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This study seeks to explore the determinants of the relationship of economic growth and water quality in the United States using an Environmental Kuznets Curve framework. Specifically this study seeks to determine whether there is evidence of improvement in water quality since passage of the 1972 amendments to the Clean Water Act, as well as whether there is a relationship between growth in income per capita and water quality. A third hypothesis considers whether sampling bias in water quality data may have prevented other authors from finding robust evidence of an EKC in the US. A county-level panel dataset spanning from 1969-2012 was constructed using water quality sampling information for concentrations of dissolved oxygen for surface waters in the contiguous US. Using fixed and random effects econometric models, this study finds very little significant evidence for the presence of an EKC; additionally the results do not support the hypothesis of improvements in overall water quality in the time period studied. Further research should focus on the appropriate matching of economic and physical water data, as well as consider the implications of water quality in the EKC framework.

An Exploration of Water Quality in the United States using an Environmental Kuznets Curve Framework

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

Annah M. Latané, Author

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DEDICATION

Dedicated to

Thomas Johnson Sanford,

who showed me the meaning of pursuing a life of learning.

I. Introduction

Nobel-prize winning economist Simon Kuznets in 1955 observed that countries experience changes in income inequality differently as income per capita changes. He posited that as per capita income increases, income inequality also rises, before reaching a turning point and declining to form an inverted U-shaped curve, later named the Kuznets Curve. The 1990s saw the expansion of the U-shaped curve to the environmental realm, substituting environmental degradation for income inequality, and giving rise to the Environmental Kuznets Curve (EKC). The basic EKC hypothesis asserts that as a country develops economically, it will initially experience an acceleration in resource use, resulting in a decline in environmental quality, but that at a "turning" point environmental degradation may level off and then decline while economic growth continues.

Water quality is one measure of environmental degradation. The United States passed the Clean Water Act (CWA) in 1972 to "restore and maintain the chemical, physical, and biological integrity of the nation's waters." While the act set into place the regulatory power to improve and protect water quality in surface waters across the country, there has been little work done to examine whether the act has achieved its goal (Smith and Wolloh, 2012). The EKC presents a unique framework through which to examine the US experience of changing water quality and economic growth.

This thesis proposes to use water quality sampling data from streams and lakes from across the continental U.S. to provide insight about trends in water quality after passage of the CWA as well as investigate the presence of an EKC relationship with per capita income growth. The size of the dataset is unique in that it allows incorporation of county-level demographic and economic factors of interest as well as data available pre- and post- passage of a major expansion of the CWA. Focusing an EKC study in the United States provides the opportunity to use widely available, reliable data, a distinct advantage from many EKC cross-country analyses. Previous studies on water quality and the EKC relationship in the US have been limited temporally or geographically; this study has the potential to determine whether sampling bias in previous studies may have been a factor in their results.

This thesis is structured as follows. A review of the EKC literature in Section II provides an understanding of the foundations of the EKC framework, followed by a brief survey of empirical studies, specifically those that have focused on water quality as the measure of environmental quality. Section III details water quality policy in the United States, and provides information about dissolved oxygen as an indicator of water quality. The research methodology describing the empirical model and data construction methods is described in Section IV. Finally, results are presented in Section V with accompanying discussion and conclusions found in section VI.

II. Review of Relevant Literature

A. Theoretical Understanding of the EKC

In one of the first studies of the relationship between economic growth and environmental degradation, Grossman and Krueger (1991) suggest that economic growth affects the environment through three avenues, which they called scale effects, composition effects, and technique effects. Scale effects occur as increasing production levels require higher levels of input, which both increase use of natural resources and also produces more waste and emissions, which combine to degrade environmental quality. Composition effects suggest that economic growth may have a positive or negative effect on the environment: the structure of the economy changes as income grows and gradually introduces differing production activities. An economy transitioning from an agrarian to an industrial basis will likely experience an increase in environmental degradation and an accompanying decrease as the economy later transitions to a service and knowledge-based one. The technique effect is evident when a nation reaches a level of wealth to allow significant investment in research and development, which may contribute to cleaner (or dirtier) production technologies and may improve environmental quality. The EKC shape suggests that the negative scale effect prevails in the initial states of economic growth, but may be eventually outweighed by the positive effects of the composition and technique effects on environmental quality (Dinda, 2004; Vukina et al., 1999).

A subsequent paper by Grossman and Krueger (1995) expands their hypothesis by including the idea that the strongest link between income and pollution is likely an induced policy response: as nations grow in prosperity, citizens begin to demand that more attention be paid to the environment. Torras and Boyce (1998) elaborated on Grossman and Krueger's conclusions: "the public good character of environmental quality means that effective demand requires solutions to market failure. ...a simple theory of induced innovation [arises]: as per capita income rises, societies become better able to redress market failure" (149). Arrow et al. agree, stating that the solution to environmental degradation is in institutional reforms that force private users of environmental resources to account for the social costs of their activities (1995). Panayotou (1997) asserts that polices and markets determine the "environmental price" of economic growth.

The speculation about the underlying mechanisms of the observed EKCs continues with a study by Dasgupta et al. (2000), which seems to confirm that strengthened regulatory institutions raise the price of pollution and provide an important incentive for pollution reduction. Dinda concludes from a survey of the EKC literature that in studies where emissions are demonstrated to decline with rising income, the reductions have been due to local and national institutional reforms, such as environmental legislation and market-based incentives (2004). Income elasticity of demand is a key factor that may contribute to this effect. As income grows, people achieve a higher standard of living and care more for the quality of the environment, which induces structural changes in the economy that tend to reduce environmental degradation. Consumers with higher incomes are willing to spend more for green products as well as create pressure for environmental protection and regulations (Dinda, 2004). Panatoyou (1997) states, however, that shifts in people's preferences and societal norms are slow adaptive processes that may fall behind a fast pace of economic growth and accompanying environmental degradation; this discrepancy between rates of economic change and social change may be another reason for the observed EKC relationship.

The theoretical literature devoted to the EKC aims to provide insight as to which of the hypothesized mechanisms may in some cases lead to the inverted-U shape. Stern (2004) points out that the estimation of a reduced form model in empirical studies restricts any conclusions about the drivers of the relationship between environmental quality and economic growth. Several authors have provided more explicit theoretical models to substantiate speculations about the mechanisms underneath the reduced form estimation of the EKC. Copeland and Taylor (2003) detail four of the most prominent explanations that provide a link between income and pollution levels, beginning with the premise that there is, in fact, no simple relationship to be found since income and pollution are both endogenous variables: the effect of growth on pollution depends on what causes the growth.

The first category of theoretical models is the "sources of growth" theory, which suggests that the EKC could arise from changes in the sources of growth in the economy. Income gains from trade may have different environmental consequences from income gains stemming from accumulation of physical capital or technological progress (Copeland and Taylor, 2003). The authors present a model that generates an inverted-U based on the assumptions that there is a difference between "dirty" and "clean" economic growth, and that there is an identifiable factor to "dirty" growth that is stimulated in the early stages of growth more than the "clean" factor leading to a composition effect from factor growth. They make a second assumption that the policy response is not so strong that it mutes any technique effects and allows the composition effects to drive pollution levels (Copeland and Taylor, 2003).

The second category of explanations for the EKC focus on a policy response to gains in income, referred to as income-effects. Lopez (1994) demonstrates that in cases where environmental goods are assumed not to have stock feedback production effects (changes in the stock level of the environmental good, such as forestry or soil quality, do not affect production) and preferences are non-homothetic, pollution does not necessarily increase with increases in factor production or technological change. The inverted-U shape path is generated under two conditions: when the income elasticity of the environmental good is sufficiently greater than one, and the elasticity of substitution in production between polluting and non-polluting inputs is sufficiently large. Intuitively, economic growth increases the value of the environment for consumers; if this increased value translates to the market, firms then have to pay more to pollute. If the income elasticity of the environmental good grows as income per capita grows, consumers are willing to give up a proportionally larger amount of potential income to demand improved environmental quality. When the elasticity of substitution in production is high enough, a small change in the price of pollution induces firms to reduce their pollution levels substantially. However, under homothetic preferences and production, the author's model does show continual increases in pollution (Lopez, 1994).

A third grouping of explanations rely on the idea of a threshold effect; growth in the economy is accompanied by a rise in pollution levels due to either an absent or ineffective policy process or too small levels of marginal benefits of abatement. Once the threshold of growth is reached, pollution levels are driven downward through either increasing returns to abatement or more effective policy responses (Copeland and Taylor, 2003). Stokey (1998) develops an abatement threshold model in which incomes below a critical level show no pollution abatement due to the fact that there is a disjuncture between costs and benefits of pollution. The costs of high pollution are seen exclusively in utility, while the benefits are derived from the higher levels of output that higher pollution allows (from use of conventional inputs). When the levels of conventional inputs are low, pollution levels are low, and the elasticity of marginal utility of consumption is high, such that consumers are less willing to substitute regular consumption for lower pollution. Therefore, the benefits from an additional unit of pollution offset the costs, and pollution rises with income. The author presents two possibilities when the levels of conventional input use rises. First, when the marginal utility of income is elastic, then pollution and inputs can be thought of as substitutes, where an increase in the use of one reduces the marginal value of the other, and pollution declines with income. An alternative possibility arises when the marginal utility of consumption is inelastic, and pollution and conventional inputs are complements, resulting in pollution increasing with income over the entire range (Stokey, 1998).

A fourth explanation focuses on increasing returns to scale in abatement technology, described by Andreoni and Levinson (2001) using a straightforward model that can be generalized to fit many of the explanations above. The authors find that using the technological link between consumption of a desired good and abatement of its undesirable byproduct an EKC can be directly derived. They set up a model in which consumption of a good generates pollution, as well as a polluting byproduct; expenditures on abatement result in declining pollution levels. When individuals have high levels of income, they demand more consumption, as well as less pollution. If abatement is possible with increasing returns, those high-income individuals can achieve both goals, and an EKC is demonstrated (Andreoni and Levinson, 2001). Copeland and Taylor also expand the model to market economy, but support the validity of increasing returns to abatement by assuming that for a given level of aggregate abatement, each individual perceives constant returns to scale. As the aggregate scale of abatement rises, each individual's abatement productivity increases. If there are knowledge spillovers between firms, then the pool of "abatement knowledge" will expand with the industry and therefore productivity will increase (Copeland and Taylor, 2003). Andreoni and Levinson note that their model supports Stokey's (1998) framework, as she assumes that poor economies use only the dirtiest production technologies, and only after passing a threshold of income do they begin to abate. Fixed costs to abatement technologies or increasing returns to abatement support the reasoning behind the timing of adoption. Jones and Manuelli (1995) develop a political process-drive model, where only advanced economies are capable of establishing policies that internalize pollution externalities. Andreoni and Levinson suggest that the advancement in political processes could be thought of as part of societal abatement technology, with fixed costs or increasing returns to scale to adopting environmental regulations.

Finally, Jaeger et al. (2011) in a working paper present an alternative theoretical model that supports those detailed above while requiring few of the assumptions by focusing more exclusively on the interaction between the utility function and the production function. They assume that stock effects of environmental damage can be ignored (as in Lopez above). The authors set up a static framework in which parametric changes in utility and production functions can result in a U-shaped trajectory between income and environmental quality as well as population density and environmental quality when the production elasticity exceeds the consumption elasticity at the optimal level of an environmental good. In circumstances where the environmental good exhibits a low elasticity of substitution, the U-shaped path is more likely to be found.

B. Empirical Studies

The EKC is an empirically observed phenomenon, and the wide range of possible explanatory mechanisms for the EKC relationship stems from the widely used reduced form model for estimation (de Bruyn, 2000). The general EKC model follows the form below in equation 1:

$$E_{it} = \alpha_{it} + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \varepsilon_{it} \tag{1}$$

Where:

E indicates a measure of environmental quality

i indexes a geographic unit (country, state, county)

t indicates time (years)

Y indicates income level

When β_1>0 and β_2<0, an inverted-U quadratic relationship is implied. In some cases, a third order polynomial is included for a more flexible fit of the relationship. The income turning point, or the threshold of income per capita where environmental quality will cease its decline and begin improvement is given by (Stern, 2004):

$$\tau = -\beta_1 / (2\beta_2) \tag{2}$$

Much of the criticism of the EKC literature has focused on econometric specification. Carson (2010) points to "the inadequacy of reduced-form specifications that presume that a common income-related process, conditional on fixed effects for political jurisdictions and a few observable covariates, adequately describes the generation of the pollutant of interest" (Carson, 2010). Many studies have employed additional control variables to improve the fit of the model and provide additional insight about the change in environmental quality with economic growth, such as population density (Jaeger et al., 2011), indicators of trade, indicators of political freedom (Torras and Boyce, 1998), and ethnicity (Rupasingha et al., 2004). However, when these variables are also related to income, their inclusion may capture part of the income-related effect on pollution, altering the turning points and possibly limiting the explanatory power of the income variables (de Bruyn, 2000). Stern (2004) states that testing these different variables individually is subject to the problem of potential omitted variable bias, and inferences are unclear.

Stern also goes on to state that little or no attention has been paid to the statistical properties of the data used or to issues of model adequacy. He suggests that econometric issues in the EKC literature fall into four main categories: heteroskedasticity, simultaneity, omitted variable bias, and cointegration issues. Stern finds that the only robust conclusions from EKC literature are that pollutant concentrations may decline from middle-income levels; however, too few quality studies have been done of indicators other than air pollution to draw any other conclusions (2004). Researches are far from agreement about whether the EKC provides a fit for available data, particularly in cross-country analyses where data for developing countries is scarce (Dasgupta et al., 2002). More generally, Stern (2004) points out that there may be misapplication of the EKC framework when using different measures of environmental degradation, where stock variables (forest cover) require a different treatment than flow variables (rate of deforestation). Finally, though not specific to the EKC literature, Anselin (2001) notes that there is often a mismatch of scale in environmental economics analyses arising from the need to integrate, for example, economic data from a census and physical data from fixed water quality monitoring stations, leading to spatially dependent and spatially heterogeneous observations.

The body of literature supporting the EKC examines a variety of measures of environmental quality (degradation) as the dependent variable of interest. The measures can be broadly categorized into measures of environmental pollution in terms of emissions or concentrations, where air quality can be gauged by carbon, sulfur dioxide, or nitrous oxide emissions or particulate matter concentrations, and water quality represented mainly through concentrations of dissolved oxygen, biological oxygen demand, chemical oxygen demand, fecal coliform, and heavy metals. Many initial studies focused on cross-country comparisons using data from the World Bank Global Economic Monitoring System (GEMS) database, though at the risk of using data that was not fully representative of developing countries and included comparability issues related to pollution measurements across countries (Carson, 2010). Harbaugh, Levinson and Wilson (2002) reexamined the original Grossman and Kreuger analysis with updated data on sulfur dioxide, smoke, and total suspended particles; they found that evidence for an EKC was less robust than previously reported. Torras and Boyce (1998) examine several pollution indicators for air and water from the GEMS database, including dissolved oxygen, under the hypothesis that changes in the distribution of power are central to the connections between environmental quality and economic growth. Interestingly, their results for high-income countries suggest a possibility that excessively high levels of income are no longer conducive to improvements in environmental quality. They hypothesize that the scale effect overshadows the composition and technique effects after a certain point, demonstrating an "N" shaped relationship with a minimum at $5085 and a peak at $19,865 (purchasing power parity adjusted $).

In order to ameliorate cross-country data issues in EKC studies, several researchers have focused their efforts on state and county level analyses. List and Gallet (1999) use EPA emissions data for sulfur dioxide and nitrogen oxide from 1929-1994 to demonstrate an EKC at the state level. Their results confirm that states' emissions have followed a typical EKC shape, where the median turning point of income per capita for sulfur dioxide was $16,826 (1987 dollars) and $14,977 for nitrogen oxide. Rupasingha et al. (2004) use county level data from EPA's toxic release inventory to investigate a variety of determinants of pollution and improve upon econometric methods by using a two-state instrumental variable approach as well as spatial estimations. They uncover an EKC relationship between toxic pollution and per capita income, as well as with income inequality and ethnic diversity of a county. They found a turning point of $22,520 (1990 dollars) using a Tobit model.

A range of conflicting policy conclusions have also been drawn from the EKC literature. Some point to EKC results as general evidence of a relationship between economic growth and environmental degradation, with the interpretation that society can grow its way out of environmental problems. A converse interpretation says that presence of an EKC relationship should not be a substitute for environmental policies; the EKC could only be an indicator that negative externalities are being shifted to low income areas or countries and may not hold in the future due to ecological carrying capacities (Cavlovic et al., 2000). A meta-analysis on 25 EKC studies by Cavlovic et al. (2000) demonstrates that methodological issues can significantly influence the results of an EKC study; the authors add that policy implications should be drawn from EKC evidence with caution. Arrow et al. (1995) state that EKC conclusions do not imply that economic growth is sufficient to induce environmental improvement in general or that the environmental effects of growth may be ignored, particularly as the Earth's resource base is incapable of supporting infinite economic growth.

C. Evidence of the EKC in Water Pollution Studies in the US

More relevant to this review are studies focused on water pollution as the environmental quality indicator and analyses using a single country. Vincent (1997) suggests that due to the local nature of water pollution, a within-country or within-state study is more appropriate than a cross-country study. A paper by Paudel, Zapata, and Susanto, 2005 responds to criticism of the misspecification of the functional form of models in cross-country EKC studies by estimating parametric and semiparametric models for water pollution in Louisiana over a fifteen year period. Their results show evidence of an EKC relationship for dissolved oxygen with a turning point of $9,612 (in 2005 dollars), but it was not statistically significant. They found that there was no significant improvement between a two-way random effects model and a two-way fixed effects model. They also demonstrated that a quadratic model is sufficient when estimating DO; a semi-parametric model did not yield significantly different results.

Smith and Wolloh produced in 2012 "the first quantitative assessment of the aggregate trends in water quality data in the U.S. using a single standard." The authors first note that the use of the typical economic indices for non-market amenities are not good fits for a national analysis of environmental quality trends for resources outside of household locations. For example, in a quality of life comparison method, hedonic property values and wage equations are used to estimate the contributions of amenities to relative implicit expenditures. While appropriate for amenities available to residents in specific communities, such as air quality, a national water quality assessment does not fit the spatial distribution required for the method. Instead, the authors use data from the USGS National Water Information System (NWIS) to construct an index of national water quality by transforming dissolved oxygen concentrations into an indicator variable using thresholds for sport fishing and swimming. The authors also construct an index according to the proportions of lakes satisfying the water quality criteria of each state and then averaging the proportions across the states for each year. Regressing the indices on the national unemployment rate resulted in a positive relationship; the authors conclude that the national economic slowdown led to improved water quality over the period of the last recession. In examination of an EKC hypothesis, the results do not show clear evidence of a relationship between the fishable/swimmable water quality indices and real per capita GDP. The authors conclude that policies intended to improve environmental quality should have a specific strategy for evaluation; the indices as they stand lend themselves to the conclusion that the CWA has not achieved its intent.

A study by Sigman (2004) investigates transboundary spillover effects and the decentralization of environmental policies, namely the Clean Water Act, in the US between 1973 and 1995. The author uses stream data from the National Stream Quality Accounting Network to model water quality as a function of whether the state or any upstream neighboring states has authorization from the EPA to administer its CWA program, time-varying state and river characteristics, and other geographic fixed effects. The dependent variable is a water quality index constructed from five pollutants, including dissolved oxygen. The water quality index is constructed only on data from May to September. Using a fixed-effects model, the results demonstrate that states that are authorized to administer their CWA programs have rivers that are 4% dirtier than elsewhere, and a state's water quality is about 6% dirtier when at least one neighboring adjacent states is authorized. In the author's words "states do free ride when authorized" (Sigman, 2004).

III. **Water Policy in the United States**

The Clean Water Act (CWA) of 1972 is the most comprehensive piece of water pollution control legislation in the United States. Passed as amendments to the Water Pollution Control Act of 1948, the CWA established the National Pollution Discharge Elimination System (NPDES) requiring all point source discharges of effluent into waters of the US to have a discharge permit. The CWA also extended the 1965 amendments directing states to develop water quality standards for interstate waters to include intrastate waters. Water quality standards are laws or regulations promulgated by states or Native American tribes with three basic parts: definition of the water quality goals of a water body through designation of uses, criteria necessary to protect the uses, and protection of water quality through antidegradation provisions. Sections 101 and 303 define the purposes of the CWA such that water quality standards should include provisions for restoring and maintaining chemical, physical, and biological integrity of State waters; provide water quality for the protection and propagation of fish and wildlife and recreation in and out of the water (also known as the fishable/swimmable standard); and consider the use and value of State waters for public water supplies, propagation of fish and wildlife, recreation, agricultural and industrial uses, and navigation.

The state response to the 1972 act and its accompanying regulatory developments was varied; some states adopted detailed standards while others did little to legislatively manage water quality issues. The CWA allowed for EPA to authorize states to manage the NPDES programs while retaining EPA oversight. Aside from the NPDES programs, states did relatively little to address ambient water quality standards; most adopted criteria to describe the water conditions but did not tackle more complex problems from toxics and other pollutants. Amendments passed in 1983 provided more specific requirements about water quality criteria; states may use the criteria developed by EPA under section 304(a), or modifications of the criteria to site-specific conditions, or other scientifically defensible criteria (EPA, 2012). Amendments in 1987 furthered strengthened the CWA by requiring states to adopt numeric criteria to control toxic pollutants in bodies of water where toxic pollutants were likely to adversely affect designated uses. Native American tribes were explicitly included in the CWA requirements under the 1987 amendments as well, with Congress directing the EPA to develop procedures for designating tribes as states for the purposes of administering their own NPDES programs. Finally, the 1987 amendments to the Act explicitly highlighted the importance of EPA's antidegradation policy by requiring that water quality standards in waters with quality that meets or exceeds levels necessary to support designated uses may only be revised if the revisions are consistent with the antidegradation policy (EPA, 2012).

The EPA lists dissolved oxygen as a criteria measure per mandate under section 304(a)(1). The criteria are not rules and do not have direct regulatory standing, but they are an assessment of the current state of scientific knowledge and are meant to be a basis for state regulatory requirements. Dissolved oxygen (DO) is a measurement of the concentration of oxygen gas incorporated in water. As described by the EPA, oxygen enters water by direct absorption from the atmosphere, which is enhanced by turbulence. Water also absorbs oxygen released by aquatic plants during photosynthesis. Sufficient amounts of DO are necessary to support aerobic aquatic life; most species are dependent upon oxygen dissolved in the water column. In unpolluted, free-flowing streams, DO concentrations are usually sufficient to maintain healthy life, but low or extremely high DO levels can impair or kill fisheries and invertebrates while large fluctuations in DO over short time periods can stress aquatic life.

A wide range of human activities in water bodies and associated watersheds affect the levels of DO, including water impoundments, releases from municipal wastewater treatment plants and industrial point-sources, non-point source runoff from urban stormwater and agricultural activities, removal of riparian vegetation, channel alteration, and groundwater inflows. Impoundment releases could increase or decrease downstream levels of DO, depending on the volume and design of the release. Water released from the top of a dam is often warmer and less able to hold oxygen, but increased turbulence from the release could also increase aeration. Conversely, water released from the bottom of a reservoir is often colder with higher DO saturation capacity, but deeper waters are also subject to oxygen deprivation. Though municipal wastewater treatment plants are regulated under the NPDES system to protect necessary levels of DO, storm events may result in diversion of excess flows that are released without treatment into surface waters. Nutrient runoff from agricultural or urban nonpoint sources can increase the amount of algae and aquatic plants, increasing oxygen inputs during the day as well as increasing oxygen demands at night from respiration. When the algae and plants die, they are decomposed by bacteria and fungi, which consume oxygen. Animal wastes and organic matter from landfills can also contribute to increased oxygen demand. Removing vegetation from riparian areas affects DO levels through several ways. Removal of shading increases water temperatures and plant production. Higher temperatures will decrease the solubility of oxygen in water; plant production affects DO as described above. Less woody debris from the surrounding vegetation may also reduce turbulence, decreasing aeration (EPA 2012).

The EPA last revised the national criteria for ambient dissolved oxygen concentrations for protection of freshwater aquatic life in 1986. While several criteria are established according to life stages of aquatic life and means for a variety of time periods, the cold freshwater minimum for one day has been established at 4 mg/L, and warm freshwater minimum at 3 mg/L. The criteria represent DO concentrations that EPA believes provides a reasonable and adequate degree of protection for freshwater aquatic life; many states have stricter regulatory requirements (EPA 1986).

Climate change adds a degree of uncertainty to the impacts of already existing human activities on surface water quality. Increasing temperatures and changes in the timing, duration, and intensity of precipitation affect water quality of watersheds differently across the U.S. The risk of drought is intensified with increasing air temperatures, decreased snowpack and earlier snowmelt, as well as decreases in summer precipitation (EPA, 2013). Climate change alters the hydrologic geography in which the CWA and other water regulations operate. Though there is no explicit legislation guiding water policy and climate change, the EPA recognizes in it's 2012 National Water Program 2012 Strategy: Response to Climate Change report the need to reflect the current knowledge about climate change in its regulatory approach to the CWA and national water policy.

IV. **Methodology: Modeling Water Quality and Economic Growth**

The literature in the area of economic assessments of water quality in the US is paltry in comparison to the literature on air quality. Olmstead (2009) notes that air quality studies have received more attention due to the direct human health impacts from air pollution, as well as the fact that there have been far fewer market based approaches to water pollution control. This study seeks to assess the United States' experience with the Clean Water Act in the context of the Environmental Kuznets Curve hypothesis. Specifically, this research will add to the literature by evaluating surface water data for both streams and lakes using a national level dataset for the U.S. The hypothesis is that evidence can be found to indicate improvement in water quality since the passage of the Clean Water Act, and that an EKC relationship can be demonstrated between income per capita and water quality using several key demographic and economic variables. An additional hypothesis seeks to discern whether sample selection bias in the EKC water quality studies previously done in the United States has prevented other authors from finding a more robust EKC pattern. Section A details the specific empirical methodology used to test the hypotheses above, while section B describes the data and expectations of findings.

A. Empirical Model

Much of the literature has dedicated itself to observation of the EKC through empirical estimation. Panel data is commonly used to test the EKC relationship, with the advantage of achieving more variation across time than would be available doing a cross-sectional analysis (Kennedy, 2008). Most studies use a reduced form equation with a quadratic or cubic specification between the pollutant and per capita income variables in a parametric specification. This analysis follows suit with a large panel dataset using county-level data on dissolved oxygen concentrations from the contiguous US spanning from 1969-2012; construction methods of the dataset are detailed below. The full general form of the empirical model to be estimated of the relationship between water quality and per-capita income growth is given in equation 3.

$$E_{it} = \alpha_i + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 Y_{it}^3 + \beta_4 D_{it} + \beta_5 D_{it}^2 + \beta_6 D_{it}^3 + \beta_7 Z_{it} + \varepsilon_{it} \tag{3}$$

Where:

i indexes counties

t refers to years (1969-2012)

E indicates a concentration level of dissolved oxygen

Y is per capita income

D population density

Z is a vector of additional variables

If $\beta_1<0$, and $\beta_2>0$, and both are statistically significant then water quality is said to display an inverse U relationship with income per capita (provided that the influence of the cubic term is minimal) (Rupasingha et al, 2004). Similarly, when $\beta_4<0$, and $\beta_5>0$, and are statistically significant, then water quality will demonstrate a U-shaped relationship with population density. As mentioned above, in the case of a quadratic form, a "turning point" income can be estimated where pollution emissions or concentrations are at a maximum by $\tau = (-\beta_1 / 2\beta_2)$ (Stern, 2004). The maximum and the minimum income levels in the cubic form require slightly more calculation. A cubic form may indicate a flattening of the income-pollution relationship as well as an N- shaped path, not well approximated in the quadratic form (Carson, 2010).

The fixed-effects and random-effects models are commonly used to estimate the EKC model, where the fixed-effects model treats α_i as a regression parameter and random effects treats it as part of the disturbance term. The fixed-effects estimator is a method of applying OLS by including dummy variables for all (in this case) geographic entities to adjust for cross-sectional heterogeneity, and therefore adjusting for omitted-variable bias that would be evident under simple OLS. Fixed effects are computationally achieved by subtracting from each observation the average of all observations for that individual (county). The drawback is the loss of degrees of freedom from implicitly including dummies for every geographic entity (in this case, the 3000+ counties of the US), leading to inefficient estimates. Additionally, it removes the possibility of using any explanatory variables that are time-invariant, such as indicators of climate, for example. The alternative is a random-effects estimation, which allows for differing intercepts (α_i), but differs in that those intercepts are assumed to be uncorrelated with the explanatory variables and so therefore are treated as random and therefore part of the error term. The composite error term includes a random part for a particular individual, and another part that indicates a random deviation for the individual in that time period. For a single individual, the first part of the error remains constant in all time periods, and the second part is time-variant. Therefore, the random effects model allows use of time-invariant explanatory variables, though under the strong assumption that the individuals intercepts can indeed be treated as random and uncorrelated (Kennedy, 2008). In the case of EKC studies, Stern (2004) finds that only the fixed effects model can be estimated consistently for those data sets considered in the review. The author suggests use of a Hausman test to find inconsistency between the models; a significant difference in the slope parameters demonstrates that the random-effects model is inappropriate due to correlation between the explanatory variables and other components.

This analysis proceeds by first estimating a county-level fixed effects model to look for evidence of improvement in water quality across the US and evidence of the EKC relationship. A random-effects model will also be estimated, followed by application of the Hausman test to determine whether random effects can be used with the water quality datasets. Use of a random effects estimator is advantageous in this context as it would allow use of a climate-indicator and conclusions about the possible effects of a changing climate on the EKC relationship with water quality. Following List and Gallet's results that state-level EKCS differ from one another, this study will analyze several individual states for evidence of an EKC relationship as well.

An additional hypothesis seeks to determine whether the presence of sampling bias may have affected results drawn in previous US water quality studies, specifically Smith and Wolloh (2012) and Sigman (2004). It is possible that the datasets the authors used, as well as the one employed in this study, suffer from sampling bias. Policy analysis using panel data is especially prone to nonrandom sample selection due to attrition (Wooldridge, 2009). There are a number of possible factors at play that explain why a location's water quality is sampled once and/or is sampled several times over a period of years. It may be the case that locations that are more heavily sampled are those places that suffer from lower water quality. Variations in state and locality funding may play a part in the level of sampling, as well as variations in application of policy. Places that are threatened by development or part of endangered species habitats and ecosystems may be more closely monitored than other locations. While econometric testing for sampling bias is not a formal part of this study, visual inspection of differences in the models using datasets with shorter and longer timespans may allow inferences as to whether sample biases are at work. Specifically, if models using datasets from a longer span of time demonstrate more evidence of an impact of per-capita income growth on water quality, then it could be inferred that water quality is measured in places with poorer overall water quality, and therefore failure to include an adequate length of time will not produce evidence of an EKC.

B. Data and Expected Findings

1. Water Quality Data

Given the widespread availability of DO data and the use of DO concentration as one of EPA's water quality standard criteria, DO concentration is proposed to be the dependent variable as a proxy for water quality in general, with the acknowledgement that there are many other possible measurements and criteria. The dataset measuring dissolved oxygen concentrations comes from the National Water Quality portal, a cooperative service sponsored by the United States Geological Survey (USGS), the Environmental Protection Agency (EPA), and the National Water Quality Monitoring Council. The database includes water quality samples previously housed in USGS NWIS, and EPA STORET databases. The STORET Data Warehouse is EPA's repository of water quality monitoring data collected by water resources management groups across the county; data is submitted by states, tribes, watershed groups, federal agencies, volunteer groups and universities to make their data publicly accessible. The NWISWeb Database contains current and historical water data from sites across the nation and is used by state and local governments, utilities, private citizens, and federal agencies involved in management of water resources.

The data available includes information on the location of each observation of DO, including degrees of latitude and longitude, a standard watershed code (HUC8) devised by the USGS, and the state and county FIPS (Federal Information Processing Standards) codes. Other information includes the date of the sample observation, and the result of the test for dissolved oxygen in mg/L. The set is divided into two major groups: rivers and streams, and lakes; no data on coastal waters has been included. The earliest observation for streams took place in 1901, and includes all measurements for dissolved oxygen until December 31, 2012. The dataset is filtered into three smaller sets to include observations that took place at monitoring locations that have 10 or more years of data available, 20 or more years, and 30 or more years. The data is further restricted in some estimations to require at least 10, 20, or 30 observations are available at the county level. The length of the dataset is unique compared to many other EKC studies. Filtering the data into three sets limiting whether an observation belongs to a location with a long history of sampling or not is a key feature that may allow comparison of trends and may help explain why previous authors found (or not) evidence of an EKC. Figures 1 and 2 demonstrate the geographic distribution of the water quality samples, and how restricting the time span may provide evidence for sampling bias.

Several additional manipulations of the water quality data were necessary to prepare it for analysis. As mentioned above, dissolved oxygen concentration is affected by water temperature. Though temperature data is not available with the dissolved oxygen data, longer-term variations through the year can be accounted for by filtering data to only include DO median concentrations for the warmer months of the year, when DO concentrations will be lowest (and water species will likely be the most stressed). The warm season is defined as May-October for data in the streams sets, and June-November for the lakes sets. The season is defined slightly differently due to the effects of water depth on dissolved oxygen. Additionally, all observations with a value above 20 mg/L were dropped, as the upper bound of dissolved oxygen concentration is determined by temperature and altitude, and values above 14 are unlikely (personal correspondence, USFS Ecologist). As noted above in Section III, acceptable levels of dissolved oxygen depend greatly on the type of body of water, the temperature range of the water, and the ecosystems dependent on the specific body of water in question and therefore the associated beneficial uses designated for the segment of stream or lake. EPA's minimum criteria state that concentrations below 4 mg/L are unacceptable, though many states have much higher criteria. For example, the Department of Environmental Quality for the State of Oregon has established the minimum acceptable concentration to be 8 mg/L for water bodies providing cold water aquatic life (OR DEQ, 2010).

Figure 1: Geographic Distribution of Water Sampling Observations for Streams

The maps show the geographic distribution of sampling events for streams, where the top left map includes observations that have been taken at locations with 10 or more years of data, the top right map for locations with 20 or more years of data, and the bottom map for 30 or more years of data.

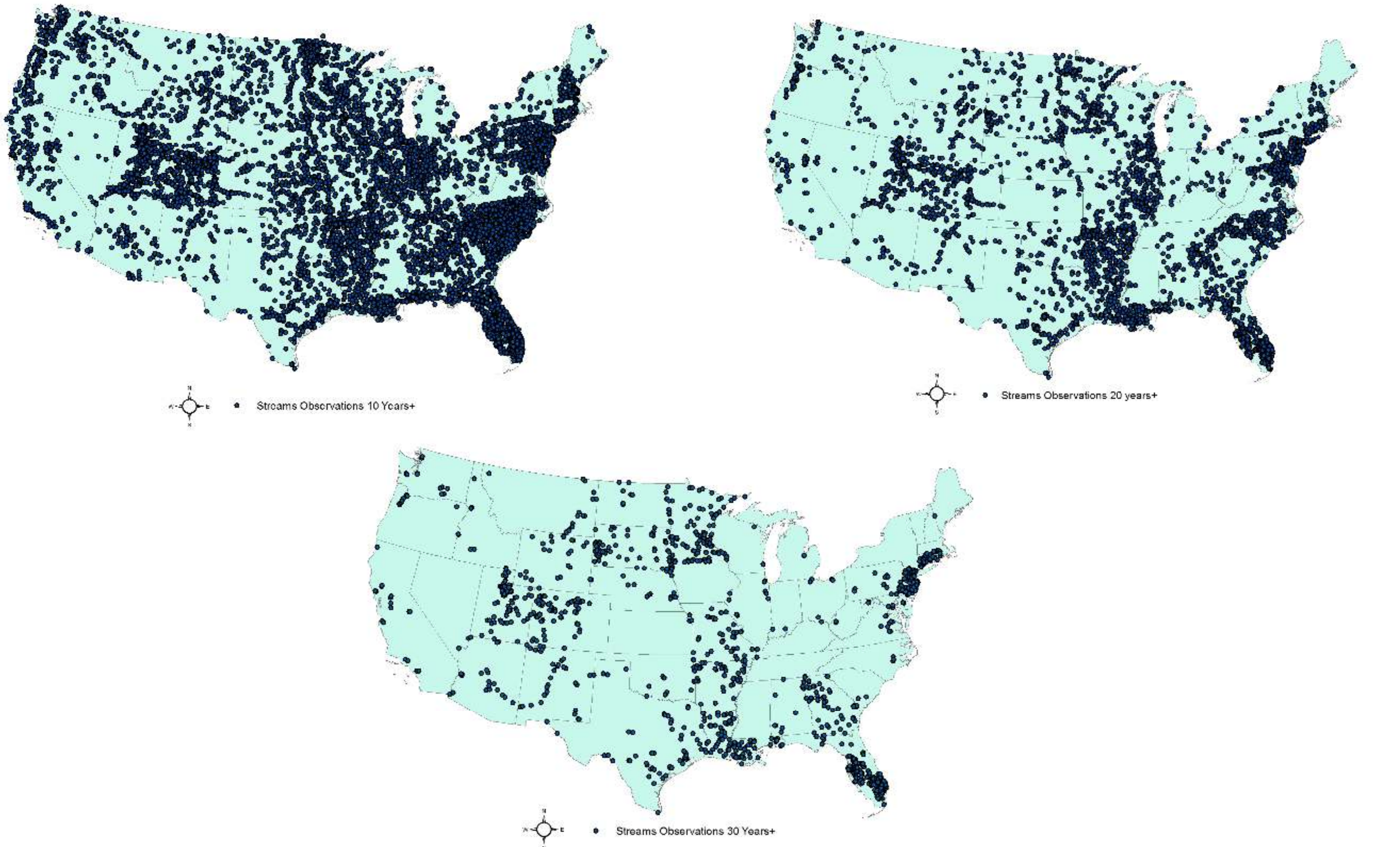
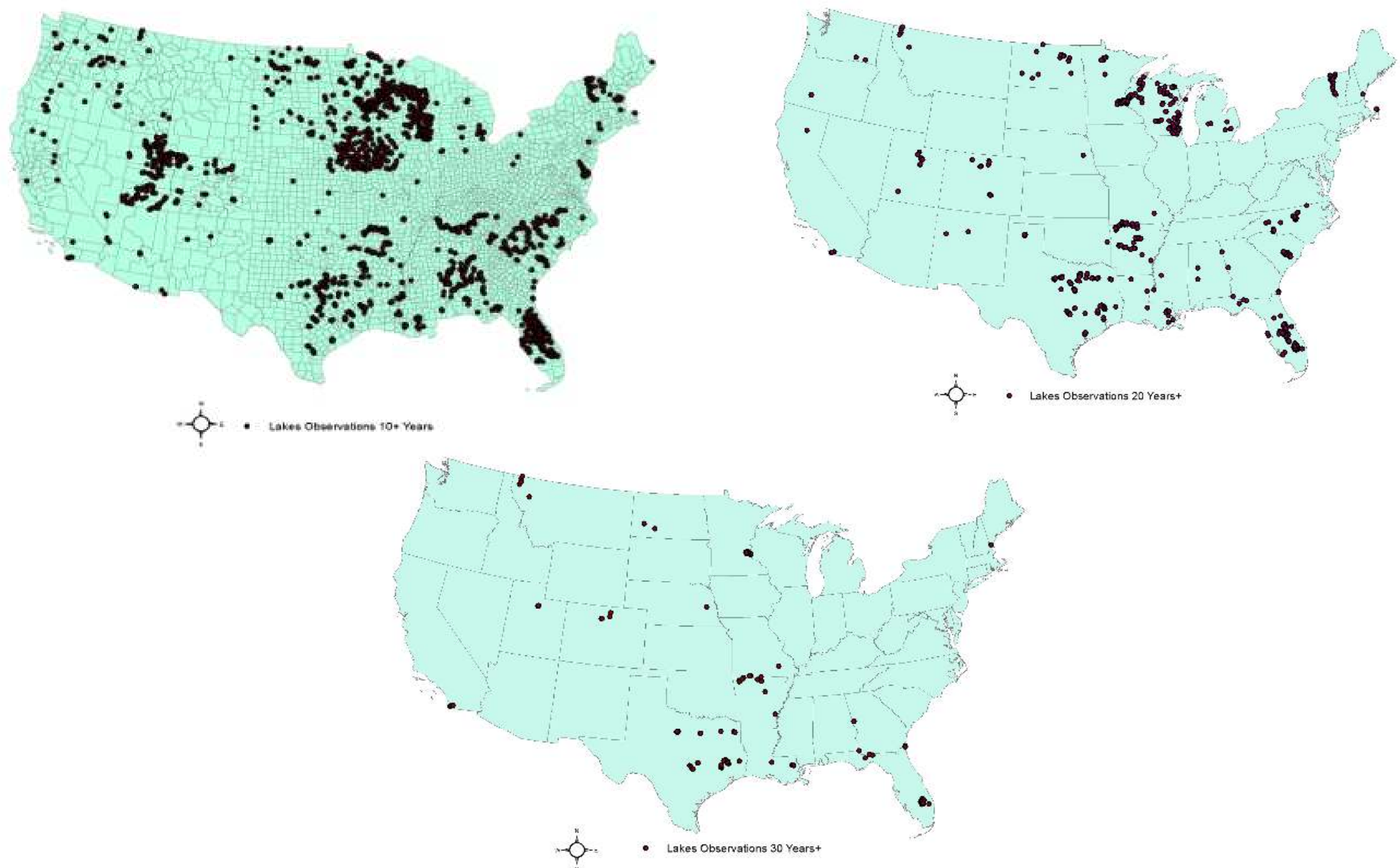


Figure 2: Geographic Distribution of Water Sampling Observations for Lakes

The maps show the geographic distribution of sampling events for lakes, where the top left map includes observations that have been taken at locations with 10 or more years of data, the top right map for locations with 20 or more years of data, and the bottom map for 30 or more years of data.



In order to use a common geographic level in the set of panel data, the water quality sample observations were aggregated into a countywide weighted average of DO concentration per year, keeping streams and lakes data separate. First, a warm-season median was calculated for each watershed, denoted by the eight-digit hydrological unit code (HUC8). The HUC8 denotes the cataloging unit, the smallest level, of geographic area within the USGS hydrologic unit classification system. A cataloging unit encompasses the geographic area representing a surface drainage basin, or watershed (USGS 2013). As watersheds follow hydrologic features, they cut across county-lines. Using GIS and the Watershed Boundary Dataset (USGS) and county boundary lines (available from US Census Bureau TIGER files), the percentage of each county that each watershed intersected was calculated to determine the weight each watershed should contribute to the county-average. Due to the fact that there was no water quality sampling data available for all watersheds, the sum of the percentage shares for which data was available was used as the denominator to weight the DO warm season average.

$$C_{it} = \sum_j W_{jt} * \left(\frac{H_{ij}}{\sum H_{ij}} \right) \tag{4}$$

Where: *i* indexes counties

t refers to years

j refers to watersheds

C_{it}: County-wide D.O. average concentration for county *i* in year *t*

W_{jt}: average of D.O. concentration for watershed *j* year *t*

H_{ij}: % share of land area of county *i* by the watershed *j*

2. Explanatory Variables

As described above, the EKC literature generally focuses on income or GDP growth per capita as the primary determinant of environmental degradation. Data for median income in 2010 dollars at the county-level from the decennial census is used for an income/capita variable. To demonstrate presence of an EKC, both an income/capita and an inc/cap squared variable is necessary; the literature also suggests that a cubic model using an additional inc/cap cubed variable could be included to allow additional flexibility in estimation. It is expected in this case that the sign on inc/cap would be negative (demonstrating the first half of the "U"), and the sign on the inc/cap squared variable would be positive (filling out the other half of the "U"). The data was most completely available beginning in 1969, thus the analysis will focus on this time point forward to 2012.

Population density (people per square mile) at the county level is another variable of interest. Paudel and Schafer (2009) include population density as a proxy for human activity on water population. Their results do not demonstrate any strong relationship with dissolved oxygen in parishes in Louisiana, but they state that the relationship may be positive or negative depending on the data. Rupasingha et al. (2004) hypothesize that a population density variable will be inversely associated with per capita pollution levels, because less populated areas are less likely to be concerned about pollution than more densely populated areas. Their results showed significance for just one of their models, but including a squared population density demonstrated an inverted-"U" shape between toxic releases and population density growth (421). Jaeger et al. (2011), as mentioned above, demonstrate that population density may exhibit an EKC relationship when properly specified. A population density variable would be expected in this context to have a negative sign, where more highly dense areas will have lower levels of dissolved oxygen from increased activities such as releases from wastewater treatment plants and stormwater runoff that negatively impact water quality. Population density data was also obtained from the decennial census, beginning in 1969.

Land use changes and development have an effect on water quality, particularly as intensity of agricultural activities change over time. Fertilizer applications in particular have a detrimental effect on dissolved oxygen when excessive levels of nitrogen and phosphorus enter surface waters from rain and storm events as well as non-use of best management practices, such as no-till farming. To account for land-use, the percentage land-area of a county in harvested cropland is calculated using harvested cropland acreage data available from the USDA Agricultural Census. The Census data is available very 5 years; the data was collected from 1969 forward for this study and imputed using a moving average. It is expected that higher percentages of county land area in harvested cropland will have a negative effect on water quality as measured by concentrations of dissolved oxygen.

A study by Sigman (2004) briefly described above on water quality improvements and the CWA suggests that the authorization of states by the EPA to run their own water quality programs to comply with CWA has an effect on water quality. The author found that states that were authorized had a small positive effect on water quality in the state. Applying Sigman's method in this context, a variable indicating whether the state is authorized to administer its NPDES program could account for differences in state water quality policies. Since authorization of a state by the EPA is related to administrative capacity and not to water quality in the state, issues of endogeneity are unlikely. The variable is constructed as an indicator according to whether the date of authorization was before or after the measurement of water quality was taken. The expectation of the result is ambiguous, though it could be the case that states authorized to administer their programs will do more to improve water quality than states whose programs remain under federal control.

An additional spatial aspect that could be studied is the disparity in water quality between rural and urban areas. The story has several possible outcomes. Urban areas could be expected to have higher water quality due to increased efforts and monitoring in those areas, while remote rivers and streams have relatively little attention paid to them. Conversely, it could be expected that urban areas are so polluted that natural levels of D.O. are no longer attainable, while rural surface water bodies are not subject to the withdrawals and releases of industrial plants and municipal water treatment facilities, resulting in better water quality comparatively. Stokey (1998) states that the shift in population from urban to rural should be considered when measuring increased exposure to pollutants as income rises. Rupasingha et al. (2003) include a variable indicating the level of urbanization at the county level under the expectation that urban areas experience higher levels of pollution due to congestion and more concentrated economic activity. The variable captures a population size or scale effect that is independent of population density, which is confirmed by their results. In this context, a rural-urban continuum (Beale) code available from the USDA ERS is used. It varies between 0 (rural) and 9 (most urban), and is available every 10 years; it has been linearly imputed for inclusion in this study.

In addition to seasonal effects, climatic variations may also exhibit an effect on the EKC relationship. List and Gallet (1999) included a climate variable in the form of the number of heating degree days; their results indicate that states with a greater number of heating days reached the EKC peak at higher levels than states that have warmer climates. Another way to describe climate variation is in the form of an aridity index, which measures how arid or humid a climate is by dividing mean average precipitation by average evapotranspiration. The index varies from 0-5, where 0 indicates very arid climates and 5 very humid climates. The Consortium for Spatial Information provides a global level aridity index map for the period 1950-2000, calculated using methods as described by Zomer et al. (2008, 2007). The map was first downscaled to the county level, and then aridity values were obtained for each county. The downside of this approach is that the aridity values do not vary over the period of study, meaning no conclusions can be drawn from a fixed effects estimation method. In the case where a random effects model may be appropriate, however, a coefficient may shed light on how future changes in climate may affect water quality. The sign on an aridity variable coefficient is not entirely clear; it could be that dryer places have better water quality since water is recognized as a scarce resource and more care is taken to keep it clean. Alternatively, dryer places could have worse water quality due to a lower carrying capacity to disperse pollution and a lower range of tolerable variation in water quality.

Table 1: Descriptive Statistics for Explanatory Variables

Variable	Data Source	Geographic Level	Mean	Range
Dissolved Oxygen (mg/L)	National Water Quality Portal	Stream	7.74	0.1-18.6
Dissolved Oxygen (mg/L)	National Water Quality Portal	Lake	6.55	0.1-16.2
Average Income/Capita (2010 $)	Decennial Census, American Community Survey	County	27,647.78	6,514.67-137,479.7
Population Density (per sq. mile)	Decennial Census	County	217.35	.08-70,923.47
% of County Area (sq miles) in Harvested Cropland	Agricultural Census, USDA	County	21.74%	0-94.8%
Rural-Urban Continuum (Beale) Code	USDA ERS	County	5.5	0-9 (0 most rural, 9 most urban)
State Authorization of NPDES program administration	EPA	State	(dummy)	0,1
Climate: Aridity Index	CGIAR-CIS	County	0.823	0-5

V. Results and Discussion

A. Results from the Streams Models

The results from each of the three streams datasets are detailed in tables 2-4 below. The dataset titled “Streams 10 Years or More” includes monitoring locations that had data points that spanned at least ten years before aggregation; however there was no restriction that there were ten continuous years. Once at the county level, it was possible to have counties that had only one data point, because some points that were above the 20 mg/L cut-off point or had incomplete data were dropped. To account for those points, a restricted model was run on only those counties that included ten (twenty, thirty) or more years of data. Many specifications of the model were run, including a quadratic specification for both income and population density, a cubic specification for both income and population, and a cubic specification for income and a quadratic for population density, and vice versa. Given that a cubic specification of population density did not demonstrate a significant relationship in any of the models, the results presented below include a cubic specification for income per capita and a quadratic specification for population density.

A pooled OLS model is presented to allow comparison and demonstrate the appropriateness of the fixed effects model. A pooled OLS model in this context is likely suffering from endogeneity from omitted variable bias (Wooldridge, 2009). There is a wide range of possible factors that affect both dissolved oxygen and per capita income that are not included in the model. Geographical features do affect concentrations of dissolved oxygen: mountainous streams will have different levels of dissolved oxygen than wide meandering rivers. Equivalently, places with different geographical features will also have different levels of per capita income and population density; for example, Lagerlöf and Basher (2005) find that early settlement patterns in North America were guided by geography and have an impact on current levels of per capita income and population density. Climate is another factor, related to geography, which may affect per capita income levels as well as dissolved oxygen concentrations. Other unobservables include the primary economic drivers of a county; while the percentage of a county area in harvested cropland is included in the model, the size of industrial and service sectors are not included, which may have an impact on income levels as well as dissolved oxygen levels if there are many industrial points releasing into surface waters. Variations in land use regulations may also affect both income per capita and water quality; places that allow uninhibited urban sprawl will have different patterns of development, than those that have more restrictive regulations.

Table 2: Regression Results for Streams Data Spanning 10 or More Years

	Pooled OLS		Fixed Effects		Restricted Fixed Effects	
	Coefficient	Std. Error	Coefficient	St. Error	Coefficient	Std. Error
Per Capita Income	0.0002245***	0.0000244	-0.0000156	0.0000135	-0.0000188	0.0000139
Per Capita Income Squared	-2.88E-09***	5.19E-10	4.15E-10	2.62E-10	4.80E-10	2.72E-10
Per Capita Income Cubed	1.16E-14***	3.08E-15	-2.80E-15	1.45E-15	-3.19E-15*	1.53E-15
Population Density	-0.0002834**	0.0001123	0.0004243	0.0003164	0.0004183	0.0003187
Population Density Squared	2.92E-08**	1.21E-08	-2.90E-08*	1.24E-08	-2.78E-08*	1.22E-08
Percentage of County Area in Harvested Cropland	0.0008432	0.0013128	-0.0066349	0.0047346	-0.005856	0.0047808
Beale Code	0.1467995***	0.0128445	-0.0132894	0.0155553	-0.0141108	0.0157998
State Authorization of NPDES Authorization	0.4425212***	0.0798525	0.0440136	0.0367139	0.0470488	0.037332
Constant	3.584509***	0.3334287	7.872633***	0.241677	7.870986***	0.2467614
R-Squared	0.0916		0.0153		0.00283	
Year Dummies	Yes		Yes		Yes	
# of Obs	41999		41999		39734	
# of FIPS			1987		1560	
Range of Obs per FIPS			1-44		11-44	
Turning Point Income	62,813 (max) 102,705 (min)		25,245 (min) 73,564 (max)		26,678 (min) 73,634 (max)	
Turning Point Population	4,853		7,315		7,523	

* p<0.05, ** p<0.01, *** p<0.001

Table 3: Regression Results for Streams Data Spanning 20 or More Years

	Pooled OLS		Fixed Effects		Restricted Fixed Effects	
	Coefficient	Std. Error	Coefficient	St. Error	Coefficient	Std. Error
Per Capita Income	0.0002379***	0.0000489	-0.0000547**	0.0000199	-0.0000562*	0.0000222
Per Capita Income Squared	-3.22E-09**	1.24E-09	1.22E-09*	4.74E-10	1.29E-09*	5.34E-10
Per Capita Income Cubed	1.42E-14	9.24E-15	-8.59E-15*	3.47E-15	-9.38E-15*	3.98E-15
Population Density	-0.0002434	0.0001366	0.0001481	0.0004031	0.0001468	0.0004361
Population Density Squared	2.45E-08	1.28E-08	-2.52E-08	1.65E-08	-2.44E-08	1.72E-08
Percentage of County Area in Harvested Cropland	-0.0000325	0.001714	-0.0053592	0.0051164	-0.0017732	0.0057327
Beale Code	0.165291***	0.0160683	-0.0296986	0.0161985	-0.0241593	0.0175892
State Authorization of NPDES Authorization	0.5098907	0.0953109	-0.0766066	0.0405776	-0.0552556	0.0430524
Constant	3.216565***	0.5704244	8.454618***	0.2938879	8.347437***	0.3256173
R-Squared	0.1015		0.0114		0.00109	
Time Dummies	Yes		Yes		Yes	
# of Obs	27272		27272		22279	
# of FIPS			1183		722	
Range of Obs per FIPS			1-44		21-44	
Turning Point Income	64,235 (max) 86,939 (min)		36,450 (min) 58,233 (max)		35,627 (min) 56,058 (max)	
Turning Point Population	4,967		2,938		3,008	

* p<0.05, ** p<0.01, *** p<0.001

Table 4: Regression Results for Streams Data Spanning 30 or More Years

	Pooled OLS		Fixed Effects		Restricted Fixed Effects	
	Coefficient	Std. Error	Coefficient	St. Error	Coefficient	Std. Error
Per Capita Income	0.0002354**	0.0000735	-0.0000264	0.0000268	-0.0000349	0.000032
Per Capita Income Squared	-3.14E-09	1.87E-09	5.70E-10	6.37E-10	8.24E-10	7.36E-10
Per Capita Income Cubed	1.45E-14	1.44E-14	-3.25E-15	4.69E-15	-5.28E-15	5.31E-15
Population Density	-0.0001873	0.0001652	0.0001967	0.0005931	0.0006609	0.0006877
Population Density Squared	2.27E-08	1.49E-08	-1.78E-08	2.36E-08	-1.11E-07	5.88E-08
Percentage of County Area in Harvested Cropland	0.00106	0.0024663	-0.0039308	0.0074208	0.0011534	0.0083881
Beale Code	0.2105552***	0.0247033	-0.0029477	0.023378	-0.0075253	0.0285679
State Authorization of NPDES Authorization	0.6348338***	0.1394346	-0.1220131**	0.0482029	-0.064329	0.0597865
Constant	3.109509***	0.862773	8.054059***	0.4137399	8.020953***	0.5048215
R-Squared	0.1320		0.0143		0.0241	
Time Dummies	Yes		Yes		Yes	
# of Obs	13385		13385		8908	
# of FIPS			516		241	
Range of Obs per FIPS			1-44		31-44	
Turning Point Income	72,184 (inflection)		31,814 (min) 85,108 (max)		29,308 (min) 76,333 (max)	
Turning Point Population	4,126		5,525		2,977	

* p<0.05, ** p<0.01, *** p<0.001

As described in section V(B), the county-level fixed effects model takes care of the unobserved heterogeneity that is time-invariant (climate, geography) by time-demeaning the data and allowing each county its own intercept. The disadvantage is the loss of any other explanatory variables that do not change over time. As an alternative, the random-effects model also assumes that each county has its own effect (estimated as an intercept), though they are treated as random and uncorrelated, a strong assumption. The Hausman test has been used in each model to determine which is appropriate; for all of the streams models the null hypothesis was rejected in favor of the fixed effects model, as noted in table 5. Robust clustered errors are used in this context to account for heteroskedasticity as well as within-county serial correlation. A modified Wald test confirms groupwise heterskedasticity in the fixed effects models, also noted in table 5. While the fixed effects model allows each county its own intercept in the estimation, it is still possible that there is serial correlation within each individual county over time. Cameron and Miller (2013) suggest that failure to control for within-group error correlation through use of clustered errors can lead to small standard errors and incorrect inferences about statistical significance. In that light, errors are clustered according to the county level.

Table 5: Results for the Hausman Test for Random Effects and the Wald Test for Heteroskedasticity in the Streams Data

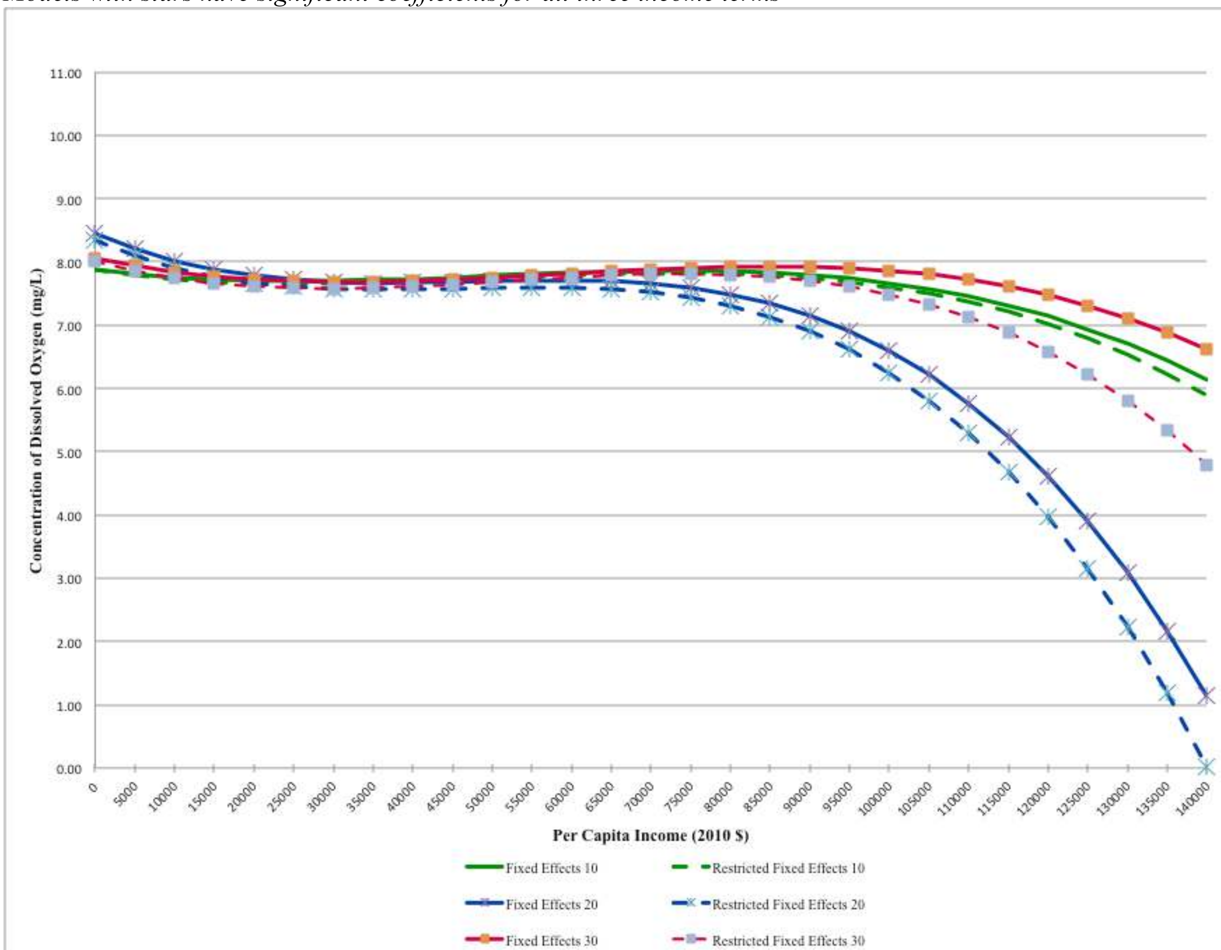
Dataset	**Hausman Test Result**	**Wald Test Result**
	Chi-Squared	Chi-Squared
Streams 10	113.78***	6.0e+34***
Streams 20	95.39***	1.8e+35***
Streams 30	79.01***	2.9e+32***

Comparing the coefficients from the pooled OLS and the fixed effects model, it is evident from the change in the signs on the income coefficients that the fixed effects model is aiding in the omitted variable bias problem in the pooled OLS model. The income coefficients are all statistically significant, though very small in magnitude. Restricting the model to included counties that had at least ten or more years of data did not appreciably change the coefficients, as is evidenced in figure 3, where the dark green line indicates the relationship for the fixed effects model and the lighter green line is that of the restricted fixed effects model. Percentage of county area harvested has a negative sign, as expected, and the Beale code was also found to have a negative effect, indicating that the more urban an area, the worse the water quality as measured by dissolved oxygen. Unexpectedly, the sign for population density is positive and that for density squared is negative, the converse of the EKC expectation. Only the population density squared variable was statistically significant among the other variables, which does not aid in tracing out an EKC relationship.

The models for the datasets including locations that had data spanning at least twenty years and thirty years demonstrated no significant relationship between income and dissolved oxygen concentration. Figure 3 shows graphically the relationships from the models; the relationship is generally flat, with a decrease in water quality shown at the highest levels of county-level income per capita, above $85,000. Just a few counties in the US do have per-capita income levels beyond that range, including Teton, Wyoming; Arlington, Virginia; Fairfield, Connecticut; Pitkin, Colorado; and Marin, California. The restricted fixed effects model for the dataset with thirty years did not demonstrate the downward sloping portion, likely because just three observations were beyond the high income point; the relationship was not found to be statistically significant.

Several states were chosen with the largest amounts of data available to examine evidence of an EKC within the state, including Arkansas, Florida, Minnesota, North Carolina, and Texas. The state models were run using the ten year data set and were specified using a cubic relationship for income and a quadratic for population density according to significance in the variables, except in the case of Florida, in which the cubic form for population density was found to be most appropriate. The signs on income variables were as expected in all models, but no statistical significance was present for income except for the cubic variable in the Minnesota estimation. The relationships, as shown in Figure 1 of the appendix, indicate a fairly flat relationship overall, with the exceptoin of Arkansas, which does demonstrate an inverted-U curve, though truncated when including the maximum per-capita income of the state. State authorization of the NPDES program had a negative and statistically significant impact in the Arkansas estimation, while the coefficient for the Beale code demonstrated a negative and statistically significant impact in the estimation for Minnesota. A negative impact of state authorization is contrary to the findings in the literature by Sigman (2004), though a negative impact of the level of urban development is as expected. Regression results as well as descriptive statitics for the state models are found in the appendix in tables 1 and 2.

Figure 3: Relationship between Per Capita Income and Dissolved Oxygen from Streams Estimations
Models with stars have significant coefficients for all three income terms



Additional graphical analysis at a lower geographic level demonstrates the difficulty of finding large national-level trends. To determine whether there were more localized improvements in water quality, the streams dataset including locations with at least thirty years of data was narrowed to counties for which the first four years of their samples had an average less than four mg/L (the lowest acceptable cold water threshold according to EPA). Analyzing a subset of example counties for each state using graphs demonstrates that some places have in fact experienced improvements in water quality, while others have not necessarily experienced a decline in water quality, but no significant improvements either. For example, Broward County, Florida shows little change in the average level of water quality over time, while Jackson County, Mississippi and Dallas County, Texas show an uptick in the average level of dissolved oxygen.

Figure 4: Trend in Water Quality for Jackson County, Mississippi

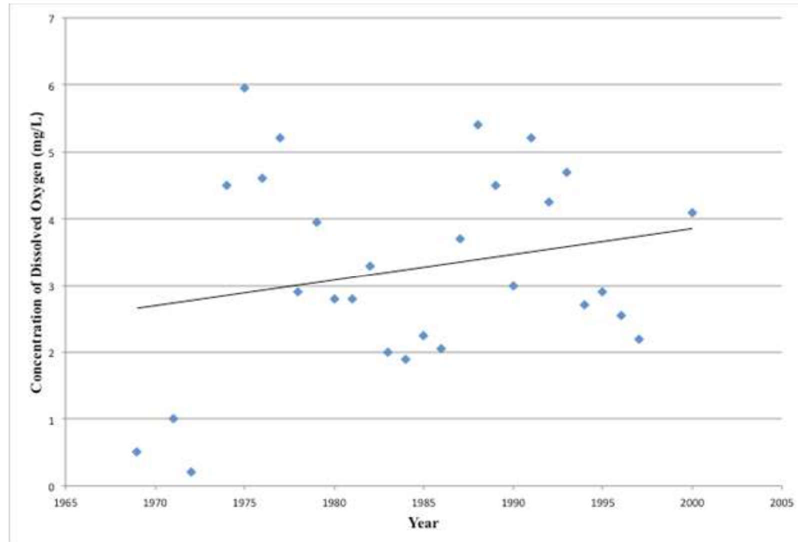


Figure 5: Trend in Water Quality for Broward County, Florida

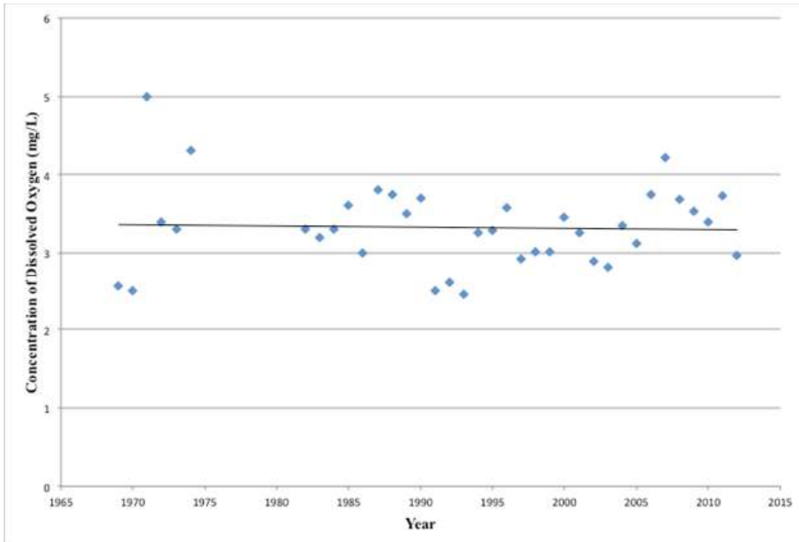


Figure 6: Trend in Water Quality for Dallas County, Texas

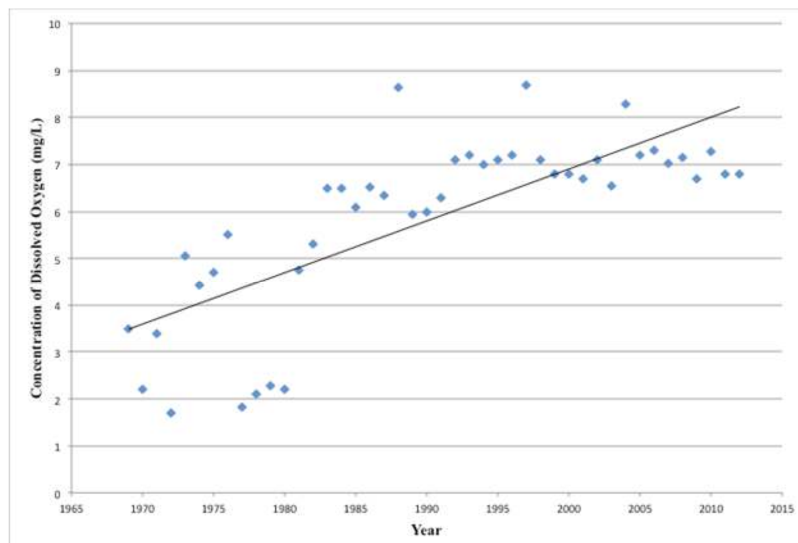
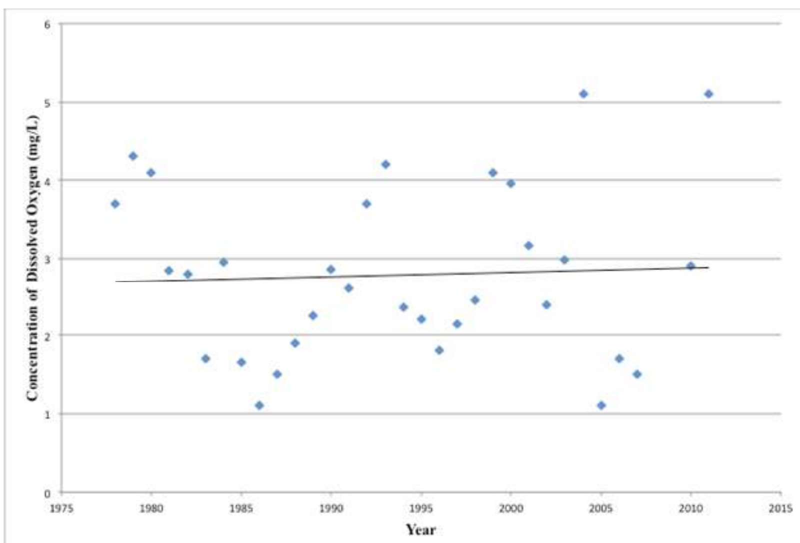


Figure 7: Trend in Water Quality for Jefferson County, Louisiana



B. Results from the Lakes Models

The results from the three models run with the three lakes datasets are presented below in tables 6-8. As in the streams models, allowing a cubic relationship with income and a quadratic relationship with population gave the best fit in all three datasets. The dataset for monitoring locations with data spanning ten or more years was the only one to exhibit a statistically significant relationship between income and dissolved oxygen; no other variables were found to be significant with the exception of the percentage of the county area in harvested cropland, where the effect was found to be unexpectedly positive, though small. A Hausman test failed to reject the null hypothesis that there was systematic difference between the fixed and random effects estimates for all of the lakes datasets, therefore the random effects results are presented below. As in the streams models, the estimated coefficients are very small. The ten year dataset does exhibit a slightly different relationship from that found in the twenty and thirty year datasets, though this is likely due to the fact that the data points beyond a per capita income of $70,000 were not found in the twenty and thirty year set.

There is no conclusive evidence for an EKC with population density; the ten year model demonstrates the expected relationship, first downward sloping and then turning at a density of 4,216 people per square mile. The relationship is reversed, however, in the twenty and thirty year models and no statistical significance is demonstrated in any of the models. The percentage of the county in harvested cropland shows a positive relationship with water quality in the lakes models as well, and is significant in the ten and twenty year models. The precise interpretation of this variable may be complicated, however, by the adoption of best management practices to reduce runoff during the time period of the study. The Beale code, indicated the level of urbanity of a county, has a positive coefficient in all three lakes models, though is not significant. The dummy variable indicated whether the state was authorized to administer its NPDES program at the time of the sampling event does not demonstrate a conclusive relationship with water quality; it is positive in the ten and thirty year models and negative in the twenty year models, with no statistical significance found. As the random effects models were not rejected by the Hausman test for the lakes data, a variable measuring aridity index was also included. As expected, it demonstrates a small positive relationship with water quality, though not of significance. Figure 6 demonstrates the estimated relationships; they appear less flat than those found in the streams data, with a slight gradual upward slope in the twenty and thirty year sets, but overall little evidence for an EKC relationship.

Those states that had the largest amounts of data available for lakes were also tested in the models, including Florida, Iowa, Minnesota, Texas, and Wisconsin. Of those estimated, Iowa was the only estimation to demonstrate full significance in both the income variables as well as the population density variables. The size of the coefficients are quite small, and so the demonstrated relationship is relatively flat with a small upward slope after an income per capita of $34,612 that turns downward after $50,647. The graph of the relationship, found in figure 2 of the appendix, shows a large downward slope, but focusing on just the range of income found in the data (19,000-56,000) puts the relationship into context. The relationship with population density for Iowa is opposite of expectation, where the relationship is first positive and then negative after an estimated 623 people per square mile (the maximum for Iowa is 323). Overall, there is no significance found in the other explanatory variables in any of the states, and the estimated coefficients for the income and population density relationships are, consistent with the above findings, quite small. The regression results and graph for the state lakes results are available in the appendix in tables 3 and 4 and figure 2.

The graphical analysis focused on county-level trends in water quality was repeated; in this case the ten-year dataset for the lakes was used due to the paucity of data in the twenty and thirty year datasets. The dataset was narrowed to locations with an average level of water quality of less than five mg/L (one mg/L higher than EPA's coldwater minimum threshold) during the first four years of sampling.

Table 6: Regression Results for Lakes Data Spanning 10 or More Years

	Pooled OLS		**Random Effects**		**Restricted Random Effects**	
	Coefficient	Std. Error	Coefficient	St. Error	Coefficient	Std. Error
Per Capita Income	-0.000056	0.0000934	-0.0001461*	0.0000675	-0.0001313	0.0000698
Per Capita Income Squared	2.81E-09	2.41E-09	3.54E-09*	1.74E-09	3.15E-09	1.81E-09
Per Capita Income Cubed	-2.81E-14	1.99E-14	-2.74E-14	1.45E-14	-2.48E-14	1.51E-14
Population Density	-0.0005868	0.0005002	0.0001483	0.0004515	0.0000537	0.0004574
Population Density Squared	1.30E-07	1.43E-07	-3.32E-08	1.23E-07	-4.95E-09	1.22E-07
Percentage of County Area in Harvested Cropland	0.026417***	0.0028064	0.029804***	0.0025553	0.0335886***	0.0026197
Beale Code	0.0839277	0.0321178	0.0435178	0.030186	0.0445035	0.0318304
State Authorization of NPDES Authorization	0.6377233***	0.175065	0.1885019*	0.0844577	0.2310783**	0.0892392
Aridity Index	0.0624874	0.1937421	0.0192423	0.2022772	0.1909598	0.2423425
Constant	5.716983***	1.347578	7.547794***	0.997351	7.113892***	1.043422
R-Squared	0.145		.0119		0.0130	
Time Dummies	Yes		Yes		Yes	
# of Obs	8448		8448		7458	
# of FIPS			570		389	
Range of Obs per FIPS			1-44		11-44	
Turning Point Income	12,195 (min) 54,471 (max)		34,275 (min) 51,857 (max)		37,068 (min) 47,610 (max)	
Turning Point Population	2258		2233		5424	

* p<0.05, ** p<0.01, *** p<0.001

Table 7: Regression Results for Lakes Data Spanning 20 or More Years

	Pooled OLS		**Random Effects**		**Restricted Random Effects**	
	Coefficient	Std. Error	Coefficient	St. Error	Coefficient	Std. Error
Per Capita Income	0.0001996	0.0001828	0.0000363	0.0001143	3.78E-06	0.0001224
Per Capita Income Squared	-5.31E-09	4.77E-09	-1.80E-09	2.93E-09	-8.90E-10	3.09E-09
Per Capita Income Cubed	4.55E-14	3.96E-14	1.89E-14	2.43E-14	1.06E-14	2.52E-14
Population Density	-0.0003607	0.0007229	0.000656	0.0008125	-0.0003456	0.0009117
Population Density Squared	3.89E-08	2.05E-07	-1.72E-07	2.11E-07	5.03E-08	2.57E-07
Percentage of County Area in Harvested Cropland	0.0261439**	0.008439	0.0230739*	0.0097814	0.0174354	0.0094539
Beale Code	0.0395588	0.0542392	0.0437625	0.0439239	-0.0019983	0.0412274
State Authorization of NPDES Authorization	0.8762997***	0.255117	0.0173981	0.1291308	0.1576028	0.1328685
Aridity Index	0.5178737*	0.2228155	0.4759819*	0.2390105	0.4875898	0.2881747
Constant	4.387509*	2.175155	6.205118***	1.355621	7.392029***	1.462026
R-Squared	.1095		0.0563		0.0610	
Time Dummies	Yes		Yes		Yes	
# of Obs	3136		3136		2476	
# of FIPS			160		88	
Range of Obs per FIPS			1-44		21-44	
Turning Point Income	31,915 (max) 46,044 (min)		12,573 (max) 50,918 (min)		53,764 (inflection)	
Turning Point Population	4636		1907		3435	

* p<0.05, ** p<0.01, *** p<0.001

Table 8: Regression Results for Lakes Data Spanning 30 or More Years

	Pooled OLS		Random Effects		Restricted Random Effects	
	Coefficient	Std. Error	Coefficient	St. Error	Coefficient	Std. Error
Per Capita Income	0.0000382	0.0002556	0.0000382	0.0002556	-0.0001762	0.0003234
Per Capita Income Squared	-1.31E-09	6.14E-09	-1.31E-09	6.14E-09	4.33E-09	7.21E-09
Per Capita Income Cubed	1.47E-14	4.78E-14	1.47E-14	4.78E-14	-3.02E-14	5.31E-14
Population Density	-0.0000722	0.0011025	-0.0000722	0.0011025	0.0001553	0.0008923
Population Density Squared	-1.22E-07	3.06E-07	-1.22E-07	3.06E-07	-2.22E-07	2.45E-07
Percentage of County Area in Harvested Cropland	0.0474567***	0.0127354	0.0474567***	0.0127354	0.0434333***	0.0121992
Beale Code	-0.0006391	0.1027579	-0.0006391	0.1027579	-0.0348985	0.1113813
State Authorization of NPDES Authorization	1.305622**	0.4146073	1.305622**	0.4146073	1.56891***	0.4528398
Aridity Index	1.380665	1.151864	1.380665	1.151864	1.151128	1.228645
Constant	4.84421	3.907567	4.84421	3.907567	7.51701	4.853791
R-Squared	0.2314		0.0611		0.0689	
Time Dummies	Yes		Yes		Yes	
# of Obs	1005		1005		811	
# of FIPS			41		23	
Range of Obs per FIPS			1-42		31-42	
Turning Point Income	29,705 (inflection)		29,705 (inflection)		29,372 (min) 66,213 (max)	
Turning Point Population	-		-		-	

* p<0.05, ** p<0.01, *** p<0.001

Table 9: Results for the Hausman Test for Random Effects and the Wald Test for Heteroskedasticity in the Lakes Data

	Hausman Test Result	**Wald Test Result**
	Chi-Squared	Chi-Squared
Lakes 10	4.44	6.8e+35***
Lakes 20	4.16	1.2e+36***
Lakes 30	2.74	5.2e+36***

* p<0.05, ** p<0.01, *** p<0.001

Figure 8: Relationship between Per Capita Income and Dissolved Oxygen from Lakes Estimations
Models with stars have significant coefficients for all three income terms

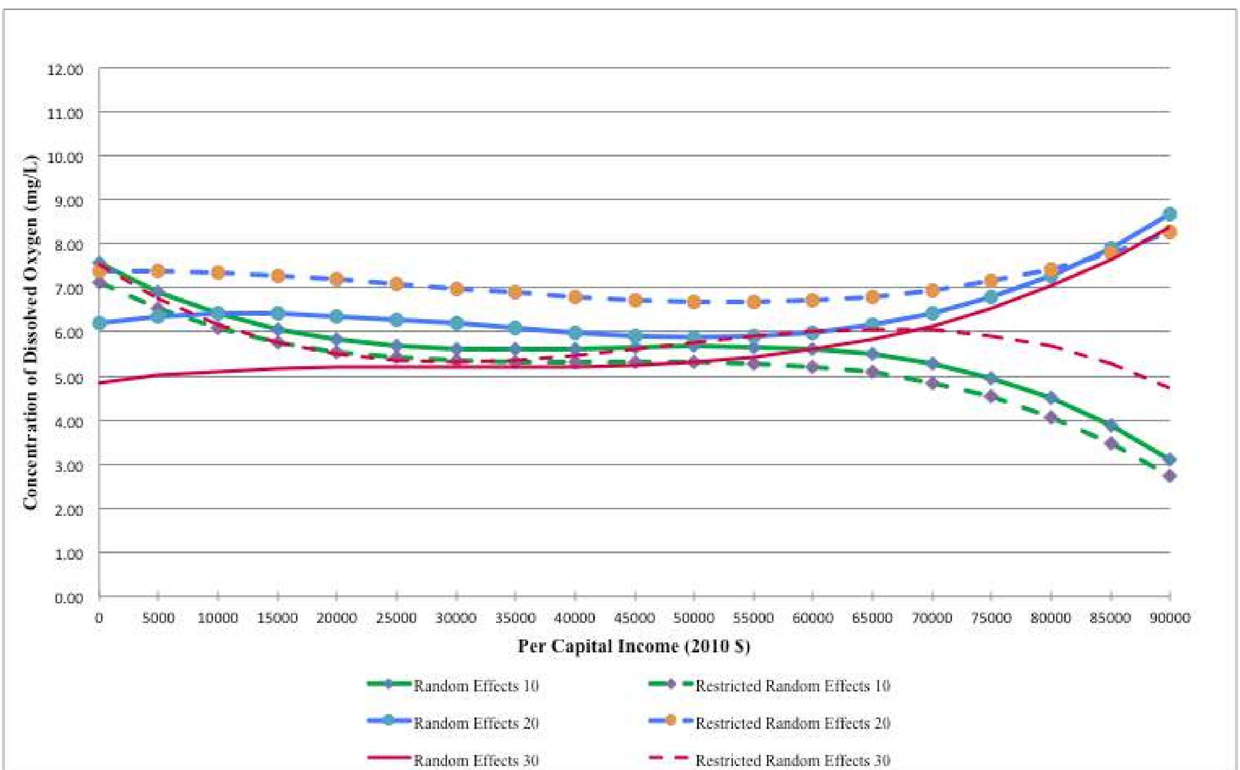


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Figure 11: Trend in Water Quality for Elmore County, Alabama

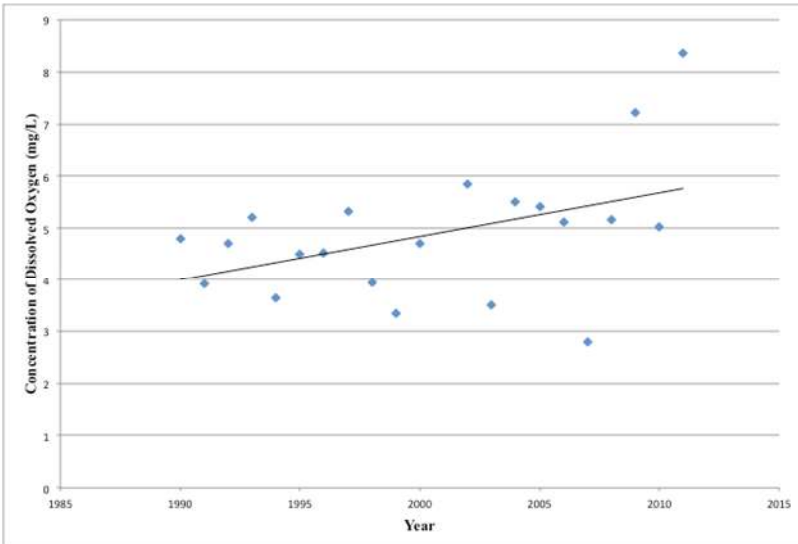


Figure 10: Trend in Water Quality for Lee County, Florida

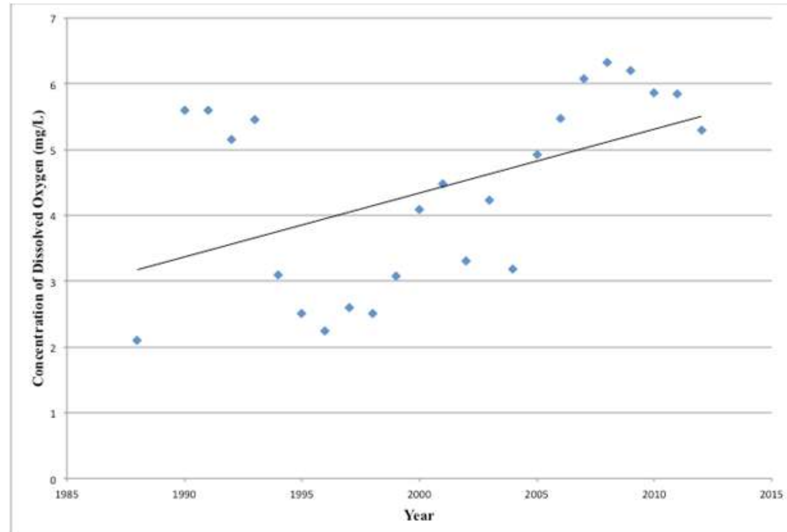
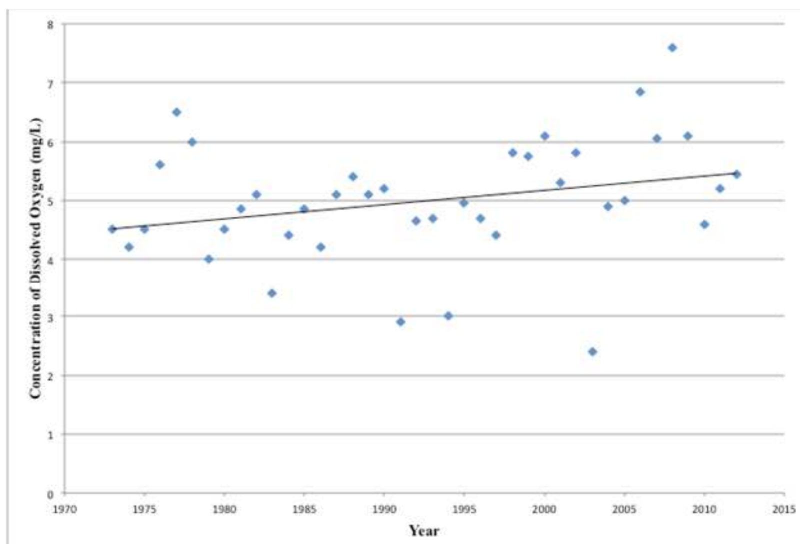


Figure 9: Trend in Water Quality for Montgomery County, Texas



C. Discussion

Though the statistical evidence from this study fails to confirm the existence of an EKC relationship between per capita income and water quality in the US, it does fall in line with previous authors' findings for US specific studies. As stated above, Smith and Wolloh (2012) found no evidence for an EKC using an index of water quality based on thresholds of dissolved oxygen for lakes. Paudel et al. (2005) do find evidence of the EKC relationship in Louisiana, but without strong statistical support. Their estimations of turning points are significantly lower than those found in this study for streams, though that is likely due to the fact that the per capita income of Louisiana is lower than the national average; the mean per capita income in their study was \$10,353 (assumed 2005 dollars), as compared to \$27,647 (2010 dollars) in this study. Table 10 compares these studies and their findings with the findings from this study for the ten year datasets.

Turning to the issue of sampling bias as a possible reason for the lack of EKC evidence in previous studies, the results presented here do not support the hypothesis that a longer set of data would provide more robust evidence for an EKC. In fact, the data sets that span longer lengths of time in both the streams and lakes data fail to provide any robust estimates for a relationship between per capita income and dissolved oxygen or population density and dissolved oxygen. This may be due to issues stemming from the data itself. The National Water Quality Portal data is a combination of data from the EPA and USGS databases; with much of the data from stream gauges placed by federal and state agencies though some coming from other sources such as academic and volunteer groups doing on-site sampling. The CWA most immediately targeted issues related to large point-source polluters whose releases affected water quality for a "shadow" downstream of 20-30 miles. While the water quality in these downstream segments of a relatively small number of large point sources may have experienced significant improvement over the time of the study, any evidence of such has likely been drowned out by the sheer volume of data (personal communication, Jay Shimshack, 2014).

Table 10: Comparison of EKC Findings for Water Quality in the Literature

Authors	Geographic Level	Measurement of Water Quality	Measurement of Economic Growth	Finding	Turning Point
Paudel, Zapato, Susanto 2005	Louisiana; Parish-level	Dissolved Oxygen	Parish per-capita income	Some evidence of an EKC; not statistically significant	Quadratic: $9,612 Cubic: $9,145
Smith & Wolloh, 2012	National; State-level	Weighted averages of dissolved oxygen	Real per capita GDP	No evidence	
Rupasingha et al. 2005	National; County-level	Toxic surface water discharge	County per capita income	Statistically significant evidence	Quadratic: $22,520
Sigman, 2004	National; State level	Water quality index based on dissolved oxygen, fecal coliform, total suspended solids, phosphorous, and nitrogen	State-level personal	Positive coefficient; no statistically significant relationship	
Estimation Results from Streams 10-Year Dataset	County	Dissolved Oxygen	Per-Capita Income	Small, statistically significant evidence	Cubic: $62,094
Estimation Results from Streams 10-Year Dataset	County	Dissolved Oxygen	Per-Capita Income	Small, statistically significant evidence	Cubic: $36,793 (min) $55,426 (max)

There is also the possibility of occurrence of a Type II error, where the evidence fails to reject the null hypothesis that there is no significant relationship between dissolved oxygen and water quality. One reason for this may be the method of construction of the dataset; aggregating the dissolved oxygen data to the county level may be losing necessary variation to see a relationship, and canceling out shadow effects from improvements under the CWA as mentioned above. An alternative would be to model the relationship at the watershed level instead, where averages are still taken from the stream level, but are not weighted according to the land area that a watershed occupies in a county. As watersheds tend to be physical units with unique characteristics to each, it is not unlikely that this method of aggregation could produce more favorable results. Expansion of the panel set to include information about enforcement of the CWA by the EPA and state agencies could also further define some of the unobservable information, and provide additional insight about the effectiveness of the CWA and its amendments. Finally, focusing the data on specific time periods (between 1980 and 1990, for example) may improve the results, as there are very few monitoring locations that are consistently followed throughout the 1969-2012 time period. Choosing a time period that has many locations followed consistently for the shorter time period may result in differing conclusions.

Aside from data issues, the lack of evidence of an EKC leads to the question of whether water quality should be a focus of policy efforts; do people care about clean water? The intuitive answer would be, yes, and authors Netusil et al. (2014) confirm that fact in a hedonic study of the metropolitan area encompassing Portland, OR and Vancouver, WA to determine the impact of water quality in streams on housing values. The water quality parameters of interest included levels of fecal coliform, pH, dissolved oxygen concentration, and stream temperature. The authors use a spatially explicit model to test the relationship between water quality and housing prices at various distances. Their results for dissolved oxygen indicate that a one mg/L increase in water quality can have an impact ranging from 2.44-13.7% of the property sale value during the dry season of the year, depending on the distance (between ¼ and greater than 1 mile) of the property from the stream. Therefore, individuals appear to be incorporating the value of water quality in their home purchasing decisions, leading to the conclusion that there should be evidence of the value of improvements in water quality that is not found in this EKC study.

One possible theoretical explanation for this disjuncture can be found by returning to the Jaeger et al. (2011) paper. Their theoretical model demonstrating the conditions under which an EKC relationship can be found is partially premised on the fact that there is low substitutability in the environmental good; an EKC occurs when the elasticity of production is higher than that of consumption, and the elasticity of consumption is dependent upon the elasticity of substitution between the environmental good and other consumptive goods. In the case of water quality in the US, however, an assumption of low elasticity of substitution may not hold. Clean drinking water is provided in municipalities and regulated to a safe standard, and for cases where drinking water is contaminated, safe water is available for purchase in stores. Therefore, the majority of the value of water quality for Americans may be in terms of recreation value and not in direct use, as noted by Smith and Wolloh (2012). Viewing water as a source of recreation, then, allows consideration of it as a highly substitutable good. Fisherman have a wide range of streams and lakes from which they can fish in most places across the US; it is unlikely that all parts of a watershed are so highly polluted that they are left with no other options but to fish in areas of low water quality. Boaters and swimmers too have a wide range of options in most places. If it is assumed the elasticity of substitution of water quality is high, then the theoretical possibility of estimating an EKC relationship may be limited. This may also be the reason as to why international studies using dissolved oxygen (Torras and Boyce,1998) have demonstrated a robust EKC relationship for dissolved oxygen. Datasets that include places where a premium is placed on safe drinking water may be estimating a different kind of relationship than the one studied here. It may be, as Carson (2010) concludes, that efforts would be better placed in identifying those factors, such as regulatory structures and incentive systems, that can translate increased income from economic growth into improved environmental quality.

VI. **Conclusion**

This study has attempted to discern the relationship between water quality and economic growth as measured by county-level per capita income in the United States for the period 1969-2012. Using fixed and random effects models and datasets divided between streams and lakes, as well as time span, in only two cases was there statistically significant evidence to support an Environmental Kuznets Curve relationship. The estimated turning point for income for the model using streams data from all counties spanning at least ten years was $62,094, while the data set for lakes spanning ten years had a turning point at the minimum of the function where income was $36,793 and a turning point at the maximum point where income was $55,426. The estimated coefficients for income per capita are found to be very small when significant, and evidence for improvement in water quality overall is limited. Focusing the study on states with the most data available for both streams and lakes did not yield significantly different results, though the turning points were found to be quite different depending on the state, confirming List and Gallet's findings (1999).

The findings of this study support those of other EKC studies in the US regarding water quality, though do not immediately reconcile with other economic analyses of water quality, such as Neutsil et al.'s hedonic analysis (2014). In this light, it is possible that the nature of substitutability of water quality in the US may make it an inappropriate choice for an EKC study that is US-specific, as compared to other measures of environmental quality, such as air emissions. Beyond theoretical considerations, it is expected that further research could improve upon the results presented here. The method of aggregation of the water quality data to the county level is one area that would likely improve the results by retaining more variation in the water quality measurements. Incorporating additional supporting data such as enforcement of the CWA through EPA Echo data could provide additional insight. The large panel dataset assembled for this study presents possibilities for analyses of regional and national water quality beyond the EKC framework. A study that incorporates transboundary issues as in Sigman (2004) and Paudel et al. (2005) could incorporate some of the missing pieces that may shed light on the interaction of water quality with economic decision-making.

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Appendix: Results from State-Specific Models

Table 1: Regression Results for Streams Data from Selected States

	Arkansas (b/ se)	Florida (b/ se)	Minnesota (b/ se)	North Carolina (b/ se)	Texas (b/ se)
PerCapInc	-0.000155	-0.000019	-0.000127	-0.000106	-0.0000559
	2.19E-04	9.33E-05	8.76E-05	6.80E-05	1.41E-04
PerCapSq	3.80E-09	1.74E-10	5.15E-09	2.88E-09	2.59E-09
	7.73E-09	2.49E-09	2.69E-09	1.81E-09	4.50E-09
IncCub	-1.57E-14	1.20E-16	-5.75e-14*	-2.39E-14	-3.70E-14
	8.83E-14	1.98E-14	2.59E-14	1.47E-14	4.38E-14
PopDen	0.0115	-0.00338**	-0.00171	0.00157	-0.00126
	0.00736	0.0011	1.24E-03	7.96E-04	0.0012
PopDenSq	-0.0000386*	0.00000249***	2.93E-07	-2.51E-07	0.00000114***
	0.0000164	0.000000721	0.000000333	0.000000254	0.000000321
PopDenCub		-4.10e-10**			
		1.28E-10			
PerHarvest	-0.0283	-2.01E-02	-0.0121	-0.0321	-0.0364
	0.0186	0.0202	0.0132	0.0219	0.0371
BealeCode	-0.0103	0.00698	-0.118*	-0.0215	-0.0775
	0.0523	0.0461	0.0545	0.0314	0.13
StateAuth	-0.372*	-0.0881	-0.0658	-0.402	-0.263
	0.141	0.0852	0.118	0.36	0.149
Constant	9.463***	6.096***	10.57***	8.359***	8.302***
	2.091	1.261	1.039	0.823	1.561
Adjusted R-Square	0.0544	0.0531	0.0223	0.0419	0.0459
Number of Observations	2447	2104	2148	1885	2057
Number of FIPS	73	66	75	93	115
Turning Point (s): Income	$23,949 (min) 137,409 (max)	$51,819 (min)	$17,401 (min) $42,309 (max)	$28,546 (min) $51,788 (max)	$16,943 (min) $29,724 (max)
Turning Point: Population	149	690	2,918	3,128	553

Table 2: Descriptive Statistics for Selected States

State	County Average Per Capita Income (2010 $) Mean Range	County Population Density (per sq mile) Mean Range	Dissolved Oxygen Concentration (mg/L) Mean Range
North Carolina	25,780 11,877-51,959	169 8.73-1,850	6.99 0.80-13.00
Arkansas	24,691 12,590-47,858	48.92 9.36-511.94	7.20 1.10-13.00
Minnesota	30,464 13,563-65,115	149.7 2.68-3,369.8	8.41 2.5-15.25
Florida	29,206 11,811-71,247	263.64 4.53-3,394.56	5.13 0.40-9.80
Texas	26,548 11,474-64,740	202.78 0.29-2,816.37	7.10 0.2-18.9

Figure 1: Graphical Representation of Regression Results for Streams from Selected States

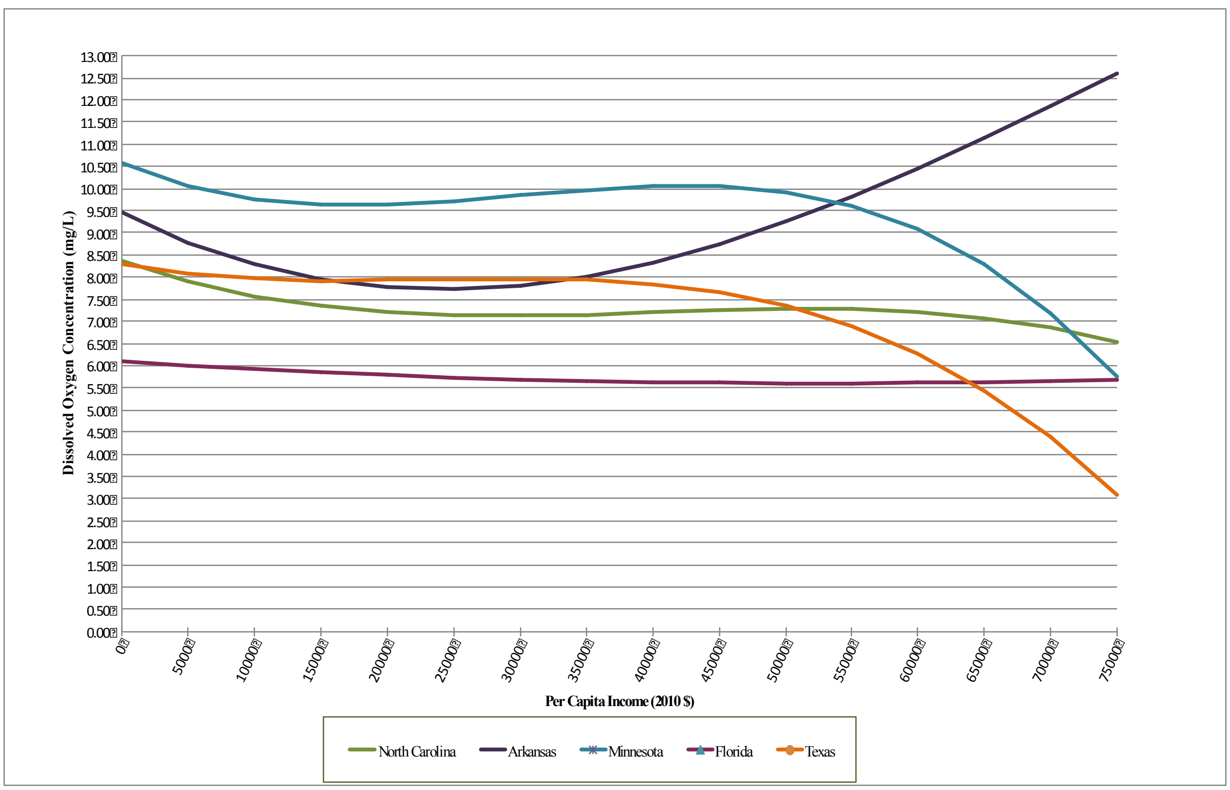

Table 3: Regression Results for Lakes Data from Selected States

	Florida (b/se)	Iowa (b/se)	Minnesota (b/se)	Texas (b/se)	Wisconsin (b/se)
PerCapInc	0.00000126	-0.00132*	-0.000947*	0.000383	0.000583
	0.000105	0.00054	0.000383	0.000219	0.000421
PerCapSq	9.66E-10	3.21e-08*	2.17e-08*	-1.46e-08*	-1.44E-08
	2.55E-09	1.26E-08	9.61E-09	6.79E-09	1.07E-08
IncCub	-1.38E-14	-2.51e-13*	-1.54E-13	1.57e-13*	1.15E-13
	1.96E-14	9.70E-14	7.69E-14	6.48E-14	8.67E-14
PopDen	0.00125	0.0298**	-0.00086	0.00263*	-0.0133**
	0.00124	0.00986	0.00157	0.00115	0.00406
PopDenSq	-0.000000293	-0.0000239**	-0.000000727	-0.000000552	0.00000564***
	0.000000186	7.24E-06	0.000000365	0.000000334	0.000000909
PerHarvest	-0.015	0.00542	0.0596	-0.0235	-0.0997
	0.0199	1.98E-02	0.0403	0.0305	0.0703
BealeCode	0.094	-0.0556	0.323	-0.0807	-0.234
	0.0795	0.228	0.263	0.0657	0.305
State Authorization	-0.0799	0	-1.042	0.565***	0
	0.195	(.)	0.581	0.124	(.)
Constant	6.040***	25.05**	18.81**	2.36	3.293
	1.354	8.212	5.53	2.322	5.827
Adjusted R-Square	0.0109	0.0104	0.114	0.0271	0.018
Number of Observations	623	884	622	952	981
Number of FIPS	31	76	32	53	50
Turning Point (s): Income	47,310 (max)	$34,612 (min) $50,647 (max)	$36,533 (min) $56,108 (max)	$18,845 (max) $51,285 (min)	$34,507 (max) $48,971 (min)
Turning Point: Population	2,133	623.43	591.47	2,382	1,179

Table 4: Descriptive Statistics for Lakes Data from Selected States

State	County Average Per Capita Income (2010 $) Mean Range	County Population Density (per sq mile) Mean Range	Dissolved Oxygen Concentration (mg/L) Mean Range
Wisconsin	33,358 19,639-58,688	159.68 7.77-4,003.41	6.57 0.10-13.11
Texas	27,771 12,806-59,361	210.68 0.61-2630.49	5.03 0.20-12.85
Iowa	31,853 19,237-56,275	31.06 0.84-300.19	6.55 3.23-8.60
Florida	32,775 16,728-66,458	397 7.77-3,394.56	7.03 1.50-10.30
Minnesota	34,260 17,898-61,696	440 2.18-3,417.28	6.8 0.2-13.36

Figure 2: Graphical Representation of Regression Results for Lakes Data from Selected States