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Health effects stemming from animal feeding operations pollution in the contiguous United States are analyzed using a 20-year, county-level data set. Several quasi-experimental, potential outcome models are used to estimate the impact of high concentrations of animal units on mortality rates and other health and economic outcomes over a 20-year period. This period saw significant federal regulatory policy development for animal farming and these policies are evaluated for efficacy. Over the period, the effects of high concentrations of animal units had some discernable effects on the community health as measured by mortality rates, but, overall, these effects shifted downward from 1997-2012. States with relatively weak prior policy saw a reduction in deleterious effects as federal policy grew stronger, whereas states with relatively strong prior policy saw no measured changes, suggesting that federal policy implementation was effective in localities with weaker prior regulations. The evidence of effects elsewhere, however, was inconclusive. Alternative economic and migratory outcome variables were also evaluated, but the findings of these models were also inconclusive. The efficacy of the current policy regime (which relies primarily on National Pollution Discharge Elimination Permits and nutrient management plans for larger, Concentrated Animal Feeding Operations) towards mitigating health externalities is considered along with potential policy alternatives.

Animal Farming, Pollution, and Community Health

by
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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Michael A. Weinerman, Author

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GLOSSARY

AFO – Animal Feeding Operation

ATE – Average Treatment Effect

ATET – Average Treatment Effect on the Treated

AUD – Animal Unit Density

CAA – Clean Air Act

CAFO – Concentrated Animal Feeding Operation

CDC – Center for Disease Control and Prevention

CERCLA – Comprehensive Environmental Response, Compensation, and Liability Act

CWA – Clean Water Act

EPCRA – Emergency Planning and Community Right-to-Know Act

ETE – Endogenous Treatment Effects

GPS – General Propensity Score

IPW – Inverse Probability Weight

IPWRA – Inverse Probability Weighted Regression Adjustment

MTBE – Methyl tert-butyl ether

NCHS – National Center for Health Statistics

NOAA – National Oceanic and Atmospheric Administration

NMP – Nutrient Management Plan

NPDES – National Pollution Discharge Elimination System

PSM – Propensity Score Matching

RA – Regression Adjustment

RCT – Randomized Control Trial

SUTVA – Stable Unit Treatment Value Assumption

TRI – Toxic Release Inventory

USDA – United States Department of Agriculture

USEPA – United States Environmental Protection Agency

USGS – United States Geological Survey

1 Introduction

Environmental issues arising from the byproducts of Animal Feeding Operations (AFOs) have grown both in size and in prominence over the last century. Animal product industries developed from a system of mostly small, mostly dispersed farms that each grow a diverse set of products to a larger, more vertically integrated industry that has fewer AFOs. The total number of AFOs declined drastically over this period and continues to decline, while the average size of each AFO has grown. Monocultures have become more prevalent and AFOs are now more regionally concentrated as well. These trends have led to both economic and environmental impacts. Production efficiency gains help satisfy consumer demands for cheaper animal products, but these increasing quantities have been matched by larger quantities of the associated animal waste products resulting in greater contributions to air, water, and land pollution. The increased concentration of AFOs has led to a greater necessity for animal confinement, which fosters lower animal growth rates[1] and increased spread of disease among the animals, necessitating greater use of antibiotics and growth hormones than in traditional, less-concentrated operations. These trends also result in greater spatial concentrations of pollutants. AFO pollution impacts community health along multiple vectors through direct exposure to the contaminants in each of the different environmental media. The extent of these health impacts depends on several factors including the distance from a given AFO to the point of exposure, type of livestock, transmission vector, scale of exposure, atmospheric and geologic characteristics, public policy, and AFO-level behavior. This project extends the research that explores the health effects of AFOs, which has attempted to estimate the extent of environmental, health, and socioeconomic impacts of AFO operations.

[1] All else equal, due to the lower level of animal mobility when confined.

Manure, manure's constituent components, and various forms of gasses are the primary pollution byproducts of animal production. A portion of these byproducts is used as fertilizer or captured to be used as biogas fuel, but some portion are also either directly or indirectly deposited into air, water, and land resources. In cases where neighboring communities are regularly exposed to contaminated air or contaminated water, human health effects often manifest. These effects are exaggerated among AFO workers who face greater exposure rates than the general population. A broad body of research has examined these exposure patterns and impacts but has usually done so for isolated mechanisms instead of at a system level. The inherent complexity in estimating the magnitudes of effects paired with the relative paucity of data, however, has left significant room for improvement in both estimation techniques and the conceptualization of policy solutions.

This paper contributes to the existing literature in four main ways: 1) we introduce a reduced-form, seemingly unrelated regression estimation of the total health impacts that stem from both water and air vectors. This technique reduces bias and increases precision relative to prior estimates; 2) the framework allows for the exploration of the intertemporal dynamics of water vectors, air vectors, and health impacts; 3) we quantitatively explore the economic impacts and distributional consequences of AFOs on regional economies; and 4) we provide an analysis of the existing policy regime in view of this new approach and contribute to AFO policy discussions.

Section 2 provides a brief overview of animal feeding operations and the major economic, environmental, and public health concerns that surround them. The literature underlying that overview are described in more detail in Section 3, which provides a review of the major strands of relevant literature. Section 4 discusses the primary conceptual frameworks that will be employed. Section 5 describes the primary data sets used in the analysis. Section 6 describes the empirical strategies that will be used to estimate the relationships modeled in

Section 4. Section 7 provides results from the empirical models employed. Section 8 provides a discussion of the results, a qualitative policy exploration in a subset of states. And Section 9 concludes with a discussion of the challenges faced in the analysis and offers a brief description of possible extensions.

2 Background

AFOs impact public health through several mechanisms. Gaseous compounds, including ammonia, methane, and airborne particulates, are deposited in the atmosphere through both the digestive processes of livestock and through volatilized manure. Air contaminants then may impact respiratory health in the form of asthma or other impairments. Air contaminants may also indirectly impact human health through contributions to climate change. AFOs are a significant contributor to greenhouse gas emissions at the global level (Steinfeld et al. 2006), but the related health effects are beyond the scope of the current project. Water pollution from the runoff and leaching of manure results in elevated levels of nitrogen, phosphorous, antibiotics, heavy metals, and hormones in surface and groundwater. Water contaminants may also foster a range of transmittable diseases and parasites that may be resistant to antibiotic treatment due to the prevalence of antibiotic use with livestock at AFOs. Researchers have found evidence for these different mechanisms and have found many mechanisms to be at an economically significant level, but precise measurement of the magnitudes of the effects remain active areas of research.

Animal farming is one of the largest polluting industries, at both the global and the U.S. scales. The EPA has estimated that the U.S. animal product industry produced roughly 1.1 billion tons of manure in 2007, about 13 times greater than quantity of human sewage produced in the same year. In light of increasing spatial concentrations between AFOs, most of the manure produced on AFOs exceeds the nutrient uptake limits of the neighboring croplands and thus must be stored or disposed of on site (USEPA 2013). AFOs produce air pollution at a scale like that of solid manure waste. Between enteric fermentation (25%) and manure management (10%), for example, AFOs produce more methane emissions in the U.S. than any other industry. Comparatively, natural gas and petroleum production industries contribute 31% of total methane emissions (USEPA 2015a). Methane does not have significant, localized health effects relative to other AFO pollutants and typically dissipates into the atmosphere quickly as a potent greenhouse gas[2]. Ammonia, however, which is also released concurrently with methane, has been shown to have significant human health impacts. There is no consensus regarding an aggregate estimate of ammonia emissions that comes from animal operations, but estimates have placed the contribution of livestock to total ammonia releases in the U.S. at or above 50% of the total amount released (Aillery et al. 2005).

The efficacy of policies aimed at mitigating AFO pollution has been a focus of many academic, legal, regulatory, and policy discussions. Despite this extant body of literature and discussions, there remains debate regarding the environmental and health impacts attributable to AFOs. Authors argue, for example, that existing policy does not fully endogenize the costs of the environmental impacts stemming from AFO pollution with the AFOs that produce the pollution, resulting in inefficiencies and that straightforward solutions are hard to find (Shortle and Horan 2017). Many factors may contribute to these potential policy failures, including regulatory capture, a lack of funding for regulatory enforcement, myopic policies that do not consider pollution spillovers or context-specific downstream transmissions processes, or other processes that result in lax regulatory applications. These policy failures may be exacerbated by the lack of consensus regarding the precise scale and dynamics of AFO pollution, its effects, and the efficacy of previous policy changes towards addressing these issues.

[2] The indirect impacts of these climate effects are not a focus of the current analysis.

Cross-media pollution is likely to be an important consideration when exploring AFO pollution but has received scant attention in the empirical research. Pollutants may often transition between media (i.e., air, water, or land) while either maintaining the original chemical composition or transitioning into another form. These changes may be the result of natural processes but may also be intentionally induced by cost-minimizing polluters who face different disposal costs relative to the disposal medium. For example, a nutrient management plan (NMP) implemented as part of permitting process of an AFO may call for a stronger liner to be installed in a manure lagoon to prevent leakage into water resources. While the liner prevents some leakage into water systems it also keeps a greater portion of the manure above ground where it is more easily volatilized into the air. Similarly, the increased marginal cost of building a new manure lagoon may induce producers to shift storage or disposal of pollutants into other media. As such, better lining a lagoon may result in lower water pollution in the short term but may increase air pollution in the long term.

Pollutants may also transfer between media after the initial polluting activity, regardless of the actions of the polluters. Many AFO pollutants are components of the nitrogen cycle, for example, where nitrogen-based compounds may change or breakdown over time and transfer between air, water, and land media. Thus, if AFO policies myopically focus on limiting air pollution then we may simply be delaying and/or spatially altering the dynamics of pollution in these various media, rather than reducing the total quantity of nitrogen-based compounds in the environment. Coordinated policies do exist in some regions. Also, and some forms of technological mitigation (e.g., biodigesters) or simply reductions in the total number of animal units produced, offer ways of reducing total pollution from AFOs, which would preclude these spillover effects altogether. The preponderance of environmental policies, however, focus on limitations in specific media rather than the total quantity of pollutants released, thus ignoring the potential for pollution spillovers in this setting.

The mechanisms by which AFO pollutants impact human health are well understood, but the details of these mechanisms remain under-researched. Most of the empirical studies in this field are small-scale, survey-based, or matched case studies and thus do not generalize to a national scale. Nevertheless, these studies show evidence that idiosyncratic causal mechanisms exist. Understanding the total scale and scope of the health impacts from animal farming depends on aggregating across many context-specific factors, such as the level of a community's reliance on a contaminated groundwater resource for drinking water, whether individuals live downwind from an AFO, and the specific type of animals raised on the AFO and the type of feed and other inputs the animals are given. In this way, small scale studies that do not include multiple AFOs across several factors offer limited generalizability.

As with pollution, there may also be interactions or spillovers between the different forms of health impacts. If a person is suffering from a respiratory ailment that is induced by ammonia, for example, this may contribute to a generally weakened immune system. An immunosuppressed person may be more susceptible to other ailments, including those caused by water contamination. Similarly, infirmities that stem from excess nutrients and other chemical compounds in drinking water may also result in compromised immune systems. In utero exposure to contaminants may result in conditions such as blue baby syndrome (methemoglobinemia), which in turn may cause long-term health impairments, susceptible immune systems, or even death. Like environmental contaminants, estimation of specific health impacts, such as asthma, in isolation may induce estimation errors by not accounting for compounding health effects.

Spillovers, at any stage in the polluting process or in the manifestation of health effects, have implications across agricultural, environmental, and health policies. Ill-suited policies could be ineffectual or even counter-productive if the health effects that stem from a spillover effect manifest at lower thresholds or result in more severe conditions because of the compounding effects of multiple forms of exposure. Thus, health and environmental policy that focuses on mitigating only one form of AFO pollution or fails to effectively coordinate between policies that regulate other forms of pollution may have significant inefficiencies in attempting to reduce impacts. These patterns have implications for researchers and policymakers. Researchers may be introducing bias into their estimation by ignoring parts of the system of pollution and effects. Likewise, policymakers may need a more general approach that accounts for environmental and health spillovers, as well as multiple forms of health effects. Overall, there is a gap between precise estimation of effects at a local level and implications of these localized findings for public policy.

An additional dimension is the potential impacts that AFOs, and especially larger Concentrated AFOs (CAFOs), may have on regional economies. AFOs provide direct wages to AFO workers as well as provide indirect wages to slaughterhouses and other food distribution jobs, induce additional consumer spending, and contribute to local tax coffers. But there may also be secondary, unintended adverse economic consequences related to AFOs. Housing markets near AFOs may face an initial boon if there is an increased demand for housing from new AFO workers, but these markets may also reflect AFO externalities to the extent that they make the immediate neighborhood less desirable or hospitable. Labor markets may also experience significant shifts following the addition of an AFO to a regional economy, as CAFOs may have significant cost advantages over smaller, less efficient operations that were there previously. Some have argued that CAFOs push out smaller, locally owned animal production operations, and push down median wages, and drive down regional economic resiliency, especially in rural regions that are already facing economic hardships (Roberts 2009; Imhoff 2010), but these questions have not been thoroughly explored in the empirical research and thus these impacts are primarily speculation.

Data shortcomings and data availability are major impediments in this field of research, which is likely why robust, general estimates of health effects have yet to emerge in the literature. Air and water contamination data are inconsistently measured over time and space, likely suffer from measurement error, and are largely unavailable in many regions that are important to the question of the health impacts of AFOs. Furthermore, interpretation of these pollution data in this context is difficult and varies from farm-to-farm: prevailing winds and other local weather variables will heavily influence the communities that will be impacted by air contamination; and water contamination will be highly dependent on geological structures, the type of manure disposal and contamination, and whether populations are reliant on those water sources for human consumption. Several researchers have estimated components of these biological and geological systems in integrated theoretical farm models, but have not expanded these findings to a general, empirical model that accounts for various forms of spillovers and health impacts. These modeling efforts offer important information regarding economic optimization at the farm level, but are, again, difficult to leverage into policy implications when balanced against broader health and environmental factors.

Much is known regarding the manner of impacts related to AFOs, but important questions regarding the dynamics of these impacts and the specific situations in which we might expect these impacts to be significant remain. The extent of spillovers, cross-media effects, and long-term implications resulting from AFO market trends remain major questions in this field, particularly in the realm of quantitative research. The next section will summarize the state of the literature relevant to these questions.

3 Literature Review

AFOs have a wide range of direct and indirect economic effects. In aggregate, livestock consume large quantities of inputs including feed crops and water (USGS 2016) and results in a wide-range of animal products. A private-sector economic impact analysis estimated that animal products were responsible for creating about 1.8 million jobs (1.3% of U.S. total) and $289 billion dollars of economic activity (1.9% of U.S. total) in 2010 (Promar International 2011; BEA). AFOs also produce several non-market outputs that are not included in standard economic impact analyses, including manure, greenhouse gasses, and other forms of pollution (Hutchins, White and Mravik 2012; Mallin et al. 2015; Copeland 2014; Copeland 2010; Pelletier and Tyedmers 2010; Sneeringer 2010; Steinfeld et al. 2006). These environmental impacts induce a wider range of human health impacts, also not included in typical impact analyses (Casey et al. 2015; Kilburn 2012; Gilchrist et al. 2007; Mitloehner and Schenker 2007; Steinfeld et al. 2006). AFOs thus produce several outputs that are distributed across multiples geographies and vary considerably in size and geographic concentration.

Linkages between AFO pollutants and health outcomes have been established in a broad literature (Sigurdarson and Kline 2006; Radon et al. 2007; Schinasi et al. 2011). Less understood, however, are the magnitudes of these relationships and the scale of the impacts. The linkages are complex and often manifest with highly variable temporal and spatial patterns. Nevertheless, causal interactions have received significant attention through, mostly, historical and qualitative research studies. Research on environmental and health factors regarding AFOs typically focus on one type of contamination (e.g., Mallin et al. 2015), one type of secondary environmental impact (e.g., Leet et al. 2012), or one type of health effect stemming from one vector of exposure (e.g., Heederik et al. 2007). These studies often acknowledge, but do not measure in concert, a larger and more complete set of impacts. Some studies also describe how direct AFO impacts may exacerbate community or individual susceptibility to other negative impacts, but empirical estimates of these effects are relatively uncommon. In general, case studies and general knowledge about the environmental effects of AFOs abound, but generalizable research is rare.

Many bodies of literature inform the current research project. The following sections summarize the literature regarding environmental degradation resulting from AFOs; cross-media pollution and how it relates to AFOs; AFOs' effect on community health; the economics of AFOs; and the policies and legal trends surrounding the regulation of AFOs.

3.1 AFOs and the Environment

Animal farming is responsible for a multitude of environmental impacts. Growing animals requires altering landscapes and dedicating inputs to animal consumption. Excessive natural resource degradation results from poor land-use decisions, fertilizer runoff associated with growing feed crops, the externalities associated with transportation of feed crops to the AFO, and large ground and surface water withdrawals. The animals themselves then produce large quantities of manure and gasses that contain nutrients, chemical compounds, and pathogens all to varying degrees depending on the context, animal, and feed crops used. Pollution outputs may adversely affect the environment through direct air emissions of large particulate matter, ammonia, methane, and other greenhouse gasses; contaminating soil and rendering unusable for long periods; and leading to runoff or leaching of manure into surface and ground water sources. Animals must also be transported from AFOs to slaughterhouses and then to consumers, generating additional fossil fuel emissions. At all junctures, opportunity costs are incurred where inputs and livestock are raised in lieu of growing crops for direct human consumption. This project and literature review focus on the waste produced by the animals themselves and leaves the question of the total environmental impacts of AFOs, including the impacts related to the inputs and consumer products, for future research.

Manure is heavy relative to its nutrient content, costly to transport across large distances, and has a market value that is small relative to that of final animal products (Roka and Hoag 1996; Keplinger and Hauck 2006). Thus, keeping, applying (as fertilizer), or disposing of manure at the site of production is often the least costly management choice (Ribaudo, Cattaneo and Agapoff 2004). When applied to croplands in excess of crop nutrient uptake limits, manure nutrients may leach into groundwater or runoff into surface water (USEPA 2013; Copeland 2010). If manure is not spread on farmland it may be stored in underground storage tanks or above ground "lagoons." Lagoons may be poorly constructed with the use of penetrable liners or the caustic nature of stored manure breaks down initially impenetrable liners, which leads to seepage into waterways (Steinfeld et al. 2006). In addition, lagoons often lack covers which results in the release of ammonia, methane, and other compounds into the air when the manure is heated or volatilized (Steinfeld et al. 2006). Likewise, manure constituents may be volatilized into the air at every juncture of the production, handling, and application processes (Copeland 2014). AFOs may mitigate some of these impacts by investing in technology such as biodigesters that reduce the total amount of manure, reduce the toxicity of the remaining manure, and allow for the capture of biogas to be used as fuel (Key and Sneeringer 2011; Petersen et al. 2013), but these technologies are costly investments and without subsidization or other economic inducements AFO operators may not be able to bear these costs.

The primary vectors for human exposure to AFO pollutants are through the air and water and thus these vectors receive much of the research attention, but an additional, economically important vector is soil. Soil is an important intermediary media where pollution is deposited and resides for a period of time before filtering in waterways or volatilizing into the air. If crops are on this land, then some portion of the pollutants are mitigated through nutrient uptake by crops. Soil pollution from manure application has been linked in some places to higher acidity of the soil, higher concentrations of heavy metals, led to the soil becoming a vector for transmittable diseases, and can lead to significant erosion which negatively effects soil quality over time (Liu et al. 2015; Ghaly and Ramakrishnan 2015). In most research on the health effects of AFOs, however, soil pollution is considered an intermediary to water and air pollution.

The primary air pollutants from AFOs are ammonia, hydrogen sulfide, carbon dioxide, methane, nitrous oxide, endotoxins, volatile organic compounds, and other allergens (Koneswaran and Nierenberg 2008; Woodbury et al. 2014; Burns et al. 2007; Baldwin et al. 2006). On a global scale livestock is a significant contributor to greenhouse gas concentrations primarily through methane emissions, but also release significant amounts of other gasses as well including carbon dioxide and nitrous oxide. In total, livestock has been estimated to directly account for 18 percent of greenhouse gasses emitted in carbon dioxide equivalent, which does not include the climate impacts stemming from land use changes such as large-scale deforestation. Seemingly secondary processes also have significant impacts due to the scale of the industry. For example, anaerobic decomposition of manure, such as that that occurs in manure lagoons, accounts for 4 percent of global anthropogenic methane emissions, but is even higher in the U.S. at 10 percent. (Steinfeld et al. 2006).

While the types of air contaminants coming from AFOs are known, research regarding the magnitudes of air emissions are rarer. Researchers must make assumptions regarding emissions per animal unit and the composition of the pollution to estimate the aggregate levels of AFO air pollution (e.g., Pelletier and Tyedmers 2010). Numerous researchers have shown that several AFO-specific factors (e.g., flock and heard dynamics) contribute to the rate and composition of AFO pollution (Muhlbauer, Moody and Burns 2008; Burns et al. 2007) and thus aggregate estimates must smooth over large variation. One approach to resolving this problem is to avoid assumptions regarding farm-level emissions rates and conduct empirical analysis at an aggregated, reduced-form level that does not require these large assumptions. Sneeringer (2010) uses variation in the concentration of heads of swine over time to identify the effects of swine animal units on ambient air pollution at the county level. Sneeringer finds that "[d]oubling the number of hogs per square mile yields a 6.6% increase in sulfur-based ambient air pollution" and the methodology does not require making per-unit assumptions.

From the literature detailing AFO-related water pollutants we know that AFO water impacts are often significant, but manifest over longer periods and are generally more difficult to measure than air impacts. Burkholder et al. (2007) find that manure contributes macronutrients, heavy metals, pharmaceuticals, and other contaminants to neighboring water resources. Burkholder et al. note that contamination occurs even where current best practices are followed and likely occurs at large scales, but monitoring efforts are slow to catch up in verifying the scale. Centner (2011) provides a more recent summary of the scientific research on water contamination from AFOs. Centner focuses on water contamination in situations where National Pollution Discharge Elimination System (NPDES) permits are required (i.e., CAFOs) and found that the analytical issues raised by Burkholder et al. (2007) remain unresolved. Bradford et al. (2007) detail EPA's permitting requirements where they require NMPs before CAFOs may apply manure to agricultural land. Bradford et al. find that this permitting process typically fails in its stated goal of staving water pollution. These studies buttress recent legal cases that have found legal AFO liability for the degradation of water resources. In sum, there is evidence of AFOs' deleterious effect on water supplies, but measurement is lacking.

Leet et al. (2012) and Copeland (2010) argue that the most dramatic environmental impact of contamination stemming from AFOs are large scale fish kills. Leached manure may lead directly to fish kills through heavy metal contamination, but the impacts of severe spikes in nutrient loads is a better documented mechanism. Excessive nutrients lead to large algae blooms, which consume oxygen in addition to nutrients. When water oxygen content reaches a dangerously low level this is referred to as hypoxia. Hypoxic regions are largely inhospitable for fish and often result in massive fish kills. The Gulf of Mexico's hypoxic region, for example, stems from both fertilizer and manure runoff stemming from farming on the Mississippi River's watershed. The hypoxic region in the gulf is roughly the size of the state of Hawai'i. About 37% of the phosphorous load in this region has been attributed to manure runoff from AFOs (USGS 2008) and a disproportionate number of farms with excess nitrogen applications are CAFOs (Ribaudo, Key and Sneeringer 2017).

Several researchers have developed computational models to estimate the prevalence of pollution for a given CAFO and the net benefits of various types of mitigating technologies. These models optimize farmer decisions across several variables including types and quantities of crops and animals, harvesting technology, and manure waste handling choices. Ribaudo et al. (2003) construct a regional manure management model that accounts for transportation costs and excess nutrient restrictions. Baerenklau, Nergis, and Schwabe (2008) include air and groundwater impacts as outputs in the model and search for farm-level steady states of a large California dairy under an NMP. They make an important contribution by adding intertemporal decision making to the model. They find that profits are reduced by 12-19%, cross-media pollution has a prominent impact on optimal behavior, and input management is the policy most likely to yield the highest marginal benefits. Wang and Baerenklau (2014) extend the previous model into a complete life-cycle analysis to compare two manure lagoon technologies. In an extension to the primary findings, they find that NMPs are the least efficient policy of a set of evaluated policies. Wang and Baerenklau (2015) expand their previous model further by including herd management and an upstream/downstream policy component to their optimization algorithm. These theoretical models are a valuable contribution and may be utilized in technical and farm management settings, but they are ill-equipped to integrate either community health models or more nuanced policy analyses.

While there is an extensive literature detailing the existence of AFO pollution, there remains important work regarding the scale and scope of AFO pollution. Air pollution may have localized impacts that can be linked to a specific set of AFOs, but AFOs are also a major contributor to greenhouse gas production. Similarly, AFO water pollution often contaminates the local water that is used for drinking and for recreation, but water pollution that starts with Midwestern AFOs, for example, has significant, known contributions to hypoxic zones as far away as the Gulf of Mexico. These broader environmental effects are an important area of research but are beyond the scope of the current project. Further complicating these wide-ranging impacts are the intertemporal and cross-media dynamics of nutrients and other compounds, as will be discussed in the following section.

3.2 AFOs, Cross-Media Pollution, and Other Spillovers

The prevalence of cross-media pollution and other pollution spillovers compound both the regulation and analysis environmental impacts of AFOs. There is some ambiguity in the literature concerning the definition of "cross-media pollution," but the term generally describes contaminants that may be conveyed in and/or transferred between different forms of media (i.e., air, water, soil). Three mechanisms related to cross-media pollution are discussed in this section. First, pollutants may undergo changes once introduced to the environment due to natural chemical processes. Pollutants may change into constituent compounds that, in turn, have a different set of ecological interactions than the original compound. Further, both the base compounds and the constituent compounds may move between environmental media, such as evaporating out of water into a gaseous form. Finally, a polluting firm may have multiple options of media in which to dispose of pollutants. Cost minimizing firms will employ technology to convert the media of the pollutant when regulations make disposal more costly than the conversion technology. Under all these scenarios, regulations that limit the emission of a specific compound into a specific media are likely to be inefficient forms of aggregate pollution control.

Many economists researching cross-media effects have focused on the changes in firm behavior following the introduction of new regulations. Researchers often rely on the EPA's Toxic Release Inventory (TRI) to examine the aggregate pollution effects of firms satisfying new Clean Air Act (CAA) Regulations. The TRI data tracks firm-level pollution by media. Sigman (1996) relies on the TRI data to estimate the cross-media effect of chlorinated solvents finding that air pollution declines following more stringent regulation, but that solid waste deposits of the same chlorinated solvents do not decline. Similar to Sigman, Greenstone (2003) tests for the substitution effects of pollutants between media in the iron and steel industries that are tracked with the TRI following the implementation of CAA regulations. Greenstone finds no evidence of a substitution between media at an industry-wide level as pollution was reduced across all media following CAA implementation. Gibson (2016) also relies on TRI Data to examine the effects of CAA enforcement on water pollution, landfill pollution, and spillovers into less-regulated regions. Contradicting prior research, Gibson finds that regulated plants' water emissions more than double and other plants within the same firm see an increase in pollution following the imposition of stricter rules. These leakages offset more than half of the reductions in air pollution. Bi (2017) extends the research of Gibson by following coal-fired power plants in the TRI between 1999-2011. Following implementation of more stringent CAA rules many plants adopted scrubbing technology that, essentially, converts air pollution into water pollution. Bi finds that the air-to-water pollution spillovers are economically significant and suggests that future research needs to consider cross-media effects. Bi also notes that the implications for human health of cross-media effects are left for future research due to the preponderance of confounding factors.

In sum, these studies suggest that cross-media effects decrease the realized level of abatement from single-media regulations, but they also highlight the difficulty in measuring cross-media substitution effects.

Research focusing on cross-media effects has also emerged surrounding a bygone policy requiring fuel additives to oxygenate vehicle fuels, resulting in what was believed to be cleaner burning fuel. Fuel producers were required to oxygenate gasoline to a specific level to reduce smog and had the option of oxygenating with either a chemical called MTBE or ethanol. Producers typically selected MTBE over ethanol due to lower marginal production costs. Producers were not required, however, to consider the environmental impacts of the two compounds, where ethanol has a greater marginal impact on air pollution and MTBE has a greater impact on water pollution. Fernandez (2005) finds that a cost-minimization framework that only considers CAA policies would reveal MTBE as the optimal choice, whereas a cross-media framework prefers ethanol. Fernandez and Dumas (2009) explore the use of MTBE in California to yield insights regarding regulatory mechanism design in the face of uncertain cross-media effects and asymmetric information. Fernandez and Dumas find that a two-part subsidy could have reduced the cost of the pollution liability by 75% relative to the historical reliance on MTBE. Relatedly, Alberini (2001) finds that regulation of underground storage tanks in Florida that meant to limit MTBE water contamination resulted in increased air pollution. Interestingly, Alberini also finds that the nature of the relationship between the two forms of contamination shifts between compliments and substitutes when the regulatory environment changes.

Much of the AFO literature mentions the existence of cross-media effects, but only a few studies control directly for cross-media effects. Aillery et al. (2005) provide a concise summary of the modes of cross-media pollution typically found on AFOs and use farm-level data to examine tradeoffs at the farm-level. They conduct an economic impact analysis of various policies given a set of cross-media coefficients. Using the same 1998 Agricultural Resource Management Survey (ARMS) data and similar methods, Key and Kaplan (2007) calibrate a quadratic cost function for a hog CAFO under three policy regimes: a land application limit for nitrogen, an ammonia emissions restriction, and a combination of these two policies. Their simulations find evidence that cost-minimizing hog CAFO operators inadvertently shift manure disposal methods depending on the policy, especially when faced with single-media policies. The study only looked at short term decisions of large AFOs and only from the AFO's perspective. The data suggest that cross-media pollution exists on AFOs and has complex and significant implications for researchers.

The complexity of cross-media effects is further compounded by geographic, institutional, social, and general market systems that impact nutrient pollution and impede straight-forward policy solutions. Researchers and theorists have found that, even in situations where only one form of negative outcome is considered (e.g., hypoxia), considerable dimensions of complex problem solving are present (Shortle and Horan 2017). Nevertheless, there is strong evidence that cross-media effects exist in general and specifically regarding AFOs. AFO researchers will want to, therefore, control for cross-media effects when conducting empirical work in this field or risk introducing estimation bias and the potential for cross-media pollution should influence all AFO policy discussions.

3.3 AFOs, Farm-Level Behavior, and Economics

AFOs are an important part of many regional economies. The U.S. agricultural industry added $992 billion to GDP in 2015, about 5.5% of the total economy (USDA - Economic Research Service 2017a). Of all cash receipts for agricultural products, animal products accounted for a larger proportion ($189.8 billion) than those for crops ($185.7 billion) in 2015 (USDA - Economic Research Service 2017b). Policies regulating the inputs and outputs of animal farms are, thus, likely to have significant economic impacts at a national scale. How farmers and neighboring populations have responded to changing industries, policies, and economic incentives are all key in anticipating how these groups will respond to theoretical policy shifts and in estimating the resulting economic, environmental, and health impacts.

Both the economic and environmental effects of AFOs have distributional consequences for the surrounding communities. Lobao and Stofferahn (2008) conduct an integrative research review of 51 previous studies regarding the distributional consequences of farm industrialization across well-being, social fabric, and environmental dimensions. Most of the reviewed studies (82%) show adverse impacts, but also find some mixed results along the well-being dimension. Populations, income inequality, and per capita income all tend to increase in areas surrounding industrial farms. Evaluating the 100 largest dairy producing counties in the U.S., Dechow (2011) finds that these counties have similar unemployment levels to the respective state as a whole, but also have higher illiteracy rates, a greater proportion of residents without high school diplomas, and lower median incomes. Donham et al. (2007) summarize a literature that has found adverse effects related to increased farming concentration since 1946. The literature finds that concentrated farms lead to higher capital flight and lower economic activity, tax receipts, and measures of social cohesion. Harrison and Getz (2014), however, find that the jobs available at larger farms are safer and have better job quality metrics than similar jobs at smaller farms. Harrison and Getz also found that these benefits disproportionately accrue to white workers.

In addition to the economic changes that may result from the concentration of farming activities, AFO pollution may disproportionately impact some groups. Much of the research in this field, usually referred to as Environmental Justice, has focused on AFOs in North Carolina. North Carolina keeps a spatial database of AFOs in the state that facilitates fine-grain spatial environmental justice analyses. This literature finds that hog operations are disproportionately located near poorer and minority populations (Wing, Cole and Grant 2000); poor African-American communities are more susceptible to severe, unanticipated events related to breached manure pits and flooding of CAFOs (Wing, Freedman and Band 2002); and lower income and higher minority population middle-schools are disproportionately subject to airborne effluent from hog AFOs (Mirabelli et al. 2006). This literature, however, is mostly speculative regarding the mechanisms that lead to these patterns. Authors typically argue that this pattern is found because low-income and minority residents have relatively low political influence and so are unable to contest AFO location decisions, whereas wealthier residents have political influence and can sway decision makers' choices. These studies, however, have been geographically limited, focusing primarily on North Carolina and Iowa, and have almost universally focused on hog farms (An exception to both this scale and scope is Harun and Ogneva-Himmelberger (2013)). Further, these studies do not provide empirical evidence for the specific causal mechanisms underlying the patterns they find and presuppose that proximity to AFOs is a known disamenity in all cases. They presume that locating at a distance from AFOs is a universal preference, but fail to consider the situations where this assumption may not hold (Banzhaf, Ma and Timmins 2019).

A more limited body of research exists for regions beyond North Carolina. Through a broader spatial analysis of the conterminous 48 states, Harun and Ogneva-himmelberger (2013) conclude that U.S. CAFOs are non-randomly clustered. Specifically, chicken CAFOs were more predominant in regions with lower incomes and higher African American populations, whereas hog and cattle CAFOs were found in areas with lower incomes, but without any significant differences by race. Importantly, the authors note that CAFO location data at the ZIP or lower level, such as that for North Carolina, is likely required to make definitive conclusions regarding environmental justice variables. Carrel, Young and Tate (2016) conduct a finer spatial grain analysis in Iowa, the largest pork producing state in the country. The authors find that AFO contamination variables are not correlated with traditional environmental justice variables within census block groups but are correlated when the analysis is adjusted to a “downstream,” within-watershed analysis that may better account for the actual impacted population.

Farmer responses to incentives also have an impact on the net economic and environmental effects of AFOs. There is a large literature that models manure (and other nutrient) handling decisions in farm-level, cost-minimization frameworks. Keplinger and Hauck (2006), for example, minimize costs while varying agronomic nutrient uptake rates and distance from the manure production point and allow manure production decisions to be endogenous to the cost function. Keplinger and Hauck’s goal is to determine optimal nutrient application rates in each scenario with a secondary goal of reducing nutrient runoff. While not directly relevant to the current research, these projects do provide a useful reference as to why farm-level manure management decisions are less than socially optimal.

Hedonic pricing methods have also been leveraged to estimate the disamenity value related to living near AFOs. Numerous studies have found that homes decrease in values as proximal animal units increase or as distance from AFO decreases. The specific form of regression model employed, the geography, climate covariates, species, and the number of animal units vary by study, but the effect of AFOs on U.S. property values are notable and summarized in Table 1. Some of these studies have found mitigating mechanisms of AFOs on property values. For example, Secchi (2007) found that being close, but not too close, to an AFO has a positive impact on property values through an overall positive impact of the AFO has on the regional economy. Ready and Abdalla (2005) argue that the positive effect of living near open spaces also mitigates some of the deleterious effects of living near AFOs. This hedonic pricing literature is important to the current research as it shows that the housing market endogenizes some of the deleterious effects of AFOs.

AFOs are a major component of the U.S. agricultural system and economically important to many geographies. AFOs may distort the behavior of agents in different markets and farmers may respond to externalities in less than optimal ways, particularly where pollution externalities are not endogenized or manifest differently across time and space. Distorted behaviors of economic agents and seemingly counterintuitive responses to some forms of pollution have been found in many situations of pollution siting. For example, a disparate impact could be due to intentional siting of the polluter near historically under-represented groups, but it may also be the case that these AFOs would site in areas that are more economically advantageous, regardless of the community's characteristics. These characteristics, however, may correlate with lower incomes, looser regulations, and other factors conducive to polluting industries. Further, workers may move closer to the pollution site if that is there employer, further increasing the level of disparate impacts (Banzhaf et al. 2019). Controlling for market-based responses is important when discussing markets as large as those for AFO inputs and outputs, whereas a partial equilibrium conceptualization may be subject to significant errors and would distort a complete view. While the responses of the market should drive the specific discussion of which policy mechanisms are ideal, the distribution of impacts remains a concern even if total net impacts are minimized.

3.4 AFOs and Community Health

AFOs impact human health in several forms. These include some forms of cancer, asthma and other chronic respiratory ailments, methemoglobinemia or "blue-baby syndrome," exposure to heavy metals, and diseases resulting from antibiotic resistant pathogens (Greger and Koneswaran 2010). Indirect health effects are also significant and include epidemics exacerbated by climate change and excessive consumption of animal products, which has been linked to heart disease, obesity, and some cancers (McMichael et al. 2007). While these indirect impacts are an important area of research, these are beyond the scope of the current research where we focus on the direct health effects.

AFOs produce several airborne compounds that may impact the neighboring community's health and the health of AFO workers who have higher exposure rates then the population in general. These compounds include ammonia, carbon dioxide, hydrogen sulfide, and various endotoxins. Exposure to these compounds has been linked to decreased lung function, accelerated decline in lung function, inflammation, asthma morbidity and mortality, psychological issues related to diminished quality of life due to significant odors, and other effects (Heederik et al. 2007). Radon et al. (2007) survey German residents living near AFOs for self-reported increases in respiratory ailments and odor prevalence as related to distance from AFOs. Radon et al. find that exposure to AFO air pollution is correlated with measurable health effects, even when correcting for over-reporting effects relative to simultaneous clinical measurements. In a small-scale case study Kilburn (2012) found that people living near swine manure lagoons suffered from higher in-home air pollution and higher incidence of neurobehavioral conditions than those living farther away from the lagoons. Several studies have linked proximity to AFOs and asthma in children (recent examples include Sigurdarson and Kline 2006; Pavilonis, Sanderson and Merchant 2013; Loftus et al. 2015). Wing and Wolf (2000), Thu (2002), and Schinasi et al. (2011) each conducted survey-based case studies to identify the causal effect of living near AFOs on respiratory health and found significant, positive effects.

These studies all shed light on the mechanisms by which AFO air pollution impacts health and establish that these effects are economically significant in some situations. The case-specific nature of their respective conclusions, however, cannot be easily extended or extrapolated to a larger, policy-relevant level and general, empirical research in this field is rarer. With a national panel data set Sneeringer (2009) examine the role of changes in swine concentrations on infant mortality over a 20 year period. Sneeringer finds that swine concentrations are a strong predictor of infant mortality, with a doubling in animal units in a county leading to a 7.4% increase in infant mortality. The data sets that Sneeringer relies on, however, have been updated since the article's publication. The additional years available encompass a period of federal policy shifting and greater industry concentration. Further, Sneeringer concludes that health effects are primarily linked to AFO air pollution, but Sneeringer's methodology did not specifically reject the possibility of effects linked to water pollution.

While less explored and more complex in both contamination and exposure patterns than air pollution, water pollution stemming from AFOs has also received some attention from researchers. Antimicrobial pathogens that result from use and overuse of pharmaceuticals are a concern for public health, but empirical evidence of the health effects of long-term exposure to these pathogens is lacking (Williams-Nguyen et al. 2016; Finley et al. 2013; Gilchrist et al. 2007). Hooiveld et al. (2016) find that proximity to CAFOs is a significant predictor of unspecified infectious diseases and pneumonia with goat CAFOs in the Netherlands but found little evidence of such effects with regards to swine, cattle, or chicken CAFOs. In a region of Indiana, the highest concentrations of veterinary pharmaceuticals were found in water systems in close proximity to CAFOs, but the rate of transport and the rate of human exposure remain unclear (Bernot, Smith and Frey 2013). Fecal coliform in North Carolina waterways was found in greater concentrations both upstream and downstream from CAFOs (Heaney et al. 2015). Algal blooms that result from excess nutrients in waterways also result in serious health effects following exposure, but like other water-related exposures, the aggregate health effects of algae blooms have not received much empirical attention (USEPA 2013). Consumption of drinking water containing high levels of nitrite or nitrate can lead to gastrointestinal problems, miscarriages, methemoglobinemia, and other pregnancy complications (Greger and Koneswaran 2010). In general, the reliance on untreated well-water for domestic consumption may cause increased exposure to contamination in addition to other factors which further complicate the models of these effects including watershed dynamics, the type of water treatment systems applied, and household behavior. Treatment of well water for consumption is possible, but first contaminants must be detected[3] and this higher level of water treatment is expensive relative to standard treatment practices (see, for example, Schechinger and Cox 2018).

The breadth of case studies regarding the health effects of AFOs has led to a few meta-analyses. O'Connor et al. (2010) conduct a systematic review of the literature to distill the causal effects of CAFOs on health, of which they find scant evidence. O'Connor et al.'s analysis, however, was funded by the United Soybean Board and the National Pork Board and deemed only nine studies out of a pool of 4,908 worthy of contributing to this conclusion. Casey et al. (2015)[4] conduct a similar review of the epidemiological literature since 2000. They find that living near AFOs is associated with "respiratory outcomes, methicillin-resistant *Staphylococcus aureus*, Q fever, and stress mood," but the authors note that this does not rule out other conditions. The reviewed literature shows that exposure to AFO pollutants does not manifest as a single-pollutant, single-health effect. Casey et al. call on researchers to expand their methods to account for more complex patterns of exposure to pollutants and the convoluted health effects. Further, they find that researchers have not adequately approached the topic of contaminated groundwater and the effects this has on communities through drinking water.

[3] Dangerous amounts of nitrites and nitrates can be present without any notable smells or tastes.
[4] For an extended discussion of the health outcomes literature see Casey et al. (2015).

The literature shows that many forms of health impacts have been conclusively linked to the forms of pollution coming from AFOs. Nevertheless, there is no widely accepted view regarding the full scale and scope of these effects given the heterogeneity in the types of impacts, the communities facing these impacts, and the regional policies in place. There is, thus, wide recognition that more research is needed to identify all the types of health effects, more precisely measure the magnitudes of known effects, and explore the complex patterns of overlapping and compounding health effects (e.g., Borlée et al. 2017; Casey et al. 2015; Greger and Koneswaran 2010; Blanes-Vidal et al. 2014; USEPA 2013).

3.5 AFOs Policy and Legal Trends

Agricultural operations are typically exempt from most environmental laws, but a notable exception is when they receive a point-source designation under the CWA. An AFO receives a point-source designation when categorized as a CAFO (Concentrated AFO) under the CWA. The CAFO designation then requires compliance with an NPDES permit (USEPA 2012). This more stringent set of requirements for large and concentrated AFOs stemmed from public concern surrounding AFO pollution that grew throughout the 1990s and culminated in a set of proposed federal rules in 2000. The EPA initially proposed final versions of these rules in 2003 and the rules were ultimately approved in 2008 after significant debate and revision. The adopted rules were considered less stringent than initial iterations and have been the subject of ongoing litigation since 2008. In general, most AFO regulations stem from the CWA, but other federal laws are the basis of regulations and litigation, including the CAA; the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA); and the Emergency Planning and Community Right-to-Know Act (EPCRA) are also the basis of some regulations that pertain to AFOs as well. Further muddying the policy landscape is the patchwork between federal and state regulations, an inconsistently applied permitting process, and litigation that has forced industry adjustments in some regions and situations (Copeland 2010; Copeland 2011; Copeland 2014)[5].

Animal farms that are designated as CAFOs are subject to CWA regulation. A CAFO designation is based on a complex set of factors including the quantity of animals on site, the size of the operation, the level of vegetative cover, and other farm-level factors. CAFOs are considered point sources under the CWA, require an NPDES permit, and must complete a NMP as part of the NPDES permit (US EPA 2012). NMPs, however, require CAFOs to self-report water deposits and enforcement actions are only taken if violations are self-reported or revealed by third parties. Furthermore, CWA provisions do not require air pollution to be as part of a NMPs and federal rules are more lenient in applying CAA restrictions to AFOs. In sum, water impacts may be ineffectively regulated under the CWA and air impacts are not even subject to the standard permitting process, despite relatively widespread knowledge regarding the existence of both forms of impacts. Each AFO's pollution disposal decisions, therefore, is critical in determining the extent of water and air pollution.

Several researchers have explored the efficacy of current policy and suggested routes for policy improvement. The Baerenklau et al. models discussed in Section 3.1 find that NMPs are an inefficient means to control harmful pollution given the cost-minimizing behavioral adjustments of AFOs (Baerenklau, Nergis and Schwabe 2008; Wang and Baerenklau 2014; Wang and Baerenklau 2015). These models, while technically impressive, only approach this issue from the AFO perspective under the assumption of full and effective policy enforcement. They do not explore the extent to which NMPs are selectively enforced or impossible to enforce. This is problematic since the question of NMP efficacy in reducing nutrient loads is moot if there is inherently incomplete coverage of enforcement from the outset. NMP enforcement typically

[5] Copeland's series of articles provides a more in-depth history of AFO policies and politics.

requires costly sampling and monitoring on a farm-by-farm basis, which is not undertaken by regulators in most situations. But even in this ideal enforcement scenario, Baerenklau et al. still find that NMPs are an inefficient regulatory approach.

In practice, CAFOs are often required to self-monitor and self-report emissions, which allows for significant under-reporting of emissions. CAFOs and employees face stiff penalties if they self-report violations, are determined to have misreported or under-reported violations, or are otherwise determined to have violated the laws, such as if information becomes available through a third party that indicates that violations are occurring through litigation or claims by groups or individual citizens. In these cases, the level of pollution may already be well above regulated levels and may be functionally irreversible in some situations (i.e., groundwater pollution). If there is a low likelihood of being caught, the result is a high incentive to under-report emissions when violating an NMP. As such, Baerenklau et al.'s studies further the case against the efficacy of NMPs as a regulatory strategy in the hypothetical situation involving full enforcement, but have little to say about the effectiveness of NMPs in real situations as they do not evaluate or determine what is likely to be a better policy approach than NMPs.

Other research has focused on AFO regulatory policy more generally, beyond the efficacy of NMPs. Sneeringer and Key (2011) employ a regression discontinuity framework based on CWA size-based regulations to determine whether firms enter the industry below the size-based standards as a means to avoid more stringent regulations. Sneeringer and Key (2013) also employ a propensity score matching model to determine the industry response to CWA size-based regulations. Sneeringer and Key find that farm-level sorting occurs with farms close to the threshold restricting their livestock quantities to below the threshold, calling into question the efficacy of animal unit thresholds under the CWA. If there were known, localized environmental thresholds that could be translated into animal units then, in theory, thresholds could be an effective policy approach. Many researchers describe the non-linear impacts of animal units, with higher concentrations of animals having a higher per-unit environmental impact, but literature evidencing specific animal unit thresholds has not been found. At the least, this suggests that existing policy should be augmented to include more per-unit stipulations, non-linear animal unit policies, or ignore animal units altogether when regulating AFOs.

From a legal theory perspective, Guruswamy (1991) argues that the EPA's fragmented approach to regulating pollutants within a specific media is both "ineffective and inefficient." Guruswamy summarizes the legal, physical, and political barriers to adopting an Integrated Pollution Control policy at the EPA. In total, the empirical and formal modeling literature related to AFO policy and cross-media pollution has formed similar conclusions to Guruswamy's (see Section 3.2). The complexity of AFO pollution suggests analysis that accounts for cross-media pollution in developing policy alternatives.

Regarding applied law, recent years have witnessed a growth in litigation related to CAFO pollution. These cases have been submitted under a range of statutes, including CAA, CWA, CERCLA, and EPCRA. Cases have also been pursued under common-law nuisance claims. Plaintiffs have had varying degrees of success (for a detailed summary see Tai 2012). From a policy perspective, the potential for enforced liability through lawsuits may have a significant effect on the polluting actions of specific CAFOs or more broadly through the application of precedent.

The range of policies that most economists analyze regarding AFOs, however, has not included liability and enforcement of precedent. Economists' incomplete selection of policy alternatives in the research design phase may, inadvertently, predispose their analyses' conclusions towards policies that are more empirically tractable than liability enforcement, even if these policies are not necessarily more efficient in practice given the complexity of the AFO policy problem. Litigation is always, to some extent, context specific in findings and enforcement and thus is difficult to operationalize, except where litigation results in stipulations for general policy changes. But there is room in the literature to incorporate liability and litigation as policy possibilities.

The AFO literature may be expanded by considering a wider range of regulatory policies, including those that are not possible under the currently fragmented federal approach. Further, the literature would benefit from consideration of additional, largely qualitative trends in AFO pollution enforcement. These trends may be difficult to depict in a statistical analysis but should at least be considered in concert with quantitative analysis as litigation is a major enforcement mechanism in practice. The level of enforcement of NMPs, the enforceability of NMPs, and the integral role that litigation plays in AFO regulation all would benefit from greater attention from researchers in this field.

There are gaps in the literature regarding estimations of system-level health effects of AFO-related contamination and especially for estimates at a national or otherwise generalizable level. The existing literature acknowledges, but does not empirically account for, the prevalence of cross-media effects and other confounding economic factors. The prior literature has, however, provided evidence that both economically significant environmental effects and health effects are likely in many cases of AFO pollution. There are also significant gaps regarding environmental justice trends related to AFO location and policy design. The frameworks described in the following section facilitate exploration of reduced-form models of health effects, socioeconomic precursors and impacts, and regulatory policy related to AFOs.

4 Conceptual Framework

AFOs and their pollution biproducts represent a complex and heterogenous system. The interactions and dependencies between various levels of decision making among AFO operators, policy makers, and regulatory agencies make AFO pollution regulation a complex problem (Shortle and Horan 2017). A formal representation of this problem, as presented here, distills some of these complexities down to a few vital components of the systems and decisions at play and suggest some broad implications for AFO regulatory policy. Perhaps unsurprisingly, even a simplified model of these pollution and regulatory systems leaves a muddied picture for policymakers.

As discussed in Section 3.2, there are several forms of cross-media pollution that occur on AFOs and that have received little attention in past research: AFOs may dispose of manure in different forms that have varied impacts on different environmental media; after the initial deposition in one medium contaminants may transition into another medium through natural degradation, oxidation, etc.; and contaminants may change through chemical processes into other pollutants. The literature shows that researchers have recognized these complex processes for decades and many have advocated for more nuanced policy that better regulates pollution while accounting for these dynamics. These processes, however, have received less attention from statisticians and theorists. Previous theoretical research, perhaps for tractability, has only accounted for the choices at the firm level regarding how to dispose of manure and the models do not account for other cross-media outcomes that may be relevant to creating appropriate policy incentives (Baerenklau, Nergis and Schwabe 2008; Wang and Baerenklau 2014; Wang and Baerenklau 2015). The model described here incorporates all three of these spillover mechanisms to highlight the inherent challenges of modeling these complex systems and the pitfalls associated with too restrictive model assumptions.

The stylized model consists of a single, profit-maximizing producer. The firm produces one good and must dispose of manure, which can be disposed of in two ways, both of which are costly and have different cost structures. Both manure disposal methods contribute to both air pollution (e.g., ammonia, NH_3) and water pollution (e.g., nitrite, NO_2, and nitrate, NO_3), but do so at rates that vary between methods. After disposal, bacterial processes and environmental conditions may cause these components to again cycle between forms and/or media in what is referred to as the nitrogen cycle (Ghaly and Ramakrishnan 2015). In this way, ammonia released into the air may eventually result in nitrate pollution in water. Similarly, ammonia is water soluble in manure, but may volatilize into the air as manure dries or as it is spread on cropland. Soil serves as an intermediary medium between air and water but is not explicitly accounted for in this framework for two reasons: population-level exposure to pollutants is minimal in soil relative to air/water and mitigation of pollutants through soil may be indirectly modeled through a the transfer coefficients used between air and water.

The model involves two decision makers, a single AFO producer and the social welfare maximizing policy maker. In the first stage, the producer makes input and output production decisions to maximize profit. Several assumptions are made for simplicity: the AFO produces a single animal product. The price of the product, p, is set by the market and independent of quantity supplied, q. Two types of inputs are required for production: x, a catchall term for technology, labor, and other production inputs and $\bar{m}$, manure produced. Per unit costs of each input are also set by the market and independent of input quantity used and represented in the cost function, f. The AFO's decision of interest in the current model is how they choose to dispose of manure, which we assume must be accounted for when the animal production decision is made and thus is part of the production decision. We then disaggregate the manure disposal decision into two broad categories of common disposal methods: m_1, manure that is dispersed on cropland and m_2, manure that is stored in an above ground lagoon.

The profit function is thus represented as

$$\Pi = p * q(x, m_1, m_2) - f(x, m_1, m_2) \tag{1}$$

With first-order conditions for profit maximization being:

$$p\frac{\partial q}{\partial x} = \frac{\partial f}{\partial x} \quad p\frac{\partial q}{\partial m_1} = \frac{\partial f}{\partial m_1} \quad p\frac{\partial q}{\partial m_2} = \frac{\partial f}{\partial m_2} \tag{2}$$

Where we assume quantity produced, q, is linear in m_1 and m_2 and increasing at a decreasing rate in x. We also assume that the marginal product of x is unchanging in m_1 and m_2:

$$\frac{\partial q}{\partial x} > 0 \quad \frac{\partial^2 q}{\partial x^2} < 0 \quad \frac{\partial q}{\partial m_1} > 0 \quad \frac{\partial^2 q}{\partial m_1^2} = 0 \quad \frac{\partial q}{\partial m_2} > 0 \quad \frac{\partial^2 q}{\partial m_2^2} = 0 \tag{3}$$
$$\frac{\partial^2 q}{\partial x \partial m_1} = \frac{\partial^2 q}{\partial x \partial m_2} = 0$$

The cost structures of manure lagoon storage and crop dispersion, respectively, is highly varied by context and farm specific. Here, for simplicity, we assume a basic, uniform cost structure for each form of disposal. Manure dispersed on cropland is assumed to have a constant, per unit cost, with no upper limit, but increasing environmental impacts as manure dispersal exceeds crop uptake limits. In practice, AFO producers may move manure greater distances at greater cost or buy/sell manure from/to other neighboring farms, but these behaviors are omitted from the current model. Thus, the crop dispersal component of the cost function conforms to the following assumptions:

$$\frac{\partial f}{\partial m_1} > 0 \qquad \frac{\partial^2 f}{\partial m_1^2} = 0 \qquad 0 \leq m_1 \tag{4}$$

Manure lagoons have large, fixed construction costs. After construction is completed, however, lagoons require less transportation and labor costs, and thus lower per unit costs, than dispersal. Thus, there is a switching point in the optimal decision where the average cost of lagoon disposal is equal to the average cost of crop dispersal. Lagoons have a limited capacity, m_l. In practice, AFOs may be able to build additional lagoons to increase manure capacity. For simplicity we assume that only one lagoon may be built, and animal production is constrained by the lagoon manure limit, m_l.

$$\frac{\partial f}{\partial m_2} > 0 \qquad \frac{\partial^2 f}{\partial m_2^2} = 0 \qquad 0 \leq m_1 \leq m_l \qquad \frac{\partial f}{\partial m_2} < \frac{\partial f}{\partial m_1} \tag{5}$$

When total manure produced is relatively low the fixed costs of a lagoon make dispersion a more cost-effective disposal method. At some manure level $\dot{m}$, however, the average costs of the lagoon switch from being greater than the average costs of dispersion to less than those average costs. This will make the lagoon disposal the optimal technology choice. Once manure levels extend past the lagoon's limitation (m_l) then the AFO will have to use dispersion for all remaining manure. In sum, the simplifying cost assumptions adopted here for these technologies result in manure dispersion as the sole method of disposal at low levels. At some medium level of manure the lagoon is the sole method of disposal. And at high manure levels a lagoon is fully utilized and then dispersion occurs for all remaining manure beyond the lagoon's limit. These patterns are highly simplified but are adopted here for exposition regarding AFO technology choices and how context may affect these choices. If there were structural market shifts, such as with additional regulatory policy on one form of manure disposal, this would cause these inflexion points to move up or down, depending on the changes to the disposal cost structures.

The second component of the model focuses on the propensity of nutrients to arrive in different environmental media following the disposal process. The total amount of manure added to the air, water, and soil transitions via naturally occurring nutrient cycles, as discussed in Section 3.2. Here we simplify the model to air and water media for exposition. The model is also simplified to be fully contemporaneous, which is not a realistic assumption, but functional for discussion with the problem at hand. In actual settings, the addition of land pollution and the significant delays between one form of pollution and the transition to another form would further confound the policy development and the subsequent AFO response. In effect, there would be less information and a reduced ability to predict the pollution impacts of disposal choices. Here, however, we wish to show the complexity of policymaking even under a highly simplified system.

In the present model, cross-media pollution is represented as some proportion of the manure from each of the two disposal methods resulting in pollution in both air and water. The total pollution in the air is denoted by A, and W is the total water pollution. Manure quantities are held over from the profit function, where m_1 and m_2 represent crop dispersion and lagoon storage quantities, respectively. The proportion of crop dispersed manure that results in air pollution is α_1, α_2 is the proportion of lagoon manure that results in air pollution, τ_1 is the proportion of dispersed manure that results in water pollution, and τ_2 is the proportion of lagoon manure that results in water pollution:

$$A = \alpha_1 m_1 + \alpha_2 m_2 \tag{6}$$

$$W = \tau_1 m_1 + \tau_2 m_2$$

$$Where \;\; 0 < \alpha_i + \tau_i < 1, \qquad i = 1,2 \quad \alpha_1 \neq \alpha_2, \qquad \tau_1 \neq \tau_2$$

The current model assumes no distinctions among either the transfer processes from each of the two disposal types to each of the two media types, the timing of these transfers, or the total proportion of disposed manure that arrives in the environmental medium (i.e., how much less than 1 each combination of α_i, τ_i is). Relevant to the current model is that these disposal methods have varying impacts on the form and scale of pollution. Finally, we adjust the stocking equations above to include cross-*media* transfers, where some amount of the pollutants that get deposited in the air converts into water pollution and vice versa, represented with the γ and τ terms below.

$$A = \gamma(\alpha_1 m_1 + \alpha_2 m_2) + (1 - \mu)(\tau_1 m_1 + \tau_2 m_2) \tag{7}$$

$$W = \mu(\tau_1 m_1 + \tau_2 m_2) + (1 - \gamma)(\alpha_1 m_1 + \alpha_2 m_2)$$

$$Where \;\; 0 < \alpha_i + \tau_i < 1, \qquad \alpha_1 \neq \alpha_2, \tau_1 \neq \tau_2, \qquad 0 < \gamma < 1, \qquad 0 < \mu < 1$$

And thus, each partial derivative is always increasing in both manure inputs, but these rates will vary depending on both the four coefficient values in these equations:

$$\frac{\partial A}{\partial m_1} = \gamma \alpha_1 + (1 - \mu)\tau_1 \tag{8}$$

$$\frac{\partial A}{\partial m_2} = \gamma \alpha_2 + (1 - \mu)\tau_2$$

$$\frac{\partial W}{\partial m_1} = \mu\tau_1 + (1-\gamma)\alpha_1$$

$$\frac{\partial W}{\partial m_2} = \mu\tau_2 + (1-\gamma)\alpha_2$$

Finally, and in line with the contemporaneous representation of the model, we assume that mitigation of pollution once it is in the air and water, respectively, are not policy options. That is, the policy maker must apply regulations at the AFO-level prior to the polluting event. There are two primary reasons for this assumption: First, pollution mitigation technology is not effective or possible in many situations. Second, monitoring of emissions (as opposed to manure production or disposal) on AFOs is costly, especially if applied to smaller operations, and there are highly contextual factors that drive the rate and timing of the transfer from the AFO to the media (e.g., geologic formations, proximity to aquifers or surface water). These are all typical issues faced with the regulation of non-point source polluters, but in this scenario, we have multiple media of pollution and an uncertain set of contributing polluters to each unit of pollution observed outside of the AFO.

Here we will assume that lagoon deposits have a relatively high direct effect on water pollution ($\tau_2 > \tau_1$) and crop dispersion has a relatively high impact on direct air pollution ($\alpha_1 > \alpha_2$). Again, these are simplifying assumptions; the important point is that the two technologies differ in their efficacy, this is known to the policymaker, and the policymaker uses this information to set policy. Whereas the AFO's production decision is driven by profit considerations, the policymaker's decision is based on a measure of social welfare which includes health considerations along with profit maximization. Here we include both the profits of the AFO and the monetized value of the health impacts related to AFO pollution. A true measure of social welfare would include a component for the value of environmental degradation related to nutrient pollution and the transaction costs related to policy implementation (i.e., monitoring and enforcement costs) in addition to the health effects, but these additional factors are omitted here for simplicity.

The additional health function is assumed to be based on the air and water pollution inputs. Obviously, these are not the only or primary factors that drive health outcomes, but these are shown to have an effect at the population level in the health literature (see Section 3.4). The model, however, implicitly accounts for several endogenous relationships through the cost function. For example, population density is a strong predictor of AFO investments (i.e., AFOs are not going to startup in city centers) and likely also has a complex impact on health outcomes. How the health impact function, $H(A, W)$ is operationalized, however, has an impact on the optimal social welfare levels of both manure production and disposal technique allocation:

$$S = \Pi - H(A, W) \tag{9}$$

The health impact function reflects complex interactions between the constituent components. Here we assume that the health effects are increasing in both air and water pollution and that these effects are increasing at an increasing rate over the relevant range of the health impact function. Above some level, however, additional pollution may have small or negligible impacts as the most severe health impacts will have already been realized, but this range of impacts is not considered in the current model as we assume that pollution is not yet endemic in the setting under study. Further, we assume that deteriorated health makes a person more immunocompromised and thus more susceptible to additional effects from other forms of pollution. Formally, we assume that there is both a standalone health effect of one form of pollution and that the marginal health effect of one form of pollution has a compounding effect on the impacts of the other form of pollution. To facilitate this effect we decompose the health impact function into three additive components.

$$H(A,W) = h_1(A) + h_2(W) + h_3(A,W) \tag{10}$$

$$\frac{\partial h_1}{\partial A} > 0 \quad \frac{\partial^2 h_1}{\partial A^2} > 0 \quad \frac{\partial h_2}{\partial W} > 0 \quad \frac{\partial^2 h_2}{\partial W^2} > 0 \quad \frac{\partial^2 h_3}{\partial A \partial W} > 0 \quad \frac{\partial^2 h_3}{\partial W \partial A} > 0 \tag{11}$$

Substituting in the profit function and pollution production functions yields a social welfare optimization problem in three terms (x, m_1, m_2), as A and W are functions of m_1 and m_2.

$$\mathrm{S} = p * q(x, m_1, m_2) - f(x, m_1, m_2) - H(A,W) \tag{12}$$

With the first order conditions for a social welfare maximizing decision being

$$p\frac{\partial q}{\partial x} = \frac{\partial f}{\partial x} \tag{13}$$

$$p\frac{\partial q}{\partial m_1} = \frac{\partial f}{\partial m_1} + \left[\frac{\partial h_1}{\partial A} * \frac{\partial A}{\partial m_1} + \frac{\partial h_2}{\partial W} * \frac{\partial W}{\partial m_1} + \frac{\partial h_1}{\partial A} * \frac{\partial A}{\partial m_1} + \frac{\partial h_2}{\partial W} * \frac{\partial W}{\partial m_1} + \frac{\partial h_3}{\partial A} * \frac{\partial A}{\partial m_1} * W + \frac{\partial h_3}{\partial W} * \frac{\partial W}{\partial m_1} * A\right]$$

$$p\frac{\partial q}{\partial m_2} = \frac{\partial f}{\partial m_2} + \left[\frac{\partial h_1}{\partial A} * \frac{\partial A}{\partial m_2} + \frac{\partial h_2}{\partial W} * \frac{\partial W}{\partial m_2} + \frac{\partial h_1}{\partial A} * \frac{\partial A}{\partial m_2} + \frac{\partial h_2}{\partial W} * \frac{\partial W}{\partial m_2} + \frac{\partial h_3}{\partial A} * \frac{\partial A}{\partial m_2} * W + \frac{\partial h_3}{\partial W} * \frac{\partial W}{\partial m_2} * A\right]$$

The health impact function invariably has a positive value and all partial derivatives in the health impact function are increasing in the manure inputs over the range of our functions. When the health impact function is added to the social welfare function, the right-hand side of the equations in (13) increases and thus the socially optimal solution differs from the profit maximizing decision. If prices are not fixed, then the socially optimal solution may result in the producer passing some of these higher prices on to consumers to offset these additional health costs. But if prices are fixed then either the marginal product of manure $\left(\frac{\partial q}{\partial m_i}\right)$ would need to increase and/or the marginal cost of manure $\left(\frac{\partial f}{\partial m_i}\right)$ would need to decrease to offset these additional health costs, which could both be accomplished through technological changes. Holding technology and all else equal, however, the producer would reduce production and x, increasing the marginal product of x $\left(\frac{\partial q}{\partial x}\right)$, since $\frac{\partial^2 q}{\partial x^2} < 0$.

The interest of the current analysis is how some policy choices will impact the profit maximizing decision and whether these induced choices approach the social optimal. The current model is insufficient for an in-depth policy analysis, but we can explore how shifts in disposal costs may impact downstream impacts, which sheds some light on how AFO-level policies may or may not impact environmental and health outcomes. Here we will consider restrictions and pricing policies on the two manure disposal techniques. As discussed previously, for higher level policy analysis a model with several polluters would be required. Many of the AFO focused policies, such as Nutrient Management Plans, are AFO-specific, and thus this level of analysis may still be instructive.

If a policy imposes a restriction on the level of manure that an AFO may dispose of through crop dispersal the AFO's response depend on the previous profit maximizing level of production. Under the assumptions of the model, if the AFO is already relying solely on a manure lagoon then no changes will occur and no changes to pollution levels will occur. An AFO with low levels of production is constrained by the policy limit will build a lagoon or will exit the market due to prohibitively high costs of building a lagoon. And if the lagoon is full and the AFO is dispersing manure in addition then the AFO may need to reduce production. In these later scenarios overall manure production will remain or drop below previous levels and the proportion of water pollution to air pollution is likely to increase since lagoons have a greater direct impact on water. These patterns, however, all depend on the imposed dispersal limit and all the relevant coefficients.

A policy that prohibits the use of lagoons would shift all manure that would be stored in lagoons to crop dispersal. Some AFOs may not use lagoons and this would have no effect on their behavior. Others either completely rely on lagoons or rely on a combination of disposal methods. In either case the switch to dispersal for the lagoon manure represents an increase in costs since the lagoon was the profit maximizing choice for at least a part of the manure. The AFO would thus reduce production by some amount since revenues would not concurrently increase for a price taking AFO. This reduction would be matched by an increase of the proportion of initial air pollution to water pollution, since dispersal is assumed to have a greater direct impact on air than lagoons. Thus, even if total manure production may reduce under a lagoon restriction, the resulting air pollution may actually increase. Again, this is contingent on the coefficient values.

Policies that impact the costs of each disposal method may be more efficient for the AFO than proscriptive policies described, but would likely have a similar range of impacts given the transfers between media and may not be more efficient from a social perspective, but these policies would not facilitate precise targeting for specific environmental or health outcomes. Regardless, restrictions on one of the specific, prevailing technologies or increasing the price of one technology is not likely to be a sound strategy towards achieving specific environmental or health goals under the current framework, assuming the cross-media transfer coefficients in equation (7) are non-trivial, as suggested in the literature (see Section 3.2). Policies that limit both technologies simultaneously or limit total manure production would be better equipped to reduce aggregate pollution and health effects, but these policies, in practice, are likely to be politically infeasible as they would entail limitations on animal product production.

Conversely, subsidies for additional technology that has lower transfer coefficients than the existing technology (lower than the α_i and τ_i terms in equation (7)) and reduces the cost of this technology to be a preferred choice for a set of profit maximizing AFOs could be a viable option. Subsidizing biodigesters and thereby making that technology relatively more cost effective than other disposal methods could, for example, would reduce the total amount of pollutants entering the environment at the same level of production. Inducing improvements to existing technology that reduce the α_i and τ_i terms, such as improving liners of manure lagoons to reduce leakage and requiring covers to limit air pollution, could have a similar effect. Again, the conditions under which these policies would be effective depend largely on the coefficients of the model.

There are a few takeaways of this basic model. First, even under an extremely restrictive set of assumptions in both production, environmental, and health components the economic model would still require significant assumptions regarding coefficient values to form actionable conclusions and likely require simulation techniques to reach concrete conclusions. Second, under the assumption that AFO technology adoption varies by AFO size[6], policy changes that impact the relative disposal rate through m_1 and m_2 will have unintended consequences due to

[6] Which is supported in the literature, even if the specific pattern presented in this model is unrealistic. For complexities in the cost structure of manure handling and heterogenous behavior by AFO size see, for example, Edmonds et al. (2003).

the spillover effects at both the environmental and health stages and are not likely to be the best approach to addressing environmental or health concerns. Third, given that realistic settings are likely to have heterogenous patterns across AFOs and even more complex systems than presented here, and assuming that health and environmental spillovers are non-trivial, policies that limit the total quantity of manure nutrients transferring from the AFO to the environmental are likely to be a good starting place for policy makers. Finally, prior theoretical research that develops more rigorous, simulated models on these topics may be limited in their policy information because of the requisite assumptions for model convergence and the limited scope of policy alternatives to compare simultaneously. These models are also ill-equipped to incorporate either AFO, environmental, or community heterogeneity and thus will struggle to form generalizable conclusions.

While the models here are simple and unrealistic, they provide some basic information from a policy-making perspective and help illuminate the complexity and challenges in modeling and estimating these systems. There is a preponderance of additional complexities not considered here. Collective behavior of multiple AFOs in a region, unequal distribution of impacts, delayed impacts over time, permanent damage to environmental resources, additional types of impacts (e.g., soil degradation, water use, methane emissions and climate change), and opportunity costs of resource use and degradation would all be included in a more complete social welfare model.

5 Data

Several statistical models are employed in the following sections to empirically estimate the health effects of AFOs community health. This section describes the data used in these analyses as well as how we expect the limitations in this data to impact the results. Summary statistics of the data can be found in Table 2, summaries of data by cohort group in Table 3, and summaries of the panel patterns of the data in Table 4.

Livestock quantities are available from the USDA Agricultural Census. The census is available once every five years and the base data set includes the years 1997, 2002, 2007, 2012, the period of focus for the current research. The available data only tracks aggregated animal units, where one animal unit is equivalent to 1000 pounds of animal weight (USEPA 2013)[7], whereas this project or future research could benefit from more detailed animal unit data in multiple dimensions: animal units disaggregated by animal species, farm level animal unit production information, and animal unit production numbers at a yearly, or smaller, level. Firm-level animal unit data, however, requires special permissions and was beyond the scope of the current research. Due to these barriers, the additional level of access also required for the mortality data, and the emphasis in the research questions on broad policy outcomes rather than measurement of the precise magnitude of health effects, aggregated animal units were used instead of pursuing more detailed animal unit information. Permission to access this data has been granted by USDA but requires that a subset of counties that each have only a few AFOs be collapsed with other neighbors to avoid identification of specific businesses within these counties. Since there is wide variance among counties in geographic area, the animal unit variable is normalized into an animal units per square mile measure.

An alternative to relying directly on animal unit data would be to directly use nutrient generation or another variable that measures emissions as the primary explanatory variable. Average nutrient content by type of animal is tracked by the USDA and could be applied to animal counts. We could, thus, estimate the total addition of nitrogen and phosphorus emissions. This could be a useful extension to the main animal unit variables and a robustness check on the primary findings, but it could also reduce the explanatory scope of the animal unit variable. For

[7] See Table A-1 in USEPA (2013). One animal unit, for example, is equivalent to 0.74 dairy cattle, 9.09 market swine, or 455 broiler chickens. Each one of these produces around 15 tons (14.69-15.24) of manure per year.

example, distilling animal units down to a measure of their nutrient contributions alone does not necessarily pick up variation in quality of life that may more directly result from total animal units. Other contaminants, such as heavy metals and veterinary pharmaceuticals that are present in many forms of manure and depend on specific AFO practices rather than animal type, would not be directly measured in the data (Burkholder et al. 2007). Whether this non-nutrient information may be teased out of the animal unit data in a statistically meaningful way is debatable, but these distinctions and extensions are left for future research.

The baseline model's dependent variable is the total mortality rate[8]. The health impacts of AFO pollution are likely to manifest along multiple vectors and thus total mortality rates are the focus of the base analysis. Mortality data comes from the CDC's National Center for Health Statistics' Compressed Mortality File. As an extension to this baseline analysis, disaggregated health effects may test important spillovers and endogenous effects between different forms of pollution and health impacts. One way to classify these effects, as has been done indirectly in the related literature, would be 1) respiratory-related health issues and 2) all other health issues including blue baby syndrome, other birth complications, and some forms of cancers, most notably including stomach cancer. As an additional extension, therefore, we consider respiratory-related mortality and infant mortality as interrelated outcomes. Total mortality is used in the baseline analysis, with an eye kept on the additional risk of endogeneity. Respiratory-related mortality is a constructed variable based on the cause of death. And the final dependent variable, infant mortality is infant mortality less those deaths that include a respiratory cause. [9] Each rate is constructed at the county level.

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[8] Calculated as the deaths in a county divided by population averaged over each five-year panel and multiplied by 100.

[9] The results of the respiratory-related mortality and infant mortality models are not substantively different than the total mortality results and thus are not included in the results.

The distributional analysis (described below) will augment the baseline analysis with an alternative set of dependent variables. The Internal Revenue Service maintains annual, county-level data that tracks immigration, emigration, exemptions, and reported income based on tax returns. These panels, along with population census information, allow for analysis of the effect of animal units on population, demographic, and socioeconomic changes over time. The data tracks the location provided on tax returns by social security number and thus can tell the number of returns (households reporting their taxes) that moved, which counties they moved to and from, and which households/returns remained in place. This data set, however, does have some important shortcomings. The pre-2011 data includes a large subset (95-98%) of the estimated income tax filing population. It is possible that the omissions are non-random and related to some covariates that will be included in the analysis. Households that are not required to file taxes, households that file taxes late, and households whose filing status changed all are more likely to be omitted from the data set (Gross 2009). Further, the data gathering methodology changed significantly for the post-2011 iterations (Pierce 2015). The current methods account for more tax returns and thus have a fuller representation of migration, but this creates issues for a longitudinal study that spans periods before and after 2011. We explore models that estimate treatment effects across each year of the analysis and so are able to determine if the years of the analysis effects these variables. Since these tax return data may have a lot of noise year-to-year, we smooth these outcome variables for each outcome of interest. For the income variable we construct a 5-year average (in constant 2012 dollars) that includes the 2 years before and after each cohort year (1997, 2002, 2007, 2012). Change in net tax returns is a similar measure but is the difference between the current year and the previous 5-year cohort[10].

[10] With one prior cohort constructed for the 1997 measure, but not used elsewhere in the analysis.

A suite of control variables is included since there are many mechanisms that are related to mortality rates beyond environmental pollution. All variables are gathered or aggregated to the county-cohort level. Demographic and economic variables are available from the Census Bureau. Labor force information including employment and wage information is gathered from the Bureau of Labor Statistics. Weather variables including precipitation rates and average temperatures are available with NOAA. Health care quality and utilization is proxied by fee-for-service Medicare expenditures and enrollments, which comes from the Center for Medicare and Medicaid Services website. Available environmental data from EPA and USGS was considered, but much of these data are low quality and, further, map poorly onto the current county-level study since these variables are not confined by political borders. Health covariates are an important component of the control variables as well. Tobacco use rates are a significant contributor to poor health outcomes, may proxy for other risky behaviors, and have been estimated at the county-level by Dwyer-Lindgren et al. (2014). The National Center for Health Statistics (NCHS) mortality file also includes select demographic variables, including categorical age and race variables. State-level policies that regulate CAFOs are likely an important predictor of the impact of AFO pollution. County, state, and/or year fixed effects could control for the variation attributed to some of these differences, but unquantifiable differences and the distinctions purged with panel methods will be discussed below. Further, enforcement and litigation divergences may yield economically important distinctions in patterns that basic panel data methods are ill-equipped to handle.

6 Empirical Strategy

Previous estimates of the health effects stemming from AFOs have been survey-based case studies or have relied on traditional regression methods. The primary modeling approach taken here expands on these methods in multiple respects. Few empirical studies have been generalizable to the contiguous U.S. level. Of the studies that have examined health effects at the national level, fewer still have leveraged panel data techniques, feature the most current data, or span twenty years of information. Further, quasi-experimental techniques have not been employed as a way to mitigate the confounding impact of important covariates and are an valuable avenue of additional exploration.

An ideal data set for this project would have a farm-level granularity in livestock quantities, water contamination, air contamination, and monthly household health data. Geologic, atmospheric, and pollution attenuation models would be integrated to account for how contamination moves across space and time. With known policy-induced breaks in levels of animal units (Sneeringer and Key 2013) and these idealized data sets, it would be possible to exploit these breaks to identify the effect of livestock on health factors in neighboring communities in a regression discontinuity and/or simultaneous equations or similar framework. The data required for this type of analysis, however, do not exist without prominent measurement gaps and errors. The following section delves further into the most prominent empirical barriers to unbiased identification of the effect of animal units and subsequent sections describe the strategies employed to overcome these barriers.

6.1 Empirical Hurdles

The focus of the current study is the health effects of AFOs at a national level. Aggregated, county-level data are the most available level of data for this analysis. Further, since the aim of this analysis are general, nation-wide policy lessons this level of granularity is more appropriate than that of prior research that focuses on finite mechanisms. The environmental data necessary to fully explicate the process of producing livestock => pollution => health effects, but are inconsistent and noisy, especially in large rural counties. Relying on this imperfect data, therefore, jeopardizes accurate estimation. Therefore, explicitly accounting for the environmental components of the model when using county-level data is likely to bias results or, at least, incorporate a significant amount of spurious variation. Therefore, omitting these environmental variables may be the most prudent econometric strategy to estimate the link between AFOs and health outcomes.

Measurement issues are likely to exist elsewhere in the datasets, although not to the same extent that we experience with environmental variables. County-level aggregation appears to be the best available geographic level at which to proxy for air and water impacts, respectively. Water and air systems near AFOs receive the brunt of the impact of AFO pollution, which due to the typical size of counties is often within the same county as the AFO. But other systems outside the county may also be impacted by contamination, particularly where watersheds cross county lines. Direct measurement of these linkages is complicated and often suggests smaller geographic limitations, but smaller geographies also pose methodological challenges. For example, the most acute impacts of pollution may be at the source of pollution, but a population center further downstream may be where the greatest quantity of impacts are experienced, even if the levels are lower. Limiting the analysis to county-level impacts may introduce additional noise into the model, but unless some AFOs intentionally locate near the edges of a county with the goal of sending pollution over county borders the variance across counties is likely to appear as random noise. This is particularly true with the tendency of rural counties to be located near other rural counties. This noise will be diluted with a national level model drawing from more than 3000 counties.

Household location sorting is a barrier to identification of the models. Households may move away from AFOs as animal units increase and they anticipate a reduction in quality of life and health from exposure to the pollutants. An increase in livestock quantities over time, thus, may appear to provide evidence that exposure to AFO pollution has negligible health impacts with naïve estimation techniques that do not account for this endogeneity. Similarly, if there are health effects of AFO pollutants then other counties, all else equal, will experience higher mortality rates as these families bring a residual health effect that was caused by prior exposure. Conversely, additional AFOs may bring with it additional AFO-related jobs and AFO workers. Regardless of the direction, form, or magnitude of sorting, there is likely to be endogenous sorting related to changes in AFO activity. This is a significant methodological concern and may lead to biased estimates health effect of exposure to AFO pollutants (Tiebout 1956; Zivin and Neidell 2013; Banzhaf et al. 2019).

There are several factors that may reduce or mitigate these sorting effects. First, some types of contamination may not be readily observable by residents. Thus, the underlying cause of some deleterious health effects may not be known. In other words, there is little reason to believe that there is perfect information about health impacts where AFO pollution exists. Second, some forms of contamination may not be detectable at low, but still impactful, levels and may not be easily linked by a household to that household’s health status. It is plausible that lower-level effects would be less likely to induce sorting than more severe effects. In this study, however, sorting remains an issue as the proxy measure for health is severe (i.e., mortality). Unfortunately, measures of less severe health outcomes, such as that for asthma morbidity, are uncommon or unreliable, especially in lower population rural areas.

Another factor mitigating the effect of people moving in response to AFO location decisions is that some of the potential behavioral responses will be absorbed by the housing market. The hedonic pricing literature discussed in Section 3.3.3 finds evidence that there are, typically, losses in housing value due to living near AFOs. Assuming well-behaved markets and that consumers monetize health risks, some of the losses induced by living near AFOs may be compensated by lower housing costs through these markets. When neighboring animal units increase, residents may sell their home at a discounted value or incur the increased health risks; buyers with knowledge of potential harm from the animal units will demand that the price of the home be reduced by the monetized value of the perceived health risk. Conversely, since information collection is costly and information regarding AFO pollution's effects is not fully known then housing decisions may exhibit significant stickiness and some portion of the population will not move away from the AFO. Employment and schooling decisions are also likely to contribute to this stickiness. In this sticky scenario, people may need large contamination shifts to catalyze migration or these decisions may require long periods of time before a relocation occurs. Regardless, the uneven distribution of environmental impacts suggests that accounting for net cross-county migration could be an important factor.

Finally, county-level aggregation may also minimize some sorting effects since household movement maybe within the county of origin. A household may move further away from an AFO following increases in contamination, but it is unknown what proportion of these moves tend to be cross-county and what proportion tend to be within-county, which makes this data set ill-suited to explore the disparate impacts across racial or other demographic groups (Banzhaf et al. 2019). Within-county migration would be more likely than between-count migration, on average, to allow residents to maintain their current employment and schooling decisions but move to an area with lower pollution exposure. In this case of within-county migration, county-level health effects stemming from AFO pollution exposure would still be observed for the migrating household and be observed within the county of exposure. Taken together, all the factors described above will not fully mitigate the effect of households moving away from pollution exposure in this case, but the impact on estimation may be somewhat muted.

Health impacts may also suffer from endogeneity issues with the animal unit variables. Past health impacts stemming from AFO pollution may influence future permitting decisions or state-level policy shifts, which could then influence livestock quantities, contamination rates, or AFO siting decisions. Whereas the household sorting effect is a plausibly contemporaneous relationship, although still likely to have a delay since housing decisions are sticky, endogenous policy shifts are likely to take more time to manifest as they are subject to bureaucratic and political processes. Controlling for this endogeneity may be a complex endeavor since our data is limited to one panel every five years. For example, health effects in 2002 may induce additional regulation and result in lower livestock quantities or lower contaminants entering water systems in the 2007 and 2012 panels. Some of these issues could be avoided by controlling for year effects in addition to county effects.

Measurement error is also an issue in the data sets, beyond the issues associated with pollution data discussed earlier. The best county-level tobacco use control variable, for example, are gathered from an academic research program that is based on survey data and extrapolated to the county level. In this case, the underlying survey data suffers from its own level of survey and sampling measurement error and then the researchers extrapolate these data to forecast annual tobacco rates over the 20-year period of their study. While this approach is less than ideal, the rates presented in this article are more consistent with known examples of known smoking rates than the collapsed CPS tobacco use information, which was found to have large inconsistencies with more directly observed rates.

Regardless of the types of endogenous relationships, the scale of measurement error that exists, or the presence of time trends, identification of the models requires controlling for observed and unobserved confounding factors. Several strategies are considered and employed in various forms across the models. These include standard instrumental variable approaches; balancing across plausibly confounding variables to purge the system of endogenous variation that may result from these relationships; directly incorporating the endogenous residuals from the treatment stage in the outcome stage; and, in general, directly comparing plausible counterfactual matches. Instrumental variables have received much attention in the literature, but despite this vast literature are still subject to many of the original critiques. This is particularly the case in the current research setting with aggregated, 5-year, county-level data variables. In this situation it is difficult to plausibly claim that one variable is exogenous *enough* to be included as a strong instrument or, conversely, that the entirety of a 5-year averaged variable is endogenous to another 5-year averaged variable. This, paired with the paucity of plausible instruments made an instrumental variable approach a less-preferred approach in this situation.[11]

Counterfactual matching techniques (e.g., Stuart 2010; Wooldridge 2010, Ch. 21) have proved to be better suited to this setting, particularly so-called double robust approaches model both the treatment decision and the outcome decision in sequential stages. Further, the baseline counterfactual models can be extended to control for some endogenous effects between the treatment decision and the impact of these decisions on the outcome, independent of the confounding variables. Endogenous treatment effect models, for example, store the residuals from the initial, treatment regression and then add them to the covariates in the outcome equation. In this way the remaining, endogenous variation from the unmeasured confounders is controlled for in the outcome equation. Thus, these unmeasured confounders do not bias the estimation of the treatment effects in the outcome model.

Matching methods have received little attention in the literature on the health effects of AFOs, but, more generally, matching methods have grown in prominence as a method for handling confounding. Thus, counterfactual matching techniques are leveraged more than these

[11] Two sets of instruments that were explored were 1) weather variables such as precipitation that are plausibly related to animal unit production, but have little direct link to health outcomes and 2) market prices for animal products that could drive production decisions and also not have a strong impact on health outcomes. The former proved to be a weak instrument and granular, historical data for the later was not found.

other methods in the current research. Further, the current scenario has a continuous, rather than binary, treatment variable, i.e., animal units. Methods for controlling for confounding in a counterfactual research design with continuous treatments have a far less-established literature or generally agreed upon methodology. The distinctions between high animal unit density (AUD) counties and low-density counties are well established, however, which makes a discretization of the AUD variable a natural starting point in this research, with the potential for extensions with these continuous variable methodologies.

Multiple unmeasured, county or time-period effects may have important impacts on treatment or outcome decisions, making multiples fixed effects important considerations. There may be county or state time-invariant variables that influence health outcomes, but are not measured or measurable, such as state or agency-level policies or regulations. There are also known federal and state policy changes that have occurred over the period of study, but are difficult to incorporate directly into the model because, in some cases, there's a lack of clarity on the precise stage and direction of a large-scale policy impact or there may be a wide swath of relevant regulatory changes that are impossible to track at the county-level for the whole country for 20 years. Since AFO policy is typically implemented at the state or federal level, but counties within a given state may be heterogeneous in enforcement or regulatory patterns or for other reasons, we explore models with state, county, and/or year fixed effects.

6.2 Empirical Approach

We construct four county-level panels for the years 1997, 2002, 2007, and 2012. Within each panel we divide the cohort into quartiles based on the AUD variable. A time-averaged cohort and quartiles are also constructed. We use the first quartile (i.e., the lowest 25% of counties by AUD) as the control group and the fourth quartile (i.e., the highest 25% of counties by AUD) as the treatment group in the preliminary models, but also use the second as the control in later models that will be discussed in more detail below. Our base analysis is a simple, one period, one outcome quasi-experimental, counterfactual matching model. Here we employ each of propensity score matching, inverse probability weight regression adjustment, and endogenous treatment effect models for comparison purposes.

We then expand on the baseline model by loosening several assumptions. First, we use all four cohorts in pooled data. We do so by examining pooled data that average all variables across the four cohorts by county, use the quartile assignment for the first panel (1997) and retain these quartile assignments across all four cohorts in pooled data, and use time-averaged animal units to determine the treatment and control groups, respectively, and apply these across all the pooled data. Next, we retain the time-averaged treatment group assignments and use these counties in a panel regression framework that employ inverse probability weights and endogenous treatment effects (each described in detail below). Finally, we employ a general propensity score framework that accounts for the continuous, “dose response,” of the animal density variable by employing a weighting scheme across the full range of AUDs so that each of the AUD quartiles is balanced against the combination of the other quartiles, respectively.

The models employed in the baseline are single cohort analyses that include a range of potential-outcome, quasi-experimental methods, each of which is described here. One technique used is treatment conditioning. This technique is intended to control for the effects of omitted confounders. Treatment conditioning involves manipulating the treatment and control groups in a way that makes an observational data set more closely resemble a randomized control trial (RCT). With a large enough sample, an RCT renders unbiased treatment effect estimates by controlling for the effect of all observed and unobserved confounding variables. The goal of treatment conditioning is to similarly control for the effect of these confounders. The strategies are, essentially, weighting schemes based on the propensity for treatment for each unit, but require some specific assumptions to hold that are moot considerations in a RCT. These assumptions include weak unconfoundedness and the stable unit treatment value assumption (SUTVA).

Weak unconfoundedness is the assumption that if all observed and unobserved confounding variables are balanced across the treatment and control groups then an unbiased average treatment effect can be calculated by taking the difference between the two groups. If we ensure that the only relevant difference between the two groups is the treatment assignment, then the average difference in outcomes between the two groups is an unbiased estimate of the average treatment effect. This assumption attempts to approximate the random assignment of experimental methods. As with many other empirical methods, the key barrier to satisfying the weak unconfoundedness assumption are the unobserved confounding variables. Treatment conditioning uses the information available in the observed confounders to weight the observations so that the treatment and control groups look similar. This balancing process is assumed to also balance the unobserved confounders, rendering their remaining influence null. Importantly, however, if the balancing process of the observed confounders did not also balance out the unobserved confounders then the resulting treatment effect estimates will be biased. Similar to the excludability assumption with instrumental variables, statisticians have developed tests that may help to indicate whether unobserved confounders remain influential, but even with these tests completed practitioners still often require theoretical justifications as well; practitioners must explore the possibility of additional, excluded variables and the possible effect they have on treatments or outcomes.

The second important assumption required to yield unbiased treatment effect estimates in treatment conditioning models is the SUTVA. The SUTVA assumption states that the treatment condition of one unit does not substantively affect the treatment or outcome of another or neighboring unit. This assumption is harder to satisfy in research programs such as the current one where units are geographically related and there may be economic externalities between counties or there are regional commonalities, such as cultural norms or policy. If, for example, an AFO begins operation in County A and this impacts the contemporaneous decision in neighboring County B to either begin or stop AFO operations then the SUTVA assumption is violated. We may expect a general trend of AFO expansion or contraction in a region for various reasons, we do not expect the economic decision in a county to be conditional on the neighboring county. There may, however, be state-level policies or trends that lead to changes in AFO behavior, but this is not a violation of the SUTVA assumption and, further, is accounted for through fixed effects where applicable.

The matching models employed here begin by estimating the probability of treatment conditional on observed confounders using a logit or probit model or by directly matching one unit to another based on specific characteristics using a Mahalanobis distance function (Rosenbaum and Rubin 1985). The predicted outcomes of this model are the predicted probabilities of treatment, also referred to as the propensity scores. With the propensity scores in hand some overlap checks are conducted. First, we check to ensure that both the treatment and control groups cover the same range of propensity scores. Control (treatment) observations that fall far outside of the range of propensity scores of the treatment (control) group are removed as they are said to fail the common support requirement. If a treated observation has a score that is well outside the range of propensity scores of the control group then any comparison between that unit and any unit in the control group does not satisfy the underlying assumptions of the analysis. Rosenbaum and Rubin (1985) recommend a caliper of 0.25 times the standard deviation of the propensity score, but other sources recommend no caliper if the overlap assumption is satisfied. Typically, the sensitivity of results to the level of the caliper are tested as a robustness check.

With a caliper in place, any treatment or control observation that does not have a matching observation within that caliper is dropped from the sample.

Matches are then made between the treatment and control groups. In general, the control and treatment observations with the nearest propensity scores are matched, but there are several decisions to be made regarding the matching process. First, the researcher must decide which metric to use. Finding the closest match for each of the treated *and* control observations yields the Average Treatment Effect (ATE), whereas only forming matches for the treatment group would yield the Average Treatment Effect on the Treated (ATET). The decision between metrics is largely determined by the context in which it is being made. In the current scenario, the contrast between these metrics is slightly different than the traditional situation, since every county has some amount of treatment and thus all counties are technically treated. Here, therefore, the question is whether we are concerned with how being a high-AUD county has impacted high-AUD counties or the hypothetical question of how we would expect a high-AUD designation to impact any given county. The question is whether we are primarily concerned with measuring the effect of animal units in counties that have high concentrations of animal units or if we are interested in the counterfactuals for the high concentration counties and low concentration counties taken as a whole. Since we are focused on policy implications of AFO adoption we focus on the more general ATE so that we can estimate the impact of animal units categories for the whole system, not just the counties that have high animal units.

Next the researcher must determine if matches are made with or without replacement, i.e., whether a control observation can be matched more than once. Matching without replacement often leads to some matches with a high divergence in propensity scores, but if the number of matches for each control observation is not kept relatively small than some observations may be heavily over-represented in the control group and thus bias the estimates of the true control group's characteristics. If replacements are not made or the number of matches allowed per control unit are limited, then the researcher must employ a method to evaluate the best set of matching observations. A method that may partially alleviate this issue is to make more than one match per treatment observation. This expands the size of the control group, tends to mitigate the impact of any single control unit on the results, but also biases the final estimates since each treatment unit now has a group of counterfactual observations that have a greater average difference in propensity scores than if the single closest control unit was selected. Thus, there is a tradeoff between the balance achieved and the level of bias in the treatment effect estimation. Here we employ one-to-one matches without replacement.

Once the matches are selected then balance checks are conducted between the final, weighted treatment and control groups. These tests ensure that the treatment and control groups appear similar across all confounding variables. The two groups will never be exactly the same, so we must use thresholds by which to evaluate the closeness of the two weighted groups. A standardized difference in means should be, at a minimum, less than 0.25 to be considered balanced, but many researchers suggest a standardized difference less than 0.1 (or 10%). Similar, an acceptable ratio of variances between the weighted treatment and control group's covariates should be between 0.5 and 2.0. (Rubin 2001; Austin 2009; Stuart 2010).

A related, but fundamentally different, treatment conditioning method is Inverse Probability Weighting (IPW). IPW begins similarly with estimation of the propensity score, but rather than matching observations based on the closest propensity score to form a counterfactual match, the IPW approach estimates weights using the propensity score and then calculates weighted averages to yield treatment effect estimates. For the treatment group these weights are

$\frac{1}{(propensity\ score)}$ and for the control group the weights are $\frac{1}{1-(propensity\ score)}$.[12] Extremely large propensity scores in the treatment group and extremely small propensity scores in the control group, i.e., the two groups of observations that are least likely to resemble units in the opposite group, have relatively small weights. Conversely, observations in the control (treatment) group that are most similar in the propensity score to the treatment (control) group receive relatively large weights. Weighted average outcomes are then derived for each group and the ATE is the difference between these values. The ATE is unbiased under a similar set of assumptions to that of the propensity score, but care must be given to the inclusion of extremely small propensity scores in the treatment group and extremely large propensity scores in the control group. Both PSM and IPW methods are known to produce unbiased estimates of average treatment effects when the baseline assumptions hold. (Stuart 2010; Austin and Stuart 2015)

Instead of weighting based on the treatment condition an alternative approach is to adjust the outcome equations based on the treatment assignments, often referred to as regression adjustment (RA). In this approach the outcome equation is estimated for each of the treatment and control groups separately. Predicted outcomes are stored and the difference in means between the two groups is the estimated ATE. Alternatively, a binary treatment variable can be directly included in the pooled model and also provides a point estimate of the average treatment effect. RA provides unbiased estimates of the ATE under the assumption that the outcome equation is properly specified.[13] (Wooldridge 2010, Section 21.3)

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[12] These weights are for the ATE. ATET weights are adjusted so that the treatment group all receive a weight of 1. Stabilized weights may also be employed, referred to as Inverse Probability of Treatment weights: treated weight $= P_T * \left(\frac{1}{propensity\ score}\right)$, control weight = treated weight $= (1 - P_T) * \left(\frac{1}{1-(propensity\ score)}\right)$, where P_T is the probability of being in the treatment group. (Austin and Stuart 2015)

[13] While IPW and RA methods are the building blocks of IPWRA methods and warrant description here, these estimation methods are omitted as stand-alone estimation methods, respectively.

Doubly robust methods are also used here. Both treatment equation conditioning and outcome equation corrections are used to estimate average treatment effects. These methods are described as “doubly robust” as the estimated ATEs have been shown to be unbiased if either the treatment equation or the outcome equations are accurately specified. The IPW Regression Adjustment (IPWRA) approach goes one step further than the IPW approach. IPWRA uses the IPW weights in the outcome regression model, whereas IPW directly estimates average differences in the outcome variable by weighting those outcomes by the IPW. Because of the doubly robust property, the IPWRA method allows for a degree of misspecification in either the treatment or outcome model, whereas PSM and IPW methods require that the treatment equation is modeled correctly in addition to the unconfoundedness and SUTVA assumptions, that are also required under IPWRA (Wooldridge 2010, Section 21.3). Thus far, research has been unclear regarding which methods among the range of treatment effect estimators perform better if both the treatment equation and the outcome equation are mis-specified.

A final extension on this set of models is an endogenous treatment effect (ETE) model. This approach incorporates information from the treatment equation and controls for this information when estimating the outcome equation, thereby controlling for endogeneity from in the treatment equation. A control function methodology is employed where we store the residuals from the treatment equation and uses these to construct a regressor in the outcome equation (Wooldridge 2010, Section 21.3; StataCorp 2017b). In this way the unobserved, non-random variation that has an impact on treatment assignment, and may result in lingering bias from confounding, is used to mitigate remaining endogeneity in the outcome equation. These methods are useful where important confounders are unmeasured or unmeasurable, as may be the case in the current research.

After employing this set of counterfactual techniques to estimate the ATEs in single cohort, cross-sectional analyses the same models are employed on broader data sets that incorporate all four cross-sections. In the first set of cross-sectional models, estimates were inconsistent across the models suggesting that there may be dynamic effects that were left unmitigated in the cross-sectional analyses or there may be idiosyncrasies in the data for a particular cohort or set of cohorts. The first treatment assignment regime uses the quartile assignment from the first (1997) cohort to assign the same treatment condition to that county in each subsequent cohort. For example, if Hennepin County is in the control group in 1997 then Hennepin County will also be in the control group for 2002, 2007, and 2012, regardless of whether Hennepin County is in the lowest quartile of AUD for each of those subsequent years. The second approach uses the treatment assignments in each cohort and pools these counties together into one treatment group. Here some counties may only be present in a subset of the treatment group cohorts or may be present in all four cohorts. Finally, the entire data set is averaged across all four cohorts and then treatment and control assignments and the resulting estimates are made using this aggregated data.

County and state fixed effects, respectively, are incorporated into these models in the next stage. To maximize panel balance, and because the treatment results from the pooled methods were not substantially different across the various treatment assignment protocols, the treatment assignment in the panel models is based on the assignments using quartiles from the averaged data. Substantive differences were not found across these cohorts because there was only marginal county switching between quartiles across the cohorts. Further, weights based on the average for each county are the only set of weights that take the full information from all four cohorts into account. Notably, the lack of movement of counties into or out of treatment groups as we move from cohort to cohort suggests that most of the variation is between rather than within counties. This stability may suggest issues with the scale of explanatory power found in the fixed effects models, as the within-variation may be limited for any given county[14]. This characteristic is discussed further in the results section.

Using the top and bottom quartiles to estimate the effect of AFOs on community health is a stark, but crude measurement. While comparing the highest density animal producers to the lowest density producers is a way to make a definitive comparison, this approach also leads to an oversimplification. There may be non-linearities in the treatment effects, insurmountable unmeasured differences in the characteristics between the lowest quartile AUD counties and the highest, or other impediments to this methodology. A newer and relatively under-utilized method for treatment effect estimation in the case of a continuous treatment variable is the General Propensity Score (GPS) strategy. The method relies on the same underlying assumptions as other matching estimators: Identification requires overlap between the groups of treatment units by stratifying the sample into subgroups and balancing across these subgroups; and that the unconfoundedness assumption holds. In the GPS case, however, the methods for evaluating the validity of these assumptions differ than those in the binary case.

General propensity score (GPS) estimators begin by predicting the propensity to receive the continuous treatment based on measured confounding variables. The sample is then stratified based on the treatment variable and weights are applied to the stratified groups to attempt to achieve balance between each subgroup. Balance is then evaluated between each group and the aggregated set of all the other groups. If these differences are statistically minimal, then a dose-response function is estimated that, in this case, predicts the mortality rate for the range of animal unit density values. The dose response function is estimated based on the continuous treatment

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[14] This hypothesis is confirmed when analyzing the between and within variation, see

Table 5

variable, the predicted general propensity score, the interaction of these variables, and up to quadratic polynomials to account for potential non-linearities. Standard errors are bootstrapped, and the dose response function and 95% confidence interval bands are plotted and evaluated. The methods and results do not lend themselves to simple causal stories in the same way that, say, OLS estimation might with the estimation of an average effect. (Hirano and Imbens 2004; Bia et al. 2008; Flores et al. 2012)

6.3 Variables

The primary variable of interest used in this study is derived from the animal units variable. To account for the variance in land area at the county level we transform this variable into an animal unit density (AUD) variable, animal units per square mile.[15] In the potential outcome framework, we control for variables that are predictors of this "treatment," in the base models the upper and lower quartiles of the AUD distribution as the untreated and treated groups, respectively. Conceptually, there are several factors that are likely to predict AUD in each county. These include 1) characteristics of the local economy: population density per square mile, median income, poverty rate, unemployment rate, and high school and undergraduate degree attainment rates; 2) demographic characteristics of the population: percent of population under the age of 19, percent over 65, and percent identified as Black; 3) characteristics of the environment and climate likely to influence agricultural activity: average temperature, average daily precipitation in millimeters, and total water withdrawals per square mile; 4) a measure of political factors: proportion of presidential votes going to the Republican in the most recent presidential election[16]; and finally 5) Census region dummy variables.

[15] The effect of land area is also mitigated in the panel models where land area remains constant within a county.
[16] For the 1997 cohort we use the 1996 election, 2002 is a weighted average of 2000 and 2004, 2007 is based on 2008, and 2012 uses the 2012 election.

The primary outcome variables in this study are county-level, 5-year average mortality rates, but subsets of total mortality were also evaluated and as well as the net change in tax returns and the net change in taxable income. In models where the outcome equation is part of the estimation strategy, we include covariates that are likely to have a causal effect on the outcome variables. Many of the covariates included in the treatment stage are also included in the outcome equation due to the influence they plausibly assert on mortality rates: population density, median income, poverty rate, unemployment rate, education levels, age variables, and percent Black.

There are also variables solely included in the outcome equation, as these variables do not have a plausible mechanism by which they influence animal unit density but are likely to have a direct impact on community health outcomes. To measure health care access and quality of healthcare we use Center for Medicare and Medicaid's fee-for-service database to construct three variables: per capita Medicare part A expenditures, per capita Medicare part B expenditures, and a measure of the proportion of the population enrolled in Medicare[17]. We also include the water withdrawals variable in the outcome equation, since one vector of influence of animal units on mortality rates is through water contamination. If this contamination is likely to have a local, measurable influence on mortality rates then this will be positively related to water withdrawal rates. And finally, two additional variables are included at this stage that have a known impact on mortality rates, the percent of the population that is female and an estimate of the smoking rate.[18]

[17] The CMS database has three separate enrollment groups: Aged, Disabled, and End Stage Renal Disease. These overall measures are sums of these three variables and, in the case of the proportion of the population, divided by total population from the Census. For the enrollment variable, we use whichever total enrollment is larger between part a and part b as there may be overlap between the two groups and doing otherwise may lead to inconsistent double counting.

[18] Descriptive statistics of all covariates can be found in Tables 2-5.

6.4 Empirical Models

Each estimation strategy employed here (propensity score matching, inverse probability weighted regression adjustment, and endogenous treatment effects) begins with estimation of the binary treatment equation. The treatment equation is estimated using a logit model via maximum likelihood estimation:

$$P(t=1) = \frac{1}{1+e^{-Z\beta_1}} \tag{14}$$

Where $P(t=1)$ is the probability of receiving treatment, here the probability of being in the highest quartile of animal unit density. And Z are the treatment equation covariates as described in Section 6.3. The models diverge, however, with how they each use the results from the treatment equation. The propensity score model next constructs the potential outcome for each observation by matching each observation with the observation from the converse group (treatment or control) with the closest propensity score. The difference between the observation's outcome and the matched observation's outcome is the estimated treatment effect for that observation. The average of these treatment effects across all the observations is the average treatment effect.

The Inverse Probability Weighted Regression Adjustment uses the propensity scores from the treatment equation in the outcome regressions. First, weights are constructed using the propensity score (see Section 6.2). These weights are then used in estimation of two outcome equations:

$$Y_{t=1} = X'\beta_1 + \varepsilon_1 \tag{15}$$

$$Y_{t=0} = X'\beta_0 + \varepsilon_0 \tag{16}$$

From which the predicted outcomes, $\hat{Y}_{t=1}$ and $\hat{Y}_{t=0}$ are retained. The average treatment effect if then calculated as difference between the averages of each of these two sets of predicted outcomes, $ATE_{ipwra} = \overline{\hat{Y}}_{t=1} - \overline{\hat{Y}}_{t=0}$.

The endogenous treatment effect models also use regression adjustment, similar to the IPWRA method, but information from the treatment equation is used in the outcome equations in a different way. Rather than using weights based on the propensity score here the residuals from the treatment equation, or the difference between the predicted probability and the actually realized outcome, $\omega_t = t - \hat{P}$, are stored and used as a regressor in the outcome equations.

$$Y_{t=1} = X'\beta_1 + \alpha_1\omega_1 + \varepsilon_1 \tag{17}$$

$$Y_{t=0} = X'\beta_0 + \alpha_0\omega_0 + \varepsilon_0 \tag{18}$$

Again, the ATE is estimated as the difference between the averages of the predicted outcomes.

7 Results

Our estimation of the treatment effects of AUD on mortality rates and other outcome variables begins with models with the most stringent assumptions. These assumptions include that there is a single, constant treatment effect over time, that no confounding variables are omitted or balance in all omitted confounding variables is achieved, and there are homogenous effects across counties. The results of these simple models were scrutinized for patterns and inconsistencies, which informed subsequent stages of modeling where these restrictive assumptions were loosened. The results from each of these iterations are summarized below.[19]

7.1 Cross-Sectional Analysis

Three forms of cross-sectional potential outcome models are estimated for each of the four cohorts: propensity score matching (PSM), inverse probability weighted regression adjustment (IPWRA), and endogenous treatment effects (ETE). The ATE and the associated statistical characteristics are presented in Table 7. In each case, the ATE is interpreted as the average effect on the total mortality rate for a county that appears in the highest quartile of AUD compared to a statistically identical county in the lowest quartile of AUD, given that the requisite assumptions hold (see Section 6.2). These models reveal a few notable patterns, the most prominent of which are the inconsistency in the statistical significance and the sign of the estimates, as well as declining ATE estimates as we progress through time from the 1997 cohort to the 2012 cohort.

The PSM models balance over a set of observables that are plausibly related to treatment selection, i.e., whether a county is in the highest or lowest quartile of AUD. These variables include population density, median income, unemployment rate, high school graduation rate, college graduation rate, percent of population under 19, percent of population over 65, percent of population that is African American, domestic water withdrawals per 1000 square miles, republican vote share, average temperature, average daily precipitation, and census region. The initial year, 1997, of the PSM model (the first line of Table 7) has a positive and statistically significant ATE. The coefficient of 0.0445 may be interpreted as follows: if a county switched from being in the lowest quartile of AUD to the highest, while holding all else equal, we would

[19] All analysis completed in Stata 15 (StataCorp 2017a)

expect an additional 44.5 deaths per year per 100,000 population. In the raw data for this same year, the control group mean value was 0.990, or a base of 990 deaths per 100,000 or about a 4.5% increase. These effects decline in magnitude in the 2002 and 2007 cohorts and is close to significance at the 0.05 level in 2002 (P=0.056) and significant in 2007. These effects turn negative in the 2012 cohort but are insignificant at the 0.05 level. In each case the balance across all included covariates improves with implementation of PSM and is within standard expected bounds for most of the confounding variables. Balance evaluation of the PSM models for each cohort are presented in Table 8. Matching universally improves balance across the covariates. The variance ratio of population density remains slightly unbalanced[20] in some cohorts and the Midwest census region dummy is also slightly unbalanced[21].

The IPWRA and ETE models each employ the same confounders in the treatment equation specification as the PSM models, but the outcome equations use a different set of variables, including some of the same treatment confounders plus an additional set of covariates. The republican vote share, average temperature, and precipitation variables from the treatment equation are not included in the health outcome equation as these variables are not expected to have an influence on health outcomes, except through other intermediary variables, some of which are already included in the treatment and outcome equations. Second, we add several additional variables to the outcome equation that do not have a theoretical link to AFO investment decisions but are important predictors for health and other economic outcomes. These additional variables include the percent female, the smoking rate, the percent of the population enrolled in Medicare, and Medicare A and B per capita expenditures, respectively. These variables are plausibly and likely directly predictive of mortality rates but are omitted from the

[20] Outside the 0.5-2.0 bounds. See Section 6.2.
[21] Greater than 0.25. See Section 6.2.

treatment equations as they are not suspected of having a direct relationship to animal production decisions.

The IPWRA models demonstrate a similar pattern to the PSM models, but with ATE point estimates at a consistently lower magnitude (lines 5-8 of Table 7). In this case the 1997 and 2002 cohorts each carry positive estimates that are significant at the 0.05 or better level. Similar to the PSM model, the 2007 and 2012 cohorts have estimates that are statistically no different than zero. The balance achieved with the IPWRA models is not as strong as that for the PSM models (Table 9), which is normal since the IPWRA models use the full set of observations rather than the subset that forms the best matches. Nevertheless, balanced improves with the weights applied and is under the acceptable thresholds for most variables.

The results for the ETE cross-sectional models (lines 9-12 of Table 7) are statistically indifferent than zero in each cohort except 2002, which is positive and significant at the 0.05 level. Wald tests for each cross-section suggest that endogeneity is present in the 1997, 2002, and 2007 cohorts, whereas the Wald test suggests no endogeneity in the 2012 cohort. While the PSM and IPWRA models display similar time trends in the ATE point estimates, the ETE models does not follow this same trend. Although the ATE point estimate is negative for the 1997 cohort and positive for the other three. Endogenous treatment effect models do not lend themselves to the same balance evaluation techniques as PSM and IPWRA methods as there is no treatment conditioning in these models.

The lack of consistency across these cohorts and models may suggest that the data generating processes have changed as we transition between cohorts. These results, however, do not suggest how or why these changes may have happened. The point estimates decline over time for the PSM and IPWRA models, notably becoming negative and statistically significant in the 2012 cohort. The ETE model also suggests that a different pattern emerges in the 2012 cohort, as the endogeneity test cannot reject the null hypothesis of no endogeneity, whereas the other three cohorts all reject the null at the 95% level or higher. In general, the inconsistency suggests that more nuanced modeling choices and/or better data are necessary to effectively account for heterogeneity and confounding variables. Regardless, impacts do appear to change over the period of analysis.

7.2 Pooled Analysis

We next pool the data across the four cohorts and re-estimate the models, the results of which are presented in Table 10. The PSM, IPWRA, and ETE estimation techniques are similarly employed at this stage, but the data is pre-processed prior to treatment group assignment. In particular, the data is pooled in three different manners and then the ATEs are estimated using these pooled treatment group assignments. The first pooling method uses the treatment group assignment from within each cross-sectional model and pools these four respective groups into a single treatment group cohort. The treatment group, for example, includes the highest quartile of AUD for each of the 1997, 2002, 2007, and 2012 cohorts ("Pooled" in Table 10). Importantly, since this model ignores the year of each observation in selecting matches, comparable observations from each treatment group may be from different years, say, 1997 and 2012, respectively. Thus, these models attribute all omitted policy changes, and other temporal shifts over the period of study, as noise rather than as important factors to be explicitly or implicitly controlled for. The pooled models also, however, increase the universe of potential matches for each observation, which, on average, increases the quality of each match.

For the second pooling method we retain the counties in the treatment group assignment for the 1997 cohort and apply these group assignments for each of the four cohorts ("1997" in Table 10). While this method does not, strictly, retain the highest and lowest AUD counties from each cohort in the same way that the first pooling method did, it does have the advantage that all the counties are consistently included/omitted across the years. Since counties tend to remain consistently high or consistently low AUD over time, even if they move slightly above or below a quarterly threshold, these group assignments are not drastically different than those made in each cohort sequentially.

Finally, we average the entire data set across the four cohorts and use this collapsed data to determine the treatment and control groups ("Average" in Table 10). This final grouping is the only one of the three pooled models that assigns treatment based on an adjusted AUD. Again, the effective treatment group assignment is similar to the previous methods, but not identical. Each of the pooling models, however, may smooth over important variation through the averaging process. In general, the pooled models make two key assumptions: first, there are no time-variant treatment effects and, second, there are no fixed county-level trends (i.e., fixed effects). In general, the estimates from these models exhibit more consistency than the cross-sectional models but, taken on their own, fail to identify a consistent and robust relationship.

The point estimates from each of the pooled PSM models are positive, with none of these models significant at the 0.05 level. Balance evaluation statistics are presented in Table 11, which show strong balance is achieved across the PSM models. The point estimates of the IPWRA models are also each positive, with both the Pooled and 1997 groupings significant above the 0.01 level. Balance results for the pooled IPWRA models are presented in Table 12, which shows improved balance compared to the unweighted data but, again, weaker balance than that achieved with the PSM models. Finally, the ETE models are also all positive, but here the magnitude of each model is of a greater magnitude than the PSM and IPWRA models, respectively. Further, each ETE model is significant above the 0.05 level with the Pooled and 1997 models significant above the 0.001 level.

In sum, the PSM models, which balance exclusively in the treatment model and do not estimate the outcome equation, all result in insignificant treatment effect estimates. All but one of the six outcome models (IPWRA and ETE), however, show statistically significant, positive treatment effects, suggesting that the inclusion of the outcome equation in the models is an important, impactful decision, even if PSM models achieve a higher level of balance than the IPWRA models.

7.3 Panel Analysis

The point estimates of four panel regressions are presented in Table 13. Here treatment group assignment was determined by first averaging animal units by county across the four cohorts and then selecting the 1st and 4th quartiles based on this average[22]. The county treatment group assignments are then applied to the original, non-averaged panel data set, creating a balanced, four-panel sub-sample. Each model employs county-level fixed effects and interactions with year dummies with a base year of 1997. Each of the four models then vary in their usage of inverse probability of treatment weights based on the predicted probabilities from the averaged panel regressions, and endogenous treatment effects, where the residuals from the treatment equation estimated for each year are retained and included as a covariate in the outcome equation.

The estimates of the marginal effects of treatment when aggregated across all years for each of the four models are statistically insignificant at the 95% level (Table 13, row 1). The baseline panel model and the panel model with ETE also showed insignificant treatment effects for each of the four cohort groups. When we include IPWs[23] or IPWs and ETE, however, we find

[22] An extension uses the 2nd quartile instead of the 4th quartile
[23] Stabilized, Inverse Probability of Treatment Weights were also employed, but the results were not substantively altered.

a statistically significant and positive impact of treatment on mortality rates (row 2, 1997)[24]. This mean effect is then not statistically different than zero in 2002 but turns negative and statistically significant in 2007. This reinforces the pattern found earlier where the impacts of AUDs on mortality rates declined over the 20-year period of study. Further, these four models suggest that controlling for the treatment selection processes (e.g., through quasi-experimental weighting techniques) is important in this setting and can shift the overall pattern of estimated effects and thus the resulting policy implications. Endogenous treatment effects appear to have only a marginal impact on estimates relative to IPWs.

The modeling choices employed to this point may put excessive strain on this limited data set. It is an aggregated data set and county fixed effects may be too fine a grain with too little variation within each county. For these reasons we also employ the same set of models, but with state fixed effects instead of county fixed effects so that there is more within-group variation. These results hold a notably different pattern to those with the county fixed effects. Here the Panel and Panel ETE models have negative and statistically significant results in 1997, but these effects are completely mitigated with the inclusion of IPWs. Notably, when IPWs are included there are no significant results in aggregate or when disaggregating by cohort. When compared to the treatment effects found with county fixed effects models one takeaway may be that unmeasured county-level factors are influential predictors of the effect of AFOs relative to state-level factors.

Balance results for the models that include IPWs are presented in Table 15. In general, more balance is achieved across several important covariates, but sufficient balance as defined in

[24] Note that these results are based on demeaned data and thus these marginal effects do not have direct, external interpretations. Rather these results should be interpreted for direction and significance of the effects as well as the magnitude of the marginal effect estimates relative to the other effects estimated from this same data set.

the literature is not achieved with some variables. The panel models employed here used a single IPW for each county that was built on the cohort averaged data set. Traditionally, IPWs are derived from and employed on a single cross-section, but here they are built based on pooled data and applied to the panel data. Thus, even though we should expect balance improvements from the weighting process, and this is indeed why we employ an IPW process here, the nature of data employed here means that the typical level of balance is unlikely to be achieved. Further, double robust IPW schemes tend to result is less balance than other, direct matching estimators, but those other matching estimators may also omit an important subset of the data (Austin 2009; Austin 2011; Austin and Stuart 2015). Population density, poverty rates, unemployment, educational attainment variables, percent of the population that is Black, and the Republican vote share variables all tend to converge regardless of cohort. Importantly, these variables are all included in the outcome equations as well and the literature suggests that balancing on these prognostically important covariates should be the focus (Austin and Stuart 2015). Overall, the weighting scheme employed here causes many variables to go from being strongly unbalanced to being less unbalanced, but in many cases these differences remain outside the standard acceptable bounds.[25] Nevertheless, the improved balance paired with the panel controls and endogenous treatment effects all contribute to removing endogeneity from the estimates.

We then reproduce both county and state fixed effects models using the 2nd quartile of AUD as the control group and retaining the 4th quartile as the treatment group. The downward trend in cohort estimates going from 1997-2012 is more stark in these models (Table 16, Table 17) than in the models that use the 1st quartile as the control group. These models were employed in an effort to achieve greater balance, i.e., the 2nd quartile of AUD counties is likely much more

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[25] Standardized differences in means that is less than 0.25 and a variance ratio between 0.5 and 2.0. See Section 6.2.

similar to the 4th quartile than the 1st quartile at the outset, which includes many urban and suburban areas, and may make the balancing techniques more effective. But while this was the goal and the balance did improve relative to the first set of results and relative to the unbalanced data, the improvements were still not as strong as recommended in the literature (Table 18).

A few patterns are worth noting in the baseline panel analyses. The county fixed effects estimates do align with the downward pattern of results for the PSM and IPWRA models when estimating each cohort individually (Table 7). We see positive, statistically significant treatment effects in 1997 that then decline over the period of analysis. This pattern does not persist in the state fixed effects models. The residuals from the treatment equation that are included in the outcome equation are not statistically significant predictors in the panel models and the treatment effect estimates do not change significantly with their exclusion/inclusion. Thus, while we include ETEs in our full model, the lack of influence of this inclusion on the estimates may suggest that the models are relatively well specified and there is not an endogenous relationship between the treatment decision (i.e., being a low or high AUD county) and the outcome (i.e., the impact of AUD group on mortality rates) when we control for county or state fixed effects, year fixed effects, and the other confounding variables.

There may, nevertheless, be unobserved, region-specific factors that are related to both AUD and higher mortality rates. These panel models purge the estimates of the confounding variation rather than estimating these relationships. Further, there may be too little variation within each county over time to measure any economically meaningful causal relationship using only that within-county over time variation. The variation between counties is much higher than the variation within counties, suggesting that these results only explain a small portion of the overall effects. And finally, the models may not be accounting for important heterogeneity by region and animal type due to limited data availability.

Most of the variation in this data set is between counties, not within counties (Table 5). Counties that raise livestock tend to continue to raise livestock and vice versa, resulting in a modest upward or downward movement in the within-county causal effect from AUDs in many counties. It would be highly unexpected, for example, for a primarily urban, non-agriculturally focused county to rapidly increase the total animal units raised within that county over a 20-year period. Introducing the requisite volume of animal units to an area with high population density, say, would be difficult due to the typical zoning, environmental, and other regulations that apply to any large agricultural or industrial activity. Variation in some rural counties may be higher, however, as AUD may rapidly shift if a CAFO opens or closes during the period of study. In general, the data shows that within-variation does indeed increase in the high AUD counties relative to the low-density counties. The lack of consistency between the state fixed effects models and the county fixed effects models suggests that while these county-level variations are predictors of the divergence in impacts of AUD on mortality rates, these impacts may be a relatively small part of the overall predictors of the effect of AUDs on mortality rate.

Further confounding this relationship is the possible heterogeneity across other unmeasured factors that specifically influence the mortality outcome. While the endogenous treatment models control for unmeasured endogenous factors in the treatment selection process and the coefficients on these residuals, in total, are insignificant, some unmeasured factors in the outcome equation may remain important omissions. CAFO operators may be important regional employers, leading to different cultural and policy dynamics that have little to do with other economic factors that likely change over time, which may in turn also influence health outcomes. Further, the policy and cultural dynamics may be completely or mostly uncorrelated to the other economic factors measured in this study.

Heterogenous manure compositions may also be an important unmeasured variable in the current study. As with the current study, much of the research in this vein also pools animal units by type, but animal waste varies in chemical composition and toxicity by animal type (e.g., Bradford et al. 2007). While each type of manure contains the primary contaminants of interest for this study, the concentration of these contaminants, the production rate of manure, and the availability of agricultural uptake of nutrients all vary by animal unit type. Geological factors and other, non-animal agricultural practices will also vary across space and influence human exposure rates. The methods employed with the current study purge some of these components through panel and ETE methods and some of the influence may also be balanced out through IPWRA weighting, but these important factors are, at best, unmeasured and, at worst, still biasing the estimates.

Overall, the individual cohort and county panel estimates show that there has been a downward trend in the impacts of AUDs on mortality rates over the period of study, but the results do not lend themselves to a conclusive and straightforward interpretation. This period of study has overlapped with significant federal policy changes and some state-level policy changes as well. But beyond observing the overlap in time periods, the analysis to this point is incapable of attributing a causal relationship to these policy changes. Further, without higher resolution spatial and geological information this analysis is incapable of estimating the effects of ecological heterogeneity; variation in the types of animal units across geographies and the associated toxicity of the waste produced is also an unmeasured factor; and the complex economic dynamics related to AFO development and how this may indirectly impact mortality rates remains unexplored. The following sections attempt to account for the heterogeneity by Census Region that may be estimable with this data set. We then explore the impacts of AUD on economic factors as measured by incomes reported through tax returns and net migration to a county as measured by the change in number of tax returns between the 5-year cohorts. The discussion section (Section 8) discusses policy differences and additional areas of variation that are not explicitly quantified here.

7.4 Heterogenous Effects by Census Region

Due to the known county, state, and regional heterogeneity in the areas of policy, culture, industrial make-up, and type of animal units across the nation, total sample average treatment effects may ignore important regional heterogeneity. To test for these patterns, we interact the treatment variable with Census Region indicator variables, respectively, and include these interaction terms in the same panel models used above (Section 7.3). In these models, treatment group assignment and the subsequent weighting schemes balance across regions, but as with the panel models balance improvements do not indicate sufficiently balanced data. Also notable is that these models also rely on the 2nd quartile of AUDs for the control group, because of the improved balance found in the panel models. Because of the heterogeneity in animal units between counties, the full analyses essentially ensure that counties are matched that belong to different regions. The matching algorithms ensure the best possible balance over the included covariates. The results of the regional extension present evidence for heterogeneity in effects by region and may help explain why the national effects estimated here are relatively small compared to the estimates found in the prior literature. Similar to the national models, the estimates pooled across cohort years are not statistically different than zero, suggesting that these regional results also show a similar time trend.

Disaggregating these regional effects by year, however, provides a more nuanced perspective. There is evidence of a positive effect of AUD on mortality rates in the South and West Region in 1997, zero effect in 2002 and 2007, and a negative effect in 2012, which essentially mirrors the aggregated national pattern from the count fixed effects model.

Conversely, the Midwest and Northeast regions show a zero effect in each of the four cohorts. Smaller stratification at the division level was also attempted, but lower cell sizes within each division may drive the lower statistical significance found with these estimates and the results are not presented here.[26]

7.5 Migration and Income Outcomes

Prior research has argued that increased animal unit density may alter economic patterns in a region (e.g., Kim, Goldsmith, and Thomas 2010; Innes 2000; De Vos, Weersink, and Stonehouse 2003). Plausibly, people with the means to move further away from AFOs as animal units increase may do so to escape the odor, traffic, or public health concerns (Boers et al. 2016; Heederik et al. 2007; Thu 2002; Weida 2002). Because of these potential economic dynamics, we also explore the effect of AUDs on two measures derived from county levels tax return data. The first is a measure of the net change in reported income from 5 years prior, to align with the agricultural census data used here. The second is the net change in the number of tax returns from the prior 5-year period. We replace the mortality rate outcome variable with each of these variables to estimate the effect of high AUD concentration. Based on the findings from the prior panel estimates we also rely solely on the 2nd quartile of AUDs for these migration and income outcome variables. Identical to the panel approach above, we then run each of the IPW-ETE panel models with the interacted census regions (Figure 3). Results starting with Table 21 through Table 28. Balance results are the same as with the other panel models as the treatment variable has not changed with these models.

[26] The Northeast – New England Division, for example, has a negative ATE in 2002 and a positive effect in 2012. These results, however, are likely an artifact of low sample and cell sizes. The New England Division had the lowest number of observations among the divisions (n=200) in the estimation sample, only 12 of which (6%) were in the high-AUD group. The next lowest division had 40 counties in the high-AUD group.

The panel treatment effect estimates show a somewhat mixed, inconsistent pattern, generally showing little evidence for a treatment effect on the total amount of income reported. This pattern holds whether county fixed effects or state fixed effects are employed. One model (Panel ETE) becomes statistically significant when we use state fixed effects instead of yearly fixed effects, but no other models. The aggregated net tax return outcome variable is similar, where the marginal effects estimates show a statistically zero effect across all the models, regardless of whether IPWs, ETEs, or both are included. A few marginal effect estimates show statistical significance when using state fixed effects instead of county fixed effects, and in general the point estimates are more negative, but there is not a discernable pattern upon which to draw inference.

The disaggregated by region models largely follow a similar pattern to the aggregate models. A notable exception is in the state fixed effects, net income model (Table 22). Here a consistent negative effect of AUD quartile on net income was found from 1997-2007 as well as a negative, but insignificant, effect in 2012 for the Midwest region. This pattern was not present in the county fixed effects models. This may suggest that fixed state level policy, the effects of which are netted out in a state fixed effects model, mitigate the deleterious income effects of high concentrations of AUDs in Midwestern states.

The net tax returns outcome models have similarly opaque results. Again, the Midwestern region has a notable, negative pattern in the state fixed effects models, but none of these effects are statistically significant. There is also some evidence that a negative migratory pattern is present in the Western region, but these results are not conclusive. In both sets of tax return outcome models the results suggest that either there is not a measurable, generalizable effect on net income or tax return migration. There may be a few explanations why the current research diverges from prior estimates. First, it may be the case that prior research did not adequately control for differences between high AUD and low AUD counties and thus could not isolate the effect of AUD's on economic factors, which are likely complex. It may instead, or in addition, be the case that AUDs do not have a discernable effect on these factors. Finally, the data in the current analysis may not be sufficient to sift out these complex effects.

7.6 Dose Response Functions

Dose-response functions are estimated for five models, one for each yearly cohort and one that averages by county across all four cohorts. Models were explored that included the full sample of all four quartiles based on the AUD variable, but inclusion of the first quartile resulted in poor balance across all specifications and thus was omitted from the presented analysis. When the first quartile was included this led to steep dose response curves, i.e., a strong treatment effect, but those results were unreliable due to poor balance. The results presented in Figure 6 and Figure 7 each include the top 75% of counties by AUD, which effectively excludes counties below around 15 animal units per square mile. Following the truncation of the data, each GPS estimation achieved sufficient balance, a necessary condition to have confidence in the results. The patterns of the dose response functions estimated here further support the themes presented in the results thus far: high-AUD counties tended to have higher mortality rates in the late nineties, but these effects have declined over the period of analysis.

The 1997 cohort has the starkest uptick among high-AUD counties. The trend in predicted mortality rates at higher AUDs turns sharply upwards with the predicted mortality rate at the highest observed AUD (469 AUD) was 1.19 compared to 0.81 at half that level (235 AUD). Further, the variance of the high-density counties was larger (0.89-1.48 compared to 0.72-0.9 95% confidence interval) suggesting a higher upside risk. Lower levels showed a slight decline as AUD increases, but not at a statistically important level. A similar pattern exists with the 2002 cohort estimates, but the uptick in the higher AUD counties is muted relative to the 1997 cohort and to the point where the confidence intervals have significant overlap. The slope of the predicted mortality curve continues to flatten as we move to the 2007 and 2012 cohorts, mimicking many of the results found in the individual cohort analyses presented earlier that suggest these larger counties do not have notably different mortality rates. Similar to 1997, the confidence intervals have relatively large increases in the upper tiers of the AUD variable, which is due to the combination of a relatively small number of high-AUD counties and a higher variance in patterns among these counties.

The averaged cohort model, as may be expected following the individual cohort dose response estimates, is somewhere in the middle of all these estimated dose response functions with a mostly flat dose response curve and a slight, but statistically insignificant, uptick in predicted mortality rates for the highest AUD counties (Figure 7). We also used GPS techniques to estimate the dose response function for Census Regions, averaged across cohorts. The Northeast Region model did not converge and thus the results are omitted. The Midwest region has a mostly flat, slightly declining dose response function. The South has an S-shaped curve, with predicted mortality rates increasing at lower levels of AUD, decreasing at middle levels, and again increasing at higher AUD. And the Western region has a mostly flat, but steadily increasing predicted mortality rates as AUD increases. In all cases, the confidence intervals increase with the high AUD counties. A similar analysis was conducted at the divisional level, but sample sizes were too small to yield meaningful results with this methodology. The divisional models had erratic movement along the dose response curve, poor balance, and large confidence intervals. Replication of the GPS models with the tax variable outcomes was not completed since these models exhibited much higher variance in the outcome variables and ATE estimates than the mortality outcomes with the binary treatment estimates. Thus, the GPS models were not expected to perform well with the alternative outcome variables.

While the GPS approach offers a loosening of the restriction on the distribution of outcome variable, the method has a balance threshold that is more difficult to achieve than binary treatment with the data set in this situation, necessitating omission of the lowest-AUD counties. Bootstrapping standard errors is also computationally intensive, making repetitive iterations with alternative outcome variables challenging. Nevertheless, the results of the GPS models presented here are consistent with the findings from the binary treatment models: some effects are found for higher-AUD counties, there is a fair amount of noise in the models particularly at upper levels of AUDs, and effects follow different patterns by region and by year.

8 Discussion & Policy Comparison

The results of the analyses presented here describe evidence of a nuanced relationship between AUD and mortality rates. The cross-sectional results in Table 7 show some mixed results. But in two of the three estimation methods we see a positive and significant treatment effect of high-AUD on mortality rates in the initial (1997) cohort. The treatment effect declines in each subsequent cohort, becoming statistically equivalent to zero or lower over the 20-year period. The ETE estimates do not follow this same pattern but are not different than zero in any cohort in these models. The pooled PSM models offered no evidence of a positive effect of AUDs on mortality, but five of the six pooled models that model the outcome equation (IPWRA and ETE) were positive and statistically significant. The overall results of the panel models offer no evidence of effects, but when we disaggregate these effects, we find that the overall ATE estimates across all the years obscure the yearly results. Here the pattern found with the individual cohorts is reinforced, where we see some positive ATEs in 1997, statistically zero ATEs in 2002 and 2007, and some statistically significant negative estimates in 2012. These results are further reinforced when we augment the analysis to use the 2nd quartile as the control group. The general propensity score methods largely confirm these patterns. Regional disaggregation suggests that these results appear to be driven by patterns in the South and West census regions. The migration (i.e., tax returns) and taxed income outcomes were inconsistent and did not offer much to confirm or detract from prior research findings with these outcomes.

A few general conclusions can be formed from these results. First, the effect of AUDs on the mortality outcome declined over the period of study. Second, there is significant noise in the data that may impede accurate estimation. This noise, at the least, suggests that there are heterogenous effects across space, time, and scale, but also may suggest that there are important, unmeasured variables or non-linear patterns in the causal effects beyond those controlled for through statistical modeling. Finally, there is also heterogeneity in the treatment effect by geographic area that suggests that the South and West regions tended to see changing patterns over time, but the other regions did not. The starkest comparison is between the Midwest region and the South region, which have higher average AUD than both the Northeast and West regions (Figure 1) and these regions also have a higher proportion of the top quartile of AUDs (Figure 5), but had different pattern in treatment effects over the period of the study. Thus, any observed divergences in policy practices between these regions will help explain why deleterious effects existed in the South in 1997 and declined thereafter, whereas we did not observe this pattern in the Midwest.

Existing AFO regulations are subject to significant implementation costs, mostly covered by local enforcement agencies. These agencies often have limited resources at their disposal, receive political pressure regarding enforcement practices, and may have limited a priori incentives to fully enforce regulations. Further, the largely prescriptive policies that currently exist in many localities may lead to lax enforcement of AFOs rather than compliance when the cost of avoiding detection are relatively low or the costs imposed when violations are detected are low. Many CAFOs do not currently have nutrient management plans, as required by the EPA, but this failure to comply is not always met with civil or criminal penalties and is largely dependent on the state in which the infractions occurred. In some situations, significant communal effects of AFO pollution are detected through the process of lawsuits and, in effect, pose significant costs on the AFO subject to the lawsuit. But these lawsuits are context specific and the punitive or injunctive results are inconsistently applied. Instead of paying for regulators to inconsistently and, in some situations, ineffectively apply regulatory measures, better designed policy could incorporate economic incentives. Incentivizing compliance may not only yield better results but may also reduce costs of enforcement and the adversarial nature of many regulator-AFO interactions. This section reviews known AFO policies, explores a few state policies as case studies, and discusses the policy implications

U.S. AFOs all experienced the same federal policy changes over the period of study (1997-2012), but had varied state-level starting points and implementation/enforcement patterns. The empirical analysis presented thus far shows that, on average at a national scale, these federal policies have been effective at mitigating the health impacts that were previously seen in counties with the largest concentrations of animal units over the period of study. We also found evidence for divergences by region in the county-fixed effects estimates of AFOs on mortality rates, showing that these national trends are likely driven by impacts in the Southern and Western US, but have not had a notable impact on the effect of AUDs on mortality rates in the Midwest or Northeast. Since federal policy has changed significantly over the period of study it is likely that these baseline changes have caused some portion of the overall decrease in the impacts of AFOs. But it is also possible that state-level implementation of additional AFO regulations that are more stringent than federal minimums are a major or the primary cause of lower-than-expected results in the estimated effect on mortality rates. It is also possible that the rigor of implementation by state or local agencies may be highly variable and is driving policy effectiveness, regardless of whether the binding policy is at the state or federal level.

Parsing these dynamics is challenging with econometric analysis as it is likely impossible to accurately operationalize state or agency regulatory stringency or efficacy, particularly with the range of possible policies and the relatively sample size of counties. This section, therefore, reviews the known literature comparing state-level policies and regulatory practices over the period of analysis and contrasts these findings with the empirical results from the current analysis. We then compare two states from each of the Midwest and Southern regions for their policy practices during the period of study. These two regions have the highest average AUD among counties in our sample, but only the Southern results are closely related to the national pattern, whereas the Midwest is not. Selecting two comparable states in each region will help to highlight both the within-region commonalities and the state-specific policy differences, enabling us to further isolate the policy drivers of AFO impacts on mortality rates.

There is a complex web of federal and state policies that may apply to a given AFO. AFOs that are determined to be a Concentrated AFO (CAFO)[27] are considered point sources and require Nutrient Management Plans to qualify for agricultural stormwater exemptions, sometimes in conjunction with NPDES permitting requirements. This current framework began to emerge in 2003 when EPA promulgated new rules but was hindered from full implementation by lawsuits and other political resistance for roughly a decade. In addition to CAFO-specific permitting restrictions, operators may also qualify for environmental subsidy programs at the federal level. These federal programs form a baseline that apply to all AFOs. The more stringent components of AFO-relevant policies have been developed, largely, over the time period of the current analysis

[27] Roughly 1000 animal units, but varies by type of animal, the level of concentration, and other characteristics of the AFO. Actual permitting and NMP decisions are the result of a complex, site-specific process, with the permitting manual totaling 673 pages. (USEPA 2012)

(1997-2012), a period that saw several severe environmental catastrophes stemming from major weather events in regions with large hog CAFOs and large hog manure lagoons (Koski 2007). As a result, the most stringent of the policies that apply to AFOs apply specifically to CAFOs. And it is with CAFOs where environmental impacts are likely strongest due to the high concentration of animal waste, the upper limits of nutrient uptake after which remaining nutrients become pollution, and the potential for catastrophic manure lagoon overflow events and exposure to high concentrations of airborne particulates. Evidence has been found that these federal policies are binding in some respects (Sneeringer, Key and Pon 2018), and thus are likely a key component of the mitigation of health impacts that we have found over time in the current analysis.

The remaining variation in regulatory impacts occurs at the state agency level, where state-level policies may vary considerably by state. Further, the funding levels and efficacy of state agencies is also state specific, particularly in states that allow county and other local governments to develop CAFO rules. In particular, some states have chosen to adopt the minimal federal standards as their sole set of AFO policies, whereas others may have previously had more stringent policies or since implementation of federal changes have chosen to apply more stringent policies than the federal standard. The responsible state agency is typically the state's agricultural agencies, but due to the limited scope of agricultural agency's regulatory power in most states, some researchers have found evidence of interest among regulators in having dual oversight of AFO operations with public health and/or environmental agencies (Fry et al. 2014). Due to federal requirements, CAFOs either fall under the supervision of state environmental agencies or the federal EPA, depending on the state's implementation strategy. Oversight of an AFO from the environmental agency is subject to a determination that the AFO is a CAFO, which is not a universally applied standard or may take several years of enforcement action in situations where information is not readily available. Prior to a CAFO determination the AFO is typically overseen by the (typically less stringent) local agricultural agency.

Although dated at time of writing the current research, Koski (2007) completed a comparative analysis of state-level AFO policies as of 2007, covering a time period that overlaps with the period of study here. In the 1990s a Federal Court ruling required the EPA to draft more stringent regulations of CAFOs. This resulted in major changes to federal rules that gradually came online over the 2000s. When combined with multiple highly publicized manure lagoon overflow events, mostly localized in North Carolina, more stringent state-level AFO regulations and state-level moratoriums on new hog farm construction also began emerging in some places by the end of the 1990s, the beginning of the current analysis. Following the major federal changes in the 2000s, several states were grappling with these new requirements and the policies implemented by the time of Koski's analysis (2007) were likely to have some impact on AFO behavior for the final cohort of the current analysis (2012). Thus, Koski's analysis may be too dated for a substantive discussion of the state of current AFO policies, but it is relevant to isolating the efficacy of state policies and practices from 1997-2012.

In general, Koski argues that traditional environmental policy analysis is too simplistic to effectually map the nuance between state-level AFO policies through application of the Clean Water Act. Koski, thus, expands on the framework of traditional policy analysis to cover six components spanning a total of three dimensions, focusing on state levels AFO policy developments through 2007. Koski classifies characteristics of each state's policies into 3 categories and 6 variables: prescription (number of definitions and length of purpose), stringency (setback requirements and design restrictions), and scope (provision items and total provisions). States are found to be highly variable with, for example, some having relatively high provisions and relatively few design restrictions and vice versa. Koski designates states as being either strong, moderate, or weak on each of these factors based on statistical differences between the groups. The magnitude in the differences in means between the groups is largest, however, between the strong and moderate groups and is smaller between the moderate and weak groups (see Table 3 in Koski (2007)), suggesting that the moderate and low groups may be more comparable to each other than either to the high group.

Each state's overall policy strength, as defined by Koski, is summarized in Table 29. The relative lack of strong AFO policies in Northeastern and Western states is not surprising as these states have far lower animal unit density than the Southern and Midwestern regions and we would expect stronger policy to emerge out of areas with a prominent AFO presence. The distributions of policy strength between the Southern and Midwestern regions, however, is stark. As of 2007, two-thirds of Midwestern states had implemented strong AFO policy compared to half of the Southern states. Further, all of the Midwestern states had implemented moderate or strong AFO policies, whereas 14% (2) of the Southern states had implemented weak AFO policies. These patterns map well onto the empirical findings presented above. Regions where states had relatively weak AFO policies up to 2007 (West and South) experienced significant reductions in the health effect of AFOs over the period of time. Conversely, regions with relatively strong AFO policies (Midwest and Northeast) did not show this downward trend in effects and showed mostly insignificant effect estimates. This pattern is compelling and thus a more detailed comparison between a selection of states in each of the Southern and Midwestern regions follows, which better highlights some of the policy and practice differences seen between states.

Based on Koski's results, the targeted comparison in this section focuses on two Southern states with weak AFO policy, Mississippi and West Virginia, and the two most similar Midwestern states in the moderate AFO policy group (among Michigan, Missouri, North Dakota, and South Dakota). Similarity here was identified in terms of county averages across cohorts of

AUD levels and the economic, environmental, and political factors used in the empirical analysis. Means of these values can be found in Table 30. Missouri was the most like Mississippi and West Virginia across the most factors and also had much more readily available information on state-level AFO policies during the period of analysis than the other Midwestern states. Michigan and South Dakota diverged further from the Southern states and North Dakota was the most dissimilar. Of Michigan and South Dakota, South Dakota was selected for comparison because of the lower population density, lower incomes, higher republican vote share, and lower percent White and these factors may be more impactful on policy development than the other confounding variables. Notably, Mississippi had a considerably higher Black population than all the potential comparisons, averaging about 37% Black across the cohorts, whereas the other states were all less than 5% Black. There are several other demographic and economic differences between the states that may partially explain the policy divergences, and many unmeasured or unmeasurable factors that are likely important (e.g., the prevalence of industry groups and their influence on local politicians through lobbying efforts). In general, the comparison states in the Midwest have higher AUDs, higher incomes, lower unemployment, and lower Black populations (in the case of Mississippi), but, given the available information, Missouri and South Dakota represent the best comparisons by removing the largest amount of confounding variation.

Missouri has the highest concentration of animal units per acre farmland and the largest total number of animal units across the four comparison states (see Table 31). Mississippi and West Virginia fall in between Missouri and South Dakota in terms of animal units per acre farmland and total manure produced per acre farmland. There are large differences in the composition of the types of animals raised in the two sets of states as well. Mississippi and West Virginia produce a small proportion of hogs, less than <1% of the state's total animal units, respectively. Mississippi also produces a smaller proportion of cattle than the Midwestern states.

Both Mississippi and West Virginia, however, produce considerably higher proportions of poultry when compared to the midwestern states. The proportion of animal units dedicated to poultry in West Virginia is more than double the proportion in Missouri. Mississippi is even more stark, where poultry accounts for about five times the proportion of the state's animal units than poultry does in Missouri. Thus, the composition of animal units may be a major driver of policy development, or lack thereof, over the period of analysis.

Missouri's Department of Natural Resources oversees the permitted CAFOs in the state, of which there were 517 in 2008. The budget for CAFO oversight in Missouri and the staffing level were both larger than most other states with data in Hendrick and Farquhar's study. Missouri also requires significant setbacks from both residences and water sources, limits the types manure injection used for disposal, restricts the creation of lagoons, monitors manure releases in water sources, and monitors levels of odorous releases. When violations occur Missouri's DNR may impose civil fines, pursue criminal penalties, mandate facility closure, and/or notify local public health officials (Hendrick and Farquhar 2008). Most of these policies go above and beyond federal statutes.

South Dakota did not return the survey of state policies completed by Hendrick and Farquhar, so a direct comparison of South Dakota to the other states based on that information is not possible. According to information on the South Dakota Department of Environment and Natural Resources website (SDDENR) 427 CAFOs were permitted under the 2003 general permit and 3 subsequent individual permits were issued as of the implementation of the 2017 general permit, which further expanded the number of CAFOs in the state. SDDENR requires that CAFOs are inspected at least once during construction, at least once during the first 18 months of operation, and on a regular schedule thereafter that depends on the CAFO size. It is unclear how many inspectors are on staff. South Dakota allows several forms of manure disposal but requires that lagoons and manure application areas be 1000 feet from public drinking water supplies and between 150-250 feet away from wells, depending on well ownership. SDDENR requires monitoring for CAFO sited above shallow aquifers. (South Dakota Department of Environment & Natural Resources. “Concentrated Animal Feeding Operations.” https://denr.sd.gov/des/fp/cafo.aspx)

Compared to Missouri, Mississippi has a comparable number of CAFOs (478, compared to 517 in Missouri) and was issuing more permits than Missouri each year as of 2008 (95 compared to 50), but Mississippi’s statutes were nevertheless less stringent than Missouri’s over the period of analysis. Mississippi has setback requirements from residencies, but not from water sources. Mississippi allows lagoon creation and composting of manure, whereas Missouri restricts these disposal methods. And Mississippi employs only two full-time inspectors (compared to Missouri’s six). But Mississippi still allows for the same, full-range of regulatory instruments as Missouri (Hendrick and Farquhar 2008). Overall, Mississippi has fewer restrictions on CAFOs that cover a smaller scope of components than the Midwestern comparison states, as broadly described by Koski. Additional, federal regulatory instruments may have served to fill in some of these regulatory gaps.

Similar to South Dakota, West Virginia was not a full participant in Hendrick and Farquhar’s survey of state policies in 2008. EPA did, however, conduct a review of West Virginia’s animal agricultural programs for FY2013, which included sections reviewing the state’s CAFO regulations. AFOs defined as CAFOs are far more limited in West Virginia than the other states in this review. While West Virginia’s animal units per farmland acre are comparable to the other states in this analysis, West Virginia is a smaller state with less farmland than the other three states compared here (Table 31). As of 2015 West Virginia had issued only two CAFO permits, received applications for 18 others, and has several other operations that should be permitted according to the EPA. Of the operations with pending applications the application process has often takes several years to complete and the expected completion dates are opaque from the outset. West Virginia had issued no permits since early 2014 and EPA writes that there are likely several poultry operations that should have received CAFO permits. This may be partially due to underfunding of the regulatory team, where the West Virginia Department of Environmental Protection allocates $100,000 to CAFO programs, enough for 1.3 FTEs. Setbacks, storage, and pollution monitoring programs are not present. Inspections of CAFOs occur once per 5-year permit cycle and regulations rely on voluntary compliance in most situations (USEPA 2015b). Again, as expected based on Koski's findings, the range of policy tools are limited in West Virginia relative to the Midwestern comparisons. While federal policy has increased stringency in the state, it remains clear that full application of federal standards remains a challenge.

In sum, Missouri and South Dakota are, proportionally, high hog producing states, have higher cattle production, and have far less poultry production than either West Virginia or Missouri. While West Virginia is generally in the same range as the other states in regard to animal units per acre of farmland and manure produced per acre farmland, the state has far fewer operations that are operating under CAFO permits. This low level of permitting is partially due to the state being smaller and having fewer total animal units, less than a tenth of the total number in Missouri. Relative to their size and based on the patterns in the other states, however, we would that West Virginia would be in a range of 40 permitted CAFOs, as opposed to the 2 CAFOs that were permitted at the time of EPA's analysis. This suggests significant under-enforcement of even the baseline federal standards in West Virginia, an issue that was not as apparent in the other states studied here.

Mississippi yields a different comparison than West Virginia. Similar to West Virginia, Mississippi has a lower level of animal units and manure per acre farmland than Missouri, but higher proportions than South Dakota. But Mississippi nevertheless reported a similar number of CAFOs to Missouri, implying that a higher proportion of the AFOs in Mississippi are the larger CAFOs or there are better tracking and reporting institutions in Mississippi. But Mississippi also had less stringent state policies than either Missouri or South Dakota. Further, in both Mississippi and West Virginia a higher proportion of all animal units produced were poultry and, in West Virginia, it was found that a large proportion of unpermitted CAFOs were poultry CAFOs. These patterns suggest that state policy stringency in regard to handling manure disposal at CAFOs has an impact on population-level health impacts and federal policy may have filled this void over the period of study.

Further, the comparison of states suggests that animal type may be a driver of policy divergences among states. The Midwestern states generally have much higher hog production as a proportion of total animal units, whereas Southern states have higher poultry production. The highly publicized environmental disasters stemming from hog manure lagoons in the 1990s likely led to additional public scrutiny in states with high levels of hog production, in turn leading to more stringent policies in states with high hog production. This pattern aligns with Koski's mapping of policy stringency. The lack of high-profile environmental disasters with regards to poultry CAFOs may explain the weaker policies in the Southern, poultry heavy states. Thus, stronger state policies may have been developed in the Midwestern states in the 1990s prior to the period of study, mitigating the otherwise harmful health effects.

Right-to-farm policies started passing in each state's legislature beginning in the 1990s and a version of the law was eventually passed in every state, which may also have forestalled AFO regulatory development in the Southern, poultry-heavy states. Right-to-farm policies universally place restrictions on the range of nuisance lawsuits that may be brought by neighbors of farms, including AFOs. These laws often also include statutes that criminalize or restrict monitoring the behavior of AFOs, except in situations that are explicitly allowed. As a result of these laws, the probability of public reporting of a given AFO pollution event or crisis has declined over the period of study, particularly in situations that do not rise to the level of catastrophic lagoon breaches as we saw with hog manure lagoons in the 1990s. The lack of public information regarding everyday pollution and less frequent crises that impact health likely leads to less pressure on representatives to consider laws placing tighter restrictions on AFOs. Thus, the conditions that led to stricter regulations in hog-heavy states may not again exist in poultry-heavy states and may decrease the likelihood of further poultry farm policies at the state level. In this case, the pursuit of further state policies regulating CAFOs in under-regulated poultry-heavy states may not have been a feasible policy approach and federal policy may have been the only recourse.

The patterns found in these states may suggest that federal policies or enforcement mechanisms may be the best approach to reigning in the impacts of AFO pollution in the areas with lingering impacts. Even though federal policy changes throughout the 2000s appear to have reduced impacts on public health, or at least coincided with state-level reductions in impacts in some areas, implementation has been a struggle in places such as West Virginia. Point-in-time estimates have estimated that only about half of the CAFOs that require NPDES permits actually have these permits (Centner 2011). Providing additional federal funds to states to implement existing NPDES permitting programs along with better defined requirements regarding inspection frequency and characteristics may be worth exploring. Recognizing the history of failed implementation of NPDES permits in some locations, the federal government may also pass legislation that reduces the barriers to action seeking legal relief from the damages stemming from AFOs. All these changes, however, are highly politically contentious and likely subject to years of litigation given the litigious history of EPA's rule changes in the 2000s. Less contentious policy alternatives may be both easier to implement and may be more cost-effective from a social welfare perspective.

An alternative policy approach would be to increase the economic incentives to complete the permitting process and thereby construct and implement a NMP for AFOs that hit the CAFO threshold, but are currently unpermitted. Ribaudo et al. (2017) recommend making all USDA program benefits contingent on creation and implementation of an NMP.[28] Assuming farms where benefits of an NMP exceed costs opt to create and comply with the NMP this would lead to a 50-60% reduction in application of excess nutrients. If completed at or below current levels of monitoring, and with the reduction in benefits given to the remaining non-compliant farms, this change in policy could also reduce oversight costs. While Ribaudo et al focus on the issue of hypoxia and excess application of nutrients in general, the policy lessons are directly applicable to existing AFO regulations and their focus on nutrient conveyance.

A simple federal policy change would be to allow more environmental credits to stack when AFOs install biodigesters. Currently, farmers may attempt to sell nutrient offset credits, carbon credits, and renewable energy credits, depending on the range of policies implemented and allowed at the state level. With federal goals of adopting biodigesters at more CAFOs, adopting incentives to induce the purchase and operation of this expensive form of technology is a viable policy option. Murray and Vegh (2015) summarize the range of federal and state incentives to adopt biodigesters and the related economic decision making at the farm level.

[28] The authors find that CAFOs are disproportionately responsible for excess nutrients in the Mississippi river basin, making CAFOs disproportionately responsible for the large hypoxic region in the Gulf of Mexico. While much of the Mississippi river basin is in the Midwest, where we do not find health effects over the length of the study, this may entirely due to these states effectively pushing the externalities downstream to the Gulf.

Murry and Vegh find that if an AFO that receives agricultural commodity revenue, bioenergy revenues (effectively cost of operation reductions), and renewable electricity credits that AFO still faces a net loss in installing and operating a biodigester. If the AFO can stack greenhouse gas credits and/or nutrient trading credits on top of these other benefits, then biodigester installation and operation can be a net gain. Thus, adoption of nutrient mitigation technology may be economically feasible with the allowance of additional credit stacking, but may also depend on local effects and trends (Cowley and Brorsen 2018). Lauer et al. (2018) find that Idaho dairies must have at least 3000 cows to make investment in a biodigester feasible. Smaller operations could coordinate with neighboring AFOs to jointly create and manage a biodigester, but this poses a range of logistical and financing challenges. Alternatively, subsidies for new installations of biodigesters may be a simple, cost-effective way to make adoption more widespread and thus reduce population exposure to manure in air and water. Expanding biodigester adoption would also avoid the need for state agencies to implement effective permitting programs and provide oversight thereafter.

Additional policy adjustments could also induce more compliance with existing air and water standards and regulations. Certainty agreements could ensure AFO operators that if they fully comply with policy requirements today they could exempt themselves from future policy changes that would likely be more stringent (Savage and Ribaudo 2013). Increasing the price of animal products that consumers face would induce a reduction in consumption of animal products (Green et al. 2013)[29], which could be caused either directly or indirectly through changes to tax or subsidy policies. A tax on all animal products would be a simple and direct way to reduce the demand for animal products by increasing prices, but this form of policy would not target the

[29] Green et al reviewed and conducted a meta-analysis of an extant, international literature on food demand elasticities. In high income nations, the authors found, for example, that a 1% increase in meat prices leads to a 0.6% reduction in meat demand, on average. Low-income nations had a 0.78% reduction.

desired outcome (health effects), would not focus on the most damaging AFOs, and may have unintended consequences. A more direct tax on manure production with allowances for processed manure credits may be more effective than a product tax. These taxing policies, however, may have several unintended distributional and downstream effects and are not politically feasible. Alternatively, feed grains have artificially low prices in the US and a rise in those prices to market levels may also lead to higher prices for animal products. US farm bills have subsidized feed grains through several iterations, which functions indirectly as a subsidy on animal products by reducing the price of an input (Gurian-sherman 2008). Eliminating farm bill grain subsidies would induce higher prices for feed grains, but there debate regarding how much of an impact these subsidies actually have on commodity prices and even the direction of the impact on prices of animal products that are not directly subsidized; agricultural commodity subsidy programs are so complex that it is difficult to parse out the expected general equilibrium effects of eliminating feed grain subsidies (Alston, Sumner and Vosti 2008). Given these researchers' cautions, these simple front-end taxing policies may be too blunt for the current state of AFO regulations.

An additional argument for broader policy development as opposed to AFO or media specific regulations stems from the complex systems of nutrient conveyance and cross-media effects, as discussed in Sections 2 & 4. Nutrient cycles and compounding health effects therefrom may reduce the relative effectiveness of NMPs, even though the evidence in the current study suggests federal policy implementation has had a positive effect in some regions, smaller scale studies and lawsuits show persistent issues in smaller settings. Thus, broader policy changes that adjust economic incentives to be in line with policy goals, rather than policies that proscribe behavior of AFOs and require oversight, may be better suited to this particular complex problem, especially in states like West Virginia that have experienced large barriers to full implementation of federal policies that the empirical results show have been, on average, effective in other settings.

Overall, the AFO regulatory environment in the US has been adversarial, litigious, and secretive. AUD impacts on mortality rates have improved over the period of this analysis, becoming statistically equivalent to zero or negative depending on the region, all other measured variables equal. But these effects are inconsistent across space and across the unmeasured confounders that are likely correlated with space. Better enforcement of existing laws could improve some of the remaining deleterious effects, but alternative policies could be more efficient due to the high cost of monitoring and less prone to the policy failures and the lax regulatory oversight or regulatory capture that has been documented in some regions. Additional federal policies such as subsidies for technology adoption can help address the health impacts of pollution[30], limit the expansion of oversight responsibilities of already budget constrained state regulators, reduce the costs stemming from legal action, and foster cooperation that may eventually lead to more transparency in monitoring and tracking the behavior and environmental impacts of AFOs. The policy summary completed here suggests inconsistency in how federal rules have been applied, ineffectual application of federal rules in some places, and widely varied state policies. In particular, areas with a higher concentration of poultry AFOs have, in general, received less attention from both regulators and state policymakers when compared to areas with relatively higher levels of hog and cattle production. As with other industry, state policymakers face a tradeoff between sustaining existing economic activity and the potential health effects of that economic activity. This tradeoff may have become starker with greater publicity of environmental contamination in high hog and cattle production areas, but less so in poultry heavy

[30] Including additional pollution factors not considered here, including soil pollution, greenhouse gas emissions, and downstream hypoxia.

regions. Additional CAFO policy should account for these patterns and help remove the burden of the economic activity-community health tradeoff from policymakers.

9 Conclusion

The current research contributes to the discussion on the health impacts of AUDs. Using a quasi-experimental methodology, we find that the adverse health impacts declined over the period of study, 1997-2012. Panel extensions on the baseline models, however, reveal that the within-county variation is a small proportion of the total variation found in this data set and this within-county variation is not predictive of higher mortality rates when aggregated across the four time period cohorts (1997, 2002, 2007, 2012). When disaggregating these effects by census region and year we find that being a high-AUD county was positively correlated with mortality in 1997 in the South and West, but these effects were not distinguishable from zero, or negative, in the subsequent years. The Midwest and Northeast regions did not follow this pattern. This suggest that AFO regulations in the South and West were relatively weak in the 1990s and this led to higher mortality rates. Subsequent federal policy implementation likely filled this gap over the period of study but did not have a detectable impact in the Midwest and Northeast based on available data, regions that have been found to have stronger state level policies during this period. These findings suggest that federal policy has contributed to mitigating broad, aggregated human health effects related to AFO pollution.

In addition to other sources of heterogeneity, high heterogeneity in individual AFO practices, however, likely plays a part in these impacts and individual level impacts are known to persist in many settings despite these aggregated results. Additional policy developments are likely needed to overcome these persistent environmental problems and mitigate other impacts unmeasured in the current analysis, such as ocean hypoxia and the significant portion of climate change stemming from methane emissions. The effects of lax enforcement are compounded by the cross-media transitions of AFO pollution once it is in the environment. Outside of CAFO-specific NPDES NMP permitting practices, environmental policies that may apply to AFOs tend to focus on pollution in single media (i.e., CAA, CWA), rather than total pollution in all media. To effectively reduce the complex and compounding deleterious effects, policymakers may consider policy that addresses the total level of nutrients entering the environment at the disposal stage. Better coordination between existing environmental policies in this particular context could also address this issue. However, subsidies for manure management and processing technology, taxes on the animal products with artificially low prices due to non-endogenized pollution externalities, or taxes directly on manure may also be considered as ways to reduce production of manure waste in future research on this topic.

In addition to highlighting some important policy patterns, this project contributes to the literature regarding the health effects related to AFO pollution in multiple directions. Prior research in this field has focused little attention on potential outcome, quasi-experimental methods. Much of the prior research was concentrated in the years after several high-profile pollution events in the 1990s and major regulatory overhauls in the 2000s, whereas the current research extends over a longer period to examine a more complete picture. Prior national-scale research on the health effects of AFOs did not extend to include the 2012 Census of Agriculture. This is an important additional cohort of data to consider since 2007-2012 was a period that saw further implementation of federal policies and the conclusion of some major litigation surrounding AFOs. The analysis, indeed, shows that this period was responsible for a substantive shift in the estimated health effects. This helps inform a national policy discussion. And finally, previous research predominantly focused on a subset of states and a subset of (mostly hog) CAFOs. The current research extends the scope to the contiguous US and uses an aggregate animal unit variable, which offers some advantages in terms of generalizability, and so complements the findings of prior research. Further, total animal units are the basis of existing federal policy and thus are important to consider as an explanatory variable when evaluating the impacts of these federal policies.

The policy discussion provided here explores the cross-media dynamics that are at play with manure pollution. These dynamics may confound traditional enforcement mechanisms, but market-based policies may also be ineffectual due to relatively unpredictable market responses and how these responses may overlap with heterogenous health effects. Finally, we also explore the distributional and migratory effects of AFO shifts but are unable to detect a distinct pattern. These models may be ill-specified or simply have inadequate data for this purpose, as within-county mobility may be the most important component of this question, but the limited data available only tracks between-county migration.

This project yielded several important lessons for the researcher and suggested several directions for future research. First, the divergence between aggregate results and disaggregated results may yield important policy insights and should be further explored. Second, aggregated, high-level data can provide a useful complement to small scale studies exploring transmission mechanisms or case studies of AFO impacts. Third, mixed methodologies remain vital to inform policy discussions. The quantitative results presented here provide evidence for multiple hypotheses about the effect of AFOs on human health and well-being over the period of study, but the data is too limited to form definitive, nuanced findings and perfect data to satisfactorily address the questions at hand are not likely to be forthcoming. The additional qualitative exploration between state case studies is helpful to inform policy discussions. The need for these mixed methods is particularly astute when faced with complex environmental problems, inconsistently enforced policies, and a wide range of policy solutions. And while a wide range of research has been conducted regarding the impacts of AFOs, even broader analyses that amalgamate the full range of externalities stemming from animal unit production remains an unexplored and useful endeavor. Beyond these lessons, several additional research extensions are discussed below that could directly build on the findings in this paper.

A subset of states maintains databases of AFO locations, animal units, and other information at the AFO level. If paired with health data at the household level, an analysis of the health effects relative to exposure levels is possible. Iowa and North Carolina, two hog-heavy states, are known to have such databases, but much AFO research has already been concentrated in these states and other states may also track some, albeit less publicly available, AFO data. Work that focuses on more specific locations of AFOs and more specific health data that extends beyond Iowa and North Carolina and beyond hog AFOs is an important area of research.

Consumption and over-consumption of animal products has been linked to numerous health outcomes, including certain forms of cancer, obesity, and heart conditions. A more complete picture of the health impacts of animal products would, therefore, also better estimate the total health effects related to animal product production. Further, this analysis could include a market analysis of the relevant policy instruments to estimate the costs and benefits of novel policies from a societal perspective.

All AFOs involve some forms of pollution that have limited, localized health effects, but also have emissions at an aggregated, global level. The most notable effects are climate change from methane emissions and hypoxic regions or “dead zones” in water systems. Climate change is expected by some researchers to have significant impacts on human health through increased severe weather events, greater variation in weather patterns, and increased disease prevalence due to warmer climates. Researchers have examined some of these patterns and speculated about the magnitude of health impacts related to AFOs in this respect, but few econometric tools have been employed and the field lacks a significant market and policy analysis. Relatedly, little research has been found regarding international markets, international policy related to animal products, and how these systems relate to the health impacts of AFO externalities.

The political economy surrounding AFOs helps explain why widespread acknowledgment of AFO pollution is matched by equally widespread regulatory ineffectiveness. As discussed in Section 3, current AFO policy is the result of a nearly decade-long policy making process that began with strong industry opposition to the proposed rules that emerged near the end of the Clinton administration in 2000 and ended with industry support for the final rules propagated in 2008. The animal product industry has also been successful in lobbying for crop subsidies that reduce their cost of production and lobbying for passage of anti-whistleblower laws ("ag-gag" laws) in several states. In addition to having significant sway at the federal level, some states have a significant concentration of AFOs, and, in some cases, a large proportion of these operations are controlled by a single corporation, such as with Tyson Foods and chicken AFOs in Arkansas. Historical and qualitative research has explored the influence that these large corporations hold over the policy making process, but no empirical analyses have been found as of writing. For example, industry concentration may be a valid proxy for the lobbying or political power that the industry has in a county or state and we may see a lower occurrence of enforcement or weaker state policy development in cases with high political power. There is enough variation at the state level in industry size, policy scope, legal precedents, and enforcement patterns to develop a rich empirical analysis of the political economy surrounding AFOs.

As discussed Section in 3, standard empirical approaches may predispose econometricians towards analyzing only those existing and hypothetical policies that are empirically tractable. Given the high variability in AFO characteristics and practices, it may be the case that liability enforcement is necessarily component of any AFO policy regime since it handles liability on a case-by-case basis in a highly heterogenous industry in highly heterogenous settings. Focused, qualitative research on the geographic pattern, scale, and timelines of AFO pollution lawsuits could yield important insights into how these lawsuits may be considered alongside tractable policies.

This project found some evidence that the current federal policy regime has been effective towards mitigating a portion of the deleterious effects on human health stemming from AFO pollution. The project was limited by available data, but nevertheless provides insights for AFO policy discussions. In general, policies that obviate cross-media and cross-health effects by directly regulating wholistic manure production and disposal seem promising in light of available evidence. These policies may reduce pollution and health effects, may do so at lower operational costs, and may be more efficient given the cross-media effects and incentives for avoiding detection found with traditional command and control, single-media policies that require significant monitoring and oversight to achieve results. Further, more general policies would likely also have further downstream positive impacts for environmental externalities not included in the current analysis.

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Tables

Table 1 Summary of Hedonic Pricing Literature Effect Estimates

Study	Distance from AFO or other exposure metric	Effect on property value at average value
Simons, Seo and Robinson (2014)	>1.25 miles	23% decrease
Isakson and Ecker (2008)	>2 miles 2-2.5 miles 2.5-3 miles	16.6% decrease 5.8% decrease 3.7% decrease
Kim and Goldsmith (2009)	>1 mile of 10,000 head AFO	23.5% decrease
Secchi (2007)	Increase distance from AFO by 1 mile	6.3% increase
Ready and Abdalla (2005)	500 meters 800 meters 1200 meters	6.4% decrease 4.1% decrease 1.6% decrease
Milla, Thomas and Ansine (2005)	1% increase in ratio of hog density/linear feet from AFO	0.03113% decrease
Herriges, Secci and Babcock (2005)	>1/2 mile	9% decrease

Table 2 Summary Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Animal unit density (animal units/square mile)	11,532	45.4	46.8	0.0	591.0
Population density (population/square mile)	11,532	149.7	458.1	0.3	13286.2
Median income (2012$)	11,532	38972.8	10662.7	15607.0	119571.0
Unemployment	11,532	6.2	2.5	1.0	33.3
Percent with high school degree only	11,532	34.9	6.5	10.5	54.6
Percent with bachelor’s degree	11,532	17.9	8.1	4.9	67.0
Percent < 19 years	11,532	27.3	3.4	9.0	48.8
Percent > 65 years	11,532	15.5	4.2	2.9	48.6
Domestic water withdrawals (millions of gallons/day)	11,532	1.9	3.1	-15.7	50.2
Percent Black	11,532	8.7	13.7	0.0	86.8
Republican vote share	11,509	55.3	13.8	9.2	93.3
Average temperature	11,528	64.9	9.1	40.2	88.0
Precipitation (millimeters/day)	11,528	2.7	0.9	0.2	9.4
Percent female	11,532	50.3	1.8	30.9	57.1
Percent smokers	11,532	25.8	4.1	0.0	41.1
Percent below poverty level	11,532	15.3	6.3	0.0	53.6
Percent enrolled in Medicare	11,532	3.2	1.0	0.4	16.2
Per capita part A expenditures (2012$)	11,532	1813.0	935.7	0.0	15050.4
Per capita part B expenditures (2012$)	11,532	2752.2	1163.8	100.2	16709.2
Mortality rate (deaths/1000 pop)	11,532	1.02	0.25	0.17	2.13
Infant mortality rate (deaths/1000 infants)	11,532	0.69	0.36	0.00	5.00
Respiratory related mortality (deaths/1000 pop)	11,532	0.11	0.04	0.00	0.47
Net change in tax returns (over previous 5 years)	11,532	123.0	5875.8	-178226	107567
Net change in reported income (over previous 5 years)	11,532	1696.0	475220.7	-14279590	8223959

Table 3 Mean of Covariates by Year

Cohort	1997	2002	2007	2012	Total
Animal unit density (animal units/square mile)	45.2	46.4	47.1	42.8	45.4
Population density (population/square mile)	140.1	146.9	153.0	158.7	149.7
Median income (2012$)	32803.2	36502.2	41762.5	44823.4	38972.8
Unemployment	5.5	5.3	6.0	7.9	6.2
Percent with high school degree only	34.9	35.0	34.9	34.8	34.9
Percent with degree bachelors	15.4	17.0	18.8	20.6	17.9
Percent < 19 years	28.8	27.9	26.7	25.6	27.3
Percent > 65 years	15.0	14.9	15.5	16.8	15.5
Domestic water withdrawals (millions of gallons/day)	1.8	1.9	1.9	1.9	1.9
Percent Black	8.4	8.6	8.8	9.1	8.7
Republican vote share	44.8	58.9	57.3	60.4	55.3
Average temperature	63.8	64.6	65.2	66.0	64.9
Precipitation (millimeters per day)	2.7	2.7	2.7	2.7	2.7
Percent female	50.6	50.4	50.2	50.0	50.3
Percent smokers	26.7	26.8	25.5	24.1	25.8
Percent below poverty level	14.8	14.5	15.6	16.2	15.3
Percent enrolled in Medicare	3.1	3.2	3.1	3.1	3.2
Per capita part A expenditures (2012$)	1205.4	1460.2	2128.8	2457.6	1813.0
Per capita part B expenditures (2012$)	1693.0	2075.1	3333.0	3907.6	2752.2
Mortality Rate (deaths/1000 pop)	1.02	1.03	1.01	1.03	1.02
Infant Mortality Rate (deaths/1000 infants)	0.74	0.70	0.68	0.63	0.69
Respiratory Related Mortality (deaths/1000 pop)	0.10	0.10	0.11	0.11	0.11
Net change in tax returns (over previous 5 years)	184.0	172.1	149.6	-13.9	123.0
Net change in reported income (over previous 5 years)	3790.8	2105.8	1633.9	-746.6	1696.0

Table 4 Mean of Covariates by Animal Unit Density Quartile

Animal Unit Density Quartile (units/sq. mile)	First (0-14.9)	Second (14.9-32.4)	Third (32.4-61.1)	Fourth (61.1-591)	Total
Animal unit density (animal units/square mile)	7.6	22.9	45.5	105.6	45.4
Population density (population/square mile)	277.5	140.0	100.2	81.0	149.7
Median Income (2012$)	39714.3	38732.9	38073.1	39371.0	38972.8
Unemployment	7.1	6.4	5.9	5.3	6.2
Percent with high school degree only	33.0	34.5	35.9	36.3	34.9
Percent with degree bachelors	19.9	18.2	17.0	16.7	17.9
Percent < 19 years	26.5	27.3	27.4	27.8	27.3
Percent > 65 years	15.3	15.3	15.8	15.8	15.5
Domestic water withdrawals (millions of gallons/day)	2.3	2.0	1.8	1.6	1.9
Percent Black	11.7	10.5	7.7	5.0	8.7
Republican vote share	51.0	54.9	57.4	58.1	55.3
Average temperature	63.2	65.1	66.3	65.1	64.9
Precipitation (millimeters per day)	2.7	2.7	2.7	2.7	2.7
Percent female	50.1	50.4	50.3	50.3	50.3
Percent smokers	25.2	25.7	26.2	25.9	25.8
Percent below poverty level	16.2	16.0	15.0	13.8	15.3
Percent enrolled in Medicare	3.1	3.1	3.2	3.2	3.2
Per capita part A expenditures (2012$)	1892.3	1809.6	1806.8	1743.3	1813.0
Per capita part B expenditures (2012$)	2905.3	2763.2	2689.2	2651.0	2752.2
Mortality Rate (deaths/1000 pop)	0.99	1.02	1.05	1.03	1.02
Infant Mortality Rate (deaths/1000 infants)	0.70	0.72	0.69	0.64	0.69
Respiratory Related Mortality (deaths/1000 pop)	0.10	0.11	0.11	0.11	0.11
Net change in tax returns (over previous 5 years)	-652.6	479.8	372.9	291.7	123.0
Net change in reported income (over previous 5 years)	-69511.5	26946.7	24787.6	24561.1	1696.0

Table 5 Within and Between Variation

Variable	Variation type	Mean	Standard deviation	Minimum	Maximum
Animal unit density	overall	45.4	46.8	0.0	591.0
(animal units/square mile)	between		45.9	0.0	487.5
	within		9.0	-138.2	182.2
Population density	overall	149.7	458.1	0.3	13286.2
(population/square mile)	between		457.6	0.3	12895.0
	within		23.9	-249.6	540.9
Median Income	overall	38972	10662	15607	119571
(2012$)	between		9381	18322	96550
	within		5069	14433	66617
Unemployment Rate	overall	6.2	2.5	1.0	33.3
	between		2.1	2.1	22.6
	within		1.4	-0.9	20.8
Percent with high school degree only	overall	34.9	6.5	10.5	54.6
	between		6.3	12.0	53.4
	within		1.5	26.8	43.8
Percent with bachelor’s degree	overall	17.9	8.1	4.9	67.0
	between		7.8	6.3	61.1
	within		2.2	6.6	30.3
Percent < 19 years	overall	27.3	3.4	9.0	48.8
	between		3.1	13.9	46.2
	within		1.4	19.7	33.8
Percent > 65 years	overall	15.5	4.2	2.9	48.6
	between		4.0	4.4	36.9
	within		1.1	5.8	27.3
Domestic water withdrawals	overall	1.9	3.1	-15.7	50.2
(millions of gallons/day)	between		2.9	0.0	25.1
	within		1.2	-27.6	31.6
Percent Black	overall	8.7	13.7	0.0	86.8
	between		13.7	0.0	86.2
	within		0.9	-9.0	25.4
Republican vote share	overall	55.3	13.8	9.2	93.3
	between		11.5	13.0	88.0
	within		7.6	21.5	83.6
Average Temperature	overall	64.9	9.1	40.2	88.0
	between		9.1	41.0	87.6
	within		1.0	62.6	68.0
Precipitation	overall	2.7	0.9	0.2	9.4
(millimeters/day)	between		0.9	0.2	7.8
	within		0.2	1.4	4.4
Percent female	overall	50.3	1.8	30.9	57.1
	between		1.8	34.3	56.8
	within		0.5	43.4	58.3
Percent smokers	overall	25.8	4.1	0.0	41.1
	between		3.8	0.0	38.9
	within		1.4	20.6	30.7
Percent below poverty level	overall	15.3	6.3	0.0	53.6
	between		6.1	3.1	46.7

	within		1.6	3.8	24.1
Percent enrolled in Medicare	overall	3.2	1.0	0.4	16.2
	between		0.9	0.5	11.7
	within		0.2	-1.4	7.7
Per Capita A Expenditures	overall	1813.0	935.7	0.0	15050.4
	between		469.8	149.8	6047.0
	within		809.2	-2377.0	11623.5
Per Capita B Expenditures	overall	2752.2	1163.8	100.2	16709.2
	between		476.6	274.5	6072.5
	within		1061.7	-2859.4	13874.6
Mortality rate (deaths/1000 pop)	overall	1.02	0.25	0.17	2.13
	between		0.24	0.18	2.05
	within		0.06	0.57	1.38
Infant mortality rate (deaths/1000 infants)	overall	0.69	0.36	0.00	5.00
	between		0.23	0.00	2.00
	within		0.27	-1.10	4.44
Respiratory related mortality (deaths/1000 pop)	overall	0.11	0.04	0.00	0.47
	between		0.03	0.01	0.25
	within		0.02	-0.02	0.33
Net change in tax returns (over previous 5 years)	overall	123.0	5875.8	-178226	107567
	between		5315.3	-122808	74173
	within		2505.9	-57983	60358
Net change in reported income (over previous 5 years)	overall	1696.0	475220	-14279590	8223959
	between		447165	-8834499	4967672
	within		161026	-5795504	4333402

Table 6 Average Land Area per County by Census Region

Census Region	Mean Area (sq. miles)	Standard Deviation	# of Counties
Northeast	803.3	693.3	202
Midwest	747.8	507.3	1,002
South	669.2	504.3	1,300
West	3,099.1	3,253.6	379

Table 7 Cross-sectional Treatment Effects

Model	Cohort	Average Treatment Effect	Robust Standard Errors	P value	95% Confidence Interval	
Propensity Score Matching	1997	0.0445***	0.0134	0.001	0.0183	0.0707
	2002	0.0286	0.0150	0.056	-0.0008	0.0580
	2007	0.0236*	0.0095	0.013	0.0049	0.0423
	2012	-0.0136	0.0125	0.274	-0.0380	0.0108
Inverse Probability Weighted Regression Adjustment	1997	0.0182**	0.0060	0.002	0.0065	0.0299
	2002	0.0169*	0.0070	0.015	0.0032	0.0306
	2007	0.0115	0.0078	0.140	-0.0037	0.0267
	2012	-0.0076	0.0072	0.290	-0.0217	0.0065
Endogenous Treatment Effects	1997	-0.0050	0.0259	0.847	-0.0557	0.0458
	2002	0.0635*	0.0263	0.016	0.0120	0.1149
	2007	0.0334	0.0323	0.300	-0.0298	0.0967
	2012	0.0190	0.0312	0.543	-0.0421	0.0801

Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 8 Balance Evaluation, Propensity Score Matching

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 1997	Population density (population/square mile)	-0.317	-0.100	0.031	0.115
	Median Income (2012$)	0.096	0.066	0.677	1.168
	Percent below poverty level	-0.443	-0.088	0.430	0.633
	Unemployment	-0.841	-0.027	0.384	1.275
	Percent with high school degree only	0.546	-0.051	0.814	1.234
	Percent with bachelor's degree	-0.318	0.065	0.458	1.377
	Percent < 19 years	0.091	-0.108	0.511	0.722
	Percent > 65 years	0.270	0.158	0.882	0.744
	Domestic water withdrawals (millions of gallons/day)	-0.129	0.019	0.393	0.592
	Percent Black	-0.445	-0.067	0.247	0.785
	Republican vote share	0.586	-0.046	0.855	0.801
	Average temperature	0.224	-0.113	0.603	0.572
	Precipitation (millimeters/day)	-0.027	0.005	0.314	0.456
	Northeast Census Region	-0.328	-0.101	0.321	0.697
	Midwest Census Region	0.670	0.256	1.743	1.371
	West Census Region	-0.733	0.046	0.152	1.084
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2002	Population density (population/square mile)	-0.368	-0.116	0.028	0.112
	Median Income (2012$)	0.037	0.160	0.555	1.389
	Percent below poverty level	-0.423	-0.147	0.460	0.797
	Unemployment	-0.764	-0.011	0.414	1.236
	Percent with high school degree only	0.607	0.005	0.680	1.258
	Percent with bachelor's degree	-0.399	0.087	0.396	1.483
	Percent < 19 years	0.303	-0.084	0.577	0.810
	Percent > 65 years	0.237	0.136	0.887	0.904
	Domestic water withdrawals (millions of gallons/day)	-0.208	0.074	0.306	0.621
	Percent Black	-0.506	-0.012	0.226	0.876
	Republican vote share	0.610	-0.139	0.624	0.714
	Average temperature	0.240	-0.118	0.553	0.521
	Precipitation (millimeters/day)	0.004	-0.023	0.454	0.562
	Northeast Census Region	-0.329	0.081	0.326	1.279
	Midwest Census Region	0.749	0.215	1.858	1.308
	West Census Region	-0.758	-0.062	0.132	0.887
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2007	Population density (population/square mile)	-0.390	-0.023	0.035	0.380

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
	Median Income (2012$)	-0.045	-0.015	0.450	0.895
	Percent below poverty level	-0.332	-0.013	0.562	0.701
	Unemployment	-0.558	0.169	0.673	2.507
	Percent with high school degree only	0.533	0.030	0.589	1.131
	Percent with bachelor's degree	-0.408	-0.001	0.379	0.970
	Percent < 19 years	0.525	-0.001	0.519	0.570
	Percent > 65 years	0.110	0.086	0.681	0.719
	Domestic water withdrawals (millions of gallons/day)	-0.260	-0.008	0.254	0.647
	Percent Black	-0.517	0.016	0.244	0.951
	Republican vote share	0.683	-0.070	0.705	0.821
	Average temperature	0.221	0.040	0.596	0.582
	Precipitation (millimeters/day)	-0.055	-0.051	0.370	0.597
	Northeast Census Region	-0.350	-0.102	0.297	0.694
	Midwest Census Region	0.730	0.155	1.772	1.189
	West Census Region	-0.699	0.017	0.158	1.031

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2012	Population density (population/square mile)	-0.373	-0.113	0.035	0.188
	Median Income (2012$)	0.034	-0.078	0.462	0.637
	Percent below poverty level	-0.288	0.054	0.560	0.681
	Unemployment	-0.780	0.131	0.768	1.829
	Percent with high school degree only	0.399	0.026	0.591	0.986
	Percent with bachelor's degree	-0.350	-0.063	0.420	0.721
	Percent < 19 years	0.599	-0.028	0.670	0.852
	Percent > 65 years	-0.034	0.089	0.659	1.416
	Domestic water withdrawals (millions of gallons/day)	-0.215	-0.064	0.191	0.403
	Percent Black	-0.514	-0.038	0.245	0.779
	Republican vote share	0.659	-0.103	0.658	0.753
	Average temperature	0.207	-0.001	0.597	0.611
	Precipitation (millimeters/day)	-0.025	0.053	0.456	0.518
	Northeast Census Region	-0.299	-0.014	0.371	0.956
	Midwest Census Region	0.686	0.088	1.712	1.101
	West Census Region	-0.640	0.019	0.219	1.033

Table 9 Balance Evaluation, Inverse Probability Weighted Regression Adjustment

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 1997	Population density (population/square mile)	-0.317	0.023	0.031	0.225
	Median Income (2012$)	0.096	0.196	0.677	1.818
	Percent below poverty level	-0.443	-0.011	0.430	0.795
	Unemployment	-0.841	0.317	0.384	2.438
	Percent with high school degree only	0.546	-0.393	0.814	1.888
	Percent with bachelor's degree	-0.318	0.219	0.458	2.377
	Percent < 19 years	0.091	0.024	0.511	1.209
	Percent > 65 years	0.270	-0.022	0.882	0.692
	Domestic water withdrawals (millions of gallons/day)	-0.129	0.002	0.393	0.517
	Percent Black	-0.445	-0.057	0.247	0.754
	Republican vote share	0.586	-0.122	0.855	0.650
	Average temperature	0.224	-0.007	0.603	0.488
	Precipitation (millimeters/day)	-0.027	-0.145	0.314	0.492
	Northeast Census Region	-0.328	-0.134	0.321	0.604
	Midwest Census Region	0.670	0.061	1.743	1.089
	West Census Region	-0.733	0.447	0.152	1.704
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2002	Population density (population/square mile)	-0.368	-0.005	0.028	0.229
	Median Income (2012$)	0.037	0.211	0.555	1.949
	Percent below poverty level	-0.423	0.068	0.460	0.917
	Unemployment	-0.764	0.273	0.414	1.967
	Percent with high school degree only	0.607	-0.358	0.680	1.778
	Percent with bachelor's degree	-0.399	0.226	0.396	2.406
	Percent < 19 years	0.303	-0.061	0.577	1.165
	Percent > 65 years	0.237	-0.003	0.887	0.809
	Domestic water withdrawals (millions of gallons/day)	-0.208	0.023	0.306	0.446
	Percent Black	-0.506	0.088	0.226	1.133
	Republican vote share	0.610	-0.372	0.624	0.978
	Average temperature	0.240	-0.006	0.553	0.455
	Precipitation (millimeters/day)	0.004	-0.218	0.454	0.668
	Northeast Census Region	-0.329	-0.137	0.326	0.596
	Midwest Census Region	0.749	0.083	1.858	1.123
	West Census Region	-0.758	0.345	0.132	1.595
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2007	Population density (population/square mile)	-0.390	0.136	0.035	0.464

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
	Median Income (2012$)	-0.045	0.411	0.450	2.602
	Percent below poverty level	-0.332	-0.180	0.562	0.844
	Unemployment	-0.558	0.103	0.673	2.128
	Percent with high school degree only	0.533	-0.373	0.589	2.170
	Percent with bachelor's degree	-0.408	0.447	0.379	2.986
	Percent < 19 years	0.525	-0.271	0.519	0.590
	Percent > 65 years	0.110	0.134	0.681	0.629
	Domestic water withdrawals (millions of gallons/day)	-0.260	-0.055	0.254	0.415
	Percent Black	-0.517	0.004	0.244	0.895
	Republican vote share	0.683	-0.514	0.705	1.140
	Average temperature	0.221	-0.119	0.596	0.529
	Precipitation (millimeters/day)	-0.055	-0.076	0.370	0.532
	Northeast Census Region	-0.350	-0.092	0.297	0.714
	Midwest Census Region	0.730	0.152	1.772	1.227
	West Census Region	-0.699	0.351	0.158	1.641

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2012	Population density (population/square mile)	-0.373	0.152	0.035	0.661
	Median Income (2012$)	0.034	0.077	0.462	1.123
	Percent below poverty level	-0.288	0.062	0.560	0.669
	Unemployment	-0.780	0.520	0.768	4.974
	Percent with high school degree only	0.399	-0.314	0.591	1.418
	Percent with bachelor's degree	-0.350	0.087	0.420	1.151
	Percent < 19 years	0.599	0.101	0.670	0.689
	Percent > 65 years	-0.034	-0.160	0.659	0.937
	Domestic water withdrawals (millions of gallons/day)	-0.215	-0.222	0.191	0.352
	Percent Black	-0.514	0.228	0.245	1.799
	Republican vote share	0.659	-0.480	0.658	1.049
	Average temperature	0.207	0.218	0.597	0.641
	Precipitation (millimeters/day)	-0.025	-0.206	0.456	0.730
	Northeast Census Region	-0.299	-0.139	0.371	0.597
	Midwest Census Region	0.686	-0.034	1.712	0.955
	West Census Region	-0.640	0.420	0.219	1.631

Table 10 Pooled Treatment Effects

Model	Cohort	Average Treatment Effect	Robust Standard Errors	P value	95% Confidence Interval	
Propensity Score Matching	Pooled[1]	0.0041	0.0067	0.542	-0.0091	0.0172
	1997[2]	0.0005	0.0096	0.957	-0.0182	0.0193
	Average[3]	0.0042	0.0166	0.799	-0.0284	0.0368
Inverse Probability Weighted Regression Adjustment	Pooled[1]	0.0100**	0.0038	0.008	0.0026	0.0175
	1997[2]	0.0101**	0.0038	0.008	0.0026	0.0176
	Average[3]	0.0094	0.0067	0.163	-0.0038	0.0225
Endogenous Treatment Effects	Pooled[1]	0.0533***	0.0140	0.000	0.0258	0.0808
	1997[2]	0.0503***	0.0137	0.000	0.0234	0.0772
	Average[3]	0.0456*	0.0228	0.046	0.0008	0.0903

Significance levels: * = 0.05, ** = 0.01, *** = 0.001

1. Nearest-neighbor county matches are determined in each cohort for the first and fourth quartiles. These are then pooled.
2. Treatment groups from 1997 are used for every cohort in a pooled model
3. Data is collapsed into a single, averaged observation for each county.

Table 11 Balance Evaluation, Pooled, Propensity Score Matching

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Aggregation Method: Pooled	Population density (population/square mile)	-0.362	-0.029	0.032	0.303
	Median Income (2012$)	0.025	0.000	0.575	0.832
	Percent below poverty level	-0.370	-0.031	0.510	0.717
	Unemployment	-0.661	0.086	0.577	1.873
	Percent with high school degree only	0.517	-0.025	0.657	1.069
	Percent with bachelor's degree	-0.358	0.008	0.425	0.933
	Percent < 19 years	0.351	0.009	0.534	0.660
	Percent > 65 years	0.141	0.063	0.743	0.873
	Domestic water withdrawals (millions of gallons/day)	-0.204	-0.001	0.264	0.545
	Percent Black	-0.495	0.008	0.241	0.906
	Republican vote share	0.567	-0.093	0.803	0.701
	Average temperature	0.222	-0.024	0.590	0.586
	Precipitation (millimeters/day)	-0.026	-0.058	0.395	0.551
	Northeast Census Region	-0.327	-0.036	0.328	0.891
	Midwest Census Region	0.709	0.221	1.770	1.308
	West Census Region	-0.707	-0.002	0.165	0.996
	1997	-0.002	-0.011	0.998	0.986
	2002	-0.002	-0.006	0.998	0.994
	2007	0.006	0.022	1.007	1.024
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Aggregation Method: 1997	Population density (population/square mile)	-0.311	0.006	0.041	0.358
	Median Income (2012$)	0.097	0.039	0.713	1.017
	Percent below poverty level	-0.400	-0.026	0.499	0.714
	Unemployment	-0.692	0.036	0.511	1.299
	Percent with high school degree only	0.447	-0.050	0.702	1.147
	Percent with bachelor's degree	-0.269	0.041	0.506	1.026
	Percent < 19 years	0.347	0.018	0.525	0.707
	Percent > 65 years	0.085	0.027	0.772	0.864
	Domestic water withdrawals (millions of gallons/day)	-0.139	0.011	0.365	0.492
	Percent Black	-0.465	-0.005	0.232	0.843
	Republican vote share	0.540	-0.071	0.785	0.769
	Average temperature	0.278	-0.040	0.598	0.546
	Precipitation (millimeters/day)	0.019	0.001	0.385	0.519
	Northeast Census Region	-0.330	-0.041	0.319	0.872
	Midwest Census Region	0.668	0.158	1.737	1.205
	West Census Region	-0.734	0.007	0.151	1.013
	1997	-0.003	-0.001	0.997	0.999
	2002	-0.003	-0.054	0.997	0.940
	2007	0.008	0.050	1.009	1.056

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Aggregation Method: Average	Population density (population/square mile)	-0.364	-0.052	0.033	0.170
	Median Income (2012$)	0.039	0.154	0.541	1.237
	Percent below poverty level	-0.389	-0.110	0.492	0.810
	Unemployment	-0.841	-0.106	0.496	1.157
	Percent with high school degree only	0.545	-0.086	0.660	1.247
	Percent with bachelor’s degree	-0.372	0.144	0.412	1.290
	Percent < 19 years	0.403	-0.061	0.590	0.702
	Percent > 65 years	0.158	0.054	0.794	0.824
	Domestic water withdrawals (millions of gallons/day)	-0.218	0.077	0.287	0.434
	Percent Black	-0.513	-0.017	0.232	0.920
	Republican vote share	0.702	-0.225	0.725	0.851
	Average temperature	0.223	-0.120	0.580	0.507
	Precipitation (millimeters/day)	-0.029	0.037	0.376	0.457
	Northeast Census Region	-0.332	0.021	0.317	1.068
	Midwest Census Region	0.719	0.227	1.749	1.315
	West Census Region	-0.714	0.021	0.155	1.041

Table 12 Balance Evaluation, Pooled, Inverse Probability Weighted Regression Adjustment

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Aggregation Method: Pooled	Population density (population/square mile)	-0.362	0.056	0.032	0.401
	Median Income (2012$)	0.025	0.176	0.575	1.628
	Percent below poverty level	-0.370	0.100	0.510	0.851
	Unemployment	-0.661	0.506	0.577	6.108
	Percent with high school degree only	0.517	-0.357	0.657	1.770
	Percent with bachelor’s degree	-0.358	0.208	0.425	2.031
	Percent < 19 years	0.351	-0.052	0.534	0.775
	Percent > 65 years	0.141	-0.014	0.743	0.738
	Domestic water withdrawals (millions of gallons/day)	-0.204	-0.145	0.264	0.424
	Percent Black	-0.495	0.179	0.241	1.773
	Republican vote share	0.567	-0.494	0.803	0.936
	Average temperature	0.222	0.143	0.590	0.669
	Precipitation (millimeters/day)	-0.026	-0.202	0.395	0.726
	Northeast Census Region	-0.327	-0.135	0.328	0.603
	Midwest Census Region	0.709	0.040	1.770	1.058
	West Census Region	-0.707	0.400	0.165	1.671
	1997	-0.002	-0.089	0.998	0.886
	2002	-0.002	-0.074	0.998	0.913
	2007	0.006	0.219	1.007	1.193
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Aggregation Method: 1997	Population density (population/square mile)	-0.311	0.071	0.041	0.413
	Median Income (2012$)	0.097	0.108	0.713	1.371
	Percent below poverty level	-0.400	0.034	0.499	0.731
	Unemployment	-0.692	0.235	0.511	1.678
	Percent with high school degree only	0.447	-0.195	0.702	1.460
	Percent with bachelor’s degree	-0.269	0.141	0.506	1.577
	Percent < 19 years	0.347	-0.047	0.525	0.812
	Percent > 65 years	0.085	0.003	0.772	0.825
	Domestic water withdrawals (millions of gallons/day)	-0.139	-0.018	0.365	0.545
	Percent Black	-0.465	0.078	0.232	1.000
	Republican vote share	0.540	-0.269	0.785	0.761
	Average temperature	0.278	-0.036	0.598	0.510
	Precipitation (millimeters/day)	0.019	-0.042	0.385	0.539
	Northeast Census Region	-0.330	-0.100	0.319	0.696
	Midwest Census Region	0.668	0.112	1.737	1.161
	West Census Region	-0.734	0.219	0.151	1.396
	1997	-0.003	-0.019	0.997	0.976
	2002	-0.003	-0.063	0.997	0.927
	2007	0.008	0.061	1.009	1.067

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Aggregation Method: Average	Population density (population/square mile)	-0.364	0.104	0.033	0.362
	Median Income (2012$)	0.039	0.344	0.541	2.232
	Percent below poverty level	-0.389	0.002	0.492	0.942
	Unemployment	-0.841	0.309	0.496	2.167
	Percent with high school degree only	0.545	-0.515	0.660	2.247
	Percent with bachelor’s degree	-0.372	0.335	0.412	2.804
	Percent < 19 years	0.403	0.013	0.590	1.198
	Percent > 65 years	0.158	-0.082	0.794	0.834
	Domestic water withdrawals (millions of gallons/day)	-0.218	-0.026	0.287	0.310
	Percent Black	-0.513	-0.013	0.232	0.868
	Republican vote share	0.702	-0.470	0.725	1.031
	Average temperature	0.223	0.013	0.580	0.467
	Precipitation (millimeters/day)	-0.029	-0.268	0.376	0.566
	Northeast Census Region	-0.332	-0.157	0.317	0.548
	Midwest Census Region	0.719	0.028	1.749	1.044
	West Census Region	-0.714	0.551	0.155	1.789

Table 13 Total Mortality, County FE, 1st Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	<-0.0001	-0.0010	-0.0011	-0.0013
1997	0.0078**	0.0068*	0.0155***	0.0153***
2002	-0.0016	-0.0027	0.0031	0.0071
2007	-0.0036	-0.0046	-0.0042	-0.0482*
2012	-0.0026	-0.0034	-0.0159***	-0.0160***
Year Dummies	✔	✔	✔	✔
County Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 14 Total Mortality, State FE, 1st Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	-0.0023	-0.0115***	0.0005	-0.0062
1997	-0.0134**	-0.0220***	0.0017	-0.0033
2002	-0.0095	-0.0195***	0.0025	-0.0040
2007	0.0024	-0.0067	0.0053	-0.0027
2012	0.0115	0.0024	-0.0067	-0.0136
Year Dummies	✔	✔	✔	✔
State Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 15 Balance Evaluation, 1st Quartile Control

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 1997	Population density (population/square mile)	-9.59	-4.35	0.05	0.73
	Median Income (2012$)	0.45	-4.53	0.54	0.76
	Percent below poverty level	-10.13	0.85	0.45	1.50
	Unemployment	-21.12	0.71	0.45	8.72
	Percent with high school degree only	15.12	0.85	0.80	1.49
	Percent with bachelor's degree	-9.96	-4.13	0.40	1.46
	Percent < 19 years	2.98	-2.48	0.55	1.02
	Percent > 65 years	7.98	3.77	0.84	0.63
	Domestic water withdrawals (millions of gallons/day)	-5.15	-2.72	0.31	0.39
	Percent Black	-11.45	-0.41	0.28	3.36
	Republican vote share	14.65	1.61	0.89	0.64
	Average temperature	4.74	-1.02	0.59	0.35
	Precipitation (millimeters/day)	-2.03	-0.84	0.30	0.36
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2002	Population density (population/square mile)	-9.40	-2.19	0.06	1.73
	Median Income (2012$)	1.97	-1.17	0.55	1.05
	Percent below poverty level	-11.32	-1.47	0.47	1.41
	Unemployment	-20.34	-3.60	0.40	2.21
	Percent with high school degree only	14.58	0.64	0.70	0.80
	Percent with bachelor's degree	-9.20	-0.51	0.42	1.88
	Percent < 19 years	8.16	-2.09	0.60	0.62
	Percent > 65 years	5.06	2.67	0.87	0.54
	Domestic water withdrawals (millions of gallons/day)	-5.06	-1.14	0.30	0.49
	Percent Black	-12.10	1.04	0.26	8.83

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
	Republican vote share	15.49	-2.17	0.71	0.70
	Average temperature	6.16	-1.76	0.55	0.32
	Precipitation (millimeters/day)	-0.19	0.06	0.45	0.32

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2007	Population density (population/square mile)	-9.07	-0.38	0.07	4.00
	Median Income (2012$)	0.23	-2.29	0.50	0.85
	Percent below poverty level	-9.11	0.41	0.54	1.07
	Unemployment	-15.59	0.59	0.56	1.39
	Percent with high school degree only	12.16	-0.26	0.63	1.16
	Percent with bachelor’s degree	-8.42	0.95	0.43	2.36
	Percent < 19 years	13.34	-0.69	0.60	0.25
	Percent > 65 years	1.96	1.67	0.77	0.52
	Domestic water withdrawals (millions of gallons/day)	-5.33	-0.52	0.28	0.44
	Percent Black	-12.18	0.81	0.26	7.05
	Republican vote share	16.08	-4.44	0.76	0.39
	Average temperature	6.14	-3.67	0.60	0.31
	Precipitation (millimeters/day)	-0.35	-0.40	0.33	0.20

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2012	Population density (population/square mile)	-7.95	1.27	0.08	10.21
	Median Income (2012$)	1.36	-5.07	0.50	1.88
	Percent below poverty level	-6.56	5.54	0.59	2.05
	Unemployment	-20.97	3.66	0.63	2.75
	Percent with high school degree only	8.60	-1.46	0.57	3.64
	Percent with bachelor’s degree	-7.39	-0.50	0.44	2.45
	Percent < 19 years	16.66	0.85	0.59	0.67
	Percent > 65 years	-2.63	-3.03	0.61	0.77
	Domestic water withdrawals (millions of gallons/day)	-4.93	1.55	0.24	1.84
	Percent Black	-11.08	4.24	0.29	23.28
	Republican vote share	15.15	-5.90	0.68	1.00
	Average temperature	7.91	0.66	0.54	0.39
	Precipitation (millimeters/day)	0.19	4.08	0.40	0.42

Table 16 Total Mortality, County FE, 2nd Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	0.0001	-0.0004	-0.0004	-0.0006
1997	0.0093***	0.0088**	0.0128***	0.0125***
2002	-0.0034	-0.0039	-0.0023	-0.0025
2007	-0.0044*	-0.0049*	-0.0042	-0.0044
2012	-0.0012	-0.0017	-0.0077*	-0.0079*
Year Dummies	✔	✔	✔	✔
County Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 17 Total Mortality, State FE, 2nd Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	-0.0005	-0.0061*	-0.0013	-0.0048
1997	-0.0015	-0.0067	0.0021	-0.0006
2002	-0.0078	-0.0135**	-0.0038	-0.0070
2007	-0.0014	-0.0072	-0.0003	-0.0047
2012	0.0088	0.0031	-0.0030	-0.0068
Year Dummies	✔	✔	✔	✔
State Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 18 Balance Evaluation, 2nd Quartile Control

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 1997	Population density (population/square mile)	-7.29	-1.63	0.19	2.31
	Median Income (2012$)	2.24	-3.86	0.60	0.65
	Percent below poverty level	-10.31	0.52	0.51	1.17
	Unemployment	-15.47	0.94	0.57	7.93
	Percent with high school degree only	9.73	-0.12	0.78	1.54
	Percent with bachelor's degree	-4.93	-3.11	0.53	1.31
	Percent < 19 years	-0.19	-0.73	0.63	2.50
	Percent > 65 years	6.20	1.42	0.91	0.81
	Domestic water withdrawals (millions of gallons/day)	-3.77	-1.68	0.53	0.74
	Percent Black	-10.58	-0.51	0.32	4.01
	Republican vote share	5.86	0.85	0.88	0.86
	Average temperature	-1.11	-0.67	0.73	0.83
	Precipitation (millimeters/day)	0.52	-1.43	0.51	0.73
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2002	Population density (population/square mile)	-7.07	-0.45	0.21	3.98
	Median Income (2012$)	2.74	-1.02	0.60	0.62
	Percent below poverty level	-10.76	-2.40	0.52	0.90
	Unemployment	-15.97	-4.13	0.61	2.79
	Percent with high school degree only	8.66	-0.53	0.73	1.28
	Percent with bachelor's degree	-4.49	-0.28	0.55	1.59
	Percent < 19 years	2.78	0.53	0.66	1.22
	Percent > 65 years	4.23	0.46	0.90	0.89
	Domestic water withdrawals (millions of gallons/day)	-3.76	-0.26	0.54	1.02
	Percent Black	-11.14	-1.15	0.29	2.69
	Republican vote share	5.79	-1.07	0.73	1.05
	Average temperature	-0.15	-1.03	0.70	0.87
	Precipitation (millimeters/day)	-0.65	-3.24	0.59	0.89
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2007	Population density (population/square mile)	-6.92	0.50	0.22	6.00
	Median Income (2012$)	2.21	-1.24	0.59	0.59
	Percent below poverty level	-9.18	-0.88	0.58	0.85
	Unemployment	-12.77	-1.91	0.64	1.73
	Percent with high school degree only	6.87	0.08	0.69	1.37
	Percent with bachelor's degree	-4.28	-0.84	0.56	1.64
	Percent < 19 years	6.00	2.31	0.66	0.87
	Percent > 65 years	2.44	-1.40	0.87	0.94
	Domestic water withdrawals (millions of gallons/day)	-4.10	0.43	0.50	1.40
	Percent Black	-11.17	-1.05	0.30	2.68
	Republican vote share	6.33	-2.26	0.76	0.92

		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
	Average temperature	-0.25	-1.83	0.72	0.77
	Precipitation (millimeters/day)	0.74	-1.64	0.49	0.67
		Standardized Difference of Means		Variance Ratio	
		Unweighted	Weighted	Unweighted	Weighted
Cohort: 2012	Population density (population/square mile)	-6.46	1.71	0.25	17.48
	Median Income (2012$)	2.37	-3.61	0.60	0.98
	Percent below poverty level	-7.09	3.68	0.64	1.58
	Unemployment	-14.06	2.44	0.75	3.49
	Percent with high school degree only	4.84	-1.17	0.66	2.40
	Percent with bachelor's degree	-4.04	-1.64	0.57	2.20
	Percent < 19 years	8.62	4.18	0.66	1.31
	Percent > 65 years	0.24	-4.72	0.81	1.44
	Domestic water withdrawals (millions of gallons/day)	-3.67	1.76	0.53	2.74
	Percent Black	-9.88	3.54	0.37	8.78
	Republican vote share	5.32	-3.87	0.73	1.67
	Average temperature	1.28	3.22	0.66	0.87
	Precipitation (millimeters/day)	0.90	1.92	0.60	1.16

Table 19 Total Mortality, County FE, Census Region, 2nd Quartile Control

Census Region	Northeast	Midwest	South	West
All Years	-0.0004	-0.0006	-0.0013	0.0011
1997	0.0034	0.0065	0.0165**	0.0199**
2002	-0.0052	-0.0081*	0.0016	0.0068
2007	-0.0047	0.0002	-0.0064	-0.0006
2012	0.0042	0.0015	-0.0148**	-0.0174*

Significance levels: * = 0.05, ** = 0.01, *** = 0.001
Year Dummies, County Fixed Effects, Endogenous Treatment Effects, and Inverse Probability Weights included in all models

Table 20 Total Mortality, State FE, Census Region, 2nd Quartile Control

Census Region	Northeast	Midwest	South	West
All Years	-0.0032	-0.0007	-0.016**	0.0223***
1997	-0.0312**	-0.0188*	0.0185*	0.0092
2002	-0.0326*	-0.0248**	0.0084	0.0167
2007	-0.0335*	-0.0067	0.0003	0.0109
2012	-0.0108	-0.0001	-0.011	-0.0008

Significance levels: * = 0.05, ** = 0.01, *** = 0.001
Year Dummies, State Fixed Effects, Endogenous Treatment Effects, and Inverse Probability Weights included in all models

Table 21 Net Reported Income, County FE, 2nd Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	-254	36	-746	-1302
1997	-8849	-8549	-1946	-2518
2002	11057	11369	13765	13150
2007	-2413	-2124	-9167	-9817
2012	-838	-580	-5281	-5675
Year Dummies	✔	✔	✔	✔
County Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Net Reported Income = Standardized, net increase in income as reported on income on tax returns
Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 22 Net Reported Income, State FE, 2nd Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	-10609	-13271*	-5978	-5774
1997	-10269	-12778	-16454	-16301
2002	-1295	-4021	2402	2592
2007	-17083	-19812	-14553	-14297
2012	-13835	-16522	4229	4448
Year Dummies	✔	✔	✔	✔
State Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Net Reported Income = Standardized, net increase in income as reported on income on tax returns
Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 23 Net Reported Income, Census Region, County FE, 2nd Quartile Control

Census Region	Northeast	Midwest	South	West
All years	-2085	1116	1476	-7257
1997	-28107	-4742	6520	-26419
2002	23046	-6220	6146	176827*
2007	40378**	2406	-4796	-161841**
2012	-32097	5657	-5408	-54884

Net Reported Income = Standardized, net increase in income as reported on income on tax returns
Significance levels: * = 0.05, ** = 0.01, *** = 0.001
Year Dummies, County Fixed Effects, Endogenous Treatment Effects, and Inverse Probability Weights included in all models

Table 24 Net Reported Income, Census Region, State FE, 2nd Quartile Control

Census Region	Northeast	Midwest	South	West
All years	-6702	1157	4721	-14370
1997	-2844	-21883*	1202	-88961
2002	45637	-28661**	4830	160459
2007	68490*	-19625*	2599	-168171*
2012	5551	-10896	17944	-43527

Net Reported Income = Standardized, net increase in income as reported on income on tax returns
Significance levels: * = 0.05, ** = 0.01, *** = 0.001
Year Dummies, State Fixed Effects, Endogenous Treatment Effects, and Inverse Probability Weights included in all models

Table 25 Net Tax Returns, County FE, 2nd Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	-4.0	3.3	-16.9	-23.3
1997	-106.1	-98.6	-94.4	-101.0
2002	148.3	156.2	233.2	226.1
2007	-27.9	20.7	-91.5	-99.0
2012	-30.7	-24.2	-107.2	-111.7
Year Dummies	✔	✔	✔	✔
County Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Net Tax Returns = Net change in the number of tax returns between cohorts
Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 26 Net Tax Returns, State FE, 2nd Quartile Control

	Panel	Panel ETE	Panel IPW	Panel IPW & ETE
All Years	-187.2*	-151.0	-157.8	-94.5
1997	-203.1	-169.0	-369.3*	-322.1
2002	-78.6	-41.6	10.4	69.3
2007	-262.1	-225.0	-220.3	-140.7
2012	-205.3	-168.8	-54.9	12.9
Year Dummies	✔	✔	✔	✔
County Fixed Effects	✔	✔	✔	✔
Endogenous Treatment Effects		✔		✔
Inverse Probability Weights			✔	✔

Net Tax Returns = Net change in the number of tax returns between cohorts
Significance levels: * = 0.05, ** = 0.01, *** = 0.001

Table 27 Net Tax Returns, Census Region, County FE, 2nd Quartile Control

Census Region	Northeast	Midwest	South	West
All years	-38.1	11.5	10.8	-61.7
1997	-294.9	0.1	220.9*	-2129.6**
2002	268.9	-36.4	58.6	3163.2*
2007	488.3**	42.2	-27	-2326.6
2012	-422	-15.7	-226.3	167.2

Net Reported Income = Standardized, net increase in income as reported on income on tax returns
Significance levels: * = 0.05, ** = 0.01, *** = 0.001
Year Dummies, County Fixed Effects, Endogenous Treatment Effects, and Inverse Probability Weights included in all models

Table 28 Net Tax Returns, Census Region, State FE, 2nd Quartile Control

Census Region	Northeast	Midwest	South	West
All years	-118.3	-27.6	-64.7	-512
1997	383.7	-204.4	5.9	-2854.5*
2002	879.2	-261	-52.7	2810.7
2007	1025.4**	-164.8	36.7	-2579.7*
2012	151.1	-136.1	22.9	-61.6

Net Reported Income = Standardized, net increase in income as reported on income on tax returns
Significance levels: * = 0.05, ** = 0.01, *** = 0.001
Year Dummies, State Fixed Effects, Endogenous Treatment Effects, and Inverse Probability Weights included in all models

Table 29 Strength of State-Level Policy by Region and State

Strength of Policies	States (% of all states in Region)			
	Northeast	South	Midwest	West
Strong	Pennsylvania, Vermont (18%)	Alabama, Arkansas, Georgia, Oklahoma, South Carolina, Texas, Virginia (50%)	Illinois, Indiana, Iowa, Kansas, Minnesota, Nebraska, Ohio, Wisconsin (67%)	Colorado (9%)
Moderate	Delaware, Maine, Maryland, New Jersey, Rhode Island (45%)	Florida, Kentucky, Louisiana, North Carolina, Tennessee (36%)	Michigan, Missouri, North Dakota, South Dakota (33%)	California, Idaho Oregon, Utah, Wyoming (45%)
Weak	Connecticut, Massachusetts, New Hampshire, New York (36%)	Mississippi, West Virginia (14%)		Arizona, Montana, Nevada, New Mexico, Washington (45%)

Source: Koski, 2007

Table 30 Potential Comparison States

	Southern states with weak AFO policies[1]		Midwestern states with moderate AFO policies[1]			
Confounding variables	Mississippi	West Virginia	Missouri	South Dakota	Michigan	North Dakota
Animal unit density (animal units/square mile)	32	20	63	58	26	25
Population density (population/square mile)	62	97	90	14	191	8
Median income (2012$)	30698	32807	35387	36650	40095	38766
Unemployment	8.0	7.3	6.2	4.0	8.2	3.7
Percent with high school degree only	32.0	42.3	39.5	35.1	36.6	31.2
Percent with bachelor's degree	14.6	13.9	15.0	19.1	17.9	18.2
Percent < 19 years	29.3	24.4	27.2	29.3	26.0	26.2
Percent > 65 years	13.7	16.3	16.3	17.6	16.3	20.0
Domestic water withdrawals (millions of gallons/day)	1.11	1.61	0.90	0.08	4.41	0.11
Percent Black	37.62	2.20	3.44	0.50	4.11	0.46
Republican vote share	54.08	53.85	56.90	56.20	48.48	56.91
Percent White	61.32	97.20	95.33	86.39	93.29	92.56
Percent female	51.44	50.62	50.47	49.94	49.91	49.52
Percent smokers	27.23	29.75	29.07	24.74	26.24	24.44
Precipitation (millimeters/day)	3.81	3.12	3.10	1.63	2.36	1.43
Average temperature	74.86	61.23	65.79	57.30	53.84	52.11

1. Source: Koski, 2007

Table 31 Comparison of Key Animal Unit Metrics in 2007 for Comparison States

Variable	Mississippi	West Virginia	Missouri	South Dakota
Total Acres (millions)	44.61	15.51	30.10	49.35
Total animal units (AUs)	1,171,555	394,816	4,178,962	3,179,772
AUs/acre farmland (Rank of 50 states)	0.1 (30)	0.11 (26)	0.14 (18)	0.07 (36)
Manure/acre farmland (Rank of 50 states)	1.27 (27)	1.23 (28)	1.66 (18)	0.83 (37)
Poultry %	30.4%	14.6%	6.2%	1.4%
Hog %	0.0%	0.4%	10.4%	6.5%
Cattle %	69.6%	85.1%	83.3%	92.0%

Source: USEPA, 2013

Figures

Figure 1 County Average Animal Unit Density by Census Region, 1997 -2012

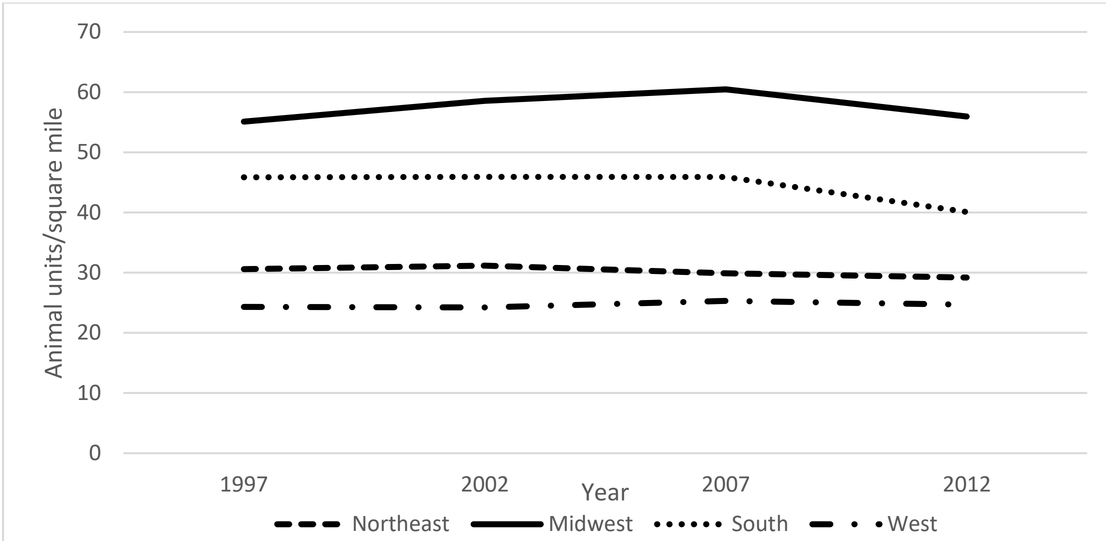
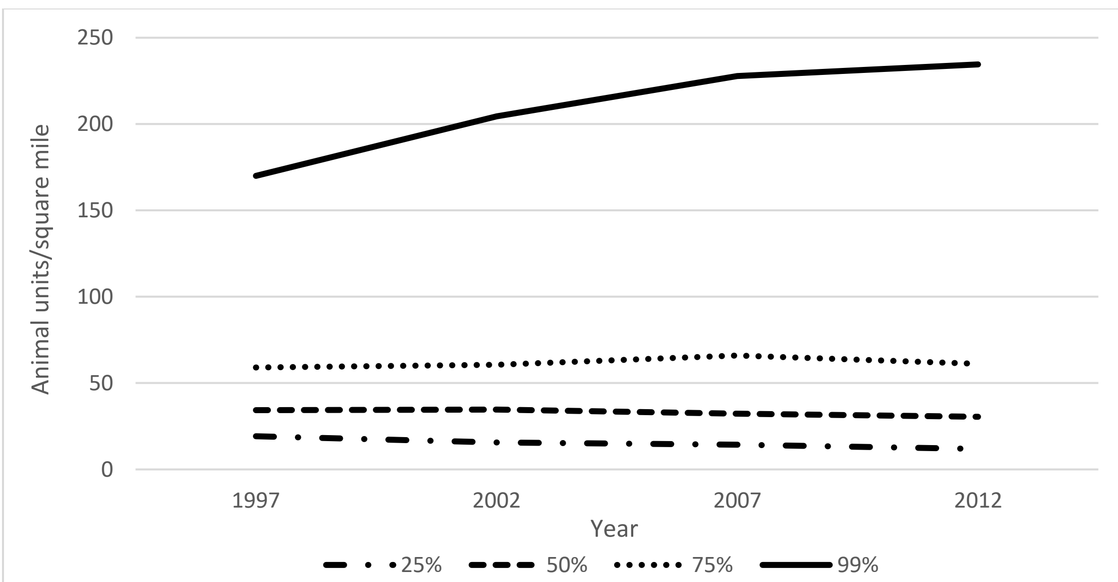
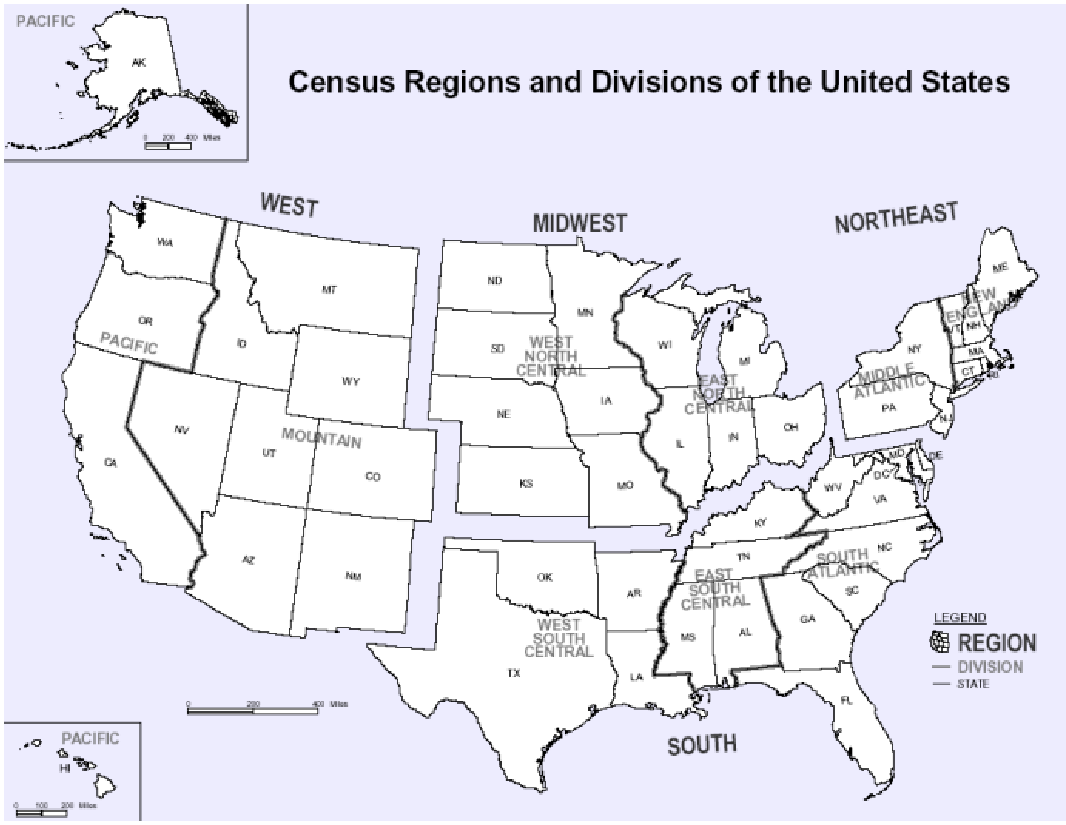


Figure 2 Animal Unit Density by Percentile of Animal Unit Density, 1997 -2012



Each observation consists of the average of the five counties grouped around the percentile value.

Figure 3 Census Regions and Divisions



Source: https://www.census.gov/geo/www/us_regdiv.pdf

Figure 4 Probability Density Distribution of Logged Animal Unit Density – All Regions

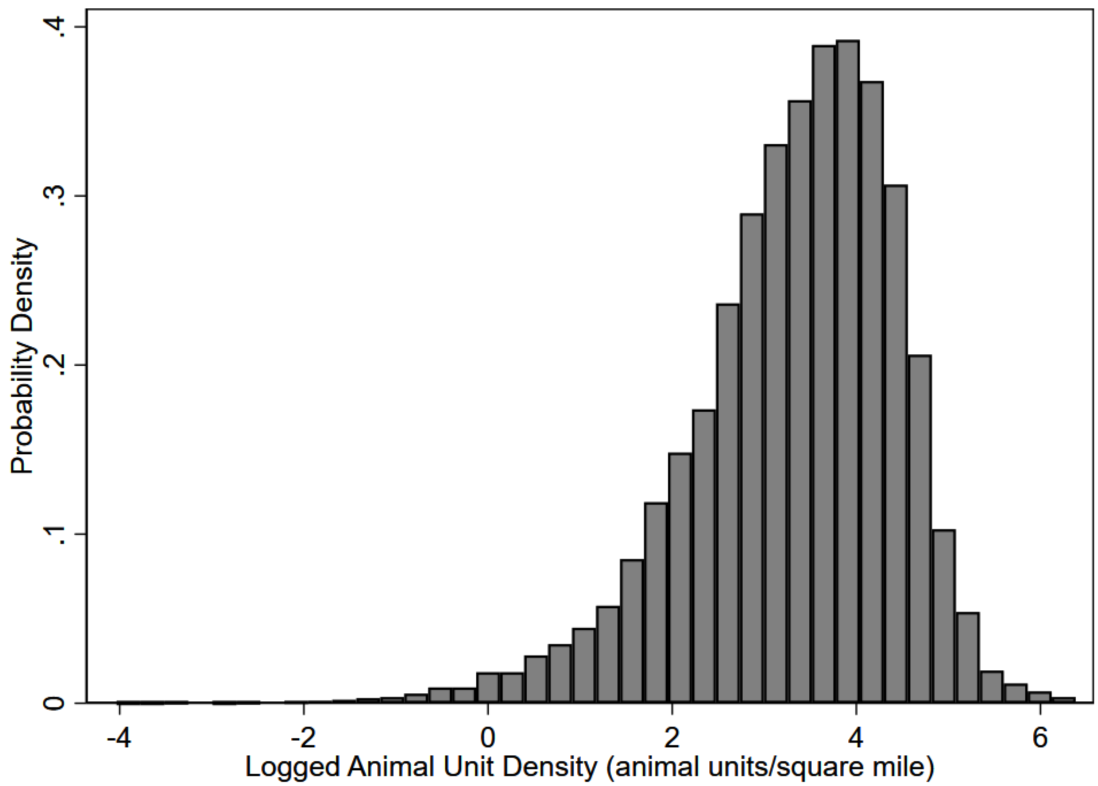


Figure 5 Probability Density Distribution of Logged Animal Unit Density by Census Region

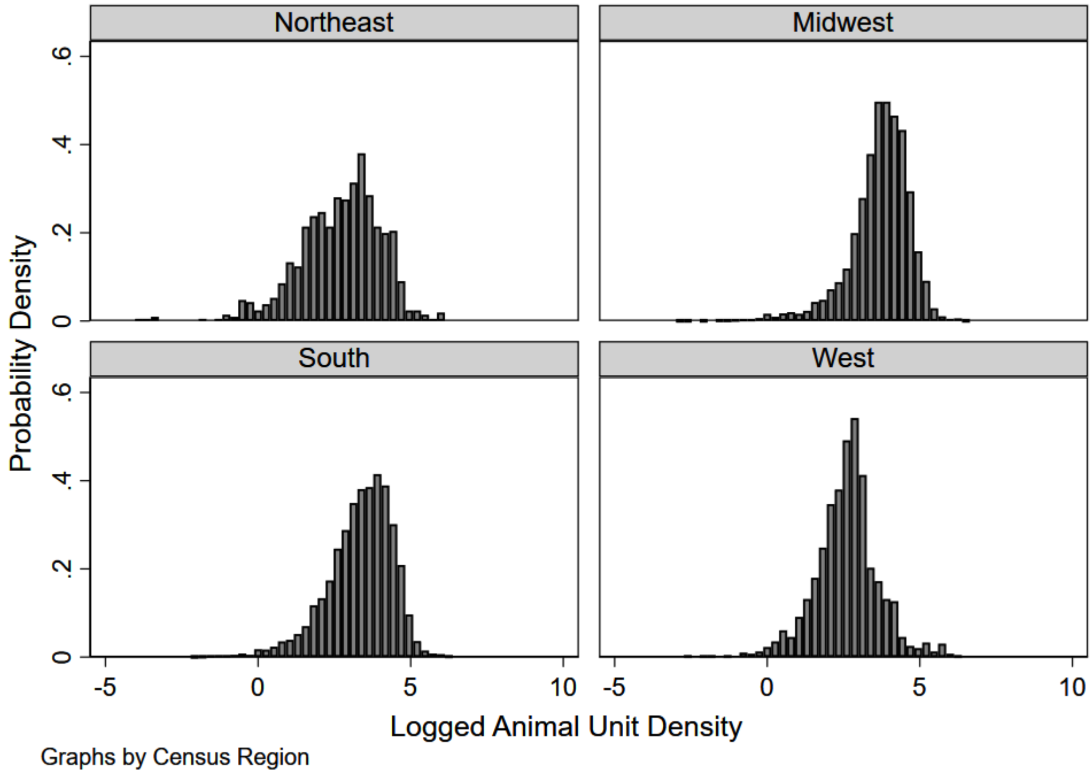
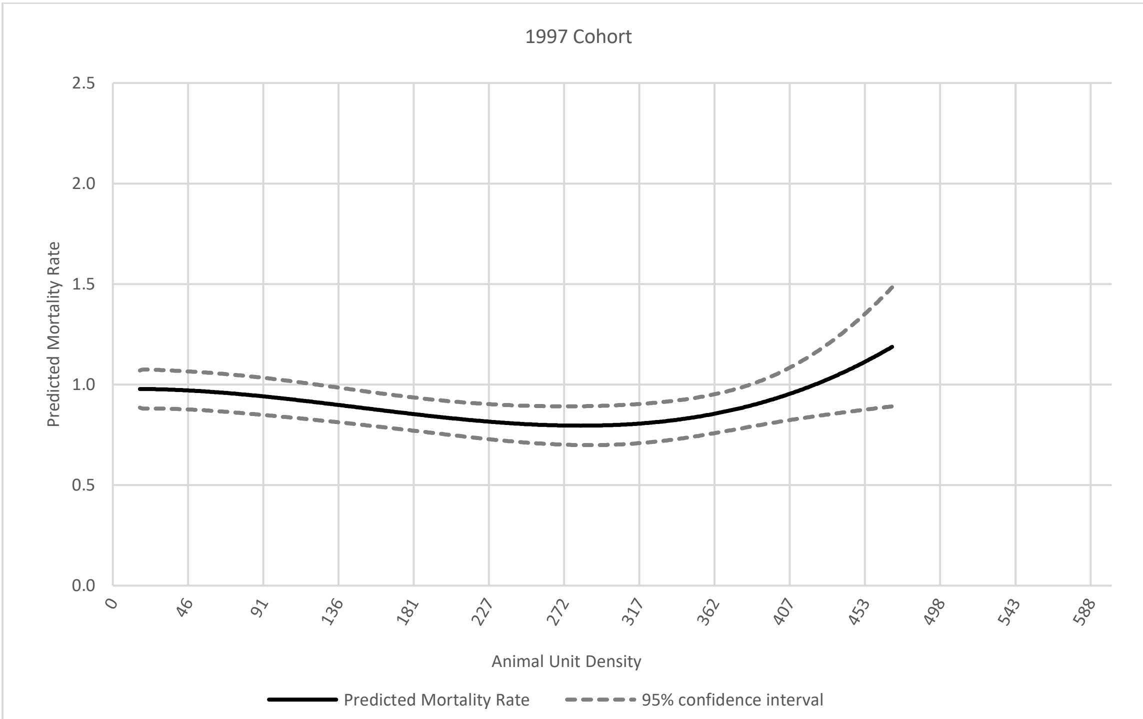
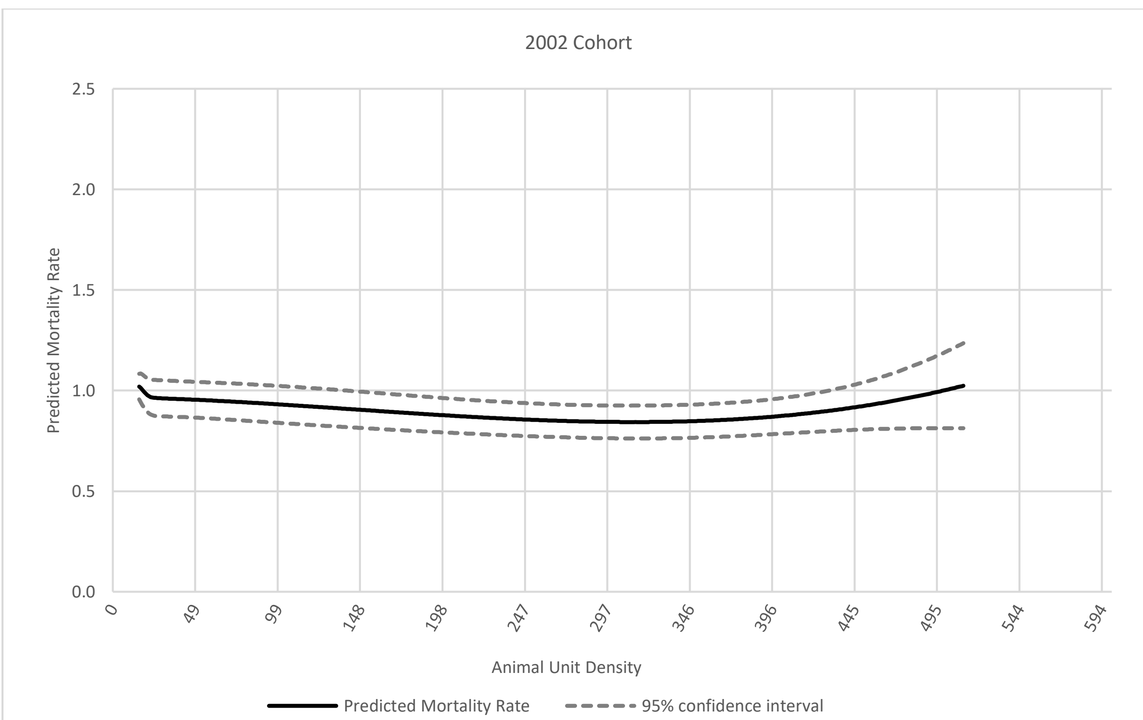
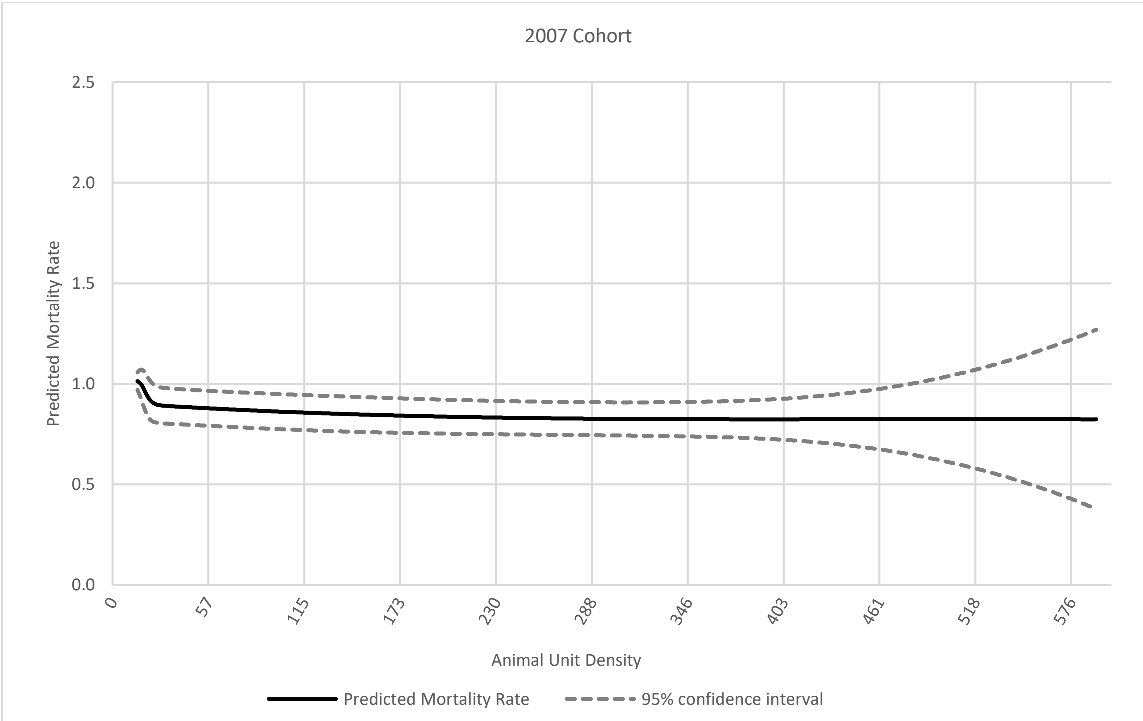


Figure 6 Estimated Dose Response Functions, Year Cohorts

Each of the following figures has predicted mortality rates on the vertical axis and animal unit density on the horizontal axis.






2007 Cohort
2.5
2.0
1.5
1.0
0.5
0.0
Predicted Mortality Rate
0
57
115
173
230
288
346
403
461
518
576
Animal Unit Density
Predicted Mortality Rate
95% confidence interval

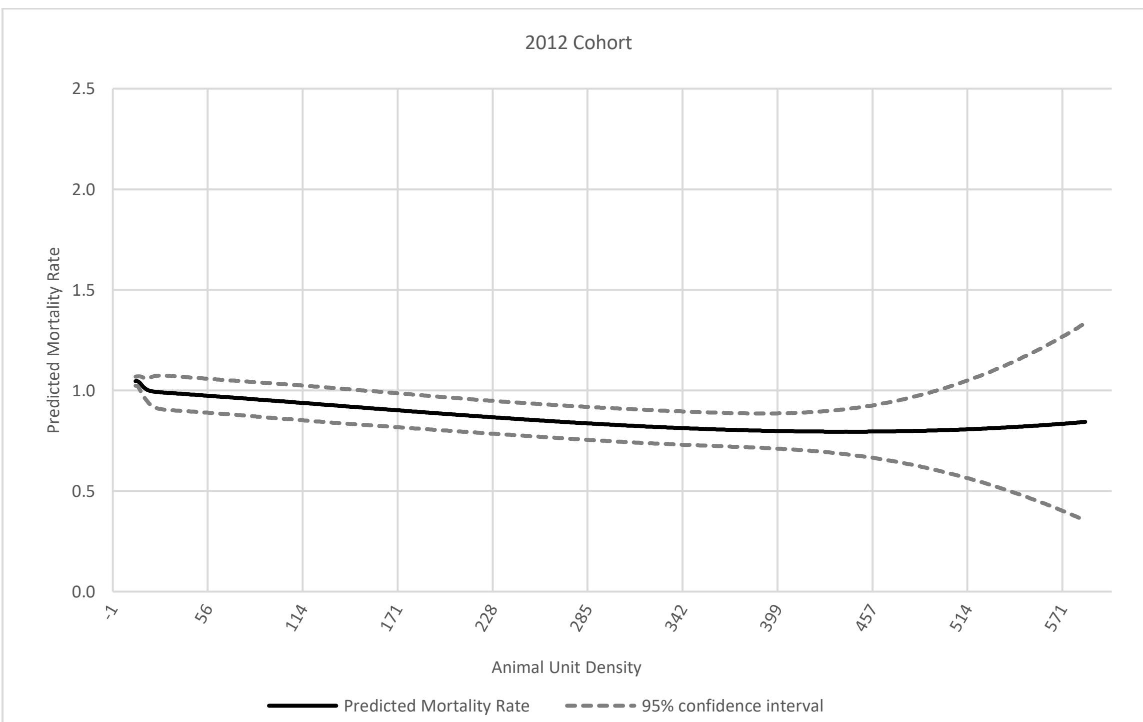
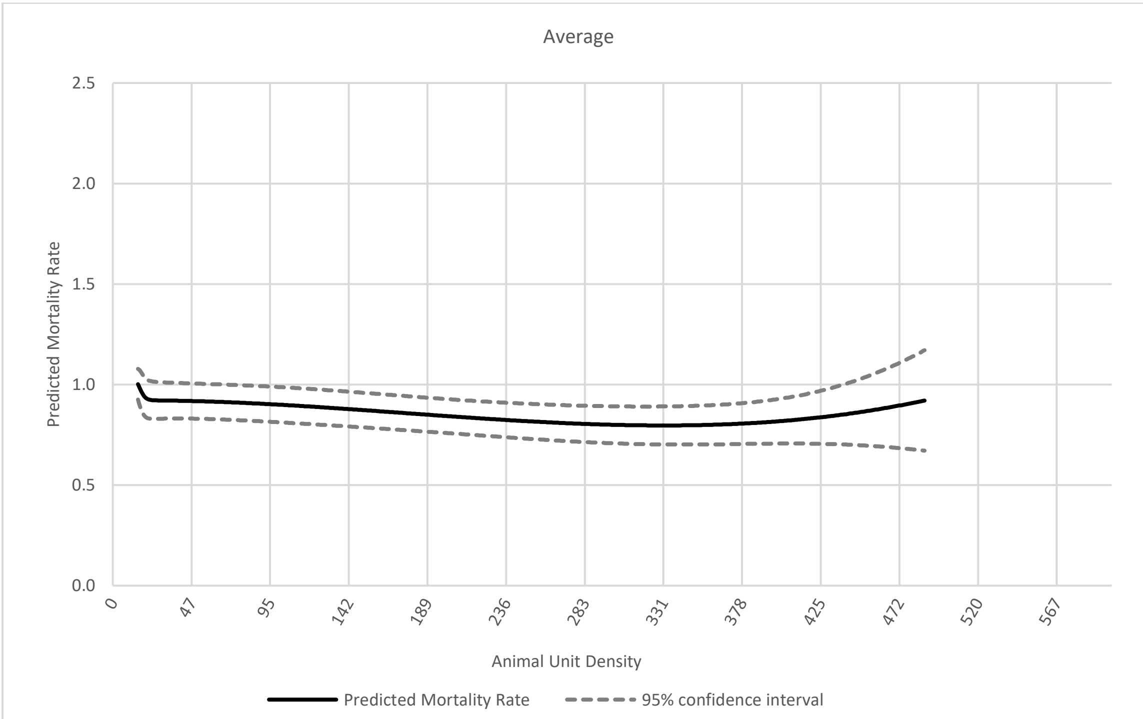
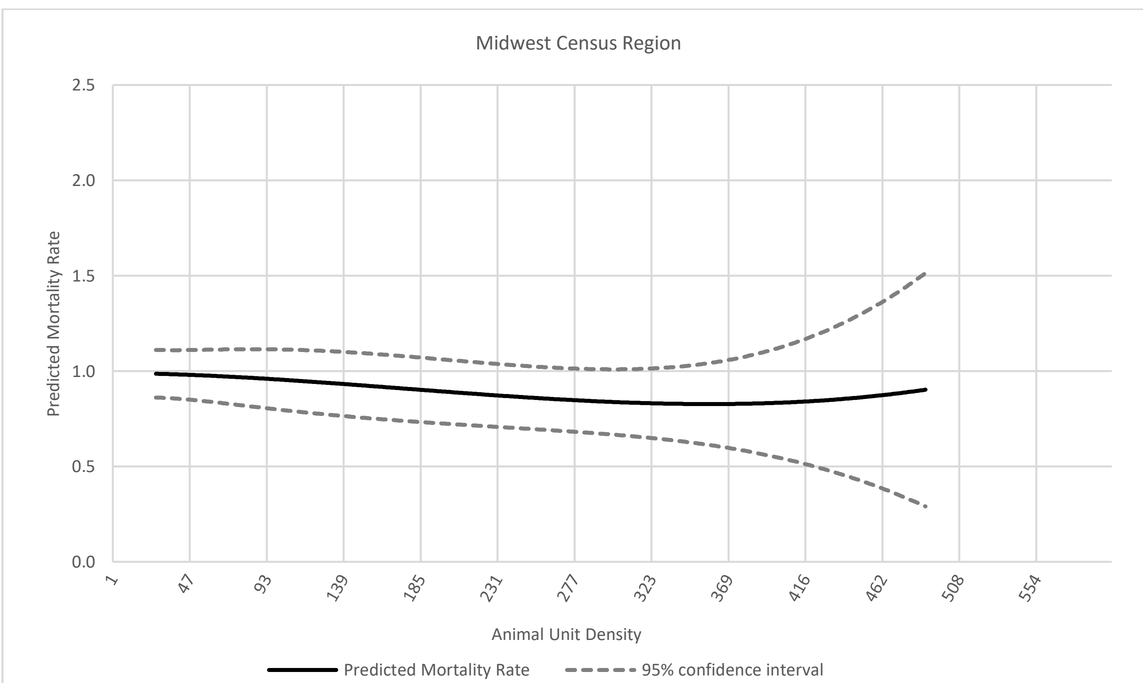
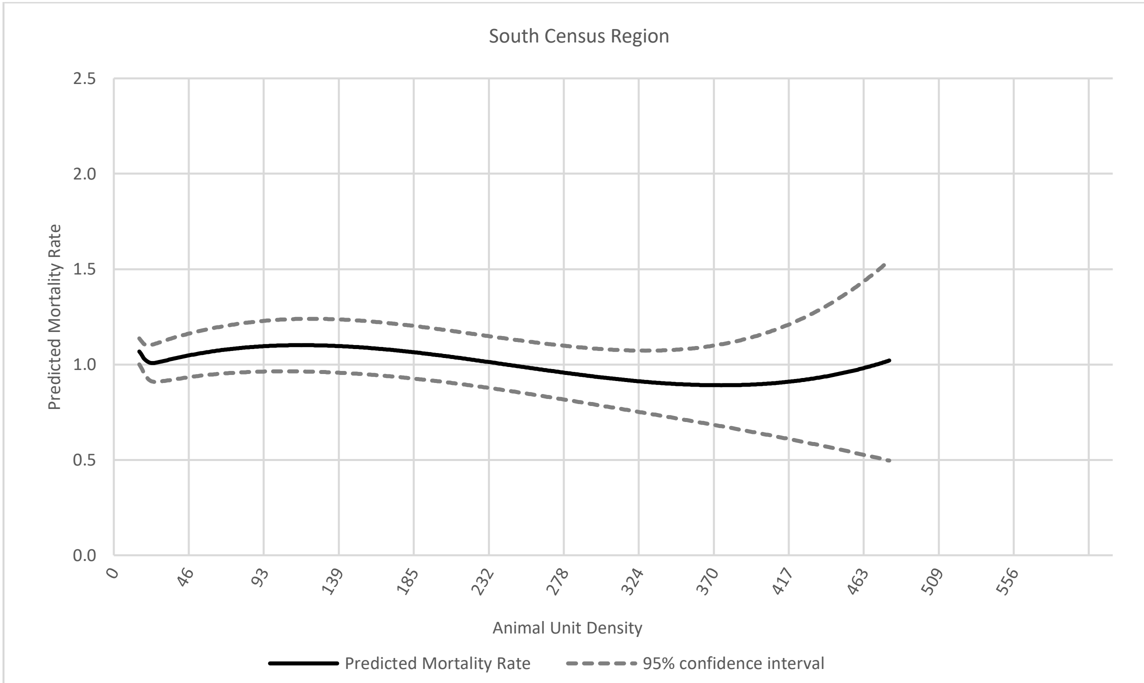

2012 Cohort
2.5
2.0
1.5
1.0
0.5
0.0
Predicted Mortality Rate
-1
56
114
171
228
285
342
399
457
514
571
Animal Unit Density
Predicted Mortality Rate
95% confidence interval

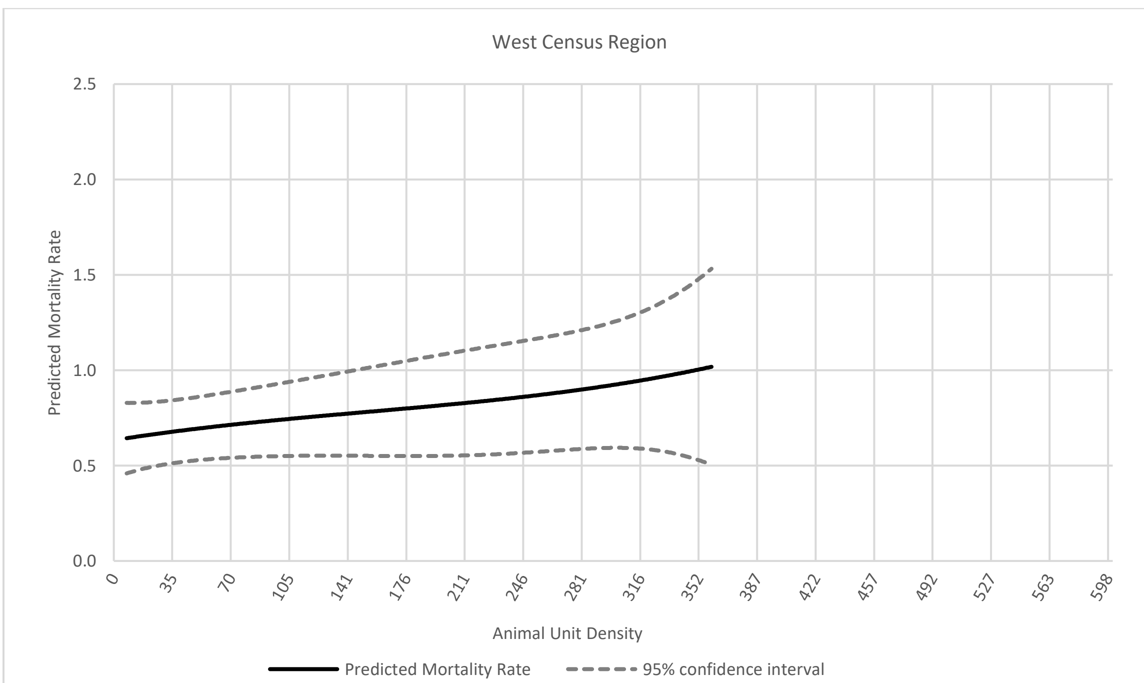
Figure 7 Estimated Dose Response Functions, Average and Regional

Each of the following figures has predicted mortality rates on the vertical axis and animal unit density on the horizontal axis.






South Census Region
2.5
2.0
1.5
1.0
0.5
0.0
Predicted Mortality Rate
0
46
93
139
185
232
278
324
370
417
463
509
556
Animal Unit Density
Predicted Mortality Rate
95% confidence interval


West Census Region
2.5
2.0
1.5
1.0
0.5
0.0
Predicted Mortality Rate
0
35
70
105
141
176
211
246
281
316
352
387
422
457
492
527
563
598
Animal Unit Density
Predicted Mortality Rate
95% confidence interval