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Commodity Storage and the Market Effects of Biofuel Policies

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Commodity Storage and the Market Effects of Biofuel Policies

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Abstract

US legislation passed in 2007 (RFS2) increased by about 1.3 billion bushels the net amount of corn required to be processed annually into ethanol for motor-fuel use. Using modern time-series methods, we estimate that corn prices were about 30 percent higher between 2006 and 2014 than they would have been but for RFS2 and if pre-2006 trends had continued. We estimate a permanent corn demand increase of 1.3 billion bushels increased the long-run price by 31% (90% confidence interval is [5%,95%]). Our identification strategy is unique in the literature because it enables estimation of the effects of transitory shocks, such as weather, separately from the effects of persistent shocks, such as the ethanol mandate.

Keywords: Ethanol; agriculture; energy policy; VAR; partial identification

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“There is fuel in corn; oil and fuel alcohol are obtainable from corn, and it is high time that someone was opening up this new use so that the stored-up corn crops can be moved.”

—Henry Ford (in collaboration with Samuel Crowther), *My Life and Work* (1922, p. 276)

More land is now planted with corn than with any other crop in the United States. In 2014, 36 percent of the US corn crop was used to make ethanol to blend with gasoline, up from 14 percent in 2005. The federal government mandated this rapid growth through the Renewable Fuel Standard (RFS), which requires a minimum annual quantity of biofuel content in motor fuel. The RFS was introduced in the US Energy Policy Act of 2005. In 2007, the US Energy Independence and Security Act, almost doubled the biofuel mandate. Under the expanded RFS, known as RFS2, corn ethanol now comprises 10 percent of finished motor gasoline in the United States, up from 3 percent in 2005.

The difference between the RFS2 and RFS mandates is approximately 5.5 billion gallons (bgal) of ethanol annually in the years 2010-2012, which corresponds to about 1.3 billion bushels of corn after accounting for feed by-products. We take these 1.3 billion bushels as the permanent increase in corn demand in the RFS2, and we estimate that it caused a 31 percent long-run increase in corn prices. Interpreting our estimates correctly requires a precise statement about counterfactual ethanol production. In our counterfactual, ethanol production would have increased from its actual 2005 value of 3.9bgal to 8.8bgal in 2014. This path represents a continuation of the trend observed between 2002 and 2005 and is slightly below the path predicted by the USDA in early 2006. We argue it is a reasonable counterfactual path in the absence of the RFS2. We also point that our long-run estimate is scalable. To estimate the effect of increasing corn demand permanently by any multiple of 1.3 billion bushels, a reader could multiply our estimate by that multiple.

Previous studies have also found that the increase in corn-ethanol production affected corn prices. The International Food Policy Research Institute (IFPRI, 2008) and the OECD (2008) both published reports claiming that biofuels were responsible for a significant proportion of the corn-price increase

during the 2007–08 commodity boom (see also Helbling et al. 2008). Other studies assert that ethanol policy strongly affected the level (Mitchell 2008; Hochman, Rajagopal, and Zilberman 2010) and the volatility (Wright 2011) of corn prices. But each of these papers is mainly qualitative; none provides rigorous empirical estimates to support its conclusions.

Two recent papers produce econometric estimates of the effect of ethanol production on agricultural markets. Hausman, Auffhammer, and Berck (2012) estimate a large factor-augmented vector autoregression of cropland allocation in the US. They calculate that removing land from food production to produce corn for ethanol raised corn prices in 2007 by \$0.24 per bushel (less than 10%). Roberts and Schlenker (2013) estimate the elasticities of world supply and demand for calories from agricultural commodities. They create a calorie-weighted index of prices and quantities and use instrumental-variables techniques to estimate the parameters. Based on their static model, they estimate that their food price index was 20 percent higher in 2007 than it would have been without ethanol production.

We focus our analysis on commodity inventory dynamics, which distinguishes our work from the extant literature. This approach enables us to estimate the price effects of persistent shocks to supply or demand separately from the effects of transitory shocks in a market for a storable commodity. This distinction is important in our context because persistent shocks have larger price effects than transitory shocks. The market can respond to a transitory shock, such as poor growing season weather, by drawing down inventory. This action mitigates the price effect. A persistent shock, such as an increase in current and expected future demand, cannot be mitigated by drawing down inventory.

To identify these two types of shocks, we exploit their differential effects on inventory levels and on the term structure of futures prices. For example, all else equal, a sudden increase in this year's consumption demand reduces available inventories and raises spot prices relative to futures prices. This is a transitory shock. In contrast, a predicted increase in next year's consumption demand generates an increase in inventory and an increase in futures prices relative to spot prices. A persistent demand shock

is an increase in both this year's consumption demand and next year's expected consumption demand. Our method is readily applicable to other problems relating to storable commodities in which the distinction between transitory and persistent shocks matters, e.g., the effects of climate change, financial speculation, and technological change such as new seed varieties.

We estimate the supply and demand for inventory using a partially identified structural vector autoregression (SVAR) model. This approach enables us to trace the dynamic effects of ethanol expansion without imposing strong identifying assumptions. We estimate that the demand for corn inventory increased in Fall 2006, as firms sought to store corn for the ethanol-production boom that would follow in 2008 and beyond. This increase in inventory demand helped to buffer the market in 2008 and 2009, when ethanol production increased dramatically. We estimate that average prices over the period from 2006 to 2014 were about 30 percent greater in log terms¹ than they would have been if US ethanol production had continued on its 2005 trend. We also estimate that ethanol demand growth increased the long-run price by 31 percent, with a 90 percent confidence interval ranging from 5 to 95 percent.

Background

Policy History

Ethanol became a significant motor-fuel ingredient in the United States only recently, but its history as a prospective motor fuel is long. In 1920, the US Geological Survey estimated that peak petroleum production would be reached within a few years (White 1920). This assessment raised expectations that ethanol, distilled from grains and potatoes, would become the dominant motor fuel.² However, ethanol production did not become profitable because newly discovered oil reserves in the US Southwest kept

¹ When reporting our results, we use the word *percent* to refer to log differences.

² Newspaper articles expressing this expectation include "Big Future for Alcohol," *Los Angeles Times*, 11/2/1919; "What's Coming in Fuel Drama?" *Los Angeles Times*, 9/12/1920; "Auto Fuel Problem," *New York Times*, 4/27/1919; "Alcohol as a Fuel," *New York Times*, 10/19/1919; "More Alcohol Wanted," *New York Times*, 2/13/1921; and "Ford Predicts Fuel from Vegetation," *New York Times*, 9/20/1925, among many others.

petroleum production high and prices low. These low prices, coupled with the fact that ethanol is 35 percent less efficient than gasoline when used to power standard combustion engines, kept ethanol from being profitable as a motor fuel. Thus, ethanol did not become a major motor-fuel ingredient without significant government support, a fact that is readily admitted by the industry.³

Although the RFS was not enacted until 2005, bills containing variants of the RFS repeatedly entered the US Congress (in 1978, 1987, 1992, 2000, 2001, 2003, and 2004).⁴ The first of these bills, the 1978 Gasohol Motor Fuel Act, had RFS-like features. It proposed that alcohol motor fuel supply at least 1 percent of US gasoline consumption by 1981, 5 percent by 1985, and 10 percent by 1990. This bill never became law, and ethanol constituted less than one percent of finished motor gasoline in 1990.

The 1990 amendments to the Clean Air Act provided the next opportunity for the corn-ethanol industry to lobby for favorable legislation. The amendments required that, in regions prone to poor air quality, oxygenate additives be blended into gasoline to make it burn more cleanly. When the amendments were first introduced to Congress in 1987, ethanol and methyl tertiary butyl ether (MTBE), a natural-gas derivative, were the main contenders to fulfill the oxygenate requirement. Johnson and Libecap (2001) document the lobbying battle between advocates for ethanol and those for MTBE. Although ethanol received favorable treatment in the final legislation,⁵ MTBE became the dominant additive because it was less expensive (Rausser et al. 2004). Subsequently, leaks in underground storage tanks caused MTBE to contaminate drinking water, and MTBE was consequently banned.

The demise of MTBE allowed ethanol to establish itself as a fuel additive in the 2005 Energy Policy Act, which essentially replaced the earlier oxygenate requirement with the RFS. The RFS mandates that a minimum quantity of ethanol be blended into gasoline in the United States each year. The 2005 RFS

³ "The frustrating fact is, without the carrot and stick of government policy, we would not have seen the growth in ethanol that we have seen." Bob Dinneen, President and CEO, Renewable Fuels Association, 17th National Ethanol Conference, 2/23/12.

⁴ The Gasohol Motor Fuel Act of 1978 (S.2533), the Ethanol Motor Fuel Act of 1987 (H.R.2052, S.1304), Amendment to the Energy Policy Act of 1992 (H.AMDT.554), Renewable Fuels Acts of 2000 and 2001 (S.2503 and S.670.IS), and the Energy Policy Acts of 2003 and 2004 (H.R.4503, S.2095).

⁵ Ethanol was allowed a 1 lb. waiver in the Reid Vapor Pressure (RVP) requirement.

mandated that 4bgal of ethanol be used in 2006 and that the amount rise gradually to 7.5bgal by 2012. This 2012 quantity corresponded to 5 percent of projected domestic gasoline use, so it represented a small expansion of the proportion of oxygenates in gasoline. In 2005, US oxygenate production (ethanol and MTBE combined) totaled 4.6 percent of finished motor gasoline. Anderson and Elzinga (2014) show that legislation banning MTBE increased gasoline prices as producers were forced to switch from MTBE to ethanol. Corn prices jumped by 25% in early 2004 due to higher than expected ethanol demand. However, the 2004 growing season produced record yields, which offset the ethanol shock.

Legislation to increase the RFS entered Congress even before the 2005 Energy Policy Act had passed, and more bills followed in 2006.⁶ These proposals led to a doubling of the RFS for corn ethanol in 2007. The RFS2 specifies minimum renewable-fuel production each calendar year from 2007 through 2022. It required 9bgal in 2008 and increased this level annually to 15.2bgal in 2012 and 36bgal in 2022. However, the RFS2 specified that no more than 13.2bgal of corn ethanol could be used to satisfy the RFS2 in 2012, and no more than 15bgal of corn ethanol could be used after 2015.⁷ By 2014, the RFS2 had reached a crossroads with ethanol use at 13.4bgal, which was 10 percent of gasoline use. The fuel industry had resisted increasing ethanol use beyond this level and chose instead to comply with the RFS2 by increasing biodiesel production (Lade, Lin and Smith, 2015)

A massive expansion in ethanol production capacity took place between the 2005 and the 2007 Energy Acts.⁸ At the beginning of 2006, 4.3bgal of operational production capacity existed, and an additional 1.8bgal of capacity was under construction. Only one year later, capacity under construction had grown to 5.6bgal, which exceeded the previous year's total ethanol production (see Panel A of Figure 1). This construction boom, which anticipated the expansion of the RFS, received considerable attention.

⁶ 20/20 Biofuels Challenge Act of 2005 (S.1609), BOLD Energy Act of 2006 (S.2571.IS, H.R.5331.IH).

⁷ The balance of the RFS, the legislation stipulated, had to be filled by so-called advanced biofuels, such as biodiesel from soybean oil and ethanol from cellulosic biomass (e.g., switchgrass, miscanthus, and corn stover). But as of 2014, negligible amounts of commercially viable cellulosic ethanol existed in the United States.

⁸ In the remainder of this article, we use the word *ethanol* to refer to ethanol made from corn. Only trivial amounts of other feedstock (e.g., sorghum, barley) have been used commercially in the United States to produce ethanol for motor fuel.

The United States Department of Agriculture (USDA), which makes annual 10-year projections of the agricultural economy, recognized the expanding RFS and the associated construction boom in its 2007 projections. Panel B of Figure 1 shows that the projections the USDA made in February 2007 (the solid black line) almost doubled the 2006 projections (the solid gray line).⁹ These 2007 projections predicted 2007–09 ethanol use extremely well. In contrast, the February 2006 projections understated 2008 and 2009 ethanol use by 33 and 39 percent, respectively. Overall, Figure 1 suggests that the 2007 expansion of the RFS generated a large jump in projected ethanol production.

[FIGURE 1 HERE]

In addition to the RFS and RFS2, numerous other federal and state policy actions aimed to expand ethanol production. The 1978 Energy Tax Act marked the beginning of federal ethanol programs; it included a provision to exempt ethanol-gasoline blends from the gasoline excise tax. Subsequent legislation offered loan guarantees for ethanol-plant investment and instituted a tariff on imported ethanol.¹⁰ The excise-tax exemption evolved into a tax credit of \$0.45 per gallon of ethanol. The ethanol tax credit and the import tariff both expired on December 31, 2011 with little opposition from ethanol producers' groups such as the National Corn Growers Association and the Renewable Fuels Association.¹¹ This lack of opposition suggests that the RFS has high value to the ethanol industry; with the RFS in place, it has acquired guaranteed demand for its product and a large implicit subsidy (Holland et al. 2011).

Incremental Effect of RFS2 on Ethanol Production

The difference between the 2007 and 2005 RFS mandates is approximately 5.5bgal of annual ethanol use in the years 2010-2012. We take these 5.5bgal as the permanent increase in ethanol demand in the RFS2.

⁹ Available at <http://usda01.library.cornell.edu/usda/ers/94005/>.

¹⁰ Omnibus Reconciliation Act of 1980 and Energy Security Act of 1980.

¹¹ "With growing concerns about gridlock in Washington and greed on Wall Street, Americans are wondering whether anyone with a stake in public policies is willing to sacrifice their short-term advantage for a greater good. Well, someone just did. Without any opposition from the biofuels sector, the tax credit for ethanol blenders (the Volumetric Ethanol Excise Tax Credit—VEETC) expired on January 1." Bob Dinneen, President and CEO, Renewable Fuels Association, 1/5/12. RFA press release.

Ethanol plants produce about 2.8 gallons of ethanol from each bushel of corn, but a third of that bushel is returned to the food system in the form of distiller's grains used for animal feed. Thus, we estimate the effect of a permanent corn demand increase of 1.3 billion bushels, or 33.4 million metric tons (mmt).

An alternative explanation for the expansion in ethanol production is that ethanol was relatively inexpensive in 2006-2014 due to high oil prices, so an expansion in ethanol use would have occurred even in the absence of the RFS2 (Tyner 2010). Counterfactual ethanol production depends on two factors that are difficult to quantify. First, ethanol production requires a large capital investment, and there are also significant fixed costs to adjust fueling infrastructure to incorporate ethanol. Without the guarantee provided by the RFS2 and given uncertainty about the future prices of oil and corn, some firms that built ethanol capacity in 2007-2008 may have waited to invest even if ethanol were less expensive than gasoline on the margin (Dixit and Pindyck 1994).

The second relevant factor is the value of ethanol to the fuel industry. Ethanol has 65 percent of the energy content of gasoline, which suggests that the competitive price of ethanol would be 0.65 times the price of wholesale gasoline. However, blending ethanol with gasoline at a 10 percent rate reduces fuel efficiency by only 3 percent, which may not be detected by consumers. Thus, the market may price ethanol by volume rather than energy content. In addition, ethanol has a high octane rating, which enables oil refiners to meet octane standards by producing a lower-cost lower-octane gasoline and blending it with ethanol (Babcock 2013). Under these arguments, the competitive price of ethanol may equal or exceed the wholesale gasoline price.

Figure 2 shows the relative price of ethanol to gasoline, both in gross terms and net of the ethanol tax credit. Two horizontal lines show the competitive prices assuming (i) ethanol is valued equal to gasoline on a volumetric basis, and (ii) ethanol is valued for its energy content only. Until its expiration in December 2011, the ethanol tax credit significantly increased the incentive to expand ethanol production. Aside from a brief dip in 2005, the relative price net of the tax credit averaged volumetric par until early

2007. Thus, even under volumetric ethanol pricing, there was little market incentive to expand ethanol production in this period. Given that building ethanol plants requires significant lead time, the 2007-2008 expansion in production capacity shown in Panel A of Figure 1 was likely induced by the RFS and RFS2.

[FIGURE 2 HERE]

From May 2007 until oil prices began declining in October 2014, the relative net ethanol price averaged 0.79. Under volumetric pricing, there would have existed a significant incentive to expand ethanol production during this period, which suggests that ethanol production would have expanded even faster than it did.¹² Without the RFS2, the incentive would have been even greater because ethanol supply and therefore ethanol prices would have been even lower. However, the fact that ethanol has been priced closer to its energy value than volumetric par implies that energy-equivalent valuation fits the data better than volumetric pricing, at least at the wholesale level.

Estimating how much ethanol production would have occurred in the absence of the RFS2 requires specification of an ethanol supply curve. Babcock (2013) uses a numerical model to estimate counterfactual ethanol production in the absence of government assistance. His model is based on a marginal analysis of the aggregate supply and demand for ethanol, i.e., he does not model the decision to invest in new ethanol plants, the cost of ethanol transportation, or the costs of adapting the petroleum refining and blending system to incorporate more ethanol. As such, his estimates provide an upper bound on the actual amount of ethanol likely to be produced in the absence of the RFS2; they are more appropriate as estimates of the likely amount of blending should the RFS2 be repealed.

Babcock presents two scenarios: (i) ethanol demand is perfectly elastic at the price of gasoline as long as ethanol makes up no more than 10 percent of the gasoline supply, and (ii) ethanol demand is perfectly elastic at its energy value. From May 2007 until oil prices began declining in October 2014, the

¹² This applies up to 2011, when ethanol use reached 10 percent of the gasoline pool. Increasing ethanol use beyond the 10 percent “blend wall” presents significant technical obstacles, and so willingness to pay for ethanol above 10 percent may be low.

average wholesale gasoline price was about \$2.50. Assuming 80 million harvested acres of corn, Babcock's estimates imply 12.97bgal of ethanol per year under scenario (i) and 7.67bgal under scenario (ii). These estimates increase to 13.43 and 9.30 bgal if we assume 85 million harvested acres. Given that ethanol has been priced closer to energy par than volumetric par, and given that Babcock's model assumes production capacity already exists, we find it reasonable to assume that ethanol use would have increase steadily to 8.8bgal by 2014 in the absence of the RFS2.

Conceptual Framework

We model the supply and demand for corn inventory. The staple of the inventory literature is the competitive rational storage model, which originated with Williams (1936). Gustafson (1958) first solved for the optimal storage rule in this model, and Williams and Wright (1991), Deaton and Laroque (1996), Routledge, Seppi, and Spatt (2000), and Pirrong (2012) made further important contributions.

The equilibrium level of inventory is determined by three integrated markets: (i) supply and demand for use in the current period; (ii) expected supply and demand in the next period; and (iii) storage from the current period to the next period. In the current period, there exists a price at which the quantity demanded for use would equal the quantity supplied. At any higher price, there will be an excess supply in the current period. This excess supply equals amount of inventory that the market is willing to supply into the storage market at the end of the current period. Thus, we define the *supply of inventory* as the horizontal difference between the current period supply and demand curves.

Market participants in the current period also look ahead to the next period and predict the willingness of next period's market participants to produce, consume, or store the commodity. If the expected price is high enough, then suppliers would produce enough next period to completely satisfy next period's expected demand. At any lower price, next period's market is expected to be able to absorb

inventories from the current period. Thus, we define the *demand for inventory* as the horizontal difference between the next period's expected demand and supply curves.

The storage market connects the current period to the next. Storage firms purchase the excess supply in the current period, hold it for one period, and sell it into next period's market. Following a long literature that originates with Working (1949), we specify the marginal cost of storage as increasing with inventory. This specification leads to the well-known "Working curve" for the supply of storage, and it allows for the marginal cost of storage to be negative. A negative marginal cost of storage can arise due to convenience yield, a concept introduced by Kaldor (1939) and developed by Brennan (1958), among others. Convenience yield represents the flow of benefits to firms that hold a commodity in storage. It is typically motivated as an option value generated by the cost of sourcing the commodity (Telser 1958) or by the possibility that inventories could be driven to their lower bound in the future (Routledge, Seppi, and Spatt 2000). In the next section, we develop the model formally.

Rational Storage Model

Let P_t denote the post-harvest price of corn in year t . The long growing season implies that corn supply is an increasing function of the expected price as of the previous year ($E_{t-1}[P_t]$) and demand for current use is a decreasing function of P_t . The storage market connects the period t to period $t+1$. Storage firms purchase the excess supply in period t , hold it for one period, and sell it into the period $t+1$ market. The willingness to supply storage is increasing in the returns to storage, as per the Working curve.

Three potential shocks drive the market: (i) a shock to net supply in period t (ε_{st}); (ii) an expectations shock (ε_{et}); (iii) a shock to the supply of storage (ε_{wt}). These shocks may be autocorrelated; we specify them as first-order Markovian with independent and identically distributed innovations. The expectations shock captures changes in expectations about the future that are independent of current supply and demand, e.g., a change in expected future demand due to ethanol expansion. The net supply

shock encompasses anything that affects either supply or demand in the current period, such as poor growing-season weather. The net supply shock is correlated with lags of the expectations shock because expectations in period t predict outcomes in period $t+1$.

Net supply in year t is

$$S_t - D_t = f(F_{t-1,t}, P_t, \varepsilon_{st}), \quad (1)$$

where we use the fact that, in the absence of a risk premium, the futures price at time $t-1$ for delivery in t equals the expected spot price, i.e., $F_{t-1,t} = E_{t-1}[P_t]$.¹³ The supply of storage is

$$F_{t,t+1} - P_t = c(I_t, P_t, \varepsilon_{wt}).$$

We specify $c(0, P_t, \varepsilon_{wt}) = -\infty$ to capture the empirical regulatory that inventories never equal zero. We include P_t as an argument in the supply of storage function to allow the possibility that some components of the price of storage are proportional to price.

Intertemporal accounting requires that the change in inventories equals net supply, i.e., $\Delta I_t \equiv S_t - D_t$. Putting this together with (1) gives the net supply function

$$\Delta I_t = f(F_{t-1,t}, P_t, \varepsilon_{st})$$

which we invert to obtain

$$P_t = h(\Delta I_t, F_{t-1,t}, \varepsilon_{st}) \quad (2)$$

This equation represents the supply of inventory; it specifies the price that would induce the market to supply I_t units to the storage market.

Next, we obtain the demand for inventory. In equilibrium, outgoing inventory can be expressed as a function of the state variables (e.g., Williams and Wright (1991), Routledge, Seppi, and Spatt (2000)):

$$I_{t+1} = J(I_t, \varepsilon_{s,t+1}, \varepsilon_{e,t+1}, \varepsilon_{w,t+1}) \quad (3)$$

¹³ This assumption is consistent with the rational storage literature and the empirical fact that average payoffs on agricultural futures have been close to zero in the past thirty years (Sanders and Irwin 2012).

From (2), the expected value of next year's inventory supply conditional on the state variables this year is

$$E_t[P_{t+1}] = E_t \left[h(\Delta I_{t+1}, F_{t,t+1}, \varepsilon_{s,t+1}) \right], \quad (4)$$

where $E_t[\cdot]$ denotes the expectation conditional on $\{I_t, \varepsilon_{st}, \varepsilon_{et}, \varepsilon_{wt}\}$. Substituting (3) into (4) implies

$$F_{t,t+1} \equiv E_t[P_{t+1}] = E_t \left[h(J(I_t, \varepsilon_{s,t+1}, \varepsilon_{e,t+1}, \varepsilon_{w,t+1}) - I_t, F_{t,t+1}, \varepsilon_{s,t+1}) \right] \quad (5)$$

Now, because the shocks are Markovian, the conditional expectation of a function of $\{\varepsilon_{s,t+1}, \varepsilon_{e,t+1}, \varepsilon_{w,t+1}\}$

is in turn a function of $\{\varepsilon_{st}, \varepsilon_{et}, \varepsilon_{wt}\}$, and we can rewrite (5) as

$$F_{t,t+1} = g(I_t, \varepsilon_{st}, \varepsilon_{et}, \varepsilon_{wt}). \quad (6)$$

This equation is the demand for inventory; it specifies the expected price that would induce the market to demand I_t units from the storage market next period.

We use the terms *inventory* and *storage* in the same way they are used in the commodity-storage literature. However, these terms leave room for confusion. *Inventory* denotes actual bushels of grain that are not used in period t and are instead saved for use in period $t+1$. *Storage* describes the service of holding inventory from period t to period $t+1$. To use an analogy in the retail industry, inventory corresponds to the units of product that a store buys from wholesalers and sells to consumers, and storage corresponds to the service of buying the product from wholesalers and selling it to consumers. The price of storage thus corresponds to the markup earned by retailers, whereas the price of inventory is the price of a unit of the commodity.

The retail analogy helps clarify the demand for storage services in our model. The willingness to pay for retail services equals the difference between the price at which consumers are prepared to buy a unit in the store and the price at which wholesalers are willing to sell that unit to the store. Similarly, the demand for storage is the vertical difference between the inventory supply and demand curves. Thus, the willingness to pay for storage is the difference between (6) and (2), i.e., the inverse demand for storage is

$$F_{t,t+1} - P_t = g(I_t, \varepsilon_{st}, \varepsilon_{et}, \varepsilon_{wt}) - h(\Delta I_t, E_{t-1}[P_t], \varepsilon_{st}) \quad (7)$$

The demand for storage slopes downward because the market is willing to save more inventories for the second period when the price of storage is low. Equilibrium occurs at prices and quantities such that the supply of storage equals the demand.

Graphical Illustration

Figure 3 illustrates the equilibrium for a case with linear supply and demand and *iid* shocks. Supply is $S_t = \gamma_0 + \gamma_1 F_{t-1,t} + \varepsilon_{st}$ and demand is $D_t = \beta_0 - \beta_1 P_t$, where $E_{t-1}[\varepsilon_{st}] = 0$, which implies that net supply is

$$S_t - D_t = \gamma_0 - \beta_0 + \gamma_1 F_{t-1,t} + \beta_1 P_t + \varepsilon_{st}$$

Panel A of Figure 3 shows the period t supply and demand curves. The supply curve is vertical because supply depends on the expected period t price as of period $t-1$. The horizontal difference between these curves is inventory supply, denoted by $h(\Delta I_t, E_{t-1}[P_t])$ in Panel C.¹⁴

[FIGURE 3 HERE]

Next, we obtain the demand for inventory. Expected total demand next period is

$$E_t[D_{t+1} + I_{t+1}] = \beta_0 - \beta_1 F_{t,t+1} + E_t[J(I_t, \varepsilon_{d,t+1}, \varepsilon_{s,t+1}, \varepsilon_{w,t+1})]$$

and expected supply is $E_t[S_{t+1}] = \gamma_0 + \gamma_1 F_{t,t+1}$. Panel B shows these two functions. The horizontal difference between these curves is inventory demand, labeled $g(I_t)$ in Panel C.

The inventory demand and supply curves in Panel C are each evaluated at different prices. The inventory supply curve is evaluated at the period t spot price P_t , and the inventory demand curve is evaluated at the expected period $t+1$ spot price $F_{t,t+1} \equiv E_t[P_{t+1}]$. Thus, the vertical difference between these curves equals the price-dependent demand for storage in (6). The market will clear at the point

¹⁴ For brevity, we suppress the shocks, which are also arguments of the inventory supply function, i.e., we write $h(\Delta I_t, F_{t-1,t})$ rather than $h(\Delta I_t, F_{t-1,t}, \varepsilon_{dt}, \varepsilon_{st})$. We do the same for the inventory demand function.

where the inventory supply and demand curves cross only if the market price of storage is zero. Panel D depicts the demand for storage derived from Panel C and plots that demand along with the supply of storage. We depict the supply of storage as linear in the log of inventory. The market clears at an inventory level with a positive price of storage, (i.e., $F_{t,t+1} - P_t > 0$). If the demand for storage shifted left, this equilibrium could result in a negative price of storage (i.e., futures-market backwardation).

From the perspective of the inventory market, both current-supply and current-demand shocks affect the amount of available inventory. It matters little whether the reduced supply of inventory comes from bad weather (which reduces the crop size) or from increased demand (which removes more of the commodity from the market). This feature helps us identify the effects of the ethanol expansion because we do not need to separately identify the elasticities of demand and supply for current use.

In the case of corn ethanol, evidence shown in Figure 1 suggests that by the end of 2006, market participants knew that ethanol production would increase in 2008. Viewed in light of Figure 3, the expected future demand curve for corn in Panel B shifted to the right (an expectations shock), which implies that the demand-for-inventory curve shifted to the right in 2006. However, current-year supply and demand remained constant. Thus, the spot price, inventory level, and price of storage all increased.

By 2008, the increase in demand for corn from ethanol plants had become permanent. Figure 4 shows this scenario. Both current and expected future demand have shifted to the right (Panels A and B), which in turn shifted the supply-of-inventory curve in Panel C to the left and the inventory-demand curve in Panel C to the right. Figure 4 shows a decline in inventory carryover because the perfectly inelastic supply in period t causes the supply-of-inventory curve to shift up by more than the demand-for-inventory curve. The graphical analysis illustrates the case in which the market is surprised, in period t , by the demand shift. The market responds by drawing down inventory. If, in period $t-1$, the market had anticipated the coming demand shift, it would have increased period t supply. Relative to the case

depicted in Figure 4, the supply-of-inventory curve would have shifted to the right, and the inventory carryover would have increased.

[FIGURE 4 HERE]

Figure 4 illustrates the advantages of our inventory-focused approach in distinguishing transitory from persistent price shocks. Poor growing-season weather is one example of a transitory price shock. Such a shock would shift the supply-of-inventory curve to the left but it would not shift the demand-for-inventory curve, so it would have a smaller price effect than a persistent shock that shifts both curves.

Empirical Framework

In the previous section, we show using a rational storage model how demand from ethanol producers for corn affects the supply and demand for inventory, the price of storage, and the price of corn. To bring this model to the data, we log-linearize the supply-of-inventory, demand-for-inventory, and supply-of-storage functions given in equations (2), (6), and (7). We then fit a structural vector autoregression model to this linearized system. Using this framework, we follow a long literature pioneered by Sims (1980) concerning estimating dynamic rational-expectations models with SVARs. Our identification scheme allows us to partially identify shocks to each of inventory demand, inventory supply, and the supply of storage, and the estimated parameters then reveal how these shocks propagate through the system.

We use annual data covering the period 1961 through 2012. We choose to model at the annual frequency because price and inventory variation is dominated by the annual harvest cycle.¹⁵ We use futures prices for the next period's expected price. In addition to prices and inventory, we follow Kilian (2009) in controlling for aggregate commodity demand. After we describe our data, we present our identification strategy, our counterfactual experiment, and our method for estimating long-run effects.

¹⁵ Inventory data exist for the United States at the quarterly frequency. These data exhibit a saw-tooth pattern: the fall harvest generates high inventory in December, and inventory declines linearly in each of the three subsequent quarters.

Data: Real Futures Price of Corn

The crop-year for corn in the United States runs from September through August. The crop is typically planted in April and May and harvested in September and October. Through the summer, the growing regions experience agro-economic conditions (especially precipitation and temperature) that determine productivity (yields). If the weather is too hot, cold, wet, or dry, then prices rise in anticipation of a small crop. After harvest, it takes some time before the size of the harvest is known. The official scorekeeper, the USDA, publishes its final estimate of the crop size in January, following the harvest. However, after November, the USDA usually revises its estimates only slightly.

We measure prices in March of each year, which occurs in the middle of the crop-year, before planting and before the weather realizations occur that determine yield on the next year's output, and after the market has full information about the size of the previous year's output. Specifically, for each crop year we take the average daily settlement price in March on the futures contract that matures in December. This price represents the (risk-adjusted) price that a firm would expect to receive in December if it were to decide in March to sell corn in December. We then deflate the price by the all-items consumer price index and take logs. The resulting futures-price variable is $f_t = \ln(F_{t,T} / CPI_t)$, where t denotes March of each year and T denotes December of the same calendar year.

Data: Futures-Cash Price Spread (Convenience Yield)

As articulated by Working (1949), the market price of storage is revealed by the difference between the futures price for delivery after the next harvest and the current spot price. In other words, the absence of arbitrage opportunities implies that the futures price equals the current cash price plus the cost of carrying the commodity until the futures contract expires. Specifically,

$$F_{t,T} = (P_t(1 + r_{t,T}) + c_{t,T})(1 - y_{t,T}), \quad (8)$$

where $r_{t,T}$ denotes the cost of capital, $c_{t,T}$ the warehousing cost of storage, and $y_{t,T}$ the convenience yield.

With this construction, we can interpret the convenience yield as the percent by which the futures price falls below the value implied by full carrying costs. We use a measure of the log convenience yield as our measure of the price of storage because it captures the component of the supply of storage that depends on inventory but not on the price level.

We use average daily Central Illinois cash bids in March to measure the spot price, although it does not make any difference to our results if we use other locations in the United States.¹⁶ Nor do our results change if we use expiring March futures prices in place of Central Illinois cash bids. We treat capital costs as exogenous to corn storage and measure them using $r_{t,T} = 0.75g_t$, where g_t denotes the yield on one-year Treasury notes plus 200 basis points, and the 0.75 factor reflects the fact that we are calculating the cost of storage over a nine-month horizon. We add 200 basis points based on the Chicago Mercantile Exchange's (CME) method for determining the price of storage in wheat-futures markets. Our results are insensitive to the choice of capital-cost measure because variation in the price of storage is dominated by variation in the other components of (8).

Warehousing fees are not directly observable from secondary sources. Moreover, because grain elevators are multi-output firms that merchandize and store several different commodities and may cross-subsidize some activities, a posted fee for storage may not clearly reflect the price of grain storage on the margin (Paul 1970). Our warehousing-cost factor is derived from a maximum storage price set by the CME on warehouse receipts and shipping certificates that are issued to make delivery on futures contracts. Since 1982, this price maximum has been between \$0.045 and \$0.05 per bushel per month. However, Garcia, Irwin, and Smith (2015) show that this price has been too low relative to the market in the last several years, and that \$0.10 would be a more appropriate price. If the storage price had been allowed to grow at the rate of CPI inflation, it would have reached \$0.10 in 2007. Thus, we define the warehousing

¹⁶ Garcia, Irwin, and Smith (2015) show that the specific futures-market delivery mechanism sometimes causes the futures price to exceed the expected future spot price. They show that these discrepancies have recently been large for wheat, but over a nine-month storage window, they are small for corn.

component of the price of storage as \$0.05/bu/mo in 1982–83 dollars, which corresponds to \$0.45 over the nine months from March to December.

Taking logs, the spread variable we use in our estimation is:

$$cy_t = -\ln(1 - y_{t,T}) = \ln\left(\frac{P_t(1 + r_{t,T})}{CPI_t} + 0.45\right) - \ln\left(\frac{F_{t,T}}{CPI_t}\right), \quad (9)$$

where CPI is indexed to equal 1 in 1982–83. The additive warehouse cost component reflects the fact that warehousing costs are not proportional to the price of the commodity. Nonetheless, our results are robust to our assumption that warehousing storage costs equal \$0.45; the estimated average price effects increase slightly if we set the warehousing storage cost to zero.

Data: Crop-Year-Ending Inventory

We use total crop-year-ending inventory in the United States as the quantity variable in our model. This variable measures total corn inventory on August 31 of each year—that is, five months after the month in which we measure price. This timing convention suggests that inventory might be endogenous to price. Specifically, if a demand shock raises the price of the December futures contract in March, firms may respond by increasing inventory demand. We use a partial-identification strategy to allow this possibility.

We use US inventory rather than world inventory for two reasons.¹⁷ First, US inventory is measured much more accurately than world inventory. Second, although the corn market is global, transportation costs are significant, so prices at any location reflect local scarcity. That is, using US inventory volume totals is commensurate with using a US price. Our inventory variable is $i_t = \ln(I_t)$.

Data: Index of Real Economic Activity (REA)

Rapid economic growth and intense industrial activity tend to coincide, especially in less-developed

¹⁷ Notwithstanding these reasons, our estimates of the price effect are only few percentage points different if we use world inventory excluding China. We exclude China because it often reports large changes in inventory holdings, but it does not tend to manage that inventory in accordance with market signals (Wright (2011)). The results are also unchanged if we exclude government-held inventory.

nations. This growth spurs demand for commodities and raises commodity prices. In a review article (Carter, Rausser and Smith, 2011), we show that both the 1973–74 and 2007–08 commodity booms were preceded by unusually high world economic growth, especially in middle-income countries. Baumeister and Kilian (2014) show that corn prices are correlated with the price of oil, but that correlation is largely “driven by common macroeconomic determinants of the prices of oil and of agricultural commodities.”

To represent global economic activity, we use the index developed by Kilian (2009) and extend it backwards using the index of Hummels (2007). These indexes are based on dry-cargo shipping rates and are designed to capture shifts in global demand for industrial commodities. As Kilian emphasizes, “the proposed index is a direct measure of global economic activity which does not require exchange-rate weighting, which automatically aggregates real economic activity in all countries, and which already incorporates shifting country weights, changes in the composition of real output, and changes in the propensity to import industrial commodities for a given unit of real output” (1056). We use the March value of the index to match the timing of our price data.

Figure 5 presents the resulting index of real economic activity (after removing a linear trend) along with the de-trended time-series for log inventory, log real futures price, and convenience yield.

[FIGURE 5 HERE]

VAR Model and Identification

We estimate the three functions in (2), (6), and (7), adding REA_t and a linear trend as arguments in each equation. We write the log of these equations as

$$\begin{aligned}
 f_t + cy_t &= \ln\left(h\left(\Delta I_t, F_{t-1,t}, REA_t, t, \varepsilon_{st}\right)\right) && \text{inventory supply} \\
 f_t &= \ln\left(g\left(I_t, REA_t, t, \varepsilon_{st}, \varepsilon_{et}, \varepsilon_{wt}\right)\right) && \text{inventory demand} \\
 cy_t &= -\ln\left(c\left(I_t, REA_t, t, \varepsilon_{wt}\right)\right) && \text{supply of storage}
 \end{aligned}$$

where we specify the log price of storage as the negative convenience yield ($-cy_t$) and the log spot price as $f_t + cy_t$. As outlined earlier, our objective in defining the cy_t variable is to obtain a supply of storage

function that does not depend contemporaneously on price.

We perform a first order expansion around the log of inventory and prices and around the levels of REA , the trend and the shocks. We then normalize the three equations by i_t , f_t , and cy_t to obtain

$$\begin{array}{ll}
i_t = \delta_0^{IS} + \delta_1^{IS}t + \delta_2^{IS}(f_t + cy_t) + \delta_3^{IS}REA_t + \delta_4^{IS}i_{t-1} + \delta_5^{IS}f_{t-1} + \varepsilon_{st} & \text{inventory supply} \\
f_t = \delta_0^{ID} + \delta_1^{ID}t + \delta_2^{ID}i_t + \delta_3^{ID}REA_t + \delta_4^{ID}\varepsilon_{st} + \varepsilon_{et} + \delta_5^{ID}\varepsilon_{wt} & \text{inventory demand} \\
cy_t = \delta_0^{SS} + \delta_1^{SS}t + \delta_2^{SS}i_t + \delta_3^{SS}REA_t + \varepsilon_{wt} & \text{supply of storage}
\end{array}$$

Defining $X_t \equiv [REA_t \quad i_t \quad f_t \quad cy_t]'$ and assuming that REA_t is exogenous to the corn market within a year,

we write the log-linear system as $A^* X_t = B^* X_{t-1} + \Gamma^* Z_t + D\varepsilon_t$, where

$$A^* = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -\delta_3^{IS} & 1 & -\delta_2^{IS} & -\delta_2^{IS} \\ -\delta_3^{ID} & -\delta_2^{ID} & 1 & 0 \\ -\delta_3^{SS} & -\delta_2^{SS} & 0 & 1 \end{bmatrix}, \quad B^* = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \delta_4^{IS} & \delta_5^{IS} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad \Gamma^* = \begin{bmatrix} \delta_0^R & \delta_1^R \\ \delta_0^{IS} & \delta_1^{IS} \\ \delta_0^{ID} & \delta_1^{ID} \\ \delta_0^{SS} & \delta_1^{SS} \end{bmatrix}$$

$$D = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & \delta_4^{ID} & 1 & \delta_5^{ID} \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \varepsilon_t = \begin{bmatrix} \varepsilon_t^R \\ \varepsilon_t^S \\ \varepsilon_t^e \\ \varepsilon_t^w \end{bmatrix}$$

$Z_t' = [1 \quad t]$, and ε_t^R denotes a Markovian shock to REA_t . The first-order Markov assumption on the shocks implies that a linear approximation to the data generating process for the shocks is

$$\varepsilon_t = \Phi \varepsilon_{t-1} + U_t, \tag{10}$$

where U_t is a vector of innovations that are independent of each other and independently and identically distributed over time. Thus, we have

$$D^{-1}A^* X_t = (D^{-1}B^* + \Phi D^{-1}A^*) X_{t-1} - \Phi D^{-1}B^* X_{t-2} + D^{-1}\Gamma^* t + U_t,$$

which write compactly as

$$AX_t = B_1 X_{t-1} + B_2 X_{t-2} + \Gamma Z_t + U_t \tag{11}$$

This model is linear in the logarithm of prices and inventory, which implies that the elasticity of total

demand with respect to price decreases when inventory decreases. To see why, note that a given percentage change in inventory corresponds to a much smaller change in total quantity when inventory is low than when inventory is high. Thus, a given percentage price change will be associated with small percentage changes in total quantity when inventory is low and larger percentage changes in total quantity when inventory is high. This implication is consistent with the standard rational storage model in which demand is less elastic when inventory is scarce.

After re-normalizing (11) so that one variable has a unit coefficient in each equation, we have

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -\alpha_{21} & 1 & -\alpha_{23} & -\alpha_{23} \\ -\alpha_{31} & \alpha_{32} & 1 & -\alpha_{34} \\ -\alpha_{41} & \alpha_{42} & 0 & 1 \end{bmatrix}, \quad (12)$$

The parameter α_{23} is the short-run (i.e., one-year) elasticity of inventory supply. As shown in Figure 3, this parameter reflects the horizontal difference between the current-year supply and demand curves; it is the difference between the supply and current-use-demand elasticities. The parameter α_{32} is the short-run inverse elasticity of net demand for inventory with respect to the expected price in the next period. Another key parameter is α_{42} , the short-run inverse elasticity of supply of storage. Our identification assumption that price does not appear in the supply of storage function produces the zero in the bottom row of A . As specified in (11) and (12), the elements of A are not identified, because inventory is endogenous in the inventory-demand and supply-of-storage equations.

Most of the year-to-year variation in inventory comes from fluctuations in inventory supply (i.e., fluctuations in current-year supply and demand). To identify α_{23} , we require independent variation in inventory demand. The dominance of inventory-supply shocks thus makes point identification of α_{23} difficult. As a result, we use a partial-identification strategy.

Partial identification, also known as set identification, permits econometric analysis without imposing strong assumptions (Manski 2003). We assume that α_{23} lies in a specified range, but we take no

position on which value in that range the parameter takes. Because we do not identify a particular value for α_{23} , the other parameters in A are also not uniquely identified; they are identified only up to the set defined by our assumption on α_{23} . This approach is similar to that employed by Kilian and Murphy (2014) in their study of the role of inventory in determining crude-oil prices. Kilian and Murphy impose sign restrictions on the elements of their A matrix and bounds on several of the short-run elasticities in that matrix. Their method extends the identification-by-sign-restrictions approach of Faust (1998) and Uhlig (2005), who impose sign restrictions only.

We make an identifying assumption that there is no feedback from the corn market to global economic activity within one year. This assumption implies zero restrictions in the first row of the matrix A . Total world trade in corn is a small fraction of seaborne trade in dry cargo, the price of which underlies our real economic activity measure. Most dry cargo is industrial commodities such as coal and iron ore. In the decade of the 2000s, total corn trade was less than 2 percent of seaborne dry-cargo trade by weight. During our sample period, world corn trade never exceeded 4.3 percent of seaborne dry-cargo trade. Thus, the effect of corn-specific price shocks on real economic activity is likely negligible.¹⁸ These zero restrictions leave a single unidentified parameter, so we place bounds only on α_{23} .

Using estimates from the literature and with some introspection, we could exactly identify our model by choosing a specific numerical value for the short-run supply elasticity. This was the approach used by Blanchard and Perotti (2002) to model the effects of government spending and taxes on output. Blanchard and Perotti impose on their model a value for the elasticity of tax receipts with respect to GDP. In our case, we could use the estimates of Adjemian and Smith (2012), who use the price response to USDA crop forecasts during the period from 1980 to 2011 to estimate the demand flexibility (inverse elasticity) for corn. We show in Appendix A that their estimates imply $\alpha_{23} \approx 4.4 - 1 / (\alpha_{32} + \alpha_{42}(1 + \alpha_{34}))$.

¹⁸ Corn trade data from the USDA (<http://www.fas.usda.gov/psdonline>), and dry cargo trade data from UNCTAD Stat (<http://unctadstat.unctad.org/ReportFolders/reportFolders.aspx>).

Rather than imposing specific values, we impose bounds on α_{23} . Here, we introduce three assumptions that imply bounds on the parameters that can be used to partially identify our model. The elasticity of inventory supply is¹⁹

$$\alpha_{23} = \eta^s \frac{Q^s}{I} - \eta^u \frac{Q^u}{I},$$

where η^s and η^u denote the production (supply) and current-use (demand) elasticities, I/Q^s is the ratio of inventory to production, and I/Q^u is the ratio of inventory to use. The inventory to use ratio never exceeded 0.4 in our sample period, and it would seem reasonable to suppose that the elasticity of demand for current use exceeds 0.1 in absolute value. The supply elasticity is non-negative and likely close to zero because planted acreage and inventory carryover are essentially determined by March of each year. Thus, we place a lower bound of $0 - 0.1/0.4 = 0.25$ on α_{23} .

The α_{32} inverse elasticity in our econometric specification reflects the potential net response of next-period's producers and consumers to expected prices. This elasticity should be at least as large as the short-run elasticity of current-period net supply with respect to the current price because firms are at least as able to respond to current shocks during the next period as they are during the current period. Thus, we place an upper bound of $1/\alpha_{32}$ on α_{23} , and we have $0.25 \leq \alpha_{23} \leq 1/\alpha_{32}$.

In sum, we base these bounds on three assumptions:

- (i) Short-run elasticity of demand for current use exceeds -0.1 in absolute value.
- (ii) Inventory-to-use ratio never exceeds 0.4, which is the sample maximum.
- (iii) Elasticity of next year's net supply is not less than elasticity of current net supply.

Proceeding under these assumptions, we estimate the model parameters using data from 1961 to 2005. Based upon the estimated parameters, we take two approaches to estimating the effects of the RFS in corn prices. First, we forecast prices and inventory for the period from 2006 to 2014 and conduct a

¹⁹ Because α_{23} is constant, the η decreases as Q/I increases, i.e., demand and/or supply is less elastic at low inventory levels.

counterfactual experiment to assess the dynamic impact of expanding ethanol production. Second, we deduce implied long-run effects from our parameter estimates through parallel shifts of the inventory supply and demand curves as in Figure 4. Next, we describe these two methods.

Estimating the Ethanol Effect Using Counterfactual Analysis

We forecast prices and inventory under various assumptions regarding the structural shocks U_t . First, we set the inventory-demand shock to zero for 2006–14 and set the remaining shocks to their values implied by the parameter estimates. This experiment predicts the prices that would have occurred if the market had experienced the same real-economic-activity, inventory-supply, and supply-of-storage shocks as in fact occurred but had not been hit by any inventory-demand shocks. Specifically, we generate

$$\begin{bmatrix} REA_t^{CF} \\ i_t^{CF} \\ f_t^{CF} \\ cy_t^{CF} \end{bmatrix} = \hat{A}^{-1} \hat{B}_1 \begin{bmatrix} REA_{t-1}^{CF} \\ i_{t-1}^{CF} \\ f_{t-1}^{CF} \\ cy_{t-1}^{CF} \end{bmatrix} + \hat{A}^{-1} \hat{B}_2 \begin{bmatrix} REA_{t-2}^{CF} \\ i_{t-2}^{CF} \\ f_{t-2}^{CF} \\ cy_{t-2}^{CF} \end{bmatrix} + \hat{A}^{-1} \hat{\Gamma} Z_t + \hat{A}^{-1} \begin{bmatrix} \hat{u}_{1t} \\ \hat{u}_{2t} \\ 0 \\ \hat{u}_{4t} \end{bmatrix},$$

where \hat{A} , \hat{B} , and $\hat{\Gamma}$ denote estimates of the structural parameters and \hat{u}_t denotes the structural residuals. If all inventory-demand shocks in 2006-14 emanated from changes to expected future ethanol demand, then the difference between the observed and counterfactual variables provides an estimate of ethanol's effect on prices and inventory through the inventory-demand channel. The absence of inventory-demand shocks would imply that the market did not display the foresight to hold inventory to meet the impending ethanol-demand boom. In that case, we would expect inventories to be drawn down as ethanol use increased, but prices would not rise as much as they would have done if the market were demanding more inventories in anticipation of future ethanol production.

As Figure 4 shows, permanent increases in ethanol production shift the inventory-supply curve to the left and the inventory-demand curve to the right. In our second experiment, we set both the inventory-demand (u_{3t}) and inventory-supply shocks (u_{2t}) to zero for 2006–14. This experiment produces

an estimate of the effect of ethanol production on corn prices under the assumption of no other inventory demand or supply shocks in the 2006–14 period.

The first six years of our counterfactual period produced no extreme Corn Belt weather events, but corn production did fluctuate significantly during this period. Then, in 2012 this region experienced its worst drought for 50 years. In our third counterfactual experiment, we allow for inventory-supply shocks from surprises in the US corn harvest. To measure these surprises, we use the difference between actual production and the World Agricultural Supply and Demand Estimates (WASDE) that are made in May of each year. The May WASDE report is the first one released in each crop year. It is based on a survey of planted acreage and projected trend yield. Production in 2007 and 2009 exceeded expectations by 5 and 8 percent, respectively, whereas production in 2010 and 2011 was 7 and 8 percent, respectively, below expectations. In 2012, production came in 27 percent below expectations. To incorporate these surprises in our counterfactual scenario, we generate

$$\begin{bmatrix} REA_t^{CF} \\ i_t^{CF} \\ f_t^{CF} \\ CY_t^{CF} \end{bmatrix} = \hat{A}^{-1} \hat{B}_1 \begin{bmatrix} REA_{t-1}^{CF} \\ i_{t-1}^{CF} \\ f_{t-1}^{CF} \\ CY_{t-1}^{CF} \end{bmatrix} + \hat{A}^{-1} \hat{B}_2 \begin{bmatrix} REA_{t-2}^{CF} \\ i_{t-2}^{CF} \\ f_{t-2}^{CF} \\ CY_{t-2}^{CF} \end{bmatrix} + \hat{A}^{-1} \hat{\Gamma} Z_t + \hat{A}^{-1} \begin{bmatrix} \hat{u}_{1t} \\ \delta_t \\ 0 \\ \hat{u}_{4t} \end{bmatrix}, \quad (13)$$

where $\delta_t = S_t / 40$ and S_t denotes the production surprise in year t , which we measure in millions of metric tons. We standardize the shock by the average inventory the last 10 years of our estimation sample, which was 40mmt. By using this functional form for δ_t , we allow an approximate linear shift of magnitude S_t in the quantity of inventory supplied.

Estimating the Long-Run Ethanol Effect Directly

We estimate the long-run effect of the mandate directly from the model parameters. We expect the long-run price effect to be less than the short-run effect as a longer run gives the opportunity for land-use change. The long-run effect would be zero if factors of production had infinitely elastic supply, but we

have no reason to expect this to be so. The dominant factor of production for corn is cropland, the expansion of which is limited (Searchinger et al (2008)).

The RFS2 implies a permanent corn demand increase of 1.3 billion bushels, or 33.4 mmt. In the long run, the supply of inventory shifts left by this amount and the demand for inventory shifts right by this amount, as illustrated in Figure 4. The short run impacts differ because the mandate was phased in over time and because inventory demand may have moved by more than the long-run amount in the short run to potentially cover multiple years.

The long-run relationships implied by the VAR can be depicted by setting all shocks to zero, i.e.,

$$AX_t^{LR} = B_1X_{t-1}^{LR} + B_2X_{t-2}^{LR} + \Gamma Z_t \quad (14)$$

This equation describes the long-run real economic activity, inventory supply, inventory demand, and supply of storage curves. We shift the inventory supply curve to the left by 33.4 mmt and the inventory demand curve to the right by the same amount. We then solve for new values of inventory, futures price and convenience yield holding REA constant. See Appendix B for details on our solution method.

These parallel shifts are nonmarginal, and their magnitude is approximately equal to the trend level of inventory in the latter part of our sample. This fact makes our results potentially sensitive to our specification of a log linear functional form. To investigate the robustness of our results to functional form, we estimate the long-run ethanol effect using several linear approximations. Specifically, we estimate the effect on prices of small parallel shifts in the inventory supply and demand curves and extrapolate linearly. Our results are robust to the amount of extrapolation.

Results

Parameter Estimates and Impulse Responses

Table 1 contains the reduced-form parameter estimates²⁰ and estimates of the structural-parameter

²⁰ The reduced-form parameters correspond to $A^{-1}B_1$ in (9) and are estimated by OLS.

matrix A . The first three variables in the system have significant autocorrelation, but all estimates of the largest root are far below the threshold for a unit root, which is consistent with the apparent mean-reverting behavior of these variables in Figure 5. The futures and inventory variables display statistically significant trends: real futures prices trend down and inventory trends up.

If we fix α_{23} based on the assumption that the difference between the inventory supply and demand elasticities equals $\alpha_{23} = 4.4 - 1 / (\alpha_{32} + \alpha_{42}(1 + \alpha_{34}))$ (as suggested by the discussion above and in Appendix A), then the estimated short-run elasticity of inventory supply equals 1.79. Under this same assumption, the estimated short-run elasticity of inventory demand equals $-1/0.29 = -3.45$. Thus, the short-run inventory-demand elasticity is substantially greater than the short-run inventory-supply elasticity; this proposition is consistent with the notion that next year's net demand is more elastic than this year's net demand. Constraining our parameters only to lie in the identified set produces a range from 3.30 to 0.25 for α_{23} . As we show in subsequent sections, this wide range has little effect on our price-impact results, but it has larger effects on our counterfactual predictions of inventory. The range for the elasticity of inventory demand is narrower; it spans from $-1/0.30 = -3.33$ to $-1/0.25 = -4.00$. The supply-of-storage parameters are largely unaffected by variation within the identified set.

Figure 6 shows impulse-response functions for one-time one standard deviation structural shocks. The shaded box in the figure signifies the identified set, and the vertical lines above and below indicate confidence intervals with greater than 90 percent coverage.²¹ A real-economic-activity shock raises futures prices significantly for several years. In contrast, it lowers inventory and convenience yield. Lower

²¹ We generate confidence intervals using a recursive-design wild bootstrap with 10,000 replications (Goncalves and Kilian 2004). For each bootstrap draw, we estimate the identified parameter set and the range of impulse responses defined by that set. We keep only draws that satisfy our identification conditions $\alpha_{23} > 0.25$ and $\alpha_{32} > 0$. This exercise produces 10,000 bootstrap draws for both the estimated lower and upper bounds of the identified set. We set the lower limit of the confidence interval equal to the 0.05 quantile across draws of the estimated lower bound and the upper limit as the 0.95 quantile across draws of the estimated upper bound. This interval covers the identified set with probability 0.90, because 90 percent of the estimated parameter sets lie entirely inside it. Imbens and Manski (2004) show that the confidence interval for the identified set is wider than the confidence interval for the true parameter within the set. Heuristically, this result follows from the fact that the true parameter (a single point within the identified set) necessarily covers a narrower range than the identified set (assuming that the set has positive measure). Thus, a 90 percent confidence interval for the whole set covers the true parameter with probability greater than 0.90.

convenience yield signifies an increased demand for inventory, so the signs of these responses are consistent with the supposition that these demand shocks elevate both current and future demand.

[FIGURE 6 HERE]

Inventory-supply shocks raise inventory levels and lower the futures price and convenience yield (as would be expected from Figures 3 and 4). Inventory-demand shocks raise inventory levels over several years, and they also raise futures prices accordingly. The convenience-yield response to inventory demand is negative, as expected. Consistent with Figures 3 and 4, a positive supply of storage shock (increasing convenience yield) implies a shift downward in the supply-of-storage curve and an increase in inventories. Overall, the impulse responses are consistent with our theory.

Both the BIC and the small-sample corrected AIC of Hurvich and Tsai (1989) indicate that a model with a single lag is the most favored model. Thus, although our conceptual model suggests that a second lag may be relevant, including the second lag reduces precision and does not improve fit significantly. In the remainder of the paper, we focus on estimates from the one-lag model, although we also report the analogous two-lag results for comparison.

Historical Decomposition and Counterfactual Analysis

Figure 7 shows a historical decomposition of the four variables for the case with $\alpha_{23} = 4.4 - 1 / (\alpha_{32} + \alpha_{42}(1 + \alpha_{34}))$. The decomposition reveals the cumulative contribution of each of the four shocks to the observed variable. It shows that most of the variation in inventory emanates from inventory-supply shocks, as expected. However, substantial increases in inventory demand occurred in 2006–14. Futures prices are affected strongly by real economic activity, which produced high prices in the 1970s and again in the most recent decade. However, inventory demand contributed significantly to price increases in 2006–07 and again in 2010–12. Inventory-supply shocks affected prices in several episodes, especially 2010–14. In 2010 and 2011, respectively, actual production was 7 and 8 percent below expectations due to below-average weather during the growing season. The 2012 drought manifests as a

negative inventory-supply shock, which raises prices and lowers inventory.

Convenience yield is driven mostly by inventory supply, which would be expected from a relatively constant supply-of-storage curve that the demand curve slides up and down as inventory levels change. High inventory demand dampens convenience yield after 2006, as implied by our theory.

[FIGURE 7 HERE]

To further explore the effect of the various shocks and draw implications for the effect of ethanol production on corn prices, we conduct the counterfactual analysis that we introduced earlier. Figure 8 shows these results for $\alpha_{23} = 4.4 - 1 / (\alpha_{32} + \alpha_{42}(1 + \alpha_{34}))$, and Table 2 shows the ranges implied by the identified set. If there had been no inventory demand shocks in 2006–14, inventory would have dropped precipitously, as shown by the green line in Figure 8. The first row of Table 2 shows that inventory levels were 68 percent higher in log terms, on average, than they would have been in the absence of realized inventory-demand shocks. In other words, the market responded to the growth in ethanol production by holding more corn in inventory than it otherwise would have. This inventory demand caused futures prices to increase by 12 percent, on average, over the nine-year period, and it lowered the convenience yield by 2 percent, on average. This result supports the hypotheses of Figure 4: an increase in inventory demand raises the demand for storage and therefore increases the price of storage, i.e., an increase in inventory demand affects cash prices less than it does futures prices. This result reinforces the findings of Garcia, Irwin and Smith (2015), who show significant decreases in convenience yield since 2006.

[FIGURE 8 HERE]

The dominant net-supply shock during 2006–14 was the growth of the ethanol industry. The red line in Figure 8 shows the counterfactual case of no inventory supply or demand shocks between 2006 and 2014. The green line indicates lower inventory and higher prices than the red line because it includes the actual current-use demand for corn. In other words, the growth in ethanol use caused inventory to be run down and prices to rise. The blue line in Figure 8 shows counterfactual paths that assume no

inventory-demand shocks and limit net-supply shocks to those that derived from US production surprises. Incorporating production shocks does change the path of prices and inventory, but prior to 2012 it has little effect on the average difference between the actual and counterfactual values. Table 2 shows that, based on this counterfactual, we estimate that ethanol production raised corn prices by 31 percent, on average, in 2006-2014. The 90 percent confidence interval for this estimate is [0.13, 0.54]. If we use the two-lag VAR, then Table 2 shows a larger estimated effect of 41 percent.

The counterfactual implications for prices depend little on the fact that our model is set- rather than point-identified. Based on the identified set, we estimate the average price effect to be between 28 and 30 percent for futures prices and between 28 and 32 percent for cash prices. The associated conservative 90 percent confidence intervals are [0.14, 0.53] for futures and [0.13, 0.54] for cash prices. Inventory, however, is much more sensitive to the location of our parameters in the identified set. Our estimated inventory effect ranges from 10 to 34 percent across the identified set; this wide range is generated by the range of α_{23} .

To check the robustness of these estimates, we applied our counterfactual analysis to the 1999-2005 crop years. This is a kind of placebo test. Using the counterfactual in (13), which allows for production shocks, we estimate an average counterfactual cash price 8 percent lower than the observed price. This estimate has a 90 percent confidence interval of [-0.20, 0.04] and so it is not statistically significant. Moreover, the confidence interval includes zero for all but one of the 7 years.

Our analysis also reveals the dynamic responses of prices and inventory to the ethanol boom. Corn prices jumped in 2006–07 and increased further in 2007–08, mainly because demand for inventory was high. In late 2008, the financial crisis and the corresponding crash in oil prices and gasoline demand caused a drop in demand for corn from ethanol producers. The counterfactual analysis shows that in the following two years, the effect of ethanol demand on corn prices was much more moderate. Then in 2010 and 2011, along with the worse-than-expected crops, increasing ethanol demand caused corn prices to

rise again significantly above the counterfactual values. In these two years, we estimate that corn prices were 53 and 56 percent greater than they would have been without the ethanol-induced shocks.

In the absence of the ethanol shocks observed since 2006, the 2012 drought would have caused inventory to decline by significantly more than it did. This difference comes from inventory demand; in the counterfactual world without ethanol, the market would choose to run down inventory and replenish it the following year. In the current market environment, which has a large component of permanent inelastic demand for corn from ethanol producers, the willingness to hold inventory is higher. The poor 2010 and 2011 harvests mean that inventories would have been relatively low entering 2012 even without ethanol production. Thus, the drought would still have had a substantial price effect; our counterfactual 2012 cash price is 32 percent below the actual price.

Estimated Long-Run Effect

Figure 9 shows the estimated long-run effect on cash prices using two different lag lengths and two different methods, which vary by the extent of linear extrapolation. As described earlier, we conduct parallel shifts of $\pi \cdot 33.4$ mmt in the inventory supply and demand curves and multiply the result by $1/\pi$ to approximate the effect of 33.4 mmt shifts. For $\pi=0.5$ and one lag in the VAR, the estimated effect is 31 percent, with the identified set covering the range [0.29, 0.32]. When we extrapolate from 0.334 mmt parallel shifts ($\pi=0.01$), we obtain a cash price effect of 0.35 and when we use the full parallel shift ($\pi=1$), we obtain an estimate of 0.28 (not shown). The estimates from the two-lag VAR are significantly less precise than the one-lag model and are also slightly more sensitive to the linear extrapolation. Overall, the estimates are robust to the linear extrapolation, especially for the for the one-lag model.

The confidence interval on the cash price effect is robust to various levels of linear extrapolation. For confidence intervals with greater than 90 percent coverage (see footnote 21), we obtain ranges of [0.06, 0.97] for $\pi=0.01$ and [0.05, 0.95] for $\pi=0.5$. For parallel shifts of the full 33.4 mmt the confidence intervals become unreasonably wide. This confidence interval is sensitive to functional form because 33.4

mmt is approximately equal to trend inventory, which means that a leftward shift of this magnitude in inventory supply can generate an equilibrium a very steep part of the inventory demand curve. Thus, in some bootstrap draws we obtain a large estimated price effect because we take the log of a number close to zero. Because the extrapolated estimates are naturally bounded away from this region, and because the point estimates from the favored one-lag model are robust to $\pi \in \{0.01, 0.5, 1\}$, we report the $\pi=0.5$ confidence interval as our preferred estimate. Our long-run estimate is that a 1.3 billion bushel increase in corn demand raised prices by 31 percent with a 90 percent confidence interval of [0.05, 0.95].

[FIGURE 9 HERE]

Conclusion

In this paper, we have measured the relationship between US ethanol expansion and corn prices in the period following the 2007 expansion of ethanol mandates. We use structural vector autoregression to model corn-inventory dynamics and use a counterfactual experiment to estimate what prices would have been in the absence of ethanol-induced shocks to inventory supply and demand. This approach enables us to separately identify persistent and transitory shocks to corn prices.

We isolate two main results that have not been previously quantified in the literature. First, the corn market anticipated the forthcoming ethanol boom and increased inventory demand accordingly. As a result, prices increased in 2006 in advance of the ethanol-production jump in 2007 and 2008. Second, we estimate that the long-run corn price would be about 31 percent lower if the ethanol mandate had not been expanded in 2007. This estimate is scalable; to estimate the effect of increasing corn demand permanently by any multiple of 1.3 billion bushels, a reader could multiply our estimate by that multiple.

The ethanol mandate is controversial and continues to face economic and political challenges. During the 2012 drought, several state governors and other groups including livestock producers requested a temporary waiver of the RFS mandate. The EPA has the authority to temporarily waive the mandate if it is causing “severe economic or environmental harm to a region or the nation”. However, the

temporary-waiver request was denied. In 2013, the mandate reached the so-called blend-wall constraint, namely that the mandate requires greater ethanol content than the 10 percent that has been approved by EPA for blending with conventional fuel. The EPA was unable to resolve this dilemma in a timely fashion. It did not release 2014 compliance requirements until May 2015, when it also announced that it would not fully enforce the mandate for 2015 and 2016. However, it stated that it intended to move back towards the RFS2 mandate in future years. This period of uncertainty has significantly affected fuel markets (Lade, Lin, and Smith, 2015). If the mandate is to be met after 2016, either alternative fuel blends that use 15 and 85 percent ethanol will have to penetrate the market or biodiesel production from soybeans will need to increase substantially. Expanding biodiesel production would have potentially large effects on another food commodity, so our methods and results are of continuing policy relevance.

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Table 1: VAR Parameter Estimates

Equation	<i>REA</i>	<i>Inventory</i>	<i>Futures</i>	<i>Conv. Yield</i>
<i>Reduced Form Estimates: A⁻¹B₁</i>				
<i>REA</i> _{t-1}	0.79* (0.18)	-0.60 (0.52)	0.45* (0.19)	0.02 (0.08)
<i>Inventory</i> _{t-1}	-0.11 (0.07)	0.33* (0.32)	-0.05 (0.09)	0.05 (0.06)
<i>Futures</i> _{t-1}	-0.35 (0.19)	0.01 (0.76)	0.33 (0.20)	0.08 (0.12)
<i>Conv. Yield</i> _{t-1}	0.06 (0.44)	-0.38 (1.41)	0.09 (0.54)	0.40 (0.29)
<i>REA</i> _{t-2}	-0.37* (0.19)	0.34 (0.44)	-0.33* (0.21)	-0.09 (0.07)
<i>Inventory</i> _{t-2}	-0.01 (0.10)	0.43 (0.22)	0.02 (0.08)	-0.05 (0.04)
<i>Futures</i> _{t-2}	0.12 (0.23)	0.89 (0.65)	0.40 (0.21)	-0.12 (0.11)
<i>Conv. Yield</i> _{t-2}	-0.99 (0.58)	2.31* (0.86)	-0.30 (0.46)	-0.15 (0.17)
Constant	1.69 (0.93)	0.59 (2.33)	0.83 (0.83)	0.17 (0.37)
Trend	-0.005 (0.004)	0.028* (0.010)	-0.009* (0.003)	-0.001 (0.002)
<i>A Matrix: imposing $\alpha_{23} = 4.4 - 1 / (\alpha_{32} + \alpha_{42}(1 + \alpha_{34}))$</i>				
<i>REA</i>	1	0	0	0
<i>Inventory Supply</i>	0.71	1	-2.15	-2.15
<i>Inventory Demand</i>	-0.37	0.29	1	0.54
<i>Supply of Storage</i>	0.15	0.10	0	1
<i>A Matrix: Identified Set</i>				
<i>REA</i>	1	0	0	0
<i>Inventory Supply</i>	[0.11, 1.07]	1	[-3.30,-0.25]	[-3.30,-0.25]
<i>Inventory Demand</i>	[-0.37,-0.37]	[0.25, 0.30]	1	[0.52, 0.57]
<i>Supply of Storage</i>	[0.15, 0.15]	[0.09, 0.10]	0	1
<i>A Matrix: >90% Confidence Interval</i>				
<i>REA</i>	1	0	0	0
<i>Inventory Supply</i>	[-0.40, 2.19]	1	[-4.37, -0.25]	[-4.37, -0.25]
<i>Inventory Demand</i>	[-0.48,-0.23]	[0.19, 0.35]	1	[0.14, 0.97]
<i>Supply of Storage</i>	[0.09, 0.21]	[0.07, 0.13]	0	1

Notes: Sample range: 1961–2005; standard errors in parentheses; * indicates significance at 5%; model selection criteria values are AIC_c=-669.92 and BIC=-639.66; for the one-lag model, we obtain AIC_c = -687.70 and BIC = -667.38, so the one-lag model is favored. We obtain the confidence intervals using a recursive-design wild bootstrap (see footnote 21).

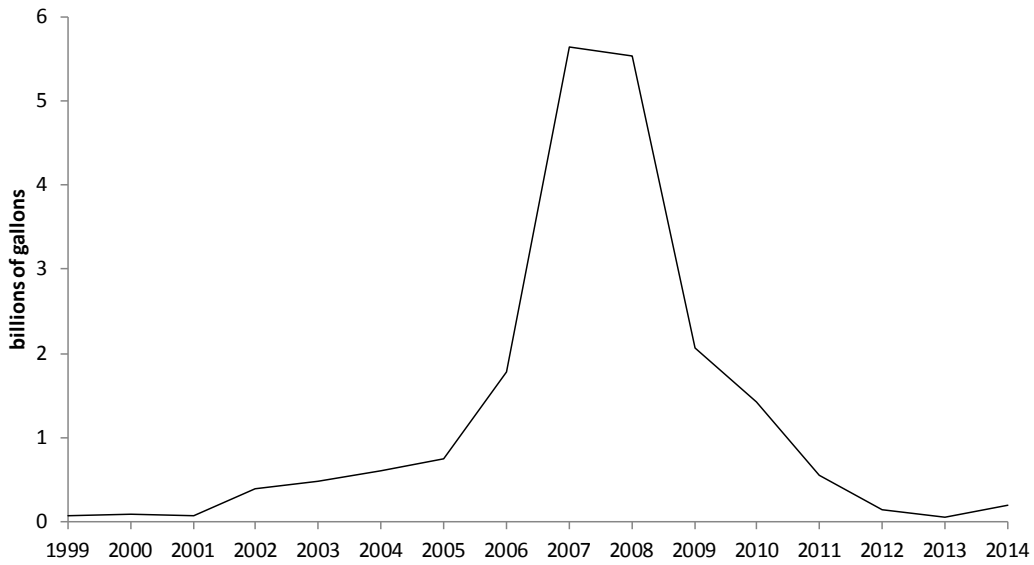
Table 2: Log Difference between Actual and Counterfactual

	2006-07	2007-08	2008-09	2009-10	2010-11	2011-12	2012-13	2013-14	2014-15	Average
<i>No Inventory-Demand Shocks</i>										
Inventory	0.31	0.62	0.44	0.36	0.89	0.92	1.01	0.73	0.81	0.68
Fut. Price	0.18	0.29	0.06	-0.05	0.27	0.22	0.17	-0.05	0.01	0.12
Conv. Yield	-0.03	-0.05	0.00	0.01	-0.05	-0.02	-0.02	0.02	0.00	-0.02
Cash Price	0.14	0.25	0.06	-0.03	0.22	0.19	0.15	-0.03	0.01	0.11
<i>No Inventory-Demand Shocks; Inventory-Supply Shocks from Production Surprises Only</i>										
Inventory	-0.08	0.16	0.42	-0.02	0.04	-0.08	0.67	0.20	0.15	0.16
Fut. Price	0.26	0.42	0.11	0.06	0.50	0.51	0.35	0.15	0.25	0.29
Conv. Yield	0.01	-0.01	-0.02	0.05	0.02	0.05	-0.03	0.05	0.04	0.02
Cash Price	0.27	0.41	0.09	0.11	0.53	0.56	0.32	0.21	0.29	0.31
<i>Identified Set; No Inventory-Demand Shocks; Inventory-Supply Shocks from Production Surprises Only</i>										
Inventory	-0.08,-0.08	0.00,0.21	0.33,0.45	-0.3,0.08	0.01,0.12	-0.18,0.20	0.29,1.74	0.04,0.73	0.11,0.36	0.10,0.34
Fut. Price	0.26,0.27	0.41,0.44	0.10,0.12	0.05,0.10	0.50,0.51	0.49,0.53	0.25,0.41	0.10,0.19	0.23,0.26	0.28,0.30
Conv. Yield	0.01,0.01	-0.02,0.00	-0.02,-0.01	0.04,0.06	0.00,0.03	0.01,0.06	-0.13,0.01	0.05,0.06	0.04,0.06	0.01,0.02
Cash Price	0.27,0.27	0.39,0.44	0.08,0.11	0.08,0.16	0.50,0.54	0.50,0.58	0.13,0.42	0.15,0.24	0.29,0.30	0.28,0.32
<i>>90% Confidence Interval on Identified Set; No Inventory-Demand Shocks; Inventory-Supply Shocks from Production Surprises Only</i>										
Inventory	-0.30,0.32	-0.37,0.66	-0.16,0.91	-0.78,0.41	-0.50,0.56	-0.65,0.57	-0.17,2.13	-0.48,1.17	-0.40,0.90	-0.29,0.66
Fut. Price	0.16,0.33	0.25,0.58	-0.10,0.36	-0.15,0.36	0.29,0.80	0.31,0.81	0.11,0.69	-0.09,0.47	0.04,0.56	0.14,0.53
Conv. Yield	-0.05,0.04	-0.07,0.05	-0.09,0.04	-0.03,0.11	-0.08,0.08	-0.04,0.10	-0.18,0.05	-0.01,0.15	-0.05,0.15	-0.05,0.06
Cash Price	0.14,0.35	0.22,0.60	-0.13,0.34	-0.11,0.42	0.28,0.83	0.32,0.85	-0.01,0.68	-0.01,0.52	0.10,0.63	0.13,0.54
<i>No Inventory-Demand Shocks; Inventory-Supply Shocks from Production Surprises Only; 2 lags in VAR</i>										
Inventory	-0.33	-0.01	0.32	-0.21	0.12	0.05	0.82	0.59	0.35	0.19
Fut. Price	0.38	0.51	0.19	0.22	0.61	0.65	0.41	0.16	0.18	0.37
Conv. Yield	0.03	0.02	0.01	0.07	0.03	0.08	0.00	0.06	0.07	0.04
Cash Price	0.42	0.52	0.20	0.29	0.64	0.73	0.41	0.22	0.25	0.41
<i>Production Surprises (MMT)</i>										
Actual Prod.	267.50	331.18	305.91	331.92	315.62	312.79	273.19	351.27	361.09	
May Forecast	267.98	316.50	307.99	307.10	339.61	343.04	375.68	358.88	353.68	
Surprise	-0.48	14.68	0.85	25.45	-23.45	-29.12	-102.49	-7.61	7.41	

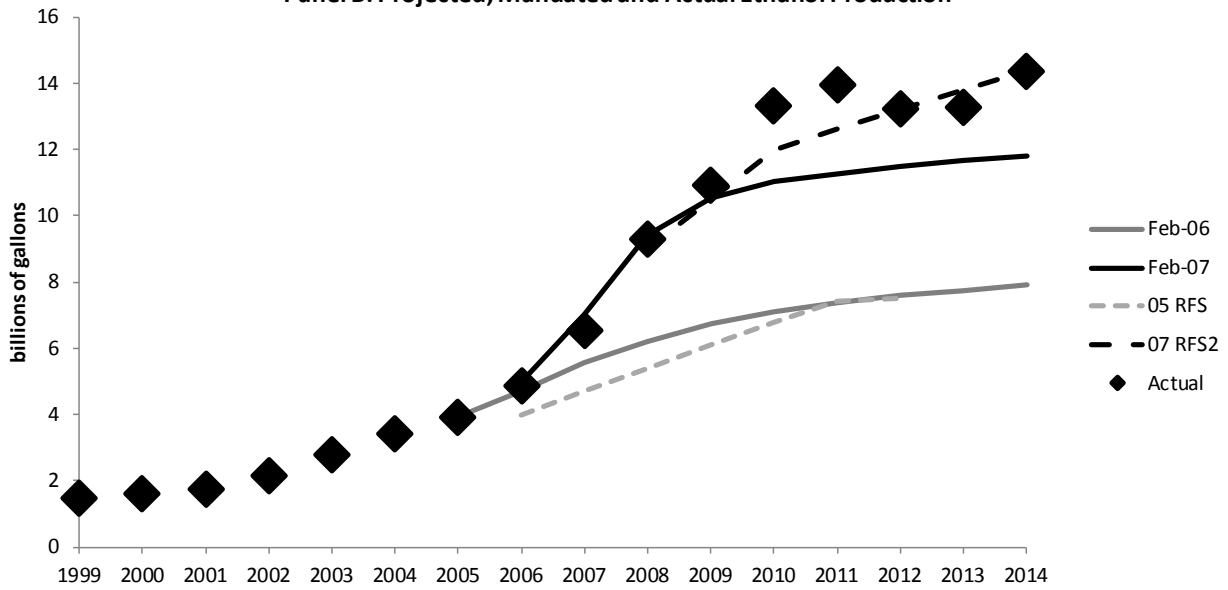
Notes: Here we define the log cash price as f_{t+cy_t} . Table entries are results from the counterfactual experiment described in the text. One-lag model unless otherwise stated.

Figure 1: Growth of the U.S. Ethanol Industry

Panel A: Capacity Under Construction or Expansion (beginning of year)

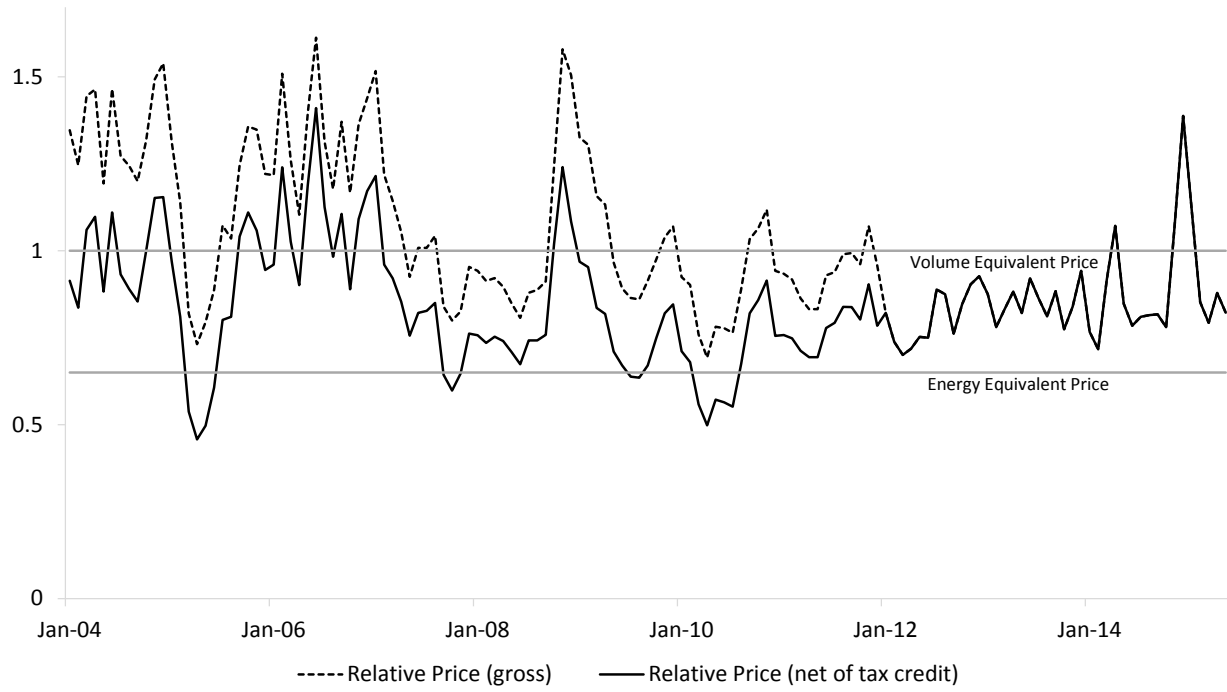


Panel B: Projected, Mandated and Actual Ethanol Production



Notes: The solid lines in Panel B, show USDA projections, the dashed lines show the mandated quantities under the RFS, and the diamonds show actual ethanol production. Data sources are USDA baseline projections, Renewable Fuels Association Annual Industry Outlook, and the Energy Information Administration of the US Department of Energy.

Figure 2: Relative Price of Wholesale Ethanol to Gasoline



Notes: Average rack prices, FOB, Omaha, Nebraska. Downloaded from the website of Nebraska Energy Office (<http://www.neo.ne.gov/statshtml/66.htm>)

Figure 3: Two-Period Commodity-Market Equilibrium

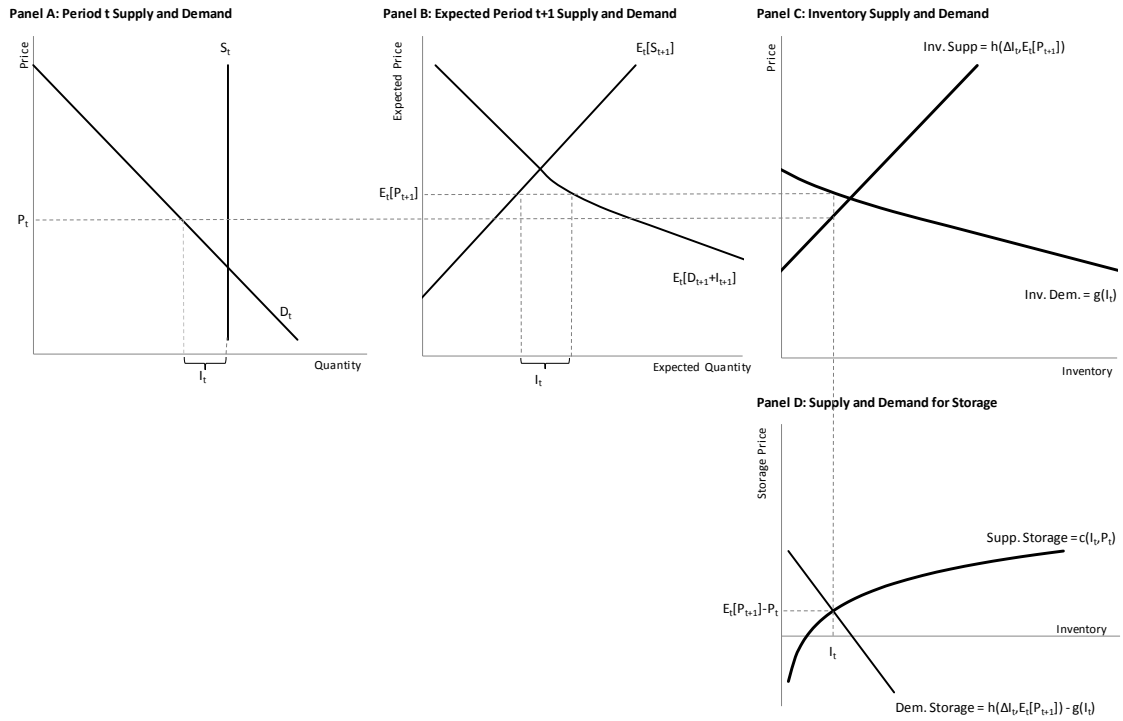


Figure 4: A Permanent Increase in Demand

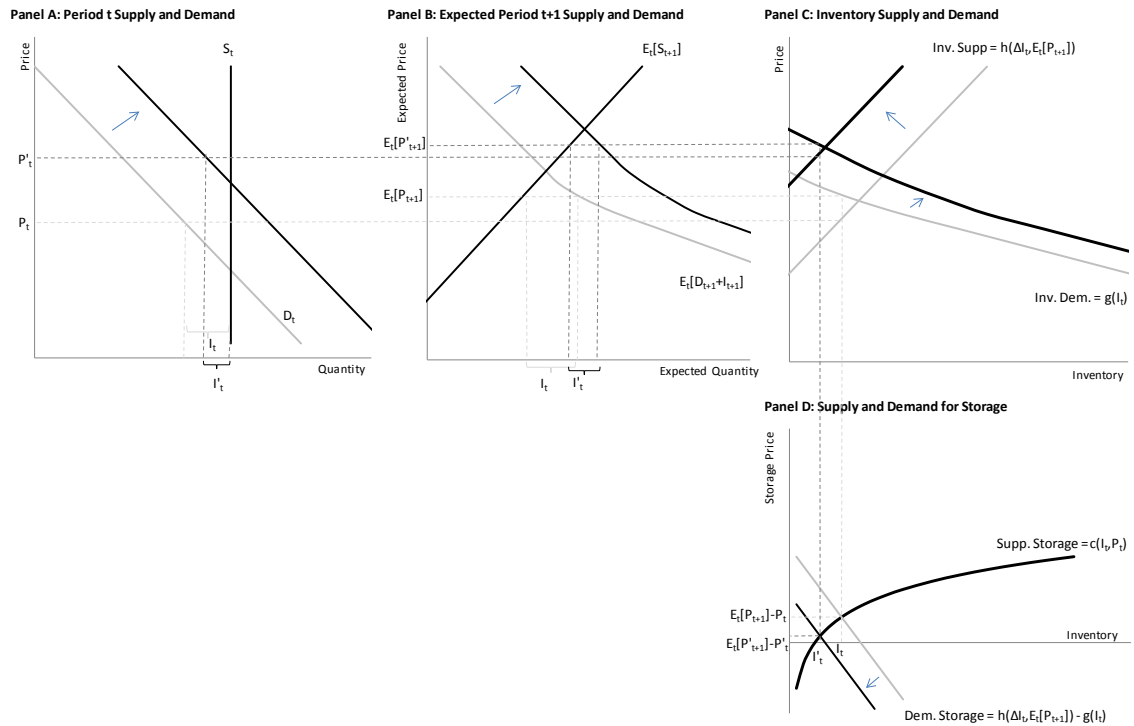
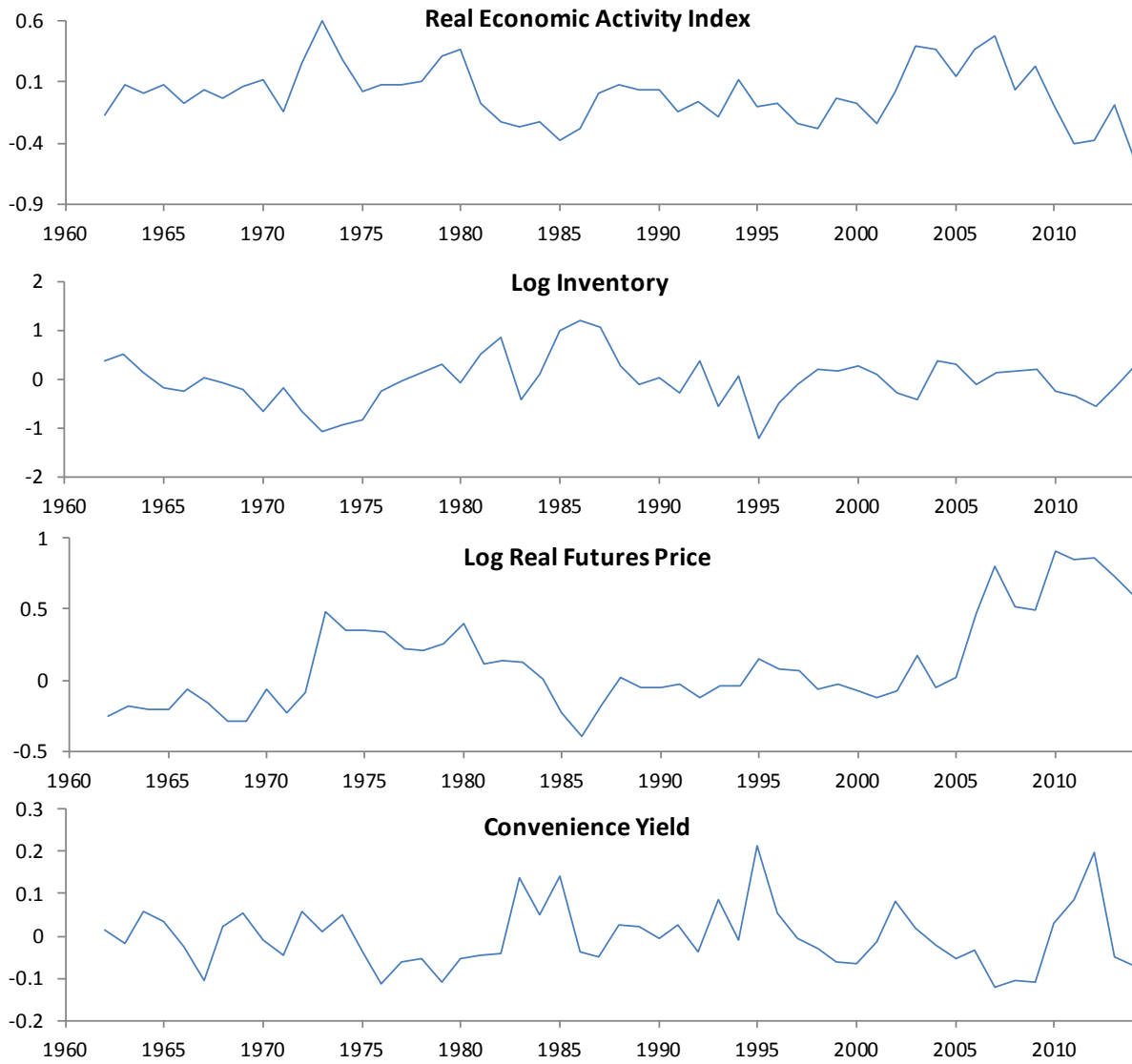
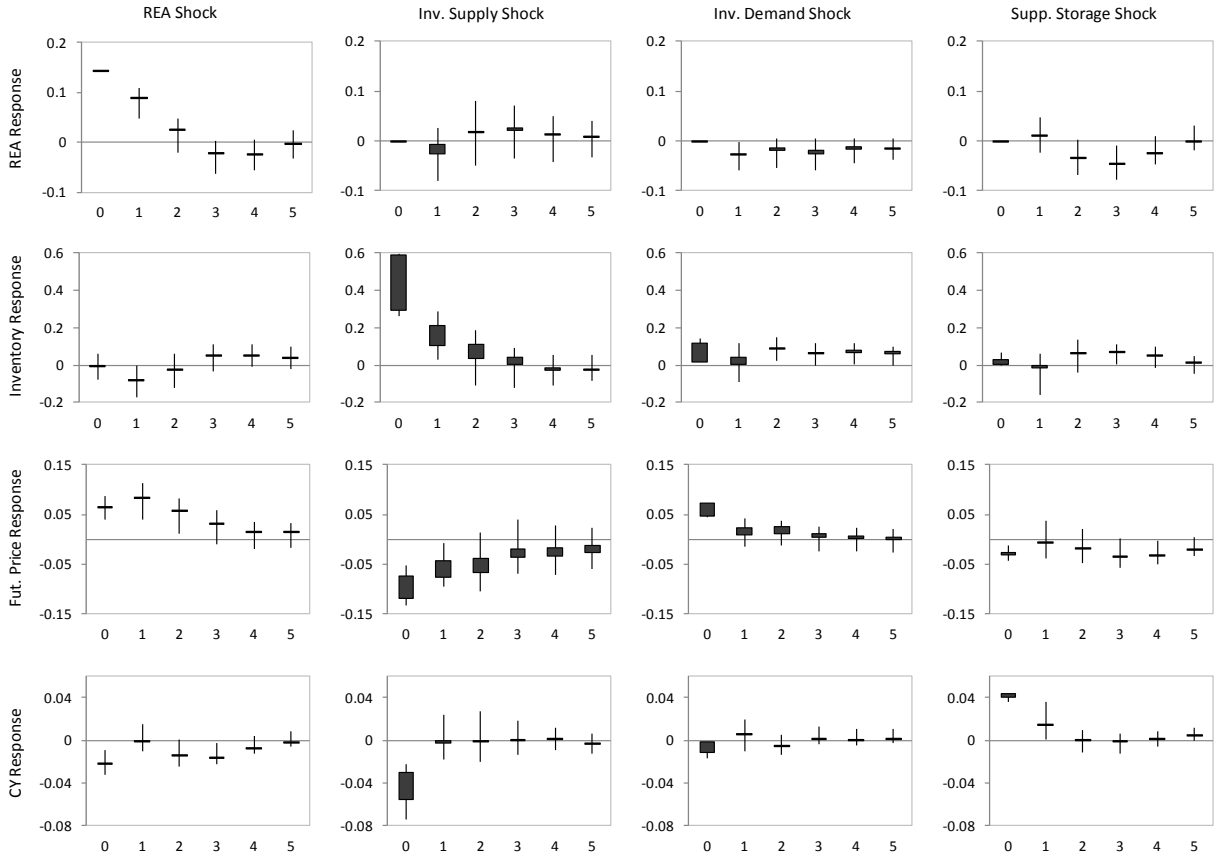


Figure 5: De-Trended Data for Key Variables



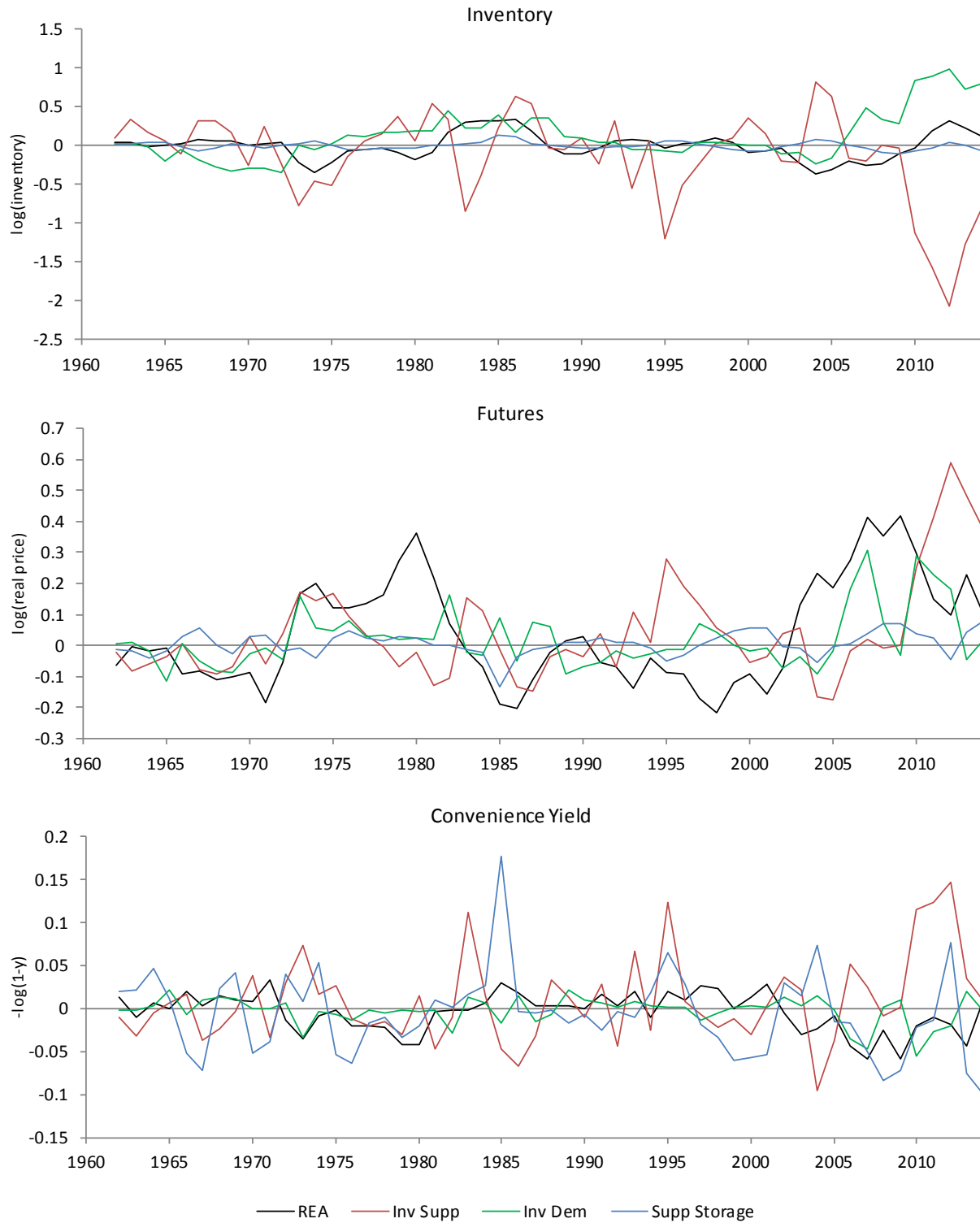
Notes: For clarity, this figure shows linearly de-trended series, where we estimate the trend in the pre-ethanol period (1962-2005). For the VAR estimation, we use the actual series and include a constant and linear trend in each equation of the model.

Figure 6: Impulse Responses



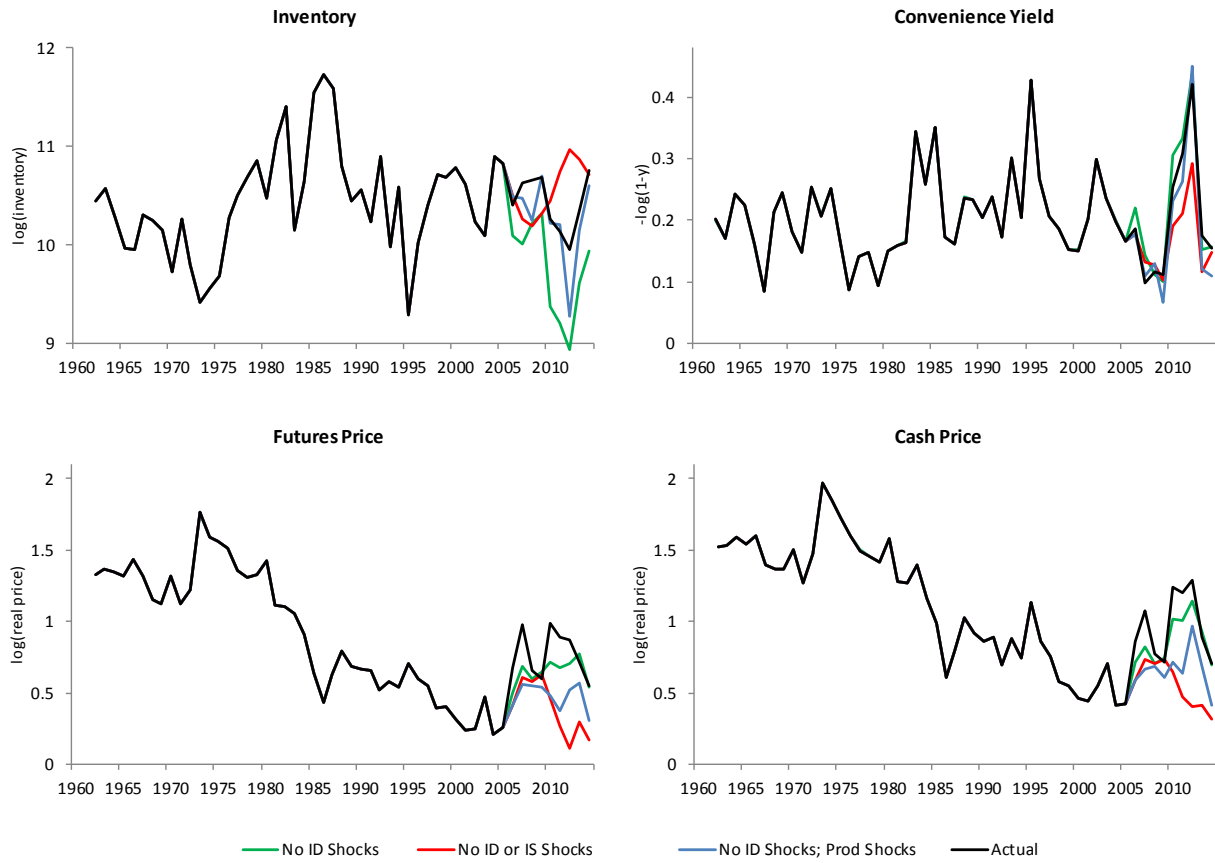
Notes: Responses to one-time one-standard-deviation shocks for the two-lag model. The dark boxes indicate the range of impulse responses in the identified set. The vertical bars indicate estimated confidence intervals that cover the true parameter with probability greater than 0.90. We obtain these intervals using a recursive-design wild bootstrap (see footnote 22).

Figure 7: Historical Decomposition



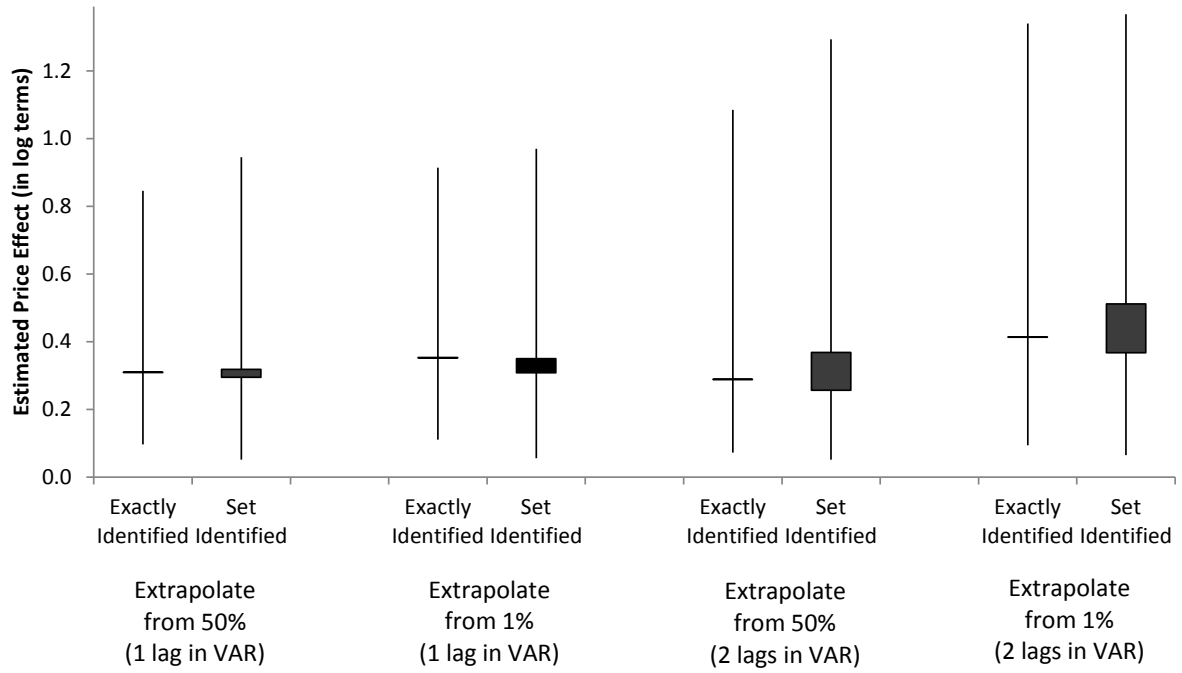
Notes: Figures show contributions of each shock to the relevant series for the one-lag model. The sum of the contributions equals the observed data (net of trend).

Figure 8: Counterfactual Analysis



Notes: Here we define the log cash price as $f_t + cy_t$. The various lines are generated from the counterfactual experiment described in the text using the one-lag model.

Figure 9: Long-Run Cash-Price Effect of Ethanol Mandate



Notes: We conduct parallel shifts of the estimated inventory supply and demand by the amounts of $\pi \cdot 33.4$ for $\pi=0.01$ and 0.5 . We multiply the resulting price change by $1/\pi$ to estimate the effect of 33.4mmt shifts. The dark boxes indicate the range of estimated price effects in the identified set. The vertical bars indicate estimated confidence intervals that cover the true parameter with probability greater than 0.90. We obtain these intervals using a recursive-design wild bootstrap (see footnote 21). We report results for VAR specifications with one and two lags.

SUPPLEMENTAL APPENDIX

Appendix A: Conditions for Exact Identification

Here, we derive a restriction on the parameters that exactly identifies our model. The supply of inventory (I^s) equals quantity supplied (Q^s) minus quantity used (Q^u). Thus, the short-run elasticity of inventory supply with respect to the cash price is

$$\theta^s \equiv \frac{dI^s}{dP} \frac{P}{I} = \frac{dQ^s}{dP} \frac{P}{I} - \frac{dQ^u}{dP} \frac{P}{I} = \left(\eta^s - \eta^u \frac{Q^u}{Q^s} \right) \frac{Q^s}{I}, \quad (\text{A1})$$

where we define the production (supply) and current-use (demand) elasticities, respectively, as

$\eta^s \equiv \frac{dQ^s}{dP} \frac{P}{Q}$ and $\eta^u \equiv \frac{dQ^u}{dP} \frac{P}{Q^u}$. Note also that total demand equals demand for current use plus

inventory demand (i.e., $Q^d = Q^u + I^d$). Thus, elasticity of total demand is

$$\eta^d \equiv \frac{dQ^d}{dP} \frac{P}{Q^d} = \frac{dQ^u}{dP} \frac{P}{Q^d} + \frac{dI^d}{dP} \frac{P}{Q^d} = \eta^u \frac{Q^u}{Q^d} + \theta^d \frac{I}{Q^d}, \quad (\text{A2})$$

where $\theta^d \equiv \frac{dI^d}{dP} \frac{P}{I}$ denotes the elasticity of inventory demand with respect to the spot price P . Using the

equilibrium condition $Q = Q^s = Q^d$, these two equations imply

$$\theta^s = \left(\eta^s - \eta^d + \theta^d \frac{I}{Q} \right) \frac{Q}{I}, \quad (\text{A3})$$

which can be rewritten as

$$\theta^s - \theta^d = \left(\eta^s - \eta^d \right) \frac{Q}{I}. \quad (\text{A3a})$$

That is, the difference between the elasticities of supply and demand for inventory is proportional to the difference between the elasticities of total supply and demand.

Using estimates from the literature and some introspection, we could exactly identify our model by choosing numerical values for the terms on the right-hand-side of (A3a). For the total demand elasticity, η^d , we could use the estimates of Adjemian and Smith (2012). They use the price response to USDA crop forecasts during the period from 1980 to 2011 to estimate that the demand flexibility (inverse elasticity)

for corn is -1.27, which implies $\eta^d = -1/1.27 = -0.79$. In our setting, the short-run production elasticity, η^s , is close to zero. Since planted acreage and inventory carryover are essentially determined by March of each year, it is nearly impossible for producers to respond to price shocks that occur after March. During our sample period, average year-ending inventories as a proportion of use equal 0.18. Thus, at average inventory levels, we expect from (A3a) that $\theta^s - \theta^d \approx (0 - -0.79) / 0.18 = 4.4$.

To translate θ^s into our econometric specification, we define the spot price of interest as $\log(P) \equiv f + cy$. Then, equations (A1)–(A3) imply $\theta^s \equiv \alpha_{23}$. Similarly, combining the inventory-demand and supply-of-storage equations (9b and 9c) implies

$$\frac{1}{\theta^d} \equiv \frac{d(f + cy)}{di} = -\alpha_{32}(1 + \alpha_{43}) - \alpha_{42}, \quad (\text{A4})$$

which implies

$$\theta^d = -1 / (\alpha_{32}(1 + \alpha_{43}) + \alpha_{42}). \quad (\text{A5})$$

Thus, we translate our expectation that $\theta^s - \theta^d \approx 4.4$ into our econometric model parameters as $\alpha_{23} + 1 / (\alpha_{32}(1 + \alpha_{43}) + \alpha_{42}) \approx 4.4$

To fully identify our model, we could impose the restriction $\alpha_{23} + 1 / (\alpha_{32}(1 + \alpha_{43}) + \alpha_{42}) = 4.4$.

Appendix B: Solving for Effect of Parallel Shifts in the Inventory Supply and Demand Curves

The long-run relationships implied by the VAR model can be depicted by setting all shocks to zero, i.e.,

$$AX_t^{LR} = B_1 X_{t-1}^{LR} + B_2 X_{t-2}^{LR} + \Gamma Z_t \quad (\text{A6})$$

where

$$X_t^{LR} = \begin{bmatrix} REA_t^{LR} \\ \log(I_t^{LR}) \\ f_t^{LR} \\ cy_t^{LR} \end{bmatrix} \quad \text{and} \quad Z_t' = [1 \quad t]$$

We write

$$A = \begin{bmatrix} A'_1 \\ A'_2 \\ A'_3 \\ A'_4 \end{bmatrix}, \quad B_1 = \begin{bmatrix} B'_{11} \\ B'_{12} \\ B'_{13} \\ B'_{14} \end{bmatrix}, \quad \text{and } B_2 = \begin{bmatrix} B'_{21} \\ B'_{22} \\ B'_{23} \\ B'_{24} \end{bmatrix}.$$

The second equation is the inventory-supply equation, which we shift to the left by amount δ , and the third equation is the inventory-demand equation, which we shift to the right by amount δ . We hold REA fixed at the long-run values in (A6) and solve for the other three variables in 2011 and 2012. We also impose that these shifts change the level of the variables but not the long-run trends.

Thus, we solve the following three equations for $f_t^*, l_t^*, cy_t^*, f_{t-1}^*, l_{t-1}^*, cy_{t-1}^*, f_{t-2}^*, l_{t-2}^*$, and cy_{t-2}^* in $t=2014$

$$\begin{aligned} A'_2 \begin{bmatrix} REA_t^{LR} \\ \log(l_t^* + \delta) \\ f_t^* \\ cy_t^* \end{bmatrix} &= B'_{12} \begin{bmatrix} REA_{t-1}^{LR} \\ \log(l_{t-1}^* + \delta) \\ f_{t-1}^* \\ cy_{t-1}^* \end{bmatrix} + B'_{22} \begin{bmatrix} REA_{t-2}^{LR} \\ \log(l_{t-2}^* + \delta) \\ f_{t-2}^* \\ cy_{t-2}^* \end{bmatrix} + \Gamma'_2 Z_t \\ A'_3 \begin{bmatrix} REA_t^{LR} \\ \log(l_t^* - \delta) \\ f_t^* \\ cy_t^* \end{bmatrix} &= B'_{13} \begin{bmatrix} REA_{t-1}^{LR} \\ \log(l_{t-1}^* - \delta) \\ f_{t-1}^* \\ cy_{t-1}^* \end{bmatrix} + B'_{23} \begin{bmatrix} REA_{t-2}^{LR} \\ \log(l_{t-2}^* - \delta) \\ f_{t-2}^* \\ cy_{t-2}^* \end{bmatrix} + \Gamma'_3 Z_t \\ A'_4 \begin{bmatrix} REA_t^{LR} \\ \log(l_t^*) \\ f_t^* \\ cy_t^* \end{bmatrix} &= B'_{14} \begin{bmatrix} REA_{t-1}^{LR} \\ \log(l_{t-1}^*) \\ f_{t-1}^* \\ cy_{t-1}^* \end{bmatrix} + B'_{24} \begin{bmatrix} REA_{t-2}^{LR} \\ \log(l_{t-2}^*) \\ f_{t-2}^* \\ cy_{t-2}^* \end{bmatrix} + \Gamma'_4 Z_t \end{aligned}$$

subject to $x_t^* - x_{t-1}^* = x_t^{LR} - x_{t-1}^{LR} = x_{t-1}^{LR} - x_{t-2}^{LR}$, where

$$x_t^* = \begin{bmatrix} REA_t^{LR} \\ \log(l_t^*) \\ f_t^* \\ cy_t^* \end{bmatrix}.$$