ENVIRONMENTAL REGULATION STRINGENCY AND U.S. AGRICULTURE

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ABSTRACT

To understand the likely impact of federal policies on nonpoint agricultural water pollution, a robust measure of state-level environmental regulation stringency is required. The objective of this paper is to derive and characterize state-level environmental regulation stringency across states and over time. I compute a measure of environmental regulation stringency for the agricultural sector from 1960-2004 by calculating the shadow price of polluting inputs. The estimation provides evidence suggesting an increase in regulation stringency across all regions over the sample period, with the exception of the Corn Belt (Heartland) and the Northern Crescent regions, which have decreased in stringency. With few exceptions, regions of the U.S. with the highest proportion of farms see the lowest levels of regulation stringency.

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ABBREVIATIONS

BMPs:	Best Management Practices
BR:	Basin and Range
CRP:	Conservation Reserve Program
CWA:	Clean Water Act
EPA:	Environmental Protection Agency
EQIP:	Environmental Quality Incentive Programs
ERS:	Economic Research Service
FR:	Fruitful Rim
MP:	Mississippi Portal
NAAQSs:	National Ambient Air Quality Standards
NGP:	Northern Great Plains
NPS	Nonpoint Source
TMDL:	Total Maximum Daily Load
VLJ:	Van Soest, List and Jeppesen

CHAPTER 1
INTRODUCTION

1.1. Background

The environmental impact of agriculture on the environment can be categorized in terms of water, soil and air, though these are not mutually exclusive in some cases. The most significant of these impacts are those of water and soil, and much of environmental protection efforts in agriculture are geared towards soil and water conservation. Environmental protection is the core mandate of the Environmental Protection Agency (EPA) and the reason for its creation. The EPA monitors, sets standards and enforces regulations to enhance environmental protection. Whereas the agricultural community in the U.S. frequently expresses concerns about the burden of recent EPA regulations, public health and environmental advocates are in support of EPA regulations, and are of the opinion that these regulations are too loose for the agricultural sector (Stubbs, 2014). Whether environmental regulations are too loose or too tight on the agricultural sector, there is likely to be variation across states. This is because the federal policies that set guidelines for environmental protection are applied and enforced at the state level. Knowing how much environmental regulation stringency varies across states will inform policy decision on which states, or regions government should put in more effort in achieving acceptable water quality standard.

Agricultural activities sometimes create negative impact on the environment, and the magnitude of the impact varies over time and across states (Stubbs, 2014). Water is one of the major natural resources that is affected by the use of some synthetic inputs in agricultural production (Reimer, Gramig, and Prokopy, 2013). Majority of agricultural water pollution is nonpoint source (NPS), meaning that the pollution comes from diffuse sources, as opposed to point source, which refers to a single identifiable source of pollution.

The agricultural sector is the largest contributor to NPS water pollution (Dowd, Press, and Los Huertos, 2008; Reimer, Gramig, and Prokopy, 2013). As such, one might expect that environmental restrictions to monitor water quality would be geared mainly towards the agricultural sector given that the major sources of water pollution are nonpoint sources. But regulation of NPS pollution is difficult and expensive to regulate due to the diverse source of such pollution. However, the severity of the problem, considering that close to 50% of water bodies are in poor conditions (EPA,2016), warrants effort to overcome this difficulty.

Some states have voluntarily imposed regulations and provided incentives to fight agricultural nonpoint source pollution. The Total Maximum Daily Load (TMDL) component of the Clean Water Act (CWA) makes provisions for states to identify impaired waters and obtain funding from the EPA to help establish plans to limit pollution. Some states have also imposed taxes on polluting farm inputs (Ribaudo, 2001). Nebraska, for example, imposed an input tax on fertilizer to limit over-application and improve water quality (Dowd, Press and Los Huertos, 2008), though it expired in 2000 and has not been reinstated.

In addition to these voluntary restrictions and the TMDL program, policies that influence commodity choice, production, input use, and land management affect the level of agricultural water pollution as well. The Farm Bill is one of the major forces influencing such policies. Through direct commodity payments, acreage allocation under the Conservation Reserve Program (CRP), crop insurance subsidies, and programs designed to incentivize the adoption of Best Management Practices (BMPs), like the Environmental Quality Incentives Program (EQIP), the Farm Bill is likely to be a significant influencing factor in the amount of agricultural nonpoint source pollution ending up in U.S. waterways. These programs can change the relative price of polluting inputs and outputs. Thus, they impose implicit "costs" on pollution.

Though the policies that influence these programs are implemented at the Federal level, their application, in terms of monitoring, enforcement and permitting, is carried out by state and local governments based on the federal EPA guidelines (Stubbs, 2014). States determine the means of attaining the goal of the federal regulatory measures, and the stringency of the implemented regulations are also determined by the state regulators. This implies that there may be variation in the stringency of regulations across states. As such, the impact of federal regulations on water quality improvement will partly depend on the environmental regulatory stringency of each state. Environmental regulatory stringency is defined by Botta and Koźluk (2014, pp.6) as "the 'cost' imposed on polluting or other harmful environmental activity".

Federal policies such as the Clean Water Act and the Farm Bill have direct effects on agricultural water pollution, but they also exert indirect effects. Individual states increase the relative stringency with which state-level environmental regulations are applied when the potential for water pollution increases (Lawley and Furtan, 2008). For example, if CRP acres were to decrease in a new Farm Bill, state-level regulators may perceive a higher potential for water pollution, subsequently increasing their environmental regulatory stringency. Thus, there is likely to be state-level variation in environmental regulatory stringency, even though the Clean Water Act and the Farm Bill are implemented at the federal level. Several other factors could account for variation in environmental regulatory stringency across states. Reimer, Gramig, and Prokopy (2013) note differences in EQIP application rates across all 50 U.S. states. They attributed this difference to variations in state settings such as topography and the major agricultural products they engage in that influence behaviour of individual farm operators

State-level enforcement could also account for variation across states. The 1980s saw a disparity in regulation stringency among states when the Federal Government delegated regulation to state authorities (Kraft and Vig, 1990; Lester, 1994; Levinson, 1996). California also subjected fertilizer sales to a 0.3% tax to support research and extension on handling of fertilizers and also placed a mill tax of $ 0.0175 per dollar of pesticide to generate funds to support education, data collection and growing training purposes (Dowd, Press, and Los Huertos, 2008).

Deriving a measure of environmental regulatory stringency is a necessary first step in determining how effective federal NPS policies will be if they are applied and enforced at the state level. Theoretically consistent empirical studies use the shadow price of polluting inputs (Althammer and Hille, 2016; Pittman, 1981; van Soest, List, and Jeppesen, 2006 (hereafter referred to as VLJ)), or polluting output (Huhtala and Marklund, 2008; Mamardashvili, Emvalomatis, and Jan, 2016) as a measure of environmental stringency. Unlike other non-shadow price techniques, the shadow price approach is based on the firm's input and output decision making (firm's behaviour). By identifying polluting inputs in the agricultural sector: pesticide, fertilizer, herbicide, and energy, and using agricultural output and input data of states in the U.S. over time, I derive a measure of environmental regulatory stringency using the shadow price following VLJ (2006).

1.2. Problem statement

The literature on environmental regulatory stringency is extensive. Most of the literature focus on international trade competitiveness and testing of the pollution haven hypothesis (jurisdictions with weaker environmental regulations attracting polluting industries relocating from more stringent jurisdictions) (Akbostanci, Tunc, and Turut-Asik, 2007; Herath et al., 2005; Jaffe et al., 1995; VLJ , 2006). Studies examining environmental stringency in the agricultural sector focus primarily on the animal sector (Huhtala and Marklund, 2008; Mamardashvili et al., 2016), which omits the difficulties of accounting for the nonpoint source pollution from crop production. One significant work in the U.S. agriculture sector is Herath et al. (2005). They create an index for environmental regulatory stringency by compiling state-level regulatory effort into a single index. This approach is ambiguous in reflecting the characteristics of the policy since some government regulatory efforts can be cost-reducing and others can be cost-increasing

(Brunel and Levinson, 2016), and can be inconsistent with neoclassical economic theory (it does not reflect the behaviour of the firm).

1.3. Objective

The main objective of this thesis is to determine how environmental regulatory stringency of the agricultural sector varies across U.S. states and over time. This objective will be achieved by pursuing the following specific sub-objectives:

1. To estimate a generalized Leontief cost function.
2. To derive the wedge between the shadow price and the market price of polluting inputs

1.4. Justification

This study provides a starting point to a bigger project that seeks to understand how policies in the Farm Bill and the CWA along with state-level institutions help mitigate water pollution from farms. The study provides a theoretically consistent measure of environmental regulation stringency in the U.S. agricultural sector. The measure covers the entire agricultural sector and not just the crop or animal sector. The study provides information that will help in identifying the trend and pattern regarding how environmental regulations are set across regions in the U.S. It provides important input for other analyses. For instance, to understand how Federal policies or state-level institutions influence the level of environmental regulations, it will first require an estimation of the stringency level. My work provides these estimates, making it possible for such an analysis. It will also be useful in understanding how environmental regulation stringency affects water pollution. The approach used in this study can be easily adapted to analyze the agricultural sectors of other countries. Finally, this study will fill a significant gap in the environmental regulatory stringency literature relating to agriculture.

1.5. Organization of thesis

The next chapter reviews the literature on the contribution of agriculture to water pollution, proposed regulatory measures, and issues relating to the measurement of environmental regulation stringency. Chapter 3 explains the theoretical rationale and empirical models I use to estimate stringency. The data used in the estimation is also described in this chapter. Chapter 4 presents and discusses the results from the estimations in Chapter 3. Chapter 5 summarizes the research results, presents conclusions on the environmental regulatory stringency across regions, and lists the limitations of the thesis. Areas for future research are also provided in this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1. Controlling nonpoint water pollution

Degradation of water quality resulting from agricultural production systems is a serious and increasing problem in many parts of the world, including the United States (Reimer et al., 2013). A recent EPA report classified more than half of the nation's rivers as "poor" (EPA, 2013).

High nutrient load in an aquatic ecosystem stimulates algae blooms resulting in plant death and decay (Craig and Roberts, 2015; Cullum, Locke, and Knight, 2010; Ongley, 1996; Walters et al., 2012). This condition, referred to as eutrophication, is a natural process which is accelerated by human activities that increase the rate at which nutrients and organic substances enter waterways. Nitrogen and phosphorus discharge into water bodies remains one of the primary accelerators of eutrophication (Craig and Roberts, 2015; FAPRI-UMC, 2007; Howarth and Marino, 2006; Parris, 2001), and agriculture is the main contributor (Cartwright, Clark, and Bird, 1991; Pretty et al., 2003; Novotny, 1999).

The major challenge for policy makers in combating water pollution is nonpoint source pollution (Dowd et al., 2008). This could be due to the difficulty in identifying NPS polluters, and the difficulty in measuring NPS pollutants. If nonpoint polluters can be easily identified and there is clear understanding of the damage by each polluter as well as the implicit cost imputed to such damages by policies, then policy makers can know to what extent policy should be tighten or loosen to achieve a particular standard.

Point source pollution can be regulated by Pigouvian taxes, standards or permits, but the same cannot be said of NPS pollutants. Xepapadeas (2011) identifies input-based instruments, ambient schemes and the application of monitoring technology in combination with standard polices as a means of controlling NPS pollutants. Input-based instruments rely on a positive correlation between a particular input and the pollution created such as fertilizer use and nitrogen runoff. Applying a mix of taxes, subsidies or permits related to the use of the input can yield efficient results, and accounting for adverse selection will yield the most efficient result if such correlation exists (Griffin and Bromley, 1982; Laffont, 1994; Shortle and Abler, 1994). An ambient tax is based on the difference between the observed ambient concentration of pollution relative to some cut-off level and it is levied on all potential polluters in the area (Cabe and Herriges, 1992; Hansen, 2002; Horan, Shortle, and Abler, 1998; Segerson, 1988; Xepapadeas, 1992). NPS pollution can be transformed into a point source pollution problem that can be regulated through policies if information regarding individual emissions can be acquired through truthful revelation or monitoring technology (Xepapadeas, 1995, 1994). The NPS pollution problem is due to the unidentifiable nature of the pollution. If there is a way of knowing how much emission is caused by any identified individual polluter, then the NPS problem becomes a point source problem which can be regulated easily through policies.

Federal and state governments implement environmental regulations to control nonpoint source pollutants, which indirectly affects the price of outputs and inputs associated with increasing water pollution. However, the effectiveness of these regulations in achieving the goal of water quality improvement is likely to depend on environmental regulatory stringency, or the cost of polluting activities. This cost can either be explicit such as expenditure on pollution prevention or implicit such as the shadow price of a polluting input or output (Brunel and Levinson, 2016; VLJ, 2006).

Some states have also made efforts to control nonpoint pollution from agriculture. To reduce nitrogen loss, Maine, Maryland, Pennsylvania and Vermont imposed some form of ban on winter application of manure or fertilizer; Wisconsin used buffers and nutrient management plans in 2011; Pennsylvania and Minnesota have adopted buffers near rivers and lakes to reduce pollution of rivers from agriculture; and in 1998, North Carolina implemented mandatory BMPs to reduce runoff into the Neuse River Basin (Kling, 2013). Another state-based effort to reduce pollution from agriculture is the Everglade Act; passed in 1994 with the intention of reducing phosphorus in the Everglades Agricultural Area located southeast of Lake Okeechobee. This Act requires farmers in the area to obtain permits indicating compliance with conservation actions before growing crops (Kling, 2013). Virginia, Utah, New York, New Mexico, Montana, Missouri, Iowa and Georgia also use nutrient standards as a means of regulating pollution from agriculture (Herath et al., 2005).

2.2. Agricultural policies and environmental regulatory stringency

The Farm Bill and the Clean Water Act (CWA) are two major policies in the U.S. with environmental protection elements. The environmental protection elements in the Farm Bill include the Conservation Reserve Program (CRP), Environmental Quality Improvement Program (EQIP), and other payments such as the federal crop insurance program. These policies and programs are interpreted at varying degrees by state regulators. How state regulators interpret federal policies at the state level is likely to influence the effectiveness of federal policies.

The CRP is a voluntary program which entitles producers with eligible land to enter into a contract with the government to establish cover on environmentally sensitive land to reduce erosion, improve soil quality and enhance wildlife habitat (FAPRI-UMC, 2007). The policy retires environmentally sensitive land from crop production and compensates owners for enrolment. The CRP limits the amount of chemicals deposited into waterways, as cover established on lands under the program does not require fertilizer application, and also reduces runoff by improving soil structure and texture. Improvement in water quality is also achieved through less fertilizer usage because acres under the program cannot be used for crop production. Comparing CRP lands planted with trees with land under crop production at the Beasley Lake Watershed, Cullum, Locke, and Knight (2010) note lower nutrient load and sediments leaving the watershed in CRP lands with tree establishment. Figure 2.1 shows the number of acres enrolled in CRP across states as of March 31, 2016. There is a substantial amount of variation in CRP acreage across states. When state-level differences such as size and industrial composition is accounted for, variation in CRP enrollment may influence water pollution and regulation stringency. When payments under the CRP are used to cultivate other lands as compensation for lands enrolled under the program, or increase in dirty input use, it is likely to result in laxity in regulations no change (or increase) in water pollution level. However, if due to enrolment under the program there is reduction in productive land and dirty input usage then one can say regulations are stringent and water quality level is expected to improve.

Broussard, Turner and Westra (2012) identify a positive relationship between government payments from the Farm Bill and increasing nitrogen concentration in rivers, commodity specialization, increased fertilizer application and reduction in crop diversity. Hendricks et al. (2014) study the relationship between higher corn prices resulting from ethanol subsidies and the subsequent expansion of the hypoxic zone (low-oxygen below the requirement for aquatic survival caused by excessive nutrient pollution) in the Gulf of Mexico. Fewer farmers choose to alternate between corn and soybeans as ethanol subsidies increase and corn becomes relatively more profitable. Soybeans is a leguminous crop hence rotation between corn and soybeans will require less nitrogen fertilizer application than planting a corn continuously. The continuous planting of corn may require more nitrogen and subsequently, more nitrogen may leave the field in the form of runoff. However, the rate and amount of runoff may vary across states depending on the intensity of agricultural activities, topography and climatic conditions of each state. The above studies indicate that payments in the Farm Bill (examples include income support, commodity-specific payments, direct commodity payments and rural development programs) are likely to lead to water quality deterioration. This may be due to laxity in regulation as a result of the payments, and hence, the positive correlation between these payments and water pollution. These programs tend to affect the relative prices of polluting inputs such as fertilizer and pesticide though the payments do not directly affect their prices. The sum of the market price and the price wedge reflects the willingness to pay (shadow price) for a polluting input.

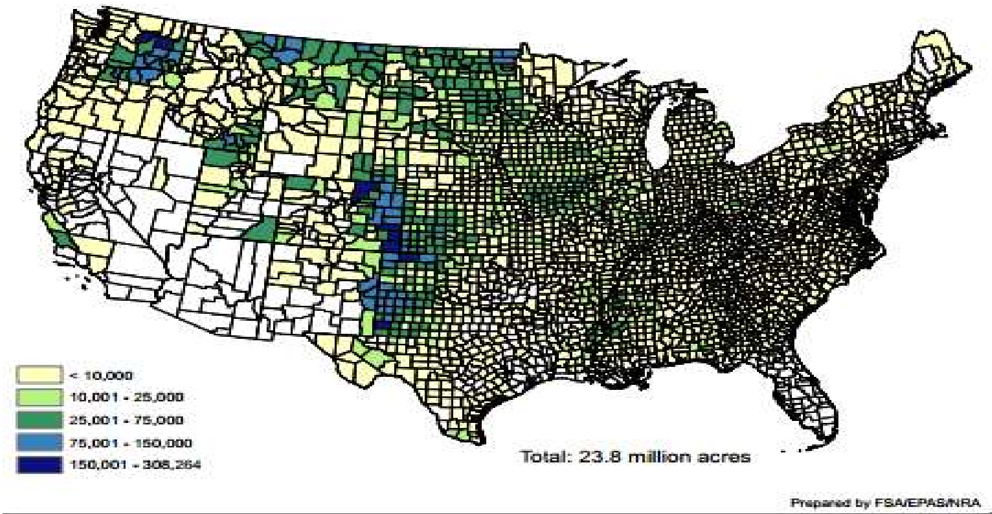

Figure 2.1: CRP Enrollment (total acres per state) - March 31, 2016
Source: USDA-FSA

EQIP is another component of the Farm Bill with direct implications on water quality. The primary focus of this program is to protect ground and surface water and to enhance efficient usage of water (USDA-NRCS, 2014). The program funds investment in equipment that can improve irrigation efficiency, structures and land leveling that can reduce water loss and runoff as well as management practices to precisely control the timing and rate of water application on irrigated fields. The application rate for EQIP differs across states (Reimer et al., 2013) (Figure 2.2). A higher proportion (60%) of funding from EQIP is allocated to livestock-related conservation (Wallander and Hand, 2011). This implies that states with high livestock concentration will receive a larger share of EQIP funding than states with more crops even if they have the same application rate. The states in Figure 2.2 (Texas, Mississippi, Arkansas, and California) showing the highest number of completed and active contracts are also major locations for livestock production. These factors may result in difference in stringency across states since states may differ in their industrial composition.

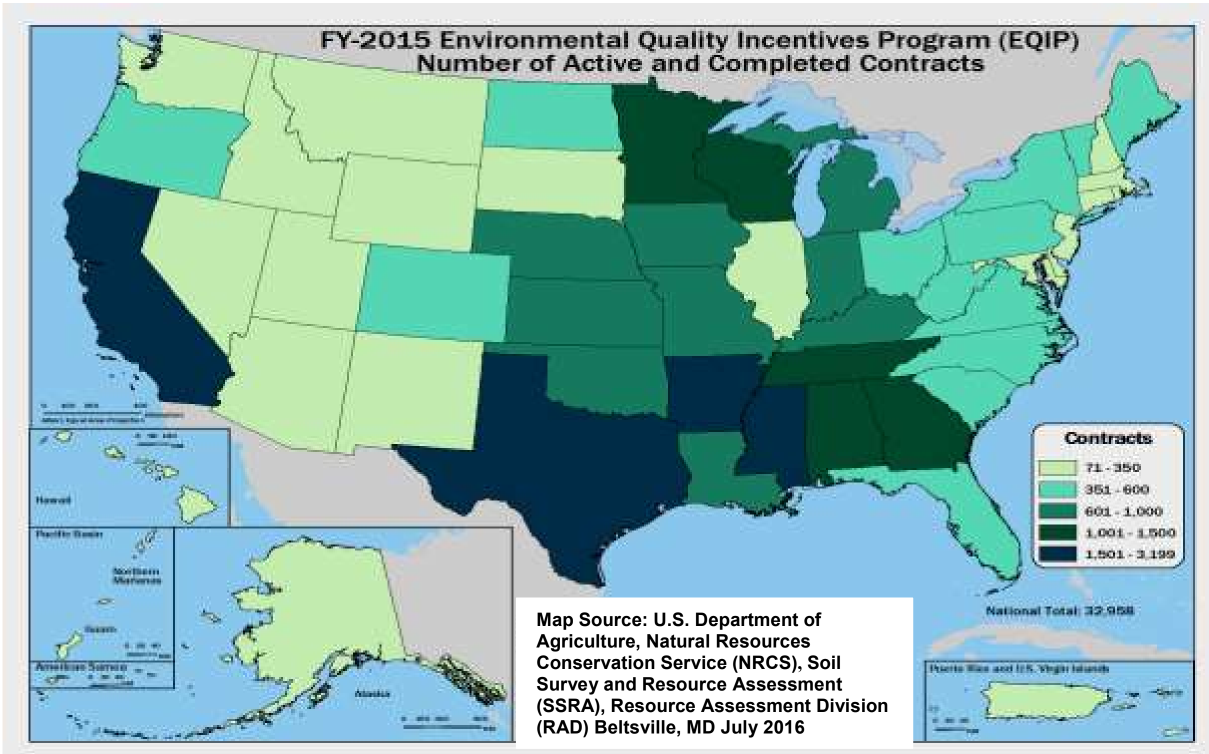

Figure 2.2: Differences in EQIP completed and active contracts across states

The Clean Water Act, which is the primary federal law in the U.S. regulating discharge of pollutants into the nation's water bodies, was enacted in 1948 with the name Federal Water Pollution Control Act (FWPCA), and was later reorganised and expanded into the Clean Water Act in 1972 (Environmental Protection Agency, n.d.). The main objective of the Act is to restore and maintain the quality of water bodies by preventing point source pollution (EPA, 2016). The Clean Water Act employs both regulatory and non-regulatory tools to reduce direct pollutant discharges and establish ambient water quality standards. The Act also provides assistance to publicly-owned treatment facilities for the improvement of wastewater treatment and helps maintain the integrity of wetlands. Despite the fact that the CWA does not place any direct regulation on agricultural nonpoint water pollution (Valcu, 2013), it could create heterogeneity in stringency across states since the initial water pollution level may vary across states. Like the National Ambient Air Quality Standards (NAAQSs), the ambient water quality standards of the CWA imply that all states face the same federal-level stringency. However, states with higher initial pollution levels will have to implement stricter regulations to meet the national standard, leading to variation in stringency across states.

Another policy that may affect prices faced by farmers is crop insurance. Like other payments in the Farm Bill, federal crop insurance may also influence the relative quantity of inputs used. Crop insurance has the potential to impact acreage decisions and the quality of land used in planting, both of which influence water quality. If a farmer has land with corn and grass, there is likely to be a shift of more land from grass to corn production since corn is an insured crop. Wu (1999) studies the impact of crop insurance for corn on chemical use in the Central Nebraska Basin. He finds that insurance predictably shifts land use towards corn, which increases chemical use and nonpoint source pollution leading to the deterioration of water quality. Evidence of the impact of crop insurance on soil erosion is mixed. Walters et al. (2012) indicate that the crop insurance impact varies significantly by geographical area, with some areas improving in environmental indicators and others declining. Claassen, Langpap, and Wu (2016) also estimate the relationship between federal crop revenue insurance, land use, cropping system, and environmental quality in the U.S. Corn Belt region, finding that insurance marginally decreases CRP and pasture acreage. Consequently, their model predicts a negligible detrimental effect of federal crop revenue insurance on environmental quality. However, they also concluded that the impact of the policy on environmental quality might vary across different regions.

2.3. Measuring environmental regulatory stringency

Measuring environmental regulatory stringency is necessary for policy inference, particularly across jurisdictions, but the measure comes with several challenges. Several factors ranging from data availability to differences in industrial composition across jurisdictions account for this difficulty. Brunel and Levinson (2016) identify four challenges to environmental regulatory stringency measurement: (1) multidimensionality—which exists because environmental policies or regulations control several different types of pollutants; (2) simultaneity emerges because pollution can influence stringency and vice versa; (3) variation in industrial composition across jurisdictions; and (4) the issue of capital vintage, which means regulations may be stricter for new firms than existing firms.

Several empirical approaches have been adopted to measure environmental regulatory stringency. Brunel and Levinson (2016) classify environmental regulatory stringency into five categories: i) direct assessment of individual regulations, ii) composite indices, iii) measures based on pollution or energy use, iv) measures based on public sector efforts, and v) private sector abatement costs. Each of these measurements has strengths and weaknesses. The five classifications are not mutually exclusive, but they include the most important body of literature.

Adopting the classification of Brunel and Levinson (2016), the body of literature covering the various measurement approaches are discussed in the subsequent paragraphs.

Direct assessment of individual regulations encompasses a stream of literature that focuses on specific regulations. These measures are useful where there is a change in policy or introduction of a new policy. Their strength lies in assessing the direct effects at a micro level, where other variables can be controlled for, differenced out or ignored (Botta and Koźluk, 2014). These measures are used to overcome two key challenges with measurement of policy and regulatory stringency: simultaneity and multidimensionality (Brunel and Levinson, 2016). However, the external validity of results using this measure is limited (Brunel and Levinson, 2016). External validity is limited due to the narrow focus on individual regulations and the use of natural experiments (Deaton, 2010). Also, individual regulations may vary across jurisdictions, making it difficult to create a consistent regulation-based measure of stringency (Althammer and Hille, 2016). This method cannot be applied to this study since this work is accessing all implemented regulations that can influence water quality.

The second type of measure, composite index, summarises the observable laws, which are mostly multidimensional into a synthetic representative measure by aggregating individual indicators on the basis of the underlying model into a holistic index (Botta and Koźluk, 2014). For example Knill et al., (2012) develop an indicator of clean air policy that captured national statutory laws in the books by coding the different clean air laws of countries as either “policy expansion” or “policy dismantling”. Though composite index measures attempt to solve the multidimensionality problem by compressing multiple regulations into a cardinal value which might provide a complete description of the legislative setting, the result could be misleading if selection of policies, weights scored, and aggregation are poorly constructed (Botta and Koźluk, 2014). The measure may also be measuring the overall quality of institution rather than only environmental regulatory stringency. This approach is not adopted in this study because of the problem of simultaneity and identification that characterised the approach as a result of respondents decision influenced by economic fluctuations (Brunel and Levinson, 2016).

The third category, measures based on pollution or energy use, uses emission, ambient pollution or energy use as a measure of policy stringency. Xing and Kolstad (2002) use high level of pollution from sulphur as evidence of laxity in regulation. McConnell and Schwab (1990) use high pollution as indication that regulations are not stringent with the assumption that government will be forced to tighten regulations to deal with the problem. This inherent simultaneity constitutes a main disadvantage of indices based on pollution or energy use (Brunel and Levinson, 2016), and the reason why it will not be appropriate for this study.

Fourthly, public-sector environmental efforts are sometimes used by researchers to measure stringency with the merit of incorporating an enforcement dimension (Brunel and Levinson, 2016). Levinson (1996) created such a measure by using number of employees at the state environmental agencies relative to the number of plants in the state. Higher relative number of employees indicates stringent regulation policy. Alternatively, Magnani (2000) use public expenditure on Research and Development (R and D) to create a measure of policy stringency. In general, using public-sector effort as a proxy for stringency has been less used, perhaps because its shortcomings overweigh the importance. The use of this measure for proxy creates ambiguity in the measurement because some public expenditure such as tax incentives and subsidies reduces private cost (Brunel and Levinson, 2016).

The last category, which is a common approach to measuring environmental regulatory stringency, is to determine private sector pollution abatement costs, which reflect the relative cost of firms' production in a given jurisdiction relative to others as a result of complying with regulations. Surveys are usually used for the collection of data on abatement cost, and industry managers are mostly the respondents. For instance, Levinson (1996) and List and Co (2000) use the annual U.S. Pollution Abatement Costs and Expenditures (PACE) data: the most comprehensive example for this type of survey data. Generally, the idea of the surveys is to determine a cardinal number of cost that directly coincides with the data needed to measure stringency. Firms report all abatement cost, some of which may not be due to regulatory stringency. Brunel and Levinson (2016) identified two major problems associated with this approach: (1) respondents might not be able to correctly separate expenditure due to environmental regulations from others such as profit seeking investment, and (2) regions with larger industries are more likely to record higher level of pollution and subsequently higher abatement cost. Pasurka (2008) adds that international comparison using different surveys is difficult. This approach may also under-or overestimate cost for new firms since only expenditure for existing firms are represented (Morgenstern, Pizer, and Shih, 2001). An alternative approach to using the firm's expenditure for estimating stringency is by using the shadow price of polluting inputs or output.

2.4. The shadow price approach

The shadow price approach is an attempt to avoid the problems associated with the cost survey. The measure relies on economic theory and firm input choices, and reflects the fact that implicit prices are placed on pollution by environmental regulations. VLJ (2006, p. 1155) define the shadow price of an input as "the potential reduction in expenditure on other variable inputs that can be achieved by using an additional unit of the input under consideration (while maintaining the level of output)." That is, in the absence of regulations, firms can maximize their profits by using more dirty inputs and fewer "clean" inputs since the price of dirty inputs becomes lower in the absence of regulations.

Assuming that firms are profit maximizers, the shadow price can be determined by estimating the firm's cost function using the data on the level of output, quantity of inputs and the prices of all inputs. The shadow price of the polluting input is then derived as the sum of the market price of the polluting input and the estimated wedges from the cost function. In the case where the polluting input is considered as a quasi-fixed input, the price of the polluting input is not required. The shadow price of the polluting input is determined from the cost function as a derivative with respect to the quantity of polluting input.

Several articles use the shadow price approach to estimate pollution abatement cost. Coggins and Swinton (1996) and Fare et al. (2005) estimate the shadow price of sulfur dioxide emissions in the electricity generation sector as pollution abatement cost. Huhtala and Marklund (2008) estimate the shadow price of manure spread in the animal sector as a measure of stringency in Finland dairy from 1994 to 2002. Another article focusing on the animal sector estimates the shadow price of a "dirty" output, nitrogen surplus, interpreting it as a measure of pollution abatement cost of Swiss diary farms (Mamardashvili et al. 2016). VLJ (2006) considered energy as a polluting input and measured the shadow price for the heavy metal and food processing industries for nine Western European countries from 1978 to 1996. The shadow price approach is theoretically consistent and allows comparability over time as well as across jurisdictions that adopts different types of regulations. The shadow price can be compared to the undistorted market price as markets are sufficiently integrated internationally (VLJ, 2006). A shadow price lower than the market value is interpreted as laxity in regulations, and when shadow prices are higher than market prices regulations are said to be stringent. VLJ's approach is extended by Althammer and Hille (2016) to cover 28 OECD countries, 33 sectors, and from 1995 to 2009. Althammer and Hille (2016) estimate shadow prices of emission-related energy use as a measure of carbon policy stringency.

One setback of the shadow price approach is that the stringency measure does not cover regulations that do not affect the shadow price. For instance, if a firm self-imposes a restriction on “dirty input usage” the shadow price is not affected (Althammer and Hille, 2016). Also, the results are partly affected by the functional form assumption (Brunel and Levinson, 2016). Correctly estimating the shadow price also partly hinges on correctly accounting for technological changes. Another limitation to the shadow price approach is that there could be other reasons apart from environmental regulations that could make market price diverge from the shadow price. For example, allocative inefficiency and other regulations on inputs other than dirty inputs (example, labour regulations) could result in the shadow price diverging from the market price. These effects cannot be separated from the sole impact of environmental regulations on dirty input if they exist, possibly leading to under-or-over-estimation of the price wedge as a measure of environmental regulatory stringency.

These notwithstanding, the shadow price approach has very desirable advantages. The problem of multi-dimensionality associated with environmental regulation is converted into a cardinal measure of cost (Brunel and Levinson, 2016). The shadow price approach also controls for capital vintage and industrial composition (Brunel and Levinson, 2016). With the incorporation of substitution possibilities between factors of production into the model, the approach is also able to deal with integrated technologies – technologies adopted to enhance productivity or maximize profit (Althammer and Hille, 2016). In addition, data is more readily available for this approach, and the shadow price can be estimated across time, regions and for several pollutants (Brunel and Levinson, 2016; VLJ, 2006). Considering all factors, the shadow price is a more promising approach for determining environmental regulatory stringency.

CHAPTER 3

METHODOLOGY

3.1. Theoretical framework

Optimal firm decisions require equivalence between marginal private benefit and marginal input cost. Marginal benefit can be measured as the marginal value product of an input when using the profit maximization approach. With cost minimization however, it can be measured as a reduction in expenditure on other inputs with a unit increase in the input under consideration while output level is maintained (VLJ, 2006). A profit-maximizing firm in a perfectly competitive industry will use inputs to the level where the benefit derived from using an additional unit of input is equal to the cost of the input, which coincides with cost minimization. However, environmental regulations can cause adjustment in the input cost and disrupt the equivalence between marginal cost and marginal private benefit required for an optimal input decision (Morrison-Paul and Macdonald, 2003). These regulations are government interventions that are used to control negative externalities from the private sector. This externality is not accounted for in the profit maximization or cost minimization condition when no regulations are in place. The discrepancy between marginal cost and marginal private benefit can be captured as a wedge between the shadow price and the market price.

To find the input demand response to these regulations, the concept of duality can be used directly through the profit function (Hotelling, 1932), or indirectly through the cost function (Shephard, 1953). However, the cost function is relatively more appealing: it allows for the estimation of a system of factor demand equations that are consistent with cost minimization and a general specification of technology; and variables that are omitted from the model but are observed by producers can influence the production decision and error term in the production function, but might not necessarily influence factor prices to the same degree in the cost function (Farsin and Filippini, 2009). Using the cost function is also preferred because cost minimization can handle production technologies with constant and increasing returns to scale, making it more flexible.

VLJ (2006) created a measure of environmental stringency that is theoretically consistent and allows comparability over time as well as across jurisdictions adopting different types of regulations. The measure is based on a polluting input's shadow price. When shadow prices are lower than the market prices, firms face lax regulations, perhaps due to subsidy in consumption of dirty inputs. On the other hand, shadow prices higher than the market price implies that firms are charged for polluting actions. This in theory, will reduce the use of polluting input and increase the use of other inputs for cost minimization objectives. Alternatively, firms may adopt a better technology which will use less of the polluting input while maintaining the use of other inputs and yet minimize cost under the environmental regulations. By identifying dirty inputs used in agriculture such as fertilizer, pesticides, agrochemicals, and energy (such as fuel), and by adopting the framework of VLJ (2006), I use the shadow price of dirty inputs to derive a measure of implemented environmental regulatory stringency in the U.S agricultural sector.

I define variable cost as $C(\mathbf{p}, \mathbf{x}, y, t)$, where **p** is a vector of variable input prices, **x** is a vector of quasi-fixed inputs used in production, *y* is output level, and *t* represents other arguments in the cost function such as technology or investment in the quasi-fixed input. The shadow price of polluting input *d* can be expressed as:

$$Z_d = \frac{\partial C(\mathbf{p}, \mathbf{x}, y, t)}{\partial x_d}, \tag{1}$$

if the polluting input is considered as a quasi fixed input, where Z_d is the shadow value of polluting input *d*. Furthermore, if total cost is denoted *TC*, the following relationship can be derived:

$$\frac{\partial TC}{\partial x_d} = p_d - Z_d, \tag{2}$$

where p_d is the market price of dirty input *d.* The wedge between the shadow price and the market price, $\lambda_d = Z_d - p_d$, can be used as an indicator of environmental regulations or policies that restrict firm's polluting input use (VLJ, 2006). If the wedge, λ_d, is negative then the firm is better off using more of the dirty input, indicating a laxity in regulation; alternatively, a positive wedge indicates stringent regulation. For instance, if government impose a tax on fertilizer the before-tax price (market price) is less than the after-tax price (shadow price). In this case the wedge becomes positive and farmers are better off using less of fertilizer (or coming up with innovative technology that requires less use of fertilizer). In the case of subsidy, the shadow price becomes less than the market price and firms are better off using more of fertilizer

3.2. Empirical model

For the purpose of estimation, a specific functional form needs to be specified for the cost function. The ideal choice is a highly general functional form that (1) places no a priori restriction on the substitutability between inputs; and (2) can be interpreted as a second-order approximation to an arbitrary twice-differentiable cost function (Bernt and Wood, 1975). The generalized Leontief, normalized quadratic, and the translog cost functions are all sufficiently flexible. I utilize the generalized Leontief cost function for estimation as it satisfies all the criteria and is frequently used in the shadow price approach.

3.2.1. The generalized Leontief functional form

Diewert and Wales (1987) introduce a generalized Leontief cost function that expands the traditional form introduced by Diewert (1971), adding technical change and variable economies of scale. This was further extended by Morrison (1988) and Morrison and Schwartz (1996) to facilitate the inclusion of additional inputs, such as variable inputs where the shadow price can deviate from the market price. This functional form is linearly homogeneous in prices and allows for the derivation of input demand functions that are homogeneous degree zero and linear in parameters, facilitating estimation. The approach used in this work is the one adopted by Morrison-Paul and Macdonald (2003) and VLJ (2006) by considering polluting inputs as variable inputs. The approach nests the shadow price directly into the cost function and allows it to vary from the market price such that $Z_d = p_d + \lambda_d$, where λ_d is the wedge driven between the shadow price and the market price due to environmental regulations as determined by the data. The cost function then reads as:

$$
\begin{aligned}
C = {} & y\left[\sum_i \sum_j \alpha_{ij} p_i^{0.5} p_j^{0.5} + \sum_i \sum_d \alpha_{id} p_i^{0.5} z_d^{0.5} + \sum_d \sum_e \alpha_{de} z_d^{0.5} z_e^{0.5}\right] + \\
& y\left[\sum_i \sum_a \delta_{ia}\, p_i t_a^{0.5} + \sum_d \sum_a \delta_{da}\, z_d\, t_a^{0.5} + \sum_i p_i \sum_a \sum_b \gamma_{ab} t_a^{0.5}\, t_b^{0.5} \right. \\
& \qquad \left. + \sum_d z_d \sum_a \sum_b \gamma_{ab}\, t_a^{0.5} t_b^{0.5}\right] + \\
& y^{0.5}\left[\sum_i \sum_g \delta_{ig}\, p_i\, x_g^{0.5} \right. \\
& \qquad + \sum_i p_i \sum_a \sum_g \gamma_{ag}\, t_a^{0.5}\, x_g^{0.5} + \sum_d \sum_g \delta_{dv}\, z_d\, x_g^{0.5} + \sum_d z_d \sum_a \sum_g \gamma_{ag}\, t_a^{0.5}\, x_g^{0.5} \\
& \qquad \left. + \sum_i p_i \sum_g \sum_f \gamma_{gf}\, x_g^{0.5} x_f^{0.5} + \sum_d z_d \sum_g \sum_f \gamma_{gf}\, x_g^{0.5}\, x_f^{0.5}\right]
\end{aligned}
\tag{3}
$$

Subscripts *i* and *j* denote variable inputs for which the shadow price is assumed to be equal to market price; subscripts *d* and *e* denote variable inputs for which the shadow price deviates from the market price; subscripts *f* and *g* denote the quasi-fixed inputs, and *a* and *b* denote the exogenous argument, *t*. The coefficients estimated are $\alpha, \delta, \ \gamma,$, and λ, where λ is derived from $Z_d = p_d + \lambda_d$. To facilitate the estimation of the coefficients in (3), I derive a demand function for each variable input using Shephard's lemma. From (3), which I denote as $C = C(\mathbf{p}, \mathbf{x}, y, t)$, the input demand functions are:

$$X_i = \frac{\partial C(\mathbf{p}, \mathbf{z}, x, y, t)}{\partial \mathbf{p}_i} \tag{4}$$

Alternatively, input-output ratios can be derived to reduce any potential heteroscedasticity (Morrison-Paul and Macdonald, 2003; VLJ, 2006). The relevant input-output ratios are

$$\frac{x_i}{y} = \frac{1}{y} * \frac{\partial C(\mathbf{p}, \mathbf{z}, x, y, t)}{\partial \mathbf{p}_i}, \text{ and} \tag{5}$$

$$\frac{x_d}{y} = \frac{1}{y} * \frac{\partial C(\mathbf{p}, \mathbf{z}, x, y, t)}{\partial \mathbf{z}_d}, \tag{6}$$

where x_d is the input demand function for the dirty input.

To estimate the econometric model, I use state-level farm production and input use data from the USDA. I estimate equations (3), (5) and (6) using seemingly unrelated regression (SUR), with capital assumed to be quasi-fixed. Labour (N) and land (L) are assumed to be fully variable. Polluting inputs included are fertilizer (F), pesticide (PE), energy (E), and other agrochemicals (A). I allow the shadow price to deviate from the market price. This deviation is estimated as a proxy for environmental regulatory stringency. The time trend, *t*, is use to proxy for exogenous technological changes.

The econometric model allows the direct effect of variable inputs (($\alpha_{r,LL}$, $\alpha_{r,NN}$, $\alpha_{r,FF,}$ $\alpha_{r,PP,}$ $\alpha_{r,EE}$, and $\alpha_{r,AA}$), where *r* index for region) to vary by region, whereas interaction effects ($\alpha_{LN}, \alpha_{LF}, \alpha_{LP}, \alpha_{LE}, \alpha_{LA}, \alpha_{NF}, \alpha_{NP}, \alpha_{NE}, \alpha_{NA}, \alpha_{FP}, \alpha_{FE}, \alpha_{FA}, \alpha_{PE}, \alpha_{PA}, \alpha_{EA}, \gamma_{KL}, \gamma_{KN}, \gamma_{KF}, \gamma_{KP}, \gamma_{KE}$, and γ_{KA}) and the quasi-fixed variable coefficient (γ_{KK}) are equivalent across regions (Morrison, 1988; VLJ, 2006). Though equation (3) is homogeneous of degree one in input prices, global concavity in variable inputs and convexity in quasi-fixed input are not guaranteed.

3.2.2. Estimating the wedge

The wedges can be captured either through the inclusion of annual jurisdiction-specific wedges $\lambda_{r,t}$, (where *r* denotes the regions and *t* denotes time periods) for polluting input prices, or time trend, or by including wedges for periods instead of a single time trend (VLJ, 2006). Using a single time trend to capture wedges will smoothen regulations and policies into a single time trend. To avoid this, I split the estimation period into 10 sub-periods (1960-65; 1965-70; 1970-73; 1973-77; 1977-81; 1981-85; 1985-90; 1990-96; 1996-2002; 2002-04) based on each Farm Bill regime starting from the first omnibus Farm Bill in 1965. The wedges are estimated as a markup or markdown by including an interaction effect of dummy variables of each time period and regions. I allow the ten-period dirty input price wedges, $\lambda_{r,g}$, to vary across USDA Farm Resource Regions, which were created by the USDA's Economic Research Service (ERS) to depict geographic specialization in the production of U.S. farm commodities. The states that constitute each USDA Farm Resource Region are represented in Table 3.1. Agricultural characteristics for each region are classified as the percentage of farms in each region; the percentage of production value; percentage of cropland; and the major agricultural products produced in each region (Table 3.2). The regions were created using county level data. Therefore, there is no clear-cut state boundary between each region. I select each state into a region depending on the physical area of the state occupied by the region (by visual inspection). My created Farm Resource Region with state boundaries is illustrated in Figure 3.1.

Table 3.1: Regions and their respective states

Regions	States
Northern Crescent	Minnesota Wisconsin Michigan Maine Pennsylvania New Jersey New York Connecticut Rhode Island Massachusetts Vermont New Hampshire
Heartland	Iowa Missouri Illinois Indiana Ohio
Northern Great Plains	North Dakota South Dakota Nebraska
Southern Seaboard	Alabama Georgia South Carolina Virginia Delaware Maryland
Fruitful Rim	Florida Arizona California Washington Idaho
Mississippi Portal	Louisiana Mississippi
Eastern Uplands	Arkansas Tennessee Kentucky West Virginia
Basin and Range	Oregon Nevada Utah Colorado New Mexico Montana Wyoming
Prairie Gateway	Texas Oklahoma Kansas

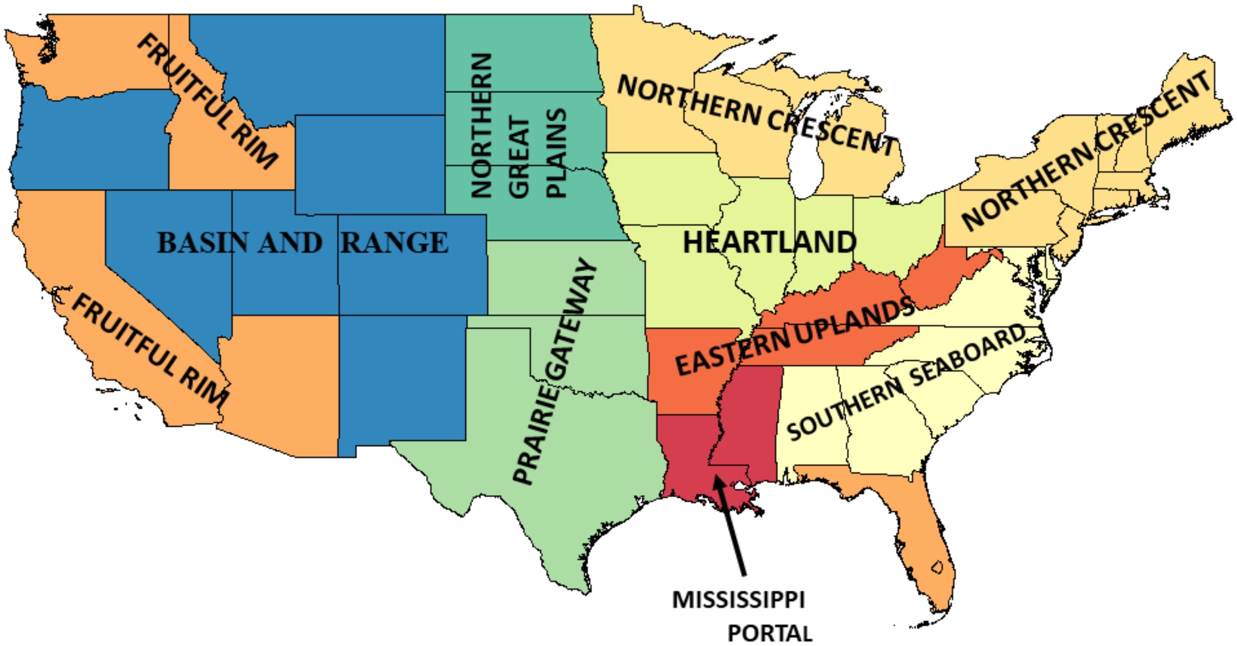

Figure 3. 1. Map of Farm Resource Regions

Table 3.2. Regional agricultural characteristics

Region	% of farms	% of prod value	% of cropland	Major ag. Products
Basin and Range	4	4	4	Cattle, wheat, sorghum
Fruitful Rim	10	22	8	Fruit, vegetables, nursery and cotton
Northern Great Plains	5	6	17	Wheat, cattle, sheep
Prairie Gateway	13	12	17	Cattle, wheat, sorghum, cotton, rice
Heartland	22	23	27	Cash grain, cattle
Mississippi Portal	5	4	5	Cotton, rice, poultry, Hog
Northern Crescent	15	5	9	Diary, general crop, cash grain
Eastern Uplands	15	5	6	Part-time cattle, tobacco, poultry
Southern Seaboard	11	9	6	Part-time cattle, general field crop, poultry

3.3. Data requirement and source

The data covers the 48 contiguous states from 1960 to 2004, yielding 2,160 observations. The quantity of output for each crop and livestock subcategory includes off-farm commodities, inventory, and consumption from farm households. The data also includes the corresponding output price in each subcategory. There are four major input categories: labour, land, capital and intermediate inputs. Labour includes hours worked and hourly compensation. The land input is a measure of the stock of land at the county level which is constructed as the value of land divided by a price index. Capital inputs include a measure of capital stock and a corresponding rental price for each asset type. The perpetual inventory method is used to calculate capital stocks from investment data for assets that depreciate while implicit quantities are derived from accounting data for capital assets that are non-depreciating such as inventories (Ball, Butault, and Nehring, 2001). Rental prices for each asset are based on the final price of the asset and the discounted value of projected future service flows.

The estimate of environmental regulatory stringency level is based on the inputs which are considered as dirty (fertilizer, pesticide, energy (petroleum fuels, natural gas, and electricity)). Fertilizer and pesticide price indices were constructed from a hedonic regression result (Ball, Butault, and Nehring, 2001). In estimating the shadow price, I am not able to use aggregated price index for the dirty inputs (though I believe that is more appropriate) due to data constraints.

I include the dirty inputs as separate variables in the model. That notwithstanding, the estimated wedge is a single aggregated measure for all dirty inputs.

I create total cost from the data as a product of the total input price and total quantity of input:

$$C = \sum_{v} p_v \times \sum_{v} Q_v,$$

where v is an index for inputs, p is price and Q is quantity. Table 3.3 indicates the variables used in the analysis, and their contents. The data and detailed information on how the variables were created can be found at https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/methods/.

Table 3.3: Variables and their sources

Variable	Description
Output quantity	Various crop and livestock species
Capital input	Includes depreciable and non-depreciable capital
Land input	Stock of land at the county level
Labour input	Includes hours worked and wage compensation
Dirty inputs	Includes fertilizers, pesticides, herbicides and energy use
Other intermediate input	Includes other farm inputs such as seeds and feed

CHAPTER 4

RESULTS AND DISCUSSION

4.1. Introduction

The previous chapter explains the theoretical framework underlying the shadow price approach of estimating environmental regulatory stringency and explained the estimation process undertaken. This chapter presents and discusses estimation results from the generalized Leontief cost function. Here, I used time maps and graphs to show evidence of variation in environmental regulatory stringency across regions and over time. I also used the average price wedge as evidence of the variations in environmental regulatory stringency. The chapter also explains the policy implications of the results.

4.2. Results from generalized Leontief model

Regional parameter estimates from the cost function are presented in Table 4.1 (The full STATA output is presented in Appendix D)**.** Though some studies found a positive coefficient for capital stock, in theory, given the presence of economies of scale, one expects that variable cost will decline if capital stock increases (Althammer and Hille, 2016; VLJ, 2006; Filippini, 1996). This is confirmed by coefficient of the capital stock (γ_{KK}), which is negative and significant at 0.05 level.

The regional own-price effects of variable inputs, which are captured by $\alpha_{r,ij}$, $(i = j)$, all had the expected signs—all the coefficients for regional own-price effects are positive and significant—indicating that all else equal, variable cost increases when either prices of land (L), or labour (N), or any of the polluting inputs (F, PE, E, and A) increases. For instance, a dollar increase in price of fertilizer in the Basin and Range region will increase variable cost by \$0.03 holding all other factors fixed. The positive coefficients of the own-price effect validate the cost function approximation. Furthermore, calculating the second derivative of equation (3) suggests that the global convexity condition with respect to quasi-fixed input (capital) and the global concavity condition with respect to the prices of variable inputs (land, labour, fertilizer, pesticide, energy and agrochemicals) of the cost function are met. This computation is provided in Appendix A. Since the interaction effects are not restricted by theory, their coefficients are of less importance to the validation of the cost function approximation. The magnitudes of the coefficients are also of less interest. However, their signs indicate the substitution possibility between two variable inputs. For example, the coefficient α_{PA}, which indicates the substitutability between pesticide and other agrochemicals, is negative, indicating that the two inputs can be substituted. A positive coefficient indicates that such substitution is likely not possible.

The estimated wedge coefficient, $\lambda_{r,g}$, serves as an indicator for environmental regulatory stringency. The estimated price wedge is the sum of the wedge between the shadow price and market price of each dirty input. All the estimated wedges are positive and significant except for the coefficient for Mississippi Portal in the first period, which is positive but insignificant. The positive wedge in all regions over time hints at the possible long-time effort to mitigate pollution from agriculture. Government effort to control environmental degradation started back in the 1930s after the dust bowl. The mission had been to protect the environment, mainly air, soil, and water.

Table 4.1. Cost Function Parameter Estimates

Regions	Parameter	Coefficient
Common Coefficient	α_{LN}	0.229*** (0.016)
	α_{LF}	0.010*** (0.003)
	α_{LP}	0.029*** (0.002)
	α_{LE}	0.002 (0.002)
	α_{LA}	0.044*** (0.004)
	α_{NF}	0.092*** (0.006)
	α_{NP}	0.063*** (0.003)
	α_{NE}	-0.004 (0.003)
	α_{NA}	0.158*** (0.007)
	α_{FP}	0.031*** (0.001)
	α_{FE}	0.032*** (0.002)
	α_{FA}	-0.031*** (0.003)
	α_{PA}	-0.033*** (0.001)
	α_{PE}	0.009*** (0.001)
	α_{EA}	0.033*** (0.001)
	γ_{KK}	-0.013** (0.005)
	δ_{KL}	-0.663*** (0.129)
	δ_{KN}	4.172*** (0.157)
	δ_{KF}	-0.057*** (0.018)
	δ_{KP}	0.003 (0.011)
	δ_{KE}	0.098*** (0.009)
	δ_{KA}	-0.053** (0.024)
Basin and Range (BR)	$\alpha_{BR,LL}$	0.596*** (0.009)
	$\alpha_{BR,NN}$	0.612*** (0.01)
	$\alpha_{BR,FF}$	0.033*** (0.001)
	$\alpha_{BR,PP}$	0.016*** (0.001)
	$\alpha_{BR,EE}$	0.054*** (0.00)
	$\alpha_{BR,AA}$	0.050*** (0.001)
	$\lambda_{BR,65}$	0.552*** (0.055)
	$\lambda_{BR,70}$	0.452*** (0.045)
	$\lambda_{BR,73}$	0.470*** (0.046)
	$\lambda_{BR,77}$	0.546*** (0.041)
	$\lambda_{BR,81}$	0.643*** (0.039)
	$\lambda_{BR,85}$	0.693*** (0.040)
	$\lambda_{BR,90}$	0.642*** (0.035)
	$\lambda_{BR,96}$	0.595*** (0.034)

Regions	Parameter	Coefficient
	$\lambda_{BR,02}$	0.649*** (0.035)
	$\lambda_{BR,04}$	0.642*** (0.043)
Fruitful Rim (FR)	$\alpha_{FR,LL}$	0.276*** (0.011)
	$\alpha_{FR,NN}$	0.647*** (0.014)
	$\alpha_{FR,FF}$	0.057*** (0.002)
	$\alpha_{FR,PP}$	0.029*** (0.001)
	$\alpha_{FR,EE}$	0.050*** (0.001)
	$\alpha_{FR,AA}$	0.086*** (0.002)
	$\lambda_{FR,65}$	0.261*** (0.037)
	$\lambda_{FR,70}$	0.252*** (0.032)
	$\lambda_{FR,73}$	0.277*** (0.030)
	$\lambda_{FR,77}$	0.329*** (0.029)
	$\lambda_{FR,81}$	0.383*** (0.029)
	$\lambda_{FR,85}$	0.459*** (0.035)
	$\lambda_{FR,90}$	0.358*** (0.031)
	$\lambda_{FR,96}$	0.365*** (0.032)
	$\lambda_{FR,02}$	0.411*** (0.033)
	$\lambda_{FR,04}$	0.406*** (0.035)
Northern Great Plains (NGP)	$\alpha_{NGP,LL}$	0.274*** (0.012)
	$\alpha_{NGP,NN}$	0.519*** (0.015)
	$\alpha_{NGP,FF}$	0.049*** (0.002)
	$\alpha_{NGP,PP}$	0.025*** (0.001)
	$\alpha_{NGP,EE}$	0.054*** (0.001)
	$\alpha_{NGP,AA}$	0.075*** (0.002)
	$\lambda_{NGP,65}$	0.422*** (0.039)
	$\lambda_{NGP,70}$	0.377*** (0.035)
	$\lambda_{NGP,73}$	0.368*** (0.034)
	$\lambda_{NGP,77}$	0.504*** (0.031)
	$\lambda_{NGP,81}$	0.536*** (0.029)
	$\lambda_{NGP,85}$	0.568*** (0.030)
	$\lambda_{NGP,90}$	0.477*** (0.027)
	$\lambda_{NGP,96}$	0.439*** (0.027)
	$\lambda_{NGP,02}$	0.434*** (0.028)
	$\lambda_{NGP,04}$	0.474*** (0.031)
Prairie Gateway (PG)	$\alpha_{GP,LL}$	0.340*** (0.012)
	$\alpha_{GP,NN}$	0.606*** (0.015)
	$\alpha_{GP,FF}$	0.054*** (0.002)
	$\alpha_{GP,PP}$	0.019*** (0.001)
	$\alpha_{GP,EE}$	0.056*** (0.001)
	$\alpha_{GP,AA}$	0.073*** (0.002)
	$\lambda_{GP,65}$	0.375*** (0.032)
	$\lambda_{GP,70}$	0.374***(0.028)
	$\lambda_{GP,73}$	0.424*** (0.028)
	$\lambda_{GP,77}$	0.480*** (0.026)
	$\lambda_{GP,81}$	0.594*** (0.026)
	$\lambda_{NGP,85}$	0.667*** (0.029)
	$\lambda_{NGP,90}$	0.608** (0.026)
	$\lambda_{NGP,96}$	0.589*** (0.026)
	$\lambda_{NGP,02}$	0.639*** (0.026)
	$\lambda_{NGP,04}$	0.629*** (0.030)
Heartland (HL)	$\alpha_{HL,LL}$	0.154*** (0.01)
	$\alpha_{HL,NN}$	0.495*** (0.012)
	$\alpha_{HL,FF}$	0.069*** (0.001)
	$\alpha_{HL,PP}$	0.025*** (0.001)
	$\alpha_{HL,EE}$	0.038*** (0.001)
	$\alpha_{HL,AA}$	0.094*** (0.002)
	$\lambda_{HL,65}$	0.413*** (0.035)
	$\lambda_{HL,70}$	0.368*** (0.031)
	$\lambda_{HL,73}$	0.350*** (0.030)
	$\lambda_{HL,77}$	0.445*** (0.030)
	$\lambda_{HL,81}$	0.385*** (0.030)
	$\lambda_{HL,85}$	0.356*** (0.035)
	$\lambda_{HL,90}$	0.275*** (0.028)
	$\lambda_{HL,96}$	0.247*** (0.030)
	$\lambda_{HL,02}$	0.316*** (0.031)
	$\lambda_{HL,04}$	0.282*** (0.033)
Mississippi Portal (MP)	$\alpha_{MP,LL}$	0.205*** (0.015)
	$\alpha_{MP,NN}$	0.652*** (0.018)
	$\alpha_{MP,FF}$	0.065*** (0.002)
	$\alpha_{MP,PP}$	0.058*** (0.001)
	$\alpha_{MP,EE}$	0.053*** (0.001)
	$\alpha_{MP,AA}$	0.126*** (0.003)
	$\lambda_{MP,65}$	0.030 (0.059)
	$\lambda_{MP,70}$	0.200*** (0.052)
	$\lambda_{MP,73}$	0.288*** (0.059)
	$\lambda_{MP,77}$	0.368*** (0.058)
	$\lambda_{MP,81}$	0.468*** (0.058)
	$\lambda_{MP,85}$	0.525*** (0.062)
	$\lambda_{MP,90}$	0.401*** (0.048)
	$\lambda_{MP,96}$	0.392*** (0.041)
	$\lambda_{MP,02}$	0.421*** (0.038)

Regions	Parameter	Coefficient
	$\lambda_{MP,04}$	0.348*** (0.048)
Northern Crescent (NC)	$\alpha_{NC,LL}$	0.108*** (0.006)
	$\alpha_{NC,NN}$	0.741*** (0.008)
	$\alpha_{NC,FF}$	0.038*** (0.001)
	$\alpha_{NC,PP}$	0.016*** (0.00)
	$\alpha_{NC,EE}$	0.038*** (0.00)
	$\alpha_{NC,AA}$	0.054*** (0.001)
	$\lambda_{NC,65}$	0.392*** (0.034)
	$\lambda_{NC,70}$	0.382*** (0.030)
	$\lambda_{NC,73}$	0.373*** (0.028)
	$\lambda_{NC,77}$	0.496*** (0.028)
	$\lambda_{NC,81}$	0.418*** (0.027)
	$\lambda_{NC,85}$	0.427*** (0.030)
	$\lambda_{NC,90}$	0.353*** (0.027)
	$\lambda_{NC,96}$	0.344*** (0.030)
	$\lambda_{NC,02}$	0.350*** (0.032)
	$\lambda_{NC,04}$	0.315*** (0.034)
Eastern Uplands (EU)	$\alpha_{EU,LL}$	0.204*** (0.011)
	$\alpha_{EU,NN}$	0.809*** (0.013)
	$\alpha_{EU,FF}$	0.053*** (0.001)
	$\alpha_{EU,PP}$	0.021*** (0.001)
	$\alpha_{EU,EE}$	0.041*** (0.001)
	$\alpha_{EU,AA}$	0.073*** (0.002)
	$\lambda_{EU,65}$	0.282*** (0.045)
	$\lambda_{EU,70}$	0.334*** (0.042)

Regions	Parameter	Coefficient
	$\lambda_{EU,73}$	0.364*** (0.044)
	$\lambda_{EU,77}$	0.445*** (0.040)
	$\lambda_{EU,81}$	0.425*** (0.038)
	$\lambda_{EU,85}$	0.385*** (0.040)
	$\lambda_{EU,90}$	0.353*** (0.034)
	$\lambda_{EU,96}$	0.372*** (0.032)
	$\lambda_{EU,02}$	0.415*** (0.031)
	$\lambda_{EU,04}$	0.411*** (0.036)
Southern Seaboard (SS)	$\alpha_{SS,LL}$	0.179*** (0.008)
	$\alpha_{SS,NN}$	0.616*** (0.01)
	$\alpha_{SS,FF}$	0.072*** (0.001)
	$\alpha_{SS,PP}$	0.023*** (0.001)
	$\alpha_{SS,EE}$	0.044*** (0.00)
	$\alpha_{SS,AA}$	0.093*** (0.001)
	$\lambda_{SS,65}$	0.311*** (0.041)
	$\lambda_{SS,70}$	0.324*** (0.034)
	$\lambda_{SS,73}$	0.338*** (0.036)
	$\lambda_{SS,77}$	0.399*** (0.033)
	$\lambda_{SS,81}$	0.426*** (0.034)
	$\lambda_{SS,85}$	0.389*** (0.035)
	$\lambda_{SS,90}$	0.347*** (0.033)
	$\lambda_{SS,96}$	0.329*** (0.031)
	$\lambda_{SS,02}$	0.429*** (0.033)
	$\lambda_{SS,04}$	0.413*** (0.036)

(Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01)

4.3. Regional variation in stringency

From the estimated wedges, I create maps showing the variation across states for each time period (Figure 4.1 to Figure 4.10). These maps indicate the considerable variation in stringency across states at different periods. Each colour gradient change represents a stringency difference of not more than 20%, with the darkest green gradient indicating the highest stringency. The first two periods (1960-65 and 1965-70) share similar stringency characteristics of states over the two periods. States in the Basin and Range (BR) region are the most stringent during these two periods (Figures 4.1 and 4.2). This is followed by states in the Heartland, Northern Great Plains (NGP), Prairie Gateway and the Northern Crescent regions. States located within the Mississippi Portal (MP) exhibit the least stringency during these periods, and states within the Southern Seaboards and Fruitful Rim (FR) are moderately stringent.

When considering environmental stringency through all time periods the Basin and Range region dominates, with the Prairie Gateway and the Northern Great Plains ranking second or third in order of stringency in most time periods. States located within the Heartland (HL) region (i.e., the Corn Belt) exhibit the least stringency in most time periods—from 1977-81 to 2002-2004. This is evident in Figure 4.11 which shows average environmental regulatory stringency over time. Starting from the 1977-1981 period to the last period covered under the study, states in the Heartland region are the least stringent. This coincides with the passage of the Federal Crop Insurance Act in 1980. Over time, corn production acreage has risen significantly (USDA-ERS, 2017). The majority of corn acreage is located within the Heartland, and about 90% of corn acreage is insured (Shields, 2017). Therefore, if crop insurance is to reduce the cost of production in any way, it is likely to indirectly reduce the relative price of polluting inputs and subsequently reduce regulation stringency. Also, due to the relative intensity and coverage of production on corn acreage and the importance of corn production to the nation's economy, states within the Heartland are likely to adopt other incentivised environmental management practices that are likely to indirectly reduce the cost of polluting inputs (Kara, Ribaudo, and Johansson, 2008). For instance, engaging in cost-share program like the Environmental Quality Improvement Program directly reduce the cost that should be incurred for installing environmental improvement technologies. If enrollment in this program increases over time, then it is likely to affect environmental stringency as well.

From the estimated wedges I compute an average price wedge across time. This is reported along with the percentage of farms in each region and the ratio of price wedge to regional average fertilizer price (Table 4.2). The ratio gives a fair idea of the magnitude of the price wedge relative to fertilizer price. The minimum and maximum values and standard deviations indicate considerable variation in stringency over time. The average wedges provide further evidence indicating that the Heartland is the least stringent region, followed by the Mississippi Portal and Fruitful Rim. The Basin and Range and the Prairie Gateway regions are also confirmed by the averages as the most stringent regions, followed by the Northern Great Plains and the Northern Crescent regions. The Eastern Uplands and the Southern Seaboard are moderately stringent.

Comparing the average price wedge to the price of fertilizer for each region, the Prairie Gateway boasts the highest wedge to fertilizer price ratio (99.83%). Thus, the average price of fertilizer in the Prairie Gateway is approximately the same as the average wedge in that region. The average price of fertilizer in the Basin and Range and Northern Great Plain regions are approximately four-fifths of their average price wedges. The region with the least average wedge-to-average fertilizer price is the Fruitful Rim with a ratio of 41%. The Northern Crescent, Eastern Uplands and the Southern Seaboard have approximately 60% average price wedge to average regional fertilizer price ratio. The average price of fertilizer in the Heartland and Mississippi Regions are about half their average price wedge. The comparison between the price wedge and the price of polluting inputs could be more complete by using the aggregated price index for all dirty inputs. This is not possible since it was not possible to create such an aggregate due to the nature of available data. Considering that NPS pollutants from agriculture are mainly nitrogen and phosphorus deposition (Dowd et al., 2008), I choose to compare the price wedge with average price of fertilizer.

An important observation from this analysis is that the region with the smallest percentage of total U.S. farms (Basin and Range; 4%) is the most stringent region and the region with the highest percentage of farms (Heartland; 22%) is the least stringent region (Table 4.2). With a correlation coefficient of -0.42, regions with greater percentage of farms are likely to have lesser stringency. Notable outliers are the Prairie Gateway and the Mississippi Portal. The Prairie Gateway possesses 13% of farms but is the second highest in ranking according to the mean price wedge, whereas the Mississippi Portal possesses 5% of farms but ranked second to last. However, I also observe that these two regions have the highest standard deviations of the average wedges. The vast deviation is likely to account for their deviation from the identified pattern. This result however, needs to be accepted with caution because the problem that characterize the use of aggregate data. Inferences for state-level base on the regional-level analysis could be misleading.

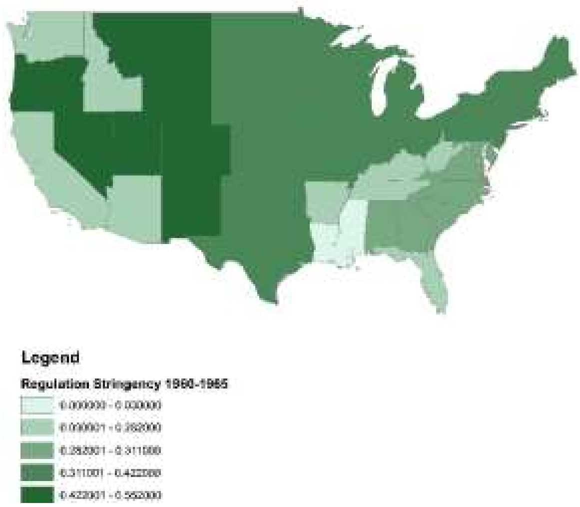

Figure 4.1. Environmental regulatory stringency 1960-65

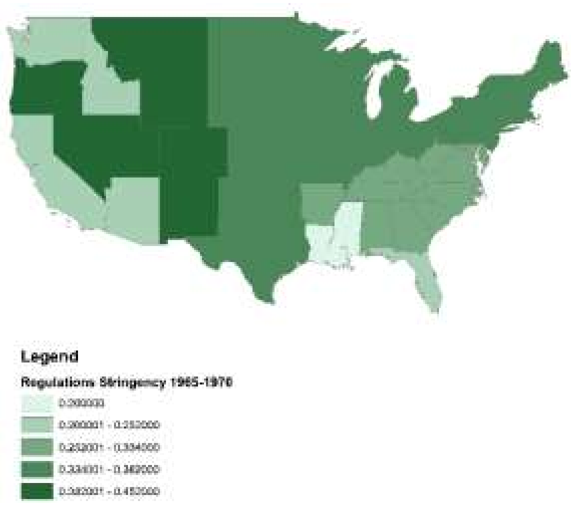

Figure 4.2. Environmental regulatory stringency 1965-70

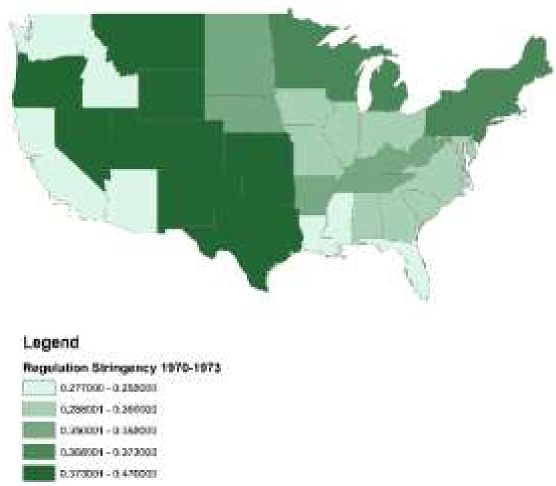

Figure 4.3. Environmental regulatory stringency 1970-73

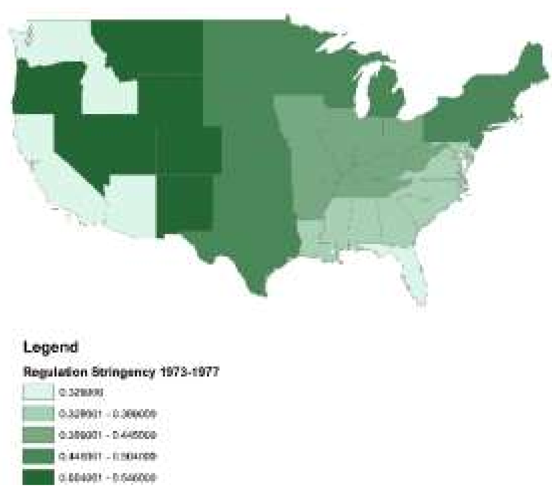

Figure 4.4. Environmental regulatory stringency 1973-77

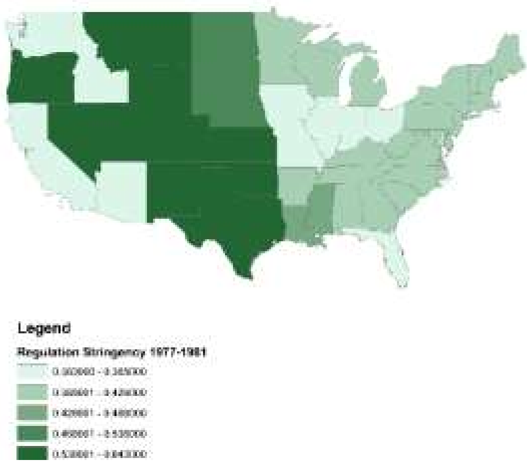

Figure 4.5. Environmental regulatory stringency 1977-81

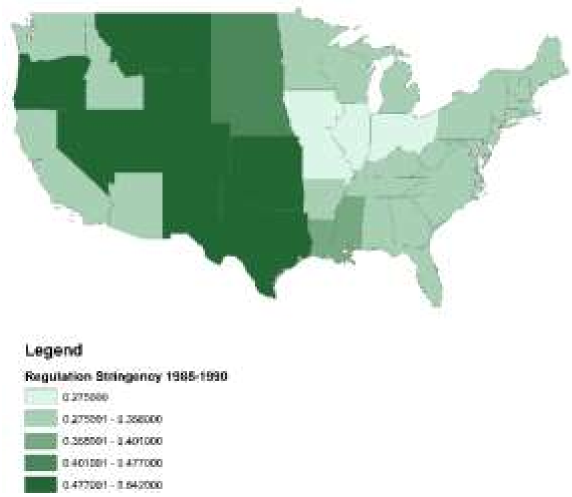

Figure 4.7. Environmental regulatory stringency 1985-90

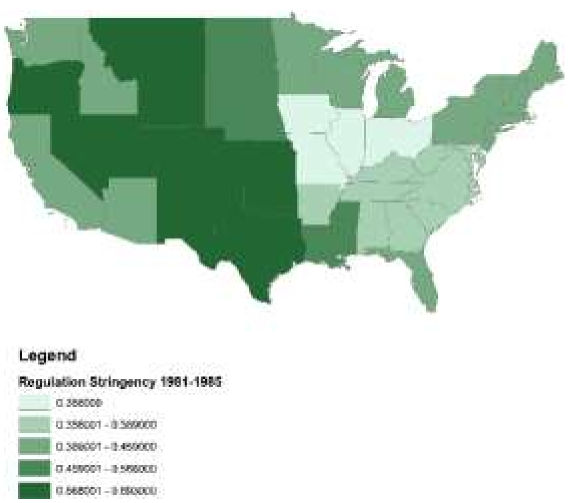

Figure 4.6. Environmental regulatory stringency 1981-85

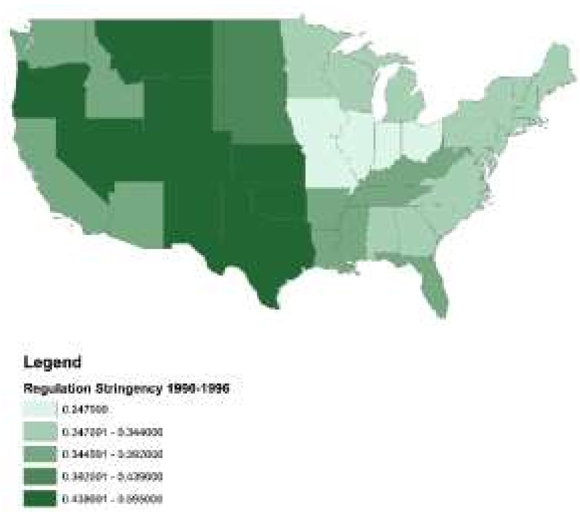

Figure 4.8. Environmental regulatory stringency 1990-1996

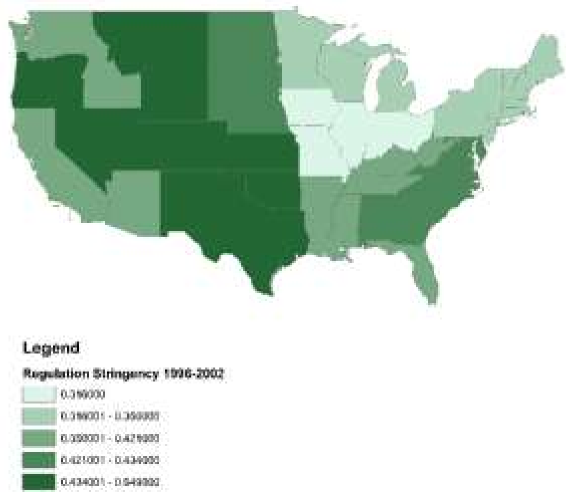

Figure 4.9. Environmental regulatory stringency 1996-2002

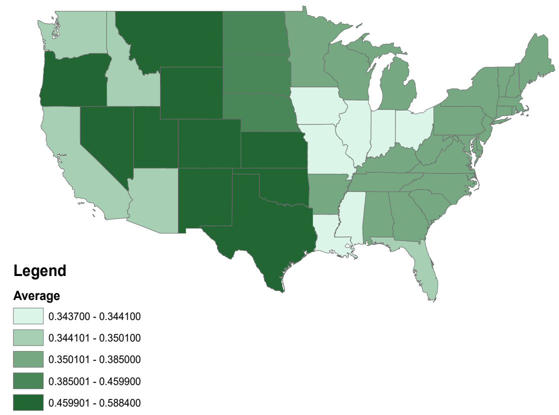

Figure 4.11. Average environmental regulatory stringency over time

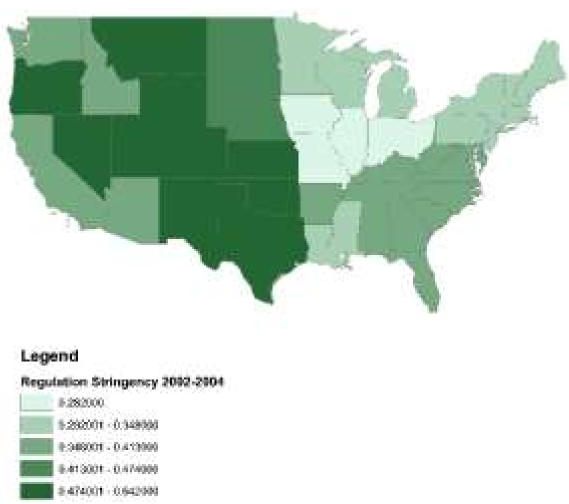

Figure 4.10. Environmental regulatory stringency 2002-2004

4.4. Regional-level temporal variation in stringency

Over the time periods evaluated in this study all regions demonstrate a general increase in stringency with the notable exception of the Heartland and Northern Crescent regions where the highest value cash crops are grown (Figure 4.12 and Figures 4.12.i to 4.12.ix). This is illustrated by the slope of the trend line (dashed) for each region in Figure 4.12.i – Figure 4.12.ix. Specifically, from the 1960-65 to the 1981-85 period, the Mississippi Portal (MP) demonstrated a sharp rise in environmental stringency followed by a decline until the last period. The Basin and Range region, which has the highest stringency in all periods, recorded a sharp decline in stringency from the 1960-65 period to the 1965-70 period, after which there was a rise in stringency until the 1981-85 period. The slope of the trend line of Prairie Gateway (Figure 4.12.ii) indicates that the Prairie Gateway has the highest rate of rise in stringency. In contrast, the Northern Crescent and Heartland regions show decline in stringency over time (Figure 4.12.iv and Figure 4.12.ix). Their highest stringencies were recorded during the 1973-77 period. Even though there was a general decline in stringency, the regions also experienced rises in stringency between the 1970-73 and the 1973-77 periods, times when most regions were also experiencing a rise in stringency. Interestingly, these two regions have cash grains as some of their major crops, particularly corn and soybean, which are very important to the economies of the regions and heavily covered by crop insurance.

With respect to the temporal environmental regulatory stringency of states in the Heartland (Corn Belt) region, the results showed that all states in the region, except for Missouri, demonstrated declining stringency over time (Figure 4.13). Illinois was the least stringent. The decline in stringency demonstrated by the four states (Illinois, Iowa, Indian, and Ohio) is likely to be driving the decline in stringency in the Corn Belt region. This state-level analysis confirms the skepticism about state-level inferences based on regional-level analysis. Albeit using regional-level conclusion suggest that Missouri also shows decline in regulatory stringency, state-level analysis suggest the otherwise.

The Eastern Upland and Southern Seaboard regions (Figure 4.12.v and Figure 4.12.vi) are the only two that showed a slight rise in stringency yet do not show rise between 1977-81 and 1981-85. These two regions follow almost the same trend, with the same rate of stringency rise and the same intercept. They also showed relatively stable stringency over time. These two regions also have the same percentage of cropland – 6 percent. The Northern Great Plains and the Fruitful Rim (Figure 4.12.iii and Figure 4.12.vii) also maintained a steady stringency over time with notable rise from 1960 to 1985.

In general, there is a rise in stringency from the 1970-73 period to the 1981-85 period when most regions reached the peak of stringency. This period of increasing stringency coincides with the introduction of the Clean Water Act in 1972. Even though the CWA does not directly place any restriction on agriculture, the National Ambient Water Quality standards could be forcing states to implement stricter regulations in all sectors to improve water quality, especially for states with poorer water quality.

Three important observations can be made from the research findings. First, there is a high degree of variation in environmental stringency within each region. Second, there is empirical evidence to support increasing efforts by states to control agricultural water pollution. This is demonstrated by the general rise in stringency over time (Fig B.1). However, the Heartland and Northern Crescent regions, comprising 22% and 15% of farms in the U.S., demonstrate a decline in stringency (slopes of trend lines are respectively -0.0157 and -0.009). This highlights the difficulty in controlling nonpoint pollution from agriculture, especially in areas where agriculture is an important component of the regional economy. Finally, that all regions follow a similar trend with slight differences in slope could indicate the impact of federal policy perturbed by variations in state-level enforcement.

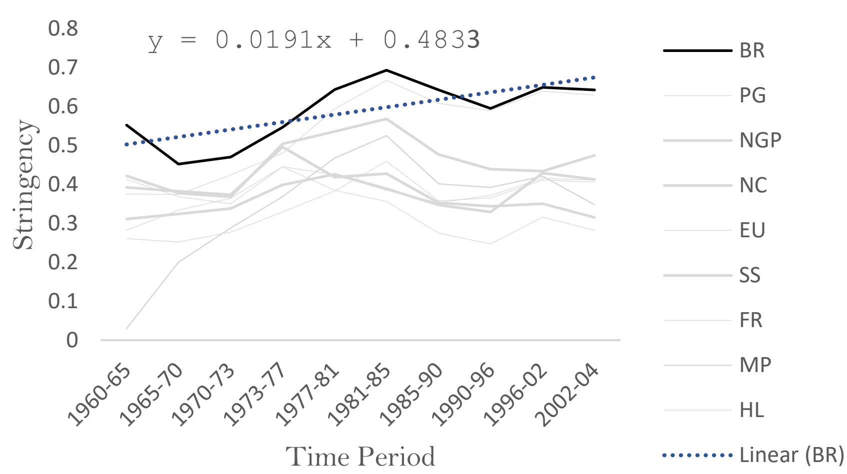

Figure 4.12. i. Basin and Range

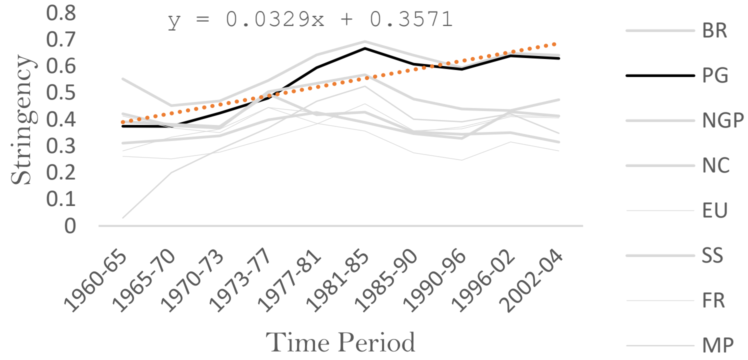

Figure 4.12. ii. Prairie Gateway

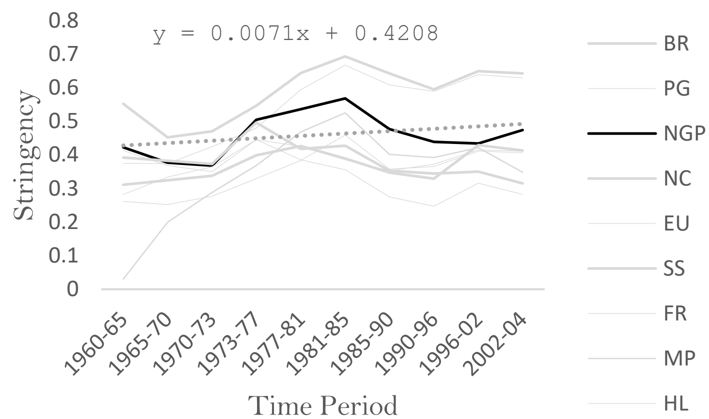

Figure 4.12. iii. Northern Great Plains

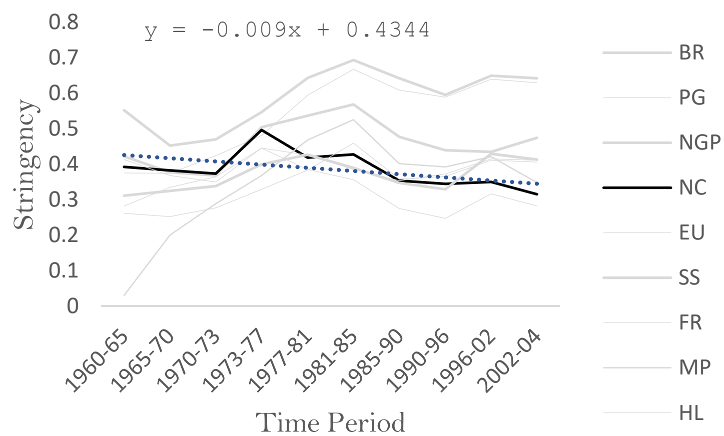

Figure 4.12. iv. Northern Crescent

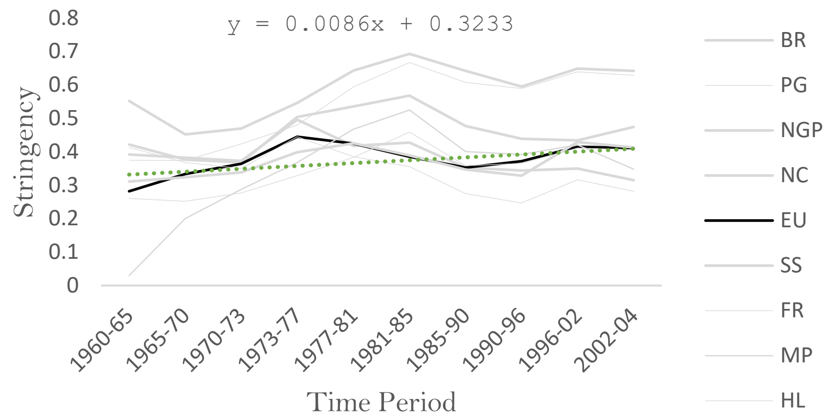

Figure 4.12. v. Eastern Uplands

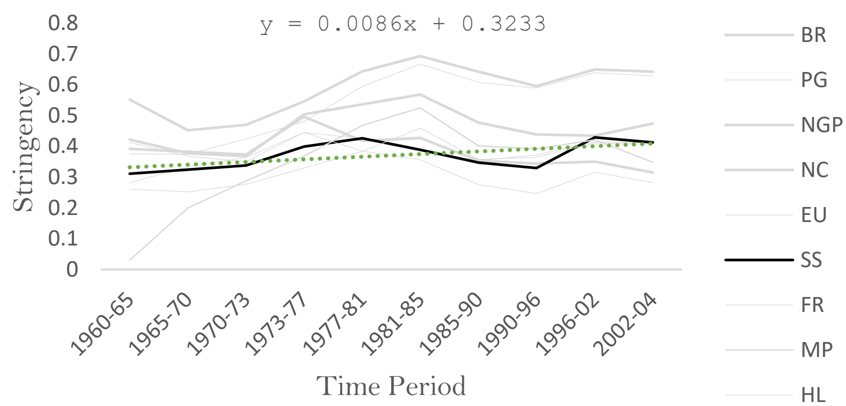

Figure 4.12. vi. **Southern Seaboard**

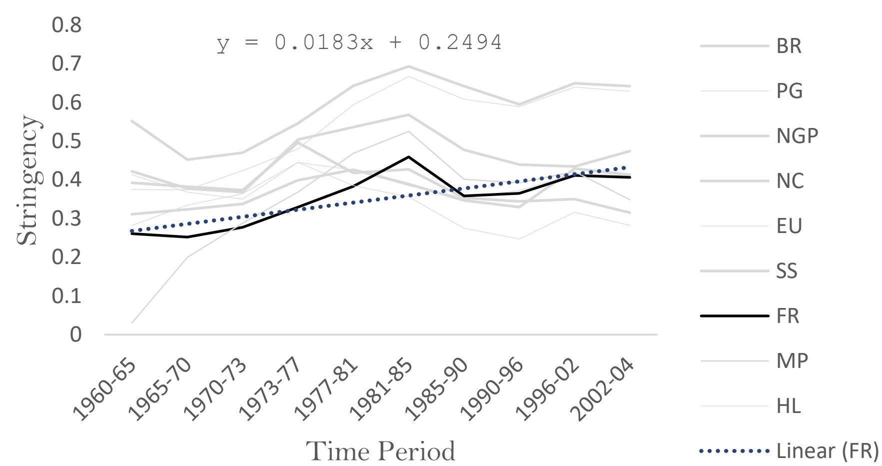

Figure 4.12. vii. Fruitful Rim

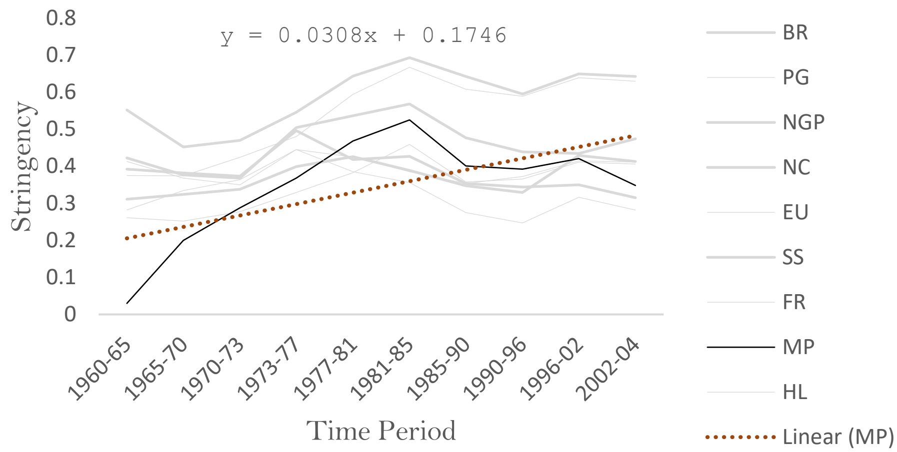

Figure 4.12. viii. Mississippi Portal

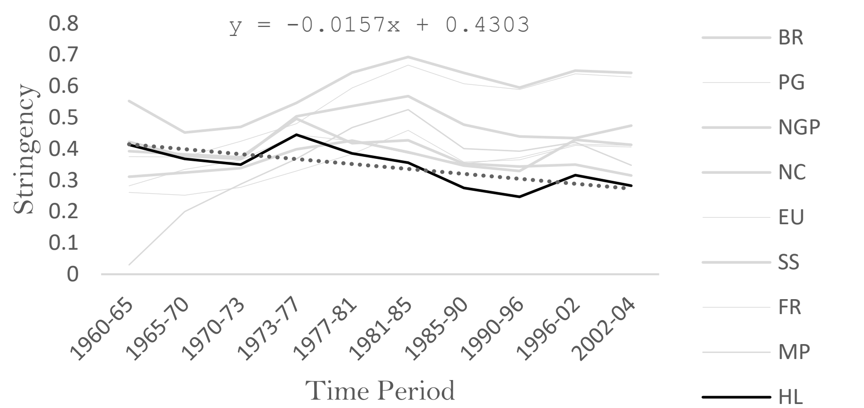

Figure 4.12. ix. Heartland

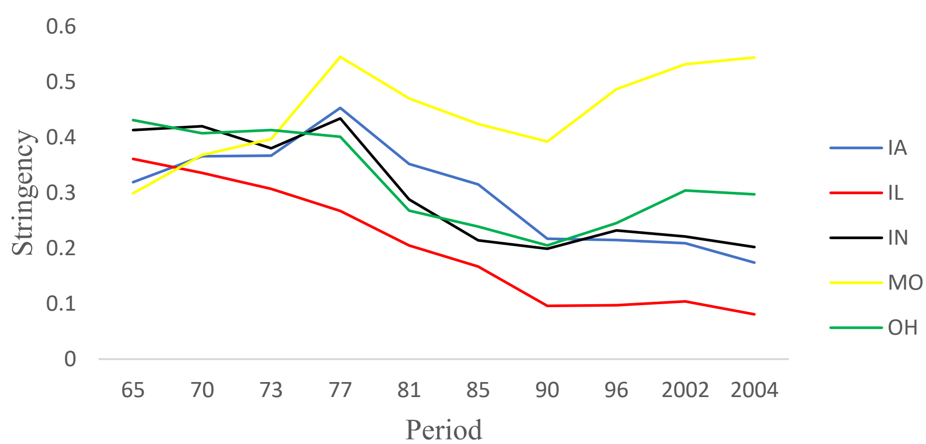

Figure 4. 12: Environmental regulatory stringency of states in the corn belt region

Table 4. 2. Average Price wedge, Percentage of U.S. Farms in Region, and wedge-fertilizer price ratio

Region	Avg. wedge (S.D)	Min.	Max.	% of US Farms in Region	Ratio of wedge to fert. Price
Basin and Range (BR)	0.5884 (0.0811)	0.4520	0.6930	4	84.18%
Prairie Gateway (PG)	0.5379 (0.1133)	0.3740	0.6670	13	99.83%
Northern Great Plains (NGP)	0.4599 (0.0648)	0.3680	0.5680	5	80.68%
Northern Crescent (NC)	0.3850 (0.0519)	0.3150	0.4960	15	58.07%
Eastern Upland (EU)	0.3786 (0.0485)	0.2820	0.4450	15	59.23%
Southern Seaboard (SS)	0.3705 (0.0453)	0.3110	0.4290	11	56.03%
Fruitful Rim (FR)	0.3501 (0.0695)	0.2520	0.4590	10	41.02%
Mississippi Portal (MP)	0.3441 (0.1425)	0.0300	0.5250	5	49.53%
Heartland (HL)	0.3437 (0.0634)	0.2470	0.4450	22	53.39%

4.5. Policy implications

Though the primary aim of this study is to determine how environmental regulatory stringency of the agricultural sector varies across U.S. states and over time, it also has important implications for policy. The study shows that there is variation in environmental regulatory stringency across regions. This implies that federal incentives to mitigate water pollution from agriculture will have different effects in different states. The repercussion of this is the potential relocation of farms that use more polluting inputs (such as the production of corn) from highly-regulated regions (for example, Basin and Range) to less-regulated regions (for example, Corn Belt) leading to further water quality deterioration in the regions with the least stringent regulations. This phenomenon is perhaps already occurring–a recent EPA assessment reports that 46% of U.S. rivers and streams are in poor biological condition, 25% are in fair condition, and 28% are good condition, with the Plains and Lowlands and the Eastern highlands possessing about 50% poor-condition rivers (EPA, 2016).

However, it is also worth noting that since agriculture production is dependent on climatic and soil factors, relocation of firms from one region to another may come with change in crop type and huge transaction cost which could deter farmers from relocating. That is, the notion of a pollution haven is a more restricted concept in agriculture than other sectors. Accordingly, further deterioration in water quality in less stringent regions could be attributed to the lobbying power of agricultural groups in these regions. Considering that corn is a very important crop to the U.S. economy and the less stringent regions dominate in the production of this crop, they are likely to have strong lobbying power either by being exempted from certain regulations or have them being less restrictive (lax).

Going forward, programs that influence water quality in the Farm Bill should be restructured to effectively achieve a standard water quality goal. These programs are limited in that they have multiple goals, and are usually disbursed as payments to farmers, which means that conservation practices largely depends on government spending (Shortle, 2017).

Addressing this in the next Farm Bill will require stricter monitoring of federal policies in regions with lax regulatory stringency. For instance, most high value croplands are clustered around important watershed and most of these croplands are located within the Heartland region (the region with the least and declining environmental regulatory stringency). Stricter monitoring of Federal policies in this region will be required to realize the full impact of policies within the region.

Programs in the Farm Bill that influence water quality should be made more specific to address water pollution rather than making them solve many problems at the same time. Most of these programs simultaneously attempt to increase producer revenue, share cost with producers, and protect the environment. In such cases, polluters tend to focus on the benefit they get from the program more than the environmental protection role of the program. For example, the CRP compensates land owners to take environmentally-sensitive land out of production. This provides revenue for the land owner as well as serving the purpose of environmental protection. That CRP enrollment increases in low price periods and decreases in high price periods indicates farmers interest in revenue over environmental protection (Morefield et al., 2016), which is expected. This could be made more effective and efficient by restricting production on such lands and compensating land owners only if they have improved the environmental state of the land. With this, the government would be paying for the outcome of the environmental activity, not the activity itself.

With the challenges that characterize NPS pollutants—measurement difficulties and not under the control of farmers—it will be difficult to adopt a performance-based approach to improve water quality. Alternatively, the activity-based approach could be altered to improve performance. This can be achieved by (i) binding instruments to measurable environmental changes, and (ii) improving the policy instrument design through targeting of specific locations and watersheds (Shortle *et al.*, 2012).

CHAPTER 5
SUMMARY AND CONCLUSION

5.1. Limitations

Deriving the average shadow price of aggregated polluting inputs will provide a better idea of the magnitude of environmental stringency. However, this is hindered by the fact that it was not possible to create an aggregated price index comprised solely of dirty inputs, because the data is available only in indexed form. The available aggregated price index comprised of all dirty inputs and contains other inputs such as seed and feed. Unfortunately, these inputs (seed and feed) represent majority of the index and hence I could not use it as a proxy for “dirty inputs”.

Another limitation to this study has to do with the creation of the regions. The USDA used county-level data to create the Farm Resource Regions, which resulted in some states appearing in more than one region. I selected states into regions based on the land area in the map. Therefore, the estimated regional wedges will be influenced by which states are included in each region.

Another important limitation is the necessity of the maintained hypothesis of functional form when using the shadow price approach. White (1980) demonstrates the misspecification bias when second-order Taylor series expansions are used to approximate unknown functions using least squares as done in this thesis. The Box-Cox functional form is able to correct this bias. This was not possible in my analysis due to the inclusion of dummies to capture the wedge. The Box-Cox functional form did not allow for dummy variable inclusion.

5.2. Summary

The nonpoint source nature of agricultural water pollution poses severe challenges to regulatory authorities seeking to mitigate water pollution. The efforts of the Federal government to control water pollution are mostly implemented at the state-level. Additionally, some states voluntarily implement measures to control water pollution from agriculture. The in-state application and enforcement of environmental regulations is likely to result in varying environmental regulation stringency across states. This variation is captured in earlier studies using aggregated government efforts to control environmental damages. However, this approach is not only theoretically inconsistent but also ambiguous. The variation in state-level stringency is likely to influence the impact of Federal policies on water quality, hence the need to create a theoretically consistent measure of environmental regulatory stringency in the agricultural sector.

Using the shadow price approach overcomes the challenges of measuring environmental stringency and reflects the fact that implicit costs are placed on polluting inputs by regulations. The method adopted in this study is built on a competitive firm's input decision under cost minimization. The method is built on the assumption that the equilibrium that exists between private marginal benefit and marginal cost is disrupted by environmental regulations. Using the generalized Leontief cost function and adopting the approach of VLJ (2006) and state-level production price data, I make the first attempt to apply the shadow price approach to measure regulatory stringency in the U.S. agricultural sector. I estimate regional wedges, which indicate stringency, using a price index for dirty inputs in agriculture. I capture the wedges through grouped time intervals according to various Farm Bill periods, from 1960 through 2004 as a proxy for environmental stringency.

The estimates show considerable variation in environmental regulatory stringency across Farm Resource Regions and variation over time. Generally, stringency in all regions followed the same trend. Estimated average wedges show that regions with the smallest percentage of farms in the U.S. have the highest level of average stringency, whereas the region with the highest percentage of farms possess the least average stringency. This is a potentially troubling finding given that much of the high-value cropland in the U.S. is clustered around major watersheds that provide essential services for a large portion of the U.S. population.

The implication of the variability in environmental regulatory stringency is that federal incentives to address water pollution from agriculture will have different effects in different states. This could result in potential relocation of high polluting farms from very stringent regions to less stringent regions, which could further deteriorate water quality in these regions (less stringent regions). Programs in the Farm Bill that address environmental pollution (water pollution) will require restructuring to be consistent with the "polluter pays" principle instead of paying the polluter. It will also require payments, where necessary, to be made for the outcome of an environmental action rather than paying for the environmental action. Since it is difficult to employ a performance-based approach to control NPS pollution from agriculture, using an improved activity-based approach that encourages the blend of both approaches, in my opinion, will yield a better outcome than any single approach. Also, stricter monitoring of Federal policies will be required in regions with lax regulatory stringency for these policies to achieve the set goals in these regions.

5.3. Areas for future research

There are several studies that assess the impact of individual government programs on water quality. Since the shadow price approach is able to capture several policy and program effects into a single index, it will be very insightful to look at how water quality indices vary with state-level stringency of implemented regulations, especially at highly polluted watershed areas. This can be achieved by selecting states that are close to the watershed and estimating their environmental regulatory stringency. The estimates can then be used with other control variables as regressors on water quality indices.

Institutions play a vital role in policy and regulation implementation and enforcement. For instance, regulations could be stringent enough to achieve a set goal. However, if the institution to implement these regulations is corrupt, the full impact of regulations might not be realized. Understanding how institutional qualities such as corruption and political stability among other indices impact environmental regulation stringency is another research area which could be investigated in the future.

My research only provides an aggregated measure of stringency of all implemented environmental regulations and policies. A future research that looks at what the individual impacts of crop insurance and policies in the Farm Bill on environmental stringency are could also provide important information to policy makers on specific environmental policies.

Given that previous measures of regulatory stringency in U.S. agricultural sector were based on government effort indices, and these results were used to test the pollution haven hypothesis (as in (USDA, 2000)), it will be prudent to test these hypotheses once again using the shadow price approach estimates to verify if there will be a change in conclusion.

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APPENDIX A

Table A. 1. Descriptive statistics of variables

Variable	Variable description	Mean	Std dev	Min	Max
y	Total output qnty	3845798	3937507	42855.61	3.16E+07
L	Land qnty	714651.8	758782.8	4014.592	5155293
N	Labour qnty	1971849	1742061	18189.34	9476398
F	Fertilizer qnty	208046.2	226377.5	1301.193	1637918
PE	Pesticide qnty	97879.22	125812.4	194.3583	964614.2
E	Energy qnty	163913	151570.7	1497.354	860383
A	Agrochemical qnty	306009.4	336847.1	1708.779	2086151
Pl	Land price	0.606616	0.575486	0.006121	3.631588
K	Capital qnty	662047	591411.5	7350.917	3330621
Pn	Labour price	0.439535	0.334196	0.048593	2.110528
Pf	Fertilizer price	0.671578	0.318431	0.068969	1.865223
Pp	Pesticide price	0.76164	0.336915	0.113744	2.533966
Pe	Energy price	0.789549	0.41604	0.176648	1.865717
Pa	Agrochemical price	0.684411	0.303011	0.080656	1.558945
t	Time trend	23	12.99018	1	45

Computing global concavity in variable input prices and convexity in quasi-fixed input

Using the variable description in Table A.1 and assuming that land, labour, fertilizer, pesticide, energy, and agrochemical are variable inputs, and capital is the only quasi-fixed input, whereas time trend proxy for technological changes, the generalized Leontief cost function then appears as;

$$\begin{aligned} C = y\big[&\alpha_{ll}P_l + \alpha_{nn}P_n + \alpha_{ff}Z_f + \alpha_{pp}Z_p + \alpha_{ee}Z_e + \alpha_{aa}Z_a + \alpha_{nl}P_n^{0.5}P_l^{0.5} + \alpha_{nf}P_n^{0.5}Z_f^{0.5} \\ &+ \alpha_{np}P_n^{0.5}Z_p^{0.5} + \alpha_{ne}P_n^{0.5}Z_p^{0.5} + + \alpha_{na}P_n^{0.5}Z_p^{0.5} + \alpha_{lf}P_l^{0.5}Z_f^{0.5} + \alpha_{lp}P_l^{0.5}Z_p^{0.5} \\ &+ \alpha_{le}P_l^{0.5}Z_e^{0.5} + \alpha_{la}P_l^{0.5}Z_a^{0.5} + \alpha_{fp}Z_f^{0.5}Z_p^{0.5} + \alpha_{fe}Z_f^{0.5}Z_e^{0.5} + \alpha_{fa}Z_f^{0.5}Z_a^{0.5} \\ &+ \alpha_{pe}Z_e^{0.5}Z_p^{0.5} + \alpha_{pa}Z_a^{0.5}Z_p^{0.5} + \alpha_{ea}Z_e^{0.5}Z_a^{0.5}\big] + \\ y\big[&\delta_{nt}P_nt^{0.5} + \delta_{lt}P_lt^{0.5} + \delta_{ft}Z_ft^{0.5} + \delta_{pt}Z_pt^{0.5} + \delta_{et}Z_et^{0.5} + \delta_{at}Z_at^{0.5} + \gamma_{nt}P_nt + \gamma_{lt}P_lt \\ &+ \gamma_{ft}Z_ft + \gamma_{pt}Z_pt + \gamma_{et}Z_et + \gamma_{at}Z_at\big] + \end{aligned} \tag{1}$$

$$y^{0.5}\left[\delta_{lk}P_l X_k^{0.5} + \delta_{nk}P_n X_k^{0.5} + \delta_{fk}Z_f X_k^{0.5} + \delta_{pk}Z_p X_k^{0.5} + \delta_{ek}Z_e X_k^{0.5} + \delta_{ak}Z_a X_k^{0.5} + P_n\gamma_{tk}t^{.5}X^{.5} + P_l\gamma_{tk}t^{.5}X^{.5} + Z_f\gamma_{tk}t^{.5}X^{.5} + Z_p\gamma_{tk}t^{.5}X^{.5} + Z_e\gamma_{tk}t^{.5}X^{.5} + Z_a\gamma_{tk}t^{.5}X^{.5}\right] + \gamma_{nk}P_n X_k + \gamma_{lk}P_l X_k + \gamma_{fk}Z_f X_k + \gamma_{pk}Z_p X_k + \gamma_{ek}Z_e X_k + \gamma_{ak}Z_a X_k$$

For concavity in variable input prices,

$$\frac{\partial^2 C}{\partial p_i^2} < 0 \tag{2}$$

And convexity in quasi-fixed input is given as,

$$\frac{\partial^2 C}{\partial X_k^2} > 0 \tag{3}$$

From equation (3), the second derivative of the cost function with respect to the variable inputs' price can be written as

$$\frac{\partial^2 C}{\partial p_i^2} = -0.25y * p_i^{-1.5} \sum_{j}^{(m-1)} \alpha_{ij} p_j^{.5} \tag{4}$$

Land

$$\frac{\partial^2 C}{\partial P_l^2} = -0.25y * p_l^{-1.5}\left(\alpha_{nl}p_n^{.5} + \alpha_{lf}p_f^{.5} + \alpha_{lp}p_p^{.5} + \alpha_{le}p_e^{.5} + \alpha_{la}p_a^{.5}\right) \tag{5}$$

$$\frac{\partial^2 C}{\partial P_l^2} = (-961447.25)(2.1166)(0.2235) = -454822.3322 < 0$$

Labour

$$\frac{\partial^2 C}{\partial P_n^2} = -0.25y * p_n^{-1.5}\left(\alpha_{nl}p_l^{.5} + \alpha_{nf}p_f^{.5} + \alpha_{np}p_p^{.5} + \alpha_{ne}p_e^{.5} + \alpha_{na}p_a^{.5}\right) \tag{6}$$

$$\frac{\partial^2 C}{\partial P_n^2} = (-961447.25)(1.9554)(0.4215) = -792372.3006 < 0$$

Fertilizer

$$\frac{\partial^2 C}{\partial P_n^2} = -0.25y * p_n^{-1.5}\left(\alpha_{nl}p_l^{.5} + \alpha_{nf}p_f^{.5} + \alpha_{np}p_p^{.5} + \alpha_{ne}p_e^{.5} + \alpha_{na}p_a^{.5}\right) \tag{7}$$

$$\frac{\partial^2 C}{\partial P_f^2} = (-961447.25)(1.8169)(0.0986) = -172239.7559 < 0$$

Pesticide

$$\frac{\partial^2 C}{\partial P_p^2} = -0.25y * p_p^{-1.5}\left(\alpha_{np}p_n^{.5} + \alpha_{fp}p_f^{.5} + \alpha_{lp}p_l^{.5} + \alpha_{pe}p_e^{.5} + \alpha_{pa}p_a^{.5}\right) \tag{8}$$

$$\frac{\partial^2 C}{\partial P_p^2} = (-961447.25)(1.5046)(0.0704) = -101909.6212 < 0$$

Energy

$$\frac{\partial^2 C}{\partial P_e^2} = -0.25y * p_e^{-1.5}\left(\alpha_{ne}p_n^{.5} + \alpha_{le}p_l^{.5} + \alpha_{fe}p_f^{.5} + \alpha_{pe}p_p^{.5} + \alpha_{ea}p_a^{.5}\right) \tag{9}$$

$$\frac{\partial^2 C}{\partial P_e^2} = (-961447.25)(1.4255)(0.0603) = -82623.4622 < 0$$

Agrochemical

$$\frac{\partial^2 C}{\partial P_a^2} = -0.25y * p_a^{-1.5}\left(\alpha_{na}p_n^{.5} + \alpha_{la}p_l^{.5} + \alpha_{fa}p_f^{.5} + \alpha_{pa}p_p^{.5} + \alpha_{ea}p_e^{.5}\right) \tag{10}$$

$$\frac{\partial^2 C}{\partial P_a^2} = (-961447.25)(1.76621)(0.1141) = -193792.0058 < 0$$

For convexity, the second derivative of the cost function with respect to the quasi-fixed input is derived as;

$$\frac{\partial^2 C}{\partial X_k^2} = -0.25y^{.5} * X_k^{-1.5}[(\delta_{nk}p_n + \delta_{lk}p_l + \delta_{fk}p_f + \delta_{pk}p_p + \delta_{ek}p_e + \delta_{ak}p_a) + t^{.5}(\gamma_{kt}p_n + \gamma_{kt}p_l + \gamma_{kt}p_f + \gamma_{kt}p_p + \gamma_{kt}p_e + \gamma_{kt}p_a)] \tag{11}$$

$$\frac{\partial^2 C}{\partial X_k^2} = [(-9.1 \times 10^{-7}) \times (1.4341) \times (-0.0489)] = 6.3115 \times 10^{-8} > 0$$

Correlation Coefficient between Regional Average Price Wedges and the Percentage of Farms in Each Region

Table A. 2. Correlation Coefficient Calculation

Region	Av. Wedge (W)	% of Farm(P)	W-w = A	P-p = B	A*B	B^2	A^2
BR	0.5884	4	0.1708	-7.1111	-1.2147	50.5679	0.0292
PR	0.5379	13	0.1203	1.8889	0.2273	3.5679	0.0145
NGP	0.4599	5	0.0423	-6.1111	-0.2586	37.3457	0.0018
NC	0.385	15	-0.0326	3.8889	-0.1267	15.1235	0.0011
EU	0.3786	15	-0.0390	3.8889	-0.1516	15.1235	0.0015
SS	0.3705	11	-0.0471	-0.1111	0.0052	0.0123	0.0022
FR	0.3501	10	-0.0675	-1.1111	0.0750	1.2346	0.0046
MP	0.3441	5	-0.0735	-6.1111	0.4490	37.3457	0.0054
HL	0.3437	22	-0.0739	10.8889	-0.8044	118.5679	0.0055
	$\sum_i^n \frac{W}{n} = w$ =0.4176	$\sum_i^n \frac{P}{n} = p$ =11.1111			$\sum_i^n (A * B) =$ -1.7996	$\sum_i^n (B^2) =$ 278.8889	$\sum_i^n (A^2)$ =0.0657

$$Correlation\ coefficient\ (r) = \frac{\sum_i^n (A * B)}{\sqrt{\left(\sum_i^n (A^2)\right)\left(\sum_i^n (B^2)\right)}}$$

$$r = -\frac{1.7996}{\sqrt{(278.8889)(0.0657)}}$$

$$r = -\frac{1.7998}{4.2805} = -0.42$$

APPENDIX B

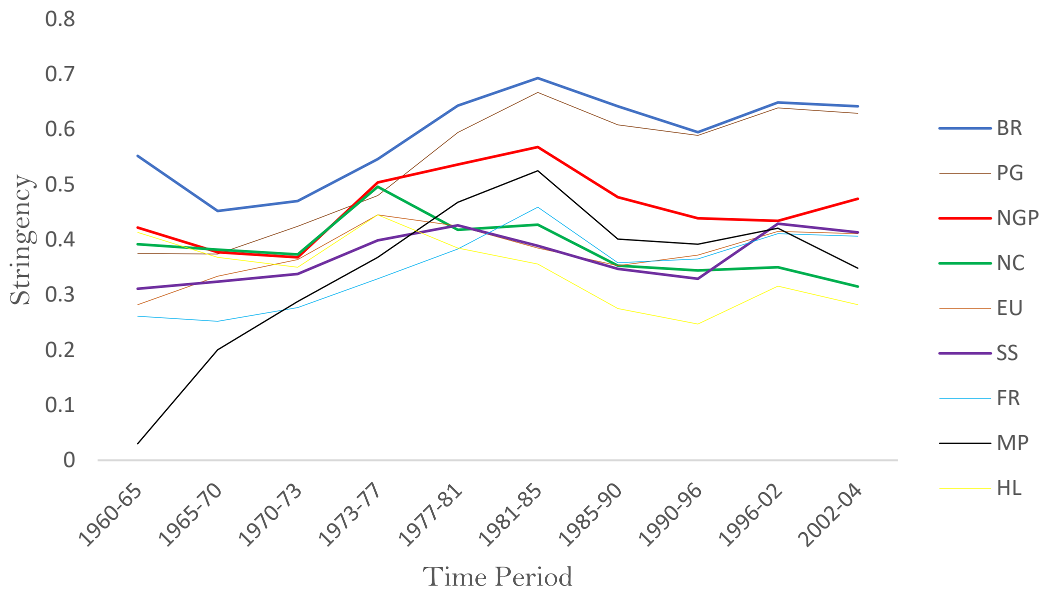

Figure B. 1. Environmental regulatory stringency: All regions

Table B. 1. State-level wedges for states in the Heartland region

States	Parameter	Wedge (s.e)
Iowa	$\lambda_{IA,65}$	0.319*** (0.076)
	$\lambda_{IA,70}$	0.366*** (0.075)
	$\lambda_{IA,73}$	0.367*** (0.072)
	$\lambda_{IA,77}$	0.453*** (0.073)
	$\lambda_{IA,81}$	0.352***(0.073)
	$\lambda_{IA,85}$	0.315*** (0.078)
	$\lambda_{IA,90}$	0.217*** (0.07)
	$\lambda_{IA,96}$	0.215*** (0.075)
	$\lambda_{IA,02}$	0.209*** (0.076)
	$\lambda_{IA,04}$	0.174** (0.074)
Illinois	$\lambda_{IL,65}$	0.361*** (0.086)
	$\lambda_{IL,70}$	0.336*** (0.08)
	$\lambda_{IL,73}$	0.307*** (0.077)

	$\lambda_{IL,77}$	0.267*** (0.082)
	$\lambda_{IL,81}$	0.205** (0.084)
	$\lambda_{IL,85}$	0.167* (0.091)
	$\lambda_{IL,90}$	0.096 (0.08)
	$\lambda_{IL,96}$	0.097 (0.082)
	$\lambda_{IL,02}$	0.104 (0.086)
	$\lambda_{IL,04}$	0.081 (0.085)
Indiana	$\lambda_{IN,65}$	0.413*** (0.125)
	$\lambda_{IN,70}$	0.420*** (0.112)
	$\lambda_{IN,73}$	0.380*** (0.106)
	$\lambda_{IN,77}$	0.434*** (0.104)
	$\lambda_{IN,81}$	0.288*** (0.097)
	$\lambda_{IN,85}$	0.214** (0.101)
	$\lambda_{IN,90}$	0.199** (0.098)
	$\lambda_{IN,96}$	0.232** (0.101)
	$\lambda_{IN,02}$	0.221** (0.104)
	$\lambda_{IN,04}$	0.202* (0.106)
Missouri	$\lambda_{MO,65}$	0.299*** (0.115)
	$\lambda_{MO,70}$	0.368*** (0.11)
	$\lambda_{MO,73}$	0.397***(0.105)
	$\lambda_{MO,77}$	0.545*** (0.108)
	$\lambda_{MO,81}$	0.470*** (0.101)
	$\lambda_{MO,85}$	0.424*** (0.102)
	$\lambda_{MO,90}$	0.392*** (0.01)
	$\lambda_{MO,96}$	0.487*** (102)
	$\lambda_{MO,02}$	0.532*** (0.097)
	$\lambda_{MO,04}$	0.544*** (0.097)
	$\lambda_{MO,65}$	0.431*** (0.125)
Ohio	$\lambda_{OH,70}$	0.407*** (0.115)
	$\lambda_{OH,73}$	0.413*** (0.108)

	$\lambda_{OH,77}$	0.401*** (0.106)
	$\lambda_{OH,81}$	0.268*** (0.095)
	$\lambda_{OH,85}$	0.239** (0.099)
	$\lambda_{OH,90}$	0.205** (0.093)
	$\lambda_{OH,96}$	0.245** (0.097)
	$\lambda_{OH,02}$	0.304*** (0.099)
	$\lambda_{OH,04}$	0.297*** (0.104)

APPENDIX C

Figure C. 1. Farm Resource Regions

Source: (USDA, 2000)

APPENDIX D

STATA OUTPUT

```
Seemingly unrelated regression, iterated
----------------------------------------------------------------------
Equation             Obs   Parms        RMSE    "R-sq"     F-Stat        P
----------------------------------------------------------------------
TC                 2,160     141    337334.8    0.9913    1968.71   0.0000
L_Q                2,160      18    .1396943    0.7082     298.01   0.0000
N_Q                2,160      18    .1735908    0.8008     553.71   0.0000
F_Q                2,160      18    .0185907    0.5242     276.42   0.0000
E_Q                2,160      18    .0078695    0.6614     268.12   0.0000
PE_Q               2,160      18    .0096337    0.6342     350.10   0.0000
A_Q                2,160      18    .0249344    0.4860     174.33   0.0000
----------------------------------------------------------------------

 ( 1)  - [L_Q]sqrPnDsqrPl_d5 + [N_Q]sqrPlDsqrPn_d5 = 0
 ( 2)  [N_Q]sqrPfDsqrPn_d5 - [F_Q]sqrPnDsqrPf_d5 = 0
 ( 3)  [N_Q]sqrPpDsqrPn_d5 - [PE_Q]sqrPnDsqrPp_d5 = 0
 ( 4)  [N_Q]sqrPaDsqrPn_d5 - [A_Q]sqrPnDsqrPa_d5 = 0
 ( 5)  [N_Q]sqrPeDsqrPn_d5 - [E_Q]sqrPnDsqrPe_d5 = 0
 ( 6)  [L_Q]sqrPfDsqrPl_d5 - [F_Q]sqrPlDsqrPf_d5 = 0
 ( 7)  [L_Q]sqrPpDsqrPl_d5 - [PE_Q]sqrPlDsqrPp_d5 = 0
 ( 8)  [L_Q]sqrPeDsqrPl_d5 - [E_Q]sqrPlDsqrPe_d5 = 0
 ( 9)  [L_Q]sqrPaDsqrPl_d5 - [A_Q]sqrPlDsqrPa_d5 = 0
 (10)  [F_Q]sqrPpDsqrPf_d5 - [PE_Q]sqrPfDsqrPp_d5 = 0
 (11)  [F_Q]sqrPeDsqrPf_d5 - [E_Q]sqrPfDsqrPe_d5 = 0
 (12)  [F_Q]sqrPaDsqrPf_d5 - [A_Q]sqrPfDsqrPa_d5 = 0
 (13)  [PE_Q]sqrPaDsqrPp_d5 - [A_Q]sqrPpDsqrPa_d5 = 0
 (14)  - [E_Q]sqrPpDsqrPe_d5 + [PE_Q]sqrPeDsqrPp_d5 = 0
 (15)  - [E_Q]sqrPaDsqrPe_d5 + [A_Q]sqrPeDsqrPa_d5 = 0
 (16)  [L_Q]K_Q - [N_Q]K_Q = 0
 (17)  [N_Q]K_Q - [F_Q]K_Q = 0
 (18)  [F_Q]K_Q - [A_Q]K_Q = 0
 (19)  - [E_Q]K_Q + [A_Q]K_Q = 0
 (20)  [E_Q]K_Q - [PE_Q]K_Q = 0
------------------------------------------------------------------------------
                 |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-----------------+------------------------------------------------------------
TC               |
        c.Q#c.Pn |  -2.941304   1.216773    -2.42   0.016     -5.32633   -.5562772
                 |
        c.Q#c.Pl |  -.2369349   .7054747    -0.34   0.737    -1.619753    1.145883
                 |
        c.Q#c.Pf |   7.205276   5.457952     1.32   0.187    -3.492984    17.90354
                 |
        c.Q#c.Pp |   1.898301   2.703431     0.70   0.483    -3.400759    7.197361
                 |
        c.Q#c.Pe |  -2.825084   .9013013    -3.13   0.002    -4.591746   -1.058422
                 |
        c.Q#c.Pa |   7.646434   8.581293     0.89   0.373     -9.17396    24.46683
                 |
      tt#frr#c.Q |
            1 1  |   .5521956   .0546513    10.10   0.000     .4450723     .659319
            1 2  |   .2606876   .0368514     7.07   0.000     .1884543     .332921
            1 3  |   .4216873   .0394525    10.69   0.000     .3443554    .4990191
            1 4  |   .3748762   .0317683    11.80   0.000     .3126065     .437146
            1 5  |   .4126928   .0349147    11.82   0.000     .3442558    .4811298
            1 6  |   .0300128   .0593263     0.51   0.613     -.086274    .1462996
            1 7  |   .3918569   .0340772    11.50   0.000     .3250614    .4586524
            1 8  |   .2815183   .0445083     6.33   0.000     .1942765    .3687601
            1 9  |   .3110777   .0405372     7.67   0.000     .2316197    .3905357
            2 1  |   .4515241   .0449482    10.05   0.000     .3634202    .5396281
            2 2  |   .2523389   .0317714     7.94   0.000      .190063    .3146148
            2 3  |    .376848   .0348753    10.81   0.000      .308488    .4452079
```

2	4	.3735107	.0284328	13.14	0.000	.317779	.4292424
2	5	.3684931	.03093	11.91	0.000	.3078664	.4291198
2	6	.199599	.0522959	3.82	0.000	.0970927	.3021054
2	7	.3815201	.0298181	12.79	0.000	.3230729	.4399674
2	8	.3344778	.0419954	7.96	0.000	.2521616	.416794
2	9	.3239379	.0342795	9.45	0.000	.2567459	.39113
3	1	.4703609	.0455697	10.32	0.000	.3810386	.5596832
3	2	.2767264	.0297973	9.29	0.000	.2183199	.3351329
3	3	.3678129	.0337407	10.90	0.000	.3016769	.4339489
3	4	.4239147	.0283236	14.97	0.000	.368397	.4794323
3	5	.3501621	.0299514	11.69	0.000	.2914537	.4088705
3	6	.2883242	.0586789	4.91	0.000	.1733064	.403342
3	7	.3733822	.0282067	13.24	0.000	.3180935	.4286709
3	8	.3640311	.0441553	8.24	0.000	.2774812	.4505809
3	9	.3376639	.0364564	9.26	0.000	.2662048	.409123
4	1	.5463939	.0406648	13.44	0.000	.4666859	.6261019
4	2	.3288732	.0287497	11.44	0.000	.2725202	.3852261
4	3	.5037665	.0309935	16.25	0.000	.4430153	.5645176
4	4	.4800651	.0255469	18.79	0.000	.42999	.5301403
4	5	.4446025	.0297854	14.93	0.000	.3862194	.5029856
4	6	.3681506	.057713	6.38	0.000	.255026	.4812751
4	7	.4955531	.0280342	17.68	0.000	.4406027	.5505036
4	8	.4447736	.0395778	11.24	0.000	.3671962	.522351
4	9	.3986365	.0329996	12.08	0.000	.3339532	.4633197
5	1	.6433539	.0392256	16.40	0.000	.5664669	.7202409
5	2	.3826591	.0292816	13.07	0.000	.3252635	.4400548
5	3	.53619	.0286814	18.69	0.000	.4799709	.5924091
5	4	.5941359	.0263666	22.53	0.000	.5424541	.6458177
5	5	.3853159	.0302218	12.75	0.000	.3260773	.4445544
5	6	.4684579	.0576218	8.13	0.000	.3555121	.5814038
5	7	.417567	.0267366	15.62	0.000	.3651599	.4699741
5	8	.4253996	.0382444	11.12	0.000	.3504359	.5003633
5	9	.4263426	.0341173	12.50	0.000	.3594685	.4932166
6	1	.6926212	.0398116	17.40	0.000	.6145855	.7706568
6	2	.4593868	.0346669	13.25	0.000	.3914354	.5273382
6	3	.5676918	.0297992	19.05	0.000	.5092816	.6261019
6	4	.667068	.0288387	23.13	0.000	.6105406	.7235953
6	5	.355544	.0345536	10.29	0.000	.2878146	.4232733
6	6	.5250769	.0622085	8.44	0.000	.4031406	.6470132
6	7	.4272096	.0296884	14.39	0.000	.3690168	.4854025
6	8	.3852534	.0396055	9.73	0.000	.3076217	.4628851
6	9	.3891919	.0352614	11.04	0.000	.3200753	.4583086
7	1	.6422732	.0353246	18.18	0.000	.5730325	.7115138
7	2	.3580747	.0307958	11.63	0.000	.2977111	.4184383
7	3	.477295	.0267734	17.83	0.000	.4248159	.5297742
7	4	.6079708	.0257131	23.64	0.000	.5575699	.6583717
7	5	.274783	.0281583	9.76	0.000	.2195893	.3299766
7	6	.4009401	.0484864	8.27	0.000	.3059008	.4959794
7	7	.353462	.0268899	13.14	0.000	.3007546	.4061694
7	8	.3527236	.0344629	10.23	0.000	.2851721	.4202751
7	9	.3466816	.0327237	10.59	0.000	.2825391	.4108241
8	1	.5954233	.033708	17.66	0.000	.5293514	.6614952
8	2	.3650462	.0322851	11.31	0.000	.3017634	.428329
8	3	.4389058	.026811	16.37	0.000	.3863528	.4914587
8	4	.5892219	.0259468	22.71	0.000	.5383629	.6400808
8	5	.2472611	.0301463	8.20	0.000	.1881706	.3063517
8	6	.3919635	.0407724	9.61	0.000	.3120445	.4718825
8	7	.3437682	.0301967	11.38	0.000	.284579	.4029574
8	8	.3717096	.0320347	11.60	0.000	.3089176	.4345016
8	9	.329237	.0312326	10.54	0.000	.2680173	.3904568
9	1	.648726	.0345945	18.75	0.000	.5809164	.7165356
9	2	.4108188	.0332345	12.36	0.000	.3456751	.4759626
9	3	.4339478	.0275817	15.73	0.000	.3798842	.4880115
9	4	.6386783	.025588	24.96	0.000	.5885226	.6888339
9	5	.3163079	.0309896	10.21	0.000	.2555644	.3770513
9	6	.4207149	.0383971	10.96	0.000	.3454519	.4959779

9 7	.3504304	.0320198	10.94	0.000	.2876676	.4131931
9 8	.4145591	.0313962	13.20	0.000	.3530187	.4760996
9 9	.428509	.032596	13.15	0.000	.3646169	.492401
10 1	.6424845	.0429877	14.95	0.000	.5582234	.7267456
10 2	.4059606	.0347592	11.68	0.000	.3378282	.4740929
10 3	.4735015	.0309111	15.32	0.000	.412912	.534091
10 4	.6292858	.0299308	21.02	0.000	.5706178	.6879539
10 5	.2823415	.0325419	8.68	0.000	.2185554	.3461276
10 6	.3482029	.04842	7.19	0.000	.2532937	.4431121
10 7	.3153912	.0339511	9.29	0.000	.2488428	.3819396
10 8	.4114521	.0359555	11.44	0.000	.3409749	.4819292
10 9	.4125076	.0358226	11.52	0.000	.3422909	.4827243
c.Q#c.sqrPlsqrPn	.1443595	.0942515	1.53	0.126	-.040385	.3291041
c.Q#c.sqrPfsqrPl	-2.199131	.6354168	-3.46	0.001	-3.444626	-.9536357
c.Q#c.sqrPpsqrPl	-.9669119	.4712696	-2.05	0.040	-1.890659	-.0431651
c.Q#c.sqrPasqrPl	3.495488	1.083703	3.23	0.001	1.371297	5.619679
c.Q#c.sqrPesqrPl	.4703926	.1246618	3.77	0.000	.2260401	.7147451
c.Q#c.sqrPfsqrPn	6.44303	1.069104	6.03	0.000	4.347455	8.538606
c.Q#c.sqrPesqrPn	-.275418	.1731423	-1.59	0.112	-.6147984	.0639624
c.Q#c.sqrPasqrPn	-10.7193	1.763739	-6.08	0.000	-14.17645	-7.262153
c.Q#c.sqrPpsqrPn	4.563278	.7312291	6.24	0.000	3.129979	5.996578
c.Q#c.sqrPpsqrPf	.5459932	3.799499	0.14	0.886	-6.901495	7.993482
c.Q#c.sqrPesqrPf	1.812575	.9795786	1.85	0.064	-.1075199	3.73267
c.Q#c.sqrPasqrPf	-14.01634	9.237277	-1.52	0.129	-32.12255	4.089862
c.Q#c.sqrPesqrPp	.6433513	.6829624	0.94	0.346	-.6953395	1.982042
c.Q#c.sqrPasqrPp	-.5763611	5.971546	-0.10	0.923	-12.28133	11.12861
c.Q#c.sqrPasqrPe	-2.153533	1.619419	-1.33	0.184	-5.327794	1.020728
c.Q#c.Pnsqrt	1.099481	.2845714	3.86	0.000	.5416856	1.657276
c.Q#c.Plsqrt	.2083805	.1863117	1.12	0.263	-.1568134	.5735744
c.Q#c.Pfsqrt	-1.053999	.8629403	-1.22	0.222	-2.745468	.637471
c.Q#c.Ppsqrt	-.7737278	.4523317	-1.71	0.087	-1.660354	.1128984
c.Q#c.Pesqrt	.2226062	.2086789	1.07	0.286	-.1864301	.6316426
c.Q#c.Pasqrt	1.211541	1.294783	0.94	0.349	-1.326394	3.749477
c.Q#c.Pnt	-.0876379	.0188399	-4.65	0.000	-.1245665	-.0507094
c.Q#c.Plt	-.0298979	.0137454	-2.18	0.030	-.0568406	-.0029552
c.Q#c.Pft	.0743804	.0548717	1.36	0.175	-.0331748	.1819356
c.Q#c.Ppt	.0298891	.0289638	1.03	0.302	-.0268836	.0866617
c.Q#c.Pet	.0116715	.0141088	0.83	0.408	-.0159835	.0393264
c.Q#c.Pat	-.0826036	.0815945	-1.01	0.311	-.242539	.0773318

c.sqrQ#c.PnsqrK	-.477106	2.713136	-0.18	0.860	-5.795188	4.840976
c.sqrQ#c.PlsqrK	-4.806809	1.280773	-3.75	0.000	-7.317283	-2.296336
c.sqrQ#c.PfsqrK	4.497123	11.3141	0.40	0.691	-17.67992	26.67417
c.sqrQ#c.PpsqrK	-5.985334	6.540013	-0.92	0.360	-18.80457	6.833901
c.sqrQ#c.PesqrK	9.253771	2.351104	3.94	0.000	4.645317	13.86223
c.sqrQ#c.PasqrK	-6.484956	17.75283	-0.37	0.715	-41.2827	28.31279
c.sqrQ#c.PnsqrKT	-.3018563	.273194	-1.10	0.269	-.8373502	.2336377
c.sqrQ#c.PlsqrKT	.3772589	.1424547	2.65	0.008	.0980302	.6564877
c.sqrQ#c.PfsqrKT	.0502526	1.086406	0.05	0.963	-2.079238	2.179743
c.sqrQ#c.PpsqrKT	.745846	.6082737	1.23	0.220	-.4464456	1.938138
c.sqrQ#c.PesqrKT	-.6605999	.2387523	-2.77	0.006	-1.128584	-.1926158
c.sqrQ#c.PasqrKT	.2535298	1.69378	0.15	0.881	-3.066489	3.573548
PnK	3.828005	2.0672	1.85	0.064	-.2239626	7.879972
PlK	4.384247	.8136466	5.39	0.000	2.789399	5.979095
PfK	-9.79959	8.535979	-1.15	0.251	-26.53116	6.931985
PpK	2.61945	5.24104	0.50	0.617	-7.653636	12.89254
PeK	-6.774833	1.661997	-4.08	0.000	-10.03255	-3.517113
PaK	11.42966	13.6379	0.84	0.402	-15.30231	38.16164
_cons	-670.8342	13652.05	-0.05	0.961	-27430.54	26088.88
L_Q						
sqrPnDsqrPl_d5	.229153	.0159365	14.38	0.000	.1979155	.2603905
sqrPfDsqrPl_d5	.0103068	.0030366	3.39	0.001	.0043546	.016259
sqrPpDsqrPl_d5	.0286503	.0018481	15.50	0.000	.0250278	.0322728
sqrPeDsqrPl_d5	.0016705	.0021178	0.79	0.430	-.0024806	.0058217
sqrPaDsqrPl_d5	.0441967	.0043075	10.26	0.000	.0357536	.0526399
sqrt	-.0917676	.022046	-4.16	0.000	-.1349805	-.0485547
t	.0002155	.0017065	0.13	0.900	-.0031295	.0035605
sqrK_sqrQ	-.6627102	.1291603	-5.13	0.000	-.9158804	-.4095401
sqrKT_Q	.2602897	.0278507	9.35	0.000	.2056988	.3148805
K_Q	-.0130845	.0052563	-2.49	0.013	-.0233875	-.0027816
frr						
1	-1.57e-18	8.31e-18	-0.19	0.850	-1.79e-17	1.47e-17
2	-.3195719	.0143696	-22.24	0.000	-.347738	-.2914057
3	-.3219543	.0143804	-22.39	0.000	-.3501417	-.2937669
4	-.2559004	.0146883	-17.42	0.000	-.2846913	-.2271095
5	-.4420589	.0132721	-33.31	0.000	-.4680739	-.416044
6	-.390709	.0174434	-22.40	0.000	-.4249002	-.3565178
7	-.4878941	.0107106	-45.55	0.000	-.5088882	-.4669
8	-.3918957	.0138998	-28.19	0.000	-.419141	-.3646504
9	-.4171898	.0123812	-33.70	0.000	-.4414585	-.392921
_cons	.5961614	.0744455	8.01	0.000	.4502389	.7420838
N_Q						
sqrPlDsqrPn_d5	.229153	.0159365	14.38	0.000	.1979155	.2603905
sqrPfDsqrPn_d5	.0915574	.0047748	19.18	0.000	.0821982	.1009167
sqrPpDsqrPn_d5	.0630354	.0030709	20.53	0.000	.0570159	.0690548
sqrPeDsqrPn_d5	-.0037838	.002903	-1.30	0.192	-.0094741	.0019065
sqrPaDsqrPn_d5	.157823	.0069022	22.87	0.000	.1442938	.1713521
sqrt	-.2364703	.0262826	-9.00	0.000	-.2879876	-.1849531
t	.039221	.0020251	19.37	0.000	.0352516	.0431905

sqrK_sqrQ	4.171593	.1573099	26.52	0.000	3.863246	4.47994
sqrKT_Q	-.5175308	.0340219	-15.21	0.000	-.5842179	-.4508437
K_Q	-.0130845	.0052563	-2.49	0.013	-.0233875	-.0027816
frr						
1	4.26e-16	1.30e-17	32.89	0.000	4.01e-16	4.52e-16
2	.0347374	.0170952	2.03	0.042	.0012288	.0682461
3	-.0932074	.0176709	-5.27	0.000	-.1278446	-.0585702
4	-.005913	.0176479	-0.34	0.738	-.0405051	.0286792
5	-.1163547	.0154915	-7.51	0.000	-.14672	-.0859894
6	.0401451	.0208417	1.93	0.054	-.0007072	.0809975
7	.1296789	.0125468	10.34	0.000	.1050856	.1542721
8	.1970015	.0164626	11.97	0.000	.1647327	.2292702
9	.0040699	.0142659	0.29	0.775	-.0238929	.0320328
_cons	-.3807629	.0865817	-4.40	0.000	-.5504737	-.211052
F_Q						
sqrPlDsqrPf_d5	.0103068	.0030366	3.39	0.001	.0043546	.016259
sqrPnDsqrPf_d5	.0915574	.0047748	19.18	0.000	.0821982	.1009167
sqrPpDsqrPf_d5	.0309812	.0012126	25.55	0.000	.0286043	.033358
sqrPeDsqrPf_d5	.0323765	.0015591	20.77	0.000	.0293206	.0354324
sqrPaDsqrPf_d5	-.0305005	.0026555	-11.49	0.000	-.0357056	-.0252954
sqrt	-.0137138	.0028693	-4.78	0.000	-.0193381	-.0080895
t	-.0006313	.0002259	-2.80	0.005	-.0010741	-.0001886
sqrK_sqrQ	-.0572862	.0182959	-3.13	0.002	-.0931484	-.0214241
sqrKT_Q	.0351193	.0037561	9.35	0.000	.0277567	.0424818
K_Q	-.0130845	.0052563	-2.49	0.013	-.0233875	-.0027816
frr						
1	1.81e-16	5.27e-18	34.35	0.000	1.71e-16	1.91e-16
2	.0234335	.0018695	12.53	0.000	.0197691	.0270979
3	.0156573	.001919	8.16	0.000	.0118958	.0194189
4	.0211712	.0019221	11.01	0.000	.0174038	.0249387
5	.0361401	.0017384	20.79	0.000	.0327327	.0395475
6	.0313745	.002259	13.89	0.000	.0269465	.0358025
7	.0050374	.0014022	3.59	0.000	.002289	.0077858
8	.0201371	.0018038	11.16	0.000	.0166015	.0236727
9	.0384393	.0015804	24.32	0.000	.0353414	.0415371
_cons	.0116529	.0095093	1.23	0.220	-.0069865	.0302923
E_Q						
sqrPlDsqrPe_d5	.0016705	.0021178	0.79	0.430	-.0024806	.0058217
sqrPfDsqrPe_d5	.0323765	.0015591	20.77	0.000	.0293206	.0354324
sqrPpDsqrPe_d5	.0088489	.0014972	5.91	0.000	.0059141	.0117836
sqrPnDsqrPe_d5	-.0037838	.002903	-1.30	0.192	-.0094741	.0019065
sqrPaDsqrPe_d5	.0328899	.0014411	22.82	0.000	.0300653	.0357146
sqrt	-.009292	.0012373	-7.51	0.000	-.0117173	-.0068667
t	.0010582	.0000965	10.97	0.000	.0008691	.0012474
sqrK_sqrQ	.0975929	.0094625	10.31	0.000	.0790452	.1161407
sqrKT_Q	.0029794	.0016231	1.84	0.066	-.0002021	.0061608
K_Q	-.0130845	.0052563	-2.49	0.013	-.0233875	-.0027816
frr						
1	-4.07e-17	2.85e-18	-14.25	0.000	-4.63e-17	-3.51e-17
2	-.0047485	.0008336	-5.70	0.000	-.0063825	-.0031145
3	.0000289	.0008131	0.04	0.972	-.0015648	.0016227
4	.0016009	.0008163	1.96	0.050	8.55e-07	.003201
5	-.0163897	.0007849	-20.88	0.000	-.0179281	-.0148513
6	-.0016191	.0009771	-1.66	0.098	-.0035343	.0002961
7	-.0166025	.0006183	-26.85	0.000	-.0178144	-.0153906
8	-.0129445	.0007892	-16.40	0.000	-.0144913	-.0113976
9	-.010746	.0007023	-15.30	0.000	-.0121225	-.0093694
_cons	-.0087642	.0044655	-1.96	0.050	-.0175172	-.0000113

```
-----------------+----------------------------------------------------------------
PE_Q             |
  sqrPlDsqrPp_d5 |   .0286503   .0018481    15.50   0.000     .0250278    .0322728
  sqrPfDsqrPp_d5 |   .0309812   .0012126    25.55   0.000     .0286043     .033358
  sqrPnDsqrPp_d5 |   .0630354   .0030709    20.53   0.000     .0570159    .0690548
  sqrPeDsqrPp_d5 |   .0088489   .0014972     5.91   0.000     .0059141    .0117836
  sqrPaDsqrPp_d5 |  -.0332344   .0014938   -22.25   0.000    -.0361624   -.0303064
            sqrt |  -.0023509    .001486    -1.58   0.114    -.0052636    .0005618
               t |  -.0000154   .0001169    -0.13   0.895    -.0002446    .0002137
       sqrK_sqrQ |   .0028804   .0106979     0.27   0.788    -.0180888    .0238496
         sqrKT_Q |   .0060771   .0019499     3.12   0.002     .0022551    .0098991
             K_Q |  -.0130845   .0052563    -2.49   0.013    -.0233875   -.0027816
                 |
             frr |
              1  |  -2.01e-17   2.31e-18    -8.68   0.000    -2.46e-17   -1.56e-17
              2  |   .0130861   .0009844    13.29   0.000     .0111566    .0150156
              3  |   .0086312   .0009935     8.69   0.000     .0066838    .0105786
              4  |    .002411   .0009969     2.42   0.016      .000457    .0043651
              5  |   .0091895   .0009108    10.09   0.000     .0074042    .0109748
              6  |   .0418162   .0011756    35.57   0.000     .0395119    .0441204
              7  |  -.0005896   .0007343    -0.80   0.422    -.0020288    .0008496
              8  |   .0045896   .0009432     4.87   0.000     .0027408    .0064385
              9  |   .0065155   .0008252     7.90   0.000      .004898     .008133
                 |
           _cons |  -.0195591   .0050948    -3.84   0.000    -.0295455   -.0095727
-----------------+----------------------------------------------------------------
A_Q              |
  sqrPlDsqrPa_d5 |   .0441967   .0043075    10.26   0.000     .0357536    .0526399
  sqrPfDsqrPa_d5 |  -.0305005   .0026555   -11.49   0.000    -.0357056   -.0252954
  sqrPpDsqrPa_d5 |  -.0332344   .0014938   -22.25   0.000    -.0361624   -.0303064
  sqrPeDsqrPa_d5 |   .0328899   .0014411    22.82   0.000     .0300653    .0357146
  sqrPnDsqrPa_d5 |    .157823   .0069022    22.87   0.000     .1442938    .1713521
            sqrt |  -.0150632   .0038398    -3.92   0.000    -.0225897   -.0075367
               t |  -.0006851   .0003027    -2.26   0.024    -.0012785   -.0000917
       sqrK_sqrQ |  -.0526104   .0239005    -2.20   0.028    -.0994583   -.0057625
         sqrKT_Q |   .0386315   .0050238     7.69   0.000     .0287842    .0484788
             K_Q |  -.0130845   .0052563    -2.49   0.013    -.0233875   -.0027816
                 |
             frr |
              2  |    .036492   .0025087    14.55   0.000     .0315747    .0414093
              3  |   .0247548   .0025729     9.62   0.000     .0197116     .029798
              4  |   .0230105     .00258     8.92   0.000     .0179534    .0280676
              5  |   .0436666    .002337    18.69   0.000     .0390859    .0482474
              6  |   .0761872   .0030356    25.10   0.000      .070237    .0821374
              7  |   .0040627    .001882     2.16   0.031     .0003738    .0077516
              8  |    .023425   .0024176     9.69   0.000     .0186862    .0281638
              9  |   .0425642   .0021229    20.05   0.000     .0384031    .0467252
                 |
           _cons |   .0239295   .0125848     1.90   0.057    -.0007383    .0485973
----------------------------------------------------------------------------------

. #delim cr
delimiter now cr
.
. est sto GLC

PREDICTED MARGINS

. margins frr, predict(xb equation(L_Q)) post

Predictive margins                              Number of obs     =      2,160

Expression   : Linear prediction, predict(xb equation(L_Q))

------------------------------------------------------------------------------
             |            Delta-method
```

```
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         frr |
          1  |   .5960202   .0085907    69.38   0.000     .5791814    .6128591
          2  |   .2764484   .0112559    24.56   0.000     .2543855    .2985113
          3  |   .2740659   .0121984    22.47   0.000     .2501556    .2979762
          4  |   .3401198   .0119553    28.45   0.000      .316686    .3635537
          5  |   .1539613   .0095773    16.08   0.000     .1351886     .172734
          6  |   .2053113   .0147623    13.91   0.000     .1763754    .2342471
          7  |   .1081262   .0062955    17.18   0.000     .0957862    .1204661
          8  |   .2041245   .0107128    19.05   0.000      .183126     .225123
          9  |   .1788305   .0082349    21.72   0.000      .162689     .194972
------------------------------------------------------------------------------
 est sto LND

est restore GLC

margins frr, predict(xb equation(N_Q)) post

Predictive margins                              Number of obs     =      2,160

Expression   : Linear prediction, predict(xb equation(N_Q))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         frr |
          1  |   .6118183   .0098721    61.97   0.000     .5924678    .6311687
          2  |   .6465557   .0138607    46.65   0.000     .6193871    .6737243
          3  |   .5186109   .0150028    34.57   0.000     .4892035    .5480182
          4  |   .6059053   .0148068    40.92   0.000     .5768822    .6349284
          5  |   .4954636   .0117554    42.15   0.000     .4724215    .5185057
          6  |   .6519634   .0182092    35.80   0.000     .6162711    .6876557
          7  |   .7414971   .0077389    95.81   0.000     .7263279    .7566663
          8  |   .8088197   .0131954    61.30   0.000     .7829551    .8346844
          9  |   .6158882   .0100234    61.44   0.000      .596241    .6355354
------------------------------------------------------------------------------

 est sto LAB

 est restore GLC
 margins frr, predict(xb equation(F_Q)) post

Predictive margins                              Number of obs     =      2,160

Expression   : Linear prediction, predict(xb equation(F_Q))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         frr |
          1  |   .0332882   .0010959    30.37   0.000       .03114    .0354364
          2  |   .0567217   .0015129    37.49   0.000     .0537562    .0596872
          3  |   .0489455   .0016289    30.05   0.000     .0457526    .0521384
          4  |   .0544595   .0016002    34.03   0.000     .0513228    .0575961
          5  |   .0694283   .0012893    53.85   0.000     .0669011    .0719556
          6  |   .0646627   .0019584    33.02   0.000     .0608241    .0685014
          7  |   .0383256   .0008461    45.30   0.000     .0366671    .0399841
          8  |   .0534253   .0014284    37.40   0.000     .0506255    .0562251
          9  |   .0717275   .0010927    65.64   0.000     .0695856    .0738694
------------------------------------------------------------------------------

est store FERT
```

```
est restore GLC

 margins frr, predict(xb equation(PE_Q)) post

Predictive margins                              Number of obs     =      2,160

Expression   : Linear prediction, predict(xb equation(PE_Q))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         frr |
          1  |   .0162352   .0005745    28.26   0.000     .0151091    .0173613
          2  |   .0293213   .0007981    36.74   0.000     .0277569    .0308857
          3  |   .0248664   .0008441    29.46   0.000      .023212    .0265209
          4  |   .0186462    .000829    22.49   0.000     .0170212    .0202713
          5  |   .0254247   .0006695    37.98   0.000     .0241125    .0267369
          6  |   .0580514   .0010153    57.18   0.000     .0560613    .0600414
          7  |   .0156456   .0004388    35.65   0.000     .0147854    .0165058
          8  |   .0208249   .0007416    28.08   0.000     .0193712    .0222785
          9  |   .0227507   .0005645    40.30   0.000     .0216441    .0238572
------------------------------------------------------------------------------
est store PEST

est restore GLC

margins frr, predict(xb equation(E_Q)) post

Predictive margins                              Number of obs     =      2,160

Expression   : Linear prediction, predict(xb equation(E_Q))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         frr |
          1  |   .0542634   .0004857   111.71   0.000     .0533113    .0552155
          2  |   .0495149   .0006722    73.66   0.000     .0481974    .0508325
          3  |   .0542923   .0007018    77.36   0.000     .0529168    .0556679
          4  |   .0558643   .0006811    82.02   0.000     .0545293    .0571994
          5  |   .0378737   .0005642    67.12   0.000     .0367678    .0389797
          6  |   .0526443   .0008328    63.21   0.000     .0510119    .0542767
          7  |   .0376609   .0003655   103.05   0.000     .0369446    .0383773
          8  |   .0413189   .0006102    67.71   0.000     .0401228    .0425151
          9  |   .0435175   .0004674    93.11   0.000     .0426014    .0444335
------------------------------------------------------------------------------

est store ENER

est restore GLC

margins frr, predict(xb equation(A_Q)) post

Predictive margins                              Number of obs     =      2,160

Expression   : Linear prediction, predict(xb equation(A_Q))

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         frr |
          1  |   .0499426   .0014742    33.88   0.000     .0470531    .0528322
          2  |   .0864346   .0020222    42.74   0.000      .082471    .0903983
```

```
         3  |   .0746974   .0021841    34.20   0.000     .0704163    .0789785
         4  |   .0729531   .0021453    34.01   0.000     .0687481    .0771581
         5  |   .0936092   .0017287    54.15   0.000     .0902208    .0969977
         6  |   .1261298   .0026275    48.00   0.000     .1209796    .1312801
         7  |   .0540053   .0011316    47.72   0.000     .0517872    .0562234
         8  |   .0733676   .0019133    38.35   0.000     .0696174    .0771179
         9  |   .0925068    .001464    63.19   0.000     .0896371    .0953765
------------------------------------------------------------------------------

est store AGCHEM

. estout LND LAB FERT PEST ENER AGCHEM, cells(b(star fmt(%9.3f)) se(par)) starlevels(*
0.1 ** 0.05 *** 0.01)

--------------------------------------------------------------------------------------
-------------------------------------
```

	LND	LAB	FERT	PEST	ENER	AGCHEM
BR	0.596***	0.612***	0.033***	0.016***	0.054***	0.050***
	(0.009)	(0.010)	(0.001)	(0.001)	(0.000)	(0.001)
FR	0.276***	0.647***	0.057***	0.029***	0.050***	0.086***
	(0.011)	(0.014)	(0.002)	(0.001)	(0.001)	(0.002)
NGP	0.274***	0.519***	0.049***	0.025***	0.054***	0.075***
	(0.012)	(0.015)	(0.002)	(0.001)	(0.001)	(0.002)
PG	0.340***	0.606***	0.054***	0.019***	0.056***	0.073***
	(0.012)	(0.015)	(0.002)	(0.001)	(0.001)	(0.002)
HL	0.154***	0.495***	0.069***	0.025***	0.038***	0.094***
	(0.010)	(0.012)	(0.001)	(0.001)	(0.001)	(0.002)
MP	0.205***	0.652***	0.065***	0.058***	0.053***	0.126***
	(0.015)	(0.018)	(0.002)	(0.001)	(0.001)	(0.003)
NC	0.108***	0.741***	0.038***	0.016***	0.038***	0.054***
	(0.006)	(0.008)	(0.001)	(0.000)	(0.000)	(0.001)
EU	0.204***	0.809***	0.053***	0.021***	0.041***	0.073***
	(0.011)	(0.013)	(0.001)	(0.001)	(0.001)	(0.002)
SS	0.179***	0.616***	0.072***	0.023***	0.044***	0.093***
	(0.008)	(0.010)	(0.001)	(0.001)	(0.000)	(0.001)