“Analyzing the Downstream Impacts of U.S. Biofuel Policies”

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Abstract

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, for example, 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).

Keywords: U.S. Beef Herd Size, Price Analysis, Renewable Fuel Standard, Structural VAR, & Agricultural Policy Analysis

Econ Lit Codes: Q14, Q18, Q48

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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, 2022c). Yet, much of the extant literature critically 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 manufacturer 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.

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.

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). Yet, 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 3, we offer background information on the cattle industry. Section 4 details our data, theoretical model, and empirical framework. Section 5 presents our results. Section 6 discusses other exogenous shocks to cattle markets. Section 7 describes our profitability results, and Section 8 concludes.

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,

[1]For example, others attributed 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).

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 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

[2]Biofuel and Environmental Policy Analysis Model

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%.

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 conclude 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 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 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 barrel. However, beginning in the early 2000s,

[3]"Silage" 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]"Digestible nutrients" is the proportion of feed that an animal can metabolize into their system

[5]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.

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 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.

[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 contracting sharply to a record low in 2014 (NASS, 2022).

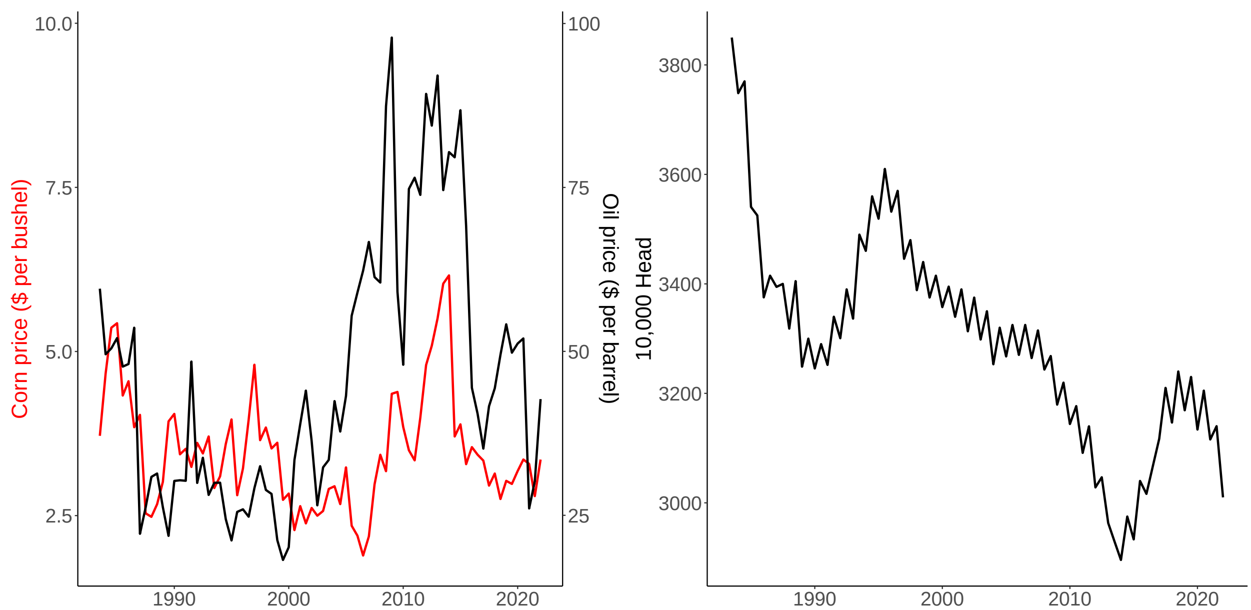

Figure 1: U.S. Beef Herd Size, Corn, and Crude Oil Prices 1983 - 2022
Source: CME 2022, Agricultural Marketing Service (AMS) 2022 & USDA Cattle Inventory Report 2022

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 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).

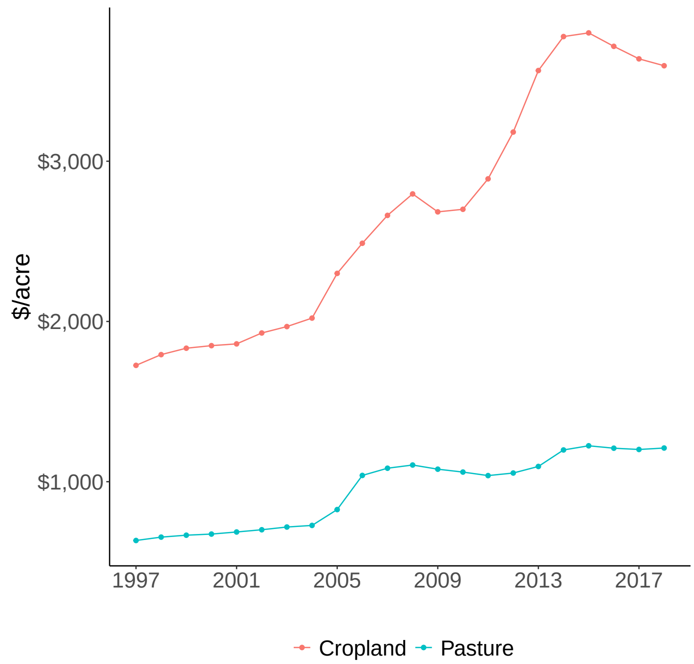

Figure 2: U.S. Real Land Values 1997-2018
Source: NASS Land Asset Values Survey 2018

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

[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

for finishing, dependent on the herd size chosen by the producer.

Table 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.

Table 1: Summary Statistics: Herd Size Model

Statistic	N	Mean	St. Dev.
REA	78	0.581	58.005
WTI $/barrel	78	45.916	20.230
Farm Corn Price $/bushel	78	3.488	0.882
Farm Cattle Price $/cwt	78	99.641	14.009
Herd Size 10000 head	76	3,302	188

Source: NASS 2022, 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 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 WPI as our measure of real aggregate demand in the appendix.

Table 2 presents the summary statistics for monthly cattle market returns from 2000 to 2020. 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 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

[9]The monthly world production index (WPI) 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

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, 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 operating interest rate from the Kansas City Federal Reserve, a readily available interest rate for short-term assets.

Table 2: Summary Statistics: Net Returns and Feed Costs on Cattle

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.

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 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 $j = 2, ..., m$: $b_t = k_t^{(2)} + \dots + k_t^{(m)}$. 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:

$$\begin{gathered}\text{Max} \quad E_t \sum_{s=0}^{\infty} \beta^s \pi_{t+s} \\ \text{where } \beta \text{ is the discount factor and} \\ \pi_t = \sum_{j=0}^{m} p_t^{(j)} \alpha_t^{(j)} (1 - \delta_j) k_t^{(j)} - w_t \sum_{j=1}^{m} k_t^{(j)}\end{gathered} \tag{1}$$

$k_t^{(j)}$ 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:

$$k_{t+1}^{(j+1)} = (1 - \delta_j)(1 - \alpha_t^{(j)})k_t^{(j)} \tag{2}$$

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

$$w_t = \phi_0 + \phi_1 w_{t-1} + \epsilon_{w,t} \tag{3}$$

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:

$$\epsilon_{w,t} = \epsilon_{e,t} + \epsilon_{c,t} + \epsilon_{b,t} \tag{4}$$

$\{\epsilon_{e,t}; \epsilon_{c,t}; \epsilon_{b,t}\}$ 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:

$$F_{t,t+1} = g(k_t^{(j)}, \epsilon_{e,t}, \epsilon_{c,t}, \epsilon_{b,t}) \tag{5}$$

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:

$$p_t^{(j)} = h(\Delta k_t^{(j)}, F_{t-1,t}, \epsilon_{et}, \epsilon_{ct}, \epsilon_{bt}) \tag{6}$$

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:

$$\begin{aligned} I_t^s &= \ln(h(\Delta k_t^{(j)}, F_{t-1,t}, \epsilon_{e,t}, \epsilon_{c,t}, \epsilon_{b,t})) \quad \text{(Herd Supply)} \\ I_t^d &= \ln(g(k_t^{(j)}, \epsilon_{e,t}, \epsilon_{c,t}, \epsilon_{b,t}) \quad \text{(Herd Demand)} \end{aligned} \tag{7}$$

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:

$$\begin{aligned} H_t^s &= \delta^s + \delta_{REA}^s REA_t + \delta_k^s k_{t-1}^{(j)} + \delta_f^s f_{t-1} + \delta_e^s \epsilon_{e,t} + \delta_c^s \epsilon_{c,t} + \delta_b^s \epsilon_{b,t} \\ H_t^d &= \delta^d + \delta_{REA}^d REA_t + \delta_k^d k_t^{(j)} + \delta_e^d \epsilon_{e,t} + \delta_c^d \epsilon_{c,t} + \delta_b^d \epsilon_{b,t} \end{aligned} \tag{8}$$

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

$$\frac{\mathrm{d}H}{\mathrm{d}t} = \lambda(H^d(\epsilon_i) - H^s(\epsilon_i)) \quad \forall \quad i \in \{b, c, e\} \tag{9}$$

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:

$$\frac{\mathrm{d}\left(\frac{\mathrm{d}H}{\mathrm{d}t}\right)}{\mathrm{d}\epsilon_i} = \lambda(\delta_i^d - \delta_i^s) \tag{10}$$

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).

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:

$$\mathbf{y}_t = A_1\mathbf{y}_{t-1} + \cdots + A_p\mathbf{y}_{t-p} + \mathbf{u}_t \tag{11}$$

A_i are (5×5) coefficient matrices for $i = 1, \cdots, p$ lags and $\mathbf{u}_t$ is 5-dimensional white-noise process. We select an autoregressive lag order of $p = 1$ using the Schwarz information Criterion, according to the procedure in Pfaff (2008). This procedure ensures we have set of variables with no evidence of autocorrelation, according to the asymptotic portmanteau test (test results are presented in Table 4 in the appendix). We can then define a structural form model as:

$$A\mathbf{y}_t = \bar{A}_1\mathbf{y}_{t-1} + \cdots + \bar{A}_p\mathbf{y}_{t-p} + \boldsymbol{B}\boldsymbol{\epsilon}_t \tag{12}$$

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:

$$\begin{pmatrix} b_{1,1} & 0 & 0 & 0 & 0 \\ b_{2,1} & b_{2,2} & 0 & 0 & 0 \\ b_{3,1} & b_{3,2} & b_{3,3} & 0 & 0 \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & 0 \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & b_{5,5} \end{pmatrix} \tag{13}$$

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.

5 Results

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 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 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.

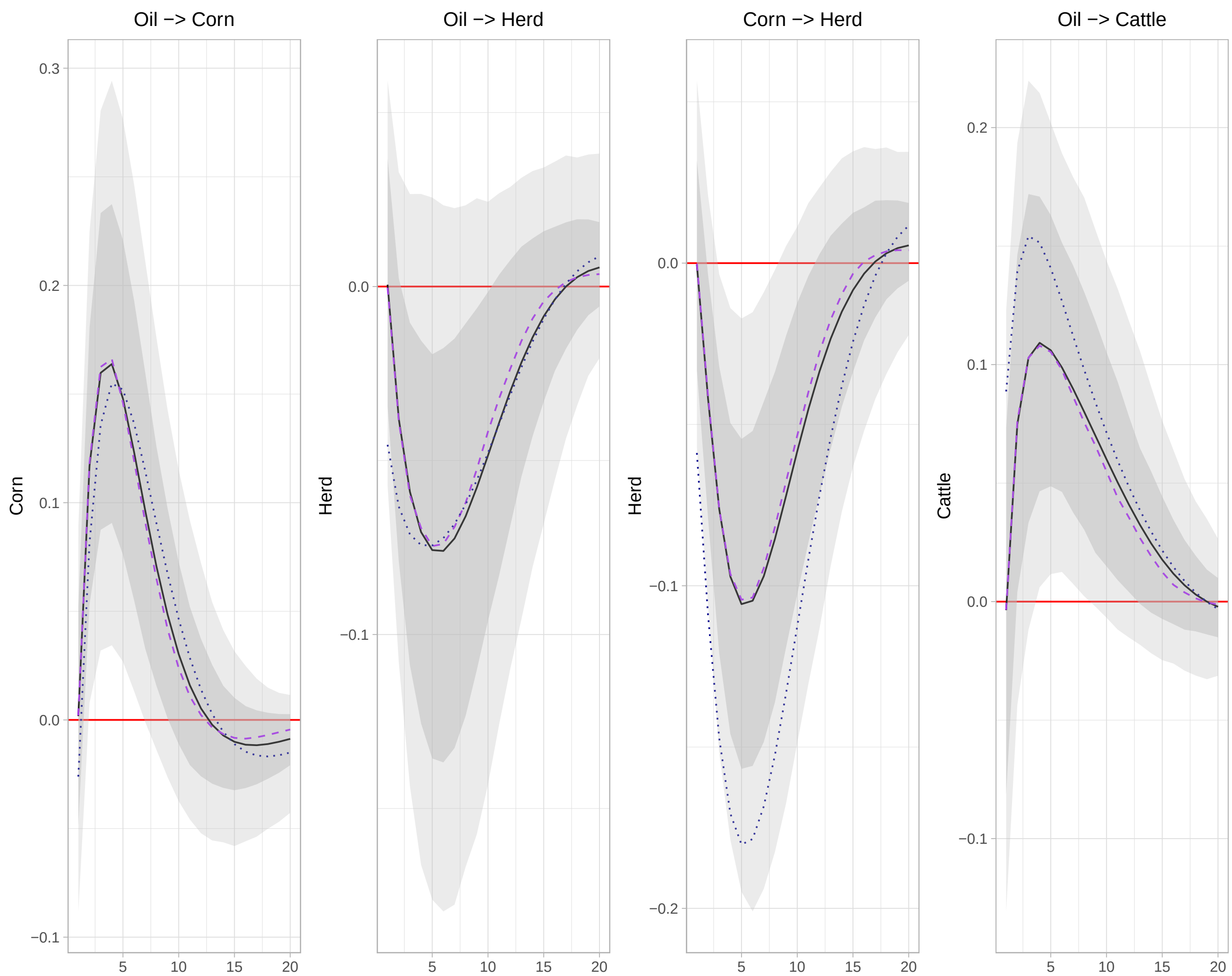

Figure 3: Cholesky Impulse Response Functions, 1983-2022
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Light grey 95% Confidence bands and dark grey 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.

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 4 illustrates our estimated FEVD for the U.S. beef herd.

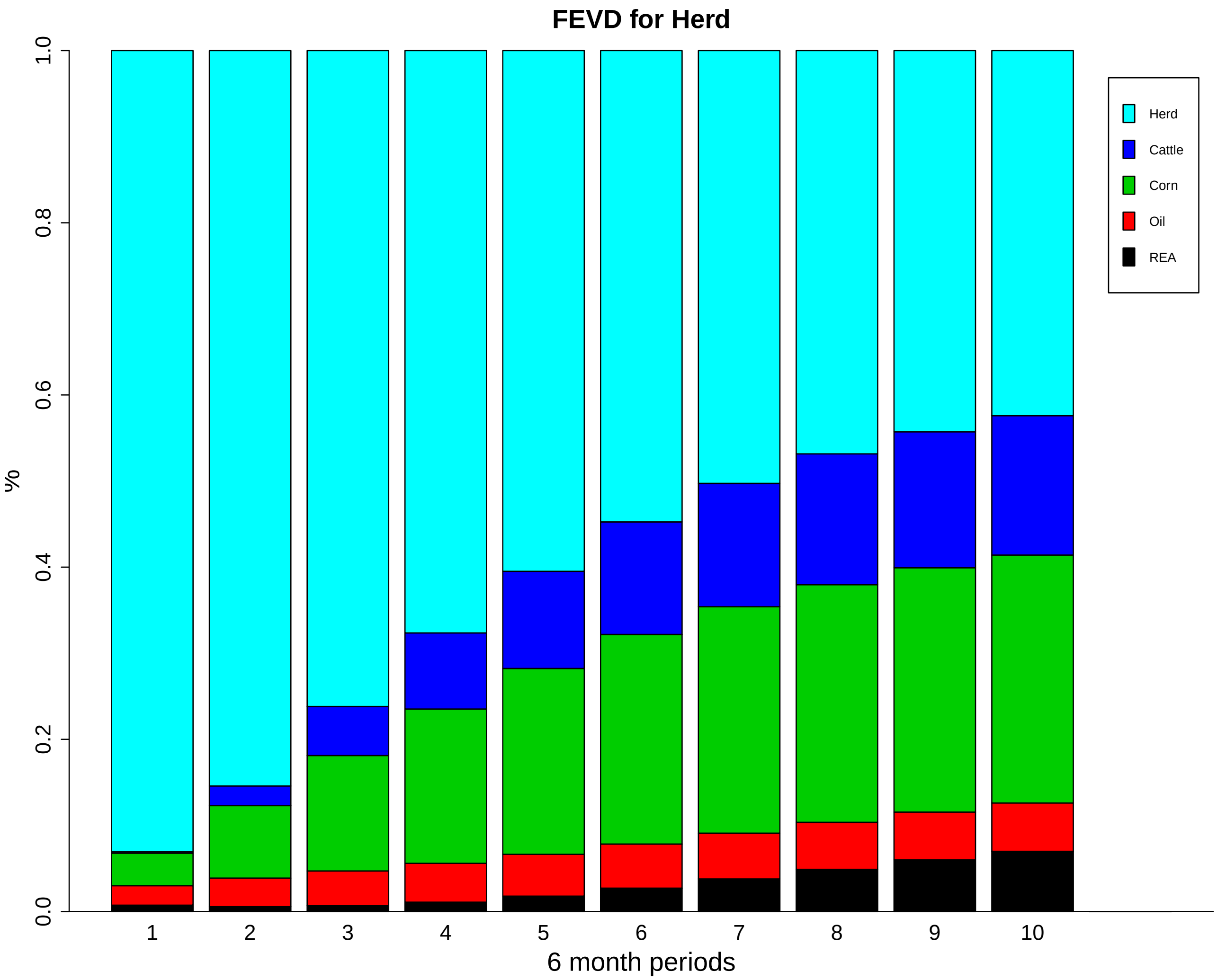

Figure 4: Forecast Error Variance Decomposition (FEVD) for Herd 10 Steps Ahead
Source: Author calculations based on data sourced from NASS 2022
Note: Counterfactual constructed from Recursive Identification Results

Figure 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:

$$\sigma_k^2(h) = \sum_{n=0}^{h-1} (\mathbf{B}_{k1,n}^2 + \ldots + \mathbf{B}_{kK,n}^2) \tag{14}$$

which can be written as:

$$\sigma_k^2(h) = \sum_{j=1}^{K} (\mathbf{B}_{kj,0}^2 + \ldots + \mathbf{B}_{kj,h-1}^2) \tag{15}$$

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 3.

Table 3: Structural Breaks
Beef Herd 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

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

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 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 10 and 11 in the appendix) consistent with our headline findings.

5.3 Sample Split: pre-and-post 2000

Figure 5 presents the impulse response functions generated for data in the period July 1983 to July 2000. Similar to figure 3, shocks to the crude oil prices, although suggestive, do not translate to significant decline in herd size (at the 90% 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.

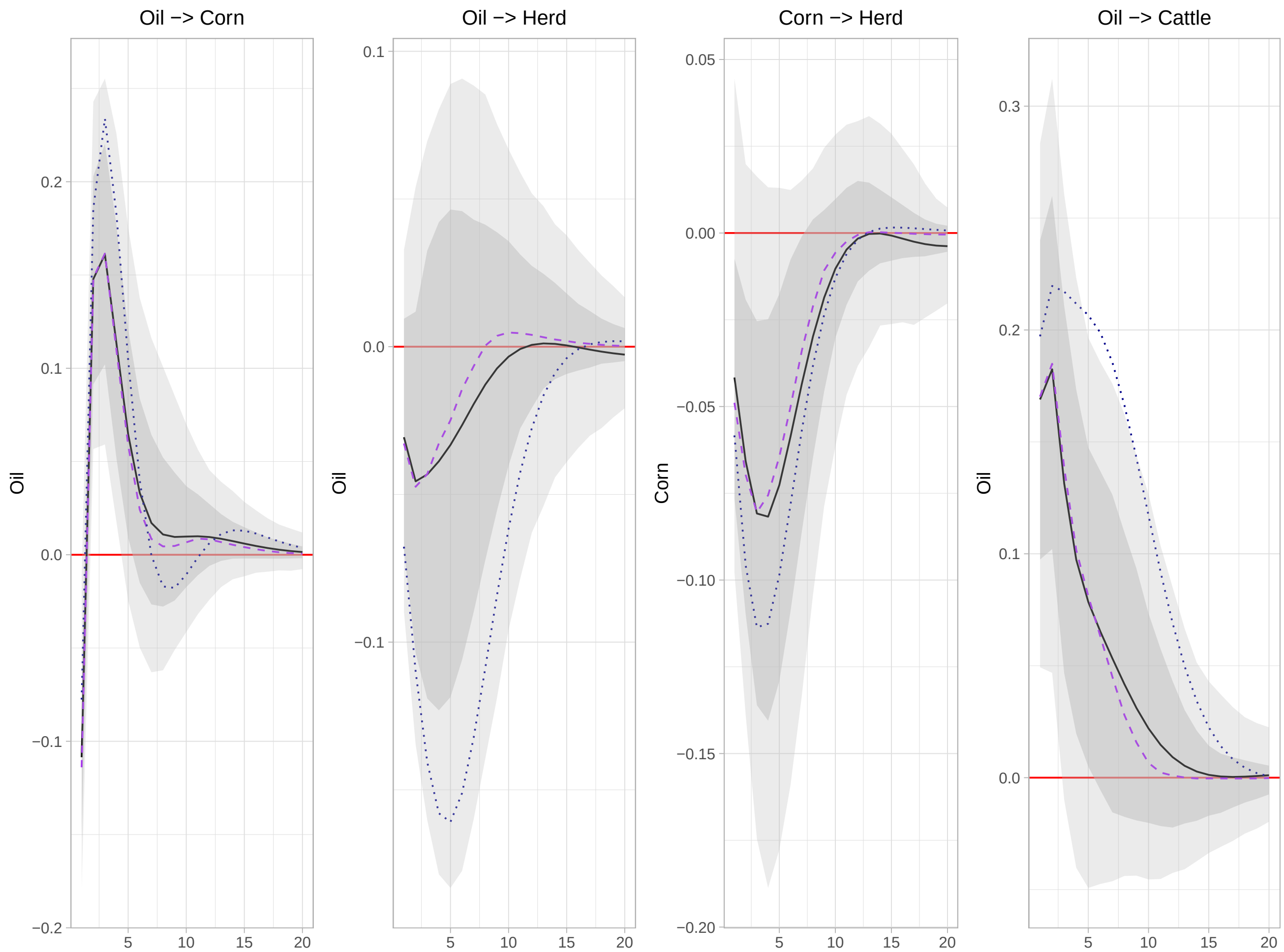

Figure 5: Cholesky Impulse Response Functions, 1983-2000
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Light Grey 95% Confidence bands and dark grey 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 6 depicts the impulse response function for the post-2000 era. In contrast to figure 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 -1.9% 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 5, prior to the break, the impulse response of herd size to oil is not significant at the 90% level. However, in figure 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 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 6. In addition, we also include results from using the alternative aggregate economic activity measure, WPI, proposed by Hamilton in figure 12 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]To address comments from colleagues, we also include in the appendix IRFs generated from the data excluding COVID-19 observations to balance the split sample analysis. Figure 13 visualizes these results using REA as the economic activity indicator. The results support our headline findings.

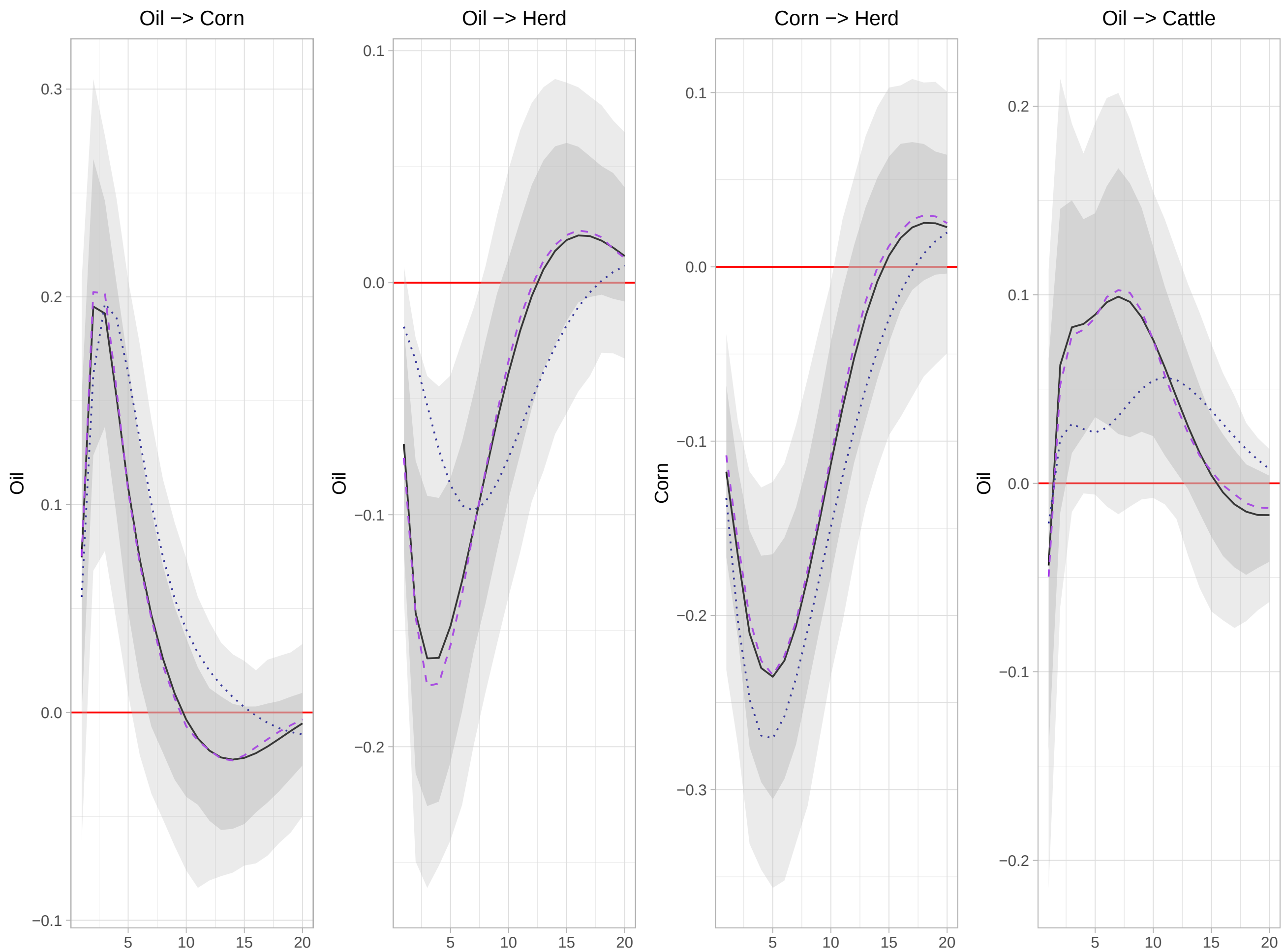

Figure 6: Cholesky Impulse Response Functions, 2001-2022

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

Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. 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 such counterfactuals in figure 7 for the beef herd series, illustrating how the beef herd cycle 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 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 1)–which lowered industry production costs–until the mid-2000, when the U.S. government enacted significant policies to promote biofuel production and adoption. Subsequently, the counterfactual herd series runs substantially higher than the observed series implying that the 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.

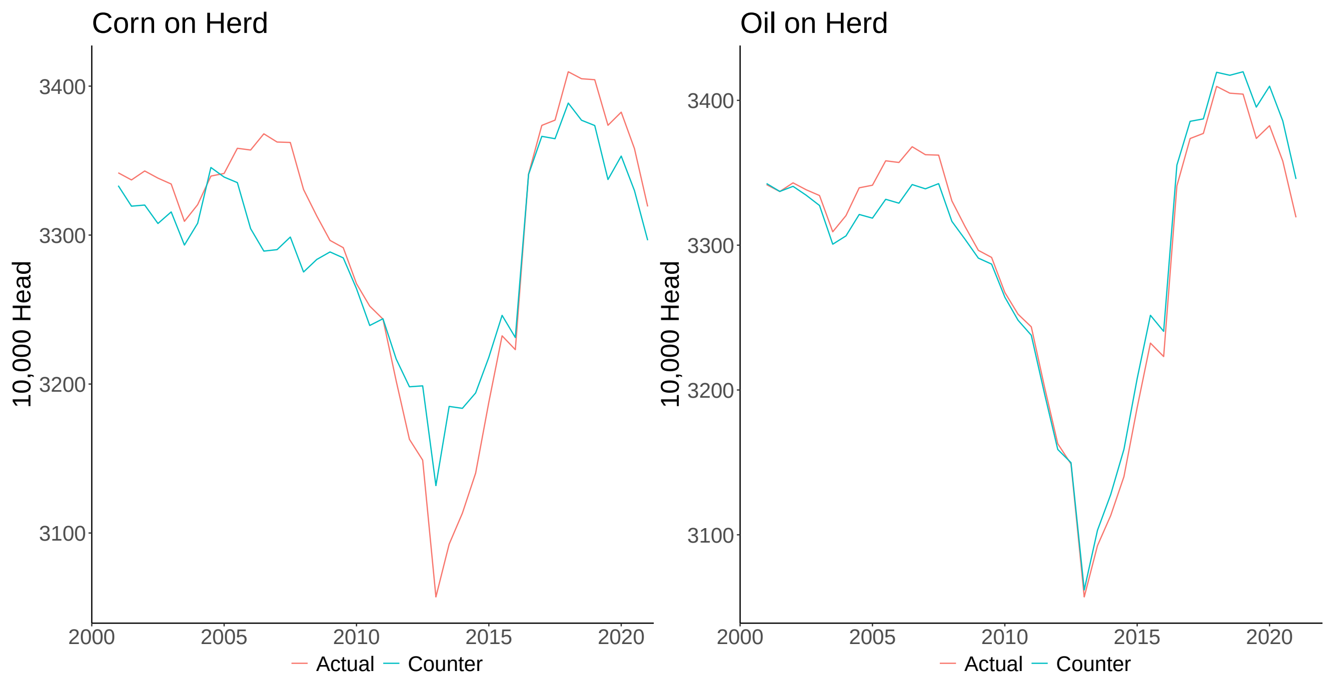

Figure 7: Counterfactual Plots with and without the Shocks from Corn and Oil
Source: Author calculations based on data sourced from NASS 2022
Note: Counterfactual constructed from Recursive Identification Results

5.4 Robustness Check: Distance Covariance

The next method we utilize is the Distance Covariance Method (DCM) (Szekely et al., 2007). The DCM relaxes the restrictions placed on our error matrix, 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:

$$\begin{pmatrix} b_{1,1} & b_{1,2} & b_{1,3} & b_{1,4} & b_{1,5} \\ b_{2,1} & b_{2,2} & b_{2,3} & b_{2,4} & b_{2,5} \\ b_{3,1} & b_{3,2} & b_{3,3} & b_{3,4} & b_{3,5} \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & b_{4,5} \\ b_{4,1} & b_{4,2} & b_{4,3} & b_{4,4} & b_{5,5} \end{pmatrix} \tag{16}$$

Matteson and Tsay (2013) provide a numerical algorithm for calculating each element of B in (12). We re-estimate model using the DCM and generate a new set of impulse response functions post-2000 era in figure 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.

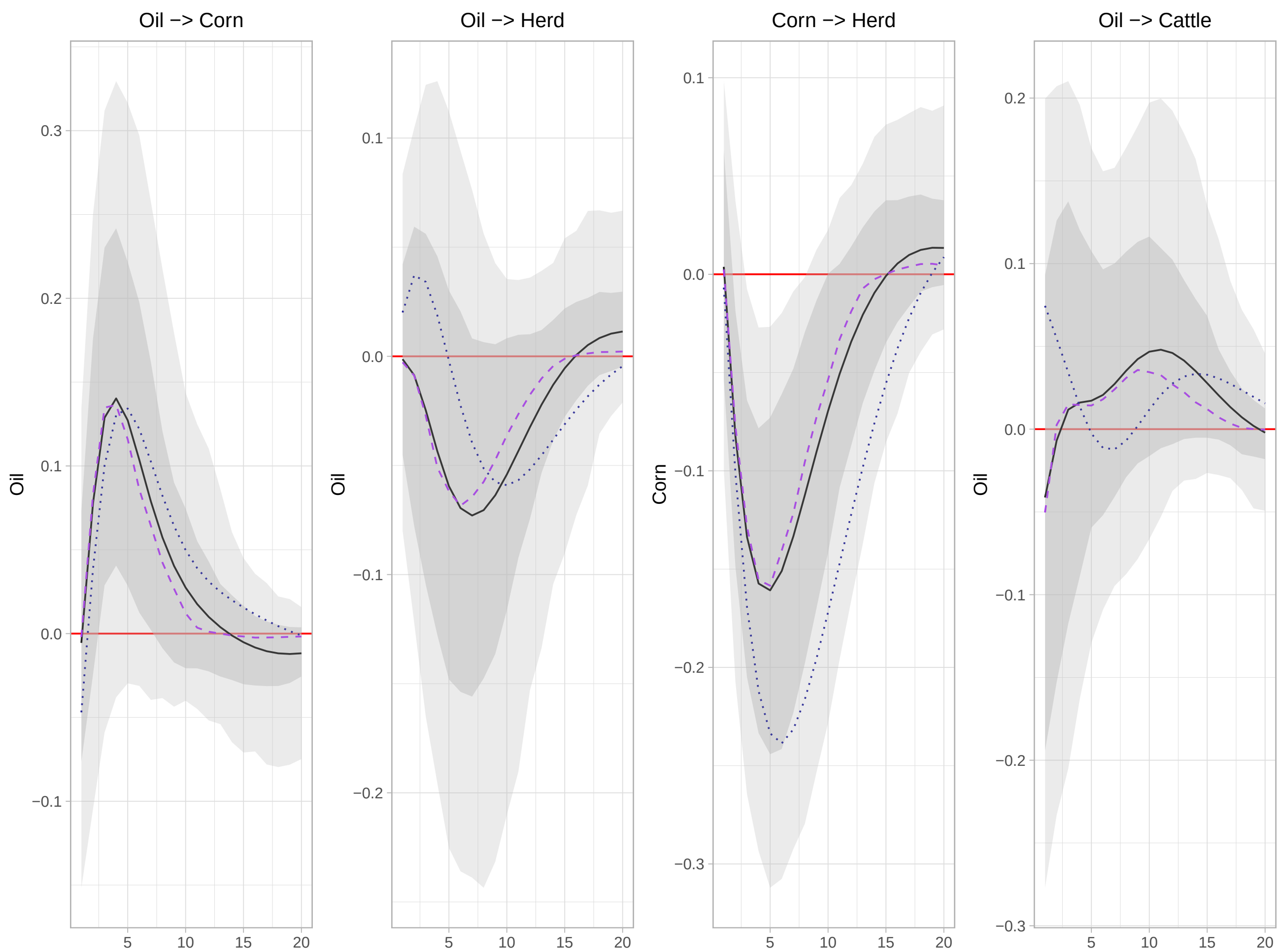

Figure 8: DCM Impulse Response Functions, 2001-2022

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

Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. 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.

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) face a similar problem, and 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 cattle 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 developed by Carter et al. (2017), this non-transitory multi-period extreme weather event may confound our 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). Figures 14 presents our 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 the severe U.S. drought in the early

2010s, are indeed transitory and provides confidence that our findings are the results of the persistent shock represented by the policy change encapsulated by the RFS-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 our 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 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 more sensitive to crude oil and corn price shocks, U.S. biofuel policy also adversely impacted cattle producer returns.

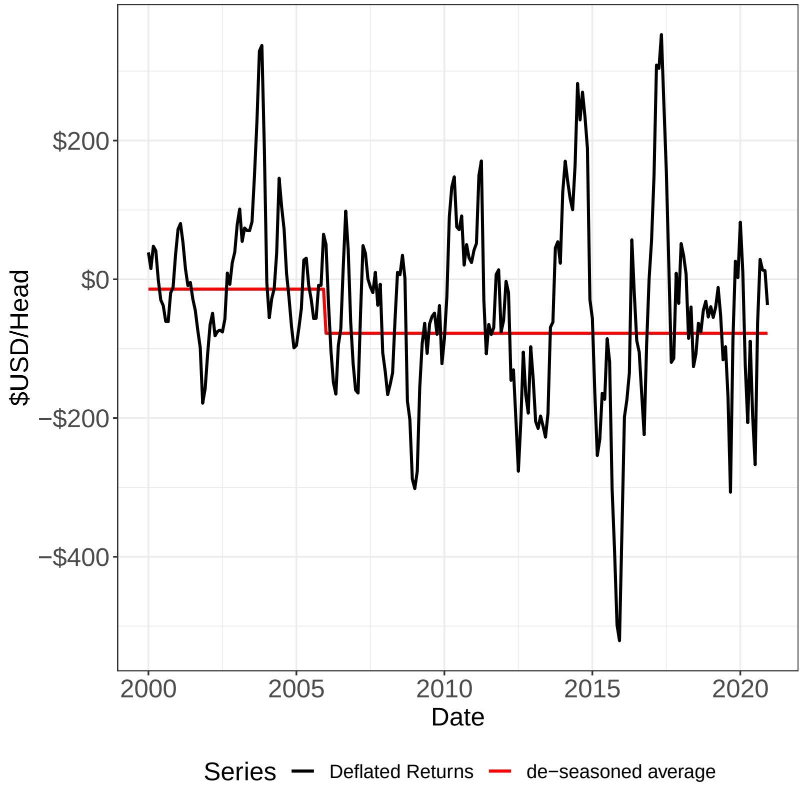

Figure 9: Deflated Net Returns $ per Head
Author calculations based on data sourced from KSU and LMIC 2020

8 Conclusions

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.

References

Aadland, D. (2004, September). Cattle cycles, heterogeneous expectations and the age distribution of capital. *Journal of Economic Dynamics and Control 28*(10), 1977–2002.

Adjemian, M. K., A. Smith, and W. He (2021). Estimating the market effect of a trade war: The case of soybean tariffs. *Food Policy 105*, 102152.

AFB-American Farm Bureau Federation (2019, March). "Where's the (Hormone-Free) Beef?". `https://www.fb.org/market-intel/wheres-the-hormone-free-beef`.

Bai, J. (1997). Estimating multiple breaks one at a time. *Econometric Theory 13*, 315–352. `https://doi.org/10.1017/S0266466600005831`.

Bai, J. and P. Perron (2003). "Computation and Analysis of Multiple Structural Change Models. *Journal of Applied Econometrics 18*, 1–22. `https://doi.org/10.1002/jae.659`.

Brown, R. C. and T. R. Brown (2012). *Why Are We Producing Biofuels*. Ames, Iowa: Brownia.

Carter, C., G. Rausser, and A. Smith (2011). "Commodity Booms and Busts". *Annual Reviews of Resource Economics 3*(1), 87–118. `https://doi.org/10.1146/annurev.resource.012809.104220`.

Carter, C. A., G. C. Rausser, and A. Smith (2017). "Commodity Storage and the Market Effects of Biofuel Policies". *American Journal of Agricultural Economics 99*(4), 1027–55. `https://doi.org/10.1093/ajae/aaw010`.

Chen, X. and M. Khanna (2013). "Food vs. Fuel: The Effect of Biofuel Policies". *American Journal of Agricultural Economics 95*(2), 289–295. `https://doi.org/10.1093/ajae/aas039`.

CME (2021). Agricultural Futures and Options. https://www.cmegroup.com/markets/agriculture.html#overview.

Condon, N., H. Klemick, and A. Wolverton (2015). "Impacts of Ethanol Policy on Corn Prices: A Review and Meta-Analysis of Recent Evidence". *Food Policy 51*, 63–73. https://doi.org/10.1016/j.foodpol.2014.12.007.

CRS (2019, September). "What Is the Farm Bill?". Technical report, United States Congressional Research Service. https://fas.org/sgp/crs/misc/RS22131.pdf.

Cui, J., H. Lapan, G. Moschini, and J. Cooper (2011). "Welfare Impacts of Alternative Biofuel and Energy Policies". *American Journal of Agricultural Economics 93*(5), 1235–56. https://doi.org/10.1093/ajae/aar053.

de Gorter, H., D. Drabik, and D. Just (2015). *The Economics of Biofuel Policies*. The Economics of Biofuel Policies. https://www.palgrave.com/gp/book/9781137414847.

Doye, D. and W. Brorsen (2nd Quarter 2011). "Pastureland Values: A 'Green Acres' Effect?". *Choices 26*(2). https://ageconsearch.umn.edu/record/109469/files/cmsarticle_25.pdf.

Duffield, J. A., R. Johansson, and S. Myer (2015). "U.S. Ethanol: An Examination of Policy, Production, Use, Distribution, and Market Interactions". Technical report, USDA. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.738.5405&rep=rep1&type=pdf.

Edelmann, D., T. Terzer, and D. Richards (2021). A basic treatment of the distance covariance. *Sankhya B: The Indian Journal of Statistics 83*(1), 12–25.

Feinman, M. (2013, September). "RFA, NCBA Debate RFS Waiver". https:

//www.dtnpf.com/agriculture/web/ag/livestock/article/2013/09/23/ncba-wants-waivers-during-natural.

Food and A. Organization (2008). "The State of Food and Agriculture, Biofuels: Prospects, Risks and Opportunities". http://www.fao.org/docrep/011/i0100e/i0100e00.htm.

Gehlhar, M. J., A. Somwaru, and A. Winston (2010, October). "Effects of Increased Biofuels on the U.S. Economy in 2022". Technical report, U.S. Department of Agriculture Economic Research Service. http://www.ssrn.com/abstract=1711353.

Hamilton, J. D. (2021). Measuring global economic activity. *Journal of Applied Econometrics 36*(3), 293–303.

Heady, E., G. Roehrkasse, W. Woods, and J. Scholl (1963). "Beef Cattle Production Functions in Forage Utilization". *Iowa Agriculture and Home Economics Experiment Station Research Bulletin 34*(517). https://lib.dr.iastate.edu/researchbulletin/vol34/iss517/1.

Hertel, T. W., A. A. Golub, A. D. Jones, M. O'Hare, R. J. Plevin, and D. M. Kammen (2010). "Effects of U.S. Maize Ethanol on Global Land Use and Greenhouse Gas Emissions: Estimating Market-Mediated Responses". *BioScience 60*(3), 223–31. https://doi.org/10.1525/bio.2010.60.3.8.

Holgrem, L. and D. Feuz (2015). "2015 Costs and Returns for a 200 Cow, Cow-Calf Operation, Northern Utah". Technical report, Utah State University Agricultural Extension Service. https://digitalcommons.usu.edu/cgi/viewcontent.cgi?article=1716&context=extension_curall.

Hughes, H. (2001, November). "The Pain of '94 to '96". https://www.beefmagazine.com/mag/beef_pain.

Kesan, J. P., H.-S. Yang, and I. F. Peres (2017). "An Empirical Study of the Impact of the Renewable Fuel Standard (RFS) on the Production of Fuel Ethanol in the U.S.". *Utah Law Review 2017*(1), 159–206. http://dc.law.utah.edu/ulr/vol2017/iss1/4.

Kilian, L. (2019). Measuring global real economic activity: Do recent critiques hold up to scrutiny? *Economics Letters 178*, 106–110.

KSU (2020). Focus on Feedlots, Newsletter. Technical report, Kansas State University, College of Agriculture. https://www.asi.k-state.edu/about/newsletters/focus-on-feedlots/monthly-reports.html.

Lapan, H. E. and G. Moschini (2009). "Biofuels Policies and Welfare: is the Stick of Mandates Better than the Carrot of Subsidies?". *Economics Working Papers (2002–2016) 139*. https://lib.dr.iastate.edu/econ_las_workingpapers/139.

Lark, T. J., N. P. Hendricks, A. Smith, N. Pates, S. A. Spawn-Lee, M. Bougie, E. G. Booth, C. J. Kucharik, and H. K. Gibbs (2022). "Environmental Outcomes of the US Renewable Fuel Standard". *Proceedings of the National Academy of Sciences 119*(9).

Lawrence, J. D., J. Mintert, J. D. Anderson, and D. P. Anderson (2008). "Feed Grains and Livestock: Impacts on Meat Supplies and Prices". *Choices 23*(2). https://www.choicesmagazine.org/UserFiles/file/article_25.pdf.

Matteson, D. S. and R. S. Tsay (2013). Independent component analysis via distance covariance.

McCarthy, J. E. and M. Tiemann (2006). "MTBE in Gasoline: Clean Air and Drinking Water Issues". Technical Report 26, Congressional Research Service, U.S. http://digitalcommons.unl.edu/cgi/viewcontent.cgi?article=1025&context=crsdocs.

Moschini, G., J. Cui, and H. Lapan (2012). "Economics of Biofuels: An Overview of Policies, Impacts and Prospects". *Bio-based and Applied Economics 1*(3), 269–96. https://lib.dr.iastate.edu/econ_las_pubs/96.

Moschini, G., H. Lapan, and H. Kim (2017). "The Renewable Fuel Standard in Competitive Equilibrium: Market and Welfare Effects". *American Journal of Agricultural Economics 99*(5), 1117–42. https://doi.org/10.1093/ajae/aax041.

NASS (2018). Land Asset Values Survey. https://usda.library.cornell.edu/concern/publications/pn89d6567?locale=en.

NASS (2022). Cattle Inventory – January 2022 Release. https://downloads.usda.library.cornell.edu/usda-esmis/files/h702q636h/pn89f870n/jw828f69f/catl0122.pdf.

NASS (2023). Cattle Inventory – January 2023 Release. https://downloads.usda.library.cornell.edu/usda-esmis/files/h702q636h/ms35vn48m/fj237f291/catl0123.pdf.

NCBA (2012, November). "EPA Denies Ethanol Mandate Waiver Requests". https://www.ncba.org/newsreleases.aspx?NewsID=2707.

NLR (2012, November). "U.S. EPA Denies Request to Waive RFS Standards to Aid Livestock Producers". https://www.natlawreview.com/article/us-epa-denies-request-to-waive-rfs-standards-to-aid-livestock-producers.

NRC (2000). *Nutrient Requirements of Beef Cattle: Seventh Revised Edition: Update 2000*. Washington D.C: The National Academies Press. https://www.nap.edu/catalog/9791/nutrient-requirements-of-beef-cattle-seventh-revised-edition-update-2000.

NWS (2012). A Recap of the 2011 Drought. https://www.weather.gov/tsa/weather-event_2011drought#:~:text=2011%20will%20go%20down%20in,across%20much%20of%20the%20region.

O'Malley, J. and S. Searle (2021, January). "The Impact of the U.S. Renewable Fuel Standard on Food and Feed Prices". Technical report, International Council on Clean Transportation. https://theicct.org/sites/default/files/publications/RFS-and-feed-prices-jan2021.pdf.

Pfaff, B. (2008). "VAR, SVAR and SVEC Models: Implementation Within R Package vars". *Journal of Statistical Software 27*(4). http://www.jstatsoft.org/v27/i04/.

Polansek, T. (2022, January). "U.S. Cow Herd Drops to Seven-Year Low, Beef Prices Set to Rise Further". Technical report, Reuters. https://www.reuters.com/article/usa-cattle-herd/u-s-cow-herd-drops-to-seven-year-low-beef-prices-set-to-rise-further-idUSL1N2UB2YT.

Reguly, E. (2008). "How the Cupboards went Bare". https://web.archive.org/web/20080415055334/http://www.theglobeandmail.com/servlet/story/LAC.20080412.FOOD12/TPStory/International/.

Schor, E. (2008, August). "Biofuel Debate Faces Showdown in USA". https://www.theguardian.com/environment/2008/aug/06/biofuels.usa.

Sims, C. A. (1980). "Macroeconomics and Reality". *Econometrica 48*, 1–48. https://www.r-econometrics.com/timeseries/varintro/.

Sims, C. A., J. H. Stock, and M. Watson (1990). "Inference in Linear Time Series Models with Unit Roots". *Econometrica 58*(1), 113–144. https://www.princeton.edu/~mwatson/papers/Sims_Stock_Watson_Ecta_1990.pdf.

Smith, A. (2019). "Effects of the Renewable Fuel Standard on Corn, Soybean, and Wheat Prices". Technical report, National Wildlife Federation. https://ipbs.org/projects/assets/RFS_Prices.pdf.

Székely, G. J., M. L. Rizzo, and N. K. Bakirov (2007). Measuring and testing dependence by correlation of distances. *The Annals of Statistics 35*(6), 2769 – 2794.

Tonsor, G. T. and E. Mollohan (2017). "Price Relationships between Calves and Yearlings: An Updated Structural Change Assessment". *Journal of Applied Farm Economics 1*(1). https://docs.lib.purdue.edu/jafe/vol1/iss1/3.

Trostle, R. (2008). "Global Agricultural Supply and Demand: Factors Contributing to the Recent Increase in Food Commodity Prices". Technical report, Economic Research Service, U.S. Department of Agriculture. https://www.ers.usda.gov/webdocs/outlooks/40463/12274_wrs0801_1_.pdf?v=3376.7.

USDA (2021). "USDA to Make Up to $800 Million Available to Provide Economic Relief to Biofuel Producers and Restore Renewable Fuel Markets Hit by the Pandemic". https://www.usda.gov/media/press-releases/2021/12/07/usda-make-800-million-available-provide-economic-relief-biofuel.

USDA (2022a). "Cattle on Feed Report". https://usda.library.cornell.edu/concern/publications/m326m174z?locale=en.

USDA (2022b). "Feedgrains Sector at a Glance". https://www.ers.usda.gov/topics/crops/corn-and-other-feedgrains/feedgrains-sector-at-a-glance/.

USDA (2023). "World Agricultural Supply and Demand Estimates". https://www.usda.gov/oce/commodity/wasde/wasde0123.pdf.

Van Amburgh, M., E. Collao-Saenz, R. Higgs, D. Ross, E. Recktenwald, E. Raffrenato, L. Chase, T. Overton, J. Mills, and A. Foskolos (2015). "The Cornell Net Carbohydrate and Protein System: Updates to the model and evaluation of version 6.5. *Journal of Dairy Science 98*(9), 6361–6380. https://www.sciencedirect.com/science/article/pii/S0022030215004488.

von Braun, J. (2007). "The World Food Situation: New Driving Forces and Required Actions". Technical report, IFPRI. http://dx.doi.org/10.2499/0896295303.

Wright, B. (2014). "Global Biofuels: Key to the Puzzle of Grain Market Behavior". *Journal of Economic Perspectives 28*(1), 73–98. https://www.aeaweb.org/articles?id=10.1257/jep.28.1.73.

Yacobucci, B. D. (2012). "Biofuels Incentives: A Summary of Federal Programs". Technical report, Congressional Research Service, U.S. https://fas.org/sgp/crs/misc/R40110.pdf.

9 Appendix

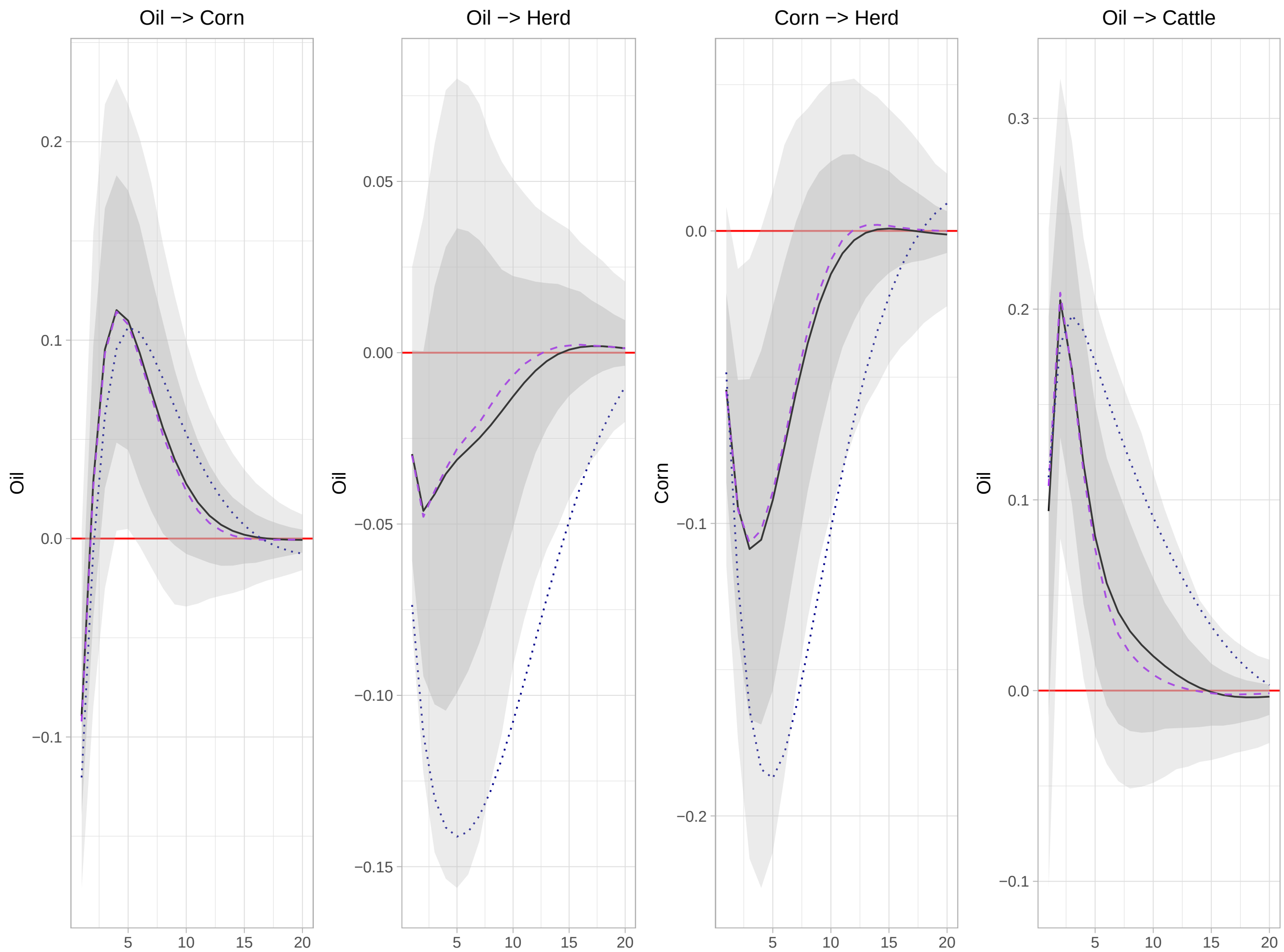

Figure 10: Cholesky Impulse Response Functions 1983-2006 (pre-RFS-2)
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Light Grey 95% Confidence bands and 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.

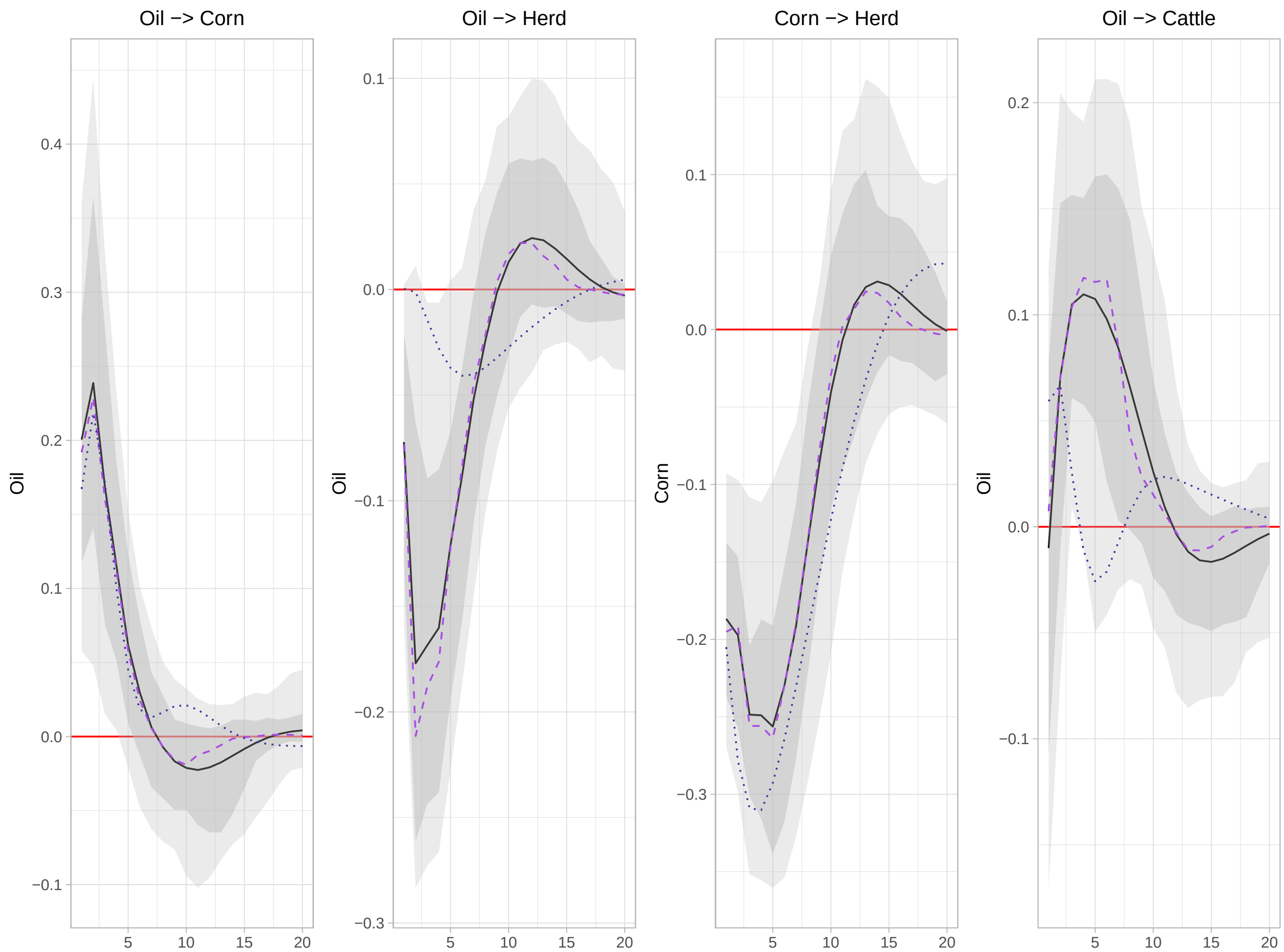

Figure 11: Cholesky Impulse Response Functions 2007-2022 (post-RFS-2)
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Light Grey 95% Confidence bands and 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.

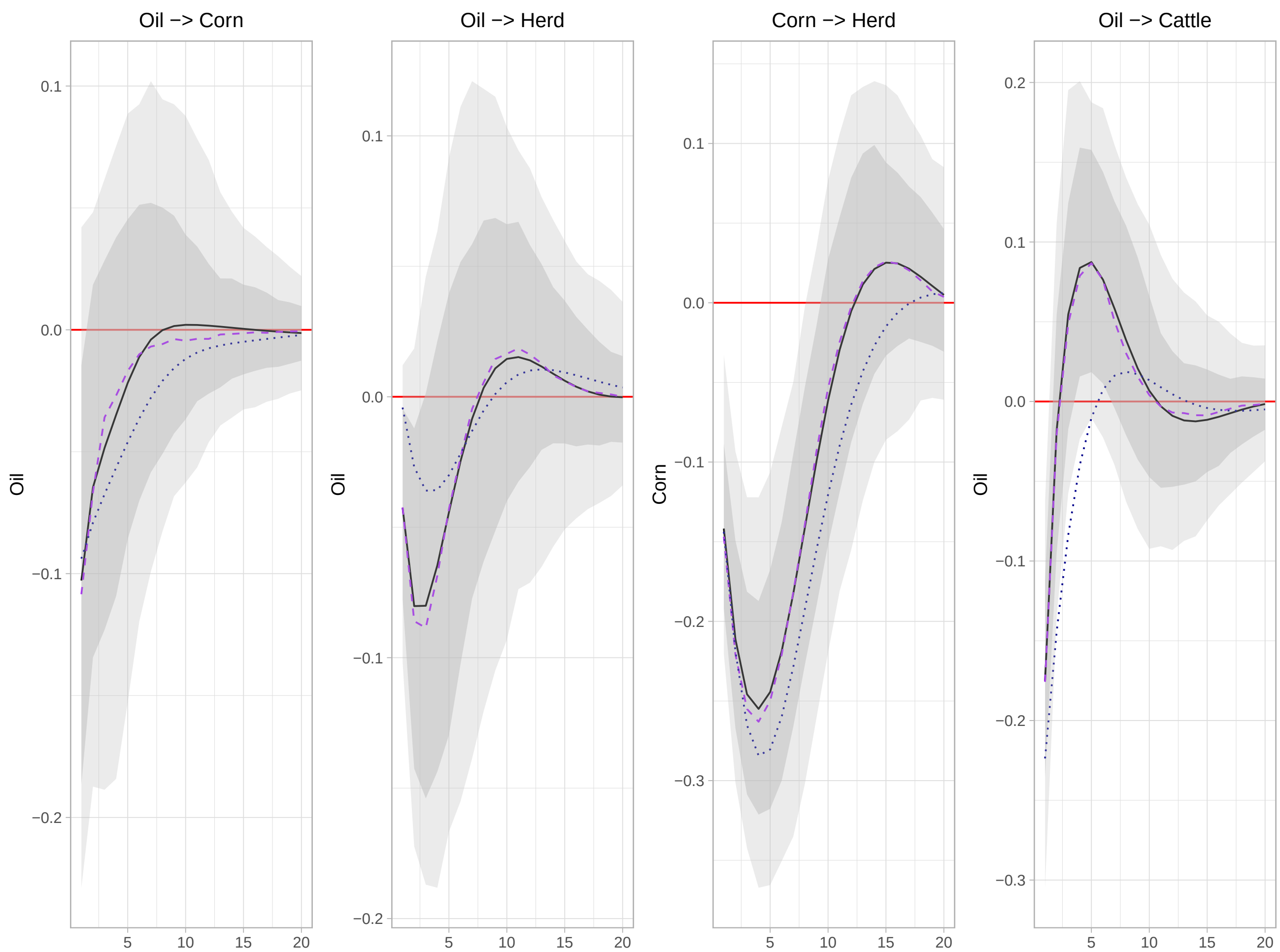

Figure 12: Cholesky Impulse Response Functions using WPI 2001-2022
Source: Author calculations based on data sourced from NASS and AMS 2022
Note: IRFs are generated from the estimated **B** matrix for 20 steps ahead, i.e. 20 six month increments or 10 years total. Light Grey 95% Confidence bands and 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.

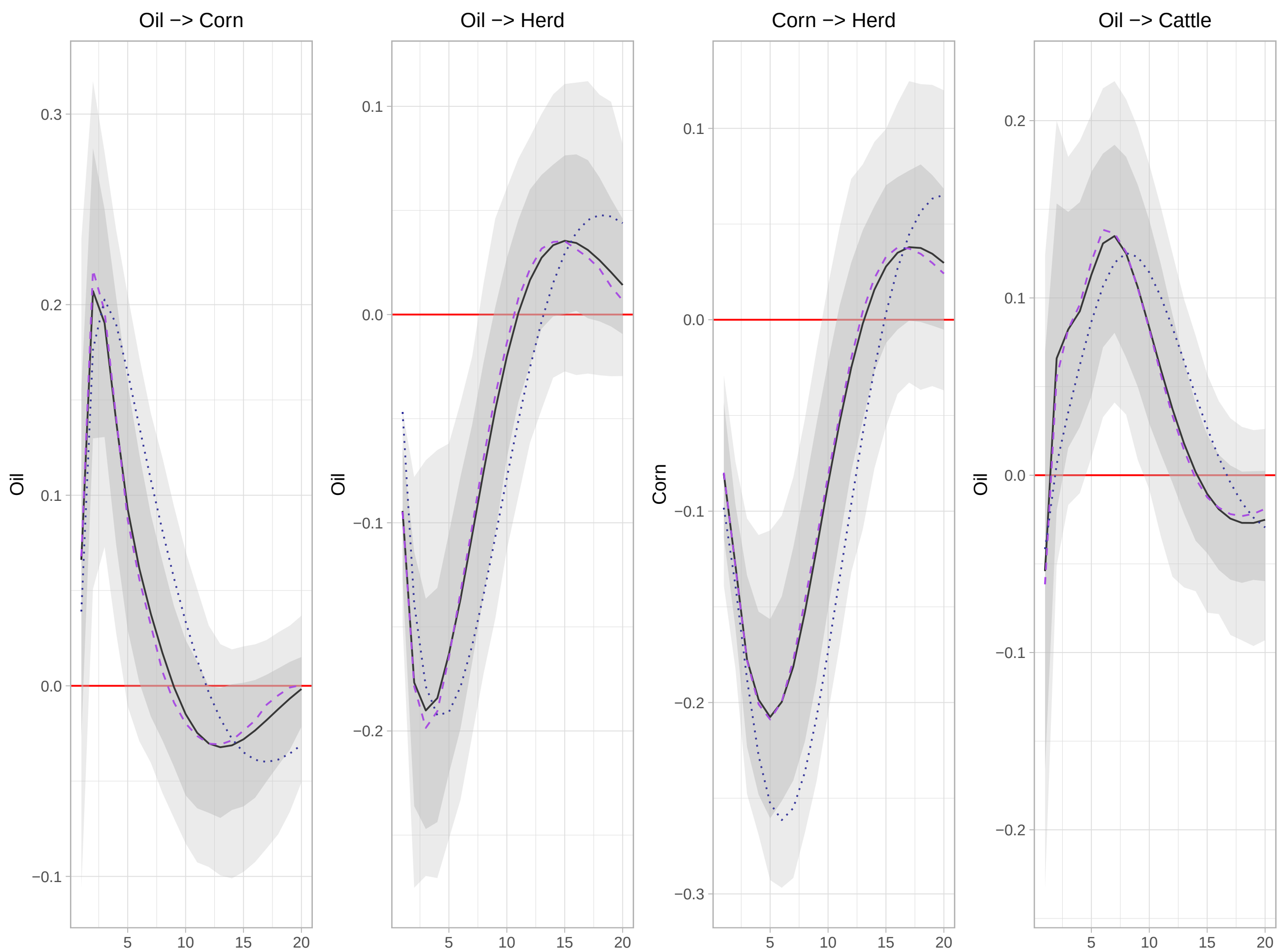

Figure 13: Cholesky Impulse Response Functions using REA 2001-2019

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. 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.

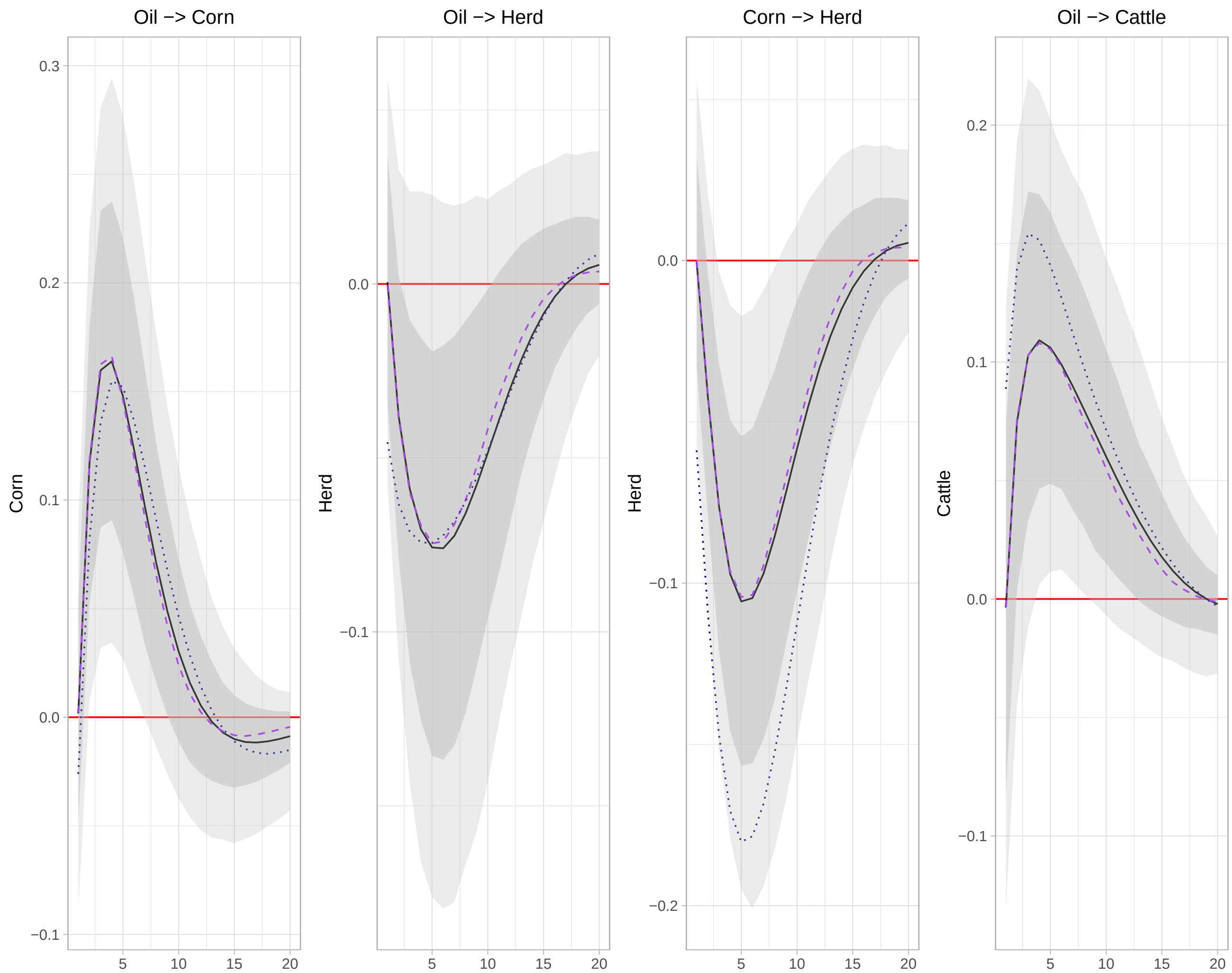

Figure 14: Cholesky Impulse Response Functions using REA 1983-2022 (Removing Drought Year Observations)

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. 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 4: 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	