Three Essays in Agricultural Policy Analysis

by

James Dewey Davis

(Under the Direction of Michael K. Adjemian)

Abstract

U.S. biofuel policies established a link between energy and grain commodity markets. Hence, a large portion of the U.S. corn crop is now used to manufacture ethanol for blending in commercial fuels. Livestock producers, especially beef producers, also heavily rely on cheap corn as the primary feed input in production. We develop and estimate a structural model of energy, grain, and beef markets that decomposes the impact of structural shocks on the U.S. beef herd size. Our results show that a positive increase in energy or corn demand has a significant negative effect on the herd size. Moreover, the unintended consequences from this government policy extend to the underlying asset: land values. We develop a theoretical model of agricultural land values that accounts for the simultaneity problem between the determinants of cropland and pastureland. We estimate our reduced form model using a two-stage event study design. We find that the combination of direct and indirect government support for cropland decreased the relative value of pastureland. Following this theme, we analyze how changes in U.S. forest policies and market structure affected the way in which prices transmit between lumber products and standing timber. In particular, we examine how gains in the productive capacity of timber producers along with increasing inventories on the part of lumber manufacturers impact vertical price transmission in the housing supply chain. We estimate a nonlinear autoregressive distributed lag model of housing to lumber price transmission, using monthly data and controlling for the cost of mortgages and new home inventory. We find that housing price shocks transmit to lumber prices asymmetrically with only positive shocks having a significant effect. Next, we apply the model to lumber and timber quarterly price data, controlling in this case for lumber inventories. We find that shocks to lumber prices, conditioning on inventories, have no significant effect on timber prices in the long-run.

Index words: Agricultural Policy Analysis, Price Analysis, U.S. Biofuel Policy, Time Series Analysis, Structural VAR, Instrumental Variables, Land Values, Forest Policy, & Asymmetric Price Transmission Models

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Dedication

This work was a labor of love, but a labor nonetheless. I would like to dedicate it to the love of my life, Elena Cuadros. I must also acknowledge my parents, Joe Davis Jr. and Sharon Ficquette, whose constant support throughout my life has set an example I hope to live up to with my own children. Lastly, but of course not the least, I would like to express my love and thanks to my brother, Pooka, for being the best big brother there could ever be.

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Chapter 1

Introduction

Agricultural policy analysis is critical to understanding the impact of policy interventions within one and across multiple supply chains. Consequently, the benefits of U.S. agricultural policy goals with regards to stabilizing commodity prices, raising farm incomes, and promoting sustainability are weighed against the cost of such market interventions. Often, the unintended consequences of agricultural policies are substantial, but neglected. In this work, we critically analyze the economic consequences of (1) U.S. biofuel policies on herd size and profitability decisions; (2) government support on the disparity between cropland and pastureland values; and (3) U.S. forestry policies on softwood lumber price transmission. Our findings contribute to the literature on agricultural land values, biofuel externalities in livestock markets, and price asymmetry across the housing supply chain.

The food vs. fuel debate emerged following the adoption of several biofuel policies in the United States. The primary focus of this literature at the time was on the impact to consumer food prices. Nonetheless, by the mid-2010s a growing body of research focusing on the impact of biofuels to farm crop commodity prices emerged. Carter et al. (2017) defines this literature. They use corn price and inventory data as well as measures of real economic activity and energy prices to estimate a structural model of grain and energy markets in the aftermath of the Renewable Fuel Standard (RFS). They compare their estimated impulse response functions to counterfactual results, assuming a business-as-usual scenario. Their results show that RFS did have a significant positive impact on corn prices. Critically, this methodological approach to price transmission is adaptable across markets. Specifically, we extend the structural model of Carter et al. (2017) to estimate price transmission effects of RFS on cattle markets, which rely upon cheap corn as the primary input. In chapter 2, we perform this analysis on the U.S. beef herd size. First, we estimate our model under a recursive design, which assumes no contemporaneous interactions between upstream and downstream variables. Our results show that following RFS adoption shocks to energy and corn prices resulted in a significant negative effect on the U.S. beef herd size. We also identify multiple structural breaks in the herd size that correspond to biofuel policy shifts. As a result, we re-estimate our model pre- and post-structural break to quantify the impact of policy changes to the evolving beef herd size. Moreover, we include robustness checks of the model under alternative measures of economic activity, identification strategies, and the presence of potential confounding variables such as extreme weather events. Finally, using simulated monthly net returns of Kansas feedlot data, we detect a significant structural break in beef producer profitability following RFS adoption.

In the third chapter, we build on our work of herd size and profitability by analyzing how government support for crop production has contributed to a divergence in cropland and pastureland values. Over the past two decades, the real value of cropland has increased, while the real value of pastureland remains flat. Yet, the market value of their derived products are almost equivalent. In addition, crop producers receive greater support in terms of direct governmental outlays as well as indirectly through policy mandates. We develop a theoretical model of cropland and pastureland markets that contributes to the agricultural land values literature. In particular, our model accounts for the simultaneity problem inherent in the determinants of cropland and pastureland values, and it incorporates real measures of producer behavior to capture the effects of U.S. biofuel policies on cropland demand. In our two-stage empirical design, we identify a set of valid external instruments, including lagged market returns, lagged government receipts, and contemporaneous weather and population characteristics. We estimate our econometric model using an event study design on county-level Census of Agriculture Data from 1997 to 2017. An event study is valid in this context given that the discrete change in cropland demand following RFS adoption is not directly capitalized in our chosen external market and government instruments. Our results show that positive changes in cropland values pass through to pastureland values, though the direct effect of government outlays on pastureland values is significantly negative. Furthermore, the marginal effect of changing demand for cropland is significantly negative. Hence, our results establish a critical link between cropland and pastureland values that impacts the welfare of both crop and livestock producers. We also formally test the validity of our model using: (1) a single equation relative price model; (2) a reverse transmission model from pastureland to cropland; (3) an internal instruments model. Each of these checks support our empirical findings and the work of previous land value studies (e.g. Kropp and Peckham, 2015). The major implication of this work is that policymakers considering, for example, expanded subsidized insurance programs within farm bill appropriations, should account for the impact to the relative value of other agricultural land uses.

The fourth chapter analyzes vertical price asymmetry along the housing supply chain. Since 2010, following the Great Recession, real lumber and new housing unit prices increased substantially, while the value of land in timber production, usually valued per stump (i.e. stumpage), did not increase. Our objective is to fill a notable gap in the literature by estimating a price transmission model of the entire housing supply chain that controls for both housing and lumber inventories. Our supposition is that lumber manufacturers strategically set inventory levels to capture sudden positive shocks to new home prices and moderate negative shocks. Upstream, we theorize that lumber manufacturers keep inventory levels such that sudden changes to the demand for lumber does not transmit into changes in demand for stumpage. In the literature, lumber price dynamics are typically modeled with threshold vector error correction models (VECM) that are inefficient for small samples and require the order of integration for each series be equal. Shin et al. (2013) develops a intuitive extension to the autoregressive distributed lag model that accounts for nonlinear positive and negative asymmetries, colloquially known as a NARDL (nonlinear autoregressive distributed lag) model. A NARDL model performs better than traditional

VECM in small samples and does not require equal order of integration between series. In our analysis, we estimate a NARDL model of housing price transmission to lumber, controlling for new home inventories. From the estimated cointegrating relationship we calculate long-run price elasticities that show that a 1% increase in new housing prices corresponds to a 0.28% (95%–C.I.: 0.03%;0.53%) increase in lumber prices. In contrast, we find that negative shocks to housing have no significant effect. Next, we estimate a NARDL model for lumber price transmission to stumpage, controlling for lumber inventories. Our results show that stumpage prices do not respond to positive or negative shocks in lumber prices.

The next chapter details our herd size model and results. Chapter three describes our analysis of land values. Chapter four presents our NARDL framework of price transmission from housing to lumber and from lumber to stumpage prices. Chapter five concludes.

Chapter 2

Analyzing the Downstream Impacts of U.S. Biofuel Policies

Researchers have shown that U.S. biofuel policies raise grain prices, increasing the welfare of grain producers. But, the downstream implications of those policies have not received much attention. By creating new demand-side competitors for feed inputs, these policies also risk harmful effects on cattle producers. We investigate the effects of biofuel policies on cattle markets along several dimensions, focusing on price dynamics and herd size. We find that the adoption of the Renewable Fuel Standard II (RFS–2) in the United States changed the relationship between ethanol, corn, and beef, such that: (1) a 1% increase in corn prices leads to a herd reduction of -2.33% in the U.S. beef herd (90%–C.I.: -3.12%, -1.54%) in the short run; (2) a 1% increase in the price of oil results in a reduction of -1.90% in the herd size (90%–C.I.: -3.80%, -0.02%) in the long run; and (3) steer returns fell on average by $59.50 per head in real 2010 dollars (90%–C.I.: -$11.14;-$107.84).

2.1 Introduction

For the past 20 years, U.S. agricultural and energy policy targeted biofuels as an effective tool to augment domestic energy production and raise demand for farm products, particularly grains and oilseeds. A substantial body of empirical evidence details how corn and soybean prices increased in response to the government-enhanced demand for biofuels (see Wright, 2014 & de Gorter et al., 2015). These policies raised the income of crop producers and also linked crop commodities with energy production. For instance, the most obvious effect of government support for biofuels is that Americans now pour a significant percentage of the U.S. corn crop into their gasoline tanks (USDA, 2022b). Moreover, corn ethanol use now rivals its feed use, according to the latest statistics (USDA, 2023). Yet, much of the extant literature critifcally assesses the impact of U.S. biofuel policies on food crop markets and consumer welfare.

On the other hand, virtually no academic attention is paid to the downstream impacts of biofuel policies, specifically with regard to livestock producers who compete with biofuel manufacturers for inputs. We investigate this question using a similar framework to the one developed by Carter et al. (2017) to understand the dynamics of U.S. biofuel policies and their effects on beef herd size and profitability. We begin by developing a structural model of the U.S. herd size consistent with individual cattle producer behavior. This allows us to test how producers respond to changes in the causal relationships between feed inputs, energy, and livestock production. Specifically, we argue the corn price increase and the enhanced sensitivity of corn prices to energy price shocks due to ethanol policy contributed significantly to the dramatic reduction in the U.S. herd size over the last decade. Our results indicate that cattle producers respond to sudden rises in corn–but also energy–prices by selling off a portion of their herd. In particular, our results suggest that when corn prices suddenly increase, beef producers reduce their herds; simultaneously, higher oil prices yield higher demand for ethanol and the corn to manufacture it, which increases the cost of beef production and leads to further herd reductions. We find also that cattle producer profitability declined following the implementation of major biofuel policy initiatives.

We analyze the contribution of U.S. biofuel policy on the evolving U.S. beef herd size by describing a theoretical model of beef producer choice. We then determine the counterfactual (business-as-usual) time series for herd size. Finally, we search for structural breaks in the beef herd series, focusing on those breaks which coincide with significant changes in U.S. biofuel policy.

2.1.1 Brief Overview of U.S. Biofuel Policy

The origins of biofuel policy in the United States traces to the Energy Tax Act of 1978, which provided a tax exemption for ethanol fuel blends at 100% of the gasoline tax (Kesan et al., 2012). Congress expanded that support with the passage of the Clean Air Act (CAA) of 1990 followed by the Energy Policy Act of 1992, appropriating resources towards research into the production and commercialization of alternative fuels. Congress continued this policy initiative with a series of reforms in the early 2000s (FAO, 2008), addressing commercial fuel blending, particularly with regard to Methyl-tert-butyl ether (MTBE). MTBE raises octane levels in gasoline and reduces fuel emissions, however it can also leach into groundwater and cause serious health outcomes. In response, in 2001 California announced a ban on MTBE. In 2003, California, the nation's largest commercial vehicle market phased out MTBE in favor of ethanol (McCarthy and Tiemann, 2006). Other states like New York, Connecticut, and Vermont followed and placed restrictions on the use of MTBE, resulting in a significant decline in the demand for MTBE as a fuel oxygenate and consequent increase in the demand for ethanol as a substitute blending agent (Duffield et al., 2015). Just a few years later, Congress decided to intervene directly in the renewable energy market by mandating biofuel production and adoption.

The American Jobs Act of 2004 introduced the Volumetric Ethanol Excise Tax Credit (VEETC), a tax credit of 51 cents per gallon of ethanol for commercial sellers. In 2005, Congress enacted the Renewable Fuel Standard (RFS-1). RFS-1 required 4 billion gallons of renewable fuel by 2006. In 2007, Congress expanded the mandate of the RFS-1 with the passage of the Energy Independence and Security Act of 2007, which stated that by 2009 domestic refiners must blend the fuel that Americans consume with 9 billion gallons of ethanol, with scheduled yearly increases to a 36 billion-gallon target in 2022 (Brown and Brown, 2012). This expansion is known as the RFS-2 and it is the primary focus of this analysis, since the RFS-1 mandates ethanol use at levels in compliance with the prior Clean Air Act of 1990 at no instrumental increase (Yacobucci, 2012; Carter et al., 2017). Various observers rationalize the government-imposed RFS and the RFS-2 mandates as pursuing a variety of objectives, including reducing carbon emissions and limiting dependence on foreign energy sources (Moschini, Cui and Lapan, 2012). However empirical support for this consensus in the scientific community remains elusive. For example, Lark et al. (2022) estimate that the land use changes involved to grow the corn required to meet the mandates of the RFS-2 are more environmentally costly than burning un-blended gasoline.

2.1.2 Downstream Consequences

While the impacts of the RFS-2 on the environment and crop prices are well-documented, the downstream impacts to beef markets of biofuel policy is effectively unexplored in the literature, even though feed (primarily corn) makes up approximately two-thirds of cattle production costs (Lawrence et al., 2008; Holgrem and Feuz, 2015). In fact, Babcock analyzed the cost increases of the ethanol tax credit and import tariffs. He found that by the summer of 2010 the average cost of feed for feeder cattle increased by $0.24 per pound (Babcock, 2010). Industry advocacy groups routinely express concerns about the additional costs imposed by biofuel policies. For example, the National Cattlemen Beef Association (NCBA) filed three RFS volume waiver petitions to request suspension of annual biofuel mandates on the basis of economic hardship (NCBA, 2012; Feinman, 2013). In each of these petitions, the NCBA consistently pointed to potential herd reductions as a likely consequence of the RFS-1 and RFS-2. The petitions sought to exempt refiners from blend requirements, especially during natural disasters (such as drought) since blending commercial fuels results in even higher feed costs. In 2008, Former Texas Governor Rick Perry pursued a volume waiver, requesting a 50% reduction in mandated biofuel volumes, arguing that the program's unintended consequences will lead to real economic harm to livestock producers and higher food prices (Schor, 2008). In 2012, a coalition of livestock farmers petitioned the EPA to reduce mandated biofuel volumes, stating that, along with extreme weather conditions, the RFS will lead to significant herd reduction across the country (O'Malley and Searle, 2021). In addition, ten U.S. states submitted RFS waivers, arguing that the program could lead to higher food costs and grain supply depletion. In each instance, EPA did not grant a waiver, concluding that the impacts of the program on livestock producers did not meet the definition of severe economic harm (NLR, 2012). And in a recent book about the challenges facing the cattle industry, Peel (2021) argues the adoption of ethanol mandates added to the cyclical contraction in the U.S. beef herd.

While the farm lobby remains divided on biofuel efficacy, top-level federal officials stress farm-level benefits of the policy. For example, in December 2021, Secretary of Agriculture Vilsack referenced the Biofuel Producer Program (authorized by the Coronavirus Aid, Relief, and Economic Security Act), which makes available $700 million in economic relief to the nation's biofuel producers. This policy intended to support ethanol manufacturers to stay in business after the pandemic-induced economic downturn, so that the added costs of ethanol production were not passed on to gasoline refiners and ultimately American car owners in the short run. The program strengthened ethanol producers and stimulated their demand for corn, while at the same time increasing competition for a major input to livestock production. Even more recently as the Russo-Ukraine conflict developed in April 2022, the

Biden Administration refused to grant blend waivers to thirty-five refiners, arguing such initiatives are necessary for domestic energy security, and essential to the profitability of both the farmer and rancher (USDA, 2021).

In this article, we critically evaluate the second part of that claim by estimating the economic impacts of U.S. ethanol policy to domestic cattle producers along several dimensions. In particular, we analyze how biofuel policies link energy prices and U.S. beef herd size, and how real returns to cattle producers fell permanently following the implementation of RFS-1 & RFS-2. In the next section, we provide an overview of the existing literature on the relationship between biofuel policy and food commodities. In section 2.3, we offer background information on the cattle industry. Section 2.4 details our data, theoretical model, and empirical framework. Section 2.5 presents our results. Section 2.6 discusses other exogenous shocks to cattle markets. Section 2.7 describes our profitability results, and Section 2.8 concludes.

2.2 Relevant Literature

Carter et al. (2011) and de Gorter et al. (2015) attribute the doubling of food commodity prices between 2008-2012 to the systemic changes in U.S. biofuel policies–specifically, the MTBE ban, RFS-1, and RFS-2. However, it is important to note that there is some contention surrounding the impact of biofuels on food commodity prices[1]. Nevertheless, several studies in the literature identify biofuel policy as an important contributing factor among many to the commodity price boom of the late 2000s.

Studies examining the relationship between food prices and the demand for biofuels traditionally follow a equilibrium or time series approach, but in general results are consistent across both methods. We focus on the time series approach employed by Carter et al. (2017) and Smith (2019) to analyze the impact of U.S. biofuel policy on livestock markets. However, we briefly discuss both methods here.

Several researchers employ either partial equilibrium (PE) or computable general equilibrium (CGE) models to demonstrate the impacts of biofuel policies across markets. For example, Chen and Khanna (2013) use the BEPAM[2] to analyze the contribution of the RFS and other complementary policies (the VEETC and import tariffs) to corn and soybean prices along with sugarcane imports in the United States relative to a counterfactual scenario with no government intervention in the biofuel sector. They estimate a 0.7% increase in the corn price per billion gallon increase in ethanol production (a 25% in the price of corn following the 36 billion RFS-2 mandate). In addition, they find in the absence of sugarcane tariffs, implemented to suppress competition with Brazilian sugarcane ethanol manufacturers, that 3.3 billion liters of ethanol would have been imported. Hertel et al. (2010) use a different computable general equilibrium model built upon the standard Global Trade Analysis Project (GTAP) framework. They estimate a smaller effect of U.S. biofuel policies on the price of corn: approximately 1.3% per billion gallons of ethanol produced. However, they also find that acreage planted to coarse grains in the United

[1]For example, others attribute the price boom to, e.g., increased demand for more resource-intensive foods in rapidly-developing nations (von Braun, 2007), financial speculation (see, e.g., Reguly, 2008)—even though the evidence supporting that view is mixed, and a combination of factors, including weather-related production shortfalls (Condon et al., 2015), U.S. monetary policy, and a leveling-out of crude oil production (Trostle, 2008).

[2]Biofuel and Environmental Policy Analysis Model.

States would rise by 10% as a result of biofuel policy mandates, while forest and pastureland areas of the United States would decrease by 3.1%. Therefore, even under conservative estimates for corn price changes, ethanol expansion under the RFS-2 has significant effects on land use in the United States. Lapan and Moschini (2009) build a simplified two-country general equilibrium model, where the energy and food sectors are linked. This competitive model assumes an upward sloping supply of corn with multiple uses: feed, energy, food, and export. They show that an ethanol mandate yields higher welfare than an ethanol subsidy. Cui et al. (2011) adapt and extend Lapan and Moschini's model to make it more suitable for simulating the consequences of alternative policies. The extension recognizes that firms produce other products when they refine oil, in addition to gasoline (such as fuel oil, jet fuel, and petroleum coke). The authors aggregate all non-gasoline output into a single good called petroleum by-products. Consistent with Chen and Khanna (2013), Cui et al. (2011) estimate that corn prices should rise by 3.75% per billion gallons of ethanol produced. Moschini et al. (2017) build a multi-market model of the U.S. supply of corn, soybeans, oil, incorporating domestic and rest-of-world demand for food products and transportation fuels. They simulate their model under a no-RFS scenario, 2022 RFS-2 scenario, and optimal (second-best) mandates scenario. Compared to the no-RFS scenario, they find that the current 2022 RFS-2 mandates increase corn prices by 3.6% per billion gallon of ethanol produced. At the low end, Gehlhar et al. (2010) found in a general equilibrium analysis that for every billion gallons of ethanol produced the price of corn will only rise by 0.4–0.7%. However, this report is focused on consumer welfare impacts as they claim that the RFS-2 would impact food prices considerably less than it would impact farm commodity prices in the long term (i.e. by mandate objectives of 2022).

Our methodology relies on the time series approach developed by Carter et al. (2017). They develop a partially identified structural vector autoregression (SVAR) model to estimate the effect of the RFS-2 on corn prices. Smith (2019) updates their model for corn with data through the 2016-17 crop year, and also applies the model to soybeans and wheat. This model rests on the fact the RFS-2 is a persistent rather than a transitory shock to agricultural markets. This distinction is important because persistent shocks have longer-lasting price effects than transitory shocks, and are signified by a structural break. Markets for storable commodities can respond to a transitory shock, such as poor weather conditions, by drawing down inventories, mitigating its effects. In contrast, inventories cannot insulate market participants from a persistent shock. Carter et al. (2017) decompose the shock to crop inventories and spot prices, owing to the increase in the demand for corn and soybeans, by generating impulse response functions for corn and soy futures prices and inventories. Their results show that inventory demand shocks increase futures prices. Their findings for the impact of the RFS-2 aligns with the general equilibrium analysis results: they estimate that every billion gallons of ethanol produced raises the price of corn by 5.6% (95% CI– 0.9%, 17%). To account for the short-term and long-term response to shocks, Carter et al. (2017) include in their model the convenience yield, allowing them to isolate RFS-2's persistent impact on agricultural commodities. Consistent with Carter et al. (2017), Smith (2019) also accounts for convenience yield and estimates the increase to the corn price over the life of the RFS-2 at approximately 30%.

2.3 Cattle Market Background

To facilitate our discussion, we provide an overview of the modern beef industry and offer important definitions, including a typical timeline for the production process. We begin by defining the set of production inputs along with a description of the production function for cattle producers. We then illustrate input costs, focusing on feed costs, and the typical feed input mix of producers. We conclude with an overview of the beef supply chain. Finally, for context, we complete this section with a brief summary of the beef cattle supply chain as well as general trends in cattle markets over the last few decades.

The cattle production function is made up of equipment and infrastructure, weather conditions, feed, supplemental nutrients, and veterinary resources. Equipment and infrastructure includes, for example, fencing, corrals for cattle handling, and machines for forage production and transporting cattle to market. Weather conditions affect cattle performance, e.g., extreme heat reduces an animal's ability to gain weight and leads to heat stress. Veterinary services ensure herd health and effective reproduction. Successful production of beef cattle necessitates good quality feed. In fact, feed is the principle component of all models of the production function for cattle (Heady et al., 1963; Lalman et al., 1993; Van Amburgh et al., 2008; Holgrem and Feuz, 2015). Specific feed rations depend on the type of operation and the time of the year. For example, in the winter, producers might opt for a low-energy ration composed of primarily fibrous hay supplemented with more high-energy silage[3] and essential minerals (e.g. calcium, phosphorus, and potassium). In contrast, in the spring and summer, producers may adopt a more high-energy diet composed of feed grains to promote rapid weight gain in the herd. In terms of total digestible nutrients[4] (TDN), up to 70% of such a feed mix would come from feed grains (Lalman et. al., 1993; NRC, 2000) like corn, sorghum, barley, and oats. In the United States, corn is far and away the primary choice of producers, accounting for more than 95% of total feed grain production and use (USDA, 2020). Byproducts of ethanol production (i.e. distillers grain) can be substituted for feed grain, and are primarily used in the Midwest and Great Plains[5].

Feed represents the primary cost for a beef producer, accounting for 60% of the cost of production (Lawrence et al., 2008; Holgrem and Feuz, 2015). Therefore, corn price changes play a dominant role in the cost of beef production. In fact, Tonsor and Mollohan (2017) show that the corn price is inversely related to cattle margins: as the price of corn increases, returns to cattle producers decrease. As a result, the cattle market is highly susceptible to corn price volatility. Figure 2.1 shows the real farm price of corn from 1983-2022. The period of corn price doubling is clearly visible, and while it does stabilize around $5.00/bushel (in real terms) toward the end of the 2010s, it remains well above prices observed during the 1980s and 1990s. Compounding the feed input cost rise is the significant increase in the cost of crude oil over the past 40 years. Figure 2.1 also shows the West Texas Intermediate (WTI) real futures price over the same time period. For the first half of the period, oil prices remained relatively stable below $50 dollars a

[3]Refers to grasses grown for forage and harvested at a relatively high moisture level; the most common types of silage include alfalfa and corn in the United States.

[4]The proportion of feed that an animal can metabolize into their system.

[5]E.g., Cottonseed, a byproduct of the ginning process for cotton, can also serve as a feed grain substitute (perhaps in times of high grain prices) in the southern United States, since it is an adequate source of protein.

barrel. However, beginning in the early 2000s, oil prices spiked and have remained elevated compared to historical levels. A direct effect of this trend is the higher cost of transportation for beef producers, packers, and distributors. In addition, the long beef cattle production cycle[6] (relative to commodity crops, for example) increases the role of uncertainty with respect to investment, and when coupled with higher feed and transportation costs places pressure on the domestic herd size. The second panel of figure 2.1 shows that, since the late 1970s, the U.S. beef herd size fell from approximately 39 million head to a 60-year low in 2014 of just over 29 million head. Since 2014, the herd size grew slightly before falling again. In fact, the latest Cattle Inventory Report for January 2023 shows that the beef cow herd totaled 28.9 million head, down 4% from a year earlier and the lowest since 2014-15 (NASS, 2023). Polansek (2022) attributes this trend to adverse weather conditions, reducing the amount of pasture for grazing and driving up the price of feed grain. However, we posit that increased competition in corn demand from ethanol production contributed significantly to the reduction in the beef herd size over the last two cattle cycles.

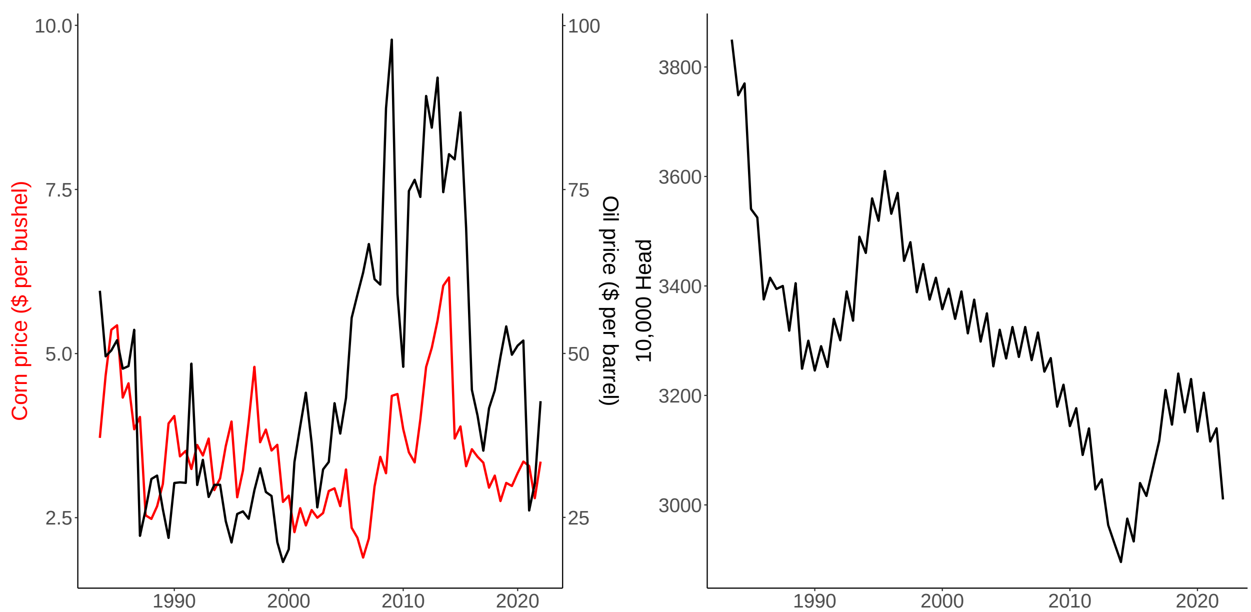

Figure 2.1: U.S. Beef Herd Size, Corn, and Crude Oil Prices 1983 - 2022
Source: CME 2022, Agricultural Marketing Service (AMS) 2022 & USDA Cattle Inventory Report 2022.

[6]The natural cattle cycle: a process in which the size of the national beef herd—including all cattle and calves—increases and decreases over time. This typically lasts between 8 to 12 years, with the last full cycle beginning in 2004. The herd size grew slightly over the next three years before increasing feed and energy prices led the herd size to contract sharply, reaching a record low in 2014 (NASS, 2022a).

One sign of the disparate impacts of biofuels policy on upstream and downstream agricultural producers is the difference in land price paths, which capitalize the value of production according to economic theory (Doye and Brorsen, 2011). Figure 2.2 shows that while cropland values nearly doubled in real terms since the late-1990's, pastureland values have increased by a much smaller factor–just a few hundred dollars per acre. U.S. Government support for agriculture, codified about every five years in the Farm Bill, provides crop producers with significant support through subsidized crop and revenue insurance programs, but little in the way of support for livestock producers. For example, the 2018 Farm Bill allocates almost $70 billion to crop insurance and commodity risk protection programs (CRS, 2019). Livestock producers do not receive the same level of support under the legislation. In fact, for the 2018 Farm Bill, the amount of spending on livestock programs is less than 1% compared to 23% for crop programs (CRS, 2019). Even ad hoc programs, such as the direct assistance to producers to remunerate them for trade war damages is targeted to the producers of crops, not livestock (Adjemian et al., 2021).

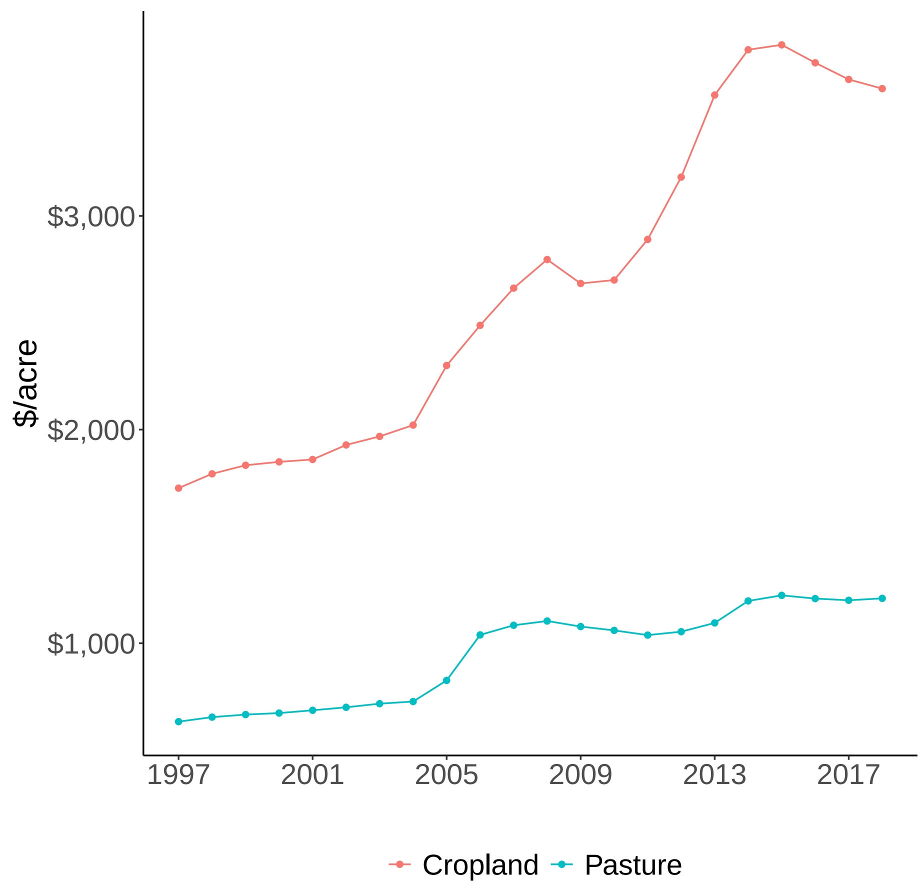

Figure 2.2: U.S. Real Land Values 1997-2018
Source: NASS Land Asset Values Survey 2018.

2.4 Data and Methods

To examine the impact of U.S. biofuels policy on the cattle industry, we first develop a theoretical model of herd supply. We then test this model following the vector autoregressive (VAR) approach applied by Carter et al. (2017) to estimate the impact of government support for ethanol on the U.S. beef herd size. We collect biannual (January and July) herd data from the National Agricultural Statistics Service (NASS) for the U.S. beef herd from 1983 to 2022. These data are available through the NASS Cattle Inventory Report[7]. We match our herd data with the farm corn price published by the Agricultural Marketing Service (AMS)[8]. For example, the Cattle Inventory Report is published at the first of the month in January and July. Therefore, we take the AMS farm corn price published in March the year prior for the January Cattle Inventory Report and November for the July report. We do the same for the farm cattle price, which is an aggregated price for beef cattle. For energy prices, we use the front-month closing price for West Texas Intermediate (WTI) crude oil. To match our energy price series consistently with our observations for corn, cattle, and herd size, we average the real WTI futures price for March prior to each January cattle report, and then the average real futures price series in November for the July cattle report. By matching this way, we generate 74 observations for the time period July 1983 to January 2022. The purpose of the 8 month lag in determining our price series is biological and is similar to the agronomic reasoning used by Carter et al. (2017). Those authors apply a one-year lag to reflect the cropping year of corn, September to August. Since it takes on average 8 months to "finish" cattle (i.e. bring them to market weight), livestock producers determine marketing decisions for December-January the prior March (or November for July decisions). These decisions consist of determining the amount and type of feed purchased for finishing, dependent on the herd size chosen by the producer.

Table 2.1 presents summary statistics for our relevant series. From 1983 to 2022, the average size of the U.S. beef herd was 33 million head, which is down from the early 1970s high of about 40 million. The corn price experienced dramatic changes over this same time period, rising to almost $11.00 per bushel (in real terms), following the RFS-2. Crude oil follows a similar trend, rising in the early 2000s to a record high in 2008-09 before collapsing during the Great Recession only to bounce back in the 2010s. Live Cattle, however, remains steady relative to the other series with short cycles of highs and lows throughout the 2000s and 2010s.

[7]The report was suspended in 2013 and 2016 due to sequestration.

[8]All prices are deflated using the Producer Price Index (PPI) base year 2010, Federal Reserve Economic Data (FRED) 2022.

Table 2.1: Summary Statistics: Herd Size Model (1983-2022)

Statistic	N	Mean	St. Dev.
REA	78	0.58	58.00
WTI $/barrel	78	45.92	20.23
Farm Corn Price $/bushel	78	3.49	0.88
Farm Cattle Price $/cwt	78	99.64	14.01
Herd Size 10,000 head	76	3,302	188

Source: NASS 2022a, AMS 2022, & CME 2022.

Note: Bi-annual data reflecting January and July herd report releases.

Our data include a measure of economic activity in the general economy. We use as a measure of real aggregate demand, the REA, or real economic activity, first developed by Kilian (2009). This index is based on dry-cargo shipping rates and is designed to capture changes in global demand for industrial products. The REA is a direct measure of global economic activity not reliant on exchange-rate weighting, aggregates across countries, and incorporates variation in the composition of real output (Carter et al., 2017). This fundamental measure captures the shock to economic activity generated, for example, by the adoption of a mandate for ethanol consumption. Subsequent work by Hamilton (2021) questions the use of REA in analysis, since when constructing the series Kilian takes a double log, making the choice of initializing value critical for the resulting series. As such, Kilian (2019) updates the index removing this double log. We use this updated measure in our analysis. Hamilton (2021) proposes an alternative global real economic activity based on monthly world industrial production from the Organization of Economic Co-operation and Development (OECD)[9]. Compared to the REA, the industrial production data– according to Hamilton–implies that the Great Recession was clearly the most significant downturn in global real activity during this period. For robustness, we include our model results using the WIP as our measure of real aggregate demand in the appendix.

Table 2.2 presents the summary statistics for monthly cattle market returns from 2000 to 2020, using Kansas feedlot data. Feeding cost of gain[10] is reported in the Focus in Feedlots newsletter[11] produced by Kansas State University (KSU). Feeder cattle prices for Kansas are reported by the Livestock Marketing Information Center (LMIC)[12]. Feeder cattle are cattle on feed that have yet to reach marketable weight. Their prices are reported for different weight categories (e.g., 600 to 700 lbs., 700 to 800 lbs., and 800 to 900 lbs.). We use this information along with feeder weight reported in the Focus on Feedlots newsletter, Kansas State University, to compute the feeder price for each month. Fed (or finished) cattle prices for steers in Kansas are reported by the LMIC. The "price ratio" is the feeder to fed cattle price ratio. Again, feeder cattle are distinct from fed cattle in that fed cattle have reached maturity (approx. 1100 lbs.) and are

[9]The monthly world industrial production index (WIP) includes the OECD plus six major countries: Brazil, China, India, Indonesia, the Russian Federation, and South Africa.

[10]An industry efficiency measure defined as the total feed cost of grain divided by total weight gain (in lbs.).

[11]Focus on Feedlots Newsletters.

[12]LMIC website.

ready for market, while feeder cattle are still maturing but can be put on feed in feedlots for finishing. Feed conversion is also reported in the Focus on Feedlots newsletter, Kansas State University, where the "feed conversion rate" is defined as the amount of feed input divided by the total mass of the fed cow/steer at finishing or its dressed (post-slaughtering) weight. In addition, the newsletter reports an inventory price for corn and alfalfa, as averaged over the previous five months–an appropriate measure for the feed cost of production. Simulated net returns per head of cattle producers are computed by subtracting feeding cost of gain and interest cost from gross returns (i.e. number of cattle marketed multiplied by the price). According to table 2.2, the average net returns are negative, but note that cattle sales are not constant over time. Sale weight, feeder weight, feeding cost of gain, and days on feed (for interest cost computation) are from the Focus on Feedlots newsletter, Kansas State University. We use the interest rate on operating loans from the Kansas City Federal Reserve, a readily available interest rate for short-term assets.

Table 2.2: Summary Statistics: Monthly Net Returns and Feed Costs on Cattle (2000-2020)

Statistic	N	Mean	St. Dev.
Net Returns $/head	252	−35.26	131
Feed Cost of Gain $/cwt	252	74.73	20.63
Price Ratio	252	1.20	0.13
Feed Conversion	252	6.04	0.21
Corn Price $/bushel	252	4.00	1.51
Alfalfa Price $/ton	252	133	45.84
Feeder Price $/cwt	252	124	35.60
Fed Price $/cwt	252	103	24.78

Source: LMIC & KSU 2020.

Note: All prices, costs, and net returns are reported monthly.

Next, we investigate whether the observed variation (and decline) in beef herd size is attributable to changes in U.S. biofuels policy by (1) deriving a theoretical model of herd supply and demand consistent with the individual producer's choice of herd size; (2) analyzing the counterfactual (i.e. no VEETC, RFS, or MTBE ban, i.e. business-as-usual) time series for herd size; and (3) searching for structural breaks in the beef herd series, especially in and around the critical dates of 2001, 2004, 2005, and 2008. After identifying structural breaks in herd size, we split our sample to estimate the relationship between beef markets and energy before and after each policy change. We implement the procedure described in Bai and Perron (2003) for simultaneous estimation of multiple breakpoints. The distribution function used for the confidence intervals for the breakpoints is given in Bai (1997), and the objective is minimize the triangular residual sum of squares (RSS) matrix to determine an optimal break segment. We then use the same procedure to search for breaks in the net returns to feed and fed cattle producer data.

2.4.1 Theoretical Model

Jarvis (1974) first developed a theoretical model of U.S. herd size, treating beef cows as capital goods that follow a stock accumulation path. However, his model does not incorporate the cyclical expansions and contractions observed in the herd size, historically. Consequently, Rosen et al. (1994) develops a dynamic model of the cattle cycles observed in figure 2.1. Nerlove and Fornari (1998) adapt Rosen's model to account for the change in the structure of the cattle supply chain, specifically, the increased industrialization (e.g. feedlots) used in finishing cattle and the concentration of firms in slaughtering and packing. Most notably, Aadland (2004) models a 10-year cattle cycle, accounting for the discounted returns of marketing a cow in year t and the cost of delaying to year $t+1$. Recent empirical applications of Aadland's model include Yuhan and Shonkwiler (2016), who use a feeder/corn price ratio to estimate a VAR model of herd size as a function of market returns and input prices. Their results suggest that the feeder/corn price ratio may Granger cause herd size. However, this is an incomplete understanding, since their model assumes feed grain price shocks are exogenous, neglecting the interrelationship between ethanol demand and corn price volatility. As a result, we expand upon this approach by modeling changes in the price of corn and farm-gate cattle prices as a linked response to changes in the energy market.

Our theoretical model of herd size is derived from Aadland (2004), though adapted to account for the recent structural changes in the U.S. beef market. The cattle producer's decision problem is to maximize the discounted value of their operation over an infinite horizon subject to initial endowment $k_0^{(j)} : (j = 0, \dots m)$ is the number of females of age j on the farm. The objective of the producer is to maximize the stream of discounted profits, π_t, by choosing a series of cull rates. And, the total breeding stock for the herd at time t is measured as the sum of all females of age $j = 2, ..., m$: $b_t = k_t^{(2)} + \cdots + k_t^{(m)}$. To further specify female stock dynamics, we let the number of female calves be proportional to the breeding stock in the previous period. That is we set the proportionality coefficient as 0.5θ, where 0.5 indicates half the calf crop is female and θ is the successful birthing rate. Formally, the producer's objective is:

$$\text{Max} \quad E_t \sum_{s=0}^{\infty} \beta^s \pi_{t+s}$$

$$\text{where } \beta \text{ is the discount factor and} \tag{2.1}$$

$$\pi_t = \sum_{j=0}^{m} p_t^{(j)} \alpha_t^{(j)} (1-\delta_j) k_t^{(j)} - w_t \sum_{j=1}^{m} k_t^{(j)}.$$

$k_t^{(j)}$ is the total stock of females of age j on the farm at time t; δ_j is the mortality rate of females in each age cohort; the producer's choice variable, $\alpha_t^{(j)}$, is the cull rate (% of females marketed from that age cohort); and m is the final productive year for each cow where all cows are assumed dead at $m+1$. In addition, $p_t^{(j)}$ is the live cattle cash price of an animal at age j. The law of motion by which each age cohort of females evolves is given by:

$$k_{t+1}^{(j+1)} = (1-\delta_j)(1-\alpha_t^{(j)}) k_t^{(j)}. \tag{2.2}$$

Typically, the cost function of the producer is assumed to follow a first-order autoregressive AR(1) process:

$$w_t = \phi_0 + \phi_1 w_{t-1} + \epsilon_{w,t}. \tag{2.3}$$

We assume that $\epsilon_{w,t}$ is i.i.d. with mean 0 and variance σ_w^2. and further decompose $\epsilon_{w,t}$ into the following linear combination:

$$\epsilon_{w,t} = \epsilon_{e,t} + \epsilon_{c,t} + \epsilon_{b,t}. \tag{2.4}$$

$\{\epsilon_{e,t}; \epsilon_{c,t}; \epsilon_{b,t}\}$ represent three observable shocks that drive a producer's herd size decision: $\epsilon_{e,t}$ is a shock to energy production in time t; $\epsilon_{c,t}$ is the shock to the demand for corn; and $\epsilon_{b,t}$ is the shock to the farm price of beef. We assume these shocks are autocorrelated, and specify them as first-order Markovian process with i.i.d. innovations. These shocks capture changes in the expectations about the future cost of holding cattle of any age until the next time period $t+1$, and thus are independent of current supply and demand conditions carried from the expectations realized by $E[w_t]$. Now, using the conditional expectation property of our Markovian assumption, we can apply the framework developed by Carter et al. (2017). Therefore, the equation for the demand of holding cattle at any age j until $t+1$ in terms of the futures price is:

$$F_{t,t+1} = g(k_t^{(j)}, \epsilon_{e,t}, \epsilon_{c,t}, \epsilon_{b,t}). \tag{2.5}$$

Intertemporal accounting requires that the difference in the stock of animals in time $t+1$ and t, accounting for culled and attrition rates, is the supply of cattle at any age j held from the market. In terms of the live cattle cash price, this supply function is:

$$p_t^{(j)} = h(\Delta k_t^{(j)}, F_{t-1,t}, \epsilon_{et}, \epsilon_{ct}, \epsilon_{bt}). \tag{2.6}$$

Before we estimate the two functions in equations (5) and (6), we first add our measure of real aggregate demand, REA, to each equation and remove seasonality and trend components from each variable. Written in log form, we then have:

$$\begin{aligned} I_t^s &= \ln(h(\Delta k_t^{(j)}, F_{t-1,t}, \epsilon_{e,t}, \epsilon_{c,t}, \epsilon_{b,t})) \quad \text{(Herd Supply)}\,, \\ I_t^d &= \ln(g(k_t^{(j)}, \epsilon_{e,t}, \epsilon_{c,t}, \epsilon_{b,t}) \quad \text{(Herd Demand)}. \end{aligned} \tag{2.7}$$

I_t^s represents the supply of cattle held over. It signifies the farm price that would induce the market to supply $\Delta k_t^{(j)}$ in inventory for the next period $t+1$. We assume it is upward sloping as producers are willing to expand their herd size in anticipation of higher live cattle prices. Similarly, I_t^d represents the demand for cattle inventory. It is also assumed to be downward sloping, reflecting the fact that during periods of low feed costs producers will demand more cattle to expand their herds. Solving (5) and (6) for the equilibrium price determines the herd size in time period t. Next, we estimate herd supply and demand, adding REA in each equation and removing seasonality and trend from each series. Taking a first-order expansion around the log of each variable in (7), we obtain equations for herd supply and demand as linear combinations:

$$\begin{aligned} H_t^s &= \delta^s + \delta_{REA}^s REA_t + \delta_k^s k_{t-1}^{(j)} + \delta_f^s f_{t-1} + \delta_e^s \epsilon_{e,t} + \delta_c^s \epsilon_{c,t} + \delta_b^s \epsilon_{b,t}\,, \\ H_t^d &= \delta^d + \delta_{REA}^d REA_t + \delta_k^d k_t^{(j)} + \delta_e^d \epsilon_{e,t} + \delta_c^d \epsilon_{c,t} + \delta_b^d \epsilon_{b,t}. \end{aligned} \tag{2.8}$$

To understand how the equilibrium herd size evolves, holding all else constant, suppose herd adjustments occur according to

$$\frac{\mathrm{d}H}{\mathrm{d}t} = \lambda(H^d(\epsilon_i) - H^s(\epsilon_i)) \quad \forall \quad i \in \{b, c, e\}\,, \tag{2.9}$$

where $\frac{\mathrm{d}H}{\mathrm{d}t}$ is the time derivative of the herd size, indicating the direction and speed of herd changes, and λ is the speed of adjustment parameter. And, ϵ_i represents shocks to each input price: corn, energy, and cattle. Next, we can determine the derivative of herd size adjustments by differentiating (9) with respect to the input price shock i:

$$\frac{\mathrm{d}\left(\frac{\mathrm{d}H}{\mathrm{d}t}\right)}{\mathrm{d}\epsilon_i} = \lambda(\delta_i^d - \delta_i^s). \tag{2.10}$$

Under our log-linear framework, δ_i^d and δ_i^s represent elasticities, so that, following a price shock, the equilibrium herd size evolves according to the relative values of the elasticities. Since corn dominates the production function, we assume that the herd size supply elasticity for corn is more inelastic than the herd demand elasticity, i.e. $|\delta_c^d| > \delta_c^s$. By applying our downward sloping demand assumption, we hypothesize that a positive shock to corn prices will yield a reduction in the herd size. The same logic applies to other input price shocks associated with maintaining or expanding herd size such as cattle and energy prices. The effects of shocks to REA are indeterminate, since they are dependent on how the changes to economic activity impact downstream markets. Before we estimate the system in (8), we first make a critical assumption that allows for identification. That is, we assume there is no feedback from the cattle market to real aggregate demand within one year. This is a reasonable assumption given the biological constraints involved with bringing cattle to market (i.e. typically 18-24 months). Furthermore, it implies that REA is exogenous (at least in the short run) so that shocks flow in one direction from REA→oil→corn→cattle price→herd size. We next formally estimate our model, applying the framework of Carter et al. (2017).

2.4.2 Structural VAR Model

We estimate the impact of biofuel policies on real economic activity, beef herd size, and corn, oil, and cattle prices with a recursive SVAR model. The benefit of the SVAR model is that unlike a reduced-form VAR, it permits the imposition of restrictions to estimate the causal relationships derived from our theoretical model of herd size. This approach extends the work of Carter et al. (2017) and Smith (2019) to include cattle. Now, we use the real farm price of corn at time t, p_t^c, to capture shocks to corn demand for the livestock producer, $\epsilon_{c,t}$. Similarly, we use the real oil futures price, p_t^o, and the farm cattle price, p_t^b to reflect shocks to energy and beef markets: $\epsilon_{e,t}$ and $\epsilon_{b,t}$. We define $\mathbf{y}$, as a set of variables

$\mathbf{y}_t = (REA_t, p_t^o, p_t^c, p_t^b, H_t)'$. The $VAR(p)$ process is:

$$\mathbf{y}_t = A_1\mathbf{y}_{t-1} + \cdots + A_p\mathbf{y}_{t-p} + \mathbf{u}_t. \tag{2.11}$$

A_i are (5 × 5) coefficient matrices for $i = 1, \cdots, p$ lags and $\mathbf{u}_t$ is 5-dimensional white-noise process. Following the procedure in Pfaff (2008), we select an autoregressive lag order of $p = 1$ using the Schwarz information Criterion. This ensures we have set of variables with no evidence of autocorrelation, according to the asymptotic portmanteau test (test results are presented in A.1 in the appendix). We can then define a structural form model as:

$$A\mathbf{y}_t = \bar{A}_1\mathbf{y}_{t-1} + \cdots + \bar{A}_p\mathbf{y}_{t-p} + \boldsymbol{B}\boldsymbol{\epsilon}_t\,, \tag{2.12}$$

where ϵ_t are white-noise structural errors, and $\bar{A}_i$ are structural counterparts to the coefficients in Equation (11). $\boldsymbol{B}$ is the structural coefficient matrix for the error term. This matrix captures the impact of "structural shocks" to our endogenous variables, or true independent innovations rather than correlations among the variables in the model. And, $\boldsymbol{\epsilon}_t$ is a vector of structural shocks $(\epsilon_{REA,t}, \epsilon_{o,t}, \epsilon_{c,t}, \epsilon_{b,t}, \epsilon_{H,t})'$. We impose restrictions on $\boldsymbol{B}$ to simulate the impact of the structural shocks. Our restriction matrix $\boldsymbol{B}$ is:

$$\begin{pmatrix} b_{1,1} & 0 & 0 & 0 & 0 \\ b_{2,1} & b_{2,2} & 0 & 0 & 0 \\ b_{3,1} & b_{3,2} & b_{3,3} & 0 & 0 \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & 0 \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & b_{5,5} \end{pmatrix}, \tag{2.13}$$

which implies oil prices (b_2) impacts corn (b_3) and cattle (b_4) prices as well as beef herd size (b_5) contemporaneously; corn impacts only cattle prices and herd size, and oil prices at a lag; cattle prices only impacts herd size, and oil and corn prices at a lag. These restrictions allow model identification by the Cholesky decomposition (Sims, 1980; Sims et al., 1990). Estimation then proceeds with OLS. They can also be viewed as a logical set of restrictions given that 40% of the U.S. corn crop is used for ethanol production and the life-cycle of feed cattle on market is approximately 2 years, much longer the growing season for corn. However, it may also be that the corn and cattle prices, at least, are determined simultaneously (i.e., in the span of the six-month frequency of the data). Given the link between feed grains and biofuels, it is also reasonable to assume that feed grain and energy prices are simultaneously determined. Hence, these restrictions may be too strong and introduce simultaneity bias into our estimates. As a result, we include as a robustness check results from an alternative identification approach that does not impose these restrictions.

2.5 Results

2.5.1 Cholesky Decomposition

We find that positive crude oil and corn price shocks reduce the beef herd size persistently for several years. In particular, in figure 2.3, our impulse response estimates imply that a 1% increase in corn prices leads to a herd reduction of -1.70% in the U.S. beef herd size (90%–C.I.: -2.49%, -0.9%) for 4 periods or 2 years. Moreover, while a 1% increase in the oil price is suggestive in figure 2.3, its effect is not significant at the 90% level. Unsurprisingly, given its importance as the primary feed input, corn accounts for the largest significant estimated effect on herd size. These results support the claim of the NCBA and other livestock industry groups that beef herd reductions can result from government intervention to promote the production and adoption of biofuels, if those policies raise the price of feed.

From our estimated coefficient matrix, we generate impulse response functions for the causal interactions of interest. Since our data are represented in logarithms and we bootstrap the standard errors for our coefficient estimates, we can interpret the resulting plots as elasticities. Our impulse responses indicate that oil shocks affect corn prices, as predicted. Specifically, our results imply that a 1% increase in the price of oil results in a 0.082% increase in the farm price of corn for almost 4 periods or 2 years (90%–CI: 0.0023%, 0.163%). This is consistent with the findings of Carter et al. (2017) and Smith (2019). And, it implies that an expanding demand (or tight supply) for oil itself raises the cost of cattle production thereby keeping downward pressure on herd size, since producers internalize a shock to oil prices as preceding a shock to ethanol and corn prices in the future. The effect is that as the price of oil increases due to a shock in economic activity we should observe a sudden reduction in the herd size, which is further reduced by the increase in the price of corn as ethanol blenders increase their demand for corn.

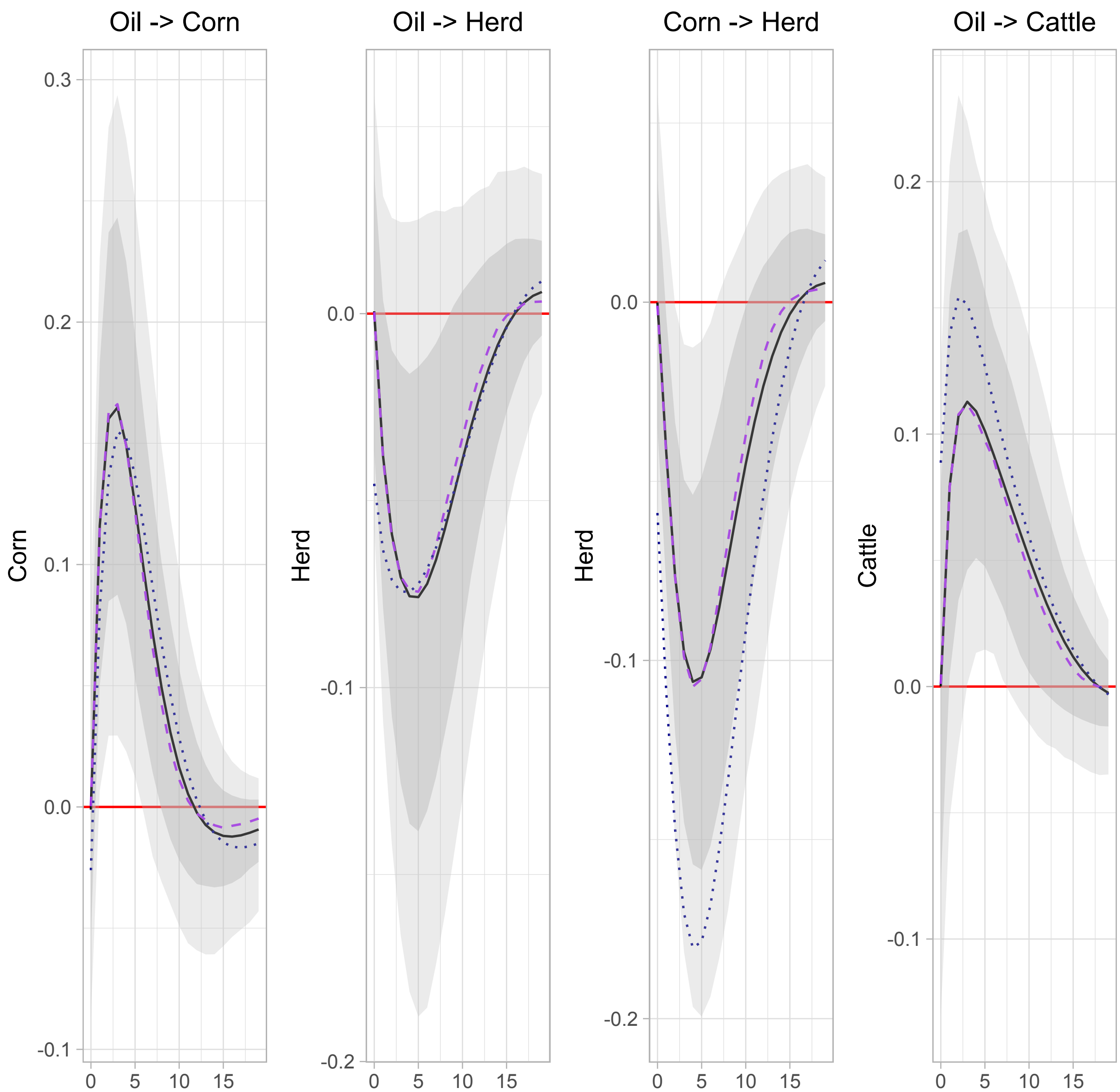

Figure 2.3: Cholesky Impulse Response Functions, 1983-2022
Source: Author calculations based on data sourced from NASS and AMS 2022.
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil → Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

2.5.2 Variance Decomposition

Forecast error variance decomposition (FEVD) is a fundamental part of structural analysis that involves "decomposing" the variance of the forecast error according to the source of the exogenous shock. This is useful, because it demonstrates how important a shock is in explaining the observed variation of the variables included in the model. Specifically, The FEVD allows the user to analyze the contribution of variable j to the h-step forecast error variance of variable k. In addition, the FEVD shows how that importance changes over time. For example, some shocks may only affect short-term variation, while others may grow in importance over time. Figure 2.4 illustrates our estimated FEVD for the U.S. beef herd.

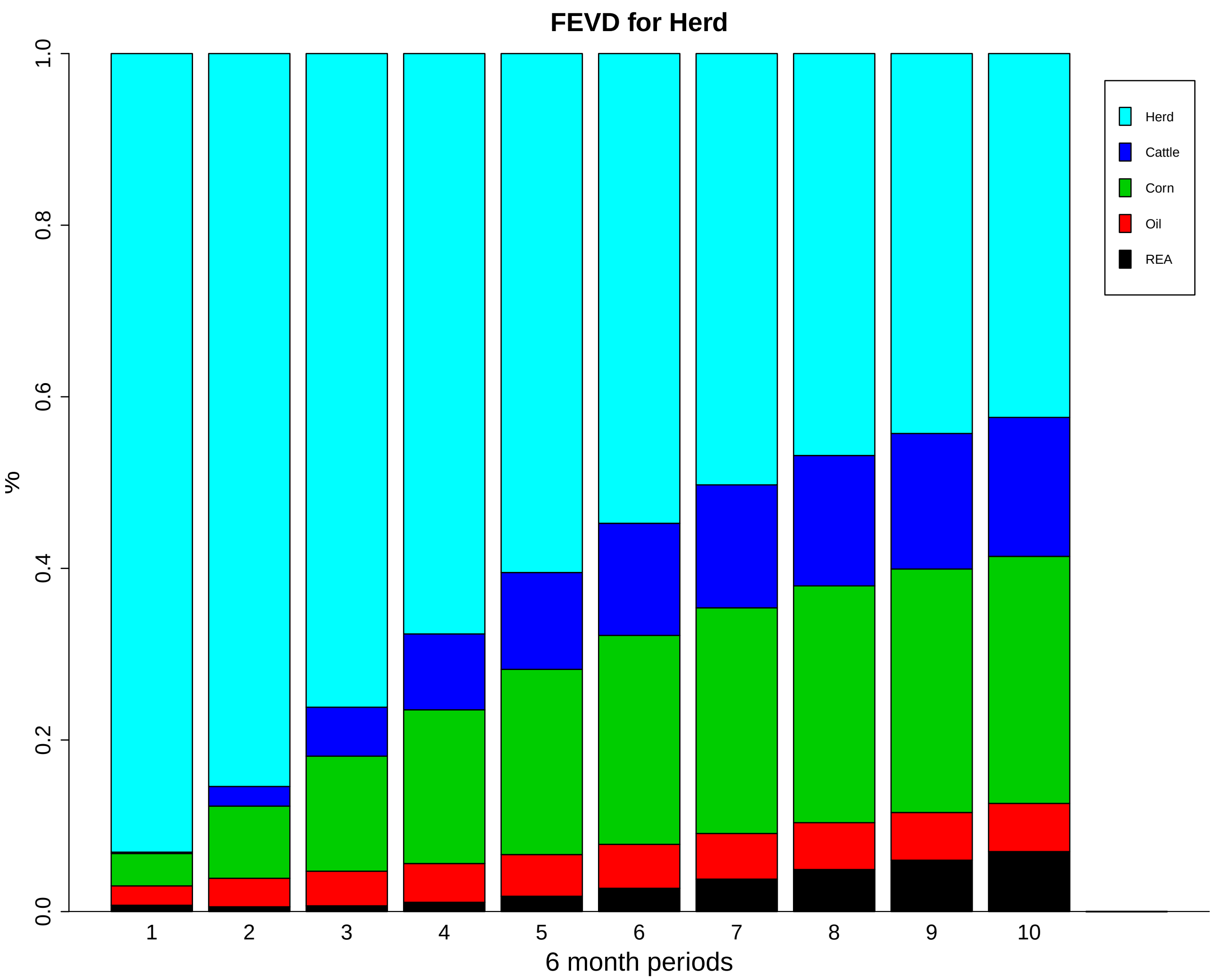

Figure 2.4: Forecast Error Variance Decomposition (FEVD) for Herd 10 Steps Ahead
Source: Author calculations based on data sourced from NASS 2022a.
Note: Counterfactual constructed from Recursive Identification Results.

Figure 2.4 is based upon the impulse response coefficient matrices $\mathbf{B}$ and allows us to study the contribution of variable $(REA_t, p_t^o, p_t^c, p_t^b, H_t)$ to the h-step forecast error variance of H_t. If the orthogonalized impulse responses are divided by the variance of the forecast error $\sigma_i^2(h)$, the result is a percentage figure (Pfaff, 2008). Formally:

$$\sigma_k^2(h) = \sum_{n=0}^{h-1}(\mathbf{B}_{k1,n}^2 + \ldots + \mathbf{B}_{kK,n}^2) \tag{2.14}$$

which can be written as:

$$\sigma_k^2(h) = \sum_{j=1}^{K}(\mathbf{B}_{kj,0}^2 + \ldots + \mathbf{B}_{kj,h-1}^2) \tag{2.15}$$

Dividing the term $(\mathbf{B}_{kj,0}^2 + \ldots + \mathbf{B}_{kj,h-1}^2)$ by $\sigma_k^2(h)$ yields the FEVD in percentage terms. Clearly, the contribution of herd size on itself is the largest source of variation (to be expected) in the short run. However, as we increase the number of steps ahead h, corn, oil, and cattle prices grow in importance. This indicates that corn and oil prices have a significant and persistent effect on the evolving path of the U.S. herd size. As a result, we propose that the transition in the crude oil market from low to high prices may have coincided with a structural break in the beef herd. Using the Bai-Perron procedure, we identify structural breaks in the beef herd series at July 1988, January 1994, July 1999, and July 2008. Test results are given in Table 2.3.

Table 2.3: Structural Break Dates & Confidence Intervals of Key Series

Ethanol Consumption Series		
Break Point	2.5% value	97.5% value
July 2002	Jan. 2001	July 2003
Jan. 2008	July 2007	July 2008
July 2013	July 2012	July 2016
Beef Herd Size Series		
Break Point	2.5% value	97.5% value
July 1988	Jan. 1988	July 1992
Jan. 1994	Jan. 1993	July 1995
July 1999	Jan.1999	July 2000
July 2008	July 2007	Jan. 2009

Notes: Computed using procedure described in Bai and Perron (2003)

These breaks coincide with significant events in the evolution of the U.S. beef herd. The 1988 break aligns with the start of the US-EU beef dispute over the use of hormones in the production process. The E.U. ban on the import of hormone-treated beef motivated the United States to retaliate with tariffs on E.U. imports (AFB, 2019). Subsequently, the domestic herd size increased. The 1994 break corresponds to the peak of the beef cattle price cycle, when feedlots swelled with an oversupply that resulted in a decline in the cattle price (Hughes, 2001). The 1999 break represents the year California sought its first waiver for the blending of MTBE in its commercial fuels, marking the beginning of the domestic shift towards ethanol as the sole oxygenate used in the blending of commercial fuels. Finally, the 2008 break directly corresponds to the implementation of RFS-2 legislation (Duffield et al., 2015). From the standpoint of our analysis, the 1999 and 2008 break are of primary interest. These dates relate to fundamental shifts in U.S. biofuel policies, while the two previous breaks correspond to trade issues and market cycles for cattle. In addition, as Table 2.3 shows, the 2007-08 break directly coincides with one of our calculated break dates for the ethanol consumption series. This time period reflects the mandated expansion period for ethanol demand as commercial blenders sought to comply with the RFS-2. Therefore, we split our sample into two periods: (1) July 1983 to July 2000; (2) January 2001 to January 2022. For robustness, we compare our results to intentionally splitting our sample in 2007, coinciding with the adoption of the VEETC and immediately following the implementation of RFS-1 and RFS-2. This latter split generates results (see figures A.1 and A.2 in the appendix) consistent with our headline findings.

2.5.3 Sample Split: pre-and-post 2000

Figure 2.5 presents the impulse response functions generated from data between July 1983 to July 2000. Similar to figure 2.3, shocks to the crude oil prices do not translate to significant decline in herd size (at the 95% level) before the MTBE ban and subsequent adoption of the RFS-1. In contrast, corn price shocks have negative impacts (at the 68% level) on herd size even prior to the MTBE ban–as expected since corn is the primary cost of feed.

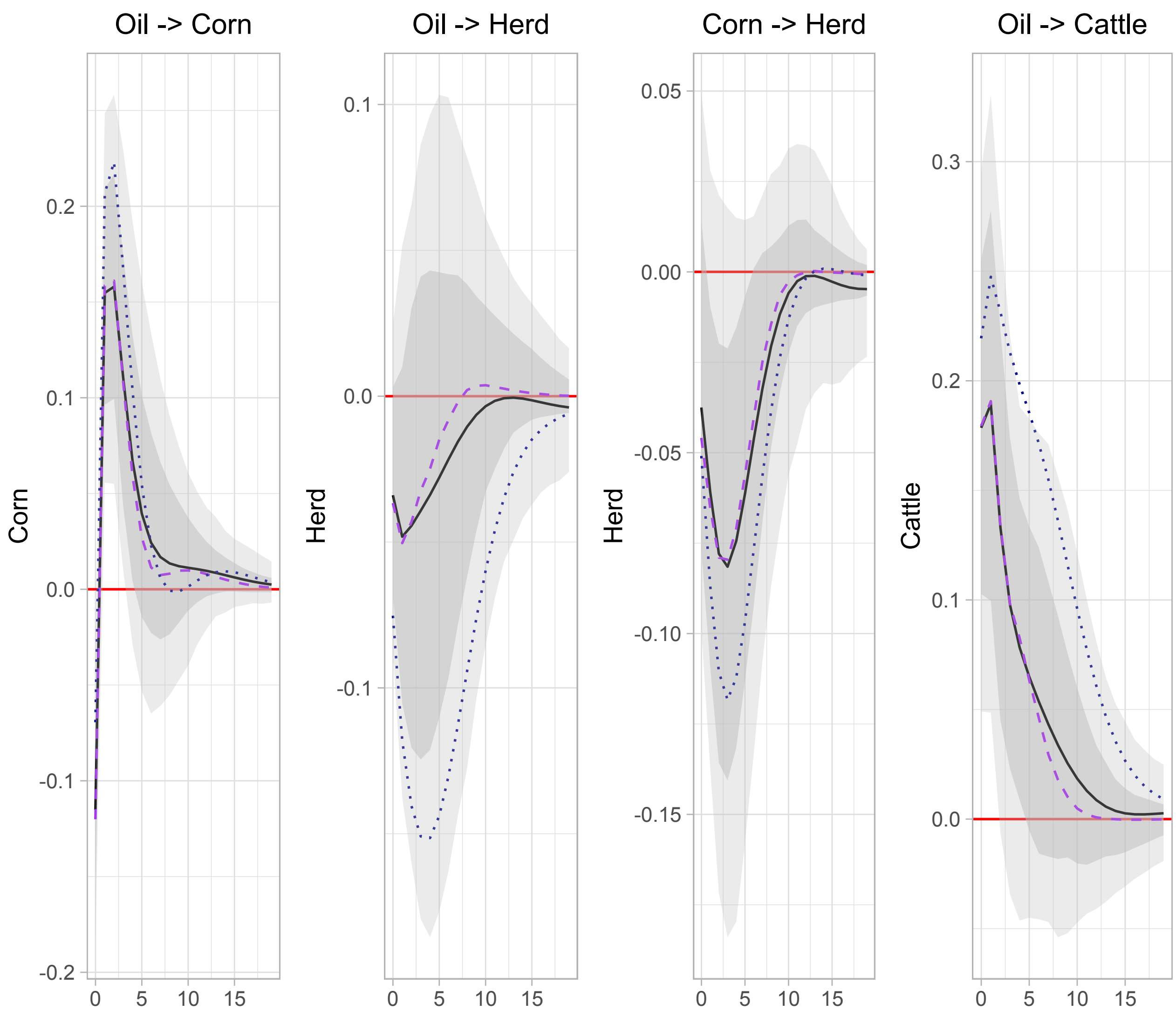

Figure 2.5: Cholesky Impulse Response Functions, 1983-2000

Source: Author calculations based on data sourced from NASS and AMS 2022.

Note: IRFs are generated from the estimated $\mathbf{B}$ matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil → Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

Figure 2.6 depicts the impulse response function for the post-2000 era. In contrast to figure 2.5, shocks to crude oil prices generate a significant decline in the domestic herd size in the long run, representing an important shift in energy and livestock markets. Now, a 1% increase in the price of corn results in a reduction of the U.S. herd size by -2.33% (90%–C.I.: -1.54%, -3.12%) in the short run (i.e. over 4 periods or 2 years). And, a 1% increase in the price of oil yields a -1.90% head reduction in the U.S. beef herd (90%–C.I.: -0.02%, -3.80%) in the long run (i.e. over 10 periods or 5 years). Our results, especially with regard to corn and oil, are consistent with the impulse response functions generated by of Carter et al. (2017) and Smith (2019). In figure 2.5, prior to the break, the impulse response of herd size to oil is not significant at the 90% level. However, in figure 2.6, after the break, oil has a clear, significant negative impact on herd size. Furthermore, the oil shocks correspond to significant increases in the corn farm price after the break, consistent with the results of Carter et al. (2017) and Smith (2019). As expected, the impulse response function for the own-price and herd size on itself is unchanged before and after the break. This suggests that the adoption of the VEETC, RFS-1, and RFS-2 established a novel link between cattle and energy markets. A sudden increase in the price of oil drives down the herd size in the short run. In addition, according to figure 2.6, a positive corn price shock has a stronger (at the mean) and more persistent negative impact on herd size after the break than before it, lasting more than 8 periods (4 years), while before the break the confidence bands cross the vertical axis at about 4 periods, or around two years. For robustness, we include results from specifying an alternative break date of 2007 – the implementation of the RFS-2. The results using this alternative break date are consistent with the results in figure 2.6. In addition, we also include results from using the alternative aggregate economic activity measure, WIP, proposed by Hamilton in figure A.3 in the appendix. Using this alternative measure of aggregate demand, we still observe a fundamental change between U.S. herd size, corn, and energy. This supports our argument that U.S. biofuel policy, especially with regard to corn for ethanol production, more closely linked cattle, corn, and energy markets, creating a new potential source of volatility for beef producers[13].

[13] We also include in the appendix IRFs generated from the data excluding COVID-19 observations to balance the split sample analysis. Figure A.4 visualizes these results using REA as the economic activity indicator. The results support our headline findings.

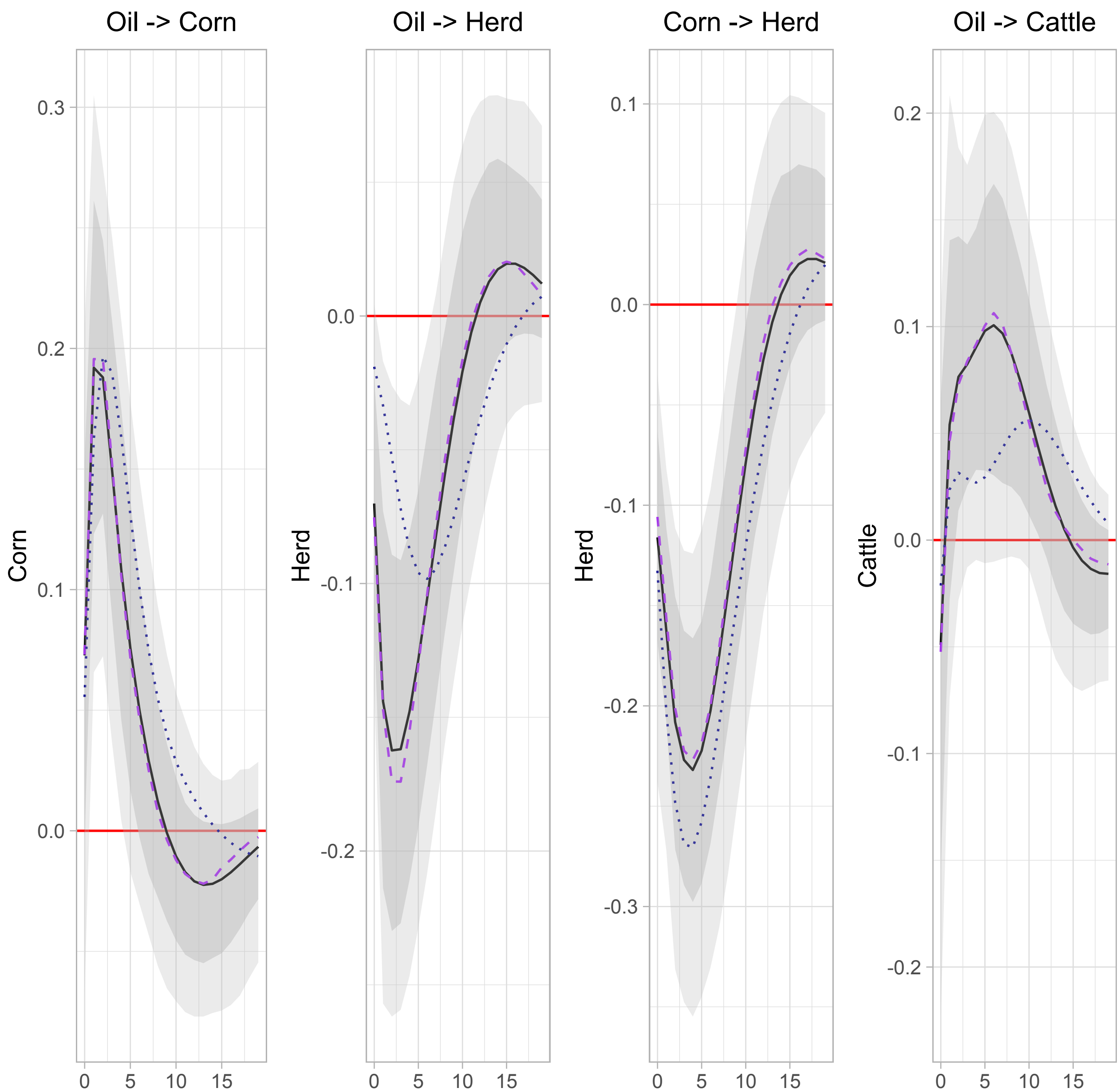

Figure 2.6: Cholesky Impulse Response Functions, 2001-2022
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated $\mathbf{B}$ matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil → Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

From our estimated SVAR model, we calculate counterfactuals with and without shocks to corn and energy prices. We present counterfactuals in figure 2.7 for the beef herd series, illustrating how the beef herd size would have evolved with and without the effects of shocks to crude oil and corn (the primary feed input). Corn and crude oil have a significant impact on beef herd beginning in the early 2000s. In figure 2.7, the first panel shows that high corn prices exacerbated the downturn in the cattle cycle between 2010 and 2015. Similarly, the second panel shows the historical decomposition for oil on herd size over our sample time period. Beginning in the mid-2000s, the observed herd size is above the counterfactual series, implying that the beef herd benefited from depressed oil prices (recall figure 2.1)–which lowered industry production costs–until the mid-2000, when the U.S. government enacted significant policies to promote biofuel production and adoption. After RFS-2, the counterfactual herd series runs substantially higher than the observed series in the first panel, implying that the spike in corn prices during the 2000s lowered the U.S. herd size, as cattle producers faced higher prices for the corn they used in production.

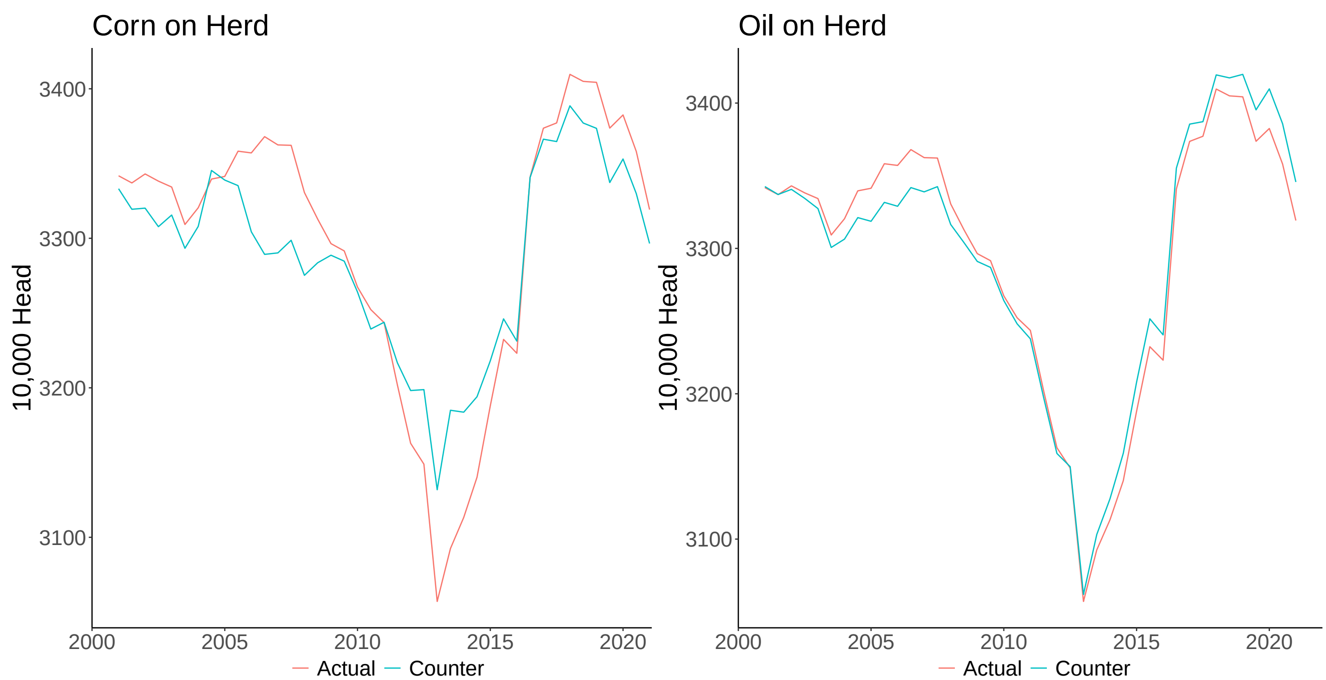

Figure 2.7: Counterfactual Plots with and without the Shocks from Corn and Oil
Source: Author calculations based on data sourced from NASS 2022a
Note: Counterfactual constructed from Recursive Identification Results

2.5.4 Robustness Check: Distance Covariance

The next method we take to the data is the Distance Covariance Method (DCM) (Szekely et al., 2007). The DCM relaxes the restrictions placed on our error matrix, $\boldsymbol{B}$, so that it is no longer assumed to take a Cholesky lower-triangular form. Edelman et al. (2020) provides a simplified treatment of the motivation behind the DCM. Formally, the DCM is a powerful measure of dependence between sets of multivariate random variables, and hence, can be applied to detect arbitrary types of non-linear associations between variables. Therefore, under this formulation, B is completely unrestricted:

$$\begin{pmatrix} b_{1,1} & b_{1,2} & b_{1,3} & b_{1,4} & b_{1,5} \\ b_{2,1} & b_{2,2} & b_{2,3} & b_{2,4} & b_{2,5} \\ b_{3,1} & b_{3,2} & b_{3,3} & b_{3,4} & b_{3,5} \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & b_{4,5} \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & b_{5,5} \end{pmatrix} \tag{2.16}$$

Matteson and Tsay (2013) provide a numerical algorithm for calculating each element of $\boldsymbol{B}$ in (12). We re-estimate model using the DCM and generate a new set of impulse response functions post-2000 era in figure 2.8. In terms of sign and mean response, the DCM impulse responses in panels 2 and 3 are consistent with the results generated under the Recursive Method. In panel 1, the impulse response, although now not significant at the 90% level–but still significant at the 68% level–mirrors the positive relationship between energy prices and corn prices observed by Carter et al. (2017). Furthermore, the herd response to a 1% increase in the farm price of corn is almost identical to our results under the Cholesky restrictions. These results imply that the shift in U.S. energy policy towards supporting biofuels contributed to the significant negative relationship we observe between feed prices and herd size.

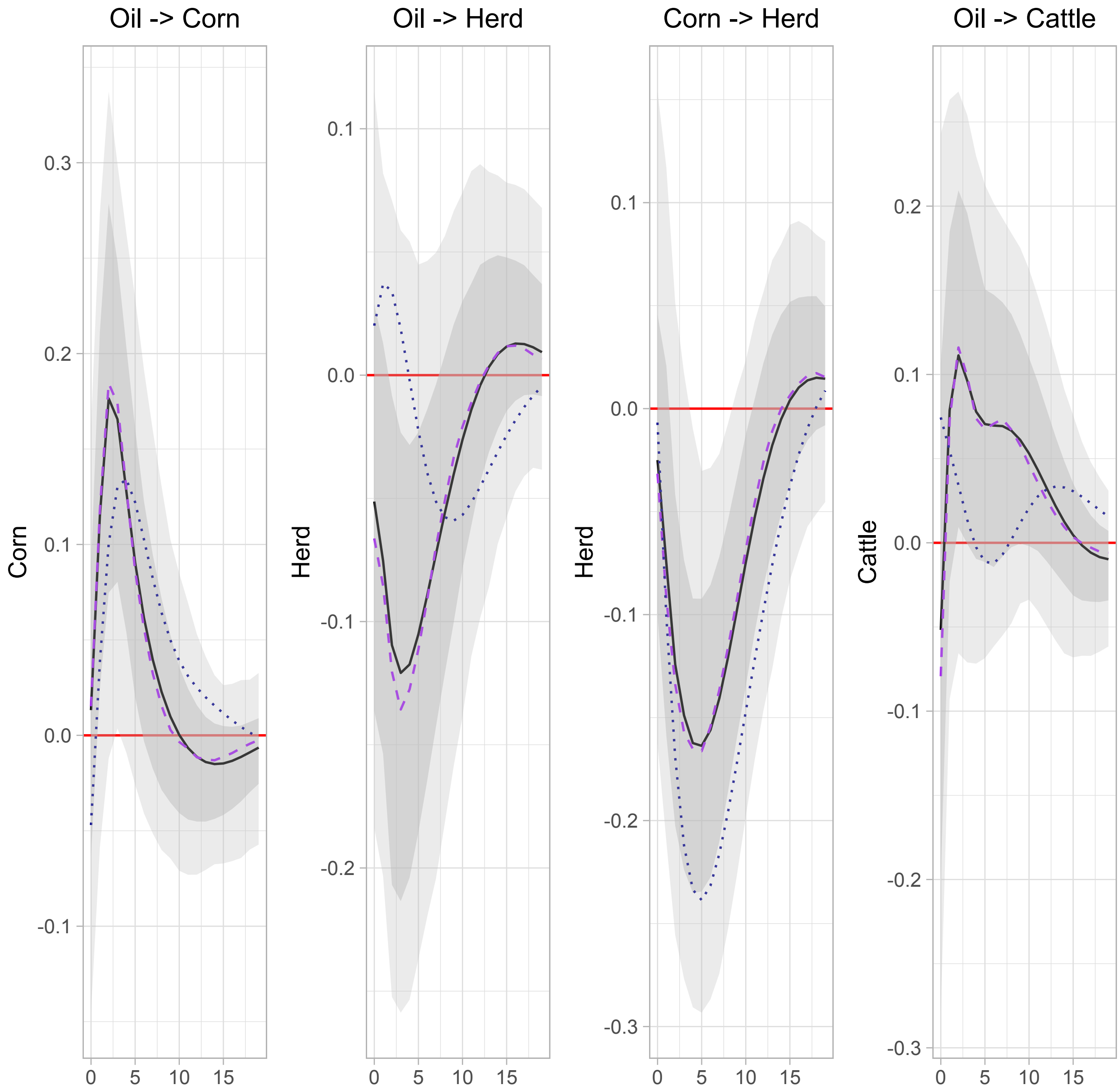

Figure 2.8: DCM Impulse Response Functions, 2001-2022
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated $\mathbf{B}$ matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil $\rightarrow$ Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

2.6 Discussion: Other Exogenous Shocks to Beef Markets

Besides RFS-2, other shocks to both corn and cattle production may be correlated with one another, and these could present a confounding problem for our analysis. In particular, weather shocks may similarly affect cattle and corn, especially in cases of severe and prolonged drought. Carter et al. (2017) address the issue of weather confounding by arguing that weather shocks are transitory, lasting one to two growing seasons, as opposed to RFS-2 which represents a decades-long policy change. Furthermore, in their lagged framework, they use March crop prices, which occur in the middle of the cropping year before any weather shocks are realized that would impact yield on crops harvested later in the fall. Our lagged model follows a similar approach. We take farm corn and cattle prices 8 months prior to the inventory report release date. Therefore, the marketing decisions of producers are pre-determined and independent of any yet-to-be realized weather shocks.

Nevertheless, major cattle producing states, including Texas and Oklahoma, saw one of the driest summers on record during 2011 (NWS, 2012). This drought continued into 2012, and in some areas into 2013. Hence, even in the lagged framework, this persistent extreme weather event may confound the estimated relationship between energy, grain, and livestock markets. One advantage of our framework is that we can directly test whether such an event has an out-sized impact on herd size. Specifically, for robustness we re-estimate our main herd model under the Cholesky decomposition restrictions, and simply remove the drought-affected observations (from July 2010 to January 2013). Figure A.5 in the appendix presents the resulting impulse response functions; they display a similar relationship between energy, corn, and herd size as the full-sample impulse response plots. This suggests that weather shocks, even ones as severe as the U.S. drought of the early 2010s, are indeed transitory and provides confidence that our findings are the results of the persistent shock due the policy change encapsulated by the RFS-2.

2.7 Structural Break: Net Returns

In the United States, cattle are brought to market in Midwestern and plains states such as Kansas, Nebraska, Texas, and Colorado. In fact these four states represented 75% of the cattle on feed inventory for the entire country in 2021 and 2022 (USDA, 2022a). These states dominate the feedlot industry because of their geographic location. In particular they are each adjacent to major input markets (i.e. the Corn Belt) and have access to large cattle producing regions.

As such, we consider the impacts to producer profitability using simulated Kansas Feedlot returns series. Following the Bai-Perron procedure, we identify a break point of October 2004 on the net returns to cattle (Bai and Perron, 2003). We then test the date of January 2006, the first month of the year after the RFS was passed. Since 2006, the average simulated return per head to steer producers at representative Kansas feedlots decreased by approximately $59.5 per head. Figure 2.9 shows the deflated series of net returns along with the de-seasonalized average value of the series. We interpret this finding to suggest that, in addition to making the domestic beef herd size more sensitive to crude oil and corn price shocks, U.S. biofuel policy also adversely impacted cattle producer returns.

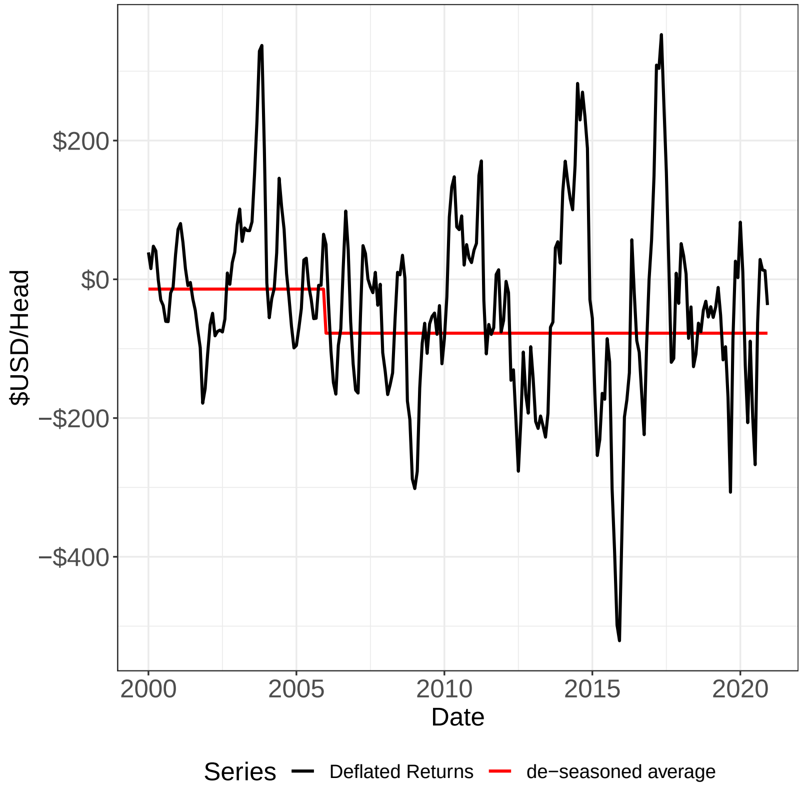

Figure 2.9: Deflated Net Returns $ per Head
Author calculations based on data sourced from KSU and LMIC 2020

2.8 Policy Implications and Further Research

By expanding ethanol production, U.S. biofuel policy increased the demand for feed grains (especially corn), raising crop prices. While these policies generated positive welfare benefits for grain producers, they also created new demand-side competitors for feed inputs. For example, cattle producers, who use corn as a major input component, now must contend with the consequences of these policy shocks. Our approach builds upon the corn-ethanol model of Carter et al. (2019), adapting the framework to include downstream markets. Moreover, we develop a simple but effective empirical procedure for identifying and quantifying structural breaks on herd size that accounts for the presence of potential confounding variables (e.g. extreme weather events). We also complete a set of robustness checks that addresses our choice of measure of economic activity and any potential multicolinearity between corn, energy and cattle prices. Our results confirm that–post-RFS-2 implementation–sudden, unexpected changes to the prices of corn and oil pressured producers to sell off a portion of their herds.

From a profitability perspective, U.S. biofuel policies had both economically and statistically significant negative impacts on the net returns to cattle producers. Thus, our results provide clear evidence of links between corn, energy, and cattle markets. This has real implications for policymakers considering policies aimed at one or more of these markets. For example, given the inflationary pressure on energy and food crop prices, an increase in RFS-2 blend mandates would likely reduce U.S. herd size and producer profitability. Federal officials focus on the beneficial impacts that biofuel policies have on *some* U.S. agricultural interests, and therefore, it is important to point out that market interventions carry inevitable downstream consequences within the agricultural sector.

Chapter 3

How Disparate Government Support for Crops and Livestock Influences Cropland and Pastureland Values

Land value studies consistently focus on the impact of government support for cropland, discounting potential impacts to other agricultural land uses such as pasture. We examine the history of disparate government support for the production of crops and livestock and its impact on land values. Furthermore, we derive a theoretical model of price transmission between cropland and pastureland that accounts for the simultaneity problem in the determination of related land values. We estimate this model under an event study design, using county level data from 2,696 counties across the United States. We find that a positive shock to cropland demand translates to significantly higher pastureland values. In contrast, direct government spending on crop production decreases the relative value of pastureland substantially. Our results show that the change in producer behavior in terms of county corn plantings, following the adoption of the Renewable Fuel Standard (RFS), has a significant negative effect on the differential between cropland and pastureland values. In fact, we estimate that each one percent increase in corn plantings reduces the relative value of adjacent pastureland by -2.13% (95%–Bootstrapped C.I.: -.2.41%; -1.85%).

3.1 Introduction

The United States has a long history of supporting crop production, while devoting comparably little support to the production of livestock. For example, the 2018 Farm Bill (P.L. 115-334) allocates almost $200 billion in projected government outlays from 2019-2029 for agricultural programs, nearly all of which is directed towards crops. These expenditures include subsidized insurance, commodity price supports, and resource conservation. At less than $10 billion, support for livestock producers is just a fraction of that–despite the fact that cash receipts for animal products in the United States routinely rival those of crops (CBO, 2022; ERS, 2022). Pastureland values lag behind cropland values in the United States, and the additional support for crops may be partially responsible according to the land value capitalization literature (Goodwin et al., 2003; Goodwin et al., 2011). Since 1997, the National Agricultural Statistics Service (NASS) has estimated that the average price for an acre of cropland increased by almost 5% annually. For Iowa cropland owners, that average change is 8-10%, according to the 2021 Iowa Land Values Survey (Zhang, 2021). In contrast, pastureland values increased less than 3% a year on average, (below the rate of inflation) since 1997 (NASS, 2022b). Critically, other factors such as strong export demand for U.S. agricultural products, particularly grains and oilseeds; changes in trade policies, beginning with the 2017 Trade War; multi-year extreme droughts; and COVID-19 supply chain disruptions also affect crop prices and land values (Schnepf, 2017; Adjemian et al., 2021; Leister et al., 2015; Weersink et al., 2021). While there is a growing body of literature addressing each of these factors, a gap remains regarding the impact of government support on cropland and pastureland jointly. In this article, we critically assess the impact of disproportionate support for crops and livestock products on cropland and pastureland values. We find that cropland and pastureland values are inexorably tied by policy, and that the choice of mechanism employed determines the direction and magnitude of policy impacts.

Beyond the advantage in direct support, other forms of indirect governmental support (i.e. U.S. ethanol policies) act to widen the support gap even further (see e.g. Carter et al., 2017; Smith, 2019a). For example, in the mid-2000s, changes in U.S. ethanol policy supported ethanol production according to the Renewable Fuel Standard (RFS-I & RFS-2), policy initiatives enacted in 2005 and expanded in 2007 that mandate a fixed percentage of ethanol blending in commercial fuel. RFS is an important example of indirect support; it indirectly raised the value of crop land by creating a new source of demand for certain crops. It is likewise possible that these policies increase the option value of substitutable pastureland. To estimate the impact of RFS-I and RFS-2 on cropland, Kropp and Peckham (2015) apply the capitalization approach of Goodwin et al. (2003) and Goodwin et al. (2011) to 10 years of cropland values. They control for distance to ethanol facility in their model and find that parcels closer to an ethanol facility are \$200-\$577 more valuable.

However, two concerns arise with respect to the capitalization approach employed in previous studies. First, researchers typically discount related types of agricultural land, omitting pastureland observations from their analyses. Since land with high croping potential carries a higher expected return on investment over other types of agricultural land, focusing on more relevant determinants (e.g., population growth or urban land demand) of cropland values and discounting pastureland is a valid approach to estimating the effect of government support on cropland. Goodwin et al. (2003), Goodwin et al. (2011), and Kropp and Peckham et al. (2015) motivate this type of partial equilibrium analysis with their cropland capitalization model. In contrast, estimating the effect of government support for agriculture on pastureland values, without including the interactions between pastureland and cropland markets, introduces an omitted variable, and therefore, potentially biases the estimated marginal effects of direct and indirect governmental support. Livestock producers rely on the derived products of cropland as inputs in their production function. For example, in beef cattle production specifically, cattle raised on pasture are typically finished (i.e. brought to market weight) with corn or other coarse grains. Furthermore, crop production requires a similar set of inputs as pasture and forage production, specifically fertilizer and pesticide inputs. Lastly, cropland and pastureland values are tied together since they may be converted (with varying rates of quality, depending on the region and specific attributes of the plot). Yet, cursory treatments of pastureland values (and cropland values for that matter) in the literature analyze them as separate and unrelated assets, highlighting distinctions and neglecting interactions. Doye and Brorsen (2011) consider pastureland and cropland as distinct classes of economic assets. From a modeling perspective, since previous studies rely on a reduced-form capitalization model of land valuation that is not derived from a structural model, interpretation of the estimated parameters is unclear. For example, using the distance to an ethanol facility incorporates no real indication of a change in producer behavior–only the potential for behavioral change (i.e. proximity to an ethanol plant may increase the likelihood of a producer selling their corn as ethanol but it is not guaranteed). This is important because land values under a capitalization framework are simply the discounted sum of expected returns to the current land use, and according to economic theory, producer behavior is the realization of those expectations in the form of the choice to devote land to crop or pasture production. In contrast, the change in average corn plantings reflects actual changes to producer behavior brought on by changes in producer expectations, and therefore have real impacts on the value of agricultural land. Thus, the complexities of the dynamics between cropland, pastureland, and their derived products necessitates a well-grounded theoretical model of producer behavior and the interrelationships between agricultural land values.

The simultaneity problem between cropland and pastureland occurs because they require similar agronomic inputs, and the outputs derived from each are inter-related. We estimate the direct effect of cropland value changes on pastureland values by instrumenting cropland values on lagged weather and market returns in the first stage. Long-run weather histories such as rainfall and temperature inform expectations as to future expected returns, and therefore satisfy the exogeneity and relevance assumptions needed to preform instrumental variable analysis. We formally test these assumptions in our results. In the second stage, we estimate the direct effect of government support on pastureland values by including government crop support spending. Furthermore, we identify the indirect effect of U.S. biofuel policies on pastureland values with an event study around the change in corn plantings in response to RFS-2. An event study is appropriate in this context because of the discrete change in our treatment variable: corn plantings, or the total amount of cropland planted in corn in a given county. In particular, following the adoption of RFS-2 in 2007, average corn plantings across U.S. counties increased from 16% to 22% of all agricultural land. This significant change in producer behavior allows for consistent estimation of the marginal effect of U.S. biofuel policies on pastureland values.

We contribute to the literature by deriving a structural model of price transmission between cropland and pastureland that decomposes the impact of government policies targeted at crop production on pastureland values. In addition, we collect complete land, weather, and population statistics for 2,696 counties across the United States. We take this model to the data, including weather and market returns indicators as instruments for our endogenous cropland and pastureland values. Our two-stage least squares design accounts for the simultaneity problem inherent in the determination of supply and demand for cropland and pastureland.

Our results show that a 1% increase in cropland values increases pastureland values by 0.71% (95%–Bootstrapped C.I.: 0.58%; 0.82%). However, the effect on pastureland values of government spending on crop production is significantly negative, since each additional dollar allocated to crop production increases the opportunity costs of keeping land in pastureland use. In fact, a 1% increase government spending on crop production decreases pastureland values by -0.28% (95%–Bootstrapped C.I.: -0.30%; -0.27%). Finally, the results of our event study design illustrate that following RFS-2 in 2007, a 1% increase in corn plantings has the net effect of decreasing adjacent pastureland values by -2.13% (95%–Bootstrapped C.I.: -.2.41%; -1.85%). These results are consistent in terms of directional effect not only with our two-stage instrumental variable findings but with the previous work of Goodwin et al. (2011) and Kropp and Peckham (2015). RFS-2 increased the demand for cropland, driving up prices for cropland as well as the opportunity costs of keeping land in pasture.

The paper proceeds with a background on the historical trend of disparate support for cropland and pastureland values. Section 3.3 compares the traditional capitalization model of land values to our expanded price transmission approach. Section 3.4 derives the theoretical model of price transmission between related land types. Section 3.5 describes our data, presents our econometric models, and details our results with appropriate model diagnostic tests and robustness checks; Section 3.6 concludes with a discussion of policy implications and avenues for future research.

3.2 History of U.S. Agricultural Land Policy

Since the nation's founding, American farmers have been the focus of an evolving series of federal support policies, which can be organized into four distinct periods in U.S. history. Conflicting interests and objectives characterize each of these periods, so that public policy pursued in one period stems directly from the consequences of the previous (Effland, 2000). A common thread, despite the debate and often reactionary nature of reform, is that farmers' problems warrant public support. Liberalization of land distribution and reform characterizes the first epoch in U.S. land policy from the 1780s to 1890. In this era, the federal government prioritized transfer of the vast quantities of public land to small, independent white farmers, offering reduced prices and eventually full title for so-called illegal "squatters." The liberalization era of U.S. land reform culminated with the Homestead Act of 1862, which provided for free distribution of land to those who would settle and *farm* it (Gates, 1962). The enactment of the first Homestead act lead to similar legislation focused on previously excluded groups, such as recently freed slaves during Military Reconstruction in the post-Civil War decade (Saloutos, 1956). However, the Homestead Acts was not an exercise in costless land allocation (Saloutos, 1962). In fact, the Homestead Act specifically required homesteaders to reside on (for at least five years) and improve property before full ownership was conferred (Novack et al., 2015). The improvement requirement could be satisfied through either the cultivation of crops of the planting of trees under the Timber Culture Act of 1873 (McIntosh, 1975). Therefore, even from the genesis of U.S. land policy, the federal government supported cropland and timberland use over pastureland use, since the maintenance of pasture for livestock production precludes crop cultivation and timber establishment.

As the federal government opened millions of acres of public land in the West to settlement throughout the 19th century, it also began support policies aimed at farm productivity and quality of life. The impetus for this additional policy initiative stemmed from the South and East. These regions suffered from declining soil fertility due to poor production methods, decreasing the value of farmland. In addition, the vast supply of virgin land in the West further decreased the relative value of land in the older farming regions. In response, farmers organized for the first time to promote the need for agricultural research and education for the growing sector (Rausser, 1992; Rausser and Zilberman, 2014). The idea was that the Federal government was partially responsible for the loss of wealth in the South and East due to the increased competition it created, and so it must help farmers improve their productivity to reestablish parity (Effland, 2000). As a result, the government began to pursue a three-prong strategy of scientific research, education, and economic development. The Morrill Act of 1862 allocated support for the public land-grant university system across the country and laid the foundation for the cooperative extension system to disseminate the new ideas developed from scientific research (Novack et al., 2015). To complement research gains, the government also invested heavily in infrastructure improvements, including canals, railroads, and electrification, to lower the transaction costs of farmers seeking market access. The culmination of this second epoch of land policy in the United States occurred with the formal creation of the Cooperative Extension Service (CES) in 1914 and the Bureau of Agricultural Economics in 1924 (forerunner of the modern Economic Research Service, ERS)(Effland, 2000). For the past 100 years, the ERS and CES distributed improved production techniques, market information, and financed infrastructure development (e.g., farm-to-market roads) for the benefit of small rural producers.

The land expansion of the 19th century coupled with the gains from federally funded research and improvements in agricultural practices lead to chronic oversupply and depressed farm prices beginning in 1900. Simultaneously, manufacturing consolidation and standardization allowed the industrial sectors of the economy to surpass agriculture as the dominant industry. Farmers demanded parity, a living wage, and expected government intervention to achieve it. The result was a series of marketing reforms in the early 1920s, specifically the Capper-Volstead Act of 1922. Capper-Volstead leveled the playing field between manufacturing and agriculture by exempting agricultural producers from anti-trust regulations, allowing for the formation of lucrative producer owned cooperatives (Guth, 1982). Agricultural cooperatives enable producers to consolidate resources for the purchasing of inputs and the marketing of finished products and yielding real economic benefits to farmers, including The National Pork Council, Dairy Farmers of America, or The National Corn Growers Association. However, cooperation is not without added costs, especially for livestock producers. For example, the Packers and Stockyard Act of 1921 is the statute regulating concentration in the meat industry. The economies of scale required to safely process meat lend the industry to monopolization, and unfortunately, the key provisions of the act have not kept pace with the changing dynamics of the industry (Aduddell and Cain, 1981; Buhr, 2010). A fact well-documented in the empirical literature (e.g., Wohlgenant, 1987; Wohlgenant 2014; von Cramon-Taubadel et al. 2021). In fact, the industry concentration of the top four packers for steers and heifer slaughter is over 80% as of

2021 (Deese et al. 2021). As a result, while other commodities benefit from cooperation and government regulation of market middlemen, livestock producers do not.

The Great Depression provided the context for direct support, which became the central tenet of U.S. farm policy from 1933 until 1996. In their first iteration, price supports for the major crop commodities targeted supply to combat falling farm incomes. Supply controls functioned by incentivizing reduced plantings along with government storage of market depressing surpluses, specifically when prices fell below 1910 parity rates. Subsequently, marketing orders allowed for more efficient supply control methods. The system of price controls was successful in stabilizing farm incomes (Bruckner, 2016). Consequently, cropland values experienced a prolonged period of stable gains by reducing uncertainty around the expected returns from crop production (Working, 1945; Floyd, 1965; Lichtenberg and Zilberman, 1986; Weersink et al. 1999). In contrast, stabilizing net farm incomes for livestock producers, and thereby raising pastureland values was not so straightforward. Instead, the U.S. government pursued an indirect protectionist policy toward livestock production. For example, the Smoot-Hawley Tarrif of 1930 prohibited importation of animal meat products from any country infected with foot-and-mouth disease (FMD). The original act made no distinction between localized contained infections or full-scale epidemics. Hence, all the countries in Europe (with few exceptions) and all the countries of South America, specifically Argentina and Brazil, were affected. The result was that domestic producers no longer had to compete with the largest beef exporter: Argentina (Blackwell, 1980). However, the 1930s and 1940s saw reduced meat consumption due to the economic depression and subsequent World War, so that while the protectionist approach towards livestock markets was supported by domestic industry groups, its benefits to farm incomes and land values were mixed at best. In fact, most affected nations implemented retaliatory trade measures against the United States in response to the continued lack of market access[1].

High price supports coupled with a rebound in European agricultural production led to chronic surpluses in the subsequent decades. An intense debate ensued between advocates of price supports and other mandatory supply controls and those who rejected the need for direct market intervention. The Food and Agriculture Act of 1965 provided a compromise, making most production controls voluntary and pegged price supports to World prices instead of historic parity prices (Effland, 2000; Lehrer, 2020). However, supplementary deficiency payments were also introduced, which compensated farmers directly for lower support prices. During this time, livestock producers saw no equivalent policy reform. The 1965 Farm Bill staved off meaningful reform until the Farm Crisis of the 1980s. The crisis saw the failure of direct support to secure U.S. farm incomes in a global economy, since U.S. price supports reduced international marketing opportunities and higher global supplies weakened relative export shares (Lehrer, 2020). As such, the 1996 Farm Bill divorced income support payments and current farm prices, a first step towards complete decoupling. The reforms laid out by the act constituted a dramatic shift in federal assistance to farmers: (1) crop insurance replaced government subsidies; (2) complete planting flexibility was introduced; and (3) conservation contracts were expanded. Advocates of a more market-oriented strategy to stabilizing farm incomes championed the move. However, following its implementation, farm

[1]FMD bans remain a fixture of U.S. agricultural import policy. Since 2000, the United States implemented bans against Argentina, the United Kingdom, France, and more in response to outbreaks. Moreover, the removal of these bans are almost always met with opposition from the domestic industry.

bill subsidies reached a record $24.7 billion (Masterson, 2011). As a result, the literature is divided on the net benefits of an insurance approach. Critics point to the issues of adverse selection and the potential for rent-seeking behavior associated with poorly designed insurance schemes. For example, farmers currently face an array of insurance plans to choose from, with the most dominant being revenue protection plans. Under one of the most popular revenue-protection plans, a farmer can purchase a policy to insure yield losses or revenue losses on certain crops, but he bases that coverage on the highest price of the season. If a low yield drives up the price of a crop from spring to harvest, the farmer is insulated for lower yields at the higher harvest-time price; if the price falls throughout the season due to overproduction, the farmer may use the higher springtime baseline when calculating compensation. Either way, this option maximizes the payout from the insurer. Less appealing plans such as yield protection policies are hardly used since the downside risk to yield loss can not be minimized as easily as through revenue protection (Fessenden, 2015 and Smith, 2019b). Furthermore, insurance programs are subsidized by the government, with about 60 percent of the cost of farmers' insurance premiums as well as 100 percent of administrative and operating costs for insurers, which means farmers can sign up for policies that provide payouts far more generous than reflected by their actual cost. In contrast, Young et al. (2002) quantifies the change in producer behavior after the creation of the subsidized indemnity programs for certain crops. They find that insurance subsidies are likely to alter producer behavior because they lower the cost of risk management. And, the cost reduction represents a benefit to producers, raising expected returns per acre and providing an incentive to expand crop production. However, their model generates relatively small changes in planted acreage after indemnification, which they argue is the result of the inelastic demand for food crop products reducing the gains from rent-seeking. Further research by Goodwin support the small but significant effect on cropland values by subsidized insurance programs (Goodwin et al. 2003; Goodwin et al. 2011). Therefore, while direct government support is no more, crop farm incomes and by extension cropland values still benefit from market intervention. Livestock producers receive no such equivalent support.

Coinciding with the shift from price supports to subsidized insurance was the advent of the Conservation Reserve Program (CRP). Began in 1985, CRP allowed farmers to take land out of cultivation and manage the fallowed land to improve environmental health and soil quality. This voluntary supply control measure reduces the amount of available cropland, and since the demand for cropland is highly inelastic, theory suggests there should be positive benefits for cropland values. However, again the literature is mixed on its benefits to land values. Shoemaker (1989) analyzed the first CRP sign-ups, from 1986 to 1987, and found that CRP participation provided a huge windfall to farmers but had little effect on cropland values. Lence and Mishra (2003) used county-level data from 1996 to 2000 to examine effects of the CRP and other farm payment programs on cash rental rates in Iowa. Their results indicate that the effect of the CRP was again only marginally positive. In contrast to previous studies that assume all governmental payments are exogenous, Wu and Lin (2010) model CRP payments as an endogenous function of the probability of CRP participation. This framework recognizes the fact that farmers are not rewarded contracts if they bid to high for their willingness-to-accept in submitting contraction applications. Their results show average cropland values increased between $18 and $25 per acre in 1997 dollars. And, the distributional impact varied spatially across regions, with the more agricultural states seeing greater returns (Wu and Lin, 2010).

Yet, even in conservation policy there is a disparity between the levels of support for cropland and pastureland conservation. The Grassland Reserve Program (GRP) targeted at pastureland owners does not receive the same level of government support. For example, the 2014 Farm Bill reduced the amount of total enrolled acreage for CRP by 12 million acres, specifically repealing the GRP (Claassen, 2014). In addition, the number of grassland contracts and acreage enrolled is a fraction of CRP, even though the value of livestock products and crop products are nearly identical. In fact, the June 2022 CRP Statistics Report lists over 135,000 general CRP contracts as opposed to only 11,000 grassland contracts. Furthermore, the value of the total rental payments for general CRP totaled $5.67 billion against only $60 million for grassland (FSA, 2022). No prior study we are aware of considers the impact of CRP payments or really any other form of government support on cropland and pastureland values simultaneously.

3.2.1 Trends in U.S. Land Values: 1997 to 2017

The most significant policy change impacting farmland values over the past 25 years is implementation of federal support for biofuel production. Beginning with the 2005 Renewable Fuel Standard (RFS-I) and its expansion in 2007 (RFS-2), the federal government provided indirect support to staple crops–especially corn and soybeans–that can be used to produce ethanol and other biofuels. Lawmakers stated a three-fold purpose of the policy: (1) increase fuel efficiency and independence by producing fuel oxygenates domestically; (2) reduce the environmental impact of burning un-blended gasoline; and (3) stimulate demand for commodity crops thereby raising farm incomes (Yacobucci, 2012). While the scientific support for the first two objectives is scarce (see Moschini et al., 2012 or Lark et al., 2022), empirical support for the third objective is well-established. Carter et al. (2017) address the price gains precipitated by the implementation of RFS-2. In particular, they model RFS-2 as a persistent shock to agricultural markets and find that every billion gallons of ethanol produced raises the price of corn by 5.6% (95% CI–0.9%,17%). Smith (2019a) applies the model to the most recent data and adds wheat and soybeans to estimate a cumulative increase to the corn price over the life of RFS-2 at approximately 30%. Beyond raising crop farm income, this price increase affected land values. According to Kropp and Peckham (2015), the new ethanol demand for corn resulted in significantly higher prices for cropland and a change in producer behavior. Specifically, producers planted more land to corn, and as a result, the sharp decline in cropland acreage from 2002 to 2007 slowed from 2007 to 2012 and then increased from 2012 to 2017. This trend is highlighted in the left-hand panel in figure 3.1. figure 3.1 also illustrates the rise in real U.S. cropland prices since the 1990s, even through the global financial crisis and economic downturn of 2008-2009 owing at least in part to the combination of direct support (like insurance subsidies and CRP supply controls) and indirect support (e.g., biofuels). In contrast, pastureland values also increased in real terms but only marginally so, compared to cropland values[2]. And, the number of pastureland acres experienced a steady decline.

[2]The trend in land values at the county level is dependent on the major land use type within a specific county. For example, figure B.1 in the appendix presents the underlying trends for 3 representative counties across the United States, using data from the Census of Agriculture. Majority crop counties, such as Kossuth County, Iowa, experienced a divergence between cropland and pastureland values, higher crop prices, and substantially more government support compared to pastureland-dominant counties (NASS, 2017a; NASS, 2017b; NASS, 2017c.

One explanation for this trend is that higher commodity crop prices significantly reduce the margins of livestock producers, leading to lower net returns and a reduction in herd size under management. Hence, pastureland values decrease as expectations about the future returns to livestock production weaken.

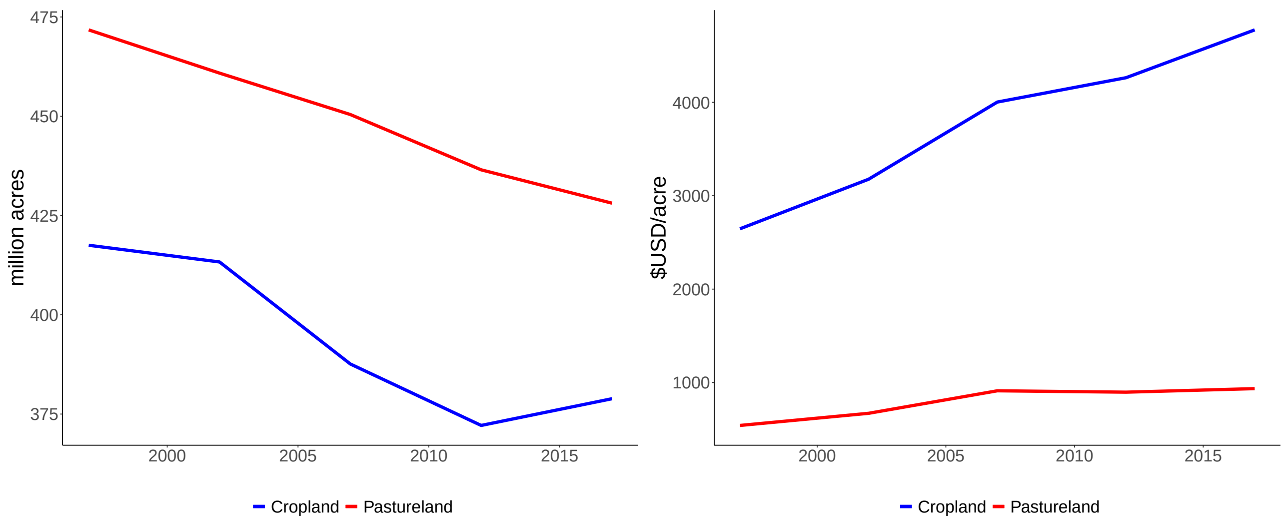

Figure 3.1: U.S. Cropland and Pastureland Acreage and Real Value, 1997-2017
Note: Land Values in Constant 2007 Dollars
Source: NASS 2022b and Author Calculations

We argue that both direct and indirect government support for crop production stimulated the demand for cropland thereby incentivizing the conversion of pastureland to crop production. This results in depressed pastureland values as the highest quality pastureland is moved into crop cultivation, leaving less-convertible pastureland behind. Complete statistics on land conversion are unfortunately are unavailable. However, NASS does compile two useful series, which may indicate its prevalence. Every five years, the agency collects data on the amount of "cropland used for pasture", land that is easily convertible between crop and livestock uses with minimal effort. figure 3.2 plots this series from 1945 to 2012 (the last year of available data). From 2002 to 2012, cropland used for pasture fell from over 60 million acres to 12 million. This change roughly coincides with the increase in cropland acres depicted in figure 3.1. There is a noticeable increase since the implementation of RFS, and the expansion of CRP enrollment by the 2002 Farm Bill.

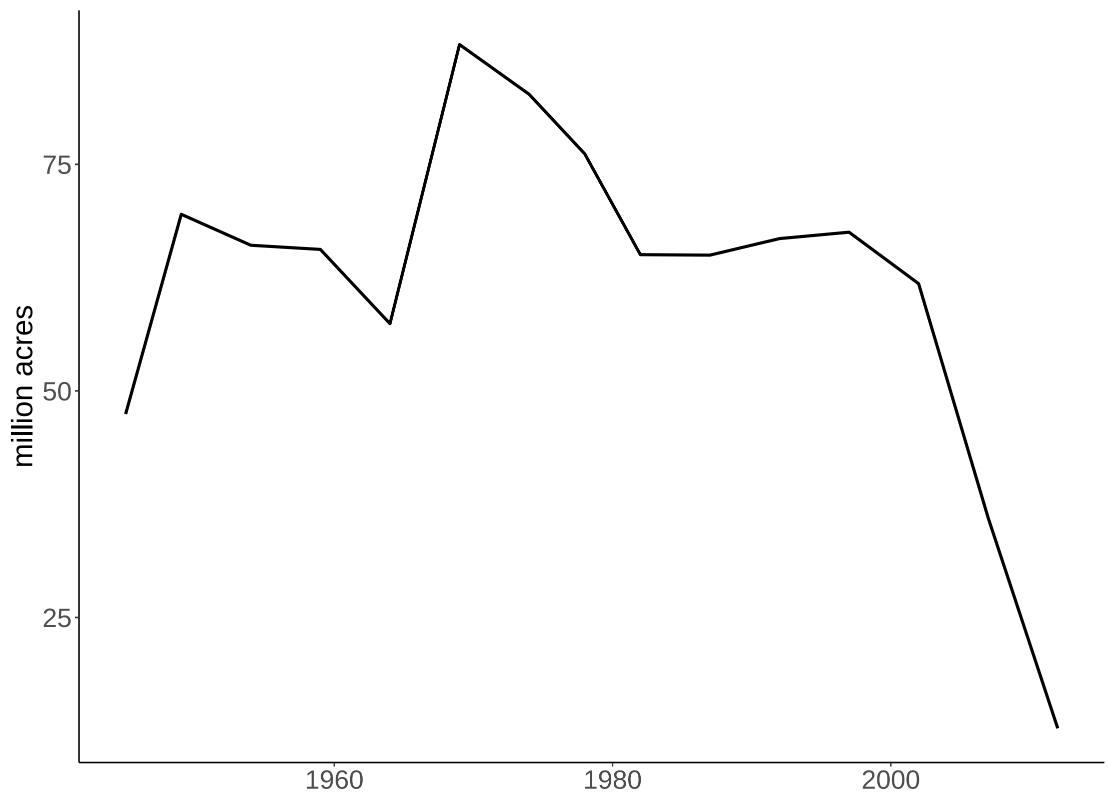

Figure 3.2: U.S. Cropland Used for Pasture 1945 - 2012
Source: NASS 2022b
Note: Series is discontinued.

The average amount of corn plantings across counties in the United States increased significantly during this time. Figure 3.3 plots average corn plantings. Prior to RFS-I and RFS-2, corn plantings accounted for approximately 16% of all agricultural land planted across each county on average. After the implementation of RFS-I and RFS-2, this percentage jumped to over 22%, suggesting farmers responded to higher corn prices and increased their demand for cropland. We use these data in our model of cropland and pastureland values for several theoretical and empirical reasons. First, corn is the primary commodity crop grown in the United States and it is present across the supply chains of almost all livestock products. Second, producers of corn and the producers of pasture and forage rely on similar inputs. Third, the change in corn plantings represents a significant change in producer behavior that motivates our theoretical model of price transmission between cropland and pastureland. In the next section, we formally derive our price transmission model as an extension to the capitalization models of land values.

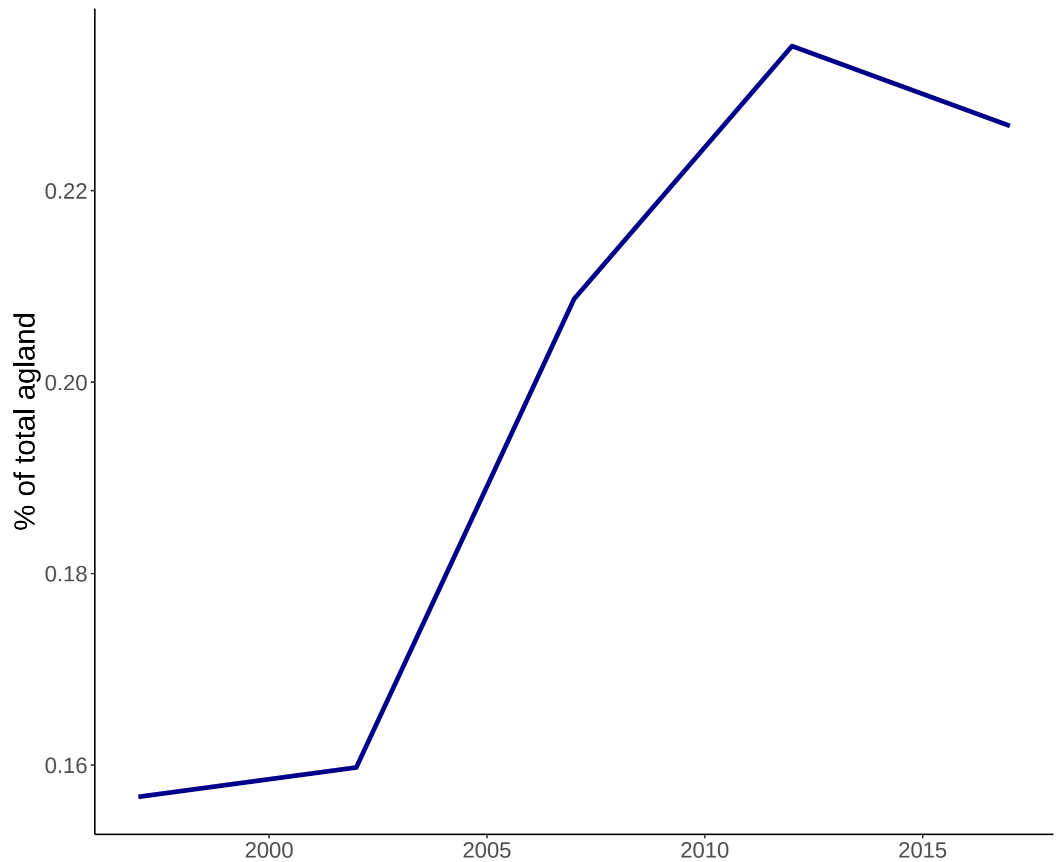

Figure 3.3: U.S. Corn Plantings 1997-2017
Source: NASS 2022b

3.3 Capitalization & Price Transmission Methodologies

In the capitalized values framework, the value of a parcel of cropland is the present discounted value of expected cash flows from crop production (e.g., market returns R_t^c, and government support) plus the option to convert it to non-agricultural uses. In addition, government support Gov_t is often disaggregated into 6 categories: (1) loan deficiency payments LDP_t, (2) decoupled payments DC_t, (3) Cropland Reserve Program payments CRP_t, (4) disaster payments DP_t, and (5) all other support. Goodwin et al. (2003) and Goodwin et al. (2011) establish and extend this framework respectively. Kropp and Peckham (2015) include the distance to the nearest ethanol processing plant to represent the monetized value of ethanol production mandates EP_t. To analyze the interaction between cropland and pastureland in this framework, the value of a parcel of pastureland can be defined in a similar way: as the present discounted value of expected cash flows from livestock production (e.g., market returns, R_t^p, and government support) plus the option to convert to cropland or urban uses. Furthermore, the option value of pastureland is defined as the sum of the present value of the stream of cash flows from converting to alternative uses, weighted by the probability of conversion.

$$\begin{aligned}
\frac{Gov_t}{(1+r_{Gov})^t} &= \frac{LDP_t}{(1+r_{LDP})^t} + \frac{DC_t}{(1+r_{DC})^t} + \frac{CRP_t}{(1+r_{CRP})^t} + \frac{DP_t}{(1+r_{DP})^t} + \\
&\qquad \frac{EP_t}{(1+r_{EP})^t} + \frac{Other_t}{(1+r_{Other})^t}\,, \\
V_0^c &= E\left[\sum_{t=1}^{\infty} \frac{R_t^c}{(1+r_R)^t} + \frac{Gov_t}{(1+r_{Gov})^t}\right] + Conv_0(Urban_t)\,, \\
V_0^p &= E\left[\sum_{t=1}^{\infty} \frac{R_t^p}{(1+r_R)^t} + \frac{Gov_t}{(1+r_{Gov})^t}\right] + \pi_1 Conv_0(Urban_t) + \pi_2 Conv_0(cropland_t).
\end{aligned} \tag{3.1}$$

Goodwin et al. (2003) identifies the econometric advantages of this approach over previous models that address agricultural land valuation. Specifically, land values are based on market expectations about the long-run stream of net returns from production and government support associated with the underlying land. These expectations are unobservable creating a latent-variables problem. Moreover, the complete set of land value determinants is also unobservable to the econometrician, resulting in attenuation bias. To account for latent expectations, the authors urge the use of appropriate strategies to identify the real long-term expectations that underscore observed asset values for agricultural land, i.e. including lagged market returns and government payments as indicators for expected returns. Similarly, to account for attenuation bias, they argue that detailed statistics from producers are needed to capture the correlation between farms and across regions and support type. For instance, they use data from the Agricultural Resource Management Survey[3]. (ARMS) for the years 1998-2001 and disaggregate government support by type of payment. In addition, they use county averages of market returns, which they argue is a more appropriate measure of the long-term expectations of the owners of agricultural land. They estimate a reduced form capitalization model of cropland values as a function of market returns and the various types of government support. In addition, they include measures of population growth, housing, and urban sprawl to account for the impact of the non-agricultural demand for land. Their results indicate that government support payments increase land values, with loan deficiency payments (LDP) resulting in the largest impact at $6.55 per acre for every additional dollar spent. However, including each type of government support introduces an endogeneity problem, since certain support payments such as LDPs are not exogenously known prior to the year they are received. To address endogeneity, Patton et al. (2008) develop an alternative two-stage design to analyze the disparate impacts of coupled and de-coupled (the latter are intended to not affect production decisions or output) government support on rental rates. Goodwin et al. (2011) apply this methodology to ARMS survey data from 1998-2005. The authors argue

[3]ARMS is a regularly conducted survey of 8,000 to 10,000 farms across the United States. Respondents fill out a detailed confidential survey from which socioeconomic and agricultural trends are summarized and applied in research and policy analysis.

that using four-year county averages for government support and market returns reduces attentuation bias. Similar to their results in Goodwin et al. (2003), the authors show that government support payments increase cash rental rates, with particular impact magnitudes dependent on payment type. They also find that government support payments, like LDP, increase the differential between cash and profit-share rental rates, while disaster payments reduce this differential. Kropp et al. (2015) expand on previous work by developing and implementing a measure of the impact of government ethanol mandates. Their metric is based on the distance between farms within a county and ethanol production facilities. Using ARMS data from 1998-2008, they estimate the impact of government -mandated ethanol production on cropland values. Their results confirm that farms located in counties with at least one ethanol production facility command a higher price and rental rate.

More recently, Chen et al. (2022) analyze the impact of a change in producer behavior on land values. In particular, they estimate the marginal effect of no-till practices on cropland values, employing a two-stage Lewbel instrumental variables (IV) approach. They use both NASS Agricultural Census Data and Iowa Farmland Values Survey data to find that no-till practices are positively associated with cropland values. A notable exception to the practice of omitting pastureland values common to the above-cited literature is the study by Classen et al. (2011), which simulates the impact of denying crop insurance to land converted from native rangeland for crop production, analyzing several alternative conversion paths under the SODSAVER[4] program.

The main criticisms for the capitalized framework are two-fold. First, estimating land values through a reduced-form capitalization model provide no causal understanding for the determinants of land values unless they are explicitly derived from a well-defined structural model. Secondly, the capitalization model omits the impact of related asset markets, presuming that changes in producer behavior brought about by a policy change are effectively capitalized by market returns or government payments.

Conceptually, consider two adjacent parcels of land, one in pasture and the other in crops. It is true that the values of the two parcels of land will be the sum of the discounted net benefits plus the option value from conversion to the next best alternative, but only if you assume that pastureland and cropland are not substitutable. That is, suppose the government introduces a new blending requirement for domestic fuels that raises the price of grains, resulting in a higher capitalized value for the cropland parcel since the blending requirement raises expectations of future returns to crop production. Furthermore, given the persistence of this new government mandate, not only will this new policy raise the value of the cropland parcel but of all unimproved open land with the capacity to be cropped (e.g., the adjacent pastureland parcel). Therefore, even though in this example the level of direct government support for pastureland is nil, the value of government outlays and mandates are indirectly capitalized into pastureland values by way of cropland. We denote this result the *appreciation effect*. Therefore, the capitalization model as written in (1) for pastureland would bias this effect as it would consider only the capitalized value of government support to pastureland products and discount any change in producer behavior not capitalized by the market. For example, RFS-2 stimulated the demand for corn land, resulting in an observable increase in

[4]The 2014 Farm Bill established the SODSAVER program. Its provisions focused on incentives to nudge farmers to protect native grasslands by tying crop insurance premium subsidies to not till native prairies.

corn plantings as shown in figure 3.3. While this change in producer behavior is capitalized in cropland values through an increased demand for cropland, its effect on pastureland values is unclear unless both cropland and pastureland values are modeled simultaneously. Further, the relationship between cropland and pastureland extends to the supply chains of their derived products. For instance, a rise in grain prices also decreases the margins of livestock producers who supplement their animals on pasture with purchased feed. In addition, pastureland owners also compete with cropland owners for inputs such as irrigation and chemical fertilizers further reducing livestock margins in the climate of higher grain prices[5]. This effect, which we denote the *depreciation effect* would not be captured by the traditional capitalization model of land values.

Generalizing the preceding thought experiment to the complete market for cropland and pastureland and assuming traditional Marshallian supply and demand relationships, we illustrate the two effects in figure 3.4. Suppose a new biofuel mandate is enacted, then in panel (A), the resulting higher grain prices lead to stronger demand for cropland on the part of producers (shift from D_C to $D_C^{'}$). This incentivizes producers to convert some pastureland to crop production at the margin, shrinking its supply (S_P to ($S_P^{'}$), while raising its price in panel (B). Simultaneously, in panel (C), tighter marketing margins for livestock products due to higher grain prices decreases the value of remaining pastureland by diminishing the expected returns to pastureland use ($P^{'}$ to $P^{"}$ & $Q^{'}$ to $Q^{"}$).

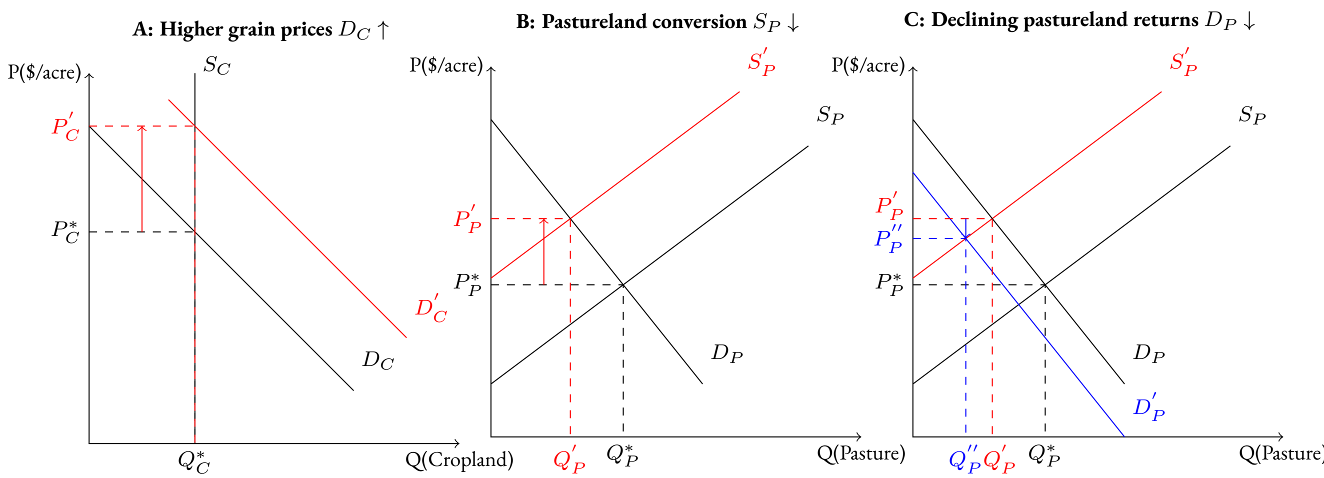

Figure 3.4: Changes in Demand and Supply for Crop and Pastureland due to a Persistent Shock (e.g., Biofuel Blending Mandates)

Note: In Panel A, biofuel policy raises the demand for cropland, increasing its price. In Panel B, this stimulates the conversion of quality pastureland, reducing its supply and raising its price. Finally, in Panel C, higher feed grain input prices decreases livestock margins and by extension the demand for pastureland.

In figure 3.4, it is clear that regardless of which effect dominates the equilibrium quantity of pastureland will decrease. However, the effect on the equilibrium price of pastureland will depend on if the appreciation effect is greater in magnitude than the depreciation effect. The same logic applies to

[5]However, these costs represent a fraction of total production costs for livestock producers relative to crop producers (Holgrem and Feuz, 2015).

a positive increase in government spending for crop production as opposed to a market mandate such as RFS-2. In fact, as spending for crop programs increases the demand for cropland incentivizes conversion of pastureland, while also tightening livestock producer margins thereby reducing demand for pastureland. Moreover, figures 2.1-2.3 suggest that in the past two decades that the appreciation effect is only slightly larger than the depreciation effect since pastureland acreage declined significantly, while pastureland values only marginally increased.

We consider an alternative framework to the capitalization approach by modeling the determinants of agricultural land in the presence of external price shocks, related to the literature on price transmission in agricultural product markets. Gardner (1975) offers the first theoretical treatment of vertical price transmission (farm to retail and vice-versa) in a competitive food industry; his model defines a three-level supply chain: farm, factor, and retail. He then assumes perfect competition and specifies a system of six equations for supply, demand, and market clearing, where the demand functions are downward sloping and supply functions are non-negative. These six equations are solved and unique market equilibria determined. By differentiation with respect to the set of retail demand shifters, Gardner derives an expression for the elasticity of price transmission (EPT) between farm and retail (and vice-versa), which represents how changes in farm supply impact retail demand prices.

Wohlgenant (1989) extends Gardner's model by deriving a system of structural equations for raw farm products, marketing, and retail markets. In the reduced form, Wohlgenant provides a simple equation for the EPT, which is the ratio of the derived demand elasticity for the retail product and the derived demand elasticity for farm product. He applies his reduced-form model to commodity data and finds that input substitutability between farm outputs and marketing inputs increases derived demand elasticities for farm outputs. Wohlgenant concludes that price elasticity decreases as one moves up the supply chain from the retail level, so that the owners of the raw material do not receive the benefits from positive consumer demand shocks. Theoretical treatments of the Gardner-Wohlgenant framework include McCorriston et al. (2001), Wohlgenant (2006), and Kinnucan and Zhang (2015).

To adapt the model for our analysis, it is sufficient for pastureland to be considered as a potential raw material for the "production of cropland." In general, this is the case. Consider that, for land to be cropped, it must be cleared, somewhat well-drained, exhibit little or no slope, and possess appropriate climatic conditions[6]. Quality pastureland satisfies all of the conditions required, so that it carries with it an option value associated with conversion to cropland. By considering that option explicitly in a price transmission framework, along with the interactions between the derived products of pastureland and cropland, we present a more complete picture of how government policies affect various types of land values.

[6]Conducive climatic conditions include, but are not limited to, consistent rainfall and sunlight during the growing season. Furthermore, in the long run, the requirement that the land be cleared need not necessarily hold, since depending on the time frame if the other requirements do hold, then the land could be cleared and converted into cropland.

3.4 Theoretical Model

In this section, we derive a reduced-form system of equations for capitalized pasture and cropland values consistent with the Gardner-Wohlgenant price transmission model, which offers a clearer understanding of the interrelationship between cropland and pastureland values. Our model generates testable comparative statics. The structural model for related assets, assuming perfect competition in each asset market, is specified as:

$$Q^p_{t,d} = D^p_t(P, Z, C, W, M)\,, \tag{3.2}$$

$$Q^p_{t,s} = S^p_t(P, T, L)\,, \tag{3.3}$$

$$Q^p_{t,s} = Q^p_{t,d} \quad \forall t\,, \tag{3.4}$$

$$Q^c_{t,d} = D^c_t(C, R, W, V, M)\,, \tag{3.5}$$

$$Q^c_{t,s} \quad \text{predetermined}\,, \tag{3.6}$$

$$Q^c_{t,s} = Q^c_{t,d} \quad \forall t\,, \tag{3.7}$$

where $Q^p_{t,d}$ is quantity of pastureland demanded and $Q^p_{t,s}$ is quantity of pastureland supplied. P is the asset price of pastureland, Z is an exogenous pastureland demand shifter such as livestock product sales, C is the asset price of cropland, and W represents county population characteristics (e.g., population growth rate). M is a set of indicators representing urban land demand, such as the ratio of county population to county agricultural land and the population growth percentage. In addition, T is average county-level government payments (of all types), L is a set of land use characteristics (e.g., cropland to pastureland ratio, corn plantings, etc.). $Q^c_{t,d}$ is the quantity of cropland demanded, R is an exogenous cropland demand shifter representing net returns to commodity crops in terms of farm sales and expenses, and V are exogenous weather variables, including precipitation and average temperature deviation during the growing season (taken to be March to September for most of the United States). The quantity of cropland supplied ($Q^c_{t,s}$) is assumed to be predetermined. This assumption allows for identification of the structural parameters and is consistent with the agronomic lags of the crop production process.

In equilibrium, (3.2-3.7) are written as:

$$S^p_t(P, T, L) - D^p_t(P, Z, C, W, M) = 0\,, \tag{3.8}$$

$$Q^c_{t,s} - D^c_t(C, R, W, V, M) = 0. \tag{3.9}$$

Following Wohlgenant's method, if we totally differentiate and take the log of (3.8) and (3.9), then:

$$(e_P - \eta_P)\text{dln}P + e_C\text{dln}C = \eta_Z\text{dln}Z + \eta_W\text{dln}W + \eta_M\text{dln}M - e_T\text{dln}T - e_L\text{dln}L\,, \tag{3.10}$$

$$-n_P\text{dln}P - n_C\text{dln}C = n_R\text{dln}R + n_W\text{dln}W + n_M\text{dln}M + n_V\text{dln}V - \text{dln}Q^c_{t,s}\,, \tag{3.11}$$

where e_P is the elasticity of pastureland supply with respect to its own price, η_P is the elasticity of pastureland demand with respect to its own price, e_C is the elasticity of pastureland supply with respect to cropland prices, η_Z is the elasticity of pastureland demand with respect to Z, i.e. the exogenous set of derived pastureland product sales, η_W is the elasticity of pastureland demand with respect to W, i.e. the set of county population characteristics, η_M is the elasticity of pastureland demand with respect to M, the set of urban land demand indicators. e_T is the elasticity of pastureland supply with respect to government outlays, and e_L is the elasticity of pastureland supply with respect to land use characteristics. Similarly, for (3.11), n_P is the elasticity of cropland demand with respect to pastureland price, n_C is the own price elasticity of cropland demand, n_R is the elasticity of cropland demand with respect to the set of exogenous derived cropland product sales, n_W is the elasticity of cropland demand with respect to W, or the set of county population characteristics, and n_M is the elasticity of cropland demand with respect to urban land demand indicators. Finally, n_V is the elasticity of cropland with respect to weather variables. Important restrictions at the farm level apply to the county-level agricultural land markets: (1) individual landowner pastureland supply and cropland demand equations are homogeneous of degree zero (HD0), implying county-level supply and demand are HD0 as well; (2) Because pastureland and cropland demand functions are assumed HD0 in prices and income, then our structural equations are constant to proportional changes in P, C, and derived product prices Z and R. Finally, unlike the Wohlgenant-Gardner model of price transmission, we cannot assume a symmetric relationship between pastureland and cropland values since the spatial makeup of cropland and pastureland is not uniform nor does pastureland experience the same level of ownership turnover or investment. Instead, we assume e_C is negative, so that, following an unexpected positive shock to cropland values, the relative value of pastureland declines. Similarly, we let n_P be positive implying that as pastureland values rise cropland values also increase due to the competition for unimproved open land. We next derive the comparative statics of the reduced-form equations:

$$\begin{aligned} P &= P(R, W, V, Z, T, L, M, Q^c)\,, \\ C &= C(R, W, V, Z, T, L, M, Q^c)\,, \end{aligned} \tag{3.12}$$

by solving accordingly for C and P yielding:

$$\begin{aligned} \mathrm{dln}C = D\mathrm{dln}Q^c_{t,s} - Dn_R\mathrm{dln}R + (C\eta_W - Dn_W)\mathrm{dln}W + (C\eta_M - Dn_M)\mathrm{dln}M \\ -Dn_V\mathrm{dln}V - C\eta_Z\mathrm{dln}Z - Ce_T\mathrm{dln}T - Ce_L\mathrm{dln}L\,, \\ \\ \mathrm{dln}P = B\eta_Z\mathrm{dln}Z + (B\eta_W - An_W)\mathrm{dln}W + (B\eta_M - An_M)\mathrm{dln}M - Be_T\mathrm{dln}T \\ -Be_L\mathrm{dln}L - A\mathrm{dln}Q^c_{t,s} - An_R\mathrm{dln}R - An_V\mathrm{dln}V\,, \end{aligned} \tag{3.13}$$

where:

$$A = \frac{e_C}{n_C(e_P - \eta_P) - e_C n_P}\,, \tag{3.14}$$

$$B = \frac{n_C}{e_C}A\,, \tag{3.15}$$

$$C = \frac{n_P}{e_C} A \,, \tag{3.16}$$

$$D = \frac{e_P - \eta_P}{e_C} A. \tag{3.17}$$

The expected signs of the reduced-form parameters A, B, C, and D are found by applying our assumptions with regard to the underlying own-price and cross price elasticities. Namely, A is (-), since $e_P - \eta_P > 0$, $e_C < 0$, and $n_P > 0$. Therefore, B is (+), and applying similar logic to C and D shows that they are (+) and (-) respectively, assuming that $0 < |n_C| < 1$. Unfortunately, since there are 14 elasticities in equations (3.10) and (3.11) and only 4 reduced-form parameters, the system is underidentified. As a result, we cannot recover unique values for the underlying supply and demand elasticities. However, if the values of the own-price elasticities of supply and demand for pastureland and cropland are known (i.e. e, n, η), then we can obtain a value for e_C by estimating the reduced form parameter ($\hat{A}$) for the quantity of cropland in Equation (3.13). This value is:

$$e_C = \frac{\hat{A} n_C (e_P - \eta_P)}{1 + \hat{A} n_P}. \tag{3.18}$$

As Wohlgenant (1989) details, the choice of functional form is an open question. For ease of estimation, we assume the elasticities in (3.13) are approximately constant so we can replace the instantaneous relative changes in the system by the first-differences in the logarithms, yielding:

$$\begin{aligned} \Delta \text{ln} C &= D \Delta \text{ln} Q^c_{t,s} - D n_R \Delta \text{ln} R + (C \eta_W - D n_W) \Delta \text{ln} W + (C \eta_M - D n_M) \Delta \text{ln} M \\ &\qquad - D n_V \Delta \text{ln} V - C \eta_Z \Delta \text{ln} Z - C e_T \Delta \text{ln} T - C e_L \Delta \text{ln} L \,, \\ \Delta \text{ln} P &= B \eta_Z \Delta \text{ln} Z + (B \eta_W - A n_W) \Delta \text{ln} W + (B \eta_M - A n_M) \Delta \text{ln} M - B e_T \Delta \text{ln} T \\ &\qquad - B e_L \Delta \text{ln} L - A \Delta \text{ln} Q^c_{t,s} - A n_R \Delta \text{ln} R - A n_V \Delta \text{ln} V. \end{aligned} \tag{3.19}$$

For robustness, we relax the assumption of instantaneous relative changes with a relative price model on the levels in Section 3.5.4.

3.5 Empirical Framework

Our two-stage least squares design accounts for the simultaneity problem inherent in the determination of cropland and pastureland values. In the first stage, we regress cropland values on our chosen set of valid instruments along with any additional exogenous predictors. Valid instruments are defined as both exogenous and relevant to the dependent variable, pastureland values, in the second stage. So long as instrument validity holds, we then estimate the second stage by regressing pastureland values on the predicted values of cropland from the first stage with the remaining set of covariates. The result is an unbiased estimate of the marginal effect of cropland value changes on pastureland values. Section 3.5.2 details the exact assumptions invoked in our two-stage model and statistically assesses the validity of our chosen instruments for each model iteration.

In addition, we adapt our two-stage model using an event study design. We begin by specifying a threshold for our treatment variable. In our formulation, we use the year 2007, the date of RFS-2 implementation, as our threshold and specify county corn plantings as our treatment. Then, we compare observations on either side of that threshold to estimate the average treatment effect of RFS-2. Crucially, for our analysis, we require that all potentially relevant variables besides the treatment variable and outcome variable be continuous at the point where the treatment and outcome discontinuities occur, such as the jump in corn plantings between 2002 and 2012 shown in figure 3.3. The discontinuous jump in corn plantings pre-and-post 2007 allows us to estimate the effect of RFS-2 on pastureland and cropland values simultaneously by exploiting observable changes in producer behavior, namely producers' decision to increase corn plantings.

3.5.1 Data

To analyze the relationship between cropland and pastureland values, we collected county-level indicators for 2,696 counties across the United States between 1997-2017 from NASS, giving us 13,480 total observations. Table B.1 in the appendix presents each variable collected along with their unique symbol identifier, number of complete observations, and summary statistics. Following Goodwin et al. (2011), we collected the total acreage of cropland and pastureland (TC and TP respectively), land values (agricultural land values AGV), and market return data such as total sales for crops. We divide total crop sales by TC, yielding crop sales per acre (CCS). We also collected livestock product sales data (LPS) along with operating expenses (OP). Furthermore, we gathered total governmental receipts (GR) for government support programs by county. Next, we compiled relevant weather variables to use as instruments, a step not taken in previous studies. Weather characteristics of a county are exogenous to current land values yet highly relevant to the expected future returns, and thus a logical choice of instrument to include in the model. Yet, they could be correlated with the expected return distribution, violating the exogeneity assumption. However, our choice of lagged rainfall and temperature represents only a snapshot of the climatic history of a county not the trend in climatic conditions, which are used to formulate the expected return distribution. In particular, we drew from the National Oceanic and Atmospheric Administration (NOAA) county-level average precipitation ($PRECIP$) and the average temperature deviance (ATD) during the growing season. For convenience, we squared ATD to remove the negative, yielding the average squared temperature deviance measure ($ATDSQ$). Finally, we include county population (POP), sourced from the Census Bureau.

We then created a series of additional variables used in our analysis. First, the cropland to pastureland ratio (CPR), a measure of the relative demand for cropland over pastureland. Second, following Goodwin et al. (2011), we calculated the population percentage growth (PPG) as an indirect measure of the demand for land. Third, the agricultural land to population ratio (APR), a measure of the demand for developed land. We use these three variables to predict cropland values in a first stage, and then estimate pastureland values as a function our exogenous controls and the predicted values of cropland from the first stage. For the two-stage event study, the variable of interest is corn plantings as a percentage of total agricultural land (CPA) within a county. CPA acts as our treatment variable and captures the discrete jump in the demand for cropland following the implementation of RFS-2. With this model, we estimate the effect this discrete exogenous shock had on pastureland values.

3.5.2 Econometric Model, Diagnostics, & Results

Econometric treatments of two-stage instrumental variables (IV) regression relies on identifying valid instruments: exogenous ($E(\epsilon|Z) = 0$) and relevant ($Corr(X, Z) \neq 0$). Canonical test are used to assess whether estimated models satisfy these assumptions, so that any meaningful conclusions drawn are consistent and unbiased. Our chosen set of instruments include lagged market returns for crops, governmental outlays, along with precipitation and temperature deviation from the mean. Goodwin et al. (2011) found that lagged market returns and government outlays are suitable instruments. Intuitively, lagged market returns and government receipts are exogenous but relevant to the capitalized value of agricultural land. We invoke the same argument for our inclusion of precipitation and average deviance from the mean temperature. We present the results for tests of relevance and exogeneity in table 3.1. First, we performed a Wald test for weak instruments. Our results show that we can reject the null hypothesis for each model, meaning that at least one of our chosen instruments is strong, and our choice of instruments satisfies the relevance condition.

Table 3.1: Diagnostic Tests for Instrument Validity

Test	Df1	Df2	Test Statistic	Pr(>F)
		Model I		
Wald	3	13479	339.8	<0.01
Hausman	1	13470	12.41	<0.01
Sargan	2		5.81	0.055
		Model II		
Wald	7	13479	241.71	<0.01
Hausman	1	13469	12.37	<0.01
Sargan	6		6.71	0.35
		Model III		
Wald	8	8710	340.64	<0.01
Hausman	1	8698	15.00	<0.01
Sargan	7		8.33	0.31

Next, we explicitly test for consistency of the IV estimator using the Hausman test. The null hypothesis is that the OLS and IV estimators are consistent, while under the alternative hypothesis only the IV estimator is consistent. As shown in table 3.1, we can reject the null and claim that our estimated IV coefficients are consistent. Finally, each of our estimated models are over-identified. Therefore, we must test whether our instruments are exogenous and uncorrelated with the model residuals using the Sargan

J test. Under the null hypothesis, the complete set of instruments is valid. In table 3.1, we fail to reject the null hypothesis for each of our estimated models.

For the two-stage empirical model, we first re-write our reduced form Eqn. (19), using composite coefficients β_i, which represent the combination of the structural parameters and elasticities. As such, we now take our reduced form model to the data. Our preliminary Model I is composed of two stages. In the first stage, we estimate cropland values as a function of our instruments: the growing season precipitation, average squared temperature deviance, and crop commodity sales. The results of our diagnostic tests in table 3.1 confirm our choice of instruments is valid. In the second stage we use those predicted values, along with a set of other variables (the cropland to pastureland ratio, government outlays, livestock product sales, and the percentage population growth) to estimate the relationship between each and pastureland values. Model I results are presented in table 3.2.

Our econometric results are in line with our model predictions. For example, our model predicts that the coefficient for cropland ($\hat{\beta}_1$) will be positively signed (i.e. the *appreciation* effect), while the coefficient for government outlays ($\hat{\beta}_3$) will be negative (i.e. the *depreciation* effect). In table 3.2, the 0.60% appreciation effect coefficient is significantly greater than zero, while the depreciation effect coefficient is likewise statistically significant at -0.31%. We can interpret these coefficients as elasticities: a 1% increase in cropland values leads to an appreciation of pastureland values of 0.60% (95%–C.I. 0.53%; 0.67%), while a 1% increase in government outlays depreciates pastureland values by -0.31% (95%–C.I. -0.32%; -0.30%). All other market returns, population, and land use variables also have the theoretically appropriate sign and are statistically significant. Livestock product sales increase pastureland values by almost 0.13% (95%–C.I. 0.12%; 0.14%) per unit percent increase. Furthermore, unit percent increases in the ratio of cropland to pastureland and population growth have a significant yet small negative impact of pastureland values.

$$
\begin{aligned}
&\text{Stage I:} \quad \Delta\ln CV_{it} = \gamma_0 + \gamma_1\Delta PRECIP_{it} + \gamma_2\Delta ATDSQ_{it} + \gamma_3\Delta CCS_{i,t-1} + u_{it}\,, \\
&\text{Stage II:} \quad \Delta\ln PV_{it} = \beta_0 + \beta_1\widehat{\Delta\ln CV}_{it} + \beta_2\Delta CPR_{it} + \beta_3\Delta\ln GR_{it} + \\
&\qquad\qquad \beta_4\Delta\ln LPS_{it} + \beta_5\Delta PPG_{i,t-1} + \eta_t + \epsilon_{it}.
\end{aligned}
\tag{3.20}
$$

We re-estimate the model, including in both stages government receipts, the cropland to pastureland ratio, the agricultural land to population ratio (APR), and population percentage growth (PPG) in Model II. Adding government spending along with measures of urban and agricultural land demand to the first and second stages improves the statistical fit of the predicted values of cropland in estimating pastureland value determinants. The result is an increase in the goodness-of-fit according to the adjusted-R^2 of the first stage of Model II compared to Model I. Table B.2 in the appendix presents the results of the estimated first stage for each model. Our second stage Model II results presented in table 3.2 are significant across all predictors with the theoretically appropriate signs. In fact, our results for Model II are somewhat similar to Model I, with an increase in the adjusted-R^2 or goodness-of-fit. The estimated marginal effects of cropland, government receipts, and livestock market returns are consistent with no significant change between Models I and II.

$$\begin{aligned}\text{Stage I:}\quad \Delta\ln CV_{it} &= \gamma_0 + \gamma_1 \Delta PRECIP_{it} + \gamma_2 \Delta ATDSQ_{it} + \gamma_3 \Delta CCS_{i,t-1} + \\ &\gamma_4 \Delta CPR_{it} + \gamma_5 \Delta\ln GR_{it} + \gamma_6 \Delta APR_{it} + \gamma_7 \Delta PPG_{i,t-1} + u_{it}\,, \\ \text{Stage II:}\quad \Delta\ln PV_{it} &= \beta_0 + \beta_1 \widehat{\Delta\ln CV}_{it} + \beta_2 \Delta CPR_{it} + \beta_3 \Delta\ln GR_{it} + \\ &\beta_4 \Delta\ln LPS_{it} + \beta_5 \Delta PPG_{i,t-1} + \beta_6 \Delta APR_{it} + \eta_t + \epsilon_{it}.\end{aligned} \tag{3.21}$$

Next, we estimate our two-stage model, using corn plantings (CPA) as a continuous treatment. Since statistics for corn plantings are not available for all counties (i.e. there are urban counties where agriculture is not a major land use), the sample size for the two-stage event study is 8,711 instead of 13,480. For Model III, our supposition is that corn plantings jumped discretely, following RFS-2, and the subsequent rise in corn prices resulted in a devaluation of adjacent pastureland relative to cropland. To implement the event study, we first identify a threshold that corresponds to the discrete jump in our treatment variable. Our threshold is the year RFS-2 was adopted, 2007, thus our Model III is written as:

$$D = \begin{cases} 1 & \text{if} \quad \eta_t > 2007 \\ 0 & \text{otherwise}\,, \end{cases}$$

$$\begin{aligned}\text{Stage I:}\quad \Delta\ln CV_{it} &= \gamma_0 + \gamma_1 \Delta PRECIP_{it} + \gamma_2 \Delta CCS_{i,t-1} + \gamma_3 \Delta CPR_{it} + \\ &\gamma_4 \ln\Delta GR_{it} + \gamma_5 \Delta PPG_{i,t-1} + \gamma_6 \Delta CPA_{it} + \tau D + u_{it}\,,\end{aligned} \tag{3.22}$$

$$\begin{aligned}\text{Stage II:}\quad \Delta\ln PV_{it} &= \beta_0 + \beta_1 \widehat{\Delta\ln CV}_{it} + \beta_2 \Delta CPR_{it} + \beta_3 \Delta\ln GR_{it} + \beta_4 \Delta\ln LPS_{it} + \\ &\beta_5 \Delta PPG_{i,t-1} + \beta_6 \Delta APR_{it} + \beta_7 \Delta CPA_{it} + \delta D + \beta_8 D \times \Delta CPA_{it} + \eta_t + \epsilon_{it}.\end{aligned}$$

We interact our threshold indicator with our continuous treatment, corn plantings, ($D \times \Delta CPA_{it}$) to capture the additional marginal impact of the increased demand corn crop acreage, following the passage of RFS-2. We include the results for Model III in table 3.2. First, we see a significant increase in the goodness-of-fit for Model III (0.65) compared to Model II (0.59) in terms of the adj-R^2. Secondly, the estimated coefficient for predicted cropland values is significantly higher compared to Models I-II. The results for Model III indicate a 1% increase in the value of cropland appreciates pastureland values by 0.81% (95%–C.I. 0.60%; 1.02%). The estimated coefficient for livestock product sales and government outlays are again theoretically consistent in terms of sign and are approximately equivalent to those found from Models I-II. In contrast, the estimated coefficient for percentage population growth, PPG, and agricultural land to population ratio, APR, are no longer significant at the 0.05–α level. The estimated results for the continuous treatment show that a unit percent increase in the amount of corn plantings decreases adjacent pastureland values by -2.62% (95%–C.I. -2.97%; -2.27%) in the same county. This effect is moderated in the years following RFS-2. Specifically, the estimated coefficient for our interaction term,

$D \times \Delta CPA_{it}$, is positive and only slightly significant: 0.32% (95%–C.I. 0.018; 0.63). We interpret this result to reflect the fact that following RFS-2 mandate, the demand for cropland increased, so that the relative value of pastureland fell and the supply of pastureland declined. Yet, as the supply of pastureland tightened, pastureland values faced upward pressure due to scarcity; hence, the positive value of the interaction term.

We control for year fixed effects with η_t in Models I-III. This term captures those effects that do not vary across counties but do vary over time. It is included, for example, to account for a change in government policy with regard to ethanol production at the national that will impact all counties, such as RFS-2. In contrast, there are unobservables that differ across counties but are constant over time. In particular, agronomic characteristics like soil fertility and agronomic practices like conservation tillage vary from county to county but remain stationary over time. Therefore, we-estimate Model III including both year and county fixed effects. Table 3.2 presents the results of this regression in the column: (Model III w/FEs).

When controlling for county and year fixed effects, our results show that a 1% increase in cropland values produces a 0.68% (95%–C.I. 0.51%; 0.86%) increase in pastureland values, a slight but noticeable reduction than controlling for year fixed effects only. Moreover, the marginal effect of corn plantings on pastureland is also less than our results from the year effects only Model III (-2.402 vs -2.623). In contrast, the marginal effects of government support on pastureland values, livestock product returns, and our interaction term are approximately unchanged. In the next section, we bootstrap the estimated marginal effects on pastureland values and interpret our results.

Table 3.2: Estimated Results from Second Stages

	Dependent variable:			
	$\Delta\ln PV_{it}$			
	(Model I)	(Model II)	(Model III)	(Model III w/FEs)
$\widehat{\Delta\ln CV}_{it}$	0.60^{***}	0.59^{***}	0.81^{***}	0.68^{***}
	(0.035)	(0.034)	(0.11)	(0.089)
ΔCPR_{it}	-0.027^{***}	-0.031^{***}	-0.026^{***}	-0.023^{***}
	(0.001)	(0.001)	(0.004)	(0.001)
$\Delta\ln GR_{it}$	-0.31^{***}	-0.31^{***}	-0.30^{***}	-0.28^{***}
	(0.005)	(0.005)	(0.12)	(0.016)
$\Delta\ln LPS_{it}$	0.13^{***}	0.13^{***}	0.14^{***}	0.12^{***}
	(0.005)	(0.005)	(0.005)	(0.014)
$\Delta PPG_{i,t-1}$	-0.043^{***}	-0.014^{***}	-0.007	0.001
	(0.003)	(0.004)	(0.005)	(0.007)
ΔAPR_{it}		-0.001^{***}	-0.0005^{*}	-0.0005
		(0.0003)	(0.0002)	(0.0004)
ΔCPA_{it}			-2.62^{***}	-2.40^{***}
			(0.18)	(0.18)
D $\times\Delta CPA_{it}$			0.32^{**}	0.30^{***}
			(0.16)	(0.075)
Constant	-0.001	-0.001	NA	NA
	(0.013)	(0.013)		
Observations	13,480	13,480	8,711	8,711
Year Fixed Effects	Yes	Yes	Yes	Yes
County Fixed Effects	No	No	No	Yes
R^2	0.59	0.59	0.65	0.59
Adjusted R^2	0.59	0.59	0.65	0.51
Residual Std. Error	0.72	0.71		
F Statistic	$2,150.34^{***}$	$1,947.98^{***}$	$2,026.02^{***}$	$1,308.99^{***}$
DF	9 & 13470	10 & 13469	8 & 8698	8 & 7410

Note: robust std. errors in parentheses; *p<0.1; **p<0.05; ***p<0.01

3.5.3 Marginal Effects

From the final model, There are two direct effects and two indirect effects we analyze. The first direct effect is the appreciation of pastureland owing to an increased demand for cropland (Demand Appreciation Effect). The second direct effect is the depreciation impact from direct government support for crop production, which increase the opportunity costs of holding land in pasture (Supply Depreciation Effect). The first indirect effect is the depreciation effect of pastureland values associated with the conversion of quality pastureland to crop production, leaving only marginal pastureland (Demand Depreciation Effect). The second indirect effect is captured by the interaction term between our threshold and continuous treatment ($D \times CPA_{it}$). This specific variable represents the indirect impact of the demand for cropland on pastureland values, following the adoption of RFS-2 (Supply Appreciation Effect). It is a positive effect because it represents the added value of holding unimproved pastureland as the amount of pastureland shrinks in the face of strong demand for such land from cropland owners. Hence, the scarcity from conversion of quality pastureland in the face of strong demand for cropland puts upward pressure on the price of pastureland. We bootstrap confidence intervals for these marginal effects in table 3.3.

Table 3.3: Bootstrapped Mean, Standard Errors, and Confidence Intervals

Direct Support Effects		Mean	S.E.	5% level	95% level
Demand Appreciation	$(\hat{\beta}_1)$	0.71%	0.062	0.58	0.82
Supply Depreciation	$(\hat{\beta}_3)$	-0.28%	0.0083	-0.30	-0.27
Indirect Support Effects					
Demand Depreciation	$(\hat{\beta}_7)$	-2.44%	0.13	-2.69	-2.19
Supply Appreciation	$(\hat{\beta}_8)$	0.30%	0.081	0.14	0.46

Note: author calculations from 1,000 replications and 10,000 random draws

It is unclear whether the net direct effects are positive. For example, if the change in government spending outpaces the change in demand cropland, then the supply depreciation effect will dominate as the relative value of pastureland falls due to the opportunity costs of keeping land in pasture. However, if the demand for cropland is strong, then pastureland values will increase, based on its potential convertibility. In terms of indirect support, it is clear that demand depreciation dominates. In fact, the net impact of the indirect effects is for each unit percent increase in corn plantings after RFS-2 adoption pastureland values decrease by -2.13% (95%–Bootstrapped C.I.: -2.41%; -1.85%). This suggests that an increase in the demand for cropland decreases the relative value of adjacent pastureland. In the next section, we present three separate robustness checks to our modeling approach and results.

3.5.4 Robustness Check I: Relative Pricing Model

One alternative approach to analyzing the relative impact of the disparate support for crops over livestock is a single-equation relative value model. Hence, we denote the relative value (RV) as the difference between the cropland and pastureland values in each county. Formally, we write write our relative value model as:

$$\begin{aligned} \ln RV_{it} = \beta_0 + \beta_1 CPR_{it} + \beta_2 \ln GR_{it} + \beta_3 \ln CCS_{it} + \beta_4 \ln LPS_{it} + \beta_5 PPG_{it} + \\ \delta D + \beta_6 CPA_{it} + \beta_7 D \times CPA_{it} + \eta_t + \alpha_i + \epsilon_{it}. \end{aligned} \tag{3.23}$$

We estimate the model using OLS, controlling for county and year fixed effects. Table 3.2 presents the estimated results. They conform to our two-stage findings. First, government outlays, crop product sales, and livestock product sales have the theoretically appropriate sign and are statistically significant. Increasing market returns to crop production act to widen the gap in cropland and pastureland values, while increasing livestock returns act to decrease the differential. Although the magnitude for the effect of crop market returns is significantly larger, in terms of direct government support, each percentage increase in government outlays increases the differential between cropland and pastureland values by 0.04% (95%–C.I. 0.015%; 0.081%). The largest effect is the impact of corn plantings after RFS-2 ($D \times CPA_{it}$). In fact, each percentage increase in cropland demand for corn significantly increases the differential in land values by 0.72% (95%–C.I. 0.47%; 0.97%).

3.5.5 Robustness Check II: Internal IV Estimation

For our second robustness check, we implement the moment-based Lewbel IV estimator to account for potential endogeneity due to correlations between county-year-varying unobservables left over in the second stage error term and land values. In Model III, we already account for endogeneity due to year and county fixed effects. However, it is possible that there may be residual endogeneity that jointly influence government spending, market returns, urban land demand and agricultural land values. For instance, county-year-varying unobservables associated with land development policies and real estate market factors (e.g., mortgage rates) or private conservation initiatives such as carbon off-set markets may be positively correlated with product market returns and urban land demand, and these unobservables may also be positively correlated to different degrees with cropland and pastureland values, thereby biasing our estimates. The typical approach in this case is to use IV based panel fixed effects models (IV-FE), as we do in our final main model, where the IVs are correlated with the potentially endogenous main independent variable but uncorrelated with the outcome variable. Although our main model results support the validity of our external instruments, we consider whether our estimated marginal effects are robust to the absence of external instruments by following the Lewbel IV procedure in Chen et al. (2022).

The Lewbel IV estimator exploits the heteroscedasticity in the error term from the first-stage regression. According to Lewbel (2012), the model is identified if the error term in the first-stage equation is heteroscedastic. If so, then the subset (or all) of the mean-centered covariates multiplied by first-stage residuals represent a valid set of instruments. We begin by removing the external instruments in the first stage of Model III. We then re-estimate it regressing cropland values on internal instruments generated from government outlays, livestock product sales, county population growth, and the agricultural land to population ratio. Hence, according to the procedure outlined in Lewbel (2012) and implemented by Chen et al. (2022), our first stage regression becomes:

$$\begin{aligned} \Delta \ln CV_{it} &= \gamma_{\boldsymbol{x}} \boldsymbol{X}_{it} + u_{it} \,, \\ \boldsymbol{X}^{'} &= [GR \quad LPS \quad PPG \quad APR]. \end{aligned} \tag{3.24}$$

If $Cov(\boldsymbol{X}_{it}, u_{it}^2) \neq 0$ and $Cov(\boldsymbol{X}_{it}, \varepsilon_{it} u_{it}) = 0$, then $(\boldsymbol{X}_{it} - \bar{\boldsymbol{X}})\hat{u}_{it}$ is a valid IV for a two-stage least squares design. The first assumption is satisfied if there is heteroscedasticity in Equation (24). We use the Breusch-Pagan (BP) test to validate the presence of heteroscedasticity in our first-stage regression (Breusch Pagan, 1979). The BP test rejects the null hypothesis of homoscedasticity the first stage with a test statistic of 77.23 (p-value « 0.05). The Sargan J of overidentifying restrictions is used to test the second assumption. We fail to reject the hypothesis that our instruments are valid at the 1% significance level.

With the necessary assumptions satisfied, we present the results of the Lewbel-IV second stage estimation in table 3.4. They are consistent with our external IV estimation results. For instance, using Lewbel-IV, we find that a 1% increase in cropland values inflates pastureland values by 0.63% (95%–C.I. 0.41%; 0.85%). This confidence region is directly comparable to the confidence region of the estimated marginal effect of cropland values using our identified external IVs. The same is true for the estimated marginal effects of government outlays, livestock product sales, and corn plantings.

3.5.6 Robustness Check III: Reverse Transmission

Another test of the consistency of our price transmission model is to consider how changes in pastureland values pass through to cropland values. To apply this test, we switch the dependent variables in the first and second stages of the final estimated model. The results of this estimation should reflect those found by previous traditional capitalization studies. Specifically, in this formulation, we expect that the marginal effect of direct government spending is small and positive, while the impact of the change in the demand for cropland following RFS-2 is large and positive. In contrast, according to our theoretical model, the direct effect of pastureland value shocks to cropland values is positive but smaller in magnitude than the effect in the opposite direction. For example, a positive shock to pastureland values implies higher prices for livestock products, which further implies stronger demand for feed crops and hence higher cropland values. Moreover, positive shocks to pastureland values signals a stimulated demand for the same land characteristics valued in cropland, in particular fertile open land. Formally, equation (25) defines our reverse transmission model, using cropland as the dependent variable in the second stage and estimating pastureland values with market returns and weather characteristics as instruments in the first stage. Again, we control for county and year fixed effects. Table 3.4 presents the estimated results. And, results from Wald, Hausman, and Sargan tests of the instruments included in this regression support the validity of our chosen instruments.

$$D = \begin{cases} 1 & \text{if} \quad \eta_t > 2007 \\ 0 & \text{otherwise} \, , \end{cases}$$

$$\begin{aligned} \text{Stage I:} \quad \Delta \ln PV_{it} = \gamma_0 + \gamma_1 \Delta PRECIP_{it} + \gamma_2 \Delta \ln LPS_{it} + \gamma_3 \Delta CPR_{it} + \\ \gamma_4 \ln \Delta GR_{it} + \gamma_5 \Delta PPG_{i,t-1} + \gamma_6 \Delta CPA_{it} + \tau D + u_{it} \, , \end{aligned} \tag{3.25}$$

$$\begin{aligned} \text{Stage II:} \quad \Delta \ln CV_{it} = \beta_0 + \beta_1 \widehat{\Delta \ln PV}_{it} + \beta_2 \Delta CPR_{it} + \beta_3 \Delta \ln GR_{it} + \beta_4 \Delta CCS_{i,t-1} + \\ \beta_5 \Delta PPG_{i,t-1} + \beta_6 \Delta APR_{it} + \beta_7 \Delta CPA_{it} + \delta D + \beta_8 D \times \Delta CPA_{it} + \eta_t + \alpha_i + \epsilon_{it}. \end{aligned}$$

Our results in table 3.4 show that pastureland values have a significant positive effect on cropland values. We find a 1% increase in pastureland values increases cropland values by 0.42% (95%–C.I. 0.37%; 0.48%). To compare the price transmission rate of pastureland to cropland versus cropland to pastureland, we divide the estimated marginal effect of cropland in Model III by the estimated marginal effect of pastureland. We find that changes in cropland values transmit to pastureland values at almost twice the rate of the reverse case 1.63 (95%–C.I. 1.33; 1.95). The estimated marginal effect of government support is also consistent with Goodwin et al. (2003), Goodwin et al. (2011), and Kropp and Peckham (2015). In fact, we find that a 1% increase in direct government spending raises cropland values by 0.088% (95%–C.I. 0.0.05%; 0.13%). Similarly, the estimated marginal effect of the demand for corn land is consistent with our two-stage results, with a 1% increase in corn plantings inflating cropland values by 1.93% (95%–C.I. 1.65%; 2.21%). However, unlike our two-stage results, the estimated marginal effect of the incremental increase in the demand for corn land after RFS-2 is insignificant. One possible explanation for this result is that cropland owners updated their expectations with regard to their land values prior to the implementation of RFS-2 as they witnessed the progressive move toward government mandated ethanol production. As such, cropland values capitalized this information more quickly than other agricultural land values were the impact of ethanol policy is not as clear.

Table 3.4: Relative Value, Internal IV, and Reverse Transmission Robustness Checks

	RV_{it} (Relative Value)	$\Delta\ln PV_{it}$ (Internal IV)	$\Delta\ln CV_{it}$ (Reverse Trasmission)
CPR_{it}	0.12^{***} (0.0016)		
$\ln \text{GR}_{it}$	0.040^{*} (0.021)		
$\ln \text{CCS}_{it}$	0.079^{**} (0.036)		
$\ln \text{LPS}_{it}$	-0.041^{**} (0.021)		
PPG_{it}	0.083^{***} (0.010)		
APR_{it}	0.0073 (0.0039)		
$\widehat{\Delta\ln CV}_{it}$		0.63^{***} (0.11)	
$\widehat{\Delta\ln PV}_{it}$			0.42^{***} (0.060)
ΔCPR_{it}		-0.022^{***} (0.001)	0.013^{***} (0.0015)
$\Delta\ln GR_{it}$		-0.28^{***} (0.010)	0.088^{***} (0.019)
$\Delta\ln LPS_{it}$		0.093^{***} (0.009)	
$\Delta CCS_{i,t-1}$			-0.004^{*} (0.002)
$\Delta PPG_{i,t-1}$		-0.008 (0.005)	-0.014^{**} (0.006)
ΔAPR_{it}		-0.0005^{**} (0.0002)	-0.0003 (0.0004)
ΔCPA_{it}	0.72^{***} (0.13)	-2.19^{***} (0.20)	1.93^{***} (0.14)
$\text{D} \times \Delta CPA_{it}$	0.11 (0.074)	0.31^{**} (0.13)	0.25^{***} (0.055)
Observations	8,712	8,712	8,711
R^2	0.17	0.68	0.22
Adjusted R^2	0.03	0.68	0.08
F Statistic	194.35^{***}	1539.00^{***}	252.89^{***}
DF	8 & 7411	8 & 6674	8 & 7410

Note: robust std. errors in parentheses $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

3.6 Policy Implications and Further Research

The implications of our results are multi-facted. First, if a county's land use mix is dominated by corn, then the relative value of pastureland will fluctuate, depending on corn market expectations and the demand for cropland. Hence, pastureland owners should diversify to limit their exposure. On the supply side, the owners of pastureland could attempt to de-couple the value of their asset with cropland by substituting inputs, i.e. using organic as opposed to industrial inorganic fertilizer. Similarly, on the demand side and in particular for cattle producers, they should consider the outside option of finishing cattle with an alternative to corn like cotton seed or alfalfa. Nevertheless, our results establish that there is a critical link between cropland and pastureland values that impacts the welfare of both crop and livestock producers. Including price transmission components in the estimation of land values represents a logical extension to the traditional model of agricultural land value determinants.

Policy makers considering prescriptions to stabilize crop farm incomes, whether directly through government spending or indirectly through demand creation, should consider spillover effects to related markets that increase economic inefficiency. Our results show that U.S. farm and land policy, as currently applied, disproportionately favors crop production yielding significant distortions to the values of pastureland. We find that positive gains in cropland values do pass through to pastureland markets, however, these gains are more than reversed due to the high of opportunity costs associated with maintaining land in pasture. The next step in evaluating the dynamics between cropland and pastureland values is to use richer data such as the ARMS data. Using farm-level survey data would allow for more precise estimation of individual farmer behavior in response to changes in government support.

Chapter 4

A Nonlinear Asymmetric Model of Lumber Price Transmission

The housing supply chain requires a constant supply of lumber products. Yet, even as housing and lumber prices have grown throughout the past decade, the underlying value of timberland remains low. We use monthly and quarterly price and inventory data to estimate a nonlinear autoregressive distributed lag model of the complete timber-lumber-housing supply chain. Our methodology builds on previous lumber price studies by developing a less rigid framework for identifying nonlinear asymmetric relationships between end-use, product, and factor prices, when controlling for inventories. Our results show that in the long-run a 1% increase in housing prices corresponds to a 0.28% (95%–C.I.: 0.03%;0.53%) increase in lumber prices. Negative shocks to housing have no significant effect on lumber prices. Furthermore, we find that lumber and stumpage are only marginally cointegrated with positive and negative shocks to lumber having no significant effect on stumpage prices.

4.1 Introduction

Vertical price transmission analysis is a useful tool in examining how changes to governmental policies affect each stage of the supply chain. For instance, since the 1950s, U.S. forest policy pursued region specific strategies with regard to timber production, e.g. restricting harvests in the West and promoting a more efficient plantation model in the South. These policies fundamentally transformed how and where Americans get their wood products, and equally important, how the owners of timberland and the manufacturers of wood products benefit from exogenous shocks to consumer demand from their end-uses (e.g. housing, industrial pallets, etc.). We assess the contention that the ample wood basket of the South, spurred into existence by federal policy and market conditions, insulate the owners of timberland from price shocks to housing and finished lumber markets. We focus on housing as our primary wood product market, since it represents the greatest proportion of total consumption. We add to the price transmission literature by considering the entire supply chain of softwood lumber from standing trees to finished framing lumber, which is used in new home construction. Using monthly price and inventory data from

January 1992 to August 2021, we use a nonlinear asymmetric framework that decomposes positive and negative price shocks between markets, from which we estimate the long-term elasticities between housing and finished lumber. Using quarterly data from first quarter of 1992-Q1 to second quarter 2021-Q2, we also estimate long-term elasticities between lumber and harvestable timber (i.e. stumpage).

We adapt the nonlinear autoregressive distributed lag model (NARDL) developed by Greenwood-Nimmo and Shin (2013) to estimate price transmission from the housing market to lumber, and then from lumber to stumpage. A NARDL modeling approach confers several econometric advantages over traditional threshold vector correction models. We estimate the housing-lumber model with monthly data and the lumber-stumpage model with quarterly data. Our estimated results show that positive housing price shocks significantly affect wholesale lumber markets, while negative price shocks do not. Further, we find that when we control for lumber inventories positive and negative shocks to the softwood lumber price do not pass through to stumpage owners. Our results also support previous findings by Haynes (1977) and Merrifeld and Haynes (1984). These studies found that stumpage demand is more inelastic than lumber demand, so that lumber prices respond more readily to price changes than stumpage prices along the supply chain. Our findings suggest that timberland owners should diversify how they market their timberland so as to maximize its value in the face of price transmission asymmetry.

4.2 Historical Background

The spatial composition of the softwood lumber industry changed dramatically in response to substantive reforms in U.S. forest policy. Until the 1990s, the Western United States was the largest lumber producing region. For example, from 1960s till the late 1970s, 55% of all lumber produced in the United States came from the West. Old-growth timber accounted for much of this production, sourced from federally owned lands in the Pacific Coast region (i.e. Washington, Oregon, and California). In the 1980s, the proportion of lumber coming from the West decreased to just under half of total production, because of declining levels of timber from public lands and increasing levels of production in the South. In the early 1990s, the federal government removed large areas of public timberlands from harvest further decreasing western production. In 1990, the South became the nation's wood basket, accounting for 35% of all softwood lumber and 80% of all hardwoods (Howard, 2007). Subsequently, softwood lumber production in the South continued to increase reaching a peak in 2005. After 2005, with the advent of the Great Recession, lumber production declined across all regions as housing demand fell. Since 2011, production rebounded across all regions, with the South still dominating production (Howard and Liang, 2019). Figure 4.1 depicts these trends.

Lumber consumption in the United States in 2020 for all uses totaled more than 54.7 billion board feet (BBF) (see figure 4.1), an increase of 17.0 BBF since 2009 at the low point of the great recession. Lumber consumption since 2009 increased in each of the last 12 years.

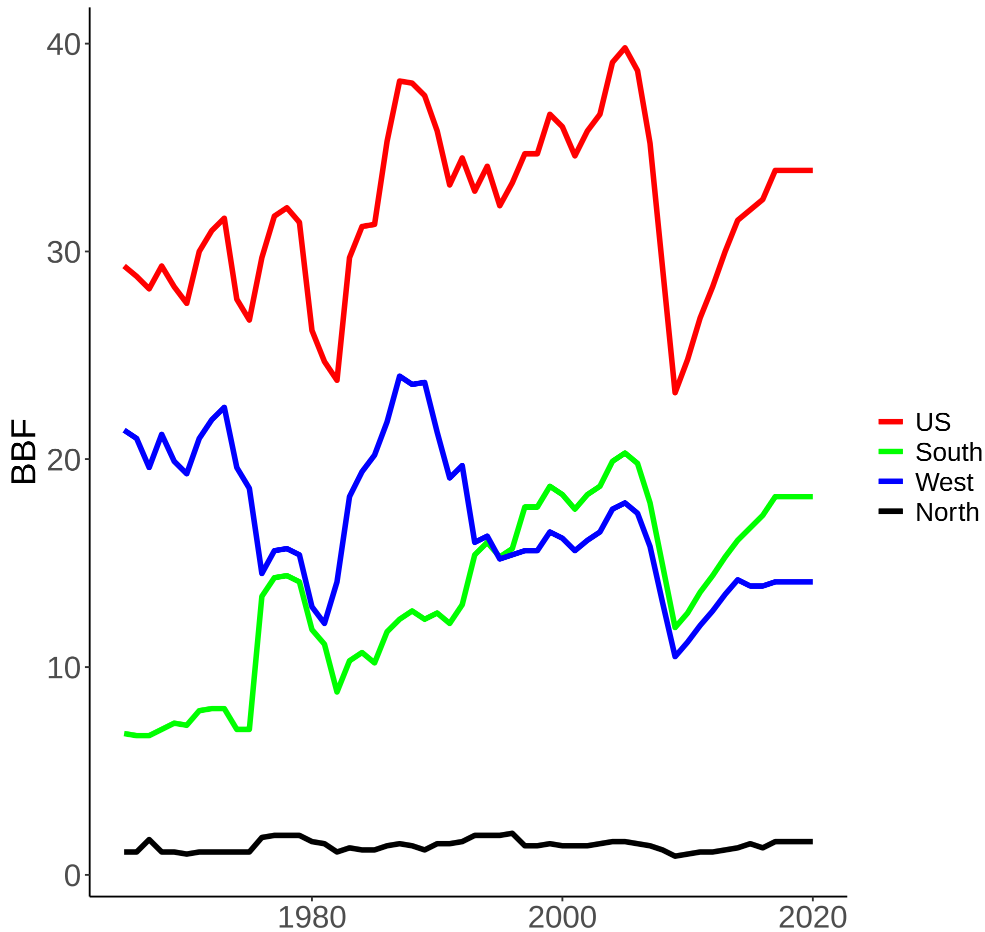

Figure 4.1: U.S. Total Softwood Lumber Production by Region 1965-2019
Source: Howard and Liang, 2019

Lumber consumption peaked at 74.5 BBF in 2005, a record high that even exceeded 1900 levels, when lumber was the most important raw material used in the United States for construction, manufactured products, and shipping (Howard and Liang, 2019).

The primary driver behind this year after year consumption growth is home construction, renovation, and maintenance. In fact, about 69% of the softwood lumber consumed in 2017 was used for housing, with 30% for the construction of new units and 39% of consumption for the upkeep and improvement of existing units. The Western Wood Products Association (WWPA) estimates that new nonresidential construction accounted for about 11.1% of consumption. Lumber consumption used for shipping (pallets, containers, etc.) accounted for 13.8%. The remaining 6.1% was for all other uses (WWPA, 2018; Howard and Liang, 2019). In 2017, softwood species made up approximately 98% of the domestic lumber production used in new housing. A decline in hardwood flooring and rapid increase in house size lead to the increase in the percentage of softwood lumber consumed by housing. Even with the heterogeneity in the different end use markets, softwood lumber consumption as a percentage of total lumber consumption has remained around 86% since the 1960s (Howard and Liang, 2019).

Given the established link between softwood lumber and housing market trends, it is unsurprising that the upward trajectory observed in lumber production and consumption directly coincides with an expanding housing market. For instance, since the Great Recession, single-family housing starts almost doubled, increasing by 97%. Furthermore, multifamily housing starts also increased by 99% since 2011. Another important industry measure of home builder expectations is new approved housing units. In December 2021, new approved housing units peaked at more than 1.8 million units, a 29% increase from December 2019 (FRED, 2022). Timely completion of new home construction requires a consistent supply of lumber. In fact, strong housing demand pushed framing lumber prices up, driving mills (primarily in the South) to expand production creating more inventory. The National Association of Home Builders estimates that for 2021 the average price of a new single-family home increased by more than $18,600 due to framing lumber costs (Emrath, 2022). As a result, the national average price to build a home increased significantly (Kilroy, 2021). Figure 4.2 shows the monthly median price of approved housing units and total merchantable wholesale lumber inventory from 1992 to 2021. The correlation between new approved housing unit prices and lumber inventory is stark. Between 2005 and 2009, housing prices and lumber inventories ballooned before a significant decline in the aftermath of the Great Recession. Since 2011, prices and inventories followed a positive linear trend, with a brief interruption due to the COVID-19 pandemic. Subsequently, housing and lumber inventories resumed an exponential growth trend.

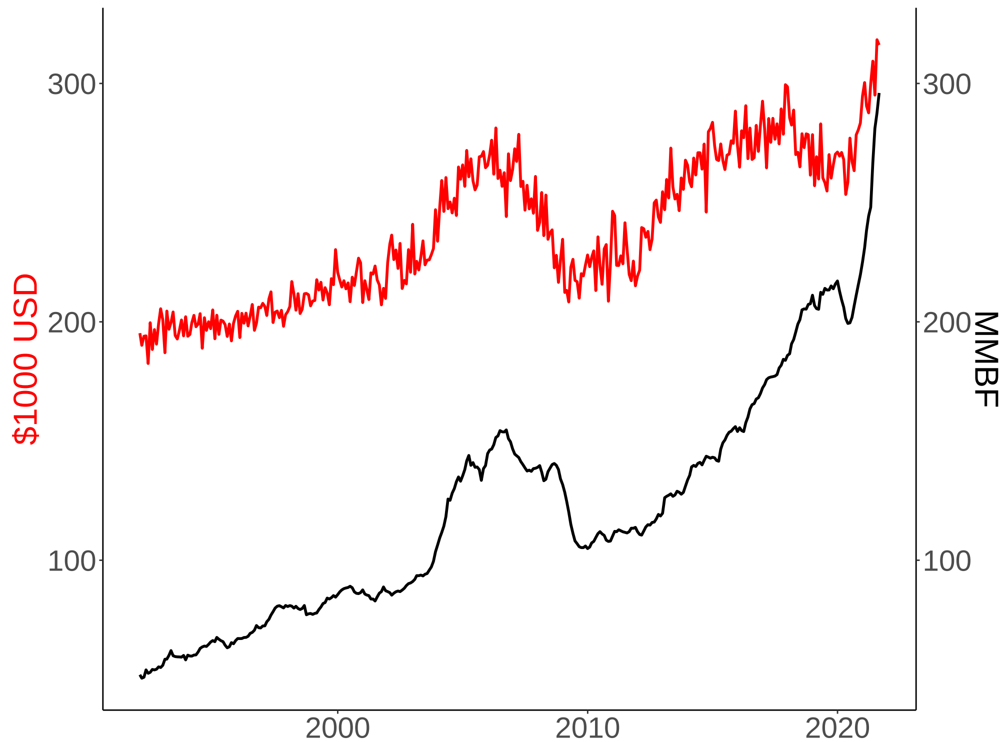

Figure 4.2: Monthly U.S. Wholesale Lumber Inventories (black) & Median New Housing Prices (red) 1992-2021

Source: Bloomberg (2021) & Census Bureau (2022)

Note: Median New Housing Prices are deflated using the FRED CPI series for City-Housing Residential at base month-year, January 2012.

The cost-sharing initiatives implemented through the Conservation Reserve Programs (CRP) increased the number of trees planted after 1988. Given the life-cycle of softwood species, the trees planted in the late 1980s only began to produce sawtimber (i.e. timber of desirable dimensions for lumber productions) during the Great Recession. Hence, many landowners delayed the harvest of their timber because of low housing prices following the housing market collapse (Maggard and Zhang, 2021). The combination of these factors resulted in a serious oversupply of standing timber across the South. The oversupply of timber is the primary cited reason for the decline in stumpage prices observed in figure 4.3, according to data from Timber-Mart South (TMS). In contrast, given the significant changes in the housing market, lumber prices were considerably more volatile during this period, according to data from the Federal Reserve Economic Database (FRED). However, in May 2021, lumber prices peaked at over $1000 per thousand board feet (MBF), an almost 250% increase from the year prior, while stumpage prices remained unchanged over that same time frame (Trading Economics, 2023). Figure 4.3 displays these trends using the Softwood Lumber Price Index from the Federal Reserve Economic Database (FRED).

Figure 4.3: Quarterly Stumpage Prices & Lumber Price Index
Source: TMS (2022) & FRED (2022)
Note: Stumpage prices are deflated using the Logging PPI series from FRED at base year-quarter, 2012-Q1. Similarly, Softwood Lumber Price Index is re-based from 1986-Q1 to 2012-Q1.

The disconnect between stumpage (input factor) and lumber (product) markets is traditionally understood in the context of derived demand theory (Tomek and Robinson, 1990). Stumpage is the primary factor of production and lumber is the most consumed value-added product. Therefore, if the demand for the product increases, ceteris paribus, the factor price increases as does the quantity produced. The resulting adjustment process culminates, when factor and product markets stabilize (i.e. reach new factor and product equilibriums). Under this framework, the price of the factor is positively affected by the price of product. Moreover, an asymmetric effect is possible, given the abundant supply of standing timber, low product market concentration, and the volatility in housing demand over time.

4.2.1 Federal Restrictions in the West

The South supplanted the West as the nation's wood basket, owing partially to the environmental restrictions implemented there by the federal government. The most significant, which we highlight here, was the federal action to preserve critical animal species. The specific prescriptions adopted included efforts to protect the habitat of the Northern Spotted Owl on federal lands as mandated by the Endangered Species Act of 1973 (ESA). To preserve the owl's habitat, the federal government proposed changes in forest management in 1986, but these changes were litigated in federal court (Wear, 1998; Wear and Murray, 2004; Riddle, 2022). As a result, the court placed a moratorium on a significant portion of the national forest timber sale program in the West in 1989. Legal issues continued until the 1993 "Forest Summit," lead by President Clinton and a subsequent federal forest plan. These forest plans adopted complex Planning Rules for management of federal forest lands. The Planning Rules are based on the economic principle of maximum sustainable yield and mandate consideration of non-timber multiple-use products sourced from forest lands (e.g. amenity value, carbon sink, and environmental protection). These rules resulted in an immediate impact on the amount of timber harvested from these lands (Sun and Ning, 2014). For example, prior to this policy change, annual harvests had risen from the 1950s through the 1980s, sometimes exceeding 10 BBF. However, following 1989, timber production from federal lands decreased year after year. Specifically, timber sales volumes from western federal forests in 1989 amounted to only 70 percent of sales in 1988. By 1995, timber sales volume dropped to 15 percent of the 1986 peak production levels. Annual harvested volumes continued to decrease in the early 1990s and remained between 1.8 and 2.8 BBF since 2003. In 2018, harvests from federal land was 2,8 BBF. In the aggregate, 15% of total U.S. timber production was harvested from federal lands in 1991. Since 2011, the share of timber harvested from federal lands is less than 2% (Riddle, 2022).

Of the 765 million acres of timberland, in the U.S. the Forest Service manages 96.1 million acres and the Bureau of Land Management (BLM) manages 6.1 million acres. Most of this productive timberland ($\approx$ 75%) is concentrated in the 15 Western states (Vincent et al., 2019; Riddle, 2022). Conversely, the South's timber landscape is dominated by private owners (90%). Roughly 20% is held by corporations that own wood-processing facilities, but the large majority is held by nonindustrial entities. This category includes Timber Real Estate Investment Trusts (or REITS), which offers investors access to a relatively stable asset class with higher avreage returns and less correlated with other investments than the wider stock market (Charles Schwab, 2023). Besides the difference in the composition of timberland ownership, in the South, harvests are more predominantly derived from agricultural forestry, with forests growing on shorter (20- to 30-year) rotations. The Forest Service Southern Region and land grant university research spurred the advancement of applied agroforestry in the South. We detail the institutional support and market incentives that enables the south to overtake the West in the next section.

4.2.2 Federal Support and Market Incentives in the South

A confluence of factors contributed to the expanded softwood production of the South. Pine species predominate due to their short rotation periods and suitability in the Southern climate and soils. In addition, the productivity gains from Southern land grant university research trials contributed significantly to increasing pine wood production. Before the 1970s, for instance, the South had only 1.8 million acres of pine plantations. And, in 2000, the South had over 32 million acres. Moreover, by one measure of yield, the mean annual increment[1] (MAI), pine plantations in the South more than doubled the MAI in the region.

From the end of the Civil War through World War II, large amounts of agricultural land was abandoned throughout the South due to declining soil fertility, low prices for the major cash crops, and pest infestations (e.g. the boll weevil plague for cotton production). As a result, the South has a significant proportion of cleared land ripe for reforestation. Concurrently, the Southern pulp and paper industry was revitalized, providing a consistent market for softwood timber (Reed, 1995; Fox et al., 2004). This reforestation required an abundant supply of quality seedlings. The Forest Service lead a concerted research effort, producing a series of informative monographs, detailing practical techniques on the planting and establishing of pine stands (Fox et al., 2004). The monographs provided foresters comprehensive information on seed collection and processing, seedling production, and planting requirements as well as a widely used grading system for determining the quality of seedlings. Subsequently, the survival rates of seedlings increased on plantations across the South. Selective breeding programs also improved the genetics in new seedlings. Breeding programs focused on improving volume growth (i.e. timber yield), tree form (e.g. desirable straight trees with few limbs), disease resistance, and wood quality (Zobel and Talbert, 1984).

In conjunction with improved seed genetics and establishment practices, Southern foresters developed site preparation strategies for pine. Removal of residual residues, followed by tillage for soil preparation, became the standard practice to limit competition from hardwood species (Fox et al., 2004). However, productivity of successive rotations can decline under intense site preparation post-harvest. Then, the challenge becomes determining the amount of soil tillage required to achieve optimal seedling establishment by not removing most of the organic matter from the soil (Dyck and Cole, 1994).

Concurrent with the push for the adoption of intense site preparation, research institutions also advocated fertilization with diagnostic testing to ensure effectiveness. In the late 1960s, the Cooperative Research in Forest Fertilization (CRIFF) Program at the University of Florida and North Carolina State Forest Fertilization Cooperative was established. CRIFF developed a rigorous soil classification system to determine the likelihood of obtaining an economic growth response from fertilization, which was widely adopted throughout the South (Fisher and Garbett, 1980). This new method of forestry increased productivity from site-specific applications of modern silviculture techniques. The effect was immediate. For example, the rate of nitrogen and phosphorus application increased from 15,000 acres annually in 1988 to 975,000 acres in 2000 (Fox et al., 2004). The economic impact of fertilization were significant. Fox et

[1]The average growth per year a stand of trees experienced up to a specified age.

al. (2007) found that mid rotation fertilization yields an internal rate of return (IRR) of 16%, assuming an average growth response from fertilization and fertilizer costs of $90 per acre.

Competition from hardwood species is the most detrimental factor in pine plantation establishment. Nevertheless, chemical site preparation declined throughout the 1970s and 1980s because of government limitations on herbicide use and difficulty accessing sites for chemical application (Fox et al., 2007). Yet, even as pesticide use declined, advances in plant breeding filled the gap. For example, McKeand et al. (1997), Jansson and Li (2004), and Bettinger et al. (2009) show that the use of clonal plant breeding from high-producing genotypes developed within a certain ecosystem improves the economics of pine plantations and increases their overall resiliency to pests and climate.

Government programs have also kept pace with technological advancements in pine production. In 2010, the National Resource Conservation Council (NRCS) piloted a program to incentivize the production of Longleaf Pine across the Southeastern United States. Under the Longleaf Pine Initiative (LLPI), NRCS works with timberland owners to establish Longleaf Pine plantations by subsidizing a significant portion of establishment costs and providing technical assistance to foresters. As a result, by 2021, NRCS has contracted over 870,000 acres under LLPI in almost 10,000 producer contracts (NRCS, 2021).

4.2.3 Lumber Market Concentration

The capacity of the top 10 U.S. softwood lumber producers is 22.8 BBF. They represent over half (52%) of the total softwood lumber production capacity in the U.S. (see figure 4.3). Capacity of the top 10 firms increased by 3.9 BBF since 2017 and by 0.5 BBF since 2019 alone. Nevertheless, the actual total production of the top 10 producers is almost 50% of the U.S. total (figure 4.1). In fact, each of the top 10 producers had at least 1 BBF in productive capacity in 2021.

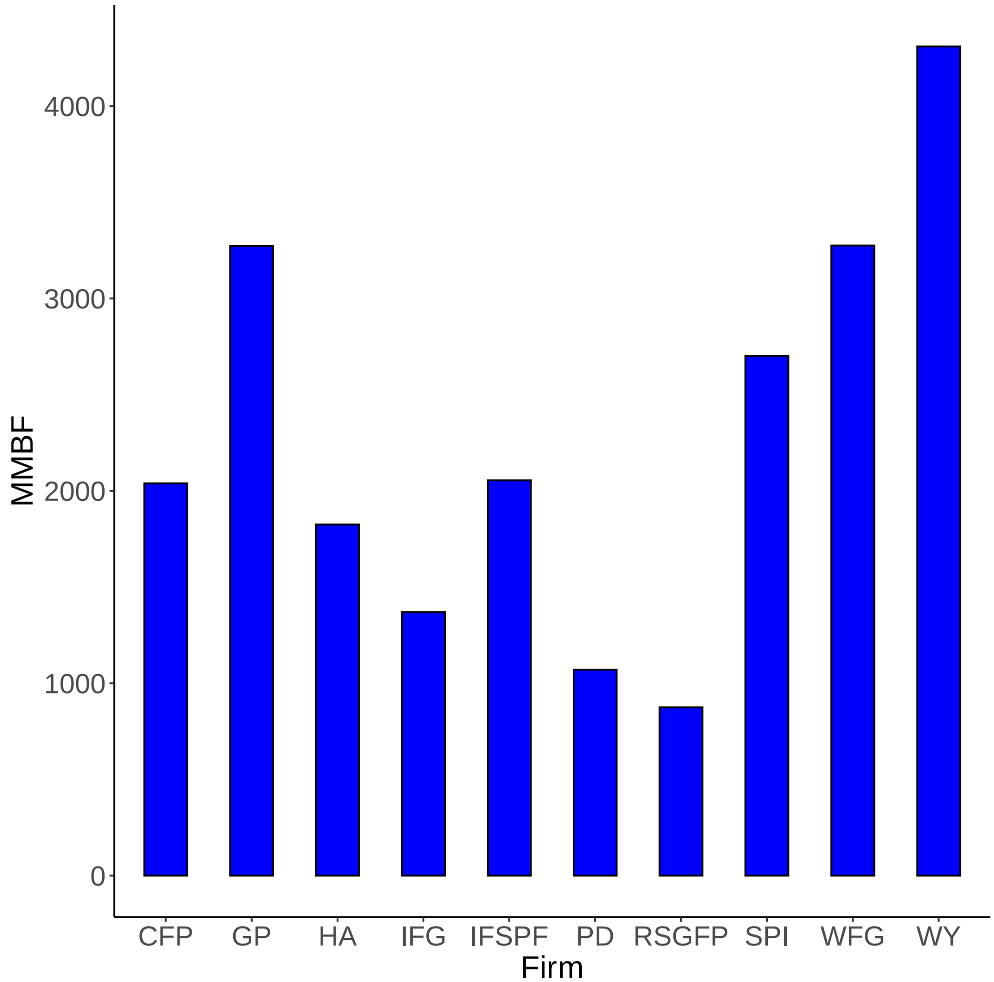

Figure 4.4: Top 10 Lumber Producers by Productive Capacity 2021
Source: Forisk 2021

Business activity in the U.S. softwood lumber industry is characterized by volatility due to the low level of firm concentration and a high dependence on sales from the domestic construction industry (United States International Trade Commission, 1999; Mehrotra et al., 2014; Howard and Liang, 2019). The softwood lumber industry is the largest U.S. forest sector industry by timber volumes processed and employment generated (Howard, 2007; Howard and Liang, 2019; Forisk, 2021). In 2007, there were approximately 1,700 softwood sawmill establishments in the United States, employing about 50,000 employees. Following the downturn in housing demand and the oversupply lumber inventories, the number of softwood mills declined to less than 990. In addition, employment numbers fell as firms scaled back production and adopted more efficient technology (Howard and Liang, 2019). Hence, the sector is now characterized by a proliferation of small-scale operations, with approximately 55 percent establishments employing fewer than 20 employees (Spelter et al., 2009; Mehrotra et al., 2014; Riddle, 2022). It is also characterized by a significant concentration of demand for its output, with residential construction (including repair and remodeling) accounting for about 60% of domestic consumption and an additional 10% (approximately) used for nonresidential construction (Howard and McKeever, 2011; Howard and Liang, 2019). Thus, the value-added lumber market is highly competitive, where many firms compete away any arbitrage opportunities that arise. Therefore, sudden changes in consumer lumber consumption are more directly felt by lumber producers compared to timberland owners (Mehrotra et al., 2014). Empricially, Haynes (1977), Zhou and Buongiorno (2005), and Sun (2011) support this finding, using traditional vertical price transmission models. These studies find consistently that the derived demand for stumpage is less elastic than the lumber demand.

Concentration in the U.S. stumpage market is, on the other hand, region specific. In 2019, Forest2Market completed a comprehensive analysis of the spatial characteristics of U.S. timberland. In particular, they found that 74% of all timberland is privately-owned while only 26% is publicly-owned. Figure 4.5 breaks down the share of public and private timberland by region. In contrast, a majority of timberland in the Northwest is publicly owned. Private ownership dominates the Northeast and Appalachia, with virtual parity in the Midwest. This feature of timberland ownership in the South confers a comparative advantage with regard to property rights. For example, private timberland owners are not held to the Planning Rules under the various federal forest plans.

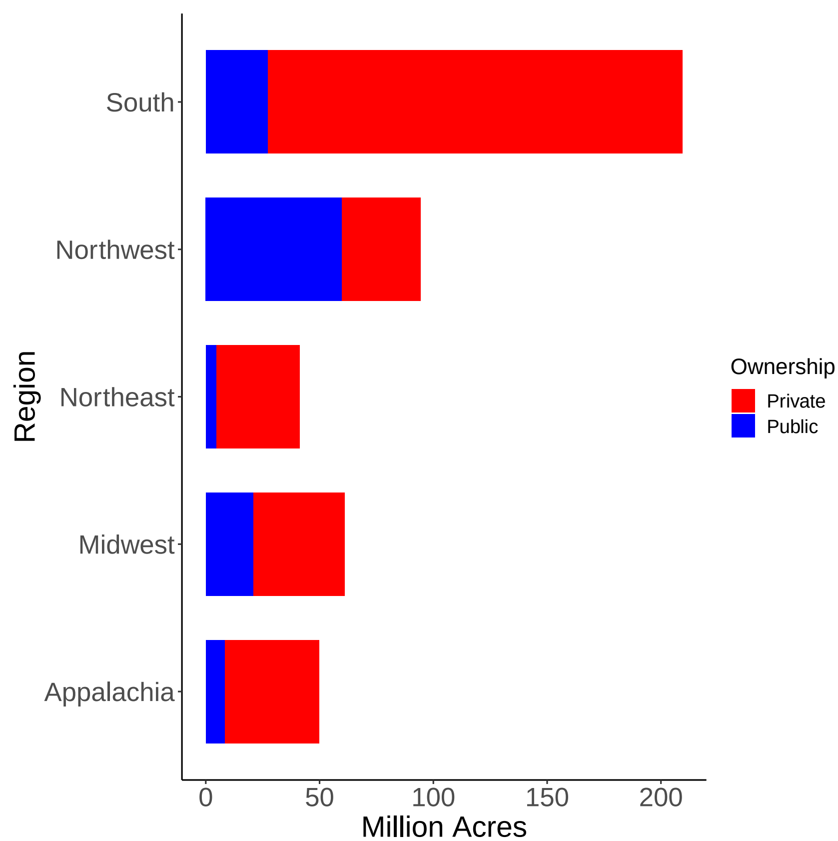

Figure 4.5: Public & Private Timberland Ownership by Region
Source: Forest2Market (2019)

Timberland owners who wish to establish a softwood pine plantation can pursue production plans that employ yield maximizing techniques such as fertilization, intense site preparation, increased planting densities and periodic chemical pesticide treatments. The application of these techniques increased the output of sawtimber from private timberland in the South relative to publicly owned timberland in the West. In response, lumber producers shifted investment in new sawmills from the West to the South. In 2020, according to the Forestry Inventory Analysis (FIA) Database, of 1560 total producing mills in the South, 240 were primarily devoted to milling softwood sawtimber. In contrast, there were only 51 mills in the Northwest milling softwood sawtimber (FIA, 2020).

4.3 Relevant Literature

Numerous studies evaluate price transmission in lumber markets. A review of this literature reveals two key factors. One factor is that the standard econometric models used are relatively inefficient, compared to recently proposed nonlinear asymmetric models. Second, linearity is assumed for price shocks between contintegrated price series, a rather strong assumption. Linear models of price transmission in the literature include Zhou and Buongiorno (2005) and Luppold et al. (2014). Ning and Sun (2014) use an Engle and Granger two-step vector error correction model (VECM) to estimate the asymmetric cointegration relationship between stumpage and lumber prices. Their results show that in terms of spatial price transmission the South shows slightly stronger market cointegration than the West. In addition, they find significant asymmetric price transmission between stumpage and delivered timber prices as well as between delivered/lumber prices. Parajuli and Chang (2015) employ a multivariate time-series approach to estimate an unrestricted Johansen VECM of price transmission between finished lumber and stumpage. Using Louisiana sawtimber data, they find that softwood inventory has near unit elasticity compared to the own stumpage price elasticity, which was highly inelastic. Therefore, inventories responded in greater magnitude to lumber price changes than downstream prices and at a greater speed. Other notable studies of lumber price transmission that use less efficient models (such as Threshold VECM) but relax the linearity assumption include (Sun , 2011; Sun and Ning, 2014; Yang et al., 2020; and Wang et al., 2021).

A major criticism of the Engle and Granger and Johansen approaches is that the NARDL approach is more advantageous, econometrically (Greenwood-Nimmo and Shin, 2013; Shin et al., 2014). First, it performs better with small samples compared to alternatives. Second, it is more efficient. Third, it does not require the restrictive assumption that all series are integrated of the same order allowing for the inclusion of both I(0) and I(1) series in a long-run relationship. Finally, it relaxes the assumption implied by linearity that adjustments be symmetric in the long and short run.

There are several empirical studies that employ the NARDL model in agricultural commodity price analysis. Fousekis et al. (2016) analyzes price asymmetry along the beef supply chain. They find significant asymmetry between farm, wholesale, and retail price levels. Chowdhury et al. (2021) estimates a NARDL model for energy and food commodities. Their results show that energy prices have an asymmetric effect on food prices. In particular, a positive shock in energy prices has a more pronounced effect on agriculture commodity prices than a negative shock. Ali et al. (2022) estimates the short- and long-run elasticites between renewable energy prices and environmental quality in South Africa. They find that renewable energy prices have a positive short- and long-run effect on environmental quality.

4.4 Data

For our analysis, we use monthly U.S. price and inventory data for new housing units and softwood lumber from FRED, Census Bureau, and Bloomberg. Median new housing unit prices are deflated by the FRED consumer price index (CPI) for city-housing residential. All prices are further expressed in January, 2012 dollars. We also collect average 30-year fixed rate mortgage data from FRED to account for the cost of home purchase borrowing. Table 4.1 presents the summary statistics for each of our monthly series.

Table 4.1: Monthly U.S. Lumber-Housing Data from Jan-1992 to August-2021

Statistic	Name	Mean	St. Dev.
Approved Housing Units (1,000 units)	new_builds	1,350	412
Nominal Median New Home Price ($)	$hous\_price$	222,347	70,122
Real Median New Home Price ($)	$hous\_price2012$	238,172	30,798
30-Year Fixed Rate Mortgage Avg. (%)	$mort\_rates$	5.76	1.70
Wholesale Lumber Inventories (MMBF)	$inven$	12,158	4,918
Softwood Lumber Price Index	$SPLI\_2012$	123.46	31.82

Source: FRED (2022), Census Bureau (2022), & Bloomberg (2021)
Note: All real prices are expressed in Jan-2012 dollar terms. Home Prices are deflated using the FRED CPI series for City-Housing Residential. $N = 356$ observations.

Table 4.2 presents the summary statistics for our quarterly lumber and stumpage market data, including the south-wide average softwood stumpage price. To create quarterly series for the U.S. lumber price index and inventories, we average over the months corresponding to each quarter. For example, the first quarter lumber price index in 1992 is the average of the monthly values from January to March. Quarterly stumpage prices are sourced from Timber-Mart South. We deflated this series using the producer price index (PPI) for logging equipment from FRED. All prices for the quarterly data reflect 2012-Q1 dollars.

Table 4.2: Quarterly Stumpage-Lumber Data from 1992-Q1 to 2021-Q2

Statistic	Name	Mean	St. Dev.
Nominal South-Wide Average Softwood Stumpage Price ($/ton)	$stump$	30.70	6.58
Real South-Wide Average Softwood Stumpage Price ($/MBF)	$stump\_2012MBF$	26.61	6.49
Softwood Lumber Price Index	LPI	122.98	30.83

Source: FRED (2022) & TMS (2022)
Note: All prices are expressed in 2012-Q1 terms. Stumpage prices are deflated using the FRED Logging PPI series. $N = 118$ observations.

Next, we determine whether or not our price series contain a unit root. First, we take the first difference of our logged price series. Then, we perform Augmented-Dicky Fuller (ADF) tests along with Phillips-Perron (PP) tests. Our test results are shown in table 4.3. We reject the null hypothesis of the presence of a unit root in each of the three price series for both the ADF and PP test statistics. The results suggest that prices along the stumpage-lumber-housing supply chain are I(1).

Table 4.3: Unit Root Tests on Stumpage-Lumber-Housing Price Data (1992-2021)

Series	ADF Test Statistic	Phillips-Perron Test Statistic
$SPLI\_2012$	-3.22	-3.34
$hous\_price2012$	-6.18***	-7.46***
$stump$	-3.25	-3.27
$\Delta\ln(SPLI\_2012)$	-12.03***	-10.63***
$\Delta\ln(hous\_price2012)$	-33.57***	-42.43***
$\Delta\ln(stump)$	-9.18***	-9.09***

Note: *** signifies p-values less than 0.01 α-level. ** signifies p-values less than 0.05 α-level.

4.5 Theoretical Model

Gardner (1975) showed under what assumptions a marketing margins approach of price relationships for factor and product prices is appropriate. In general, under zero elasticity of substitution between factors the approach is valid. That is, factors are transformed into product at fixed rates. Haynes (1977) argues this is not an unreasonable assumption given the rather inflexible nature of forestry technology and timber harvesting. As a result, marketing margins between stumpage and lumber are typically modeled using one of three assumptions: (1) constant percentage markup, (2) linear in product prices, (3) a fixed coefficient regression model. Merrifield and Haynes (1984) estimate supply, demand, and price transmission elasticities for Pacific Northwest lumber and stumpage. They find that stumpage demand is more inelastic than lumber demand and find evidence to suggest that there is substitution between labor and capital at the factor market level[2]. One extension to this modeling framework is to account for the influence of inventories.

Equation (4.1) adapts the regression model for lumber-stumpage marketing margins to include inventories. We denote m as the marketing margin; p^x represents the product price; and p^a represents the factor price. β describes the linear relationship between product and factor prices. γ denotes the linear relationship between inventories and price markups. ϕ represents nonlinearities between prices and inventories. We let $\gamma > 0$ and $0 < \phi < 1$.

$$\begin{aligned} p^x &= p^a + m \\ m &= \beta p^x + \gamma I^{\phi}. \end{aligned} \tag{4.1}$$

Comparative statics for product and factor prices quickly show that:

$$\begin{aligned} \frac{\partial p^x}{\partial I} &= \gamma\phi I^{\phi-1} > 0 \quad \text{and} \quad \frac{\partial^2 p^x}{\partial I^2} = \gamma\phi(\phi-1)I^{\phi-2} < 0\,, \\ \frac{\partial p^a}{\partial I} &= \gamma\phi I^{\phi-1} < 0 \quad \text{and} \quad \frac{\partial^2 p^a}{\partial I^2} = \gamma\phi(\phi-1)I^{\phi-2} > 0. \end{aligned} \tag{4.2}$$

Hence, product prices grow with inventories at a decreasing rate, while factor prices decrease as inventories grow at an increasing rate. We can now examine the elasticity of price transmission by rearranging (4.1) and examining how it changes from one time period (i) to the next:

$$\begin{aligned} p^a &= \beta p^x - \gamma I^{\phi}\,, \\ p_i^a &= p_{i-1}^a + \beta(p_i^x - p_{i-1}^x). \end{aligned} \tag{4.3}$$

If we normalize the product price to 1 and solve for the price ratio, we have an expression for the elasticity of price transmission (η):

$$\eta = \left(\frac{1-p_i^a}{\gamma}\right)^{\frac{1}{\theta}}. \tag{4.4}$$

Therefore, by assuming prices are a nonlinear function of inventories, the resulting price transmission elasticity is primarily a function of inventory response parameters and the stumpage price.

[2]Lewandrowski et al. (1994) develops a structural model of lumber markets that accounts for inventories. They estimate their model using simultaneous equation methods and find that short-run vs. long-run inventory parameters have significant opposite effects on lumber supply and price expectations

4.6 Empirical Framework

The NARDL(p, q) is obtained for two time series $\{y_t, x_t\}$, where y_t is downstream prices and x_t is the upstream price, by partitioning x_t into positive and negative partial sums and combining the resulting long-run equilibrium relationship with the standard linear ARDL(p, q):

$$\begin{aligned}\Delta y_t = a_0 + \rho y_{t-1} + \theta^+ x^+_{t-1} + \theta^- x^-_{t-1} + \gamma z_{t-1} + \sum_{j=1}^{p-1} a_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi^+_j \Delta x^+_{t-j} + \\ \pi^-_j \Delta x^-_{t-j}) + \epsilon_t\,, \\ \text{s.t.} \qquad x^+_t = \sum_{j=1}^{t} \Delta x^+_j = \sum_{j=1}^{t} \max(\Delta x_j, 0)\,, \\ x^-_t = \sum_{j=1}^{t} \Delta x^-_j = \sum_{j=1}^{t} \min(\Delta x_j, 0).\end{aligned} \tag{4.5}$$

We estimate two equations of the above form: (1) wholesale lumber $\rightarrow$ stumpage; and (2) new housing prices $\rightarrow$ wholesale lumber. In equation (4.5), the nonlinear long-run asymmetric relationship is given by $\theta^+ x^+_{t-1} + \theta^- x^-_{t-1}$, where x^-_t an x^+_t are the negative and positive partitions of the partial sums. z_{t-1} is a vector of controls including the average 30-year fixed rate mortgage and lumber inventories, and lagged differences for y_t are included to account for seasonals and trends. π^+_j, π^-_j are the asymmetric distributed-lag parameters, and ϵ_t is an i.i.d. process with zero mean and constant variance, σ_ϵ. Our estimated models are then:

$$\begin{aligned}\Delta SPLI\_2012 = a_0 + \rho SPLI\_2012_{t-1} + \theta^+ hous\_price^+_{t-1} + \theta^- hous\_price^-_{t-1} + \\ \sum_{l=0}^{L} (\gamma_{1,l} mort\_rate_{t-l} + \gamma_{2,l} new\_builds_{t-l}) + \sum_{j=1}^{p-1} a_j \Delta SPLI\_2012_{t-j} + \\ \sum_{j=0}^{q-1} (\pi^+_j \Delta hous\_price^+_{t-j} + \pi^-_j \Delta hous\_price^-_{t-j}) + u_{1t}.\end{aligned} \tag{4.6}$$

And,

$$\begin{aligned}\Delta stump = a_0 + \rho stump_{t-1} + \theta^+ LPI^+_{t-1} + \theta^- LPI^-_{t-1} + \\ \sum_{l=0}^{L} \gamma_{1,l} inven_{t-l} + \sum_{j=1}^{p-1} a_j \Delta stump_{t-j} + \\ \sum_{j=0}^{q-1} (\pi^+_j \Delta LPI^+_{t-j} + \pi^-_j \Delta LPI^-_{t-j}) + u_{2t}.\end{aligned} \tag{4.7}$$

The long-run relationships for positive and negative shocks are defined by:

$$\beta^{+} = -\frac{\theta^{+}}{\rho},$$
$$\beta^{-} = -\frac{\theta^{-}}{\rho}. \tag{4.8}$$

4.7 Results & Discussion

We estimate the housing→lumber model in (4.6) by least squares. The results are shown in table 4.4. The calculated t-stat for $\hat{\rho}$ is significant at 0.01 α-level, indicating we can reject the null hypothesis of no cointegration. In addition, the diagnostic F-test developed by Pesaran et al. (2001) is significant at 0.01 α-level, so we can reject the null hypothesis of no cointegration ($\rho = \theta^{+} = \theta^{-} = 0$). In fact, we find a significant cointegration relationship with respect to positive shocks to home prices, according to the significant t-statistic for θ^{+}. We also conduct a standard Wald test for short- and for long-run asymmetry. The test for long-run asymmetry assumes a null of symmetry in the long-run price transmission elasticities ($\beta^{+} = \beta^{-}$). In the short-run version, the null assumes $\pi_j^{+} = \pi_j^{-} \forall j = 1, \cdots, q-1$. For the estimated model, we fail to reject the null of symmetry in the short-run, but reject the null for the long-run version. Finally, we find amongst our controls only new housing units has a significant positive short-run effect on lumber prices.

Table 4.4: Estimated NARDL Results: Housing → Lumber (Monthly, 1992-2021)

Coefficient	Estimate	S.E.	t-stat	p-value
Intercept	0.08	0.08	0.94	0.94
$\hat{\rho}$	0.39	0.05	7.40	$<$0.01***
$\hat{a}_1$	-0.68	0.09	-7.67	$<$0.01***
$\hat{a}_2$	0.22	0.06	3.50	$<$0.01***
$\hat{\theta}^{+}$	-0.11	0.05	-2.28	0.02**
$\hat{\theta}^{-}$	0.002	0.10	0.02	0.98
$\hat{\gamma}_{1,0}$	-0.006	0.004	-1.5	0.13
$\hat{\gamma}_{2,0}$	0.042	0.01	3.6	$<$0.01***

Note: *p<0.1; **p<0.05; ***p<0.01
$N = 356$ observations.
Residual standard error 0.04316 on 344 DF; Adjusted-R^2 0.24
Pesaran et al. (2001) cointegration test F-statistic I(1): 13.53*** on 8 and 344 DF
Wald test for short-run asymmetry test statistic: 1.24
Wald test for long-run asymmetry test statistic: 8.15**

From (4.8), we now calculate the long-run price transmission elasticities for housing prices and new housing units. Point estimates, standard errors, and asymptotic Wald 95% confidence intervals are shown in table 4.5. We find that a 1% increase in median new housing prices corresponds to a 0.28% (95%–C.I.:

0.03%;0.53%) increase in lumber prices. This results supports the correlation in housing prices and lumber inventories we observed in figure 4.2. That is lumber manufacturers take advantage of large inventories to capture long-run positive trends in housing prices and insulate themselves from negative housing price shocks -0.004% (95%–C.I.: -0.49%;0.49%). New housing inventories have a significant negative effect on lumber prices. We interpret this result to reflect the fact that more new housing units increases the supply of housing so that demand for new homes is decreasing along with the demand for the products needed to build them.

Table 4.5: Housing → Lumber Asymmetric Long-Run Elasticities

	Estimate	S.E.	95% Wald CI
$\beta^+_{hous\_price}$	0.28	0.13	(0.03; 0.53)
$\beta^-_{hous\_price}$	-0.004	0.25	(-0.49; 0.49)
β_{new_builds}	-0.11	0.036	(-0.18; -0.04)

Next, we estimate the lumber→stumpage model in (4.7) using the same procedure. The results are shown in table 4.6. The calculated t-stat for $\hat{\rho}$ is only marginally significant at 0.1 α-level, indicating that lumber and stumpage prices may not be cointegrated. In contrast, the diagnostic F-test is significant at 0.01 α-level, so we can reject the null hypothesis of no cointegration. Again, we detect using a Wald test no asymmetry in the short-run and the presence of asymmetry in the long-run. However, θ^+ is not significant, while θ^- is only in the short-run. Furthermore, the adjusted-R^2 for this regression, which controls for lumber inventories, is less than 0.10.

Table 4.6: Estimated NARDL Results: Lumber → Stumpage (Quarterly, 1992-2021)

Coefficient	Estimate	S.E.	t-stat	p-value
Intercept	-0.072	0.30	-0.240	0.81
$\hat{\rho}$	-0.053	0.028	-1.92	0.058*
$\hat{\theta}^+$	0.027	0.035	0.79	0.43
$\hat{\theta}^-$	0.066	0.025	2.62	0.01**
$\hat{\gamma}_{1,0}$	0.03	0.041	0.75	0.46

Note: *p<0.1; **p<0.05; ***p<0.01

$N = 118$ observations.

Residual standard error 0.044 on 112 DF; Adjusted-R^2 0.085

Pesaran et al. (2001) cointegration test F-statistic I(0): 3.71*** on 4 and 112 DF

Wald test for short-run asymmetry test statistic: 3.02

Wald test for long-run asymmetry test statistic: 1072.73***

Using the estimated cointegration coefficient and asymmetry parameters, we calculate the long-run elasticities. Table 4.7 includes the point estimates, standard errors and asymptotic Wald 95% confidence intervals. Each confidence interval includes zero, and so positive nor negative lumber shocks have a significant effect on stumpage prices. The same is true for the effect of lumber inventories. We interpret these results to imply that lumber and stumpage prices are conditionally independent, when controlling for lumber inventories. As a result, the value of stumpage in the long-run is distinct from lumber prices.

Table 4.7: Lumber $\rightarrow$ Stumpage Asymmetric Long-Run Elasticities

	Estimate	S.E.	95% Wald CI
β^{+}_{LPI}	0.51	0.84	(-1.14; 2.16)
β^{-}_{LPI}	1.26	0.88	(-0.46; 2.98)
β_{inven}	0.58	0.63	(-0.65; 1.81)

4.8 Policy Implications and Further Research

Using monthly housing and lumber market data, we estimate a NARDL model of housing supply chain price transmission. We find a significant positive asymmetric relationship between housing and lumber prices. We also find that as the inventory of new housing units increases there is a significant negative effect on lumber prices. And, negative shocks to housing prices has no significant impact on lumber prices.

We apply the same procedure to quarterly stumpage and lumber market data. We find little evidence of a cointegrating relationship between stumpage and lumber prices, when controlling for inventories. The implication is that the cost of holding inventories for lumber manufacturers is such that they can strategically plan inventories to asymmetrically capture positive housing price shocks, preventing pass-through to stumpage markets.

Possible extensions of this work include estimating the asymmetric relationships under alternative approaches. Specifically, a NARDL implicitly assumes rather strict assumptions with regard to the set threshold in the estimated VECM. Therefore, estimating the model under different threshold regimes is a logical next step for this work.

Our results show that stumpage lumber prices are conditionally independent, when controlling for lumber inventories. The result is that the owners of softwood timberland cannot rely on lumber products alone to maximize the value of their timber products. Alternative timber use products such as payment for ecosystem services provide viable diversification strategy for timberland owners.

Chapter 5

Conclusion

Each of the preceding chapters stress the importance of critical policy analysis in agricultural markets. For instance, our work highlights the impact on herd size decisions by beef producers in response to greater competition for feed inputs. In addition, our structural model of land values implies that government support for crop production reduces the relative value of pastureland. Finally, we show that market incentives and strategic behavior on the part of lumber firms drive long-run price asymmetry along the housing supply chain.

Nevertheless, our work permits extensions. First, with regard to the herd size model, our model includes no direct measure of market concentration, which characterizes the downstream elements of the beef supply chain. As such, the market power held by slaughtering and packing operations is likely to impact the supply and demand of the U.S. beef herd. Further research on incorporating market power attributes into the model is a logical next step.

In terms of our land values model, there are two direct avenues of further research. The first it to take the model to higher resolution data, in particular the ARMS data of farm-level observations. The purpose is to account for farm-to-farm level heterogeneity not captured with county-level data. The second extension is to incorporate additional agricultural land uses into the model, such as forest land. The idea is that in the long-run crop, pasture, and forest land uses are exchangeable under certain climatic, agronomic, and market conditions, so that our model which accounts for this specific simultaneity problem applies.

For the final chapter, the higher interest environment that began in 2022 offers a followup to our analysis. Specifically, since the Federal Reserve began raising interest rates, real housing and lumber prices declined from peak 2021 levels. And in our results, we show that the cost of home borrowing has had no significant effect on lumber price transmission. Therefore, the Federal Reserve's decision to raise rates is a natural experiment from which we can perform an event analysis on whether or not the shift to a high interest rate regime has altered the cointegrating relationships between stumpage, lumber, and housing.

Appendix A

Analyzing the Downstream Impacts of U.S. Biofuel Policies

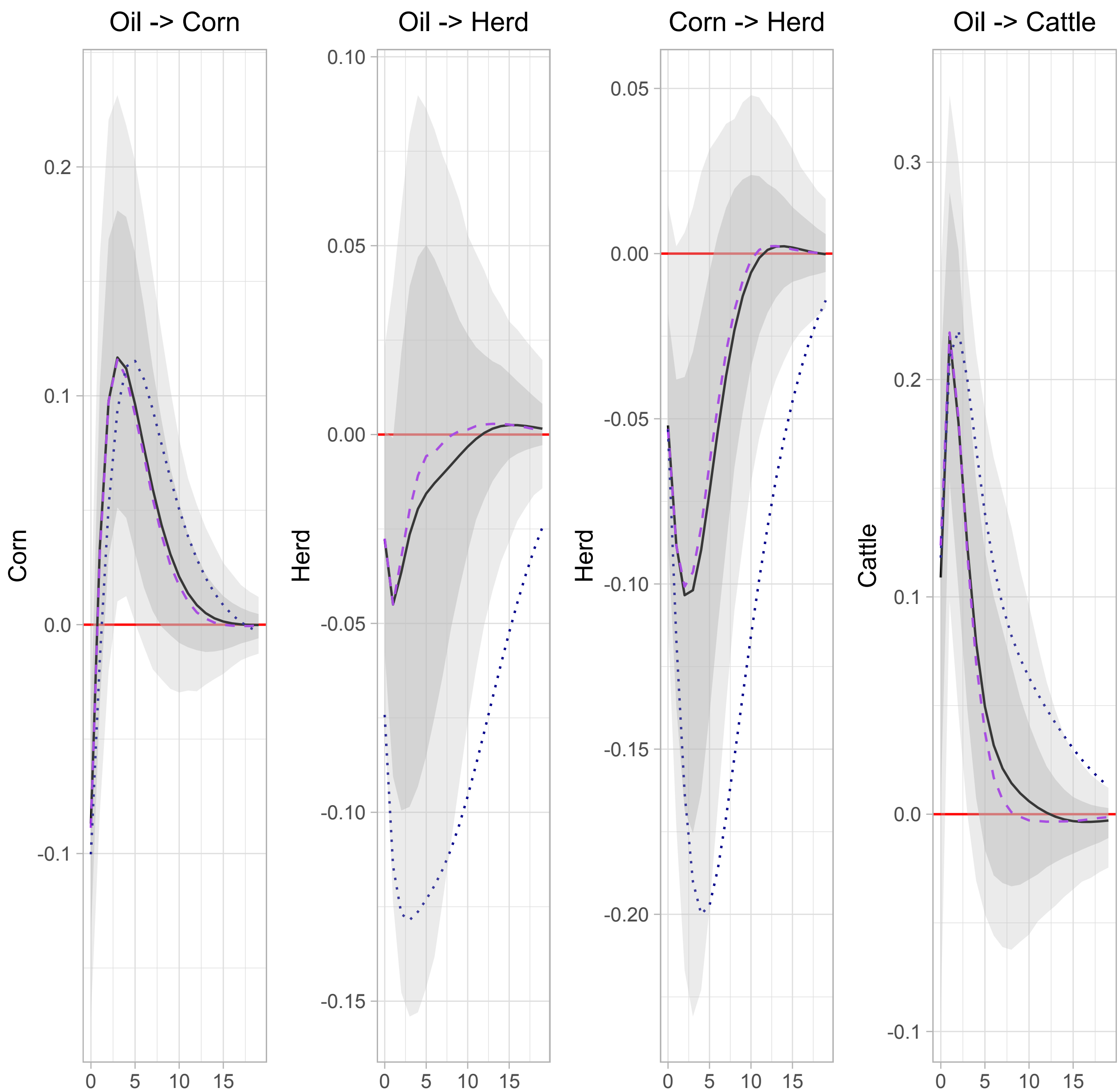

Figure A.1: Cholesky Impulse Response Functions 1983-2006 (pre-RFS-2)
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil → Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

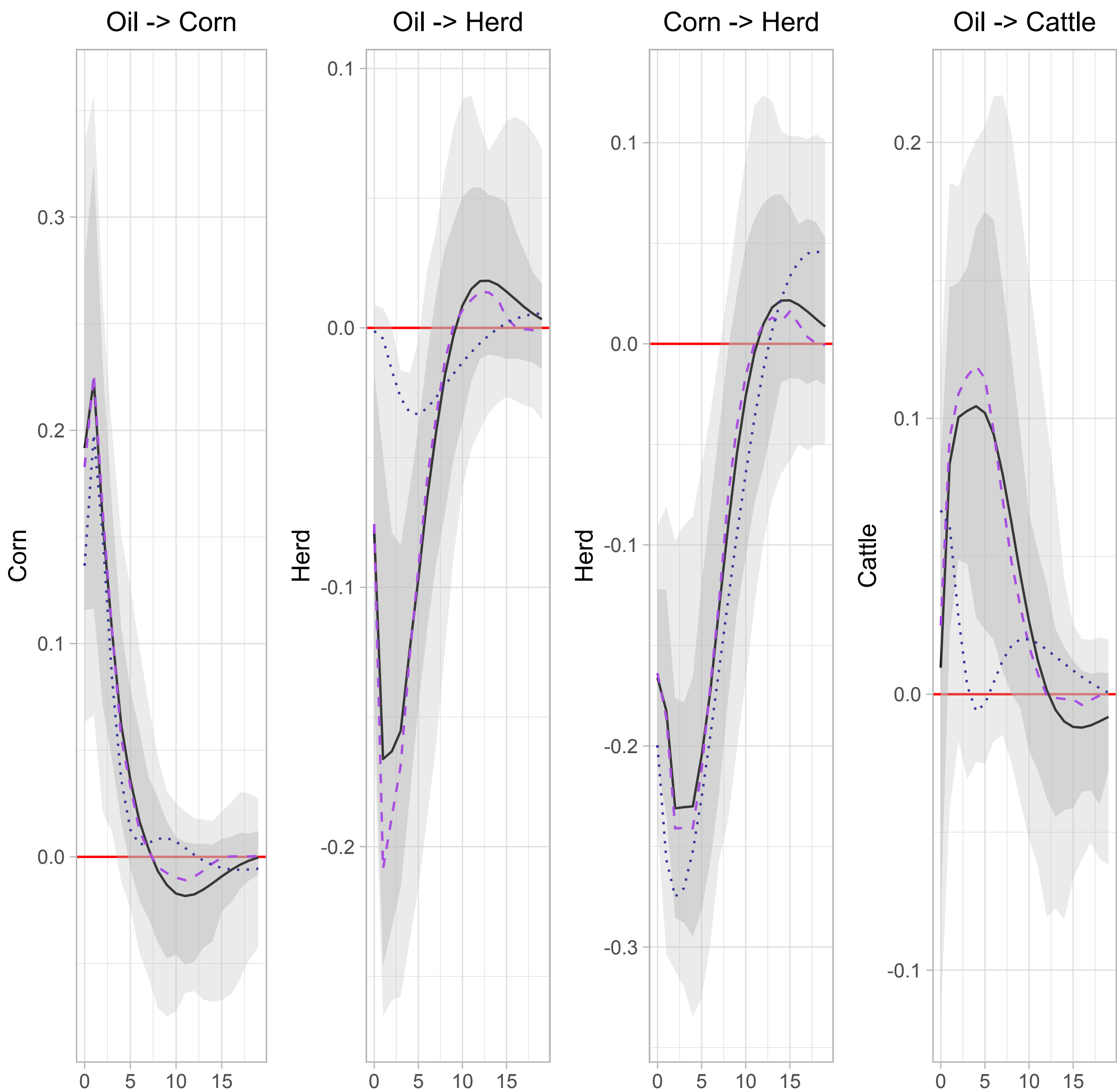

Figure A.2: Cholesky Impulse Response Functions 2007-2022 (post-RFS-2)
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated $\mathbf{B}$ matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil $\rightarrow$ Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

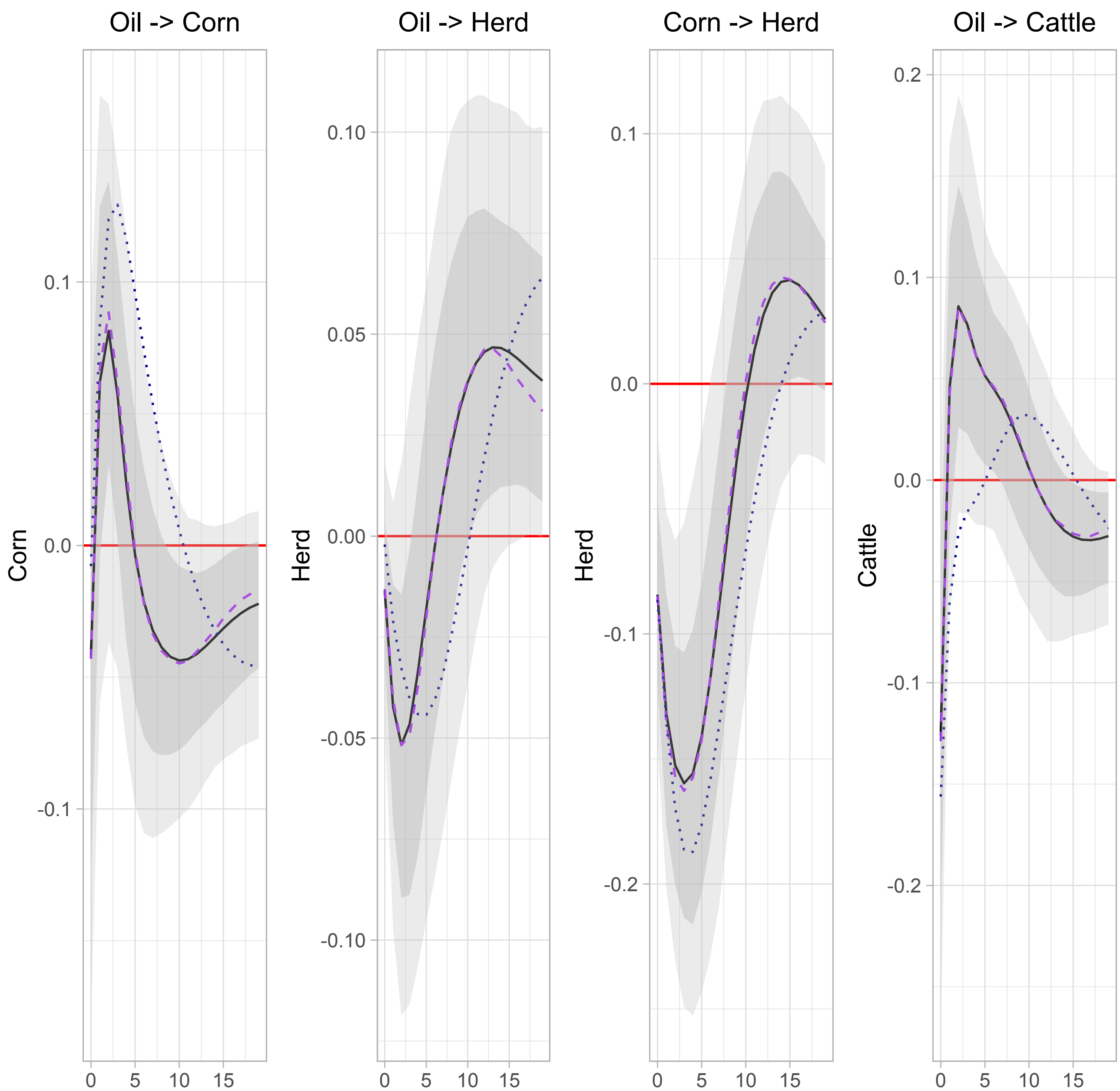

Figure A.3: Cholesky Impulse Response Functions using WIP 2001-2022
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil → Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

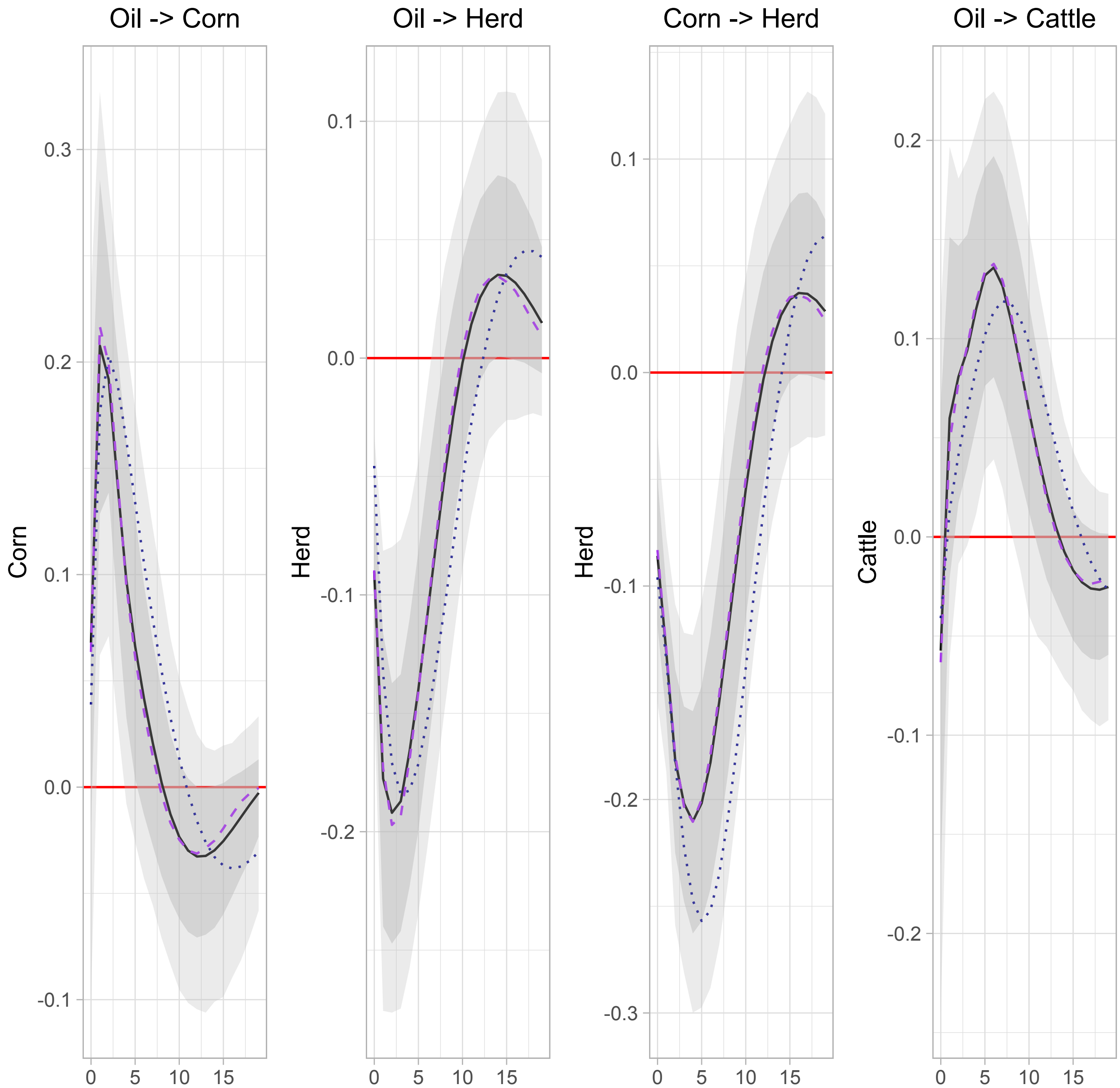

Figure A.4: Cholesky Impulse Response Functions using REA 2001-2019
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., “Oil → Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

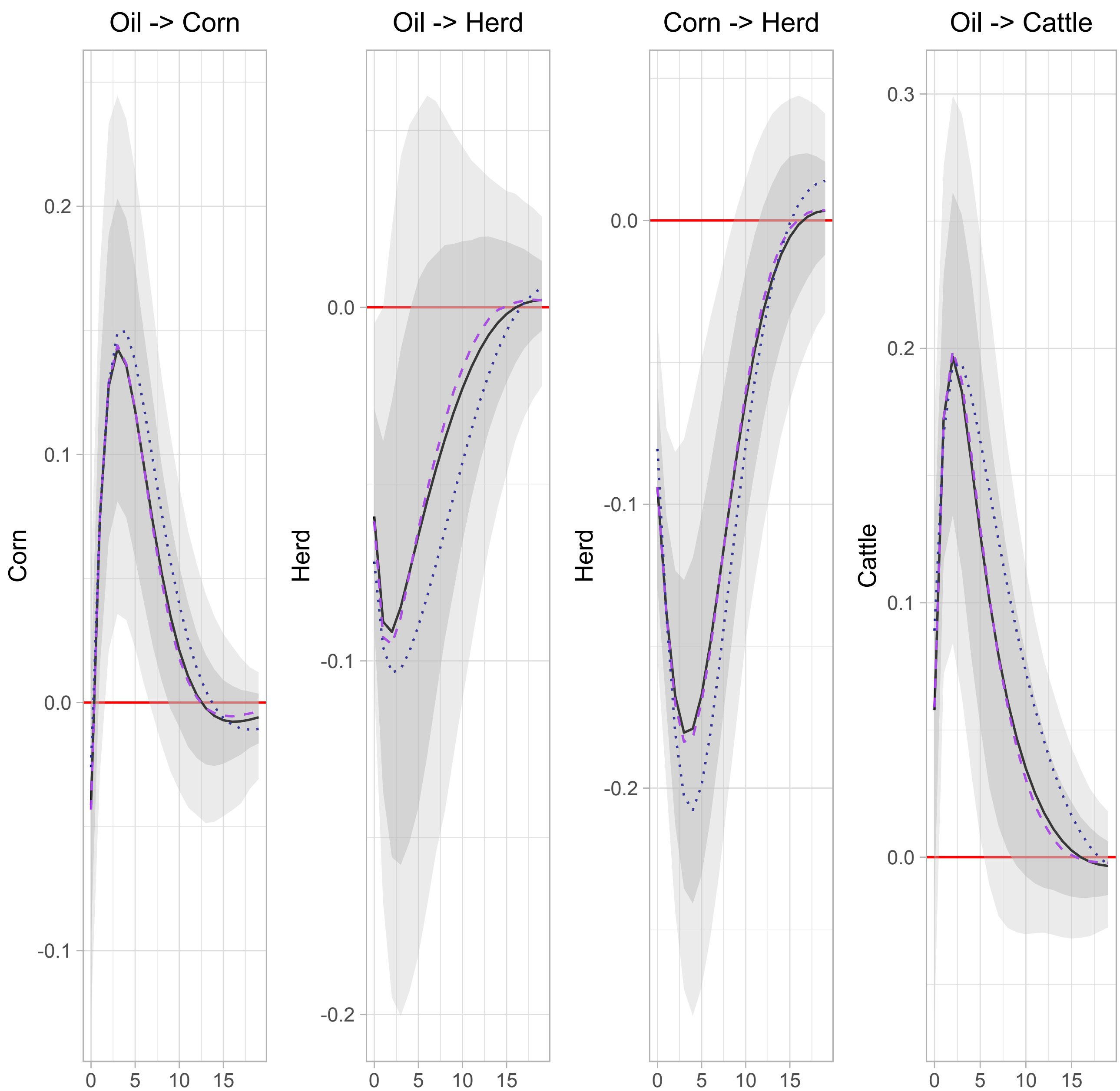

Figure A.5: Cholesky Impulse Response Functions using REA 1983-2022 (Removing Drought Year Observations)

Source: Author calculations based on data sourced from NASS and AMS 2022

Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Each panel represents the percentage response of one of our variables to a 1% independent shock from another (e.g., "Oil → Corn" depicts a 1% oil price shock on corn price). Light grey 95% confidence bands and dark grey 68% confidence bands are generated using wild bootstrap method with 2000 runs. The analytical IRF estimate appears as the dark blue dotted line, while the dashed purple and black lines represent the bootstrapped median and means respectively.

Table A.1: p-values for Autocorrelation Tests

lags	pt.asymptotic	pt.adjusted	BG	ES
1	0	0	0.250	0.368
2	0.008	0.006	0.035	0.090
3	0.084	0.064	0.041	0.103
4	0.139	0.096	0.020	0.053
5	0.129	0.074	0.011	0.024
6	0.238	0.135	0.014	0.025
7	0.457	0.284	0.017	0.016
8	0.561	0.343	0.020	0.024
9	0.645	0.385	0.019	0.024
10	0.714	0.415	0.032	0.030
11	0.856	0.579	0.045	0.049
12	0.915	0.655	0.051	0.073
13	0.961	0.753	0.082	0.302
14	0.952	0.655	0.101	
15	0.862	0.333	0.350	
16	0.894	0.336	0.696	
17	0.907	0.304	0.918	
18	0.964	0.446	0.988	
19	0.986	0.561	0.999	
20	0.991	0.546	1.000	
21	0.998	0.683	1.000	
22	0.997	0.588	1	
23	0.999	0.646	1	
24	1.000	0.719	1	
25	1.000	0.700	1	

Appendix B

How Disparate Government Support for Crops and Livestock Influences Cropland and Pastureland Values

Table B.1: Summary Statistics: Variables of Interest 1997-2017

Variables Name	**Symbol**	**Observations**	**Mean**	**St.dev**	**Description**
Total Cropland (acres)	TC	13,480	143,997	153,466	County level cropland from
Total Pastureland (acres)	TP	13,480	156,036	327,449	County level cropland from
Crop vs. Pastureland Ratio	CPR	13,480	6.77	16.25	Ratio of County Cropland to Pastureland
Agland Values ($/acres)	AGV	13,480	2,924	2,765	Average Agland Values by County 1997-2017
Cropland Values ($/acres)	CV	13,480	4,857	4,790	Average Cropland Values by County
Pastureland Values ($/acres)	PV	13,480	990.971	1,252	Average Cropland Values by County
Crop Commodity Sales ($)	CCS	13,480	147,918	236,827	Gross Crop Commodity Sales per Operation by County
Operating Expenses ($)	OP	13,480	123,744	203,561	Crop Commodity Operating Expenses per Operation by County
Livestock Product Sales ($)	LPS	13,480	50,866,556	108,211,872	Gross Animal Product Sales by County
Government Receipts ($)	GR	13,480	2,507,446	3,027,567	Total Government Support for Agriculture (e.g., Crop Insurance, Disaster Payments, etc.)
Precipitation (in.)	PRECIP	13,480	20.401	8.13	Total Rainfall by County from April to September
Average Temperature Deviance (°F)	ATDSQ	13,480	0.89	1.57	Squared Deviance from the Mean Temperature by County from April to September
Population (# of residents)	POP	13,480	90,474	308,195	Total Population by County
Population Percent Growth (%)	PPG	13,480	0.39	1.52	Percentage Growth Rate by County
Agland vs Population Ratio (acres/# of residents)	APR	13,480	2.28	22.60	Agland Acres per Number of Residents by County

Note: These data were sourced from NASS Census of Agriculture Database using 2,696 (out of 3,143 counties in the United States) counties across the United States from Census years: 1997, 2002, 2007, 2012, and 2017. The result is 13, 480 observations.

Table B.2: First-Stage Estimated Model Results

	Dependent variable:		
	$\Delta \ln CV_{it}$		
	(Model I)	(Model II)	(Model III)
$\Delta PRECIP_{it}$	0.033^{***}	0.033^{***}	0.023^{***}
	(0.001)	(0.001)	(0.001)
$\Delta ATDSQ_{it}$	-0.004	-0.005^{**}	
	(0.003)	(0.003)	
$\Delta CCS_{i,t-1}$	-0.003^{***}	-0.002^{**}	-0.003^{***}
	(0.001)	(0.001)	(0.001)
ΔCPR_{it}		0.006^{***}	0.002^{***}
		(0.0003)	(0.0003)
$\Delta \ln GR_{it}$		0.001	-0.020^{***}
		(0.004)	(0.004)
$\Delta PPG_{i,t-1}$		-0.047^{***}	-0.040^{***}
		(0.003)	(0.004)
ΔAPR_{it}		-0.001^{***}	-0.001^{***}
		(0.0002)	(0.0002)
ΔCPA_{it}			1.794^{***}
			(0.046)
D			0.037^{***}
			(0.013)
Constant	-0.0001	-0.0001	0.040^{***}
	(0.006)	(0.006)	(0.008)
Observations	13,480	13,480	8,711
R^2	0.070	0.112	0.238
Adjusted R^2	0.070	0.111	0.238
Residual Std. Error	0.732	0.716	0.582
F Statistic	339.800^{***}	241.713^{***}	340.637^{***}
DF	3 & 13476	7 & 13472	8 & 8702
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

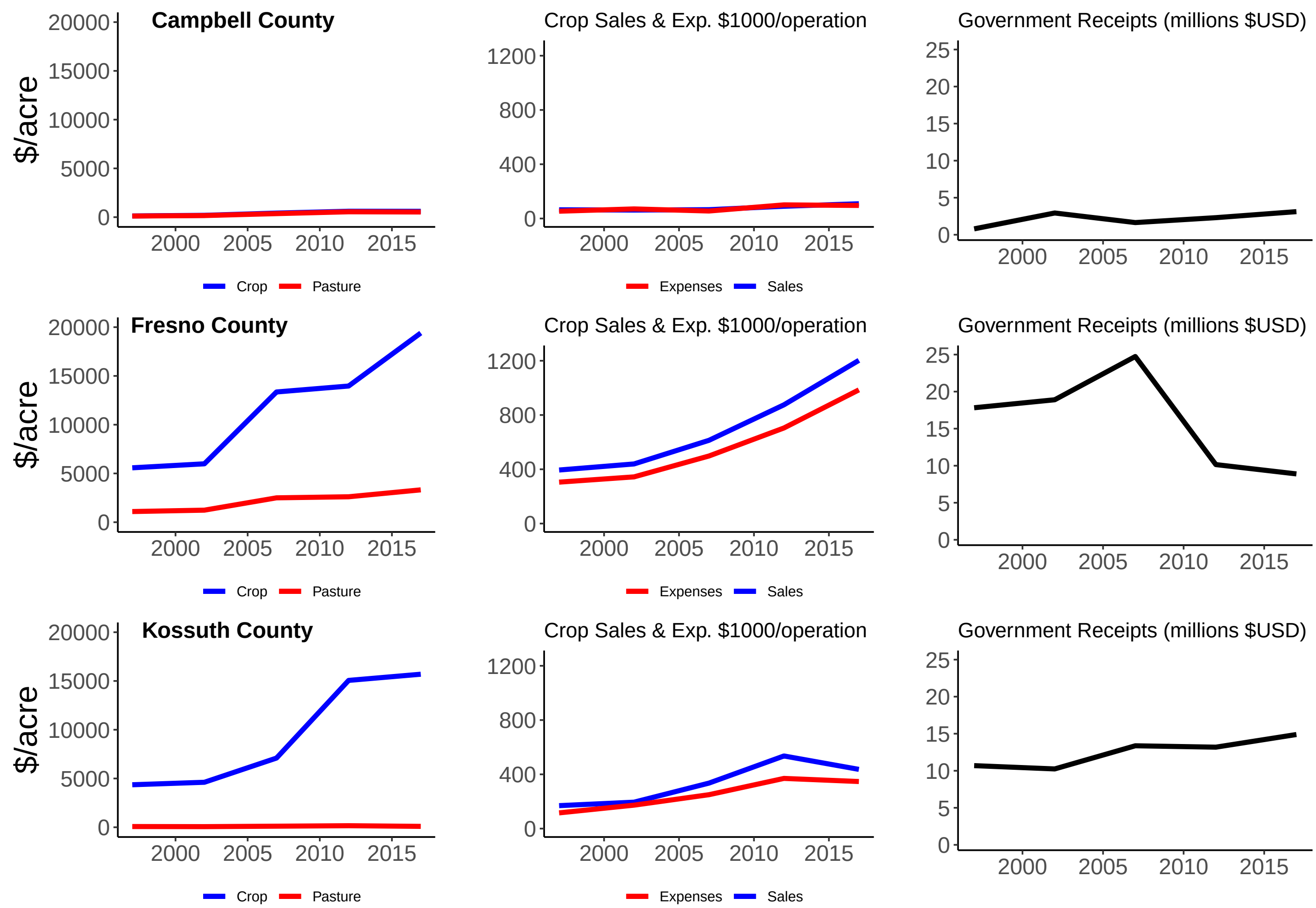

Figure B.1: Land Values, Market Returns, and Government Receipts for Three Representative Agricultural Counties

Source: NASS 2017a, NASS 2017b, & NASS 2017c

Note: Campbell, Wyoming > 96% of all Ag land in pasture according to 2017 Census. Fresno County, California 69% of Ag land in crops with greater than 70% of sales from crops. Kossuth County, Iowa 96% of Ag land in crops.

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