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Green versus brown: Comparing the employment impacts of energy efficiency, renewable energy, and fossil fuels using an input-output model

Heidi Garrett-Peltier

Political Economy Research Institute, University of Massachusetts Amherst, 418 N. Pleasant St, Amherst, MA 01002, United States

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ABSTRACT

Global carbon emissions have reached unsustainable levels, and transforming the energy sector by increasing efficiency and use of renewables is one of the primary strategies to reduce emissions. Policy makers need to understand both the environmental and economic impacts of fiscal and regulatory policies regarding the energy sector. Transitioning to lower-carbon energy will entail a contraction of the fossil fuel sector, along with a loss of jobs. An important question is whether clean energy will create more jobs than will be lost in fossil fuels. This article presents a method of using Input-Output (I-O) tables to create "synthetic" industries – namely clean energy industries that do not currently exist in I-O tables. This approach allows researchers to evaluate public and private spending in clean energy and compare it to the effects of spending on fossil fuels. Here we focus on employment impacts in the short-to-medium term, and leave aside the long-term comparison of operations and maintenance employment. We find that on average, 2.65 full-time-equivalent (FTE) jobs are created from $1 million spending in fossil fuels, while that same amount of spending would create 7.49 or 7.72 FTE jobs in renewables or energy efficiency. Thus each $1 million shifted from brown to green energy will create a net increase of 5 jobs.

1. Introduction

Employment in the clean energy sector, or so-called "Green Jobs," has become an important issue politically as an avenue to reduce unemployment while growing the economy on a sustainable path. Carbon emissions have reached an unsustainable level, and the global energy system must be transformed in order to limit global climate change to a 2 degree Celcius rise above pre-industrial levels by 2100 (Bruckner et al., 2014). Many studies have evaluated the relationship between economic growth, energy use, and emissions (Bloch et al., 2015; Chen et al., 2016; Narayan et al., 2016). There is debate both among economists and environmentalists as to whether economic growth is necessary and what level is sustainable. "Green Growth" is sometimes seen as a way for standards of living to rise while carbon emissions fall (e.g. Pollin et al., 2014).

National governments have long used both fiscal policy and regulation in the energy sector. Fiscal policy has included tax preferences, direct public spending, loan guarantees and other financing mechanisms, investments in research and development, and many other forms of financial support and incentives. In simultaneously addressing questions of job creation, emissions reduction, and energy use, it is important to understand the economic effects of energy policy and public spending within the energy sector. Particularly when the policy goal is to reduce unemployment, it is useful to compare the employment effects of clean energy as opposed to fossil fuels. For a given level of public spending, how many jobs would be supported by renewable energy (RE) and energy efficiency (EE) industries compared to fossil fuel (FF) industries? What would be the net effect on employment if spending shifts from fossil fuels to clean energy?

There is a small but growing body of literature examining the economic benefits of a clean energy transition, including those of job creation (Pollin et al., 2014; Lehr et al., 2012). While the peer-reviewed literature is still limited and the impacts on employment are sometimes noted as being disputed (Lambert and Silva, 2012), a number of researchers using input-output modeling have found positive employment impacts resulting from the growth of renewable energy industries (Malik et al., 2014; Markaki et al., 2013; Tourkolias and Mirasgedis, 2011) Input-output models are often used for these studies because they have the advantage of being transparent, having few assumptions built in, are easily replicable, and are built from current or recent data from national accounts.

One current drawback of using I-O models to study clean energy impacts is that renewable energy industries and energy efficiency industries are not explicitly identified as industrial categories in national accounts. While industries such as oil extraction, natural gas distribution, and petroleum refining exist in most national accounting

E-mail address: hpeltier@econs.umass.edu.

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systems, industries such as wind, solar, or home weatherization do not. Thus we cannot readily compare the employment impacts of demand for fossil fuel to demand for clean energy, making policy assessment difficult. Some researchers have overcome this obstacle by disaggregating and re-aggregating the industries in the I-O tables in order to separate green from traditional activities, or by adding a new set of industries to the existing tables (Malik et al., 2014; Garrett-Peltier, 2011).

A re-aggregation approach is useful for analyzing mature industries and has been used to study "satellite accounts" such as the Health Care Satellite Account and the Travel and Tourism Satellite Accounts of the U.S. Bureau of Economic Analysis (U.S. BEA). The main drawback to such an approach is the collection or availability of data sufficient for detailed disaggregation, a problem that is particularly concerning with nascent industries such as clean energy. This re-aggregation approach is generally time-consuming, requiring detailed survey data as well as compilation and re-balancing of the input-output tables.

This article presents an alternative approach for analyzing the employment impacts of renewable energy and energy efficiency industries. I use an input-output model, but rather than re-aggregating the tables to separate green from non-green activities, I treat clean energy spending as a demand shock. That is, I treat additional spending as investments in the industry, and simulate the effects of expanding the clean energy sector by creating vectors of demand that include the manufacturing, construction, and service industries that comprise the clean energy sector. As shorthand, I refer to this as the "synthetic industry" approach.

In essence, what the "synthetic industry" approach does is use existing data in the national accounts, in existing I-O tables. While "wind" or "solar" are not identified as industries as such, the activities and materials making up the wind and solar industries are already implicitly captured in existing I-O tables. In the synthetic industry approach, we use existing data from national accounts and create a proxy, a vector of demand for the package of goods and services making up each synthetic industry.

The advantages of the "synthetic industry" approach are twofold: First, the data requirements are fewer than those necessary for re-aggregation; and second, this method could be used as a complementary modeling technique to re-aggregation, where this "synthetic industry" approach is used to assess the initial impacts of investments in creating or expanding an industry, and then the re-aggregation technique is used to model ongoing operations and maintenance of an established industry.

In this article I perform synthetic industry analysis for renewable energy industries such as wind, solar, and bioenergy, as well as for energy efficiency industries including building weatherization, mass transit and freight rail, and electrical grid upgrades. I build from the methods first presented in Garrett-Peltier (2011) but update with the most recent data available, which are the 71-industry "Summary" tables for 2013 from the U.S. BEA. In addition, I generate new cost vectors for various renewable and efficiency industries and compare the results with those using previously-established cost structures. I then present a method of analyzing the sensitivity of the results to the choice of specification.

I present the methodology for simulating demand for RE and EE industries, then use existing literature and survey data to form vectors of demand. I estimate employment multipliers for 9 clean energy industries and 2 fossil fuel industries. I then present a simple policy example estimating the overall impact of shifting $1 billion in fossil fuel subsidies into investments in renewable energy or energy efficiency. I provide the weights used in composing all of these 11 energy industries to allow replication by other researchers.

I find that on average, renewable energy creates 7.49 full-time-equivalent (FTE) jobs per $1 million spending, energy efficiency creates 7.72 FTE jobs per $1 million spending, and fossil fuels create 2.65 FTE jobs per $1 million spending. These job numbers include both direct and indirect (supply-chain) jobs, and the multipliers are the same regardless of whether the source of demand is public or private spending. It is important to note that these employment effects are relevant for the short-to-medium term, in which an expansion of clean energy involves significant increases in manufacturing and installation of renewable and efficiency technologies. Here we leave aside the long-run comparison of operations and maintenance employment in the energy sector. Overall, I find that the expansion of clean energy creates three jobs for each job lost in the fossil fuel sector, and for each $1 million shift from fossil fuels to clean energy, an average of five additional jobs are created.

2. Data and methods

2.1. Brief background on input-output analysis

Input-output (I-O) analysis is useful in estimating the impact of changes in demand for the output of an industry or group of industries. I-O tables provide a "snapshot" of the economy. In any given year, they show the inputs used by each industry, the outputs produced by each industry, and the relationship between industry output and final demand among various users.

I-O tables are constructed from surveys of businesses as well as from administrative records and are generally available at various levels of detail ranging from sector (~12 industries) to detailed or benchmark tables (~400–500 industries). In the U.S., benchmark tables are produced by the U.S. BEA every 5 years, include approximately 500 industries, and are updated annually to produce sector and summary level tables. I-O tables provide a useful framework for policy and business analysis (Horowitz and Planting, 2009). A detailed description of the basic I-O framework is readily available in publications such as Miller and Blair (2009).

The U.S. BEA's I-O tables include a "make" table (the commodities produced by each industry), a "use" table (the use of commodities by intermediate and final users), a "direct requirements" table which is an algebraic manipulation of the make and use tables showing the amount of a commodity required by an industry to produce a dollar of the industry's output, and a "total requirements" table which is also known as the "Leontief Inverse Matrix," described below.

The I-O model allows us to estimate economy-wide impacts of investments in a range of RE and EE technologies, and thus has useful macroeconomic implications. Further, it also allows us to evaluate the effects on specific sectors and industries, which is useful for industrial policy as well as employment, training, and readjustment policies.

The input-output model I will use here to study the EERE (Energy Efficiency and Renewable Energy) industry is based on the U.S. BEA 2013 annual tables at the 71 industry ("summary") level. The BEA "Total Requirements" table shows how an increase in demand for a particular industry's product will lead to increased output in that industry and all related industries. For example, an increase in demand for farm products would increase farm output and would also increase output in other industries that provide inputs to the farm industry, such as fertilizer and farm machinery manufacturing. The total requirements table will be an $n \times n$ matrix where n is the number of industries. Once we obtain this table, we can post-multiply it by a vector of final demand (Y) to estimate the effects on output (X). Thus our basic equation to estimate a change in output resulting from a change in final demand is:

$$\Delta X = (I - A)^{-1} \Delta Y$$

Where $(I\text{-}A)^{-1}$ is the Leontief inverse matrix or "Total Requirements" table.

Using the above impact equation, we can see how changes in alternative types of final demand (personal consumption, private investment, federal government expenditures, or exports) affect output. We can also isolate a change in final demand for one industry or a group of industries (for instance, increased procurement of solar panels by the federal government) to estimate the economy-wide impacts of such a demand shock.

2.2. Creating vectors of demand to model renewable energy and energy efficiency

In comparing the effects of spending on clean energy versus spending on fossil fuels, we are interested in the total change in output, ΔX, that results from an increase in demand, ΔY. In established industries, such as coal mining, we can simply use the Leontief inverse matrix to obtain the output effects from an increase in demand. But to estimate the impacts from a change in demand for a group of industries, we need to form our vector of demand, ΔY, where we allocate shares across the various industries. Below we present a method for doing this for clean energy.

I-O tables in the U.S. are based on the North American Industrial Classification System (NAICS), which currently does not identify any renewable energy or energy efficiency industries. The only energy-related industries identified in the BEA I-O tables are oil/gas extraction, coal mining, support services for these extraction activities, power generation and distribution, and various petroleum- or coal-based manufacturing activities. Renewable energy industries such as wind, solar, bioenergy, geothermal, and so on, are not explicitly identified. Energy efficiency industries such as building weatherization, "Smart Grid",[1] energy-efficient appliances, and so on are also not explicitly identified. Nonetheless, the activities of these industries are captured implicitly in the input-output accounts. For example, the manufacture of hardware and electrical equipment used for solar panels are categorized respectively in the hardware and electrical equipment industries. If we can thus identify the various components and their weights that make up the energy efficiency and renewable energy (EERE) industries, we can study the impact of increased demand for EERE products and services. The methodology for what I am calling the synthetic industry approach is presented in Miller and Blair (2009) as one of two I-O methods to assess the impacts of a new industry.

The synthetic industry approach may serve as a complementary or alternative strategy to gathering survey data and explicitly identifying EERE industries in order to augment or re-aggregate existing I-O tables, or what I will call the "integrated approach". The integrated approach presented in Garrett-Peltier (2011) models both forward and backward linkages between various industries, with the EERE industry as both a consumer and producer of goods and services. This approach is what Miller and Blair (2009) refer to as "complete inclusion in the technical coefficients matrix." In the synthetic approach presented here, however, I simulate an exogenous increase in final demand for the goods and services used in the EERE industry. This method requires data for the inputs into EERE production without requiring knowledge of the structure or magnitude of demand for output from EERE industries. As noted by Tourkolias and Mirasgedis (2011), in most countries the size of the renewable energy industry is still small and the data on inputs still limited and variable.

The exogenous demand for clean energy products could be the result of direct public spending, such as a government agency purchasing solar photovoltaic panels for its buildings, or it could be private spending by businesses or households, perhaps incentivized by government tax or regulatory policy. In order to simulate this increased demand, we calculate a bill of goods, or demand vector, that is essentially a weighted average of various industries that exist within the I-O tables. To estimate the weights and industries involved, we could use survey data, expert interviews, financial data from energy industries or firms, or various other sources. Ideally we would implement a survey on a large enough scale that it is representative of the geography and industries in our I-O tables. But since this type of survey can be time-consuming and costly, we can instead rely on survey data that has already been collected.

For example, in generating the demand vector for the wind energy industry, I rely on data from a survey conducted by the European Wind Energy Association (EWEA, 2004), as previously presented in Garrett-Peltier (2011). The EWEA administered a survey of various European firms in the wind energy industry, eliciting data on the components and costs of wind turbine production. The EWEA publication shows that for wind turbine manufacturing, the various components and their shares of total costs are as follows:

37% machinery
26% construction
12% fabricated metal products
12% plastic products
7% scientific/technical services
3% mechanical power transmission equipment
3% electronic connector equipment

In order to generate a vector of demand for wind energy, we map this survey data into the industrial categories of our I-O table, which may be more or less aggregated than the survey data itself. The industries and weights for the wind industry, as well as other energy industries, are shown in Table 1.

Similarly, to construct vectors of demand for building weatherization, I rely on survey data from the U.S. Department of Energy. For home weatherization, I use data on home energy consumption from the U.S. Department of Energy's *Residential Energy Consumption Survey* (U.S. DOE, 2013). I attribute 30 percent of the total spending on home weatherization to the construction industry, then allocate the remaining 70 percent to materials and technologies based on their shares in home energy consumption, which is 41.5% space heating, 34.6% appliances, electronics and lighting, 17.7% water heating, and 6.2% air conditioners, as shown in Table 4.

To create a synthetic industry representing commercial retrofits, I refer to a 2012 U.S. Department of Energy report on the Energy Service Company (ESCO) industry (Larsen et al., 2012). In particular, Figure 6 of this report shows a variety of energy efficiency measures installed by ESCO companies, according to a database of ESCO projects maintained by the Lawrence Berkeley National Laboratory. I select the five most implemented projects: lighting; controls; distribution/ventilation; boilers; and water conservation. I develop a new vector of demand for commercial retrofits that is composed of 30 percent construction (installation), with 70 percent of costs evenly distributed across the five technologies and measures just listed. The resulting industry shares are included in Table 4.

In Tables 1 and 2 I present vectors of demand that were previously constructed (Garrett-Peltier 2011; Pollin et al., 2015), and in Tables 3 and 4 I present vectors of demand that I have newly constructed from secondary data. In some cases, those data were drawn from extensive surveys or databases of projects (such as the database of thousands of ESCO projects maintained by the Lawrence Berkeley National Laboratory), and in other cases the data result from a combination of sources, such as business journals, industry associations, and tenders (e.g. IRENA (2012a) and IRENA (2012b)). In all cases, I used the costs and components identified by these various agencies and organizations, assigned I-O industry categories to the components, and assigned weights as presented in Tables 3 and 4.

[1] "Smart Grid" is a term used to describe a modernized electricity transmission infrastructure which relies on information-technology to increase reliability and reduce demand of the electrical grid system. The Smart-Grid is more interactive and distributed than the current electrical grid in that it allows end-users to interface with power use through 'Smart Meters' and allows for more de-centralized power production (such as wind and solar) to be distributed to users. For more information, see for example publications by the U.S. Dept. of Energy's Office of Electricity & Energy Reliability, accessible here: http://www.oe.energy.gov/smartgrid.htm.

Table 1
Weights in Garrett-Peltier 2011.

I-O Industry (from 71-industry table)	**Synthetic EERE Industry**						**Fossil Fuels**	
	Weatherization	Mass Transit & Freight Rail	Smart Grid	Wind	Solar	Biomass	Oil & Gas	Coal
Farm products (unprocessed)	–	–	–	–	–	0.250		
Forestry, fishing and related	–	–	–	–	–	0.250		
Oil and Gas extraction							0.300	
Coal Mining								0.440
Support activities for extraction and mining							0.040	0.080
Natural gas distribution							0.100	
Construction	1.000	0.450	0.250	0.260	0.300	0.250		
Petroleum and Coal Products							0.530	0.480
Chemical products	–	–	–	–	–	0.125		
Plastics and rubber products	–	–	–	0.120	–	–		
Fabricated metal products	–	–	–	0.120	0.175	–		
Machinery	–	–	0.250	0.370	–	–		
Computer and electronic products	–	–	0.250	0.030	0.175	–		
Electrical equipment, appliances, and components	–	–	0.250	0.030	0.175	–		
Rail transportation	–	0.100	–	–	–	–		
Transit and ground passenger transportation	–	0.450	–	–	–	–		
Pipeline transportation							0.030	
Miscellaneous professional, scientific and technical services	–	–	–	0.070	0.175	0.125		
sum of weights	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 2
Weights in Pollin et al. 2015.

	Wind	Solar	Bioenergy	Geothermal	Hydro (small)	Weatherization	Industrial EE	Smart Grid	Oil and Gas	Coal
Farms			0.250							
Forestry, fishing, and related activities			0.250							
Oil and gas extraction									0.500	
Mining, except oil and gas										0.500
Support activities for mining				0.150						
Construction	0.260	0.300	0.250	0.450	0.180	1.000	0.200	0.250		
Fabricated metal products	0.120	0.175			0.180					
Machinery	0.370	0.175		0.100	0.070		0.500	0.250		
Computer and electronic products	0.030	0.175						0.250		
Electrical equipment, appliances, and components	0.030				0.140			0.250		
Petroleum and coal products									0.250	0.500
Chemical products			0.125							
Plastics and rubber products	0.120									
Pipeline transportation									0.250	
Miscellaneous professional, scientific, and technical services	0.070	0.175	0.125	0.300	0.430		0.300			
Sum of weights	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 3
Composition of RE industries using alternative cost structures.

	Wind – Tegen et at. (2013)	Wind - IRENA (2012b)	Wind (onshore) B & V (2012)	Solar PV (central) – B & V (2012)	Solar - IRENA (2012a)	Solar -BNEF - SEA 2013	Geothermal – B & V 2012
Support activities for mining							0.390
Construction	0.200	0.276	0.255	0.095	0.125	0.290	0.250
Nonmetallic mineral products	0.030	0.160		0.120	0.050		
Fabricated metal products	0.160	0.160	0.340	0.410	0.210	0.200	0.140
Machinery	0.370						
Computer and electronic products					0.385		
Electrical equipment, appliances, and components	0.150	0.314	0.340	0.330	0.122	0.250	0.080
Truck transportation	0.030						
Insurance carriers and related activities	0.030						
Miscellaneous professional, scientific, and technical services	0.020	0.090	0.040	0.020	0.109	0.210	0.070
Management of companies and enterprises	0.010		0.025	0.025		0.050	0.070
Sum of weights	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 4
Composition of Residential and Commercial Energy Efficiency from DOE cost sources.

	Home weatherization	Commercial Retrofits
Support activities for mining		
Construction	0.300	0.300
Nonmetallic mineral products		
Fabricated metal products		0.140
Machinery	0.414	0.140
Computer and electronic products		0.140
Electrical equipment, appliances, and components	0.286	0.140
Truck transportation		
Insurance carriers and related activities		
Miscellaneous professional, scientific, and technical services		0.140
Management of companies and enterprises		
Sum of weights	1.000	1.000

2.3. Generating the Employment Requirements Table

To study the effects on employment, rather than simply output, we must convert our Leontief Inverse Matrix into an Employment Requirements (ER) Table. This table is used to estimate the number of jobs throughout the economy that are needed, both directly and indirectly, to deliver $1 million of final demand for a specific product or service. In order to create the employment requirements table, we first need to obtain employment/output ratios for each industry in the model. Here we use gross output by industry as well as full-time-equivalent (FTE) employment by industry from the BEA tables (US. Bureau of Economic Analysis 2015a, 2015b). We use 2013 data for both FTE employment and Gross Output.

To create the employment requirements table, ER, we take the diagonal matrix of employment/output ratios, e, and post-multiply it by the Leontief inverse matrix as follows:

$$ER = e(I - A)^{-1}$$

Where $(I\text{-}A)^{-1}$ is the Leontief inverse table and e is the diagonal matrix, both of which have the dimension 71×71.

The employment requirements table shows us both the number of jobs directly created and indirectly created, as a result of demand for a particular industry's product. For example, if demand for coal mining is $1 million, we can immediately see both the number of coal mining industry jobs (direct jobs) supported by this demand, as well as the number of jobs supported in other industries such as trucking and mining equipment manufacturing which supply inputs to the coal mining industry (indirect jobs). While the Leontief inverse matrix yields output requirements and an output multiplier, the employment requirements table yields employment requirements and an employment multiplier. Each industry will have a unique multiplier.

We can use this framework to see how an increase in spending in any industry will generate jobs. The basic impact equations are:

$\Delta X = (I\text{-}A)^{-1}\Delta Y$ (to measure change in output); and

$\Delta X = ER\Delta Y$ (to measure change in employment).

The employment multipliers from this static model include both direct and indirect employment resulting from a given type of demand. The direct employment effects are found along the diagonal of the ER matrix. The indirect effects for a given industry are the sum of all of the values in a column of the ER matrix, minus the direct value along the diagonal.

2.4. Employment Multipliers: Understanding their use and the assumptions contained in the I-O model

We can trace the causes of differences in employment multipliers to three main reasons: labor intensity; domestic content; and compensation of workers. Labor intensity is captured by the employment/output ratio. In comparison to industries that are capital-intensive, labor-intensive industries will employ a greater number of FTE workers for the same level of output. Secondly, an industry with a higher share of domestically-produced inputs will have a higher employment multiplier. Higher domestic content implies that more output, and therefore more employment, is created within the domestic economy, rather than being imported or outsourced and creating output and employment in foreign economies. Thirdly, all else equal an industry will have a higher employment multiplier if average compensation is lower. For example, if $1 million in final demand generates $600,000 in total compensation (and the remainder in other inputs), and average compensation is $30,000, then 20 FTE workers will be employed. However, if the $600,000 is paid out to workers earning on average $60,000, then only 10 FTE workers will be employed. Thus in general, industries with higher labor intensity, higher domestic content, and/or lower compensation, will have higher employment multipliers.

2.4.1. Assumptions embodied in the input-output model

Miller and Blair (2009) note that the two main assumptions in input-output tables are those of fixed technical coefficients and fixed input proportions. Fixed technical coefficients means that the inter-industry flows from industry *i* to industry *j* depend entirely on the output of industry *j*. In other words, if the output of industry *j* doubles, its input from industry *i* will also double. Fixed proportions implies that industry *j* will use the same mix of inputs from all industries even as demand increases for industry *j*'s output. That is, the production function, which is a Leontief minimization function, is homogenous. Rather than a classical production function which assumes diminishing marginal returns, the Leontief production function assumes constant returns to scale. The returns are fixed by technology, and technology is assumed to remain constant as output grows. The BEA refers to these two assumptions as the principles of homogeneity and proportionality.

We must keep these assumptions in mind when conducting any impact analysis with the I-O tables. First, this suggests that I-O tables are best suited to studying the current state of the economy and making short-term projections and we should therefore exercise caution when using I-O models to conduct long-range forecasts. In the long-term, we would expect technological change to occur, which would change the production function and therefore the factor proportions. Furthermore, the assumption of constant returns to scale is relevant only for relatively small changes in levels of output. If an industry increases output by, say, 5 or 10 percent, we might be able to assume constant returns to scale. But a doubling of the size of the industry, such as we might expect to occur with renewable energy, will no doubt lead to changes in the returns to scale alongside changes in technology. Thus, we should exercise caution in using input-output models for long-range forecasting purposes.

Furthermore, because the data underlying the I-O tables are an “economic snapshot,” the resulting I-O tables themselves are static. Thus, we must be aware of not only homogeneity and proportionality, but also of fixed prices. If, over time, input prices change, then we would expect industries to substitute cheaper inputs for the more expensive inputs.

The limitations of the input-output model lie in these three assumptions (homogeneity, proportionality, and fixed prices) which are of course made for simplification as we know that no industry operates in this type of environment. Its strength, however, lies in the simplicity of the model and the relatively limited number of assumptions in comparison to more complex general equilibrium models which typically rely on a far greater number of assumptions.

2.5. Estimating employment multipliers for energy efficiency and renewable energy

In this article, I estimate the employment multipliers of EERE industries using the vectors of demand described above and presented here in Tables 1–4. For this analysis I use the most recent available I-O data in the U.S., the 2013 Summary level I-O tables from the U.S. BEA, which include 71 industries. I use the Industry-by-Industry Total Requirements Table, and then to calculate employment-output ratios and create the employment requirements table, I use 2013 data from the U.S. BEA for full-time-equivalent (FTE) employment and gross output by industry (U.S. BEA 2015a, 2015b).

I start by replicating the demand vectors presented in Garrett-Peltier (2011), presented here in Table 1. Next, I replicate various energy demand vectors using the industries and weights presented in Pollin et al. (2015) as presented in Table 2. I also generate new vectors of demand for RE industries using cost data from the International Renewable Energy Agency (International Renewable Energy Agency 2012a, 2012b), the National Renewable Energy Laboratory (Black and Veatch, 2012; Tegen, et al., 2013) and from Bloomberg New Energy Finance (2013). I create two new energy efficiency demand vectors – one for home weatherization based on the U.S. Department of Energy's Residential Energy Consumption Survey (U.S. DOE 2013), and one for commercial building retrofits based on an extensive database maintained by the Lawrence Berkeley National Laboratory (Larsen et al. 2012). I perform the same synthetic industry analysis with these various cost data in order to compare my results with those generated from previous cost assumptions. The alternative weighting assumptions are presented in Tables 3 and 4.

3. Results and discussion

3.1. Employment multipliers

The employment multipliers for RE (wind, solar, bioenergy, hydro, and geothermal), EE (building weatherization, freight rail & transit, industrial EE, and Smart Grid), as well as for FF (oil & gas and coal) are presented in Table 5. It is important to note that the multipliers for RE and EE relate specifically to the expansion of these industries, and thus are composed primarily of manufacturing and construction industries as well as related goods and services. The multipliers do not represent operations and maintenance employment in RE or EE and thus should not be used for comparisons of clean energy and fossil fuel employment in the long run.

We find that on average, $1 million of demand for RE generates 7.49 FTE jobs (4.50 direct plus 2.99 indirect). That same level of demand generates 7.72 FTE jobs in EE (4.59 direct, 3.13 indirect). These averages are nearly three times the level of job creation in FF, which averages a total of 2.65 FTE jobs per $1 million demand (0.94 direct, 1.71 indirect). Below, as well as in Table 5, we present the estimates for individual industries that make up these averages.

Table 5
Employment multipliers for renewable energy.

	Direct FTE Jobs per $1 million	Indirect FTE Jobs per $1 million	Total FTE Jobs per $1 million
Wind (a)	3.91	3.53	7.45
Wind (b)	3.91	3.53	7.45
Wind (c)	3.88	3.61	7.48
Wind (d)	4.29	3.28	7.57
Wind (onshore) (e)	4.30	3.37	7.67
Average wind	**4.06**	**3.46**	**7.52**
Solar (a)	4.37	2.83	7.20
Solar (b)	4.31	2.94	7.25
Solar PV (central) (e)	4.16	3.44	7.60
Solar (f)	4.01	2.55	6.56
Solar (g)	4.46	3.12	7.58
Average solar	**4.26**	**2.98**	**7.24**
Bioenergy (a)	5.22	2.44	7.65
Bioenergy (b)	5.22	2.44	7.65
Average bioenergy	**5.22**	**2.44**	**7.65**
Geothermal (b)	**4.67**	**2.73**	**7.40**
Hydro (b)	**4.55**	**2.98**	**7.53**
Average across renewable technologies	**4.50**	**2.99**	**7.49**
Weatherization (a)	5.14	3.06	8.21
Weatherization (b)	5.14	3.06	8.21
Home weatherization (h)	3.71	3.71	7.41
Commercial retrofits (i)	4.22	3.04	7.26
Average home weatherization & commercial retrofits	**4.55**	**3.22**	**7.77**
Industrial EE (b)	**3.98**	**3.43**	**7.41**
Smart Grid (a)	3.66	3.10	6.76
Smart Grid (b)	3.66	3.10	6.76
Average smart grid	**3.66**	**3.10**	**6.76**
Mass Transit & Freight Rail (a)	**6.16**	**2.77**	**8.93**
Average across energy efficiency industries	**4.59**	**3.13**	**7.72**
Oil and Gas (a)	0.70	1.51	2.20
Oil and Gas (b)	0.71	1.48	2.19
Average oil and gas	**0.70**	**1.49**	**2.20**
Coal (a)	1.28	1.90	3.17
Coal (b)	1.08	1.94	3.02
Average coal	**1.18**	**1.92**	**3.10**
Average fossil fuels	**0.94**	**1.71**	**2.65**
Average difference renewable energy - fossil fuels	**+3.56**	**+1.28**	**+4.84**
Average difference energy efficiency - fossil fuels	**+3.65**	**+1.42**	**+5.07**

(a) Garrett-Peltier, 2011; (b) Pollin et al., 2015; (c) Tegen et al., 2013; (d) IRENA, 2012b; (e) Black & Veatch, 2012; (f) IRENA, 2012a; (g) BNEF-SEA, 2013; (h) DOE, 2013; (i) Larsen et al. 2012

3.2. Wind

Wind industry multipliers were calculated using five alternative cost structures, as presented in Tables 1–3. Despite differences in the weights and industries used, the estimates are all fairly similar. On average a $1 million increase in demand for the wind industry generates a total of 7.52 FTE jobs (4.06 direct plus 3.46 indirect). Since the I-O model is linear, this is equivalent to a $1 billion increase in demand resulting in 7520 FTE jobs.

3.3. Solar

The solar industry estimates result from five different sets of cost assumptions. Here again the range of the employment multipliers is rather narrow, ranging from a total of 6.56 to 7.60 FTE jobs per $1 million demand, for an average of 7.24 FTE jobs for each $1 million spent in the solar industry. Of these, 4.26 are direct jobs and 2.98 are indirect.

3.4. Bioenergy, geothermal, and hydropower

Bioenergy estimates result from two sources with the same cost structure. The bioenergy employment multiplier averages 7.65 FTE jobs per $1 million demand, with 5.22 direct and 2.44 indirect. Geothermal had only one source for its cost structure, and from it we estimate that 7.40 total FTE jobs are created per $1 million demand (4.67 direct, 2.73 indirect). Hydropower employment totals 7.53 FTE jobs per $1 million demand, with 4.55 of those being direct and 2.98 indirect.

3.5. Building weatherization

Table 5 presents estimates for home weatherization based on three different sources, as well as commercial building retrofits drawn from one source. Averaging home weatherization and commercial retrofits, we find the total employment generated by $1 million in demand to be 7.77 FTE jobs (4.55 direct plus 3.22 indirect)

3.6. Industrial EE, smart grid, mass transit & rail

For each $1 million spent in energy efficiency, Industrial EE supports 7.41 FTE jobs (3.98 direct, 3.43 indirect); Smart Grid, or electrical grid upgrades along with energy conserving end-use technology, supports 6.76 FTE jobs (3.66 direct, 3.10 indirect); and Mass Transit & Freight Rail creates 8.93 total FTE jobs (6.16 direct, 2.77 indirect).

3.7. Oil and gas

The extraction and production of oil and gas products is one of the most capital-intensive sectors of the economy. As expected, the employment multipliers are much lower than for RE or EE. $1 million demand for oil and gas production results in 2.20 FTE jobs on average (0.70 direct plus 1.49 indirect).

3.8. Coal

Likewise, coal extraction and processing is a heavily capital-intensive industry. For each $1 million demand for coal industry production, 3.10 FTE jobs are supported (1.18 direct plus 1.92 indirect).

3.9. Discussion

3.9.1. Interpreting employment multipliers

As discussed above, the I-O model is a static, linear model with fixed prices and fixed input and output proportions. I-O tables are useful for comparative static analysis, which is best suited for shorter time periods when we would not expect prices or production functions to change much in response to an increase in demand. Since the I-O model is a snapshot of the current state of the economy, comparative static analysis here means estimating the effects of a change in demand *given* that current state, and comparing those effects to a different change in demand given that same state. In this article we compare a $1 million change in demand for EE, RE, or FF industries, given the state of the U.S. economy in 2013. The employment multipliers we estimate are a function of the prices and production functions at that time. We would expect the multipliers to change over time, as the prices of inputs change and as labor productivity increases, particularly in the younger clean energy industries.

The I-O analysis presented here focuses only on employment, and does not address the broader welfare implications of a transition to a low-carbon economy, including the effects on personal or national income, on consumption, or other advantages or disadvantages of a transition to clean energy. Larger macro models such as CGE or econometric models could incorporate some of these effects.

Here we also note that the multipliers estimated above do not include ongoing operations and maintenance of clean energy. These multipliers would likely be quite different, and we would need to estimate separate demand vectors from data not presented here. In this article, we focus instead on the shorter-term employment effects of scaling back fossil fuel production while increasing clean energy production. Since clean energy is a relatively young industry with a lot of potential for expansion, employment in the short-to-medium term will entail a lot of manufacturing and installation of EERE technologies. As the clean energy infrastructure becomes more mature, employment multipliers in EERE will likely fall closer to, or even possibly below, those of ongoing fossil fuel operations.

The limitations of I-O analysis aside, it is nonetheless a useful method for quantifying and comparing clean energy to fossil fuels, or in comparing any two industries, since we are making the comparison at the same point in time for both. In this case, using 2013 data we have found that EE and RE industries support nearly three times as many jobs per given amount of spending as do FF industries. While the level of the individual multipliers may change slightly over time, the relative size of the EERE and FF multipliers is telling.

3.9.2. Sensitivity of EERE multipliers to input structure

The multipliers for both the wind and the solar industries vary minimally using four different cost structures from five different studies. This might imply that the results are relatively robust to the choice of demand vector specification. One other method to address the sensitivity of the results to the choice of specification would be to look at the underlying multipliers. The EERE employment multipliers generated using the synthetic industry approach are essentially weighted averages of the industries comprising each synthetic EERE industry. Therefore, we could look at the multipliers of the included industries – those in fabricated metal, construction, electrical equipment, and so on – and see what the range of these underlying multipliers is. This range would show what the minimum multiplier would be if our synthetic industry were comprised of 100% of its least labor-intensive comprising industry, versus the maximum if it were composed of 100% of the most labor-intensive underlying industry.

So, for example, in some formulations of the wind industry vector, “computer and electronic equipment,” is included, and this has a total employment multiplier of 4.74 jobs per $1 million demand, which is the lowest of all the industries that comprise the synthetic wind industry. Construction, with a total multiplier of 8.21, has the highest multiplier of the underlying industries comprising the wind industry. Thus the total employment multiplier in the wind industry could be no lower than 4.74 jobs per $1 million demand and no higher than 8.21 using any set of weights for the included industries we could specify. The median multiplier for industries comprising the wind industry is 7.24. The minimum, median, and maximum values for the underlying industries comprising the EERE industries are presented in Table 6.

Looking at the results for all the EERE multipliers presented in Table 5, we see that most are fairly close to the median value of the underlying multipliers presented in Table 6. In fact, most of the included industries are manufactured goods with fairly similar multipliers in the I-O tables. Therefore, changing the specification of the demand vector by changing the weights of the underlying industries will ultimately have very little effect on the size of the EERE multiplier. Thus the results we obtained here, using multiple studies and various cost structures, all come out to be consistent and comparable.

3.2.3 A simple policy simulation: Shifting $1 billion in public spending from fossil fuels to clean energy

Table 6
Range of incorporated multipliers across all studies - Lowest and highest values incorporated within each energy industry multiplier.

	MIN	MEDIAN	MAX
Wind	4.74	7.24	8.21
Solar	4.74	7.24	8.21
Bioenergy	3.82	7.24	12.08
Geothermal	5.43	7.14	8.21
Hydro	6.90	7.24	8.21
Home Weatherization	5.14	8.21	8.21
Commercial Retrofits	4.74	7.22	8.21
MT & FR	4.89	8.21	10.56
Industrial EE	7.20	7.24	8.21
Smart Grid	4.74	7.05	8.21

Table 7
Policy simulation – shifting $1 billion from FF to EERE.

	Reduction in FF employment (direct plus indirect)	Increase in EERE employment (direct plus indirect)	Net increase in employment from $1B shift
Scenario A: Reduce FF tax preferences by $1 billion, increase EE spending by that amount	2650 FTE jobs	7720 FTE jobs	5070 FTE jobs
Scenario B: Reduce FF tax preferences by $1 billion, increase RE spending by that amount	2650 FTE jobs	7490 FTE jobs	4840 FTE jobs

3.9.2.1. Shifting $1 billion from FF to EE. In fiscal year 2015, the U.S. federal government gave $3.7 billion in tax preferences to fossil fuel industries (CBO, 2015). Imagine shifting $1 billion of these tax preferences for fossil fuels into energy efficiency programs, such as home weatherization. While it is possible that reducing fossil fuel subsidies would only reduce industry profits without affecting output and employment, we can make the assumption here that output and employment decline in response to a $1 billion decrease, and similarly that EE expands in response to a $1 billion increase in demand. In this scenario, employment in the fossil fuel industries would fall by a total of total of 2650 jobs (940 direct plus 1710 indirect), while employment in EE industries would increase by a total of 7720 jobs (4590, direct plus 3130 indirect), for a net increase in employment of 5070 total jobs economy-wide.

3.9.2.2. Shifting $1 billion from FF to RE. Similarly, if we were to shift $1 billion out of fossil fuel subsidies and into public spending for RE, for example through procurement of renewable energy for government buildings, we can estimate the net employment effect. In this case, employment in the fossil fuel industries would fall by a total of 2650 jobs (940 direct plus 1710 indirect) while employment in RE and related industries would increase by 7490 jobs (4500 direct plus 2990 indirect), for a net increase in employment of 4840 total jobs economy-wide. Table 7 shows the results of both of these policy exercises.

4. Conclusion

In this article I have presented a method to estimate employment multipliers for industries that are not explicitly identified in input-output tables, termed “synthetic industries.” Specifically, I have estimated employment multipliers for clean energy industries including wind, solar, bioenergy, geothermal, hydropower, building weatherization, mass transit & freight rail, industrial EE, and Smart Grid. These clean energy industries are not identified as such in national accounts or in input-output tables, yet the various materials and services of which these EERE industries are composed do already exist in the tables. By creating “synthetic industries” we enable policy evaluation of green versus brown industries, or more precisely, we are able to estimate the number of jobs created by public or private spending for clean energy in comparison to spending the same amount on oil, gas, or coal production.

In order to estimate these employment multipliers, I used data on the cost structure of each clean energy industry to generate a vector of demand for the output of that industry. Using survey data, databases, and other sources of data collected by various agencies and organizations, I assigned weights to the various industries in the I-O tables that represent the component costs of the clean energy industries. I also re-created the vectors from Garrett-Peltier (2011) and Pollin et al. (2015) in order to provide a comparison with the new estimates provided in this article and to update these earlier findings with newer data.

We found that EE and RE industries generate nearly three times as many jobs as FF industries, for the same level of spending. Each $1 million spent on oil, gas, and coal supports an average of 2.65 FTE jobs economy wide (0.94 jobs directly in those industries, and 1.71 jobs indirectly created through their supply chains). In comparison, $1 million in RE supports 7.49 FTE jobs (4.50 direct plus 2.99 indirect) while that same amount in EE supports 7.72 FTE jobs (4.59 direct plus 3.13 indirect). Thus a $1 million shift from fossil fuels to clean energy generates a net increase of about five jobs. We present a simple policy scenario in which government subsidies for fossil fuels are reduced by $1 billion and that funding is invested in procurement of RE or increasing EE. This $1 billion shift from fossil fuels to clean energy results in a net increase of about 5000 FTE jobs.

A de-carbonization of the energy sector through reduced reliance on fossil fuels, increased energy efficiency, and increased use of renewables can be spurred by both fiscal and regulatory policy. Emissions reductions have become an ever-more pressing goal, and it is of paramount importance that we understand the economic impacts of public spending and other public policies concerning the energy sector. In particular, policy makers need and want to know whether investments in EE and RE will generate more employment opportunities than continuing to use energy from fossil fuels. There will certainly be job losses in fossil fuel industries as that sector contracts, but can more jobs be created than lost if we shift to more efficient use of energy and to using lower carbon energy? This is an important question that this paper has attempted to answer.

There are of course other methods to estimate employment in green versus brown industries. Extensive surveys of energy firms, or use of dynamic models such as computable general equilibrium models (e.g. AlShehabi 2013), are two other approaches. But these are generally time-consuming and often cumbersome methods. By using the synthetic industry approach presented here, we can avoid lengthy data-collection or model building exercises. By relying on survey and other data previously collected, we can create proxies for new industries such as wind, solar, home weatherization, and so on. This method allows users to more quickly assess the employment impacts of a change in energy policy, using national or regional I-O tables from any country, along with the demand vectors presented in this article.

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