A Longitudinal U.S. State-Level Analysis of Organic Food Production and Greenhouse Gas Emissions

A Longitudinal U.S. State-Level Analysis of Organic Food Production and Greenhouse Gas Emissions

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Abstract

The question of whether organic farming is environmentally beneficial is not only contentious but also not well understood. Organic farming, which has been centered on the idea that increased soil health and vitality would result in more nutritious food and pest resistant crops, can also represent a significant means to tackle climate change. My research addresses the following question: Controlling for other sources of greenhouse gas (GHG) emissions, how do GHG emissions vary across U.S. states and over time with the proportion of total farmland devoted to organic cropland? This research question leads to three testable hypotheses. The first hypothesis, denoted as the Neutrality Hypothesis, posits that there exists no statistically significant relationship between organic cropland acreage and GHG emissions. The second hypothesis, denoted as the Mitigating Effect Hypothesis, is that increased organic cropland acreage is associated with lower GHG emissions. The final hypothesis, denoted as the Polluting Hypothesis, is that more organic cropland acreage is associated with higher GHG emissions. Most previous research has relied on lifecycle analysis (LCA) and has yielded estimation results that varied across products, product groups, locations, methodology, data, and even across studies assessing the same products. On the other hand, a recent study using multiple regression analysis presented questionable evidence contending a negative environmental impact for organic farming.

My research deviates from LCA by making use of U.S. state-level data over the 1997-2010 period excluding the years 1998, 1999, and 2009, multiple regression analysis, and a model consistent with the Stochastic Impacts by Regression on Population,

Affluence, and Technology approach. Overall, there is evidence supporting the Mitigating Effect Hypothesis. Indeed, after controlling for other sources of GHG emissions, a one percent growth in organic farming is estimated to lower GHG emissions by 0.06% across U.S. states. This suggests that at the current rate of growth in organic farming, GHG emissions could decrease by about 7.7% by 2030 and by 12.8% by 2050 relative to the current level of emissions. In addition, in an assessment of the interaction between organic farming and the transportation sector, I find that the effect of organic farming on CH_4 and N_2O emissions depends on a state's transportation output share (% of total state GDP). More specifically, at the current levels of transportation output, growth in organic farming is expected to mitigate CH_4 and N_2O emissions across most U.S. states. This would suggest that the environmental harm that transportation output contributes to organic food production might be too negligible to outweigh the environmental benefits of organic farming practices. A cluster analysis confirms these findings by showing that the environmental impact of organic farming is below the country average for most U.S. states and across three measures of emissions.

Although organic farming practices are already environmentally beneficial, further improvements can be achieved through the adoption of regenerative organic farming and by replacing the current competitive environment between conventional and organic farming with a more symbiotic coexistence. The current study reveals GHG mitigation benefits associated with organic food production. Policymakers and scientists can build on these results to further develop the evidence base and policies needed to maximize the benefits of adopting organic farming practices.

Acknowledgments

My interactions with classmates and faculty members have played a paramount role in making my experience at Harvard rewarding and intellectually stimulating. My success in the Sustainability and Environmental Management program would not have been possible without the support of my family to whom I am extremely grateful. My sincere gratitude also goes to Mark Leighton and Gary Adamkiewicz whose constructive suggestions and comments have tremendously improved this thesis.

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Chapter I

Introduction

Although organic farming practices date back to the Neolithic era, Lord Northbourne is credited for having been the first person to use the term “organic” to describe the alternative farming process currently practiced worldwide (Paull, 2014). In his book *Look to the Land,* Northbourne (2003) warned that the reliance on synthetic fertilizers and pesticides deprived farms of “biological completeness” (p. 96). Northbourne’s holistic view was that a farm had to be treated as a living organism where the soil, microorganisms, insects, and plants were naturally symbiotic. He encouraged the use of biodynamic practices in organic farming based on the work of Rudolf Steiner (2004), which involved a focus on revitalizing soil health and fertility.

To this day, organic farming has been centered on the idea that increased soil health and vitality would result in more nutritious food and pest resistant crops (Kuepper, 2010). Current thinking has further evolved to posit that in addition to better nutrition and pest resistance the adoption of organic farming practices worldwide can be a significant means to tackle climate change. Indeed, such practices are estimated to have the potential to sequester up to one third of current anthropogenic emissions (Jordan, Müller, & Oudes, 2009). Organic agriculture owes this ability to its reliance on natural ecological processes in land, soil, and crop management in lieu of synthetic inputs. As a result, soils that are managed using organic practices are not only healthier but also more resilient to extreme weather events (Niggli, Fließbac, Hepperly, & Scialabba, 2009).

With the agricultural sector accounting for about 24% of global carbon emissions

(IPCC, 2015), it represents the single most promising carbon mitigator and a potentially significant net carbon sink (Bellarby, Foereid, Hastings, & Smith, 2008). In fact, the annual mitigation potential for agriculture has been estimated at 6 Gt of CO2-eq, with soil carbon sequestration contributing about 89% to this potential (Bellarby et al., 2008). According to some estimates, the economic value of ecosystem services in organic farming can range from $1,610 to $19,420 per hectare (ha) per year versus $1,270 to $14,570 in conventional farming (Sandhu, Wratten, Cullen, & Case, 2008). In addition, non-market ecosystem services in organic farming can range from $460 to $5,240 per ha per year versus $50 to $1,240 in conventional farming (Sandhu et al., 2008).

Surprisingly, despite increasing consumer interest in organic foods, proponents of organic food production have been labeled as "activists" (Paarlberg, 2013), and by implication, anti-science and devoid of objectivity. Previous research has contributed to this categorization by providing largely mixed results about the environmental impact of organic farming, with some reporting a positive association (e.g. Wood, Lenzen, Dey, & Lundie, 2006) and others reporting a negative association (e.g. Cooper, Butler, & Leifert, 2011) or no significant difference across organic and conventional sites (e.g. Syvasalo, Regina, Turtola, Lemola, & Esala, 2006). Admittedly, there are concerns that the increase in land use arising from a larger organic farming sector could increase carbon emissions and reduce global carbon sequestration capacity. Combined with the concerns about climate change and the environmental implications of food production, there is an urgent need to more thoroughly understand organic food production's association with GHG emissions.

Most previous research addressing this relationship has relied on site-specific methods contrasting emissions across organic and conventional sites. For instance, lifecycle analysis (LCA) is a common tool used to assess the environmental impact of farming. LCA uses a “ground-up” approach, which considers the impacts of individual stages of a product’s lifecycle. Estimates based on LCA are typically derived through assumptive processes, which can involve the use of different data sources and underlying assumptions about energy consumption across studies, especially those analyzing the same products (Ayres, 1995). LCA research often lacks generalizability and yields estimates that vary depending on products, product groups, geography, methodology, and data. Multiple regression is another method that has been used to assess the environmental impact of organic food production. However, it is limited to a study by McGee (2015), which made use of U.S. state level data but suffered from significant weaknesses that cast doubt on the reliability of its results.

Research Significance and Goals

My research deviates from LCA by applying a “top-down” approach similar to McGee’s (2015) in the assessment of the environmental impact of organic food production. More specifically, rather than focus on specific sites, my research aims to assess organic food production and greenhouse gas emissions at the aggregate level. The benefit of this approach lies in the ability to derive estimates measuring the proportionate change in greenhouse gas emissions arising from a change in organic food production at the state level. These estimates essentially measure the net state-level environmental impact of organic food production. As a result, they allay concerns about lack of generalizability arising from idiosyncratic differences across sites. In addition, by using appropriate data and an empirical model grounded in a well-established theoretical literature, I expect to effectively address McGee's weaknesses. This research should be of interest to scientists, policymakers, and activists alike, and could have significant policy implications. They should also provide the necessary foundation for future research on the environmental impact of organic food production.

Background

The Organic Foods Production Act of 1990 introduced the United States Department of Agriculture's (USDA) National Organic Program (NOP) to provide systematic oversight of organic certification of food production in the United States (Kuepper, 2010). The NOP is designed to prevent producers from claiming that their food is organic unless they have satisfied the standards set by the law. Broadly speaking, producers are not permitted to use any substances prohibited by the NOP in their land for at least three years before their first organic harvest. They are also required to manage soil health through tillage, crop rotations, cover crops, composting, and animal waste. Furthermore, pest control and weed management are primarily handled using biological and manual practices and in exceptional cases using approved synthetic substances (Kuepper, 2010).

The organic farming sector in the United States grew from 1.77 million acres in 2000 to 5.3 million acres in 2011 (USDA, 2013) and from $3.6 billion in sales in 1997 to $43.3 billion in 2015 (Organic Trade Association, 2016). This substantial growth puts the annual compound growth rate for acreage at about 9.5% and that for sales at about 15%. However, in 2014, average organic cropland in the United States represented less than

1% of total state farmland despite organic food sales making up about 5% of total food sales (Organic Trade Association, 2016). Figure 1 shows that average state-level organic cropland barely represented 0.54% of total state farmland in 2010, up from about 0.19% in 2000. As for organic sales, as shown in Figure 2, they were slightly below 9% of total farming sales in Vermont in 2007, representing the country's largest share. Organic sales in other states were below 3.5%, with the vast majority falling below 1%.

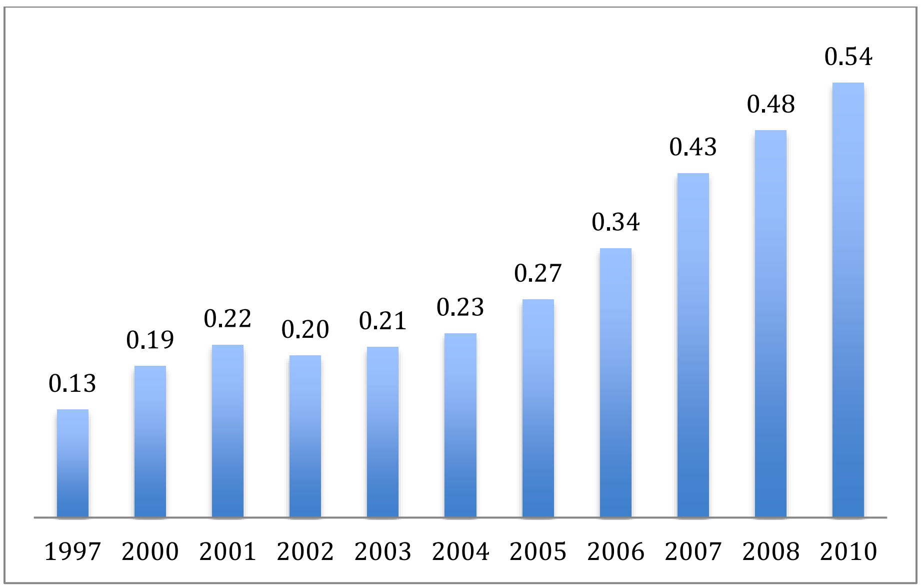

Figure 1. Average state-level organic cropland acreage (% of total farmland) (Data Source: USDA).

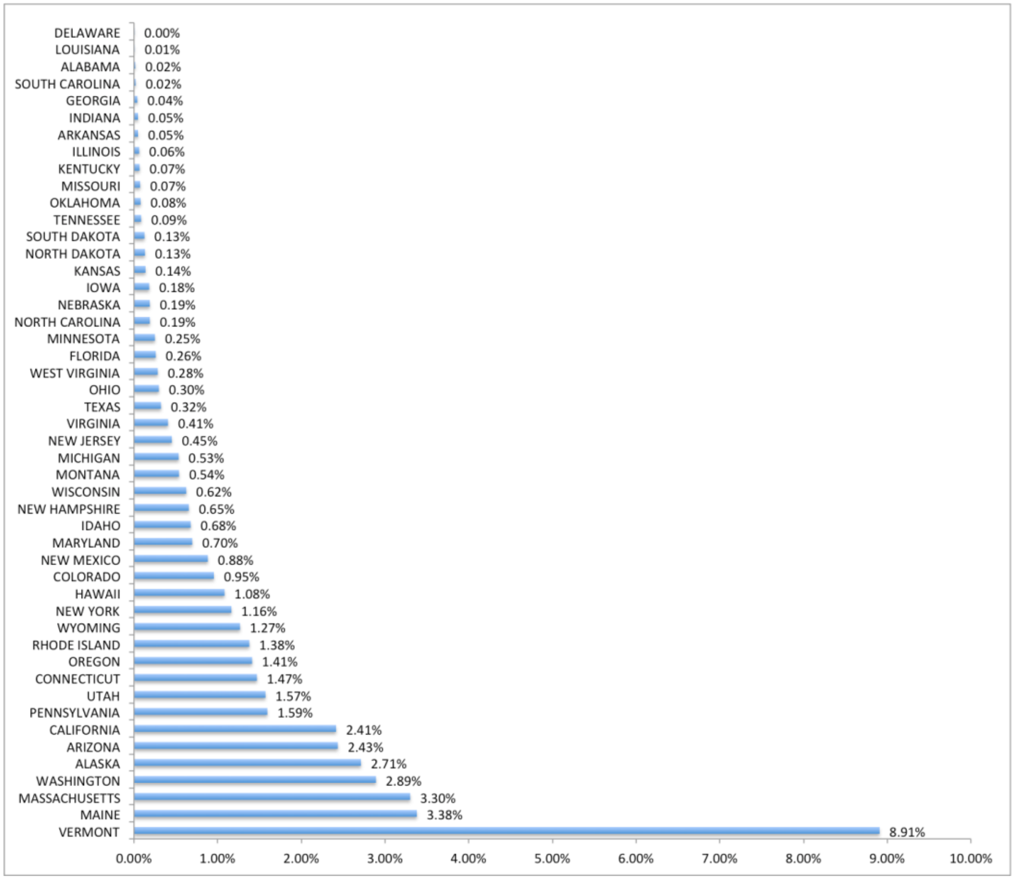

Figure 2. Organic farming sales (% of total state farming sales), 2007 (Data Source: USDA).

Environmental Impact of Agriculture

Food production can contribute to GHG emissions in a number of ways. Figure 3 shows a simplified systems diagram that summarizes the various channels through which food production can affect GHG emissions, amongst others. The most important environmental concerns that food production raises are soil erosion and the spillover of fertilizers and pesticides onto third parties (Papendick, Elliott, & Dahlgren, 1986). Soil erosion can adversely affect plant growth by depriving land of organic matter and associated nutrients. As a result, farmers usually resort to synthetic fertilizers to maintain soil productivity. These in turn release nitrogen in the atmosphere and increase nitrate runoff into streams, rivers, and groundwater reserves. It is estimated that emissions from agricultural soil management make up about 5% of total emissions and about 61% of agricultural emissions (Takle & Hofstrand, 2008).

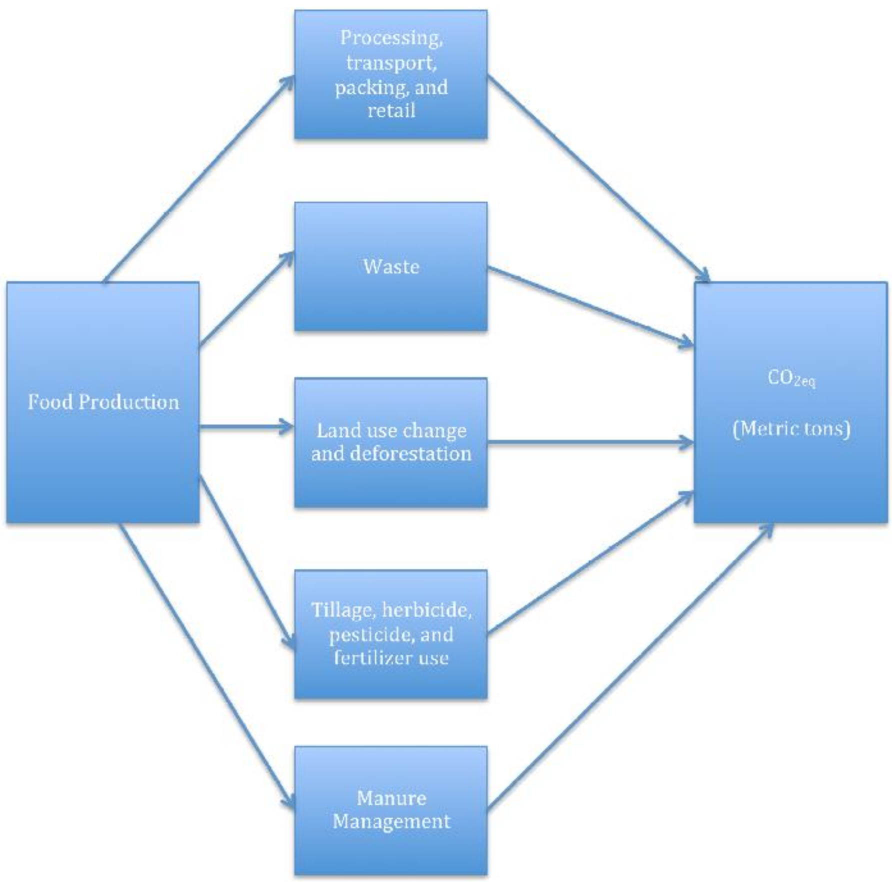

Figure 3. Simplified systems diagram of how food production contributes to GHG emissions.

Farms involved in manure management whether as a by-product of raising cattle for meat production or for use as fertilizers also contribute to GHG emissions. Methane emissions are released through enteric fermentation of ruminant animals and anaerobic decomposition from manure storage. It is estimated that emissions from these sources make up about 2.2% of total emissions and about 27% of agricultural emissions (Takle & Hofstrand, 2008).

The consumption of fossil fuel also contributes to carbon emissions. These emissions arise from transportation and energy use throughout all stages of production including the use of on-farm equipment for the provision of inputs, irrigation, application of fertilizer and pesticides, harvesting, processing, and packing. Additional carbon is also emitted during the transportation of the final products to their wholesale and retail destinations. Emissions from fossil fuel consumption in agriculture are estimated to make up 0.6% of total emissions and about 7% of agricultural emissions (Takle & Hofstrand, 2008).

Food production undoubtedly results in deforestation and increased land use especially to meet the ever-increasing demand for food. Such changes deprive our environment of the important ecosystem services that forests provide. Soil tillage, which is often combined with herbicides to rid land of weeds and to prepare the soil for planting, also releases previously sequestered carbon into the atmosphere. Emissions arising from agriculture represent about 8.2% of total emissions and forests are estimated to sequester the equivalent of about 9.6% of total carbon emissions (Takle & Hofstrand, 2008). This suggests that forests can result in a net carbon reduction. In addition, agricultural soils are estimated to sequester the equivalent of about 0.4% of total emissions (Takle & Hofstrand, 2008). It is worth noting that the carbon mitigation potential of soils can be substantial depending on agricultural practices such as restoration and reclamation of degraded soils, tillage, and crop residue management, amongst others. Indeed, the annual carbon sequestration potential for soils in the United States is estimated to range between

144 Tg and 432 Tg (equivalent to a range of 0.52 to 1.58 Gt of CO_2-eq) over a 30-year period compared to the current sequestration rate of barely 17 Tg (Lal, Follett, & Kimble, 2003). Globally, the annual sequestration potential can reach up to 6 Gt of CO_2-eq (Smith et al., 2008).

Agricultural waste is not limited to food but also includes hazardous solid waste, such as nitrogen, biological pathogens, additives, metals, and salts, amongst others (Loehr, 1978). While these undoubtedly have major public health and environmental implications, food wastage remains a major concern. In fact, it is estimated that about one third of all food produced for human consumption is wasted or lost throughout various stages of the food supply chain (Food and Agriculture Organization of the United Nations, 2013). The carbon footprint of food wastage after accounting for land use changes is estimated at 3.3 gigatonnes of CO_2e (Food and Agriculture Organization of the United Nations, 2013), which is equivalent to about one third of global emissions from fossil fuels (Boden, Marland, & Andres, 2015).

Organic farming practices can mitigate GHG emissions in a number of ways. First, the fact that they limit the application of synthetic fertilizers, herbicides, pesticides, and fungicides and their high embodied energy can potentially reduce GHG emissions and the runoff of nitrate and toxic chemicals. It is estimated that the total energy needs covering all stages of the lifecycles of nitrogen, phosphorous, and potash exceed 90 GJ per metric ton (Bhat, English, Turhollow, & Nyangito, 1994). On the other hand, the total energy needs for the production of the active ingredients used for major U.S. herbicides, pesticides, and fungicides are estimated to exceed 816 GJ per metric ton (Bhat et al., 1994). Second, reduced water runoff and evaporation could decrease water use and energy needs for irrigation. In fact, based on farming trials across various countries, organic farms are estimated to use 45% less energy than their conventional counterparts (Rodale Institute, 2014). In these trials, organic farming is also found to produce fewer GHG emissions and to perform better in years of drought than its conventional counterpart.

The fact that organic farming already makes use of cover crops, crop rotations, and compost can play an important role in maintaining optimal soil health, increasing carbon sequestration, and reducing GHG emissions. Cover crops can limit competition for nutrients with weeds and reduce water runoff and evaporation. They also represent a nitrogen sink especially for subsequent crops (Hartwig & Ammon, 2002). As for crop rotation, it can increase groundwater storage (Dakhlalla, Parajuli, Ouyang, & Schmitz, 2016), enhance microbial richness and diversity (Venter, Jacobs, & Hawkins, 2016), and result in lower N_2O emissions (Petersen et al., 2006). Finally, organic farming can eliminate emissions from waste by converting organic waste into compost for use as fertilizer. However, special attention should be given to bulking agents as in their absence composting may contribute more significantly to climate change than do other direct sources of GHG emissions (Bong et al., 2016).

Previous Evidence on the Environmental Impact of Organic Food Production

Previous assessments of the environmental impact of organic food production have yielded mixed results largely due to high variability in LCA research across products, product groups, geography, and sometimes even across studies of the same product or product group. The following represent examples of relevant previous research.

In a study using LCA based on an input-output framework differences in environmental impact were estimated across organic and conventional farming sites in Australia (Wood et al., 2006). The study found that direct energy use, energy related emissions, and greenhouse gas emissions were higher in the organic site, but argued that accounting for indirect contributions, emissions could be higher in the conventional site. While using an input-output framework can enhance completeness and specificity, it suffers from a number of limitations. The most important is the fact that the parameters determining the technical requirements across input and output sectors are assumed to be constant over time and across products and product groups. In other words, estimates typically rely on the expectation that no changes in technology, relative prices, and trade patterns that can alter the mix of inputs used across sectors have occurred over time.

Another study made use of a randomized block design in three farming systems in Western Finland (Syvasalo et al., 2006). GHG fluxes and nitrogen leaching and concentration were compared in grass production and livestock raising across organic and conventional production systems and were measured in cereal production without livestock under conventional production. There was no statistically significant difference in measured GHG emissions between organic and conventional plots. In contrast, however, Cooper et al. (2011) used LCA but found emissions to be much larger per hectare in conventional farms. Moreover, after accounting for on-site bio-energy generation in conventional farms, emissions from farming operations were offset by energy production, whereas accounting for pyrolysis of crop remains in organic farms resulted in negative net emissions.

In a meta-analysis of 71 studies covering 170 cases, the environmental impact of organic farming was assessed relative to conventional farming (Tuomisto, Hodge, Riordan, & Macdonald, 2012). The study found soil organic matter to be 7% higher in organic farms and estimated nitrogen leaching in organic farms to be 31% lower per unit of area but 49% higher per unit of product. The analysis associated the lower nitrogen level to fewer nitrogen input applications and the higher nitrogen level to a mismatch between nitrogen availability and a crop's nitrogen intake. It also posited that lower nitrogen leaching per unit of product arose from the use of cover crops in organic farming. The study also found that organic farms used 21% less energy. However, differences in greenhouse gas emissions between conventional and organic farms seemed to vary across product groups. For instance, emissions in organic farms were lower for the production of olives, beef, and some crops but were higher for milk, cereals, and pork.

In 2009, the International Federation of Organic Agriculture Movement (IFOAM) compiled case studies contrasting organic farming with its conventional counterpart across a number of countries, of which the most notable were the United States, The Netherlands, Egypt, and Switzerland. The American case was based on Rodale Institute's farming trials, which assessed energy use, carbon sequestration, and yields in the production of corn, wheat, and soybeans. The conventionally managed system was estimated to use 30% more energy than its organic counterpart (IFOAM, 2009). The annual carbon sequestration potential for the organic system was estimated to reach 2.3 metric tons per hectare and organic yields were found to be 28 to 34% higher especially during dry and wet seasons.

A similar farming trial spanning over 21 years was conducted in Switzerland. The trial was referred to as the DOK (bio-Dynamic, bio-Organic, and Konventionell) system comparison trial, which compared soil fertility, nutrient input, energy input, and yields across organic and conventional farming systems. These systems were for the production of grass-clover, potatoes, and winter wheat. The results of the DOK trial were covered by a number of studies (Mäder et al., 2002; Fließbach, Oberholzer, Gunst, & Mäder, 2007; Leifeld, Reiser, & Oberholzer, 2009). In particular, Mäder et al. (2002) estimated that the organic system required 34 to 51% less nutrient input and 20 to 56% less energy input than the conventional system. Yields, on the other hand, were found to be lower in the organic system across all analyzed crops.

The Dutch case was based on a meta-analysis contrasting GHG emissions in organic and conventional dairy farms across the Netherlands (Bos, De Haan, & Sukkel, 2007). It estimated organic dairy farms to emit between 11 and 17 metric tons of CO_2 equivalent (MTCE) per hectare and between 1.31 and 1.46 MTCE per 1,000 kg of milk versus between 14.5 and 34 MTCE per hectare and between 1.45 and 1.65 MTCE per 1,000 kg of milk in their conventional counterparts. The lower emissions in the organic dairy farms were attributed to the absence of chemical fertilizers, less reliance on concentrate feed, and increased grazing. In particular, grazing during up to ten months of the year was expected to contribute to carbon sequestration by continuously adding organic matter to the soil. In fact, organic dairy farms were estimated to sequester annually 0.4 metric tons of carbon per hectare.

The Egyptian case focused on the effectiveness of composting in improving the carbon content of reclaimed desert soils (Luske and van der Kamp, 2009). The compost applied to the trial farms consisted of chicken and cow manure, rice straw, and green waste procured locally. Over a 30-year period, the per-hectare soil carbon stock increased from 3.9 metric tons to 30.3 metric tons, resulting in an annual increase of 0.85 metric tons per hectare.

In one of the most comprehensive studies to date, a meta-analysis of 107 studies published between 1977 and 2012 assessed the environmental impact of organic farming (Lee, Choe, & Park, 2015). The study found that the effect of organic farming on energy intensity varied depending on data source, sample size, and farm products, whereas the effect on greenhouse gas emissions varied depending on farm products, cropping patterns (i.e. monocropping versus multicropping), and measurement unit (i.e. emissions per area versus per unit).

Of particular relevance to my research, McGee (2015) examined the relationship between organic farming acreage and agricultural emissions using multiple regression analysis. He found that organic farming at the U.S. state level was associated with higher greenhouse gas emissions. The author relied on data from the World Resources Institute, which disaggregates state emissions into specific sectors. In particular, emissions from the agricultural sector are constructed using data from the USDA, Commercial Fertilizers report, and the Fertilizer Institute (WRI, 2015). He also used data from the USDA on total farmland and organic cropland acreage. However, the fact that environmental emissions data and acreage are at least in part from the same source raises important concerns. More specifically, the data used for the response variable (emissions) are by construction similar to those for the key predictor variables (total farmland and organic cropland acreage). This is especially problematic for total farmland acreage, which is likely highly correlated with agricultural emissions. It is evident that increased farmland acreage will inevitably result in an increase in the use of pesticides, fertilizers, herbicides, and fungicides, which in turn will increase GHG emissions. Indeed, based on the same data that McGee used for his analysis, correlation between these total farmland and agricultural emissions is estimated at 0.75 versus 0.55 when using total GHG emissions. On the other hand, correlation between agricultural emissions and organic cropland acreage is estimated at 0.47 versus 0.21 when using total GHG emissions. Thus, positive association between organic farming acreage and emissions is not surprising when both variables are highly collinear.

Another surprising dimension in McGee's analysis is the contention that organic farming practices harm the environment is connected to what he dubbed as the "displacement paradox theory." The basic idea of this theory is that an expansion of organic farming practices, which are largely viewed as sustainable, does not necessarily result in the displacement of conventional farming practices. Rather, market forces are believed to create the necessary conditions for the addition of organic food products to existing markets. In other words, consumers of organic products would essentially represent new demand, with no noticeable impact on the demand for conventionally produced products. McGee (2015) also added that higher emissions were likely caused by lax USDA organic production standards and the corporatization and scaling of organic farming operations especially to compensate for lower yields under organic production. These conclusions, however, ignored not only the fact that yields in organic farming are not always lower than those in conventional farming but also the existing evidence supporting lower energy use and higher carbon sequestration by organic farming. More importantly, the author failed to substantiate his contentions with supportive evidence of any sort.

In sum, site specificity in previous research introduces variability in environmental impact estimates across products, product groups, and geography. In addition, the subjectivity in data selection and assumptions about energy consumption limit the generalizability of the results.

Research Question and Hypotheses

My research addresses the following question: Controlling for other sources of GHG emissions, how do GHG emissions vary across U.S. states and over time with the proportion of total farmland devoted to organic cropland? This research question leads to three testable hypotheses. The first hypothesis, denoted as the Neutrality Hypothesis, posits that there exists no statistically significant relationship between organic cropland acreage and GHG emissions. The second hypothesis, denoted as the Mitigating Effect Hypothesis, is that organic cropland acreage is associated with lower GHG emissions. The final hypothesis, denoted as the Polluting Hypothesis, is that organic cropland acreage is associated with higher GHG emissions.

Chapter II

Methods

The broad nature of the research question described in the previous chapter necessitates addressing the relationship between organic food production and GHG emissions from an aggregate perspective. Rather than focus on specific sites, which would yield results that are not necessarily generalizable to the state or country level, this analysis focuses on state-level indicators. As a result and contrary to LCA research, which relies on primary data collected from selected sites, I make use of state-level secondary data. Using secondary data has a number of advantages. First, such data are usually publicly available and free of charge. Second, easy and free access to data allows the replication and extension of my research by other researchers. Third, the available data come from well-known and reliable sources. In what follows, I describe the data used to assess the relationship between organic food production and GHG emissions in addition to the empirical framework.

Data

This research makes use of U.S. state-level data over the 1997-2010 period, excluding years 1998, 1999, and 2009, which are missing from USDA data. All other datasets cover the 1997-2010 period. Environmental data come from CAIT-US, a database developed by the World Resources Institute (WRI), which consists of state-level emissions of the six major greenhouse gases. The data used in this research is limited to total greenhouse gas (GHG) emissions, methane (CH_4), and nitrous oxide (N_2O) emissions, all measured in metric tons of CO_2 equivalent. The first set of data consists of total GHG emissions including land-use change and forestry (LUCF), which represents net emissions/removals attributable to forest and land use changes. Such data essentially account for the role that deforestation, reforestation, and land use changes play as sources of carbon emissions or as carbon sinks. The remaining data consist of CH_4 and N_2O emissions, respectively. Data for CO_2 emissions are available but are excluded from the analysis due to high correlation with total GHG emissions ($r = 0.92$). Indeed, CO_2 emissions represent the largest share of GHG emissions. As a result, environmental impact estimates using total GHG emissions will closely match those using CO_2 emissions.

CAIT-US reports emissions across various energy sectors, namely residential, commercial, industrial, transportation, fugitive emissions, industrial processes, agriculture, and waste (WRI, 2015). In addition, it also reports fuel use during cross-border transportation as well as changes in emissions related to land use changes and forestry (LUCF). CAIT-US data are developed based on the State Inventory Tool (SIT) of the Environmental Protection Agency (EPA), which represents an interactive spreadsheet model that helps develop state-level GHG inventories. The SIT default data consists primarily of data collected by federal agencies such as the EPA, the Energy Information Administration (EIA), Federal Highway Administration (FHA), Mineral Management Services (MMS), the USDA, and the U.S. Geological Survey (USGS) as well as other sources such as the Fertilizer Institute (WRI, 2015). For instance, the agricultural component of GHG emissions is estimated using data from the USDA, Commercial Fertilizers Report, and the Fertilizer Institute, whereas LUCF is estimated based on data from the EPA and USGS (WRI, 2015). While the SIT is also designed to allow for the provision of potentially more reliable data by state agencies, CAIT-US only makes use of SIT's default data. According to WRI (2015), CAIT-US follows this approach to ensure a reasonable degree of consistency across states.

There are evidently uncertainties about CAIT-US as would normally be the case for databases estimating hard-to-measure variables. Relying exclusively on SIT default data raises a number of concerns. First, the provision of potentially more reliable activity data supplied by individual states may cast doubt on the reliability of EPA's data. Second, simplifying assumptions in the EPA's methodology introduces further uncertainties. For instance, the SIT assumes that landfills across all locations have the same type of waste, which is inconsistent with reality. Third, estimates produced by CAIT-US suffer from data omissions. In particular, CAIT-US excludes CH_4 emissions arising from activities related to oil and natural gas, emissions from the production of nitric acid, adipic acid, HFCF-22, and various minerals, and emissions from industrial wastewater (WRI, 2015).

Data for per capita GDP (in chained 2009 dollars), real utilities output (percent of state GDP), real manufacturing output (percent of state GDP), and real oil and natural gas output (percent of state GDP) are from the Bureau of Economic Analysis. Data for vehicle miles traveled (VMT) are from the U.S. Department of Transportation's Federal Highway Administration. Finally, data on state organic cropland, organic pasture, and total farmland acreage are from the USDA's Economic Research Service.

Using state-level data has important advantages. Such data are from the same sources and ensure a reasonable degree of consistency, accuracy, and reliability.

Moreover, U.S. states have a common language and similar social norms and must comply with common federal laws, thus reducing potential unobserved heterogeneity. Of course, unobserved heterogeneity across states arising from demographic, geographic, natural resource, and regulatory idiosyncrasies, amongst others, can raise important concerns. Such concerns are undoubtedly legitimate and are addressed next.

Preliminary Analysis of the Data

Table 7 in the appendix provides summary statistics of the main variables used in this analysis. Although most variables have 550 longitudinal observations, there are some that suffer from missing observations, thus reducing the sample size to as low as 421 observations. Broadly speaking, the between and within standard deviations (SD) appear to vary for each of the listed variables. This suggests that the variation in these variables across states differs greatly from that observed within a state over time. In other words, the variables of interest are driven by variation across states and across time. It is also important to note that data for GHG and CH_4 emissions may take negative values for some states, such as Idaho, Montana, Oregon, and Vermont for total GHG and New Hampshire for CH_4. For instance, in New Hampshire the reduction of CH_4 emissions from the conversion of landfill gas to energy may outweigh emissions arising from other sources. Indeed, the agricultural sector in New Hampshire, which is generally a major source of CH_4 emissions, represented barely 0.09% of the state's economy in 2011 (BEA, 2016). Thus, to avoid problems in log transformation, a value of 20 metric tons of CO_2 equivalent is added to each GHG observation, whereas a value of 5 metric tons of CO_2

equivalent is added to each CH_4 observation. The values presented in Table 7 reflect these adjustments.

In a preliminary assessment of the association between organic food production and environmental emissions, Figure 4 plots the relationship between organic cropland share and log total GHG emissions based on mean values over the 1997, 2000-2008, and 2010 periods. While the fitted regression line shows a negative relationship, it appears to be heavily influenced by observations from the state of Vermont. To verify this contention and identify potential influential observations, I derive median and median average deviation (MAD) values for each state. This approach is superior to using the standard deviation around the mean, which is known to be sensitive to outliers (Leys, Ley, Klein, Bernard, & Licata, 2013). To be consistent with previous research (e.g. Leys et al., 2013), I use the following moderately conservative decision criterion:

$$\frac{x_i - Median}{MAD} > |\pm 2.5|$$

which suggests that observations for which the deviation from the median exceeds 2.5 times the median average deviation should be considered for potential exclusion from the analysis. Table 1 provides a snapshot of the states for which corresponding values are relatively high. There are at least six states that meet the decision criterion and that could be considered outliers. These states are Vermont, Maine, New York, California, Idaho, and Wisconsin. Indeed, this finding appears to be consistent with Figure 4, which distinctively shows observations for these states farther from the origin and from the observable cluster of other states. As for the remaining states, with the exception of New Hampshire, none meet the decision criterion. Although New Hampshire's decision criterion value is equal to 2.5, it does not appear to be influential enough to be excluded.

Table 1. Decision criterion values for identifying outliers.

State	**|(xi - Median)/MAD|**
VT	25.59447
ME	11.6047
NY	6.791471
CA	6.624961
ID	4.878464
WI	4.380838
NH	2.50074
MI	2.455881
MN	2.194822

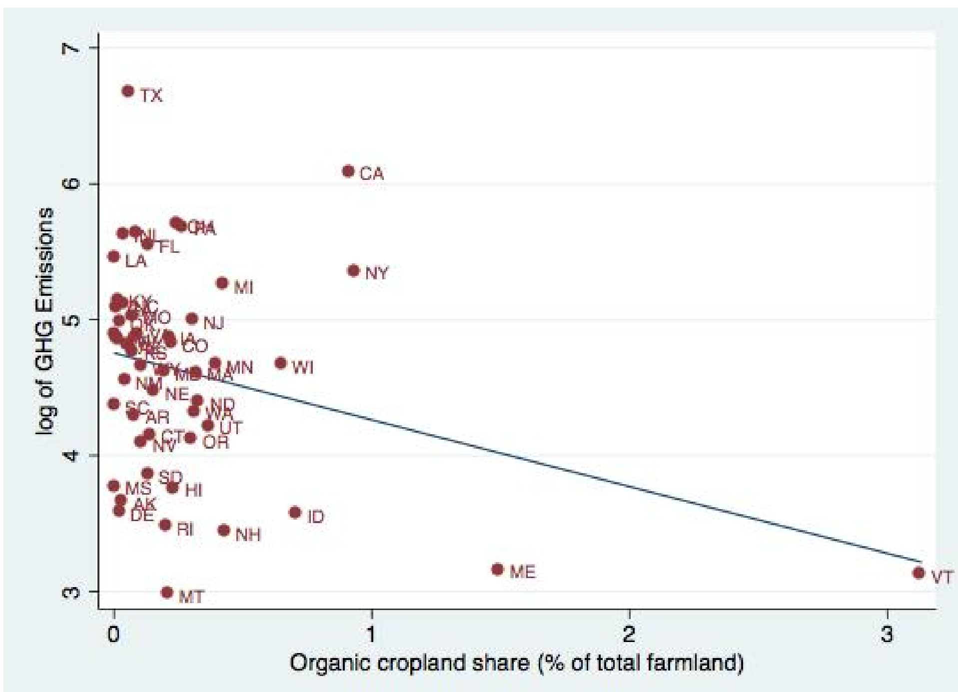

Figure 4. Scatter plot of the relationship between organic cropland share and GHG emissions (mean over 1997, 2000-2008, and 2010 years).

Figure 5 helps explore the change in the fitted regression line after excluding the six states identified as outliers. While the relationship between organic cropland share and GHG emissions appears to remain negative, its corresponding fitted line is less steep suggesting that the excluded states may have previously heavily influenced the relationship. It is important to note, however, that although the relationship between organic cropland share and GHG emissions appears to be negative, the scatter plot is bivariate and ignores other sources of emissions that may interact with organic cropland share and other variables in explaining GHG emissions.

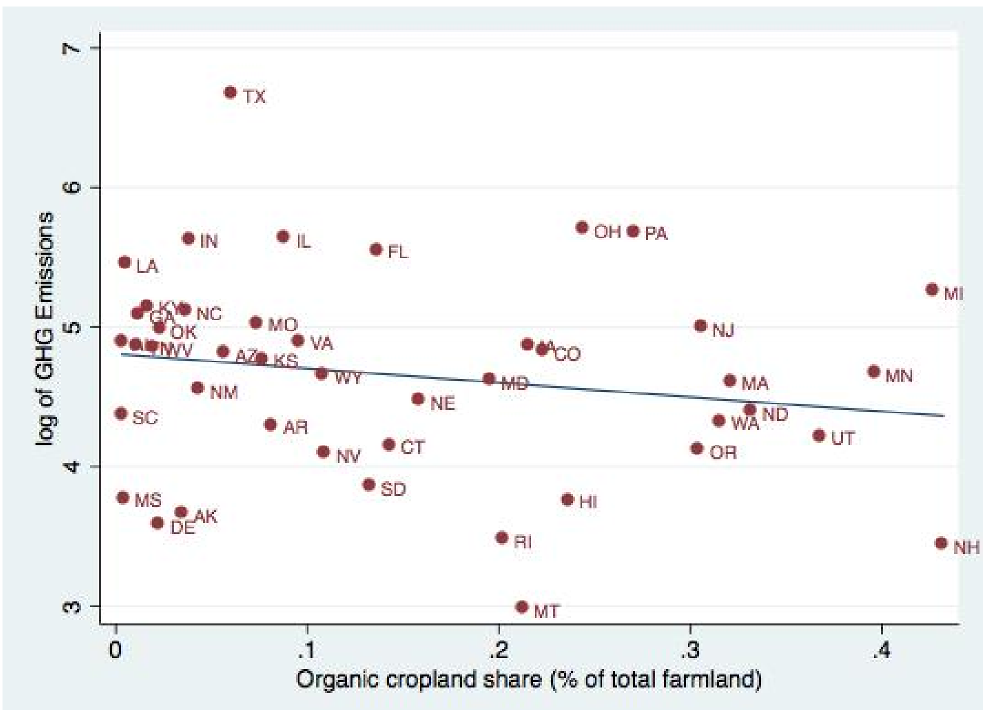

Figure 5. Scatter plot of the relationship between organic cropland share and GHG emissions without outliers (mean over 1997, 2000-2008, and 2010 years).

Statistical Methods

In order to assess the relationship between organic farming and GHG emissions, I develop a set of models based on the extensive literature on the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) approach (e.g. Dietz

& Rosa, 1994; Cole & Neumayer, 2004; Squalli, 2009, 2010, 2014). The STIRPAT approach sets up the framework for analyzing the various factors contributing to environmental impact and is particularly useful in estimating ecological elasticities, which measure the responsiveness of emissions to changes in certain explanatory variables. The STIRPAT approach is based on the IPAT mathematical identity, which posits that I = PAT. The STIRPAT equation can be generally expressed as:

$$I_{it} = aP_{it}^{b}A_{it}^{c}T_{it}^{d}$$

where environmental impact (I) in state *i* during period *t* is a function of population (P), affluence (A), and technology (T). Given that per capita GDP is generally a proxy for affluence, the product of population and affluence is such that $P \times A = GDP$. Thus, the technology component can be written as $T = I/GDP$, which represents impact per unit of GDP. Although the technology component is typically captured by the error term, it can be disaggregated into impact components (York, Rosa, & Dietz, 2003), an approach that I pursued in this thesis. It is worth noting that the literature estimating the STIRPAT model using U.S. state-level data is limited to a handful of studies (i.e. Squalli, 2010; Squalli, 2014; McGee, 2015).

After log-linearization and the introduction of relevant explanatory variables, the first base model is specified as follows:

$$\begin{aligned} \ln GHG_{it} &\\ = \alpha_0 + \alpha_1 \ln POP_{it} + \alpha_2 \ln INCOME_{it} + \alpha_3 (\ln INCOME_{it})^2 + \alpha_4 \ln VMT_{it} &\\ + \alpha_5 OIL_{it} + \alpha_6 UTIL_{it} + \alpha_7 MANUF_{it} + \alpha_8 TRANS_{it} + \alpha_9 \ln FARMLAND_{it} &\\ + \alpha_{10} \ln ORGCROP_{it} + \mu_i + \mu_t + \varepsilon_{it} & \end{aligned} \tag{1}$$

where log total GHG emissions including LUCF for state *i* in period *t* are estimated with respect to log population (POP), log real per capita GDP (INCOME), log real per capita GDP squared, log vehicle miles traveled (VMT), oil and natural gas output as % of state GDP (OIL), output from the utilities sector as % of state GDP (UTIL), output from the manufacturing sector as % of state GDP (MANUF), output from the transportation sector as % of state GDP (TRANS), log total farmland acreage (FARMLAND), and log organic cropland acreage (ORGCROP). Augmented specifications are also estimated after adding log organic pasture acreage (ORGPAST) and an interaction term representing the product between ln ORGCROP and TRANS (ORGCROP-TRANS). The model also includes an error term, which is decomposed whenever applicable into a state-specific component, μ_i, a year-specific component, μ_t, and an idiosyncratic shock, ε_{it}.

Similarly, the remaining base models for CH_4 and N_2O emissions are specified as follows:

$$\ln CH4_{it} = \beta_0 + \beta_1 \ln POP_{it} + \beta_2 \ln INCOME_{it} + \beta_3 (\ln INCOME_{it})^2 \quad (2)$$
$$+ \beta_4\, OIL_{it} + \beta_5 TRANS_{it} + \beta_6 \ln FARMLAND_{it} + \beta_7 \ln ORGCROP_{it} + \theta_i + \theta_t + \tau_{it}$$

$$\ln N2O_{it} = \delta_0 + \delta_1 \ln POP_{it} + \delta_2 \ln INCOME_{it} + \delta_3 (\ln INCOME_{it})^2 + \delta_4 \ln VMT_{it} \quad (3)$$
$$+ \delta_5\, MANUF_{it} + \delta_6 TRANS_{it}$$
$$+ \delta_7 \ln FARMLAND_{it} + \delta_8 \ln ORGCROP_{it} + \gamma_i + \gamma_t + \xi_{it}$$

where Equation 2 includes the primary sources of CH_4 emissions, namely livestock farming, and the production, processing, transportation, storage, distribution, and use of natural gas and petroleum. Equation 3 also controls for the primary sources of N_2O emissions, namely industrial or chemical production and transportation, amongst others.

The variable POP controls for the potential impact of population on emissions and also represents a scale variable. As a proxy for affluence, I used real per capita GDP (also known as income) and also introduced it as a quadratic term to control for potential nonlinearity in the relationship between income and greenhouse gas emissions. This is consistent with the Environmental Kuznets Curve hypothesis (Grossman & Krueger, 1995), which posits that the relationship between income and emissions can be bell-shaped, suggesting that emissions increase with income up to a certain level before eventually declining.

As for the technology variable, it is decomposed into the OIL, UTIL, MANUF, and TRANS variables, which are used to control for emissions that are driven by large oil and natural gas production, manufacturing, utilities, manufacturing, and transportation sectors, respectively. Given that CH_4 data omit emissions arising from activities related to oil and natural gas, including the OIL variable serves a particular purpose. A properly specified CH_4 model requires the coefficient estimate for OIL to be statistically insignificant. I also introduced log VMT as an explanatory variable to control for the potential effect of driving and transportation on GHG emissions. Finally, I included an interaction term between log organic cropland acreage and TRANS in order to assess to what degree the interaction between organic farming and the transportation sector contributes to GHG emissions. In other words, by including this variable, it is possible to estimate how changes in transportation output affect GHG emissions for given levels of organic cropland acreage and how changes in organic cropland acreage affect GHG emissions for given levels of transportation output. The transportation sector is particularly important as it is not necessarily expected to mitigate emissions from its interaction with organic farming practices. Organically produced food could possibly depend on the transportation sector just as much as its conventionally produced counterpart.

The key variables of interest include ln ORGCROP, ln FARMLAND, ln ORGPAST, and the interaction term between TRANS and ln ORGCROP. The ORGCROP variable represents organic cropland acreage and is used in conjunction with the FARMLAND variable, which represents total farmland acreage. These two variables when jointly included control for emissions arising from the agricultural sector and for the relative size of the organic farming sector. Special attention must be given to the interaction term. Without it, the coefficient estimate for TRANS would be interpreted as a measure of the partial effect of TRANS on GHG emissions, for given levels of other factors. However, with its inclusion, the effect of TRANS on GHG emissions must be interpreted by taking into account both the coefficient estimate of TRANS and that of the interaction term.

It is important to note that log transformation yields a number of benefits. First, estimates using log-transformed variables are less sensitive to outliers and heteroskedastic residuals. Second, coefficient estimates can be interpreted as ecological elasticities, measuring the % responsiveness of the dependent variable to % changes in a dependent variable, for given levels of other variables. Third, the interpretation of coefficient estimates is more meaningful because log transformation scales the data to a common unit of measurement.

Unobserved heterogeneity is virtually inevitable and cannot be expected to be independent of the included variables in the empirical specifications. Estimations not accounting for such heterogeneity would suffer from omitted variable bias and would yield biased and inconsistent estimates. Such heterogeneity usually arises from time-invariant factors such as demographic distribution, location, natural resource endowment, regulatory regime, and other hard-to-measure factors. The fixed effects estimator allays such concerns due to its ability to control for time-invariant factors, for potential geographic non-independence of data points (spatial autocorrelation), and for the potential spillover effects that can arise from being in a particular location. For completeness and whenever applicable, I estimated my specifications using random and fixed effects, one-way (state) random and fixed effects, and two-way (state and time) random and fixed effects. The choice of the appropriate estimator is determined using a Hausman test, whereas the choice of including the year-specific component is determined using a Wald test. All estimations are completed using standard errors that are cluster-robust to arbitrary heteroskedasticity and arbitrary intragroup correlation.

As described in the previous chapter, the regression estimations test the null hypothesis that the coefficient estimate for organic food production is statistically equal to zero. The null hypothesis represents the Neutrality Hypothesis, which when not rejected suggests the absence of statistically significant association between organic cropland acreage and GHG emissions. If the null hypothesis is rejected, a positive coefficient estimate for organic cropland acreage would provide support for the Polluting Hypothesis, whereas a negative coefficient estimate would support the Mitigating Effect Hypothesis.

Chapter III

Results

In order to identify the most suitable estimator, I first made use of a Hausman test for the null hypothesis that the differences in coefficients between random and fixed effects estimations were not systematic. I then tested for the inclusion of the year-specific component using a Wald test for the null hypothesis that the coefficient estimates for the year dummies were jointly equal to zero. Table 2 shows that for the GHG model, the null hypothesis is not rejected, favoring the random effects estimator. In contrast, however, the null hypothesis for both CH_4 and N_2O models is rejected ($p < 0.01$), providing support for the fixed effects estimator.

Table 2. Hausman test for estimator selection and Wald test for the introduction of year dummies.

	GHG Model	**CH_4 Model**	**N_2O Model**
Hausman Test			
χ^2	12.94	49.28	81.48
p value	0.37	0.00	0.00
Wald Test			
χ^2	80.07	7.56	20.43
p value	0.00	0.00	0.00

As for the year-specific component, Table 2 shows that the null hypothesis that the coefficient estimates of all year dummies are jointly statistically significant is rejected for all three models ($p < 0.01$). This suggests that temporal variation must be accounted for by including a set of dummy variables for each year of the data sample except a reference year. Accordingly, dummy variables are introduced for the years 1997 and 2000-2008 and the year 2010 is assumed as the reference year and is omitted from the estimations.

Estimation Results for total GHG Emissions Including LUCF

Table 3, Table 4, and Table 5 summarize the main estimation results. Column (1) of Table 3 shows the random effects estimation results for the base model specified in Equation 1 of the previous chapter. Column (2) shows estimation results for the augmented specification introducing the interaction term, whereas column (3) shows results for the specification introducing the ln ORGPAST variable. Columns (4) through (6) show results for the same specifications but after accounting for the year-specific component.

The gradual introduction of variables appears to increase the explanatory power of the estimated specifications. However, the specification results in column (3) appear to have relatively similar explanatory power to those in column (2) despite the fact they are based on a smaller sample. Indeed, the explanatory variables included in the specifications reported in columns (1) and (2) explain about 83% of the variation in GHG emissions with a sample size of 496, whereas those for the specification reported in column (3) explain 82.8% of the variation in GHG emissions with a sample size of 421.

Focusing on column (3) estimation results, the coefficient estimate for population has the expected sign and is statistically significant ($p < 0.01$). The coefficient estimates for oil and natural gas, utilities, and manufacturing also have the expected sign and are statistically significant at the 0.01, 0.05, and 0.01 levels, respectively. As for the variables of interest, the coefficient estimate for log farmland is positive and statistically significant ($p < 0.01$). This suggests that for a one percent increase in farmland acreage, GHG emissions are expected to increase by 0.13%. On the other hand, the ecological elasticity coefficients for log organic cropland and log organic pasture are both negative and statistically significant ($p < 0.05$). This suggests that as organic farming acreage increases by one percent, total GHG emissions are likely to decrease by about 0.06% and as organic pasture acreage increases by one percent, GHG emissions are expected to decrease by about 0.007%. Finally, neither the coefficient estimate for the transportation variable nor that for the interaction term are statistically significant, suggesting that the effect of transportation output on GHG emissions does not vary with changes in organic farming.

The introduction of the year-specific component leaves some results unchanged but also yields a number of important changes. All specifications in columns (4) through (6) yield similar results. The coefficient estimates for population, oil and natural gas, manufacturing, and farmland maintain the same sign and remain statistically significant. However, the coefficient estimate for utilities, log organic cropland, and log organic pasture are no longer statistically significant. This suggests that organic farming has no statistically significant impact on GHG emissions. It is important to note, however, that the explanatory power of the estimated specifications has decreased after the introduction of the year-specific component (i.e. R^2 decreased from 0.828 to 0.81). Although the change is relatively small, it may still suggest that the interpretations based on the specifications that exclude the year-specific component may be more statistically robust.

As a result, and for consistency, I will revert to the estimation results in column (3) for future discussions.

Table 3. Random effects estimation results for GHG emissions incl. LUCF (n = 50).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
log population	0.400**	0.433**	0.541**	0.434**	0.464**	0.520**
	(0.142)	(0.142)	(0.165)	(0.159)	(0.154)	(0.173)
log income	21.271	23.675	22.139	21.953	24.325*	21.996
	(12.930)	(12.768)	(15.883)	(12.081)	(12.358)	(14.978)
(log income)^2	-0.973	-1.087	-1.012	-0.994	-1.106	-0.999
	(0.600)	(0.593)	(0.737)	(0.560)	(0.573)	(0.696)
log vmt	0.183	0.148	0.042	0.177	0.146	0.090
	(0.142)	(0.142)	(0.169)	(0.169)	(0.165)	(0.187)
Oil & natural gas	0.030**	0.030**	0.035**	0.031**	0.032**	0.037**
	(0.007)	(0.007)	(0.010)	(0.009)	(0.009)	(0.011)
Utilities	0.097**	0.093**	0.068*	0.048	0.040	0.004
	(0.029)	(0.030)	(0.034)	(0.052)	(0.055)	(0.064)
Manufacturing	0.017**	0.017*	0.020**	0.017*	0.017*	0.020*
	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)
Transportation	0.019	-0.044	-0.058	0.031	-0.032	-0.042
	(0.027)	(0.032)	(0.055)	(0.027)	(0.027)	(0.051)
log farmland	0.118**	0.118**	0.131**	0.103**	0.103**	0.105**
	(0.036)	(0.035)	(0.036)	(0.034)	(0.033)	(0.034)
log organic crop	-0.015*	-0.039*	-0.059*	-0.001	-0.025	-0.040
	(0.006)	(0.018)	(0.027)	(0.006)	(0.015)	(0.027)
log organic crop x		0.007	0.010		0.008	0.010

Transportation		(0.005)	(0.007)		(0.004)	(0.007)
log organic			-0.007*			-0.002
pasture			(0.003)			(0.004)
Constant	-121.717	-134.381	-127.066	-126.976	-139.457*	-126.921
	(69.960)	(69.063)	(85.718)	(65.535)	(66.970)	(80.822)
Year dummies	No	No	No	Yes	Yes	Yes
N	496	496	421	496	496	421
Overall R^2	0.830	0.831	0.828	0.819	0.820	0.810

Notes: Robust standard errors in parentheses. The coefficient estimates of the year dummies are omitted from the estimation results. ** p<0.01, * p<0.05.

Estimation Results for CH_4 Emissions

Table 4 summarizes the fixed effects estimation results for CH_4 emissions. Column (1) reports estimation results for the specification described by Equation 2, whereas columns (2) and (3) augment this specification with the interaction term and log ORGPAST, respectively. Columns (4) through (6) report the same specifications but after introducing the year-specific component. As expected, the coefficient estimate for population is positive and statistically significant ($p < 0.01$) across all specifications. As described earlier, the OIL variable could have been excluded from the model due to the fact that the data used omit CH_4 emissions from oil and natural gas. This is confirmed by the fact that the coefficient estimate for OIL is statistically insignificant across all estimations. The coefficient estimate for transportation output is statistically significant ($p < 0.05$) but only in the base specification in column (1). Adding the interaction term in column (2) not only increases the explanatory power of the specification but also results in a negative and statistically significant coefficient estimate for log organic cropland and a positive and statistically significant coefficient estimate for the interaction term.

Table 4. Fixed effects estimation results for CH_4 emissions (n = 50).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
log population	0.517**	0.525**	0.782**	0.683**	0.664**	0.870**
	(0.164)	(0.161)	(0.181)	(0.173)	(0.168)	(0.226)
log income	-0.298	1.576	1.748	3.138	5.059	4.584
	(7.374)	(6.474)	(4.847)	(6.634)	(6.061)	(4.524)
(log income)^2	0.018	-0.070	-0.072	-0.130	-0.220	-0.194
	(0.347)	(0.305)	(0.229)	(0.312)	(0.284)	(0.212)
Oil & natural gas	0.015	0.014	0.011	0.011	0.009	0.009
	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)
Transportation	0.039*	-0.027	-0.064	0.036	-0.036	-0.040
	(0.016)	(0.025)	(0.038)	(0.022)	(0.027)	(0.043)
log farmland	0.059	0.116	0.156	-0.058	0.008	0.070
	(0.233)	(0.226)	(0.203)	(0.240)	(0.234)	(0.233)
log organic crop	-0.010	-0.033*	-0.052**	-0.008	-0.033*	-0.047**
	(0.006)	(0.013)	(0.010)	(0.006)	(0.014)	(0.011)
log organic crop		0.007*	0.012**		0.008**	0.010**
x Transportation		(0.003)	(0.003)		(0.003)	(0.003)
log organic pasture			-0.007			-0.007
			(0.004)			(0.004)
Constant	-5.085	-15.884	-21.789	-25.583	-36.304	-38.191
	(38.298)	(33.017)	(25.276)	(33.854)	(30.596)	(23.305)
Year dummies	No	No	No	Yes	Yes	Yes

N	496	496	421	496	496	421
Overall R^2	0.400	0.478	0.436	0.183	0.266	0.327

Notes: Robust standard errors in parentheses. The coefficient estimates of the year dummies are omitted from the estimation results. ** $p<0.01$, * $p<0.05$.

The augmented specification in column (3) yields similar results in addition to a slight increase in the size of the relevant coefficient estimates. However, although the introduction of the year-specific component leaves the estimation results relatively unchanged, the CH_4 model faces a decrease in explanatory power (i.e. R^2 decreases from 0.436 to 0.327). Consistent with estimations for the GHG model, interpretations will be based on the results reported in column (3).

The fact that the coefficient estimate for the interaction term is positive and statistically significant suggests that the effect of transportation output on CH_4 emissions varies with organic farming. This means that as log organic cropland takes different values, the effect of transportation output on GHG emissions changes accordingly. The relationship between transportation output and CH_4 emissions can be expressed by rewriting Equation 2 to reflect the main effect of transportation output on emissions at given levels of log organic cropland. The relevant expression is shown in the following:

$$
\begin{aligned}
&\ln CH4_{it} \\
&= \beta_0 + \cdots + \beta_5 TRANS_{it} + \cdots + \beta_7 \ln ORGCROP_{it} + \beta_8 (\ln ORGCROP \times TRANS) \\
&= \beta_0 + \cdots + (\beta_5 + \beta_8 \ln ORGCROP)\, TRANS_{it} + \cdots + \beta_7 \ln ORGCROP_{it} \\
&= \beta_0 + \cdots + (-0.064 + 0.012 \ln ORGCROP)\, TRANS_{it} + \cdots + \beta_7 \ln ORGCROP_{it}
\end{aligned}
$$

where the main effect of transportation output is a combination of the partial effect that is captured by β_5 and the one from the interaction component $\beta_8 \ln ORGCROP$. After substituting with the relevant coefficient estimates from Table 4 and taking into account all decimals in the regression output, log organic cropland must take a value approximately equal to 5.43 for transportation output not to affect CH_4 emissions. This threshold value is calculated by dividing 0.0639871 (β_5) by 0.011781 (β_8). The coefficient estimate for TRANS is negative when $-0.064 > 0.012 \ln ORGCROP$ and positive when $-0.064 < 0.012 \ln ORGCROP$. Thus, an increase in transportation output will decrease CH_4 emissions when $\ln ORGCROP < 5.43$ and increase emissions when $\ln ORGCROP > 5.43$.

The relationship between transportation output and CH_4 emissions can be better visualized using a predictive margins plot. This plot helps show how changes in log organic farming influence the impact of transportation on CH_4 emissions. A meaningful plot requires the selection of relevant values for each of the two variables in the interaction term.

Table 7 provides important insight about these two variables. In fact, according to this table, values for log organic cropland range between 0.69 and 13.12, whereas values for transportation output range between 1.34 and 11.79.

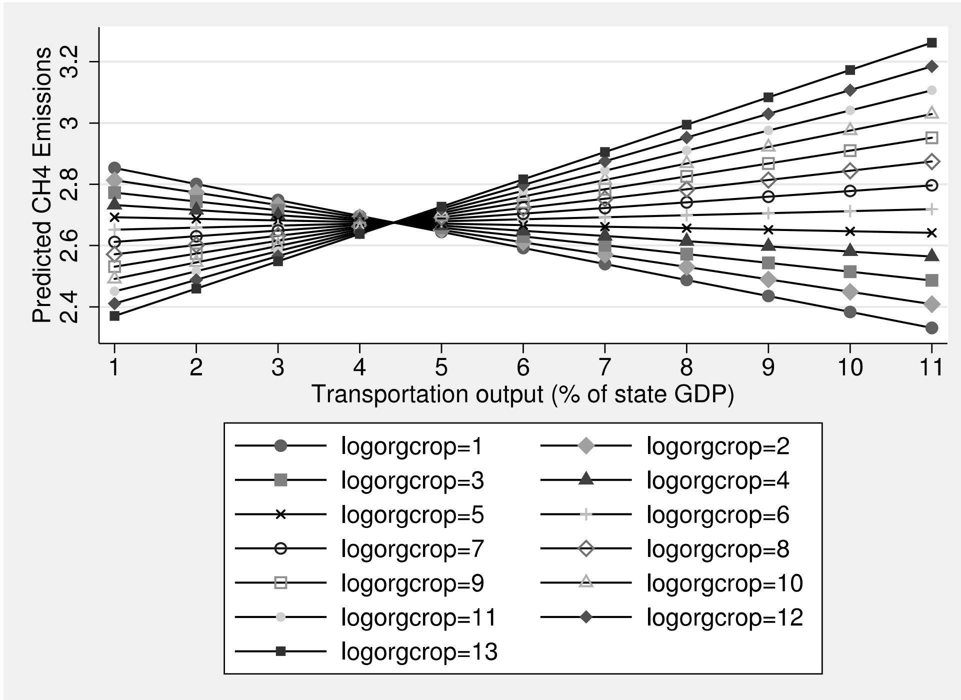

Figure 6. Predictive margins plot of the effect of transportation output on CH_4 emissions for given levels of log organic cropland.

Figure 6 shows a "butterfly"-shaped predictive margins plot. Each line shown reflects the effect of transportation output on CH_4 emissions for given levels of log organic cropland acreage. The lines starting from the left wing of the plot represent values ranging from 1 to 13 increasing from top to bottom. For instance, the first line from the top shows that when log organic cropland takes a value of 1, an increase in transportation output results in lower CH_4 emissions. This is true until log organic cropland reaches a threshold of 5.43 at which higher transportation output will have no effect on CH_4 emissions. For values beyond this threshold, as organic farming expands, the effect of transportation output on CH_4 emissions is positive and rises at an increasing rate.

Similarly, the main effect of organic farming can be captured with the following expression:

$$
\begin{aligned}
&\ln CH4_{it} \\
&= \beta_0 + \cdots + \beta_5 TRANS_{it} + \cdots + \beta_7 \ln ORGCROP_{it} + \beta_8(\ln ORGCROP \times TRANS) \\
&= \beta_0 + \cdots + (\beta_7 + \beta_8 TRANS) \ln ORGCROP_{it} + \cdots + \beta_5 TRANS_{it} \\
&= \beta_0 + \cdots + (-0.052 + 0.012\, TRANS) \ln ORGCROP_{it} + \cdots + \beta_5 TRANS_{it}
\end{aligned}
$$

from which the transportation output threshold is estimates at approximately 4.41, calculated by dividing 0.0520068 (β_7) by 0.011781 (β_8). Thus, an increase in organic cropland acreage will mitigate CH_4 emissions when $TRANS < 4.41$ and will increase CH_4 emissions when $TRANS > 4.41$.

It is worth noting that although the coefficient estimate for log organic cropland acreage is negative and statistically significant ($p < 0.01$), it does not mean that organic farming mitigates CH_4 emissions, net of other sources of emissions. Rather, since log organic cropland interacts with transportation output, it must be interpreted for given levels of transportation output. In other words, a one percent increase in organic crop acreage would result in a 0.052% decrease in CH_4 emissions when transportation output takes a value of zero. This is evidently unrealistic and does not capture the true interaction between organic farming and transportation output.

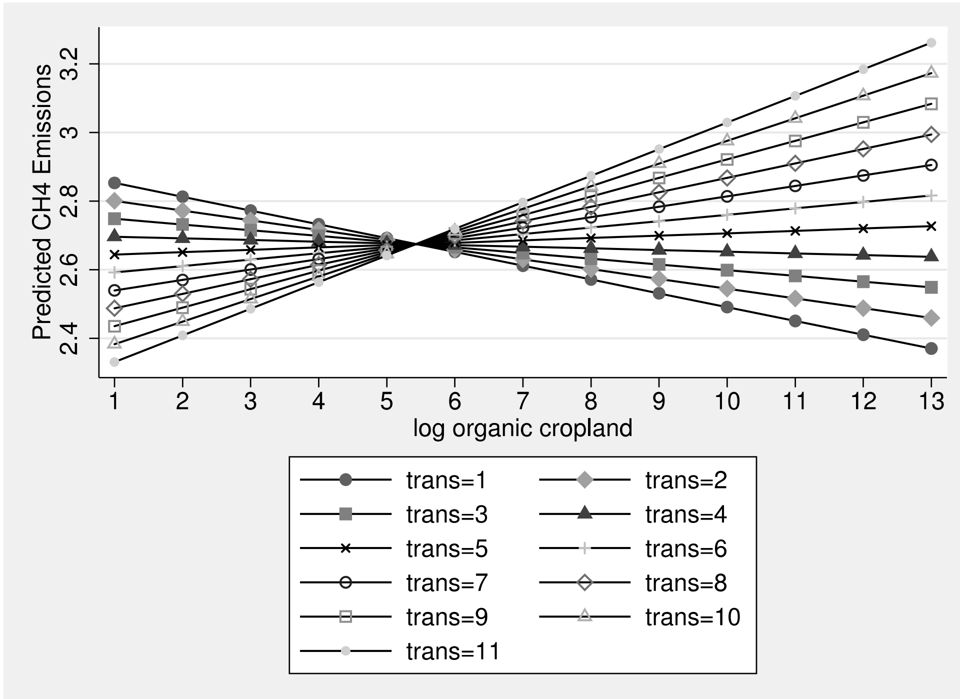

Figure 7. Predictive margins plot of the effect of organic farming on CH_4 emissions for given levels of transportation output.

As described above, transportation output observations take values ranging between 1.34 and 11.78. A predictive margins plot can provide insight on how organic farming affects CH_4 emissions for given levels of transportation output. Figure 7 shows a plot with a pattern relatively similar to that shown in Figure 6. The lines starting from the left wing represent values for transportation output ranging from 1 to 11. Once again, for low levels of transportation output, an increase in organic farming appears to mitigate CH_4 emissions. Once transportation output exceeds the 4.41 threshold, the effect of organic farming on emissions reverses to start causing CH_4 emissions to rise.

Estimation Results for N_2O Emissions

Table 5 summarizes the estimation results for N_2O emissions. Just like previous estimations, column (1) shows the estimation results of the base specification as described by Equation 3. This is followed by the estimation results of two specifications that are augmented with the interaction term and log organic pasture, respectively. Columns (4) through (6) show estimation results for the same specifications but with the introduction of the year-specific component.

Table 5. Fixed effects estimation results for N_2O emissions (n = 50).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
log population	-1.013**	-0.956**	-0.962**	0.062	0.024	0.006
	(0.210)	(0.220)	(0.209)	(0.278)	(0.269)	(0.342)
log income	26.529*	31.129**	37.225**	32.861**	36.479**	41.012**
	(11.199)	(8.793)	(10.847)	(7.917)	(6.874)	(7.854)
$(\text{log income})^2$	-1.242*	-1.457**	-1.744**	-1.501**	-1.673**	-1.887**
	(0.525)	(0.412)	(0.509)	(0.368)	(0.317)	(0.364)
log vmt	0.028	-0.027	0.063	-0.048	-0.078	0.082
	(0.237)	(0.240)	(0.222)	(0.242)	(0.242)	(0.213)
Manufacturing	0.008	0.009	0.012*	-0.001	0.001	0.002
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Transportation	0.035	-0.140**	-0.304**	0.047	-0.101**	-0.200*
	(0.024)	(0.043)	(0.077)	(0.035)	(0.035)	(0.085)
log farmland	-0.363	-0.215	-0.340	-0.455	-0.325	-0.364
	(0.489)	(0.463)	(0.548)	(0.381)	(0.372)	(0.444)
log organic crop	-0.027**	-0.088**	-0.160**	-0.011	-0.063**	-0.110**

	(0.008)	(0.025)	(0.027)	(0.008)	(0.019)	(0.024)
log organic crop		0.020**	0.035**		0.016**	0.026**
x Transportation		(0.005)	(0.007)		(0.004)	(0.006)
log organic pasture			0.004			0.008
			(0.004)			(0.004)
Constant	-119.413	-146.09**	-176.61**	-171.71**	-191.51**	-215.820**
	(59.828)	(46.904)	(55.944)	(42.928)	(37.682)	(42.445)
Income TP ($)	43,396	43,432	43,199	56,742	54,463	52,510
Year dummies	No	No	No	Yes	Yes	Yes
N	535	535	454	535	535	454
R^2	0.650	0.518	0.612	0.599	0.614	0.470

Notes: Robust standard errors in parentheses. Income TP stands for income turning point. The coefficient estimates of the year dummies are omitted from the estimation results. ** p<0.01, * p<0.05.

The estimation results reported in column (1) show that the coefficient estimate for population is negative and statistically significant ($p < 0.01$). This is somewhat surprising as after controlling for other sources of emissions, population is expected to increase N_2O emissions (e.g. Squalli, 2014). There is also evidence of an EKC suggesting that N_2O emissions increase with income up to a turning point of $43,396 after which emissions decline. The coefficient estimate for log organic cropland is negative and statistically significant ($p < 0.01$) suggesting that a one percent increase in organic farming acreage would result in a 0.027% decrease in N_2O emissions, net of other factors. After the introduction of the interaction term and log organic pasture, the results remain relatively unchanged. However, with the interaction term being statistically significant

($p < 0.01$), the interpretation of the effect of organic farming on N_2O emissions will depend on the values that transportation output may take.

The introduction of the year-specific component appears to leave the estimation results largely unaffected. With the exception of the coefficient estimates for population, which become statistically insignificant, all other results remain relatively unchanged. Based on the estimation results in column (6), there is still evidence of an EKC but at a higher turning point of $52,510. The coefficient estimates for transportation output, log organic cropland, and the interaction term are all statistically significant ($p < 0.05$, $p < 0.01$, and $p < 0.01$, respectively). Consistent with previous estimation results, explanatory power declines with the introduction of the year-specific component (i.e. R^2 declines from 0.612 to 0.470).

Interpreting the effect of transportation output on N_2O emissions requires an analysis similar to the one completed for CH_4 emissions. Since the coefficient estimates for log organic cropland and for the interaction term are statistically significant, the main effect of transportation output on N_2O emissions will vary with values of log organic cropland. The following expression reflects the main effect of transportation output on N_2O emissions:

$$\ln N2O_{it} = \beta_0 + \cdots + (-0.30 + 0.035 \ln ORGCROP) TRANS_{it} + \cdots + \beta_7 \ln ORGCROP_{it}$$

from which a threshold for log organic cropland at which transportation output does not affect N_2O emissions can be identified. After substituting with the relevant coefficient estimates from Table 5 in the appendix, log organic cropland is estimated to take a value approximately equal to 8.77. Thus, an increase in transportation output will decrease N_2O emissions when $\ln ORGCROP < 8.77$ and increase emissions when $\ln ORGCROP >$

8.77. This threshold value is calculated by dividing 0.3042878 (β_5) by 0.0346843 (β_8).

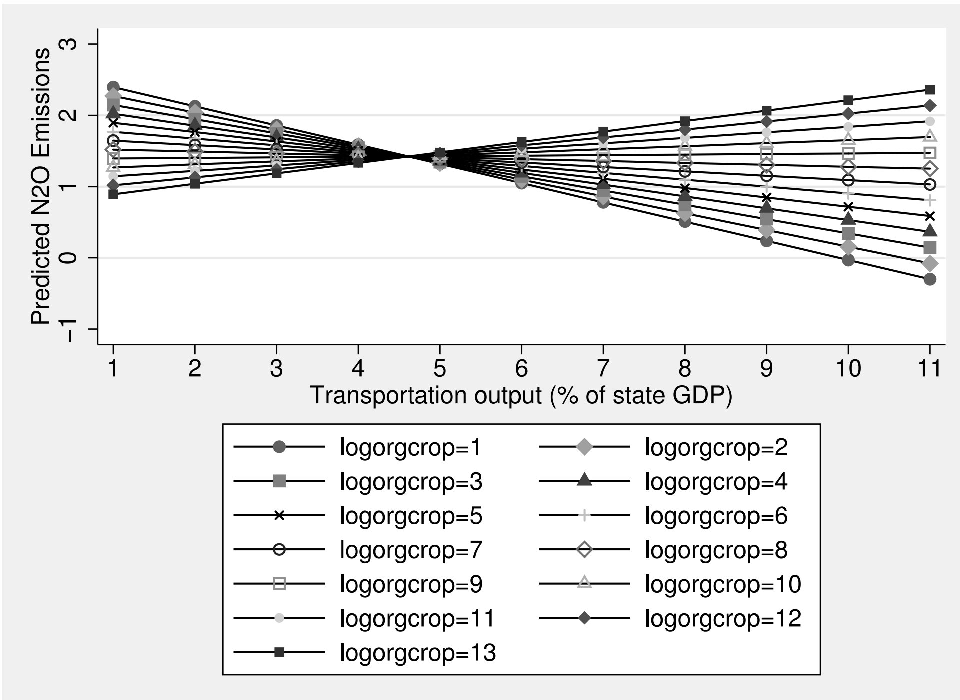

Figure 8. Predictive margins plot of the effect of transportation output on N_2O emissions given levels of log organic cropland.

A predictive margins plot can once again confirm this threshold and provide a visual representation of the interaction between organic farming and transportation output in influencing N_2O emissions. As Figure 8 shows, for any value ranging between 1 and 8 for log organic cropland, an increase in transportation output results in lower N_2O emissions. For values of log organic cropland that are higher than 8.77 (≥ 9 in the figure), changes in transportation output increase N_2O emissions at an increasing rate.

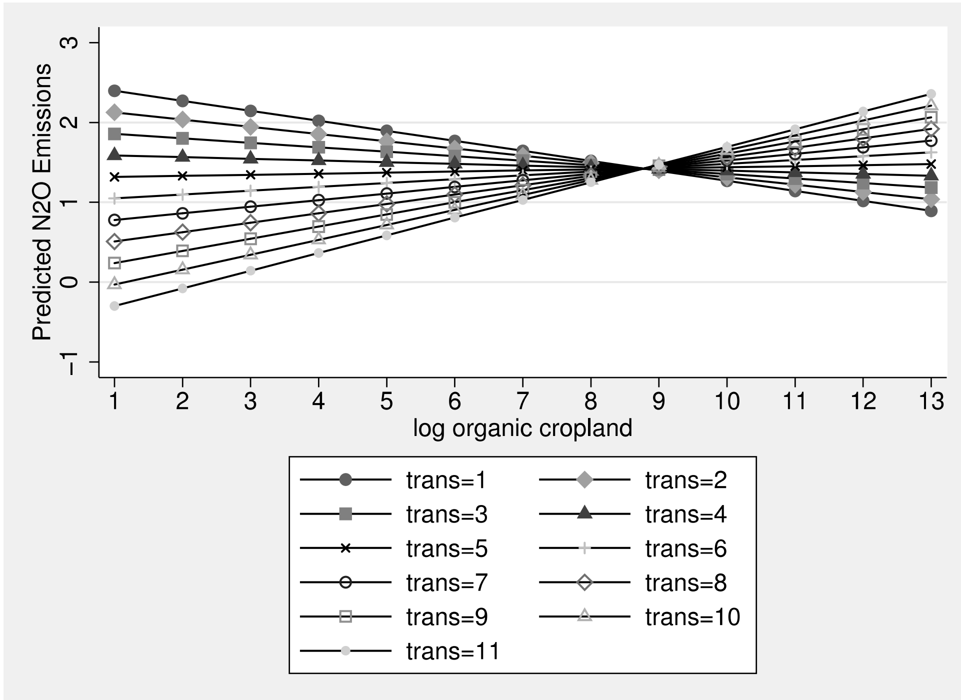

Figure 9. Predictive margins plot of the effect of organic farming on N_2O emissions given levels of transportation output.

The effect of organic farming on N_2O emissions can also be expressed with the following simplified equation and visualized using predictive margins plots:

$$\ln N2O_{it} = \beta_0 + \cdots + (-0.16 + 0.035\, TRANS) \ln ORGCROP_{it} + \cdots + \beta_5 TRANS_{it}$$

for which the corresponding threshold is approximately equal to 4.61, calculated by dividing 0.1599946 (β_7) by 0.0346843 (β_8). Thus, an increase in organic farming will mitigate N_2O emissions when $TRANS < 4.61$ and will increase N_2O emissions when $TRANS > 4.61$. Figure 9 shows a predictive margins plot of the effect of organic farming on N_2O emissions, which confirms these findings.

Sensitivity Analysis

As described in the previous chapter, the relationship between organic farming and emissions may be biased from the inclusion of influential observations. Based on absolute deviation around the median, the following states were identified as outliers: Vermont, Maine, New York, California, Idaho, and Wisconsin. Although the exclusion of these states from the analysis does not guarantee improved robustness, it helps allay concerns about biased estimates.

Table 8 in Appendix 1 summarizes random effects estimation results for GHG emissions including LUCF and excluding the states classified as outliers. Overall, the estimation results are similar to those reported in Table 3. The key difference between the results reported for the original specification and those reported for the outlier-adjusted model is that the coefficient estimate for log organic cropland is no longer statistically significant in the base specification and in the one augmented with the interaction term as reported in columns (1) and (2), respectively. Nevertheless, the results in column (3) show that even with the exclusion of outliers, the coefficient estimates for the key variable log organic cropland remain negative across both specifications, statistically significant ($p < 0.05$), and relatively equisized (-0.059 in the original specification versus -0.061 in the outlier-adjusted specification). One important exception is that the coefficient estimate for log organic pasture becomes statistically insignificant after the exclusion of outliers.

Recall that the introduction of a year-specific component into the original specification stripped the key variable log organic cropland of statistical significance (Table 3). This is also the case in the outlier-adjusted specification under the base model as well as under those augmented with the interaction term and log organic pasture. In addition, explanatory power declines with R^2 decreasing slightly from 0.77 to 0.75. Thus, the main conclusions drawn from the original specifications remain relatively unchanged.

Table 9 in Appendix 1 summarizes the fixed effects estimation results for CH_4 emissions after the exclusion of outliers. Overall, the results reported in columns (3) and (6) appear to mirror those in Table 4. The coefficient estimate for log organic cropland is negative, that for the interaction term is positive, and both parameters are statistically significant ($p < 0.01$). In addition, both coefficient estimates approach those reported in Table 4. However, contrary to previous estimations, the coefficient estimate for log organic pasture is negative and statistically significant ($p < 0.05$).

Since the coefficient estimates for log organic cropland and for the interaction term are statistically significant, the main effect of transportation output on CH_4 emissions will vary with values of log organic cropland. Consistent with the previous section and focusing on the estimation results in column (3), an expression reflecting the main effect of transportation output on emissions is shown in the following:

$$\ln CH4_{it} = \beta_0 + \cdots + (-0.067 + 0.013 \ln ORGCROP)TRANS_{it} + \cdots + \beta_7 \ln ORGCROP_{it}$$

for which a threshold for log organic cropland at which transportation output does not affect CH_4 emissions can be identified. After substitution with the relevant coefficient estimates from Table 9, log organic cropland is estimated to take a value approximately equal to 5.3. Thus, an increase in transportation output will decrease CH_4 emissions when $\ln ORGCROP < 5.3$ and increase emissions when $\ln ORGCROP > 5.3$. This threshold value is calculated by dividing 0.0665248 (β_5) by 0.0125356 (β_8).

With the exclusion of outlier states log organic cropland ranges between 0.69 and 12.79, whereas transportation output ranges between 1.34 and 11.78. Based on these values, a predictive margins plot of the effect of transportation output on CH_4 emissions can provide a visual description of these results. Figure 10 confirms that for values of log organic cropland less than 5.3, an increase in transportation output results in lower CH_4 emissions. Beyond this threshold, an increase in transportation output results in higher CH_4 emissions.

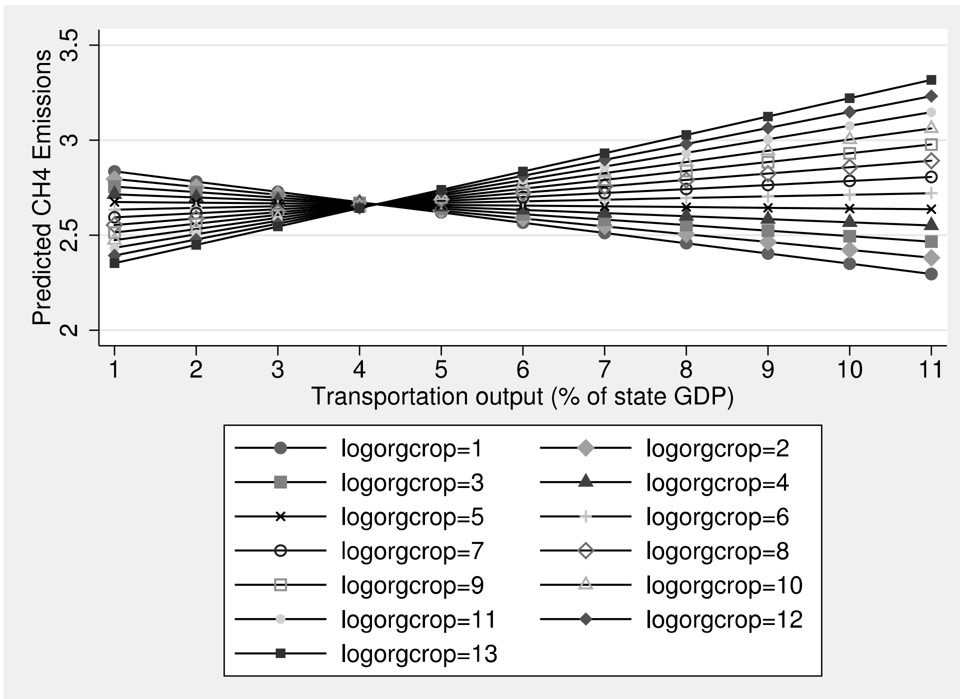

Figure 10. Predictive margins plot of the effect of transportation output on CH_4 emissions for given levels of log organic cropland (excluding outliers).

Consistent with previous estimates, the main effect of organic farming on CH_4 emissions can be captured with the following simplified expression:

$$\ln CH4_{it} = \beta_0 + \cdots + (-0.053 + 0.013\ TRANS) \ln ORGCROP_{it} + \cdots + \beta_5 TRANS_{it}$$

from which the threshold for transportation output is estimated at about 4.21, calculated by dividing 0.0527906 by 0.0125356. That is, an increase in log organic cropland will mitigate CH_4 emissions when $TRANS < 4.21$ and will increase CH_4 emissions when

$TRANS > 4.21$. Once again, the predictive margins plot in Figure 11 confirms these findings.

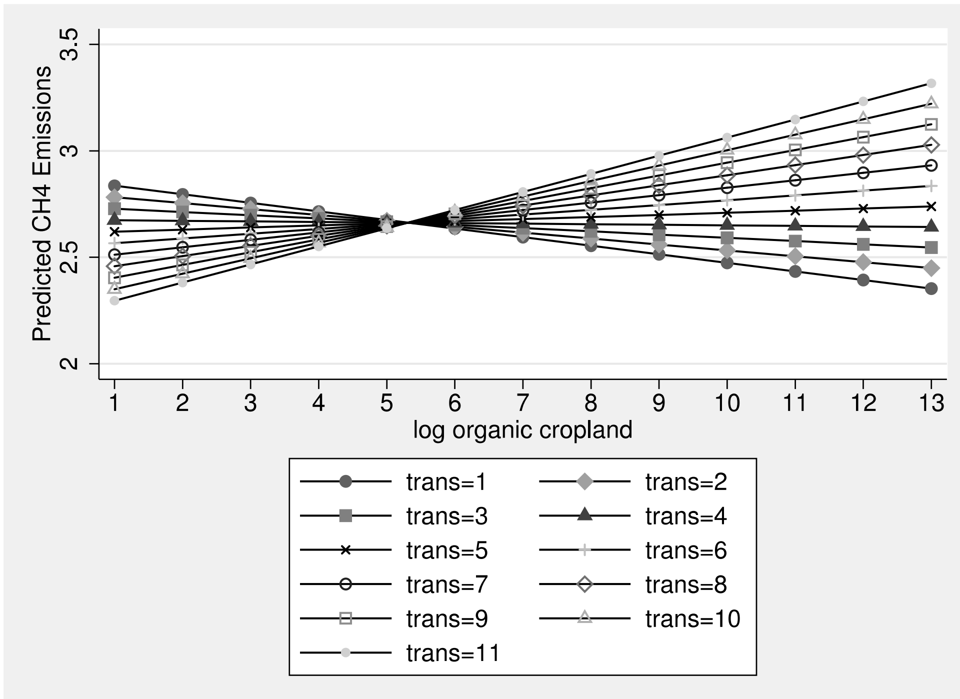

Figure 11. Predictive margins plot of the effect of organic farming on CH_4 emissions for given levels of transportation output (excluding outliers).

Table 10 in Appendix 1 reports fixed effects estimation results for N_2O emissions after the exclusion of outlier states. In comparison to those for the original specifications reported in Table 5, the new estimation results leave the key conclusions unchanged. Focusing on column (3) of Table 10, the coefficient estimates for transportation output and log organic cropland remain both negative and statistically significant ($p < 0.01$). In addition, the coefficient estimate for the interaction term also stays positive and statistically significant ($p < 0.01$). The size of such parameters appears to also be affected only slightly by the exclusion of outliers. Similarly, the estimation results reported in column (6) do not appear to be affected by the missing states.

The following simplified expressions capture the effect of transportation output on N_2O emissions for given levels of log organic cropland and the effect of organic farming on N_2O emissions for given levels of transportation output:

$$\ln N2O_{it} = \beta_0 + \cdots + (-0.27 + 0.032 \ln ORGCROP) TRANS_{it} + \cdots + \beta_7 \ln ORGCROP_{it}$$

$$\ln N2O_{it} = \beta_0 + \cdots + (-0.145 + 0.032\, TRANS) \ln ORGCROP_{it} + \cdots + \beta_5 TRANS_{it}$$

from which the log organic cropland threshold is estimated at about 8.5, calculated by dividing 0.2709086 by 0.0318446. On the other hand, the transportation output threshold is estimated at about 4.54, computed by dividing 0.1445786 by 0.0318446. Thus, an increase in transportation output will mitigate N_2O emissions as long as $LOGORGCROP < 8.5$ and will increase emissions as long as $LOGORGCROP > 8.5$. In addition, an increase in organic farming will mitigate N_2O emissions as long as $TRANS < 4.54$ and will increase emissions as long as $TRANS > 4.54$.

Figure 12 shows a predictive margins plot of the effect of transportation output on N_2O emissions. For given levels of log organic cropland below 8.5, an increase in transportation output mitigates N_2O emissions. However, as log organic cropland moves towards the threshold, the mitigating impact decreases. Furthermore, for values of log organic cropland exceeding 8.5, an increase in transportation output will increase N_2O emissions and the effect worsens as log organic cropland expands.

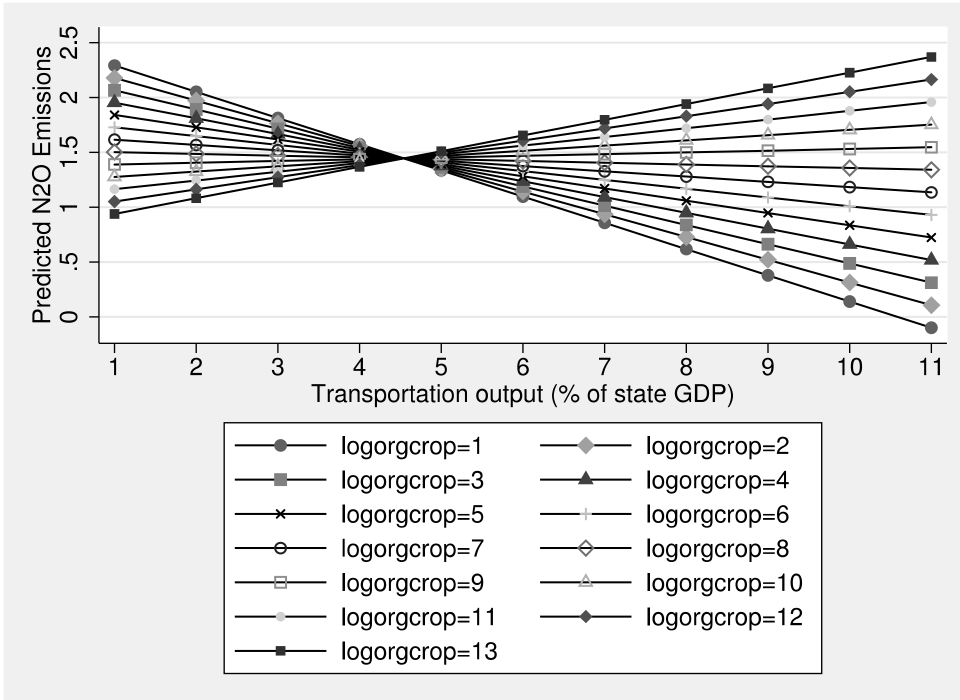

Figure 12. Predictive margins plot of the effect of transportation output on N_2O emissions for given levels of log organic cropland (excluding outliers).

The predictive margins plot in Figure 13 illustrates the main effect of organic farming on N_2O emissions. This figure confirms again that for given levels of transportation output below the threshold of 4.54, an increase in organic farming will mitigate N_2O emissions but the effect declines as transportation output approaches the threshold. On the other hand, an increase in organic farming will increase emissions for given levels of transportation output exceeding 4.54 and this effect worsens as transportation output increases.

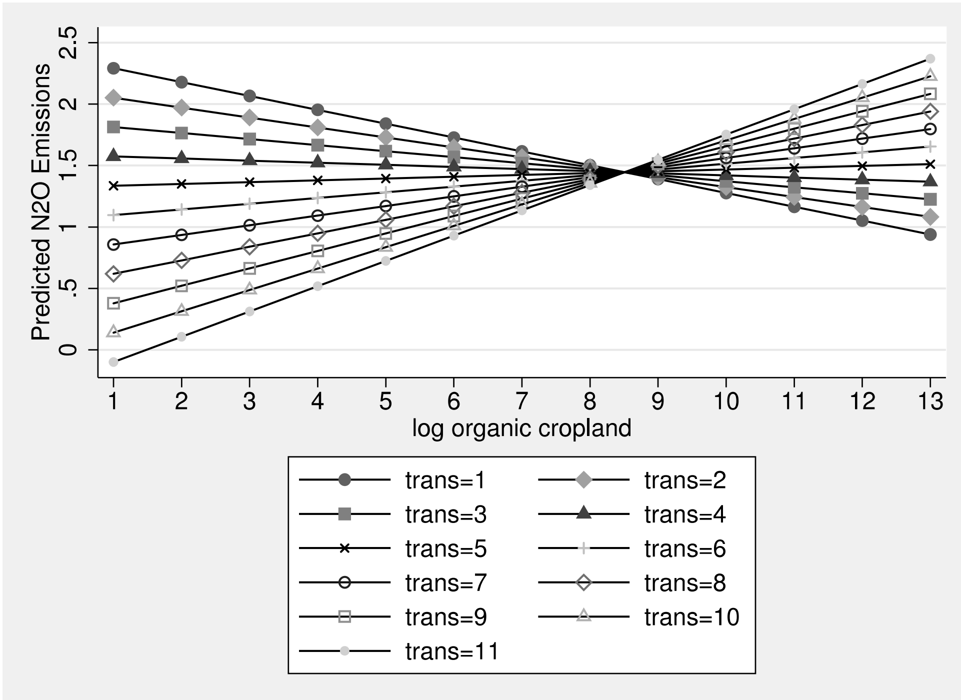

Figure 13. Predictive margins plot of the effect of organic farming on N_2O emissions for given levels of transportation output (excluding outliers).

Cluster Analysis

Although regression analysis helps estimate the relationship between organic farming and GHG emissions, it can also be insightful in spatial analysis. More specifically, regression estimates can be used to derive environmental impact estimates for individual states. This type of analysis can help identify potential patterns and group environmental impact across states according to identifiable characteristics. Accordingly, Equations 1 through 3 are re-estimated in order to derive estimates for the error term. It is worth noting that in random effects estimations the error component is comprised of the state-specific component and the idiosyncratic shock, whereas in fixed effects estimations, the state-specific component is captured by the intercept. Thus, cluster analysis requires point estimates of the state-specific component and the idiosyncratic shock from random effects estimations and point estimates of only the idiosyncratic shock from fixed effects estimations.

The error terms are derived from the estimations while ensuring that the idiosyncratic shock is different for each state at each point in time and that the state-specific component varies across states but not across time. Thus, in order to compute individual values of the idiosyncratic shock for each state, I first derive estimates for each state at different periods then take the mean of these values for each state across time. The state-specific component and idiosyncratic shock are summed together to derive the error term for GHG estimations, whereas only the idiosyncratic shock is used for N_2O estimations.

The following environmental impact equations are derived using only statistically significant coefficient estimates for the key variables and point estimates of the state-specific component and idiosyncratic shock. Mean values for each of the relevant variables are then substituted into these equations to derive point estimates of the state-level environmental impact. For consistency, I focus on the results presented in column (3) of Table 3, Table 4, and Table 5 given the fact that they have higher explanatory power (based on the reported R^2 values) than those in column (6).

$$\begin{aligned}\ln GHG_{it} &= 0.131 \ln FARMLAND_{it} - 0.059 \ln ORGCROP_{it} - 0.007 \ln ORGPAST_{it} + \mu_i + \varepsilon_{it}\end{aligned}$$

$$\ln CH4_{it} = -0.052 \ln ORGCROP_{it} + 0.012\ (\ln ORGCROP_{it} \times TRANS_{it}) + \tau_{it}$$

$$\begin{aligned}\ln N2O_{it} &= 176.61 - 0.304\, TRANS_{it} \\ &- 0.16 \ln ORGCROP_{it} + 0.035\ (\ln ORGCROP_{it} \times TRANS_{it}) + \xi_{it}\end{aligned}$$

It is worth noting that only the key variables of interest are considered for the environmental impact calculations since including all variables would yield environmental impact estimates arising from all included sources of emissions. Table 11 in Appendix 1 shows environmental impact estimates that are based on the equations above and relevant point estimates of the included variables. However, these estimates are relatively meaningless on their own unless used within the context of a comparative cluster analysis. Thus, environmental impact estimates can be interpreted as the effect of organic farming independently of other sources of emissions.

The values presented in Table 11 can be plotted on a map of the United States to provide a visual depiction of the spatial distribution of the environmental impact of organic farming across states. However, it is important to first visually inspect the statistical distribution of the data. Figure 14 show histograms plotted using the data representing environmental impact estimates for total GHG, CH_4, and N_2O emissions. The histogram for GHG emissions appears right-skewed with the majority (more than 80%) of the observations around the mean. There are even a few observations that take extreme values exceeding the mean plus three standard deviations. The histogram for CH_4 provides a similar picture although not as heavily skewed, and shows some extreme values. In contrast, the histogram for N_2O shows a distribution that approaches normality with no noticeable extreme values.

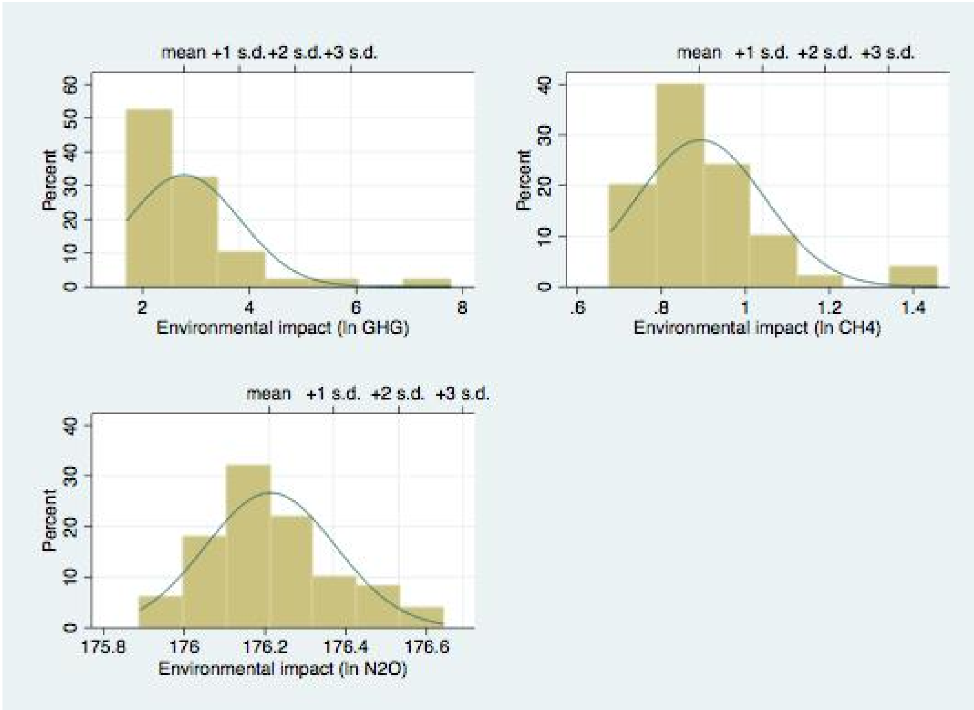

Figure 14. Histograms of environmental impact estimates.

The mapping of these estimates provides a spatial perspective of the distribution of the environmental impact of organic farming across the United States. I make use of a user-written Stata *spmap* command to derive distributional maps of the United States following the approach introduced by Madu (2009). Different shades of blue are used to show quintiles for environmental impact, with the darker shades representing quintiles with a larger environmental impact. Furthermore, to allay concerns about skewed data distribution, as it is the case for GHG and CH_4 data, I plot maps using deviation from the mean in addition to those plotted in quintiles. In fact, these ought to highlight the importance of using the proper class breaks in interpreting spatial distributions. Figure 15 in Appendix 2 shows the spatial distribution of the environmental impact of organic farming based on total GHG emissions data. Each color represents one of five quintiles with a darker shade of blue representing a higher environmental impact class. Nine states appear in the top quintile registering environmental impact exceeding 3.2. In particular, five of these states, namely Indiana, Kentucky, Ohio, Pennsylvania, and West Virginia, appear to form a cluster. However, other than geography, it is not clear what is common across these states that could help explain such a high environmental impact from organic farming. In fact, as Table 12 in Appendix 1 shows, Indiana's mean organic cropland share (% of total farmland) is barely around 0.04%, Kentucky's is 0.017%, Ohio's is 0.244%, Pennsylvania's is 0.271%, and West Virginia's is 0.02%. Of course, there are a number of factors other than organic farming that can help explain such differences. For instance, the error terms, which vary across states can play a role. In addition, how certain variables interact with each other may vary significantly across states. This is evidently a multi-dimensional question that cannot have a categorical answer and is beyond the scope of this research.

Rather than delve into an endless number of scenarios, it is evident that using equal classes (e.g. quintiles) may not necessarily yield meaningful interpretations. This is particularly problematic when analyzing data that are skewed and where the division of the data into equal groups may not provide useful insight. Thus, it may be more appropriate to assess the spatial distribution of the environmental impact of organic farming using deviation from the mean rather than quintiles or a division of the data into equal groups. In fact, this approach helps identify states or clusters of states and their corresponding deviation from the country's average environmental impact.

Figure 16 in Appendix 2 captures the spatial distribution of the environmental impact of organic farming in terms of total GHG emissions using such a criterion. The different shades of color going from the lightest shade to dark blue represent classes measuring the U.S. states for which the environmental impact is less than the country mean, ranges between the mean and $mean + 1\ sd$, ranges between $mean + 1\ sd$ and $mean + 2\ sd$, ranges between $mean + 2\ sd$ and $mean + 3\ sd$, and exceeds $mean + 3\ sd$, respectively. The area that raises the most concern is when environmental impact exceeds $mean + 3\ sd$ as this suggests that a particular state experiences abnormally high environmental harm in the outlier range.

The most important observation from Figure 16 is that most U.S. states have the lightest shade of blue, suggesting overall lower than average environmental impact from organic farming. For instance, with the exception of California and North Dakota, the fifteen states with the largest organic cropland share in Table 12 appear among such states. West Virginia is the only state where the environmental impact of organic farming exceeds the $mean + 3\ sd$ level. North Dakota and Wyoming come next with corresponding environmental impact ranging between $mean + 2\ sd$ and $mean + 3\ sd$. Texas stands on its own with environmental impact ranging between $mean + 1\ sd$ and $mean + 2\ sd$. As for states with environmental impact ranging between the mean and $mean + 1\ sd$, the Southern part of the United States is represented by California, New Mexico, Louisiana, Alabama, and Florida, whereas the mid-central and mid-eastern region is represented by a cluster of states comprised of South Dakota, Iowa, Illinois, Indiana, Kentucky, Ohio, and Pennsylvania. The remaining 34 states cover all parts of the country and have an environmental impact that is less than the country's average impact (including Alaska and Hawaii, although not displayed on any of the plotted maps).

Figure 17 in Appendix 2 plots the spatial distribution of environmental impact estimates in terms of CH_4 emissions. Each quintile is represented by a variety of U.S. states stretching across the entire country. For instance, California, Colorado, Michigan, and most of the Northeastern region except RI represent the lowest quintile, whereas the second quintile consists of Washington, Oregon, Idaho, Arizona, New Mexico, Florida, South Dakota, Minnesota, Virginia, and North Carolina. On the other hand, Figure 18 in Appendix 2 plots the spatial distribution of environmental impacts following the deviation from the mean criterion used in Figure 16. Alaska and Nebraska are the only states with environmental impact values exceeding the $mean + 3\ sd$ level. This is followed by Wyoming, which takes a value ranging between $mean + 2\ sd$ and $mean + 3\ sd$ and by Montana and Arkansas, which take values ranging between $mean + 1\ sd$ and $mean + 2\ sd$. Values ranging between the mean and $mean + 1\ sd$ appear primarily within a cluster of 13 states overlapping across the mid-west, southwest, and southeast. As for the remaining 30 states, they have an environmental impact below the country average and form clusters along the mid-Atlantic, northeast, the west coast, the western part of the southwest, and the northern part of the mid-west.

Figure 19 in Appendix 2 shows the spatial distribution of the environmental impact in terms of N_2O emissions using quintiles. Each quintile appears to be represented by a relatively similar number of states, which is largely due to the distribution of the relevant data. For instance, eight states from various parts of the northeast, mid-Atlantic, southeast, and Midwest appear in the top quintile. The second top quintile consists of nine states also stretching across the same area in addition to the west and northwest. Figure 20 provides a more meaningful map using the deviation from the mean criterion.

No states appear in the range exceeding the $mean + 3\ sd$ level. Only Delaware and Rhode Island take values ranging between $mean + 2\ sd$ and $mean + 3\ sd$ and only Connecticut, South Carolina, Alabama, Louisiana, and Nebraska take values between $mean + 1\ sd$ and $mean + 2\ sd$. Sixteen states (including Hawaii) take values ranging between the mean and $mean + 1\ sd$, whereas values for the remaining 26 states are below the country mean.

Chapter IV

Discussion

About ten years ago, The Economist (2006) warned that organic farming was so unsustainable that its global adoption could result in the virtual destruction of the rain forest. The question of whether organic farming is environmentally beneficial is undoubtedly contentious. However, such alarmist message only turns the well-needed constructive debate about our choice of sustainable farming practices into a pipe dream. The most obvious threat that organic farming poses is to the survival of several industries connected to the development, transportation, distribution, and consumption of fossil fuels, synthetic fertilizers, pesticides, herbicides, and genetically modified organisms. Indeed, alarmists and proponents of conventional farming represent cautionary signals that highlight the challenges of balancing the pressures from special interests in protecting their stake with those related to fighting climate change through sustainable practices.

Our poor understanding of the environmental impact of organic farming is largely due to the fact that most relevant research often lacks generalizability and fails to exhibit consistency in the assessment of food production's environmental impact. Such research has varied across products, product groups, geography, methodology, and data, thus resulting in mixed messages and confusion. Although organic farming may indeed lag behind conventional farming in terms of land use and yield, it undeniably provides important ecosystem services. Organic farming practices are by design sustainable in the role they play in maintaining optimal soil health, increasing carbon sequestration, and reducing GHG emissions. Yet, various articles in the media and research outlets (e.g. Gray, 2015; McGee, 2015; Paarlberg, 2013) make an effort to discredit organic food production on the grounds that it cannot be scaled without causing environmental harm. Such parties usually focus their attention on conventional farming practices for their ability to take advantage of technological improvements that are designed to increase yield, but fail to acknowledge the resulting potentially irreparable environmental degradation. Most importantly, they often base their contentions on speculation, questionable, inadequate, or non-existent empirical evidence.

Table 6. Summary of the main results.

	***n* = 50**			***n* = 44**		
	GHG	**CH_4**	**N_2O**	**GHG**	**CH_4**	**N_2O**
Organic Farming	-0.059*	-0.052**	-0.16**	-0.061*	-0.053**	-0.145**
Interaction with transport	X	0.012**	0.035**	X	0.013**	0.032**
Pasture	-0.007*	X	X	X	-0.008*	X
Thresholds				X		
log organic cropland	X	5.43	8.77	X	5.3	8.5
Transportation	X	4.41	4.61	X	4.21	4.54

Notes: ** $p<0.01$, * $p<0.05$. The thresholds represent the value that log organic cropland takes at which transportation output does not affect emissions and the value that transportation output takes at which organic farming does not affect emissions. X denotes a statistically insignificant coefficient estimate.

This thesis provides such empirical evidence. The key finding in this research is that organic farming is generally beneficial to the environment. Table 6 provides a summary of the main results. After controlling for other sources of emissions, a one percent increase in organic farming acreage is estimated to result in a 0.06% decrease in total GHG emissions. This estimate is also robust to the exclusion of U.S. states with potentially influential observations.

The relationship between organic farming and CH_4 emissions depends on the interaction between organic cropland acreage and transportation output. An increase in transportation output is expected to lower CH_4 emissions for given levels of log organic cropland below 5.43 and to increase CH_4 emissions for levels above 5.43. This threshold decreases slightly to 5.3 with the exclusion of outliers. On the other hand, growth in organic farming is expected to decrease CH_4 emissions for given levels of transportation output below 4.41 and to increase CH_4 emissions for levels above 4.41. This threshold also decreases slightly to 4.21 after the exclusion of outliers.

These thresholds are evidently more meaningful when put in context. Although the relationship between organic farming and CH_4 emissions is negative and statistically significant, it must be interpreted with respect to transportation output. In fact, a closer look at log organic cropland data reveals that 92.3% of the observations take values greater than or equal to the 5.43 threshold. More specifically, only 45 observations out of 585 have values less than or equal to 5.43. Thus, growth in transportation output will inevitably contribute to more emissions from a growing organic farming sector. In addition, approximately 85.33% of transportation output observations are less than or equal to 4.41, suggesting that for most cases, organic farming will have a mitigating impact on CH_4 emissions. In fact, on average, only seven states currently have transportation output that exceeds this threshold. These states include Alaska (9.76), Nebraska (7.67), Wyoming (5.93), Tennessee (4.84), Arkansas (4.75), Montana (4.73), and Kentucky (4.56). It is worth noting that states with a large organic farming sector do not necessarily have high transportation output. Indeed, log organic cropland and transportation output are far from being correlated ($r = 0.08$) and transportation output is even negatively correlated with organic cropland share (% of total farmland) ($r = -0.24$).

Organic farming is evidently not the only contributing factor to emissions. California and Vermont are important examples illustrating this concern. California on average has the most organic acreage in the country but its transportation output share ranks in the 37th spot at 2.44%. On the other hand, Vermont has the largest share of organic cropland (% of total farmland) but takes the 43rd spot in transportation output with 2.09%. Thus, based on the presented evidence, growth in organic farming will likely mitigate CH_4 emissions in most states at the current levels of transportation output.

The relationship between organic farming N_2O emissions also depends on the interaction between organic cropland acreage and transportation output. Growth in transportation output is expected to mitigate N_2O emissions for given levels of log organic cropland below 8.77 and increase N_2O emissions for levels higher than 8.77. On the other hand, growth in organic farming is expected to mitigate N_2O emissions for given levels of transportation output below 4.61 and to increase N_2O emissions for given levels above 4.61. Both of these threshold values decrease slightly after the exclusion of outliers to 8.5 and 4.54, respectively.

Putting these thresholds in context, the data reveal that about 39% of log organic cropland observations take values less than or equal to 8.77. This is not surprising given that organic farming remains at its infancy in the United States. However, the fact that it will likely expand in the future suggests that growth in transportation output will increase

N_2O emissions. In addition, approximately 88% of transportation output observations are less than or equal to 4.61. In fact, on average, only six states currently have transportation output that exceeds this threshold. Just like before, these states include Alaska (9.76), Nebraska (7.67), Wyoming (5.93), Tennessee (4.84), Arkansas (4.75), and Montana (4.73). Thus, based on the estimates presented above, at the current levels of transportation output, growth in organic farming in the remaining states would likely mitigate N_2O emissions.

The findings related to the interaction between transportation output and organic cropland lead to two important conclusions. First, transportation output is perhaps one of few economic activities that cannot be influenced by the adoption of organic farming practices. This is confirmed by the results presented above, which assert that growth in transportation output will inevitably increase CH_4 and N_2O emissions at the current levels of organic cropland across most U.S. states. Second, while transportation output may be a "necessary evil," growth in organic farming will likely mitigate CH_4 and N_2O emissions at the current levels of transportation output. This would suggest that the environmental harm that transportation output contributes to organic production might be too negligible to outweigh the environmental benefits of organic farming practices.

This important finding is supported by the cluster analysis described in the previous chapter in which the environmental impact of organic farming is below the country average for most U.S. states across all three measures of GHG emissions. These findings are contrary to McGee's (2015) contention that scaling organic farming is harmful to the environment. In fact, with organic farming acreage in the United States growing at about 9.5% annually, at this growth rate, GHG emissions would decrease by about 7.7% by 2030 and by 12.8% by 2050 relative to the level of emissions of 2016. While this projected decrease in emissions may seem insignificant, it is important to note that average organic cropland acreage, which represents less than one percent of total farmland, has substantial growth potential. For instance, if organic cropland were to double annually for the next six years to reach 32% of total farmland, GHG emissions could decline by 32% relative to the current levels of emissions within the same time frame.

In sum, the estimation results presented in this research show that after controlling for various sources of emissions, there is evidence supporting the mitigating effect hypothesis. That is, growth in organic food production is likely to mitigate GHG emissions. The estimation results also show that the mix between organic cropland acreage and transportation output plays an important role in determining the environmental effect of organic food production. In particular, organic food production is likely to mitigate CH_4 and N_2O emissions at the current level of transportation output and potentially moving forward across most U.S. states.

How Can Organic Farming Mitigate GHG Emissions?

Current organic farming practices can already allay many of the environmental concerns about conventional agricultural and play an important role in mitigating GHG emissions. However, scaling organic farming to meet increasing demand for organically grown food calls for an enhancement of farming practices and the movement towards increased sustainability. Regenerative organic agriculture and its management practices are potentially significant means to sequester more than current global annual emissions and to reverse the greenhouse effect (Rodale Institute, 2014). Regenerative organic agriculture's premise lies on nature's ability to regenerate and correct imbalances internally rather than through external inputs. This requires the creation of an ecosystem endowed with diverse and symbiotic populations of plants, insects, and organic matter. Indeed, the shifting of current cropland and pasture to regenerative organic agriculture is expected to sequester up to 111% of annual carbon emissions, thus resulting in annual negative emissions (Rodale Institute, 2014). It is important to note that although the estimated models in this thesis made use of data for GHG emissions including LUCF, which accounts for sequestered carbon arising from land use and forestry management, they do not capture stored soil carbon from organic farming practices. Thus, the potential environmental benefits of organic food production may be even larger than those presented in this research. Since stored soil carbon may vary greatly across sites and product groups, it would be better suited for LCA analyses. This is an area that undoubtedly deserves more attention in future research.

An important channel through which regenerative organic farming can mitigate GHG emissions is by minimizing soil erosion and runoff through the use of conservation tillage (CT). CT involves leaving at least 30% of the previous year's crop residue on fields to minimize soil erosion, runoff, and to maintain organic material into the soil (Abdalla et al., 2013). CT is expected to improve soil health and the soil's ability to sequester more carbon. Thus, replacing conventional tillage practices with CT is expected to reduce GHG emissions through the soil's ability to sequester more carbon.

Of course, organic farming practices must be viewed as moving targets that can always benefit from further improvements. In particular, the strict adhesion to a fixed set of principles by organic farming should be seen as a barrier to progress rather than an advantage. A farming activity that is not flexible enough to take advantage of scientific discoveries cannot be environmentally or economically sustainable. For instance, modern conventional farming has limited its environmental impact by making use of pest-resistant genetically modified seeds and precision farming (e.g. application of fertilizers to specific areas) using GPS-based technologies (Paarlberg, 2013). While organic farming understandably rejects genetic modification, it can undoubtedly benefit from precision farming. Thus, an important question remains: can the current competition between conventional and organic farming be replaced with a more symbiotic relationship?

Research Limitations and Suggestions

Contrary to LCA studies, which yield inferences on the various stages of organic food production's lifecycle, the present analysis makes general inferences. This is not problematic given the aggregate nature of the data and the fact that total GHG emissions data control for land use and forestry changes. Nevertheless, there are always concerns that omitted variable bias may result in not rejecting the null hypothesis because of potentially large residual error and the error in estimating other variables. While this is indeed true in virtually all studies applying multiple regression and that suffer from omitted variable bias, it does not apply to the current research. This research benefits from the use of random effects and fixed effects estimators and a nonlinear STIRPAT-inspired empirical model that is consistent with a large and established literature. These factors jointly limit the bias arising from omitting variables potentially highly correlated with GHG emissions. Indeed, the fact that most empirical models have high R^2 values suggests that the estimated models have high explanatory power and are relatively complete and properly specified.

There are, however, a number of concerns about data quality. Ideally, the CH_4 model would include a variable capturing municipal solid waste from homes and businesses while accounting for the conversion of CH_4 emissions to energy, cross-state diversion, disposal, and transfer of municipal solid waste. However, to the author's knowledge, no appropriate data are available at the state level. The N_2O models could also benefit from the inclusion of a variable capturing agricultural soil management (i.e. the use of nitrogen-based fertilizers). However, no data are available at the state level.

The current study reveals GHG mitigation benefits associated with organic food production. Policymakers and scientists can build on these results to further develop the evidence base and policies needed to maximize the benefits of adopting organic practices.

Appendix 1

Ancillary Statistical Results

Table 7. Summary statistics of the variables included in estimations.

Variables		Max	Min	SD	Mean	Obs.
log GHG	Overall	6.70	2.30	0.79	4.63	N = 550
	Between	6.68	2.99	0.79		n = 50
	Within	5.12	2.88	0.14		T = 11
log CH_4	Overall	4.31	1.40	0.55	2.55	N = 550
	Between	4.21	1.54	0.56		n = 50
	Within	2.81	2.30	0.06		T = 11
log N_2O	Overall	3.28	-1.82	1.15	1.33	N = 550
	Between	3.11	-1.47	1.15		n = 50
	Within	1.65	0.89	0.10		T = 11
log population	Overall	17.44	13.10	1.01	15.10	N = 550
	Between	17.38	13.15	1.02		n = 50
	Within	15.26	14.83	0.04		T = 11
log GDP	Overall	11.15	10.25	0.18	10.69	N = 550
	Between	11.06	10.32	0.17		n = 50
	Within	10.92	10.42	0.06		T = 11
log VMT	Overall	12.70	8.39	0.98	10.52	N = 550
	Between	12.67	8.49	0.99		n = 50
	Within	10.74	10.21	0.06		T = 11
Oil & natural gas	Overall	38.05	0.00	3.91	1.50	N = 511
	Between	19.54	0.00	3.66		n = 50
	Within	20.01	-3.79	1.11		T = 10.2
Utilities	Overall	4.37	0.61	0.63	2.12	N = 550
	Between	3.51	0.69	0.57		n = 50
	Within	3.08	1.22	0.28		T = 11
Manufacturing	Overall	29.81	1.75	5.48	12.46	N = 550
	Between	27.24	1.97	5.34		n = 50
	Within	26.13	4.43	1.42		T = 11
Transportation	Overall	11.79	1.34	1.51	3.30	N = 550
	Between	9.97	1.43	1.50		n = 50
	Within	5.13	1.79	0.28		T = 11
log farmland	Overall	18.69	11.00	1.57	15.95	N = 550
	Between	18.69	11.11	1.59		n = 50
	Within	16.10	15.84	0.03		T = 11
log organic cropland	Overall	13.12	0.69	2.26	9.01	N = 535
	Between	12.27	4.73	2.18		n = 50
	Within	13.24	3.52	0.77		T = 10.7
log organic	Overall	14.19	1.61	2.53	7.88	N = 456

pasture	Between	13.03	3.43	2.37		n = 50
	Within	11.93	2.39	1.16		T = 9.12
log organic	Overall	98.81	0.95	14.84	29.84	N = 535
crop x	Between	86.39	6.75	14.56		n = 50
Transportation	Within	46.70	-5.30	3.87		T = 10.7

Table 8. Random effects estimation results for GHG emissions incl. LUCF without outliers (*n* = 44).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
log population	0.485*	0.523**	0.671**	0.543**	0.573**	0.637**
	(0.199)	(0.198)	(0.249)	(0.204)	(0.197)	(0.238)
log income	25.96	29.16*	30.41	26.07	29.44*	29.36
	(14.48)	(14.33)	(18.18)	(13.31)	(13.51)	(16.42)
$(\text{log income})^2$	-1.189	-1.341*	-1.397	-1.189	-1.348*	-1.348
	(0.673)	(0.665)	(0.844)	(0.617)	(0.627)	(0.764)
log vmt	0.0688	0.0266	-0.115	0.0540	0.0226	-0.0436
	(0.190)	(0.190)	(0.244)	(0.208)	(0.202)	(0.245)
Oil & natural gas	0.028**	0.029**	0.034**	0.031**	0.032**	0.038**
	(0.00690)	(0.00709)	(0.0105)	(0.00915)	(0.00947)	(0.0122)
Utilities	0.105**	0.099**	0.075*	0.0421	0.0315	-0.00710
	(0.0308)	(0.0318)	(0.0362)	(0.0434)	(0.0482)	(0.0581)
Manufacturing	0.018**	0.018**	0.021**	0.018*	0.018*	0.021**
	(0.0055)	(0.0058)	(0.0056)	(0.0072)	(0.0074)	(0.0076)
Transportation	0.0178	-0.0489	-0.0700	0.0288	-0.0411	-0.0604
	(0.0293)	(0.0314)	(0.0571)	(0.0307)	(0.0269)	(0.0500)
log farmland	0.110**	0.111**	0.127**	0.099**	0.099**	0.102**
	(0.0361)	(0.0359)	(0.0397)	(0.0343)	(0.0333)	(0.0361)
log organic crop	-0.0105	-0.036	-0.061*	-0.0012	-0.028	-0.048

	(0.00668)	(0.0197)	(0.0301)	(0.00545)	(0.0167)	(0.0282)
log organic crop x		0.00805	0.0116		0.00843	0.0121
Transportation		(0.00534)	(0.00819)		(0.00471)	(0.00768)
log organic			-0.00444			2.84e-05
pasture			(0.00309)			(0.00407)
Constant	-147.2	-164.0*	-171.7	-149.0*	-166.7*	-166.0
	(78.52)	(77.68)	(98.22)	(72.33)	(73.34)	(88.65)
N	433	433	360	433	433	360
Overall R^2	0.794	0.793	0.777	0.774	0.774	0.754

Notes: Robust standard errors in parentheses. The coefficient estimates of the year dummies are omitted from the estimation results. ** p<0.01, * p<0.05.

Table 9. Fixed effects estimation results for CH_4 emissions without outliers (*n* = 44).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
log population	0.480**	0.505**	0.762**	0.616**	0.621**	0.815**
	(0.175)	(0.171)	(0.193)	(0.181)	(0.178)	(0.247)
log income	0.267	2.797	3.647	3.676	6.365	6.575
	(8.280)	(7.263)	(5.858)	(7.570)	(6.836)	(5.469)
(log income)^2	-0.008	-0.128	-0.161	-0.156	-0.283	-0.288
	(0.390)	(0.342)	(0.277)	(0.356)	(0.321)	(0.257)
Oil & natural gas	0.015	0.014	0.012	0.011	0.010	0.009
	(0.008)	(0.009)	(0.007)	(0.008)	(0.009)	(0.008)
Transportation	0.040*	-0.031	-0.067	0.035	-0.042	-0.046
	(0.016)	(0.026)	(0.038)	(0.022)	(0.029)	(0.044)
log farmland	0.062	0.150	0.197	-0.047	0.048	0.122
	(0.246)	(0.234)	(0.210)	(0.251)	(0.238)	(0.236)

log organic crop	-0.009	-0.034*	-0.053**	-0.008	-0.036*	-0.050**
	(0.006)	(0.014)	(0.010)	(0.006)	(0.015)	(0.011)
log organic crop		0.008**	0.013**		0.009**	0.011**
x Transportation		(0.003)	(0.003)		(0.003)	(0.003)
log organic pasture			-0.008*			-0.008*
			(0.004)			(0.004)
Constant	-7.630	-22.621	-32.321	-27.519	-43.123	-48.696
	(43.364)	(37.325)	(30.951)	(39.101)	(34.962)	(28.937)
Year dummies	No	No	No	Yes	Yes	Yes
N	433	433	360	433	433	360
Overall R^2	0.298	0.425	0.353	0.0818	0.201	0.248

Notes: Robust standard errors in parentheses. The coefficient estimates of the year dummies are omitted from the estimation results. ** p<0.01, * p<0.05.

Table 10. Fixed effects estimation results for N_2O emissions without outliers (*n* = 44).

Variables	(1)	(2)	(3)	(4)	(5)	(6)
log population	-0.962**	-0.893**	-0.916**	0.111	0.100	0.078
	(0.232)	(0.237)	(0.245)	(0.318)	(0.310)	(0.422)
log income	28.287*	33.247**	41.395**	35.390**	39.466**	46.172**
	(11.356)	(9.343)	(11.943)	(8.506)	(7.612)	(8.791)
(log income)^2	-1.313*	-1.547**	-1.929**	-1.612**	-1.806**	-2.122**
	(0.534)	(0.439)	(0.562)	(0.396)	(0.353)	(0.409)
log vmt	-0.333	-0.368	-0.313	-0.397*	-0.412*	-0.264
	(0.196)	(0.202)	(0.259)	(0.186)	(0.189)	(0.275)
Manufacturing	0.005	0.006	0.009	-0.003	-0.001	0.000
	(0.006)	(0.006)	(0.007)	(0.004)	(0.004)	(0.005)
Transportation	0.028	-0.130**	-0.271**	0.041	-0.099**	-0.181*

	(0.023)	(0.040)	(0.073)	(0.036)	(0.035)	(0.082)
log farmland	-0.597	-0.413	-0.524	-0.622	-0.460	-0.500
	(0.498)	(0.481)	(0.573)	(0.388)	(0.384)	(0.466)
log organic crop	-0.023**	-0.079**	-0.145**	-0.010	-0.060**	-0.102**
	(0.008)	(0.024)	(0.026)	(0.008)	(0.019)	(0.022)
log organic crop		0.018**	0.032**		0.016**	0.025**
x Transportation		(0.005)	(0.007)		(0.004)	(0.006)
log organic pasture			0.004			0.008
			(0.004)			(0.005)
Constant	-123.216	-152.70**	-193.87**	-180.35**	-203.61**	-239.39**
	(62.204)	(51.642)	(64.665)	(48.200)	(43.823)	(50.823)
Income TP ($)	47,473	46,427	45,604	58,361	55,629	53,146
Year dummies	No	No	No	Yes	Yes	Yes
N	469	469	390	469	469	390
Overall R^2	0.698	0.608	0.638	0.731	0.726	0.669

Notes: Robust standard errors in parentheses. The coefficient estimates of the year dummies are omitted from the estimation results. ** p<0.01, * p<0.05.

Table 11. Environmental impact estimates of organic farming.

State	**GHG**	**CH_4**	**N_2O**	**State**	**GHG**	**CH_4**	**N_2O**
AK	2.294	1.446	175.891	**MT**	1.711	1.056	176.236
AL	2.908	0.898	176.439	**NC**	2.204	0.813	176.265
AR	2.094	1.046	176.225	**ND**	5.489	1.015	176.208
AZ	2.469	0.828	176.156	**NE**	2.349	1.457	176.518
CA	2.989	0.715	175.932	**NH**	1.837	0.774	176.359
CO	2.708	0.786	176.051	**NJ**	2.697	0.883	176.256
CT	2.065	0.787	176.442	**NM**	3.062	0.795	176.148
DE	2.665	0.831	176.643	**NV**	2.275	0.913	176.234
FL	3.262	0.814	176.157	**NY**	2.435	0.679	175.990
GA	2.313	0.955	176.250	**OH**	3.462	0.829	176.125
HI	2.682	0.969	176.215	**OK**	2.749	0.912	176.210

IA	2.798	0.892	176.133	**OR**	1.770	0.816	176.076
ID	2.520	0.819	176.063	**PA**	3.691	0.842	176.149
IL	2.886	0.899	176.162	**RI**	2.789	0.834	176.631
IN	3.639	0.902	176.222	**SC**	2.101	0.883	176.520
KS	2.679	0.947	176.180	**SD**	2.909	0.806	176.068
KY	3.742	1.022	176.226	**TN**	2.515	1.043	176.205
LA	3.205	0.940	176.400	**TX**	4.025	0.903	176.135
MA	2.353	0.766	176.341	**UT**	2.243	0.918	176.147
MD	2.565	0.773	176.248	**VA**	2.365	0.792	176.186
ME	1.696	0.767	176.129	**VT**	2.072	0.714	176.051
MI	2.471	0.757	176.069	**WA**	1.729	0.792	176.089
MN	2.058	0.826	176.045	**WI**	1.867	0.829	176.074
MO	2.539	0.908	176.166	**WV**	7.773	0.910	176.347
MS	1.953	0.942	176.365	**WY**	4.892	1.202	176.314

Table 12. Mean organic cropland (% of total farmland), 1997, 2000-2008, and 2010.

State	Organic Cropland	State	Organic Cropland
VT	3.130	FL	0.137
ME	1.496	SD	0.133
NY	0.933	NV	0.110
CA	0.914	WY	0.109
ID	0.710	VA	0.096
WI	0.652	IL	0.089
NH	0.432	AR	0.082
MI	0.427	KS	0.077
MN	0.396	MO	0.074
UT	0.368	TX	0.061
ND	0.332	AZ	0.057
MA	0.322	NM	0.044
WA	0.316	IN	0.039
NJ	0.306	NC	0.037
OR	0.305	AK	0.035
PA	0.271	OK	0.023
OH	0.244	DE	0.023
HI	0.236	WV	0.020
CO	0.223	KY	0.017
IA	0.216	GA	0.012
MT	0.213	TN	0.012
RI	0.203	LA	0.005
MD	0.196	MS	0.004
NE	0.159	SC	0.003

CT	0.143	AL	0.003

Note: The values are computed using data from the USDA.

Appendix 2

Cluster Analysis Maps

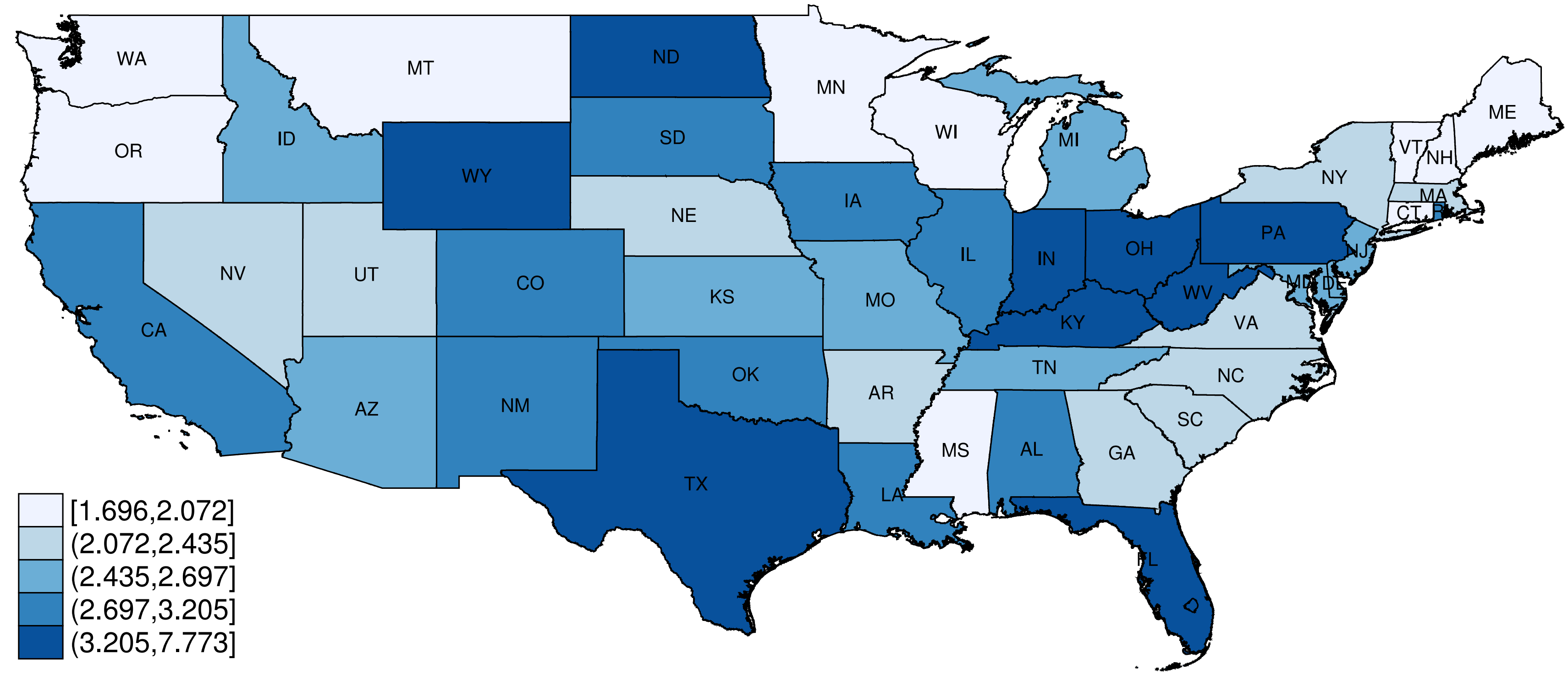

Figure 15. Spatial distribution of the environmental impact (ln GHG) of organic farming (quintiles).

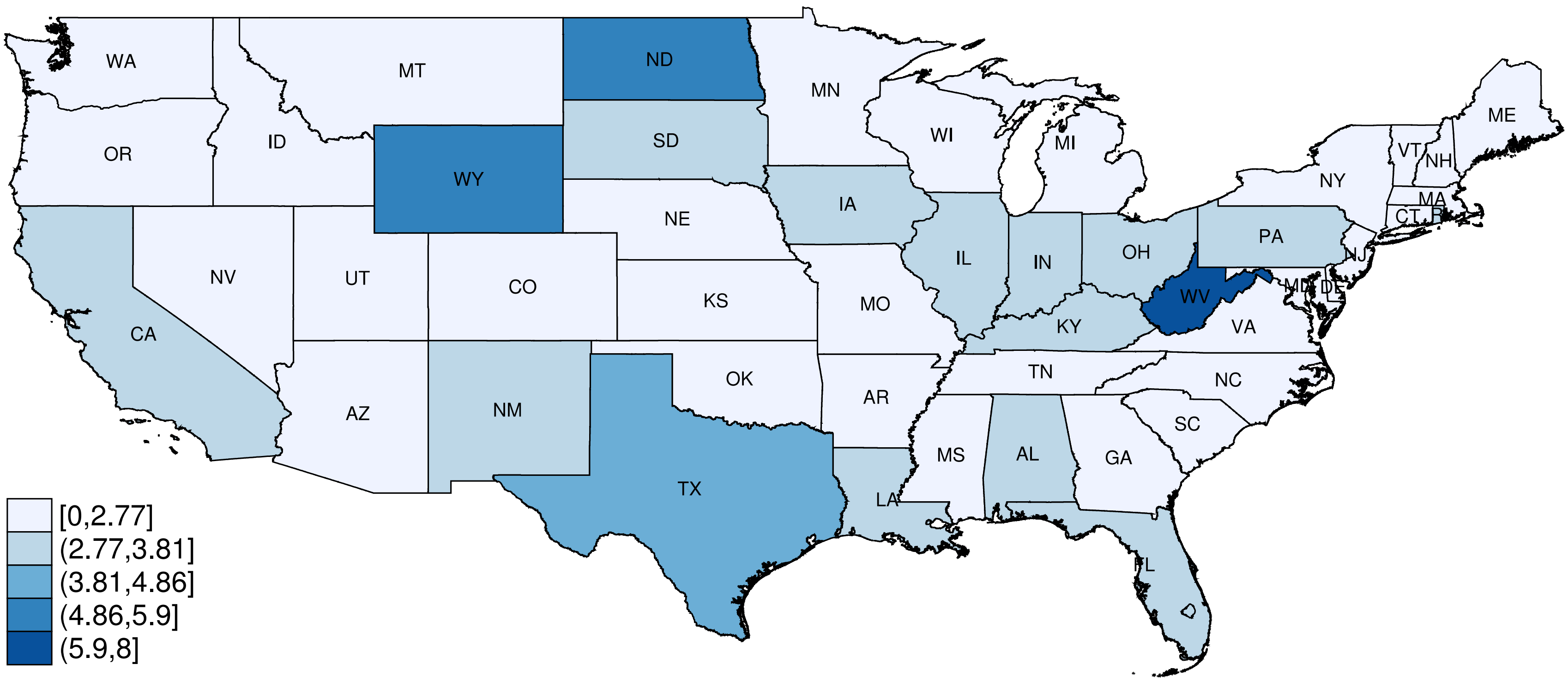

Figure 16. Spatial distribution of the environmental impact (ln GHG) of organic emissions (deviation from the mean).

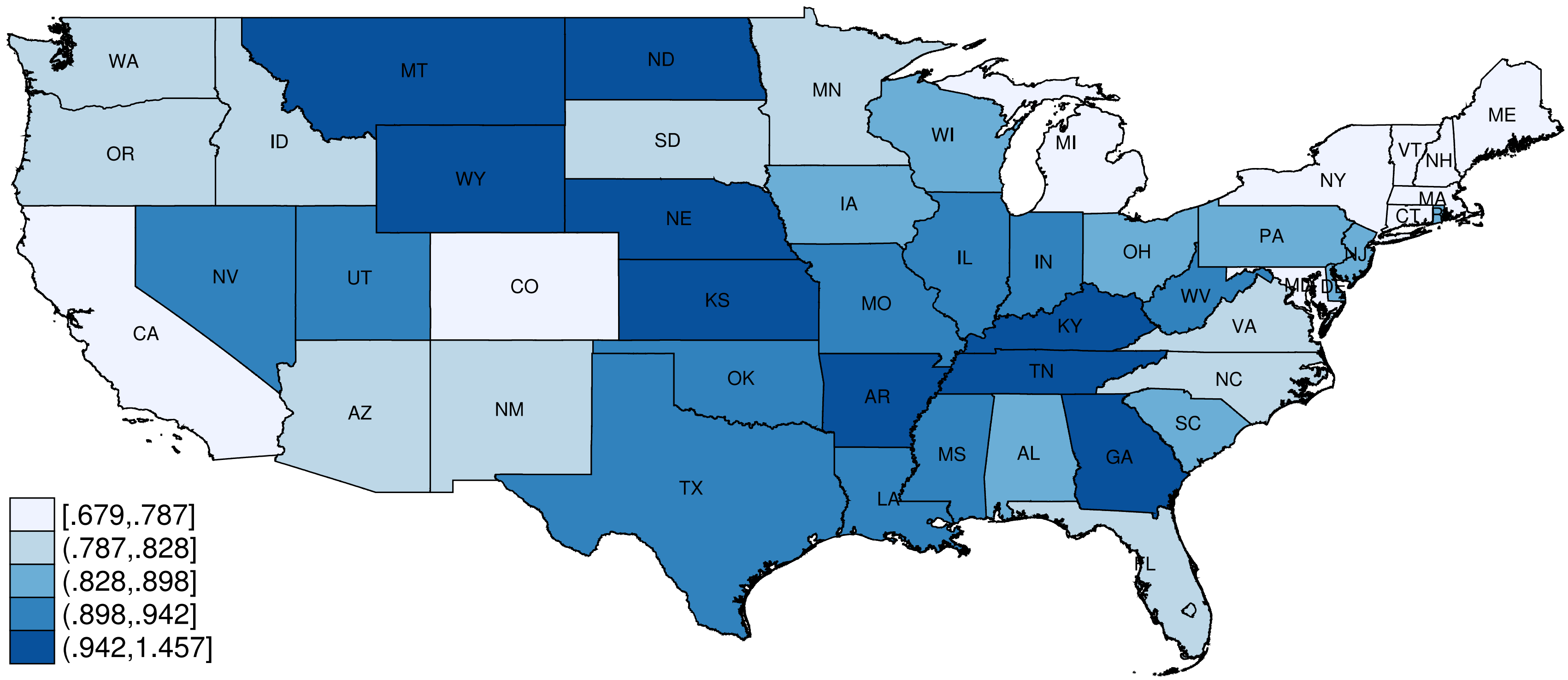

Figure 17. Spatial distribution of the environmental impact (ln CH_4) of organic farming (quintiles).

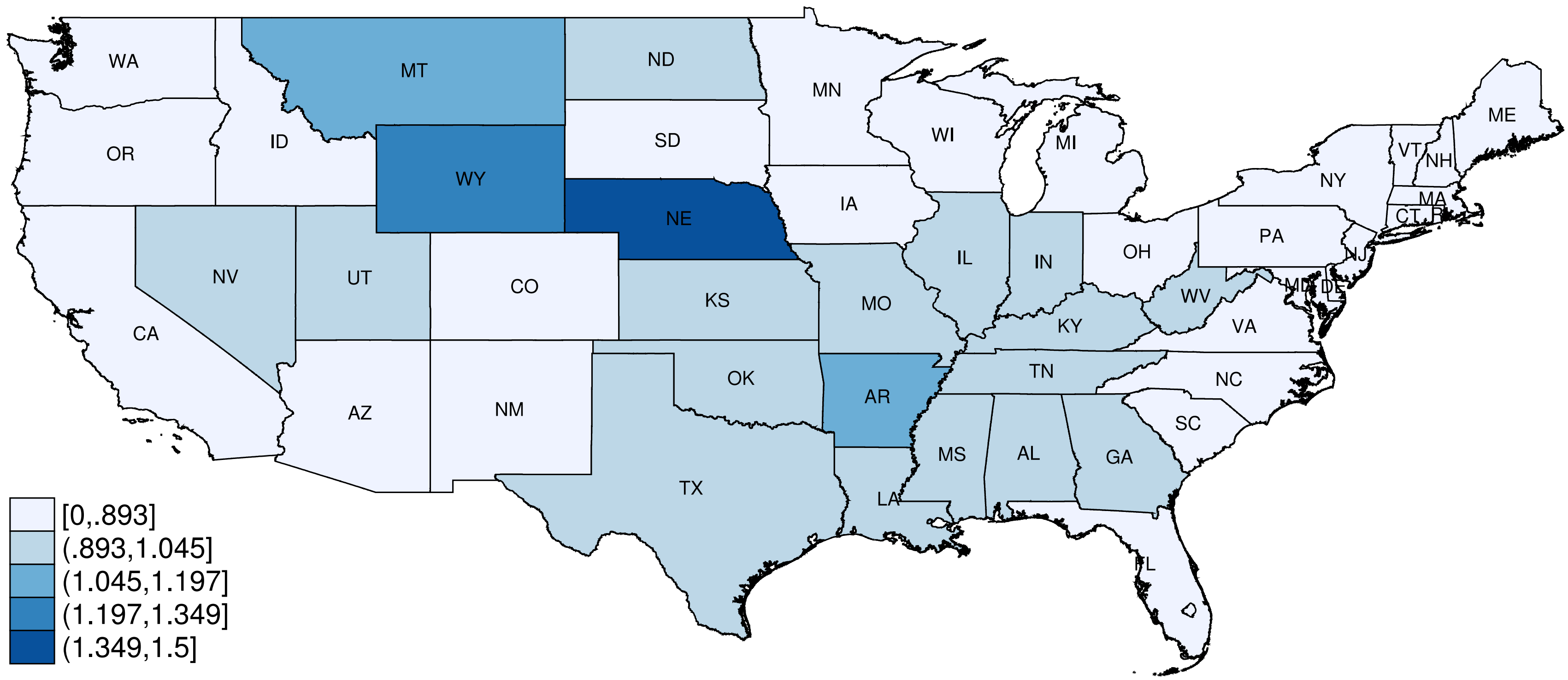

Figure 18. Spatial distribution of the environmental impact (ln CH_4) of organic farming (deviation from the mean).

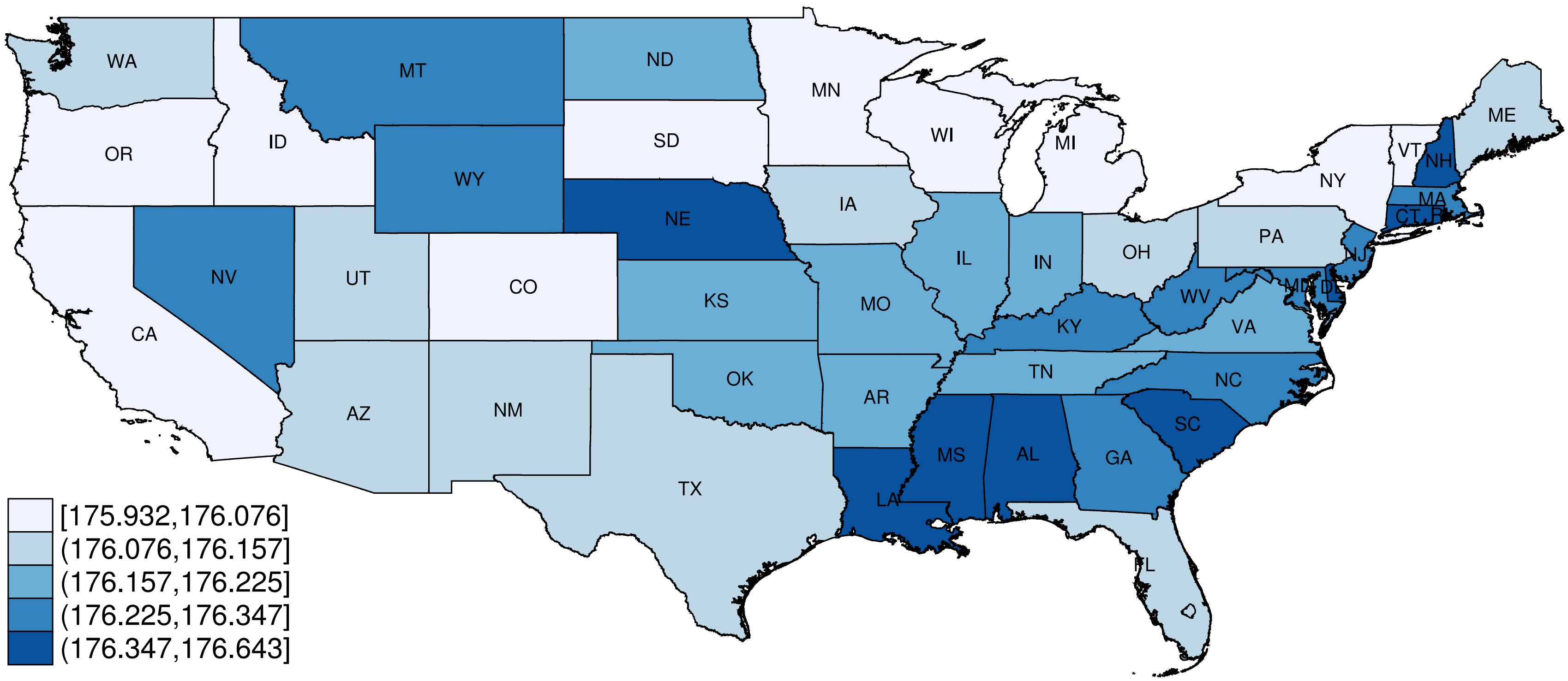

Figure 19. Spatial distribution of the environmental impact (ln N_2O) of organic farming (quintiles).

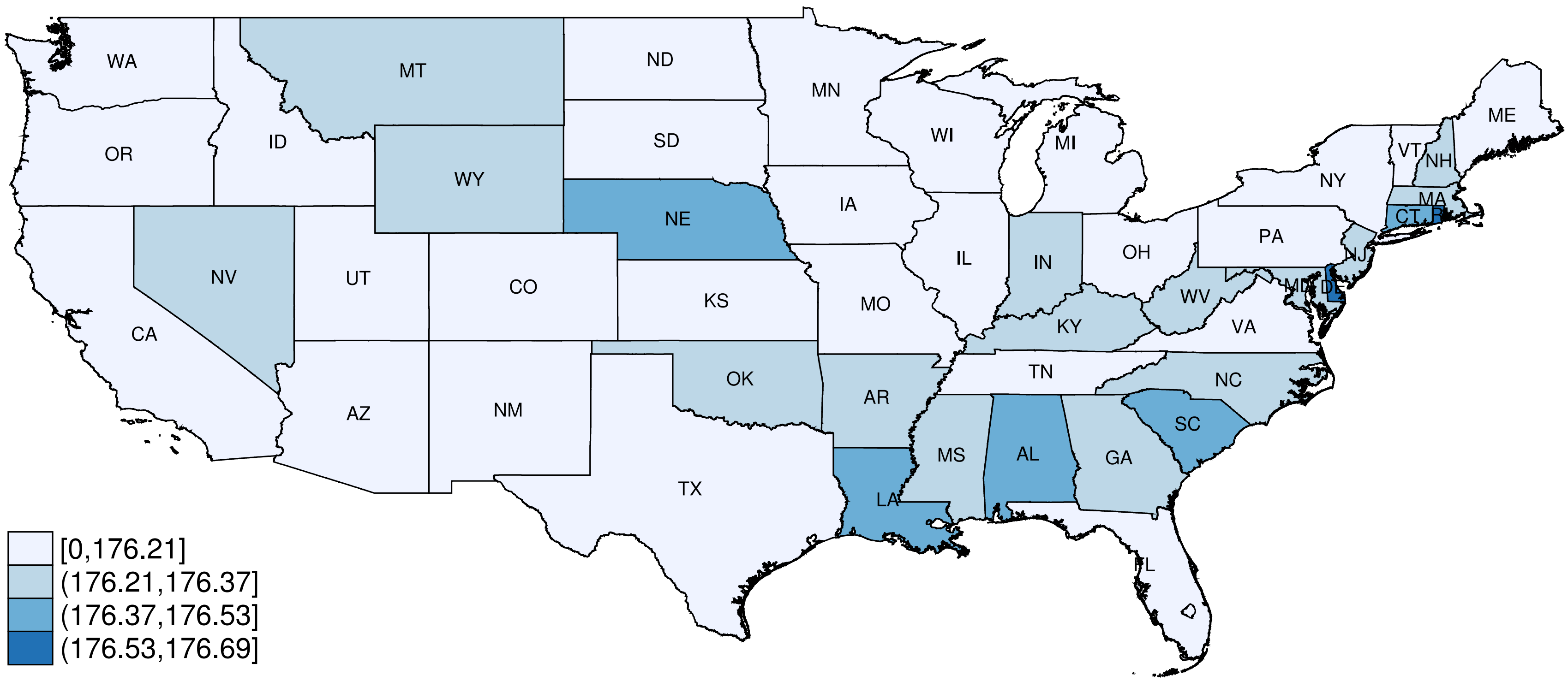

Figure 20. Spatial distribution of the environmental impact (ln N_2O) of organic farming (deviation from the mean).

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