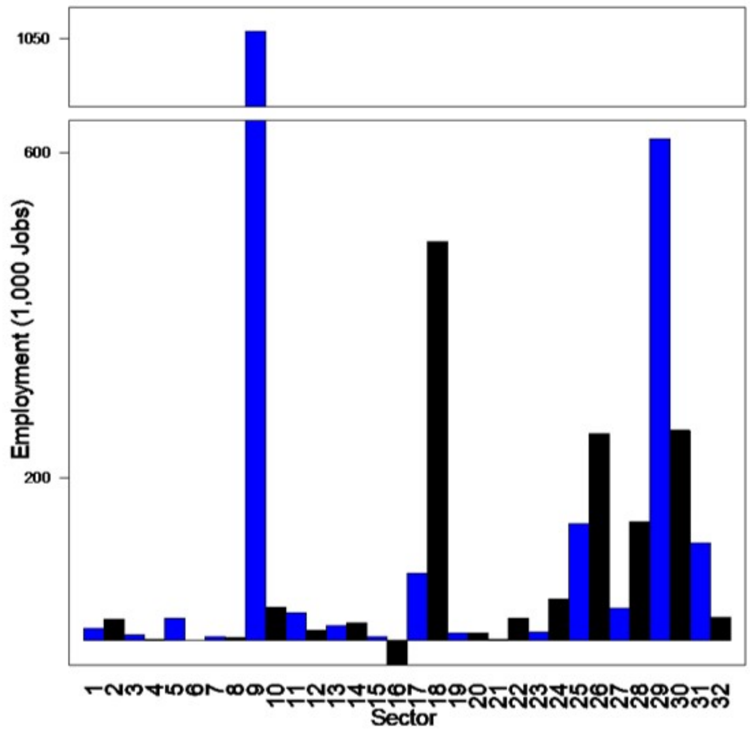
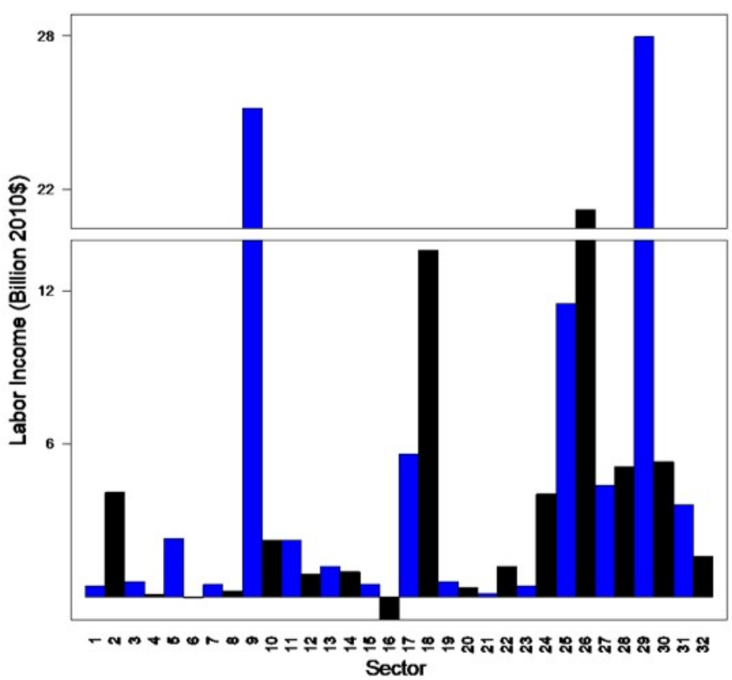


Figure 7: Income Impacts by Industry



4 Conclusions

The NETL/WVU ECIO model processes a set of energy technology and economic information to estimate changes in GDP, jobs, and income that result from a variety of long-term energy-economy forecast scenarios. The model was developed by NETL and WVU as a complement to the NEMS framework, specifically the NETL CTUS-NEMS model, providing an alternative frame of reference that can overcome certain insensitivities of macroeconomic parameters within NEMS to large changes in energy-related prices and RD&D spending. The ECIO model was designed to be dynamic and transparent methodologically.

The ECIO model leverages the strengths of macroeconometric time-series relationships and the strengths of the interindustrial structural relationships of the IO framework. It embeds the salient features of energy systems analysis from NEMS while, like all ECIO models, it "focuses on the inclusion of important structural dynamics into the analytics. The EIO approaches introduce a dynamic time path for the economy; this means that the model does not have to return to equilibrium, allowing the underlying dynamics to better replicate reality" (Crawley and Hewings 2020, p. 4).[19] In comparison to the NEMS framework, the ECIO model has less overall price sensitivity, but does incorporate scenario-specific energy sector price determinations. In general, whereas at its core, NEMS is an energy-systems model, the ECIO is a more general economic systems model. Just as ECIO leverages the strengths of macroeconometric forecasting and IO, it can also take advantage of the superior energy-systems capabilities of NEMS, MARKAL, or similar models.

The ECIO model integrates a macroeconomic econometric forecasting framework with an IO framework. It has three main modules: 1) macroeconomic econometric module, 2) industrial output module, and 3) the employment and income module. Input data come from a variety of sources including the FAIR macroeconometric model, the U.S. Bureau of Labor Statistics, and CTUS-NEMS. Notable modeling capabilities include the ability to adapt to and include changes to energy sector prices and updates to the aggregated electricity generation, transmission, and distribution sector.

The example case presented demonstrates the ECIO model's capabilities along with its standard model outputs. Details on jobs and income impacts are presented for 32 industrial sectors. The magnitudes and sectoral distributions of impacts can contribute to critical decisions on energy policy and federal RD&D programs. The input scenario can accommodate exogenous system shocks throughout the forecast horizon and is sensitive to the timing and distribution of investment by investment type.

Several priority model extensions have been identified. At present, the technology mix within the power generation sector must be pre-specified, and a composite production function time series is generated for the forecast horizon. A priority extension is to collect and incorporate better data on existing energy technologies and their production functions to create standalone power generation sectors distinguished by type. This will provide a mechanism for introducing additional power and non-power generating industries to the model, to accommodate modeling entirely new technologies. This will further enable greater control over scenario development and specification, and increased impacts detail for power-generating technologies.

In an earlier version of the model, a rudimentary regional impacts module was developed to provide estimates of impacts at the subnational level. The regionalization method was effectively an enhanced proportional allocation technique that was used to distribute national impacts to subnational regions based on a combination of pre-shock distributions of industry activity and locations of direct investments. However, the approach proved not to be robust to a wide variety of impacts, particularly when the scenario included a mix of positive and partially offsetting negative shocks. Future versions of the ECIO model will incorporate a more sophisticated, bottom-up, rather than top-down, regional impacts allocation module.

As is the case with the multi-year development of many new modeling approaches, the ECIO model was developed using a set of software tools that made it necessary to run the model as a multi-step process. For this reason, and because it has proved its utility as a complement to NEMS, it is now benefitting from a consolidation and porting of supporting code to a single programming language, which will facilitate operation. As the model continues to develop, ECIO will continue to adapt to and support the application needs of NETL.

[19] In Crawley and Hewings (2020) EIO is an acronym used for econometric input-output.

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Appendix A: Notation

A: matrix of direct coefficients

AA: total net wealth

AG: age distribution of population

B: bridge matrix

C: personal consumption expenditures

CCB: capital consumption

CD: consumption of durable goods

CN: consumption of non-durable goods

COG: federal government consumption and investment of goods purchased

COS: state government consumption and investment of goods purchased

CS: consumption of services

$DELH$: depreciation rate of housing stock

$DELK$: physical depreciation rate of capital stock

E: total employment

EX: exports

F: industry final demand

FD: aggregate final demand from Macroeconomic Econometric module

$GDPR$: real gross domestic product

HG: average number of hours paid per civilian job

HM: average number of hours per military job

HS: average number of hours per state job

IHB: firm residential investment

IHF: financial sector residential investment

IHH: household residential investment

IKB: firm non-residential fixed investment

IKF: financial sector non-residential investment

IKG: government sector nonresidential investment

IKH: household non-residential investment

IM: imports

IVF: financial sector inventory investment

JF: jobs in private sector

JG: civilian jobs

$JHMIN$: minimum number of jobs required to produce the output of that period

JM: military jobs

JS: state jobs

KH: housing stock

KK: stock of capital

L: labor force

LM: moonlighters

M: set of related independent variables that help explain the influence of changes in input-output coefficients

PF: domestic price level

PH: price deflator of consumption

$PIEB$: before tax profits

PIM: import price level

POP: total population

$PSI13$: ratio of gross product of federal and state government to total employee hours in federal and state government

R: interest rate

RMA: mortgage interest rate

$STATP$: statistical discrepancy pertaining to the use of the chain weighted data in the derivation of the variables

U: unemployment

V: stock of inventory

X: industry gross output

Y: gross domestic product

YD: disposable income

Z: forecasts of industrial output

Subscripts

t: time

i: sector

Appendix B: Description of Sectors of in the ECIO model's IO module

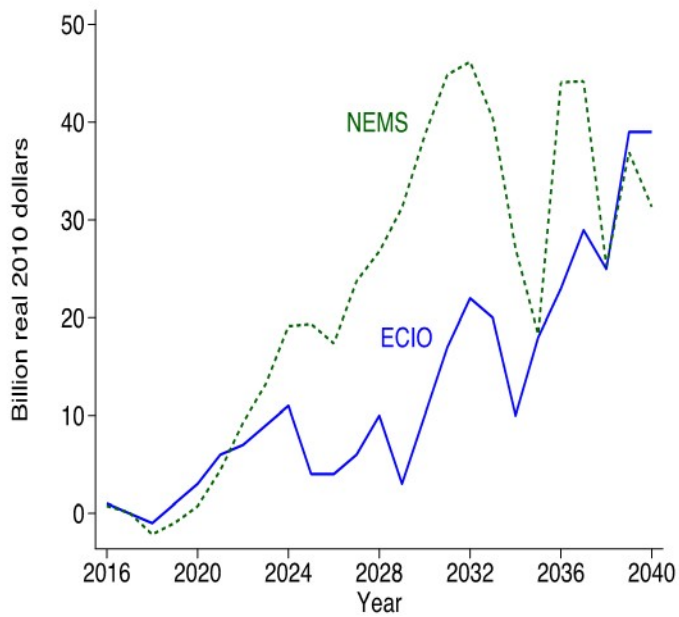
Table 1: ECIO Model Sector Descriptions

Code	Sector Name	NAICS Codes
IND 01	Agriculture, forestry, fishing, and hunting	11
IND 02	Oil and gas extraction	211, 21311
IND 03	Coal mining	2121
IND 04	Mining, except coal, oil, and gas	212X
IND 05	Support activities for mining	213X
IND 06	Electric power generation and distribution	2211, 491
IND 07	Natural gas distribution	2212
IND 08	Water, sewage, and other systems	2213
IND 09	Construction	23
IND 10	Primary and fabricated metals	331X, 332X
IND 11	Machinery	333X
IND 12	Motor vehicles and other transportation equipment	336X
IND 13	Other durable manufacturing	321X, 327X, 334X, 335X, 337X, 339X
IND 14	Other nondurable manufacturing	311X, 321X, 314X, 315X, 316X, 322X, 323X
IND 15	Petroleum and coal products	324X
IND 16	Chemical, plastics, and rubber products	325X, 326X
IND 17	Wholesale trade	42
IND 18	Retail trade	441-448, 451-454
IND 19	Air, rail, and water transportation	481-483
IND 20	Truck transportation	484
IND 21	Pipeline transportation	486
IND 22	Transit and sightseeing transportation and transportation support services	485
IND 23	Warehousing and storage	493
IND 24	Information	51
IND 25	Finance, insurance, real estate, rental, and leasing	52-53
IND 26	Professional, scientific, and technical services	54
IND 27	Management of companies and enterprises	55
IND 28	Administrative and support and waste management and remediation services	56
IND 29	Educational services, health care, and social assistance	6
IND 30	Arts, entertainment, recreation, accommodation, and food services	7
IND 31	Other services (except public administration)	8
IND 32	Government and non-NAICS	92

Appendix C: Comparison of total output impacts estimated via NEMS MAM and ECIO

The notable difference in impacts estimates from NEMS MAM versus the ECIO are shown in Figure C1 and likely result from the NEMS general equilibrium structure versus the ECIO's partial equilibrium impacts forecasting framework. The NEMS MAM structure could result in more rapid rebounds from shocks to equilibrium and the ECIO structure could result in greater levels of inertia due to differing wage rates and productivity forecasts. Within the ECIO model, if productivity rises, then in the face of increases in demand, fewer new workers are needed, generating lower level of income to be spent.

Figure C1: Comparison of NEMS vs. ECIO estimate of impacts to total output from RC to



PGC