U.S. STATE-LEVEL CONSUMPTION-BASED ACCOUNTING OF GREENHOUSE GAS EMISSIONS: A SCENARIO ANALYSIS

By

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ABSTRACT OF THE DISSERTATION

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With President Trump's decision to withdraw from the Paris Agreement on climate change, some local governments and states are taking their own initiatives to reduce greenhouse gas (GHG) emissions. But with interstate trade, state environmental policies may cause emission rises in neighboring states as goods can be shipped from anywhere to meet local consumption needs. This would undermine the intentions of such subnational climate policies. Given that states can set up their own policies to reduce greenhouse gases, state-level accounting is important within the U.S. The primary objectives of this research are to measure GHG emissions associated with the consumption of goods and services in each state and how state emissions might change with state environmental policies, e.g. carbon taxes. Moreover, regarding the close relationships between interstate trade and freight transportation, this research allocates interstate freight emissions to industries within each state. As freight emissions increase much faster than transportation emissions as well as overall emissions in the U.S., by identifying the state responsibility, interstate freight emissions can be regulated by state environmental policies. This

research also examines whether fuel price increases could drive substantial mode shifts away from emissions-intensive modes (i.e. truck and air) to reduce interstate freight emissions.

This research uses a multiregional input-output (MRIO) framework that provides a concise and accurate means for articulating the interrelationships among industries of different states. Building a state-level MRIO model within the U.S. requires two sets of data: state input-output (I-O) tables and interstate trade flows. This research estimates state I-O tables based on the 2012 U.S. benchmark I-O tables (the most recent ones with 405 sectors at the highest level of disaggregation) (BEA, 2018a). Due to limited interstate trade data, gravity models are used to estimate trade flows based on the Freight Analysis Framework 4 State Database for 2012 (BTS, 2016).

Comparing state consumption-based emissions to the corresponding production-based ones, states along the east and west coasts are net importers of GHG emissions and states in the Central and Mountain regions are net exporters. The emissions embodied in state consumption are mainly from within the home-state and nearby states. Texas and California pollute for all other states as they export a relatively large amount of embodied emissions nationwide. For interstate freight emissions, emissions-intensive states, e.g. Wyoming, North Dakota, and Nebraska, have the highest inbound and outbound transportation emissions per capita, besides Hawaii and Alaska. Mining (except oil and gas), food and beverage and tobacco products, and wood products involve both large transportation emissions and significant shares of trade-related emissions from transportation.

The MRIO framework is applied to examine the sensitivity of state consumption-based GHG emissions to potential state carbon taxes. Besides the taxing state, nearby states and states with strong economic connections with the taxing one have larger emission reductions and bear more economic loss in the short run. The MRIO framework also allows me to estimate changes in interstate freight emissions due to fuel price increases. Emission reductions from interstate freight transportation are very limited with fuel price increases alone. The findings of this research can be used to advise policy-making that accounts for both producer and consumer responsibilities.

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1 Introduction

1.1 Motivation

Greenhouse gases (GHGs) like carbon dioxide, methane, nitrous oxide, and fluorinated gases warm the earth by trapping heat in the lower atmosphere. Due to human activity, the amount of major greenhouse gases (GHGs) in the atmosphere have increased exponentially since the mid-20th century (IPCC, 2007). The rapid increase of GHGs has caused global warming, which experts predict will lead to serious climate change. Climate change will cause abrupt changes in forest and agriculture systems, increasing loss of biodiversity, accelerated sea-level rise, and more-frequent extreme weather events which could be disastrous for human development (Rockström et al., 2009). The U.S. emits about 13% of the global GHG emissions annually and is the second largest emitter worldwide (UNEP, 2019). As one of the top global GHG emitters as well as one of the world's largest consumer economies, the U.S. could play a key role in controlling global GHG emissions. But it has failed to commit to emissions reduction, except for some states (e.g. California), according to the United Nations Environment Emissions Gap Report 2018.

After a continuing growth of GHGs from 1990 to 2007, there has been a gradual reduction in annual GHG emissions in the U.S. with some fluctuations since 2008, after the great recession (EPA, 2020). The recent reductions do not necessarily suggest that the U.S. is doing enough to control GHGs, as it is the largest net emissions importer among developed countries (Peng et al. 2016). Trade enables the geographical separation between the consumption of goods and services and the environmental burdens of production (Peng et al., 2016). In 2018, GHG emissions in the U.S. increased almost 3% (EPA, 2020).

Due to the U.S. decision to withdraw from the Paris Agreement on climate change, more local and state governments within the U.S. are likely to create their own policies to reduce GHG emissions (Worland, 2017). So far, 22 U.S. states and the District of Columbia set their own emissions reduction targets ("State Climate Policy Maps," n.d.). But with interstate trade, state environmental policies may cause emission increases in neighboring states since goods can be shipped from anywhere to meet local consumption needs. For example, California’s cap-and-trade program and the Regional Greenhouse Gas Initiative (RGGI) of northeastern states both increase emissions in surrounding regions through the import of electricity (Caron et al., 2015; Fell & Maniloff, 2018). Given that states can design policies to reduce greenhouse gases, state-level accounting is important within the U.S. It informs decision makers on the potential of alternative designs of state and regional environmental policies from the perspective of both producer and consumer responsibilities. This research measures GHG emissions associated with the consumption of goods and services by state using a multi-regional input-output (MRIO) framework, which depicts interindustry relationships among states.

Traditional production-based emissions are measured based on where emissions are generated. Consumption-based accounting captures emissions in local consumption as embodied in local production as well as those involved in the inflow of goods from other states to meet local consumption; traditional production-based accounting involves only the local consumption as embodied in local production plus the export of local production to other states. The differences between consumption- and production-based emissions are the net emissions embodied in trade (Aichele & Felbermayr, 2012).

Many researchers have measured consumer responsibility for GHG emissions at the national level, using readily available international trade data (Munksgaard & Pedersen, 2001; Weber & Matthews, 2007; 2008; Ackerman et al., 2007; Wiedmann, 2009; Feng et al., 2013; Peng et al., 2016). For example, Weber and Mathews (2008) report that 30% of the CO_2 emissions due to American household consumption were generated outside the U.S. in 2004. The increase of CO_2 embodied in U.S. imports outweighs the increase of emissions embodied in its exports from 1997 to 2004 (Weber & Matthews, 2007). But few researchers focus on state-level consumption-based emissions, due to limited data on domestic trade. Some researchers have estimated interstate trade flows (Jackson et al., 2006; Lindall et al., 2006; Park et al., 2009; Caron et al., 2013, 2017). So far, the latest analysis of U.S. state-level consumption-based emissions is for 2004 (Caron et al., 2013, 2017), and it was performed at a 52-sector level. My research examines a more recent data for the year 2016 and with more sectoral detail—403 industries.

With state consumption-based GHG emissions, emissions embodied in interstate trade are clear. This allows me to examine the impacts of state environmental policies. Some researchers examine the leakage problem (the emission reductions of carbon-constrained regions could be partially offset by the increased emissions of other regions) due to subnational climate policies, e.g., California's cap-and-trade program and the RGGI (Caron et al., 2015; Fell & Maniloff, 2018). These two programs are both market-based environmental policies that cap the amount of allowable GHG emissions and allow trading between producers. Another common market-based measure is a carbon tax, which puts a price on emissions. Market-based measures let the market decide the cost of reducing emissions, and let firms and households adjust their behaviors without specifying how (Center on Budget and Policy Priorities, 2015). Theoretically, cap-and-trade programs and carbon taxes cost the same to achieve a given emissions-reduction objective (Hanemann, 2009). This work investigates the environmental and economic impacts of potential state carbon taxes.

Besides GHGs emitted in the production process, freight transportation also contributes to trade-related emissions. Although only accounting for less than 10% of the total U.S. GHG emissions, emissions from freight transportation have been rising rather rapidly of late (EPA, 2019a). From 2000 to 2017, freight emissions rose about 11% as total transportation emissions *decreased* by 2.6% and overall U.S. emissions *decreased* by 10.8% (EPA, 2019a). The rapid growth of freight emissions is largely due to the increase in the volume of freight movement and the rising use of trucks (Davies et al., 2008; Wu & Pienaar, 2019; EPA, 2019a). Current research mainly analyzes emissions from freight transportation by major modes (Horvath, 2006; Davies et al., 2008; Nealer et al., 2012; Wu & Pienaar, 2019). There is little research that links emissions from freight transportation to trade flows, especially domestic trade. Again, this is due to the limited amount of data available on domestic shipments within the U.S. (Giuliano et al., 2010). Given that freight transportation is driven by demands of trade, this research fills the gap to examine the magnitude of freight transportation's contribution to trade-related emissions. Moreover, as a major source of mobile emissions, freight transportation is difficult to regulate or monitor with state-level policies, especially interstate freight transportation. This research allocates emissions from interstate freight transportation to industries in each state with the help of a MRIO framework; in this way it enables me to identify the state share of interstate freight transportation emissions.

There are many strategies to reduce transportation emissions, e.g., two examples are improving fuel economy (Greene et al., 2020) and enabling green supply chains (Tiwari et al., 2015). Since truck usage is rising and grabbing an ever-greater share of freight transport, it is mostly responsible for the rapid growth of freight transportation emissions. In this vein, one obvious strategy would be to shift to a less emissions-intensive mode, e.g. truck to rail. Many researchers use scenario analysis to investigate the extent to which a mode shift might enable achievement of emissions-reduction goals (Nealer et al., 2012; Llano et al., 2018). Rather than examine explicit mode-shift scenarios, I investigate possible fuel price changes due to extra fuel taxes. The carbon intensity of each mode is related to its technology, fuel mix, vehicle loading, and traffic (Kamakate & Schipper, 2009). Regarding fuel mix, the U.S. transportation sector relies heavily upon petroleum-related products—more than 90% of the total transportation energy use (EIA, 2020b). Extra fuel taxes would drive fuel prices increase and induce modal shifts. I focus on the extent to which rising crude oil prices could trigger mode shifts that might reduce transportation GHG emissions.

1.2 Research Objectives

My work integrates economy, transportation, and environment through the estimation of GHG emissions embodied in domestic trade, especially interstate trade. This is because interstate trade flows—in other words, interstate freight movements—reflect the economic structure of each state as well as the relationships among industries, households, and government across states (Park et al. 2011). The main purpose of this work is to provide a detailed and comprehensive picture of GHG emissions in the U.S. from both consumption and production perspectives.

The second chapter focuses on building consumption-based accounting of GHG emissions for each state to complement the traditional production-based accounting. Consumption-based emissions underline consumer responsibilities. Differences between state consumption- and production-based emissions are the emissions embodied in state's inflows (from other states) minus those embodied in state's outflows (to other states). I develop a state-level MRIO model which simulates state economies and the interstate supply chain in the U.S. Emissions generated in the production process can be traced to final consumers. Moreover, I estimate the total emission intensity for each industry by state (GHG emissions per unit of industry's output) accounting for emissions generated in the upstream supply chain. The objective of Chapter 2 is to identify who pollutes for whom among states within the U.S. through estimation of emissions embodied in interstate trade by industry. The model results shed light on which state economies will be most affected by a new federal emissions policy, and which states are most and least able to afford to take independent environmental action.

The third chapter extends the analysis of interstate trade-related GHG emissions to freight transportation. Trade-related emissions come from two sources: emissions generated during production and emissions emitted while transporting. Given the close relationship between trade and freight transportation, it is important to link transportation emissions to trade flows in order to investigate freight transportation's contribution to trade-related emissions in detail. Only goods-producing industries that require freight transportation services are included in the analysis; Other industries are not traded nearly so much across state boundaries. Interstate trade flows are converted into freight movements by mode. I consider all five major modes: truck, rail, water, air, and pipeline. The domestic part of international trade is excluded in this analysis because the destination of imports is unknown as is the port of call for exports. By multiplying ton-mile emission factor by mode and freight movements, emissions from freight transportation are estimated for each interstate trade flow by industry. The objective of Chapter 3 is to identify the responsibilities for interstate freight transportation emissions by state and by industry so that this mobile source of emissions can be regulated by state environmental policies.

After the comprehensive evaluation of the current trends of state-level GHG emissions, the fourth chapter examines how might emissions change in responding to potential state carbon taxes and new fuel taxes. Since state environmental policies not only affect emissions within a state but also emissions of surrounding regions, I investigate the short-term environmental and economic impacts of potential carbon taxes in one state on all states holding state economic structure and interstate trade patterns constant. While carbon tax scenarios examine the sensitivity of overall emissions by state and by industry, fuel price scenarios focus on emissions from interstate freight transportation alone. I explore whether fuel price changes can trigger modal shifts away from emission-intensive modes (e.g. truck and air) to environmentally friendly modes (e.g. rail and water). In this way, I examine the likely extent to which emission reductions might be achieved via freight transportation. The objective of this chapter is to enable a better understanding of the relationships between economic systems and environmental impacts. To clarify, the model results of Chapter 4 are not a forecast of future nor a thorough impact analysis. This analysis is necessarily rough and *ceteris paribus*, as I do not consider substitution effects in carbon tax scenarios nor changes in state supplies and demands in the course of effecting the fuel price scenarios. Still, I identify the industries and states that likely would be most and least affected by state carbon tax policy, impacts on state GDP and employment, and the set of interstate freight shipments that are likely to be most sensitive to changes in fuel prices.

1.3 Research Approach

Figure 1-1 Research Approach

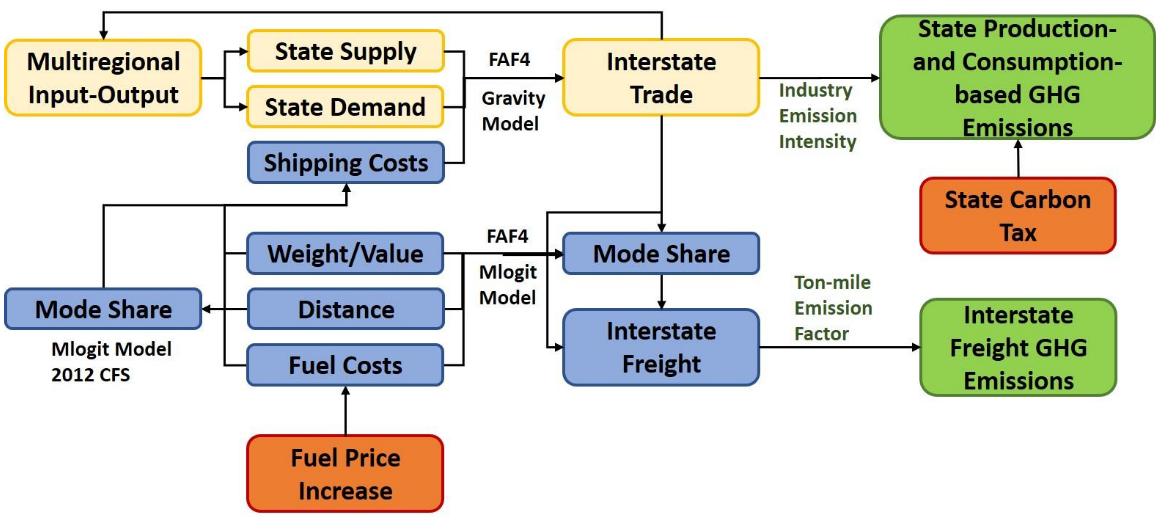


Figure 1-1 shows the research approach for this work. The core is a MRIO framework (yellow part) strengthened by a transportation module (blue part) and an environment module (green part). The orange part in Figure 1-1 shows the scenarios included in this work. The MRIO model treats each U.S. state as an independent economic region and includes 403 industries from the U.S. benchmark input-output (I-O) tables (BEA, 2018a). States are connected through interstate trade in the MRIO model. The transportation module includes regression models to estimate freight transportation mode choice. In the environmental module, I use emissions intensities by industry and ton-mile emission factors for freight transportation to estimate GHG emissions.

In Chapter two, I estimate state I-O tables based on the 2012 U.S. benchmark I-O tables with 405 sectors (BEA, 2018a); and use the Freight Analysis Framework version 4 (FAF4) 2012 State Database to estimate interstate trade flows (BTS, 2016). Estimates of freight transportation mode choice are fed into the calculation of interstate travel costs, which are used in interstate trade flow estimation. I then estimate consumption- and production-based GHG emissions for each state by combining the MRIO model and emission intensities by industry. The interstate trade of goods-producing industries that require freight transportation services are converted into freight flows in ton-mile by mode in Chapter 3 with the help of transportation multinomial logit regression model for mode choice. The interstate freight movements multiplied by ton-mile emission factors generates estimates of transportation emissions. In Chapter 4, I apply the state economic structure and interstate trade patterns from the MRIO model for state carbon tax scenarios. Sectoral supply and demand for each state as produced by the MRIO model together with the mode choice regression model are used for estimating the fuel price scenarios. Details of the methods are explained in the following chapters.

1.4 Contribution

This research will contribute to the literature by conducting a more current analysis for the year 2016 at the highest possible level of industry disaggregation (403 industries, available in the 2012 U.S. benchmark I-O tables). This level of disaggregation is important since economic models tend to assume that a given sector has the same production technology; thus, analysis of a more fine-grained set of industries can significantly minimize the potential for aggregation bias. The MRIO framework built in this research can be used for future analysis to construct general equilibrium model.

The United Nations Environment Programme (2018) calls for all nations to strengthen domestic emission reduction policies. In this regard, this research has important policy implications. Firstly, it yields a comprehensive picture of consumption-based GHG emissions within the U.S.—one that complements the better-known geographic portrait of production-based emissions. Such state-level consumption-based accounting would help policymakers to better understand the effects of incentives to adopt state or regional climate policies and to design policies in a way that accounts for consumer responsibility. Secondly, by identifying how much freight transportation contributes to interstate trade-related GHG emissions, I allocate transportation emissions—mobile source of emissions to industries within states. This will enable the regulation of interstate freight transportation emissions by state policies (e.g. improve efficiency of supply chains for industries with large transportation emissions). Thirdly, this research provides a blueprint for evaluating the environmental and economic impacts of state/regional climate policies, e.g. state carbon taxes and state fuel taxes (rising fuel prices could be the result of extra fuel taxes to control energy usage and then emissions).

2 Consumption- and Production- Based Greenhouse Gas Emissions for U.S. States

2.1 Introduction

Many U.S. states have established their own targets for reducing greenhouse gas (GHG) emissions ("State Climate Policy Maps," n.d.). Given that states can design their own policies to reduce greenhouse gases, state-level accounting is important as some states are national pollution havens. States with stiffer regulations can import goods and services from other unconstrained states, thereby negating some of the benefits of state-level emissions reductions. Traditional production-based emissions are those emissions from local production, which include emissions embodied in local products that consumed locally plus the exports to other states and nations. Emissions embodied in local consumption include emissions generated by local producers plus emissions embodied in the imports from other states and nations. State-level accounting of GHG emissions can help in designing of alternative state and regional environmental policies via perspectives of both producer and consumer responsibility.

The differences between consumption- and production-based accounting are the emissions embodied in the imports minus those in exports. The availability of pertinent trade data makes it possible to examine emissions embodied in U.S. international trade (Ackerman et al., 2007; Weber & Matthews, 2007, 2008). The U.S. exports low-energy commodities while importing energy-intensive goods (Weber & Matthews, 2007). On net, the U.S. imports emissions and is the largest net emissions importer among developed countries (Peng et al., 2016; Weber & Matthews, 2007). Due to limited data on domestic trade, little research has focused on emissions embodied in U.S. domestic trade.

Available data are based on a limited survey—U.S. Commodity Flow Survey (Census Bureau, 2015). That is, there is no census of interstate trade; and the limited survey might not cover all possible commodities, let alone all shipments for any given commodity. Moreover, data for trade in services are not available at all. While we cannot directly observe all shipments for all commodities, some researchers have estimated trade flows among U.S. states (Jackson et al., 2006; Lindall et al., 2006; Park et al., 2009; Caron et al., 2013, 2017).

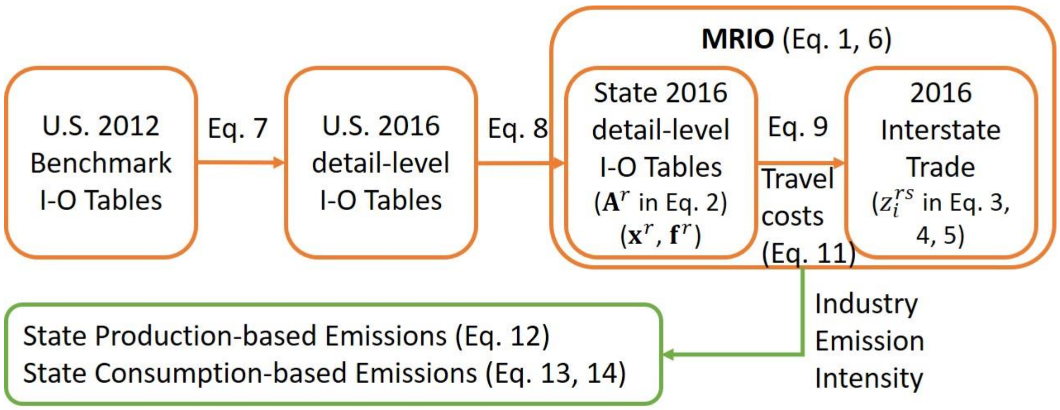
In fact, Caron et al. (2013, 2017) performed a fairly detailed analysis of U.S. state level consumption-based CO_2 emissions. They combined U.S. state-level data with data outside of the U.S. at a country level. They find that domestic trade explains most of the differences in state responsibilities for emissions. State-level consumption-based emissions are quite different from the equivalent production-based emissions. For example, they find New England and New York are both net importers of embodied CO_2 while the Midwest is almost balanced with similar imports and exports of emissions. The differences in state-level CO_2 intensity of consumption (kg/$) are mainly due to differences in CO_2 intensity of production rather than differences in state consumption patterns (Caron et al. 2017). The base year of their research is 2004, however, so it does not reflect more recent trends in emissions, especially cannot reflect many states' recent GHG-emissions mitigation strategies. Their model also contains only 52 sectors, so it lacks the technology detail required to accurately track interregional commodity trade, let alone direct energy resource use and, hence, emissions discharges.

Due to the nation's strong economic integration and geographic size, domestic trade within the U.S. is much larger than that of its international trade. The larger volume of domestic trade suggests that the potential carbon leakage due to interstate trade (emission reductions of states with stronger emissions policies partially offset by the increase of emissions from other states due to imports from those states) may be larger than its international equivalent (Caron et al., 2015). Following Caron et al. (2013, 2015, 2017), my research focuses on GHG emissions embodied in interstate trade by estimating state-level consumption-based emissions using a multiregional input-output (MRIO) framework. I assume that detailed production technologies (at the 403-industry level) are homogeneous within the U.S. This assumption clearly understates any differences in state-level emissions responsibilities that may exist in real technological differences for a certain industry among states (Caron et al., 2017). Still, the MRIO framework allows me to account for the different production and trade patterns among states. Compared to Caron et al. (2013, 2015, 2017), I measure the state-level GHG emissions at a more detailed level of industry (403 industries versus their 52 sectors) for a more current year (2016 versus 2004). In this chapter, I discuss how I develop the model including any data sources I use. I then show model results and end with discussion of research limitations. I then summarize and conclude.

2.2 Methods and Data

The goal of my research is to measure GHG emissions associated with the consumption of goods and services by state. The MRIO framework is suitable toward achieving this goal since it provides a concise, accurate means for articulating the interrelationships among industries across all states. The input-output (I-O) model has been widely used for environmental issues and as early as Leontief (1970). Emissions can be tracked through and across both industries and states to final consumers. The MRIO approach allows me to trace the origins of emissions due to final consumption through the production chain no matter where the emissions are produced. Thus, I can answer the question "who pollutes for whom?" Figure 2-1 shows the flow of building a 2016 U.S. state-level MRIO model and estimating state GHG emissions.

Figure 2-1 Flow Chart of the Research Approach for Chapter 2



2.2.1 MRIO model development

I construct a multiregional input-output (MRIO) model for 50 states plus the District of Columbia within the U.S. for the year 2016. Similar to the standard I-O framework, the total output of the economy, $\mathbf{x}$, is the sum of intermediate consumption, $\mathbf{CAx}$, and final demand, $\mathbf{Cf}$.

$$\mathbf{x} = \mathbf{CAx} + \mathbf{Cf} \tag{1}$$

Assuming there are n industries and p regions, $\mathbf{x}$ is a $51n$ vector of output (net taxable business income) by state for each industry. The variable $\mathbf{f}$ also denotes a $51n$ vector, but for final demand by state for each industry. $\mathbf{A}$ is a $51n \times 51n$ matrix (Eq. 2) in which $\mathbf{A}^r$ ($n \times n$ matrix) is the direct requirements table for state r. The element in $\mathbf{A}^r$, a_{ij}^r, suggests the amount of inputs of industry i needed to produce one unit of output of industry j in state r including those inputs from outside of state r. $\mathbf{C}$ is a $51n \times 51n$ trade share matrix (Eq. 3).

$$\mathbf{A} = \begin{bmatrix} \mathbf{A}^1 & 0 & \dots & 0 \\ 0 & \mathbf{A}^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{A}^p \end{bmatrix} \tag{2}$$

$$\mathbf{C} = \begin{bmatrix} \hat{\mathbf{c}}^{11} & \hat{\mathbf{c}}^{12} & \dots & \hat{\mathbf{c}}^{1p} \\ \hat{\mathbf{c}}^{21} & \hat{\mathbf{c}}^{22} & \cdots & \hat{\mathbf{c}}^{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\mathbf{c}}^{p1} & \hat{\mathbf{c}}^{p2} & \cdots & \hat{\mathbf{c}}^{pp} \end{bmatrix} \tag{3}$$

In the trade-share matrix $\mathbf{C}$, $\hat{\mathbf{c}}^{rs}$ is a $n \times n$ diagonal matrix (Eq. 4) in which the nonzero element, c_i^{rs}, indicates the share of products of industry i consumed in state s that come from state r (Eq. 5). z_i^{rs} is value of shipments from industry i in state r that is shipped to s. By multiplying the trade share matrix with both state intermediate demand and final demand (Eq. 1), the MRIO model assumes the same proportion of intermediate and final demand in state s are fulfilled by state r.

$$\hat{\mathbf{c}}^{rs} = \begin{bmatrix} c_1^{rs} & 0 & \dots & 0 \\ 0 & c_2^{rs} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & c_n^{rs} \end{bmatrix} \tag{4}$$

$$c_i^{rs} = \frac{z_i^{rs}}{\sum_{r=1}^{p} z_i^{rs}} \tag{5}$$

Eq.1 can also be written as follows. The output is the result of pre-multiplying final demand by the Leontief inverse, $(\mathbf{I} - \mathbf{CA})^{-1}$, where $\mathbf{I}$ is a $51n \times 51n$ identity matrix.

$$\mathbf{x} = (\mathbf{I} - \mathbf{CA})^{-1}\mathbf{Cf} \tag{6}$$

Since survey-based state I-O tables are not available in the U.S. (in fact, subnational $\mathbf{A}$ matrices are rarely available for nations), I explain how I estimate them in the following subsection. In particular, I estimate states' industry outputs, direct requirements, final demands, and interstate trade flows. I use all 403 industries included in the 2012 U.S. benchmark I-O tables.

2.2.1.1 The 2016 detail level U.S. I-O tables

In order to build the state level MRIO model for 2016, two steps are necessary: estimating the 2016 detail-level U.S. I-O accounts and subsequently for each state. There are three main parts of the I-O tables: the inter-industry transactions, value added, and final demand.

Each column of the industry transaction table shows the value of shipments purchased from all other industries by a specific industry. The **A** matrix, "direct requirements matrix," is calculated by dividing each column of industry transaction table by that specific industry's output. To apply 2012 production technology to 2016, I assume production technology is on average stable as suggested by Carter (1970). The 2012 U.S. **A** matrix is modified to account for shifts in production values, which reflect the differences in value added (w_j) and output (x_j) by industry (Round, 1972, 1983) as follows:

$$a_{ij}^{2016} = a_{ij}^{2012} \times \frac{1 - (w_j^{2016}/x_j^{2016})}{1 - (w_j^{2012}/x_j^{2012})} \tag{7}$$

While value added, also known as gross domestic product (GDP) by the income approach, and output by industry are available for 2016 from the BEA in 71 industries (BEA, 2019a), they are not available at the same extreme detail as in 2012 benchmark U.S. I-O tables (405 industries) (BEA, 2018a). Fortunately, payroll data for 2016 are available at a very detailed industry level; and payroll data tend to closely approximate BEA's labor compensation estimates for most industries except for agriculture, railroad, private households, etc. (BLS, 2017b). Labor compensation is a component in both the less-detailed 2016 GDP data as well as in the more detailed data available in the 2012 benchmark tables. I therefore use annual payroll data from the Quarterly Census of Employment and Wages (QCEW) published by the U.S. Bureau of Labor Statistics (BLS, 2017b) to convert 2016 compensation of employees (GDP component) into the same detailed industry level as the benchmark I-O tables. I do so by assuming the share of annual payroll for a detailed industry in the aggregate sector is the same as that of compensation suggested by Lahr (2001). I then estimate 2016 GDP and output at the detailed industry level using a compensation to output ratio and a compensation to GDP ratio by industry (both ratios are obtained from 2012 I-O tables) and adjust them proportionally to match official data in more aggregated form (again, see Lahr, 2001, for estimation details).

Personal consumption expenditures (PCE) compose a substantial part of the final demand (about 68% in 2016) (BEA, 2019a). They too are available from BEA for 2016 but in 398 categories and purchasers' value (BEA, 2019c) rather than by industry in producers' value as in the final demand of I-O table. Differences between purchasers' and producers' value are transportation costs and trade margins from wholesale and retail (BEA, 2018b). I convert these PCE categories into the model industries using a PCE bridge table available from BEA (BEA, 2018b). The 2016 PCE bridge table also has a more-aggregate set of industries, so I use the 2012 detailed bridge table as a reference by assuming commodity composition in an aggregated expenditure category remained stable between 2012 and 2016; I made similar assumptions for shares of transportation costs and trade margins in purchasers' value to estimate PCE in producers' value. I subsequently adjusted the results of this translation to match totals in the more-aggregate

2016 bridge table. Other final-demand sectors—government consumption, private and public investment, change in private inventories, imports and exports —are established from the more-aggregate 2016 I-O tables. I again use benchmark 2012 final-demand data to convert these totals to the model's industry detail by assuming stable expenditure shares.

My focus is the domestic accounting among states, however. So, I "domesticate" the U.S. direct requirements matrix by proportionally removing imports from both intermediate and final demand assuming no exports derive from imports (Jackson, 1998; Lahr, 2001).

2.2.1.2 State industry transaction table

Assuming production technologies are spatially constant, I estimate the state direct-requirements matrix ($\mathbf{A}^r$) by adjusting the 2016 U.S. direct requirements matrix to account for the regional fabrication effects—the relative differences in regional factor payments for labor by industry (Round, 1972, 1983). Similar to Eq. 7, the adjusting parameter for each column of $\mathbf{A}^r$ uses state value added (w_j^r) and output (x_j^r), as well as national value added (w_j^n) and output (x_j^n) as follows:

$$a_{ij}^r = a_{ij}^n \times \frac{1 - (w_j^r / x_j^r)}{1 - (w_j^n / x_j^n)} \tag{8}$$

While state GDP data are readily available from BEA—albeit for aggregate industries akin to those in the 2016 national I-O table—state output data are not available at all (BEA, 2019b). So, I assume a similar compensation/output ratio by industry within the U.S. (obtained from the previous step) to estimate state output by industry as compensation suggests a worker's marginal value product (Lahr, 2001). For state GDP by industry, I apply national compensation/GDP ratio to state compensation to estimate the share of GDP for a detailed industry in an aggregate sector. These shares are then used to allocate the official state GDP data from BEA in aggregate sectors to the detailed 405 industries. To produce state compensation estimates, I use a parallel process to that I used to update the national data. I use state annual payroll data from QCEW to estimate state compensation at the detail level of industry (BLS, 2017b). State compensation estimates must match those available by aggregated industry. Meanwhile, the compensation by industry across states must sum to the national compensation by industry. I apply the iterative biproportional adjustment procedure (the RAS technique, see Miller & Blair, 2009, for details) to assure state compensation by industry satisfies both requirements. The same data constraints also apply to state GDP estimates by detailed industry which are adjusted using RAS as well. Moreover, state output estimates by industry are adjusted to assure output is not smaller than GDP because GDP is only the value-added part of industry output.

The electric power sector is one of the largest sources of GHG emissions, and each state uses mixes of energy resources to generate electricity. So, I adjust the energy inputs for the power industry in the 51 state $\mathbf{A}^r$ matrices using the State Energy Data System (SEDS) of the U.S. Energy Information Administration (EIA, 2016a). The SEDS provides the state annual energy expenditure estimates for the electric power sector including coal, natural gas, petroleum, nuclear fuel and biomass (other renewable energy such as hydro, solar, wind, etc. not have direct expenditures). But the definition of the electric power sector used by the EIA is broader than that of the BEA, even after federal, state, and local government electric utilities are combined with electric power generation, transmission, and distribution (North American Industry Classification System (NAICS)

221100) in the I-O tables. So, instead, I use the state share of each energy expenditure from the SEDS to reallocate the state energy inputs for the power industry. I adjust the results by using RAS to assure the sum of state energy expenditures are equal to those at the national level while retaining state total energy expenditures for the power industry. Through this aggregation of the electric power sector, my model has 403 industries, instead of the original 405 industries in the 2012 benchmark I-O tables.

2.2.1.3 State final demand

State personal consumption expenditures (PCE) are available from the BEA, but only for 24 aggregate categories (BEA, 2019b). I, thus, use the Consumer Expenditure Surveys Public-use Microdata (CE-PUMD) (BLS, 2017a) to parse state PCE shares into more detail. The CE-PUMD provides monthly household expenditures in more than 500 categories by universal classification codes (UCC) (BLS, 2017a). I use these monthly consumer spending data across 2016 to estimate annual state household expenditures into detailed PCE categories. There are a few small states (e.g. Montana, Wyoming, Vermont, Maine, etc.) without identified data in CE-PUMD; thus, I proxy their expenditure detail by using the average spending patterns of surrounding states. The state PCEs are then converted into 403 industries using the national PCE bridge table that I obtained when converting the 2016 U.S. PCE into industries (see Section 2.2.1.1).

Note, the PCE are in terms of *purchasers' value* while data in the I-O tables are in terms of *producers' value*. As mentioned earlier for the national case, the differences between the two values are transportation costs and trade margins—purchaser's value include these items, while producer's value excludes them (BEA, 2018b). By using the national PCE bridge table to convert state PCEs, I actually assume the commodity composition in each PCE category, and the shares of transportation costs and trade margins in purchasers' value are similar among states.

For other parts of state final demand, I assume homogenous personal-income-based state preferences for U.S. Government expenditures and private investment. That is, I allocated these national expenditures to states by their shares of aggregate national personal income in 2016. I similarly allocated international exports and change in private inventories to states according to the states' shares of national output for each industry.

2.2.1.4 Interstate trade flow estimation

In order to obtain the trade share matrix $\mathbf{C}$, I use a gravity-model formula to estimate interstate trade flows by industry. Gravity models are very useful and popular empirical tools to calibrate trade flows. They are typically mathematically simple and intuitive in nature (Sen & Smith, 2012). The basic idea is that the interactions between any two regions (e.g. bilateral trade flows) are proportional to the amount of activities in each region, and inversely proportional to impeding frictions (freight related costs) between them (c.f. Kockelman et al. 2005).

I use the following gravity model (Eq. 9), where g_i is a constant by industry, s_i^r is the excess supply of state r (outbound supply), d_i^s is the excess demand of state s (inbound demand), with α and β as weights, respectively. $c_{i,travel}^{rs}$ represents the travel cost between state r and s, with ω as distance decay parameter that measures the sensitivity of trade flow to spatial friction. Intervening opportunities typically rule in gravity models; that is, product demanders prefer to have their needs fulfilled by suppliers who are closer.

$$z_i^{rs} = g_i \frac{(s_i^r)^\alpha (d_i^s)^\beta (l_i^r)^\gamma}{(c_{i,travel}^{rs})^\omega} \tag{9}$$

The degree of specialization, l_i^r, is measured by the location quotient of state r; this measure indicates the degree of excess supply by industry (Eq. 10). s_i^r is the excess supply of industry i in state r, $\sum_{i=1}^{n} s_i^r$ is the excess supply of all industries in state r, $\sum_{r=1}^{51} s_i^r$ is the excess supply of industry i from all states, and $\sum_{i=1}^{n}\sum_{r=1}^{51} s_i^r$ is the excess supply of all industries from all states. Sargento (2009) suggests that adding this variable improves trade-flow estimates of simpler gravity models.

$$l_i^r = \frac{s_i^r / \sum_{i=1}^{n} s_i^r}{\sum_{r=1}^{51} s_i^r / \sum_{i=1}^{n}\sum_{r=1}^{51} s_i^r} \tag{10}$$

Before estimating the excess supply and the excess demand by industry, I first estimate each state's regional purchase coefficients (RPC) following Treyz and Stevens (1985). An RPC is the share of state demand that is fulfilled by supplies produced within the state (c_i^{rr} in trade-share matrix). After domesticating the I-O tables (removing international imports), the state total supply is state output minus international exports, and change in private inventories (Treyz & Stevens, 1985; Lahr, 2001; Horowitz & Planting, 2006); the state total demand is the sum of intermediate demand ($\mathbf{A}^r\mathbf{x}^r$), personal consumption expenditures, government consumption, and investment. Industries' excess supplies are calculated as the state total supply minus local demand (the product of the state total demand and RPC). And their excess demands are states' total demands minus their local demands.

Travel costs are represented by the weighted average of the fuel cost to ship one unit of product from certain industry (Eq. 11). The weight is a freight transportation mode's share (s_m') of each industry's products. By doing so, I account for the characteristics of the industry (w_i, weight/value ratio), the transportation network distances of different modes (d_m^{rs}), and the different fuel cost by mode (λ_m, fuel cost per ton-mile). The calculations of mode share, transportation network distances, and fuel cost are presented in Chapter 3. The weight/value ratios of the 403 industries are from the 2012 Commodity Flow Survey (CFS) (Census Bureau, 2015).

$$c_{i,travel}^{rs} = \sum_m s_m^{'} \cdot w_i \cdot d_m^{rs} \cdot \lambda_m \quad (11)$$

For the goods industries, also I use the Freight Analysis Framework version 4 (FAF4) State Database for 2012 (BTS, 2016) to calibrate the gravity model. FAF4 incorporates data from the CFS, agriculture, utility, construction, and other sectors and provided interstate trade values by commodity (Standard Classification of Transported Goods (SCTG)). Anderson et al.'s (2013) cross-reference between SCTG and North American Industry Classification System (NAICS) (the industry code of the I-O tables) enables an initial trade matrix for goods by industry.

Trade information on services is lacking in the U.S. But Sargento et al. (2012) suggest that gravity results on trade flows look empirically reasonable and tend to be suitable in the absence of actual trade flows. Following Sargento et al. (2012), I use the simple gravity model for all service industries. That is, I assign 1.0 to parameters α, β, γ and ω, as well as the constant g_i in Eq. 9. I also use the straight-line distances between state population centers rather than freight travel costs. This is because services tend to be delivered either via broadband or passenger transportation both of which have relatively less-expensive and, yet, thicker networks than do freight transportation modes. Interstate trade-flow estimates of the gravity model are adjusted using the RAS technique.

2.2.2 GHG Emissions Estimation

I use the U.S. Environmental Protection Agency's (EPA) United States Environmentally-Extended Input-Output (USEEIO) v1.1 dataset (Ingwersen et al., 2017) to generate the direct GHG emission intensity to estimate GHG emissions in CO_2 equivalent. The direct emissions intensity by industry ($\boldsymbol{\epsilon_d}$) is the amount of GHGs generated in the process of producing one unit of the industry output. For states, I apply the U.S. GHG emissions intensity based on the energy resources used as inputs for each industry except for the electric power industry. This assumption follows the general assumption of homogeneous technologies across states within the U.S. that I apply in the MRIO model. The production-based GHG emissions by state by industry, $\mathbf{E_p}$, are calculated as the state output by industry, $\mathbf{x}$, multiplied with the corresponding direct emission intensity, $\boldsymbol{\epsilon_d}$ (a 51×403 vector).

$$\mathbf{E_p} = \boldsymbol{\epsilon_d}\mathbf{x} \tag{12}$$

The USEEIO dataset fulfills the detail level of industry for my analysis but are for the year 2013. By using this dataset, I assume relative stable emissions per unit of industry output from 2013 to 2016. I should note that the USEEIO dataset does not include direct emissions from households' direct consumption of fossil fuels, e.g., via personal vehicle use and home heating; so, the USEEIO understates the annual total GHG emissions in the U.S. Fortunately, such household emissions are included in both consumption-based and production-based accounting of a given state, so omitting this bit of emissions will not affect the relationship of "who pollutes for whom" among states.

Again, knowing the electric power industry is a dominant polluter that must report its emissions, I obtained direct GHG emissions from power plants by state through the

EPA Facility Level Information on Greenhouse Gases Tool (FLIGHT) (EPA, 2019b). So, in the case of the electric power sector by state, I estimated their direct emission intensities as the direct emissions from a state's power plants divided by the electric power sector's output for that state.

I calculate consumption-based GHG emissions for each state ($\mathbf{E}_c^r$, a 51×403 vector as state r could consume products from all industries in all states) are calculated as the state final demand ($\mathbf{Cf}^r$ in which $\mathbf{C}$ is the trade share matrix as in Eq. 3, $\mathbf{f}^r$ is a 51×403 vector with the nonzero elements from $(403(r-1)+1)^{\text{th}}$ to $403r^{\text{th}}$ indicating the final demand by industry in state r) multiply with the corresponding total emission intensity ($\boldsymbol{\epsilon}_t$, a 51×403 vector) (Eq. 13; Kitzes, 2013). The total emission intensity ($\boldsymbol{\epsilon}_t$) is the total GHG emissions associated with one unit of output to final demand. The total intensity includes the total emissions emitted in the upstream supply chain to produce one unit of output to final consumers. It can be obtained by multiplying direct emission intensity, $\boldsymbol{\epsilon}_d$ ($51n-$ sector vector), with the Leontief inverse matrix (Eq. 14), where the prime (') denotes an array transpose.

$$\mathbf{E}_c^r = \boldsymbol{\epsilon}_t \mathbf{C} \mathbf{f}^r \tag{13}$$

$$\boldsymbol{\epsilon}_t' = \boldsymbol{\epsilon}_d' (\mathbf{I} - \mathbf{CA})^{-1} \tag{14}$$

2.3 Results

2.3.1 State consumption- and production-based GHG emissions

Figure 2-2 shows the differences between state consumption- and production-based GHG emissions. The consumption-based emissions vary from 7.6 million metric tons (MMT) (Vermont) to 473.1 MMT (California), while the production-based emissions vary from 5.4 MMT (District of Columbia) to 580.6 MMT (Texas). Nine of the top ten states in consumption-based emissions are also among the largest production-based emitters (Table 2-1, Table 2-2). California, Texas, and Florida are the top three states in GHG emissions via both production- and consumption-based accounting; they are followed by New Yok, Pennsylvania, Ohio, Michigan, Illinois, and Georgia. These nine states account for 45% to 49% of the nation's total GHG emissions. Eight of the ten bottom-most states in terms of consumption-based emissions also yield the least production-based emissions (Table 2-1, Table 2-2). Not surprisingly, these states also have small populations, and include South Dakota, Alaska, and some states in the Northeast U.S.

After normalizing consumption- and production-based emissions by aggregate state GDP and total state population, California and New York score among the least emissions-intense states, despite their large amount of total emissions; meanwhile West Virginia, Wyoming, Kentucky, Montana, and North Dakota have among the highest emissions intensity via such measures (Figure 2-3). Other states with low consumption- and production-based emissions per unit of GDP are in the Northeast and along the Pacific Coast (Washington) of the U.S. Based on per capita emissions measurements, the ten states with the lowest production emissions are concentrated in the Northeast (New York, New Jersey, Maryland, District of Columbia, and New England); four of the New England states also have very low consumption emissions intensities, as do states in the West (Oregon, Washington, Idaho, and Arizona) (Table 2-1, Table 2-2).

Interestingly, Alaska has one of the highest production emissions per capita despite its small total emissions. District of Columbia has one of the highest consumption emissions per capita in contrast to its lowest emissions per unit of GDP (both consumption and production). Compared with production-based accounting, differences of GHG emissions per capita and per unit of GDP among states are much smaller when using consumption-based accounting. The ratio of highest to lowest consumption-based emissions per capita is about 3.0 while the ratio for production accounting is about 20.0. For emissions per unit of GDP, the ratio of highest to lowest using consumption accounting is less than 7.0 while the ratio for production accounting is more than 45.0.

Table 2-1 Consumption-based GHG Emissions of Selected States

Top 10 Consumption-based Emissions					
by state (MMT CO_2 Eq.)		per \$ GDP (g CO_2 Eq. / \$GDP)		per capita (MT CO_2 Eq.)	
California	473.1	West Virginia	680.1	Wyoming	35.8
Texas	434.4	Wyoming	579.5	West Virginia	25.9
Florida	311.7	Kentucky	537.2	North Dakota	25.7
New York	260.1	Mississippi	431.2	Kentucky	23.7
Ohio	198.7	Montana	430.5	Louisiana	19.7
Pennsylvania	198.7	Arkansas	401.5	Indiana	19.6
Illinois	193.0	Louisiana	401.0	District of Columbia	19.4
Michigan	150.0	Indiana	380.7	Montana	19.2
North Carolina	145.0	Missouri	372.6	Iowa	18.4
Georgia	140.3	North Dakota	370.8	Missouri	18.2
Bottom 10 Consumption-based Emissions					
by state (MMT CO_2 Eq.)		per \$ GDP (g CO_2 Eq. / \$GDP)		per capita (MT CO_2 Eq.)	
Vermont	7.6	District of Columbia	98.5	Idaho	11.3
South Dakota	12.3	New York	168.8	Vermont	12.1
District of Columbia	12.8	California	177.5	California	12.2
Alaska	13.2	Washington	184.1	Oregon	12.3
Rhode Island	14.0	Massachusetts	195.1	Maine	12.4
Delaware	14.0	Delaware	198.7	Washington	12.8
Maine	16.5	Connecticut	199.5	Arizona	12.9
New Hampshire	17.7	Maryland	211.5	New York	13.2
Idaho	18.5	New Hampshire	225.5	Rhode Island	13.3
North Dakota	18.9	New Jersey	227.4	New Hampshire	13.3

Figure 2-2 Consumption- and Production-based GHG Emissions by State (MMT CO_2 Eq.)

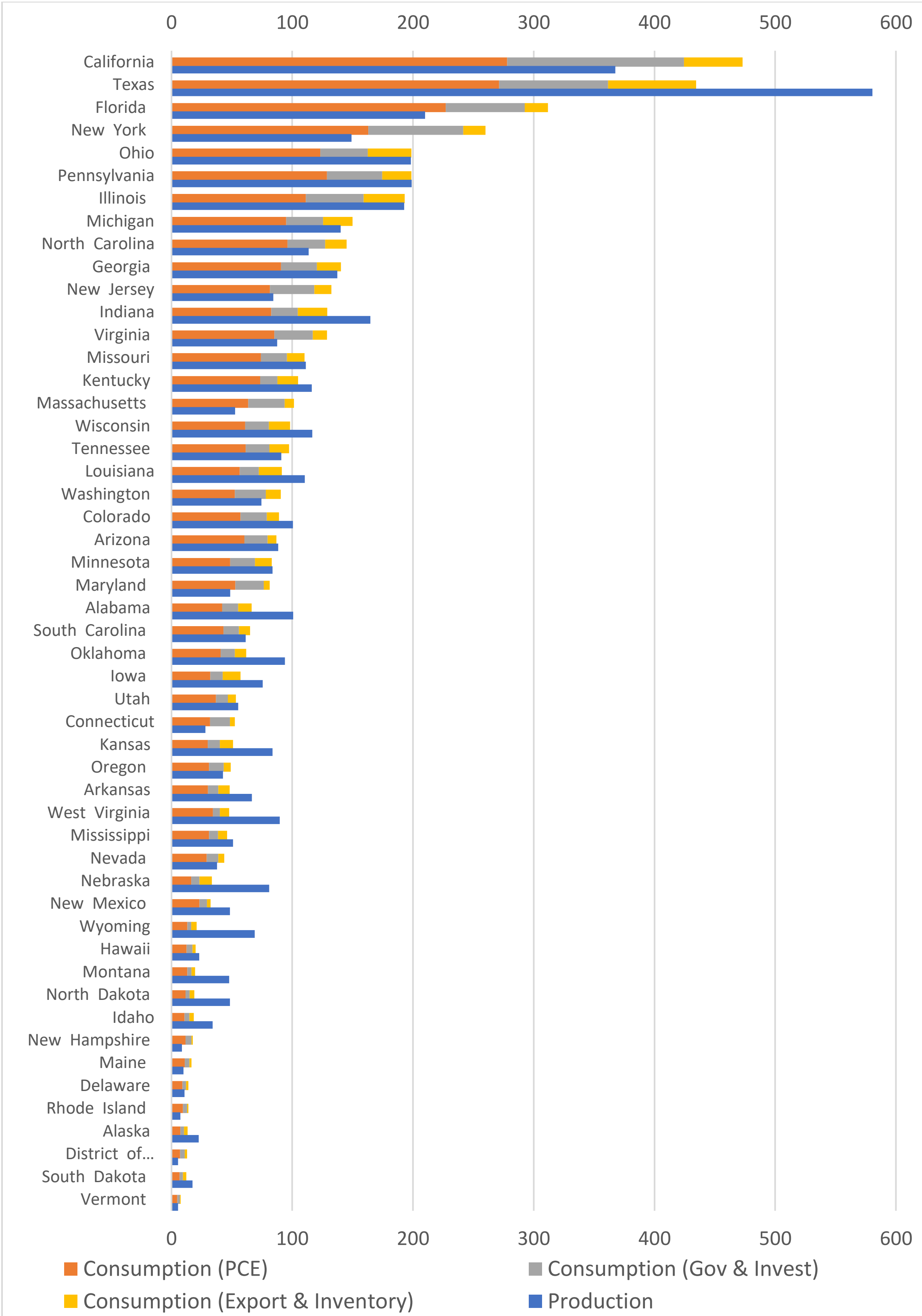
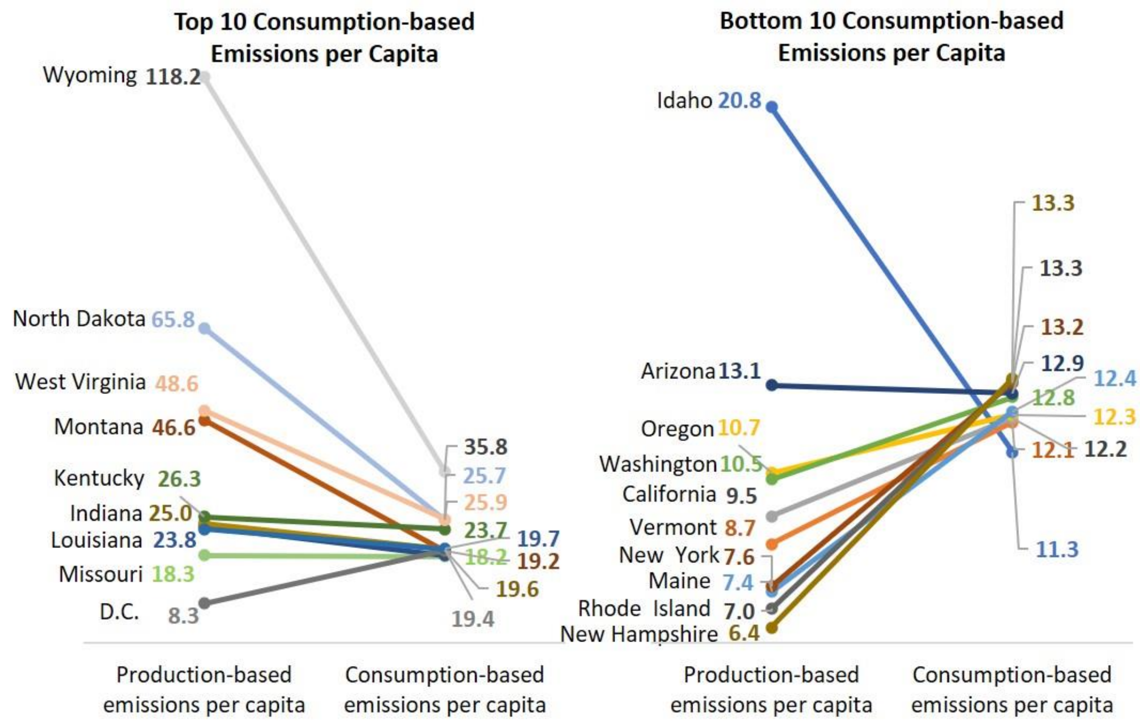


Table 2-2 Production-based GHG Emissions of Selected States

Top 10 Production-based Emissions					
by state (MMT CO_2 Eq.)		per $ GDP (g CO_2 Eq. / $GDP)		per capita (MT CO_2 Eq.)	
Texas	580.6	Wyoming	1915.2	Wyoming	118.2
California	367.5	West Virginia	1277.4	North Dakota	65.8
Florida	210.1	Montana	1045.6	West Virginia	48.6
Pennsylvania	198.9	North Dakota	948.4	Montana	46.6
Ohio	198.2	Nebraska	695.7	Nebraska	43.0
Illinois	192.7	Kentucky	595.9	Alaska	30.5
Indiana	164.7	Arkansas	554.3	Kansas	28.9
New York	149.1	Kansas	537.8	Kentucky	26.3
Michigan	140.1	New Mexico	533.4	Indiana	25.0
Georgia	137.3	Oklahoma	525.3	Iowa	24.3
Bottom 10 Production-based Emissions					
by state (MMT CO_2 Eq.)		per $ GDP (g CO_2 Eq. / $GDP)		per capita (MT CO_2 Eq.)	
District of Columbia	5.4	District of Columbia	41.8	New Hampshire	6.4
Vermont	5.5	New York	96.7	Rhode Island	7.0
Rhode Island	7.3	Massachusetts	101.4	Maine	7.4
New Hampshire	8.5	Connecticut	106.9	New York	7.6
Maine	9.9	New Hampshire	108.9	Massachusetts	7.8
Delaware	10.7	Maryland	126.5	Connecticut	7.8
South Dakota	17.4	Rhode Island	126.8	Maryland	8.2
Alaska	22.5	California	137.9	District of Columbia	8.3
Hawaii	23.0	New Jersey	144.8	Vermont	8.7
Connecticut	28.1	Washington	151.3	New Jersey	9.5

Figure 2-3 Per Capita Consumption- and Production-based GHG Emissions of Selected States (Metric Ton CO_2 Eq. per capita)



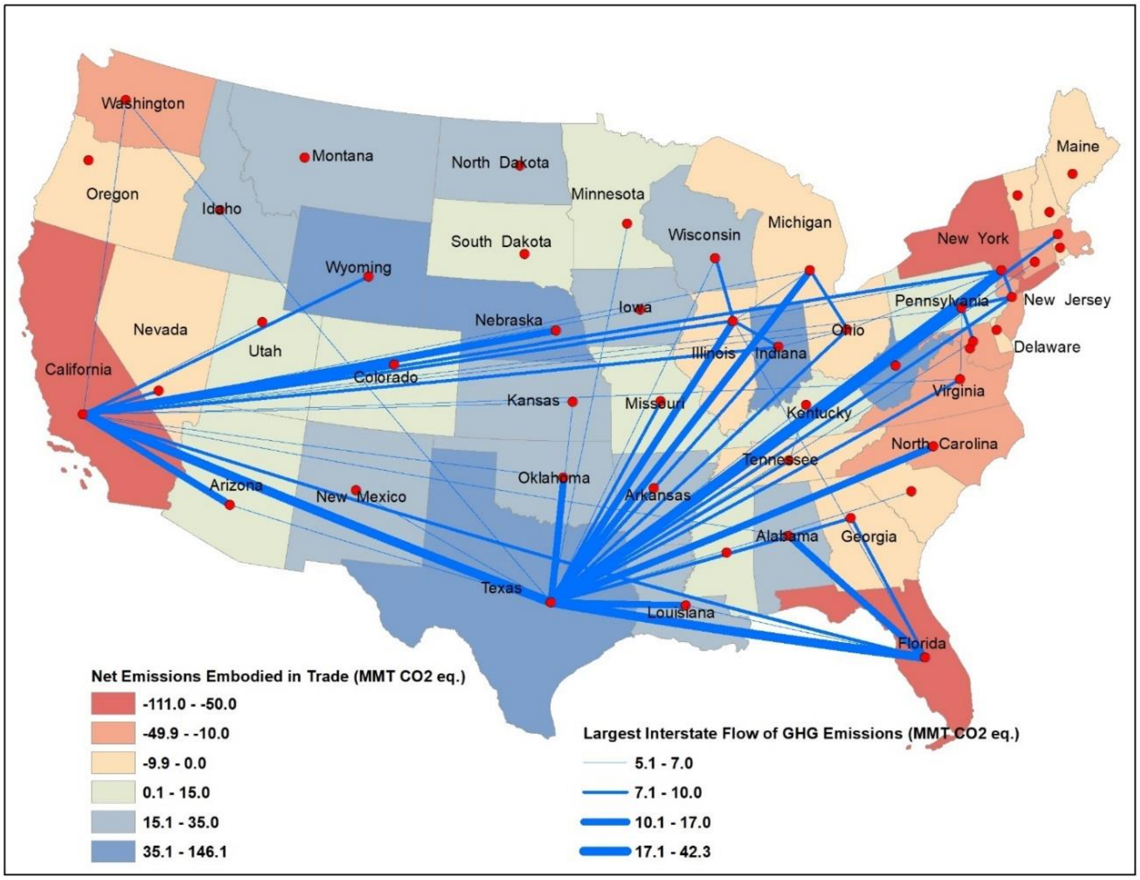
I divide the consumption-based emissions into three parts: household consumption (PCE), government consumption and investment (Gov & Invest), international exports and inventory changes (Export & Inventory) (Figure 2-2). Household consumption accounts for the largest share of the state consumption-based emissions, ranging from 49% (Nebraska) to 73% (Florida). This suggests that encouraging people to consume green goods should help reduce emissions. International exports account for a small proportion of state-level emissions since the U.S. in general exports less-energy-intensive commodities (Weber and Matthews, 2007).

I also calculate the average GHG emissions (consumption-based) per dollar of consumption by state, which includes the states final demands from household, government, and investment. This measure ranges from 0.177 kg/$ (California) to 0.486 kg/$ (West Virginia). States with lowest emission intensity of consumption are in the west coast (California, Washington, Idaho) and northeast (Vermont, New York, New Hampshire). There are two reasons for the differences in the emission intensity: differences in consumption patterns and the state origins of commodities and services. The high production emission per unit of GDP combined with the large share of consumption-based emissions from within the state contribute to the highest emission intensity of consumption for states such as West Virginia, Wyoming and North Dakota. States with low consumption emission per unit of GDP and relatively large share of imported consumption emissions have low emission intensity of consumption, such as California and New York.

2.3.2 GHG emissions embodied in interstate trade

The differences between production- and consumption-based emissions are net GHG emissions embodied in trade. Figure 2-4 shows that net domestic importers of embodied emissions are concentrated along the east and west coasts. New York is the largest net importer with 111 million metric tons (MMT) of embodied emissions, followed by California (105.5 MMT) and Florida (101.7 MMT). In the case of net domestic import of emissions per unit of GDP and per capita, New York, Florida, New Jersey, Maryland, and some states in New England are still among the largest (Table 2-3). The net domestic exporters are concentrated in the Central and Mountain regions (Figure 2-4). Texas is the largest net exporter with 146.1 MMT emissions, followed by Wyoming (48.1 MMT) and Nebraska (47.4 MMT). Except for Texas, states with top net domestic export of emissions also have the largest emissions per unit of GDP and per capita, such as Wyoming, West Virginia, and Nebraska (Table 2-3). If GHG emissions-reduction targets are set up based on state production-based emissions, these net exporting states are less likely to set such targets independently.

Figure 2-4 Major Interstate Flows of GHG Emissions Embodied in Trade



The MRIO model not only allows me to estimate the state consumption-based emissions but also to identify the emissions embodied in interstate trade, suggesting "who pollutes for whom." Figure 2-4 shows that Texas is the top "polluter" for all other states, due to its rich fossil fuel resources. The largest interstate flow of GHG emissions as embodied in trade are from Texas to California with 42.3 MMT. California also exports large embodied emissions to states nationwide because of its farming industry. At the same time, California imports large amount of emissions embodied in trade from not only nearby states but also from Great Lakes states. Florida is another major importer of embodied emissions, mainly from surrounding states in addition to Texas and California. Other major flows of embodied emissions mainly occur among nearby states, such as those in the Mid-Atlantic region (largely Pennsylvania, New York, New Jersey) and Great Lakes states. With the exception of Texas, net exporting states in the Central region have smaller emissions embodied in trade among one another.

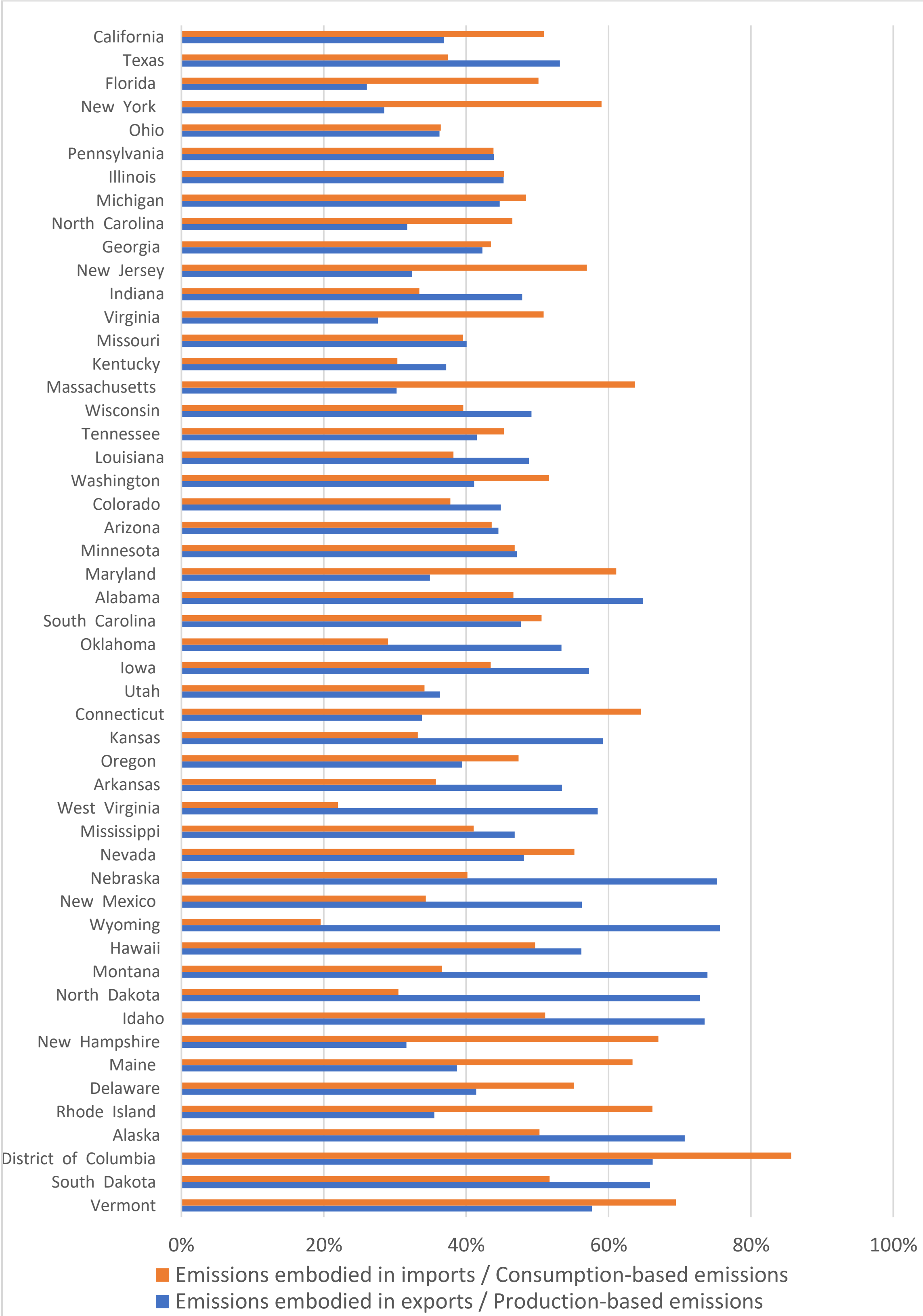
Table 2-3 Net Domestic Import and Export of GHG Emissions

Top 10 Net Domestic Import of Emissions					
by state (MMT CO_2 Eq.)		per $ GDP (g CO_2 Eq. / $GDP)		per capita (MT CO_2 Eq.)	
New York	111.0	New Hampshire	116.6	District of Columbia	11.2
California	105.5	Rhode Island	114.9	Massachusetts	7.2
Florida	101.7	Maine	111.6	New Hampshire	6.9
Massachusetts	48.7	Florida	108.4	Connecticut	6.8
New Jersey	48.1	Massachusetts	93.7	Rhode Island	6.3
Virginia	41.4	Connecticut	92.7	New York	5.6
Maryland	32.7	Maryland	85.0	Maryland	5.5
North Carolina	31.4	Virginia	83.8	New Jersey	5.4
Connecticut	24.4	New Jersey	82.6	Florida	5.1
Washington	16.1	New York	72.0	Maine	5.0
Top 10 Net Domestic Export of Emissions					
by state (MMT CO_2 Eq.)		per $ GDP (g CO_2 Eq. / $GDP)		per capita (MT CO_2 Eq.)	
Texas	146.1	Wyoming	1335.7	Wyoming	82.4
Wyoming	48.1	Montana	615.1	North Dakota	40.1
Nebraska	47.4	West Virginia	597.3	Montana	27.4
West Virginia	41.9	North Dakota	577.6	Nebraska	25.2
Indiana	35.8	Nebraska	407.8	West Virginia	22.7
Alabama	34.4	Idaho	225.2	Alaska	12.5
Kansas	32.6	Kansas	209.6	Kansas	11.3
Oklahoma	32.3	Alaska	186.6	Idaho	9.5
North Dakota	29.5	Oklahoma	180.2	Oklahoma	8.3
Montana	28.0	New Mexico	178.2	New Mexico	7.8

Figure 2-5 shows the share of emissions embodied in the exports of state production-based emissions and the share of emissions embodied in the imports of state consumption-based emissions. For example, 51% of the consumption emissions in

California are imported from other states, while 37% of its production emissions are exported to other states. The share of emissions embodied in the exports (to other states) varies from 26.1% (Florida) to 75.7% (Wyoming) with an average of 48%. The share of emissions embodied in the imports (from other states) varies from 19.5% (Wyoming) to 85.6% (District of Columbia) with an average of 46.6%. These large shares suggest the strong interactions among states. States in the Northeast (New England, New York, New Jersey, Maryland, and District of Columbia) have the largest shares (more than 57%) of emissions embodied in imports. Wyoming, Nebraska, Montana, Idaho and North Dakota have the largest shares (more than 70%) of emissions embodied in exports. Another proof of the strong interactions among states comes from the large share of emissions embodied in intermediate goods. The average share of emissions embodied in outbound intermediate goods of emissions embodied in state exports is 79.5% with a range of 58.3% (District of Columbia) to 91.3% (Kansas). For emissions embodied in inbound intermediate goods, the average share is 80.8% with a range of 70.5% (Nevada) to 86.6% (Oklahoma).

Figure 2-5 Share of Emissions Embodied in Trade



2.3.3 Consumption- and production-based GHG emissions by industry

Although I only include state-specific direct emission intensity for the electric power industry, state total emission intensities by industry vary widely, suggesting sources of goods (the supply chain) matters within the U.S. Table 2-4 shows the summary statistics of the top 15 industries (out of 403 industries) with total GHG emissions intensity, ordered by the U.S. total emission intensity. Cement manufacturing has the highest emission intensity on average. Electric power is second highest but has the largest standard deviation. Agriculture and energy industries all have high total emission intensities. For manufacturing, lime and gypsum, fertilizer, and aluminum are the most polluting industries after including emissions of upstream supply chain. Although pipeline transportation has the lowest direct emission intensity among the freight transportation modes, its total emission intensity is pretty high for all states.

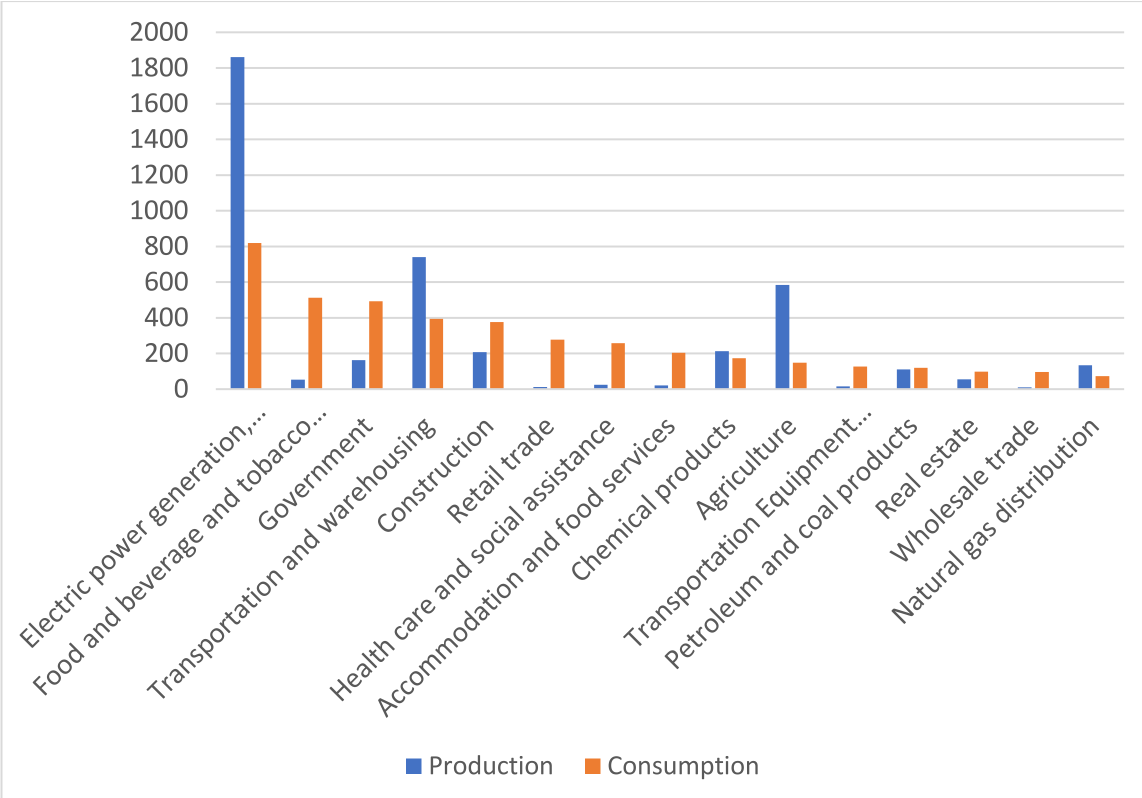
Figure 2-6 shows the 15 industries (aggregated) with top consumption-based GHG emissions. Among all industries, these 15 industries included in Figure 2-6 account for more than 86% of total national GHG emissions in both production- and consumption-based accounting. Some industries have larger production-based than consumption-based emissions, such as, the electric power, transportation, agriculture, and natural gas distribution, as they supply intermediate inputs to support other industries. Service industries (health care, accommodation, retail, wholesale, etc.) and government, in contrast, have much larger consumption-based emissions. Food and beverage and tobacco products have the second highest consumption-based emissions (much higher than the production-based), suggesting people’s food choices can affect total emissions.

Table 2-4 Total GHG Emission Intensity (kg CO_2 eq. per thousand dollars) Summary Statistics across States for Selected Industries

Industry	U.S. total emission intensity	Mean	Std. dev.	Min	Max
Cement manufacturing	7901.2	7816.5	536.8	7063.6	9495.5
Electric power	4523.5	5381.0	4833.6	194.8	24542.2
Beef cattle ranching and farming	4356.2	4310.4	460.3	2875.4	4975.3
Lime and gypsum product manufacturing	3605.6	3540.9	262.0	3053.9	4184.8
Dairy cattle and milk production	3167.8	3173.3	187.7	2496.1	3625.8
Grain farming	2460.9	2451.6	154.9	1953.9	2746.8
Wet corn milling	2353.9	1530.8	796.3	819.1	2788.1
Industrial gas manufacturing	2104.4	2384.6	999.0	1216.1	6336.5
Animal (except poultry) slaughtering, rendering, and processing	2058.9	2075.3	325.8	33.7	2569.4
Fertilizer manufacturing	1945.2	1977.4	167.9	1443.1	2326.5
Pipeline transportation	1939.0	1941.3	51.5	1880.5	2052.4
Alumina refining and primary aluminum production	1860.7	1395.8	857.3	682.2	5074.5
Natural gas distribution	1777.0	1776.0	107.0	1567.4	2123.0
Flour milling and malt manufacturing	1649.4	1418.5	599.4	87.1	2435.4
Coal mining	1636.9	1421.7	209.3	1216.8	1853.8

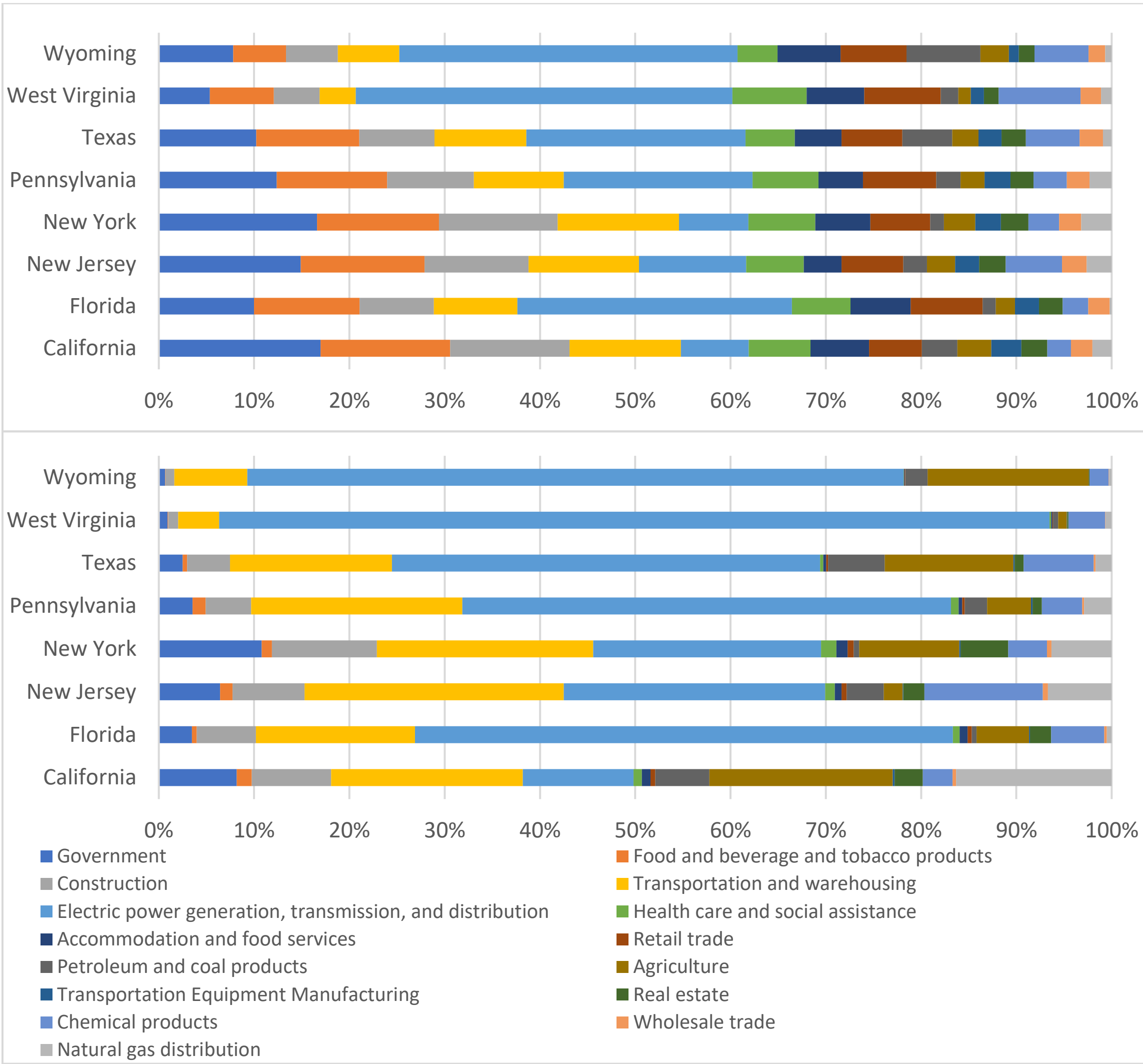
In Figure 2-7, I compare the shares of consumption- and production-based emissions by industry for selected states. I show findings for the same set of industries as in Figure 2-7. GHG emissions from these industries account for more than 80% of the state total emissions in both production- and consumption-based accounting for all selected states. I select states with large amount of emissions (California, Texas, Florida, New York, Pennsylvania, New Jersey) as well as states with the highest emission intensity of consumption (West Virginia and Wyoming). Figure 2-7 shows that differences in the selected states' shares of emissions by industry are much larger in

Figure 2-6 Consumption- and Production-based GHG Emissions of Selected Industries ($MMT\ CO_2$ Eq.)



production-based emissions (bottom) as production-based emissions suggest the state economic structure to some extent. Wyoming and West Virginia have the largest share of emissions from the electric power industry because a large share of the energy source used by the power industry is coal. The other six states have a large share from transportation as they have ports and hubs. California has a large share of agriculture emissions, and New Jersey has a large share of emissions from chemical products. In contrast, the differences of the industry percentage in consumption-based emissions (Figure 2-7, upper) are somewhat smaller than those for production-based emissions, which to some extent may reflect the relatively similar consumption patterns among states. In this vein, it may be no surprise that major differences emanate from the electric power industry (Figure 2-7). The larger the share of consumption emissions from electric power production, the higher the GHG emission intensity of consumption for the state.

Figure 2-7 Percentage of Consumption- (upper) and Production-based (bottom) GHG Emissions of Selected Industries for Selected States



2.4 Discussion

There are several uncertainties inherent in the MRIO framework. First, I use the 2012 U.S. benchmark I-O tables to estimate 2016 situations assuming no change in technology. This is reasonable as Carter (1970) has suggested that production technology does not tend to change radically over short periods. Admittedly her work is outdated and needs to be revisited. When domesticating the U.S. I-O tables, I assume that states have similar shares of imports; this surely is not the actual case. Surely coastal states use more imports, particularly Hawaii and Alaska. I say this because these two states are quite isolated from the rest of the nation, and thus are more likely to use higher shares of imported inputs. In addition, I assume that production processes are spatially invariant and are well represented by the nation's average technology for detailed industries when estimating state I-O tables. Jackson (2001) found evidence that this is a strong assumption, at least at a rather aggregated two digit-SIC (Standard Industrial Classification) level. Although MRIO analysis accounts for the heterogeneity of production patterns among states, each industry has the same and constant cost production functions; they, thus, cannot account for either the different production patterns (or at least differences in within-industry commodity production mix) within the sector or the use of alternative technologies used to abate emissions. Moreover, I did not *fully* explore differences among state consumption patterns, I only attempted to articulate state household consumption very well. Admittedly, it accounts for the lion's share of total state final demand—around 60% to 70% of it.

Data limitations pose uncertainties. I estimated interstate trade flows using a gravity model. For goods, I used the FAF4 state database to calibrate my gravity model. But, FAF4 only has 40 commodity categories while my MRIO model include 257 goods-producing industries. Each goods industry is mapped to a single FAF4 commodity. Since the FAF4 commodity categories are much more aggregated than are industries in my model, products of some industries belong to the same FAF4 commodity category. For example, the FAF4 trade flows of electronic and other electrical equipment and components include electronic computer, and small electric appliances, which are products of two separate industries in my model. Applying such aggregated trade flows to a model with more-refined industries induces error to model estimates by industry (Lahr & Stevens, 2002). For service industries, no trade data are available for model calibration. As a result, I used a simple gravity model for service industries following Sargento et al. (2012). While those parameters that I use may be reasonable, I am unable to verify the veracity of my approach. Interstate movements of electricity are also estimated by gravity model. But the power transmission network is comprised of interconnections that operate independently/separately with very limited power exchange in-between (EIA, 2016b). Interstate trade estimates of electric power generated by a gravity model may introduce interconnections between states that have few or no exchanges. Moreover, I use RAS to assure state outflows do not exceed state supplies and that state inflows do not exceed state demands. RAS minimizes changes from the structure of the initial trade matrix (Sargento et al., 2012). Thus, when I use travel cost or Euclidean distances to proxy transport costs between states, changes in state GHG emissions inventories are inevitably very small. Future work should use different approaches other than the gravity models to estimate interstate trade flow and to examine the robustness of the MRIO framework.

By applying the national direct emission intensity to the states, I ignore real differences in emission intensities among states, some of which is undoubtedly due to different environmental regulations across states. Future work should use real state-level direct emissions intensity based on the state energy consumption obtained from the SEDS. In my model, I find that even just using state direct emission intensity for the electric power production would generate significant state-to-state differences in total emissions intensity by industry. Differences in the state direct emission intensity for the electric power industry are based on the energy source used for generation. While the share of coal consumed decreased in the U.S., most of that which remains is consumed by the electric power industry. Coal-producing states, like Wyoming and West Virginia, which use coal for generation, naturally have much higher GHG emission intensity of consumption. In addition, the USEEIO data do not include direct emissions from household fossil fuel consumption. In this vein, the state inventory of GHG emissions is underestimated in this work. The total U.S. GHG emissions from my analysis is 4,843.2 MMT for 2016, which is substantially less than the one reported by EPA (6,445.7 MMT). This is because emissions from household direct consumption of fossil fuels (e.g. natural gas for heating, gasoline for driving, etc.) are missing in my estimates.

2.5 Conclusions

I build a state-level MRIO model for the U.S. with 403 industries that roughly simulates domestic supply chains. I use the model to compare state-level consumption- and production-based GHG emissions. In general, states with highest consumption emissions also have high production emissions; states with lowest consumption emissions also have low production emissions. States in the Northeast and Pacific Coast have the lowest emissions per unit of GDP in both consumption- and production-based accounting and also are top net domestic importers of emissions. Some states in the interior of the U.S. (e.g. Wyoming, North Dakota, etc.) have the highest emissions per unit of GDP in both forms of accounting and, hence, are among the top net domestic exporters. In answer to the core research question “who pollutes for whom?” the largest amount of emissions embodied in consumption derive from within each state. Not surprisingly, nearby states are far more likely to exchange embodied emissions between each other than with states further away. Texas and California spread their exports of a relatively large amount of embodied emissions across states nationwide.

The importance of consumer versus producer responsibility is critical from a policy perspective. My findings point out which states are likely willing to take actions to control GHG emissions, and the kinds of actions that they would likely take. Net importing states, such as California and states in the Northeast, should be willing to regulate production-based emissions since more emissions are embodied in their consumption. But states with low production emission intensities per unit of GDP are likely to object to further attempts to reduce their emissions. Some of these states undoubtedly already deploy substantial shares of renewable energy resources to generate electric power. Further expansion of the capacity of renewable energy may raise the costs of their electric power, at least in the near term. In this vein, without external nudging, net exporting states are unlikely to be willing to reduce their production-based GHG emissions as it is likely to come at a cost to their net wealth (GDP levels). While costs can be passed along to final consumers elsewhere, it is just as likely, if not more so, that rising costs will make their products less competitive on both interstate and international stages. Net exporting states are therefore more likely to be inclined to adopt policies that target consumption-based emissions. If the federal government opts to regulate GHG emissions via consumption-based accounting across all states, states with higher-than-average emissions intensities of consumption will undoubtedly suffer cost burdens that will affect *their* economies. Therefore, some federal compensation to net exporting states may provide enough incentive for firms in these states to mitigate emissions. Moreover, since nearby states have more economic exchange, regional polices of emissions management are likely to be more effective than strictly state-based policies. Such regional emissions management policies do exist. One example is the cooperative effort of northeastern states called the “Regional Greenhouse Gas Initiative” (RGGI, 2020).

Most GHG emissions are emitted by the industries that closely relate to our daily lives. Thus, changing people’s consumption patterns can be another way to effectively reduce GHG emissions. As Weber and Matthews (2008) find out that emissions embodied in household consumption are not necessarily related to household income, so policies can be designed to change consumption patterns towards low-carbon intensive goods. For example, encourage people to reduce consumption of meat, especially beef, since livestock farming and animal processing are among the set of industries with the highest total emission intensity.

3 U.S. Interstate Trade-Related Greenhouse Gas Emissions from Freight Transportation

3.1 Introduction

This chapter examines the magnitude of trade-related greenhouse gas emissions (GHG) emissions from inter-state freight transportation through the MRIO framework which offers a link between economic activities and freight. Many researchers study emissions from freight transportation through its major modes (Horvath, 2006; Davies et al., 2008; Nealer et al., 2012; Wu & Pienaar, 2019). There is little research that links emissions from freight transportation to U.S. interstate trade flows, however. Given the inseparable relationship between trade and freight transportation, my research fills this gap and compares emissions from transportation with emissions from production of traded goods. This helps reveal the impact of state economic structure on freight transportation and the magnitude (by industry and by state) of freight transportation's contribution to GHG emissions.

Transportation is a major contributor of GHG emissions in the U.S.— 28.5% of the total emissions in 2017 (EPA, 2019a). About 30% of the transportation emissions are due to freight. Emissions from transportation are growing much faster than overall U.S. emissions. Between 1990 and 2017, GHG emissions from transportation increased 21% even though total U.S. GHG emissions rose by less than 1% (EPA, 2019a). Within the transportation sector, the GHG emissions from freight transportation grew 11% from 2000 to 2017 while that from passenger transportation has *decreased* by 6% (EPA, 2019a).

Transportation emissions mainly derive from the combustion of petroleum-based products (EPA, 2019a). Many factors contribute to the rapid growth of GHG emissions from freight transportation, e.g., emission factor, energy intensity, energy structure, freight volume, mode share (Davies et al., 2008; Wu & Pienaar, 2019). The core contributor has been an increase in demand for freight and, hence, its transportation: the growth has been due to both enhanced demand for international and domestic goods (Davies et al., 2008; EPA, 2019a). My research focuses on the link between freight transportation and domestic trade, specifically interstate trade. Some states are taking more active roles in controlling GHG emissions; but it is difficult to regulate emissions from interstate freight transportation via state policies since freight transportation is not regulated or monitored and since transportation is a mobile source of emissions. My research suggests that the responsibility for GHG emissions from interstate freight transportation can be assigned to industries within states. In this vein, my research should inform state environmental policy makers as they attempt to regulate emissions.

Freight transportation, as derived demand, is closely related to economic activities. Some researchers use input-output (I-O) tables to analyze the environmental impacts of freight transport by industry. Nealer et al. (2012) find that food, construction, and vehicle manufacturing are main sectors emitting GHGs as embodied in freight transportation (include freight emissions in the upstream portions of their supply chains). But O'Rourke et al. (2013) suggests the top *consuming* sectors should be responsible for the GHG emissions and that they are personal consumption expenditure (households), construction, food manufacturing, and government. Cadarso et al. (2010) assess CO_2 emissions from international freight transport used in Spain; they find that sectors (such as motor vehicles) with a greater value content of international intermediate inputs are responsible for the larger increases in international transport emissions.

A few researchers link emissions from freight transport to trade flows. Cristea et al. (2013) examine how much international freight transport contributes to trade-related emissions by industry and by trading partner. Moreover, using scenario analysis, they find that lower tariffs combined with economic growth in China and India has led to emissions growth from transportation growing faster than growth of the trade value. They attribute the differential to ever more-distant trading partners (Cristea et al., 2013). Llano et al. (2018) estimated GHG emissions from intra- and inter-provincial freight transportation within Spain and find that the emission reductions from 1995 to 2015 are due to the economic downturn of 2008-2012. They further show how shifts from road to rail reduce freight transportation emissions.

In line with the approach used by Cristea et al. (2013) and Llano et al. (2018) for international and intra-national trade, I estimate the GHG emissions from interstate freight transportation in the U.S. Unfortunately, insufficient data for analysis are typically available for domestic freight transport (Cristea et al., 2013; Southworth, 2018). That is, while there is plenty of information on import/export flows, little data typically exist on intra-regional shipments, and this is particularly the case within the U.S. The lack of regulation in interstate commerce explains the dearth of information. While some data are available on domestic port and airport inflows/outflows, few data are available on truck or rail interstate inflows/outflows (Giuliano et al., 2010). Because of this, I use a multiregional I-O (MRIO) framework based on a gravity model formulation to estimate interstate trade flows. It is guided by information from the Freight Analysis Framework version 4 (FAF4) State Database (BTS, 2016).

Even if data were not lacking, heterogeneity of both the services that freight transportation renders (different modes, different types of carriers, etc.) and the customers it serves (different commodities and different uses: intermediate industries, government, households, exports) makes the analysis of freight transportation somewhat more complicated than that of passenger transportation (Boyer 1997). Herein, I account for the five major freight transportation modes (truck, rail, water, air, and pipeline) for 257 commodities (that require freight transportation services from among 405 goods and services in the 2012 U.S. benchmark input-output tables) to estimate the interstate supply and demand for transported goods (interstate trade). Despite this detail, I estimate aggregate behavior: I do not examine the motivations behind decisions of individual agents (such as producers, shippers, carriers, receivers, households, etc.). That is, I estimate aggregate interstate freight flows by industry not individual shipments. This chapter lays out how I estimate interstate freight flows and the GHG emissions that correspond to them. This is followed by an analysis of trade and emissions patterns by state, industry, and mode. I then discuss the uncertainties involved in the estimation approach. The chapter concludes with a summary of findings and a few policy recommendations.

3.2 Methods and Data

In freight flow modeling, I-O tables are often used. I-O tables contain industry-specific estimates of the total value of commodities produced and consumed (supplied and demanded) for specific geographies. Estimates of supply and demand across all industries across two or more regions are needed to estimate freight flows (Giuliano, et al. 2010; Southworth, 2018). For this reason, MRIO frameworks are often used to estimate freight flows.

Through the MRIO framework described in Chapter 2, I estimate supply and demand for each of 403 industries for each state. Then I use a gravity model to estimate interstate trade flows for 2016 using estimates of excess supplies and excess demands (the amount of each industry's supplies and demands that the state does not fulfill on its own). I then convert the trade flow values (z_i^{rs}) to interstate freight in ton-mile by mode ($f_{i\mathrm{m}}^{rs}$) (Eq. 1). I multiply the trade flow of industry i between state r and state s (z_i^{rs}) using the weight/value ratio of each industry's main commodity (w_i) to estimate the aggregate interstate shipment weight by industry. The shipment weight is then multiplied by the freight mode share of the commodity (s_m) and an estimate of the modal shipping distance (d_m^{rs}) to estimate freight transportation activity of industry i between states r and s by mode ($f_{i\mathrm{m}}^{rs}$). I then apply ton-mile emission factors by mode to estimate the GHG emissions for interstate freight transportation. GHG emissions are measured in CO_2 equivalent (CO_2 eq.).

$$f_{im}^{rs} = z_i^{rs} \cdot w_i \cdot s_m \cdot d_m^{rs} \tag{1}$$

In the following, I further explain these interstate trade flow estimates, freight transportation mode shares, GHG emission estimates, and related data.

3.2.1 Inter-State Trade Flow Estimation

Given limited data on interstate trade, I first apply a gravity model to estimate trade flows. The basic idea of a gravity model is that the magnitude of economic or social interaction between any two regions (e.g. bilateral trade flows) is proportional to the amount of relevant activity in each region, inversely proportional to impeding frictions (e.g. transportation costs) between them (c.f. Kockelman et al., 2005; Sen & Smith, 2012), and, further, dampened by intervening opportunities available to both regions. Gravity models are very useful and, hence, popular empirical tools for calibrating trade flows by industry, i.e., the spatial distribution of freight flows (NASEM, 2008; Llano et al., 2018).

The interstate trade flows of an industry i (z_i^{rs}) are proportional to the excess supply (s_i^r) of the origin state r (state total supply minus locally supplied demand) and excess demand (d_i^s) of the destination state s (state total demand minus locally supplied demand), and inversely proportional to the carrying costs between the two states ($c_{i,travel}^{rs}$) (Eq. 2). As Sargento (2009) suggests, I add the degree of specialization (l_i^r) to the model, i.e., the industry location quotient of supplying state r (see Eq. 10 in Chapter 2). I calculate the excess supply, excess demand, and degree of specialization of all 50 states plus the District of Columbia under the MRIO framework (details can be found in Chapter 2). Domestic freight transportation triggered by international trade is not included in my analysis.

$$z_i^{rs} = g_i \frac{(s_i^r)^\alpha (d_i^s)^\beta (l_i^r)^\gamma}{(c_{i,travel}^{rs})^\omega} \qquad (2)$$

The travel cost ($c_{i,travel}^{rs}$) is the weighted-average fuel cost to ship one unit of the main commodity produced by industry i (Eq. 3). Freight transportation mode shares (s'_m) are used as weights. The travel cost not only accounts for the interstate shipping distance by mode (d_m^{rs}), but also includes the fuel cost by mode (λ_m, $ per ton-mile) and the characteristics of the industry's commodities (w_i, weight/value ratio).

$$c_{i,travel}^{rs} = \sum\nolimits_{m} s_{m}^{'} \cdot w_{i} \cdot d_{m}^{rs} \cdot \lambda_{m} \tag{3}$$

I use the transportation network to estimate interstate shipping distances by mode. The network of each of three main transportation modes are considered: truck, rail, and water. I used transportation network geospatial data from the National Transportation Atlas Database (NTAD) provided by the U.S. Bureau of Transportation Statistics (BTS). I use the Freight Analysis Framework (FAF) Network (including National Highway System, National Network, and state primary and secondary roads) for trucking distances, North American Rail Lines for rail freight distances, and Navigable Waterway Lines for water freight distances. For each state, I use its population centroid (the center of concentration based on population of census tracts within the state) as the point of origin/destination. This is because supply and demand are more likely to occur in population centers. By using GIS network analysis, I estimated network distances between state population centroids as the average interstate shipping distances by mode. For the other two transportation modes--air freight and pipelines--I use aerial distances between state population centroids. This likely grossly understates pipeline distances, but the overall costs per mile for pipelines are extraordinarily low in any case.

The fuel cost per ton-mile, λ_m, is calculated as the product of fuel consumption by mode multiplied by the fuel price, all divided by the ton-miles of freight (Table 3-1). Fuel consumption by mode were collected from BTS (2018b), and the U.S. ton-miles of freight from BTS (2018a) –publicly available as National Transportation Statistics. The annual fuel prices come from the U.S. Energy Information Administration (EIA, 2020a). In addition, the weight/value ratios for each industry (w_i) are estimated from BTS's 2012 Commodity Flow Survey data.

Table 3-1 Fuel Cost per Ton-Mile by Mode, 2016

Transportation mode	Ton-mile (million)	Fuel consumption		Fuel cost per ton-mile ($)
Truck	2,010,881	Gasoline, diesel and other fuels (million gallons)	44,893	0.03237
Rail	1,585,440	Distillate / diesel fuel (million gallons)	3,385	0.00295
Water	477,861	Residual fuel oil (million gallons)	2,930	0.01929
Air	13,157	Jet fuel (million gallons)	11,167	1.12037
Pipeline	896,320	Natural gas (million cubic feet)	686,732	0.00200

Source: U.S. ton-miles of freight and fuel consumption by mode are from BTS, annual fuel prices are from EIA.

I use FAF4 State Database for 2012 (BTS, 2016) for interstate trade values by commodity (domestic trade only) to calibrate the gravity model, i.e., to obtain estimates of constant g_i and other parameters in Eq. 2. This process netted estimates of interstate trade flows for 257 goods-producing industries (excluding utilities) that require freight transportation services.

3.2.2 Freight Transportation Mode Share

Freight transportation mode shares (s_m in Eq. 1 and s'_m in Eq. 3) are needed to calculate interstate freight transportation activities and travel costs between states. I use multinomial logit models to estimate mode shares for each state by industry. Rational choice theory underlies the choice among transportation modes. It is originated from consumer utility theory (Shen & Wang, 2012). Basically, a shipper's choice is determined by various characteristics of each mode and s/he chooses the mode that is most satisfactory among different alternatives (Shen & Wang, 2012). In the case of freight transportation mode choice, shippers/carriers select the mode that minimizes total overall carrying costs of the shipment (NASEM, 2008). I cannot identify individual shippers/carriers' choice because I work with data that are industry aggregates of shippers' behaviors. So, I instead assume that all shippers in an industry within a state make similar mode-choice decisions. Aggregate models focus on group behavior, so estimates of aggregate mode-choice shares for freight must be made for specific geographic sets (Shen & Wang, 2012; Wang et al., 2013). For example, Southworth et al. (2007) use a logit model of truck–rail/truck–water mode choice for wheat shipments originating in the Pacific Northwest; Shen and Wang (2012) use binary logit and regression models of truck/rail mode choice for cereal grain shipments between states; Wang et al. (2013) use binary probit and logit models of truck/rail mode choice for freight movements in Maryland. As I consider all major freight modes (truck, rail, water, air, and pipeline) in this research, I apply multinomial logit models based on state-level data.

Freight transportation mode choice depends on the characteristics of each mode and what is being shipped (Southworth et al., 2007; Shen & Wang, 2012; Wang et al., 2013). Key characteristics of transportation modes are network distances and fuel costs. Key characteristics of shipments are the type of commodity shipped, the volume of the shipment, the relative weight of what is being shipped, and the fragility of the shipment. This last includes the propensity for hazards associated with the product, such as its breakability, flammability, and environmental toxicity. I include shipment value and a dummy variable that identifies the product as petroleum-related. In addition, I use the product's weight/value ratio to represent the commodity's characteristics of each industry (assuming each industry produces similar commodities). It is a common rule of thumb to use commodity weight/value ratio to estimate freight mode choice proportions, especially at the planning level when detailed shipment data is not available (Sou & Ong, 2015). Carrying costs of high value/weight products tend to be relatively high, forcing shippers to send them via more expensive transportation modes like air or truck to reduce overall shipping costs (Treyz & Sevens, 1985; Harrigan, 2010; Shabani & Figliozzi, 2012).

I use slightly different independent variables for the mode share models in the travel costs and freight activities and a different dataset for model calibration. For the mode share in the travel costs (s'_m in Eq. 3), I use weight/value ratio by industry (w), network distance by mode (d_m), and a dummy variable denoting petroleum-related products (p) to estimate the shipping costs by mode (c'_m) (Eq. 4). In Eq. 4, μ'_m is the mode specific constant, μ'_m, a'_{1m}, a'_{2m}, and a'_{3m} are empirically derived mode specific parameters. Then the proportion by mode other than truck (Eq. 5) and by truck (Eq. 6) can be estimated using the utilities.

$$c'_m = \mu'_m + a'_{1m}w + a'_{2m}d_m + a'_{3m}p \tag{4}$$

$$s'_m = \frac{e^{c'_m}}{1 + \sum_{m \neq truck} e^{c'_m}} \tag{5}$$

$$s'_{truck} = \frac{1}{1 + \sum_{m \neq truck} e^{c'_m}} \tag{6}$$

When estimating travel costs between states, shipment values are unavailable and, thus, not included in Eq. 4. I use 2012 Commodity Flow Survey (CFS) Public Use Microdata sample to derive parameters in Eq. 4 (see Appendix A). The CFS provides detailed information for more than four million shipments with ancillary data on transportation mode, shipment value, weight, routed distance between origin and destination, commodity type, etc. (Census Bureau, 2015). These data are the first generation of CFS Public Use Microdata, so they include data for only one year. When I added 2012 fuel costs by mode to the CFS data for model calibration, I can only use fuel costs per ton-mile as shipment values are unavailable at this stage. The model cannot produce parameter estimates (model not concave) because all shipments using the same mode have the same fuel costs per ton-mile. So, I remove fuel costs from the model (Eq. 4). The multiple modes in the CFS are converted to single mode (Table 3-2). Although pipeline is a mode included in the CFS, its sample size of shipments is relatively very small compared to that of other modes. It, therefore, might not provide reasonable parameter estimates. Since pipelines are mainly used to transport petroleum-related products and the cost of adding more pipeline infrastructure is expensive, the share of pipelines is relatively stable overtime compared to other modes (BTS, 2016). I therefore used the pipeline mode shares ($s'_{pipeline}$) between states directly from FAF4 rather than via estimates in Eq. 5. Rail services have similar constrains of infrastructure as pipelines but are used to ship various types of commodities thus have a relatively large sample size in the CFS.

Table 3-2 Multiple mode to single mode allocation

Multiple mode	**Allocated to single mode**
Truck and rail	Rail
Rail and water	Water
Truck and water	Water
Parcel	Truck

For the mode share of freight transportation activities (s_m in Eq. 1), I use the industry weight/value ratio (w), network distance by mode (d_m), a dummy variable indicating whether petroleum-related products (p), interstate trade value ($v = z_i^{rs}$), and fuel costs of shipping one unit of commodity by mode ($\lambda_m \times w \times d_m$) to estimate the costs of shipping commodities of a certain industry by mode (c_m) (Eq. 7). In Eq. 7, μ_m is the mode specific constant, λ_m is the fuel cost per ton-mile by mode, μ_m, a_{1m}, a_{2m}, a_{3m},

a_{4m}, and a_{5m} are empirically derived mode specific parameters. The mode share (s_m) then is estimated using the shipping cost by mode (c_m) (similar to Eq. 5 and Eq. 6).

$$c_m = \mu_m + a_{1m}w + a_{2m}d_m + a_{3m}p + a_{4m}v + a_{5m}(\lambda_m \times w \times d_m) \qquad (7)$$

I use the FAF4 State Database to derive parameters in Eq. 7 (see Appendix A). Although the CFS Public Use Microdata provide detailed information for individual shipments, it has just one-year of data and a relatively small sample size of shipments for pipelines. Therefore, when using the CFS data for model calibration, the model cannot account for changes in fuel costs by mode through time and cannot provide reasonable estimates for the pipeline share. I tried to use the CFS data for model calibration in Eq. 7 using the total fuel costs ($\lambda_m \times v \times w \times d_m$) of each interstate trade flow by industry so that the model can derive parameter estimates. But the estimated share of air freight was unreasonably high. This is because the parameter estimates for air freight when using the CFS data suggest the higher the total fuel costs for a certain shipment, the more likely air is used. But the total fuel costs in my model are for the interstate trade flow by industry rather than for any individual shipment, which are obviously much higher than individual shipment. This leads to the unreasonably high estimates of air usage when using parameter estimates derived by the CFS data.

The FAF4 State Database incorporates data from the CFS, agriculture, utility, construction, and other sectors for the year of 2002, 2007, and 2012 (BTS, 2016). It provides origin-destination state, aggregate shipment weight and value between states by mode for each commodity group rather than individual shipment information. So, FAF4 has a much smaller number of observations (360,013) compared to the CFS. As I tried to estimate aggregate mode share for commodities of a certain industry at state level, I chose the FAF4 State Database combined with interstate network distances by mode (self-calculated see Section 3.2.1) and fuel costs by mode to calibrate the model.

3.2.3 GHG Emissions Estimation

I use ton-mile emission factors (ϵ_m) to estimate GHG emissions from interstate freight transportation assuming a linear relationship between emissions and freight (Eq. 8). ϵ_m is the amount of GHG emissions generated by mode m to ship one ton-mile of freight. Multiplying ϵ_m by the freight activity for mode m to ship commodities of industry i from state r to state s (f_{im}^{rs}), and summing over all modes yields the transportation emissions for industry i from state r to state s (e_{iT}^{rs}).

$$e_{iT}^{rs} = \sum\nolimits_m \epsilon_m \times f_{im}^{rs} \tag{8}$$

In addition, I estimate GHG emissions generated in producing the traded commodities so that I can compare transportation emissions with production emissions and identify how much transportation emissions contribute to trade related GHG emissions. In Eq. 9, ϵ_i is the emission factor of industry i indicating the GHG emissions generated in the process of producing one dollar of commodities by industry i. Multiplying ϵ_i with the trade value of industry i from state r to state s (z_i^{rs}) yields the production emissions e_{iP}^{rs}. The trade-related GHG emissions of industry i from state r to state s (e_i^{rs}) are the sum of transportation emissions and production emissions (Eq. 10).

$$e_{iP}^{rs} = \epsilon_i \times z_i^{rs} \tag{9}$$

$$e_i^{rs} = e_{iT}^{rs} + e_{iP}^{rs} \tag{10}$$

The ton-mile emission factor by mode (ϵ_m) is developed using domestic freight transportation GHG emissions from the U.S. GHG Inventory (EPA, 2019a) and the U.S. ton-miles of freight from the National Transportation Statistics (BTS, 2018a) (Table 3-3).

GHG emissions due to domestic freight transportation from EPA include both direct emissions from transportation as well as electricity-related emissions distributed to transportation (EPA, 2019a). Air and truck have the highest emissions factors, while rail and water are more environmentally friendly. By assigning a single emission factor to each mode, I do not account for the heterogeneity of emissions within a mode due to differences in transportation equipment types, their vintages, operating status, etc. The production emission factor by industry (ϵ_i) is developed using the U.S. Environmentally-Extended Input-Output (USEEIO) v1.1 dataset (Ingwersen et al., 2017) and U.S. I-Otables (BEA, 2015). USEEIO provides the GHG emissions in producing one dollar of commodity (Ingwersen et al., 2017). I convert the USEEIO emission intensities to emission factor by industry using the U.S. I-O tables. By using the national-average production emission factors, I do not account for the heterogeneity of emissions intensities by industry within or across states.

Table 3-3 GHG Emissions per Ton-mile of Domestic Freight Transport Services, 2016

Mode	GHG emissions (MMT)	Ton-mile (million)	Intensity (gram CO_2 eq. per ton-mile)
Truck	420.9	2,010,881	209.31
Rail	35.6	1,585,440	22.45
Water	16.4	477,861	34.32
Air	16.8	13,157	1,276.89
Pipeline	39.2	896,320	43.73

Source: GHG emissions from domestic freight transportation are from EPA, U.S. ton-miles of freight are from BTS.

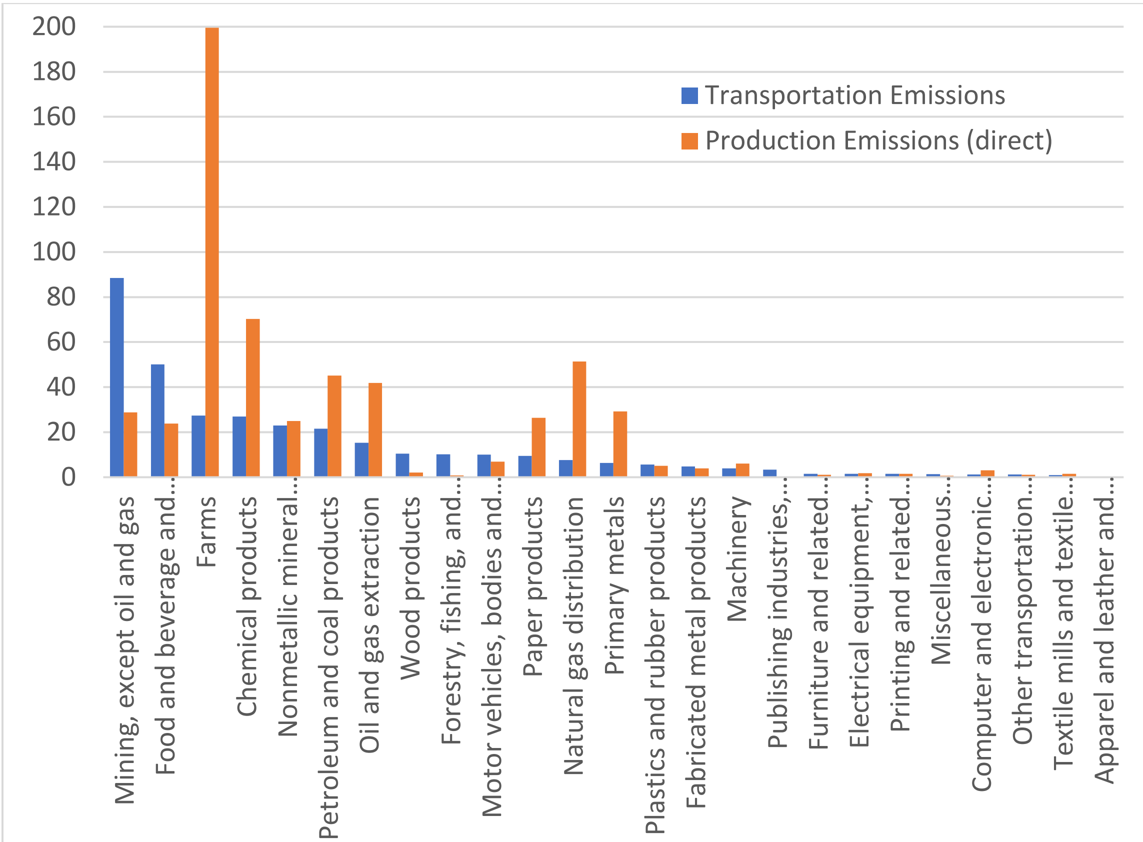
3.3 Results

Based on my estimates, annual total interstate trade-related GHG emissions in the U.S. are about 911 million metric tons (MMT) CO_2 eq. in which 37% (333.7 MMT CO_2 eq.) are from interstate freight transportation alone. These transportation emissions are linked to each origin-destination-industry-mode freight flow in ton-mile. This estimate is based on 3,276,750 freight flows ($51\ states \times 50\ states \times 257\ industries \times 5\ freight\ transportation\ modes$). In this section, I compare the transportation emissions to production emissions affiliated with interstate trade by industry. I then perform a similar comparison by state. I highlight the top origin-destination-industry freight flows and their corresponding emissions. Moreover, I analyze these emissions by mode.

3.3.1 Transportation Emissions versus Production Emissions by Industry

I examine the contribution of transportation emissions to interstate trade-related emissions by industry first. I aggregate the 257 goods industries into 25 sectors for ready presentation. Figure 3-1 shows the contributions of both transportation and production to interstate trade-related GHG emissions by industry. There are substantial variations across industries with respect to both transportation and production emissions. Transportation emissions by industry vary from 0.17 MMT (apparel and leather and allied products) to 88.39 MMT (mining, except oil and gas). The range of production emissions by industry is from 0.08 MMT (apparel and leather and allied products) to 199.53 MMT (farms). Top sectors with respect to transportation emissions are mining, food and beverage and tobacco products, farms, chemical products, nonmetallic mineral products, and petroleum and coal products (Figure 3-1). Combined they account for more than 70% of the total transportation emissions. Products of these sectors are relatively heavier per unit of value compared to those sectors that produce the least transportation emissions (apparel and leather products, textile products, computer and electronic products, etc.). Among the top ten sectors of transportation emissions, five generate more emissions from transportation services than from production alone: mining, food and beverage and tobacco products, wood products, forestry, fishing, and related activities, and motor vehicles and parts.

Figure 3-1 Interstate Trade Related GHG Emissions by Industry (MMT CO_2 eq.)



In order to compare transportation and production emissions on a per dollar basis, I aggregate the transportation/production emissions by industry from all state pairs then divide by the total trade values by industry. Figure 3-2 shows the results sorted by transportation emission intensity. The transportation emission intensity varies from 8.5 grams CO_2 eq. per dollar (computer and electronic products) to 2,236.1 grams CO_2 eq. per dollar (Forestry, fishing, and related activities). Farms have the highest production emission per dollar (1,590.3 grams CO_2 eq.). Mining, and nonmetallic mineral products are among the top in both transportation and production emission intensity. Per dollar, emissions due to the transport of wood products and natural gas distribution become more prominent, while the contribution from machinery and motor vehicles and parts fall precipitously due to their relatively low weight/value ratio.

Figure 3-2 Interstate Trade Related GHG Emissions Intensities by Industry (gram CO_2 eq./$)

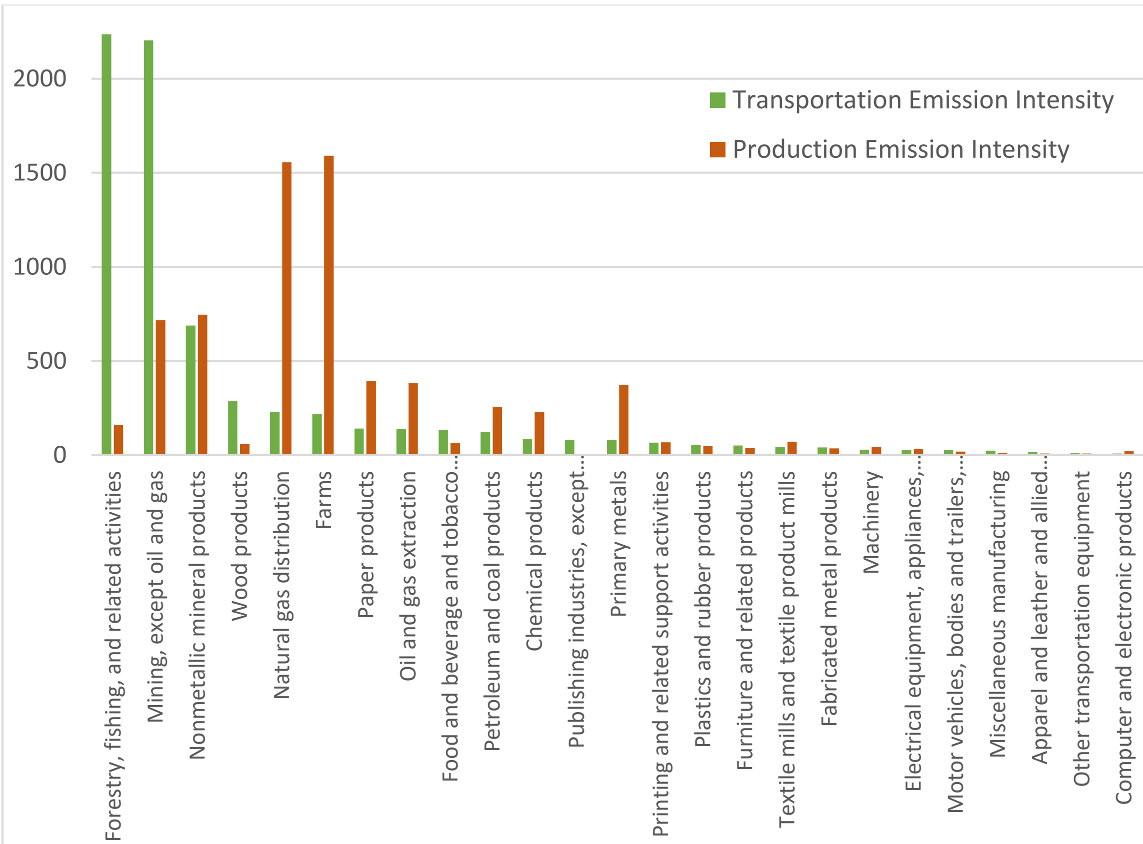
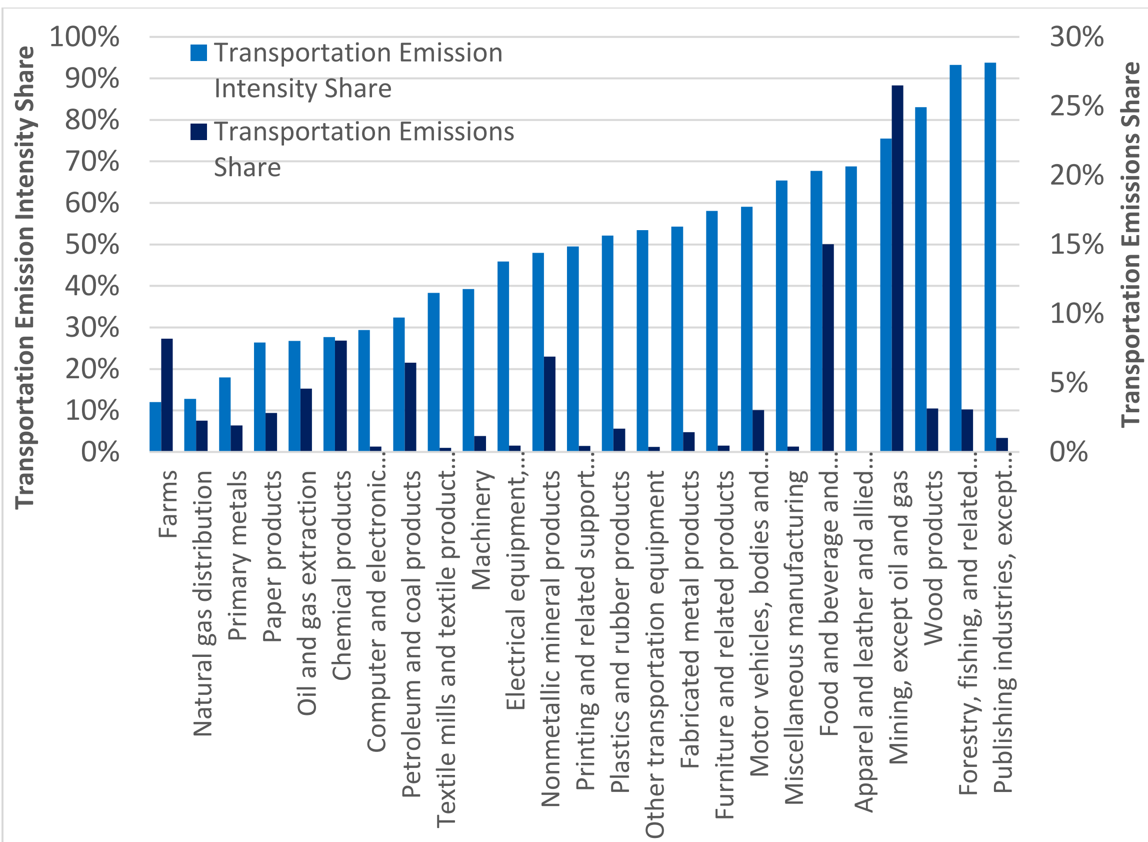


Figure 3-3 shows the contribution of transportation to trade-related GHG emissions through transportation emission intensity shares (transportation emission intensity divided by sum of transportation and production emission intensity by industry). The share of each industry's transportation emissions in the total transportation emissions is also presented in Figure 3-3. While emissions from interstate freight transportation account for about 37% of trade-related emissions, it varies widely across industries: from

12% (farms) to 93.8% (publishing industries). On the low end, farms, natural gas distribution, primary metals, paper products, oil and gas extraction, and chemical products all have low shares of trade-related emissions from transportation despite owning large transportation emissions. In contrast, more than 65% of trade-related emissions of publishing industries, apparel and leather products, and miscellaneous manufacturing are from transportation but contribute relatively few transportation emissions. Mining, and food and beverage and tobacco products have large shares in both transportation emissions and emission intensity.

Figure 3-3 The Contribution of Transport to Interstate Trade-related GHG Emissions

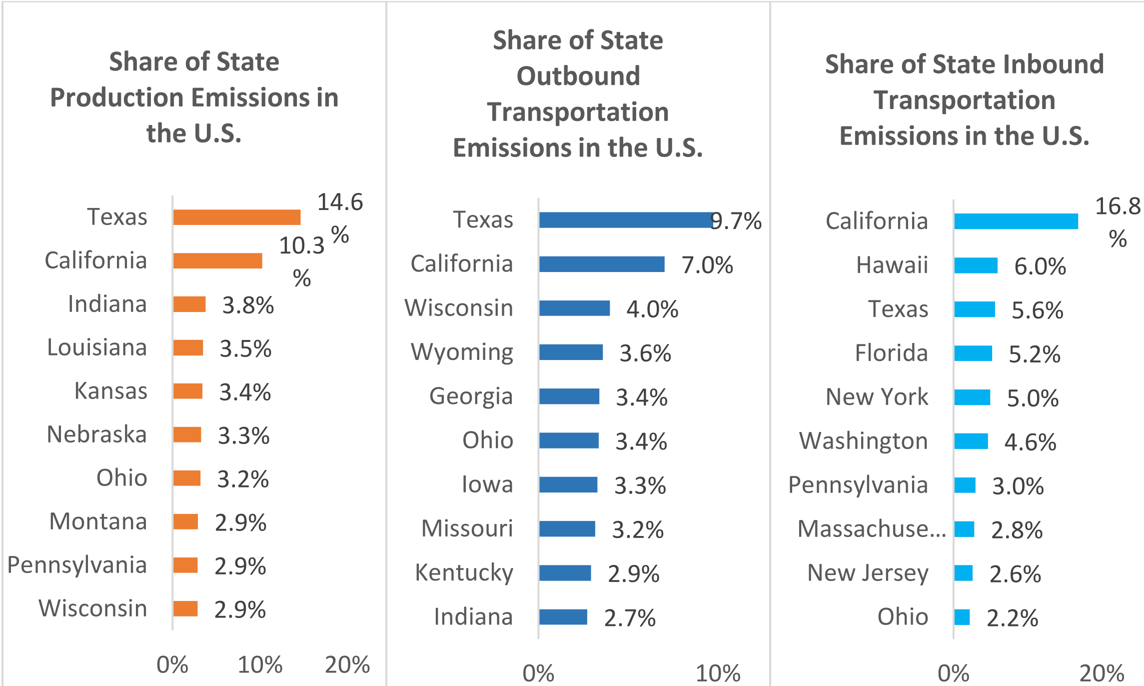


3.3.2 Transportation Emissions versus Production Emissions by State

There are large variances in trade-related emissions across states. This is in part due to differences in the size of the states, their economic reliance on trade, the commodity composition of their trade, the economic structure of their trading partner states, etc. The outbound trade-related emissions (production plus transportation) range from 0.86 MMT CO_2 eq. (District of Columbia) to 117.03 MMT (Texas), while the inbound trade-related emissions vary from 2.47 MMT (Wyoming) to 97.59 MMT (California).

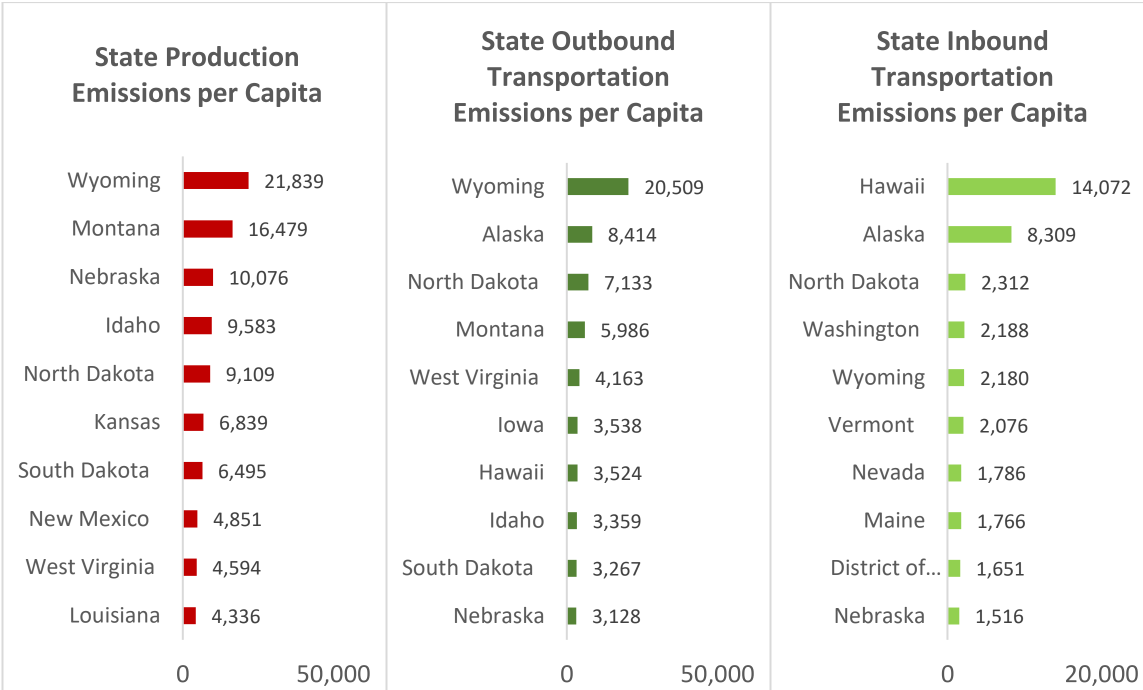
Figure 3-4 shows the contribution of selected states to interstate trade-related emissions: the left-hand side of the figure presents the top ten states in terms of production emissions; the center of the figure presents the top ten states in terms of outbound transportation emissions; and the right-hand side of the figure presents the top ten states in terms of inbound transportation emissions. Texas, California, and Ohio have significant shares of all three. Texas and California account for about 25% of trade-related production emissions and more than 16% of the outbound transportation emissions. California alone is responsible for 17% of the inbound transportation emissions. Some states with large production emissions have significant outbound transportation emissions as well, for example, Indiana, Wisconsin, Wyoming, and Iowa. In contrast, Hawaii, New York, New Jersey, and Massachusetts are responsible for few production emissions but substantial inbound transportation emissions. Some states contribute large shares of both inbound and outbound transportation emissions, e.g., Illinois, Florida, and Washington. Most states display a substantial imbalance between inbound and outbound transportation emissions. For example, New York is only responsible for 3.39 MMT of outbound transportation emissions but for 16.53 MMT of inbound transportation emissions, while Wyoming is responsible for 11.96 MMT of outbound transportation emissions but only 1.27 MMT of inbound transportation emissions.

Figure 3-4 Interstate Trade-related GHG Emissions Shares (Top Ten States)



After normalizing interstate trade-related emissions by state population, states with substantial production emissions per capita have highest outbound transportation emissions per capita as well, such as Wyoming, Montana, Nebraska, North Dakota and West Virginia. Wyoming, North Dakota, and Nebraska are also among the top with largest inbound transportation emissions per capita. Hawaii and Alaska both have quite large inbound and outbound transportation emissions per capita as these two states are distant from all other states. Some small states in the east coast (i.e. Vermont, Maine, and District of Columbia) have highest per capita inbound transportation emissions. States with significant total trade-related emissions (e.g. California, Texas, Ohio, New York, and Florida) are not among the top with per capita trade-related emissions.

Figure 3-5 Per Capita Interstate Trade-related GHG Emissions by State (Top Ten States) (Kilogram CO_2 equivalent per capita)



I calculate the emission intensities (gram CO_2 eq. per dollar) for each state's inbound and outbound trade by dividing trade-related emissions by trade value (Table 3-4). On average, the emission intensity of U.S. interstate trade is 347 grams CO_2 eq. per dollar of which 220 grams are from production and 127 grams are from transportation. After controlling for the volume of trade, there are still large differences in emission intensities by state due to the commodity composition of trade. The emission intensities of outbound trade vary from 109 grams per dollar (New Hampshire) to 2,353 grams per dollar (Hawaii). States with top outbound emission intensities are among the top in both production and transportation emission intensities, e.g., Hawaii, Wyoming and Montana. For inbound trade, emission intensities range from 236 grams per dollar (District of Columbia) to 1,268 grams per dollar (Hawaii), about half that for the remote state's outbound trade. This is because inbound trade is determined by state consumption patterns while outbound trade aligns with state production. Among states with top inbound emission intensities, some have large production emission intensities but small transportation emission intensities (such as, Iowa, Nebraska, and Illinois) while others have large transportation emissions but small production emissions on a per dollar basis (more-remote states like, Hawaii, Alaska, and California). Moreover, states with large trade-related emissions need not have high emission intensities. For example, despite their large total outbound transportation emissions, the outbound transportation emission intensities for Texas and California are close to the national average. Similarly, many states leading the nation in inbound transportation emissions have average emission intensities, e.g., Texas, Florida, and Pennsylvania.

When comparing the contributions of transportation versus production interstate trade-related emissions, I find that Georgia, Oregon, Missouri, and Utah have larger outbound transportation emissions than their corresponding production emissions. The same applies to New Mexico, California, Wyoming, and Maine with regard to inbound transportation emissions. Hawaii, Alaska, Washington, and Nevada contribute more than half of the trade-related emissions from transportation for both inbound and outbound trade. Hawaii and Alaska are far more distant from all other states; so, the extreme shipping distances undoubtedly explain their transportation emissions variance.

Table 3-4 Production and Transportation Emission Intensities by State (gram CO_2 eq./$)

State	Outbound				Inbound			
	Total	Production	Transport	Transport share (%)	Total	Production	Transport	Transport share (%)
Alabama	296	189	107	36	247	181	66	27
Alaska	860	278	583	68	770	183	587	76
Arizona	409	316	93	23	292	152	140	48
Arkansas	383	248	136	35	288	188	100	35
California	402	288	114	28	415	176	239	58
Colorado	582	394	188	32	300	181	119	40
Connecticut	114	80	34	30	263	161	102	39
Delaware	244	216	27	11	292	197	96	33
D.C.	351	304	47	13	236	161	75	32
Florida	773	417	356	46	257	142	116	45
Georgia	308	120	189	61	301	219	82	27
Hawaii	2,353	1,096	1,257	53	1,268	155	1,114	88
Idaho	1,231	911	319	26	365	218	147	40
Illinois	190	112	78	41	451	377	74	16
Indiana	205	145	60	29	316	241	74	24
Iowa	380	203	177	47	651	536	115	18
Kansas	583	446	138	24	391	296	95	24
Kentucky	230	121	109	47	243	183	60	25
Louisiana	399	283	117	29	327	226	101	31
Maine	334	223	111	33	372	184	188	51
Maryland	138	122	16	12	245	169	77	31
Massachusetts	117	70	46	40	333	206	126	38
Michigan	151	99	52	35	314	235	80	25
Minnesota	261	135	126	48	447	327	120	27
Mississippi	231	147	84	36	257	181	75	29
Missouri	245	101	144	59	335	262	73	22
Montana	1,887	1,385	503	27	333	202	130	39
Nebraska	685	523	162	24	505	394	111	22
Nevada	1,072	477	596	56	327	151	176	54
New Hampshire	109	75	34	31	274	169	105	38
New Jersey	169	135	34	20	331	226	105	32
New Mexico	1,543	1,068	476	31	281	110	172	61
New York	152	87	65	43	288	190	97	34
North Carolina	160	85	75	47	337	247	90	27
North Dakota	1,201	673	527	44	361	190	170	47
Ohio	212	132	80	38	361	269	92	25
Oklahoma	542	389	153	28	273	177	96	35
Oregon	493	202	291	59	365	196	169	46
Pennsylvania	268	190	78	29	394	270	125	32
Rhode Island	116	81	34	30	334	220	114	34
South Carolina	224	141	83	37	307	221	86	28
South Dakota	721	480	241	33	414	312	102	25
Tennessee	204	111	93	46	323	251	72	22
Texas	480	346	133	28	316	194	122	39
Utah	392	162	229	59	457	270	187	41
Vermont	426	301	125	29	414	242	171	41
Virginia	206	121	85	41	257	161	95	37
Washington	327	161	166	51	398	165	232	58
West Virginia	912	479	434	48	249	173	76	31
Wisconsin	323	179	144	45	460	345	115	25
Wyoming	2,094	1,080	1014	48	355	172	183	52
U.S.	**347**	**220**	**127**	**37**	**347**	**220**	**127**	**37**

3.3.3 Industry-State Trade Pairs

Within 655,350 ($51\ states \times 50\ states \times 257\ industries$) possible interstate trade pairs by industry, 553,674 display non-zero interstate trade flows. About 67% of these non-zero trade flows (370,485) generate more GHG emissions via transportation services than via production. But trade flows with the highest trade-related emissions are those with high shares of production emissions (Table 3-5). Among the top ten trade flows with emissions, seven occur between distant trading partners, including Texas, California, New York, Illinois, Florida, and Virginia. The remaining three occur between neighboring states (Texas-Louisiana, Nebraska- Iowa, Kansas-Nebraska). These top paths are mainly in the form of energy goods–oil and gas extraction, petroleum refineries, and natural gas distribution. Besides energy goods, beef cattle ranching and farming generates substantial emissions via production processes, which account for more than 95% of trade-related emissions for the corresponding three trade flows in Table 3-5.

Table 3-6 shows the top twenty freight flows by mode with transportation GHG emissions. The transportation emissions per ton-mile for each freight flow are determined by the freight modes used (see Table 3-3). The Texas-California path shipping oil and gas extraction products not only has the highest trade-related emissions but also the highest emissions via *water transportation through Panama Canal*. Other similar flows with both top trade-related emissions and top transportation emissions are California-Virginia by water and Texas-New York by truck both shipping petroleum refinery products. Fifteen of these twenty freight flows are shipped to California (state with highest inbound transportation emissions). Among these twenty flows, most are shipped between distant

Table 3-5 Top Ten Interstate Trade Flows with GHG Emissions, 2016

Rank	Origin State	Destination State	Industry	Trade Value (Million)	Total Trade-related GHG Emissions (MMT CO_2 eq.)	Transportation		Production	
						Emissions (MMT CO_2 eq.)	Share (%)	Emissions (MMT CO_2 eq.)	Share (%)
1	Texas	California	Oil and gas extraction	15,400	8.994	3.100	34%	5.894	66%
2	Texas	Louisiana	Oil and gas extraction	12,100	5.077	0.446	9%	4.631	91%
3	Texas	New York	Petroleum refineries	13,208	4.352	1.154	27%	3.197	73%
4	Nebraska	Iowa	Beef cattle ranching and farming	1,356	3.941	0.043	1%	3.898	99%
5	Texas	Illinois	Beef cattle ranching and farming	1,306	3.899	0.142	4%	3.757	96%
6	California	Florida	Natural gas distribution	2,120	3.881	0.583	15%	3.298	85%
7	California	New York	Natural gas distribution	2,059	3.833	0.629	16%	3.204	84%
8	Texas	Illinois	Oil and gas extraction	7,650	3.588	0.660	18%	2.928	82%
9	California	Virginia	Petroleum refineries	7,748	3.253	1.377	42%	1.876	58%
10	Kansas	Nebraska	Beef cattle ranching and farming	1,084	3.149	0.032	1%	3.117	99%

trading partners, requiring longer-than-average shipping distances. Regarding shipped goods, more than half of these top twenty flows ship stone mining and quarrying products, which have a high weight/value ratio. Other goods include energy goods (oil and gas extraction, petroleum refineries, and coal mining) and fertilizer (fertilizer manufacturing). Most flows are shipped by truck, which has a higher emission factor. Still, there are several water-based freight flows (e.g. Texas-California shipping products of oil and gas extraction) or rail freight flows (e.g. Wisconsin-California shipping stone mining and quarrying products), which have lower emission factors.

Table 3-6 Top Twenty Interstate Freight Flows by Mode with Transportation GHG Emissions, 2016

Rank	Origin State	Destination State	Industry	Mode	Transportation Emissions (MMT CO_2 eq.)
1	Texas	California	Oil and gas extraction	Water	2.089
2	Wisconsin	California	Stone mining and quarrying	Truck	1.179
3	Missouri	California	Stone mining and quarrying	Truck	0.880
4	Iowa	California	Stone mining and quarrying	Truck	0.866
5	Kentucky	California	Stone mining and quarrying	Truck	0.836
6	Wisconsin	California	Stone mining and quarrying	Rail	0.808
7	Georgia	California	Stone mining and quarrying	Truck	0.746
8	California	Virginia	Petroleum refineries	Water	0.729
9	Wisconsin	California	Stone mining and quarrying	Water	0.706
10	Wyoming	California	Coal mining	Truck	0.699
11	North Carolina	California	Stone mining and quarrying	Truck	0.635
12	Oklahoma	California	Oil and gas extraction	Water	0.583
13	Florida	California	Fertilizer manufacturing	Truck	0.563
14	Kentucky	California	Stone mining and quarrying	Rail	0.507
15	West Virginia	Michigan	Coal mining	Truck	0.505
16	Florida	Hawaii	Fertilizer manufacturing	Air	0.502
17	Georgia	Florida	Stone mining and quarrying	Truck	0.482
18	Alaska	Washington	Oil and gas extraction	Truck	0.481
19	Texas	New York	Petroleum refineries	Truck	0.472
20	Indiana	California	Stone mining and quarrying	Truck	0.471

3.3.4 Interstate Freight Transportation Emissions by Mode

Table 3-7 shows the interstate freight ton-miles and the corresponding GHG emissions by mode. Interstate freight accounts for about 57% of the U.S. ton-miles (4,983.7 trillion) and about 63% of the total emissions from domestic freight transportation (528.9 MMT CO_2 eq.). Most GHG emissions are due to trucking. Freight by truck accounts for 39.9% of the interstate ton-miles but more than 70% of the GHG emissions from interstate freight transportation. In contrast, freight by rail accounts for a third of the interstate ton-miles but only 6.3% of emissions from interstate freight transportation as rail has the lowest emission factor. My model grossly underestimates freight by pipeline: 84.53 trillion ton-miles (my estimation) versus 896.32 trillion ton-miles (U.S. ton-miles from BTS). There are several reasons for this. First, I do not include freight movements within states nor for domestic aspects of international trade. Second, as I mentioned previously (in Section 3.2.1) I understate pipeline mileages because I represent them via aerial distance rather than by actual network pipeline distances. And, third, I only permit petroleum-related products to be shipped by pipeline in my model. This unfortunately means that freight by water and air are likely overestimated in my model compared to the total U.S. ton-miles by mode. For water, when I observed multiple modes (rail and water, truck and water) I assigned them strictly to water in the dataset used for model calibration, which overstates the share of freight by water. As I use the Navigable Waterway Lines from the NTAD to decide whether states can be connected by water, I do not consider heterogeneity in the types of vessels used or even whether they could navigate specific waterways all year round (e.g., due to shallowness in summer). The navigable paths for some commodities in my model are longer than they actually are; this clearly leads to the overestimation of freight by water. For air, I use aerial distances between states and do not consider the airport location or an airline's use of its hub-spoke system. This leads to the underestimation of air shipping distances and substantial underestimation of total fuel cost by air, resulting in overestimates of the use of air freight.

Table 3-7 Ton-miles and GHG Emissions of Interstate Freight by Mode

	Truck	Rail	Water	Air	Pipeline	Total
Inter-State Freight	1,129.91	942.20	636.06	39.55	84.53	2,832.24
(Trillion ton-miles)	39.9%	33.3%	22.5%	1.4%	3.0%	100.0%
U.S. Freight (Trillion ton-miles)	2,010.88	1,585.44	477.86	13.16	896.32	4,983.66
GHG Emissions	236.50	21.16	21.83	50.50	3.70	333.68
(MMT CO_2 eq.)	70.9%	6.3%	6.5%	15.1%	1.1%	100.0%

3.4 Discussion

Due to limited data on domestic freight flows, it is difficult to ground truth estimates from the model I have developed. So, in this section, I discuss some uncertainties inherent to the model estimates.

First, each state's supply and demand of goods by industry are estimated through the MRIO framework. The quality of the state I-O tables determines the accuracy of estimates for supply and demand. The weakness of the I-O modeling is that usually only spatially aggregate I-O tables are available (Southworth, 2018). Survey-based state I-O tables are rarely available in the U.S. Still, I account for differences in production mix and magnitude across states in developing the MRIO framework. I gauge them via labor income estimates (see Section 2.2.1), so my estimates of supplies are reasonable approximates. I use each state's excess supply and demand to estimate interstate trade. This requires removing (from both supply and demand) that part of demand that is fulfilled by instate supplies. I estimate this quantity by industry using regional purchase coefficients (RPCs) as detailed in Treyz and Stevens (1985).[1]

Second, when I applied the gravity model to estimate trade flow, I tried different formulas for travel costs—aerial distances between states, weighted-average shipping distances that account for mode shares and using network distances by mode (except air and pipeline), and weighted-average fuel costs as in Eq. 3. The estimates for interstate trade flow were surprisingly robust to these variations in travel costs. Undoubtedly this was because I used the same dataset to calibrate the various models (the same initial trade pattern) and used the same biproportional adjustment technique (RAS) to assure that all the outbound flows sum to the state's excess supply and all the inbound flows sum to the state's excess demand. RAS tends to minimize change to patterns that underly the data that it works upon (Sargento et al., 2012). Thus, initial guesses of trade patterns are critical to interstate trade-flow estimation when RAS is employed.

I derived initial trade patterns from the 2012 FAF4 State Database that was derived from 2012 Commodity Flow Survey data and other data from agriculture, extraction, utility, construction, etc. (BTS, 2016). Although FAF4 provides transportation origins and destinations, they are not necessarily same as places of production and consumption. I choose 2012 FAF4 data rather than 2016 data because 2012 data incorporates survey data while 2016 data are merely updates of it developed by BTS. By doing so, I assume the interstate trade patterns are relatively stable from 2012 to 2016, which might not be the case. More recent data of freight movements in the U.S. should be used for interstate trade flow estimates when it is available.

[1] While I update the economic data therein and deflate it appropriately, their formulation is quite old (35 years old, in fact) and might no longer accurately capture current consumption patterns of instate supplies.

Third, in the multinomial regression that I used to model mode choice, I only include as industry characteristics the main commodity's weight/value ratio and whether or not the industry produces petroleum-related products. In addition, I used network distances by mode as calculated by GIS software; I did not consider the capacity of the transportation system. Moreover, I used aerial distances rather than network distances for air freight and pipelines. All of this contributes to the underestimates of pipeline usage and the overestimates for water and air freight. As I only include limited independent variables, the pseudo R^2 for the two mode share models are relatively low: .128 for s'_m in the travel costs and .174 for s_m in estimating freight activities (see Appendix A). I tried to add binary variables that indicate products could be shipped by air or water. But after doing so, the coefficient for fuel costs by mode ($\lambda_m \times w \times d_m$) became statistically insignificant for some modes. Wang et al. (2013) came to similar conclusions; in their model weight, value, distance, or fuel cost become statistically insignificant in explaining mode choice between truck and rail after controlling the commodity type and origin. Other than commodity type, variables of shipment characteristics can be added in the model in further study to improve the mode share estimates, such as, shipment origin and value of time by industry (perishable products have high value of time and are more likely shipped by air and truck). Moreover, other data sources are needed to better represent the characteristics of transportation modes, such as the pipeline network, hub-spoke system of airline, speed limit of highways, etc.

Finally, for the estimation of GHG emissions from freight transportation, I use a constant ton-mile emission factor for each mode. I also assume a linear relationship between emissions and the weight of goods, distance traveled, and the mode used. I do not account for much heterogeneity. Such heterogeneity can be particularly important if it plays out differently across economic and geographic space in the form of different vehicle types, fuel efficiencies, loading factors, and fixed costs. In estimating production emissions, I use the national-average emission factor by industry so could not account for any state differences. The average emission factor by each industry helps to show the overall contribution of freight transport in trade-related emissions (production plus transportation emissions). But it is worth mentioning that, for the same industry, the actual commodities produced and shipped could be different, as could the production technology, specifically the energy it uses (type and amount). Either could cause a substantial difference in emission factors within the same industry and across states.

3.5 Conclusion

This chapter allocates the GHG emissions from interstate freight transport to freight flows, considering 51 states (including District of Columbia) within the U.S., 257 industries and five modes (truck, rail, water, air, and pipeline) for the year 2016. In total, interstate freight transport contributes to 37% of interstate trade related GHG emissions in the U.S. About 67% of the non-zero interstate trade flows by industry have more emissions from transportation than production. But trade flows with the highest trade-related emissions have a larger share of production emissions and mainly ship energy goods. Regarding the freight flows with the highest transportation emissions, most are between distant trading partners. Freight by truck accounts for the largest share of the GHG emissions (about 70%) from interstate freight transportation. This mode of transport has a high emission factor, one exceeded only by air transport.

The bottom-up approach that I use to estimate emissions due to interstate trade reveals the responsibility for interstate freight transportation emissions by state and by industry. Texas, California, Ohio, Florida, Washington, and Illinois are among the top in both inbound and outbound transportation emissions. After normalizing trade related emissions by state population, Wyoming, North Dakota, and Nebraska have the highest inbound and outbound transportation emissions per capita, besides Hawaii and Alaska. Industries with both large transportation emissions and significant shares of trade-related emissions from transportation are mining (except oil and gas), food and beverage and tobacco products, wood products, forestry, fishing, and related activities, and motor vehicles and parts. Better accountability makes better coordination between state government, government and private sectors, shippers and carriers possible. Trading partners with top transportation emissions (e.g. Texas and California) as well as industries with substantial freight emissions (e.g. food and beverage and tobacco products) can work on improving the efficiency of the supply chain to reduce emissions.

4 A Scenario Analysis of State Greenhouse Gas Emissions

4.1 Introduction

In this chapter, I apply scenario analysis to examine how might state consumption- and production-based greenhouse gas emissions change for state environmental policies. Following the analysis of previous chapters, I include two sets of scenarios. In the first, I apply state-based carbon tax to examine economywide emissions by industry for a pair of states. In the second, I examine how alternative fuel prices (due to fuel tax) might affect emissions from interstate freight transportation.

Many countries and regions adopt market-based environmental policies to address climate change, e.g. the European Union Emissions Trading System, Spain's carbon tax, and California's cap-and-trade program (World Bank, 2020). The principle of market-based measures is that an increase in costs of emitting environmental pollutants generally reduces the demand for the production of goods and services that generates pollution. There is an economic advantage to market-based measures in that the market decides the cost of emissions reduction (Center on Budget and Policy Priorities, 2015). In the U.S., in addition to federal emissions standards, states can set up their own greenhouse gas emissions reduction goals, I investigate the environmental and economic impacts of potential state carbon tax.

Many researchers have studied the impacts of market-based environmental policies. Some have examined the leakage problem, i.e., that emission reductions in carbon-constrained regions is often partially offset by a rise in emissions elsewhere. Within a nation, this can be due to different subnational climate policies as well as variations in industry mix across regions. Caron et al. (2015) modeled 15 regions within the U.S. and 15 regions overseas to examine carbon leakage from California's cap-and-trade program. They found that leakage is mainly intra- as opposed to inter-national, and largely via the electricity grid. Fell and Maniloff (2018) investigate carbon leakage from the regional greenhouse gas initiative (RGGI) and found that lowering carbon-intensive (coal-fired) power generation in RGGI states enables rises of less carbon-intensive (natural gas combined cycle) power generation in states that surround them.

Some research focuses on the economic and environmental impacts of national climate policies. Choi et al. (2010) find that increasing the cost of U.S. carbon-based emissions causes coal- and petroleum-fired electric power to decline vis-à-vis other commodities and that CO_2 emissions decrease even faster, suggesting that more inefficient power plants should be retired first. In my research effort, I attempt to examine the impacts of subnational climate policies—a state carbon tax—by using a multiregional input-output (MRIO) framework.

Input-output (I-O) analysis has long been widely used for environmental issues (Leontief and Ford, 1972). It provides straightforward engineering-economic connections between the economic system, resource usage, and externalities associated with their use. But the fixed average technology of I-O models usually makes them more applicable to short-term analyses. Still, the history of this policy-model pairing is rich and deep. Most relevant to my work are Chen et al. (2015) and Chang and Han (2020), who investigate the environmental costs of coal burning and price effects by sector of a carbon tax in China. Labandeira and Labeaga (2002) and Gemechu et al. (2014) estimate short-term price effects and environmental impacts of CO_2 taxation in Spain. Choi et al. (2010; 2016) study the economic and environmental implications of energy policies, e.g. fuel taxes and subsidies in the U.S. Following Choi et al. (2010; 2016), I use a MRIO framework that combines price and quantity changes.

Freight transportation is a mobile source of GHG emissions, and different freight transport modes contribute quite differently to GHG emissions. Thus, enabling a shift across freight transport modes is one potential strategy a government could apply to reduce environmental emissions. One way to effect such a shift is to induced a fuel tax of some sort; so I examine the sensitivity of freight transportation mode shares to fuel prices and discover changes in GHG emissions that emanate from interstate freight transportation.

Many studies have been performed to examine how to reduce U.S. transportation emissions, e.g., by reducing travel demand, improving vehicle efficiency, reducing carbon intensities, fuel taxes, mode shifts, etc. (Yang et al., 2009; McCollum & Yang, 2009; Morrow et al., 2010; Nealer et al., 2012). For freight transportation emissions, some have examined the impacts of trade (Cadarso et al., 2010; Cristea et al., 2013; Llano et al., 2018), others have, instead, examined the greenness of international supply chains (e.g. efficient vehicle loading) (Tiwari et al., 2015), others selected improved fuel economy (i.e., fleet configuration, vehicle technology, and fuel mix) as a solution (Greene et al., 2020), and yet others have examined the potential effects of mode shifts (Nealer et al., 2012; Nelldal & Andersson, 2012; Llano et al., 2018).

Of particular interest, Nealer et al. (2012) compare freight GHG emission reductions of different extreme scenarios, including a shift of all trucked freight to rail and, alternatively, limiting such a shift only to sectors with the top 20% emissions using trucked freight. Nelldal and Andersson (2012) investigate a scenario in which they shift freight in the European Union from road to rail only for those shipments over 100 kilometers, since rail is really only more competitive over longer distances due to its higher transshipment costs (short drays are required to rail loading zones). Llano et al. (2018) examine a moderate mode shift from truck to rail (maximum share of rail is 40% for travel distance over 600 kilometer) and an extreme mode shift from truck to rail (maximum share of rail is 60% for travel distance over 150 kilometer). Rather than establish arbitrary shifts, I investigate the extent to which mode shifts can be triggered by fuel price changes due to fuel taxes. Thus, I probe how much fuel prices would need to change (rise) to enable sizeable mode shift away from emission-intensive modes in order to reduce freight emissions noticeably. I assume such mode shifts are possible without considering the capacity constraints of the transportation system, especially for rail and pipeline.

In the following, I start by explaining the set of state carbon tax and fuel price scenarios that I examine, as well as the corresponding research approaches. I then present and analyze results for the two sets of scenarios. I also briefly discuss the uncertainties and frailties of my research approach. The chapter conclude with a summary of major findings and concordant policy recommendations.

4.2 Methods and Data

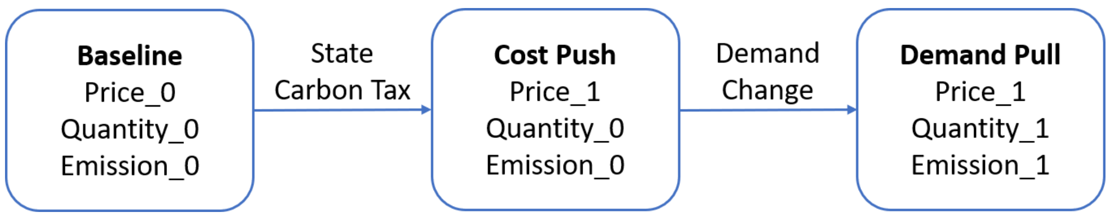
4.2.1 State Carbon Tax Scenarios

The design of a carbon tax involves the jurisdictional allocation, tax rate, and an assumption about the size of the tax base (Labandeira & Labeaga, 2002). Since my purpose is to examine the impacts of state climate policies on the overall emissions, I allocate a single jurisdiction in my scenarios—a single state. I opt for the State of Texas and New York State. Among states, Texas has the largest production-based emissions (580.6 MMT CO_2 equivalent) and second largest consumption-based emissions (434.4 MMT). It also is the highest net exporter of emissions (146.1 MMT). In contrast, New York State is the top net importer of emissions (111 MMT) and is also among the highest in production- and consumption-based emissions. As a Pigouvian tax, a socially optimal carbon tax rate is set so that it maximizes social welfare (Labandeira & Labeaga, 2002; Chen et al., 2015). But tax rate setting is not the focus of this study. Instead, I apply a rate suggested by the World Bank (2020): \$50-\$100 per metric ton of CO_2 equivalent by 2030, which should effectively enable achievement of global emission reduction goals as set out in the Paris Agreement. I select the lower bound \$50 per ton of CO_2 equivalent in my scenarios as current carbon prices in the U.S. are quite low; they are now about \$15 per ton in California's cap-and-trade program and \$5 per ton for RGGI (World Bank, 2020). I choose state production- and consumption-based GHG emissions as the tax base. I estimated them in in Chapter 2, although they do not include emissions directly consumed by households burning fossil fuels (e.g., via the use of automobiles and home heating). This will not affect outcomes for the purpose of my research, which is to show the impacts of production- or consumption-based carbon taxes as they apply to state GHGs as embodied in freight outflows and inflows (Table 4-1). Figure 4-1 charts the flow of my approach to analyze the short-term economic and environmental impacts of state carbon taxes.

Table 4-1 State Carbon Tax Scenarios

State Carbon Tax Scenarios	Description
Texas Production-based Tax	New Carbon Tax applies to industries in Texas according to GHG emissions generated in their production process.
Texas Consumption-based Tax	New Carbon Tax applies to final consumers in Texas according to GHG emissions embodied in their consumption of goods and services.
New York Production-based Tax	New Carbon Tax applies to industries in New York according to GHG emissions generated in their production process.
New York Consumption-based Tax	New Carbon Tax applies to final consumers in New York according to GHG emissions embodied in their consumption of goods and services.

Figure 4-1 Flow Chart of the Research Approach for Chapter 4



4.2.1.1 Cost-push Price Model

When a carbon tax is applied to industries within a state based upon GHG emissions generated in production, prices of the commodities produced within the state clearly increase by the amount of that tax. Industries that use that commodity as an intermediate input then suffer an indirect price rise from the carbon tax. In turn, their commodity prices rise as well. Further, prices of commodities produced by those industries in all other states would also increase as the carbon-taxing state's commodities are used as interindustry inputs within domestic supply chains. It is generally assumed that price increases are completely transferred to consumers within short period. Afterall, in the short run, few technology innovations are likely and quick substitution of interindustry inputs is rare (Wiebe et al., 2018). I use Leontief's cost-push I-O price model (Dietzenbacher, 1997) to identify likely price impacts of a new state carbon tax. The unitary price of each commodity is determined by the cost of intermediate inputs from other industries ($\mathbf{p}'\mathbf{CA}$), primary inputs ($\mathbf{v}'\hat{\mathbf{x}}^{-1}$, value added per unit of output), and imported inputs ($\mathbf{m}'\hat{\mathbf{x}}^{-1}$, imports per unit of output) (Eq. 1) (Miller & Blair, 2009).

$$\mathbf{p}' = \mathbf{p}'\mathbf{CA} + \mathbf{v}'\hat{\mathbf{x}}^{-1} + \mathbf{m}'\hat{\mathbf{x}}^{-1} \tag{15}$$

Assuming there are n industries, $\mathbf{p}'$ is a $1 \times 51n$ row vector of price for products of each industry by state. $\mathbf{A}$ is a $51n \times 51n$ matrix with direct requirements table for each state (see Eq. 2 in Chapter 2). $\mathbf{C}$ is a $51n \times 51n$ trade share matrix (see Eq. 3 in Chapter 2). $\mathbf{v}'$ is a $1 \times 51n$ row vector of value added for each industry by state. $\mathbf{m}'$ is a $1 \times 51n$ row vector of imported inputs for each industry by state. $\hat{\mathbf{x}}^{-1}$ is a $51n \times 51n$ diagonal matrix in which the nonzero element, x_{ir}^{-1}, is the inverse of the output for each industry (i) by state (r). Eq. 1 can also be written as follows using the Leontief inverse, $(\mathbf{I} - \mathbf{CA})^{-1}$ (Eq. 2).

$$\mathbf{p}' = (\mathbf{v}'\hat{\mathbf{x}}^{-1} + \mathbf{m}'\hat{\mathbf{x}}^{-1})(\mathbf{I} - \mathbf{CA})^{-1} \tag{2}$$

After the new production-based state carbon tax, the value added of the taxed state changes ($\Delta\mathbf{v}'$) induces price changes for commodities of all states ($\Delta\mathbf{p}'$) (Eq. 3). $\Delta\mathbf{v}'$ is a $1 \times 51n$ row vector (Eq. 4) in which the nonzero element, Δv_{ir} indicating the new carbon tax for industry i in state r, which is calculated as the product of carbon tax rate (τ) and the GHG emissions of industry i in state r ($\epsilon_{d,ir}x_{ir}$) (Eq. 5). Emissions of industry i in state r are determined by the direct emission intensity ($\epsilon_{d,ir}$, GHG emissions per unit of output) and the industry output (x_{ir}). The price change instigated by a new carbon tax is determined by the carbon tax rate and direct emission intensities by industry within the emissions-regulating state (Eq. 6).

$$\Delta\mathbf{p}' = \Delta\mathbf{v}'\hat{\mathbf{x}}^{-1}(\mathbf{I} - \mathbf{CA})^{-1} \tag{3}$$

$$\Delta\mathbf{v}' = [0,0,0,\cdots,\Delta v_{1r},\Delta v_{2r},\cdots,\Delta v_{nr},\cdots,0,0] \tag{4}$$

$$\Delta v_{ir} = \tau\epsilon_{d,ir}x_{ir} \tag{5}$$

$$\Delta v_{ir}/x_{ir} = \tau\epsilon_{d,ir} \tag{6}$$

Conventionally within the Leontief cost-push model, the current price of products by industry is assumed to be \$1, which is achieved by normalizing via the physical unit of measurement (Miller & Blair, 2009). In this regard, it is more like a price index or, in economics parlance, "numeraire." Then $\Delta\mathbf{p}'$ is a $1 \times 51n$ row vector indicating the percentage increase of the price for each commodity by state (Eq. 7) in which $\mathbf{p}_1'$ is the vector of price after the carbon tax and $\mathbf{p}_0'$ is the vector of current price.

$$\Delta\mathbf{p}' = \frac{\mathbf{p}_1' - \mathbf{p}_0'}{\mathbf{p}_0'} \tag{7}$$

When state carbon taxes directly apply to final consumers, the price changes realized by final consumers in the taxing state r for the products of industry i in state s is determined by the product of the tax rate (τ) and consumption-based emissions ($\epsilon_{t,is}y_{0r,is}$) divided by the final demand ($y_{0r,is}$) (Eq. 8). $\epsilon_{t,is}$ is the total emission intensity, indicating the GHG emissions per unit of final demand for products of industry i in state s. The final consumers in the taxing state not only consume within-state products but also spend on products produced outside of their home state. Consumers outside the taxing state are not directly affected. Since I assume a numeraire for all commodities of \$1, the percentage price increase for a consumption-based carbon tax is identified by the tax rate and total emission intensities by industry in all states (Eq. 8).

$$p_{1r,is} - p_{0r,is} = \tau\epsilon_{t,is}y_{0r,is}/y_{0r,is} = \tau\epsilon_{t,is} \tag{8}$$

4.2.1.2 Changes in Quantity Demanded

Consumers' behaviors change quickly in response to the price change. I use price elasticities of demand to quantify the changes in final demand quantities. The elasticity for products of industry i in state r (ε_{ir}) is the ratio of changes in final demand quantities to the corresponding price changes (Δp_{ir}) (Eq. 9). $f_{0,ir}$ is the current physical amount of final demand for products of industry i in state r, and $f_{1,ir}$ is the demand quantities after price changes.

$$\varepsilon_{ir} = -\frac{(f_{1,ir} - f_{0,ir})/f_{0,ir}}{\Delta p_{ir}} \tag{9}$$

It is very difficult to obtain the price elasticities for all commodities. Following Choi et al. (2010), I use a fixed elasticity of 0.3 for all commodities in all states. By doing so, I assume consumers' behaviors to price changes are identical across states and that a given commodity produced in one state cannot substitute for the same commodity produced by another state. This can seem like an overly strong assumption, but, even with 403-industry detail, there is a great deal of commodity variety within an industry. For example, potato farmers in one state may produce baking potatoes and another might produce those for boiling. In any case, the final demand quantities after price changes ($f_{1,ir}$) can be calculated using the price elasticities of demand and percentage price changes from the price model (Eq. 10).

$$f_{1,ir} = (1 - \Delta p_{ir}\varepsilon_{ir})f_{0,ir} \tag{10}$$

The final demand change can come from two sources: price changes and quantity changes. In order to remove the impacts of price changes, I calculate the value changes of final demand in original prices ($1 for all commodities) by multiplying its current final demand value ($y_{0,ir}$, estimated in Chapter 2) by percentage changes in prices and price elasticities of demand (Eq. 11).

$$\Delta y_{ir} = f_{1,ir}p_{0,ir} - f_{0,ir}p_{0,ir} = -\Delta p_{ir}\varepsilon_{ir}f_{0,ir}p_{0,ir} == -\Delta p_{ir}\varepsilon_{ir}y_{0,ir} \qquad (11)$$

4.2.1.3 Demand-pull Quantity Model

With changes in final demand, I use the traditional demand-pull I-O model to estimate changes of output (Eq. 12) (Miller & Blair, 2009). As I assume no technology changes or substitutions among intermediate inputs in the short-term, the Leontief inverse is unchanged given values are in original prices. $\Delta\mathbf{x}$ is a $51n$ vector of output changes by state for each industry. $\Delta\mathbf{y}$ is a $51n$ vector of total final demand changes (from all states) for products of each industry by state.

$$\Delta\mathbf{x} = (\mathbf{I} - \mathbf{CA})^{-1}\Delta\mathbf{y} \qquad (12)$$

Changes of state GDP by industry (ΔGDP_{ir}) can be estimated using the ratio of GDP to state output (GDP_{ir}/x_{ir}) (Eq. 13). Similarly, changes in compensation of employees and employment by industry for each state can be estimated using the corresponding ratio (Eq. 14, 15). State GDP, compensation of employees and employment are estimated in Chapter 2.

$$\Delta GDP_{ir} = (GDP_{ir}/x_{ir})\Delta x_{ir} \qquad (13)$$

$$\Delta compensation_{ir} = (compensation_{ir}/x_{ir})\Delta x_{ir} \qquad (14)$$

$$\Delta employment_{ir} = (employment_{ir}/x_{ir})\Delta x_{ir} \qquad (15)$$

4.2.1.4 Changes in GHG Emissions

With output changes in original values, changes of production-based emissions ($\Delta\mathbf{E}_{\boldsymbol{p}}$) by state can be estimated using the direct emission intensities ($\boldsymbol{\epsilon}_{\boldsymbol{d}}$) (Eq. 16).

$$\Delta\mathbf{E}_{\boldsymbol{p}} = \boldsymbol{\epsilon}_{\boldsymbol{d}}\Delta\mathbf{x} \qquad (16)$$

Consumption-based emission changes for each state ($\Delta\mathbf{E}_c^r$) are estimated using total emission intensities ($\boldsymbol{\epsilon}_t$) multiply changes of state final demand in original prices ($\Delta\mathbf{y}^r$) (Eq. 17).

$$\Delta\mathbf{E}_c^r = \boldsymbol{\epsilon}_t \Delta\mathbf{y}^r \tag{17}$$

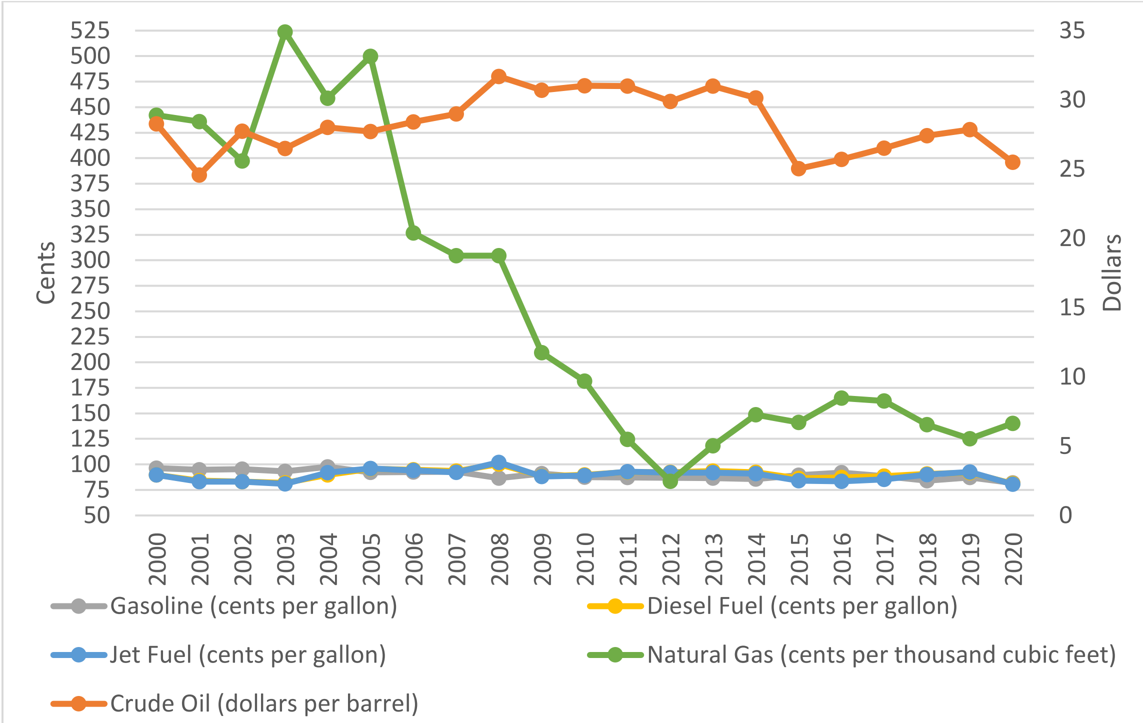
The direct emission intensities and total emission intensities remain the same as estimated in Chapter 2 because I assume the constant production recipe in the short run.

4.2.2 Fuel Price Scenarios

Different transportation modes use different energy resource mixes, e.g. gasoline, diesel fuel, electricity, jet fuel, etc. In order to develop scenarios of fuel price changes, I examined trends of real fuel prices from 2000 to 2020 (EIA, 2020a). With the exception of natural gas, energy prices—gasoline, diesel fuel, and jet fuel—are highly related to crude oil prices (Figure 4-2). I did not include coal as it is not directly used for freight transportation. Crude oil prices increased more than 20% from 2001 to 2008, then remain in the relatively high level until 2014. The crude oil prices dropped to 2001 level in 2015 and increased slightly after. The prices in 2020 decline to the bottom again.

Since my purpose is to examine whether fuel price changes could drive mode shifts away from emission-intensive modes and my baseline is for the year 2016, I based my scenarios on variations from 2016 levels. Given that different modes use different types of fuels and the prices of all fuels except natural gas are linked to crude oil prices, I chose crude oil prices as the reference for any fuel price rises. Considering past fuel price fluctuations, I examine three moderate increments (50%, 100%, and 200%) and two extremes (300% and 500%).

Figure 4-2 Fuel Prices from 2000 to 2020 (year 2000 Prices)



Source: U.S. Energy Information Administration

Using annual fuel prices from 2000 to 2017 (EIA, 2020a), I build the relationship between crude oil price (p_{oil}) and fuel cost per ton-mile by mode (λ_m). The fuel cost per ton-mile, λ_m, is calculated as the product of fuel consumption by mode and the fuel price, all divided by the ton-miles of freight. The U.S. ton-miles of freight and fuel consumption by mode from 2000 to 2017 are publicly available as National Transportation Statistics (BTS, 2018a; 2018b). The fuel cost per ton-mile by mode in each scenario (λ'_m) is then calculated using the corresponding increased crude oil price (p'_{oil}) (Eq. 18). In Eq. 18, a_m and b_m are empirically derived mode specific parameters using historical data for crude oil prices and fuel cost per ton-mile between 2000 and 2017.

$$\lambda'_m = a_m + b_m p'_{oil} \tag{18}$$

I use Eq. 18 to estimate the fuel cost per ton-mile for truck, rail, water, and air. For pipeline, whose energy source is mainly natural gas, crude oil price is not a good predictor of natural gas price. I keep the fuel cost per ton-mile of pipeline at 2016 levels in all scenarios since pipelines are limited to transporting petroleum-related products and substantive cost rises would require substantial infrastructure additions that are not presently scheduled. For this reason, perhaps, pipeline's mode share has remained relatively stable compared to other modes over the past few years (BTS, 2016). Thus, although pipeline's fuel cost per ton-mile is the lowest among all modes, fuel costs are not a prime determinant for a commodity's mode shift to pipelines. Table 4-2 presents the fuel cost per ton-mile by mode in each scenario. Based on the historical relationship between crude oil prices and fuel costs per ton-mile by mode (except for pipeline), the percentage increases in fuel costs per ton-mile are different from that of crude oil price increases. The fuel mix varies among different modes as well (Eq. 18).

Table 4-2 Fuel Costs per Ton-mile ($/ton-mile) by Mode for Scenarios

Fuel Price Scenarios	Truck	Rail	Water	Air	Pipeline
Baseline (2016)	0.0324	0.0029	0.0193	1.1204	0.0020
Crude Oil Price Increases 50%	0.0351	0.0042	0.0246	1.6865	0.0020
Crude Oil Price Increases 100%	0.0463	0.0054	0.0329	2.2259	0.0020
Crude Oil Price Increases 200%	0.0687	0.0078	0.0496	3.3046	0.0020
Crude Oil Price Increases 300%	0.0912	0.0103	0.0663	4.3833	0.0020
Crude Oil Price Increases 500%	0.1360	0.0152	0.0997	6.5407	0.0020

In each scenario, I first estimate interstate trade flows by industry using gravity models. These flows are then converted into interstate freight by mode (ton-miles) based on the aggregate interstate mode shares of each commodity. I estimate GHG emissions from interstate freight transportation by multiplying interstate freight flows by mode (ton-mile) and ton-mile emission factors by mode. For details see Section 3.2 of Chapter 3. I hold state supplies and demands by industry constant when estimating interstate trade flows for each scenario. Emission factors by mode remain the same as well. Recall, the purpose of this exercise is strictly to identify the impacts of fuel price changes on freight mode shares.

Here I explain how my approach diverges from that in Section 3.2 where I used a multinomial logit model (Eq. 4, 5, 6 of Chapter 3) to estimate mode shares in interstate travel cost estimates (s'_m in Eq. 3, gravity model in Chapter 3). In the previous chapter, I used the 2012 Commodity Flow Survey (CFS) Public Use Microdata sample to calibrate the model (Census Bureau, 2015). But since 2012 CFS data are for a single year with a very small sample of pipeline shipments, the model cannot include fuel costs by mode as an independent variable and, most importantly, cannot validly predict pipeline usage. For fuel price scenarios, I calibrate mode shares using the Freight Analysis Framework version 4 (FAF4) State Database of 2002, 2007, and 2012 (BTS, 2016) so that I can include fuel costs of shipping one unit of commodity by mode ($\lambda_m \times w \times d_m$) (see Appendix A). It also enables estimates of pipeline usage. This is at the expense of substantial shipment detail, however. The FAF4 State Database incorporates data from the CFS, agriculture, utility, construction, and other sectors (BTS, 2016). So, the sectoral details of the FAF4 and CFS are the same: about 40 groups of commodities. But the FAF4 data only provides aggregate shipment weight and value between origin-destination state by mode for each commodity group rather than individual shipment information as in 2012 CFS data. In fact, the FAF4 has far fewer observations (360,013) compared to the CFS.

4.3 Results

4.3.1 Carbon tax scenarios

Table 4-3 presents a summary of the environmental and economic impacts for the state carbon tax scenarios. The reductions of GHG emissions (production-based) in both Texas carbon tax scenarios are much larger than those in the two New York scenarios (Table 4-3). The emission reductions are mainly in the taxing state. New York's emission reductions only account for 36% of the total U.S. reductions in the New York consumption-based carbon tax scenario (smallest in all scenarios) because New York imports the largest amount of emissions as embodied in trade from other states.

The short-term GDP loss due to the state carbon taxes are also mainly from the taxing state (Table 4-3). Texas suffer larger GDP loss in its production-based carbon tax scenario compared to its consumption-based carbon tax scenario, while the opposite is true for the New York. The total national GDP loss in the two Texas carbon tax scenarios are also much larger than those in the two New York scenarios.

Consumer expenditures increase after implementation of the state carbon taxes as the carbon taxes elevate the overall price level. In Texas and New York production-based carbon tax scenarios, increases in expenditure not only arise directly within the focal state but also unfold indirectly across all other states. For consumption-based carbon tax scenarios, expenditures only increase for final consumers within the taxing state and the amount of increase is larger compared to the expenditure rise in the taxing state in the corresponding production-based carbon tax scenarios. This is because final consumers in the taxing states have to pay carbon taxes directly according to the GHG emissions embodied in the goods and services regardless of their origins. While in production-based carbon tax scenarios, consumers ultimately pay the carbon tax via higher prices that emerge downstream in the supply chain when taxes are paid for emissions in the taxing state only.

Table 4-3 Environmental and Economic Impacts for State Carbon Tax

State Carbon Tax Policy		Texas Production-based Tax	Texas Consumption-based Tax	New York Production-based Tax	New York Consumption-based Tax
GHG Emission Reductions (thousand tons of CO_2 Eq.)	Taxing State	10,698.0	7,944.7	839.6	936.1
	U.S.	12,468.8	11,670.1	1,125.1	2,572.7
Share of Reductions in the Taxing State to Total U.S. Reductions		86%	68%	75%	36%
GDP Loss (millions $)	Taxing State	4,578.9	3,956.9	1,468.4	1,928.6
	U.S.	7,877.0	6,169.7	2,067.1	3,478.9
Share of Reductions in the Taxing State to Total U.S. Reductions		58%	64%	71%	55%
Increases in Expenditures (millions $)	Taxing State	9,615.6	15,269.8	3,733.0	8,759.0
	U.S.	19,785.5	15,269.8	5,175.9	8,759.0
Share of Reductions in the Taxing State to Total U.S. Reductions		49%	100%	72%	100%
State Carbon Tax Revenues (millions $)		28,494.3	22,064.0	7,412.2	12,567.9

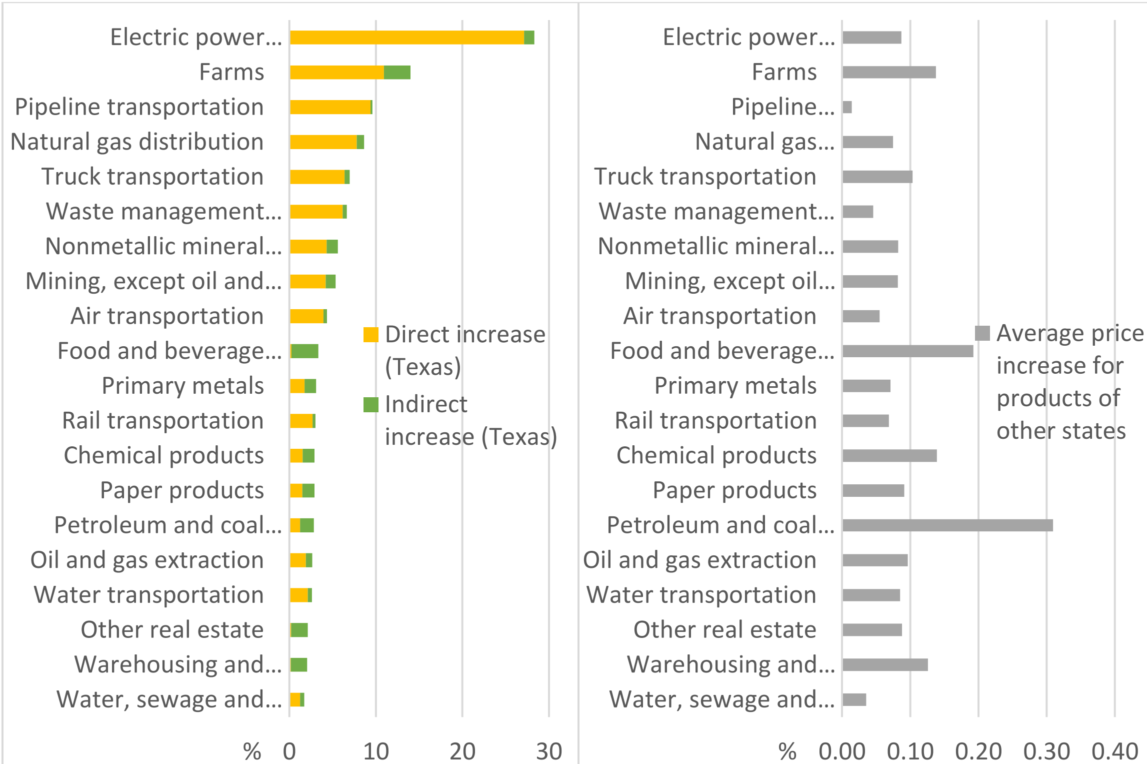
Increases in expenditures in both Texas carbon tax scenarios are larger than those of the two New York scenarios. The same applies to the state carbon tax revenues. Revenues from state carbon taxes are calculated using negative changes in both output and final demand in original prices. The amount of new tax revenues in each scenario is larger than the sum of the increases in expenditures by final consumers (suggest reductions of real income) and GDP loss (without carbon taxes) in the U.S. This suggests that the rises in state tax revenues could be used to compensate agents for any losses attached to the taxation. For Texas, revenues from its production-based carbon taxes are larger than those from consumption-based taxes because Texas is a net exporting state of GHGs. The opposite is true for New York as it is a net importing state of GHGs.

In the following subsection, I explain the price increases due to the new carbon tax, final demand declines due to the price rises, which causes output and GDP to fall, not to mention also drops in employment and labor compensation. Of course, GHG emission reductions are also achieved in each carbon tax scenario.

4.3.1.1 Price and Production Changes

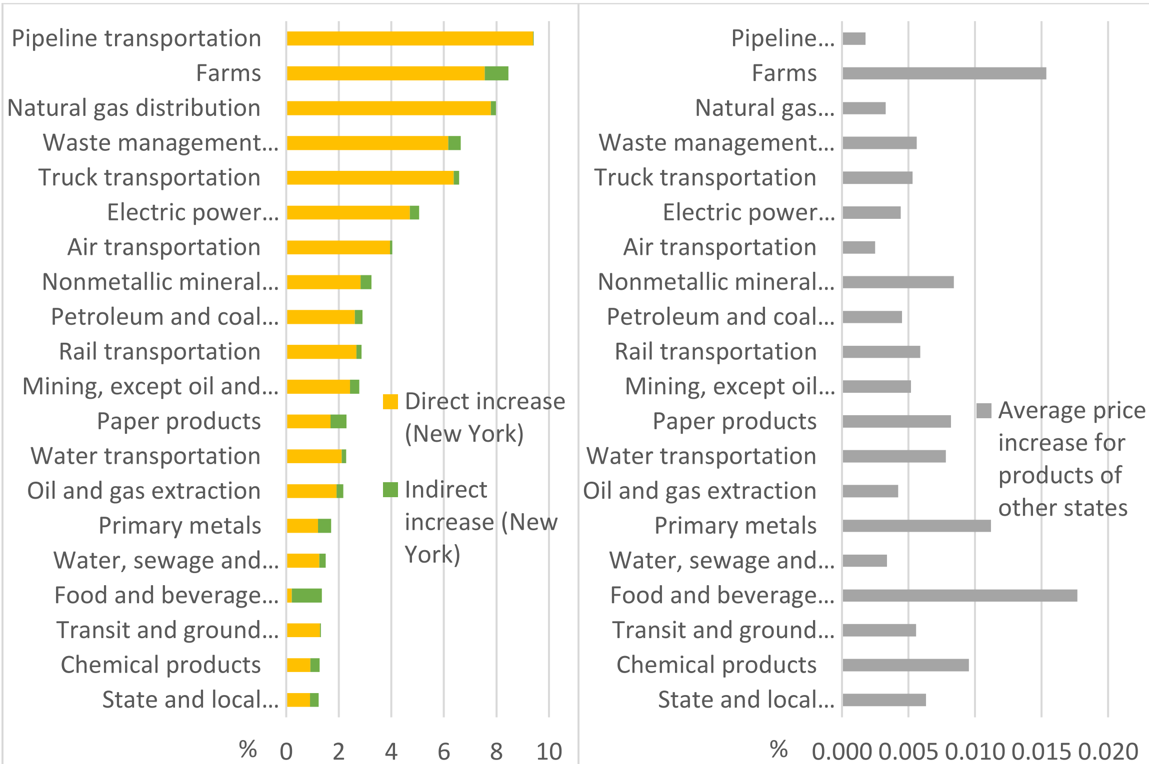
Figure 4-3 shows percentage price increases in the wake of a carbon tax of $50 per ton of CO_2 equivalent that applies to GHG emissions in all production in Texas. The price increase varies from 0.08% (insurance) to 28.3% (electric power industry) among industries within Texas. The price rises incurred by industries outside of Texas are, not surprisingly, substantially lower, from 0.01% (housing) to 0.31% (petroleum and coal products). Industries suffering the price increases most in Texas are the electric power industry, farms, pipeline transportation, natural gas distribution, and truck transportation. Most industries incur high price increases in Texas due to direct taxation, but food, beverage and tobacco products, other real estate, and warehousing and storage are harder hit via their supply chains, which heavily embody goods and services that are produced by firms that pay the tax directly. Industries in other states suffering the highest price rises due to the “new tax” in Texas are petroleum and coal products, food, beverage and tobacco products, chemical products, farms, warehousing and storage.

Figure 4-3 Percentage Price Increase of Top Industries for Production-based State Carbon Tax in Texas (%)



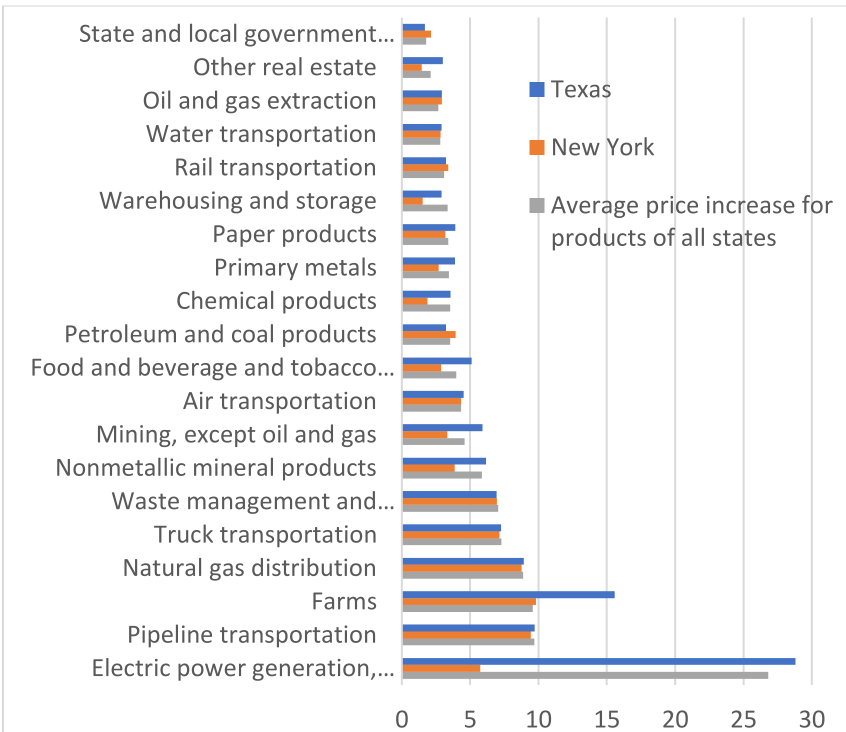
When a similar carbon tax is applied to production-based GHG emissions in New York, price increases by industry within New York range from 0.02% (insurance) to 9.4% (pipeline transportation). As in Texas, the price increase outside New York are much smaller, averaging from 0.0015% (housing) to 0.03% (funds, trusts, and other financial vehicles). New York industries with the highest percentage rise in prices are pipeline transportation, farms, natural gas distribution, waste management, and truck transportation (Figure 4-4). As in Texas, the increases mainly derive from changes in direct taxation. In New York, however, only prices of food, beverage and tobacco products rise substantially in an indirect manner. The highest average percentage price increases suffered by out-of-state industries due to New York taxation arise in the following: trusts and funds, food, beverage and tobacco products, farms, warehousing and storage, and other real estate.

Figure 4-4 Percentage Price Increase of Top Industries for Production-based State Carbon Tax in New York (%)



When the carbon tax applies to final consumers directly, total emission intensity (GHG emissions per unit of final demand) determines the percentage price increase by industry (Eq. 8). Since consumers tend to purchase more goods and services that are within their home state (results from Chapter 2), they are naturally affected most by price increases from home state-based producers. Figure 4-5 shows the percentage price increase when carbon taxes apply to state consumption-based emissions. For both Texas and New York, industries with the highest percentage price increases parallel those to which carbon taxes are most heavily applied on production due to emissions. The range of the percentage price rise in Texas is 0.13% (housing) to 28.8% (electric power industry); while the range in New York is somewhat lower from 0.05% (insurance) to 9.8% (farms). The ranges nearly equate to those for the sources of production-based carbon taxes. The average percentage price increases by industry for all states encountered by consumers in the taxing state vary from 0.11% (housing) to 26.8% (electric power industry) due to the same carbon tax rate.

Figure 4-5 Percentage Price Increase of Top Industries for Consumption-based State Carbon Tax



The percentage price increases are much larger for Texas carbon taxes than those of New York. This is because the emission intensity (GHG emissions per unit of output) of the electric power industry in Texas is much higher than that for New York: New York's power industry uses more renewables (e.g., wind and hydroelectric power) and lower-carbon fossil fuels, like natural gas. When the carbon tax applies to industries, the price of Texas electricity increases more than 27% due to direct taxation. It is transferred to all other industries within and outside Texas through their direct and indirect usage of

Texas electricity in their supply chains. When the carbon tax applies to final consumers, the total emission intensities by industry in Texas also account for the use of in-state emission-intensive electricity.

After the price increases, final demand quantities decrease due to the price elasticities of demand. When state carbon taxes apply to production-based emissions, final consumers of states other than the taxing one (Texas / New York) would also encounter the price increases through the supply chain, resulting in the reductions of final demands in those states. In the Texas production-based carbon tax scenario, the percentage decreases of state final demands vary from 0.016% (Oregon) to 0.268% (Texas). Texas final demand declines by $4.281 billion in original prices (about $159 per capita), accounting for about half of the nation's final demand change (Table 4-4). Other states suffering large percentage decreases in final demands are Louisiana (0.064%), Mississippi (0.041%), Arkansas (0.038%), and Florida (0.034%). These states also bear significant decreases in per capita final demand, as well as some states in the Northeast (e.g. District of Columbia, Massachusetts, etc.), ranging from $18 to $35 per person. Final consumers in Idaho, Oregon, West Virginia and Wyoming only decrease their consumption slightly—about $10 per person. In the New York production-based carbon tax scenario, the percentage decreases of state final demands range from 0.001% (Arizona) to New York (0.112%), which are smaller compared to those in the Texas production-based carbon tax scenario. New York ($1.616 billion, about $82 per capita) accounts for more than 70% of the nation's total decline in final demand (Table 4-4). Surrounding states—New Jersey, Connecticut and Pennsylvania, and other Northeastern states also suffer mightily (state final demands decrease by 0.004% to 0.015%) since firms there trade heavily with those in New York. Arizona, Utah, and Colorado suffer little reductions in final demands (around 0.001%). Except for New York, the decreases in per capita final demands of all other states are smaller than $11. When consumption-based carbon taxes are applied, only consumers within the taxing state pay the price increase, but the taxes applied equally to commodities whether they are produced in-state or out-of-state. Only final demands of the taxing states decrease: Texas's declines by 0.426% ($6.794 billion, $252 per capita) and New York's by 0.265% ($3.809 billion, $193 per capita).

Reductions in output resulting from final demand decreases are mainly in the taxing states (more than 50% of total U.S. reductions). Of course, these translate into reductions in GDP, labor compensation, and employment (Table 4-4). Although final demand reductions in the Texas are smaller in its production-based tax scenario compared to its consumption-based tax scenario, its output declines due to the former are much larger since Texas is a net GHGs exporting state. The opposite is true for New York: it suffers a greater economic contraction via a consumption-based carbon tax since it is a net GHGs importing state (Table 4-4).

Table 4-4 Economic Impacts of State Carbon Tax

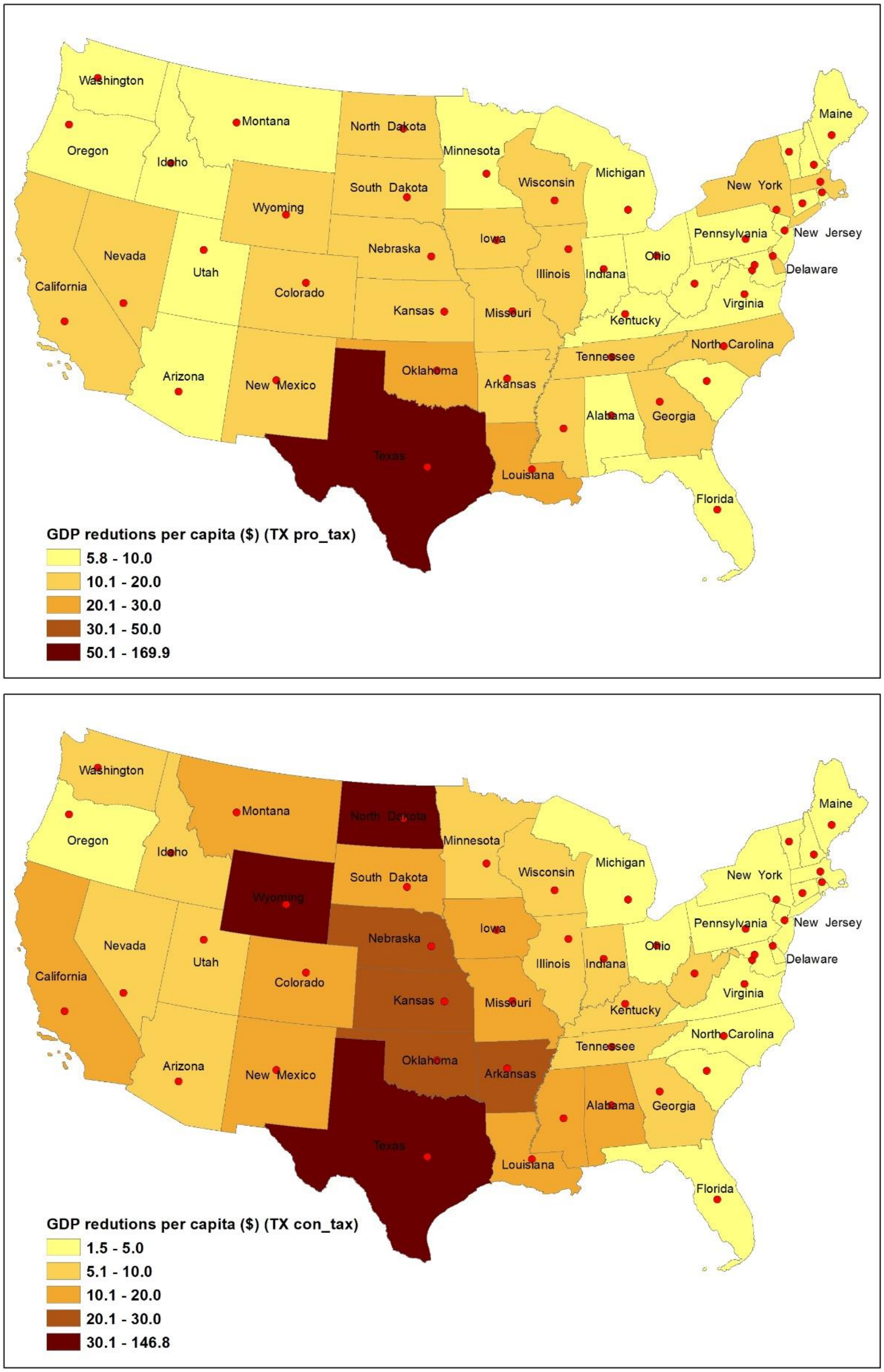
State Carbon Tax Policy		Texas Production-based Tax	Texas Consumption-based Tax	New York Production-based Tax	New York Consumption-based Tax
Final Demand Reductions (millions $)	Taxing State	4,280.7	6,794.3	1,616.1	3,809.0
	U.S.	8,708.8	6,794.3	2,236.3	3,809.0
Share of Reductions in the Taxing State to Total U.S. Reductions		49%	100%	72%	100%
Output Reductions (millions $)	Taxing State	9,016.8	7,842.0	2,755.9	3,644.3
	U.S.	15,575.5	12,268.7	3,948.4	6,896.7
Share of Reductions in the Taxing State to Total U.S. Reductions		58%	64%	70%	53%
GDP Loss (millions $)	Taxing State	4,578.9	3,956.9	1,468.4	1,928.6
	U.S.	7,877.0	6,169.7	2,067.1	3,478.9
Share of Reductions in the Taxing State to Total U.S. Reductions		58%	64%	71%	55%
Compensation Reductions (millions $)	Taxing State	2,117.2	1,902.4	833.6	1,121.1
	U.S.	3,926.5	3,037.9	1,155.2	1,911.4
Share of Reductions in the Taxing State to Total U.S. Reductions		54%	63%	72%	59%
Employment Loss (jobs)	Taxing State	43,380	40,909	14,103	19,208
	U.S.	79,922	63,457	20,573	35,372
Share of Reductions in the Taxing State to Total U.S. Reductions		54%	64%	69%	54%

In the Texas production-based carbon tax scenario, the percentage decreases of state output range from 0.013% (Maryland) to 0.325% (Texas). Texas bears the largest loss in output as well as in GDP (0.292%), labor compensation (0.26%), and employment (0.26%) (Table 4-4). The surrounding states bear the highest percentage decreases in output: Louisiana (0.064%), Arkansas (0.056%), Oklahoma (0.048%), and Mississippi (0.044%); while states in the east and west coast (e.g. Maryland, New Hampshire, New

Jersey, Oregon and Washington) suffer the lowest percentage decreases (smaller than 0.017%). The surrounding states also suffer substantial losses in GDP (0.03% to 0.054%), labor compensation (0.03% to 0.049%), and employment (0.03% to 0.048%). In contrast, states with small percentage decreases in output display small declines in GDP, labor compensation, and employment—smaller than 0.015%. The upper part of Figure 4-6 presents the per capita state GDP loss for the Texas production-based carbon tax. Besides Texas with about $170 loss per capita in GDP, District of Columbia, California, New York, and the surrounding states also bear relatively large GDP loss per capita ($12 to $29).

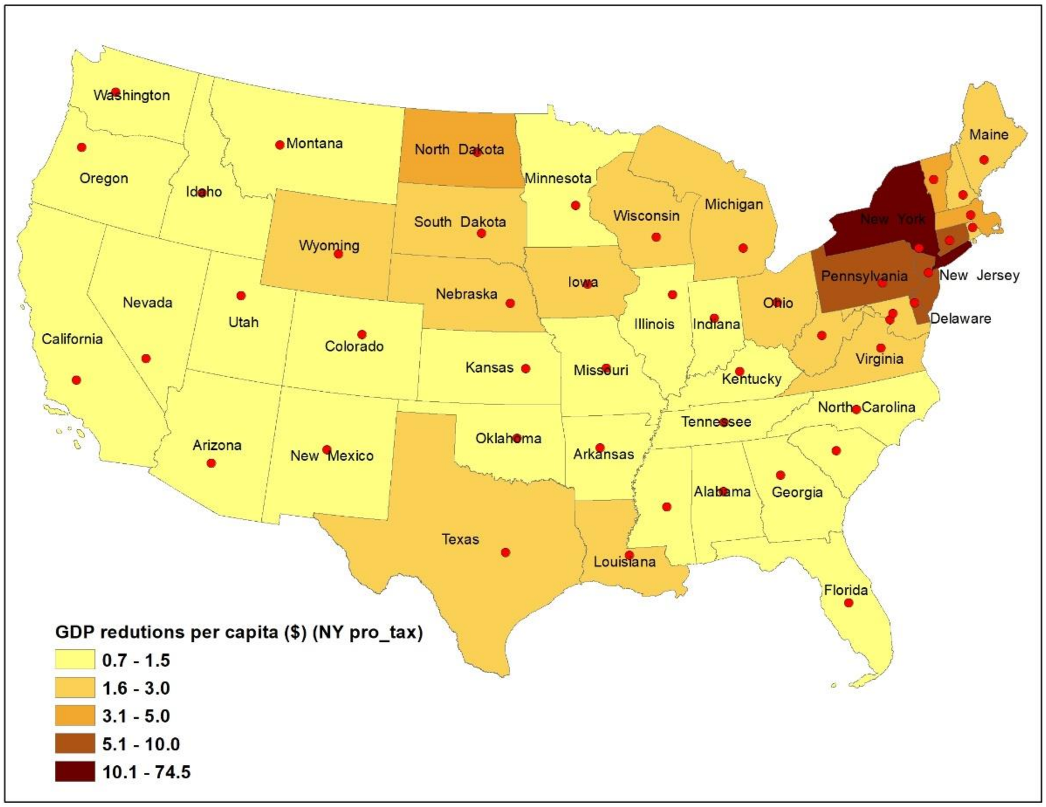
When the carbon taxes directly apply to Texas final consumers, the percentage decreases of state output vary from 0.004% (Maine) to 0.283% (Texas). The large reductions in the Texas output translate into substantial loss in GDP (0.253%), labor compensation (0.234%), and employment (0.245%) (Table 4-4). Neighboring states are among those suffering the highest percentage decrease in output, e.g. Arkansas, Oklahoma, and Kansas, as well as Wyoming and North Dakota, ranging from 0.05% to 0.083%. These states also bear relatively large percentage decrease in GDP (0.038% to 0.083%), labor compensation (0.03% to 0.62%), and employment (0.032% to 0.055%). States in the Northeast are seemingly unhampered with percentage decrease in output, GDP, labor compensation and employment all smaller than 0.01%. The lower part of Figure 4-6 shows the per capita state GDP loss for the Texas consumption-based carbon tax. Texas ($146.8), Wyoming ($51.5), and North Dakota ($32.1) bear the largest per capita loss in GDP. The surrounding states and District of Columbia also suffer relatively large GDP loss per capita ($15 to $26).

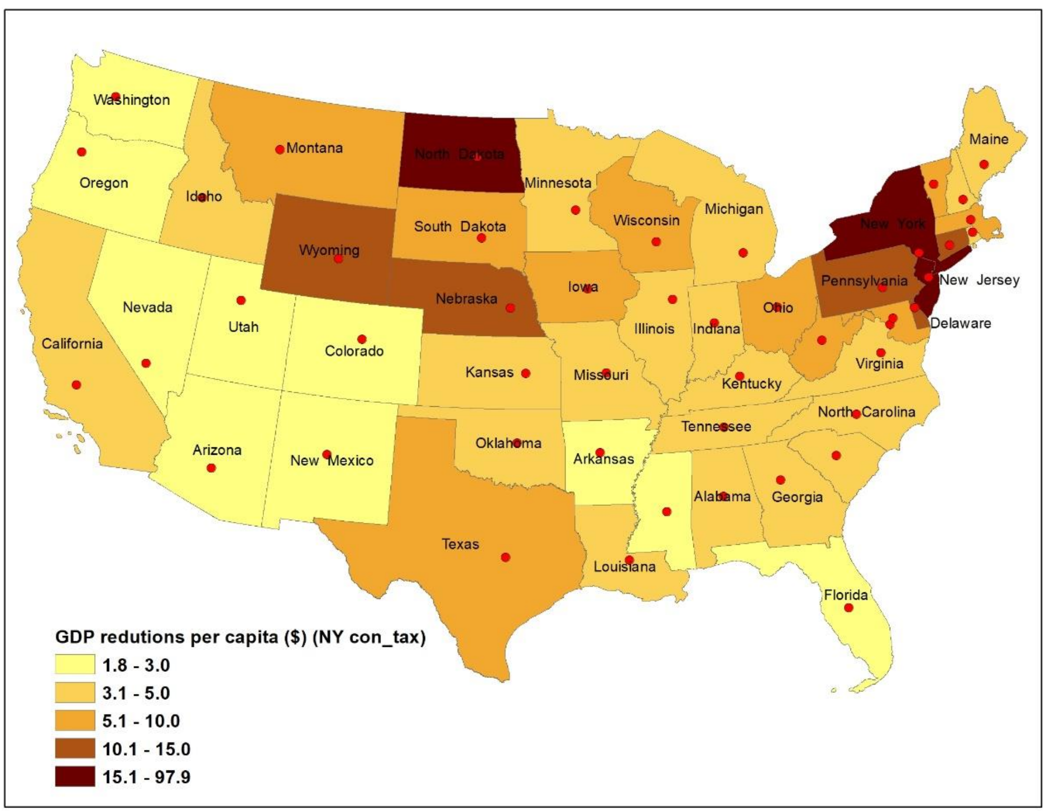
Figure 4-6 GDP Reductions per Capita for State Production-based (Upper) and Consumption-based (Lower) Carbon Tax in Texas ($)



In the case of a New York production-based carbon tax, the percentage decreases in state output are much smaller (from 0.002% (Arizona) to 0.108% (New York)) compared to those in the Texas carbon tax scenarios. The largest decrease occurs in the taxing state—New York ($2.76 billion), which translates into the largest percentage decrease in its GDP (0.095%), labor compensation (0.106%), and employment (0.115%). The surrounding states, e.g. New Jersey, Pennsylvania, and Connecticut, also receive large percentage decreases in output (0.01% to 0.015%), as well as GDP (0.009% to 0.012%), labor compensation (0.009% to 0.013%), and employment (0.009% to 0.013%). But the economies of states in the West (e.g. Arizona, Utah, Nevada, and Colorado) almost do not contract at all with output, GDP, labor compensation and employment decline by about 0.002%. The upper part of Figure 4-7 shows the per capita GDP loss in the New York production-based carbon tax scenario. The surrounding states (e.g. New Jersey, District of Columbia, and Connecticut) bear the relatively large GDP reductions per capita ($5 to $8), besides New York ($75).

Figure 4-7 GDP Reductions per Capita for State Production-based (Upper) and Consumption-based (Lower) Carbon Tax in New York ($)





When the carbon tax applies to New York final consumers, the percentage decreases in state output vary from 0.004% (Arizona) to 0.143% (New York), slightly larger than those in the New York production-based carbon tax scenario. Besides output, New York also suffer the largest loss in GDP (0.125%), labor compensation (0.142%), and employment (0.157%). In addition to those surrounding states in the Northeast (e.g. New Jersey, Pennsylvania), emissions-intensive states (e.g. West Virginia, North Dakota, and Wyoming) also bear relatively large percentage decrease in output (0.022% to 0.029%), GDP (0.02% to 0.025%), labor compensation (0.015% to 0.024%), and employment (0.015% to 0.022%). States in the West (e.g. Arizona, Utah, Oregon) as well as California and Florida change very little with percentage decreases in output, GDP, labor compensation, and employment all smaller than 0.006%. The lower part of Figure 4-7 displays the per capita GDP loss in the New York consumption-based carbon tax scenario. New York bears the largest GDP loss per capita—$98. The neighboring states, as well as District of Columbia, Wyoming, North Dakota, and Nebraska also suffer relatively large GDP loss per capita ($10 to $18).

Regarding output reductions by industry in different carbon tax scenarios, the two Texas scenarios have similar sets of industries that are most affected: electric power industry, chemical products, petroleum and coal products, construction, farms, food, beverage and tobacco products, etc. In Texas, the electric power industry has the highest percentage decreases in output: 3.6% in the production-based carbon tax scenario and 2.6% in the consumption-based carbon tax scenario. While for the two carbon tax scenarios in New York, industries with large reductions of output concentrate in food, beverage and tobacco products, construction, state and local general government, wholesale trade, and electric power industry. In New York, the industries with the largest percentage decreases in output (1.1% to 1.4% in both carbon tax scenarios) are farms, natural gas distribution, and truck transportation.

4.3.1.2 GHG Emissions Changes

I calculate changes in both production- and consumption-based GHG emissions for each state in the state carbon tax scenarios. Table 4-5 presents a summary for Texas and New York. When carbon taxes apply to production-based emissions in Texas, the reductions of total U.S. emissions are the largest among all scenarios (12.5 MMT, 0.26%), in which reductions of emissions in Texas (10.7 MMT) account for 86%. The reductions of Texas consumption-based emissions are relatively smaller—7.9 MMT. The percentage decreases in Texas production- and consumption-based emissions are around 1.8%. In contrast, in the New York production-based carbon tax scenario, reductions of its production-based emissions (0.84 MMT accounting for 75% of total U.S. reductions) are smaller than those of consumption-based (0.94 MMT). The New York production-based emissions decline by 0.56%.

Table 4-5 GHG Emission Reductions for State Carbon Tax (thousand tons of CO_2 Eq.)

State Carbon Tax Policy		Texas Production-based Tax	Texas Consumption-based Tax	New York Production-based Tax	New York Consumption-based Tax
GHG Emissions Reductions in the Taxing State	Production-based	10,698.0	7,944.7	839.6	936.1
	Consumption-based	7,944.7	11,670.1	936.1	2,572.7
GHG Emissions Reductions in the U.S.		12,468.8	11,670.1	1,125.1	2,572.7
% Decrease of GHG Emissions in the Taxing State	Production-based	1.843%	1.368%	0.563%	0.628%
	Consumption-based	1.829%	2.686%	0.360%	0.989%
Percentage Decrease of GHG Emissions in the U.S.		0.257%	0.241%	0.023%	0.053%

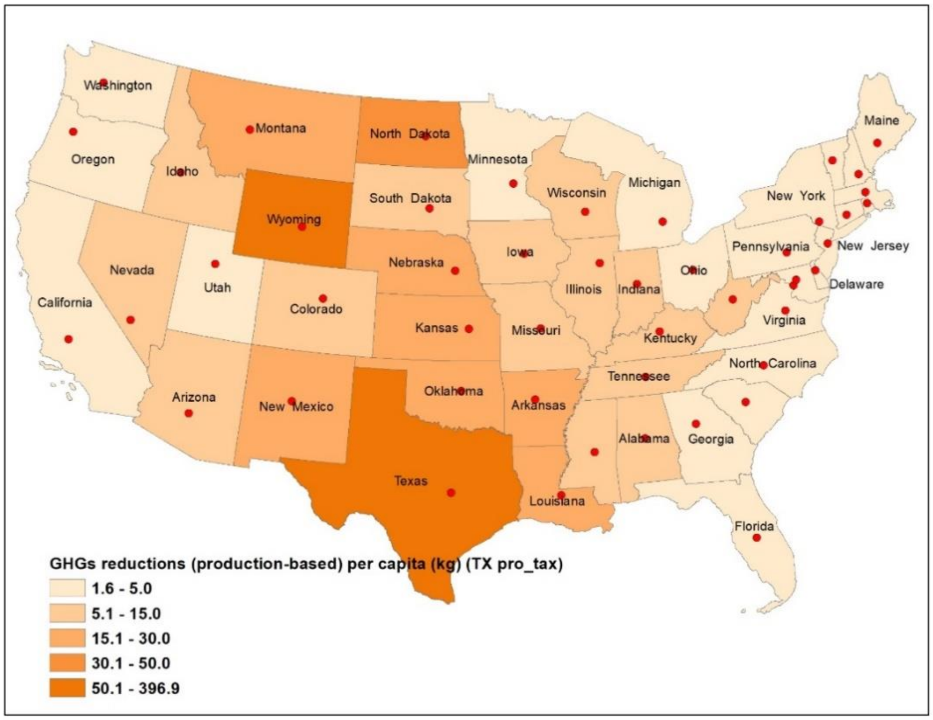
For both consumption-based carbon tax scenarios, reductions of consumption-based emissions for the taxing state are equal to total U.S. emission reductions as only final consumers in Texas or New York have to pay the carbon tax. Reductions of production-based emissions in these two states are smaller than those of consumption-based. Texas production-based emissions decline by 1.4% (7.9 MMT accounting for 68% of the total U.S. reductions). In the New York consumption-based carbon tax scenario, reductions of emissions in New York (0.94 MMT, decline by 0.63%) only account for 36% of the total U.S. reductions.

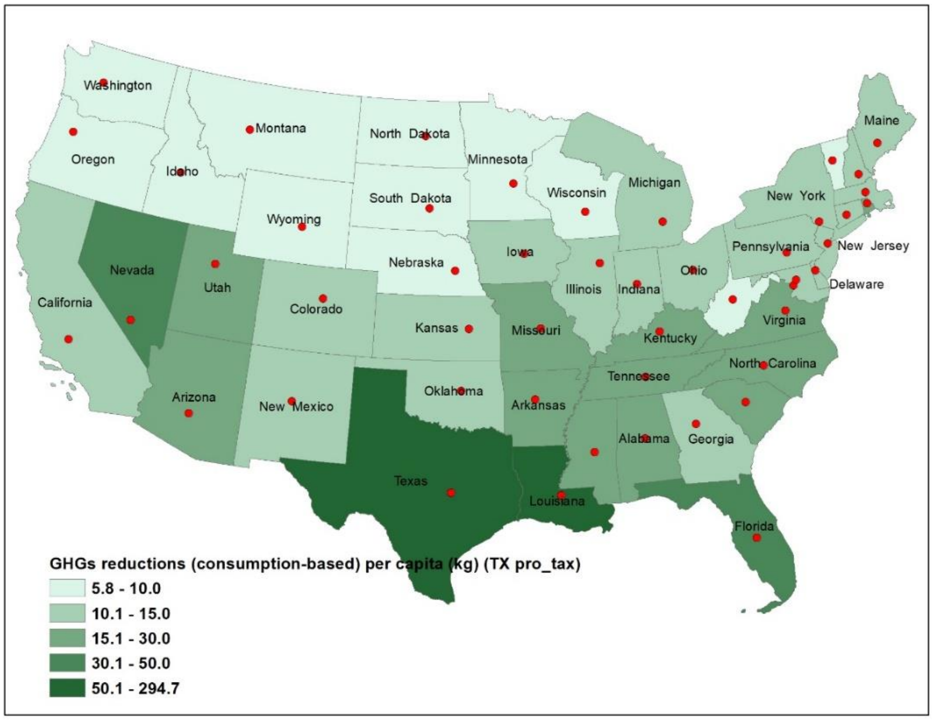
In the Texas production-based carbon tax scenario, the production-based emission reductions are mainly in Texas. Other than Texas, the nearby states (e.g. Kansas, Oklahoma, Arkansas) have the largest percentage decreases (around 0.09%) in their production-based GHG emissions. States in the Northeast (e.g. Maryland, New Jersey, Rhode Island) have the smallest percentage decreases in production-based emissions (around 0.025%). For consumption-based emissions, states with the largest percentage decreases are Louisiana (0.28%), Nevada (0.23%), Florida (0.21%), Mississippi (0.18%), and Rhode Island (0.15%). Wyoming, North Dakota, and West Virginia have the smallest percentage decrease in consumption-based emissions (around 0.03%).

Figure 4-8 shows the per capita reductions in state production- (upper) and consumption-based (lower) emissions. Besides the surrounding states, Texas (397 kg), Wyoming (61 kg), and North Dakota (30 kg) have the largest decline in their production-based emissions per capita. For reductions in state consumption-based emissions per capita, the largest decline occurs in Texas (295 kg), Louisiana (55 kg), Nevada (35 kg), Florida (33 kg), and some northeastern states (i.e. Rhode Island, Virginia, and District of

Columbia) (around 20 kg). This is because Texas products and services are exported to other states all over the country.

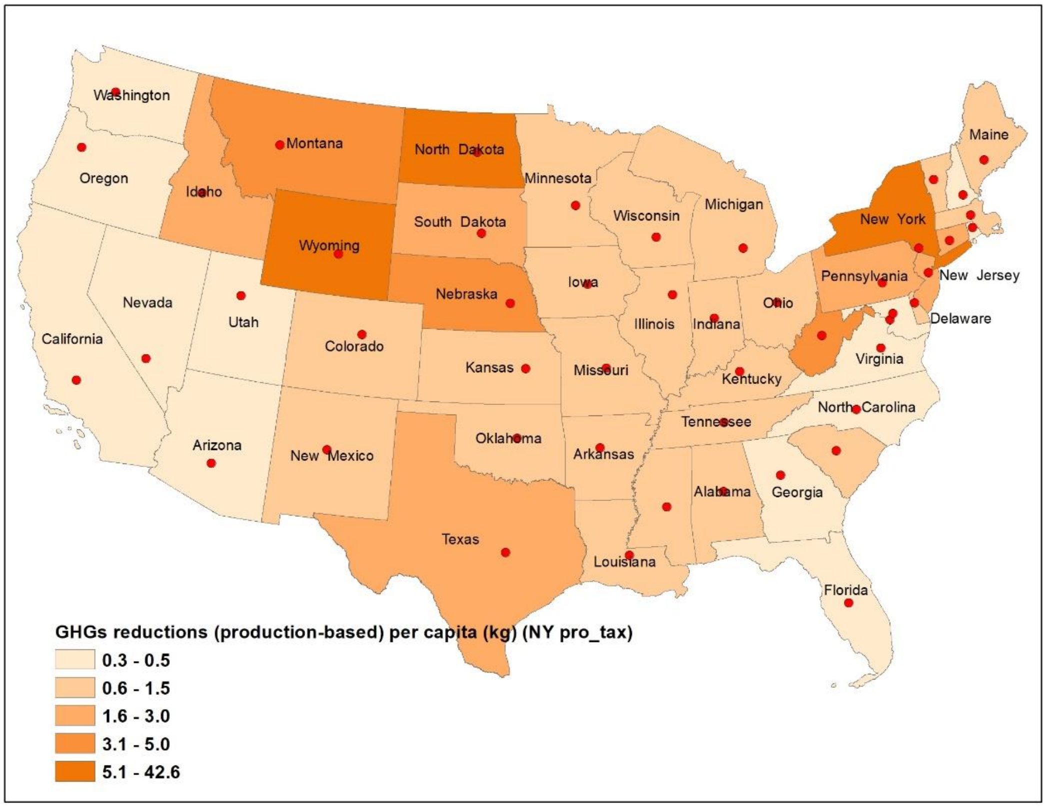
Figure 4-8 Per Capita GHG Emission Reductions by state for the Texas Production-based Carbon Tax (Kilogram CO_2 Eq. per capita)

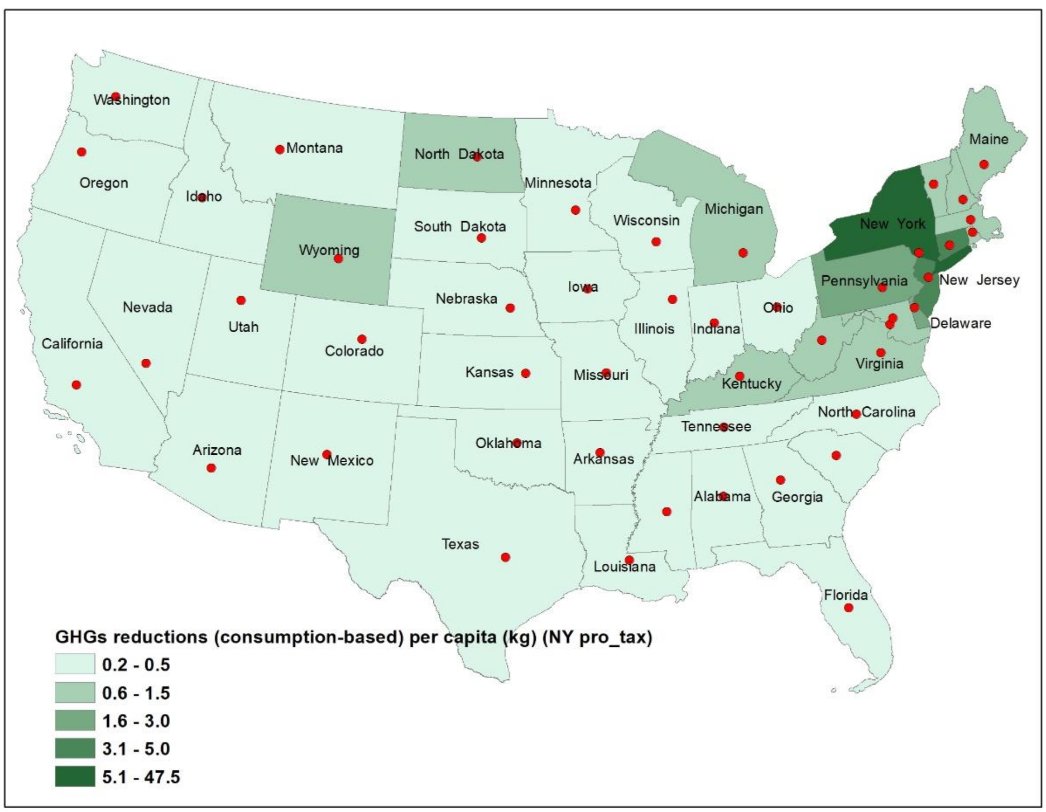




For the New York production-based carbon tax scenario, the percentage decreases in state production-based emissions vary from 0.002% (Utah) to 0.56% (New York) and the range of the percentage decrease in state consumption-based emissions is 0.001% (Utah) to 0.36% (New York). States close to New York (e.g. New Jersey, Connecticut, and Pennsylvania) have relatively large percentage decrease in both production- (0.019% to 0.022%) and consumption-based emissions (0.011% to 0.033%). Utah, Nevada, Missouri, and Florida have relatively small percentage decrease in production-based emissions (around 0.003%); while Utah, Arizona, Colorado, and Wyoming have relatively small percentage decrease in consumption-based emissions (around 0.001%). Figure 4-9 presents the per capita reductions in state production- (upper) and consumption-based (lower) emissions for the New York production-based carbon tax scenario. New York (43 kg), Wyoming (6.2 kg), North Dakota (5.4 kg), Montana (4.3 kg), and Alaska (3.7 kg) have the largest reductions in production-based emissions per capita. For reductions in state consumption-based emissions per capita, the largest decline occurs in New York (47.5 kg) and its nearby states (e.g. New Jersey, Connecticut, Delaware, etc.) (1kg to 5 kg).

Figure 4-9 Per Capita GHG Emission Reductions by state for the New York Production-based Carbon Tax (Kilogram CO_2 Eq. per capita)

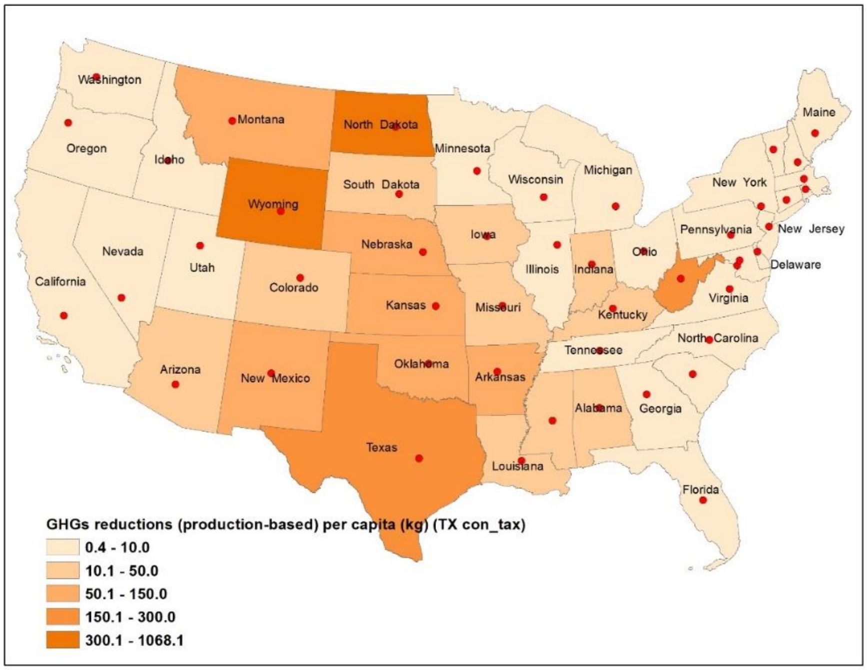


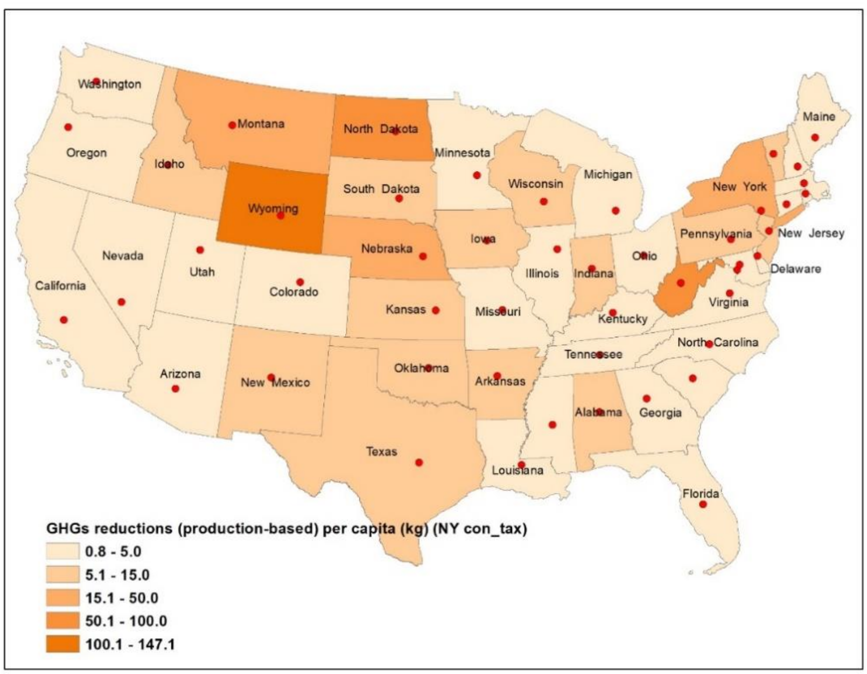


When Texas or New York adopt carbon taxes predicated upon consumption-based emissions, consumer expenditures in other states remain the same as the new tax only applies to final consumers in the taxing states. Thus, the consumption-based emissions remain the same for states other than the taxing one. In the Texas consumption-based carbon tax scenario, Texas production-based emissions decline 1.4% and its consumption-based emissions decline 2.7%. Other than Texas, its surrounding states (e.g. New Mexico, Arkansas, Oklahoma) (0.24% to 0.34%) as well as Wyoming (0.9%), North Dakota (0.5%), and West Virginia (0.3%) have the largest percentage decrease in production-based emissions. States in the Northeast (e.g. Vermont, New York) have the smallest percentage decrease in production-based emissions (around 0.006%). The upper part of Figure 4-10 shows the reductions in state production-based emissions per capita for the Texas consumption-based carbon tax scenario. States with large percentage decrease in production-based emissions also have large per capita reductions in production-based emissions. Emission-intensive states, such as Wyoming, North Dakota, and West Virginia, as well as Texas have the highest decline in production-based emissions per capita.

In the New York consumption-based carbon tax scenario, New York production-based emissions decline 0.63% and its consumption-based emissions decline about 1%. Besides New Jersey and Pennsylvania (both decline about 0.08%), Wyoming (0.124%), North Dakota (0.12%), and West Virginia (0.2%) still have the largest percentage decrease in production-based emissions as in the Texas consumption-based carbon tax scenario. Utah, Florida, and Nevada have the smallest percentage decrease in their production-based emissions (around 0.012%). For the reductions in state production-based emissions per capita, the lower part of Figure 4-10 suggests that emission-intensive states (e.g. Wyoming, North Dakota, and West Virginia) still have the largest per capita reductions in production-based emissions, besides New York.

Figure 4-10 Per Capita GHG Emission Reductions by state for the Consumption-based Carbon Tax in Texas (Upper) and New York (Lower) (Kilogram CO_2 Eq. per capita)



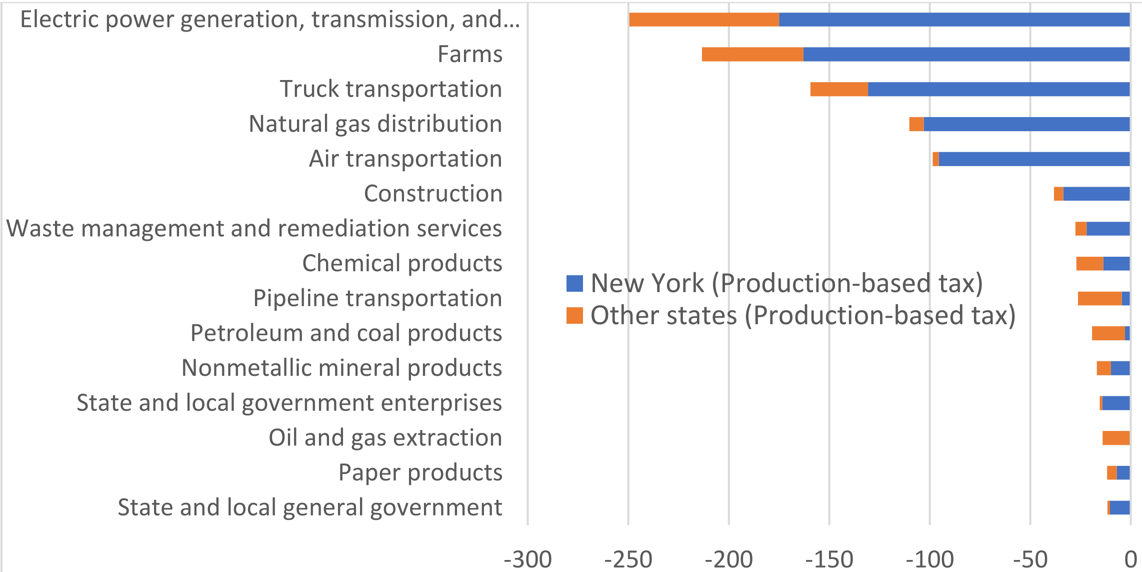


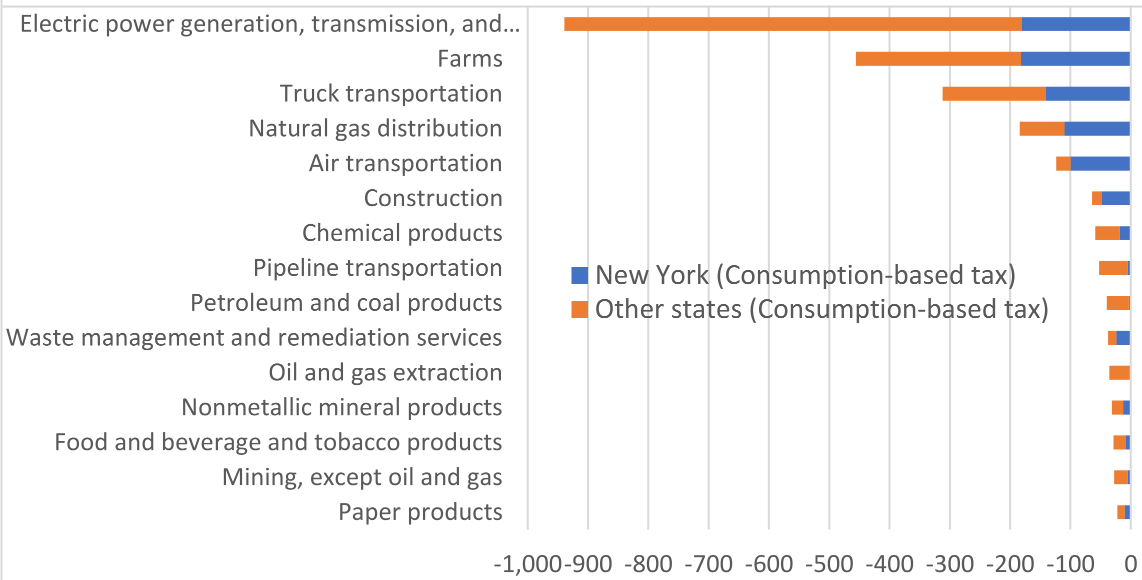
Regarding emission reductions by industry, Figure 4-11 shows the industries with the largest emission reductions for the two Texas carbon tax scenarios. When the tax is applied to Texas production-based GHG emissions, the largest emission reductions are from the electric power industry (8.5 MMT), farms (1.4 MMT), truck transportation (0.6 MMT), and oil and gas extraction (0.2 MMT). The majority of the reductions occur within Texas. For example, Texas emission reductions account for more than 90% of the total reductions from the electric power industry and oil and gas extraction. In the Texas consumption-based carbon tax scenario, industries with the largest emission reductions are the electric power industry (8.4 MMT), farms (1.3 MMT), truck transportation (0.5 MMT), and chemical products (0.2 MMT). But the proportions of Texas emission reductions in the total U.S. emission reductions by industry become smaller compared to those in the Texas production-based carbon tax scenario. For example, Texas emission reductions from the electric power industry only account for 67% of the total U.S. reductions from the power industry.

For the two New York carbon tax scenarios, Figure 4-12 presents the most affected industries from the state carbon tax. Still, the electric power industry, farms, and truck transportation achieve the largest GHG emission reductions in both scenarios. The magnitude of reductions is much larger in the consumption-based tax scenario, as well as the proportions of emission reductions from other states (Figure 4-12). In the production-based tax scenario, New York emission reductions account for more than 70% of the total reductions of those three industries. But in the consumption-based tax scenario, emission reductions from New York only account for 19% of the total U.S. reductions in the electric power industry.

Figure 4-11 GHG Emissions Reductions of Top Industries for State Carbon Tax in Texas (thousand tons of CO_2 Eq.)

Figure 4-12 GHG Emissions Reductions of Top Industries for State Carbon Tax in New York (thousand tons of CO_2 Eq.)





4.3.2 Fuel price scenarios

Table 4-6 shows a summary of the interstate freight activities and the corresponding GHG emissions by mode in different scenarios compared to the baseline. Because I modify the mode shares in estimating interstate trade flows, the results of baseline change slightly from those presented in Chapter 3 (Table 3-7). Compared to the baseline (S0), crude oil price rises of 50% (S1), 100% (S2), 200% (S3), 300% (S4), and 500% (S5), cause shipments by truck and by air to increase and those by rail and water to decrease (Table 4-6). This seems unreasonable which I provide explanations in the following part. In S2, S3, S4, and S5, the ton-miles by pipeline slightly increase compared to S0 and S1. The GHG emissions from interstate freight transportation by mode follow the same pattern of changes as ton-miles but are less exaggerated (Table 4-6). The largest decrease of total transportation GHG emissions are between S5 and S1—only 16.4 thousand tons of CO_2 equivalent (Eq.), while the annual changes of U.S. freight transportation emissions are usually in million tons of CO_2 Eq. (EPA, 2020).

Table 4-6 Ton-miles and GHG Emissions of Interstate Freight by Mode for Scenarios

Fuel Price Scenarios	Truck	Rail	Water	Air	Pipeline	Total
Ton-miles (millions)						
Baseline (2016)	1,135,896	932,800	613,310	39,871	81,766	2,803,644
Crude Oil Price Increases 50%	1,138,062	932,710	612,728	39,891	81,764	2,805,156
Crude Oil Price Increases 100%	1,138,054	932,727	612,597	39,891	81,774	2,805,044
Crude Oil Price Increases 200%	1,138,045	932,745	612,463	39,892	81,785	2,804,930
Crude Oil Price Increases 300%	1,138,041	932,754	612,396	39,892	81,790	2,804,872
Crude Oil Price Increases 500%	1,138,036	932,763	612,328	39,892	81,795	2,804,815
GHG Emissions (thousand tons of CO_2 Eq.)						
Baseline (2016)	237,755.8	20,945.4	21,048.6	50,911.4	3,576.0	334,237.2
Crude Oil Price Increases 50%	238,209.2	20,943.4	21,028.6	50,936.8	3,575.9	334,694.0
Crude Oil Price Increases 100%	238,207.5	20,943.8	21,024.1	50,936.9	3,576.4	334,688.6
Crude Oil Price Increases 200%	238,205.6	20,944.2	21,019.5	50,937.0	3,576.8	334,683.1
Crude Oil Price Increases 300%	238,204.7	20,944.4	21,017.2	50,937.0	3,577.0	334,680.3
Crude Oil Price Increases 500%	238,203.8	20,944.6	21,014.9	50,937.0	3,577.3	334,677.6

To figure out why shipments by truck and air increase when fuel prices rise, I calculated the percentage changes of fuel costs per ton-mile and percentage changes of

GHG emissions by mode (Table 4-7). Because I use a single ton-mile emission factor for each mode, the percentage changes in ton-miles by mode across scenarios are the same as those of GHG emissions in Table 4-7. Although the ton-miles by truck and air as well as the corresponding GHG emissions increase in all scenarios compared to the baseline (S0), the ton-miles by truck decrease while those by rail increase in S2, S3, S4, and S5 compared to S1 (crude oil prices increase 50%). This is due to the different percentage changes of fuel cost per ton-mile by mode in scenarios. When crude oil price increases 50% (S1), compared to S0, the fuel cost per ton-mile by truck increases the least—8.5% among all modes. This explains why trucking rises as does its GHG emissions—0.19%. The fuel cost per ton-mile by air increases the most—50.5%. But due to the constraints of rail and water transportation networks (not all states can be connected through railway or waterway), air shipments and their corresponding emissions still increase slightly—0.05%. When comparing S2, S3, S4, S5 to S1, the percentage increases of fuel cost per ton-mile by truck are larger than those by rail (Table 4-7), which drives mode shifts away from truck to rail, albeit negligibly. The percentage rise in fuel cost per ton-mile by air are larger than those by rail but smaller than those by water (Table 4-2, 4-7). The ton-miles by air and its emissions still increase but very little (from 0.0001% (S2) to 0.0004% (S5)). As I keep fuel costs per ton-mile by pipeline stable, the pipeline usage and its emissions increase in S2, S3, S4, and S5 compared to S1. The range of the increase is from 0.0124% (S2) to 0.0381% (S5).

Table 4-7 Changes in GHG Emissions and Fuel Costs of Interstate Freight by Mode for Scenarios

Fuel Price Scenarios	Truck	Rail	Water	Air	Pipeline
Changes of GHG Emissions					
(S1-S0)/S0	0.1907%	-0.0096%	-0.0949%	0.0500%	-0.0021%
(S2-S1)/S1	-0.0007%	0.0019%	-0.0215%	0.0001%	0.0124%
(S3-S1)/S1	-0.0015%	0.0038%	-0.0433%	0.0003%	0.0251%
(S4-S1)/S1	-0.0019%	0.0048%	-0.0543%	0.0003%	0.0316%
(S5-S1)/S1	-0.0023%	0.0057%	-0.0653%	0.0004%	0.0381%
Changes of Fuel Costs per Ton-mile					
(S1-S0)/S0	8.5%	42.2%	27.3%	50.5%	0.0%
(S2-S1)/S1	31.9%	29.1%	34.0%	32.0%	0.0%
(S3-S1)/S1	95.7%	87.2%	102.0%	95.9%	0.0%
(S4-S1)/S1	159.5%	145.3%	170.0%	159.9%	0.0%
(S5-S1)/S1	287.1%	261.5%	306.0%	287.8%	0.0%

4.3.2.1 Changes in Interstate Trade by Industry

Recall, state supplies and demands are constant across scenarios. But travel costs among states change with fuel prices, which should affect interstate trade patterns. Table 4-8 shows the industry-state trade pairs with largest trade value changes when crude oil prices increase 50%. The largest decrease occurs in the Texas-California pair for oil and gas extraction products (117 million). But the amount of decline is very small compared to the original trade value of this industry-state trade pair (16.6 billion). Table 4-8 suggests that states switch suppliers to different states in S1 compared to the baseline. Some states switch to suppliers in nearby states. For example, in S1, part of the demand for oil and gas extraction products in California are fulfilled by Colorado suppliers instead of suppliers in Texas or Oklahoma. But some states obtain supplies from further away. For products of petroleum refineries, Michigan switches supplies from Indiana to Texas, and New York switches supplies from Texas to California. Changes also happen between nearby states: part of Michigan’s demand for animal processing products are fulfilled by Wisconsin suppliers in S1 instead of Illinois suppliers.

Table 4-8 Industry-State Trade Pairs with Top Trade Value Changes between S1 and S0

Rank	**Origin State**	**Destination State**	**Industry**	**Trade Value Change (S1-S0)** (millions $)	**Percentage Change in Trade Value** (%)
Largest Decrease in Trade Value					
1	Texas	California	Oil and gas extraction	-117.08	-0.7%
2	Texas	New York	Petroleum refineries	-86.26	-0.6%
3	Indiana	Michigan	Petroleum refineries	-61.96	-4.3%
4	Alaska	Hawaii	Oil and gas extraction	-50.47	-5.0%
5	Ohio	Michigan	Oil and gas extraction	-45.81	-4.6%
6	Texas	Illinois	Beef cattle ranching and farming	-40.58	-2.9%
7	Arkansas	California	Poultry processing	-38.03	-2.6%
8	Oklahoma	California	Oil and gas extraction	-37.82	-2.7%
9	Texas	Washington	Oil and gas extraction	-36.53	-1.5%
10	Illinois	Michigan	Animal (except poultry) slaughtering, rendering, and processing	-35.61	-5.7%
Largest Increase in Trade Value					
1	Colorado	California	Oil and gas extraction	120.26	4.5%
2	Texas	Michigan	Petroleum refineries	86.32	2.7%
3	Nebraska	California	Animal (except poultry) slaughtering, rendering, and processing	69.85	2.0%
4	California	New York	Petroleum refineries	62.83	2.1%
5	Nebraska	Texas	Grain farming	49.48	14.0%
6	Texas	Hawaii	Oil and gas extraction	47.76	22.8%
7	Ohio	Indiana	Oil and gas extraction	38.64	1.8%
8	Wisconsin	Michigan	Animal (except poultry) slaughtering, rendering, and processing	37.37	8.2%
9	Alaska	Washington	Oil and gas extraction	35.30	1.5%
10	Texas	Michigan	Oil and gas extraction	33.70	4.2%

When comparing S2, S3, S4, S5 to S1, the largest changes in trade value are from trading energy goods from petroleum refineries and oil and gas extraction (Table 4-9). The more crude-oil prices increase, the larger the changes in trade values. More California demands for oil and gas extraction products are fulfilled by Colorado suppliers when fuel prices increase further rather than supplies from Texas or Oklahoma. Table 4-9 also shows that states switch suppliers to different states when fuel prices rise more. For example, part of Indiana's demand for oil and gas extraction products are fulfilled by suppliers in Ohio rather than Texas suppliers; part of Kentucky's demand for petroleum refinery products are fulfilled by supplies from Indiana instead of Texas. States switch to supplies from nearby states and from further away as well.

Table 4-9 Industry-State Trade Pairs with Top Trade Value Changes Comparing S2, S3, S4, S5 to S1

Rank	Origin State	Destination State	Industry	Trade Value Change (millions $)			
				S2-S1	S3-S1	S4-S1	S5-S1
Largest Decrease in Trade Value							
1	Indiana	Michigan	Petroleum refineries	-10.62	-21.44	-26.94	-32.48
2	Texas	California	Oil and gas extraction	-7.72	-15.61	-19.62	-23.67
3	Ohio	Michigan	Oil and gas extraction	-6.12	-12.38	-15.55	-18.76
4	Texas	Indiana	Oil and gas extraction	-6.06	-12.25	-15.38	-18.55
5	Oklahoma	California	Oil and gas extraction	-4.90	-9.86	-12.37	-14.90
6	Minnesota	Wisconsin	Petroleum refineries	-4.85	-9.80	-12.32	-14.87
7	Texas	Kentucky	Petroleum refineries	-3.67	-7.41	-9.32	-11.25
8	Texas	Iowa	Petroleum refineries	-3.01	-6.10	-7.68	-9.27
9	Texas	Ohio	Petroleum refineries	-2.90	-5.85	-7.35	-8.86
10	Colorado	Montana	Oil and gas extraction	-2.82	-5.71	-7.18	-8.66
Largest Increase in Trade Value							
1	Texas	Michigan	Petroleum refineries	9.70	19.61	24.65	29.74
2	Colorado	California	Oil and gas extraction	9.64	19.47	24.46	29.49
3	Ohio	Indiana	Oil and gas extraction	8.24	16.65	20.91	25.21
4	Indiana	Kentucky	Petroleum refineries	7.27	14.72	18.50	22.33
5	Minnesota	Iowa	Petroleum refineries	5.02	10.15	12.76	15.40
6	Indiana	Ohio	Petroleum refineries	4.84	9.78	12.28	14.80
7	Texas	Michigan	Oil and gas extraction	3.93	7.95	9.99	12.05
8	Louisiana	Michigan	Petroleum refineries	3.61	7.29	9.17	11.06
9	Texas	New Jersey	Oil and gas extraction	3.51	7.10	8.92	10.76
10	Texas	New York	Oil and gas extraction	3.37	6.82	8.57	10.34

4.3.2.2 Transportation Emission Changes by State

Although changes in interstate trade value of industry-state trade pairs can be as large as $100 million, after aggregation by state, changes in state inbound and outbound trade values are very small across scenarios. The changes between S1 and S0 are largest when crude oil prices increase by 50%. The changes of state outbound trade vary from -$15,000 (Illinois) to $13,000 (Florida), while that of inbound trade varies from -$22,000 (California) to $8,000 (Michigan). When comparing S2, S3, S4, S5 to S1, changes in state inbound and outbound trade are less than $1,000, almost negligible given the aggregate size of interstate trade.

For interstate freight transportation emissions, when comparing S1 to S0, total emissions increase about 457,000 tons of CO_2 Eq. For outbound transportation emissions, Georgia, Iowa, Kansas, Missouri and California have the largest increase (larger than 30,000 tons of CO_2 Eq. each); Oklahoma, Wisconsin, and West Virginia have the largest decrease (larger than 20,000 tons of CO_2 Eq. each). For inbound transportation emissions, the largest increases occur in Florida, Washington, Colorado, and California (larger than 30,000 tons of CO_2 Eq.); while the largest decreases happen in New York, Maine, Ohio, and West Virginia (larger than 5,000 tons of CO_2 Eq.). California has substantial rise in both inbound and outbound transportation emissions. In contrast, West Virginia has sizeable decline in both. Regarding per capita outbound transportation emissions, the largest increases are from Wyoming, North Dakota, Montana, as well as Iowa and Kansas (15 kg to 45 kg); West Virginia, Oklahoma, Alaska, and South Dakota have the largest decreases in per capita emissions (6 kg to 13 kg). For per capita inbound transportation emissions, North Dakota, Wyoming, and Hawaii have the largest increase (12 kg to 17 kg); Vermont, Maine, and West Virginia have the largest decreases in per capita emissions (3 kg to 7.5 kg). Most of these states with large changes in per capita transportation emissions originally have substantial transportation emissions per capita.

When comparing S2, S3, S4, S5 to S1, total emissions decreases are 5.4, 10.9, 13.6, and 16.4 thousand tons of CO_2 Eq. correspondingly. The reductions in transportation emissions become larger when the fuel prices rise further. For outbound transportation emissions, the largest increases occur in Michigan, Georgia, and Montana, and the increased amount gets bigger as fuel price goes up for each state. In contrast, Alaska, Oklahoma, California, and Texas have the largest amount of decrease in outbound emissions. The decreases also rise with fuel prices. Regarding inbound transportation emissions, Michigan, New Jersey, and Montana have the largest increases while California, Indiana, and Ohio have the largest decreases. Similarly, the amount of changes become larger as the fuel prices go up. When fuel prices increase further, California's inbound and outbound transportation emissions decline significantly; Michigan and Montana have sizeable increases in both. For changes in outbound transportation emissions per capita, like changes between S1 and S0, Montana, Wyoming, and North Dakota still have the largest increases; Alaska, Oklahoma, West Virginia, and South Dakota still have the largest decreases in per capita emissions. For per capita inbound transportation emissions, Montana, Michigan and North Dakota have the largest increases; Hawaii, Delaware, and West Virginia have the largest decreases. The changes in per capita transportation emissions by state when comparing S2, S3, S4, S5 to S1 are much smaller than those between S1 and S0.

4.3.2.3 Transportation Emission Changes by Industry

Regarding aggregate transportation emission changes by industry, mode shifts away from emission-intensive modes does not necessarily result in transportation emission reductions with rising fuel prices. There are only three aggregated sectors that obtain emission reductions when fuel prices increase: oil and gas extraction, natural gas distribution, and petroleum and coal products. All other sectors' aggregate transportation emissions increase in all five scenarios. Rises in fuel prices should drive freight away from emission-intensive modes; they are also likely to force producers in some states to switch to more localized supplies (in nearby states). Shorter-distance shipments tend to be made by truck, as opposed to rail, water or air freight. For example, part of Texas's demand for grains switches from North Dakota to Nebraska supplies in S1 (Table 4-8). Although the share of truck shipments from Nebraska to Texas for grains decreases in S1 (61.2%) compared to S0 (62.3%), the ton-miles by truck increase by 108 million in S1 as the trade value increases. Thus, this pair of economic forces emanating from fuel price rises suggest no clear expectation for changes in the ton-miles of shipments by truck. Thus, aggregate transportation emissions for other sectors can conceivably increase with the rise of fuel prices. When crude oil prices increase 50%, the increase in transportation emissions is the largest among all scenarios: from 0.14 (apparel and leather products) to 191.7 (mining) thousand tons of CO_2 Eq. Transportation emissions for petroleum and coal products also increase in S1 compared to S0. The large amount of increase is mainly due to the rising truck ton-miles for all sectors except natural gas distribution.

When comparing S2, S3, S4, S5 to S1, the decreases in transportation emissions become larger for oil and gas extraction, natural gas distribution, and petroleum and coal products as the fuel prices rise. This is achieved by the decline in truck and water ton-miles together with the increased usage of rail and pipeline. For oil and gas extraction, more emission reductions come from the decrease in shipments by water. Actually, shipments by water decrease for all sectors in S2, S3, S4, and S5. For sectors other than those producing energy goods, as the fuel prices rise, their transportation emissions increase more. But the increased amount is smaller than emission reductions from shipping energy goods. The largest increases are from shipments of food and beverage and tobacco products (329 tons), nonmetallic mineral products (262 tons), and farms (232 tons) in S5 when crude oil price increases 500%. This is mainly due to more usage of trucks.

4.3.2.4 Industry-State Trade Pairs

I examine the changes of transportation GHG emissions from each freight flow (origin-destination-industry-mode) for the five fuel price scenarios. Table 4-10 shows the freight flows by mode with the largest changes of transportation emissions when crude oil price increases 50% (S1) compared to baseline (S0). The largest reductions are from the Texas-California path for shipping oil and gas extraction products via *water transportation through Panama Canal*, which is the freight flow with largest transportation emissions in 2016 (see Table 3-6). There are several freight flows shipping stone mining and quarrying products to California, which create significant changes in transportation emissions: reductions from Kentucky-California (by rail, truck, and water), Oklahoma-California (by truck and water) and Tennessee-California (by truck and rail); and rise from Georgia-California (by truck and rail) and Missouri-California (by truck and rail). The largest increase is on the Nebraska-Texas path, upon which grains ship by truck.

Several flows originating from Wyoming have significant increases in transportation emissions: the Wyoming-Florida path shipping nonmetallic mineral products and coal by truck, and the Wyoming-California path shipping coal by truck. This is because the percentage increase of fuel cost per ton-mile by truck is higher than that of rail in S1 compared to the baseline. Shipments of mining products originating in Wyoming by truck increase as well as the corresponding transportation emissions.

Table 4-10 Changes of Transportation GHG Emissions of Top Industry-State Trade Pairs by Mode between S1 and S0

Rank	Origin State	Destination State	Industry	Mode	Change of GHG Emissions (S1-S0) (thousand tons of CO_2 Eq.)
Largest Decrease of Transportation GHG Emissions					
1	Texas	California	Oil and gas extraction	Water	-15.706
2	Kentucky	California	Stone mining and quarrying	Rail	-14.720
3	Kentucky	California	Stone mining and quarrying	Truck	-14.694
4	Oklahoma	California	Stone mining and quarrying	Truck	-13.465
5	Kentucky	California	Stone mining and quarrying	Water	-11.111
6	Tennessee	California	Stone mining and quarrying	Truck	-10.524
7	Georgia	Texas	Stone mining and quarrying	Truck	-8.474
8	Alaska	Hawaii	Oil and gas extraction	Water	-8.234
9	Oklahoma	California	Stone mining and quarrying	Water	-7.676
10	Tennessee	California	Stone mining and quarrying	Rail	-7.519
Largest Increase of Transportation GHG Emissions					
1	Nebraska	Texas	Grain farming	Truck	22.538
2	Wyoming	Florida	Other nonmetallic mineral mining and quarrying	Truck	20.397
3	Texas	Hawaii	Oil and gas extraction	Water	19.030
4	Georgia	California	Stone mining and quarrying	Truck	14.348
5	Wyoming	Florida	Coal mining	Truck	12.355
6	Missouri	California	Stone mining and quarrying	Truck	11.457
7	Wyoming	California	Coal mining	Truck	9.848
8	Georgia	California	Stone mining and quarrying	Rail	9.600
9	Missouri	California	Stone mining and quarrying	Rail	9.402
10	Kansas	California	Stone mining and quarrying	Truck	9.221

Table 4-11 Changes of Transportation GHG Emissions of Top Industry-State Trade Pairs by Mode Comparing S2, S3, S4, S5 to S1

Rank	Origin State	Destination State	Industry	Mode	Change of GHG Emissions (thousand tons of CO_2 Eq.)			
					S2-S1	**S3-S1**	**S4-S1**	**S5-S1**
Largest Decrease of Transportation GHG Emissions								
1	Texas	California	Oil and gas extraction	Water	-1.036	-2.094	-2.632	-3.176
2	Oklahoma	California	Oil and gas extraction	Water	-0.817	-1.644	-2.063	-2.483
3	Texas	Hawaii	Oil and gas extraction	Water	-0.697	-1.393	-1.740	-2.087
4	Texas	Indiana	Oil and gas extraction	Truck	-0.315	-0.637	-0.800	-0.965
5	Texas	Ohio	Oil and gas extraction	Truck	-0.252	-0.508	-0.637	-0.768
6	Texas	Washington	Oil and gas extraction	Water	-0.236	-0.477	-0.599	-0.722
7	California	Wisconsin	Petroleum refineries	Water	-0.237	-0.477	-0.598	-0.720
8	Texas	Kentucky	Petroleum refineries	Truck	-0.211	-0.427	-0.537	-0.649
9	California	Minnesota	Petroleum refineries	Water	-0.206	-0.416	-0.522	-0.628
10	Ohio	Michigan	Oil and gas extraction	Water	-0.188	-0.379	-0.476	-0.575
Largest Increase of Transportation GHG Emissions								
1	Colorado	California	Oil and gas extraction	Truck	0.572	1.154	1.449	1.747
2	California	Michigan	Natural gas distribution	Water	0.444	0.891	1.116	1.342
3	Texas	Montana	Oil and gas extraction	Truck	0.376	0.760	0.954	1.151
4	Texas	Michigan	Petroleum refineries	Truck	0.344	0.696	0.875	1.055
5	Alaska	Hawaii	Oil and gas extraction	Water	0.301	0.602	0.752	0.902
6	Texas	Michigan	Oil and gas extraction	Truck	0.278	0.561	0.704	0.849
7	Colorado	California	Oil and gas extraction	Pipeline	0.218	0.441	0.554	0.669
8	California	Massachusetts	Petroleum refineries	Water	0.208	0.419	0.526	0.633
9	Colorado	California	Oil and gas extraction	Rail	0.206	0.416	0.522	0.630
10	Texas	Michigan	Petroleum refineries	Water	0.205	0.414	0.521	0.629

When crude oil prices increase further (S2, S3, S4, and S5), the total transportation emissions start to decrease compared to S1. Table 4-11 shows the freight flows with largest changes in transportation emissions comparing S2, S3, S4, S5 to S1. These top freight flows remain the same with greater extent of changes as fuel prices rise. Substantial increase and decrease are both from shipping energy goods: oil and gas extraction, petroleum refineries, and natural gas distribution. The largest transportation emission reductions are via water transportation shipping products from oil and gas extraction: Texas-California, Oklahoma-California, and Texas-Hawaii. Several freight flows by truck also have significant emission reductions: Texas-Indiana and Texas-Ohio both for products from oil and gas extraction. The largest increases are via truck, rail, water, and pipeline transportation. The Colorado-California path shipping products of oil and gas extraction has significant transportation emission increase via three modes: truck, pipeline, and rail. This is because part of California's demand for oil and gas extraction products switches from Texas to Colorado supplies.

4.4 Discussion

There are some uncertainties inherent to the model estimates. For state carbon tax scenarios, I use the I-O cost-push model and quantity model to estimate the short-term economic and environmental impacts of possible state carbon taxes. Since economic structures are relatively stable over short periods (Wiebe et al., 2018), I use a static MRIO model. I assume a state carbon tax would completely pass on to final consumers through the supply chain (forward linkage) in the cost-push model and changes in final demand would result in changes in output without supply constraints (backward linkage) in the quantity model. These are strong assumptions. Although average production technologies are unlikely to change in the short-run, producers might use fossil fuels more efficiently so that price increases from a new tax would be a bit sticky and not completely pass through to final consumers. The improvement of fuel efficiency would affect the backward linkage as well. In the long-run, industries would change their input structures to some degree and emission intensities would change accordingly. Then the long-term economic and environmental impacts would be quite different as both forward and backward linkages differ from the baseline.

In addition, I apply a constant price elasticity of demand that is the same for all commodities in all states to estimate the final demand changes after the price increase. I do this because it is difficult to obtain price elasticities for all commodities in all states. It is, nonetheless, quite a strong assumption as price elasticities undoubtedly differ across industries and geography. Future studies should test different price elasticities of demand, especially for energy goods, to examine the economic and environmental impacts.

The state carbon tax scenario analysis is *ceteris paribus.* That is, I do not consider substitution effects. I do not even allow for the substitution of the same commodity from a different state, let alone substitution among different commodities. This is undoubtedly unrealistic as final consumers typically do not differentiate between commodities by their production point. Consumers would be expected to switch to other products when price changes substantially, e.g., switch from rice to noodles when rice gets too expensive. Moreover, trade patterns across states remain constant in my model although trade structures can change quickly depending on policies (Wiebe et al., 2018). With a new state carbon tax, state supply and demand change as well as the interstate travel costs since the carbon tax would drive the increase in fuel prices. All these undoubtedly lead to changes in interstate trade patterns which I did not account for in the model.

My approach does simplify interpretation of results, however. By holding economic structures, interstate trade patterns, and GHG emission intensities by industry constant, I am able to focus instead on state- and industry-specific economic and environmental impacts of possible state carbon taxes. But I only test a partial equilibrium. My findings cannot examine the ***extent*** of carbon leakage due to state environmental policies. In this vein, it is not a thorough policy impact analysis since I do not consider how revenues from carbon taxes are spent (Dietzenbacher & Velázquez, 2007).

The extent of GHG emission reductions with a state carbon tax rate of $50 per ton of GHG emissions (in CO_2 equivalent) in this work is relatively small compared to other researchers' findings. The largest percentage decrease is about 1.8% for Texas production-based emissions in the Texas production-based carbon tax scenario. Choi et al. (2010) suggest that an economywide tax of $50 per ton of CO_2 could enable about 7% reductions in the U.S. CO_2 emissions based on an I-O framework as well. There are several reasons for the differences. First, I use a constant price elasticity of demand (-0.3) for all commodities in all states while Choi et al.'s (2010) estimates are based on a smaller price elasticity of demand (<-0.3) for all commodities other than the electricity. A smaller price elasticity of demand suggests final consumers are more sensitive to price changes. Thus, reductions in final demand would be larger with the same price increase, which would result in larger reductions in the output as well as the corresponding emissions. I tested a price elasticity of demand of -0.7 for all commodities in the Texas production-based carbon tax scenario. The resulting reduction in Texas production-based

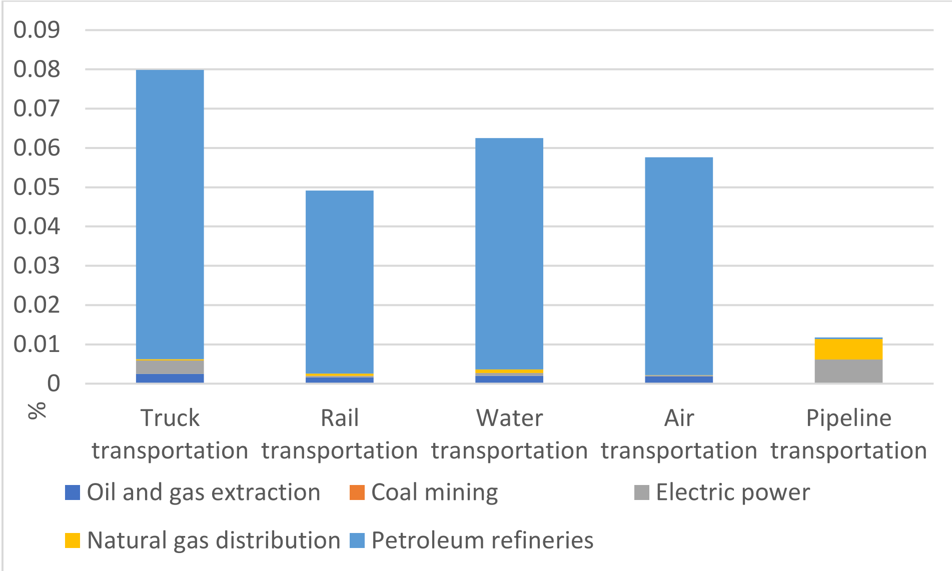
GHG emissions is about 4.3%, much closer to Choi et al.'s (2010) estimates. Another reason is that I apply the carbon tax to GHG emissions from a certain state (e.g. Texas) while Choi et al. (2010) apply the tax to the U.S. CO_2 emissions. Compared to the nationwide coverage, a single state exchanges much larger share of goods and services with other states. This leads to smaller reductions in the final demand of the taxing state as consumers can purchase commodities from other states with much lower price increases compared to the home state. The smaller reductions in state final demand lead to smaller reductions in state output as well as the GHG emissions. Other researchers suggest that an economy-wide carbon tax of $50 per ton on U.S. CO_2 emissions could achieve around 30% reductions from 2005 levels in the near future using computable general equilibrium (CGE) models (Kaufman & Gordon, 2018; Chen & Hafstead, 2019). These researchers make assumptions about technology innovations and how to spend tax revenues, thus have more profound emission reductions compared to my estimates for a state carbon tax in the short run.

Regarding fuel price scenarios, my analysis is also *ceteris paribus*, as I fix state supplies and demands despite obvious price changes across states that unfold with the change in fuel prices. Less problematic is that I maintain ton-mile emission factors constant across modes, and I did not include emissions due to pipeline leakage over the scenarios examined. But fuel price rises do not only affect freight transportation. Other industries and final consumers would alter their energy consumption behavior too. Fuel price rises would trigger some detectable price rises in other industries. The demand for commodities produced by these industries would likely decline, leading to further shrinking of supply. In this vein, the modeling assumption of constant state supply and demand by industry is, unfortunately, quite unrealistic. In addition to altering the demand for freight transportation, fuel prices would also likely reduce intermediate industry supplies and demands, which would undoubtedly further limit emissions in light of likely decreases in concomitant interstate trade declines. But changes in interstate trade patterns can unfold in two ways: firms could switch to nearby suppliers, and firms could also search further afield to meet their input needs at even lower cost.

This may explain the limited reductions even increases in transportation emissions with the fuel price increases in my model. When firms switch to nearby suppliers, the shorter shipping distance may derive more truck usage and, thus, higher emissions. Even the share of truck shipments for this particular trade flow decreases as the fuel price rises, the ton-miles by truck may still increase due to the larger trade value also resulting in the emission rises. If firms switch to suppliers further away, the longer shipping distance together with the fuel price increases could lead to a greater use of less-emissions-intensive freight transport modes (e.g. rail). But longer distances and increases in trade could also enable more ton-mileage of freight being shipped by less-emissions-intensive modes, which could result in an increase in transportation emissions.

In addition, energy inputs from various fuels typically account for only a very small part in producing transportation services (an exception is air transport). Figure 4-13 shows the energy inputs required for transportation services by mode in the U.S. from 2016 U.S. I-O tables (self-calculated). The required energy inputs for all five major modes are smaller than 0.08%. This also helps explain the limited changes in transportation emissions with fuel price increases.

Figure 4-13 Energy Inputs for Transportation in the U.S.



Source: U.S. BEA, 2016 U.S. I-O tables

Moreover, my model assumes the mode shifts are possible without accounting for capacity constraints of each mode. Future work should consider the capacity constraints, especially for rail and pipeline. For example, rail is now mainly used to ship coal and oil products. As the coal consumption decreases, the available capacity of rail might be used to ship other products. Capacity constraints of pipeline might prevent further expansion in shipments for petroleum-related products.

My model results suggest that without changes in travel demand, rising fuel prices alone have limited power in reducing GHG emissions from interstate freight transportation. This echoes Yang et al. (2009) and McCollum and Yang (2009) who suggest no individual “silver bullet” strategy can enable deep cuts in the U.S. transportation emissions. Other limitations involving the use of an MRIO model to estimate state supplies and demands, using gravity model to estimate interstate trade flows, and multinomial logit models for mode choice, and single and constant emission factor for each mode are detailed in Chapter 3.

4.5 Conclusions

This chapter uses state carbon tax scenarios and fuel price scenarios to examine the sensitivity of the overall GHG emissions by state and by industry and emissions from freight transportation. For GHGs net exporting states like Texas, when carbon tax is applied to production-based emissions, the reductions in state emissions as well as total U.S. emissions are greater compared to adopting a similar consumption-based carbon tax. The opposite is true for GHGs in net importing states like New York. The amount of emission reductions depends on the state economic structure. Texas carbon tax scenarios would induce larger emission reductions compared to New York scenarios with the same carbon tax rate because the inventory of Texas GHG emissions (in both production- and consumption-based accounting) is greater and Texas electricity is more emissions-intensive. Moreover, the largest emission reductions and economic impacts (e.g. output reduction, GDP loss, employment cut, etc.) occur in the taxing state. Impacts on other states depend on their economic connections with the taxing state. The most affected states are those close to the taxing states (e.g. Arkansas and Oklahoma for the Texas carbon tax scenarios, New Jersey, and Pennsylvania for the New York carbon tax scenarios) as well as emissions-intensive states (e.g. Wyoming and North Dakota). District of Columbia suffers relatively large per capita GDP losses in all scenarios. Regarding impacts by industry, the electric power industry, food, beverage and tobacco products, and construction are among those with the largest reductions of output in all carbon tax scenarios. The largest GHG emission reductions concentrate in the electric power industry, farms, and truck transportation. The differences among scenarios are the extent of reductions and the contribution from the taxing state.

With a new state carbon tax, final consumers would suffer from the increase in expenditures. My model estimates suggest that the revenues from state carbon taxes can cover the increase in expenditures and GDP loss. Thus, how the tax revenues are spent is very important: either compensate final consumers or support investment in green technology or subsidize key industries. In addition, the feasibility of a carbon tax is another significant factor. My scenarios choose either state production- or consumption-based GHG emissions as the tax base, which is troublesome and contentious because direct emission intensities and total emission intensities by industry are required. Total emission intensities by industry, in particular, are measured per unit of final demand and account for the complete upstream supply chains, which are relatively complicated. Current carbon tax policies are normally set according to the fossil-fuel consumption given the majority of GHG emissions are created in the course of fossil-fuel combustion (Labandeira & Labeaga, 2002; World Bank, 2020). Although my carbon tax scenarios cover economywide GHG emissions, future work should examine the impacts when carbon tax is only applied to fossil-fuel consumption. Also, future work should test different price elasticities of demand and different state carbon tax rates as emission reductions are limited in my model. Other factors need to be considered including substitution effects, technology innovation, and the use of tax revenues, in order to conduct a thorough impact analysis of state carbon taxes.

For the fuel price scenarios, results show that fuel price changes alone would not trigger substantial mode shifts away from emission-intensive modes (e.g. truck and air) resulting in limited emission reductions from interstate freight transportation. This is because the extent of changes in fuel costs per ton-mile by mode differ with the same amount of changes in crude oil prices. When crude oil prices increase 50% from the 2016 level, the overall shipments by truck increase because the percentage increase in fuel costs per ton-mile by truck is the lowest among all modes. Even when fuel price increases drive mode shifts away from truck (comparing S2, S3, S4, S5 to S1), the reductions in GHG emissions are very limited, even with very high fuel prices (crude oil prices increase 500%). Compared to intrastate freight, typically interstate freight flows traverse longer distances and, thus, more apt to shift from truck and toward rail (Nelldal & Andersson, 2012). But my scenario analysis suggest that mode shifts are very limited via fuel price rises alone, when state supply and demand are held constant. Thus, in order to achieve ambitious transportation emission reduction goals, combining different strategies is necessary, e.g., use alternative fuels, improve fuel efficiency, reduce travel demand through land use, etc. (Yang et al., 2009).

When using mode shift as a strategy for transportation emission mitigation, one option might be to impose taxes specifically on fuels for trucks and airplanes. This might help reduce the shipments by truck and air. Besides fuel taxes, other policy tools are needed to encourage more shifts to more-environmentally friendly modes. Future work should also account for the capacity constraints of the transportation system, especially for rail and pipeline.

5 Summary and Conclusions

5.1 Summary

In this dissertation, I try to answer three research questions. What are the consumption-based GHG emissions for each U.S. state? How much does freight transportation contribute to interstate trade related GHG emissions? And how might these emissions change in response to a state carbon tax or fuel price increases.

I estimate state-level consumption-based GHG emissions in the U.S. to complement the traditional production-based accounting. The differences between the two are the net emissions embodied in trade (Aichele and Felbermayr, 2012). Traditional production-based accounting involves emissions by local producers, including those exporting to other regions. Consumption-based emissions are emissions embodied in the consumption of locally produced goods and services as well as in the inflows of products required to fulfill local demands.

To make these estimates, I build, almost from scratch, a state-level MRIO model with 403 industries for the U.S. It roughly simulates interstate supply chains. The model enables me to track emissions from the producers to final consumers (i.e. household, government, investment, etc.). My estimates suggest substantial differences exist between states' consumption- and production-based emissions. Even without accounting for international imports and exports, I find that coastal states tend to be net importers of GHG emissions, largely because their consumption-based emissions are larger than their corresponding production-based emissions. It logically follows that states in the Central and Mountain regions are, therefore, net exporters of emissions. After normalizing consumption- and production-based emissions by state populations and, alternatively, GDP, it appears that California, New York, and some Northeastern states are among the nation's least emission-intensive states in both forms of accounting. But, West Virginia, Wyoming, Kentucky, Montana, and North Dakota have the highest emissions intensities in both forms of accounting due to their industry structures, since I use national emissions intensities by industry except for the electric power industry. That is, differences in state consumption-based emissions are mainly due to the production sources of consumed products as opposed to differences of consumption patterns across states, which do vary with geography.

By tracking emissions via interstate supply chains, I identify who pollutes for whom among states within the U.S. Although the largest amount of emissions embodied in consumption almost always derive from within each state, many states are quite interconnected via interstate trade. For example, more than 70% of Wyoming, Nebraska, Montana, Idaho and North Dakota's production-based emissions are embodied in their outflows to other states; about 60% of the emissions embodied in the consumption of Northeastern states derive from the inflow of goods. Naturally, neighboring states tend to be far more likely to exchange goods embodying emissions as opposed to states that are further away. Texas and California pollute for all other states as they are large states that export relatively large amounts of embodied emissions to nearly all other states.

GHG emissions embodied in interstate trade come from two sources. Besides production, emissions also derive from freight transportation, which contributes to trade related emissions (about 37% in the U.S.). By linking transportation emissions to interstate trade, I identify responsibilities for interstate freight transportation emissions by state and by industry. Texas, California, Ohio, Florida, Washington, and Illinois are among the top in both inbound and outbound freight transportation emissions. After normalizing trade related emissions by state population, emissions-intensive states, e.g. Wyoming, North Dakota, and Nebraska, have the highest inbound and outbound transportation emissions per capita, besides Hawaii and Alaska. Industries with both large transportation emissions and sizeable shares of trade-related emissions from freight transportation are mining (except oil and gas), food and beverage and tobacco products, wood products, forestry, fishing, and related activities, and motor vehicles and parts.

Many states set up their own emissions-reduction goals. So, I decided to test the sensitivity of emissions if one state opted to implement carbon taxes while the rest did not. I selected Texas (big producer) and New York (big consumer) as candidates for my experiments. For a GHG net-exporting state, e.g. Texas, I found that a carbon tax of $50 per ton of CO_2 equivalent on production-based emissions would reduce emissions in both the taxing state (10.7 MMT, a reduction of 1.8% in the Texas) and the U.S. (12.5 MMT, a reduction of 0.26%) more so than would a similar consumption-based carbon tax (7.9 MMT, a reduction of 1.4% in the Texas and 11.7 MMT, a reduction of 0.24% in the U.S.), at least in the short-run. The opposite is true for a GHG net-importing state like New York. There GHG emissions decline 0.9 MMT (a reduction of 0.63%) in New York and 2.6 MMT (a reduction of 0.05%) in the U.S. for consumption-based carbon taxes vis-à-vis 0.8 MMT (a reduction of 0.6%) in New York and 1.1 MMT (a reduction of 0.02%) in the U.S. via the same production-based carbon tax. Impacts in states other than the taxing one are larger when their economic connections with the taxing state are stronger. The most affected states are those close to the taxing states (e.g. Arkansas and Oklahoma for the Texas carbon tax scenarios, New Jersey, and Pennsylvania for the New York carbon tax scenarios) as well as emissions-intensive states (e.g. Wyoming and North Dakota). Major trading-partner states also bear relatively large losses in GDP per capita: e.g. California and New York in the Texas production-based carbon tax scenario. But compared to state and total U.S. emissions (i.e. production-based, 580.6 MMT in Texas, 149.1 MMT in New York, and 4,843.2 MMT in the U.S.), the emission reductions are quite limited in the short-run when a state carbon tax of $50 per ton of CO_2 equivalent alone is introduced (with no technological change possible).

Moreover, I investigate whether fuel price increases (e.g., due to fuel taxes) could trigger significant mode shifts that might reduce emissions from interstate freight transportation. Results in Chapter 3 suggest that freight by truck accounts for the lion's share of interstate freight transportation emissions (about 70%). And it has the second highest emission factor after air transport. Thus, it would seem mode shifts away from truck and air would be an ideal strategy to reduce freight emissions. But results suggest that fuel price increases alone without changes in state supply and demand enable only limited emissions reductions via interstate freight movements. This is partially because shipments by truck do not necessarily decline as fuel prices rise. States may switch to suppliers in nearby states since travel costs among states change with fuel prices. This may introduce more shipments by truck. Thus, fuel taxes must be accompanied by other policy tools to achieve substantial reductions in transportation emissions.

5.2 Contribution

My contribution starts with the construction of a multiregional input-output (MRIO) model that covers all 50 states plus the District of Columbia. It is built on the most recent 2012 U.S. benchmark input-output (I-O) table with 405 industries (BEA, 2018a), which I update to 2016 using official interindustry flows in the U.S. (BEA, 2019a), state GDP, employment, wage, personal income and consumption expenditures data (BEA, 2019b; BLS, 2017b).

The MRIO model of recent vintage helps to reveal recent conditions with respect to state-level consumption-based GHG emissions. Not only is my model more recent than Caron et al.'s (2013, 2017) but it also has substantially more sectoral detail (403 versus 52). Since I-O models assume a given industry has the same production technology, my model's greater detail minimizes effects of potential aggregation bias that might be inherent to the work by Caron et al. (2013, 2017). For example, Caron et al. (2017) indicate that Texas has the highest consumption-based CO2 emissions per capita in the U.S. in 2006, while my model suggests Texas's consumption-based GHG emissions per capita is barely above the national average in 2016.

The MRIO framework enables state-level consumption-based accounting of GHG emissions. This approach can inform policy design of state or regional environmental policies that should consider both consumption and production responsibilities. Moreover, it provides a more comprehensive picture of "who pollutes for whom" among states. By linking GHG emissions with economic interconnections among states, the net impacts of regional climate and state economic policies is much clearer.

Regarding the close relationship between trade and freight transportation, the model enables me to allocate GHG emissions from interstate freight transportation—***the mobile source*** of emissions to industries among states. The magnitude of interstate freight transportation's contribution to trade-related emissions is elaborated in detail. My approach enables the exploration of alternative ways to control freight transportation emissions, such as state environmental policies that target supply chains of industries with top freight emissions.

After establishing the baseline of state consumption-based emissions and interstate freight emissions, I apply the model to examine how state GHG emissions might vary with potential state carbon taxes and how interstate freight emissions might change with fuel price increases (due to new fuel taxes). This research showcases how to evaluate the environmental and economic impacts of state/regional environmental policies. This is particularly important as the impacts of such subnational policies are not only in the home-state but also in other states and nationwide.

5.3 Recommendations

My first recommendation is to improve the state I-O tables by integrating state-specific economic data, such as international imports and exports by state, production technologies of key industries for each state as well as better government spending for each state (particularly at federal and state level) among others. Survey-based state I-O tables are now rare in the U.S. My state I-O tables rely heavily on the U.S. benchmark I-O table. This means assuming spatially constant production technology for a particular industry. This may bias estimates of state supplies and demands by industry. More information on state technology by industry would allow better estimates of state I-O tables.

Estimating interstate trade flow is another essential part in building MRIO models. Mine for 2016 are based on relationships inherent to the Freight Analysis Framework version 4 (FAF4) State Database for 2012 (BTS, 2016). Thus, my model assumes interstate trade patterns were unchanged from 2012 to 2016, which is unlikely to be the case, although variations between them might be small. So, it would be helpful to have more and up-to-date information on trade flows. When the 2017 Commodity Flow Survey data become available, the estimates of interstate trade flows can be updated to reflect more current trade patterns.

Third, modelers of state emissions need more information on state production-based GHG emissions by industry. My work suggests that differences in state consumption-based emissions are mainly due to the production locations of goods and services consumed. So, differential direct emission intensities by industry among states would clearly yield more precise estimates of state consumption-based emissions than those I employed based upon nationwide averages by industry. Note, however that I did use specialized information for energy use by electric utilities to better inform emissions in that industry. In that vein, a greater amount of state energy consumption information from the State Energy Data System (SEDS) (EIA, 2016a) could more fully inform state-specific emissions by industry.

For interstate freight emissions estimation, I have two recommendations: one on mode choice, the other on ton-mile emissions factor by mode. To improve mode choice estimates by industry among states, information on the interstate pipeline network, airport locations, and categories of waterways (shallow water or not) could be used to better inform the shipping distances by mode. In addition, other mode-specific variables, industry specific variables, and shipment specific variables could be added. In addition, instead of using one single ton-mile emission factor for each mode, a range of emission factors or different emission factors by shipping distance or freight path could improve freight emission estimates by mode.

To better evaluate the impacts of state environmental policies (e.g. carbon tax), improvements to the current model could include accounting for substitution among commodities as well as interstate substitution of the same commodities; using unique price elasticities of demand by industry by state, and allowing for changes in interstate trade patterns. Such improvements would enable better estimation of overall emission reductions due to state policies. For the analysis of fuel price scenarios, my assumption of fixed state supplies and demands in the face of changes in energy prices could be relaxed and, perhaps, enable more realistic simulations. Path capacity constraints of different freight transport modes (like northern-tier rail freight lines), especially those of environmentally friendly modes, should also be considered.

5.4 Policy Implications

My work has some important policy implications for achieving GHG emissions reduction goals. I suggest that U.S. states should consider both producer and consumer responsibilities when choosing environmental policies. There are several factors need to be considered for a state climate policy either targeting production- or consumption-based emissions, such as feasibility, emission reduction goals, economic impacts, and social impacts (Labandeira & Labeaga, 2002; Aldy, 2017). Net importing states of GHG emissions might prefer to regulate production-based emissions since they import more emissions as embodied in goods and services from other states. In contrast, net exporting states are more likely to adopt policies that apply to the consumption end to reduce the risk of their own GDP decline. As in my state carbon tax scenario analysis, although emission reductions are relatively smaller when GHG net-importing states regulate production-based emissions and net-exporting states regulate consumption-based emissions, the negative economic impacts (i.e. GDP loss, labor compensation decline, and employment loss) are lessened as well. However, due to the clear trade-offs between emission reductions and the structure and growth of a state's economy, other measures are needed to complement state environmental policies. For example, the revenues from state carbon taxes could be used to compensate households or subsidize key industries within the state or invest in cleaner technology innovations.

A core problem of policies that target consumption-based GHG emissions is the feasibility of their implementation. Unlike production-based emissions, which are generally quite readily measured where they are generated, estimating consumption-based emissions requires tracing consumed goods and services from their production point, something not typically performed for most commodities. If a new carbon tax directly applies to final consumers, it is difficult to collect taxes as emissions embodied in the same commodities could be different due to different places of origin within the U.S. and even overseas. Moreover, even it is possible to adopt consumption-based carbon tax, it may turn out to be regressive; that is, low-income households may suffer the burden of such tax (Haug et al., 2010). Such policy may not be welcomed by the public. Policies targeting production-based emissions also need to consider policy feasibility. For example, it is better to apply a production-based carbon tax to upstream fossil fuel suppliers or based on fossil fuel consumption to ensure broad coverage and reduce the costs of administration.

Although market-based climate policies (e.g. cap-and-trade program, carbon tax, emission trading system) are the most cost-efficient measures in reducing GHG emissions, such policies may lack public support as disadvantaged group might bear larger burden (Haug et al., 2010). Other state climate policies include investing in green technologies, energy efficiency, and renewable energy (e.g. wind, solar, biomass), phasing out emission-intensive manufacturers (e.g. coal-fired power generation), making comprehensive emission mitigation plans, etc. According to state consumption-based GHG emissions, states can design policies such as labeling green products to make people aware of the emissions embodied in their consumed goods and take actions correspondingly. States may also tax emission-intensive products.

Second, regional GHG policies should be developed via a collective of neighboring states and major trading partners. My findings suggest that such a strategy would be more effective than would the same policy implemented by a single state. This is due to the intensive economic exchanges among neighboring states and major trading partners. Neighboring states appear to bear substantial economic loss when an adjacent state adopts environmental policies, yet they are uncompensated for this, unlike the state invoking the policy. By collaborating, neighboring states and major trading partners (e.g. Texas, California, New York, and Florida) could achieve more ambitious emissions reduction goals and, perhaps, facilitate expansion of investments in more environmentally friendly production technologies. For example, the “Regional Greenhouse Gas Initiative” (RGGI, 2020) is a cap-and-trade program among northeastern states to reduce CO_2 emissions from the electric power industry. This program enables more investments in energy efficiency and renewable energy and creates green jobs in the participating states. To control interstate freight emissions, major trading partners could also collaborate to improve supply-chain efficiency in industries with high transportation emissions (e.g. energy goods, food and beverage and tobacco products, etc.).

Third, national environmental policies can cover all states (solve the incomplete coverage of state/regional policies) but may raise equity issues. For example, the GHG emissions intensities of consumption by state vary from 0.177 kg/$ (California) to 0.486 kg/$ (West Virginia) (results from Chapter 2). If the U.S. federal government opts to regulate GHG emissions via consumption-based accounting, states with higher-than-average emissions intensities of consumption will undoubtedly suffer more and, hence, object to the legislation. Although carbon taxes and cap-and-trade programs theoretically cost the same to achieve a given emissions-reduction objective, cap-and-trade program allows those industries that can most cost-efficiently reduce emissions sell credits to others. In this way, cap-and-trade program can alleviate some extra burden on emissions-intensive states. Federal environmental policies should consider the heterogeneity of state emissions intensities (either of production or consumption) and, so, provide incentives for firms in emissions-intensive states to mitigate emissions.

Regarding emissions by industry in each state, several industries contribute more than 80% of the total GHG emissions after accounting for emissions from their upstream supply chain: cement manufacturing, electric power, agriculture (e.g. beef cattle, farming, diary, grain, etc.) and energy goods (i.e. natural gas and coal). State carbon tax scenario analysis also shows that the largest GHG emission reductions concentrate in the electric power industry, farms, and truck transportation. These imply that industry-specific environmental policies should be implemented to efficiently achieve emissions reduction goals. For example, the Clean Power Plan and the RGGI are targeting the electric power industry; and fuel efficiency and GHG emission program for medium- and heavy-duty trucks are targeting truck transportation.

Above all else, my research suggests that in order to achieve substantial GHG emissions reductions, it is necessary to apply multiple policy tools simultaneously. My scenario analysis shows overall emissions reductions are limited via state carbon taxes alone and reductions of interstate freight emissions via fuel prices increase alone are even weaker. Thus, it appears that no single environmental policy is a panacea for mitigating climate change. Policies like carbon taxes need to be combined with industry-specific policies, subsidizing renewable energy, encouraging innovations in the green technologies, etc. To control freight emissions, increasing trucking efficiencies, using alternative fuels, and strategies to reduce travel demand must be combined.

5.5 Future Work

Interstate trade patterns play an essential role in the MRIO framework. However, with limited data of domestic freight movements, it is hard to verify the estimated interstate trade flows. Thus, future work should improve the gravity model or use other regression models for interstate trade flow estimation. More recent Commodity Flow Survey data should be used for model calibration. The robustness of the MRIO framework need to be tested.

Moreover, the U.S. MRIO model that I built could be connected to the world input-output models account for the international trade. This is very important as the U.S. economy relies heavily on imports: firms import intermediate inputs; households buy imported commodities. By linking a U.S. MRIO to a world model like that available through the World Input-Output Database (Timmer et al. 2015), impacts of international environmental policies or even climate policies of other regions/countries in U.S. states can be examined.

Another future line of research is to relax some assumptions in my scenario analysis. In order to provide more realistic estimates of the impacts due to a state carbon tax or a new fuel tax, computable general equilibrium (CGE) models could be used to account for the substitution effects, changes in state supply and demand, production technology improvements, changes in interstate trade patterns, and the application of tax revenues. With the MRIO framework, other scenarios can be analyzed to further explore the sensitivity of state GHG emissions, such as, reducing coal-fired electricity generation plants, improving energy efficiency for some industries, increasing usage of renewable energy, adopting autonomous driving technologies or electric trucks for truck transportation, etc. Evaluating various scenarios will provide greater insight into selecting environmental policy tools and enable a better understanding of the relationships between the economy and the environment.

Similar models can be developed and applied to other countries (particularly larger ones like Russia, Canada, China, Brazil, India) with substantial regional differences within the country. As the COVID pandemic strikes the world economy, this might be a good opportunity to reboot the economy in a more environmentally friendly way.

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Appendices

Appendix A Multinomial Logistic Regression Models for Freight Mode Share

Table A-1 Estimated Effects of Log-transformed Weight/Value Ratio, Log-transformed Shipping Distance, and Petroleum-related Products on Freight Mode Choice, Multinomial Logistic Regression Mode (s'_m), 2012 CFS

Freight Transportation Mode		B	Sig.	Exp(B)
	(Reference Category is Truck and Parcel)			
Rail	ln (Weight/Value Ratio)	0.852	0.000	2.345
	ln (Distance)	0.905	0.000	2.471
	Petroleum	1.103	0.000	3.013
	Intercept	-10.771	0.000	
Water	ln (Weight/Value Ratio)	0.559	0.000	1.748
	ln (Distance)	0.593	0.000	1.809
	Petroleum	1.522	0.000	4.581
	Intercept	-10.848	0.000	
Air	ln (Weight/Value Ratio)	-0.245	0.000	0.783
	ln (Distance)	0.687	0.000	1.988
	Petroleum	-4.223	0.000	0.015
	Intercept	-9.556	0.000	
N				4,347,692
Pseudo-R2				0.1281

Table A-2 Estimated Effects of Log-transformed Weight/Value Ratio, Log-transformed Shipping Distance, Petroleum-related Products, Log-transformed Trade Value and Fuel Costs of Shipping $1000 of Commodity on Freight Mode Choice, Multinomial Logistic Regression Model (s_m), FAF4 State Database

Freight Transportation Mode		B	Sig.	Exp(B)
	(Reference Category is Truck, Multiple Modes and Mail)			
Rail	ln (Weight/Value Ratio)	0.574	0.000	1.775
	ln (Distance)	0.490	0.000	1.633
	Petroleum	0.700	0.000	2.014
	ln (Trade Value)	0.375	0.000	1.455
	Fuel Costs of Shipping $1000 of Commodity	-3.99E-12	0.000	1.000
	Intercept	-11.708	0.000	
Water	ln (Weight/Value Ratio)	0.566	0.000	1.761
	ln (Distance)	0.918	0.000	2.505
	Petroleum	2.912	0.000	18.398
	ln (Trade Value)	0.363	0.000	1.437

	Fuel Costs of Shipping $1000 of Commodity	-1.34E-13	0.006	1.000
	Intercept	-17.459	0.000	
Air	ln (Weight/Value Ratio)	-0.138	0.000	0.871
	ln (Distance)	-0.126	0.000	0.882
	Petroleum	-2.604	0.000	0.074
	ln (Trade Value)	-0.067	0.000	0.935
	Fuel Costs of Shipping $1000 of Commodity	1.53E-14	0.024	1.000
	Intercept	-0.980	0.000	
Pipeline	ln (Weight/Value Ratio)	0.723	0.000	2.061
	ln (Distance)	-0.194	0.000	0.823
	Petroleum	6.000	0.000	403.394
	ln (Trade Value)	0.476	0.000	1.609
	Fuel Costs of Shipping $1000 of Commodity	-4.56E-09	0.341	1.000
	Intercept	-14.658	0.000	
N				360,013
Pseudo-R2				0.1740

Table A-3 Estimated Effects of Log-transformed Weight/Value Ratio, Log-transformed Shipping Distance, and Petroleum-related Products on Freight Mode Choice, Multinomial Logistic Regression Model (s'_{m}), FAF4 State Database

Freight Transportation Mode		B	Sig.	Exp(B)
(Reference Category is Truck, Multiple Modes and Mail)				
Rail	ln (Weight/Value Ratio)	0.128	0.000	1.137
	ln (Distance)	0.005	0.624	1.005
	Petroleum	0.625	0.000	1.869
	Fuel Costs of Shipping $1000 of Commodity	-1.26E-12	0.000	1.000
	Intercept	-2.829	0.000	
Water	ln (Weight/Value Ratio)	0.116	0.000	1.123
	ln (Distance)	0.400	0.000	1.492
	Petroleum	2.806	0.000	16.536
	Fuel Costs of Shipping $1000 of Commodity	8.96E-16	0.929	1.000
	Intercept	-8.516	0.000	
Air	ln (Weight/Value Ratio)	-0.144	0.000	0.866
	ln (Distance)	-0.073	0.000	0.930
	Petroleum	-2.395	0.000	0.091
	Fuel Costs of Shipping $1000 of Commodity	2.23E-14	0.001	1.000
	Intercept	-2.307	0.000	
Pipeline	ln (Weight/Value Ratio)	0.103	0.000	1.109

	ln (Distance)	-0.793	0.000	0.453
	Petroleum	6.121	0.000	455.283
	Fuel Costs of Shipping $1000 of Commodity	-9.50E-08	0.000	1.000
	Intercept	-3.288	0.000	
N				360,013
Pseudo-R2				0.1041