TRANSFORMATION OF U.S. FOOD SYSTEM ELECTRICITY USE: MODELING EMISSIONS REDUCTION

by

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ABSTRACT

To avoid significant negative climate change consequences, the Intergovernmental Panel on Climate Change (IPCC) advises that global warming be limited to 1.5° C from pre-industrial times, a target adopted under the Paris Agreement framework. The University of Maryland Center for Global Sustainability suggests that the U.S. would remain consistent with the IPCC target by reducing emissions 51% below 2005 levels by 2030, or 44.8% below 2012 levels, my base year. This paper examines the changes necessary in primary energy sources in order for the U.S. agri-food system to reduce its emissions from electricity use by 44.8% from 2012 to 2030.

First, an environmental input-output (EIO) model is used to determine electricity consumption associated with different activities, commodities, and final uses within the U.S. food system. Additionally, electricity consumption is disaggregated by primary energy source, to which emissions levels are attributed using life cycle emissions estimates. Second, the EIO model output serves as an input into two optimization problems. Subject to the same constraints on energy use and total emissions, the first problem minimizes the cost of meeting the emissions target, while the second minimizes the change from existing electricity consumption patterns. United States Energy Information Agency (EIA) projections through 2030 for the growth of fossil-fuels, renewable energies, and nuclear are key data parameters for the optimization constraints.

Given the EIA projections, my principal finding is that the U.S. food system is not on track to reduce emissions from electricity use in a manner consistent with the 1.5°C target. That is, the optimization problems cannot yield a feasible solution given the projected growth of each energy source used for electricity generation. However, solutions for both problems become feasible by relaxing the energy type constraint—adding eight percentage points to the EIA projected growth for all energy types. The paper concludes with a discussion of policy implications, model limitations, and the potential for future research.

LIST OF ABBREVIATIONS

Billion British Thermal Units (bBTU)

Carbon dioxide equivalent (CO2e)

Emissions Gap Report (EGR)

Environmental input-output (EIO)

Food and Agriculture Organization (FAO)

Industrial processes and product use (IPPU)

Input-output (I-O)

Input-output table (IOT)

Intergovernmental Panel on Climate Change (IPCC)

International Energy Agency (IEA)

International Renewable Energy Agency (IRENA)

Land use, land use change and forestry (LULUCF)

Levelized cost of electricity (LCOE)

Life Cycle Analysis (LCA)

Linear programming (LP)

Mathematical programming (MP)

Million metric tons (MMt)

Social Accounting Matrix (SAM)

Supply and Use Table (SUT)

United Nations Environment Programme (UNEP)

United Nations Framework Convention on Climate Change (UNFCCC)

United Nations System of National Accounts (SNA)

United Nations System of Environmental Economic Accounting (SEEA)

United States Department of Commerce, Bureau of Economic Analysis (USDOC-BEA)

United States Department of Energy, Energy Information Administration (USDOE-EIA)

United States Department of Labor, Bureau of Labor Statistics (USDOL-BLS)

United States Environmental Protection Agency (USEPA)

United States Federal Reserve (USFED)

United States National Renewable Energy Laboratory (NREL)

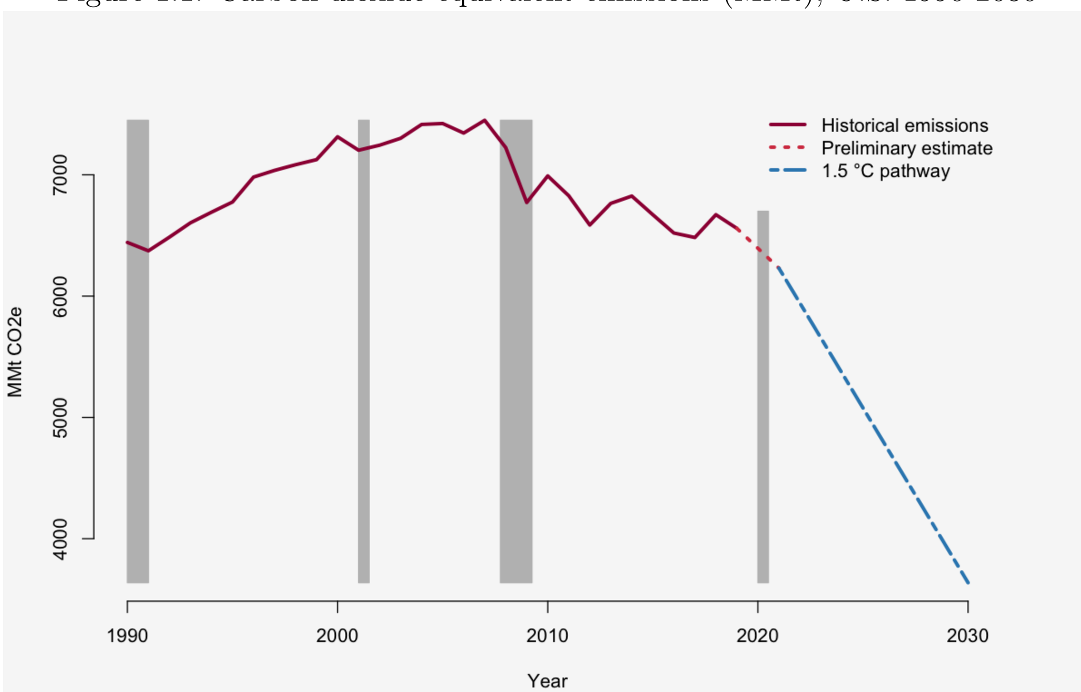
Introduction

In 2018, the Intergovernmental Panel on Climate Change (IPCC) advised that global warming must be limited to 1.5°C from pre-industrial times to avoid significant negative consequences (IPCC 2018). At 2°C warming, the IPCC predicts increased prevalence of heat waves, food insecurity, drought, flooding, and migration crises, together with greater incidence of disease, reduced GDP growth, sea-level rise, ecosystem loss, and species extinction, which all contribute to more premature deaths. Research suggests that less than ten years remain to avert "catastrophic" climate change; that the climate system is approaching "tipping points" (IPCC 2021) and a "point of no return" (Aengenheyster et al. 2018) beyond which certain damages are irreversible. Achieving the 1.5°C target requires substantial emissions reductions across all sectors of the economy, including the agri-food system, which accounted for 19.8% of emissions in the U.S. in 2019 (FAOSTAT 2021).

To meet the target, the 2021 UN Environment Programme (UNEP) Emissions Gap Report (EGR) suggests that global emissions must be reduced from 58.1 gigatons of carbon dioxide equivalent (CO2e) emissions in 2019 to 25 gigatons by 2030, a 57% reduction. Due to unprecedented Covid-19 measures, global emissions fell 5.4% in 2020 (UNEP 2021). However, preliminary estimates suggest emissions could grow 4.8% in 2021 (UNEP 2021). In contrast to the global trend, the U.S. has achieved minor emissions reductions in recent years. Excluding downturns during the Great Financial Crisis and Covid-19 pandemic, which generated reductions, the U.S. averaged an annual 0.69% decline in emissions between 2010-2019 (*see Figure 1.1*).

According to the University of Maryland Center for Global Sustainability, "emissions reductions of 51% below 2005 levels by 2030 [would] put the U.S. on a trajectory to net-zero emissions in 2050, consistent with limiting global warming to 1.5°C" (Hultman et al. 2021), which was the target announced by the Biden administration in April 2021 (Friedman and Davenport 2021). This means reducing U.S. annual CO2e emissions from 7,423 million metric tons (MMt) in 2005 to 3,637 by 2030.

Figure 1.1: Carbon dioxide equivalent emissions (MMt), U.S. 1990-2030



Data source: USEPA (2022) and USFED (2022).
Note: Recessions are shaded gray.

This paper examines the energy input changes for electricity generation that are required in the U.S. food system to remain consistent with the IPCC target of 1.5°C, assuming reductions in line with national targets. Starting from 2012—my base year—this implies a 44.8% necessary reduction in food system emissions by 2030. Using an environmental input-output (EIO) analysis framework, I model the U.S. agri-food system, identifying major energy sources and their associated emissions. Additionally, applying mathematical programming (MP) models, I determine separately the change-minimizing and cost-minimizing adjustments to energy inputs that satisfy the emissions reduction constraint while producing the same amount of food to satisfy existing demand.

1.1 Organization of the Paper

The Introduction provides an overview of agri-food system emissions, background on EIO and MP models, and the contribution of this paper to existing literature. The Data and Methods section outlines data sets used and develops the EIO and MP models. Results are presented in the Findings Section. The Discussion section reviews policy implications, model limitations, potential for future research, and concluding thoughts.

1.2 Agri-food System Emissions

The share of total emissions attributable to agri-food systems varies by country. In 2019, agri-food systems were estimated to contribute roughly one third of total emissions globally, while accounting for only 19.8% of emissions in the U.S. (Crippa et al. 2021; FAOSTAT 2021). Agri-food system emissions can be defined as "those generated by farm production activities (crops and livestock), land use change and pre- and post-production processes" (FAOSTAT 2021). The first category is considered to be emissions directly attributable to agriculture and has been regularly tracked by the Food and Agriculture Organization of the United Nations (FAO) and the IPCC (FAOSTAT 2021). The latter two categories expand upon this traditional emissions category, moving beyond the "farm-gate" to form the broader agri-food system definition, which more comprehensively identifies the emissions generated from food production, distribution, and consumption. Land use change refers to the conversion of land to agricultural purposes, with prominent examples including deforestation and peatland degradation (FAOSTAT 2021). Pre- and post-production processes include: "i) the production of inputs (fertilizers, materials for food packaging); ii) energy generation and consumption in food supply chains (food processing, transport and retail) and at the household level (cooking and refrigeration); and iii) waste disposal (such as in landfilling, incineration and wastewater management)" (FAOSTAT 2021).

Whereas the narrower category of agricultural emissions has long been studied, the study of agri-food system emissions is more recent. For the share of total emissions generated by agri-food systems, Rosenzweig et al. (2020) produced global estimates, at 21–37%, while Crippa et al. (2021), Tubiello et al. (2021), and FAOSTAT (2021) have generated both global and country-level estimates [1]. As delineated by the United Nations Framework Convention on Climate Change (UNFCCC), the traditional economic sectors to which emissions have been attributed include agriculture, land use, land use change and forestry (LULUCF), energy, industrial processes and product use (IPPU), and waste (FAOSTAT 2021). Distinct from the UNFCCC classification, the agri-food system measure cuts across these sectors, encompassing agriculture, LULUCF, waste, and energy use at all stages [2]. Recent literature argues that this broader measure supports more effective policy responses to climate change (Crippa et al. 2021; Rosenzweig et al. 2020; Tubiello et al. 2021).

Based on the UNFCCC sector classification, the greatest contributor to global emissions is energy, at 70%, while agriculture and LULUCF combined contribute 14% (FAOSTAT 2021). Industrial processes and product use accounts for 9%, with waste at 5% (FAOSTAT 2021). However, using the FAO sector classification for the agri-food system, energy emissions associated with food are captured in the overarching "pre- and post-production processes" category *(see Appendix Figure A.1)*. Accordingly, within the agri-food system

[1] Common among these studies, the measure of carbon dioxide equivalent (CO2e) emissions combines multiple greenhouse gases into a single metric, based on their warming potential. FAOSTAT (2021) includes carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and fluorinated substances. In this paper, the reader can assume that "emissions" refers to CO2e emissions.

[2] For a visual of food supply chain activities by category, see Appendix *Figure A.1*.

globally in 2019, roughly 7 billion tonnes of CO2e emissions were attributable to farm-gate activities, 6 billion to pre- and post-production processes, and 4 billion to land use change (FAOSTAT 2021). Pre- and post-production processes account for a larger share of food system emissions in developed countries, while emissions from farm-gate activities and land use change predominate in developing countries (FAOSTAT 2021).

In the U.S., the largest share of agri-food system emissions comes from energy, at 36-37%[3]. As the focus of this paper, electricity use accounts for 57% of energy consumed by the food system (Canning, Rehkamp, Waters, et al. 2017). This includes electricity use embodied in inputs for the agricultural stage of production, as well as the post farm-gate stages of processing, packaging, transport, wholesale, retail, and household consumption. Out of scope are emissions from waste, land-use change, and farm-gate activities (agriculture), except for on-farm electricity use. Because electricity accounts for a major portion of emissions in the U.S. food system, this paper is analyzing a significant emissions source. However, in addition to other primary energy sources, the categories agriculture and land use change are vitally important, particularly in developed countries, where these sources generate the majority of emissions. Hitaj et al. (2019) accounts for agriculture and land use change by supplementing their EIO model with a biophysical model, which captures sources such as enteric fermentation and burning of crop residues and savanna. Incorporating additional emissions sources beyond electricity is taken up in the Discussion section.

[3]FAOSTAT (2021) estimates that energy accounted for 36.2% of agri-food system emissions in 2019. However, the LULUCF and IPCC Agriculture categories *combined* accounted for 39.4%. With a similar categorization, Crippa et al. (2021) estimates that energy and "land-based" sectors each accounted 39% of emissions in 2015.

1.3 Environmental Input-Output Analysis

As a way to model national economies and represent the interrelationships among different economic sectors, input-output (I-O) analysis was originally developed by Wassily Leontief beginning in the 1920s, for which he was awarded the Nobel Memorial Prize in Economic Sciences in 1973. Building on the I-O framework, Leontief (1970) introduced the theoretical foundation for EIO, which was further developed in subsequent studies (Wiedmann 2009). Like I-O models that analyze national economic sectors—e.g., assessing how changes in final demand impact production and output—EIO models can analyze the environmental impact of production activities throughout the economy (Canning, Rehkamp, and Yi 2022; Kitzes 2013) [4].

Impacts are categorized as direct or indirect. First, "direct impacts account for production activities that provide direct outputs to meet a specified demand," considered a first-tier activity (Canning, Rehkamp, and Yi 2022). As an example, a direct impact of meat production includes emissions generated when transporting meat products to market—transportation services being a direct input. Second, indirect impacts account for secondary inputs, considered "second-tier activities to support first-tier activities" (Canning, Rehkamp, and Yi 2022). For the meat commodity, whereas the grain fed to livestock is a direct input, an indirect impact includes the emissions generated by operating a combine to harvest the grain (second-tier activity). A third-tier could include emissions from producing steel, an input into combine harvester production, and so on.

A major strength of input-output models is their ability to fully capture these direct and indirect economic relationships throughout the production process, and EIO models are ideal for capturing their corresponding environmental impacts (Canning, Rehkamp, and

[4] While national economies were the original unit of observation, I-O analysis has also been applied at lower levels—sub-national, regional models—and at higher levels—multi-country regional or global models.

Yi 2022). Moreover, along with accounting for emissions in production, EIO models can associate those emissions with final consumption categories, either at the sectoral level or for disaggregated commodity groups. While EIO offers a "top-down" sectoral approach, Life Cycle Analysis (LCA) is a "bottom-up" alternative that analyzes the environmental impact across the supply chain of *individual* products. Unlike EIO analysis, which can comprehensively account for direct and indirect impacts, the LCA analyst must determine an eventual cutoff point in the supply-chain, beyond which impacts are not recorded [5] (Hitaj et al. 2019; Ingwersen and Li 2020).

In addition to offering a comprehensive accounting at lower or higher levels of aggregation, benefits of EIO models include consistency, ability for decomposition, and data reliability. First, EIO models are structured in a manner such that double-counting of emissions sources across products is avoided (Kitzes 2013). Second, these models facilitate supply chain analysis via decomposition techniques. Third, EIO data inputs are reliably tracked by national governments, using common international standards, the United Nations System of National Accounts (SNA) and its companion System of Environmental Economic Accounting (SEEA).

Limitations of EIO models are based in part on certain grounding assumptions. Core assumptions are that:

1. there are no supply constraints, "because the supply of primary factors (labor, capital, natural resources) exceed the demand for these production inputs" (Canning, Rehkamp, and Yi 2022);

2. inputs *do not* experience diminishing marginal productivity, because "any additional use of these primary factors is equally productive as what is already in use" (Canning, Rehkamp, and Yi 2022);

[5] Depending on the LCA design, this issue may be negligible. Additionally, hybrid EIO-LCA models can also avoid this issue, gaining the benefits of each methodology (Yang et al. 2017).

3. prices are constant over the period of analysis, because "the new scenario being studied does not change existing relative prices in factor and commodity markets or existing production technologies such as factor productivities and material discharge rates" (Canning, Rehkamp, and Yi 2022);

4. because a Type I model is used—explained under methods—"all proceeds accruing to primary factor owners from the scenario induced production outcomes do not induce further spending by factor owners in the period of analysis" (Canning, Rehkamp, and Yi 2022); and

5. a given commodity group contains homogeneous products (Kitzes 2013).

One potential limitation is that these assumptions preclude the analysis of how a given final demand scenario can *induce* additional changes in final demand or in primary factors[6] (Canning, Rehkamp, and Yi 2022). However, this study is interested in how production inputs can be optimized to reduce emissions while meeting a *fixed* level of final demand. Thus, induced demand is not a point of focus here. By assuming homogeneity within a commodity group, the EIO analyst cannot account for product variation—e.g., organic versus conventional food products—whereas the LCA analyst can (Hitaj et al. 2019). The EIO approach adopts a kind of average, flattening any variation in product characteristics. Regarding prices, if they are stable, then EIO modeling can be appropriate (Canning, Rehkamp, and Yi 2022). Further, final demand being held constant mitigates the issue of potential price changes.

[6]See the Methods section for the difference between Type I and Type II models with respect to induced effects.

1.4 Mathematical Programming

Mathematical programming (MP) is a well-established method—particularly in operations research—that has increasingly been used for environmental applications (Miller and Blair 2009; Vogstad 2009). The I-O model itself can be interpreted as a type of linear programming (LP) problem (Miller and Blair 2009; Vogstad 2009). This paper defines an LP problem and a non-linear programming (NLP) problem, corresponding to cost- and change-minimizing objective functions, respectively. These LP and NLP optimization problems minimize their objective functions (total energy cost and change in energy source) subject to various environmental and energy constraints.

Utilizing the MP methodology enables me to extend the initial EIO model analysis, using its output as an input for the optimization problems described above. Whereas the EIO model yields a detailed accounting of existing electricity consumption patterns and corresponding emissions, the MP models examine how those patterns must change in order to meet the IPCC 1.5° target.

1.5 Contribution

Previous papers applying EIO analysis to study emissions from food production include Hitaj et al. (2019) and Boehm et al. (2018), examining the U.S. food system, Hendrie et al. (2014), examining Australia, and Camanzi et al. (2017), examining the EU. This paper is a unique contribution to these past studies because it assesses the impact of a supply-side change, rather than changes in final demand, and estimate least-cost and least-change energy input changes consistent with a 1.5°C target. This supply-side approach can serve as a benchmark for understanding the magnitude of energy input changes required in the generation of electricity.

My focus is on the reduction of U.S. food system emissions from electricity use. While this represents only a subset of total U.S. emissions, the methodology developed could be applied to other energy sources as well as other sectors of the economy beyond the food system. Additionally, electricity generation is a critical component of decarbonization strategies. In their 2015 study, Jacobson et al. (2015) argued there exist viable "solutions to the grid reliability problem with 100% penetration of [wind, water, and solar] (WWS) across all energy sectors in the continental United States between 2050 and 2055." That is, powering the U.S. economy entirely with WWS. Doing so would entail an unprecedented expansion of electricity generating capacity and battery production, to power everything that currently requires fossil fuels or nuclear (Jacobson et al. 2015; Griffith 2021). Although these findings were challenged (Clack et al. 2017), the study raises the question of whether renewable energy potential is underestimated (Creutzig et al. 2017) and highlights the importance of electricity generation (Griffith 2021).

Data and Methods

Data requirements for this paper can be broadly categorized as economic and environmental. First, I use an EIO model and associated data developed by Canning, Rehkamp, and Yi (2022). Then, output from the EIO model is an input into the MP model, supplemented by additional parameter data. This section discusses data inputs and then develops the EIO and MP methodology.

2.1 Data

The EIO model includes an input-output table (IOT) characterizing the U.S. economy and data for electricity consumption by primary energy source. For the 2012 U.S. national economy, the IOT covers high-level economic sectors as well as more detailed food industries and commodities. Data for 2012 is the most recent available [1], but other key energy use metrics are updated to recent years, as described below. Canning, Rehkamp, and Yi (2022) follow a standard methodology for constructing their IOT from an underlying Supply and Use table (SUT) [2].

In turn, the SUT is constructed from three data sets. Published by the U.S Department of Commerce, Bureau of Economic Analysis (USDOC-BEA), these include a more detailed

[1]Input-output modeling is data-intensive but uses high-quality data sources compiled by government statistical agencies. Representing entire economies, comprehensive nationwide surveys musts be administered, followed by additional compilation, which contributes to the gap between publication year and year of analysis.

[2]See Appendix A Figure A.2 for a schematic showing an example of mapping Supply and Use tables to an IOT.

Benchmark SUT and a less detailed Summary table, released every five years and annually, respectively (Canning, Rehkamp, and Yi 2022; USDOC-BEA 2021). An SUT published annually by the U.S. Department of Labor, Bureau of Labor Statistics is utilized as well (Canning, Rehkamp, and Yi 2022; USDOC-DOL 2021). Additionally, to develop a more granular picture of the food system—achieving further disaggregation than is possible in the Benchmark and Summary tables noted above—the Personal Consumption Expenditures (PCE) Bridge table [3] from the National Income and Product Accounts (NIPAs) is also utilized. Lastly, the economic data used in the EIO model includes multiple secondary sources that enable the identification of "expenditures and uses of goods and services for U.S. households to run their home kitchens," a process described in Canning, Rehkamp, Waters, et al. (2017) (Canning, Rehkamp, and Yi 2022).

As described by Canning, Rehkamp, and Yi (2022), the resulting IOT developed from these sources contains:

- 229 activities (A001 to A229),
- 231 commodities (C001 to C231),
- four leakage matrix elements (L01 to L04),
- four non-food expenditure related institutional matrix elements (X01 to X04), and 32 food commodity and home kitchen operation expenditure matrix elements (XF01 to XF32) [4]

The EIO model section below provides definitions and context for these matrices and Appendix Tables B.1, B.2, B.3, and B.4 list each matrix element along with a brief description. This paper adopts the Social Accounting Matrix (SAM) terminology—in

[3]This data is located under the 'Underlying Estimates' section of the USDOC-BEA Input-Output Accounts Data page (USDOC-BEA 2021).

[4]Only 27 categories are relevant to this paper, denoted XF01 to XF27.

accordance with Canning, Rehkamp, and Yi (2022)—where the "leakage" matrix corresponds to "value-added" from IO models and the "institutional", or "injection", matrix corresponds to "final demand." The above data elements are depicted in an IOT for a simplified economy in Appendix A Figure A.3.

A core attribute of EIO models is supplementing economic with environmental data. Following Canning, Rehkamp, and Yi (2022), this paper uses primary energy consumption and price [5] data from the State Energy Data System (SEDS), published by Department of Energy, Energy Information Administration (USDOE-EIA 2021; Canning, Rehkamp, and Yi 2022). As shown in Table 2.1 below, total primary energy use in the U.S. in 2012 was 94 quadrillion BTUs (quads), of which electricity was the largest contributor, with 38 quads. As a user of electricity, the food system accounted for 7 quads (Canning, Rehkamp, and Yi 2022), which is the focus of this paper. In turn, total bBTU from electricity can be disaggregated into primary energy sources, using SEDS data for electricity generation by source (USDOE-EIA 2021; Canning, Rehkamp, and Yi 2022).

In order to conduct a detailed supply chain analysis of food system electricity usage, total electricity used by source is allocated among every commodity, activity, and institutional element of the IOT. Population (USDOC-BEA 2022b; DMDC 2022) and employment (USDOC-DOL 2022; Census Bureau 2022; USDOT 2022) data are used to estimate electricity consumed by every element, as detailed by Canning, Rehkamp, and Yi (2022). As the primary output of interest from the EIO model, this result [6], Σ_0^{3f}, is a three-dimensional matrix showing bBTUs of electricity consumed by the food system by energy source, food category, and supply chain stage [7]. Examples of the 27 food categories include "food at home: cereals," "food away from home," (eating out), and "home

[5] From SEDS, only the natural gas and petroleum prices are used in a price ratio, as a replacement for levelized cost of electricity (LCOE) estimates used for all energy sources except petroleum, as described in Appendix C.

[6] See "Supplemental_info.xlsx" for a table of 2012 baseline electricity consumption.

[7] See Table 2.2 for all energy sources. See Appendix B Table B.4 for food categories and Table B.5 for supply chain stages.

Table 2.1: Primary energy use by source and user, U.S. 2012, bBTU

Source	Industrial	Commercial	Transportation	Residential	Total
All petroleum products	8,054,349	550,001	25,272,426	869,788	34,746,564
Biofuel	710,871				710,871
Coal	1,516,013	43,650			1,559,663
Electricity	10,287,524	13,640,682	73,842	14,149,504	38,151,552
Geothermal	4,200	19,702		39,600	63,502
Hydroelectric	22,393	261			22,654
Natural gas	8,822,590	2,968,401	781,762	4,252,794	16,825,547
Solar	7,196	33,300		78,844	119,340
Wind	182	513			695
Wood				438,094	438,094
Wood and biomass waste	1,621,149	105,929			1,727,078
Total	31,046,467	17,362,439	26,128,030	19,828,624	94,365,560

Source: Canning, Rehkamp, and Yi (2022)

kitchen operations: utilities," while the 13 supply chain stages include "agribusiness," "crops," "transportation and storage," and "utilities for kitchen" (Canning, Rehkamp, and Yi 2022). Aggregating Σ_0^{3f} to two dimensions, Figure 2.1 shows how the food system consumed electricity by energy source and supply chain stage. Figure 2.2 shows the same for food categories.

Figure 2.1: Food system electricity by energy and stage (bBTU), U.S. 2012

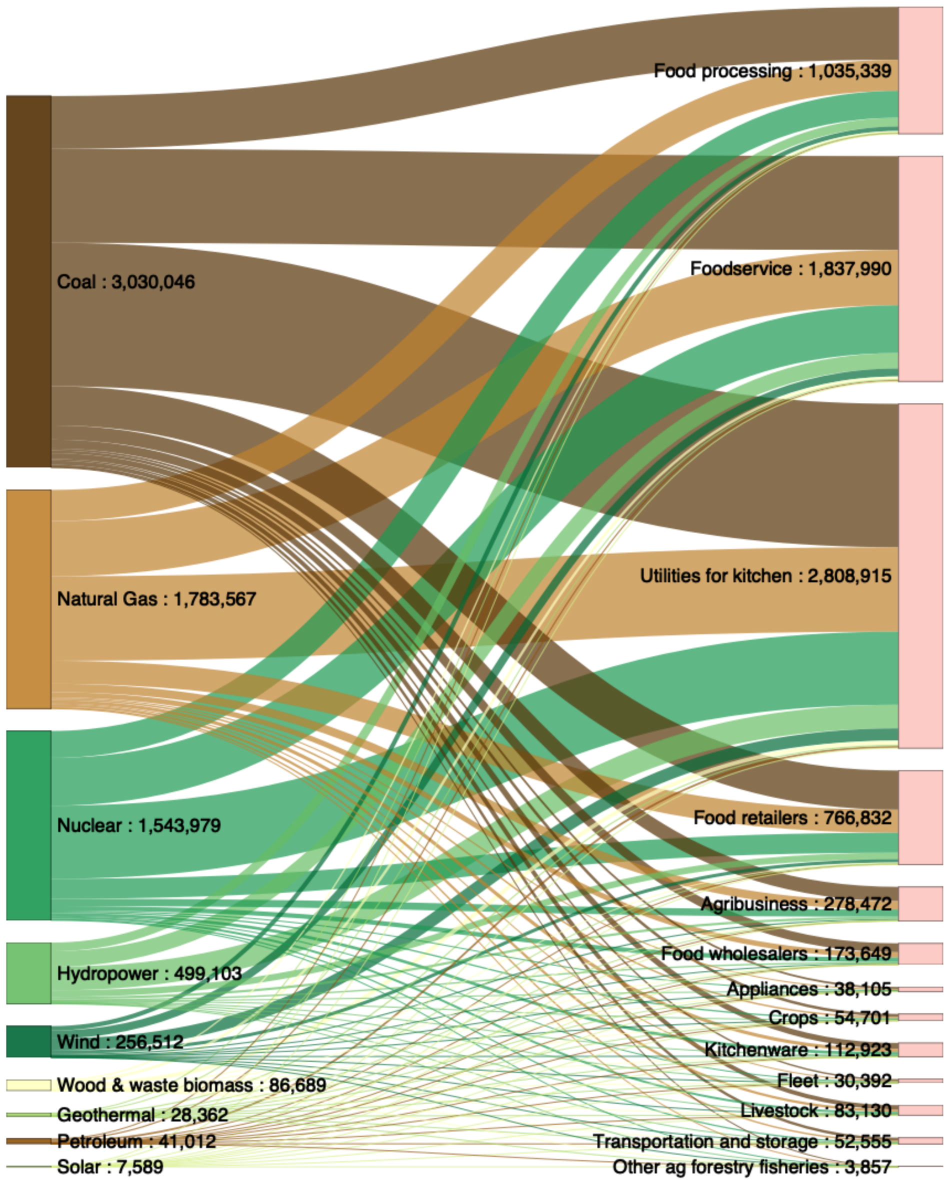


Figure by author based on data from Canning, Rehkamp, and Yi (2022).

In 2012, coal generated the most electricity consumed by the U.S. food system, followed by gas, while "utilities for kitchen" was the largest supply chain stage consumer, followed by "foodservice". In Figures 2.1 and 2.2, the most emitting energy sources are darker brown (coal), while the least emitting sources are darker green (wind).

Figure 2.2: Food system electricity by energy and food category (bBTU), U.S. 2012

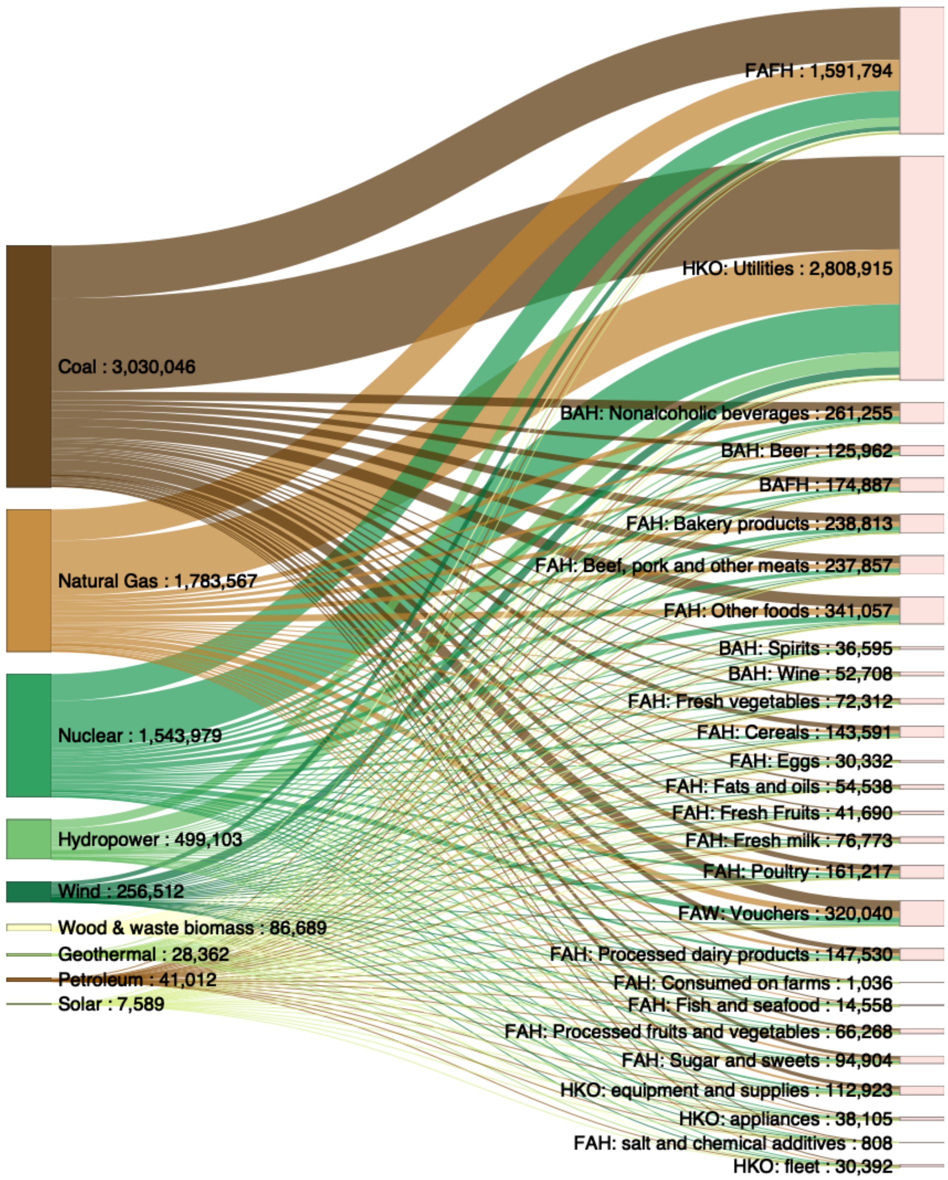


Figure by author based on data from Canning, Rehkamp, and Yi (2022).

In Figure 2.2, food and beverage final uses are categorized by “food at home” (FAH), “food away from home” (FAFH), “beverage at home” (BAH), “beverage away from home” (BAFH), “food at work” (FAW), and “home kitchen operations” (HKO). Among these, HKO - Utilities accounted for the largest electricity consumption, followed by FAFH.

Together with food system electricity consumption by energy source—as output from the EIO model—the MP model require additional data inputs as parameters. These include data for life cycle emissions, electricity growth rates by energy source, total growth rates, depreciation rates of fossil fuel plants, and estimates of the levelized cost of electricity (LCOE).

First, Life Cycle Assessment (LCA) provides a methodology for considering emissions generated from all life cycle stages of energy technologies, including upstream, operation, and downstream (NREL 2022b). This paper uses energy source life cycle CO2e emissions estimates by the National Renewable Energy Laboratory (NREL), compiled from their meta-analysis of roughly 3,000 publications (NREL 2022a; NREL 2022b). According to this analysis, wind and nuclear power are the least emissions-intensive energies, while petroleum and coal are the most emissions-intensive (see Table 2.2) [8]. Model results were derived with the median NREL [9] estimate.

Table 2.2: Life Cycle Emissions Factors (g CO2e / mBTU)

Generation Technology	1Q	Median	3Q
Biopower (All Technologies)	8,206	15,240	32,238
Photovoltaic (All Technologies)	8,792	12,719	18,170
Geothermal (All Technologies)	6,418	10,756	15,093
Hydropower (All Technologies)	2,452	6,008	8,021
Wind (All Technologies)	2,373	3,810	6,515
Nuclear - Light Water Reactor (LWR)	2,257	3,810	9,085
Natural Gas - Conventional Gas	125,215	142,433	161,336
Oil	211,597	246,180	265,816
Coal (All Technologies)	261,126	293,364	332,343

Source: NREL (2022a)

The life cycle emissions factor data is combined with the EIO model output for bBTU consumption to yield total CO2e emissions by energy, supply stage, and food category.

[8] The original data set in grams CO2e per kWh was converted to grams CO2e per mBTU.

[9] The NREL category "biopower" is used for estimating the EIA combined categories of "wood" and "waste", denoted in this paper as "wood and waste biomass".

As done for Figures 2.1 and 2.2, this three-dimensional data, $\mathbf{\Theta}_0^{3f}$, can be visualized along two dimensions. Figure 2.3 shows emissions by energy and stage, while figure 2.4 shows emissions by energy and food category. As can be seen, in 2012 coal accounted for an outsized proportion of emissions, 888 MMt, at 76% of the total. Natural gas is the second largest emitter, 22%, while all other sources contribute less than 1%.

Figure 2.3: Food system CO2e emissions by energy and stage (MMt), U.S. 2012

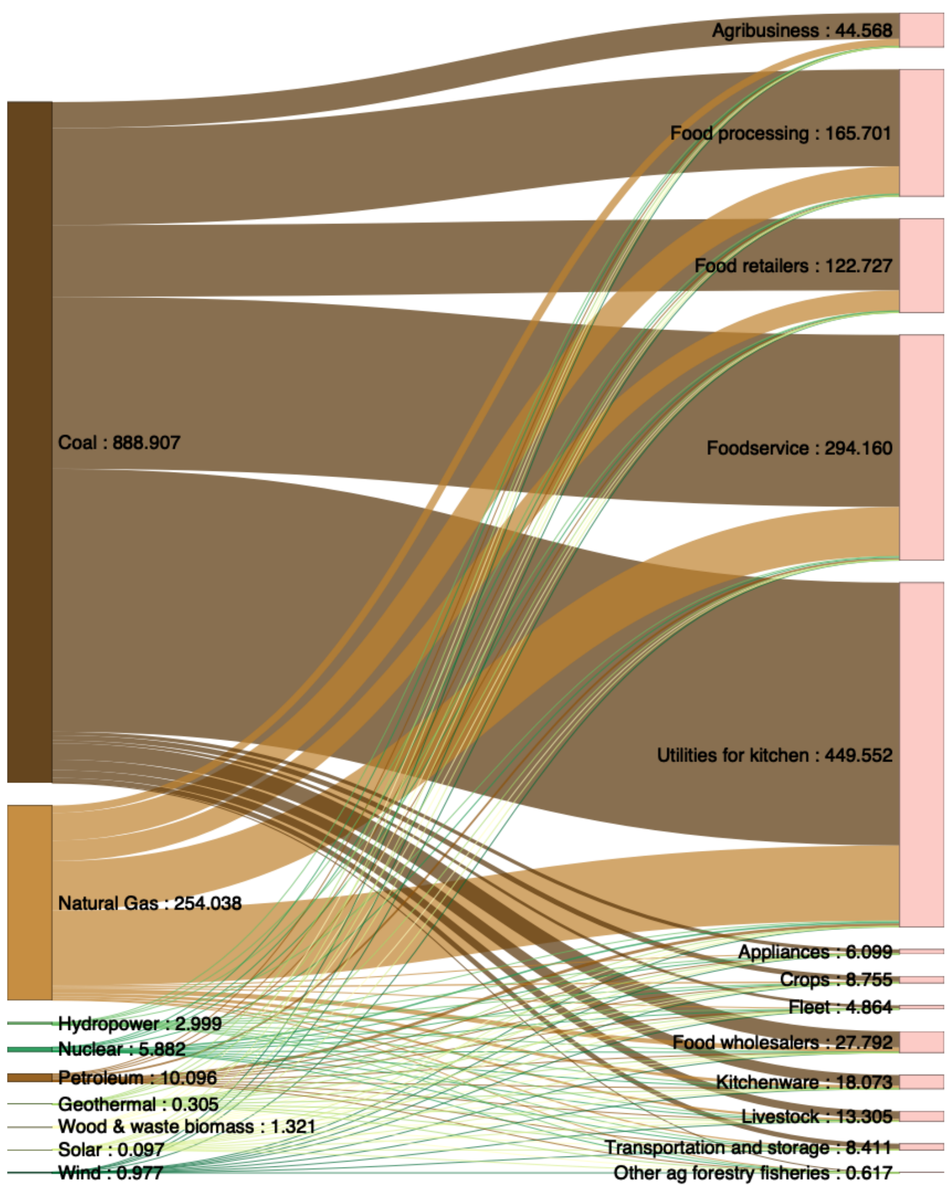


Figure by author based on data from Canning, Rehkamp, and Yi (2022).

Figure 2.4: Food system Co2e emissions by energy and food category (MMt), U.S. 2012

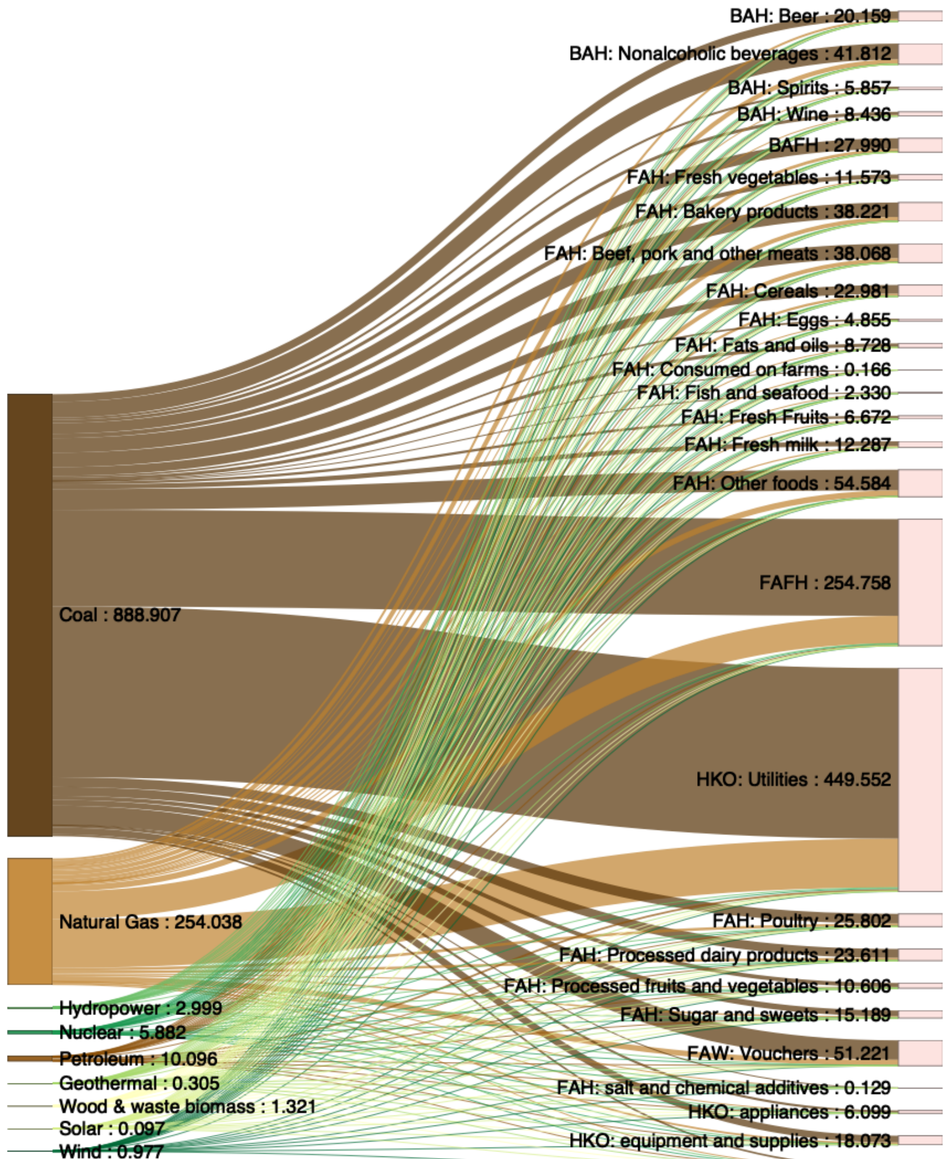


Figure by author based on data from Canning, Rehkamp, and Yi (2022).

Relative to the left-hand side (energy source), the right-hand side of Figures 2.3 and 2.4 do not show the same disproportional relationship with respect to Figures 2.1 and 2.2. The stages and food categories are assumed to consume electricity with the same energy mix—as if a single utility—and so their CO2e emissions output has a linear relationship to bBTU consumption. Thus, because the utilities for kitchen stage is largest electricity consumer, it also generates to most emissions. Likewise, as the energy mix is optimized to reduce emissions, the largest electricity consumers will necessarily yield the largest emissions reductions.

Electricity growth rate data includes actual rates achieved and projections. First, the EIO model output, Σ_0^{3f}, is updated to reflect 2021 electricity generation. Summing over Σ_0^{3f} by supply chain stage, z, and food and beverage final demand category, f, yields total electricity consumption by energy type, d, for the U.S. food system in 2012—$\sum_{f=1}^{27} \sum_{z=1}^{13} \sigma_{d,z,f}, \sigma \in \Sigma$. In the MP model, these 2012 energy totals are multiplied by actual national energy growth rates [10] (USDOE-EIA 2022c) to yield 2021 totals, which are then multiplied by the projected national energy growth rates to yield 2030 totals (USDOE-EIA 2022a; USDOE-EIA 2022b) *(See Table 2.3)* [11]. This represents the projected total bBTUs by energy source available for the U.S. food system in 2030, serving as a theoretical upper bound in the optimization problem. However, as we will see in the Findings section, a feasible solution for meeting the emissions reduction target does not exist if renewable energy growth is restricted according to these EIA projections.

In addition to upper bounds on energy sources, a lower bound on *total* electricity generation—the minimum bBTU required to support the food system—also requires actual and projected growth rates. Total electricity growth is derived by aggregating the same figures for actual and projected electricity generation by source *(See Tables 2.3 "Total")* (USDOE-EIA 2022c; USDOE-EIA 2022a; USDOE-EIA 2022b). The resulting total projected electricity growth term from 2012 to 2030 is:

$$\rho = (1 + \rho^{2021}) \times (1 + \rho^{2030}) = (1 + (-.016)) \times (1 + .043) = 1.02$$

[10] This assumes that national trends apply to the food system. The growth rate is derived from EIA kWh totals in the EIA *Monthly Energy Review March 2022.*

[11] My category "wood and waste biomass" combines EIA categories "wood" and "waste", sub-categorized under their biomass category.

Table 2.3: Electricity by source, U.S. Food System, bBTU

Source	2012	% change 2012-21 (national actual)	2021	% change 2021-30 (national projection)	2030
Coal	3,030,046	-40.6%	1,798,521	-28.3%	1,290,164
Hydropower	499,103	-5.8%	470,167	15.6%	543,415
Natural gas	1,783,567	28.5%	2,291,820	-1.4%	2,258,852
Nuclear	1,543,979	1.1%	1,561,681	-9.1%	1,419,746
Petroleum	41,012	-19.0%	33,216	-25.7%	24,672
Solar	7,589	2550.5%	201,143	250.1%	704,287
Geothermal	28,362	4.3%	29,593	48.5%	43,933
Wood and waste biomass	86,689	-3.7%	83,465	15.3%	96,260
Wind	256,512	169.7%	691,760	57.2%	1,087,140
Total	7,276,860	-1.6%	7,161,366	4.3%	7,468,469

Data Source: Canning, Rehkamp, and Yi (2022), USDOE-EIA (2022c), USDOE-EIA (2022a), and USDOE-EIA (2022b)

Using depreciation rates from USDOC-BEA (2022a), a lower bound on fossil fuel energy types is enforced in the optimization problem. This prevents the model from reducing a high-emitting energy by more than that amount projected by depreciation *(See Appendix Table B.6)*. As an example, this means existing coal power plants cannot be shut down and replaced before their natural lifespan.

Lastly, levelized cost of electricity (LCOE) data from the International Energy Agency (IEA) is used to determine the cost-minimizing changes in energy sources that will meet emissions reduction targets. Levelized cost of electricity is a widely used metric despite some limitations (IEA 2020), which will be reviewed in the Discussion section. The USDOE suggests three useful characteristics of this metric: that it (i) "measures lifetime costs divided by energy production," (ii) "calculates present value of the total cost of building and operating a power plant over an assumed lifetime," and (iii) "allows the comparison of different technologies (e.g., wind, solar, natural gas) of unequal life spans, project size, different capital cost, risk, return, and capacities" (USDOE 2022). For these reasons, LCOE is an ideal tool for evaluating the long-term cost of different energy sources in this paper. As shown in Table 2.4 [12], the IEA finds that natural gas and wind have lowest cost, while coal and petroleum have the highest cost. Note that solar is estimated to be higher cost than nuclear. On the one hand, the inclusion of residential and commercial solar in a weighted average raises overall solar LCOE, being relatively more expensive than utility-scale solar. On the other hand, averaging "new build" nuclear with ten- and twenty-year "long-term operation" (LTO) nuclear lowers its LCOE. Whereas new nuclear plants are more costly, extending the life of existing plants—long-term operation—can make nuclear the "most cost-effective low-carbon solution," according to the IEA (IEA 2020). Also note that while the IEA reference estimates include a $30 carbon price, my estimates exclude carbon pricing, which would raise the cost of fossil fuels further. In Appendix C, additional detail is provided on the core assumptions and key decisions in compiling LCOE estimates.

Table 2.4: Levelized Cost of Electricity, U.S. 2020

Source	LCOE (USD / MWh)	LCOE (USD / bBTU)
Petroleum	95.25	27,916.27
Coal	84.34	24,716.89
Hydropower	78.89	23,120.39
Geothermal	77.69	22,767.24
Wood and waste biomass	76.00	22,273.41
Solar	70.75	20,735.64
Nuclear	46.38	13,592.12
Wind	39.02	11,435.64
Natural gas	34.78	10,193.02

Source: IEA (2020), IEA (2022), and IRENA (2022)

[12] All Table 2.4 estimates are provided by the IEA for the U.S., except wood and waste biomass, a global estimate from the International Renewable Energy Agency (IRENA). See Appendix C for details on the compiling each LCOE estimate.

2.2 Methods

This paper utilizes an EIO model, the output from which is an input into optimization problems, together with additional parameter data as outlined above. This section develops the EIO model and optimization problems in turn, where the latter is the primary contribution of this paper.

2.2.1 The Environmental Input-Output Model

As noted in the introduction, this paper adopts the Type I EIO multiplier model developed by Canning, Rehkamp, and Yi (2022), which "provides a measurement of how \$1 injected into the economy as an expenditure on a specific good or service (commodity) changes total production or output of each activity and commodity across the entire economy." Further, the multiplier effect of a \$1 injection increasing production activity has an analogous effect on increasing electricity required to support that production. A Type I model measures direct and indirect effects but not induced effects. When households are endogenous to the model—Type II model—greater production activity induces greater consumption, which in turn increases production. Because we are interested in the electricity required for a fixed level of food consumption, the Type I model is appropriate, excluding induced effects.

The key result of a standard I-O model derivation is a matrix equation describing how a change in final demand—\$1 injected into the economy—will impact output, mediated by a multiplier matrix that contains elements for every economic activity. The derivation gives:

$$\boldsymbol{y} = \boldsymbol{M} \times \boldsymbol{x}, \tag{2.1}$$

where $\boldsymbol{y}$ is the gross output vector, $\boldsymbol{x}$ is the injection, or final demand, vector, and $\boldsymbol{M}$ is the total requirement matrix [13]. The total requirement matrix [14] represents the direct and indirect monetary amount of every activity and commodity element that is required for production in order to meet final demand. When considering only food-related purchases, equation 2.1 becomes:

$$\boldsymbol{y}^f = \boldsymbol{M} \times \boldsymbol{x}^f, \tag{2.2}$$

where $\boldsymbol{y}^f$ and $\boldsymbol{x}^f$ denote the food-related gross output and injection vectors, respectively. This basic I-O model is extended to an EIO model by introducing our environmental metric, electricity consumption, which is further translated to CO2e emissions as a linear relationship. The environmental matrix, $\boldsymbol{E}$, shows electricity required by energy source (matrix rows) for every activity and commodity (matrix columns), measured in bBTU per \$1 output [15]. Including $\boldsymbol{E}$ in the model gives:

$$\boldsymbol{\sigma}^f = \boldsymbol{E} \times \boldsymbol{y}^f + \boldsymbol{\sigma}^x, \tag{2.3}$$

where the $\boldsymbol{\sigma}^f$ vector represents the total bBTU consumed by energy source d [16]. The $\boldsymbol{\sigma}^x$ vector represents electricity consumed directly by end users through home kitchen operations—e.g., running a coffee maker—which is added to $\boldsymbol{E} \times \boldsymbol{y}^f$, total bBTU required by activities and commodities in the production process. Diagonalizing $\boldsymbol{y}^f$ and introducing

[13] See Appendix D Section D.1 for notes on matrix notation and Section D.2 for a listing of all matrices and vectors with brief descriptions. See Appendix D for a complete derivation of the EIO model, as adapted from the supplemental information of Canning, Rehkamp, and Yi (2022)

[14] The total requirement matrix is sometimes termed the Leontief inverse.

[15] In their model, Canning, Rehkamp, and Yi (2022) have the rows of $\boldsymbol{E}$ correspond to the energy sources listed in Table 2.1. This paper instead selects only the electricity row from Table 2.1 and disaggregates electricity by its primary energy source, as seen in Table 2.3. The model equations detailed in this section are applicable in either case.

[16] Table 2.3 shows the nine energy sources.

$\boldsymbol{E}^{*}$, the gives:

$$\boldsymbol{\Sigma}^{2f} = \left[\boldsymbol{E}^{*} \times (\boldsymbol{y}^{f})'' | \boldsymbol{\sigma}^{f}\right], \qquad \text{('|' denotes horizontal concatenation)} \tag{2.4}$$

where:

- $\boldsymbol{\Sigma}^{2f}$ is a two-dimensional matrix representing the total bBTU consumed by energy source d (rows) and food category f (columns);
- $\boldsymbol{E}^{*}$ is the environmental multiplier matrix derived through a supply chain analysis procedure [17] using "double-inversion", as outlined in Canning, Rehkamp, and Yi (2022), with (rows) for energy source d and (columns) for supply chain stage z; and
- The $(\boldsymbol{y}^{f})''$ matrix is $\boldsymbol{y}^{f}$ diagonalized.

The supply chain analysis procedure reduces the full set of activities and commodities *(See Table B.1)* to a smaller set of supply chain stages *(See Table B.5)*, attributing electricity use to these stages, rather than to an activity or commodity. Equation (2.4) can be restated as:

$$\boldsymbol{\Sigma}^{2f} = \left[\boldsymbol{E}^{*} \times (\boldsymbol{y}^{f1} | \boldsymbol{y}^{f2} | ... | \boldsymbol{y}^{f23}) | \boldsymbol{E} \times (\boldsymbol{y}^{f24} | \boldsymbol{y}^{f24} | \boldsymbol{y}^{f26}) | \boldsymbol{\sigma}^{f27}\right] \tag{2.5}$$

In equation (2.5):

- $\boldsymbol{y}^{f1}$ to $\boldsymbol{y}^{f23}$ are gross output vectors corresponding to the food-related demand categories $XF1$ to $XF23$ from Table B.4, and The rows of $\boldsymbol{y}^{f1}$ to $\boldsymbol{y}^{f23}$ are the supply chain stages z;

[17]See Appendix D.3.1.

- $\boldsymbol{E}$ is the standard environmental multiplier matrix;
- $\boldsymbol{y}^{f24}$ to $\boldsymbol{y}^{f26}$ are gross output vectors corresponding $XF24$ to $XF26$; and
- $\boldsymbol{\sigma}^{f27}$ is the final demand vector for energy consumed directly through home kitchen operations, corresponding to $XF27$, with rows for energy source d.

Lastly, the two-dimensional matrix $\boldsymbol{\Sigma}^{2f}$ can be rewritten as a three-dimensional matrix, $\boldsymbol{\Sigma}^{3f}$:

$$\boldsymbol{\Sigma}^{3f} = \left[\boldsymbol{E}^{*} \times \left((\boldsymbol{y}^{f1})''|(\boldsymbol{y}^{f2})''|...|(\boldsymbol{y}^{f23})''\right)|\boldsymbol{E} \times \left((\boldsymbol{y}^{f24})''|(\boldsymbol{y}^{f24})''|(\boldsymbol{y}^{f26})''\right)|\boldsymbol{\sigma}^{f27}\right] \tag{2.6}$$

The result $\boldsymbol{\Sigma}^{3f}$ represents the entire annual food system electricity budget allocated across three indices. The matrix rows are energy source d, while the columns are supply chain stage z *and* food-related final demand category f. The electricity consumed for the baseline year 2012 is denoted $\boldsymbol{\Sigma}_0^{3f}$, which is represented graphically in Figures 2.1 and 2.2 above. Below, we will see how $\boldsymbol{\Sigma}_0^{3f}$ is a key parameter input into the MP model.

Letting $\boldsymbol{g}_d$ be a vertical vector of emissions coefficients by energy sources *(See Table 2.2)*, a matrix for food system emissions is given by:

$$\boldsymbol{\Theta}_0^{3f} = \boldsymbol{\Sigma}_0^{3f} \circ \boldsymbol{G}, \tag{2.7}$$

In equation (2.7):

- $\boldsymbol{G} = (\boldsymbol{g}_d|...|\boldsymbol{g}_d)$, with $\boldsymbol{g}_d$ repeatedly column-concatenated such that $\boldsymbol{\Sigma}^{3f}$ and $\boldsymbol{G}$ have the same dimensions; and
- $\circ$ denotes an element-wise multiplication.

2.2.2 The Mathematical Programming Model

Mathematical programming (MP) problems are executed for two objective functions, with both achieving a certain level of emissions reduction. First, change is minimized relative to existing electricity consumption patterns. Second, cost is minimized. Both objective functions are subject to the same constraint on total emissions and various constraints on electricity use and primary energy sources. The choice variable is indexed over energy source, $d = \{1, ..., 9\}$. As a model input, $\mathbf{\Sigma}_0^{3f}$ is collapsed from a matrix to a vector by taking the row sums:

$$\boldsymbol{\phi}_0^f = \mathbf{\Sigma}_0^{3f} \times \boldsymbol{i},$$

where $\boldsymbol{i}$ is a unit vector. The given MP parameters are denoted:

- g_d, for life cycle emissions factors (g CO2e / mBTU)
- ϕ_d^0, for 2012 baseline bBTU by energy source, as the row sum of Σ_0^{3f}
- δ_d, for the annual depreciation rate for physical plant by energy source
- $\lambda_d = (1 + \lambda_d^{2021}) \times (1 + \lambda_d^{2030} + \lambda_d^{plus})$, for the growth rate of electricity generation by source d from 2012 to 2030
  - λ_d^{2021}, for the actual recorded growth rate from 2012 to 2021
  - λ_d^{2030}, for the projected growth rate from 2021 to 2030
  - λ_d^{plus}, for the extra percentage points growth beyond EIA projections required for a feasible solution
- $\rho = (1 + \rho^{2021}) \times (1 + \rho^{2030})$, for the growth rate of total electricity generation from 2012 to 2030

- ρ^{2021}, for the actual recorded growth rate from 2012 to 2021
- ρ^{2030}, for the projected growth rate from 2021 to 2030

- $LCOE_d$, for the levelized cost of electricity for every energy source

The choice variable is σ_d^1, the optimal bBTU in 2030 by energy source. With these parameters and variable, the optimization problem that meets the emissions target while minimizing change is:

$$\min_{\phi_d^1} Z1 = \sum_{d=1}^{9} \frac{(\phi_d^1 - \phi_d^0)^2}{\phi_d^0}, \tag{2.8}$$

subject to:

$$\sum_{d=1}^{9} \phi_d^1 \times g_d \leq 0.552 \times \sum_{d=1}^{9} \phi_d^0 \times g_d \tag{2.9}$$

$$\sum_{d=1}^{9} \phi_d^1 \geq \rho \times \sum_{d=1}^{9} \phi_d^0 \tag{2.10}$$

$$\phi_1^1 \geq \phi_1^0 \times e^{\delta_1 \times 18} \tag{2.11}$$

$$\phi_3^1 \geq \phi_3^0 \times e^{\delta_3 \times 18} \tag{2.12}$$

$$\phi_5^1 \geq \phi_5^0 \times e^{\delta_5 \times 18} \tag{2.13}$$

$$\phi_1^1 \leq \phi_1^0 \times \lambda_1 \tag{2.14}$$

$$\phi_2^1 \leq \phi_2^0 \times \lambda_2 \tag{2.15}$$

$$... \leq ... \tag{2.16}$$

$$\phi_9^1 \leq \phi_9^0 \times \lambda_2, \tag{2.17}$$

where:

- equation (2.8) is the change minimizing objective function;
- equation (2.9) is the total emissions constraint, requiring that CO2e emissions in 2030 meet the reduction target, 55.2% of baseline 2012 emissions;
- equation (2.10) is the total energy constraint, requiring that bBTUs used in 2030 not be less than bBTU used in 2012, increased by the EIA projected rate of total electricity growth, ρ;
- equations (2.11) to (2.13) are the energy *lower* bound constraints—for coal, natural gas, and petroleum respectively—requiring that bBTU used in 2030 not be reduced by a rate greater than depreciation, δ_d;
- and equations (2.14) to (2.17) are the energy *upper* bound constraints—for nine energy types—requiring that bBTU used in 2030 not be increased by a rate greater than EIA projections, λ_d.

Note that the energy lower bounds only apply to the fossil fuels. This is because the GAMS optimization program seeks to replace high-emissions energy sources by low-emissions sources, where consumption of all non-fossil fuel sources increases relative to the baseline. Subject to the same constraints, the cost minimization problem is given as:

$$\min_{\phi_d^1} Z1 = \sum_{d=1}^{9} \phi_d^1 \times LCOE_d \tag{2.18}$$

Both MP models yield total electricity use by energy source, from which energy shares are derived. The 2030 three-dimensional matrix for electricity use, $\mathbf{\Sigma}_1^{3f}$, for both objective functions is computed by a matrix multiplication of the baseline 2012 electricity use row totals vector, $\left(\left(\mathbf{\Sigma}_0^{3f}\right)' \times i\right)$, and the energy shares vector, $\boldsymbol{\pi}$, together with the scalar growth term, ρ *(See equation 2.19)*.

$$\boldsymbol{\Sigma}_1^{3f} = \rho \times \left(\left(\boldsymbol{\Sigma}_0^{3f} \right)^{'} \times i \right) \times \boldsymbol{\pi}' \tag{2.19}$$

Given equation (2.19), target 2030 emissions are derived by:

$$\boldsymbol{\Theta}_1^{3f} = \boldsymbol{\Sigma}_1^{3f} \circ \boldsymbol{G} \tag{2.20}$$

As will be seen, the cost- and change-minimization problem yield similar results for electricity and corresponding emissions.

Findings

This section first presents my principal findings, detailing energy mix changes for the food system's electricity use that are consistent with the IPCC target of limiting warming to 1.5 °C. Then, the supply chain stages and food categories are analyzed. Because stages and food categories are assumed to consume electricity generated by the same energy mix, emissions reductions are directly proportional to their total energy use. That is, the largest electricity consumers realize the largest emissions reductions.

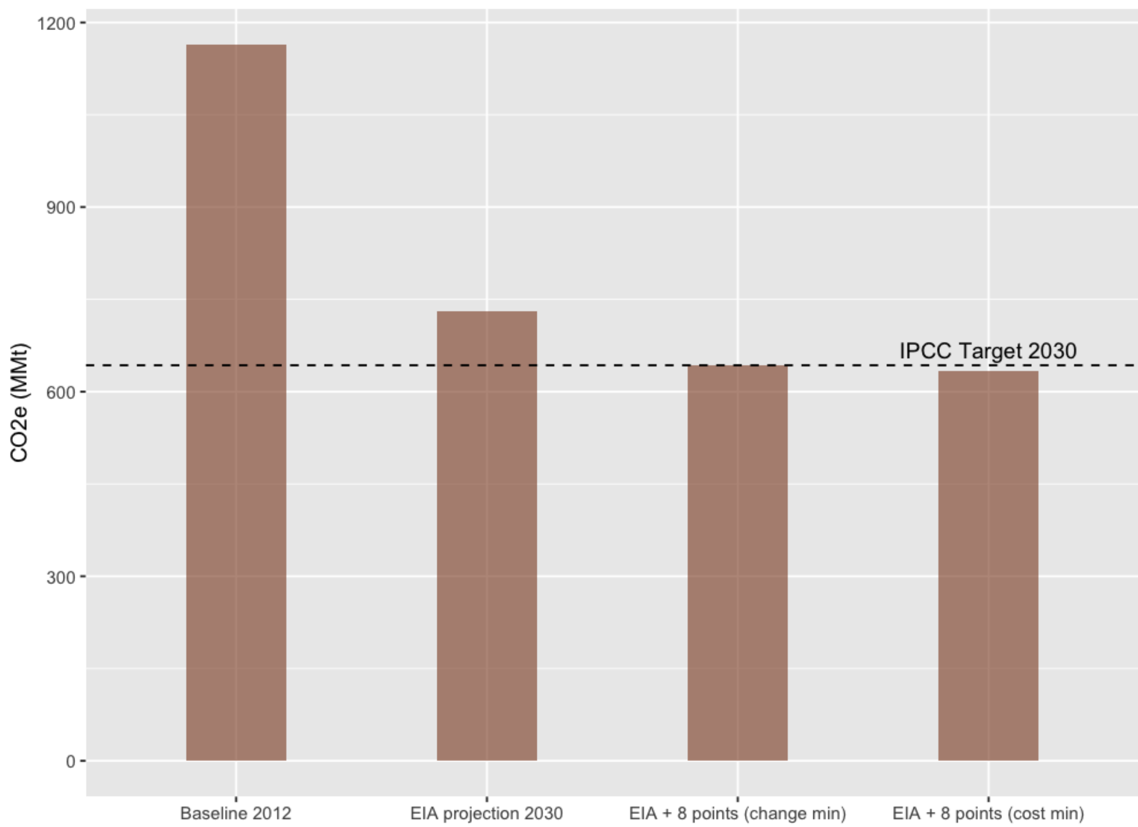
3.1 Overall energy mix

My principal finding is that the EIA projected changes in electricity generation—with declining fossil fuels and increasing renewables as shown in Table 2.3—are not consistent with limiting warming to 1.5°C. If the U.S. food system were to consume electricity as projected by the EIA through 2030, then it would exceed its share of the CO2e emissions budget, assuming that a 44.8% emissions reduction from 2012 is required to meet the IPCC target.

Before presenting estimates, a note on totals is needed. For a given year, total *life cycle* CO2e emissions generated by U.S. food system electricity consumption can be derived by multiplying bBTU consumed by energy source *(see Table 2.3)* by the respective life cycle emissions estimates *(see Table 2.2)*. For 2012, this yields 1,164 MMt CO2e *life cycle* emissions from U.S food system electricity consumption. By comparison, annual 2012 CO2e emissions for the entire U.S. economy were estimated at 6,585 MMt (USEPA 2022), with U.S. food system generating an estimated 1,448 MMt (Crippa et al. 2021). In the U.S. in 2012, 36% of food system emissions were attributed to energy (FAOSTAT 2021) while 57% of food system energy use was from electricity (Canning, Rehkamp, Waters, et al. 2017). Thus, my *life cycle* emissions estimate from annual electricity consumption is significantly larger than the *annual* estimates cited elsewhere. This is because LCA considers the entire life of energy sources, encompassing upstream, operation, and downstream emissions. Whereas burning coal generates 95.7 kg CO2/mBTU (USDOE-EIA 2022d), coal as an energy source generates an estimated 293 kg CO2e/mBTU life cycle emissions (NREL 2022a). As an example, the latter includes methane from coal mines, as well as other upstream emissions. I argue it is appropriate to model the lifetime emissions of energy choices because i) these choices entail significant investment in new energy infrastructure, ii) this paper considers long-term energy consumption, and iii) cumulative emissions drive climate change. Additionally, the LCA approach enables a more accurate trade-off between fossil fuels, nuclear, and renewables, where the latter categories generate zero or negligible emissions from operation but have emissions embedded elsewhere in their supply chain. That is, expanding generating capacity from renewables will produce emissions.

To meet the IPCC target, life cycle emissions from U.S food system electricity consumption must decline from 1,164 MMt CO2e in 2012 to 643 MMt in 2030. However, if energy source growth followed EIA projections, CO2e emissions would reach only 730 MMt. Using EIA projections, no feasible solution exists for the MP model, for either the cost- or change-minimizing objective functions. Given this infeasibility, I incrementally relaxed the upper constraint on energy source until a solution was feasible. Across all energy sources, adding eight percentage points to the EIA growth projections yields the first feasible solution limiting emissions for both objective functions *(See Figure 3.1)*. Thus, rather than nuclear energy declining 9.1% from 2021 to 2030, as projected by EIA *(see Table 2.3)*, a solution is just feasible when nuclear declines 1.1%. Likewise, solar energy growth is adjusted from 250.1% to 258.1% and so on. Under cost-minimization, total CO2e is 632 MMt, while change-minimization yields 642 MMt. This small difference is partially attributed to the former model choosing more of the lower cost energy, solar, whereas the latter chooses the higher-cost, change-minimizing energy, petroleum.

Figure 3.1: Agri-food system emissions totals (actual, projected, target)

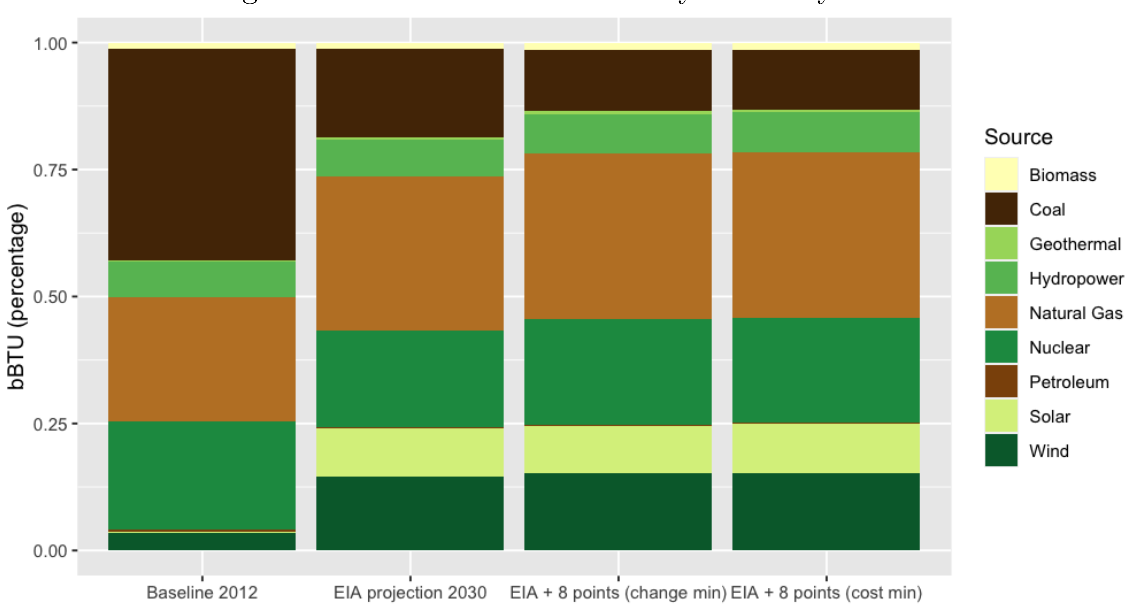


The category "EIA + 8 points" denotes 8 percentage points added to EIA projected energy growth.

Under both change- and cost-minimization optimization problems, coal's share of electricity declines substantially from 41% in 2012 to 12% and 11.8% in 2030, respectively, representing declines of 70% and 71%. For both optimization problems, the lower bound on coal is not binding: coal is not reduced the maximum amount allowed by depreciation of existing infrastructure. The EIA projections also predict a lower than baseline coal share of electricity, 17%, albeit higher than the target solutions *(See Figure 3.2)*. The only energy source decreased the maximum amount is petroleum, under the cost-minimizing solution, as it is the costliest source.

Also of note, the share of wind and solar is substantially higher under the EIA projections, change-minimization, and cost-minimization scenarios. The solar share of electricity increases from 0.1% to 9.4%, 9.1%, and 9.6%, respectively [1]. The change minimization solution yields less solar than EIA projections, whereas cost minimization yields more. For wind, change- and cost-minimization yield identical results, 15.3%, slightly higher than EIA projections, 14.6%. Because the solution is just feasible—with an incremental relaxation of the energy upper bound—both optimization problems yield similar results overall. Both problems maximize the use of hydropower, natural gas, nuclear, geothermal, wind, and biomass such that the upper bound in binding *(see Appendix Table E.2.1)*. The key difference between the two solutions is that cost-minimization maximizes the use of solar—lower LCOE—whereas change-minimization maximizes the use of petroleum—higher LCOE [2]. Another key difference between EIA projections and the target solutions is that the former have a greater share of natural gas, which is maximized.

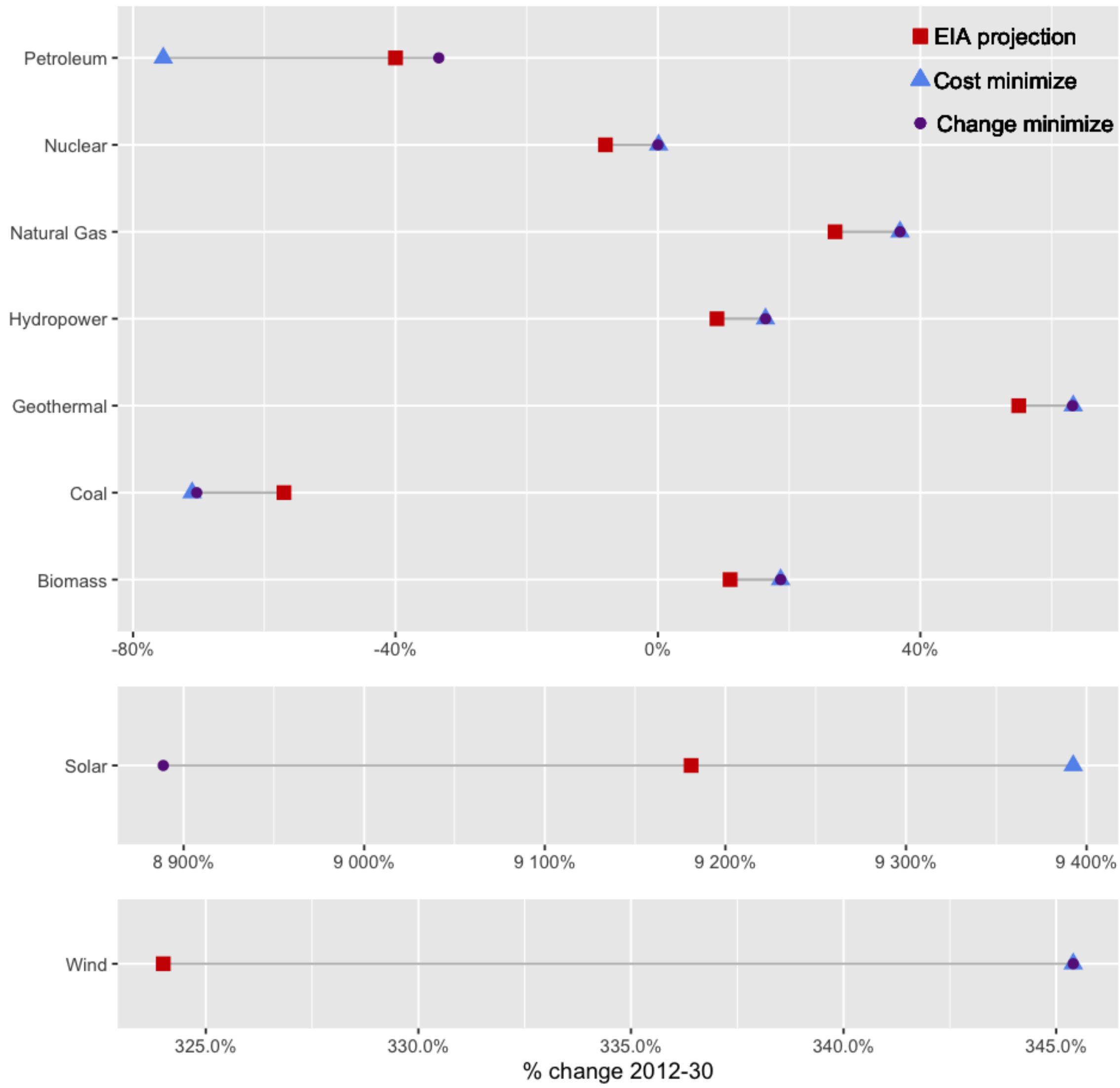
Figure 3.2: Percent total electricity bBTU by source



[1] Appendix Table E.2.3 reports the shares for each energy source.
[2] See Appendix E for full results

In terms of percent change from the 2012 baseline, results suggest that solar experiences by far the largest growth, increasing by a factor of more than 88 across all three scenarios—the EIA projections, cost- and change-minimization solutions *(See Figure 3.3)*. With the exception of petroleum, solar, and coal, both optimization solutions increase all energy sources by a greater percentage than projected by the EIA. Both solutions decrease coal more than what the EIA projects. For solar and petroleum, the solutions yield opposite results with respect to the EIA. However, because the energy provided by petroleum is relatively small in 2012, the change minimization solution increasing this source has minimal impact on total emissions.

Figure 3.3: Percent change bBTU generation by source, 2012-2030



Note the different axes scales for solar and wind energy, relative to other energy source. Solar increases by a factor of more than 88 under all three scenarios.

3.2 Emissions in the Food Supply Chain

First, in terms of electricity consumption derived from cost-minimization, Figures 3.4 and 3.5 show how 2030 projected coal generation has decreased relative to 2012—shown in Figures 2.1 and 2.2. Generating capacity is shifted from coal to various other energy sources, except petroleum, which also decreases under the cost-minimization problem [3]. Both optimization problems yield solutions with the greatest generating capacity coming from natural gas, nuclear, wind, coal, and solar, in that order. Due largely to their relative baseline totals, coal-powered electricity still exceeds solar-powered, despite the significant decline and growth experienced by each respectively.

On the right side of Figures 3.4 and 3.5, the supply chain stages and food categories, respectively, all increase by the same factor, ρ, and do not change their relative composition. Thus, "utilities for kitchen" and the corresponding "HKO: utilities" remain the two largest stage and food category consumers of electricity.

[3] Figures 3.4 and 3.5 show the solution for cost minimization, where change minimization is nearly identical, as discussed above.

Figure 3.4: Food system electricity by energy and stage (bBTU), U.S. 2030

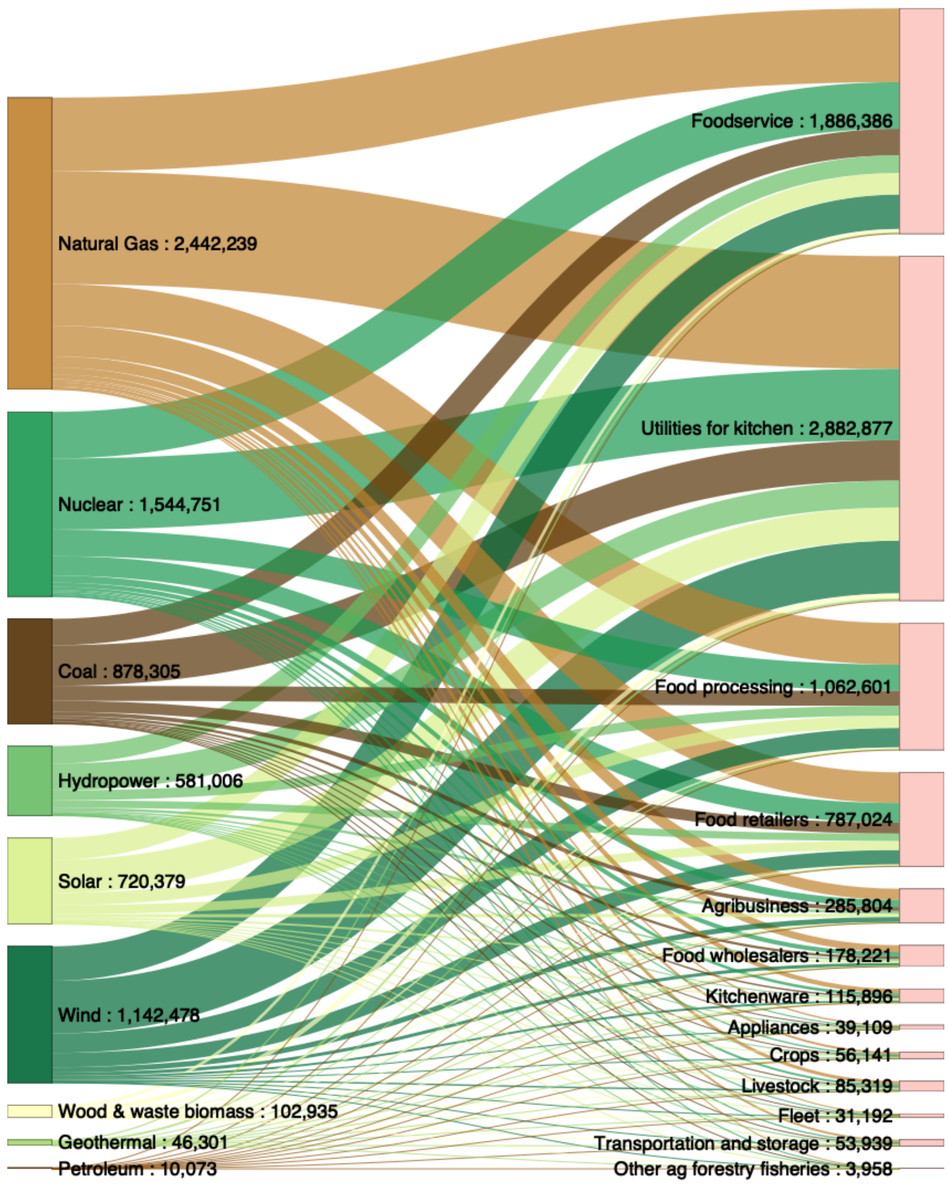
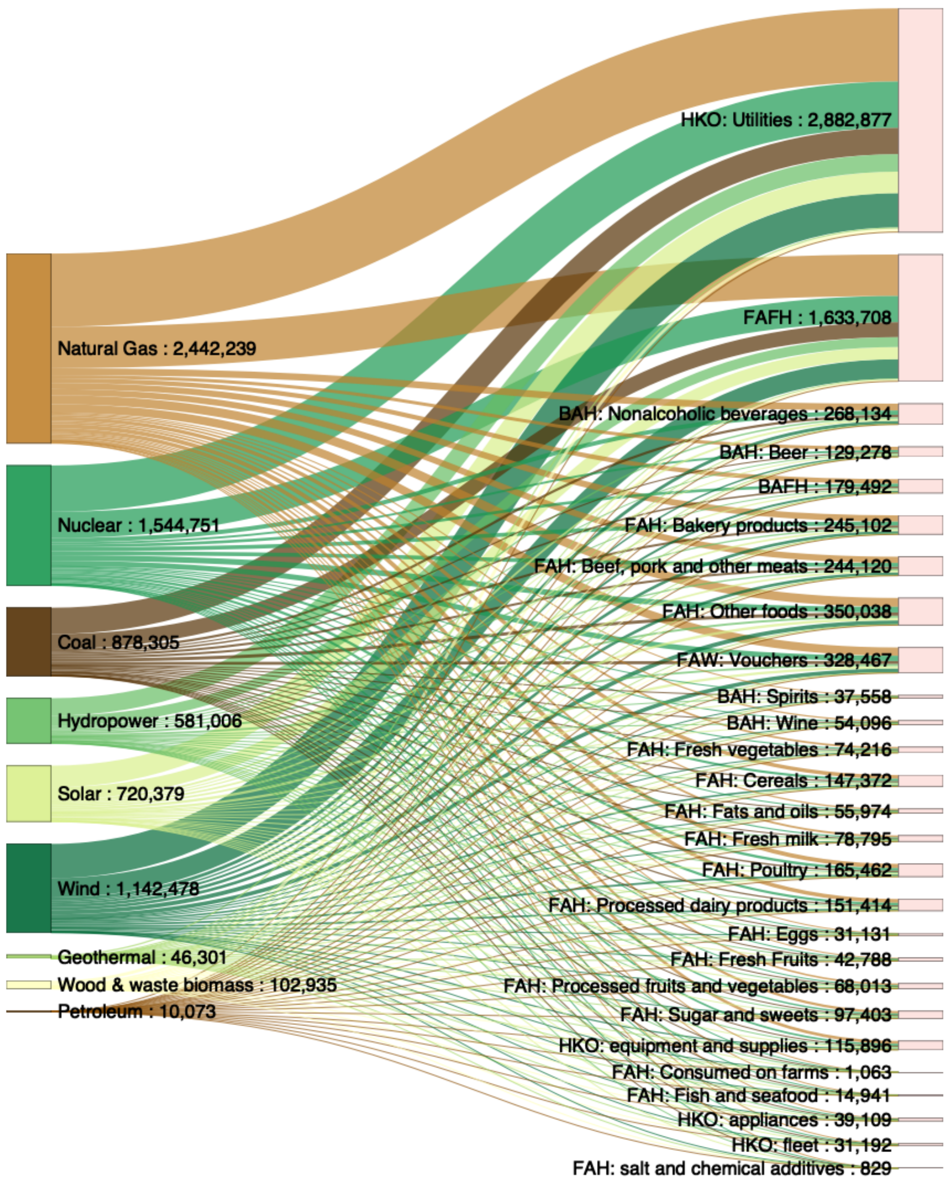


Figure 3.5: Food system electricity by energy and food category (bBTU), U.S. 2030



By holding the demand side constant, adjusted for overall electricity demand growth, reductions in emissions are achieved entirely through changes in production. Electricity is demanded in the same proportions, but electricity production generates less emissions by replacing high-emitting energy—coal and petroleum—with lower-emitting alternatives. As the counterparts to Figures 2.3 and 2.4, emissions for the cost-minimization solutions are shown in Figures 3.6 and 3.7. Whereas coal was the primary emitter in 2012, natural gas becomes the primary emitter in the 2030 solution, at 347 MMt CO2e emissions (54%), followed by coal at 257 MMt (40%). The remaining 6% of emissions are attributed to the other seven energy sources, with solar accounting for the third most emissions, 9 MMt (1.4%).

Figure 3.6: Food system CO2e by energy and stage (MMt), U.S. 2030

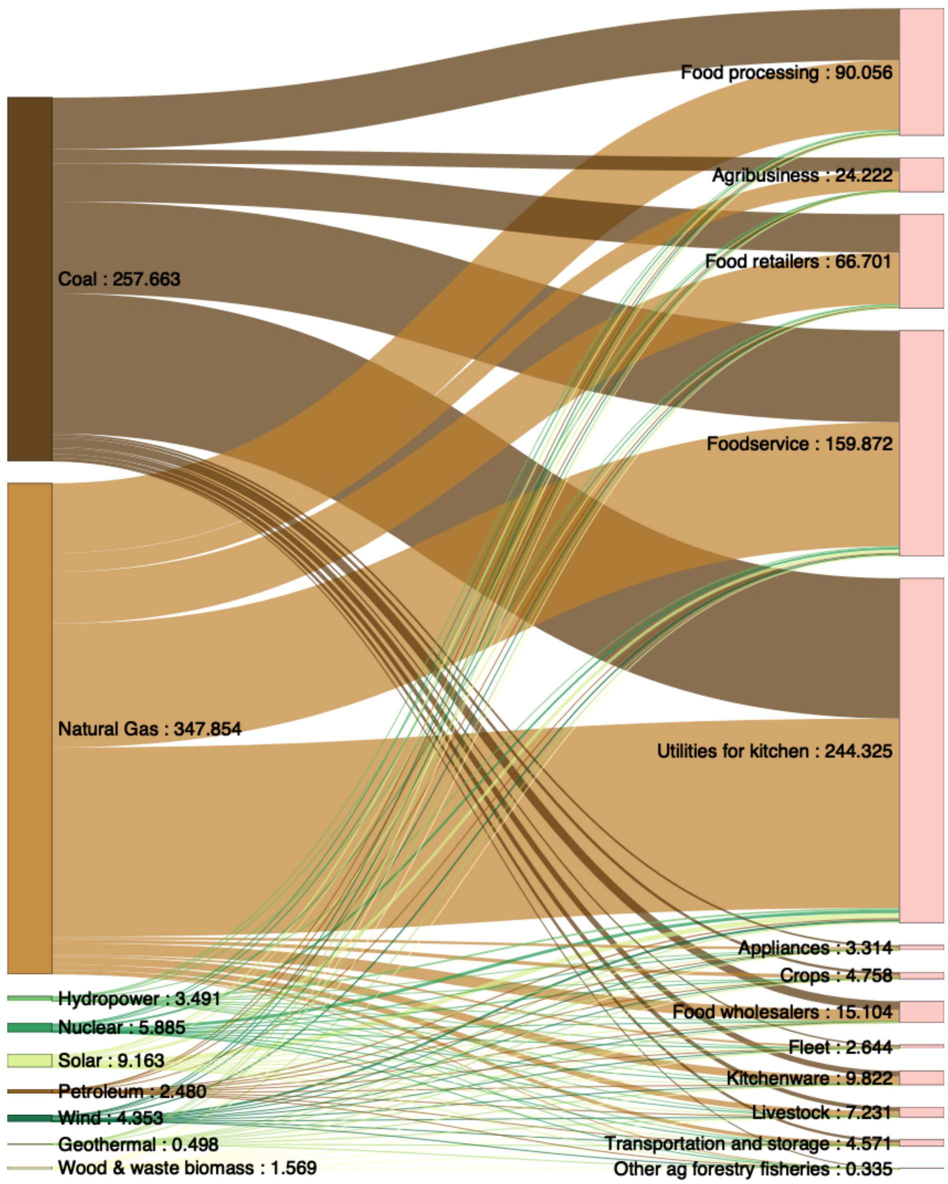
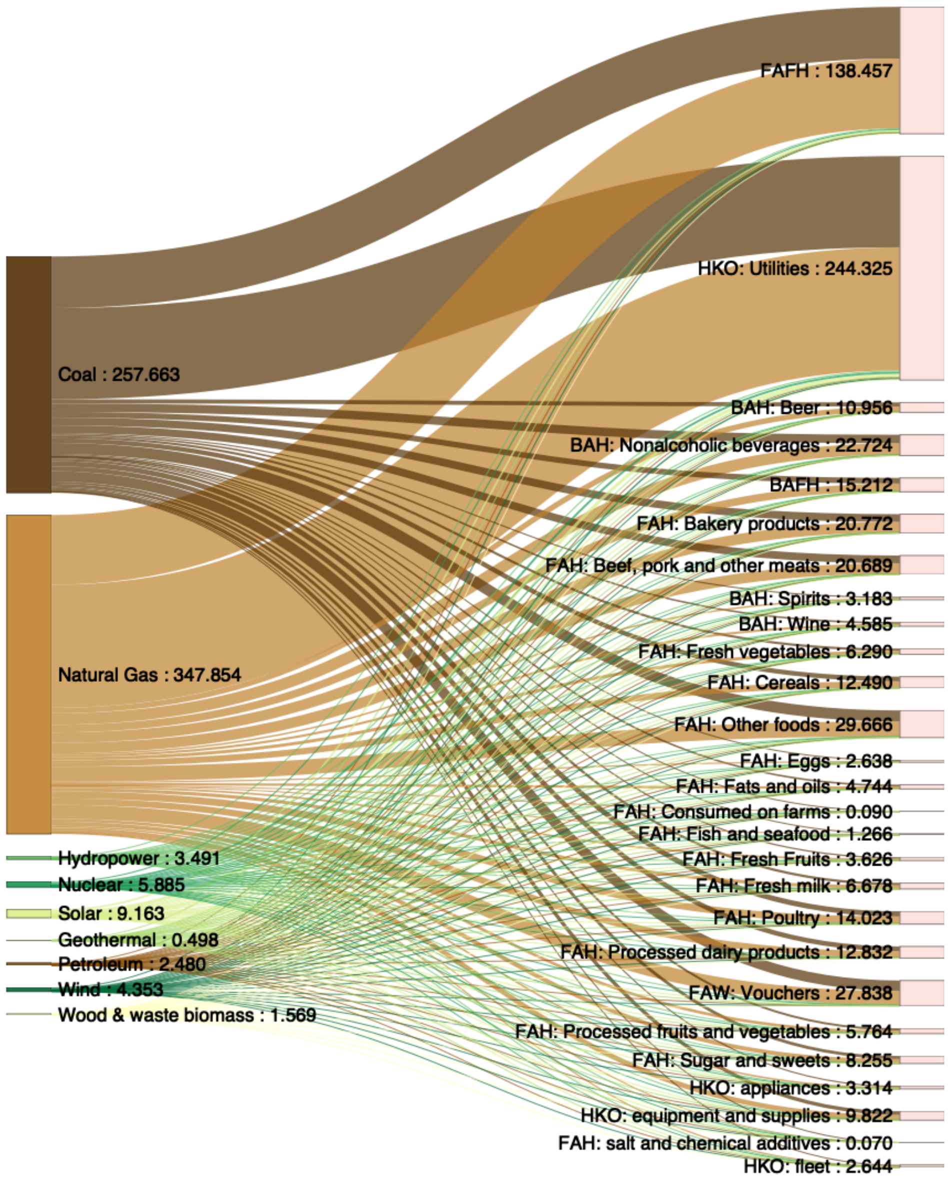


Figure 3.7: Food system CO2e by energy and food category (MMt), U.S. 2030



As is clear from comparing Figures 3.4 and 3.6, nuclear and wind generate a comparatively small amount of emissions, despite becoming the second and third largest electricity providers. As the largest provider of electricity, natural gas becomes the largest emitter. For its part, coal becomes the fourth largest provider of electricity, slightly ahead of solar, while still generating the second most emissions. Of note, even if all fossil fuels were eliminated from electricity generation, the remaining energy sources would still produce emissions. This point will be discussed further below, when considering the path to net zero emissions by 2050.

The right hand sides of Figures 3.5 and 3.6 are directly proportional to Figures 3.3 and 3.4—greater electricity consumption generating greater emissions. As the largest electricity consumers, the largest emissions reduction is achieved by “utilities for kitchen” and “HKO: utilities”. Emissions from the stage “utilities for kitchen” are nearly cut in half, declining from 449,552 MMt in 2012 to 233,325 MMt in 2030.

Discussion

This final section presents the policy implications of my findings, model limitations, potential for future research, and concluding remarks.

4.1 Policy Implications

My findings suggest that more must be done to reduce emissions from food system electricity use, if the IPCC target of 1.5° is to be achieved. Given the latest EIA projections for growth of primary energy sources—grounded in their analysis of expected market and policy trends—sufficient decarbonization would not be realized in electricity generation for the U.S. food system to meet the IPCC target. This finding is consistent with other research suggesting the U.S. economy as a whole is not on track to limit warming to 1.5°C (UNEP 2021).

However, my findings suggest that the additional growth required is modest relative to EIA projected changes, in some cases. Whereas I added 8 percentage points of growth across all energy sources to achieve a feasible solution, the EIA predicts solar will increase 250% from 2021 to 2030 *(See Table 2.3)*. Likewise, the EIA predicts wind, geothermal, and hydropower will grow 57%, 48%, and 15%, respectively. With a projected 9% decline for nuclear, the added growth would instead mean declining at a slower rate, nearly holding steady. Relative to the projections, the growth rates seem achievable.

4.2 Model Limitations and Future Research

A primary limitation of my model is the supply-side focus. While holding demand fixed enables the analysis of production changes specifically, in reality changes in food demand could have a significant impact on energy use and corresponding emissions (Hitaj et al. 2019). Moreover, because a solution is not feasible at existing EIA projections for energy growth, I incrementally increase the percentage growth of *all* sources. This uniform increase does not capture the true nature of energy supply.

Additionally, key model parameters—LCOE and life cycle emissions factors—are assumed constant over the period of analysis even though these are expected to change. Given this paper's assumptions, the path to net zero in 2050 would be impossible. This is because non-fossil fuel energy sources still have emissions embedded in their supply chains—with rates assumed constant through 2030 *(See Table 2.2)*—and because negative emissions technology is not modeled. This limitation of the model reflects real-world challenges: i) the need to invent negative emissions technologies that are as yet unproven at scale, and ii) the need to decarbonize "clean" energy sources. Because the former is unproven, more researchers are advocating an emphasis on the latter, with a strategy of "electrifying everything" and generating that electricity through a combination of renewable energy and potentially nuclear (Prentiss 2015; Griffith 2021).

These limitations point towards potential research opportunities. First, developing energy supply functions could more accurately model energy growth beyond the EIA projections, incorporating energy prices and elasticity. In turn, food demand could be allowed to vary in response to changing food prices generated by energy production changes. Under this model, emissions reduction would be achieved by *both* supply- and demand-side changes.

Negative emissions technologies—principally carbon capture and storage—could be modeled based on estimates of when such technology will be deployed at scale. This modeling is standard in IPCC climate pathways (IPCC 2018). Additionally, instead of holding life cycle emissions factors constant across time through 2030, these factors could be projected annually, reflecting changes in production processes that reduce the energy source's embodied supply chain emissions. Likewise, the LCOE estimates could be annual, incorporating "learning by doing" rates such that cost decreases as deployment increases, lowering the costs of those sources projected to grow the most. Regarding cost, the IEA suggests that supplementing LCOE estimates with the value-adjusted levelized cost of electricity (VALCOE) could more accurately model deregulated electricity markets [1] (IEA 2020).

To expand modeling scope, incorporating the other energy sources listed in Table 2.1 would provide a comprehensive view of energy consumption and emissions in the U.S. food system. Further, incorporating all economic sectors tracked by USDOL-BLS would enable the modeling of energy use for the entire U.S. economy. However, such modeling would likely entail greater data aggregation, sacrificing the specificity of supply chain analysis.

4.3 Conclusion

My principal finding is that the U.S. food system is not on track reduce emissions from its electricity use in a manner consistent with limiting warming to 1.5° C. Neither the cost- nor change-minimizing MP problems yield a feasible solution given EIA projections

[1]The IEA states: "The LCOE is the principal tool for comparing the plant-level unit costs of different baseload technologies over their operating lifetimes. The LCOE indicates the economic costs of a generic technology, not the financial costs of a specific project in a specific market. Due to the equality between discounted average costs and the stable remuneration over lifetime electricity production, which is at its heart, LCOE is in spirit closer to the costs of electricity production in regulated electricity markets with stable tariffs, for which it was developed, than to the variable prices in deregulated markets. By adjusting the discount rate for the implicit cost of price volatility, the LCOE concept can, in principle, also be applied in the context of deregulated markets.... While there is an increasing need to complement it with information, such as provided by VALCOE, on the system contribution of different technologies under different constellations, the LCOE retains its fundamental usefulness as a widely used tool for modelling, policy making and public debate" (IEA 2020).

for energy source growth through 2030. However, solutions become feasible when adding eight percentage points to the EIA projections, suggesting that the target remains within reach. Notably, the solutions yield results showing natural gas as the largest source of electricity and the largest source of CO2e emissions in 2030. While this may satisfy the model constraints as designed—a 44.8% emissions reduction from 2012 levels by 2030—investment in natural gas electricity generation would not lead to net zero emissions by 2050, absent the deployment at scale of unproven negative emissions technologies. Further research can model the potential impacts of such technology, as well as the impacts of dynamic LCOE estimates and emissions factors. Modeling energy supply and food demand response could more accurately capture market behavior. Lastly, expanding the scope of energy sources and economic sectors can enable comprehensive modeling of the U.S. economy.

References

Aengenheyster, Matthias et al. (2018). "The point of no return for climate action: effects of climate uncertainty and risk tolerance". In: *Earth System Dynamics* 9 (3), pp. 1085–1095.

Anchondo, Carlos and Edward Klump (2022). *CO2-free natural gas? CCS project powers grid for first time*. eenews.com. URL: https://www.eenews.net/articles/co2-free-natural-gas-ccs-project-powers-grid-for-first-time/ (visited on 04/25/2022).

Boehm, R. et al. (2018). "A Comprehensive Life Cycle Assessment of Greenhouse Gas Emissions from U.S. Household Food Choices". In: *Food Policy* 79, pp. 67–76.

Brown, Alex (2022). *Offshore Wind Takes Off at Last. States Have Been Counting on It.* pewtrusts.org/. URL: https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2022/02/07/offshore-wind-takes-off-at-last-states-have-been-counting-on-it (visited on 04/25/2022).

Calma, Justine (2022). *Plans to capture CO2 from coal plants wasted federal dollars, watchdog says*. theverge.com. URL: https://www.theverge.com/2021/12/30/22860207/carbon-capture-coal-plants-wasted-federal-dollars-watchdog-gao (visited on 04/25/2022).

Camanzi, Luca et al. (2017). "The impact of greenhouse gas emissions in the EU food chain: A quantitative and economic assessment using an environmentally extended input-output approach". In: *Journal of Cleaner Production* 157, pp. 168–176.

Canning, Patrick, Sarah Rehkamp, Arnold Waters, et al. (2017). *The Role of Fossil Fuels in the U.S. Food System and the American Diet*. URL: https://www.ers.usda.gov/publications/pub-details/?pubid=82193.

Canning, Patrick, Sarah Rehkamp, and Jing Yi (2022). "9 - Environmental Input-Output (EIO) Models for Food Systems Research: Application and Extensions". In: *Food Systems Modelling*. Cambridge, MA: Elsevier, pp. 179–212.

[Dataset] Census Bureau, U.S. (2022). *County Business Patterns: 2012, Complete County File*. URL: https://www.census.gov/data/datasets/2012/econ/cbp/2012-cbp.html (visited on 04/25/2022).

Clack, Christopher T. M. et al. (2017). "Evaluation of a proposal for reliable low-cost grid power with 100% wind, water, and solar". In: *Proceedings of the National Academy of Sciences of the United States of America* 114 (26).

Creutzig, Felix et al. (2017). "The underestimated potential of solar energy to mitigate climate change". In: *Nature Energy* 2 (17140).

Crippa, M. et al. (2021). "Food systems are responsible for a third of global anthropogenic GHG emissions". In: *Environmental Science & Technology* 2 (3), pp. 198–209.

[Dataset] DMDC (2022). *DoD Personnel, Workforce Reports & Publications*. URL: https://dwp.dmdc.osd.mil/dwp/app/dod-data-reports/workforce-reports (visited on 04/25/2022).

FAO (2021). *The share of food systems in total greenhouse gas emissions. Global, regional and country trends, 1990–2019.* Food and Agricultural Organization.

[Dataset] FAOSTAT (2021). *Emissions shares: DOWNLOAD DATA*. URL: https://www.fao.org/faostat/en/#data/EM/visualize.

Friedman, Lisa and Coral Davenport (Apr. 2021). *Biden Will Pledge to Cut Greenhouse Gas Emissions Nearly in Half*. New York Times. URL: https://www.nytimes.com/2021/04/20/climate/biden-climate-change.html.

Gianfrancesco, A.Di (2017). "1 - The fossil fuel power plants technology". In: *Materials for Ultra-Supercritical and Advanced Ultra-Supercritical Power Plants*. Elsevier, pp. 1–49.

Griffith, Saul (2021). *Electrify: An Optimist's Playbook for Our Clean Energy Future*. Cambridge, MA: MIT Press.

Hendrie, Gilly A. et al. (2014). "Greenhouse gas emissions and the Australian diet—comparing dietary recommendations with average intakes". In: *Nutrients* 6 (1), pp. 289–303.

Hitaj, Claudia et al. (2019). "Greenhouse Gas Emissions in the United States Food System: Current and Healthy Diet Scenarios". In: *Environmental Science & Technology* 53 (9), pp. 5493–5503.

Hultman, N. et al. (2021). *Charting an Ambitious US NDC of 51% Reductions by 2030*. Center for Global Sustainability Working Paper. College Park, MD: University of Maryland Center for Global Sustainability. URL: https://cgs.umd.edu/research-impact/publications/working-paper-charting-ambitious-us-ndc-51-reductions-2030.

IEA (2020). *Projected Costs of Generating Electricity 2020 Edition*. URL: https://www.iea.org/reports/projected-costs-of-generating-electricity-2020.

[Dataset]– (2022). *Levelised Cost of Electricity Calculator*. URL: https://www.iea.org/articles/levelised-cost-of-electricity-calculator (visited on 04/25/2022).

Ingwersen, Wesley and Mo Li (2020). *Supply Chain Greenhouse Gas Emission Factors for US Industries and Commodities*. U.S. Environmental Protection Agency.

IPCC (2018). *Global Warming of 1.5° C. An IPCC Special Report on the impacts of global warming of 1.5° C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. UN Intergovernmental Panel on Climate Change. Chap. Summary for Policymakers.

– (2021). *Climate Change 2021: The Physical Science Basis*. UN Intergovernmental Panel on Climate Change. Chap. Technical Summary. URL: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_TS.pdf.

IRENA (2022). *Renewable Power Generation Costs in 2020*. URL: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2021/Jun/IRENA_Power_Generation_Costs_2020.pdf (visited on 04/25/2022).

Jacobson, Mark Z. et al. (2015). "Low-cost solution to the grid reliability problem with 100% penetration of intermittent wind, water, and solar for all purposes". In: *Proceedings of the National Academy of Sciences of the United States of America* 112 (49).

Kitzes, Justin (2013). "An Introduction to Environmentally-Extended Input-Output Analysis". In: *Resources* 2 (4), pp. 489–503.

Leontief, W. (1967). "An Alternative to Aggregation in Input-Output Analysis and National Accounts". In: *Review of Economics and Statistics* 49 (3), pp. 412–419.

– (1970). "Environmental Repercussions and the Economic Structure: An Input–Output Approach". In: *Review of Economics and Statistics* 52, pp. 262–271.

Miller, Ronald E. and Peter D. Blair (2009). "10 - Environmental Input–Output Analysis". In: *Input-Output Analysis Foundations and Extensions*. Cambridge University Press, pp. 446–498.

Neill, Simon P. and Reza Hashemi (2018). "Chapter 1 - Introduction". In: *Fundamentals of Ocean Renewable Energy*. Elsevier, pp. 1–30.

[Dataset] NREL (2022a). *Life Cycle Emissions Factors for Electricity Generation Technologies, by Life Cycle Phase*. URL: https://data.nrel.gov/submissions/171 (visited on 04/25/2022).

– (2022b). *Life Cycle Greenhouse Gas Emissions from Electricity Generation: Update*. URL: https://data.nrel.gov/submissions/171 (visited on 04/25/2022).

Prentiss, Mara (2015). *Energy Revolution: The Physics and the Promise of Efficient Technology*. Belknap Press.

Rodríguez, Laura (2022). *Breaking down growth and perspectives of solar energy: utility, commercial and residential*. ratedpower.com. URL: https://ratedpower.com/blog/utility-commercial-residential-solar/ (visited on 04/25/2022).

Rosenzweig, Cynthia et al. (2020). "Climate change responses benefit from a global food system approach". In: *Nature Food* 1, pp. 94–97.

Trabish, Herman K. (2022). *Cheapest is not always best: Concentrated solar power could beat lower price PV with new market rules*. utilitydive.com. URL: https://www.utilitydive.com/news/cheapest-is-not-always-best-concentrated-solar-power-could-beat-lower-pric/574154/ (visited on 04/25/2022).

Tubiello, Francesco N et al. (2021). "Greenhouse gas emissions from food systems: building the evidence base". In: *Environmental Research Letters* 16 (6).

UNEP (2021). *Emissions Gap Report 2021: The Heat Is On – A World of Climate Promises Not Yet Delivered*. United Nations Environment Programme.

[Dataset] USDOC-BEA (2021). *Input-Output Accounts Data*. URL: https://www.bea.gov/industry/input-output-accounts-data (visited on 04/25/2022).

– (2022a). *BEA Depreciation Estimates*. United States Department of Commerce, Bureau of Economic Analysis. URL: https://apps.bea.gov/iTable/index_FA.cfm (visited on 04/25/2022).

[Dataset]– (2022b). *Local Area Personal Income: New Estimates for 2012; Comprehensive Revisions for 2001-2011*. URL: https://apps.bea.gov/regional/histdata/releases/1113lapi/index.cfm (visited on 04/25/2022).

[Dataset] USDOC-DOL (2021). *Inter-industry relationships (Input-Output matrix)*. URL: https://www.bls.gov/emp/data/input-output-matrix.htm (visited on 04/25/2022).

[Dataset]– (2022). *Quarterly Census of Employment and Wages*. URL: https://www.bls.gov/cew/downloadable-data-files.htm (visited on 04/25/2022).

USDOE (2022). *Levelized Cost of Energy (LCOE)*. URL: https://www.energy.gov/sites/prod/files/2015/08/f25/LCOE.pdf (visited on 04/25/2022).

USDOE-EIA (2021). *State Energy Data System (SEDS): 1960-2019 (complete)*. URL: https://www.eia.gov/state/seds/seds-data-complete.php#Consumption.

[Dataset] USDOE-EIA (2022a). *Annual Energy Outlook 2022, Table: Table 56. Renewable Energy Generation by Fuel*. URL: https://www.eia.gov/outlooks/aeo/tables_ref.php (visited on 04/25/2022).

[Dataset]– (2022b). *Annual Energy Outlook 2022, Table: Table 8. Electricity Supply, Disposition, Prices, and Emissions*. URL: https://www.eia.gov/outlooks/aeo/tables_ref.php (visited on 04/25/2022).

– (2022c). *March 2022 Monthly Energy Review*. URL: https://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf.

– (2022d). *Carbon Dioxide Emissions Coefficients*. USDOE-EIA. URL: https://www.eia.gov/environment/emissions/co2_vol_mass.php (visited on 04/25/2022).

– (2022e). *Most U.S. wind capacity built since 2011 is located in the center of the country*. USDOE-EIA. URL: https://www.eia.gov/todayinenergy/detail.php?id=48476 (visited on 04/25/2022).

[Dataset] USDOT (2022). *Employment in For-Hire Transportation and Selected Transportation-Related Industries*. URL: https://www.bts.gov/content/employment-hire-transportation-and-selected-transportation-related-industries-naics (visited on 04/25/2022).

USEPA (2022). *Greenhouse Gas Inventory Data Explorer*. U.S. Environmental Protection Agency. URL: https://cfpub.epa.gov/ghgdata/inventoryexplorer/#allsectors/allsectors/allgas/econsect/all (visited on 03/14/2022).

USFED (2022). *Dates of U.S. recessions as inferred by GDP-based recession indicator*. United States Federal Reserve. URL: https://fred.stlouisfed.org/series/JHDUSRGDPBR (visited on 03/14/2022).

Vogstad, Klaus-Ole (2009). "Input-Output Analysis and Linear Programming". In: *Handbook of Input-Output Economics in Industrial Ecology*. Springer Dordrecht, pp. 801–818.

Wiedmann, Thomas (2009). "Editorial: Carbon Footprint and Input–Output Analysis – An Introduction". In: *Economic Systems Research* 21 (3), pp. 175–186.

Yang, Yi et al. (2017). "USEEIO: A new and transparent United States environmentallyextended input-output model". In: *Journal of Cleaner Production* 158, pp. 308–318.

Bibliography

Aengenheyster, Matthias et al. (2018). "The point of no return for climate action: effects of climate uncertainty and risk tolerance". In: *Earth System Dynamics* 9 (3), pp. 1085–1095.

Anchondo, Carlos and Edward Klump (2022). *CO2-free natural gas? CCS project powers grid for first time*. eenews.com. URL: `https://www.eenews.net/articles/co2-free-natural-gas-ccs-project-powers-grid-for-first-time/` (visited on 04/25/2022).

Boehm, R. et al. (2018). "A Comprehensive Life Cycle Assessment of Greenhouse Gas Emissions from U.S. Household Food Choices". In: *Food Policy* 79, pp. 67–76.

Brown, Alex (2022). *Offshore Wind Takes Off at Last. States Have Been Counting on It.* pewtrusts.org/. URL: `https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2022/02/07/offshore-wind-takes-off-at-last-states-have-been-counting-on-it` (visited on 04/25/2022).

Calma, Justine (2022). *Plans to capture CO2 from coal plants wasted federal dollars, watchdog says*. theverge.com. URL: `https://www.theverge.com/2021/12/30/22860207/carbon-capture-coal-plants-wasted-federal-dollars-watchdog-gao` (visited on 04/25/2022).

Camanzi, Luca et al. (2017). "The impact of greenhouse gas emissions in the EU food chain: A quantitative and economic assessment using an environmentally extended input-output approach". In: *Journal of Cleaner Production* 157, pp. 168–176.

Canning, Patrick, Sarah Rehkamp, Arnold Waters, et al. (2017). *The Role of Fossil Fuels in the U.S. Food System and the American Diet*. URL: `https://www.ers.usda.gov/publications/pub-details/?pubid=82193`.

Canning, Patrick, Sarah Rehkamp, and Jing Yi (2022). "9 - Environmental Input-Output (EIO) Models for Food Systems Research: Application and Extensions". In: *Food Systems Modelling*. Cambridge, MA: Elsevier, pp. 179–212.

[Dataset] Census Bureau, U.S. (2022). *County Business Patterns: 2012, Complete County File*. URL: `https://www.census.gov/data/datasets/2012/econ/cbp/2012-cbp.html` (visited on 04/25/2022).

Clack, Christopher T. M. et al. (2017). "Evaluation of a proposal for reliable low-cost grid power with 100% wind, water, and solar". In: *Proceedings of the National Academy of Sciences of the United States of America* 114 (26).

Creutzig, Felix et al. (2017). "The underestimated potential of solar energy to mitigate climate change". In: *Nature Energy* 2 (17140).

Crippa, M. et al. (2021). "Food systems are responsible for a third of global anthropogenic GHG emissions". In: *Environmental Science & Technology* 2 (3), pp. 198–209.

[Dataset] DMDC (2022). *DoD Personnel, Workforce Reports & Publications*. URL: https://dwp.dmdc.osd.mil/dwp/app/dod-data-reports/workforce-reports (visited on 04/25/2022).

FAO (2021). *The share of food systems in total greenhouse gas emissions. Global, regional and country trends, 1990–2019*. Food and Agricultural Organization.

[Dataset] FAOSTAT (2021). *Emissions shares: DOWNLOAD DATA*. URL: https://www.fao.org/faostat/en/#data/EM/visualize.

Friedman, Lisa and Coral Davenport (Apr. 2021). *Biden Will Pledge to Cut Greenhouse Gas Emissions Nearly in Half*. New York Times. URL: https://www.nytimes.com/2021/04/20/climate/biden-climate-change.html.

Gianfrancesco, A.Di (2017). "1 - The fossil fuel power plants technology". In: *Materials for Ultra-Supercritical and Advanced Ultra-Supercritical Power Plants*. Elsevier, pp. 1–49.

Griffith, Saul (2021). *Electrify: An Optimist's Playbook for Our Clean Energy Future*. Cambridge, MA: MIT Press.

Hendrie, Gilly A. et al. (2014). "Greenhouse gas emissions and the Australian diet—comparing dietary recommendations with average intakes". In: *Nutrients* 6 (1), pp. 289–303.

Hitaj, Claudia et al. (2019). "Greenhouse Gas Emissions in the United States Food System: Current and Healthy Diet Scenarios". In: *Environmental Science & Technology* 53 (9), pp. 5493–5503.

Hultman, N. et al. (2021). *Charting an Ambitious US NDC of 51% Reductions by 2030*. Center for Global Sustainability Working Paper. College Park, MD: University of Maryland Center for Global Sustainability. URL: https://cgs.umd.edu/research-impact/publications/working-paper-charting-ambitious-us-ndc-51-reductions-2030.

IEA (2020). *Projected Costs of Generating Electricity 2020 Edition*. URL: https://www.iea.org/reports/projected-costs-of-generating-electricity-2020.

[Dataset]– (2022). *Levelised Cost of Electricity Calculator*. URL: https://www.iea.org/articles/levelised-cost-of-electricity-calculator (visited on 04/25/2022).

Ingwersen, Wesley and Mo Li (2020). *Supply Chain Greenhouse Gas Emission Factors for US Industries and Commodities*. U.S. Environmental Protection Agency.

IPCC (2018). *Global Warming of 1.5° C. An IPCC Special Report on the impacts of global warming of 1.5° C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty*. UN Intergovernmental Panel on Climate Change. Chap. Summary for Policymakers.

– (2021). *Climate Change 2021: The Physical Science Basis*. UN Intergovernmental Panel on Climate Change. Chap. Technical Summary. URL: https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_TS.pdf.

IRENA (2022). *Renewable Power Generation Costs in 2020*. URL: https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2021/Jun/IRENA_Power_Generation_Costs_2020.pdf (visited on 04/25/2022).

Jacobson, Mark Z. et al. (2015). "Low-cost solution to the grid reliability problem with 100% penetration of intermittent wind, water, and solar for all purposes". In: *Proceedings of the National Academy of Sciences of the United States of America* 112 (49).

Kitzes, Justin (2013). "An Introduction to Environmentally-Extended Input-Output Analysis". In: *Resources* 2 (4), pp. 489–503.

Leontief, W. (1967). "An Alternative to Aggregation in Input-Output Analysis and National Accounts". In: *Review of Economics and Statistics* 49 (3), pp. 412–419.

– (1970). "Environmental Repercussions and the Economic Structure: An Input–Output Approach". In: *Review of Economics and Statistics* 52, pp. 262–271.

Miller, Ronald E. and Peter D. Blair (2009). "10 - Environmental Input–Output Analysis". In: *Input-Output Analysis Foundations and Extensions*. Cambridge University Press, pp. 446–498.

Neill, Simon P. and Reza Hashemi (2018). "Chapter 1 - Introduction". In: *Fundamentals of Ocean Renewable Energy*. Elsevier, pp. 1–30.

[Dataset] NREL (2022a). *Life Cycle Emissions Factors for Electricity Generation Technologies, by Life Cycle Phase*. URL: https://data.nrel.gov/submissions/171 (visited on 04/25/2022).

– (2022b). *Life Cycle Greenhouse Gas Emissions from Electricity Generation: Update*. URL: https://data.nrel.gov/submissions/171 (visited on 04/25/2022).

Prentiss, Mara (2015). *Energy Revolution: The Physics and the Promise of Efficient Technology*. Belknap Press.

Rodríguez, Laura (2022). *Breaking down growth and perspectives of solar energy: utility, commercial and residential*. ratedpower.com. URL: https://ratedpower.com/blog/utility-commercial-residential-solar/ (visited on 04/25/2022).

Rosenzweig, Cynthia et al. (2020). "Climate change responses benefit from a global food system approach". In: *Nature Food* 1, pp. 94–97.

Trabish, Herman K. (2022). *Cheapest is not always best: Concentrated solar power could beat lower price PV with new market rules*. utilitydive.com. URL: https://www.utilitydive.com/news/cheapest-is-not-always-best-concentrated-solar-power-could-beat-lower-pric/574154/ (visited on 04/25/2022).

Tubiello, Francesco N et al. (2021). "Greenhouse gas emissions from food systems: building the evidence base". In: *Environmental Research Letters* 16 (6).

UNEP (2021). *Emissions Gap Report 2021: The Heat Is On – A World of Climate Promises Not Yet Delivered*. United Nations Environment Programme.

[Dataset] USDOC-BEA (2021). *Input-Output Accounts Data*. URL: https://www.bea.gov/industry/input-output-accounts-data (visited on 04/25/2022).

– (2022a). *BEA Depreciation Estimates*. United States Department of Commerce, Bureau of Economic Analysis. URL: https://apps.bea.gov/iTable/index_FA.cfm (visited on 04/25/2022).

[Dataset]– (2022b). *Local Area Personal Income: New Estimates for 2012; Comprehensive Revisions for 2001-2011*. URL: https://apps.bea.gov/regional/histdata/releases/1113lapi/index.cfm (visited on 04/25/2022).

[Dataset] USDOC-DOL (2021). *Inter-industry relationships (Input-Output matrix)*. URL: https://www.bls.gov/emp/data/input-output-matrix.htm (visited on 04/25/2022).

[Dataset]– (2022). *Quarterly Census of Employment and Wages*. URL: https://www.bls.gov/cew/downloadable-data-files.htm (visited on 04/25/2022).

USDOE (2022). *Levelized Cost of Energy (LCOE)*. URL: https://www.energy.gov/sites/prod/files/2015/08/f25/LCOE.pdf (visited on 04/25/2022).

USDOE-EIA (2021). *State Energy Data System (SEDS): 1960-2019 (complete)*. URL: https://www.eia.gov/state/seds/seds-data-complete.php#Consumption.

[Dataset] USDOE-EIA (2022a). *Annual Energy Outlook 2022, Table: Table 56. Renewable Energy Generation by Fuel*. URL: https://www.eia.gov/outlooks/aeo/tables_ref.php (visited on 04/25/2022).

[Dataset]– (2022b). *Annual Energy Outlook 2022, Table: Table 8. Electricity Supply, Disposition, Prices, and Emissions*. URL: https://www.eia.gov/outlooks/aeo/tables_ref.php (visited on 04/25/2022).

– (2022c). *March 2022 Monthly Energy Review*. URL: https://www.eia.gov/totalenergy/data/monthly/pdf/mer.pdf.

– (2022d). *Carbon Dioxide Emissions Coefficients*. USDOE-EIA. URL: https://www.eia.gov/environment/emissions/co2_vol_mass.php (visited on 04/25/2022).

– (2022e). *Most U.S. wind capacity built since 2011 is located in the center of the country*. USDOE-EIA. URL: https://www.eia.gov/todayinenergy/detail.php?id=48476 (visited on 04/25/2022).

[Dataset] USDOT (2022). *Employment in For-Hire Transportation and Selected Transportation-Related Industries*. URL: https://www.bts.gov/content/employment-hire-transportation-and-selected-transportation-related-industries-naics (visited on 04/25/2022).

USEPA (2022). *Greenhouse Gas Inventory Data Explorer*. U.S. Environmental Protection Agency. URL: https://cfpub.epa.gov/ghgdata/inventoryexplorer/#allsectors/allsectors/allgas/econsect/all (visited on 03/14/2022).

USFED (2022). *Dates of U.S. recessions as inferred by GDP-based recession indicator*. United States Federal Reserve. URL: https://fred.stlouisfed.org/series/JHDUSRGDPBR (visited on 03/14/2022).

Vogstad, Klaus-Ole (2009). "Input-Output Analysis and Linear Programming". In: *Handbook of Input-Output Economics in Industrial Ecology*. Springer Dordrecht, pp. 801–818.

Wiedmann, Thomas (2009). "Editorial: Carbon Footprint and Input–Output Analysis – An Introduction". In: *Economic Systems Research* 21 (3), pp. 175–186.

Yang, Yi et al. (2017). "USEEIO: A new and transparent United States environmentallyextended input-output model". In: *Journal of Cleaner Production* 158, pp. 308–318.

Charts and Schematics

Figure A.1: Agri-food systems categories: Mapping from IPCC to FAO

IPCC		Agri-food systems activity	GHG CH_4	GHG N_2O	GHG CO_2	FAO		
AFOLU	LULUCF	Net forest conversion	x	x	x	LAND USE CHANGE	AGRICULTURAL LAND	AGRI-FOOD SYSTEMS
		Tropical forest fires	x	x	x			
		Peat fires	x		x			
		Drained organic soils	x		x	FARM GATE		
	AGRICULTURE	Burning – Crop residues	x	x				
		Burning – Savanna	x	x				
		Crop residues		x				
		Drained organic soils		x				
		Enteric fermentation	x					
		Manure management	x	x				
		Manure applied to soils		x				
		Manure left on pasture		x				
		Rice cultivation	x					
		Synthetic fertilizers		x				
ENERGY		On-farm energy use	x	x	x			
		Fertilizer manufacturing	x	x	x	PRE- AND POST-PRODUCTION		
		Processing	x	x	x			
		Packaging	x	x	x			
		Transport	x	x	x			
		Household consumption	x	x	x			
		Retail – Energy use	x	x	x			
INDUSTRY		Retail – Refrigeration	x	x	x			
WASTE		Solid food waste	x					
		Incineration			x			
		Industrial wastewater	x	x				
		Domestic wastewater	x	x				

Source: FAO (2021)

Figure A.2: Supply, Use, and Input-Output tables — example

Supply of commodities by activity

		Commodity: Crop and animal products	Goods	Services	Total
Activity	Agriculture	23	2		25
	Manufacturing	4	128	3	135
	Other			86	86
Imports		2	20	31	53
Total		29	150	120	

Use of commodities by activity and GDP components, and use of primary factors by activity

Commodity	Activity*: Agri-culture	Manu-facturing	Other	Final Uses*: PCE	PDI	Govt	Exp.	Total
Crop and animal products	5	10	1	5	1	2	5	29
Goods	5	40	25	50	15	5	10	150
Services	5	30	25	50	4	1	5	120
Salary and wages	2	25	23					
Operating surplus	8	30	12					
Total	25	135	86					

* PCE = personal consumption expenditures; PDI = private direct investment; Gov = government consumption and investment expenditures; Exp = exports

Activity by commodity input-output table

	Commodity	Activity: Agri-culture	Manu-facturing	Other	Commodity: Crop and animal products	Goods	Services	Final uses: PCE+PDI+Govt+Exp	Total
Activity	Agriculture				23	2			25
	Manufacturing				4	128	3		135
	Other						86		86
Commodity	Crop and animal products	5	10	1				13	29
	Goods	5	40	25				80	150
	Services	5	30	25				60	120
Factors+imports	Salary/wages+Operating surplus+Imports	10	55	35	2	20	31		120
	Total	25	135	86	29	150	120	120	

Source: Canning, Rehkamp, and Yi (2022)

Figure A.3: EIO model schematic for simplified IOT

		Activities			Commodities			Institutions and rest of world	
		Agri-culture	Manu-facturing	Other	Crop and animal products	Goods	Services	PCE+PDI+Govt+Exp	Total
Activities	Agriculture								
	Manufacturing	$\mathbf{T}_{I,I}$(=0)			$\mathbf{T}_{I,J}$				
	Other								
		Endogenous transactions (**T**)						Injection vector (**x**)	Gross output (**y**)
Commodities	Crop and animal products								
	Goods	$\mathbf{T}_{J,I}$			$\mathbf{T}_{J,J}$(=0)				
	Services								
Factors and rest of world	Salary and wages+Operating surplus+Imports	Leakage vector (**l'**)						Exogenous transactions (**lx**)	GDI + imports
	Total	Gross output (**y'**)						GDP + imports	

Source: Canning, Rehkamp, and Yi (2022).

Tables

B.1 Input-Output table elements

Table B.1 shows the activities and commodities from the IOT used for the EIO model. Because the first 222 commodities are a one-to-one match with activities, only the remaining commodities are shown. The combined activities and commodities form the first rows and columns of the IOT, which are symmetrical, as shown in *Figure A.3*.

Table B.1: IOT activities and commodities

Row	Row Description	Row	Row Description
A001	Oilseed farming	A120	Other durable goods merchant wholesalers
A002	Grain farming	A121	Drugs and druggists sundries
A003	Vegetable and melon farming	A122	Petroleum and petroleum products
A004	Fruit and tree nut farming	A123	Other nondurable goods merchant wholesalers
A005	Greenhouse nursery and floriculture production	A124	Wholesale electronic markets and agents and brokers
A006	Other crop farming	A125	Customs duties

A007	Beef cattle ranching and farming including feedlots and dual purpose ranching and farming	A126	Grocery and related product wholesalers
A008	Dairy cattle and milk production	A127	Motor vehicle and parts dealers
A009	Animal production except cattle and poultry and eggs	A128	Food and beverage stores
A010	Poultry and egg production	A129	General merchandise stores
A011	Forestry and logging	A130	All other retail
A012	Fishing hunting and trapping	A131	Air transportation
A013	Support activities for agriculture and forestry	A132	Rail transportation
A014	Oil and gas extraction	A133	Water transportation
A015	Coal mining	A134	Truck transportation
A016	Metal ore mining	A135	Transit and ground passenger transportation
A017	Nonmetallic mineral mining and quarrying	A136	Pipeline transportation
A018	Support activities for mining	A137	Scenic and sightseeing transportation and support activities for transportation
A019	Electric power generation transmission and distribution	A138	Couriers and messengers
A020	Natural gas distribution	A139	Warehousing and storage
A021	Water sewage and other systems	A140	Newspaper periodical book and directory publishers
A022	Construction	A141	Software publishers

A023	Dog and cat food manufacturing	A142	Motion picture video and sound recording industries
A024	Other animal food manufacturing	A143	Radio and television broadcasting
A025	Flour milling and malt manufacturing	A144	Cable and other subscription programming
A026	Wet corn milling	A145	Wired telecommunications carriers
A027	Soybean and other oilseed processing	A146	Wireless telecommunications carriers (except satellite)
A028	Fats and oils refining and blending	A147	Satellite telecommunications resellers and all other telecommunications
A029	Breakfast cereal manufacturing	A148	Data processing hosting and related services
A030	Sugar and confectionery product manufacturing	A149	Other information services
A031	Frozen food manufacturing	A150	Monetary authorities credit intermediation and related activities
A032	Fruit and vegetable canning pickling and drying	A151	Securities commodity contracts fund trusts and other financial investments and vehicles and related activities
A033	Cheese manufacturing	A152	Insurance carriers
A034	Dry condensed and evaporated dairy product manufacturing	A153	Agencies brokerages and other insurance related activities

A035	Ice cream and frozen dessert manufacturing	A154	Real estate
A036	Fluid milk and butter manufacturing	A155	Owner occupied dwellings
A037	Animal (except poultry) slaughtering rendering and processing	A156	Automotive equipment rental and leasing
A038	Poultry processing	A157	Consumer goods rental and general rental centers
A039	Seafood product preparation and packaging	A158	Commercial and industrial machinery and equipment rental and leasing
A040	Bread and bakery product manufacturing	A159	Lessors of nonfinancial intangible assets (except copyrighted works)
A041	Cookie cracker pasta and tortilla manufacturing	A160	Legal services
A042	Snack food manufacturing	A161	Accounting tax preparation bookkeeping and payroll services
A043	Coffee and tea manufacturing	A162	Architectural engineering and related services
A044	Flavoring syrup and concentrate manufacturing	A163	Specialized design services
A045	Seasoning and dressing manufacturing	A164	Computer systems design and related services
A046	All other food manufacturing	A165	Management scientific and technical consulting services

A047	Soft drink and ice manufacturing	A166	Scientific research and development services
A048	Breweries	A167	Advertising and related services
A049	Wineries	A168	Other professional scientific and technical services
A050	Distilleries	A169	Management of companies and enterprises
A051	Tobacco manufacturing	A170	Office administrative services
A052	Textile mills and textile product mills	A171	Facilities support services
A053	Apparel leather and allied product manufacturing	A172	Employment services
A054	Sawmills and wood preservation	A173	Business support services
A055	Veneer plywood and engineered wood product manufacturing	A174	Travel arrangement and reservation services
A056	Pulp paper paperboard mills other wood product manufacturing including wood tv radio and sewing machine cabinet manufacturing	A175	Investigation and security services
A057	Converted paper product manufacturing	A176	Services to buildings and dwellings
A058	Printing and related support activities	A177	Other support services
A059	Petroleum and coal products manufacturing	A178	Waste management and remediation services

A060	Basic chemical manufacturing	A179	Elementary and secondary schools
A061	Resin synthetic rubber and artificial synthetic fibers and filaments manufacturing	A180	Junior colleges colleges universities and professional schools
A062	Pesticide fertilizer and other agricultural chemical manufacturing	A181	Other educational services
A063	Pharmaceutical and medicine manufacturing	A182	Offices of physicians
A064	Paint coating and adhesive manufacturing	A183	Offices of dentists
A065	Soap cleaning compound and toilet preparation manufacturing	A184	Offices of other health practitioners
A066	Other chemical product and preparation manufacturing	A185	Outpatient care centers
A067	Plastics product manufacturing	A186	Medical and diagnostic laboratories
A068	Rubber product manufacturing	A187	Home health care services
A069	Clay product and refractory manufacturing	A188	Other ambulatory health care services
A070	Glass and glass product manufacturing	A189	Hospitals
A071	Cement and concrete product manufacturing	A190	Nursing and residential care facilities

A072	Lime gypsum and other non-metallic mineral product manufacturing	A191	Individual and family services
A073	Iron and steel mills and ferroalloy manufacturing	A192	Community and vocational rehabilitation services
A074	Steel product manufacturing from purchased steel	A193	Child day care services
A075	Alumina and aluminum production and processing	A194	Performing arts companies
A076	Nonferrous metal (except aluminum) production and processing	A195	Spectator sports
A077	Foundries	A196	Promoters of events and agents and managers
A078	Forging and stamping	A197	Independent artists writers and performers
A079	Cutlery and handtool manufacturing	A198	Museums historical sites and similar institutions
A080	Architectural and structural metals manufacturing	A199	Amusement parks and arcades
A081	Boiler tank and shipping container manufacturing	A200	Gambling industries (except casino hotels)
A082	Hardware manufacturing	A201	Other amusement and recreation industries
A083	Spring and wire product manufacturing	A202	Accommodation

A084	Machine shops turned product and screw nut and bolt manufacturing	A203	Service at full service restaurants
A085	Coating engraving heat treating and allied activities	A204	Service at limited service restaurants
A086	Other fabricated metal product manufacturing	A205	Service at all other food and drinking places
A087	Agriculture construction and mining machinery manufacturing	A206	Automotive repair and maintenance
A088	Industrial machinery manufacturing	A207	Electronic and precision equipment repair and maintenance
A089	Commercial and service industry machinery manufacturing including digital camera manufacturing	A208	Commercial and industrial machinery and equipment (except automotive and electronic) repair and maintenance
A090	Ventilation heating air conditioning and commercial refrigeration equipment manufacturing	A209	Personal and household goods repair and maintenance
A091	Metalworking machinery manufacturing	A210	Personal care services
A092	Engine turbine and power transmission equipment manufacturing	A211	Death care services
A093	Other general purpose machinery manufacturing	A212	Drycleaning and laundry services

A094	Computer and peripheral equipment manufacturing excluding digital camera manufacturing	A213	Other personal services
A095	Communications equipment manufacturing	A214	Religious organizations
A096	Audio and video equipment manufacturing	A215	Grantmaking and giving services and social advocacy organizations
A097	Semiconductor and other electronic component manufacturing	A216	Civic social professional and similar organizations
A098	Navigational measuring electromedical and control instruments manufacturing	A217	Private households
A099	Manufacturing and reproducing magnetic and optical media	A218	Federal enterprise
A100	Electric lighting equipment manufacturing	A219	Federal general government (defense)
A101	Household appliance manufacturing	A220	Federal general government (nondefense)
A102	Electrical equipment manufacturing	A221	State and local government
A103	Other electrical equipment and component manufacturing	A222	State and local enterprise
A104	Motor vehicle manufacturing	A223	Export assembly
A105	Motor vehicle body and trailer manufacturing	A224	Food at full service restaurants

A106	Motor vehicle parts manufacturing	A225	Food at limited service restaurants
A107	Aerospace product and parts manufacturing	A226	Food at all other food and drinking places
A108	Railroad rolling stock manufacturing	A227	Vouchers for full service restaurants
A109	Ship and boat building	A228	Vouchers for limited service restaurants
A110	Other transportation equipment manufacturing	A229	Vouchers for all other food and drinking places
A111	Household and institutional furniture and kitchen cabinet manufacturing excluding wood tv radio and sewing maching cabinet manufacturing	C223	Used second hand and scrap
A112	Office furniture (including fixtures) manufacturing	C224	Noncomprable imports and rest of world adjustment
A113	Other furniture related product manufacturing	C225	Export assembly
A114	Medical equipment and supplies manufacturing	C226	Food at full service restaurants
A115	Other miscellaneous manufacturing	C227	Food at limited service restaurants
A116	Motor vehicle and motor vehicle parts and supplies	C228	Food at all other food and drinking places

A117	Professional and commercial equipment and supplies	C229	Vouchers for full service restaurants
A118	Household appliances and electrical and electronic goods	C230	Vouchers for limited service restaurants
A119	Machinery equipment and supplies	C231	Vouchers for all other food and drinking places

Table B.2 shows the last rows of the IOT (leakage matrix rows) used for the EIO model.

Table B.2: Leakage rows

Row	Row Description
L01	Compensation of employees
L02	Taxes on production and imports less subsidies
L03	Gross operating surplus
L04	Imports

Table B.3 shows the columns of the IOT representing non-food injection matrix categories.

Table B.3: Injection columns (non-food)

Column	Column Description
X01	Nonfood personal consumption expenditures
X02	Investment
X03	Government
X04	Exports

Table B.4 shows the columns of the IOT representing food injection matrix categories.

Table B.4: Injection columns (food)

Column	Column Description
XF1	Beverages at home: Beer
XF2	Beverages at home: Nonalcoholic beverages
XF3	Beverages at home: Spirits
XF4	Beverages at home: Wine
XF5	Beverages away from home
XF6	Food at home: Fresh vegetables
XF7	Food at home: Bakery products
XF8	Food at home: Beef, pork and other meats
XF9	Food at home: Cereals
XF10	Food at home: Consumed on farms
XF11	Food at home: Eggs
XF12	Food at home: Fats and oils
XF13	Food at home: Fish and seafood
XF14	Food at home: Fresh Fruits
XF15	Food at home: Fresh milk
XF16	Food at home: Other foods
XF17	Food at home: Poultry
XF18	Food at home: Processed dairy products
XF19	Food at home: Processed fruits and vegetables
XF20	Food at home: salt and chemical additives
XF21	Food at home: Sugar and sweets
XF22	Food at work: Vouchers

XF23	Food away from home
XF24	Home kitchen operations: appliances
XF25	Home kitchen operations: equipment and supplies
XF26	Home kitchen operations: fleet
XF27	Home kitchen operations: Utilities

Table B.5 shows food system supply chain stages.

Table B.5: Supply Chain Stages

Stage	Stage Description
1	Agribusiness
2	Appliances
3	Crops
4	Fleet
5	Food processing
6	Food retailers
7	Food wholesalers
8	Foodservice
9	Kitchenware
10	Livestock
11	Other ag forestry fisheries
12	Transportation and storage
13	Utilities for kitchen

B.2 Depreciation

Table B.6 shows depreciation rates for coal, petroleum, and natural gas plants. Because the optimization model naturally seeks to reduce high-emitting energies and increase low-emitting energies, the lower bound imposed by depreciation rates does not constrain the choice variables for nuclear and renewables. The rate of decay formula is $e^{\delta_d \times 18}$, for $d \in \{\text{coal}, \text{natural gas}, \text{petroleum}\}$.

Table B.6: Depreciation and rate of decay

Source	BEA Depreciation rate	Rate of decay
Coal	-0.0780	0.2456125
Natural gas	-0.0237	0.6527246
Petroleum	-0.0780	0.2456125

Data Source: USDOC-BEA (2022a)

LCOE Estimates

This paper uses LCOE estimates prepared by IEA from their latest report published every five years, "Projected Costs of Generating Electricity 2020 Edition" (IEA 2020). However, rather than use the reference estimates, I use the IEA "Levelised Cost of Electricity Calculator" to generate estimates with a zero carbon price (IEA 2022). Where multiple technologies are used in a given category—e.g., commercial, residential, and utility-scale solar—if data was available for their respective share of total capacity, then a weighted average was computed based on capacity shares. If such data was not available, a simple average was taken. In either case, technologies not yet deployed or with negligible use—less than 1% of total capacity—were not included in the LCOE estimate. Additional key assumptions include a 7% discount rate and an 85% capacity factor [1]. Below each energy source is discussed in turn.

C.1 Solar

For each solar category, the IEA "median case" was selected, and all IEA estimates are given in Table C.1. Although utility-scale solar cost is cost-competitive, at $44.25, the LCOE estimates for residential solar, commercial solar, and solar thermal power are $126.54, $94.18, and $112.34, respectively, measured as USD / MWh. These LCOE estimates were weighted by market shares for utility, commercial, residential, and solar thermal of 56%, 29%, 12%, and 2%, respectively (Rodríguez 2022; Trabish 2022).

[1] The capacity factor "is defined as the actual electricity production divided by the maximum possible electricity output of a power plant, over a period of time" (Neill and Hashemi 2018).

C.2 Coal

Equal weighting was given to the IEA coal categories of "Coal (641 MW)," "Pulverised (138 MW)," "Pulverised (140 MW)," and "Pulverised (650 MW)," with prices of $93.28, $99.79, $81.26, and $63.02. Because ultra-supercritical coal and carbon capture and storage technologies have not been deployed in the U.S., these categories were not included in the average (Gianfrancesco 2017; Calma 2022).

C.3 Natural Gas

For natural gas, a single LCOE estimate of $34.78 was used. As with coal, because carbon capture and storage has not been widely deployed—with only one plant in the U.S. as of late 2021—this category was excluded (Anchondo and Klump 2022).

C.4 Nuclear

Equal weighting was given to the IEA nuclear categories of "LTO (10 years) (1000 MW)," "LTO (20 years) (1000 MW)," and "LWR (1100 MW)," with prices of $36.04, $33.25, and $71.25.

C.5 Petroleum

Neither IEA, EIA, nor IRENA provide LCOE estimates for petroleum, likely because it remains an exceedingly small share of total electricity generation, less than 1%. Thus, to estimate a petroleum LCOE, I multiply the ratio of petroleum to natural gas prices—obtained from SEDS (USDOE-EIA 2021; Canning, Rehkamp, and Yi 2022)—by the natural gas LCOE estimate from IEA. This gives:

$$LCOE_{petro} = LCOE_{gas} \times \frac{price_{petro}}{price_{gas}}$$

C.6 Other

For hydropower, a simple average is taken of the two median cases, listed as "Run of river (>= 5 MW) (median case) (44.7 MW)," and "Run of river (>= 5 MW) (median case) (94.0 MW)," with respective LCOE estimates of \$70.58 and \$87.2. A single onshore wind median estimate is given, \$39.02, while offshore wind is excluded because only one plant exists in the U.S. (Brown 2022). Despite a Biden Administration goal to reach 30 GW of offshore wind power by 2030, onshore wind had already accounted for 118.3 GW in 2020, and that same year a record 14.2 GW in new capacity was added (USDOE-EIA 2022e; Brown 2022). Thus, offshore wind should remain a negligible share overall in the near term. A simple average is taken of the two geothermal estimates, of \$93.54 and \$61.83. Lastly, biomass is the only estimate taken from IRENA, rather than the IEA. This estimate of \$76.00 is global, rather than specific to the U.S. (IRENA 2022).

Table C.1: IEA LCOE Estimates

Category	Plant type	LCOE (USD / MWh)
Coal	Coal (641 MW)	93.28
Coal	Coal (CCUS) (499 MW)	143.23

Gas	Gas (CCGT) (727 MW)	34.78
Gas	Gas (CCGT, CCUS) (646 MW)	69.07
Geothermal	Geothermal (25.0 MW)	93.54
Geothermal	Geothermal (30.0 MW)	61.83
Nuclear	LTO (10 years) (1000 MW)	36.04
Nuclear	LTO (20 years) (1000 MW)	33.25
Nuclear	LWR (1100 MW)	71.25
Coal	Pulverised (138 MW)	99.79
Coal	Pulverised (140 MW)	81.26
Coal	Pulverised (650 MW)	63.02
Coal	Pulverised (CCUS) (650 MW)	115.43
Hydro	Run of river (< 5 MW) (3.7 MW)	128.67
Hydro	Run of river (< 5 MW) (4.2 MW)	90.52
Hydro	Run of river (< 5 MW) (4.8 MW)	117.72
Hydro	Run of river (>= 5 MW) (44.1 MW)	100.77
Hydro	Run of river (>= 5 MW) (82.2 MW)	90.21
Hydro	Run of river (>= 5 MW) (median case) (44.7 MW)	70.58
Hydro	Run of river (>= 5 MW) (median case) (94.0 MW)	87.20
Solar	Solar PV (commercial) (0.30 MW)	116.44
Solar	Solar PV (commercial) (0.30 MW)	100.45
Solar	Solar PV (commercial) (0.30 MW)	80.59
Solar	Solar PV (commercial) (0.30 MW)	74.46
Solar	Solar PV (commercial) (median case) (0.30 MW)	94.18

Solar	Solar PV (residential) (0.005 MW)	156.35
Solar	Solar PV (residential) (0.005 MW)	135.42
Solar	Solar PV (residential) (0.005 MW)	153.12
Solar	Solar PV (residential) (0.005 MW)	140.17
Solar	Solar PV (residential) (median case) (0.005 MW)	126.54
Solar	Solar PV (utility scale) (100 MW)	54.96
Solar	Solar PV (utility scale) (100 MW)	47.69
Solar	Solar PV (utility scale) (100 MW)	38.06
Solar	Solar PV (utility scale) (100 MW)	34.59
Solar	Solar PV (utility scale) (median case) (100 MW)	44.25
Solar	Solar thermal (CSP) (100 MW)	142.21
Solar	Solar thermal (CSP) (100 MW)	117.11
Solar	Solar thermal (CSP) (median case) (100 MW)	112.34
Coal	Supercritical pulverised (650 MW)	63.66
Coal	Supercritical pulverised (CCUS) (650 MW)	114.10
Wind	Wind offshore (600 MW)	61.35
Wind	Wind offshore (600 MW)	63.53
Wind	Wind offshore (600 MW)	68.07
Wind	Wind offshore (600 MW)	70.63
Wind	Wind offshore (600 MW)	82.40
Wind	Wind offshore (600 MW)	111.78
Wind	Wind offshore (600 MW)	59.37

Wind	Wind offshore (600 MW)	61.19
Wind	Wind offshore (600 MW)	64.21
Wind	Wind offshore (600 MW)	68.18
Wind	Wind offshore (600 MW)	74.09
Wind	Wind offshore (600 MW)	93.59
Wind	Wind offshore (600 MW)	119.21
Wind	Wind offshore (median case) (600 MW)	65.62
Wind	Wind onshore (>= 1 MW) (100 MW)	35.19
Wind	Wind onshore (>= 1 MW) (100 MW)	36.80
Wind	Wind onshore (>= 1 MW) (100 MW)	37.81
Wind	Wind onshore (>= 1 MW) (100 MW)	41.17
Wind	Wind onshore (>= 1 MW) (100 MW)	48.13
Wind	Wind onshore (>= 1 MW) (100 MW)	55.50
Wind	Wind onshore (>= 1 MW) (100 MW)	73.29
Wind	Wind onshore (>= 1 MW) (100 MW)	92.88
Wind	Wind onshore (>= 1 MW) (100 MW)	155.13
Wind	Wind onshore (>= 1 MW) (median case) (100 MW)	39.02

EIO Model Derivation

Appendix D defines the EIO notation, lists all model indices, matrices, and vectors with a short description, and then presents the EIO model derivation, as developed by Canning, Rehkamp, and Yi (2022).

D.1 Notation

- Matrices are uppercase bold
- Vectors are lowercase bold
- Scalars are lowercase non-bold
- Matrix transpose is denoted by $'$
- Vector diagonalization is denoted by $''$
- Matrix inverse is denoted by $^{-1}$
- Element-wise multiplication is denoted by $\circ$
- The column concatenation of two vectors or matrices with the same number of rows is denoted by $|$
- The row concatenation of two vectors or matrices with the same number of columns is denoted by $/$

D.2 Indices, Vectors, and Matrices

Table D.1: Indices, vectors, and matrices

Term	Description
$ACT = \{1, ..., 299\}$	Index for activities *(See Table B.1 for list)*
$COM = \{230, ..., 458\}$	Index for commodities *(See Table B.1 for list)*
$\boldsymbol{i}$	Column unit vector
$\boldsymbol{I}$	Identity matrix
$\boldsymbol{T}$	Transaction matrix
$\boldsymbol{y}$	Gross output vector
$\boldsymbol{A}$	Direct requirement matrix
$\boldsymbol{x}$	Injection vector
$\boldsymbol{M}$	Total requirement matrix
$\boldsymbol{v}$	Value-added multiplier vector
$\boldsymbol{l}$	Leakage vector
$\boldsymbol{y}^f$	Food-related gross output vector
$\boldsymbol{x}^f$	Food-related injection vector
$\boldsymbol{E}$	Environmental factors matrix (bBTUs)
$\boldsymbol{E}^*$	Supply-chain modified environmental factors matrix (bBTUs)
$\boldsymbol{\sigma}$	Electricity consumption for the national economy (bBTUs), vector
$\boldsymbol{\sigma}^f$	Electricity consumption for the food system (bBTUs), vector
$\boldsymbol{\Sigma}^{2f}$	Electricity consumption by energy source and food category for food-related items (bBTUs), two-dimensional matrix

$\boldsymbol{\Sigma}^{3f}$	Electricity consumption by energy source, supply chain stage, and food category for food-related items (bBTUs), three-dimensional matrix
$\boldsymbol{g}_d$	Vertical vector of emissions coefficients by energy sources
$\boldsymbol{G}$	Matrix of column concatenated emissions vectors
$\boldsymbol{\Theta}^{3f}$	CO2e emissions by energy source, supply chain stage, and food category for food-related items (MMt), three-dimensional matrix
$\boldsymbol{\pi}_d$	Energy shares computed from optimization solutions, vertical vector
$\boldsymbol{\Pi}$	Row concatenation of $\boldsymbol{\pi}_d'$

D.3 Derivation

The model elements are represented in the EIO model schematic in Appendix A Figure A.3. Each element name and description is listed in the Appendix B tables. This derivation follows the method defined in the supplemental information of Canning, Rehkamp, and Yi (2022).

To derive the multiplier model, we first divide each element in the the internal transactions matrix, $\boldsymbol{T}$, by its corresponding column total, $\boldsymbol{y}$, which yields the direct requirement matrix, $\boldsymbol{A}$:

$$\boldsymbol{A} = \boldsymbol{T} \times \{\boldsymbol{y}''\}^{-1} \tag{D.1}$$

Alternatively, post-multiplying boths sides of equation (D.1) by $\{\boldsymbol{y}''\}^{-1}$ yields $\boldsymbol{A} \times \boldsymbol{y} = \boldsymbol{T}$. Then, adding the final demand, or injection, vector, $\boldsymbol{x}$, gives the gross output vector, $\boldsymbol{y}$:

$$\boldsymbol{A} \times \boldsymbol{y} + \boldsymbol{x} = \boldsymbol{y}$$

The equation for gross output can be manipulated as follows:

$$\boldsymbol{x} = \boldsymbol{y} - \boldsymbol{A} \times \boldsymbol{y}$$

$$\boldsymbol{x} = \boldsymbol{i}'' \times \boldsymbol{y} - \boldsymbol{A} \times \boldsymbol{y},$$

$$\boldsymbol{x} = (\boldsymbol{i}'' - \boldsymbol{A}) \times \boldsymbol{y}, \qquad \text{(applying the distributive property of matrix multiplication)}$$

$$(\boldsymbol{i}'' - \boldsymbol{A})^{-1} \times \boldsymbol{x} = \boldsymbol{y}, \qquad \text{(multiplying both sides by the inverse of the parenthetical term)}$$

Denoting the above parenthetical term as $\boldsymbol{M}$ yields:

$$\boldsymbol{M} \times \boldsymbol{x} = \boldsymbol{y} \tag{D.2}$$

In equation (D.2), $\boldsymbol{M}$ is termed the Leontief or "total requirements" matrix, which is a key component of our EIO model. Equation (D.2) states that multiplying the final demand vector, $\boldsymbol{x}$, by the total requirements matrix yields the gross output vector, $\boldsymbol{y}$. That is, $\boldsymbol{M}$ represents the total requirements necessary—for activities and commodities—to deliver a given level of final demand, $\boldsymbol{x}$.

The second key component of our EIO model is derived by "dividing" [1] each element of the leakage vector, $\boldsymbol{l}$, by its corresponding gross output total, $\boldsymbol{y}$. This yields the value-added multiplier vector:

$$\boldsymbol{v} = \{\boldsymbol{y}''\}^{-1} \times \boldsymbol{l} \tag{D.3}$$

Pre-multiplying both sides of equation (D.3) by $\boldsymbol{y}'$ yields:

$$\boldsymbol{y}' \times \boldsymbol{v} = \boldsymbol{i}' \times \boldsymbol{l}, \qquad (\text{where } \boldsymbol{y}' \times \{\boldsymbol{y}''\}^{-1} = \boldsymbol{i}') \tag{D.4}$$

Equation (D.4) tells us that gross domestic income (GDI) plus imports, $\boldsymbol{i}' \times \boldsymbol{l}$—the sum of the leakage vector—is equal to the product of transposed gross output and the value-added multiplier. By Walras Law, GDI plus imports equals GDP plus exports, and this point is elaborated in Canning, Rehkamp, and Yi (2022). Also by Walras Law, this identity holds:

$$\boldsymbol{v}' \times \boldsymbol{M} \times \boldsymbol{x} = \boldsymbol{i}' \times \boldsymbol{x}, \tag{D.5}$$

[1] Division is not a defined operation in matrix algebra. Instead, matrices can be multiplied by the inverse of another matrix to achieve division.

which means that totals from corresponding elements of the leakage vector, $\boldsymbol{l}$, and the injection vector, $\boldsymbol{x}$, are equal.

Linear homogeneity is a core property and assumption of EIO models. This means that "a proportional change to any element of the injection vector, $\boldsymbol{x}$, produces the same proportional change in the gross output vector, $\boldsymbol{y}$" (Canning, Rehkamp, and Yi 2022). As an example, if final demand, $\boldsymbol{x}$, increases threefold, then output, $\boldsymbol{y}$, must increase threefold—defined as $\boldsymbol{M} \times (\boldsymbol{x} \times 3) = \boldsymbol{y} \times 3$.

This property also holds for a subset of the final demand vector. In our case, for $f = 1$, we let $\boldsymbol{x}^f$ be the vector representing final demand specifically for food purchases. Then, modifying equation (D.2), linear homogeneity implies that the gross output—including both activities and commodities—required to meet final demand for food expenditure is given by:

$$\boldsymbol{y}^f = \boldsymbol{M} \times \boldsymbol{x}^f, \qquad (f = 1) \tag{D.6}$$

If we let $f = 2$ represent the projected food final demand for another period, then the equality capturing the change in gross output resulting from a change in food final demand is given by:

$$(\boldsymbol{y}^2 - \boldsymbol{y}^1) = \boldsymbol{M} \times (\boldsymbol{x}^2 - \boldsymbol{x}^1) \tag{D.7}$$

The environmental factors matrix, $\boldsymbol{E}$, can be incorporated into a modified equation (D.7), yielding the change in electricity use by energy source:

$$(\boldsymbol{\sigma}^2 - \boldsymbol{\sigma}^1) = \boldsymbol{E} \times \boldsymbol{M} \times (\boldsymbol{x}^2 - \boldsymbol{x}^1) \tag{D.8}$$

In equation (D.8), $\boldsymbol{\sigma}$ has rows d for primary energy sources.

D.3.1 Supply Chain Modeling

Supply chain analysis enables us to track electricity use for specific stages of the food system. Leontief (1967) developed an alternative to aggregation that facilitates supply chain analysis. Following the Leontief method, as outlined in Canning, Rehkamp, and Yi (2022), data is organized into supply chain activities, $SA \subset ACT$, non-supply chain activities, $NA \subset ACT$—where $SA \cup NA = ACT$—supply chain commodities, $SC \subset COM$, and non-supply chain commodities, $NC \subset COM$—where $SC \cup NC = COM$.

With this framework, equation (D.2)—$\boldsymbol{M} \times \boldsymbol{x} = \boldsymbol{y}$—can be represented as follows:

$$\begin{bmatrix} \{\boldsymbol{M}_{SA,SA}\} & \{\boldsymbol{M}_{SA,NA}\} & \{\boldsymbol{M}_{SA,SC}\} & \{\boldsymbol{M}_{SA,NC}\} \\ \{\boldsymbol{M}_{NA,SA}\} & \{\boldsymbol{M}_{NA,NA}\} & \{\boldsymbol{M}_{NA,SC}\} & \{\boldsymbol{M}_{NA,NC}\} \\ \{\boldsymbol{M}_{SC,SA}\} & \{\boldsymbol{M}_{SC,NA}\} & \{\boldsymbol{M}_{SC,SC}\} & \{\boldsymbol{M}_{SC,NC}\} \\ \{\boldsymbol{M}_{NC,SA}\} & \{\boldsymbol{M}_{NC,NA}\} & \{\boldsymbol{M}_{NC,SC}\} & \{\boldsymbol{M}_{NC,NC}\} \end{bmatrix} \times \begin{bmatrix} \{\boldsymbol{0}_{SA}\} \\ \{\boldsymbol{0}_{NA}\} \\ \{\boldsymbol{x}_{SC}\} \\ \{\boldsymbol{x}_{NC}\} \end{bmatrix} = \begin{bmatrix} \{\boldsymbol{y}_{SA}\} \\ \{\boldsymbol{y}_{NA}\} \\ \{\boldsymbol{y}_{SC}\} \\ \{\boldsymbol{y}_{NC}\} \end{bmatrix} \tag{D.9}$$

All non-supply chain enterprises—e.g, hospitals [2]—can be considered subcontractors such that their required inputs and environmental flows (electricity use) are purchased by the supply chain enterprise to which they subcontract. That is, the contractor (supply chain enterprise) purchases items on behalf of the subcontractor (non-supply chain enterprise). This relationship is modeled as:

$$\boldsymbol{E}^* = \boldsymbol{E}_{d,SCA} + \boldsymbol{E}_{d,NCA} \times \boldsymbol{M}_{NCA,SCA} \times \{\boldsymbol{M}_{SCA,SCA}\}^{-1}, \tag{D.10}$$

As an example, let $\boldsymbol{x}^f$ be the subset of final demand representing personal consumption expenditure on food. As seen in Table B.1, a commodity consumed within $\boldsymbol{x}^f$ would be "C226 Food at full service restaurants."

[2] Table B.1 shows all activities and commodities, including A189 Hospitals. An example of a supply chain activity is A002 Grain farming.

Now, *before* applying supply chain analysis, or limiting final demand to food-related expenditure, we can represent the electricity budget for the entire economy as:

$$\boldsymbol{\sigma} = \boldsymbol{E} \times \boldsymbol{y} + \boldsymbol{\sigma}^{x} \tag{D.11}$$

Then, applying supply chain analysis and considering only a subset of final demand, denoted by f, the analog to equation (D.11) is:

$$\boldsymbol{\Sigma}^{2f} = \left[\boldsymbol{E}^{*} \times (\boldsymbol{y}^{f})'' | \boldsymbol{\sigma}^{f}\right] \tag{D.12}$$

Note, equation (D.12) corresponds to equation (2.4) of the Methods section, where I also elaborate on converting from a two-dimensional matrix, $\boldsymbol{\Sigma}^{2f}$, to a three-dimensional matrix, $\boldsymbol{\Sigma}^{3f}$. This derivation focuses on the steps preceding those outlined in the Methods section.

Lastly, equation (D.12) can be restated as:

$$\boldsymbol{\Sigma}^{2f} = \left[\boldsymbol{E}^{*} \times (\boldsymbol{y}^{f1} | \boldsymbol{y}^{f2} | ... | \boldsymbol{y}^{f23}) | \boldsymbol{E} \times (\boldsymbol{y}^{f24} | \boldsymbol{y}^{f24} | \boldsymbol{y}^{f26}) | \boldsymbol{\sigma}^{f27}\right], \tag{D.13}$$

which corresponds to equation (2.5) from Methods. To create the environmental factor matrix, $\boldsymbol{E}$, as used above, additional matrices are introduced which allocate state-level energy usage to specific activities and commodities, which is described in Canning, Rehkamp, and Yi (2022).

Full Optimization Results

The GAMS software yields solutions with results for "level", "marginal", "lower", and "upper". Level denotes the solved solution while, while lower and upper denote the respective lower and upper bounds, where applicable. As an example, in Table E.1, the cost minimizing solution yields a total emissions level of 632,955,867,326 thousand grams CO2e, which is less than the upper bound enforced by the IPCC target, 642,871,802,500.

The marginal results show the impact on the objective function by reducing a given constraint by one unit. As an example, for the cost-minimization energy upper bound results in Table E.2.1, the marginal result for natural gas is -14,523.87. This means that relaxing the natural gas bBTU constraint by one unit—adding one percentage point of growth—will generate a 14,523.87 reduction in the objective function, total LCOE. Because natural gas has the lowest LCOE, it follows that allowing more usage of that energy will have the greatest impact on reducing total LCOE. The marginal values have an interpretable significance for the energy upper bounds depending on the given results and meaning of each constraint.

E.1 Emissions Totals

Table E.1: Emissions Totals - Cost-Minimization

Level	Marginal	Upper
632,955,867,326	0	642,871,802,500

Thousands grams CO2e.

Table E.2: Emissions Totals - Change-Minimization

Level	Marginal	Upper
642,871,802,500	-0.000638	642,871,802,500

Thousands grams CO2e.

E.2 Energy Totals

E.2.1 Energy Upper Bound

Table E.3: Energy Upper Bound - Cost-Minimization

Energy source	Level	Marginal	Upper
Coal	878,305.43	0.00	1,434,120.97
Hydropower	581,006.28	-1,596.50	581,006.28
Natural Gas	2,442,238.72	-14,523.87	2,442,238.72
Nuclear	1,544,751.39	-11,124.77	1,544,751.39
Petroluem	10,073.00	0.00	27,330.22
Solar	720,378.80	-3,981.25	720,378.80
Geothermal	46,301.29	-1,949.65	46,301.29
Wood and waste biomass	102,934.77	-2,443.48	102,934.77
Wind	1,142,477.63	-13,281.25	1,142,477.63

bBTU

Table E.4: Energy Upper Bound - Change-Minimization

Energy source	Level	Marginal	Upper
Coal	899,282.31	0.000	1,434,120.97
Hydropower	581,006.28	-181.732	581,006.28
Natural Gas	2,442,238.72	-94.219	2,442,238.72
Nuclear	1,544,751.39	-183.462	1,544,751.39
Petroluem	27,330.22	-29.386	27,330.22
Solar	682,144.70	0.000	720,378.80
Geothermal	46,301.29	-177.764	46,301.29
Wood and waste biomass	102,934.77	-175.791	102,934.77
Wind	1,142,477.63	-176.555	1,142,477.63

bBTU

E.2.2 Energy Lower Bound

Table E.5: Energy Lower Bound - Cost-Minimization

Energy Source	Level	Marginal	Lower
Coal	878,305.43	0.00	744,217.415
Natural Gas	2,442,238.72	0.00	1,164,178.244
Petroluem	10,073.00	3,199.38	10,072.996

bBTU

Table E.6: Energy Lower Bound - Change-Minimization

Energy Source	Level	Marginal	Lower
Coal	899,282.31	0	744,217.415
Natural Gas	2,442,238.72	0	1,164,178.244
Petroluem	27,330.22	0	10,072.996

bBTU

E.2.3 Energy Source Share of Total

Table E.7: Energy Source Share - Cost-Minimization

Energy Source	Level	Share of total
Coal	878,305	0.118
Hydropower Gas	581,006	0.078
Natural Gas	2,442,239	0.327
Nuclear	1,544,751	0.207
Petroluem	10,073	0.001
Solar	720,379	0.096
Geothermal	46,301	0.006
Wood and waste biomass	102,935	0.014
Wind	1,142,478	0.153
Total	7,468,467	NA

Table E.8: Energy Source Share - Change-Minimization

Energy Source	Level	Share of total
Coal	899,282	0.120
Hydropower Gas	581,006	0.078
Natural Gas	2,442,239	0.327
Nuclear	1,544,751	0.207
Petroluem	27,330	0.004
Solar	682,145	0.091
Geothermal	46,301	0.006
Wood and waste biomass	102,935	0.014
Wind	1,142,478	0.153
Total	7,468,467	NA

E.2.4 Total Electricity Minimum Requirement

Table E.9: Total Electricity Minimum - Cost-Minimization

Level	Marginal	Lower
7,468,467	24,716.89	7,468,467

bBTU

Table E.10: Total Electricity Minimum - Change-Minimization

Level	Marginal	Lower
7,468,467	185.8956	7,468,467

bBTU

E.3 Totals Stage and Food Category

Totals for electricity consumption (bBTUs) and CO2e emissions (MMt) by i) energy source, ii) supply chain stage, and iii) food demand category are provided in the document:

"Supplemental_info.xlsx"