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Corn and Carbon: Essays on the Interaction of Agricultural and Environmental Policies

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Corn and Carbon: Essays on the Interaction of Agricultural and Environmental Policies

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Abstract: U.S. agricultural policy strives to boost farm incomes and secure the nation's food supply, yet new policies are also tasking agriculture with reducing or offsetting the country's greenhouse gas emissions. California's Low Carbon Fuel Standard uses a system of tradable compliance credits to incentivize the consumption of alternative fuels instead of fossil fuels. These credits provide additional value for the production of agricultural biofuels including ethanol. My dissertation examines the effects of the LCFS on commodity prices by first building a spatial corn market model of ethanol plants selling to California and then empirically estimating the pass-through of LCFS credit values changes in local corn prices. I find that the LCFS could be providing a competitive advantage in the corn market to ethanol plants with lower emissions, and these plants only pass-through around 40% of LCFS credit value changes to local corn farmers as a result. Moreover, policymakers across the globe see working farms as a possible carbon sink through increasing the carbon sequestered in cropland soils. The Inflation Reduction Act of 2021 provides billions of dollars to USDA programs that tangentially influence carbon sequestration. However, soil carbon sequestration is a complex process that cannot be easily influenced by policy. I review the scientific literature on soil carbon sequestration and relate it to economic research on environmental externalities. While practices like no-till or biochar can increase carbon sequestration on agricultural lands, effective policy design faces substantial challenges due to heterogeneity, costly measurement, and uncertainty.

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Part I

Introduction

Chapter 1

A New Era of Environmental and Farm Policy

United States agricultural policy strives to increase rural development, raise farm incomes, and provide stable food production to feed a growing national population. Policy makers wish to accomplish these goals while maintaining the natural resources that the agricultural industry so heavily depends on. Dust clouds descending on Washington D.C. led to the creation of the National Resource Conservation Service in the 1930s. Concerns about the over-production of commodities in the 1980s led the U.S. Congress to set aside farmland for the return of native grasses. Environmental effects have become an important if secondary focus of agricultural policies. The prospect of climate-change has only enhanced the intermixing of environmental and agricultural policy. This dissertation focuses on recent developments in programs at the boundary of environmental and agricultural policy: California's Low Carbon Fuel Standard (LCFS) and the Inflation Reduction Act of 2021 (IRA).

California's LCFS uses a greenhouse gas intensity metric and tradable compliance credits to incentivize substitution away from petroleum fuels towards lower emission fuels. Biomass-based diesel and ethanol are the two largest sources of renewable energy for the program. Much of the demand for biofuels is driven by the Renewable Fuel Standard enacted in the 2000s. The LCFS enhances this national policy by providing additional subsidies to ethanol producers based on their plant-level emissions. Because California is the most populous U.S. state and one of the largest consumers of motor fuels, the LCFS has an out-sized ability to impact biofuel markets. Corn and soybean markets now form a linchpin in the decarbonization of California's transportation sector.

In the wake of the Covid pandemic, IRA is providing funding for decades-old USDA programs that may indirectly reduce the country's greenhouse gas emissions. The USDA uses cost-sharing programs like the Environmental Quality Incentive Program (EQIP) to incentivize the adoption of practices that benefit soil and water quality. A key metric of soil health is the amount of carbon stored in the soil, and EQIP incentivizes practices like no-till that may indirectly increase soil carbon. The IRA provides billions of dollars in additional funding to EQIP and other programs for the explicit purpose of reducing or offsetting agricultural greenhouse-gas emissions. Nonetheless, the historic focus of these programs is preserving the natural resources necessary for agricultural and rural economies not climate-change mitigation. Soil carbon sequestration is a complex process that depends on local weather, soil types, and crop types to name a few, and existing USDA programs are not designed for maximizing carbon sequestration above all else.

The goal of mitigating climate-change emissions has led to the blending of environmental and agricultural policy. The LCFS was never meant to be an agricultural policy, but it subsidizes agricultural biofuels nonetheless. EQIP was never meant to be a climate-change program; now the co-benefit of carbon sequestration is becoming the driver of increased funding. Whether intentionally or not, policymakers are now asking far more of farmers than to simply supply the country and the world with food for a growing population. These policies could impact agricultural markets in unforeseen ways, and thus they deserve greater research than academic literature currently offers.

My dissertation first focuses on the impacts of the LCFS on local commodity markets. The LCFS is a complicated policy that nests within the ethanol market created by the Renewable Fuel Standard. My second chapter provides an overview of the ethanol industry and the national biofuel policies shaping corn markets, and then it shows how the LCFS works within the boundaries set by the Renewable Fuel Standard. In particular, I describe how LCFS creates additional incentives for ethanol plants to reduce their carbon emissions and receive more compliance credits. A key piece of the policy is that ethanol plants receive more credits, depending on the type of distillers grains produced. Distillers grains–a co-product of ethanol production–are the second largest source of revenue for ethanol plants, and they are a high-protein feed ration for livestock. Ethanol plants have the option to dry distillers grains for easier storage and transport but receive less LCFS credits per gallon or sell distillers grains in their less stable, raw form without drying and receive more credits. The LCFS could indirectly affect corn farmers and buyers of ethanol co-products through the prices ethanol plants offer for corn and their choice of distillers grains production.

My third chapter examines how spatial market power in the corn market interacts with the subsidies from the LCFS. Ethanol producers consume roughly one-third of all corn supply in the U.S., and many ethanol plants individually consume more corn than their county produces every year. Ethanol plants may have market power in procuring corn because corn is costly for farmers to transport over long distances. I use a two-stage spatial model to analyze the corn pricing and distillers grains choices of ethanol plants selling into California. In the first-stage, ethanol plants choose a type of distillers grains, a co-product of ethanol production, and in the second-stage, plants choose their corn procurement price while competing for grain in a spatial duopsony with other ethanol producers.

I find that the ability of ethanol plants to capture subsidies from the LCFS depends on heterogeneity in LCFS subsidies across ethanol plants. Competition from other corn buyers causes ethanol plants to pass-through higher a portion of LCFS subsidies to corn farmers than in a spatial monopsony, yet, the LCFS provides lower emission plants with a higher subsidy than their competitors. They can exploit this advantage by less than fully passing-through their value of LCFS credits to corn farmers while their competitors more than fully passing-through their LCFS credit value. Thus, while the LCFS may benefit corn farmers through higher prices, it may also be providing ethanol plants with an advantage over their competitors.

The profit functions from each subgame perfect equilibrium provide conditions on the dominant strategies for distillers grains choices of ethanol plants selling into California. Ethanol plants will choose the distillers grains type with the highest combined value of LCFS credits and distillers production net. Their choice of distillers grains does not depend on their competitor's distillers grains type or corn procurement decisions. The combined value of distillers grains production depends on distillers grains prices, LCFS credit prices, the number of credits produced with each type, and natural gas prices. These factors are all observable, and thereby, I use this result for empirically estimating the pass-through of LCFS credit value changes to ethanol plants.

If ethanol plants change their corn procurement decisions in response to changes in LCFS credit prices, then these price changes may pass-through to local corn prices. In my fourth chapter, I use a cumulative dynamic multiplier model to empirically estimate the pass-through of changes in the per bushel value of LCFS credits to the local corn prices of ethanol plants in Iowa and Nebraska. The value of LCFS credits depends on which type of distillers grains each plant is producing, but I do not directly observe the distiller grain types for each plant. I parameterize the distillers grains choices of ethanol plants using the result that distillers grain choices depend on observable prices and the number of LCFS credits produced for each type.

My results show that ethanol plants pass-through around 40% of the changes in LCFS credit values to local corn prices. This pass-through persists for at least 8 weeks after the initial change in credit values occurs. Moreover, ethanol plants organized as cooperatives pass-through a greater portion of LCFS subsidies, and I cannot rule out the case of full pass-through from cooperatives. Therefore, farmers near ethanol plants selling into California are capturing a substantial portion of LCFS credit value changes in the form of higher corn prices, but whether farmers fully benefit from the LCFS depends on the organizational structure of ethanol plants.

I also empirically estimate the pass-through differences in the value of LCFS credits by distillers grains type to the price spreads between different distillers grains price pairs. I find more than full pass-through of LCFS credit value changes to to distillers grains price spreads for wet and dry distillers grains. My results have very wide confidence intervals that far exceed 1, so they should be interpreted with caution. The per bushel value of distillers grains and LCFS credits appear to move in tandem.

In my final chapter, I review the scientific literature on carbon sequestration on working agricultural lands. Adopting climate-smart agricultural practices like cover crops, no-till, and biochar amendments can increase the amount of carbon sequestered in soil. These practices, however, must continue for decades to measurably increase the amount of carbon sequestered in soils. Regions of the country such as the Great Lakes may see little to no soil carbon benefits and decreases in yield from cover crops and no-till. As such, using programs like EQIP that are not designed for climate-policy benefits could provide small soil carbon gains at a high cost to U.S. taxpayers. Rather, increasing agricultural productivity can allow for greater intensification of working agricultural lands and, thereby, prevent further land-use change and increase global food security.

Part II

Corn, Carbon, and Competition: The Impact of California's Low Carbon Fuel Standard on Local Commodity Markets

Chapter 2

The Interaction of Ethanol Markets and The Low Carbon Fuel Standard

California is the second largest gasoline market in the United States, and the state has set a goal of reducing transportation emissions by 20% by 2030 compared to 2010 levels. The California Air Resources Board (CARB) created the Low Carbon Fuel Standard (LCFS) as a means to achieve this goal. The LCFS incentivizes substitution away from fossil fuels towards alternative fuels with less greenhouse gas emissions. It achieves this goal by setting an annual carbon emission standard and then issuing marketable compliance credits to fuels with emission below the standard. Petroleum fuels above the standard generate compliance deficits that must be offset with compliance credits from the sale of renewable fuel. The program in effect provides hundreds of millions of dollars in subsidies to renewable fuel producers, and other west coast states like Oregon and Washington have created their low-carbon fuel programs emulating California.

Ethanol is a primary source of credits for the LCFS, and the fuel is the second largest source of renewable energy to California (CARB, 2023b). Corn ethanol is by far the most common feedstock for ethanol in California, and it accounts for roughly 90% of consumption by volume (CARB, 2023b). As such, American farms play an important role in supplying renewable energy to California. The national Renewable Fuel Standard (RFS) created the first ethanol boom in 2005 by mandating the blending of ethanol with gasoline. National ethanol consumption is now close to 15 billion gallons and 10% of all motor gasoline because of the RFS. Ethanol demand, however, has stagnated at these levels since 2015, and the ethanol industry is searching for a means to stimulate new revenue sources. The LCFS could be part of the answer.

The LCFS enhances ethanol's importance as a transportation fuel by distributing compliance credits to ethanol producers according to their emissions and sales of ethanol. These compliance credits can be traded on an open market to suppliers of petroleum fuels, and they encourage individual ethanol producers to reduce their green-house gas (GHG) emissions and earn more credits. Almost no ethanol producers incur a compliance deficit, so the credits act as an indirect subsidy for ethanol producers. Ethanol producers earn an additional \$0.10 to \$0.25 per gallon of ethanol by selling to fuel blenders in California. Biofuel producers are now openly lobbying for an LCFS policy to supplement the RFS (RFA, 2022).

Nevertheless, who actually gains from these subsidies is an open question. Subsidizing ethanol production not only affects California's ethanol market, but also the local markets for corn and ethanol co-products, such as distillers grains. A portion of the LCFS subsidies may pass-through to corn producers and other local market participants. Measuring the pass-through provides insights into the incidence of LCFS subsidies, e.g. who benefits from the program. For the LCFS to be successful, the value of LCFS credits must spread throughout the supply chain to encourage the greater production of low-carbon fuels. In the case of ethanol, the passing through of LCFS credit prices sends a signal for corn producers to supply more corn to ethanol plants supplying California, particularly the plants with the lowest emissions. A lack of pass-through indicates that either ethanol plants are not responding to changes in the LCFS or local market frictions like market power are preventing the transmission of the price signal.

The LCFS also provides a competitive advantage to ethanol producers with lower emissions than their competitors. The LCFS accounts for heterogeneity in emissions among ethanol plants. Ethanol plants with the lowest emissions per gallon will receive the most credits. Other corn users like grain marketing cooperatives or livestock feeders cannot participate in the LCFS and do not receive any credits. As a result, the LCFS provides additional revenues to some ethanol plants not received by their competitors. Many ethanol producers already have market power in their local corn market (Jung et al., 2022), and the LCFS could be enhancing the market power of some ethanol plants through distributing heterogeneous amounts of credits per gallon. Previous research on the RFS and ethanol producers does not account for the possibility of heterogeneity in ethanol subsidies. Therefore, additional research is needed to understand how heterogeneity in ethanol plant emissions could indirectly impact the incomes of thousands of American farms.

This chapter provides background knowledge on the workings of the LCFS and the ethanol industry. The LCFS works within the policy framework set by the national Renewable Fuel Standard (RFS) and the ethanol industry as a whole. I begin by first explaining the RFS and ethanol production in general. Unlike the LCFS, the RFS is purposely designed to encourage biofuel consumption, yet the LCFS provides unique policy incentives that may cause emission-reducing actions by ethanol plants that the RFS does not. Therefore, after explaining the broader ethanol market, I cover the particulars of the LCFS as it relates to ethanol production. I especially emphasize how the LCFS encourages ethanol plants to change their co-product mix to reduce their emissions.

2.1 Ethanol Production Background

2.1.1 National Biofuel Policies

The Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007 created the most important national policy for biofuel consumption–the Renewable Fuel Standard (RFS). The goals of the RFS are to increase energy security and lower national carbon emissions by replacing gasoline and diesel with renewable fuels. The RFS uses annual consumption mandates for biofuels to accomplish its goals. To qualify renewable fuels must prove that their emissions are significantly less than the petroleum fuels they replace. The emissions threshold for corn ethanol is at least a 20% reduction below petroleum gasoline. As long as a corn ethanol plant meets this threshold according to the EPA, they are eligible to participate in the RFS.[1]

The RFS mandated dramatic increases in the consumption of ethanol in the transportation sector. Prior to 2005, corn use for ethanol was less than 10% of total supply, and now fuel accounts for over 30% of total corn use (ERS, 2023). The ethanol boom caused corn prices to rise by 30% and millions of acres previously devoted to other crops or grass pastures were converted into corn land (Carter et al., 2017; Lark et al., 2022). The land-use change caused by the ethanol boom has led many scientists to doubt the clean-fuel status of ethanol (Lark et al., 2022).

Policymakers hoped the RFS would spur production of ethanol from waste biomasses like corn-stalk residuals or grasses like miscanthus, but producing ethanol from these sources has proven to be technically and economically infeasible. The EPA was granted discretionary authority to waive consumption mandates in the event of exceedingly high processing costs, so almost the entire mandates for ethanol from these cellulosic sources is waived every year (Lade et al., 2018a,b). Nonetheless, ethanol from corn starch has remained close to its 15 billion gallon by 2015 mandate while ethanol from other sources remains negligible, and California consumes roughly 10% of national ethanol production (ERS, 2023; CARB, 2023b). Corn-starch ethanol accounts for almost 90% of consumption (CARB, 2023b), even though ethanol from plant fibers has significantly lower emissions.

Another rule that affects the technical feasibility of ethanol consumption levels is the EPA's blend wall. Standard internal combustion engines cannot consume fuel containing 100% ethanol. Ethanol needs to be blended with gasoline to allow for use in conventional engines. For mechanical and environmental reasons, the percentage of ethanol in conventional blends is no more than 10%. This blended fuel is called E10. Higher blends with 51 to 83% ethanol called E85 do exist, but their market share remains quite small despite substantial subsidies.

[1] Ethanol plants built prior to 2005 are grandfathered into the RFS regardless of estimated emissions.

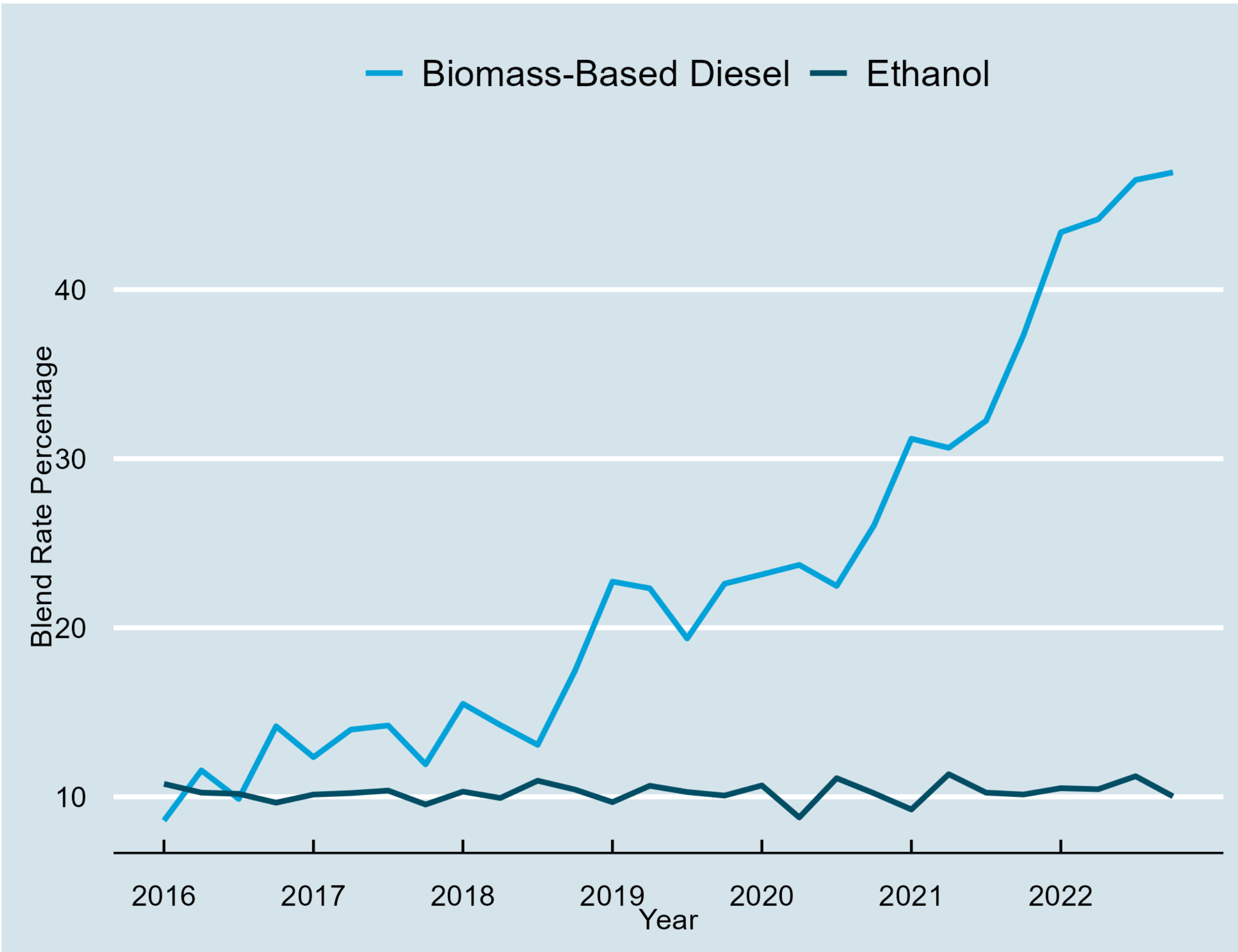
Thereby, ethanol consumption has been largely stuck at 10% of total gasoline consumption-a level called the “blend wall". As a result of the 10% blend wall, compliance costs are relatively constant before the blend wall and then increase sharply after the 10% threshold (Pouliot and Babcock, 2016). That is, the compliance costs for increasing ethanol consumption from 7 to 10% of gasoline are relatively constant while the compliance costs for increasing ethanol consumption from 10 to 13% are far higher and increase rapidly. The ethanol industry has tried to move past the blend wall by lobbying for the blending of 15% ethanol in conventional gasoline, but 15% ethanol blends have yet to gain much traction outside of corn producing states.

The effect of the blend wall can be clearly seen by examining the blend rate of ethanol, e.g. ethanol's share in the gasoline market. Figure 2.1 shows the blend rate of ethanol and biomass-based diesel since 2019 in California. The ethanol blend rate has remained close to 10% with the low of 8% and a high of 12% in 2020. In California, E85 sales only totaled 40 million gallons in 2019 and 2020 (CARB, 2021).[2]. While the LCFS can incentivize additional ethanol consumption, the blend wall may prevent any large increase beyond 10% of total gasoline-ethanol consumption.

On the other hand, the biomass-based diesel share in the diesel market has doubled since early 2020 to over 50%. Biomass-based diesel comes in two forms: biodiesel or renewable diesel. Biodiesel itself has blending limitations at 5% for use in commercial vehicles like semi-trucks. Renewable diesel is not hampered by blending limitations and usage has risen substantially since 2019 (CARB, 2023b). The LCFS does not differentiate between credits from the diesel or gasoline sectors. As a result, meeting LCFS compliance is easier with renewable diesel than substitutes in the gasoline market until electric vehicles gain more market share or the ethanol blend wall becomes void.

[2]Ethanol and pure gasoline combined for 15 billions in the state of California in 2019 (CARB, 2023b).

Figure 2.1: Blend Rate of Biofuels in California



Note: Ethanol includes all feedstocks, not just corn starch. Biomass-based diesel includes biodiesel and renewable diesel from all organic lipid feedstocks. Blend rate for ethanol is the amount of ethanol consumed divided by total gasoline consumption, and blend rate for biomass-based diesel is the amount of biomass-diesel consumed divided by the total diesel consumption including petroleum diesel. Source: (CARB, 2023b).

2.1.2 Ethanol Production

Corn is roughly composed of 70% starch, 10% protein, 5% oil, and 2% of fiber. The rest is moisture. Ethanol plants use all of the components of a corn kernel in some form. Ethanol primarily comes from the starch. The high-protein livestock feed called distillers grains comes from the mash leftover after ethanol production. Distillers corn oil is primarily used as a livestock supplement, but it also increasingly being used to make biomass-based diesel. The fiber component has historically been included with distillers grains, but some ethanol plants are using a new enzyme to make a very small percentage of their ethanol from corn fiber. Ethanol is the largest source of revenue at 75% while distillers grains are second at 20% (Batres-Marquez, 2018). Corn oil maintains a small share of revenue. Ethanol and corn oil are both homogeneous commodities. They both can be used for either food or fuel purposes, but the quality of the individual commodities is the same. Distillers grains, however, has three main types that differ by moisture content.

The three distillers grains types are called dry, modified, and wet. Dry distillers grains contain only 10% moisture, modified contains 55 to 60% moisture, and wet distillers grains contains 65 to 70% moisture.[3] Dry distillers grains accounts for over 70% of the total feed matter production from distillers grains, and wet distillers grains accounts for 20% (NASS, 2023). Wet distillers grains are the raw form, and then they are turned into either modified distillers grains or dry using large drying bins. Unlike wet or modified, dry can be exported, but ethanol plants generally rely on natural gas to power their dryers. As a result, ethanol co-produced with dry has higher emissions than ethanol co-produced with modified or wet, and likewise, for modified compared to wet.

Moreover, the physical composition of corn kernels allows the use of constant-returns to scale from corn to the products of ethanol production. The relative value of ethanol to distillers grains or corn oil can fluctuate with market prices, but the amount of ethanol per bushel of corn or corn oil per bushel of corn is largely fixed by the starch and oil content of corn. The amount of distillers grains per bushel can vary, but these variances are largely due to differences in the moisture content across the different types of distillers grains, not the amount of feed matter in each type. Thus, ethanol producers are generally modeled using fixed rates of conversion from corn into the multiple outputs of ethanol production (Cui et al., 2011; Saitone et al., 2008). I will use this simplification in both my spatial model and empirical model of LCFS pass-through.

[3] Another form of dry distillers grains separates out the sugar solubles left in the mash after ethanol production. Ethanol plants can then sell the solubles as a feed supplement. Production of this type of distillers grains is a very small portion of the distillers grains market (NASS, 2023).

2.1.3 Organizational Structure of Ethanol Producers

The effects of the LCFS on local agricultural markets will depend on the organizational structure of ethanol plants and the role of competition in local commodity markets. Ethanol plants consume roughly one-third of all corn in the United States, and the capacity of many ethanol plants can exceed the annual corn production in their local counties. The sheer size of ethanol plants can enable them to impact local prices (McNew and Griffith, 2005). However, the organizational structure of ethanol plants shapes their impact markets and how they compete with rivals in local markets.

Many agricultural commodity buyers are organized as cooperatives, firms that are owned by the farmers they serve. Cooperatives seek to maximize value to their farmer-owners instead of maximizing profits. Cooperatives return value to their members in two primary ways: better prices or distributions from profits called patronage. In the context of ethanol plants, offering better prices can mean higher corn prices for farmers and lower distillers grains prices for livestock feeders. Patronage distributions can take the form of cash dividends or equity distributions from net earnings before taxes.[4] Biofuel producers can be organized as cooperatives. For example, AGP, Inc. is one of the largest producers of soybean biodiesel, and it is a cooperative owned by the farmers that sell to it.

Ethanol plants organized as cooperatives may pass-through a higher portion of the value of LCFS credits to their farmer members. LCFS credits represent additional value per bushel for ethanol plants. Ethanol plants organized as cooperatives can maximize value to their corn-farmer members by distributing the value of LCFS credits back to their farmers. These distributions could come in the form of cash refunds, equity, or higher corn prices. If they come in the form of higher corn prices, then cooperative ethanol plants may pass-through a greater portion of changes in the value of LCFS credits to their corn prices.

However, the ethanol industry is dominated by non-cooperatives whether as public or private companies. The five largest ethanol producers are all non-cooperatives (RFA, 2024). In my empirical estimation of the pass-through of LCFS credits, I use a sample of 23 ethanol plants in Iowa and Nebraska. Of these 23 ethanol plants, 20 are non-cooperatives either publicly or privately owned. Two are organized as cooperatives, and one is a privately-owned firm that contracts out its corn buying operations to a local cooperative. In my empirical estimation of the pass-through, I partition the data by cooperative status to test for heterogeneity in the pass through of LCFS credit price changes. In the spatial modeling section, however, I assume that ethanol plants are organized as profit-maximizing firms because of the relatively few number of cooperatives in my empirical sample.

[4] Equity distributions also come in two forms: qualified and non-qualified distributions. With qualified distributions, farmers pay income taxes on the equity distribution. The cooperative pays corporate income taxes on non-qualified distributions.

2.1.4 Local Corn Markets

Most farmers sell their grain to a local buyer within a few dozen miles of their farm over the course of the grain marketing year. The vast majority of corn is harvested from September to November, and farmers can either choose to sell their corn during the harvest process or store their grain and sell it at a later time.[5] Farmers choose to store their grain because local cash prices are usually lowest during fall harvest and higher during the summer when grain stocks are declining before the next fall's harvest. Thus, many farmers market their grain throughout the year to take advantage of higher prices post-harvest and to smooth out their cash flows.

Large corn buyers also have the ability to buy and store grain through out the marketing year. A large processor like an ethanol plant minimizes costs by maintaining a high throughput with only a small amount of idle productive capacity. (Jung et al., 2022) find that ethanol plants in Indiana operate around 95% of their total capacity during their study period. To prevent running out of grain, they have large storage facilities capable of handling millions of bushels of corn.[6] The ability to store weeks if not months worth of grain allows ethanol plants to manage costs and maintain a constant throughput of grain.

The ability of both ethanol plants and corn farmers to store grain provides both sides with multiple ways to transact grain. Buyers and sellers can agree for delivery in the near future or at a predetermined future date using forward contracts. Forward contracts enable ethanol plants to plan corn throughputs and know their future costs while the same contracts allow farmers to take advantage of higher future prices by storing their grain on the farm. The terms are based on the expectation of prices from both parties, and in general, ethanol plants will offer the same terms for a particular delivery date to all of their buyers.[7]

The spot market for grain consists of transactions in which delivery is expected within a week or two. Ethanol plants could entirely forgo the use of spot markets and instead only use forward contracts. However, only using forward contracts could leave ethanol plants with too much grain during periods of unexpected declines in ethanol demand or too little grain during periods of higher than expected demand. Ethanol plants also have storage facilities far larger than farmers. Economies of scale in storage may lead to ethanol plants having lower storage costs than farmers, and buying on the spot market and storing for several months may be cheaper for ethanol plants than using forward contracts. For these reasons, many ethanol plants maintain constant open cash bids with delivery in the near term, and they purchase a portion of their grain using these open market bids, though the open-market portion could be substantially smaller than the forward contract portion. Farmers can observe these bids on the websites of ethanol plants or on grain marketing

[5]USDA grain stock reports show on-farm storage peaking in December after harvest and bottoming out in September before the next year's harvest (USDA National Agricultural Statistical Service (NASS), 2024).

[6]The largest single grain bins in the world can hold over 2 million bushels of corn.

[7]Some very large farms could see better terms, e.g. splitting of transportation costs.

apps like Geograin Inc.

For my empirical estimation, I use spot prices instead of forward contracts, and for my measure of spot prices, I use basis. Basis is the difference between the local buyer's price and the nearest futures contract from the Chicago Board of Trade. For example, if the Chicago futures price is \$4.00 per bushel and an ethanol plant is buying corn at \$4.25 per bushel, then the basis is \$0.25 per bushel. Basis is a reflection of local supply and demand for corn after accounting for global demand and supply conditions. Futures prices move for a variety of reasons unrelated to the LCFS. California only represents 10% of the national ethanol market. Changes in LCFS credit prices may only have a small impact on futures prices. Also, the number of credits generated varies from plant to plant and by distillers grains type. Weekly changes in futures prices will only provide noise that drowns out the value of LCFS credits, so weekly changes cash prices that incorporate futures prices will also reflect this noise. Using basis can difference out the noise in national price movements unrelated to the LCFS by focusing on the relative value of corn to ethanol plants participating in the LCFS.

Grain purchased on the spot market may not be used for several months, but storage is costly and ethanol plants will only buy grain to store if consuming the grain in the future provides greater value than processing the grain now. Foregoing current consumption is the opportunity costs of storing the grain for future consumption. That is, ethanol plants will only buy and store grain if the stored grain has at least the same value as current consumption after accounting for storage costs. If the physical costs of storage are constant, then movements in spot prices will reflect changes in the relative value of corn for consumption whether for now or in the future.[8] As a result, spot prices will reflect changes in the value of LCFS credits even if the corn being purchased is for use at a later date.

Forward prices may still incorporate the value of LCFS credits, but they could provide a more noisy estimate than spot prices. Prices for forward contracts depend on the expectations of ethanol plants and corn farmers. Ethanol plants will offer forward prices based on expectations for LCFS credit prices, the demand of ethanol, and expected distillers grains production decisions among other factors. Using actual credit values at the time forward contracts terms are posted could provide a noisy approximation to what ethanol plants actually anticipate credit prices to be in the future. For example, credit prices started to decline significantly in 2021. During the fall of prices, some ethanol plants may have anticipated the fall to continue and priced their forward contracts anticipating a much lower credit price than the current price of LCFS credits would suggest. Spot prices, on the other hand, reflect the current value of corn for ethanol production including the current value of LCFS credits.

[8]Corn stocks exhibit seasonal fluctuations caused by harvesting patterns. As a result, the value of storing grain can have seasonal patterns unrelated to changes in physical storage costs. Therefore, seasonal controls are necessary to account for patterns in the value of storage.

Farm Credit Services, an agricultural bank serving farmers throughout the country, conducted a grain marketing survey of farmers in the Cornbelt during 2017. The survey finds that a majority of farmers use forward contracting and the spot market to sell a portion of their grain and at least 80% use some form of grain storage (FCS,2017). Moreover, two-thirds of farmers market their grain in small increments throughout the marketing year rather than using a single lump-sum sale. Therefore, spot prices are a reliable measure of the grain marketing decisions of ethanol plants and corn farmers with respect to changes in the value of LCFS credits.

2.1.5 Distillers Grains Markets

Distillers grains are a key source of revenue for ethanol plants, but a lack of a national market implies that local dynamics play a greater role in the price discovery process. The production of distillers grains expanded rapidly during the initial ethanol boom from 2005 to 2010 caused by the RFS. Total production increased from 10 million metric tonnes in 2005 to over 36 million metric tonnes by 2010 (ERS, 2023). The Chicago Board of Trade created a dried distillers grains futures market in response to this rapid increase in production, but the contract was delisted in 2015. The U.S. Grains Council and the USDA Agricultural Marketing Service produce reports on local prices on a weekly basis, providing valuable information to both livestock feeders and ethanol plants. Nonetheless, distillers grains markets lack the formality and clear price discovery price process underlying exchange traded commodities like corn, particularly for wet and modified distillers grains that cannot be exported. Thus, understanding local market dynamics is necessary for taking into account the importance of distillers grains prices to ethanol plants.

Researchers from Kansas State University conducted a distillers grains marketing survey of ethanol producers in 2010 (Stroade et al., 2010). While the survey is over a decade old, it provides insights into the strategies ethanol plants use to market their distillers grains and manage price risk without the availability of a national reference price. Survey respondents stated that corn futures played the most important role in providing new information about prices, and the authors find that ethanol plants use a mix of forward contracts, cash spot markets, and formulas based on the futures prices of corn and soybean meal to market their distillers grains (Stroade et al., 2010). Formula pricing uses a fixed rate from the nearest corn or soybean meal futures price while forward and spot pricing work as described in the previous subsection. Of these methods, cash spot prices and formula pricing are by far the most used methods. These survey responses indicate that cash spot prices are the most used method of marketing distillers grains after weighting survey responses by ethanol plant size. Therefore, I use cash spot prices of distillers grains prices from USDA Agricultural Marketing Service for the empirical analysis in Chapter 4.

2.2 LCFS Background

2.2.1 LCFS Basics

California AB 32 tasked the California Air Resources Board (CARB) with reducing greenhouse gas (GHG) emissions from California's transportation sector. CARB created the LCFS to accomplish this goal. The LCFS incentivizes a transition to fuels with lower GHG emissions using a system of tradable compliance credits. CARB sets an annual standard for the carbon intensity (CI) for transportation fuels in the gasoline and diesel markets. CI is a measure of the carbon emissions of a fuel per megajoule of energy supplied with units of gCO_2/MJ. Wholesale fuel suppliers earn credits if their product is below the standard, and they incur a credit deficit if their fuel is above the standard. Fuel suppliers with net deficits must buy credits from suppliers with credit surpluses at market prices on the LCFS credit exchange.[9] If the program is successful, then by 2030 the CI of the transportation sector will decrease by 20% as compared to 2010 levels (CARB, 2020).

Credit surpluses or deficits are incurred based on the CI rating of the fuel, the annual standard, the amount of fuel supplied, and the energy content of the fuel.[10] Suppliers of gasoline and diesel fuels are the primary parties incurring credit deficits. Hundreds of alternative fuel suppliers produce credit surpluses. The largest sources of credits come from renewable diesel, biogas, electric vehicles, and ethanol (CARB, 2023a).

Ethanol plays an important role in the LCFS credit market, but its share in the market has declined steadily over time 2016. Figure 2.2 displays the credit surpluses per quarter from each of these sources. Ethanol is currently the fourth largest source of credits, and the number of credits generated by ethanol producers has remained relatively constant except for periods of Covid-19 shutdowns in the second quarter of 2020 and the first quarter of 2021. However, the other sources show a steady upward trend since 2020, and the number of credits generated by these sources has more than doubled. As a result, ethanol has become an infra-marginal source of credits while biomass-based diesel, biogas, and electricity suppliers are driving shifts in the supply of credits at the margin (Mazzone et al., 2022).

Despite its declining share in the credit market, ethanol still remains an important fuel in terms of renewable energy supplied to California. Figure 2.3 presents the amount of energy supplied by renewable fuel type. Comparing gallons of gasoline to kilowatts requires a single unit of comparison. CARB uses megajoules of energy to determine the total energy supplied by a fuel. Biomass-based diesel is by far the largest source of renewable energy in the transportation sector, and the fuel has experienced rapid growth since 2020. Ethanol is the second largest source of renewable energy, and until the recent boom in biofuel

[9] To cap compliance costs, CARB offers credits at $200 in 2015 dollars.

[10] Some fuels like electricity also account for higher efficiency in transforming energy into miles moved relative to an internal combustion engine.

diesel, ethanol was the largest source of renewable energy. Other renewable sources like biogas and electricity provided a comparatively small amount of energy.

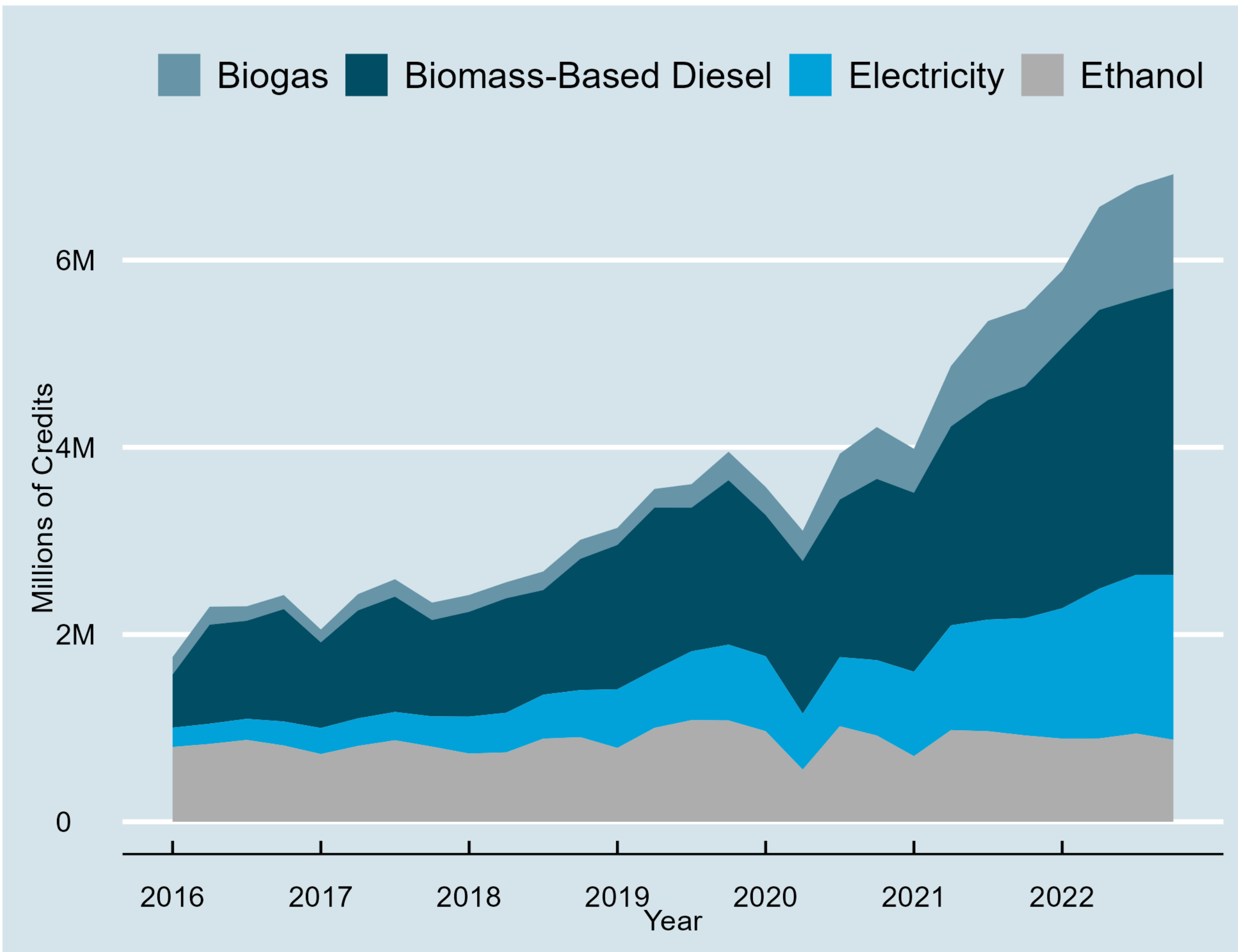
Ethanol provides much fewer credits than electricity and biogas because the carbon intensity of ethanol is higher per megajoule of energy supplied. The average CI of ethanol is close to 60 gCO_2e/MJ while the average CI of electricity is 15 gCO_2e/MJ (CARB, 2023b). Biogas has an average CI below 0, so it actually has negative emissions according to CARB.[11] Thus, the relatively high emissions of ethanol per megajoule of energy supplied explains why its share in the credit market is much less than its share of energy supplied.

Furthermore, the blend wall prevents the consumption of conventional blended-gasoline with 10% ethanol from generating net credits. The CI of gasoline is roughly 100 gCO_2e/MJ and the carbon intensity standard has been below 90 gCO_2e/MJ since 2021. Even if ethanol had a CI of 0, the CI of E10 gasoline would still be above 90 after accounting for differences in the energy content of gasoline and ethanol. The consumption of conventional E10 therefore always generates a net deficit. Ethanol as such cannot be the sole compliance fuel for the LCFS as long as the blend wall binds.

Finally, ethanol itself is a homogeneous commodity, but it can be produced from different feedstocks. Corn ethanol remains the dominant feedstock in terms of volumes and credits. Biomass is the second most important feedstock, but in conversations with CARB regulators, this feedstock is also derived from corn-ethanol. Ethanol producers have developed an enzyme to produce ethanol from the corn fiber. Since the corn fiber was previously a waste product, corn fiber ethanol has a CI below 30 gCO_2e/MJ. Nonetheless, volumes for corn fiber ethanol remain well-below corn starch, and CARB regulators only allow ethanol plants to claim 1 to 4% of their ethanol is derived from corn fiber. Thus, corn-starch still accounts for around 90% of the volume of ethanol in California.

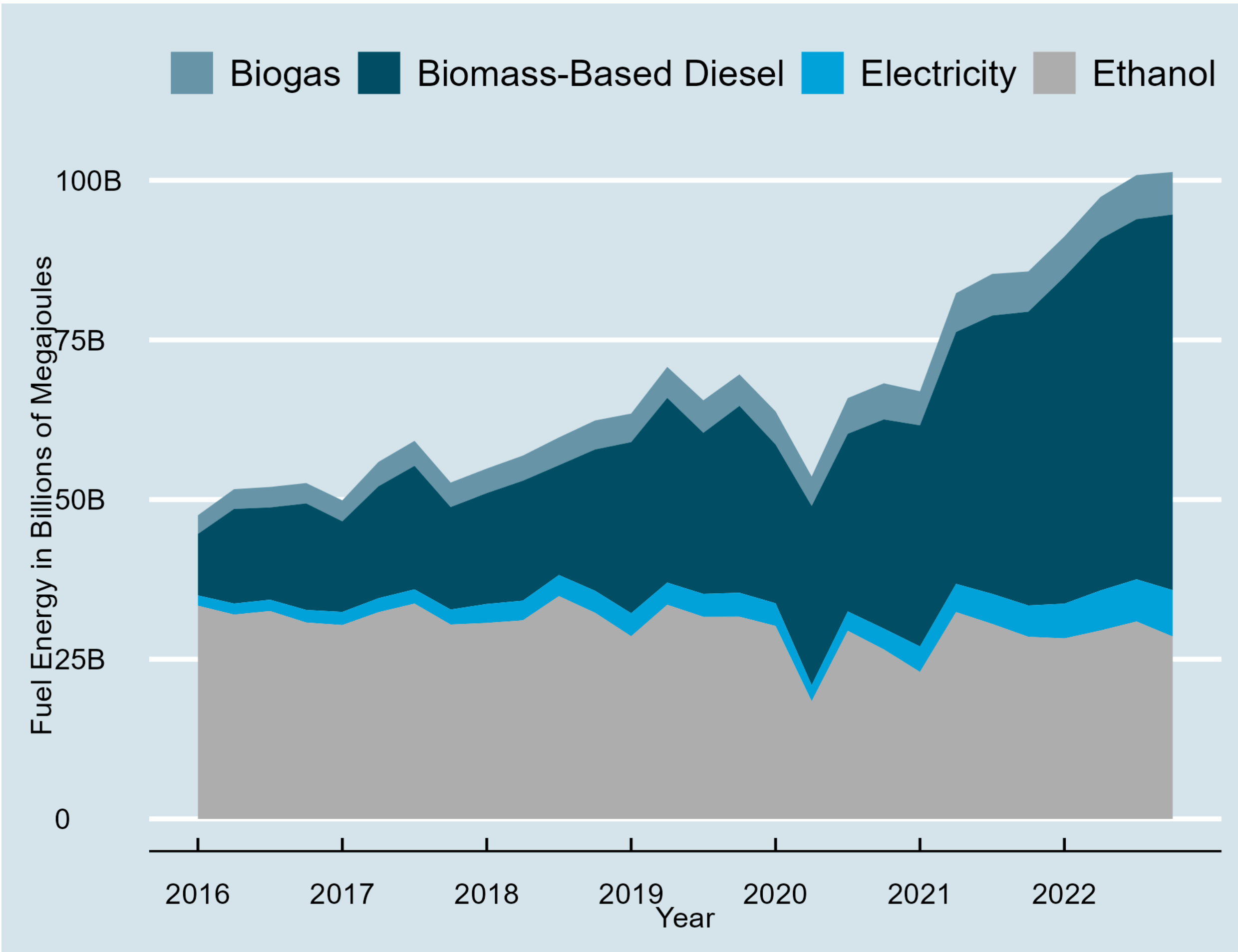
[11] The negative emissions are driven by the fact that the baseline for biogas is emitted methane which has a much higher global-warming potential than CO_2. Combusting biogas therefore converts methane into CO_2, reducing the overall global-warming impact (CARB, 2020).

Figure 2.2: LCFS Credits by Fuel Type



NOTE: Ethanol includes all feedstocks, not just corn starch. Biomass-based diesel includes biodiesel and renewable diesel from all organic lipid feedstocks. Electricity includes on-road and off-road sources of credits, and biogas includes compressed natural gas and liquid natural gas from renewable sources. Credits are measured in metric tonnes of carbon dioxide equivalent units. “M" stands for millions of credits. Source: (CARB, 2023b).

Figure 2.3: Renewable Energy Supplied by Fuel Type



NOTE: Ethanol includes all feedstocks, not just corn starch. Biomass-based diesel includes biodiesel and renewable diesel from all organic lipid feedstocks. Electricity includes on-road and off-road sources of credits, and biogas includes compressed natural gas and liquid natural gas from renewable sources. Fuel energy is measured in megajoules, and “B" stands for billions of megajoules. Source: (CARB, 2023b).

2.2.2 Heterogeneity in Ethanol Emissions

To participate in the LCFS, each alternative fuel supplier must register with CARB and quarterly verify its sales volumes. For alternative fuel suppliers, CARB requires highly detailed data on feedstock, energy sources, co-products, and plant efficiency characteristics. Heterogeneity across these factors for suppliers also produces heterogeneity in the CI ratings of alternative fuel producers. For example, California has a higher percentage of renewable energy than most Midwestern states. The few ethanol plants in California receive a lower CI number than most Midwestern plants because of the higher percentage of renewable energy on their power grid. Once a fuel supplier's emissions are calculated, the supplier receives an approved fuel pathway. Fuel pathways certify that the producer is approved to sell in California and all sales are attached to a specific pathway. Each quarter, CARB publishes its current certified producers in a publicly available data set that provides information on the approved pathways for each supplier including fuel type, plant location, feedstock, CI, and unique production characteristics (CARB, 2023a).

Moreover, the same production facility may have multiple pathways that differ by production technique. For example, a renewable diesel facility that makes fuel out of soybean oil or canola oil will have separate pathways for each type of feedstock. Producing different types of distillers grains changes the emissions of ethanol. Drying wet distillers grains into dry or modified increases the emissions of the ethanol co-produced with either type. Therefore, ethanol plants can have multiple pathways depending on their distillers grains type. The pathways provided by CARB denote the type of distillers grains produced for each ethanol pathway.

Table 2.1 shows the CI for a sample of ethanol pathways from plants in Iowa and Nebraska by distillers grains type.[12] Dry DG pathways have higher average CI ratings than wet DG pathways by at least 6 points in both states. The average difference between dry and modified pathways is close to 5 points for plants in the two states. Ethanol plants in Nebraska also have a slightly lower CI for most categories of distillers grains. CARB counts emissions in transporting the fuel to California if it is produced out of state. Most ethanol is transported by rail, and ethanol plants in Nebraska are closer to California than plants in Iowa. This difference to California explains why ethanol plants in Nebraska have a roughly 1 to 2 point CI advantage over ethanol plants in Iowa.

Moreover, each type of distillers grains has a significant range in CI. Ethanol plants producing dry distillers grains in Iowa have CIs ranging from 69 gCO_2/MJ to 75 gCO_2/MJ. In Nebraska, the CI of wet production ranges from 61 to 67 gCO_2/MJ. These differences in CIs then translates into some plants receiving

[12] I focus on Iowa and Nebraska ethanol plants for several reasons. First, Iowa and Nebraska are the top two ethanol producing states. Second, their location at the western edge of the Corn Belt gives them better access to the California market via the original Transcontinental Railroad line from Omaha, NE to San Francisco, CA. Finally, there is a much higher density of feeder cattle-and thereby non-dry distillers grains demand-in Nebraska and Iowa as compared to other states like Illinois or Indiana.

10% more credits per gallon than nearby competitors producing the same type of distillers grains. Thus, the LCFS could provide a unique advantage to plants with lower emissions than their competitors.

Table 2.1: Carbon Intensities of Corn Ethanol Pathways by Distillers Grains Type

Iowa					
Type	Pathways	Mean	Std. Dev.	Minimum	Maximum
Dry	16	72.55	2.01	69.32	75.16
Modified	7	68.30	1.74	66.07	70.53
Wet	9	66.03	2.34	62.54	68.44
Nebraska					
Type	Pathways	Mean	Std. Dev.	Minimum	Maximum
Dry	1	74.08	NA	74.08	74.08
Modified	2	67.70	2.434	65.97	69.42
Wet	4	64.03	2.62	61.26	66.71

Note: Dry represents DGs with 10% moisture. Modified represents DGs with 55 to 60% moisture. Wet represents DGs with 65 to 70% moisture. Pathways are the number of approved fuel pathways by CARB for each distillers grains type. The pathways are drawn from a subsample of Iowa and Nebraska ethanol plants that could be matched to pricing data from Geograin, Inc., as described in Chapter 4. Carbon intensity is measured in gCO_2e/MJ. Source: (CARB, 2023a),(Geograin, Inc., 2023).

2.2.3 Credit-Generating Process

CARB uses its own formula for calculating the number of credits generated by alternative fuel suppliers. The main parameters for CARB's credit formula are the CI of the fuel, the CI standard for the year the fuel is sold, and the energy density of the fuel. CARB also includes a conversion factor to change grams of CO_2 into metric tonnes. Electric vehicles also include a weighting factor that accounts for more efficiently transferring energy into moving the vehicle. There are also some differences in the formula across liquid fuel types.

The main differences across fuel types are the energy density of the fuel and the type of petroleum fuel it replaces. Each type of petroleum fuel has its own emissions standard, and the CI of the fuel pathway is compared against the standard for which the fuel is replacing. For ethanol, the relevant standard is gasoline whereas for biodiesel the relevant standard is the diesel pool standard. To encourage more emissions reductions over time, the standards for gasoline and diesel are slowly declining. Because each fuel type has a different amount of energy compared to a gallon of gasoline or diesel, the credit formula adjusts to these energy differences. A gallon of ethanol has roughly 66% of the energy content of gasoline, so it experiences a discount to account for the smaller energy content compared to gasoline.

For each ethanol producer, the key components are the CI of their pathway(s), the year's CI standard for gasoline, and the energy density of ethanol which is 81.51 MJ/gallon. Multiplying the number of gallons sold with each pathway then determines the number of credits generated. The credit-generating formula for ethanol plants can be expressed as

$$credits_{i,t,y,k} = Q_{i,t,k} * (\sigma_y - CI_{i,k}) * ED * C \tag{2.1}$$

where $credits_{i,t,y,k}$ is the number of credits generated for plant i, in time period t in year y from ethanol co-produced with distillers grains type k.[13] $Q_{i,t,k}$ is the gallons of ethanol sold for plant i co-produced with distillers grains type k in time period t. σ_y is the CI standard for the gasoline pool that varies by year y. $CI_{i,k}$ is the carbon intensity score for plant i's ethanol produced with distillers grains type k. ED is the energy density of ethanol that is always constant at 81.51 MJ/gallon. C is a constant that converts grams to metric tonnes and is equal to 10^{-6}.

[13]The LCFS credit formula also takes into account differences in the efficiency of converting fuel into moving the vehicle. The standard for judging this factor is the combustion engine, so for liquid fuels like ethanol, this factor is equal to one. The exact formula for ethanol can be found on pages 70-73 of (CARB, 2024)

2.2.4 Valuing LCFS Credits

The dollar value of the credits generated from each pathway is determined by the market price of LCFS credits. CARB reports prices and volumes as far back as May of 2016 (CARB, 2023c). However, in January of 2019, they started reporting transactions in three types. Type 1 are transactions that are completed within 10 days of the agreed upon terms. Type 2 are transactions that occur more than days after the terms are agreed upon and the terms of the agreement are therefore not reported until the completion data. Type 3 transactions are transactions with a listed price of $0/credit.[14]

For example, if an ethanol plant sells 10,000 credits for $100 each to a large gasoline supplier but the transaction will not be completed for 20 days, then this is a Type 2 credit transaction, and it will not be reported until the transaction occurs. If the same sale were to occur in 7 days, then the transaction will be a Type 1 transaction and it will be reported on the day of the transaction. Part of the reason for this distinction is that credits are issued on a quarterly-basis after a third-party has verified alternative fuel sales. As a result, a alternative fuel supplier may have earned the credits through alternative fuel sales, but may not have the physical credits to transfer for several weeks or months.

During the empirical estimation in Chapter 4, I use Type 1 credit prices to measure the dollar value of LCFS credit to ethanol plants. Type 1 credits are a reflection of the spot market value of LCFS credits because credits must change hands within a matter of days. The terms for Type 2 transactions are settled upon weeks possibly months before the transaction actually takes place. Thus, Type 2 credits are similar to forward pricing for corn. Using Type 1 credits matches the corn and distillers grains spot market prices. Thus, Type 1 transactions are a better measure of the pass-through LCFS credit values to spot corn prices.

The value of the LCFS credits from equation (2.1) is determined by the current price of LCFS credits. The price of LCFS credits varies according to the demand and supply of credits. These prices are determined by transactions of LCFS credits between the suppliers and demanders of credits. CARB reports these transactions on a weekly basis with a two week lag. Letting the number of gallons sold $Q_{i,t,k}$ equal one and multiplying (2.1) by the credit price gives the value of LCFS credits per gallon sold for ethanol plant i co-produced with distillers grains type k in time period t. The per gallon value of credits in dollars is then

$$creditvalue_{i,t,y,k} = P_t^L * (\sigma_y - CI_{i,k}) * ED * C \tag{2.2}$$

where P_t^L is the price of LCFS credits in time t. Thus, determining the value of LCFS credits per gallon requires knowledge on credit prices, the CI rating for each pathway, the credit standard, energy density, and

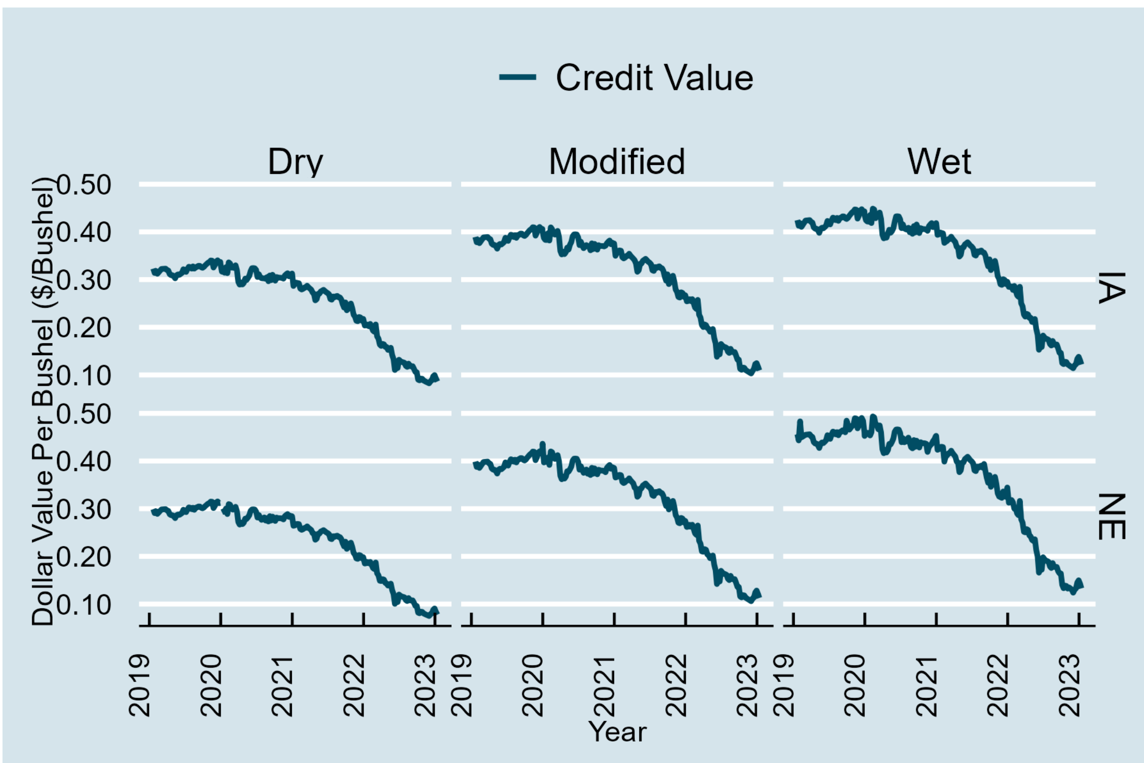
[14] Many of the largest fossil fuel firms also own alternative fuel production plants such as renewable diesel plants. These plants often transfer credits from their alternative fuel divisions to their fossil fuel divisions at prices near zero. In October 2019, CARB started reporting these transactions as well, but prior to this date, these transactions did not affect the pricing data published by CARB.

metric tonne conversion unit.

Using a CI standard of 88 gCO_2/MJ and the average CI scores for ethanol plants in Iowa found in Table 2.1., equation (2.1) shows that 100 gallons of ethanol produced with wet distillers grains generates around 0.18 credits while the same number of gallons generates 0.12 credits, If credits are valued at $100/ton, then the ethanol co-produced with wet distillers grains receives an additional $6.00 in LCFS subsidies. Ethanol plants receive almost $0.01 per gallon for every one-point reduction in their CI when credits are valued at $100/ton. In the Midwest, plants routinely surpass 100 million gallons in productive capacity. A 1 point reduction in CI is worth roughly $1 million for 100 million gallons sold in California, and 100% wet distillers grains production would generate almost $6 million in extra revenue.

Figure 2.4 shows the average per gallon subsidy of ethanol by state and distillers grain type. I use the average CI for each type of distillers grains from Table 2.1 for each state, and the annual CI standard chosen by CARB in each year from 2019 to 2022 (CARB, 2024). Credit prices are the volume-weighted average Type 1(CARB, 2023c). In both states, ethanol co-produced with wet distillers grain receives an additional $0.15 per gallon over dry distillers grains when credit prices were near $200, but the advantage of wet shrinks to roughly $0.04 per gallon once credit prices fall to $60 in 2023. The relative value between wet and modified distillers grains is close to $0.05 when credit prices are at their peak in 2020 and only one or two cents once prices bottomed out. Thereby, even at their peak, the relative advantage of wet compared to modified is quite small. The most important margin for distillers grains from the LCFS is between dry and wet or between dry and modified.

Figure 2.4: Value of LCFS Credits per Gallon of Ethanol by Distillers Grains Type



NOTE: Value of credits is expressed in dollars per gallon terms. Dry represents distillers grains with 10% moisture. Modified represents distillers grains with 55 to 60% moisture. Wet represents distillers grains with 65 to 70% moisture. Number of credits is calculated using average carbon intensities by state and distillers grain type in Table 2.1, the annual carbon intensity standard from CARB, and CARB's formula for credits per gallon of ethanol as expressed in equation 2.1. These values are then multiplied by each week's volume-weighted average Type 1 credit price as described in equation (2.2). Source: (CARB, 2023c; CARB, 2024).

2.3 Discussion

Corn-ethanol production boomed during the creation of the RFS almost two decades ago, and the LCFS now enhances the value of ethanol production through its system of tradable compliance credits. Ethanol plants can earn an additional \$0.10 to \$0.40 per gallon by selling to blenders in California, depending on the emissions of their fuel and the current price of LCFS credits. Ethanol is an important source of renewable energy for California, and the impacts of California's energy policies could spread throughout the energy supply chain. In particular, the producers of ethanol feedstocks–primarily corn farmers–could be benefiting from selling to the suppliers of alternative fuel in California. However, the transmission of LCFS credit values to corn prices will depend on local market conditions and the distillers grains production decisions of ethanol plants. In the next chapter, I build a spatial corn procurement model to understand how the LCFS influences the distillers grains choices and corn pricing decisions of ethanol plants selling into California.

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Chapter 3

To Dry or Not to Dry: A Spatial Model of the LCFS' Impacts on Corn Prices and Ethanol Plant Distillers Grain Choices

3.1 Introduction

How the LCFS affects commodity markets depends on the characteristics of local markets. Ethanol plants in Cornbelt states regularly exceed 150 million gallons in annual capacity, and they need over 50 million bushels of corn per year to meet this capacity. That level of corn consumption can exceed the entire annual corn production in major corn producing counties. Corn is a homogeneous commodity with relatively small variation in quality across farms, but corn farmers are spread out over space. Corn farmers also bear the costs of transporting grain and are limited to buyers that can be reasonably reached by semi-trucks. These factors could provide ethanol plants with spatial market power, and Jung et al. (2022) find that local market power enables Indiana ethanol plants to mark down corn by $0.60. Thus, spatial market power could impact how ethanol plants set their corn prices in response to the subsidies provided by the LCFS.

This chapter builds a spatial market model to analyze the corn procurement decisions made by ethanol plants receiving subsidies by selling ethanol into California. To account for the endogenous distillers grains (DG) choice decision, I use a two-stage approach in which two competing ethanol plants choose their DG type in the first stage and then their corn procurement price in the second stage. This two-stage spatial game builds off the work of (Zhang and Sexton, 2000) and (Mérel et al., 2009) by allowing producers to choose between multiple outputs in a non-cooperative, two-stage spatial model. Moreover, previous work analyzing the effects of ethanol plants on local corn markets generally assumes that the subsidies for ethanol plants are uniform and DG types are treated as a homogeneous commodity Jung et al. (2022); Saitone et al. (2008). Relaxing these assumptions, I show that the LCFS by introducing a heterogeneous subsidy could be providing a competitive advantage to ethanol plants with lower emissions per bushel of corn processed, and ethanol plants with lower emissions may be capturing a significant portion of the LCFS subsidies without passing it through to corn prices.

Moreover, solving the two-stage model reveals that each plant's dominant DG choice depends on observable values, and using these observables, I can parameterize the DG decisions of ethanol plants. I find that each plant's dominant DG choice does not depend on their corn procurement decision or the choices of competing ethanol plants. Rather, it depends on each plant's net revenues from either DG type. Thus, predicting the optimal DG choice for each plant participating in the LCFS depends on each plant's carbon emissions, LCFS credit formulas and prices, DG prices, and natural gas prices. In Chapter 4 of this dissertation, I apply this result to Nebraska and Iowa corn ethanol plants with certified LCFS pathways.

3.2 Spatial Market Power

Ethanol consumes roughly one-third of national corn production annually (ERS, 2023). Ethanol plants in Cornbelt states regularly exceed 150 million gallons in annual capacity, and they need over 50 million bushels of corn per year to meet this capacity. That level of corn consumption can exceed the entire annual corn production in major corn producing counties. As a result, ethanol plants can substantially affect corn prices in their local markets. McNew and Griffith (2005) find that the building of a new ethanol plant increases local grain prices by up to $0.50 and increases in corn prices were observed from competitors up to 50 miles away from new ethanol plants. Additionally, the expansion of an ethanol plant increases local competition for corn and causes land to be converted towards corn production (Wang et al., 2020).

On the other hand, corn farmers generally bear the costs for transporting grain to market and are limited to shipping grain by trucks. The costs of shipping grain to market give farmers a preference for local buyers, and Bybing et al. (2023) find that farmers' first preference for shipping corn is only 15 miles away while their second choice is 20 miles away. Baumel et al. (2001) find that Iowa farmers at most transport their corn 100 miles to market their grain. As a result of their relative size and the costs of shipping corn longer distances, ethanol plants could exert spatial market power in the corn market surrounding their location (Graubner et al., 2011; Graubner and Sexton, 2023). Jung et al. (2022) find that ethanol plants in Indian markdown the price of corn by up to \$0.60 in their local markets. Therefore, in the next section, I build a model of spatial market power for the corn procurement decisions of individual ethanol plants certified to sell into California.

The structure of the DG market, on the other hand, is more complicated. The high-moisture content of wet and modified DG prevents their storage for more than a few weeks and limits their transportation to trucks (Dooley and Martens, 2008). Therefore, consumption of modified and wet DG is generally limited to livestock feeders within 100 miles of ethanol plants (Dooley and Martens, 2008), and Stroade et al. (2010) find that 100% of wet and modified DG transportation occurs by truck. As result, ethanol plants in western Nebraska that compete with ethanol plants in eastern Iowa in the ethanol market do not necessarily compete with each other in the wet and modified DG markets. Dry DG can be stored for extended periods and shipped by rail/barge, but trucking distances rarely exceed 150 miles (Dooley and Martens, 2008). Almost 70% of ethanol plants report transporting dry DG by rail while 40% almost state that they transport dry DG using barges (Stroade et al., 2010). As a result, 50% of dry DG travels over 100 miles according to the authors of the Kansas State survey (Stroade et al., 2010).

Moreover, the local market for animal feed is highly competitive. Animal feeders have many options including DG, soybean meal, corn, soybeans, hay, and pasture. Many large livestock feeders like Cargill buy corn and soybeans direct from farmers, and smaller operations often produce some of their own feed. As a result, the supply of DG in major ethanol producing states could far exceed the local demand for animal feed after accounting for these other sources (Dooley and Martens, 2008). Ethanol plants in states like Iowa and Nebraska have to ship a significant portion of their DG to regions like Texas, Mexico, and Canada that have large livestock markets but very few ethanol plants. Therefore, individual ethanol plants likely face a highly elastic demand curve at the margin. The Kansas State DG marketing survey supports this result. Around 50% of ethanol plants report using a DG pricing formula based on corn futures and/or soybean meal futures (Stroade et al., 2010). This finding indicates that ethanol plants consider corn and soybean meal to be close substitutes for their DG. As a result, the ability of individual ethanol plants to exert market power in the DG market should be quite small. I, therefore, only consider spatial market power in the corn market and model DG prices as exogenous to ethanol plants.

3.3 Model Setup

This section builds a two-stage spatial model in which ethanol producers buy corn to convert into ethanol and DG. The two-stage approach reflects the fact that converting corn into ethanol and DG is a fermentation process that occurs over several days and the fact that ethanol plants can routinely process over 1 million bushels per week. Additionally, the higher moisture content of wet and modified DG prevents storage beyond a week or two. As such, switching between DG types requires planning based on corn throughput, storage conditions, and drying capacity. Moreover, to limit the choice scenarios and allow for closed form solutions, I confine the model to two competing ethanol plants, A and B, that each have a choice between the two DG types dry and wet.

Ethanol plants set their own price of corn in a spatially competitive market, but they take the price of their outputs as fixed. The type of DG each plant produces is fixed in the short run, and plants compete across space in a Bertrand-Nash manner to acquire corn by setting their own corn price. Each plant first chooses its DG type, DG_i, where $DG_i = 0$ for dry production and $DG_i = 1$ for wet production. In the second stage, each plant choose its corn price w_i given its DG type, the type of DG for its competitor, and its competitor's corn price.

The subgame perfect equilibrium $(DG_A^*, w_A^*; DG_B^*, w_B^*)$ occurs when neither plant can increase its profits by changing its price or DG choice given the choices made by the other plant. Since each plant has two DG choices, there are four pairs of optimal prices in the second stage. I will use backwards induction to first find four sub-game Nash equilibrium prices given the DG choice pair (DG_A, DG_B), e.g. $(w_A^*, w_B^* | (DG_A, DG_B))$. The sub-game Nash equilibrium prices are defined in terms of exogenous parameters, and they can be substituted into the objective functions for each plant to yield the profit functions for each DG choice pair. Defining the profit functions in terms of exogenous parameters allows comparisons in profits for each plant across the different DG choice pairs, and as a result, dominant strategies for wet and dry DG are defined in terms exogenous parameters.

Plants A and B are assumed to be homogeneous except for the subsidies they receive for co-producing ethanol with either dry or wet DG. Ethanol plants can vary in their production methods, plant size, and access to railroad networks among other things. I focus on how variation in LCFS subsidy impacts the decisions and market power of ethanol plants. Variation in these other characteristics likely impacts the pass through of LCFS subsidies, but their inclusion will only complicate isolating the effects of the LCFS subsidy with only a small impact on the qualitative interpretations of the results.

Each plant receives a subsidy for producing ethanol with dry DG and ethanol produced with wet DG. The subsidy for wet DG is defined as $\alpha_i^1 p_L$, where α_i^1 is a constant for credits per gallon of ethanol co-produced with wet DG that varies by plant and p_L is the price of credits. The subsidy for dry DG is defined as $\alpha_i^0 p_L$, where α_i^0 is a constant for credits per gallon of ethanol co-produced with dry DG that varies by plant. For each plant, $0 < \alpha_i^0 < \alpha_i^1$.

Variation in plant emissions causes ethanol plants to receive different amounts of credits for each type of DG. Variation in plant emissions is caused by differences in distance to California, the energy mix from the local power grid, the production of corn oil, and differences in production efficiency. For example, ethanol plants in California have 15% lower emission than plants in the Midwest because they do not have to transport ethanol to California using diesel engine trains and because local power grids in California use more renewable energy.

I discuss cases when plants A and B do and do not have the same emissions for each type of DG. That is, I cover cases when $\alpha_A^k \neq \alpha_B^k$ and when $\alpha_A^k = \alpha_B^k$ for each type of DG. I assume equal production technologies through out, so variations in carbon intensity are driven by location differences in ethanol plants. Thus, plant A receiving more credits than plant B for the same type of DG is caused by its location (0) being closer to California than plant B's location (1) and vice versa.

I focus on the case where the market is covered, and the price received by each corn farmer net of transportation costs is equal to or greater than zero to at least one ethanol plant. The covered market case ensures a duopsony solution to the spatial market model and reflects the relatively high density of grain procurement options for farmers in the Midwest (Bekkerman and Taylor, 2020). Additionally, (McNew and Griffith, 2005) find that ethanol plants can exhibit positive price effects up to 70 miles away. The larger spatial impact of ethanol plants and the high density of corn procurement options emphasizes the relevance of the covered market case over the uncovered market, monopsony solution.[1].

Moreover, the transportation costs of corn, t_c, act as an index of competition (Mérel et al., 2009). In the case of perfectly homogeneous ethanol plants, $t_c = 0$ leads to the Bertrand solution where the corn prices offered by plants A and B are equal to their output price net of processing costs (Tirole, 1988), and if $t_c > 0$, the gap between the procurement price offered by each ethanol plant and their output price net of processing costs is equal to t_c. Thus, the lower the transportation cost parameter t_c, the more the procurement prices offered will tend towards the Bertrand solution. Larger values of t_c will widen the wedge between the corn procurement price offered by and the net output price received by ethanol plants. If t_c is large enough, then some farmers may not meet their opportunity cost of producing a different crop instead of supplying corn to either ethanol plant. As a result, a portion of the market would not be covered, and each ethanol plant would have a monopsony in their local market. The covered market case, therefore, implicitly assumes that transportation costs are low enough for each farmer to at least meet their opportunity cost of corn

[1]One possible extension would be to compare the case of an ethanol plant competing against a coop or grain exporter

production.

Finally, I assume a fixed-conversion rate from corn to the products of ethanol production. Fixed-conversion rates are standard practice when analyzing the commodity procurement decisions of a large processor (Zhang and Sexton, 2000; Mérel et al., 2009; Saitone et al., 2008). While there are some variances in the yield of ethanol and DG per bushel of corn, these factors are mostly constrained by the starch, fiber, protein, and moisture content of corn. The moisture content is the most variable, so changes in conversion ratios may simply be due to wetter harvests with higher moisture content corn. Also, changes in commodity procurement decisions from the LCFS mostly effect ethanol plants at the margins, and thereby, any impacts on plant-specific returns to scale should be negligible. Section 2.1.2 provides a more detailed discussion on the ethanol production process and why a fixed-conversion model applies in this context.

3.4 Profit Maximizing Prices

Corn farmers are assumed to be homogeneous and uniformly distributed along the line defined by the interval [0,1]. Plants A and B are located at points 0 and 1 respectively. Each farmer's location is denoted as x_j. Each farmer sells a single unit of corn normalized to 1 to the plant that offers the highest net price. The net price for each farmer to plants A and B are respectively $W_j^A = w_A - t_c x_j$ and $W_j^B = w_B - t_c(1 - x_j)$, where w_A represents the corn price at plant A, w_B the corn price at plant B, and t_c is the cost of transporting corn.[2] Setting $W_j^A = W_j^B$ and solving for $\bar{x}$ yields the farmer indifferent to selling her grain to either plant A or B. Integrating over the market space for both ethanol plants yields the corn supply curves facing both plants:

$$S_A(w_A, w_B) = \int_0^{\bar{x}} 1 d\tau = \frac{w_A - w_B + t_c}{2t_c} \tag{3.1}$$

$$S_B(w_A, w_B) = \int_{\bar{x}}^1 1 d\nu = \frac{w_B - w_A + t_c}{2t_c} \tag{3.2}$$

Both ethanol plants use the same production technology. Corn R is converted into ethanol e using a quasi-fixed proportions technology that is homogeneous across plants. All non-corn variable inputs are represented by the composite input X_e, and ethanol plants cannot substitute X_e for corn. The production technology for ethanol plants i is denoted as

$$e^A = min\{R^A/\lambda_e, h(X_e^A)\}, \tag{3.3}$$

[2]Corn prices are conceived as cash prices though ethanol plants only control the basis portion of cash prices as discussed in Section 2.1.4.

$$e^B = min\{R^B/\lambda_e, h(X_e^B)\}, \tag{3.4}$$

where $\lambda_e \leq R/e$ is the conversion possibilities set from corn to ethanol and $h(X_e)$ is concave in X_e. Using (3.3) and (3.4) ethanol is expressed in per bushel terms as $e\lambda_e = R$. Likewise, credits are generated in per gallon units and can be converted to per bushel terms using $\alpha_i^k \lambda_e = R$. The value of credits per bushel is then $\alpha_i^k \lambda_e p_L$.

Corn is converted into wet DG, q_1, and dry DG q_0 using a quasi-fixed proportions technology that is homogeneous across producers for both types of DG. All non-corn variable inputs are represented by the composite input $X_0$for dry production and X_1 for wet production. The production technology for q_1 is

$$q_1^A = min\{R^A/\lambda_1, g(X_1^A)\}, \tag{3.5}$$

$$q_1^B = min\{R^B/\lambda_1, g(X_1^B)\}, \tag{3.6}$$

where $\lambda_1 \leq R/q_1$ is the conversion possibilities set from corn to wet, and $g(X_1)$ is concave in X_1. Likewise, for dry DG

$$q_0^A = min\{R^A/\lambda_0, g(X_0^A)\}, \tag{3.7}$$

$$q_0^B = min\{R^B/\lambda_0, g(X_0^B)\}. \tag{3.8}$$

Each type of DG can be converted to per bushel terms using the appropriate conversion factor. Thus, dry DG can be expressed in per bushel terms as $R = q_0\lambda_0$, and wet can be expressed in per bushel terms as $R = q_1\lambda_1$.

To simplify notation, I suppress all uses of the conversion factors for ethanol, credits, and DG. Thus, all prices for the outputs of ethanol production are interpreted in per bushel terms. This simplification also allows for convenient interpretation of the pass through of LCFS credits to the per bushel margins for ethanol plants.

Ethanol plants sell ethanol e as perfectly competitive sellers at the price p_e. They also sell DG into perfectly competitive markets with price p_1 for wet DG and p_0 for dry DG. Plants also receive the per bushel subsidy of $\alpha_i^1 p_L$ for ethanol made with wet DG and $\alpha_i^0 p_L$ for ethanol made with dry DG, where the price of credits p_L is exogenous to ethanol plants. Because of the fixed-proportions technology and separability of variable non-corn inputs, variable processing costs for ethanol co-produced with wet DG are expressed as $m_1(R) = m_e(R) + m_1(R)$, where $m_1'(R) = c_e + c_1$, and variable processing costs for ethanol co-produced with dry DG are expressed as $m_0(R) = m_e(R) + m_0(R)$, where $m_0'(R) = c_e + c_0$. Because dry DG requires extra resources to remove the moisture content, $c_0 > c_1$, and as a result, I assume that $p_0 > p_1$. For each plant, the net revenues for ethanol production is defined as $\rho_e = p_e - c_e$, and the net revenues for each DG type are $\rho_0 = p_0 - c_0$ and $\rho_1 = p_1 - c_0$.[3] To focus on the different types of DG and the LCFS subsidies, I normalize $\rho_e = 1$. This normalization means all per bushel values are weighted relative to the per bushel value of ethanol.[4]

As discussed in Section 2.1.3, the ethanol plants in my empirical study are primarily organized as for-profit entities. A few plants are organized as farmer-owned cooperatives, or they contract out their corn buying to cooperatives. Cooperatives generally maximize member value not necessarily profits, and thus, profit maximization objective functions are not necessarily appropriate for modelling cooperatives (Sexton, 1990). Nonetheless, I use a profit-maximizing objective function because only a handful of plants are cooperatives.

Ethanol plant A chooses its price w_A to maximize its profit given the price w_B from its competitor and the pair of DG choices (DG_A, DG_B). Likewise for plant B. The set of four possible pairs of DG choices is $\{(0,0),(0,1),(1,0),(1,1)\}$. There are two primary cases of DG choices: the homogeneous case where $DG_A = DG_B$ and the heterogeneous case where $DG_A \neq DG_B$. I will describe the profit maximization problems for each of these types separately. Given a DG choice pair (DG_A, DG_B), a sub-game Nash equilibrium $(w_A^*, w_B^* | (DG_A, DG_B))$ occurs when neither plant can increase its profits by changing its corn price given the price of the other plant and the DG choices. The profit maximization problems for plants A and B with DG choice pair of (0,0) are

$$\max\, \pi^A(w_A|(0,0)) = \left(1 + \rho_0 + \alpha_A^0 p_L - w_A\right)\left(\frac{w_A - w_B + t_c}{2t_c}\right), \tag{3.9}$$

$$\max\, \pi^B(w_B|(0,0)) = \left(1 + \rho_0 + \alpha_B^0 p_L - w_B\right)\left(\frac{w_B - w_A + t_c}{2t_c}\right). \tag{3.10}$$

In equations (3.9) and (3.10), plants A and B choose their corn price to maximize profits given the fact that each plant is producing dry DG and the corn price of their competitor. Plants A and B will each solve their optimization problem simultaneously. Taking the derivative of each plant's objective function with respect to its own corn price yields the first-order conditions

$$\frac{d\pi^A}{dw_A} : \frac{1 + \rho_0 + \alpha_A^0 p_L - w_A}{2t_c} - \frac{w_A - w_B + t_c}{2t_c} = 0, \tag{3.11}$$

$$\frac{d\pi^B}{dw_B} : \frac{1 + \rho_0 + \alpha_B^0 p_L - w_B}{2t_c} - \frac{w_B - w_A + t_c}{2t_c} = 0. \tag{3.12}$$

Equations (3.11) and (3.12) represent the conditions plants A and B will follow to choose their profit

[3] I only consider the case where $R > 0$, and I do not include the possibility of entry by competing ethanol plants. As a result, I do not include fixed costs.

[4] I still simply refer to all net prices as their per bushel values to eliminate additional technical jargon.

maximizing prices given the values of parameters, their choice of dry DG production, and the competitor's price. The numerator in the first term of each equation represents the per bushel margin for each plant. Thus, each plant maximizes profits by setting their per bushel margin equal to the difference in corn price between plants plus the costs of transporting corn.

Rearranging each equation for each plant's own price produces the reaction functions, e.g. the profit maximizing price for each plant given their competitor's price. The two reaction functions form a system of equations, and solving this system of equations yields the sub-game Nash equilibrium prices $(w_A^*, w_B^*|(0,0))$ of plants A and B in terms of the parameters:

$$w_A^*(0,0) = 1 + \rho_0 - t_c + \frac{2\alpha_A^0 p_L + \alpha_B^0 p_L}{3}, \tag{3.13}$$

$$w_B^*(0,0) = 1 + \rho_0 - t_c + \frac{\alpha_A^0 p_L + 2\alpha_B^0 p_L}{3}. \tag{3.14}$$

Moreover, with a DG choice pair of (1,1) instead of (0,0), equations (3.13) and (3.14) can be easily adapted for the case of both ethanol plants producing wet DG instead of dry. The prices for $(w_A^*, w_B^*|(1,1))$ are

$$w_A^*(1,1) = 1 + \rho_1 - t_c + \frac{2\alpha_A^1 p_L + \alpha_B^1 p_L}{3}, \tag{3.15}$$

$$w_B^*(1,1) = 1 + \rho_1 - t_c + \frac{\alpha_A^1 p_L + 2\alpha_B^1 p_L}{3}. \tag{3.16}$$

When both ethanol plants choose the same type of DG, the net profits for both outputs and transportation costs are fully reflected in each plant's corn price. That is, each plant fully passes through the net ethanol price, dry DG price, and transportation costs. In the absence of the LCFS subsidy, each plant would match its competitor's price, and even though plants have spatial market power, the degree to which plants can set their corn price below their net profits depends on the transportation cost parameter t_c. Thus, t_c acts as means by which to measure the competitiveness of the market as compared to a pure Bertrand market wherein with perfectly homogeneous ethanol plants $w_A^*(0,0) = w_B^*(0,0) = 1 + \rho_0 + \alpha_A p_L$ and likewise for choice pair (1,1). If $t_c = 0$ and plant A has lower emissions than plant B, e.g. $\alpha_A^0 > \alpha_B^0$, then plant A could offer a slightly higher price than plant B's breakeven price and acquire the whole market while still earning positive profits. Thus, one plant could serve the entire market in cases of near zero transportation costs or large differences in emissions.

Likewise, with homogeneous DG choice pairs competition between the two plants causes changes in non-

LCFS parameter values to be fully and equally reflected in each plant's corn price. This result is driven by the perfectly inelastic supply from each farmer.[5] Because each farmer only supplies a single unit, the only way to increase supply for plant A or B is to acquire more market share from its competitor. As a result, for plant A to increase its market share, the gains from a larger market area must offset the losses from offering a higher price to all the farmers in its market area without receiving any additional supply from those farmers. Yet, for the characteristics in which the two plants are equal, plant B faces the same net returns as plant A and can readily match any encroachment on its market area with an equal price change. Thus, competition over market share leads to the full reflection of equal factors in the procurement prices. However, the credit parameters α_A^k and α_B^k create the possibility of plants A and B offering different prices, even when they choose the same DG type. That is, differences in emissions lead to different prices from each plant despite similar DG choices.

The final terms in each equation represent the effect of the LCFS subsidy on the price of corn, and for both (0,0) and (1,1), each ethanol plant places a higher weight on its own subsidy than the subsidy of its competitor. The optimal corn procurement prices will only equal each other if emissions for each plant are equal. Thus, $w_A^*(0,0) = w_B^*(0,0)$ only if $\alpha_A^0 = \alpha_B^0$ and likewise for the case of (1,1). If $\alpha_A^0 > \alpha_B^0$, then plant A earns more credits per bushel of corn than plant B. As a result, plant A's price $w_A^*(0,0)$ will be greater than plant B's price $w_B^*(0,0)$. Moreover, if plant A generates more credits per gallon than plant B, competitive pressure from plant A causes plant B to more than fully pass-through its subsidy to its own corn price; on the other hand, plant A's competitive advantage over plant B enables it to pass through less than its full subsidy. That is, if $\alpha_A^0 > \alpha_B^0$, then $\alpha_B^0 p_L < \frac{\alpha_A^0 p_L + 2\alpha_B^0 p_L}{3}$ and $\alpha_A^0 p_L > \frac{2\alpha_A^0 p_L + \alpha_B^0 p_L}{3}$.

This result can be easily seen when $\alpha_B^0 = 0$, i.e. when plant B does not sell into California. In this case, plant B still passes through $\frac{\alpha_A^0 p_L}{3}$ to its own price $w_B^*(0,0)$ while plant A only passes through $\frac{2\alpha_A^0 p_L}{3}$ to its price $w_A^*(0,0)$. If $\alpha_B^0 = 0$, the total difference between $w_A^*(0,0)$ and plant A's per bushel net value marginal product (NVMP) is $t_c + \frac{\alpha_A^0 p_L}{3}$, and the difference for plant B is $t_c - \frac{\alpha_A^0 p_L}{3}$.

Heterogeneity in the LCFS subsidies then causes heterogeneity in the market shares for corn. Using the price pairs from equations (3.13) and (3.14), plant A's corn supply is $S_A(w_A^*(0,0), w_B^*(0,0)) = \frac{\alpha_A^0 p_L - \alpha_B^0 p_L + 3t_c}{6t_c}$ and plant B's corn supply is $S_B(w_A^*(0,0), w_B^*(0,0)) = \frac{\alpha_B^0 p_L - \alpha_A^0 p_L + 3t_c}{6t_c}$. Because each farmer's supply is normalized to 1, the supply equations also represent market shares. Therefore, plant A's market share is $\frac{\alpha_A^0 p_L - \alpha_B^0 p_L}{6t_c} + \frac{1}{2}$, and plant B's market share is $\frac{\alpha_B^0 p_L - \alpha_A^0 p_L}{6t_c} + \frac{1}{2}$. When credits per bushel are equal between plants, $S_A(w_A^*(0,0), w_B^*(0,0)) = S_B(w_A^*(0,0), w_B^*(0,0))$, and both plants acquire exactly half of the corn market. With heterogeneous ethanol plants, any deviation from a 50-50 market share is determined by the difference in the value of LCFS credits $\alpha_A^0 p_L$ and $\alpha_B^0 p_L$. If $\alpha_A^0 > \alpha_B^0$, the difference between A's market

[5] (Sexton, 1990) covers examples for relaxing this assumption.

share and B's is $\frac{\alpha_A^0 p_L - \alpha_B^0 p_L}{3t_c}$. That is, the difference in corn market share is determined by the difference in credits per bushel, weighted by transportation costs. Thus, the difference in the each plant's LCFS subsidy directly determines the difference in each plant's corn market share, holding transportation costs constant.

Nonetheless, transportation costs are a primary determinant of market dominance when plant A earns more credits than plant B. As transportation costs increase, fewer farmers located closer to plant B gain from plant A's higher price, and the market shares then approach an even 50-50 split. Likewise, as transportation costs decrease, the plant with the greater LCFS subsidy captures an increasing share of the market. In this manner, transportation costs determine the level of competition between the two plants. Thus, the costs of transporting grain from farms to ethanol plants and the difference in credits co-determine the level of market dominance by the plant with lower emissions.

The next set of cases occurs when $DG_A \neq DG_B$. The profit maximization setup is the same as in equations (3.9) and (3.10) except for the DG choices. If the pair of DG choices are $(0,1)$, then the profit maximization problems for plants A and B are

$$\max \pi^A(w_A|(0,1)) = \left(1 + \rho_0 + \alpha_A^0 p_L - w_A\right)\left(\frac{w_A - w_B + t_c}{2t_c}\right), \tag{3.17}$$

$$\max \pi^B(w_B|(0,1)) = \left(1 + \rho_1 + \alpha_B^1 p_L - w_B\right)\left(\frac{w_B - w_A + t_c}{2t_c}\right). \tag{3.18}$$

Equations (3.17) and (3.18) now differ by DG prices and any difference in LCFS credits, yet the basic problem remains the same wherein each plant chooses its own price to maximize profits, given the DG choice pairs. Taking the derivative with respect to own prices yields the first-order conditions

$$\frac{d\pi^A}{dw_A} : \frac{1 + \rho_0 + \alpha_A^0 p_L - w_A}{2t_c} - \frac{w_A - w_B + t_c}{2t_c} = 0, \tag{3.19}$$

$$\frac{d\pi^B}{dw_B} : \frac{1 + \rho_1 + \alpha_B^1 p_L - w_B}{2t_c} - \frac{w_B - w_A + t_c}{2t_c} = 0. \tag{3.20}$$

Equations (3.19) and (3.20) represent the profit maximization conditions when plant A chooses to produce dry DG and plant B chooses to produce wet DG. Rearranging these equations to find own price in terms of the parameters and competitors price yields the reaction functions for each plant. Simultaneously solving the two reaction functions yields the subgame Nash equilibrium prices $(w_A^*, w_B^*|(0,1))$ which are

$$w_A^*(0,1) = 1 - t_c + \frac{2\rho_0 + \rho_1}{3} + \frac{2\alpha_A^0 p_L + \alpha_B^1 p_L}{3}, \tag{3.21}$$

$$w_B^*(0,1) = 1 - t_c + \frac{2\rho_1 + \rho_0}{3} + \frac{\alpha_A^0 p_L + 2\alpha_B^1 p_L}{3}. \tag{3.22}$$

Equations (3.21) and (3.22) can be adapted to find the sub-game Nash equilibrium prices for DG choice pair of $(1,0)$. These prices are

$$w_A^*(1,0) = 1 - t_c + \frac{2\rho_1 + \rho_0}{3} + \frac{2\alpha_A^1 p_L + \alpha_B^0 p_L}{3}, \tag{3.23}$$

$$w_B^*(1,0) = 1 - t_c + \frac{2\rho_0 + \rho_1}{3} + \frac{\alpha_A^1 p_L + 2\alpha_B^0 p_L}{3}. \tag{3.24}$$

Just as in the homogeneous DG choice pairs of (0,0) and (1,1), equations (21) through (24) show that the when both plants choose different DG types, transportation costs and the net price of ethanol are fully reflected in each plant's corn price. However, with heterogeneous DG choice pairs of (0,1) and (1,0), each plant now weights its own DG net price different than its competitor's. For example, with a DG choice pair of (0,1), plant A places a weight of 2/3 on its own net price ρ_0 while it places a weight of 1/3 on plant B's net price ρ_1. Thus, if wet DG provides a higher net price than dry DG, e.g. $\rho_1 > \rho_0$, then competitive pressure from plant B will cause plant A to pass through more than its own DG net price ρ_0 to its corn price $w_A^*(0,1)$ while plant B will pass through less than its DG price ρ_1 to its own price $w_B^*(0,1)$. That is, if $\rho_1 > \rho_0$, $\frac{2\rho_0+\rho_1}{3} > \rho_0$ and $\rho_1 > \frac{2\rho_1+\rho_0}{3}$. However, if $\rho_0 = \rho_1$, then just like with the homogeneous DG choice pairs, each plant will fully pass through its net DG price. Therefore, heterogeneous DG choice pairs will result in heterogeneous pass through of net DG prices if the net prices are different, e.g. $\rho_1 \neq \rho_0$.

As in the case of equations (3.13) through (3.16), the last terms of (3.21) through (3.24) represent the effects on prices from the LCFS subsidies. However, any difference between each plant's price now depends on the difference in subsidies and the difference in net DG prices. That is, for a plant with a greater subsidy to offer a higher corn price than its competitor, the subsidy difference must more than match any difference in net DG prices. For example, if $\rho_0 > \rho_1$, then $w_B^*(0,1) > w_A^*(0,1)$ only if $\alpha_B^1 p_L - \alpha_A^0 p_L > \rho_0 - \rho_1$. Moreover, competition from plant A would cause plant B to more than completely pass through its DG net price ρ_1 while it would less than fully pass through its LCFS subsidy $\alpha_B^1 p_L$. The opposite would occur for plant A. The difference between plant B's corn price $w_B^*(0,1)$ and its NVMP per bushel is then $t_c + \frac{\rho_1 - \rho_0 + \alpha_B^1 p_L - \alpha_A^0 p_L}{3}$, and for plant A, the difference is $t_c + \frac{\rho_0 - \rho_1 + \alpha_A^0 p_L - \alpha_B^1 p_L}{3}$. With different types of DG production, any relative advantage one plant has from a larger LCFS subsidy could be more than completely offset if the other plant has an even greater advantage in the DG market.[6] The difference between these two factors will determine

[6]For example, if plant A is closer to California than plant B, the location difference would at least partially mitigate plant B's credit advantage from selling wet DG instead of dry like plant A.

which plant can offer a higher corn price and to what degree either plant can set its corn price below its per bushel NVMP.

The difference between the sum of each plant's net DG price and LCFS credits also determines the relative market shares between the two plants. With DG choices of (0,1), the supply for plant A is $S_A(w_A^*(0,1), w_B^*(0,1)) = \frac{\rho_0+\alpha_A^0 p_L-\rho_1-\alpha_B^1 p_L+3t_c}{6t_c}$ and for plant B $S_B(w_A^*(0,1), w_B^*(0,1)) = \frac{\rho_1+\alpha_B^1 p_L-\rho_0-\alpha_A^0 p_L+3t_c}{6t_c}$. In the case of heterogeneous DG choices, any difference in corn market shares now also depends on the net price for each DG type, not just on differences in the LCFS subsidies. The difference in market share between plants A and B is then $\frac{\rho_0+\alpha_A^0 p_L-\rho_1-\alpha_B^1 p_L}{3t_c}$. That is, with heterogeneous DG choices, acquiring more LCFS credits is not sufficient for acquiring a greater share of the corn market. Rather, a plant's sum of its DG net price and its LCFS subsidy must exceed its competitor's to acquire a greater market share in the corn market.

Finally, regardless of the DG choice pair, the presence of spatial competition increases the pass through of the LCFS subsidy to corn prices. If each ethanol plant operated as a pure monopsonist, then its corn price would be $w_i^* = \frac{1+\rho_k+\alpha_i^k p_L}{2}$, where $k = 0, 1$. The pass through of LCFS subsidies to corn prices is $\frac{\alpha_i^k p_L}{2}$, which is lower than pass through of $\frac{2\alpha_i^k p_L}{3}$ for an ethanol plant with a competitor that does not sell into California. The presence of spatial competition, even from a less profitable competitor, still causes an ethanol plant to pass through a greater portion of its LCFS subsidy than in a pure monopsony corn market.

3.5 Profit Functions and Distillers Grains Choices

Each pair of sub-game Nash equilibrium prices are used to find the profit functions for plants A and B given the parameters and the pair of DG choices. The profit functions are defined by substituting the sub-game Nash equilibrium prices into the appropriate objective functions for each plant and DG choice pair. The profit functions allow the finding of dominant strategies for the choices of DG to be defined in terms of exogenous parameter values. The profit functions for each DG choice pair are the following:

Homogeneous Distillers Grains Choices

Profit Functions with $(0,0)$

$$\Pi^A(0,0) = \left(\frac{\alpha_A^0 p_L - \alpha_B^0 p_L}{3} + t_c\right)\left(\frac{\alpha_A^0 p_L - \alpha_B^0 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.25}$$

$$\Pi^B(0,0) = \left(\frac{\alpha_B^0 p_L - \alpha_A^0 p_L}{3} + t_c\right)\left(\frac{\alpha_B^0 p_L - \alpha_A^0 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.26}$$

Profit Functions with $(1,1)$

$$\Pi^A(1,1) = \left(\frac{\alpha_A^1 p_L - \alpha_B^1 p_L}{3} + t_c\right)\left(\frac{\alpha_A^1 p_L - \alpha_B^1 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.27}$$

$$\Pi^B(1,1) = \left(\frac{\alpha_B^1 p_L - \alpha_A^1 p_L}{3} + t_c\right)\left(\frac{\alpha_B^1 p_L - \alpha_A^1 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.28}$$

With both plants choosing the same distiller grain type, the only differentiating factors are the LCFS credit parameters $\alpha_A^0, \alpha_A^1, \alpha_B^0,$ and α_B^1. Differences in the LCFS parameters then generate heterogeneity in corn market outcomes. The last terms in the profit functions represent the market shares of each plant. The plant with the larger credit parameter will have a market share exceeding $\frac{1}{2}$ by $\frac{\alpha_i^k p_L - \alpha_{\sim i}^k p_L}{6t_c}$.

The left-term in parentheses for each equation represents the per bushel margins for each plant given the DG choices. The margins for each plant fully incorporate the costs of transportation, but differences in emissions leads to variation in the margins for corn. In each case, the plant with lower emissions enjoys a higher margin per bushel of corn than the plant with higher emissions.

The difference in profits between A and B is $\frac{(\alpha_A^k p_L - \alpha_B^k p_L + 3t_c)^2}{18t_c} - \frac{(\alpha_A^k p_L - \alpha_B^k p_L + 3t_c)^2}{18t_c}$. Plant A will have greater profits than plant B provided that $\alpha_A^k > \alpha_B^k$. Additionally, the plant with a larger credit parameter will not fully pass through its LCFS subsidy while the plant with a smaller credit parameter will more than fully pass through its credit parameter.

However, the difference in market shares and profits also depends inversely on the transportation cost parameter t_c. As transportation costs increase, spatial competition between the two plants becomes less stringent, and gaining a greater market share requires an even corn higher price. In summation, as long as the market is fully covered, having a larger credit parameter enables a plant to capture a greater share of the corn market, offer a higher corn price, and obtain greater profits than its rival, but the degree of spatial competition as gauged by transportation costs determines the extent to which the plant can exert its competitive advantage at the expense of its rival.

Heterogeneous Distillers Grains Choices

Profit Functions with $(1,0)$

$$\Pi^A(1,0) = \left(\frac{\rho_1 + \alpha_A^1 p_L - \rho_0 - \alpha_B^0 p_L}{3} + t_c\right)\left(\frac{\rho_1 + \alpha_A^1 p_L - \rho_0 - \alpha_B^0 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.29}$$

$$\Pi^B(1,0) = \left(\frac{\rho_0 + \alpha_B^0 p_L - \rho_1 - \alpha_A^1 p_L}{3} + t_c\right)\left(\frac{\rho_0 + \alpha_B^0 p_L - \rho_1 - \alpha_A^1 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.30}$$

Profit Functions with $(0, 1)$

$$\Pi^A(0,1) = \left(\frac{\rho_0 + \alpha_A^0 p_L - \rho_1 - \alpha_B^1 p_L}{3} + t_c\right)\left(\frac{\rho_0 + \alpha_A^0 p_L - \rho_1 - \alpha_B^1 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.31}$$

$$\Pi^B(0,1) = \left(\frac{\rho_1 + \alpha_B^1 p_L - \rho_0 - \alpha_A^0 p_L}{3} + t_c\right)\left(\frac{\rho_1 + \alpha_B^1 p_L - \rho_0 - \alpha_A^0 p_L}{6t_c} + \frac{1}{2}\right) \tag{3.32}$$

With heterogeneous DG choices, the same principles hold but differences in market share, prices, and profits are not determined by differences in $\rho_k + \alpha_A^k p_L$ and $\rho_{\sim k} + \alpha_B^{\sim k} p_L$, where $\sim k$ represents not plant k. That is, the difference in the sums of each plant's LCFS subsidy and net DG price determines which plant is dominant. The difference in profits between plant A and plant B for heterogeneous DG choices is $\frac{(\alpha_A^k p_L + \rho_k - \alpha_B^{\sim k} p_L - \rho_{\sim k} + 3t_c)^2}{18t_c} - \frac{(\alpha_B^{\sim k} p_L + \rho_{\sim k} - \alpha_A^k p_L - \rho_k + 3t_c)^2}{18t_c}$. Plant A will earn greater profits than plant B if $\rho_k + \alpha_A^k p_L > \rho_{\sim k} + \alpha_B^{\sim k} p_L$. Likewise, if $\rho_k + \alpha_A^k p_L > \rho_{\sim k} + \alpha_B^{\sim k} p_L$, then plant A will have a larger market share than plant B. The larger market share for plant A is caused by plant A offering a higher price than plant B.

Nonetheless, the size of these differences still depends on the spatial competition parameter t_c. For example, plant A covers the entire corn market if $t_c \geq \frac{\alpha_A^k p_L + \rho_k - \alpha_B^{\sim k} p_L - \rho_{\sim k}}{3}$ and $\alpha_A^k p_L + \rho_k > \alpha_B^{\sim k} p_L + \rho_{\sim k}$. However, plant A's advantage in market share approaches zero as t_c increases because increasing transportation costs reduces the spatial competition between ethanol plants. Therefore, while greater revenues from LCFS subsidies and DG gives a plant a competitive edge, spatial competition through transportation costs still plays a role in determining the size of the advantage.

Dominant Distillers Grains Strategies

The profit functions enable the definition of dominant DG strategies in terms of the exogenous parameters. A dominant DG strategy results when one choice always delivers greater payoffs regardless of the DG choice by the other plant-provided that both plants offer the optimal corn price. Therefore, dry is dominant to wet for either plant if and only if $\Pi^i(0,0) > \Pi^i(1,0)$ and $\Pi^i(0,1) > \Pi^i(1,1)$ are simultaneously true. Both of these inequalities hold provided that

$$\rho_0 + \alpha_i^0 p_L > \rho_1 + \alpha_i^1 p_L. \tag{3.33}$$

The left-hand side of the inequality represents the total net revenues from dry DG production while the right-hand side is the total net revenues from wet DG production. Therefore, dry strictly dominates wet as long as the total per bushel net benefits from dry DG production is greater than the total per bushel net benefits from wet DG production. Since $\alpha_i^0 p_L < \alpha_i^1 p_L$ by definition, then the difference in net price between dry and wet DG must be more than enough to offset wet's advantage in credits.

Likewise, wet is dominant to dry if and only if $\Pi^i(1,0) > \Pi^i(0,0)$ and $\Pi^i(1,1) > \Pi^i(0,1)$. Both of these statements hold true if

$$\rho_1 + \alpha_i^1 p_L > \rho_0 + \alpha_i^0 p_L. \tag{3.34}$$

Again, wet is dominant to dry if the total net benefits from wet DG production is more than from dry. Since wet always produces more credits than dry DG, wet strictly dominates dry if $\rho_1 \geq \rho_0$. Therefore, during periods when ethanol plants would normally be indifferent between wet and dry DG production, the LCFS subsidies tip the balance in favor of wet production over dry.

A Nash equilibrium with heterogeneous DG choices, $(DG_A^* w_A^*, DG_B^* w_B^*)$ where $DG_A^* \neq DG_B^*$, will occur if dry production is dominant for one plant while wet production is dominant for the other plant. For example, if dry is dominant for plant A and wet is dominant for plant B, then the Nash equilibrium DG choice pair will be (0,1). Since $\alpha_i^0 < \alpha_i^1$ by definition, then with (0,1) equation (3.33)implies that the net price for dry DG must be more than the net price for wet. Furthermore, equations (3.33) and (3.34) imply that $\alpha_A^0 - \alpha_A^1 > \alpha_B^0 - \alpha_B^1$. That is, the difference in the number of credits between wet and dry production is less for plant A than for plant B with a Nash equilibrium DG choice pair of (0,1), and for plant A, wet's credit advantage is not enough to offset dry's net DG price advantage. For plant B, wet's credit advantage is more than enough to offset dry's higher net price.

On the other hand, if one type is dominant for both plants, then a Nash equilibrium with homogeneous DG choices will occur. From equation (3.33), if dry production is dominant for both plants then $\rho_0 - \rho_1 > \alpha_i^1 p_L - \alpha_i^0 p_L$. This condition states that if dry is dominant for both plants then the dry net price must more than compensate wet's credit advantage for both plants. On the other hand, from equation (3.34), if wet is dominant for both plants, then $\alpha_i^1 p_L - \alpha_i^0 p_L > \rho_0 - \rho_1$, and even if dry has a higher net price than wet, the larger subsidy for wet more than offsets the price difference. Thus, the total net revenues for wet are greater than the total net revenues for dry.

Finally, there does not exist non-dominant strategies in which a plant would change its DG choice based on the choice of the other plant. If dry is the optimal choice over wet for plant A, then inequality (3.33) holds regardless of the choice made by plant B. Likewise, if wet is the optimal choice over dry, then inequality (3.34) for either choice made by plant B. These two inequalities cannot strictly hold at the same time, and thus, if wet is the optimal choice for plant A when plant B chooses dry, then wet will continue to be the choice if plant B switches to wet production, holding all else constant. Therefore, predicting which type of DG production is optimal only depends on knowing each plant's per bushel net returns for dry and wet production, not on knowing the DG choice of the other plant.

3.6 Discussion

The LCFS provides ethanol plants with additional subsidy on top of the any value from the RFS. I find that heterogeneity in the value of this subsidy, whether driven by differences in plant-level emissions or DG choices, enable plants with a greater subsidy to capture more market share, earn higher profits, and less than fully pass-through the LCFS subsidy to the corn price it offers to farmers. Ethanol plants with a lower subsidy, on the other hand, more than fully pass-through their subsidy to corn farmers in order to stay competitive with the plant receiving a higher subsidy. The actual effects of the LCFS on corn prices will vary from plant-to-plant depending on relative advantages provided by the LCFS. Nonetheless, any heterogeneity in subsidies from the LCFS provides lower emission ethanol plants with an advantage over their competitors, and thus, provide these plants with a means to gain greater market share while also less than fully passing through the value of LCFS credits to corn prices.

The actual value of the LCFS subsidies for ethanol plants varies by which type of DG the ethanol plant chooses. Empirically estimating the pass-through of LCFS subsidies to corn prices depends on knowing which type of DG an ethanol plant is producing at a given moment. Equations (3.33) and (3.34) show that the dominant DG strategies of ethanol plants depend on knowable parameter values and prices. Therefore, the dominant DG strategies for each ethanol can be predicted using publicly available data. These predictions can then assist in estimating the pass-through of LCFS credit value changes to the corn prices offered by ethanol plants, which I accomplish in the next chapter.

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Chapter 4

Corn, Carbon, and Competition: Estimating The Pass-through of LCFS Subsidies to Local Corn and Distillers Grain Prices

4.1 Introduction

The LCFS enhances the value of corn ethanol by issuing tradable compliance credits to ethanol plants supplying California. An ethanol plant participating in California's LCFS could earn an additional \$0.10 to \$0.25 per gallon on top of the value of the ethanol sold to California blenders. Part of this value may then spread out into other parts of the ethanol supply chain. In particular, corn farmers may benefit from the pass through of LCFS subsidies to corn prices, and livestock feeders may benefit from the transmission of the LCFS credit values into the prices of distillers grains (DG), the primary co-product of ethanol production. However, the actual size of these price effects depend on local market conditions including elasticities, transportation costs, competitive structure, and DG choices.

In this chapter, I empirically estimate the pass through of changes in the value of LCFS credits to the corn prices offered by ethanol plants in Iowa and Nebraska using a cumulative dynamic multiplier model. I also use a similar model to estimate the pass through of LCFS credit value changes to price spreads between different types of DG. The per bushel value of LCFS credits depends on which type of DG ethanol plants are producing. I do not directly observe the DG production types for each plant, and thus, I exploit the result from Chapter 3 that the dominant DG strategies on observable DG prices and LCFS parameters. That is, I use analogues to equations (3.33) and (3.34) to predict the DG choice for each plant in each week given each plant's available LCFS pathways, DG prices, and LCFS credit prices.

I find that around 40% of the per bushel value of LCFS credit changes pass through to the corn prices offered by Iowa and Nebraska ethanol plants 2 weeks after the initial change in LCFS credit values. This pass through appears to persist for around 2 months. Moreover, I find that ethanol plants organized as cooperatives pass-through a higher proportion of LCFS credit value changes than non-cooperatives. I cannot reject the case of full pass-through of cooperatives using standard confidence intervals while I can reject the case of full pass-through for non-cooperatives with 95% confidence intervals.

Also, I find that changes to the differential credit values between different DG types more than fully pass through to the price spreads between different DG types within two weeks. However, these pass-through estimates have very large confidence intervals that far exceed the value of 1. Therefore, these results should be interpreted cautiously.

Pass-through estimates are a key parameter that express how markets are responding to policy changes. My results show that the effects from the LCFS pass all the way to farm gate prices. Farmers in Iowa and Nebraska may be benefiting from the attempts of California policymakers to reduce the state's transportation emissions. As a result, ethanol plants participating in the LCFS may be incentivizing greater corn production in their local markets by raising local prices. Moreover, the pass-through of LCFS credit price changes to DG markets indicates that local livestock feeders could benefit from the LCFS by purchasing lower carbon wet DG instead of dry DG.

Nonetheless, the lack of full pass through could indicate that LCFS could be enhancing the market power of ethanol plants. Market power is commonly viewed simply in terms of relative size. However, my results in Chapter 3 show that differentiation in emissions could provide a competitive advantage for one of two otherwise equal ethanol plants who both participate in the LCFS. That is, the LCFS allows for variation in per bushel subsidies across ethanol plants. This variation in subsidy amount allows plants with lower emissions to retain a greater share of their subsidy than than their competitors. This point is especially true if their competitors are not ethanol plants selling into California. A market power conclusions of incomplete pass-through should be drawn carefully because the elasticities of supply and demand, market shares, and marginal cost structures could all impact pass through (Weyl and Fabinger, 2013). However, the lack of full pass-through could indicate that the LCFS is enhancing the market power of some ethanol plants.

The pass-through of economic policies has experienced a resurgence in general interest within the last decade, especially in relation to market power and energy markets. Weyl and Fabinger (2013) show that the degree of market power and the pass-through co-determine changes in dead-weight loss and the share of welfare surpluses from changes in tax rates. Additionally, Pless and van Benthem (2019) and Weyl and Fabinger (2013) show that empirical tests for more-than complete pass-through of a tax could be a reliable test of market power, depending on the concavity of market demand and supply curves. In the case of liquid fuels, limitations on refinery capacity, state-level policies, and inventory constraints can constrain supply responses and reduce the pass-through of fuel taxes to prices (Marion and Muehlegger, 2011). For high-ethanol blends, reduced spatial competition can also reduce the size and speed of the pass-through of ethanol subsidy changes to retail prices (Lade and Bushnell, 2019). In the case of corn markets and ethanol, McNew and Griffith (2005) find that the creation of a new ethanol plant increases corn prices for over 50 miles from the new site. However, there is also evidence that the size of ethanol plants relative to local corn markets could give them enough market power to mitigate the pass-through (Saitone et al., 2008; Jung et al., 2022).

Moreover, measuring the pass-through of LCFS subsidies to corn and DG markets builds off previous work in three primary ways. Thus far, the liquid fuels pass through literature has primarily focused on the pass through of RFS policy effects to retail fuel prices (Lade and Bushnell, 2019; Knittel et al., 2017; Irwin et al., 2020). These authors find full-pass through of changes in Renewable Identification Number credit prices to retail fuel prices unless there is a low degree of spatial competition. This chapter applies much of the same framework but to an entirely different policy: the LCFS. Additionally, the literature on the LCFS has focused on its inefficiencies as compared to a carbon tax and how to address these inefficiencies with additional policy mechanisms (Holland et al., 2009; Holland, 2012; Lade and Lin Lawell, 2021). Empirical research on the LCFS's effects on prices is just beginning (Mazzone et al., 2022), and thus far, no work has been published on the LCFS's effects on feedstock or co-product markets. Finally, the effects of ethanol production on corn prices is not a new question (Babcock, 2008; Drabik et al., 2016; McNew and Griffith, 2005). These papers, however, are primarily focused on shocks to national-level corn prices such as corn futures (Carter et al., 2017; Hausman et al., 2012; Roberts and Schlenker, 2013), not the pass-through of policy changes to local corn prices. This study exploits plant-level variation in subsidies to empirically estimate the pass through to local markets. As a whole, the work provides insights into how agricultural producers may benefit from future energy policies that are not specifically directed towards their markets.

4.1.1 Comparing Per Bushel Returns Across Distillers Grains Types

This section discusses the process for comparing the per bushel value of different types of DG. As discussed in Chapters 2 and 3, the number credits generated per gallon of ethanol sold to California depends on the type of DG co-produced with that ethanol.Because ethanol plants buy corn in bushels, accurately measuring the pass through to corn prices requires scaling per gallon credit values to per bushel terms. Likewise, each type of DG varies significant in moisture content and so simply comparing prices between different types of DG does not account for these differences.

Moreover, I cannot directly observe the type of DG being produced at any point in time. If I simply assume ethanol plants are producing dry or producing wet DG, this could lead to measurement error and bias in my regression results. Therefore, I predict the type of DG being produced using results from equation (2.33) and (2.34). These equations show that the optimal DG strategy depends on comparing the total per bushel value of DG types to each other for each plant, not on the strategic choices of competing ethanol plants. Scaling to dollars per bushel enables an even comparison between DG prices and LCFS credit values.

The per bushel value of each type of DG depends on two parts: the value of LCFS credits and the value of DG production itself. Moreover, comparing the per bushel returns for each type of DG requires assumptions on the returns to scale for ethanol and DG production. I have assumed throughout this dissertation that ethanol plants convert corn into different outputs using constant-returns to scale technology. The LCFS credit formula described in equations (2.1) and (2.2) provides the value of LCFS credits per gallon of ethanol produced given the type of DG. Multiplying equation (2.2) by the number of ethanol gallons produced per bushel yields the per bushel value of LCFS credits. The result is

$$bushvalue_{i,t,y,k} = creditvalue_{i,t,y,k} * \mu \tag{4.1}$$

where μ is the number of gallons of ethanol per bushel of corn. All other terms have the same meaning as described in equation (2.2). I discuss my choice of μ in Section 4.3.

DG prices are normally sold in dollars per ton of DG. The prices across each type can vary significantly because of the differences in moisture content. By converting to dollars per bushel, price differences due to moisture content can be mitigated. Moreover, converting to dollars per bushel for each type of DG allows finding the total value for each type of DG. This can be accomplished with a fixed-conversion parameter from corn to DG unique to each type. The dollar per bushel value of each type of DG is then expressed as

$$DGvalue_{i,t,y,k} = P_{s,t,k} * \delta_k + bushvalue_{i,t,y,k} \tag{4.2}$$

where $P_{s,t,k}$ is the price per ton of DG type k in time t and δ_k is the specific conversion parameter for each type of DG. I use state-level DG prices as discussed in the next section.

The primary marginal expense in converting wet DG into dry or modified is the natural gas used to run the dryers. I, however, find that at the per bushel level the additional expense in converting a bushel's worth of wet DG into a bushel's worth of dry DG is generally quite small. For example, using a CI difference between wet and dry DG of 8 gCO_2/MJ and natural gas emissions of 55 gCO_2/MJ gives approximately 0.025 million btus of natural gas to convert a bushel's worth of wet DG into dry DG. Natural gas prices are normally \$4 to 5 per million btus. The cost of natural gas per bushel is around \$0.10 while the per bushel value is normally between \$1 to 3 before considering the value of LCFS credits. As a result, drying expenses have almost no effect on which type of DG strategy is dominant. I, therefore, only use net revenues for comparing the per bushel returns for each type of DG. Following equation (3.33) and (3.34) a DG type k is the dominant strategy provided that

$$DGvalue_{i,t,y,k} > DGvalue_{i,t,y,\sim k}. \tag{4.3}$$

That is, a DG type is the dominant strategy if its total per bushel value per bushel value is greater than the total per bushel value for all other types of DG. For example, if the combined value of dry DG production is \$3.50 per bushel while wet is \$3.25 and modified is \$3.30 per then dry DG has the greatest per bushel value. I then use equation (4.3) to predict which type of DG each plant is producing in each week, so in my example, I would predict that the plant was producing dry DG for that week.

4.2 Data Description

Estimating the pass-through of LCFS credit price changes to corn prices requires 6 primary pieces of data: fixed conversion ratios, LCFS parameters, plant-level carbon intensity data, LCFS credit prices, local corn prices, and prices of other outputs. The fixed parameters are drawn from reports on ethanol production, particularly from AMS. All of the necessary LCFS data and plant-level emission data comes from CARB on their website. For local corn prices, basis is an excellent measure since it is the difference between the front-month CME corn futures contract and the cash bid offered by local sellers. Basis, thereby, reflects local supply and demand decisions. Geograin, Inc. provides daily basis data for over 100 ethanol plants starting in the early 2000's. The USDA's AMS provides state-level data on DG, spot ethanol prices, and corn oil prices-another co-product of ethanol production. This section will describe each of these data sources in greater depth.

4.2.1 Fixed-Conversion Ratios and LCFS Parameters

The fixed proportions and LCFS parameters from equations (2.1) to (2.4) are available from publicly accessible data sources. USDA AMS publishes weekly reports on bioenergy and co-product markets. The

National Weekly Grain Co-Product Report publishes prices for bioenergy co-products, and it publishes fixed-conversion ratios (AMS, 2023a). For ethanol, the report publishes fixed-conversion parameters for the number of gallons of ethanol per bushel, pounds of corn oil per bushel, and pounds of DG per bushel for dry and wet. The report does not report pounds per bushel for modified, so I calculate this number from the dry matter content of dry and wet DG. Likewise, the California Air Resources Board publishes their full regulation online (CARB, 2024). This regulation includes carbon intensity standard data and energy densities. All of the values for these parameters are published in Table 3.1.

The CI standard for gasoline starts at 93.23 gCO_2/MJ in 2019 and declines to 88.25 by the start of 2023. Thus, even credit prices do not change the per bushel returns for selling into California are slightly declining over time because the standard is decreasing. The per bushel yield from dry DG is roughly one-third the yield for wet DG according to AMS. The difference in yield is entirely due to moisture content. Multiplying 16.5 by the dry matter content of dry DG provides 14.85 lbs/bushel, and doing the same process using for 70% moisture for wet DG gives 18.7 lbs/bushel. I, therefore, use dry matter content of 14.85 lbs/bushel and a moisture content of 57.5% to derive the per bushel yield for modified DG including moisture of 35 lbs/bushel.

Table 4.1: Ethanol Production and LCFS Parameters

Ethanol Production Parameters	
Lbs. Dry DG per Bushel	16.5
Lbs. Mod DG per Bushel	35.0
Lbs. Wet DG per Bushel	49.0
Gal. Ethanol per Bushel	2.85
LCFS Parameters	
2019 Standard	93.23
2020 Standard	91.98
2021 Standard	90.74
2022 Standard	89.50
2023 Standard	88.25
Energy Density of Ethanol	81.51

Note: Lbs. is for pounds. Dry DG is dry distillers grains, Mod DG is modified distillers grains, and Wet DG is wet distillers grains. Gal. is for gallons. The LCFS standards are for the gasoline pool. Ethanol production parameters are from USDA AMS except for pounds of modified which is calculated from dry matter content of dry and wet distillers grains. All LCFS parameters come from the official LCFS regulation. Carbon intensity standards are measured in gCO_2/MJ. Energy density is measured in MJ/gallon. Source:(CARB, 2024), (AMS, 2023a)

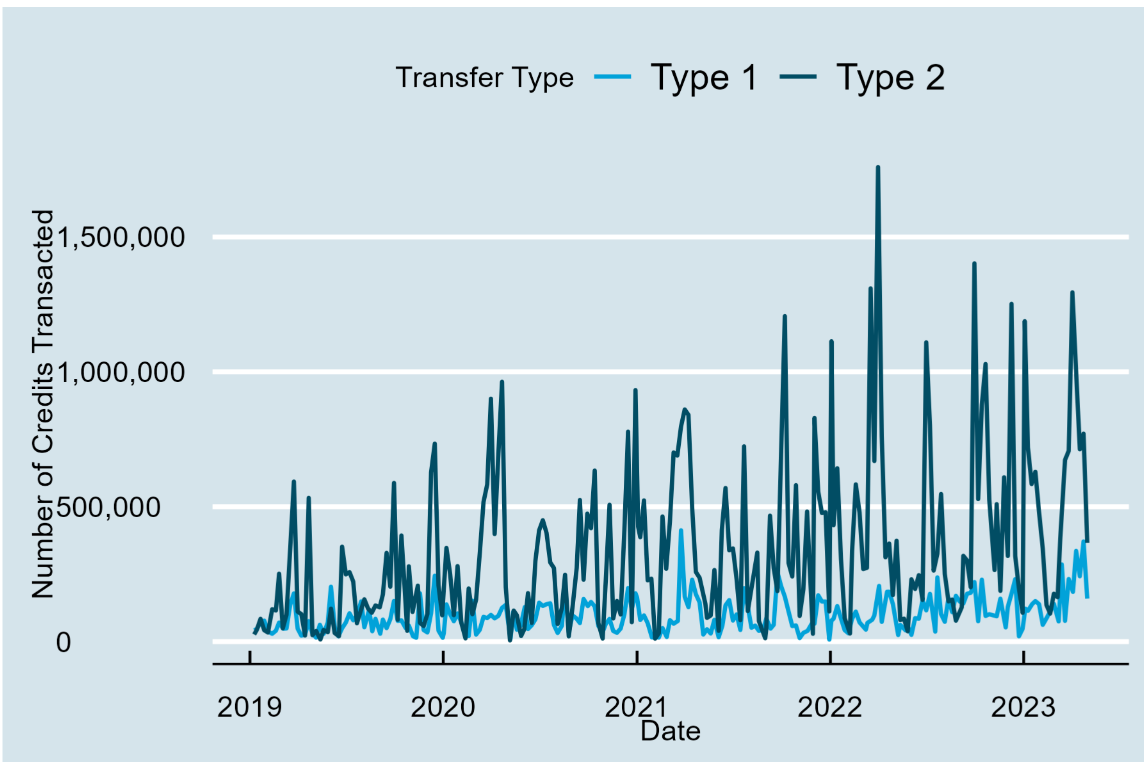
4.2.2 LCFS Credit and Pathway Data

Every week the California Air Resources Board publishes all reported weekly credit transactions between the buyers and sellers of LCFS credits with a two week lag (CARB, 2023b). Starting in 2019, CARB reports credit transactions based on the number of days till the fulfillment of the transaction. Type 1 transactions reflect the spot market because they are fulfilled within no more than 10 days while Type 2 transactions take 10 days or more to be fulfilled. In this manner, Type 2 transactions act like forward prices for corn.

Figures 4.1 displays the number of credits transacted in each week for Type 1 and Type 2 credits. The figures show that Type 2 transactions regularly surpass Type 1 transactions in the number of credits transacted; however, both types exhibit significant peaks and troughs in volume because of the cyclical nature of when credits are issued. As a result, The significant volatility in transaction volume results in Type 2 credits having a 0.90 coefficient of variation while Type 1 credits have a 0.68 coefficient of variation.

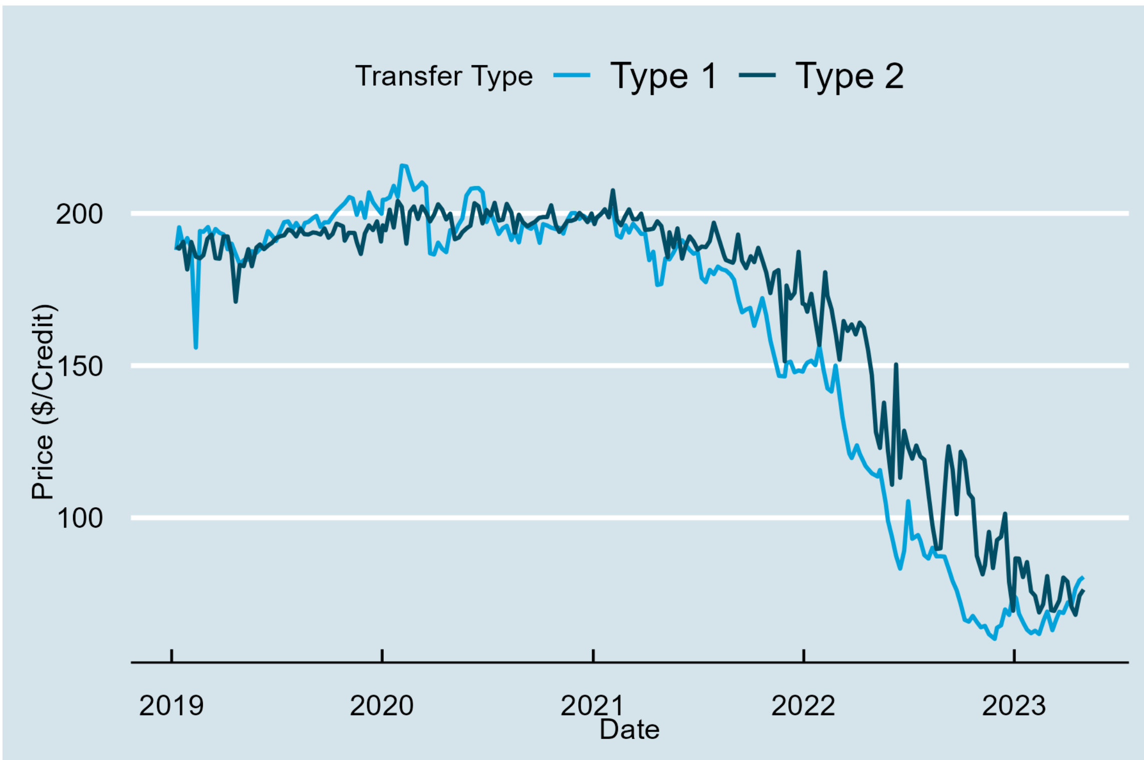
Figure 4.2 displays the volume-weighted average price for Type 1 and Type 2 transactions. It is quite clear that Type 2 price changes appear to lag behind Type 1 price changes. This result is not surprising as the terms of Type 2 transactions could have been agreed upon several weeks or months before the transaction took place and the credits were transferred, and large unanticipated movements in price may not fully reflect in Type 2 credit prices for several weeks. As a result, Type 1 credits represents a better picture of the spot market for LCFS credit prices, and thereby, a better reflection of the contemporaneous credit prices. Therefore, Type 1 credit price changes are the preferred measure of credit price changes in the empirical section.

Figure 4.1: LCFS Credit Transactions by Credit Type



NOTE: Type 1 LCFS credit transactions are defined as transactions in which the physical credits change possession within 10 days of the agreement on transaction terms. Type 2 LCFS credit transactions are defined as transactions in which the physical credits change possession in more than 10 days after the agreement on transaction terms or in which more than two parties participate in the transaction. Transactions for both types are reported once the credits change possession. Source: (CARB, 2023b).

Figure 4.2: LCFS Credit Prices by Credit Type



NOTE: Credit prices are in dollars per credit and are calculated using weighted-average of prices and number of credits for each transaction of each type. Type 1 LCFS credit transactions are defined as transactions in which the physical credits change possession within 10 days of the agreement on transaction terms. Type 2 LCFS credit transactions are defined as transactions in which the physical credits change possession in more than 10 days after the agreement on transaction terms or in which more than two parties participate in the transaction. Source: (CARB, 2023b).

The next piece of CARB data are the data on ethanol plant carbon intensity ratings. Once a quarter CARB, updates their LCFS Pathway Certified Carbon Intensities(CARB, 2023a). These data contain all of the available information on a certified alternative fuel production pathway. These pathways contain information on the certified carbon intensity of a fuel pathway, the fuel type, the fuel's feedstock, the production plant's name, the production plant's location, and a column for the fuel provider to include factors that affect carbon intensity such as co-products produced, primary electricity source, and the method of delivery the fuel to California if produced in another state or country. For this project, the primary importance of the description variable is the ability to distinguish the DG type for each pathway. Most description entries indicate what type of DG is being produced with that pathway, and plants that produce multiple types have multiple pathways. However, there are some corn ethanol pathways in which the type of DG is not mentioned or multiple types of distiller grain are mentioned. These examples are dropped from the data set because of the inability to identify DG types.

The carbon intensities pathway data are then matched to the meta data on ethanol plants in Iowa and Nebraska from Geograin, Inc (Geograin, Inc., 2023). Geograin, Inc. provides a facility type for all locations in their data set. If a facility was not listed as an ethanol plant, then I dropped it from my sample. Sometimes the names for facilities from CARB and Geograin are do not directly match because ethanol plants may contract out their grain buying operations to a local merchandiser in the same town. Geograin, Inc. then lists the grain merchandiser as the ethanol plant even if the merchandiser and ethanol plant are separate organizations. For these cases, I manually checked for ethanol plants in the city listed by CARB and listed by Geograin, Inc. If an internet search reveals that the listed city only includes one ethanol plant, then I matched the grain merchandiser listed by Geograin, Inc. to the ethanol plant listed by CARB. If a pathway could not be matched to the Geograin data, then I dropped this pathway. In this manner, I match pathways from CARB to grain prices offered by ethanol plants listed in the Geograin, Inc. database. Table 4.2 presents the DG choice sets from matching available CARB pathways to the Geograin, Inc. database.

Tables 4.2 presents the DG choice sets for ethanol plants in Iowa and Nebraska. 14 out of the 17 ethanol plants in Iowa in my sample have the option to sell ethanol co-produced with at least 2 types of DG and 1 plant has the option to sell ethanol co-produced with all three types. In Nebraska, only 1 plant can switch between types while the other 5 only have one option. Moreover, in Iowa, every plant but 1 has the option to produce dry DG while in Nebraska only 1 plant has the option to sell ethanol co-produced with dry in Nebraska. Therefore, the ability to switch between dry and wet or dry and modified is far more important in Iowa than it is in Nebraska.

Table 4.2: Number of Plants For Each Possible Set of Distillers Grains Choices

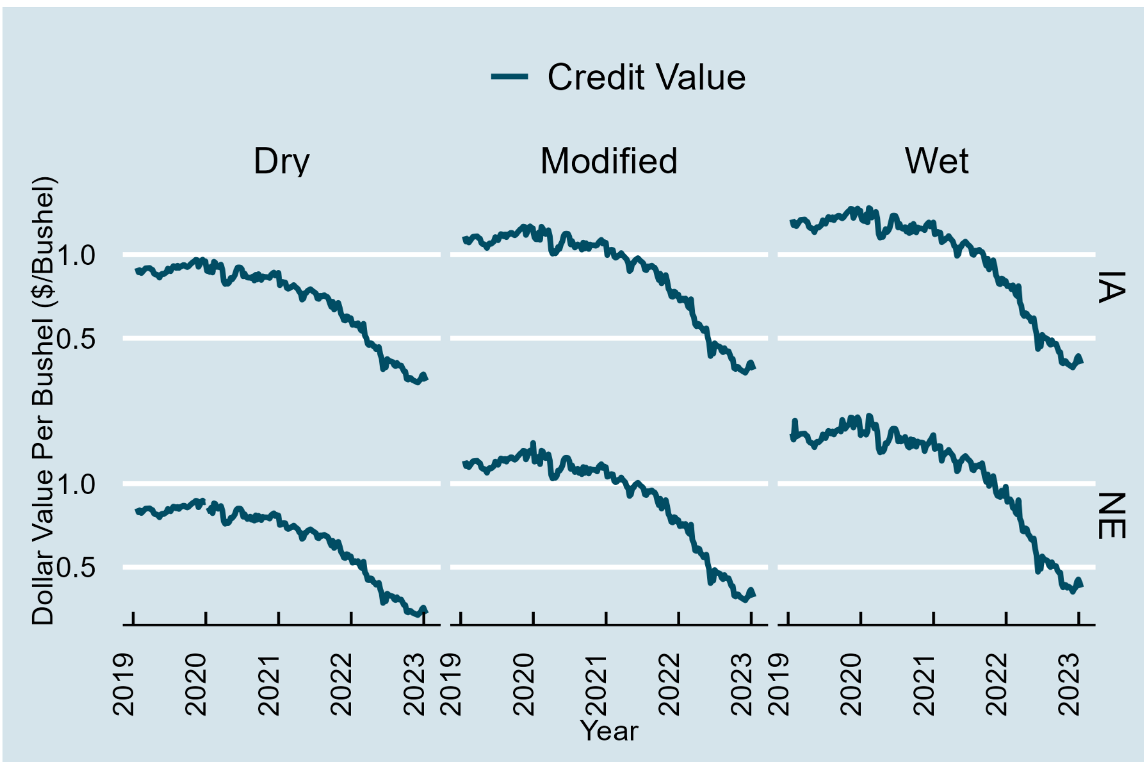
Iowa	
Choice Set	Number of Plants
Dry Only	2
Wet Only	1
Dry and Modified	6
Dry and Wet	7
Dry, Modified, and Wet	1
Total Ethanol Plants	17
Nebraska	
Choice Set	Number of Plants
Modified Only	1
Wet Only	4
Dry and Modified	1
Total Ethanol Plants	6

Note: Dry represents distillers grains with 10% moisture. Modified represents distillers grains with 55 to 60% moisture. Wet represents distillers grains with 65 to 70% moisture. Choice set lists the types of distillers grains an ethanol plant can co-produce with ethanol sold in California. Number of plants lists the number of plants for each choice set. Total ethanol plants is the sum of the number of ethanol plants from each choice set for each state.

Using each plant's carbon intensity data, fixed parameter data, and equation (4.1), I construct the per bushel value of LCFS credits for each DG type. Figure 4.3 displays the per bushel value of LCFS credits by DG type and state. For credit prices, I use Type 1 prices, and the number credits per bushel for each type is calculated by averaging the per bushel number of credits for the ethanol plants in each week of the matched corn price dataset described in the next subsection.

Several clear patterns emerge from Figure 4.3 First, the per bushel value of credits is greatest for wet followed by modified and then dry DG. Second, the per bushel value of credits for all types fell by over half from 2021 to 2023 when the price of LCFS credits fell from $200 to $75. Thus, the gap in credit values per bushel between wet, modified, and dry closed considerably from 2021 to 2023. As a result, the relative importance of LCFS credit values in determining which type of DG to produce decreased from 2021 to 2023 as well.

Figure 4.3: Per Bushel Value of LCFS Credits



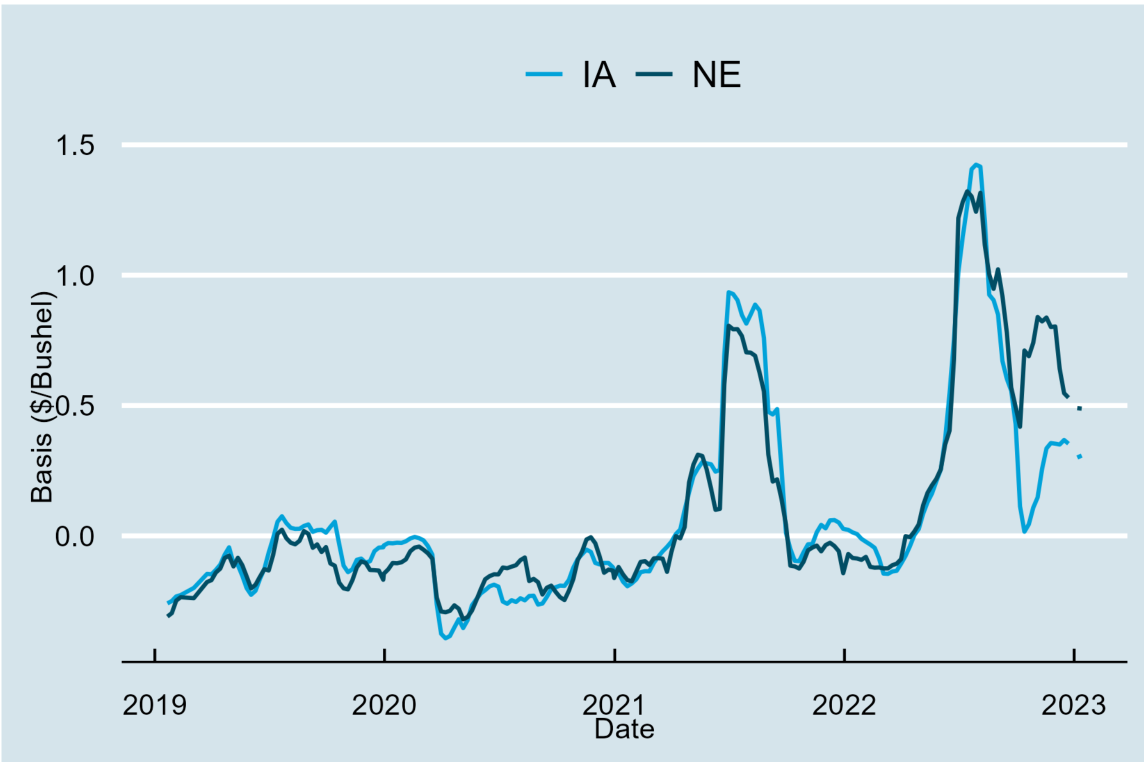
Note: Dry represents distillers grains with 10% moisture. Modified represents distillers grains with 55 to 60% moisture. Wet represents distillers grains with 65 to 70% moisture. Dollar value per bushel is determined by equation (4.1) with parameters from Table 4.1. Source: (CARB, 2023b).

4.2.3 Corn Price Data

Geograin, Inc. provides daily corn basis data for thousands of locations across the United States. The meta data provided by Geograin also includes information on facility type, so locations can be easily identified as ethanol plants. Geograin's database has over 100 ethanol plants with data on many plants predating the passage of RFS in 2005 (Geograin, Inc., 2023). Because credit price data is reported weekly, basis data are aggregated from daily to weekly data by taking an average of the daily prices in each week. Moreover, not every ethanol plant in Geograin's database could be identified with a facility name from CARB's database, and likewise, not every registered ethanol plant with CARB could be matched to an ethanol plant in Geograin's database. Only those ethanol plants which could be matched between both data sets are retained. There are 23 individual ethanol plants in Nebraska and Iowa matched to the Geograin, Inc. database, accounting for roughly 33$ of the ethanol plants in those two states.

Figure 4.4 displays the average basis for these ethanol plants aggregated at the state-level. As can be noted from comparing Figure 4.4 to Figure 4.2, both the basis data and the credit price data display considerable trends. Therefore, the basis data and the per bushel value of LCFS will be transformed using first-order differences. Finally, scatter plots of plant-level basis data points over time reveals that some plants will post the same basis for several weeks and possibly even several months at a time and then have a single large movement in basis. Such phenomena could be due to reporting conditions or very little spot market activity from ethanol plants. In either case, these observations bring considerable noise to the data, and therefore, observations in which basis does not changed for 4 weeks straight are dropped. The difference in average basis between Iowa and Nebraska remains relatively constant from 2019 to the middle of 2022, but in late 2022, the basis diverges considerably. This divergence is caused by severe drought across the Cornbelt that affected Nebraska more than Iowa.

Figure 4.4: Average Basis Data by State



Note: Basis is the difference between the current cash price for corn at ethanol plants and the price on the nearest futures contract on the Chicago Board of Trade. Average is arithmetic mean of all ethanol plants reporting a price during current week. Ethanol plants must have a current certified pathway from CARB to appear in data set. "IA" indicates Iowa, and "NE" indicates Nebraska. Source: (Geograin, Inc., 2023).

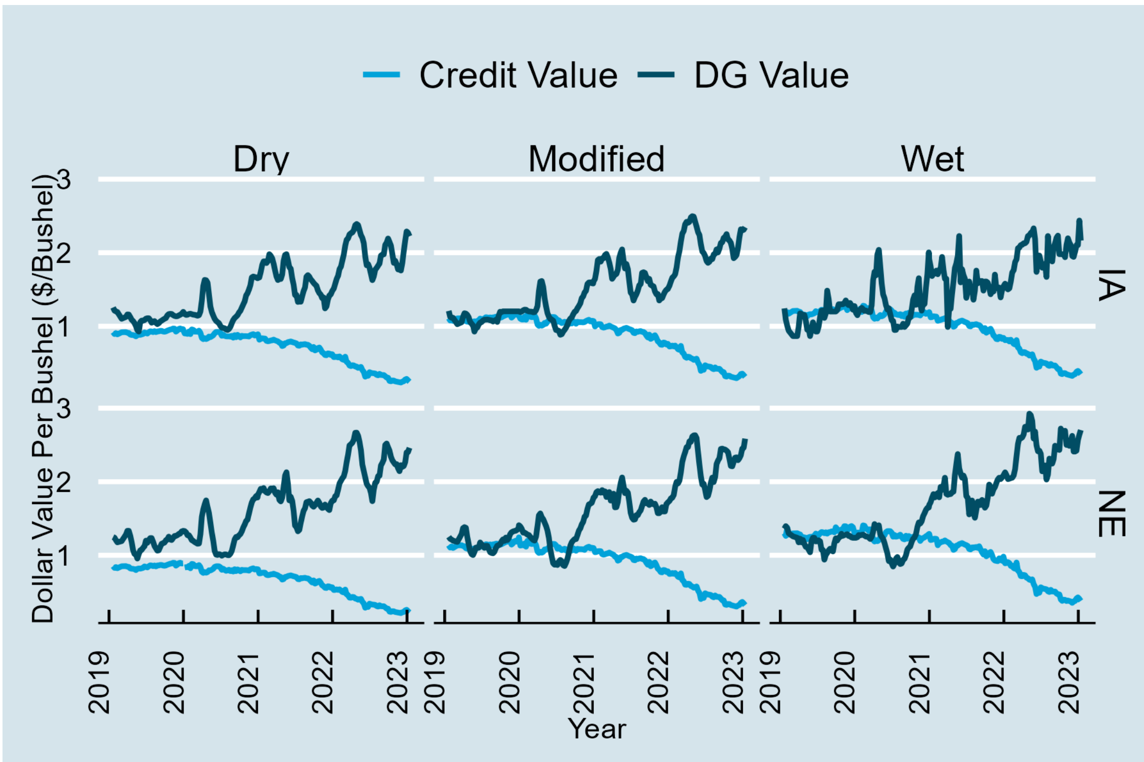
4.2.4 Distillers Grains and Other Output Price Data

The final pieces of data are the output prices from AMS. AMS publishes weekly reports on bioenergy statistics including DG prices, ethanol prices, and corn oil prices at the state-level (AMS, 2023a; AMS, 2023b). These reports are compiled from state-level surveys of spot transactions for corn oil, ethanol, and DG. Until July 2022, AMS only reported the low and high price for each series. As a result, the simple midpoint is used as the daily price for each series until AMS began to publish survey average prices in July 2022. I take an average of the daily prices in each week to produce weekly price series. These weekly price series match the observational frequency from the LCFS credit price data and the weekly basis data.

Just like LCFS credits, the value of each type of DG is converted into per bushel values using the fixed-proportions parameters in Table 4.1 and equation (4.2). Figure 4.5 shows the per bushel value of DG production by type and state. The figure also includes the value of LCFS credits for each type of DG. It is clear from the figure that when the value of LCFS credit prices fell in 2021 the per bushel value of each type of DG increased significantly. Figure 4.6 shows the total value of each type of DG. The total value for each type of DG appears to be much more stable when adding the per bushel value of LCFS credits to the per bushel value of each type of DG. However, it is clear from Figure 4.5 that each price series has a long-run trend. As such, the value of LCFS credits and the value of DG will need to each be separated transformed using first-differences to produce a stationary times series and remove the long-run price trends before running regressions.

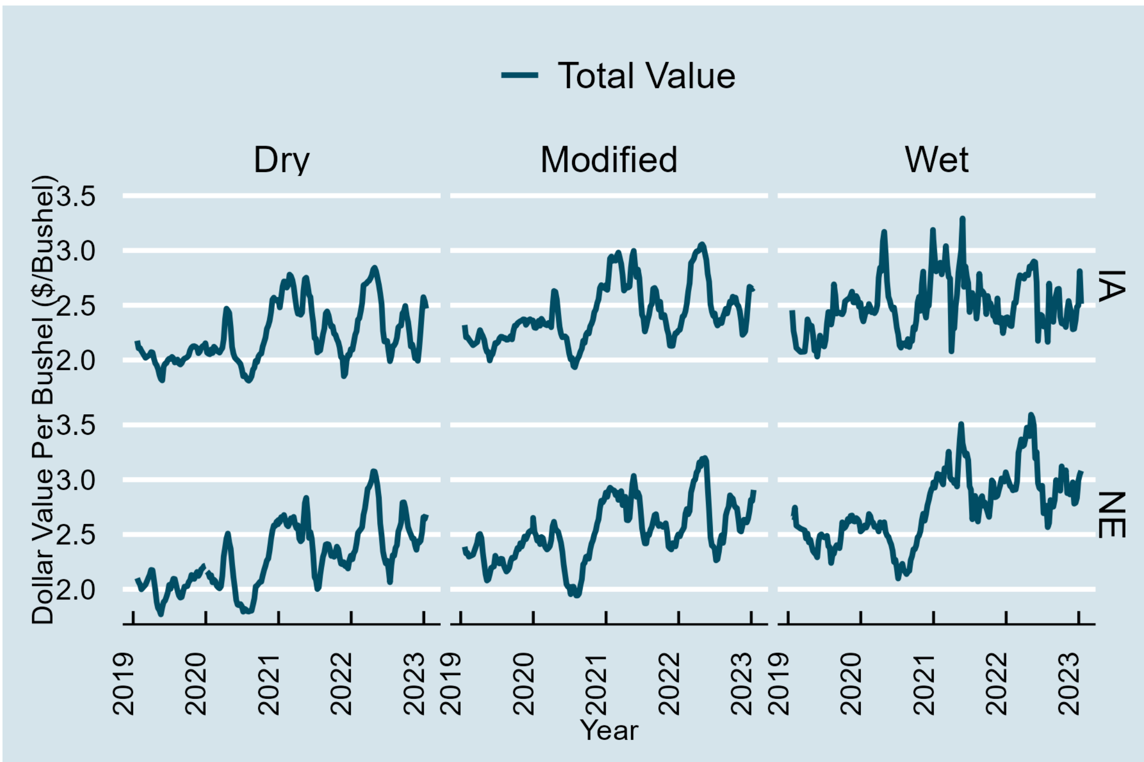
The other set of important prices are the other outputs besides DG including ethanol prices and corn oil prices. Figures 4.7 and 4.8 show ethanol and corn oil prices by state. These prices are tightly integrated together. This result comes from the fact that ethanol and corn oil are easily transported by rail for consumption all over the country. As such, the prices follow national trends. The price of ethanol dipped significantly during the Covid lockdowns of 2020, but boomed in value during reopenning period in 2021. The prices of corn oil, on the other hand, increased during the Covid lockdowns, indicating that declining demand for ethanol caused a shrinkage in the supply of corn oil.

Figure 4.5: Per Bushel Value of Distillers Grains and LCFS Credits



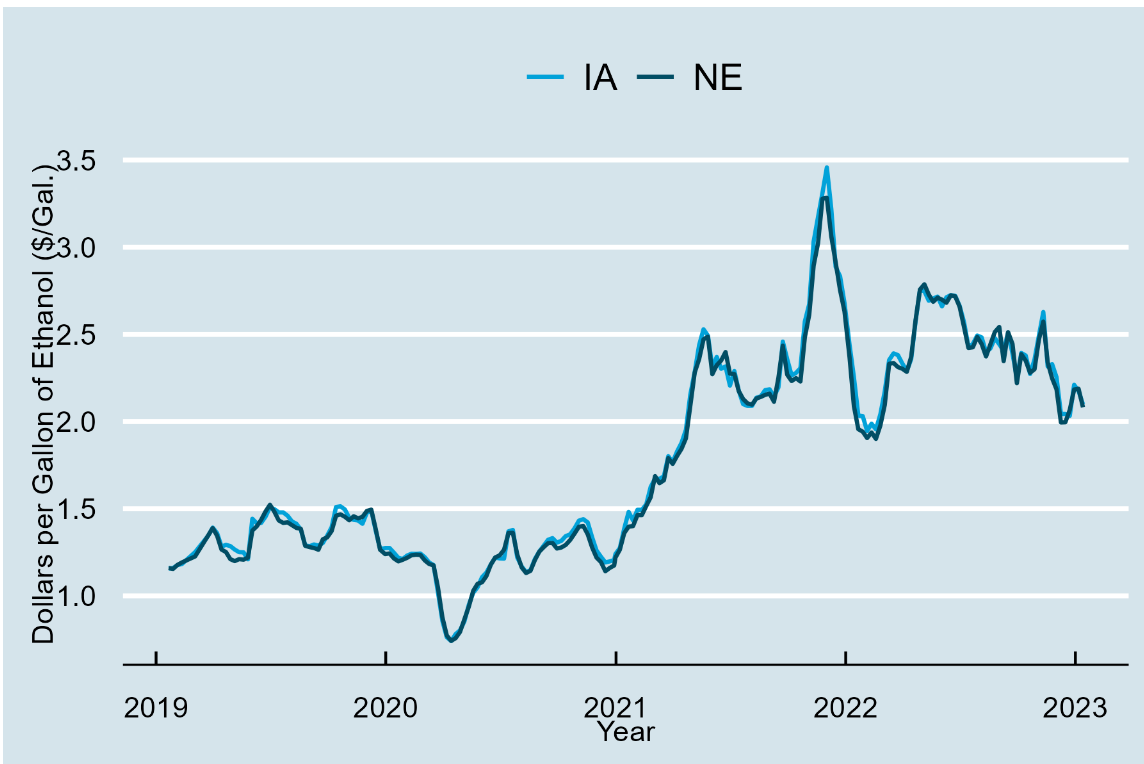
Note: Dry represents distillers grains with 10% moisture. Modified represents distillers grains with 55 to 60% moisture. Wet represents distillers grains with 65 to 70% moisture. Credit value per bushel is determined by equation (4.1) with parameters from Table 4.1. DG Value is the per bushel value of distillers determined by multiplying the price per ton by the fixed proportions for lbs. per bushel from Table 2.1. “IA" indicates Iowa, and “NE" indicates Nebraska. Source: (AMS, 2023b) and (CARB, 2023b).

Figure 4.6: Total per Bushel Value of Each Type of Distillers Grains



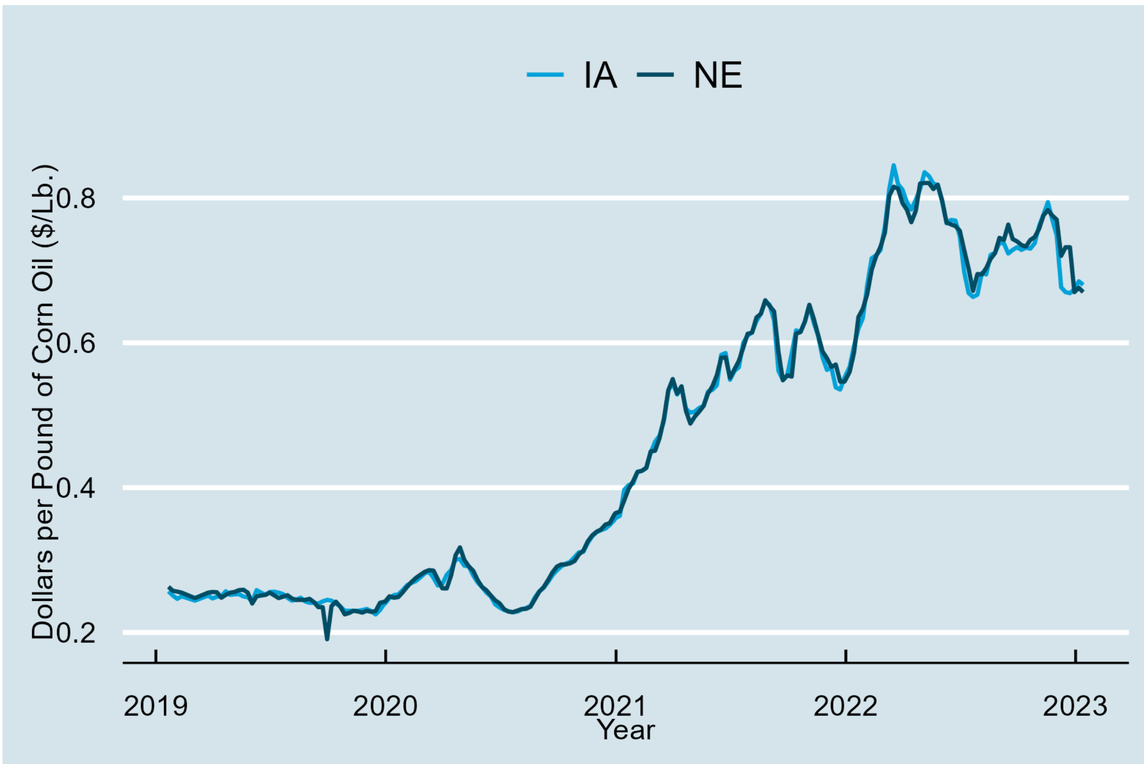
Note: Dry represents distillers grains with 10% moisture. Modified represents distillers grains with 55 to 60% moisture. Wet represents distillers grains with 65 to 70% moisture. Total value is the sum of the per bushel value of distillers grains production and LCFS credits for each type as defined by equation (4.2). "IA" indicates Iowa, and "NE" indicates Nebraska. (AMS, 2023b) and (CARB, 2023b).

Figure 4.7: Ethanol Prices by State



NOTE: Prices account for spot transactions of ethanol in dollars per gallon terms. Prices come from state-level surveys of ethanol plants reported by AMS. “IA" indicates Iowa, and “NE" indicates Nebraska. Source: (AMS, 2023a).

Figure 4.8: Corn Oil Prices by State



NOTE: Prices account for spot transactions of corn oil in dollars per pound terms. Prices come from state-level surveys of ethanol plants reported by AMS. “IA" indicates Iowa, and “NE" indicates Nebraska. Source: (AMS, 2023b).

4.3 Empirical Framework

This section explains the empirical framework I use for estimating the pass through of LCFS credit value changes to the corn prices offered by ethanol plants in Nebraska and Iowa and DG prices in those states as well. As shown by Table 4.2, many ethanol plants have the possibility of choosing to co-produce ethanol with one of several types of DG. The type of DG chosen by the ethanol plant will determine the per bushel value of the LCFS credits for that ethanol plant and the means by which I estimate the pass-through of LCFS credit value changes to corn prices. Therefore, I first explain the empirical framework for determining the type of DG, and then I explain the empirical framework estimating the pass through to LCFS corn prices and DG price spreads.

4.3.1 Predicting Distillers Grains Production Types

For each ethanol plant, I observe their basis values on a week-to-week frequency. In each weekly observation for each ethanol plant, there is only one observed value of basis, but for ethanol plants with multiple approved pathways, there are multiple options their per bushel value of LCFS credits could have depending on which type of DG they are co-producing for ethanol to be sold in California. However, only one LCFS credit value can be used for each ethanol plant for each week when estimating the pass-through to corn prices. Which exact type is being co-produced will determine the per bushel value of LCFS credits for each ethanol plant in each week, and choosing the wrong type could bias the regression results and create noisier estimates with too wide of confidence intervals. Therefore, for ethanol plants with multiple pathways for selling into California that differ by DG type, I need to predict which type of DG is being co-produced for ethanol sold in California.

The process for predicting the type of DG produced for each ethanol plant in each week is drawn directly from equations (3.33) and (3.34) in Chapter 3. The dominant DG choice for an ethanol plant depends on the total per bushel value across the types of DG for each ethanol plant. That is, the dominant DG choice depends on which type of DG has the greatest combined per bushel value from the production of DG itself and the value of LCFS credits as expressed in equations (4.2) and (4.3). The prediction for the each plant's DG choice in any given week is then determined by

$$creditvalue_{i,t,y,k} * \mu + P_{s,t,k} * \delta_k > creditvalue_{i,t,y,\sim k} * \mu + P_{s,t,\sim k} * \delta_{\sim k}. \tag{4.4}$$

where $\sim k$ represents any DG type but k.

For example, if ethanol plant, i, can choose to co-produce ethanol with dry or wet DG, then its choice set is $(0, 1)$ where 0 represents dry DG and 1 represents wet DG as in Chapter 3. Given the plant's carbon intensities, Iowa DG prices, credit prices, and fixed parameters, I predict plant i chooses to co-produce dry DG instead of wet if $DGvalue_{i,t,y,0} > DGvalue_{i,t,y,1}$ in week t and year y. Using equations (4.3) and (4.4), this inequality is fully expressed as

$$creditvalue_{i,t,y,0} * \mu + P_{s,t,0} * \delta_0 > creditvalue_{i,t,y,1} * \mu + P_{s,t,1} * \delta_1. \tag{4.5}$$

This prediction process is then conducted for each ethanol plant in each week based on that particular ethanol plant's choice set of DG. The only difference across ethanol plants is their particular carbon intensity ratings and the DG prices in each state. Because dry DG can be sold exported while wet and modified must be sold to more regional livestock feeders, I allow for a non-strict inequality for the dry DG version of equation 4.4. I then use the results from this process to choose which pathway each ethanol plant is using in each week for those ethanol plants that have multiple pathways.

Moreover, as I argue in the next section, changes in LCFS credit prices are largely exogenous from the ethanol market and individual ethanol plants have little to no ability to impact credit prices. Changes in the per bushel value of LCFS credits across DG types from week-to-week are determined by changes in LCFS credit prices. The only way ethanol plants can impact their per bushel LCFS credit values is by changing their DG choice. Therefore, any bias introduced by using the largest total per bushel value for each ethanol plant comes from incorrectly assigning the wrong DG type to a plant, not from changes in the value of LCFS credits from credit price changes. For example, any bias introduced by this process will come from assigning wet DG production to plant i in week t when that plant was actually producing dry DG production.

The two primary avenues for incorrectly assigning DG choices are incorrect fixed parameter values or the ability of ethanol plants to impact DG prices, particularly wet and modified types. As can be seen from inequality (4.4), the only fixed parameter that impacts the credit value term is the fixed conversion ratio from corn to ethanol. The fixed conversion ratios from corn to DG do not impact the per bushel value of LCFS credits; they only impact the predicted choice on DG production. Therefore, to test for bias from the incorrect DG choice, I use multiple values of the DG parameters. Altering the ethanol fixed parameter, while keeping the other factors fixed, primary acts to scale the pass through term with only a marginal impact on the optimal choice of DG.[1] As a result, misjudging this parameter could lead to under- or overestimating the size of the pass-through. Therefore, I alter the ethanol production fixed parameter to check for robustness on the size of the pass-through.

As I argue in Chapter 2, the highly competitive nature of feed grains markets and the fact that many

[1] This can be seen from Figure 4.5. After credit prices began to fall in 2021, the per bushel value of LCFS credits is far below the per bushel value of DG production for all types of DG. However, there could be some impact on DG choices before credit prices fell in 2021.

ethanol plants price DG based on corn futures indicate that ethanol plants likely have a small degree of pricing power in the DG market. Nonetheless, if individual ethanol plants can impact DG prices, this only affects the second term, the DG price term, on either side of inequality (4.5). If ethanol plants impact prices by increasing output similar to a Cournot competition manner, then the per bushel value of DG production $P_k * \delta_k$ needs a discount term that accounts from the negative impact on price from increased production. This effect could primarily impact wet and modified DG production, as they cannot be exported. However, again, this effect could only bias the pass through estimate through incorrectly assigning the DG type because $P_k * \delta_k$ does not directly enter into the calculation of the per bushel value of credits, as is shown in equation (4.1). Therefore, altering the DG choices through changing the fixed DG parameters should serve as a proxy for the incorrectly assigning DG choices because of ethanol plants' ability to impact DG prices.

4.3.2 Estimating the Pass-Through to Corn Prices

I use a cumulative dynamic multiplier model to estimate the pass-through of per bushel LCFS credit values changes to corn prices at ethanol plants in Iowa and Nebraska. The cumulative dynamic multiplier model uses a series of lagged, differenced regressors to estimate the total pass-through up to the final lag term. This model is often used when measuring the pass-through of changes in one price series into another (Lade and Bushnell, 2019; Knittel et al., 2017). This model allows the pass-through of credit price changes to corn prices to be non-instantaneous and take several weeks to fully express itself.

As can be seen from Figures 4.2 and 4.4 of credit prices and basis, both time series exhibit significant trends. To avoid spurious regression results, the basis series and credit value series are both transformed with first-order differences to produce stationary time-series. The credit value series is then transformed using second week-to-week difference to produce the regressors for the cumulative multiplier model. This second difference does not change the specification of the model. Rather, it allows for each lagged term to estimate the total pass-through up to that point in time, and inference on the total effect is then possible using the standard errors from each coefficient of the OLS regression (Stock and Watson, 2015). Each successive double-differenced lag term shows the cumulative pass-through up to that point. The last lag for the differenced regressors is then the simple first-difference instead of the second difference, and it estimates to total pass through after adding all the lagged coefficients together.

The first-order difference in basis is calculated in a straightforward manner as $\Delta basis_{i,t,y} = basis_{i,t,y} - basis_{i,t-1,y}$, where Δ signifies the first-difference operator and $t-1$ represents one week lag. Likewise, the firs-order difference in the per bushel value of credits is calculated as $\Delta bushvalue_{i,t,y,k} = bushvalue_{i,t,y,k} - bushvalue_{i,t-1,y,k}$. A major difference is that the DG type k in week t is not necessarily the same DG type as k in week $t-1$. That is, k can vary from week-to-week according to the results from inequality (2.6). The double difference in per bushel values is then $\Delta^2 bushvalue_{i,t,y,k} = \Delta bushvalue_{i,t,y,k} - \Delta bushvalue_{i,t-1,y,k}$, where again k can vary for each t.[2]

The regression model for estimating the pass-through of per bushel credit value changes to basis is then

$$\Delta basis_{i,t} = \sum_{d=0}^{p-1} \beta_d \Delta^2 bushvalue_{i,t-d,y,k} + \beta_p \Delta bushvalue_{i,t-p,y,k} + \psi_{m,t} + \epsilon_{i,t} \tag{4.6}$$

$\psi_{m,y}$ are year-month fixed effects, and $\epsilon_{i,t}$ is the idiosyncratic error term.

The inclusion of DG prices, ethanol prices, corn oil prices, and natural gas prices could all impact basis and possibly correlate with changes in LCFS credit values. However, after differencing both basis and credit value changes, the inclusion of year-month fixed effects accounts for almost all of the additional value from including other prices. As a result, these other price series fail to have any major impact on the regression results once year-month fixed effects are added. The downside to year-month fixed effects is that they can form too fine of a filter, especially for pass-through estimates that take more than a month to occur.

When I test for the persistence of the pass-through estimate, I also include lagged differences of ethanol and corn prices. Including additional lagged values that have little to no affect on the point estimates for the pass-through helps to soak up the noise caused by additional lags beyond 2 weeks that have low explanatory power. I also considered a series of sine and cosine waves as fixed effects while including other output prices as controls. However, there appear to be no qualitative difference between using oscillating terms or year-month fixed effects as controls, so I choose the year-month fixed effects as my preferred model because it is a more conservative approach.

The primary coefficients of interest are the β's. β_0 is the contemporaneous effect from a change in the value of LCFS credits on the change in basis during the same week. β_{t-p} is the long-run cumulative dynamic multiplier which captures the total pass-through for p weeks after the initial change in the value of LCFS credits occur. If $\beta_p = 1$, then the full per bushel value change in LCFS credits is passed through to the basis farmer's receive from selling their corn. However, if $\beta_p = 0$, then there is no detectable pass-through. Any value of $\beta_p \in (0, 1)$ is defined as incomplete pass-through, and $1 - \beta_p$ is the amount of changes in the value of LCFS credits that ethanol plants capture at the feedstock-level.

In my main specification, I use two lags on LCFS credit value changes. The second lag measures the cumulative pass-through from a credit value change two weeks after it occurs. Increasing the number of lags has a small impact on the cumulative pass-through estimate after two weeks while reducing the precision of the estimate.[3] That is, after increasing the number of lags, the point estimate for cumulative effect after two

[2] $\Delta^2 bushvalue_{i,t,y,k}$ is fully defined as $bushvalue_{i,t,y,k} - 2bushvalue_{i,t-1,y,k} + bushvalue_{i,t-2,y,k}$.

[3] The year-month fixed effects could be driving the lack of precision from models with more lags. With year-month fixed

weeks remains relatively steady, but the confidence intervals widen. Using one lag instead of two reduces the pass-through estimate by $0.10 while the statistical significance of the estimate remains the same. Using the first-order difference specification of (4.6) reveals that no additional lags beyond the second are statistically significant from zero. Thus, including additional lags does not appear to provide any additional information about the size of the pass-through that can be precisely estimate. Therefore, I follow the approach in Nakamura and Zerom (2010) and stop adding new lags once the additional lags begin to be statistically indistinguishable from zero.

Week-to-week variation in the per bushel value of LCFS credit can come from two sources: the DG choice or LCFS credit price changes. The previous section discussed any possible bias from the DG choice. The other key identifying assumption for my empirical framework is that LCFS credit price changes are independent from actions taken by individual ethanol plants.

Trading for LCFS credits encompasses the entire liquid transportation pool, and total weekly volumes regularly surpass 100,000 credits (CARB, 2023b). The demanders of credits are often large multi-national corporations, and it is unlikely that ethanol plants would be able to exert market power over them. Furthermore, the suppliers of credits not only include biofuel producers but also utilities selling power for electric vehicles, biogas capture facilities, and renewable diesel made from animal tallow or soybean oil. Because total ethanol demand is largely constrained by the blend wall, ethanol is an infra-marginal source of credits with almost no ability to increase supply. Other fuels like biomass-based diesel are most likely driving price changes caused by marginal changes in the supply of credits (Mazzone et al., 2022).

Evidence from the credit market itself supports the argument that changes in credit prices are exogenous to individual ethanol plants. Figure 2.2 shows the number of credits generated for each alternative fuel type. Over the data period of 2019 to the end of 2022, the number of credits generated by ethanol has remained steady except during periods of lockdowns from Covid-19. However, during this same period the number of credits generated by biomass-based diesel, electricity, and biogas dramatically increased. These factors, not changes in the ethanol market, have led to the steep decline in credit prices since 2021. Only an extraordinary change in the supply of ethanol would substantially affect credit prices. However, as Figure 2.1 shows, the blend rate of ethanol has remained largely constant at 10% of total gasoline demand, even during the Covid-19 lockdowns. Biomass-based diesel, on the other hand, has risen from 25% to almost 50% of the total diesel consumption. As a result, the ethanol market is not a main driver of price changes in the credit market, and the actions of individual ethanol plants should have little to no effect on the prices of LCFS credits.

effects, the cumulative effect must be estimated across multiple fixed-effect groups, especially as the total number of terms exceeds 3, and thus, creating noisier estimates as the number of lags increases.

Finally, I use Driscoll-Kraay standard errors to account for both cross-sectional and serial-correlation in the error term.[4] The Driscoll-Kraay estimator is robust to serial-correlation and heteroskedasticity in a similar manner to Newey-West standard errors (Driscoll and Kraay, 1998). However, the Driscoll-Kraay estimator also allows for the standard errors to be correlated cross-sectionally. Temporal clustering like year-month clustering are often used in the pass-through literature (Lade and Bushnell, 2019). However, the disadvantage to year-month clustering is the discrete breaks between months. If there is serial correlation present, clustering by year-month only accounts for observations within the same year-month and may miss correlations between observations in separate year-months. The Driscoll-Kraay estimator accounts for serial correlation by allowing for correlation based on the number of lags like Newey-West. However, the Newey-West estimator is not robust to cross-sectional correlation for panel regressions. The Driscoll-Kraay estimator accounts for this correlation.

4.3.3 Pass-through to Distillers Grains Price Spreads

If the LCFS influences the DG choices of ethanol plants, then changes in the value of LCFS credits could pass through to DG prices. Moreover, the LCFS gives an advantage to wet and modified DG over dry because of the lower emissions from their production. As a result, changes in the differential value of LCFS credits for ethanol co-produced with two different types of DG could pass through to the price spread between those two types of DG. Increases in LCFS credit prices could in turn increase the relative value of DG types with lower carbon intensities. If these changes in relative credit values are being passed through to DG prices, then the spread between DG prices should grow as credit values increase and decrease as credit values decline.

The price spreads and LCFS credits values are estimated in per bushel terms. As can be seen from Table 4.1, more corn is needed to produce a ton of dry DG than wet or modified. More ethanol is co-produced with a ton dry DG than wet or modified as well. I account for these differences by first converting the prices of DG to their per bushel terms using the conversion factors in Table 4.1. Since I only observe DG prices at the state-level in each week, this produces a time series for the per bushel value of DG production in each state. The spread's are then expressed as

[4] An autoregressive distributed lag model or GLS model could also account for serial correlation with more efficient estimators than the Driscoll-Kraay standard errors (Stock and Watson, 2015). However, these regression specifications require the primary regressors to be strictly exogeneous, i.e. both past and future values of the credit value changes need to be exogenous from the error term in time t. If current and past values of credit changes can partially predict future credit changes, then this condition will not hold for credit values in $t + p$ with $p > 0$.

$$\text{Dry-Wet DG Spread: } DGspread_{s,t,0-1} = P_{s,t,0} * \delta_0 - P_{s,t,0} * \delta_0 \tag{4.7}$$

$$\text{Dry-Modified DG Spread: } DGspread_{s,t,0-2} = P_{s,t,0} * \delta_0 - P_{s,t,2} * \delta_2 \tag{4.8}$$

$$\text{Modified-Wet DG Spread: } DGspread_{s,t,2-1} = P_{s,t,2} * \delta_2 - P_{s,t,1} * \delta_1 \tag{4.9}$$

where 0 indicates dry, 1 indicates wet, and 2 indicates modified.

Because I observe DG prices at the state-level, I use the state averages for each type of DG from Table 2.1 to estimate the state-level credit values using equations (2.2) and (2.3). I then take the state-level averages in the per bushel value of LCFS credits and produce the spread in the per bushel value of LCFS credits for each type of DG. The spreads are defined as

$$\text{Dry-Wet Credit Spread: } Creditspread_{s,t,0-1} = bushvalue_{s,t,y,0} - bushvalue_{s,t,y,1} \tag{4.10}$$

$$\text{Dry-Modified Credit Spread: } Creditspread_{s,t,0-2} = bushvalue_{s,t,y,0} - bushvalue_{s,t,y,2} \tag{4.11}$$

$$\text{Modified-Wet Credit Spread: } Creditspread_{s,t,2-1} = bushvalue_{s,t,y,2} - bushvalue_{s,t,y,1}. \tag{4.12}$$

Since wet has a lower carbon intensity than modified which has a lower carbon intensity than dry, each of the spreads is negative in value. Therefore, the signs of the pass-through estimate will be flipped, i.e. a negative coefficient indicates that monotonic increases in the credit spreads are passing through to the spread in DG prices. Or stated differently, a negative sign indicates that as the advantage of LCFS credits for wet over dry production decreases in magnitude-from falling credit prices-the spread between wet and dry DG prices also increases in magnitude, but because dry DG is generally more expensive than wet while wet has a greater value in terms of LCFS credits, the pass-through coefficient is negative.

Also, each LCFS credit spread is entirely determined by the state averages in carbon intensities because all other parameters and the credit prices are the same. Therefore, the weekly values for each LCFS credit spread follows the same general trend as LCFS credit prices in Figure 4.2 . As a result, I perform a first-order difference on the LCFS credit spreads to produce a stationary transformation and eliminate the possibility of spurious regression results. After performing the difference in credit value spreads, weekly differences in the series are entirely determined by weekly changes in LCFS credit prices. The new series are then

Dry-Wet Credit Difference: $\Delta Creditspread_{s,t,0-1} = Creditspread_{s,t,y,0} - Creditspread_{s,t,y,1}$ (4.13)

Dry-Modified Credit Difference: $\Delta Creditspread_{s,t,0-2} = Creditspread_{s,t,y,0} - Creditspread_{s,t,y,1}$ (4.14)

Modified-Wet Credit Difference: $\Delta Creditspread_{s,t,2-1} = Creditspread_{s,t,y,2} - Creditspread_{s,t,y,1}$. (4.15)

After performing these transformations, I again employ a cumulative dynamic multiplier model to estimate the pass through of changes in the per bushel value of LCFS credits to the spread of DG prices. To account for heterogeneity in the pass through for each price spread, I run a separate regression for each DG pair. My cumulative dynamic multiplier model is then

$$DGspread_{s,t,k-\sim k} = \sum_{d=0}^{p-1} \beta_d \Delta^2 Creditspread_{s,t-d,k-\sim k} + \beta_p \Delta Creditspread_{s,t-p,k-\sim k} + \alpha_m + \pi_y + \psi_{m,t} + \epsilon \tag{4.16}$$

where $k- \sim k$ represents the DG pair for each spread.

The β's is this model have the same interpretation as in equation (2.8) where the β_p represents the cumulative pass through p weeks after the initial change in LCFS credit values occurred. As stated above, each of the credit spreads are negative, so a negative coefficient indicates that absolute increases in the credit value spreads are leading the DG price spreads to expand. Since I am using state-level price series, I now only have two cross-sectional units. The asymptotic performance of the Driscoll-Kraay estimator depends primarily on the size of T because as N approaches one the Driscoll-Kraay estimator behaves like the Newey-West. Nonetheless, I also used year-month clustering as a robustness check, but the differences in statistical significance between either standard error estimator are negligible. In each specification, I used eight lags as later lags showed higher individual significance than some earlier lags. Therefore, the pass-through to DG prices could take over a month to be fully realized.

4.4 Results

This section reviews the results of the regression specifications presented in Section 4. I first discuss the results from predicting the dominant DG strategies using LCFS data and AMS DG prices. I then show the results from estimating the pass-through of LCFS credit values changes to local corn prices. Finally, I show my results from estimating the pass-through of LCFS credit value changes to the price spreads between different pairs of DG.

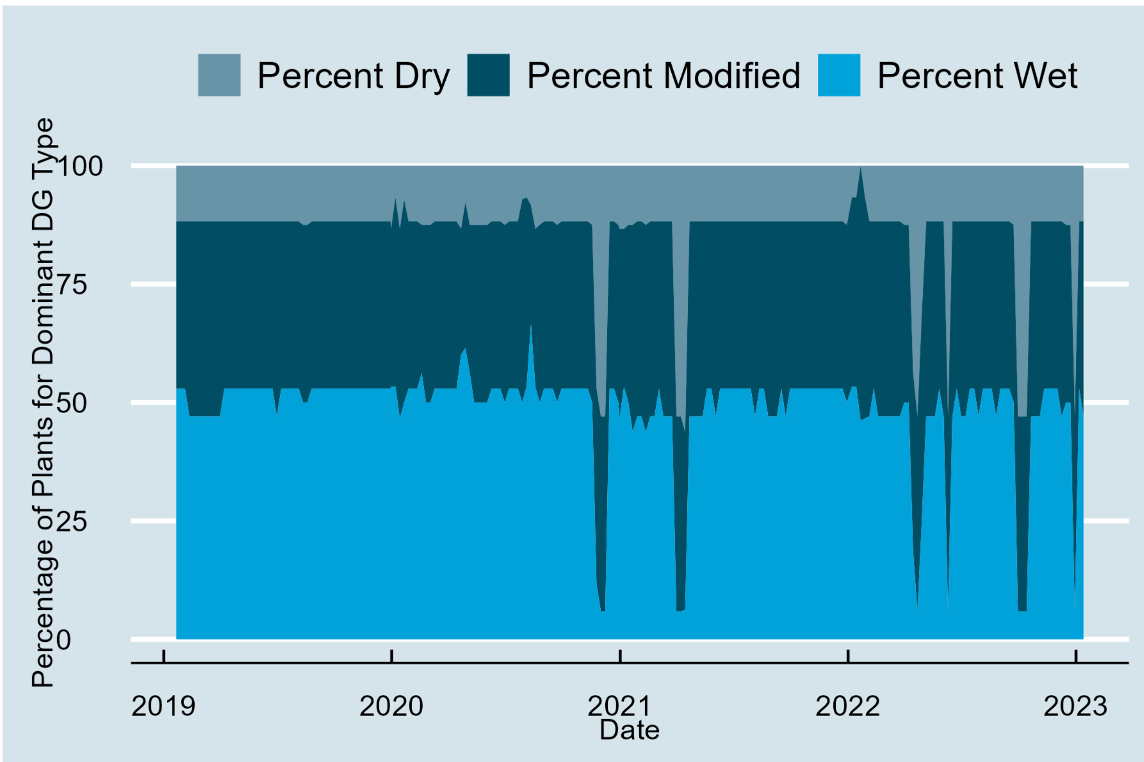
4.4.1 Distillers Grains Strategy Predictions

For the first set of results, Figure 4.9 and Figure 4.10 display the predicted best DG choice for ethanol plants in Iowa and Nebraska in each week of the year. Because Nebraska only has one plant that can switch between DG types, I show the results for both states separately. Also, the results are presented in percentage terms because some ethanol plants do not appear in the sample every week when they do not report a basis value to Geograin. Showing the results in percentage terms helps to remove up noise in the DG choices caused by non-reporting of basis values.

As can be seen for both figures, wet and modified DG appear to be the best choices during most of the study period for ethanol plants in Iowa and Nebraska. In Iowa, the only ethanol plants that consistently choose dry DG are the two plants that only have pathways for dry DG. Fourteen of the seventeen plants in Iowa have the option to choose dry or modified/wet DG. The results shows that for at least the initial parameter values provided in Table 4.1 the DG type with the lowest carbon intensity appears to be the optimal strategy for almost all ethanol plants.

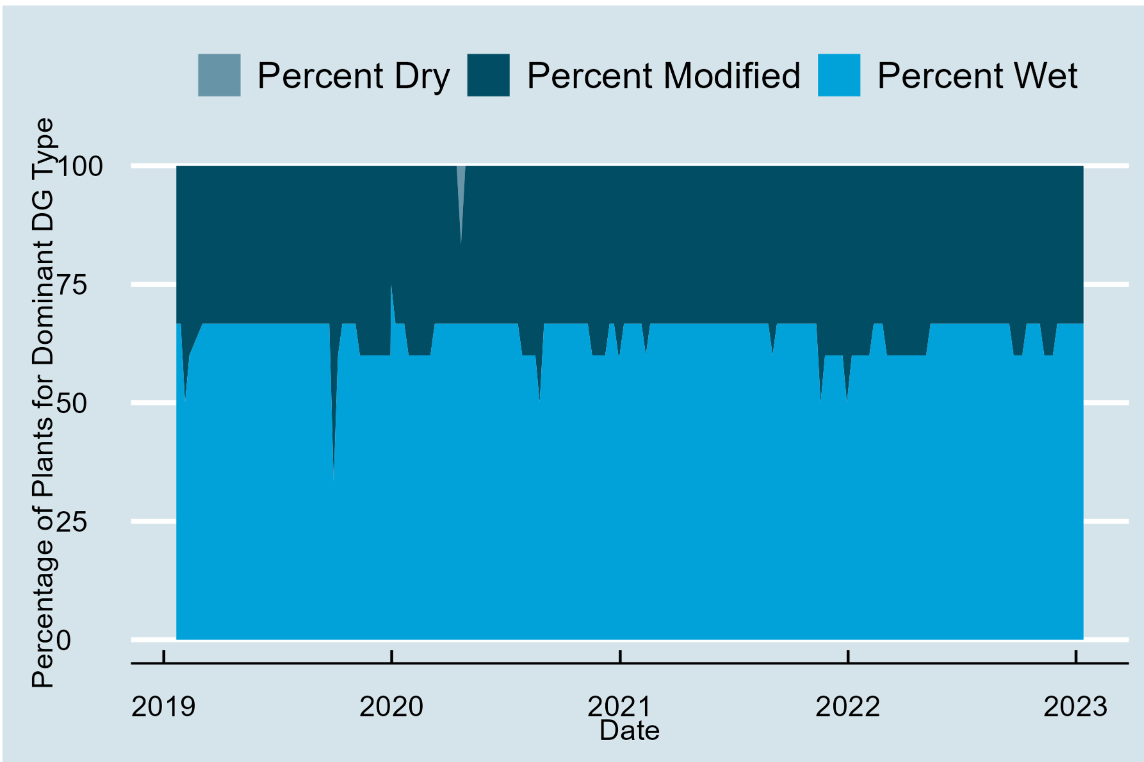
Next, I then use these results to determine the per bushel value of LCFS credits for each ethanol plant for my estimation of the pass-through of LCFS credit value changes to the basis offered at ethanol plants.

Figure 4.9: Iowa Distillers Grains Predicted Choices



Note: Percent dry is the percentage of ethanol plants for which dry distillers grains production is the predicted dominant distillers grains strategy. Percent modified is the percentage of ethanol plants for which modified distillers grains production is the predicted dominant distillers grains strategy. Percent wet is the percentage of ethanol plants for which wet distillers grains production is the predicted dominant distillers grains strategy.

Figure 4.10: Nebraska Distillers Grains Predicted Choices



Note: Percent dry is the percentage of ethanol plants for which dry distillers grains production is the predicted dominant distillers grains strategy. Percent modified is the percentage of ethanol plants for which modified distillers grains production is the predicted dominant distillers grains strategy. Percent wet is the percentage of ethanol plants for which wet distillers grains production is the predicted dominant distillers grains strategy.

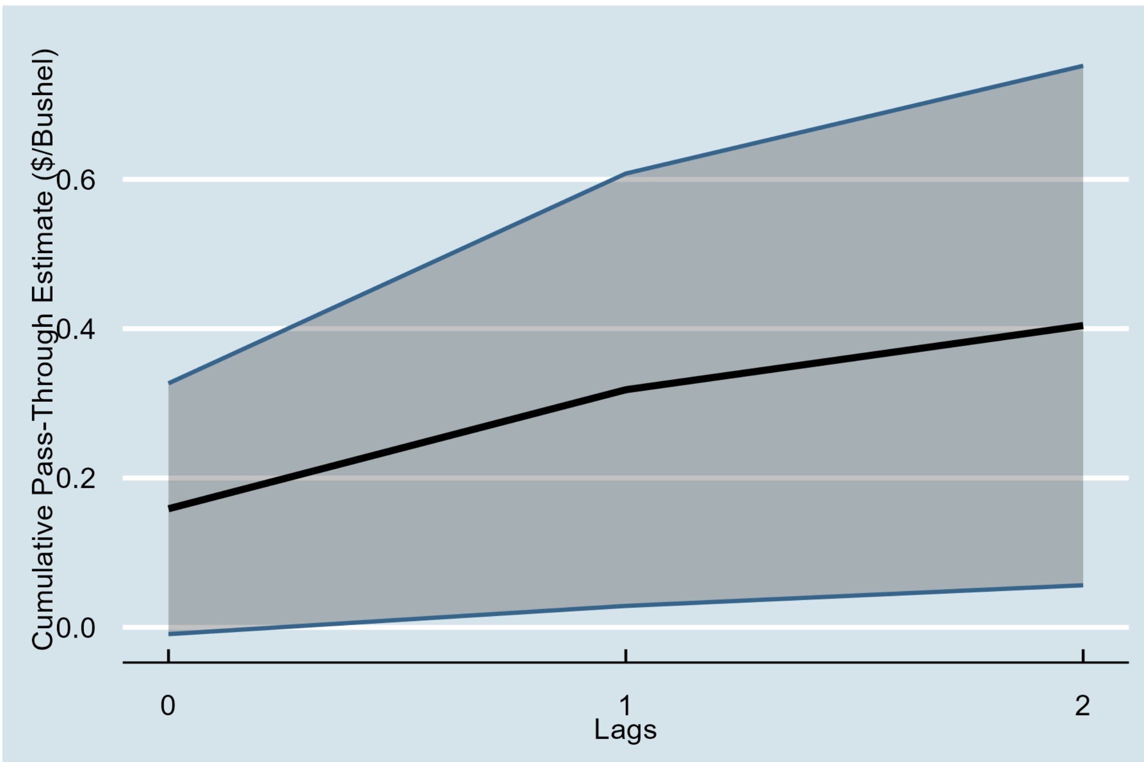
4.4.2 Pass-Through of LCFS Credit Value Changes to the Basis at Corn Ethanol Plants

Figure 4.11 displays the pass-through estimate from changes in the per bushel value of LCFS credits to corn prices, and it can be interpreted similarly to an impulse response function. The solid black line displays the cumulative pass-through up to the listed lag while the solid blue lines and gray shading show the 95% confidence intervals. I find that for every \$1.00 in the increase of the per bushel value of LCFS credits \$0.16 passes through during the same week as the credit value change. This initial pass through is significant at the 0.06% level. In the next week, an additional \$0.16 is passed through for a cumulative pass-through of \$0.32, and two weeks after the initial change in credit values, a total of \$0.40 from a \$1.00 increase in the per bushel value of LCFS credits is passed-through to corn prices. Moreover, these effects are significant at less than the 0.05% level for the first and second lag terms. 1 is not included in the 95% confidence interval, and thereby, I cannot reasonably conclude that changes in LCFS credit values fully pass-through to corn prices. Rather I find that farmers capture almost half of the changes in the value of LCFS credits that initial accrue to ethanol plants through higher corn prices. In Appendix A, Table A.1 includes the point estimates and standard errors for Figure 4.11.

Several reasons could explain the lack of full pass-through. First, as I show in Chapter 3, heterogeneity in the subsidy amount at the plant-level can lead to ethanol plants with a comparatively low CI failing to fully pass-through their LCFS subsidies. The \$0.40 pass-through estimate includes \$0.66 in its 95% confidence interval. My pass-through estimates are consistent with an ethanol plant competing against another corn buyer that does not sell into California from Chapter 3. While ethanol plants drawing from a wide spatial area do directly compete against each other, the nearest competitor for many ethanol plants is most likely a local cooperative or private grain buying firm. These competitors do not participate in the LCFS. Therefore, participating in the LCFS should provide ethanol plants with a competitive advantage over these competitors. Second, Jung et al. (2022) find that ethanol plants already have a significant mark down on corn prices, and they find a corn supply elasticity of 10 for ethanol plants. These factors point to ethanol plants only needing to pass-through a portion of the LCFS credit prices to meet their extra demand for corn to send more ethanol to California.

The pass-through estimate appears to persist for at least 8 weeks after the change occurs. Figure 4.12 shows the cumulative pass-through for up to 8 weeks after the credit change occurs. Moreover, I also included 8 week lags for changes in ethanol prices and corn oil prices to try to suppress the noise on the lags past week 2. The inclusion of these lags only changes the pass-through estimate by a few cents, but it helps remove some of the noise in the estimates for the additional lags. The pass-through estimate after two weeks is \$0.35

Figure 4.11: Cumulative Pass-Through Estimate



Note: The solid black line is the cumulative pass-through estimate. The solid blue lines and gray shading represent the 95% confidence intervals. Standard errors are calculated using Driscoll-Kraay specification with three lags. The cumulative pass-through is the amount of a $1.00 increase in the per bushel value of LCFS credits that passes through to the basis at ethanol plants selling into California. O lag represents the initial pass-through during the week of the credit value change while the other lags show the cumulative effect after the indicated number of weeks has past.

which is very close to the cumulative pass-through estimate in Figure 4.11 of \$0.40, and the cumulative effect bounces between a low of \$0.24 to a high of \$0.41. Therefore, the point estimate of the pass-through appears to persist for around 2 months. However, the confidence intervals widen considerably for the cumulative pass-through terms past the second lag. This result is driven by the fact that the additional effect from lags past 2 are all close to 0, and their inclusion is only creating additional noise in the regression. The inclusion of weekly changes in ethanol and corn prices helps to reduce the noise from including the additional lags past week 2, but the confidence intervals are still quite wide. The point estimates and standard errors are also included in appendix Table 1.

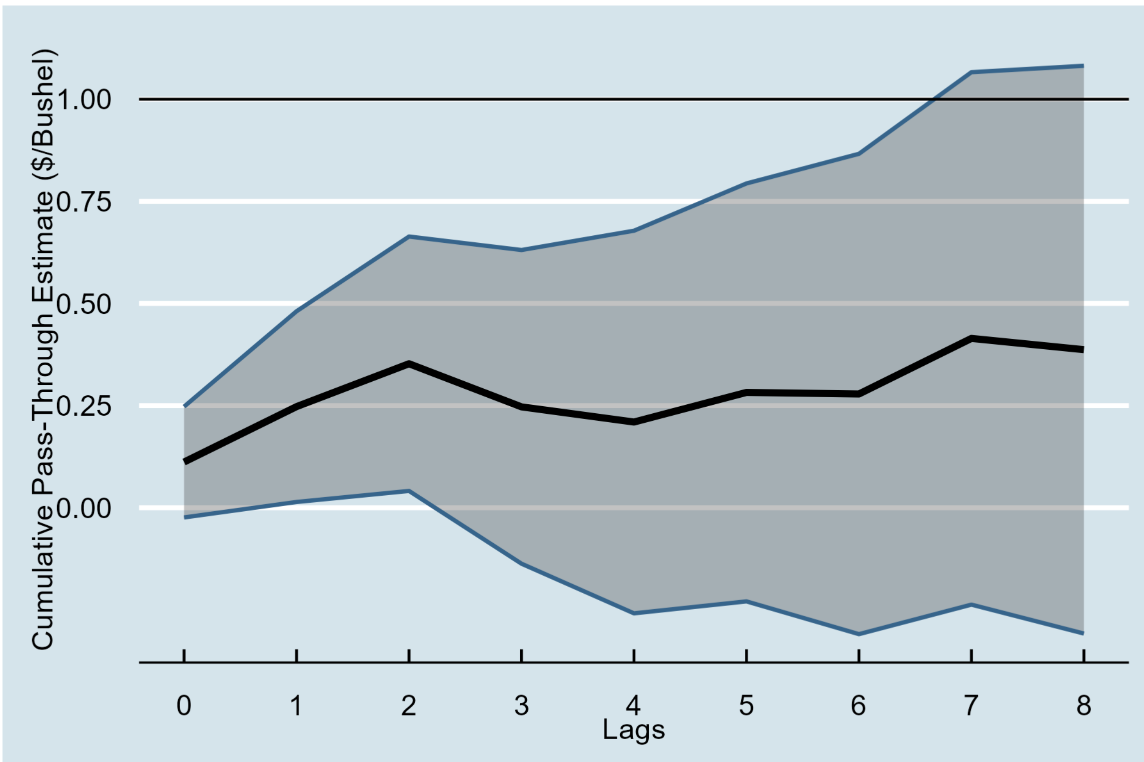
Nonetheless, my results appear to be primarily driven by the state of Iowa. Figure 4.13 displays the pass-through estimate for the states of Iowa and Nebraska separately. The total pass-through estimate for Nebraska remains steady at roughly \$0.25, but the confidence intervals are quite large and include zero. The flat pass-through after the initial week of the credit value change could indicate that additional lags are only providing noise to the estimates for the cumulative pass-through estimator, but decreasing the lag length does not improve the confidence intervals.[5] Therefore, I do not find that the pass-through in the state of Nebraska is statistically distinct from zero.

In Iowa, the pass-through estimates mirror the result from the full sample in Figure 4.11. Again, I find that the total pass-through is \$0.42 two weeks after the initial credit value change, but \$1.00 is not within the 95% confidence interval. While Nebraska is the second largest state for ethanol production, the state of Iowa has roughly double the number of ethanol plants and production capacity. Therefore, ethanol plants in Iowa selling into California may experience a much greater level of competition compared to ethanol plants in Nebraska. This greater level of competition could be driving them to pass-through more of the changes in LCFS credit values to corn farmers supplying their plants.

I also test for heterogeneity in the pass-through estimate by ethanol plant organization structure. Co-operatives are organized to maximize returns to returns to farmers, not to maximize profits. Therefore, they may pass-through more of the LCFS than for-profit plants. My sample of ethanol plants includes 3 cooperative plants and 20 non-cooperatives. I run separate regressions by plant organization structure, and Figure 4.14 displays these results. I find that cooperatives pass-through \$0.61 compared to \$0.38 for non-cooperatives. I use 90% confidence intervals for both subsets because the p-values for the cooperative subset are near 0.06 due to the smaller sample size. Nonetheless, 1 is clearly within the confidence interval for the cumulative pass-through after 2 weeks while the upper bound for non-cooperatives is \$0.70. I, therefore, find evidence that cooperatives pass-through the entirety of their LCFS credit values while non-cooperatives

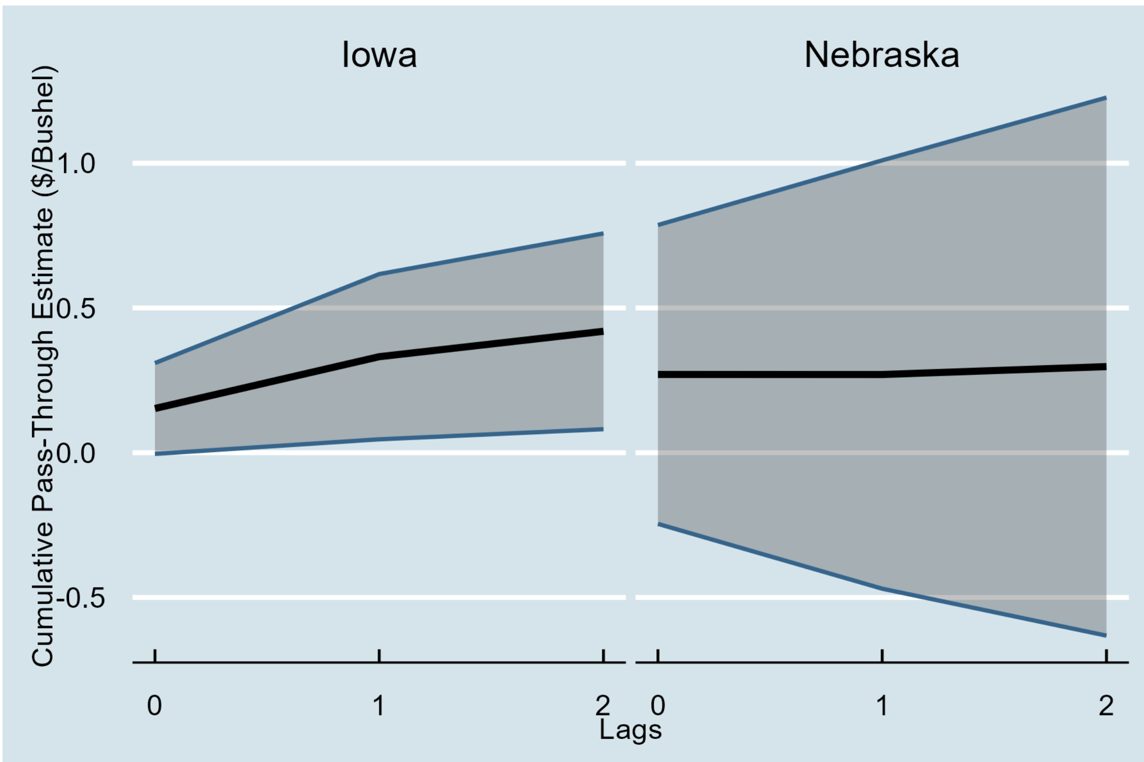
[5]The asymptotic efficiency of the Driscoll-Kraay estimator is primarily determined by having a large sample period relative to the number of cross-sectional units, so having only 6 ethanol plants in Nebraska with over 200 temporal observations per ethanol plant should behave well asymptotically.

Figure 4.12: Cumulative Pass-Through Estimate



Note: The solid black line is the cumulative pass-through estimate. The solid blue lines and gray shading represent the 95% confidence intervals. Standard errors are calculated using Driscoll-Kraay specification with three lags. The cumulative pass-through is the amount of a $1.00 increase in the per bushel value of LCFS credits that passes through to the basis at ethanol plants selling into California. O lag represents the initial pass-through during the week of the credit value change while the other lags show the cumulative effect after the indicated number of weeks has past.

Figure 4.13: Cumulative Pass-Through Estimate by State



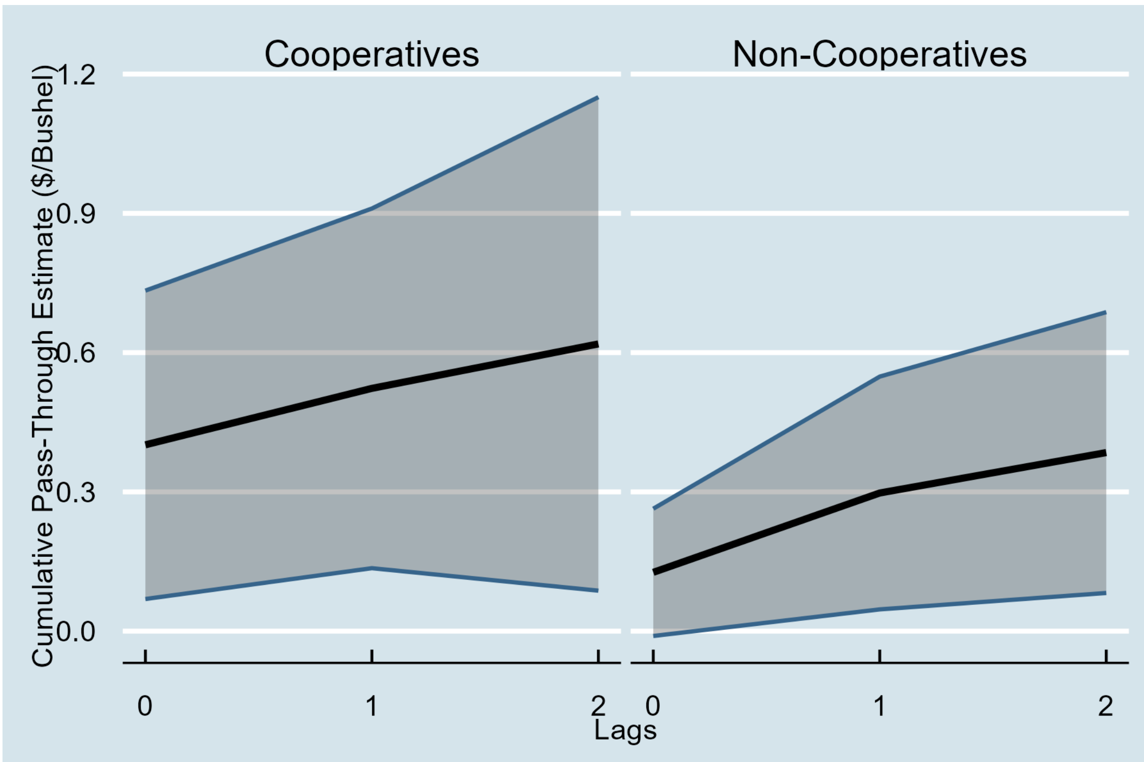
Note: The solid black line is the cumulative pass-through estimate. The solid blue lines and gray shading represent the 95% confidence intervals. Standard errors are calculated using Driscoll-Kraay specification with three lags. The cumulative pass-through is the amount of a $1.00 increase in the per bushel value of LCFS credits that passes through to the basis at ethanol plants selling into California. O lag represents the initial pass-through during the week of the credit value change while the other lags show the cumulative effect after the indicated number of weeks has past.

only pass-through a portion of their credit values.

Table 4.4 and Table 4.5 display the cumulative pass-through results for when I adjust the parameter values for the amount of dry and modified DG per bushel of corn and the amount of ethanol per bushel of corn respectively. Each specification is the same as in equation (4.6). The only difference are adjustments to the parameter values from those listed in Table 4.1. The estimation results appear to be robust to different parameter specifications. The cumulative pass through estimate after two weeks dips to as low as \$0.32 with dry DG yield of 18 lbs per bushel and modified yield set at the original value of 35 lbs per bushel. However, for all specifications the pass-through estimate remains statistically significant at the 0.05%, and every estimate is within the 95% confidence interval of the original estimate of \$0.40.[6] In Table 4.5, adjusting the per bushel yield of ethanol has almost no discernible effect on the pass-through estimate. Therefore, a cumulative pass through estimate of \$0.30 to \$0.40 after two weeks appears to be a relatively robust result.

[6]This result holds even despite the case of 18lbs for dry and 32 lbs for modified. In this scenario, there are almost no ethanol plants choosing to produce modified. Yet, the pass through estimate only decreases by \$0.06.

Figure 4.14: Cumulative Pass-Through Estimate by Ethanol Plant Organizational Type



Note: The solid black line is the cumulative pass-through estimate. The solid blue lines and gray shading represent the 95% confidence intervals. The cumulative pass-through is the amount of a $1.00 increase in the per bushel value of LCFS credits that passes through to the basis at ethanol plants selling into California. Standard errors are calculated using Driscoll-Kraay specification with three lags. O lag represents the initial pass-through during the week of the credit value change while the other lags show the cumulative effect after the indicated number of weeks has past. Cooperatives are ethanol plants that clearly state they recognized as cooperative entities by the IRS or use a cooperative to purchase their grain for them. Non-cooperatives are for-profit entities either privately or publicly owned.

Table 4.3: Robustness of Results to Changes in Dry and Modified Distillers Grains Yields

		Modified Yield		
		35	32	38
Dry Yield	**16.5**	.40**	0.33***	0.38**
	17.4	.32**	.35***	.37**
	18	.31**	.34**	.32**

Note: Original modified and dry distillers grains yields per bushel are indicated in bold text. Yields are in pounds per bushel of corn. Original values come from AMS, 2023b. Standard errors are calculated using Driscoll-Kraay specification with three lags.*,**,*** indicate p-values less than 0.10, 0.05, and 0.01, respectively.

Table 4.4: Robustness of Results to Changes in Dry and Modified Distillers Grains Yields

Ethanol Yield	Pass-through Estimate
2.85	0.40**
2.95	0.40**
2.75	0.42**

Note: Original ethanol yield is in bold text. Yields are in pounds per bushel of corn. Original yield value comes from AMS, 2023b. Standard errors are calculated using Driscoll-Kraay specification with three lags.*,**,*** indicate p-values less than 0.10, 0.05, and 0.01, respectively.

4.4.3 Pass Through to Distillers Grains Prices Spreads

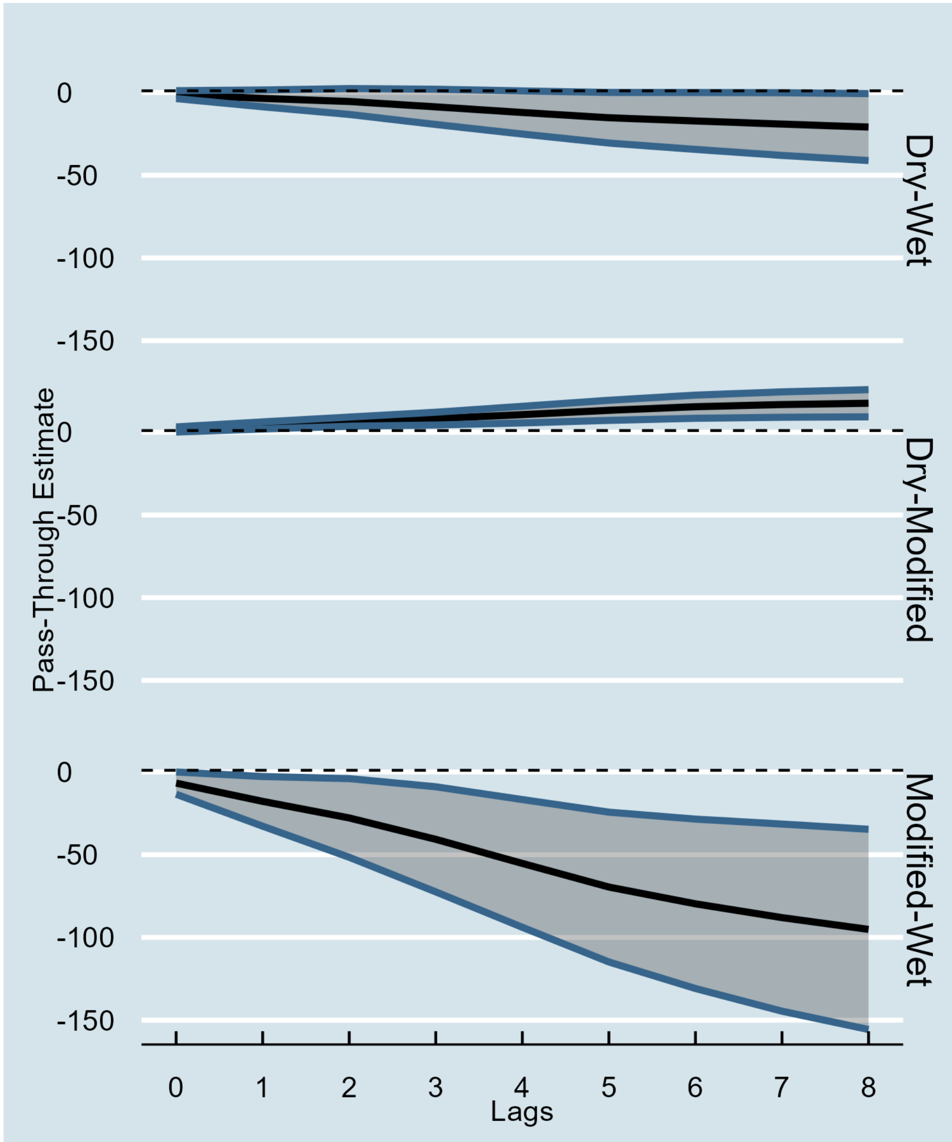
Figure 4.16 shows the pass through estimates from changes in the LCFS credit spread to the spread of the DG prices. In all cases except the dry-to-modified price spread, the cumulative pass through estimate is negative. The negative sign indicates that the price spread between DG types grows as the relative value of LCFS credits increases. However, for the dry-to-modified spread, the per bushel price of modified DG is often greater than the per bushel price of dry DG, particularly in Nebraska. As a result, Nebraska is driving a positive sign.

However, for each of the three price spreads, the cumulative pass through is very large, and the estimates are orders of magnitude greater than full pass through. The primary factor driving the exceeding large pass through estimate is the relatively small week-to-week changes in the spread for LCFS credit values. When credit prices are near \$100, co-producing wet DG instead of dry DG provides an extra \$0.20 per bushel of corn. An average weekly change in credit prices is close to \$5.00 in absolute terms, and as a result, weekly changes in the spread for LCFS credit values are often \$0.01 or less. On the other hand, weekly changes in the spread between DG prices are frequently surpass \$0.10. The difference in magnitudes for the weekly changes is thus producing a very noisy estimate and the explanatory power of the regression is almost entirely by the fixed effects. Moreover, the magnitudes for the pass-through estimates appear to be highly sensitive to changes in the per bushel yields from DG types. While it is possible that changes in the value of LCFS credits could be driving changes in the spread between DG prices, weekly changes in credit prices are far too noisy and small to be the identifying source of variation. Therefore, while the cumulative pass-through estimates are statistically significant, interpretations from and statistical conclusions of the estimates are highly uncertain and should be drawn with caution.

DG markets lack the formal structure of exchange traded markets that exist for corn. Thus, the price discovery process could be more noisy and take more time to occur. Figure 4.17 shows the per bushel value of DG and the value of LCFS credits using average carbon intensities from Table 2.1 after accounting for the costs of natural gas for dry and modified DG.[7] Figure 4.18 shows the total value of DG after removing natural gas costs. The total value of DG appears to have a relatively stable mean across types and states. That is, the total per bushel returns across DG types have a relatively stable long-term average. While summing total per bushel returns is not a formal econometric analysis, it does indicate that ethanol plants are passing through LCFS credit values to DG prices. Therefore, while the actual process of passing through LCFS credit value changes to DG prices is too noisy to produce reliable estimates, the overall trends in the DG markets show the effects of the LCFS on DG prices nonetheless.

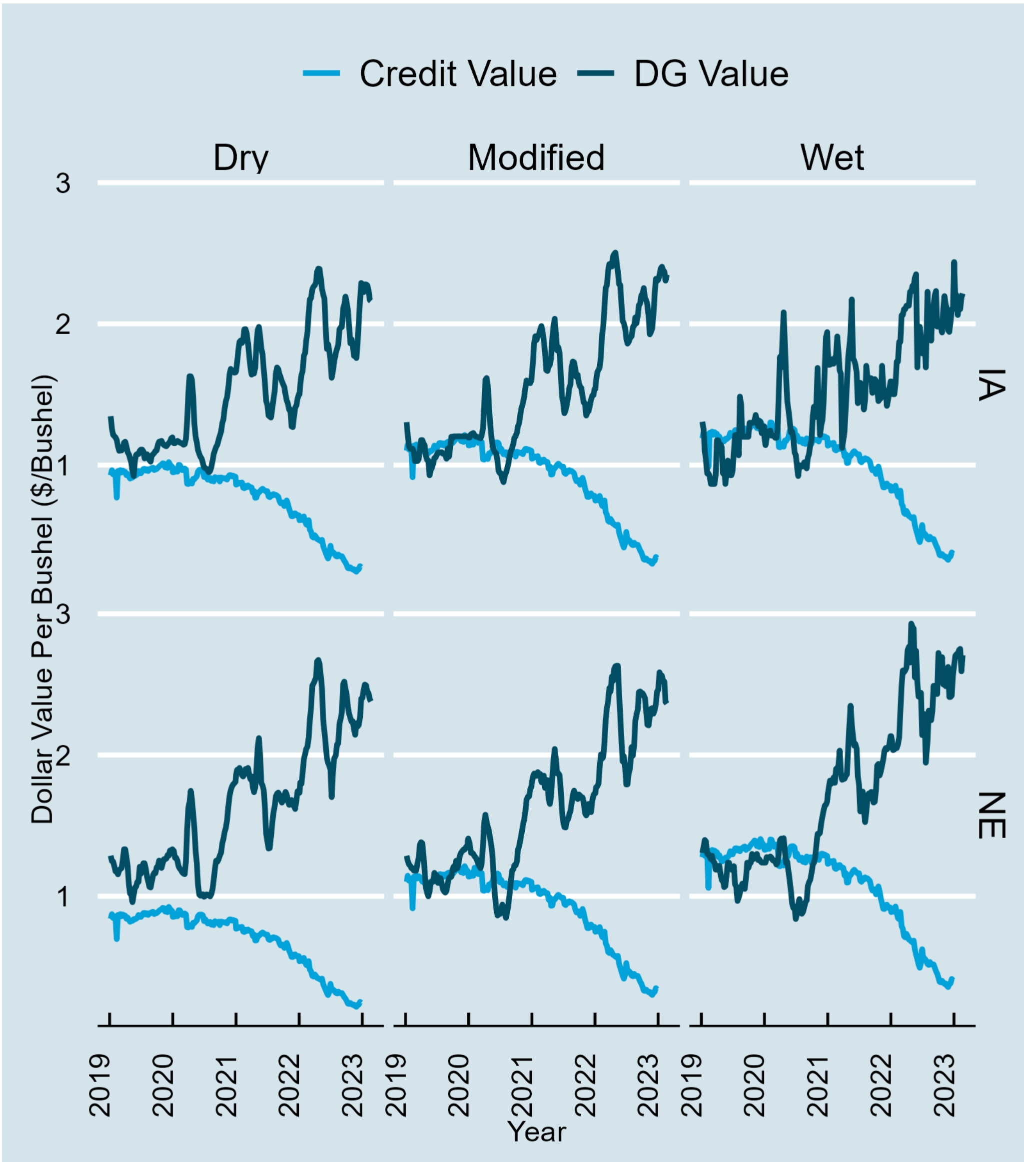
[7] Using the average difference in CI by DG type and the CI of natural gas at 53 kilograms of CO_2 per million btus, a back-of-the-envelope calculation can remove the costs of natural gas for dry and modified DG.

Figure 4.15: Cumulative Pass-Through of LCFS Credit Value Spreads to Distillers Grains Price Spreads



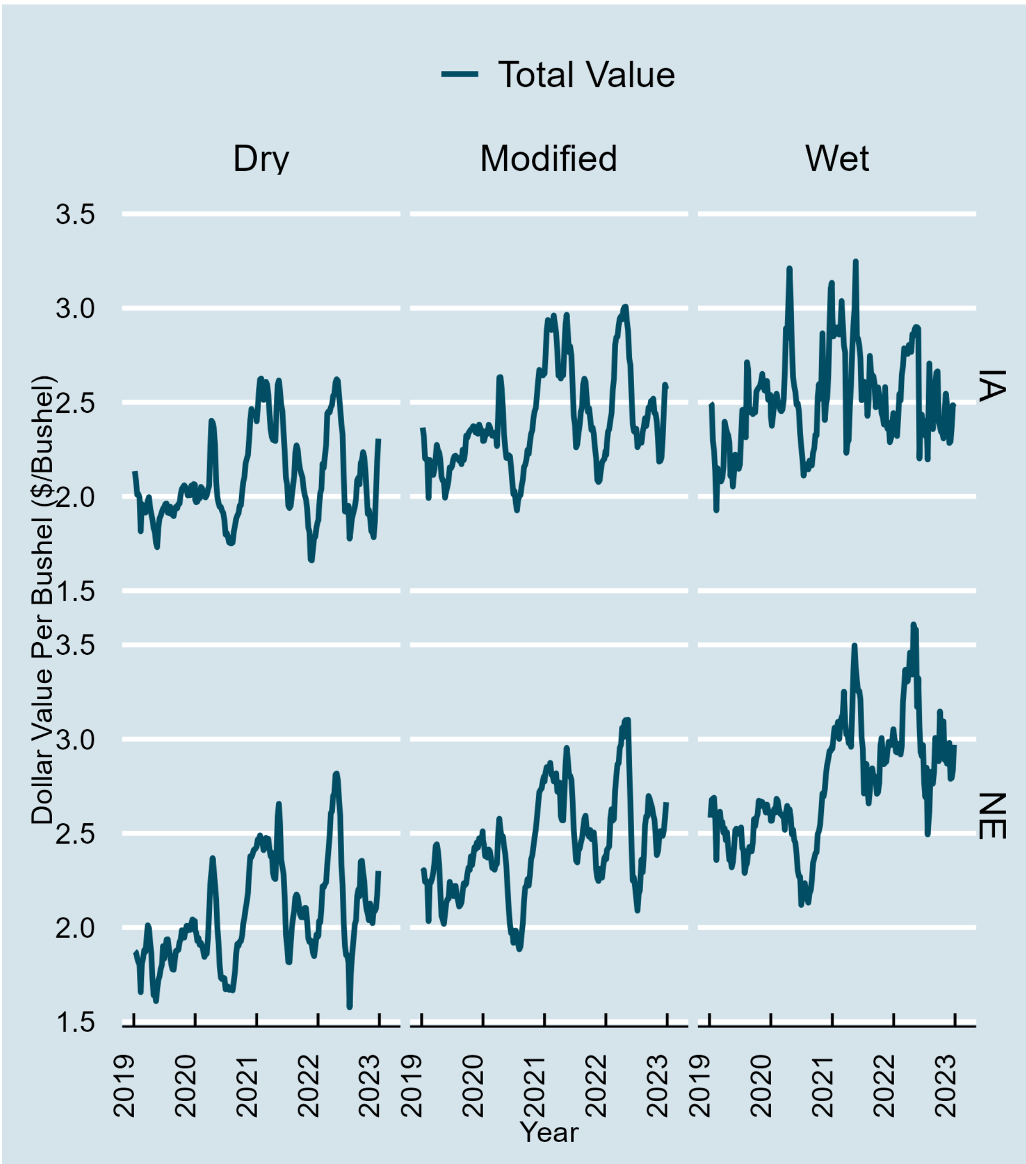
Note: Dry-Wet is the pass-through to the spread between dry and wet distillers grains. Dry-Modified is the pass-through to the spread between dry and modified distillers grains. Modified-Wet is the pass-through to the spread between modified and wet distillers grains. The solid black line is the cumulative pass-through estimate. The solid blue lines and gray shading represent the 95% confidence intervals. The cumulative pass-through is the amount of a $1.00 increase to the distillers grains price spreads. O lag represents the initial pass-through during the week of the credit value change while the other lags show the cumulative effect after the indicated number of weeks has past.

Figure 4.16: Per Bushel Value of Distillers Grains and LCFS Credits Net of Natural Gas Costs



Note: Dry represents distillers grains with 10% moisture. Modified represents distillers grains with 55 to 60% moisture. Wet represents distillers grains with 65 to 70% moisture. Credit value per bushel is determined by equation (2.3) with parameters from Table 2.1. DG Value is the per bushel value of distillers determined by multiplying the price per ton by the fixed proportions for lbs. per bushel from Table 2.1. “IA" indicates Iowa, and “NE" indicates Nebraska. Source: (AMS, 2023b) and (CARB, 2023b).

Figure 4.17: Total per Bushel Value of Each Type of Distillers Grains Net of Natural Gas Costs



Note: Dry represents distillers grains with 10% moisture. Modified represents distillers grains with 55 to 60% moisture. Wet represents distillers grains with 65 to 70% moisture. Total value is the sum of the per bushel value of distillers grain production and LCFS credits for each type as defined by equation (2.4). “IA" indicates Iowa, and “NE" indicates Nebraska. (AMS, 2023b) and (CARB, 2023b).

4.5 Discussion

Using exogenous changes in credit prices, I find that 40% of changes in the value of LCFS credits pass-through to corn farmers 2 weeks after the change occurs. Heterogeneity in carbon emissions, a highly elastic corn supply, and spatial market power could all be playing a role in ethanol plants capturing over half of the value of LCFS credit value changes. This result appears to persist for at least 2 months. However, cooperatives pass-through a higher proportion of LCFS credit value changes than non-cooperatives, and I cannot rule out cooperatives fully passing through credit value changes. Thus, the organization structure and the role of spatial market power may be playing a role in the pass-through of LCFS credit value changes. My pass-through estimates are, thereby, consistent with my results from Chapter 3 in which I find that the LCFS may be enhancing the spatial market power of ethanol plants who sell into California.

To derive these results, I predicted the type of DG each ethanol plant was producing in each week from 2019 till the beginning of 2023. I find that ethanol plants with the ability to sell multiple types of DG into California generally chose the type of the lowest overall emissions. Nonetheless, I also find that my results are robust to changes in the parameter values that determine the optimal DG choice. In particular, I find that placing a higher weight on DG types associated with higher emission only marginally decreases the long-run pass-through estimate from \$0.40 to \$0.32 while the statistical significance remains the same.

I also find more than full pass-through of LCFS credit value changes to the price spreads between DG types. However, my confidence intervals are very wide and the long-run pass-through estimates are orders of magnitude beyond 1. As such, these results should be approached with caution. Week-to-week changes in the spreads of LCFS credit values are quite small and average close to \$0.01. Thus, other differences between DG types will need to be difference out to more precisely estimate the pass-through of credit value changes to DG prices. Nonetheless, long-term trends in the total value of DG production appears to show full pass-through of LCFS credit values to DG prices.

A primary limitation for this result is the fact that I only use data from ethanol plants with registered LCFS pathways in Nebraska and Iowa. Nebraska and Iowa represent the two largest ethanol producing states, and nearly one-third of ethanol plants in these states are in my sample. Nonetheless, other states with several ethanol plants that also serve California such as Minnesota and South Dakota may see different results. Future approaches could take into account the relative costs of transporting ethanol to California. States in the Western Cornbelt with better rail access may have greater integration with California energy markets than states on Eastern Cornbelt like Illinois. Likewise, credit prices decreased by over 50% during the period of 2021-2022, indicating relatively large changes to benefits of supplying ethanol to California. In periods with less dramatic credit price changes, the pass-through could again be relatively smaller as plants do not need to change their corn procurements as much.

In the next chapter, I explore the science behind sequestering carbon on working agricultural lands. Through the Inflation Reduction Act, the United States government are supplying greater incentives for farmers to adopt "climate-smart" agricultural practices. Policymakers claim that these practices can reduce greenhouse gas emissions, provide environmental co-benefits, and boost rural economies. Nonetheless, the science on these practices is rarely presented with a focus for policymakers. The work in my next chapter will help to present to make the science of soil carbon sequestration in a condensed manner for policymakers and economic researchers.

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Chapter 5

Farming for Carbon: A Review of the Science and Policy of Soil Carbon Sequestration

5.1 Introduction

Past research on climate change and agriculture has emphasized how the changing climate will affect agriculture (Mendelsohn et al., 1994; Schlenker et al., 2006; Ortiz-Bobea, 2020). The current policy emphasis is in the opposite direction: how can agriculture mitigate climate change? In 2022, the United States Department of Agriculture (USDA) spent $3.1 billion for "pilot projects that create market opportunities for commodities produced using climate-smart practices." The US Inflation Reduction Act of 2022 includes $21.25 billion for climate change mitigation through conservation programs. In addition, multiple commercial firms operate carbon credit markets in which companies looking to offset their emissions purchase credits from farmers who adopt "climate smart" practices.

Climate-smart agricultural practices have three main channels through which they affect atmospheric greenhouse gas (GHG) concentrations: carbon sequestration in soils, reduced nitrous oxide emissions from nitrogen fertilizers, and reduced methane emissions from livestock. We focus this paper on the first channel for two reasons.

First, the sheer size of soil carbon stocks has attracted the attention of scientists and policy makers looking to reduce GHGs in the atmosphere. Global soils store 2,400 GT C to 2m depth whereas the atmosphere contains only 830 GT C Paustian et al. (2019).[1] In recent years fossil fuel emissions are 9.5 GT C per year. The vast quantity of soil carbon means a small-sounding 0.4% increase in soil carbon is needed to offset global fossil fuel emissions. This fact has given rise to the international initiatives like the United Nations "4 per Mille" program, which supports soil carbon research and government carbon sequestration schemes (Stanley et al., 2023).

Second, agricultural land has generated large historic emissions. Intensive agriculture disrupts the natural carbon cycle of plants. Removing native vegetation, draining marshes, and years of heavy tillage have depleted carbon stocks that had been stored in perennial vegetation and soils. An estimated 133 GT C have been lost because of intensive agriculture over the last 12,000 years of human civilization (Sanderman et al., 2017). By comparison, total fossil fuel emissions are estimated at 465 GT C (Friedlingstein et al., 2022), so agricultural land use change emissions are close to 30% of historic fossil fuel emissions. Also, some soils have lost almost two-thirds of their carbon content (Lal, 2004b). The heavy depletion of soils creates the potential for soils to act as a large sink to partially offset fossil fuel emissions. Optimistic estimates project that restoring soil carbon on a global scale could possibly sequester around one GT C per year—roughly 10% of current fossil fuel emissions—while also enhancing crop productivity (Lal, 2004a,b). Therefore, sequestering soil carbon could act as an adjustment on the margin to mitigate greenhouse-gas emissions.

Agricultural systems coexist alongside natural cycles, and these natural cycles are far more complex than extracting and burning fossil fuels. If someone extracts coal, oil, or gas out of the ground and burns it, then they warm the earth. If they leave it in the ground, then they don't. Agriculture is more complicated because it both absorbs and emits greenhouse gas. The symbiotic relationship between plants, soils, climate, and microbes creates a natural cycle that can over time change the carbon content of soils. Total photosynthesis from all plants is about 130 GTC per year, 13% of which is from cropland agriculture (Guanter et al., 2014). Yet, these cycles cannot be compared one-to-one with fossil fuel emissions. Net changes in atmospheric carbon cannot be inferred from the amount of carbon moving through the cycle.

This melding of science and policy creates a need for a deeper understanding of the science behind soil carbon sequestration for economists. This paper focuses primarily on these dynamics while relating them to economic theory and recent policy decisions. This is an active area of policy making and one in which scientific understanding is still developing. There is relatively little economic literature evaluating past policies, because most of the policies are new. The purpose of this paper is to synthesize the scientific literature and provide an economic framework for formulating and evaluating policy. We hope this paper

[1] We use metric tons (t) and gigatons (GT) of carbon (C) as standard units of measurement throughout this paper. One gigaton is one billion metric tons. One ton of carbon (C) equals 3.67 tons of carbon dioxide (CO_2), and carbon dioxide equivalent units (CO_2e) are converted using same factor.

helps to spur future research on this important topic.

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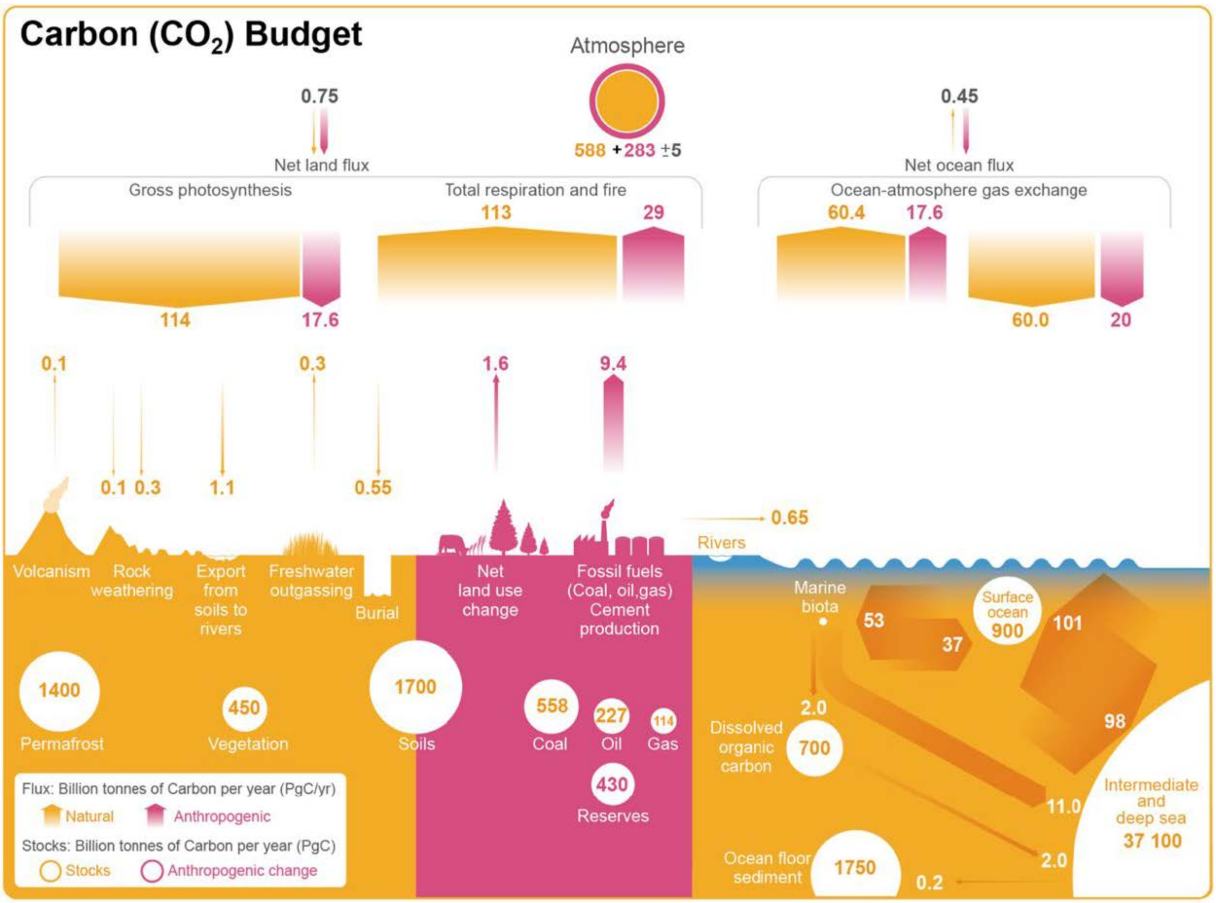
5.2 Background

5.2.1 Soil Carbon Cycle

During photosynthesis, plants capture atmospheric carbon dioxide. They convert some of this carbon into plant matter, they lose some to plant respiration, and they exude some into the soil through various compounds in their roots. After plants die, plant matter decomposes into soil organic matter, much of which is naturally respired by soil organisms that feed on it. However, some of the carbon may remain in the soils in the form of both organic and inorganic soil carbon. The amount of carbon that remains in the soil depends on soil type, climate, soil moisture, soil microbial composition, and plant matter density. With constant natural factors and a lack of human intervention, the carbon content of soils will naturally tend towards a steady state such that the carbon lost via soil microbial respiration is replenished through the life cycle of plants (Stewart et al., 2007)

Every year, plants absorb about 142 GT C from the atmosphere through photosynthesis. Crops contribute about 13% (18 GT) of photosynthesis (Guanter et al., 2014), which is approximately double the 9.4 GT emitted by burning fossil fuels (Figure 5.1). However, this does not mean photosynthesis from crops more than offsets fossil fuel emissions, or even that it helps mitigate climate change at all. For crop agriculture to contribute to climate change mitigation, its carbon absorption must exceed its emissions. Merely reducing emissions would not necessarily change the atmospheric concentration of CO_2. For example, one way to reduce emissions is to plant less productive crops. Less plant growth means less respiration but also less photosynthesis, so it need not make emissions less than absorption.

Intensive agriculture, both cropland and grazing, disrupts the natural carbon cycle of plants. Removing native vegetation, overgrazing, draining marshes, and years of heavy tillage have depleted carbon stocks stored in perennial vegetation and soils. When new cropland is cleared, the loss of biomass and disturbed soils create a one-time emission of carbon that is analogous to fossil fuel emissions. An estimated 133 GT have been lost because of intensive agriculture over the last 12,000 years of human civilization (Sanderman et al., 2017). Changing current cropping practices has the potential to mitigate some soil carbon loss and possibly even increase the carbon sequestered in soils. Cropping practices that increase net carbon inputs and reduce the disturbance of soil can increase soil carbon stocks and decrease erosion. Practices such as conservation tillage, cover crops, and carbon amendments are the most studied means of sequestering carbon



Source: Figure 5.12 in Canadell et al. (2021). Yellow arrows represent annual carbon fluxes (in GT C/yr) associated with the natural carbon cycle, estimated for the time prior to the industrial era, around 1750. Pink arrows represent anthropogenic fluxes averaged over the period 2010–2019. Circles with yellow numbers represent pre-industrial carbon stocks in GT C. Circles with pink numbers represent anthropogenic changes to these stocks (cumulative anthropogenic fluxes) since 1750.

Figure 5.1: Global Carbon Budget (2010–2019)

in farmland soils (see Section 5.3).

Although there exist promising means to increase the amount of carbon sequestered in soils, soils are not an infinite carbon sink. Rather, they can reach a saturation point in which the stock of carbon can no longer physically increase, and increasing carbon inputs will move soils to a steady-state rather than increasing linearly over time (Stewart et al., 2007). This steady-state is reached both under native vegetation and agriculture, and it may be lower (or in some cases higher) than the initial amount of carbon sequestered in soils prior to agricultural intensification.

Saturation is different from steady-state. Saturation represents the technical limit on the physical ability of the soil to sequester more carbon, conditional on soil type and climate. A steady-state occurs when repeated actions and natural conditions no longer sequester more carbon in the soil, but the carbon content of soils could still increase if new practices were undertaken. For example, after 30 years, practicing no-till may no longer sequester additional carbon in a farmer's soil, but if the farmer then added a winter crop or an additional summer crop, then the farmer's soil may sequester more carbon every year until a new steady-state is reached. Factors such as temperature, moisture levels, and soil types affect how quickly a new steady-state is reached and on high the natural saturation point is (Smith, 2012, 2016).

Because of saturation, soil carbon stocks do not increase linearly over time in response to sequestration practices. The rate of increase declines as soil carbon stocks reach their saturation point (Georgiou et al., 2022; Gulde et al., 2008). More degraded soils may see faster gains than less degraded soils (Georgiou et al., 2022). Saturation limits mean that successful soil carbon sequestration policies on croplands would provide more benefits in the years immediately after implementation than in later years (Smith, 2016). Furthermore, degraded soils could provide much greater carbon sequestration benefits than healthy soils (Stewart et al., 2007, 2008).

Soil carbon stocks can take decades to build, so any additional soil carbon needs to persist into the future to measurably impact climate change. The persistence and preservation of soil carbon is an ecosystem property dependent on environmental, biological, and physicochemical characteristics, not a property inherent to soil carbon itself (Schmidt et al., 2011; Dynarski et al., 2020). That is, soil carbon's stability and resistance to decay depends on a complex interaction of the wider ecological system and soil microbes, as the microbes move, transform, and decompose carbon throughout the soil profile (Schmidt et al., 2011; Dynarski et al., 2020; Lehmann et al., 2020). Moreover, soil carbon can become more or less stable as the ecological system itself evolves like with climate change (Schmidt et al., 2011; Heckman et al., 2023). A primary example is the carbon stored in permafrost soils for thousands of years that may be released as arctic regions warm (Schmidt et al., 2011; Plaza et al., 2019).

Many policymakers are concerned with the "permanence" of soil carbon stored by human actions induced by public policy. However, permanence is better understood as referring to human actions rather than a property of soil carbon because the stability of soil carbon is subject to change (Dynarski et al., 2020). For example, permanence could describe a farmer applying a certain quantity of manure to an acre of cropland in perpetuity rather than the persistence of any additional soil carbon sequestered as a result.

Additional sequestered soil carbon may persist even if a farmer temporarily stops the practice that induced the sequestration (Dynarski et al., 2020). A prime example is no-till. Policymakers often assume that a single-tillage event will undo all or most of the soil carbon stored during the assumption of no-till. However, studies indicate that the majority of sequestered soil carbon persists after occasional light tillage, i.e. less than 15cm every 5 to 10 years (Blanco-Canqui and Wortmann, 2020; Conant et al., 2007). This finding is the inverse of the slow build of soil carbon stocks: just as sequestration practices build stocks slowly, small deviations from those practices depletes stocks slowly. Nonetheless, large and frequent deviations in kind such as switching to annual moldboard plowing could deplete gains much quicker (Conant et al., 2007).

5.2.2 Measurement

Much of the research on soil carbon uses simulation models, but being able to measure, report, and verify (MRV) changes in soil carbon stocks is crucial for any soil carbon policy that seeks incentivize an increase (or slow the decrease) of soil carbon stocks. Measuring changes in soil carbon stocks is incredibly difficult. Wuest (2014) finds that soil carbon stocks can experience over 5-10% variation simply due to seasonal fluctuations. Historically, the primary means for measuring soil carbon stocks involves taking multiple soil samples up to the desired depth and then using dry combustion or chemical oxidation to measure carbon content. However, recent advances in remote sensing technology and spectral imaging have enabled cheaper and less laborious, but also less accurate, methods.

Determining soil carbon changes requires detailed data on the original soil carbon stocks, which typically requires physical soil samples (Smith et al., 2020). Kravchenko and Robertson (2011) show that the statistical power of soil samples decreases as the depth increases because soil organic carbon stocks experience more natural variation as soil depth increases. For example, in the case of 11 experimental sites with 3 replicate plots and 5 subsamples for each plot, they estimate that the probability of detecting a 10% change in soil organic carbon stocks is less than 20% for every soil profile. For a 100% change, they find a greater than 80% chance of detecting the change in the 5-10cm layer but less than 50% chance of detecting the same change in the 50-60cm layer. Thus, in the deeper profile, a large number of samples are needed to detect reasonable changes with sufficient probability. Each soil profile needs to be assessed independently of the others, and changes for the whole profile should be assessed based on the results from the individual profiles Kravchenko and Robertson (2011).

Moreover, there can be significant heterogeneity in soil carbon stocks across landscapes, and common sample sizes of 10-30 are insufficient to measure the changes desired by programs such as the "4 per mille" campaign (Stanley et al., 2023). With 50 samples and surface area of 0.1 km^2, Maillard et al. (2017) find minimum detectable differences for 0-10, 0-30 and 0-100 cm of 12, 14, and 18%. With 50 samples, a sampling depth of 30 cm, and initial soil carbon of 60 t/ha , Maillard et al. (2017) detect a significant change on a hectare of cropland with 20% probability. Stanley et al. (2023) advise the soil carbon verification programs need explicitly state their Type I and Type II error probabilities with their sampling schemes, and suggest that in small samples they avoid t-tests in favor of non-parametric methods because changes are not normally distributed.

To calibrate these numbers to agricultural practices, an upper bound of carbon that can be sequestered through practices such as no-till or cover cropping is 0.5 t C/ha/yr, which is substantially less than 1% of the carbon in the soil (Section 5.3). Maillard et al. (2017) estimate that, to detect a 0.5 t C/ha/yr change with 90% power in soil with 60 t C/ha in the first 30 cm would take 17, 19, 24, and 35 years for land areas of 0.1, 1, 10, and 10000 km^2. Detecting a significant change over 5 years would require 516, 730, 1051, and 2260 samples for 0.1, 1, 10, 10,000km^2. Similarly, Smith (2004) estimate that if a sampling method can detect 3% changes, around 100 soil samples, then increasing carbon inputs by 10% would result in a detectable change within 28 to 47 years, depending on initial soil conditions. If sample size is closer to the average experimental size of 10-20 samples and only a 15% increase in soil organic carbon is detectable, then carbon inputs would need to increase by 50% from initial carbon stocks to detect changes within 28 to 47 years (Smith, 2004).

In sum, it is important to know minimum detectable changes given the time frame, sample size, soil sample depth, surface area, and size of expected increase from management change. Because carbon stock increases are quite small from year to year, decades are often needed to detect changes (Smith, 2004). USDA (2023a) EQIP payment schedules list the estimated cost of intensive soil carbon studies using 12 samples at roughly $5,000. Thus, validating model-based predictions of small soil-carbon changes can be very expensive, even when implemented at the farm-level.

Because immense measurement difficulties with physical soil sampling needed for national or global soil carbon sequestration schemes, physical soil sampling is not a feasible option to measure soil carbon stock changes. Digital soil mapping has quickly progressed with falling costs in computing power over the last 20 years (Minasny and McBratney, 2016). New methods such as spectral imaging, inferring fluxes from carbon budgets, and remote sensing could help to dramatically bring down costs (Smith et al., 2020). However, remote sensing methods are so far limited to data on the top 1 cm of soil (Smith et al., 2020), and they are not yet usable for measuring soil carbon at the farm-level even with advancements in resolution and machine learning models (Hengl et al., 2017).

Spectral methods are still developing and calibrating them requires large amounts of data on soil physical characteristics and some repeated sampling (England and Viscarra Rossel, 2018; Brown et al., 2006). That is, because soil carbon stocks can vary drastically with climate and soil characteristics, particularly across space, prediction models using spectral imaging need to be calibrated across varying climates and soil types, which is feasible (Ramírez et al., 2021; Minasny et al., 2017; Sanderman et al., 2020).

The major drawback to proximity spectral imaging is that prediction values have less precision than traditional methods (Sanderman et al., 2020). Goodwin et al. (2022) finds a handheld visible near-infrared spectrometer combined with remote sensing data had prediction accuracy as high as $\pm 0.3\%$; however, the accuracy decreased dramatically when soil organic carbon concentrations exceeded 2%. In addition, soil moisture and other surface characteristics can dramatically reduce prediction accuracy, though machine learning methods may help offset some of these effects (Cao et al., 2020). In the case of handheld X-ray fluorescence tools, preparing the soil samples by drying them or compressing them into power pellets significantly increases the accuracy of soil nutrient measurements compared to untreated soil samples (Goff et al., 2020). Moreover, there are multiple types of spectral imaging and their use in combination could prove to be more accurate than any single method by itself (O'Rourke et al., 2016). Diffuse reflectance spectroscopy using mid-infrared light shows the most promise for measuring soil carbon, but this equipment is more expensive and not practical for in situ measurements when samples need to be dried (Reeves, 2010).

However, as with all machine learning methods, there is a substantial risk of over-fitting models and improper validation may lead to models performing poorly in predicting out of sample (Goff et al., 2020; McBride, 2022). Problems occur because these spectral models often have too many regressors with little theoretical justification being trained on too little data, and therefore, high R^2 can happen simply by chance (McBride, 2022). Reyna et al. (2017) find that while their vis-NIR model had an $R^2 = 0.82$ cross-validation showed their model to exhibit overfitting characteristics. Brown et al. (2006) use almost 4,000 samples to predict soil carbon levels using vis-NIR and DRS sepctroscopy, and they estimate that future similar projects could require 10,000 to 100,000 spectral samples to properly calibrate spectral models. Therefore, there is no work around for large, detailed physical soil samples to accurately predict soil carbon stocks (McBride, 2022).

Therefore, MRV will likely require a mixture of carbon flux budgets, spectral methods, remote sensing data, soil carbon models, long-term experimental data and repeated soil samples (Smith et al., 2020).

Table 5.1: Summary Statistics for Soil Carbon Sequestration Practices

Practice	Carbon Sequestration (t C/ha/yr)	Benefits Estimate ($/ha/yr)	Global Potential (GT C/yr)	Cost Estimate ($ t/C)	Crop Productivity (% Yield Gain)	References
Conservation Tillage	0.06 to 0.54	41 to 367	0.08 to 0.17	93 to 833	- 10 to 10	Ogle et al. (2019); Powlson et al. (2014); Graham et al. (2021); Sun et al. (2020); Rennert et al. (2022); USDA (2023a)
Cover Crops	0.16 to 0.48	109 to 326	0.06 to 0.18	104 to 1250	-4 to 13	Poeplau and Don (2015); Abdalla et al. (2019); Rennert et al. (2022); USDA (2023a)
Biochar	0.16 to 5.34	109 to 3626	0.27 to 1.72	54 to 757	10 to 16	Eagle et al. (2012); Roberts et al. (2010); Lehmann et al. (2021); Smith (2016); Schmidt et al. (2021); Rennert et al. (2022)
Rock Weathering	0.7 to 1	475 to 679	0.14 to 0.55	293 to 660	12 to 16	Beerling et al. (2020, 2024); Rennert et al. (2022)

Note: We use $679 t/C ($185 t/$C0_2$) for social cost of carbon for benefits estimate (Rennert et al., 2022). Neither cost nor benefits estimates include the value of co-benefits including yield. Cost estimate for conservation tillage is based on USDA NRCS EQIP cost estimate of roughly $50/ha, and cover crops cost estimate is based on USDA NRCS EQIP cost estimate of $125-200/ha (USDA,2023a). Yield effects for conservation tillage assume rotational cropping pattern and crop residuals are left in the field. Carbon estimates for biochar include effects from non-CO_2 GHG gases and estimates are calculated in terms of carbon equivalents.

5.3 Agricultural Practices and Soil Carbon

We focus this paper on soil carbon on existing agricultural land, which requires understanding and measuring both absorption and emissions. We consider three main practices: conservation tillage, cover crops, and amendments. In this section, we describe these practices and their estimated effects on soil carbon. We summarize the literature in Table 5.1. Through out this section, we use a social cost of carbon on $679 t/C ($185 t/CO_2) to estimate the benefits of additional soil carbon sequestration (Rennert et al., 2022). This value assumes persistent sequestration because it is derived based on the marginal cost of carbon emissions. To the extent that sequestered carbon does not persist, the benefits would be lower.

A key assumption for conservation tillage, cover crops, and soil amendments is they will cause no land use effects. That is, these practices do not have indirect effects that cause new land to be brought into production. Rather, they are expected to improve the productivity of land already in production. This assumption may be true when farmers adopt these practices for individual reasons, but policies that encourage the widespread adoption of new practices could have land use impacts. Any policy subsidizing farming has the possibility of creating indirect land use impacts if it is not explicitly designed to prevent land use change. We largely do not discuss the possible land use impacts of conservation tillage, cover crops, and soil amendments because the scientific literature generally assumes these effects are zero; nonetheless, policies that encourage widespread adoption of these practices may have indirect land use impacts, particularly if they do not account for the heterogeneity in the soil carbon and yield impacts of these practices.

5.3.1 Conservation Tillage

Farmers use conventional tillage as a mechanical method to break apart the soil, which serves various purposes such as weed control, disruption of crop residue, and enhancement of soil profiles for seeding. This practice allows increased oxygen penetration into the soil, leading to heightened microbial activity and therefore greater consumption of soil compounds and increased CO_2 respiration. Moreover, tillage can loosen more than a foot of topsoil, making it susceptible to erosion risks from wind and flooding. Graham et al. (2021) estimate that intensive tillage caused global carbon losses of 9.8 GT from 1850 to 2014.

In contrast, conservation tillage practices aim to minimize soil disturbance, with reduced tillage limiting both the depth and frequency of soil disruption, and no-till completely abstaining from soil tillage. By doing so, conservation tillage promotes the accumulation of soil carbon, slowing down the breakdown of organic matter, and making the topsoil more resistant to erosion. However, it may necessitate increased herbicide use or in-season cultivation to control weed infestations.

Estimates for average carbon sequestration from conservation tillage range from 0.06 and 0.54 t C per hectare per year during 2015-2100 depending on soil, climate and land use factors (Powlson et al., 2014; Eagle et al., 2012; Ogle et al., 2019). Using a social cost of carbon of $679 implies benefits of $41-$367 per hectare or $17-$100 per acre. USDA (2023a) cost estimates for conservation tillage are roughly $20 per acre, providing a cost estimate of $93 to 933 t/C. The wide range of costs per ton of carbon and benefits per hectare underscore how heterogeneity in tons of carbon sequestered per hectare can drastically alter the benefit-cost analysis for farmers and policymakers.

Most of the benefits tend to occur in the first 20 years (West and Six, 2007), but a steady-state may not be reached for over 100 years, depending on the depletion of soil carbon stocks (Graham et al., 2021). The US is at the upper end of these ranges because of heavy soil carbon loss over the last 100 years, and Asia and Africa at the lower end due to low baseline carbon stocks and less depletion from intensive tillage (Graham et al., 2021).

On a global scale, estimated benefits are 0.08-0.17 GT C additional carbon sequestered per year during the same period (Powlson et al., 2014; Graham et al., 2021). These numbers imply that global implementation of no till throughout the 21st century would only offset one year's emissions of fossil fuels if every farmer were to adopt (Graham et al., 2021). Moreover, (Graham et al., 2021)'s may have overestimated additional sequestration because of relatively high current adoption rates in the United States, Canada, and Australia.

Hundreds of studies demonstrate that conservation tillage increases soil organic carbon in the top 10cm of the soil profile (Powlson et al., 2014; Bai et al., 2019), but studies often show no change in soil carbon stocks at greater depths. In some cases, there may even be a decrease in soil carbon at greater depths, but cumulative effect appears to be positive up to at least 60cm (Ogle et al., 2019). Moreover, the ability of conservation tillage to increase soil carbon stocks is heavily dependent on climate and soil types (Powlson et al., 2011, 2014; Bai et al., 2019; Paustian et al., 2019; Sun et al., 2020; Ogle et al., 2019). In cooler and wetter environments such as the Great Lakes region, no till has no discernible effect on soil carbon stocks and may actually decrease soil carbon (Sun et al., 2020; Paustian et al., 2019; Ogle et al., 2012; Bai et al., 2019).

No-till practiced for decades can lead to soil compaction, rain runoff, and weed infestations, and these effects could cause decreased yield for farmers (Raper et al., 2000). In response, farmers may restart tillage, which could undo the gains in soil carbon (Powlson et al., 2014; Conant et al., 2007). However, some of the added carbon would likely have translocated from topsoil to deeper soils and therefore not be disturbed by occasional tillage (Dynarski et al., 2020). Blanco-Canqui and Wortmann (2020) estimate that light tillage ($<$ 15cm) once every 5 to 10 years would have little to no long-term impact on soil organic carbon stocks. Conant et al. (2007) estimates that shallow, bi-annual cultivation may achieve 80% of the soil organic carbon benefits of no till while also controlling weeds and compaction. However, the resumption of heavy tillage is likely to undo all or most of the additional carbon sequestered (Powlson et al., 2014).

The yield benefits of conservation tillage also vary by climate. Sun et al. (2020) find that humidity negatively impacted both carbon sequestration and yield benefits of no till. In particular, cool and moist climates tended to experience both negative yields and decreased soil carbon from the adoption of no-till (Ogle et al., 2012; Sun et al., 2020). The greatest benefits in terms of carbon sequestration and yield occurred in arid and semi-arid environments, provided that crop residues remained in the field Ogle et al. (2012); Sun et al. (2020). For example, conversion to no-till increased crop yields by 7-10% in semi-arid western Canada while decreasing yields by 6% in the cool, wet environment of eastern Canada (VandenBygaart and Liang, 2024). Therefore, conservation tillage should not be used as a universal practice irrespective of local climate and soil types.

In the United States, 202 million acres of cropland are already in some form of conservation tillage while only 73 million acres were farmed using heavy tillage (USDA, 2024). The amount conventional tillage has steadily decreased as 106 million acres were farmed using conventional tillage in 2012 (USDA, 2014). Outside the United States, over 60% of Canadian cropland is farmed using conservation tillage (Statistics

Canada, 2022), and in Australia, over 90% of farms in major agricultural provinces use no-till (Llewellyn and D'Emden, 2010). Most of these adopters have not received any direct financial payment for adopting conservation tillage, and thus, a significant portion of farms with the potential for net positive benefits from conservation tillage may have already adopted.

5.3.2 Cover Crops

Cover crops are non-cash crops grown during fallow periods, which may be winter or summer depending on the cash crop. In the US corn belt, farmers may plant a crop such as rye or clover in the fall after completing the harvest and then terminate it the following spring using mowing, tillage, or herbicides in time to plant the next year's cash crop. Cover crops can increase soil carbon stocks through two mechanisms: increased carbon inputs and reduced erosion. Using legumes such as clover as a cover crop has the added benefit of fixing nitrogen into the soil, which allows reduced synthetic nitrogen fertilizer application the following year.

Many factors can influence the rate of carbon sequestration from cover crops including biomass accumulation, the season applied, local climate, and soil types Blanco-Canqui (2022). Sequestration estimates range from 0.16 to 0.48 t C/ha/yr (Eagle et al., 2012; Ardenti et al., 2023; Kaye and Quemada, 2017; Poeplau and Don, 2015). Poeplau and Don (2015) find that saturation may not occur until 155 years of implementation, and average sequestration potential is 16.7 t C/ha over that time frame, and they estimate that, if implemented globally, cover crops could result in 0.12 GT C/yr.

Costs for cover crops can vary by plant. USDA (2023a) lists costs for cover crops at close to $50 per acre for single species and $80 per acre for mixed species blends. Thus, estimated costs per ton of carbon range from $104 to 1250. Using a social cost of carbon at $697 per ton, per hectare benefits are between $109 to 326 or $44 to 132 per acre. Farmers may be able to recover some of these costs from crop productivity benefits of cover crops, but private costs could still be a significant barrier for farmers (Blanco, 2023). These larger private costs could partially explain why only 18 million acres of US farmland are cover cropped while over 202 million acres are farmed with conservation tillage (USDA, 2024).

As with conservation tillage, the actual soil carbon gains from cover crops depend on management decisions by the farmer. Blanco-Canqui (2022) finds that only 29% of cover crop studies have a statistically significant positive effect for soil carbon accumulation. A major determining factor is low biomass accumulation, i.e. under 2 t/ha, and using cover crops for less than 5 years (Blanco-Canqui, 2022; Ardenti et al., 2023). To improve the odds of measurably increasing soil carbon, cover cropping needs to be practiced for at least 5 years and the cover crop needs to be terminated late enough in the season to allow for enough biomass accumulation.

Moreover, the fact that only about 5% of US farmers use cover crops points to economic and agronomic barriers. The costs for cover crops can exceed $200/ha while the direct benefits on yield and indirect benefits on input use may only cover a portion of these costs (Blanco, 2023). Soil moisture usage of cover crops in arid environments during summer fallow can limit the benefits of cover crops while early frost and snow in temperate climates can prevent the seeding and or establishment of cover crops after fall harvests. These issues combined with the expiration of short-term incentive payments could explain disadoption of cover crops by many farmers in the US (Sawadgo and Plastina, 2022).

5.3.3 Amendments: Biochar and Rocks

One way to increase soil carbon is to apply exogenous amendments to a field. If the carbon in these amendments stays in the soil, then soil carbon increases. In contrast to conservation tillage and cover cropping, which seek to manipulate the cropping carbon cycle, amendments bring carbon from outside the system. Assessing the carbon benefits from applying amendments to cropland therefore requires an estimate of counterfactual emissions.

Biochar is a coal-like product formed from super-heating plant matter in the absence of oxygen. Biochar has been used as a soil amendment to enhance fertility for several hundred years, though its effects on soil carbon have only been studied for a few decades (Schmidt et al., 2021). Biochar is an inert carbon material that could take hundreds if not thousands of years to decompose (Verheijen et al., 2010; De Gryze et al., 2010; Roberts et al., 2010), and biochar's application to crop fields may also encourage the accumulation and persistence of soil carbon beyond the inherent carbon content of the biochar itself (Schmidt et al., 2021). How long it lasts will depend on climate, soil type, cultivation methods, feedstock, and production methods (Eagle et al., 2012; De Gryze et al., 2010).

Potential carbon sequestration benefits range from 0.2 to 5.3 t Ce/ha/yr depending on the feedstock biomass, application rate, climate, and other factors (Eagle et al., 2012). The sequestration benefits are then estimated at $109 to 3,626/ha/yr. Biochar from corn stover is on the lower end of the spectrum at 0.2 t Ce/ha/yr (Roberts et al., 2010). Application rates in most studies range from 30 to 60 tons of biochar per hectare (Smith, 2016), but application rates below 10 t per hectare paired with fertilizers could be realistic for farmers (Schmidt et al., 2021; Ye et al., 2020). Costs can vary by production method and feedstock. Meyer et al. (2011) estimates cost per ton of biochar at $51 to 394, and using this cost estimate, Smith (2016) finds a range of $54 to 757/tC sequestered.

Net greenhouse gas benefits from biochar depend on counterfactuals over the life cycle. In particular, the amount of carbon that was lost in growing the feedstock to make the biochar affects net emissions. Roberts et al. (2010) use a lifecycle assessment to find emissions reductions of 0.24 t C equivalent per metric ton of corn stover or yard waste, but emissions increases for switchgrass were 0.01 t C equivalent per ton because of land-use change.

If implemented globally, biochar could reduce global emissions by a estimated 1 to 1.8 GT Ce/yr without accounting for land use change (Woolf et al., 2010; Lehmann et al., 2021; Smith, 2016). Around 70% of the emissions gains would come from carbon sequestration while 30% come from displaced emissions from feedstock decay and fossil fuels (Woolf et al., 2010; Smith, 2016). These estimates imply that the mitigation potential of biochar would be almost double the mitigation of a comprehensive implementation of soil carbon sequestration including no-till, cover crops, and improved grazing management (Smith, 2016), and soil carbon sequestered from biochar could persist for thousands of years (Woolf et al., 2010).

However, producing the biomass to make biochar could require 30 to 240 million hectares if used globally (Smith, 2016). Limiting land use change by using crop and wood residues and grasses from marginal land is necessary for negative lifecycle emissions from biochar (Roberts et al., 2010). By using crop residuals and biomass from marginal land, biochar may be able to succeed where cellulosic ethanol has thus far failed. On the other hand, biochar could also face many of the same land-use change pitfalls as biofuels if collection of the feedstock encourages large land-use change emissions either directly or indirectly.

Biochar could be spread on non-cropland or buried and it would still sequester carbon. However, it can potentially increase agricultural productivity through a mechanism similar to lime and by increasing water holding capacity (Verheijen et al., 2010), and it may possess other co-benefits such as reducing soil nutrient loss and synthetic chemical leaching (Woolf et al., 2010). Average yield benefits fall between 10 to 16%, though effects can be negative (Schmidt et al., 2021). Acidic soils tend to benefit more from biochar (Schmidt et al., 2021), and the application of biochar in conjunction with inorganic fertilizers may lead to greater yield gains than fertilizers alone (Ye et al., 2020). Nonetheless, the lack of long-term studies on biochar create uncertainty and need for further research on the co-benefits of biochar(Verheijen et al., 2010; De Gryze et al., 2010).

Rock weathering removes carbon from the atmosphere by the natural interactions of silicate minerals and water, and enhanced rock weathering quickens this natural cycle by grinding silicate minerals, also known as basalt or olivine, into a fine powder and applying the powder to a moisture rich environment (Vienne et al., 2022; Beerling et al., 2020). Beerling et al. (2020) estimates that China, India, Brazil, and the US could sequester 0.14 to 0.55 GT C/yr at an annual cost of $293-660 t C ($80-180 t CO_2). The process takes several years to reach full potential sequestration, but the carbon it stores is highly resistant to decay and can persist for 100,000 years (Beerling et al., 2020, 2024).

Like biochar, basalt can sequester carbon whether or not it is spread on cropland. Also like biochar, enhanced rock weathering may boost cropland productivity through a process similar to liming (Beerling et al., 2024). Beerling et al. (2024) estimate that applying crushed basalt at 50 t/ha for 4 years sequestered around 2.86 t C/ha and increased corn and soybean yields by 12 to 16%. Kantola et al. (2023) find that applying basalt at 50 t/hayr^{-}1 sequestered close to 1 t C/ha/yr on corn-soybean rotated fields.

5.3.4 Other Practices

Conservation tillage, cover crops, and enhanced rock weathering all have the unique advantage of not requiring any changes to existing land use practices. However, other practices that require some land-use change could have even greater carbon sequestration benefits than the other methods mentioned so far. Nonetheless, as with any land use change, these gains need to be weighed against possible indirect land use change in other sectors caused by policies attempting wide-scale land conversion.

One simple change is converting cropland to grasslands. Much of the current croplands across the Midwest and Great Plains of the US used to be native grasslands. Reconverting these croplands to grasslands could have significant carbon sequestration benefits. Ogle et al. (2005) find that croplands that have been conventionally tilled for over 20 years can recover 82% to 93% of their original soil carbon stocks if set aside as grasslands for 20 years. Numerous studies find that converting croplands to perennial pastures could sequester between 0.67 to 1.01 t C/ha/yr Eagle et al. (2012); Conant et al. (2001, 2017). However, the size of these effects will vary depending on climate, soil types, and grass types (McSherry and Ritchie, 2013). Some studies point towards greater sequestration in warmer and moist climates because of greater perennial biomass (Eagle et al., 2012), but the benefits of greater moisture appear to decrease with clay soils versus sandy soils (McSherry and Ritchie, 2013).

Furthermore, how grasslands are managed partially determines the amount of carbon they sequester. Grazing grasslands stimulates plant growth and provides nutrients necessary for plant growth, and as a result, grazing can enhance carbon sequestration on grasslands (Eagle et al., 2012; Bai and Cotrufo, 2022; Jiang et al., 2020). Grazing also may lead to greater persistence in soil carbon stocks (Jungkunst et al., 2023). Numerous studies have found that carbon sequestration is reduced when livestock are removed from grasslands (Eagle et al., 2012), but a decrease in livestock methane emissions may negate these losses if total livestock numbers are decreased and not simply moved to another location (Eagle et al., 2012). Excessive grazing can reduce soil carbon stocks. Ren et al. (2024) find that over grazing has reduced soil carbon stocks by 46 GT C over the last 60 years with 75% of grazed grasslands being overgrazed. Conant et al. (2017) find that improved grassland management could result in an of average 0.47 t C/ha/yr, and Bai and Cotrufo (2022) find that improved grazing management could lead to global carbon sequestration of 0.04 to 0.19 GT

Ce/yr.

Compost and manure are crop productivity amendments that may also sequester additional carbon in agricultural soils by improving crop yields and increasing carbon inputs. Gross and Glaser (2021) find that soil carbon stocks increased on average by 10.7 t C/ha with cumulative manure application rates of less than 500 and more than 2000 t/ha. Sequestration rates can vary drastically with application rates as rates up to 500 sequestered 9.2 t C/ha while rates greater than 2000 t C/ha sequestered 29.7 t C/ha (Gross and Glaser, 2021). Livestock manure, particularly hog and cattle, sequestered close to 15 t C/ha while green manure like straw only sequestered 5 t C/ha (Gross and Glaser, 2021).

Another practice is the installation of woody and/or perennial grass buffers near field edges and riparian zones. Perennial grasses and woody vegetation develop deeper root systems than annual crops, so their implementation in low-productivity land could increase soil carbon sequestration while also providing significant environmental and wildlife benefits. (Eagle et al., 2012) report a mean effect of 0.56 t C/ha/yr for perennial grass strips. Gross et al. (2022) find that woody hedgerows have 3 times the stored carbon as nearby cropland in Alberta, Canada.

Finally, preventing agriculture from bringing new land into production could prevent massive amounts of soil carbon and carbon stored as biomass from being lost. Spawn et al. (2019) find that bringing native grasslands into corn production led to emissions of 55 t C/ha between 2008-12. Likewise, Gelfand et al. (2011) find that converting Conservation Reserve Program grasslands leads to a GHG debt of 62 t C/ha for no-tilled corn-soybean rotation cropland and 222 t C/ha for fully tilled cropland because of greater soil carbon losses in the first few years of production. Converting forests to pasture land does not necessarily decrease soil carbon (Guo and Gifford, 2002; Fujisaki et al., 2015); however, the biomass losses for longer-rotation forests (30 yrs) could be quite substantial (Xiao et al., 2003; McNicol et al., 2018). Even turning thawing permafrost in the Arctic into cropland or pasture could result in substantial soil carbon losses (Peplau et al., 2022). These results show why reducing land use change and restoring natural habitat could be the most cost effective land-based means for mitigating climate change (Roe et al., 2021).

5.4 Current Actions and Policy

The importance of maintaining soil carbon stocks and preventing erosion on cropland is not a new idea. See Baylis et al. (2022) for a comprehensive review of past and present North American agri-environmental policy, Pannell and Rogers (2022) for a review of Australian and New Zealand policies, and Hasler et al. (2022) for a review of European policies. Many of these programs have a long history reaching back to the 1930s. In particular, clouds of dust from the drought stricken Great Plains blocked out the sun, destroyed crops, and drifted all the way to the Atlantic Ocean. The experience of the Dust Bowl and resulting rural poverty spurred the US Congress and Canadian Parliament to pass several acts to limit soil erosion in the Great Plains. The legacy of these depression era programs can still be seen through terraced land in Iowa or long stretches of trees on the open prairies of Kansas, and many current USDA programs are the direct result of almost a century of soil conservation policies.

The USDA National Resource Conservation Service (NRCS) is the current US government agency responsible for maintaining the quality of natural resources in rural, agricultural spaces across the US. A century of government programs and advising by extension agents have led to over 50% of US cropland using some form of soil conservation. The US has just over 382m acres of cropland according to the 2022 Census of Agriculture (USDA, 2024), and 202m acres are farmed using some form of reduced tillage while 18m acres were cover cropped excluding CRP (USDA, 2024). The number of acres farmed using conventional tillage has been steadily decreasing with 73m acres in 2022. These practices have led to substantial reductions in soil erosion. NRCS, 2017 estimates that conservation practices such as reduced tillage and structural barriers have reduced 54% of possible sediment loss compared to a no-practice scenario during the years of 2003-06. In addition, NRCS soil carbon model estimates that 51% of cultivated cropland experienced an increase in soil carbon stocks over the 47 year modeling period NRCS, 2017.

The primary programs for the NRCS are the Environmental Quality Incentives Program (EQIP), the Conservation Stewardship Program (CSP), Regional Conservation Partnership Program (RCPP), and the Agricultural Conservation Easement Program (ACEP). These programs provide financial assistance for a mixture of conservation practices designed to preserve the quality of agricultural soils, river basins, air quality, and wildlife habitat. EQIP and CSP provide the most funding for soil conservation practices, and they both rely on short-term contracts to mitigate adoption costs for farmers. EQIP primarily targets farmers wanting to start new conservation practices while CSP primarily helps farmers to expand their current conservation practices. Soil conservation practices include no-till, cover crops, erection of structural barriers, and drainage control. In addition to NRCS programs, the Farm Service Agency runs the Conservation Reserve Program and the Wetlands Reserve Program which pay farmers to plant perennial grasses on almost 20m acres of environmentally sensitive land.

The goal of sequestering carbon in agricultural soils has renewed interest in NRCS conservation programs, and the Inflation Reduction Act (IRA) of 2022 provides a substantial funding increase for these programs. NRCS programs are funded through the Farm Bill with 2018 being the most recent Farm Bill. From 2015 through 2022, annual funding for EQIP ranged from \$1.5b to \$2b. The IRA increases 2025's baseline to \$3b and 2026's to roughly \$3.5b with the possibility for additional funding from the next Farm Bill. However, the funding from the IRA is earmarked for practices that have known climate change benefit while practices that primary target other objectives such as water quality may not be eligible for IRA funding.

The IRA also provided additional \$3.1b in funding for climate-smart commodities partnerships. These partnerships are cooperative agreements between farmers, private companies, and public institutions, and private companies must match at least 50% of the public funding. They aim to foster market-based solutions to reducing agricultural emissions through explicitly marketing agricultural products as "climate-smart." Furthermore, each project must explicitly outline methods for monitoring, reporting, and verifying emission fluxes, and many projects have university scientists assisting in the implementation of these MRV schemes.

Outside of the US, Canada and Australia have observed the largest uptake of soil conservation practices and programs. Canada's programs also started during the Dust Bowl in the 1930s, and they have undergone several cycles of reform since then (Baylis et al., 2022). These programs have largely focused on education and helping farmers create management plans, and they have been quite successful. Over 60% of Canadian cropland is farmed using no-till Statistics Canada (2022). In Australia, over 90% of farms in major agricultural provinces use no-till (Llewellyn and D'Emden, 2010), though most of the uptake is attributed to private gains to farmers not government programs (Pannell and Rogers, 2022).

In 2019, Australia launched the Australian Carbon Credit Unit Scheme which created a voluntarily carbon offset market with multiple pathways to generate offsets outside of carbon farming. The program covers a wide range of actions such as converting cropland to pastures, conservation tillage, cover crops, and erecting erosion barriers (Thamos et al., 2020). The number of cropland soil carbon projects is quite low (Pannell and Rogers, 2022), and the March 2023 auction did not include any new projects from the agriculture sector (Clean Energy Regulator of the Australian Government (CER), 2023). New Zealand has proposed to bringing agriculture into its emissions trading scheme, a cap and trade program. In 2022, a partnership between the government and the agricultural sector, known as He Waka Eke Noa, developed a proposal that focused on methane emissions from livestock and nitrous oxide emissions from fertilizer. They rejected credits for soil carbon on the grounds that the science and measurement is not sufficiently well developed.

A major international soil carbon initiative is the 4 per Mille program. The program was announced at the 21st Conference of the Parties to the United Nations Framework Convention on Climate Change in Paris, and it reflects the fact that global soil carbon stocks would need to increase by 0.4% each year to offset the 9 GT C of emissions from global use of fossil fuels (Minasny et al., 2017). Since global average soil carbon is 161 t C/ha, each hectare would need to sequester roughly 0.6 t C per year (Minasny et al., 2017). The program, however, remains entirely voluntary, and member organizations and countries are free to set their own goals and methods of reaching these goals.

In addition to government programs, private organizations have created credit markets for companies and individuals to buy carbon offsets from farmers sequestering carbon in their soils. Plastina (2021); Plastina and Wongpiyabovorn (2021) provide an overview of different private programs for interested farmers. These private programs differ in their approaches for ensuring additionality, preventing voluntary releasing of sequestered carbon, qualifying practices, and data required for MRV. Additionally, some providers pay for specific practices, such as no-till, while others pay for the estimated amount of carbon sequestered. However, without any centralized standard, these carbon credit markets could face many of the same difficulties as other non-regulated credence goods, and the wide-range of program standards and qualifications could lead to low adoption rates by both farmers and buyers because of difficulties in discerning quality Wongpiyabovorn et al. (2023). The Growing Climate Solutions Act of 2022 and $300m in USDA funding towards MRV research could provide stability to this developing market (USDA,2023b), but these government programs have yet to produce significant guidance or standards for voluntary credit markets.

5.5 Economic Framework

The preceding discussion highlights five features that characterize the economics of carbon sequestration on working agricultural lands.

1. Heterogeneity. The potential for carbon sequestration varies massively across space and time depending on current carbon stocks, climate, weather, soil type, and crop choice.

2. Dynamics. For a given set of management practices in a given location, there is a steady-state level of soil carbon. A change in practices will change the steady state level, but it may take decades to reach it.

3. Co-benefits. Changing the carbon content of the soil, and other changes associated with a change in management practices, will usually affect crop yield and production costs.

4. Measurement. It is very costly to measure accurately the changes in soil carbon stocks induced by a change in management practices.

5. Uncertainty. Future carbon policies and incentives are uncertain, as are agricultural market prices and the potential co-benefits of changes in practices. Uncertain weather may affect the amount of carbon sequestered in a given year. Heterogeneity and the difficulty in measurement combine to create uncertainty in the amount of carbon that can be sequestered on a field.

5.5.1 Policy in a World with Certainty and Costless Measurement

We begin by assuming away the last two features in the above list (costly measurement and uncertainty) and focusing on the first three. To do so, we imagine a competitive market economy in which the assumptions underlying the fundamental theorems of welfare economics hold except for the presence of a single externality: farming practices affect the climate by changing soil carbon stocks. The value of this externality — the social cost of carbon — is known with certainty.

In this economy, both farmers and regulators have full information about soil carbon dynamics under various practices, future weather realizations, and future prices throughout the economy. This means they know the effects on soil carbon stocks of any practices farmers may adopt. These effects depend not just on a farmer's practices in the current year, but also on past and future land use and farming practices. For example, consider a farmer who alternated between growing corn and soybeans on a field in the past and plans to continue that cropping pattern. They have used conventional tillage in the past and have not planted cover crops, but are considering planting a cover crop every winter in the future. This new practice would change both the steady state carbon content and the trajectory towards that steady state.

A menu of Pigouvian taxes and subsidies can produce an efficient outcome in this stylized setting, but determining them requires setting a benchmark, or defining property rights. Does a farmer have the right to operate the farm as they please, tilling the soil and choosing cover and cash crops to maximize profit? If so, then the benchmark becomes the profit maximizing level of tillage and farmers would receive payments for adopting practices that increase soil carbon relative to this benchmark. Agricultural policy in the US and many other countries essentially adopts this benchmark, as evidenced by conservation programs such as EQIP and CSP. However, if society defines idle cropland as the benchmark, then farmers would face a tax for any actions, such as tillage, that reduce carbon stocks and they would receive a subsidy for any actions, such as planting trees, that increase carbon stocks relative to idling the land.

From the Coase theorem (Coase, 1960), the equilibrium level of carbon stocks is unaffected by the chosen benchmark. Hahn and Stavins (2011)call this the independence property. If the independence property holds, then policy makers can assign the benchmark to favor their most valued constituents without sacrificing the efficiency of the policy. Hahn and Stavins (2011) argue that the independence property holds in the seven cap-and-trade systems they study,[2]

Every potential future schedule of practices and crops on a farm implies a trajectory of carbon stocks. The efficient Pigouvian tax or subsidy would be based on the difference between this schedule and the benchmark. An ideal policy would pay the farmer an amount equal to the present value of future increases in the carbon

[2]Lead trading, CFCs under the Montreal Protocol, the SO_2 allowance trading program, RECLAIM in Southern California, the eastern ozone transport NO_X market, EU ETS, and Article 17 of the Kyoto Protocol.

stock under their planned schedule relative to the benchmark. The payment would be negative (a tax) in the event that the practice reduces carbon stocks. The payments would vary by farmer according to the external costs or benefits of their actions. Farmers would be incentivized to follow their planned schedule because they would be assessed a tax on any change that reduces carbon stocks relative to the plan.

This ideal policy would be a subsidy or tax on a schedule of planned future practices. The farmer is not penalized for past depletion or rewarded for past sequestration, which many stakeholders may view as unfair. However, in this stylized world with full information about the future, the independence property implies that farmers could be punished or rewarded financially for past behavior using a one-time payment without affecting the economic efficiency of the policy.

A change in practice may also change atmospheric greenhouse gas concentrations by, for example, reducing nitrous oxide emissions through a reduction in fertiliser use or increasing carbon emissions through increased use of a diesel-powered tractor. These effects would also factor into an optimal carbon payment, but we abstract away from them here to focus on soil carbon.

Next, we discuss various ways in which the real world deviates from this idealized setting.

5.5.2 Costly Measurement and Imperfect Attribution

Comprehensively measuring changes in the soil carbon stock is prohibitively costly, as explained in Section 5.2.2. The implications of imperfect measurement are accentuated by the extensive heterogeneity in the response of carbon stocks to changes in agricultural practices. If changes in carbon stocks were homogeneous across fields and farms using the same practices, then regulators would need to measure stocks in only one location. In addition to carbon stocks being expensive to measure, it is difficult to attribute changes in carbon stocks to specific actions taken by a farmer. Stocks may change due to weather shocks and other factors unrelated to farmer actions. These two features mean that soil carbon has characteristics of a non-point-source pollutant. The classic example of non-point-source pollution in agricultural context is nitrogen leaching into natural water systems.

The main approaches to regulating non-point-source pollution are input-based schemes, ambient schemes, and investment in measurement technologies Xepapadeas (2011). The climate-smart agriculture analog to input schemes is policy based on practices such as cover crops or tillage, which are the dominant policy measures in the US at present. Spatial heterogeneity makes a constant subsidy for agricultural practices inefficient (Antle et al., 2003). For example, heterogeneity in sequestration potential creates gives conservation tillage a cost estimate of $93 to 833 for an additional tonne of carbon (see Table 5.1). Simply adding another $60/ha to EQIP payments for soil carbon benefits ignores this heterogeneity. Varying subsidies based on observables such as soils and climate could improve the efficiency of climate smart agriculture policies.

Input-based schemes with varying subsidies could generate first-best outcomes if the functional relationship between practices and soil carbon stocks were known. There exist numerous models of this relationship, which underscore both the scientific modeling of the potential effects of agricultural practices on soil carbon stocks and the payments to farmers under existing policies. The accuracy of these models is constrained by the inability to cost effectively measure initial carbon stocks, which is an important determinant of future sequestration, and by the accuracy of the models in capturing the effects of factors such as temperature, moisture levels, and soil type. Cost effective and accurate measurement would improve policy outcomes by better aligning policy with outcomes.

In many non-point-source problems, the challenge is that the emitter knows their pollution level, but the regulator does not. In this case, neither party knows, which implies that the agency problems inherent in many NPS problems are not a feature of this problem. An ambient scheme (Segerson, 1988)would tax or subsidize producers based on the ambient concentration of pollution. Because greenhouse gases are a global pollutant, the link between ambient GHG concentrations and local soil carbon is very weak. Therefore, this approach is infeasible for regulating soil carbon.

5.5.3 Incomplete Markets and Persistance

The idealized economy in Section 5.5.1 has complete markets, which allows the ideal policy to assess a tax or subsidy on the present value of future carbon stocks under a given production plan. If a farmer were to change their plan in a future year in a way that reduces carbon stocks, then they would be assessed a tax reflecting the present value of the decrease in carbon stocks. In practice, if a farmer were to receive a subsidy to adopt carbon-friendly practices and then stop those practices in a future year, regulators be unlikely to tax them for the change or recover the subsidy payments. After all, one reason policy makers start with the farmer-friendly benchmark is because taxing them is politically difficult to do.

Long-term contracts provide a solution to this problem because they could prohibit reversals or, at least, include penalties for breaking the contract. However, it is challenging to make contracts long enough, as the greatest benefits of carbon sequestration occur when it is sequestered for multiple decades. Contracts could be made incentive compatible by making annual payments rather than a lump sum payment at initialization of the contract. Gramig (2012) proposes a two-part payment for adopting practices that sequester carbon. Farmers would receive an annual payment for the period during which sequestration is occurring and then a lower maintenance payment annually after the soil carbon stock reaches steady state. The maintenance payment would need to be large enough for farmers to continue using the practice, which may become expensive.

If sequestered carbon were to persist for decades independently of on-farm practices, as may be the case with biochar or enhanced rock weathering, then an efficient subsidy policy would make annual payments for as long as the farmer continued applying amendments that sequestered carbon. The payments would stop if carbon reached steady state.

5.5.4 Carbon Offsets and Additionality

Soil carbon sequestration policies and programs typically interact with other programs. For example, on-farm practices could be used to offset emissions in another sector. Such an offset would not reduce net global emissions if the practice would have been adopted anyway. One example would be crediting of on-farm practices when producing biofuels for transportation. Under California's low carbon fuel standard, fuels with a higher carbon intensity than the standard must be balanced by fuels with a lower carbon intensity than the standard. The lower the carbon intensity of a fuel such as ethanol made from corn or renewable diesel made from soybeans, then more petroleum firms can sell without violating the standard. Assigning a lower carbon intensity to a biofuel based on non-additional practices would merely enable more petroleum to be used.[3] Whether such an outcome is inefficient would depend on how policy makers respond. They could respond by tightening the standard, which they may do because substantial non-additional credits would likely imply low credit prices. Such a policy change would offset the non-additionality of the original offset.

Even if they are not used for offsetting other emissions, non-additional payments still need not be inefficient. If policymakers set a farmer-friendly benchmark as described in Section 5.5.1, then subsidy payments under the efficient policy would be determined by what farmers do and not by what they would have done in the absence of the policy. Such non-additional payments could create inefficiencies through the taxes that are levied to fund them, but they would not be inefficient themselves. In a standard pollution setting, everyone pays the same Pigouvian tax regardless of whether the tax causes them to reduce pollution. Similarly, everyone receives the same Pigouvian subsidy regardless of whether the subsidy causes them reduce emissions.

Non additional payments may generate inefficiencies if the independence property does not hold. The independence property would fail in the presence of asymmetric information (Hahn and Stavins, 2011). Numerous companies have announced goals to reduce their carbon footprint, often including promises to achieve net-zero emissions by some date. One way for a firm to achieve a lower carbon footprint is to offset their emissions by paying for carbon emissions reductions or sequestration in other sectors. To the extent that consumers believe the claims and buy more products from the company, emissions will increase.

[3] This is a hypothetical example as California does not currently offer credit for on-farm practices.

Horowitz and Just (2013) build a conceptual model of conservation credits for agricultural practices that are sold to industrial firms to offset their emissions. They assume incomplete information about additionality and that agricultural sources would not be penalized for above-baseline emissions. They find that the optimal baseline includes some non-additional payments so as to incentive more inframarginal abatement.

5.5.5 Uncertainty and Risk

Uncertainty pervades environmental policy, including in the settings we focus on in this paper. If the cost and benefit functions are linear, and if damage and costs are reversible, then we can set and evaluate policy based on expected outcomes (Pindyck, 2007). Future carbon policies and incentives are uncertain, as are agricultural market prices and the potential co-benefits of changes in practices. Uncertain weather may affect the amount of carbon sequestered in a given year. Heterogeneity and the difficulty in measurement combine to create uncertainty in the amount of carbon that can be sequestered on a field. Uncertainty could affect the decisions of risk averse suppliers or demanders of carbon sequestration services, whether public or private. For example, farmers may hesitate to enter long-term contracts that restrict their future flexibility.

Dixit and Pindyck (1994) provides a classic model for understanding how uncertainty may affect the decisions of farmers. Dixit's model considers economic agents who face a decision with an uncertain stream of payments that is costly to reverse and which has the possibility of future investment when more information is known. Even if the project has a net positive expected value, economic agents may need an additional payment on top of the positive expected future income flows to convince them to forego the option to invest at a future date when more information is known. If farmers are unsure of the yield benefits or the costs of adopting the practices in Section 5.3, then payments to those who adopt may facilitate learning.

Gramig and Widmar (2018) use surveys of farmers preferences for no-till to test Dixit and Pindyck's model of investment under uncertainty. They find that US farmers who have not yet adopted would require a payment of $40 per acre to adopt, and they would require an additional payment of $10 per acre to sign a multi-year contract requiring them to use no-till. Moreover, government payment programs like EQIP and CSP provide constant payments per acre of practice while many private offset schemes use carbon credits that fluctuate in price. Gramig and Widmar (2018) also find that farmers prefer government programs with defined benefits to private credit markets with uncertain future payments.

5.6 Conclusion

Agricultural carbon sequestration has the potential to play a sizeable role at the margins of climate change mitigation policy. Global implementation of practices like no-till, cover crops, and other practices could sequester a combined 0.35 GT C/yr until 2100 (Table 5.1). Advanced soil amendments like biochar and enhanced rock weathering could help sequester an additional 1 to 2 GT C/yr (Table 5.1). Nevertheless, even optimistic estimates such as these are a fraction of annual fossil fuel emissions, and soil carbon should be seen as only one policy lever.

Moreover, the natural cycles of soil carbon make measuring and manipulating soil carbon stocks on working cropland exceedingly difficult. Practices like no-till may take decades to measurably impact soil carbon stocks and have already been widely adopted. Natural factors like climate and soil types create heterogeneity in outcomes that makes a homogeneous approach inefficient. In fact, incentivizing practices like no-till in the wrong fields could lead to soil carbon losses and decreased crop productivity (Sun et al., 2020).

We conclude by emphasizing two points. First, factors like heterogeneity, costly measurement, and uncertainty prevent simple policy solutions. While a simple Pigouvian tax may be the go-to policy recommendation for fossil fuel emissions, the costliness to accurately measure each farm's emissions or sinks on an annual basis makes an analogous policy infeasible in agriculture. Improving carbon models and spectral imaging, and otherwise reducing the MRV costs, would help improve policy efficiency. The Growing Climate Solutions Act is one positive initiative in this direction (USDA,2023b). In the interim, it is important to make policy robust to the heterogeneity and uncertainty.

Second, movement of land in and out of crops has large effects on soil carbon stocks, as we discuss in Section 5.3.4. Gains from marginal changes in tillage or cover-cropping practices could easily be swamped by carbon losses from cropland conversion. To avoid such outcomes, continued increases in agricultural productivity are imperative. Burney et al. (2010) estimate that increased agricultural productivity from higher yields is estimated to have avoided up to 161 GT C emissions since 1961. Moreover, they estimate that investments in agricultural R&D have reduced carbon emissions at a cost of \$ 15 t/C—a much lower cost than any of the practices listed in Table 5.1. At the same time, these higher yields have contributed to global food security and lifted millions of lives out of poverty. Investing more in research and development to increase agricultural productivity could provide a true win-win scenario of reducing climate change emissions while also increasing global welfare, but it faces a stiff challenge because the changing climate will likely reduce agricultural productivity growth (Ortiz-Bobea et al., 2021).

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Appendix A

Additional Tables

Appendix Table A.1 shows the cumulative pass-through estimates for two different versions of empirical model (4.6). Model 1 shows the results presented in Figure 4.11 while Model 2 shows the results from Figure 4.12. Model 2 includes 8 lagged differences of weekly changes in ethanol and corn oil prices. The inclusion of corn oil and ethanol differences has very little effect on the point estimate of the pass-through up to two weeks, but their inclusion reduces the noise in the standard errors of the pass-through estimates. The cumulative point estimates for the two models are very close at \$0.40 and \$0.35 cents after two weeks, and it is clear that the point estimate remains relatively constant as time progresses.

Table A.1: Cumulative Pass-Through Estimates from LCFS Credit Value Changes to Basis

	Model	
	1	2
Initial Pass-through	0.1587*	0.1119
	(0.0857)	(0.0692)
1 Week Total Pass-through	0.3171**	0.2475**
	(0.1482)	(0.1191)
2 Week Total Pass-through	0.4042**	0.3525**
	(0.1775)	(0.1589)
3 Week Total Pass-through		0.2469
		(0.1959)
4 Week Total Pass-through		0.2098
		(0.2389)
5 Week Total Pass-through		0.2823
		(0.2610)
6 Week Total Pass-through		0.2785
		(0.2999)
7 Week Total Pass-through		0.4145
		(0.3325)
8 Week Total Pass-through		0.3869
		(0.3545)
Lags Credit Value Differences	2	8
Lags Ethanol Prices Differences	0	8
Lags Corn Oil Prices Differences	0	8
Fixed Effects	Year-Month	Year-Month

Note: Initial Pass-Through is the pass-through estimate during the week the LCFS credit value change occurs. Total Pass-Through represents the cumulative pass-through after the listed number of weeks has past. Model 1 includes measures pass-through up to 2 weeks while Model 2 measures pass-through after 8 weeks has passed. Model 2 also includes lagged differences in ethanol and corn oil prices from previous 8 weeks. Point estimate is above the standard errors in parentheses. Standard errors are calculated using Driscoll-Kraay method with 3 lags (Driscoll and Kraay, 1998). *,**,*** indicate p-values less than 0.10, 0.05, and 0.01, respectively.