Equilibrium and Real Options in the Ethanol Industry: Modelling and Empirical Evidence

Matt Davison **Nicolas Merener***

Western University *Universidad Torcuato Di Tella*
mdavison@uwo.ca nmerener@utdt.edu

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Abstract

In the last twenty years a large number of competitive ethanol firms have established operations in the US. Ethanol, produced from corn, is blended with pure gasoline to produce fuel. Producers hold an option to turn off unprofitable plants. Blenders choose to substitute ethanol for gasoline at or beyond the minimum ratio set by the government. We propose and test an equilibrium model for blenders and producers that accounts for the real optionality embedded in the industry. The model, driven by corn and gasoline prices, leads to analytical expressions for the price and physical output of ethanol, and for the value of an ethanol producer. We confront the model with data between 2000 and 2017. In line with the model, we confirm that ethanol was largely priced as the maximum of rescaled gasoline and corn prices. Historical output levels between the mandate and installed capacity were explained by the model. Finally, the share price dynamics for the largest public ethanol producer in the US was consistent in some aspects with the value of a real option.

Keywords: Ethanol Production; Real options; Biofuels; Valuation

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1. Introduction

The ethanol industry in the US has grown rapidly since the adoption of the Renewable Fuel Standard (RFS) in 2005 and the passage in Congress of the Energy Policy Act. The Energy Independence and Security Act widened the scope of the RFS in 2007. The RFS mandates that transportation fuel in the US contain a minimum volume of renewable fuel, hence generating a large demand for ethanol. This has led to massive investment in production capacity and physical output as seen in figure 1. In 2017 there were 211 ethanol plants in the US, compared to 81 in 2005. The ethanol blend rate, defined as the proportion of gasoline fuel provided by ethanol, increased from 2.9% in 2005 to 10.0% in 2017. The gross value of ethanol industry output surpassed 30 billion dollars in 2017. Ethanol, produced in the US primarily from corn, has recently used more than 30% of the corn that is grown domestically. [1] The US ethanol industry is comprised of two different types of participants: ethanol producers and ethanol blenders. In addition to the RFS, incentives for the ethanol industry have included a tax credit to blenders.

In this paper we study, through theory and empirical analysis, the production and valuation of ethanol as a function of stochastic corn and gasoline prices. We explicitly consider the incentives faced by competitive ethanol producers and gasoline blenders operating under government ruled mandates and capacity limits. Producers purchase corn and use it to produce ethanol. A producer holds the option to turn production on and off in response to the profitability of her operation. Blenders purchase ethanol from producers and mix it with gasoline to produce fuel. A blender has the option to decide on the composition of the fuel mix which must satisfy a minimum proportion of ethanol dictated by the government mandate. Producers and blenders hold real options driven by corn and gasoline prices. They trade with each other and set ethanol prices

[1] Renewable Fuels Association. (2017) The RFS2: Then and now.

and output in equilibrium.

Our contributions in this paper are the following: first, we propose an equilibrium model for producers and blenders that embeds the operational flexibility that they hold in the context of a government mandate and fixed capacity. The model is driven by stochastic gasoline and corn prices. Second, we confirm that the historical price of ethanol between 2000 and 2017 was well explained as the maximum of properly scaled gasoline and corn prices. This is a consequence of the possibility of substitution between gasoline and ethanol. Between 2008 and 2017 ethanol was alternatively priced as gasoline or as corn with similar frequency. Therefore, we find that models for the ethanol market should include these two drivers.

Third, the volume of ethanol production in the model reaches full capacity utilization when gasoline is sufficiently expensive relative to corn. Production is as low as the government imposed mandate when corn is sufficiently expensive relative to gasoline. We find empirical support for this rule between 2008 and 2017, with the RFS under full effect. Hence, we find that the government mandate and installed capacity are quantitatively important in a proper description of the ethanol market.

Fourth, we represent the theoretical value of an ethanol producer as that of a real option on the spread between gasoline and corn. Then we find in the historical data that the value of the largest publicly traded pure ethanol producer in the US had certain attributes consistent with the value of a real option. Although our model assumes no switching costs, we extend our empirical analysis to test for their presence in the data. We find mixed evidence for switching costs. Our equilibrium setting fully takes into account the flexibility available to blenders but we choose not to focus on their valuation as blenders are typically diversified large firms for which the ethanol component is relatively small.

Overall, our main contribution is finding that a complete description of the ethanol market must include gasoline and corn prices as drivers, in combination with incentives

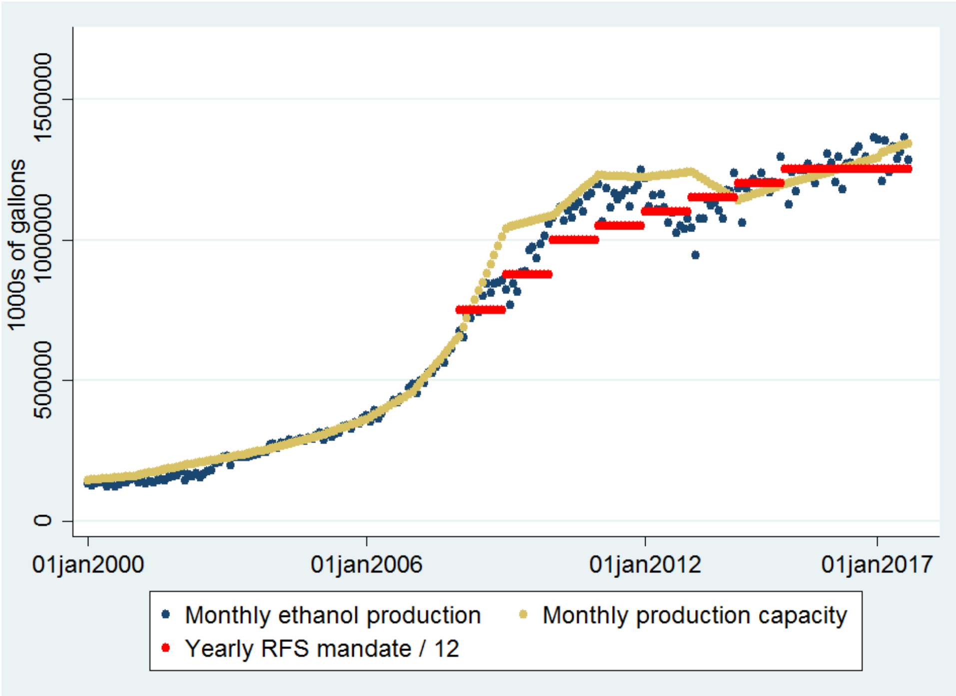

Figure 1: US Ethanol production, capacity and mandate (in 1000s of gallons). Source: USDA.

and constraints faced by producers and blenders. We find clear empirical support for significant real optionality in the ethanol market. Unlike purely econometric models, our model requires no estimated parameters fit from data.

Several lines in the literature are close to this paper. First, significant work has aimed to understand the fundamental economic mechanisms that determine output, pricing and investment in the ethanol industry. Profits in ethanol production are primarily determined by the spread between the price of ethanol and its cost of production. Producers have the ability to turn their facilities on and off. The value of the real option in ethanol and biofuel production under optimal operation has been studied in the literature. Kirby and Davison (2010) valued an ethanol producer as a real option on the spread between gasoline and corn, and studied the impact of their correlation. Schmit et al. (2011) and Maxwell and Davison (2014) estimated the influence of ethanol policies on investment and optimal operation using ethanol and corn as exogenous variables in real options models. We differ from these works in that we derive the price of ethanol endogenously from stochastic gasoline and corn prices, and in that we explicitly consider the equilibrium between producers and blenders constrained by a fixed mandate and installed capacity. Zhang et al. (2016) developed a static equilibrium model for the biofuel supply chain but, unlike our work, their model has no uncertainty nor time-series empirical testing. Cheng and Anderson (2017) studied profit maximization in ethanol production under long-term fixed rate contracts. Our modelling approach, close to Ghoddusi (2017), focuses on the equilibrium between ethanol producers and blenders in the presence of mandates and fixed capacity. Ghoddusi (2017) noted that, at least in theory, ethanol may serve either as a complement or a substitute for gasoline and studied the theoretical impact of this dual role in the valuation of an ethanol producer. In this setting, Ghoddusi (2017) could find closed form solutions for the ethanol price only under the assumption of zero corn price volatility. Our work, by contrast, focuses only on the substitution effect between ethanol and gasoline but keeps unrestricted corn and gasoline processes. This is a significant modelling difference with Ghoddusi (2017). It allows us to keep realistic dynamics for the main drivers of ethanol while deriving closed form equilibrium expressions for ethanol output and prices. Analytical expressions are essential for the implementation of our extensive empirical testing, which is also novel relative to Ghoddusi (2017). Empirical testing of real optionality in a variety of industries includes Quigg (1994), Moel and Tufano (2002), Grullon et al (2012) and Sabet and Heaney (2017) but, as shown by Trigeorgis and Tsekrekos (2018), it is generally scarce in the literature and particularly so in ethanol.

A significant body of work has focused on econometric and time series analysis of the ethanol market and related commodities. These are fitted econometric models that generally are not linked explicitly to the underlying microeconomics of the ethanol market. Serra et al. (2011) found a non linear relationship between ethanol, corn and oil on data up to 2008. Mallory et al. (2012) estimated a pricing formula for ethanol in terms of futures prices of natural gas and corn using a no-profit condition mediated by storage. Serra and Zilberman (2013) reviewed the transmission between corn and energy markets in prices and volatilities for several geographies and time periods. Abbott (2014) focused on corn volatility resulting from ethanol demand and in the contributions of capacity constraints versus mandates. Carter et al. (2016) estimated and attributed a 30% increase in the price of corn to the production of ethanol in 2006-2014. Serletis and Xu (2019) found stronger volatility spillovers between oil and biofuels in the aftermath of the government ruled ethanol mandate. Complementary to this literature, our empirical work tests a model derived from equilibrium considerations and without estimated parameters.

2. The Model

The structure of the model is as follows. Ethanol producers, in subsection *2.1*, purchase corn and use it to generate ethanol. They have the option to turn production on or off depending on their instantaneous profitability. Blenders, in subsection *2.2*, purchase ethanol and mix it with pure gasoline to produce fuel. Blenders choose the composition of the mix to maximize profits while satisfying the minimum mandate. Producers and blenders operate in a competitive environment. The matching of aggregate supply and demand for ethanol in equilibrium in subsection *2.3* leads to endogenous ethanol price and aggregate output. The real option value of a producer within the model is computed in subsection *2.4*. We omit the valuation of a blender as that of a real option because blenders in reality are large fuel companies for which the ethanol business component is small. As in Ghoddusi (2017), our model has blenders and producers in equilibrium under government mandates and fixed capacity. Unlike Ghoddusi (2017), we concentrate on the substitution of gasoline by ethanol while keeping general volatility processes for the prices of gasoline and corn.

2.1. Producers

A large number $K(t)$ of competitive ethanol firms produce up to a unit of ethanol each by using corn. The corn price $C(t)$, in US dollars per bushel, is the sum of a global corn market component $Z(t)$ driven by exogenous variations in global supply and global demand, unrelated to ethanol market dynamics, plus an increasing function of ethanol industry output $h(Q(t))$

$$C(t) = Z(t) + h(Q(t)). \tag{1}$$

The economics of production largely follows Mallory et al. (2012) and Irwin (2016): let $L(t)$ be the market price of a gallon of ethanol. The production of a gallon of ethanol requires 0.37 bushels of corn. Let F be a production cost that sums a fixed component plus the historical average cost of 30 cubic feet of natural gas employed in the process of producing 1 gallon of ethanol. We replace actual natural gas costs by their historical average because the mean and standard deviation of these costs are much smaller than the cost of corn. Let $DG(t)$ be revenues from 6 pounds, or approximately 0.1 bushel, of dried distillers grain, a byproduct of the production of a gallon of ethanol. The instantaneous profit from the production of a gallon of ethanol is

$$\Pi(L(t), C(t)) = L(t) + DG(t) - 0.37C(t) - F. \tag{2}$$

Between January, 2000 and September, 2017, the average price of dried distiller grain was 143 US dollars per ton while the average price of corn was 159 US dollars per ton. Moreover, the correlation of their contemporaneous monthly prices was 88%. Therefore, in rest of the paper we approximate the income associated with dried distiller grain by (minus) the cost of 0.09 bushels of corn and include it in the net cost of corn. The instantaneous profit from the production of a gallon of ethanol is

$$\Pi(L(t), C(t)) = L(t) - 0.28C(t) - F. \tag{3}$$

The aggregate supply of ethanol from competitive producers taking into account the endogenous price of corn is

- $K(t)$ if $L(t) > 0.28(Z(t) + h(K(t))) + F$. The ethanol price is larger than its production cost. Supply is set at its maximum.
- $0 < Q(t) \leq K(t)$ if $L(t) = 0.28(Z(t) + h(Q(t))) + F$. The ethanol price equals its production cost. Supply is pinned down by competition among producers at a zero profit level.
- 0 if $L(t) \leq 0.28(Z(t)+h(Q(t)))+F$. The ethanol price is smaller than its production cost. Supply is set at zero.

The supply curve is represented in figure 2.

2.2. Blenders

A blender manufactures fuel by mixing pure gasoline with ethanol. In line with Knittel and Smith (2015) and most of the literature we assume that the price $G(t)$, of a gallon of gasoline, is exogenous to the production of ethanol. Firms execute an optimal production policy to maximize profits. Blenders must comply with a US government mandate which sets a floor $M(t)$ on the demand for ethanol. In practice, the Environmental Protection Agency (EPA) regulates compliance with the Renewable Fuel Standard through a system of tradable renewable identification numbers (RINs) which must be submitted by blenders. Each blender is liable for a renewable volume obligation, calculated as the product of blender fuel sales and the percentage standards set by the EPA. Therefore total ethanol demand in a given year is greater or equal to a certain proportion of gasoline consumption. For the purpose of our analysis we will assume that the floor is set at the level specified by the EPA in its ruling. We assume that $M(t) \leq K(t)$. Figure 1 largely supports this assumption, although there are a few instances in which the mandate appeared to be larger than installed capacity. We attribute this to the fact that actual mandates are yearly, but represented as monthly in figure 1 only for visualization and modelling convenience. In addition, figure 1 shows monthly production being often larger than monthly installed capacity. We attribute this to measurement error on both variables, and to the fact that the USDA reports installed capacity on a yearly frequency. We estimate a monthly time series for modelling purposes through linear interpolation. We abstract from the entry/exit problem by assuming that $K(t)$ and $M(t)$ are deterministic. In addition, blenders accrue a tax credit b per gallon of ethanol used.

The energetic content in 1.5 gallons of ethanol is equivalent to that in a gallon of gasoline. However, consumers do not fully penalize ethanol for this lower energy content. Petrolia et al. (2010) and Anderson (2012) show that consumers are willing to pay a sizeable premium for gasoline blends with 10% and 85% ethanol blend ratios relative to what would be implied by their energetic content. Hence we assume that gasoline blenders reflect this consumer preference by equating the value of purchasing a gallon of pure gasoline with that of purchasing 1.25 gallons of ethanol and accruing the blend credit. Under this substitution threshold, blenders produce fuel by mixing pure gasoline with ethanol. Their goal is to maximize profit by minimizing the cost of fuel and simultaneously satisfying the US mandate. Blenders use more ethanol than the strict minimum mandate if optimal for their profits. In addition, there is an upper limit in the demand for ethanol, so called *blending wall*, at $W > K(t)$, given by technical specifications in automobile engines.

The demand of ethanol from competitive blenders is

- $M(t)$ if $L(t) > \frac{G(t)}{1.25} + b$. The ethanol price is larger than its value as a substitute for gasoline. Ethanol demand is set at the minimum mandate.

- W if $L(t) \leq \frac{G(t)}{1.25} + b$. The ethanol price is less or equal than its value as a substitute for gasoline. Ethanol demand is set at its maximum.

The demand curve is represented in figure 2.

2.3. Equilibrium

Ethanol producers and gasoline blenders maximize profits. Under frictionless trading and operation with instantaneous adjustment to market conditions, equilibrium output and prices are determined by the supply and demand curves in figure 2. The equilibrium has three regions:

- Ethanol production cost lower than its value as substitute for gasoline. Supply and demand intersect at point A in figure 2. $0.28(Z(t) + h(K(t))) + F \leq \frac{G(t)}{1.25} + b$.

  Ethanol output reaches production capacity: $Q(t) = K(t)$.

  Ethanol is priced by its value as a gasoline substitute: $L(t) = \frac{G(t)}{1.25} + b$.

  Ethanol producers extract rent and their profit is $\frac{G(t)}{1.25} + b - 0.28(Z(t) + h(K(t))) - F$

- Ethanol production cost is equal to its value as substitute for gasoline. Supply and demand intersect at point B in figure 2. $0.28(Z(t) + hQ(t)) + F = \frac{G(t)}{1.25} + b$.

  Ethanol output is determined by the price of gasoline and the relative contribution of the unobservable global market component $Z(t)$ to the price of corn.

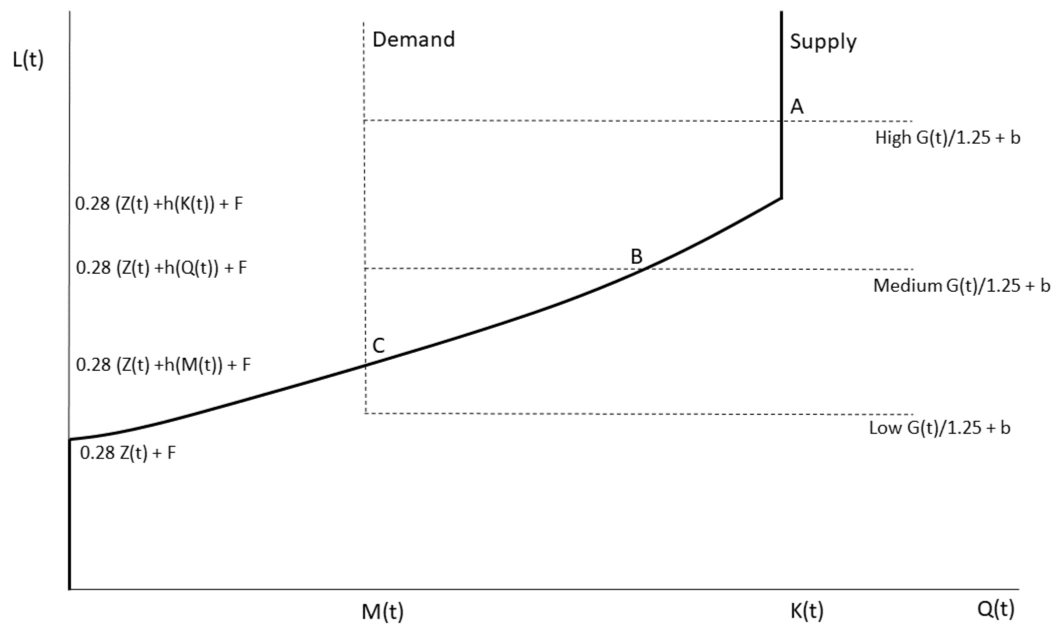

Figure 2: Supply and demand curves for ethanol

Ethanol is priced by its value as substitute and by its cost of production, which coincide.

Ethanol producers have spare capacity and their profit is 0.

- Ethanol production cost larger than its value as substitute for gasoline. Supply and demand intersect at point C in figure 2. $0.28(Z(t) + hM(t)) + F > \frac{G(t)}{1.25} + b$.

  Ethanol output equals the mandate: $Q(t) = M(t)$.

  Ethanol is priced by its cost of production: $L(t) = 0.28(Z(t) + hM(t)) + F$

  Ethanol producers have spare capacity and their profit is 0.

Therefore, the price of ethanol in equilibrium can be summarized by

$$L(t) = \max(0.28(Z(t) + hQ(t)) + F, \frac{G(t)}{1.25} + b) = \max(0.28C(t) + F, \frac{G(t)}{1.25} + b) \quad (4)$$

Let $\alpha = F - b$ and define the spread between gasoline and corn as

$$X(t) = \frac{G(t)}{1.25} - 0.28C(t).$$

Aggregate output $Q(t)$ and ethanol producer profit $\Pi(t)$ are:

$$Q(t) = K(t) \text{ and } \Pi(t) = X(t) - \alpha, \text{ iff } X(t) > \alpha \quad (5)$$

$$Q(t) \in (M(t), K(t)) \text{ and } \Pi(t) = 0, \text{ iff } X(t) = \alpha \quad (6)$$

$$Q(t) = M(t) \text{ and } \Pi(t) = 0, \text{ iff } X(t) < \alpha \quad (7)$$

Producer profits are determined by $X(t)$. We work under the assumption of instantaneous adjustment to exogenous shocks in gasoline and corn prices, and positive price impact of ethanol production on corn. Then, there is a range of output value given by $Q(t) \in (M(t), K(t))$ for which the spread $X(t)$ remains fixed at α. This is a consequence of the endogenous component of corn being simultaneously set with ethanol output through the zero profit condition. In practice this is rare as the gap between installed capacity and the mandate has been relatively narrow and averaged 8% between 2008 and 2017. The spread ceases to remain at α for instances in which the price of gasoline and the global component of corn $Z(t)$ are sufficiently apart and then either capacity or the mandate becomes binding.

2.4. Producer valuation as a real option

We assume that an ethanol plant may either be active or remain idle at zero cost. A producer of ethanol maximizes its value by continuously choosing to produce ethanol or to be inactive. Production can be turned on and off without cost. Let $q(s)$ be ethanol output at time s under a certain production strategy and q be the set of production strategies that can be implemented dynamically based on the market information revealed up to the time of its execution. Under an appropriate pricing measure, which we need not specify for our empirical exercise, we assume that the spread follows

$$dX(t) = \mu_x(t)dt + \sigma_x(t)dW, \tag{8}$$

with $\mu_x(t)$ and $\sigma_x(t)$ possibly stochastic. Special cases could involve arithmetic Brownian Motion or Ornstein-Uhlenbeck processes. The value of the production facility under perfect competition among producers is

$$V(t, X(t)) = \max_q E[\int_{s=t}^{T} e^{-r(s-t)} q(s)\Pi(X(s))ds], \tag{9}$$

where r is an appropriate discount rate and the process $X(s)$ is independent from $q(s)$. As there are no switching costs, the optimal producer strategy is to remain active if and only if profit is nonnegative. The value function can then be expressed as a that of a sum of European options with different maturities

$$V(t, X(t)) = \int_{s=t}^{T} \int_{x=-\infty}^{\infty} e^{-r(s-t)} \max(0, \Pi(x, s))p(x, s|X(t))dxds, \tag{10}$$

where $p(x, s|X(t))$ is the conditional distribution of the spread at time s.

Alternatively, through Bellman's optimality principle and Ito's Lemma, the value of the firm under optimal operation in (9) can be represented as the solution of a partial differential equation

$$0 = \Pi(x) - rV(t, x) + \frac{\partial V(t, x)}{\partial x}\mu_x(t) + 1/2\frac{\partial V^2(t, x)}{\partial x^2}\sigma_x(t)^2 + \frac{\partial V(t, x)}{\partial t},$$

with $\Pi(x) = 0$ if $x \leq \alpha$, $\Pi(x) = x - \alpha$ if $x > \alpha$, and an appropriate terminal value condition $V(T, x)$.

If the ethanol plant has a distant closing date, it can be approximated as a perpetual production asset. Hence, $\frac{\partial V(t,x)}{\partial t} = 0$ and $V(t, x) = V(x)$. In this case the PDE for the value function becomes an ordinary differential equation that can be solved in each region under the following boundary conditions:

- $V(x)$ and $V'(x)$ continuous at $x = \alpha$ by the smooth pasting condition (Dixit and Pindyck (1994)).
- $V(x \to -\infty) = 0$ because the value of the producer becomes zero when the chance of positive profits vanishes.
- $V'(x \to \infty) = 1/r$ as seen by interchanging expectation and integration in time in (10) under the limit of guaranteed positive profits.

2.5. Testable implications

In sum, the testable implications of the model are the following:

- The price of ethanol is the maximum of the price of gasoline and the price of corn, properly adjusted by certain constant parameters.
- Ethanol industry output is at capacity when the price of gasoline is sufficiently higher than the price of corn. Output is at the government mandate when corn is sufficiently expensive relative to gasoline.
- The value of an ethanol producer is that of a portfolio of European call options on a spread between gasoline and corn prices. Independently of the parametric form of the dynamics for $X(t)$ in (8), the first and second derivatives of the producer's

value with respect to the spread and the first derivative with respect to spread volatility are all positive. In financial engineering terms, *delta*, *gamma* and *vega* are all positive.

2.6. Policy implications

Identifying the impact of policy choices on investment is important for policy makers. Zhang et al. (2016) in ethanol, and Boomsma et al. (2012) in electricity generation from renewable sources, are examples in this direction. Li et al (2015) also studied the determinants of investment in cellulosic biofuel capacity. The government mandate, blend credit and installed capacity are all exogenous in our model. Hence, it is not a model tailored for studying the impact of policy changes on entry and aggregate capacity. However, we can inform policy by studying the impact of the mandate and blend credit under the assumption of constant capacity. The evaluation of a policy should take into account its fiscal cost, effect on ethanol adoption, and impact on the fuel cost faced by the consumer.

The equilibrium in which gasoline is expensive relative to corn implies that ethanol is priced as gasoline plus a blend credit (4) and aggregate output is at capacity. Competitive blenders mix ethanol with gasoline and sell it as fuel. By competition among blenders, the cost per gallon of fuel paid by consumers is the cost per gallon of gasoline. The blend credit originally accrued by blenders is therefore passed on to ethanol producers who make a profit operating at capacity. Hence, within this regime, ethanol consumption and fuel prices are not sensitive to a marginal increase in the mandate. A marginal increase in the blend credit improves the profit margin of ethanol producers but leaves ethanol consumption unchanged.

The equilibrium in which corn is expensive relative to gasoline implies that ethanol is priced by its cost of production (4). Ethanol demand is low and industry output is at the mandate. The blend credit is shared by blenders and consumers. The cost of fuel faced by consumers is, from (4), strictly higher than that of pure gasoline. A marginal increase in the mandate, which is binding, leads to higher ethanol consumption at a cost borne by consumers. Finally, a transition across equilibria can be triggered by a sufficiently large change in blend credit but not by a change in the size of the mandate.

A policy maker interested in evaluating the effectiveness of a particular combination of blend credit and mandate, should compare the ethanol consumption goal G at horizon T with the expected ethanol production in the model under this policy. The distribution of the spread $X(T)$ in (8) properly calibrated to historical data implies certain probabilities $P(X(T) < F - b)$ and $P(X(T) > F - b)$ for each of the equilibria in (5) and (7). The intermediate equilibrium defined by $X(T) = \alpha$ is, in reality, unlikely. Therefore, the consumption goal G should match the weighted average of mandate and installed capacity. To satisfy this, while minimizing the cost of the subsidy, optimal policy parameters $\{b, M\}$ must satisfy

$$G = \min_{\{b\}} \{P(X(T) < F - b) * M + P(X(T) > F - b) * K\}$$

under $0 \leq b$ and $M \leq K$. As mentioned earlier, this prescription is oblivious to the fact that installed capacity K is in reality endogenous to M and b. This is a limitation of our model.

3. Empirical Analysis

3.1. Data

We obtained monthly data from the USDA [2] on corn, gasoline and ethanol spot prices. We also gathered monthly ethanol production and installed capacity, and additional pa-

[2] https://www.usda.gov/topics/data

Ethanol mandates, production and capacity

	Final mandate	Mandate by law	Production	Capacity
Mean	1,064,102	1,083,333	1,112,501	1,162,543
St. dev.	147,496	163,145	165,662	135,253
N obs.	117	117	117	117

Table 1: Statistics for monthly ethanol mandates and capacity (interpolated from yearly data) and monthly ethanol production (in 1000s of gallons). Jan. 2008 - Sept. 2017. Source: USDA and EPA.

rameters such as extra costs and credits. Ethanol production in the US showed very rapid growth between 2000 and 2009, and it was slower between 2010 and 2017 as seen in figure 1. We also gathered from the EPA information on yearly ethanol mandates, both as prescribed by law in 2007 and by rulings finalized in later years. In late 2015 the EPA reduced ethanol requirements for 2014, 2015 and 2016 to levels below those initially established by Congress. For normalization and modelling purposes we constructed monthly mandate measures simply by dividing the annual mandates by 12, although in practice there is no notion of a monthly mandate. We produced a monthly measure of installed capacity by linearly interpolating yearly production figures recorded each January. The rationale behind this choice is the assumption that the plant building process occurs gradually during the year. Summary statistics, for the 2008-2017 period with the RFS mandate under full effect, are displayed in table 1.

Mallory et al. (2012) developed and tested a model for the relationship between futures prices of natural gas and corn for the 2007-2012 period. Motivated by their work and by the fact that information revelation might occur more efficiently in futures markets than in spot markets, we gathered futures prices between 2007 and 2017. We choose to work with CME corn futures (4th contract) and ICE NY RBOB gasoline futures (6th contract). The expirations associated with these contracts are approximately between 6 and 9 months away from the pricing date.

Largest ethanol producers in the US in 2017			
	Capacity (m gallons / year)	Focus on ethanol	Public firm
Archer Daniels Midland	1,716	NO	YES
POET	1,660	YES	NO
Green Plains	1,461	YES	YES
Valero	1,400	NO	YES
Flint Hills	820	NO	NO
Top 5 total	7,057		
US total	15,555		

Table 2: Largest ethanol producers in the US in 2017. Source: Renewable Fuels Association

The theory proposed in this paper is grounded on the incentives faced by ethanol producers and blenders. The predictions of the model apply to aggregate output and prices, and to individual producers regardless of their private or public character. However, an empirical test of firm valuations requires the identification of firms that are publicly traded for their prices to be know. Firms must also focus exclusively on ethanol for the model to be an accurate representation of their activity. The Renewable Fuel Association produces every year a list of ethanol producers, their locations and capacities.[3] Table 2 shows the largest firms in 2017. Of those, only Green Plains was simultaneously a publicly traded firm and primarily dedicated to ethanol production. It had a production capacity of 1.5 billion gallons per year in 2017, out of 17 plants distributed across the US. This was approximately 10% of US ethanol production that year. In our empirical analysis we take this firm as a proxy for a pure ethanol producer. We manually collected data for Green Plains on number of shares, production capacity, debt and liabilities from the 10K reports to the SEC. [4]

[3]The RFS2: Then and now. Published by the Renewable Fuels Association in 2017
[4]https://www.sec.gov/edgar.shtml

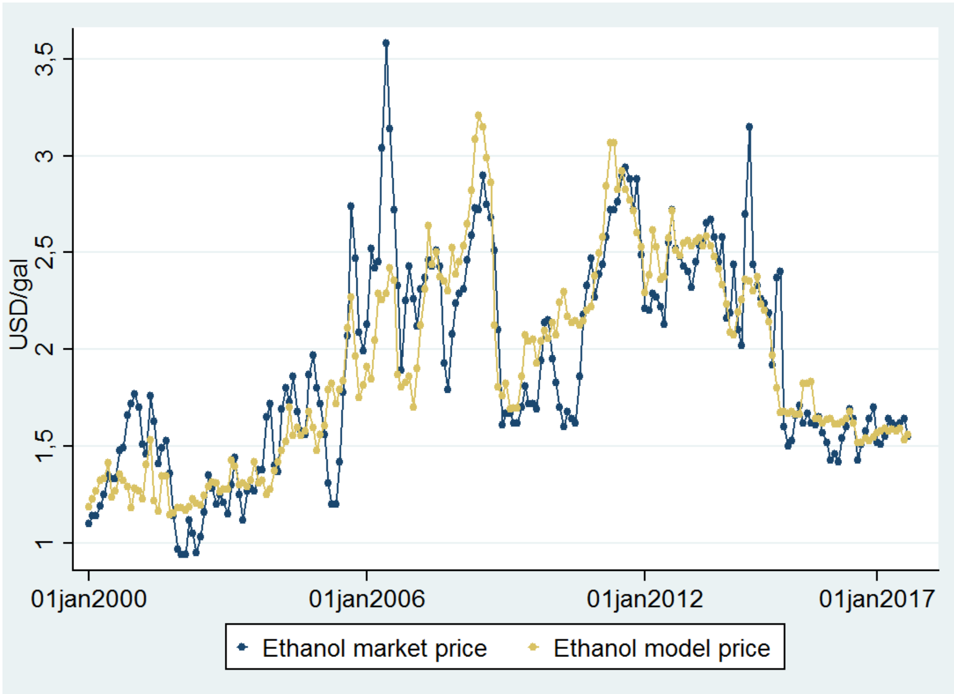

Figure 3: Market and model-based ethanol prices by using (4) on historical gasoline and corn spot prices. Monthly data. Source: USDA.

3.2. A non linear relationship between gasoline, corn, and ethanol

The possibility of substitution of gasoline by ethanol in section 2 implies in (4) that the ethanol price should be the maximum of properly rescaled gasoline and corn prices. In order to test its quantitative accuracy we generate a time series of the ethanol model-based price, defined as the right side of (4) implemented on historical monthly corn and gasoline prices. Notice that (4) does not depend explicitly on the size of the government mandate. In line with statistics published by the USDA we assume an additional fixed cost of 65 cents per gallon of ethanol. The blend credit was 54 cents from January 2000 until December 2004, then 51 cents through December 2008, 45 cents until December 2011 and zero afterwards. Figure 3 displays model-based and historical ethanol prices and it is suggestive of the ability of the theoretical price to approximately reproduce the market price.

We evaluate the statistical performance of the model in matching historical ethanol prices. We do this by comparing the fitting error of our model to the errors from vector error correction models (VECM), discussed in Gourieroux et al. (2004). VECMs are standard tools in empirical finance work to estimate linear relationships, or cointegration, among time series data while avoiding spurious results obtained from standard OLS regressions. The literature has extensively explored the presence of cointegration between ethanol, corn and energy prices (Serra and Zilberman (2013), Mallory et al. (2012)). Hence, as an alternative to the theoretical model proposed in this paper we consider vector error correction models (VECM) built on ethanol, gasoline and corn prices. A Johansen's trace test cannot reject the null hypothesis of the existence of a cointegrating equation between ethanol, gasoline and corn monthly prices at the 1% significance level for the periods 2000-2007 and 2008-2017. This is the case using either spot or futures prices for gasoline and corn. Therefore, a purely statistical approach supports the notion of a long term relationship between ethanol, gasoline and corn. A Johansen's test also supports the existence of a cointegrating equation between the ethanol market price and the theoretical market price defined as (4) on spot gasoline and corn prices. Next, we compare the performance of our model with VECM models fit to the data. This is in table 3. The monthly fitting error is defined as the difference between the model-based price and the ethanol market spot price in US dollars per gallon. For each model we report its root mean square error (RMSE), which is a measure of overall discrepancy between the model and historical price behavior. The theoretical model derived in this paper (Model 1) has a RMSE of 32 cents prior to the EPA mandate and 24 cents afterwards. For proper economic context, the average price of ethanol between 2000 and 2017 was 1.91 US dollars, with a range between 0.94 and 3.58 dollars. Model 2, in table 3, is a VECM driven by the theoretical ethanol price. Its estimated linear coefficient is not significantly different from 1, and therefore not an improvement over the theoretical model despite

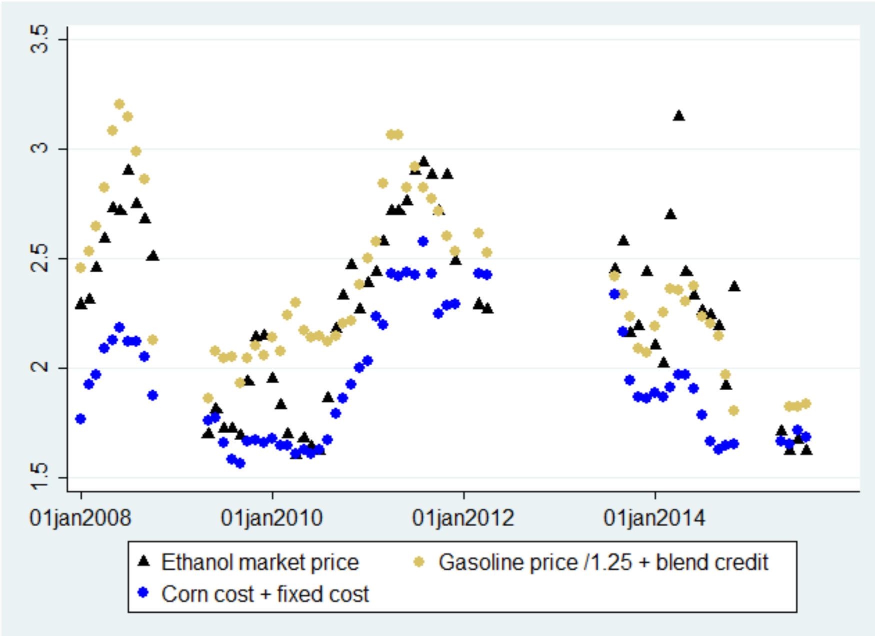

Figure 4: US Ethanol price, production cost, and substitution value, displayed for instances of expensive gasoline relative to corn ($X(t) > \alpha$).

having more free parameters. Models 3 and 4 are VECM based on gasoline and corn, spot and futures prices. Despite their increased flexibility, these models do not show an economically significant improvement in RMSE relative to our theoretical model. The parameters of Model 3, estimated on spot prices, are unstable over time hence their out-of-sample behavior is poor. Model 4, based on futures prices only available for the second period, performs in RMSE terms similarly to other models. In sum, the theoretical model, built from first principles rather than through a fitting exercise, performs as well in RMSE as low dimensional fitted models. The theoretical model is stable across time and its coefficients have a transparent and immediate interpretation.

In principle, the theoretical price for ethanol switches between its value as substitute for gasoline and its cost of production. Hence we investigate the occurrence of this transition in our sample. The switching condition is given by the spread $G(t)/1.25 - 0.28C(t)$ being above or below α. Figure 4 displays ethanol market prices, cost of production, Empirical performance of alternative ethanol pricing models.

$$TheoEthanolPrice_t = \max(0.28CornPrice_t + FixedCost, \frac{GasPrice_t}{1.25} + BlendCredit_t)$$

Model 1 (Theory): $error_t = EthanolMktPrice_t - TheoEthanolPrice_t$
Model 2 (VECM): $error_t = EthanolMktPrice_t - \beta_1 TheoEthanolPrice_t$
Model 3 (VECM): $error_t = EthanolMktPrice_t - \beta_1 GasPrice_t - \beta_2 CornPrice_t$
Model 4 (VECM): $error_t = EthanolMktPrice_t - \beta_1 GasFutPrice_t - \beta_2 CornFutPrice_t$

RMSE $= \frac{1}{NObs}\sqrt{\sum_t^{NObs} error_t^2}$

	Jan. 2000 - Dec. 2007			Jan. 2008 - Sept. 2017			
Coeffs.	Model 1 Theory	Model 2 VECM	Model 3 VECM	Model 1 Theory	Model 2 VECM	Model 3 VECM	Model 4 VECM
Theo. Eth.	1.0	1.03***		1.0	0.96***		
Gasoline			1.04***			0.71***	
Corn			-0.40***			0.02	
Gas. Fut.							0.56***
Corn Fut.							0.10***
Const		0.05	1.19		-0.02	0.34	0.35
RMSE	0.32	0.31	0.31	0.24	0.22	0.25	0.22
N obs.	96	96	96	117	117	117	117

Table 3: Empirical performance of ethanol pricing models.

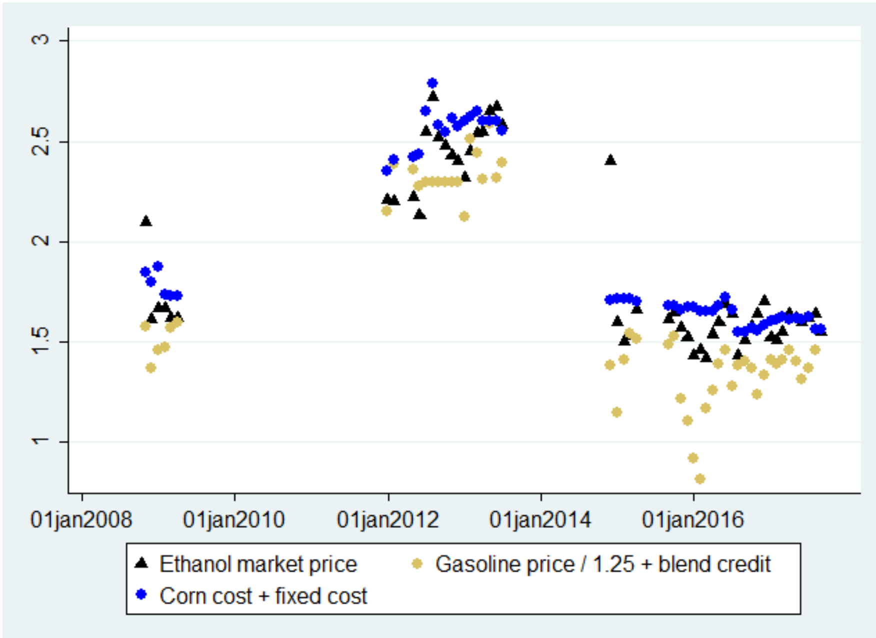

Figure 5: US Ethanol price, production cost, and substitution value, displayed for instances of expensive corn relative to gasoline ($X(t) < \alpha$).

and gasoline substitution values, for instances in which gasoline was expensive relative to corn, in the sense of spread larger than α. Inspection of figure 4 shows that the market price of ethanol was in these instances closer to its value as substitute for gasoline than to its cost of production. Symmetrically, figure 5 shows ethanol market prices being closer to the cost of production than to the value of gasoline when corn was expensive relative to gasoline. Therefore, figures 4 and 5 show that ethanol was priced historically as the maximum of properly scaled gasoline and corn. Quantitative measures of the conditional behavior of empirical ethanol prices are in table 4. For instances of spread larger than α the historical ethanol price was closer (smaller RMSE) to the ethanol's value as gasoline substitute (Model 6) than to its cost of production (Model 5). This is consistent with the testable implications of the model. Also, the cost of production was generally a better predictor of ethanol prices when the spread was smaller than α. Therefore, the non linearity in the model implied by the maximum operator in (4) is relevant for its empirical

Conditional empirical performance of alternative ethanol pricing models.

$$TheoEthanolPrice_t = \max(0.28\,CornPrice_t + FixedCost, \frac{GasPrice_t}{1.25} + BlendCredit_t)$$

Model 1 (Theory): $error_t = EthanolMktPrice_t - TheoEthanolPrice_t$
Model 5 (Production cost): $error_t = EthanolMktPrice_t - (0.28 CornPrice_t + FixedCost)$
Model 6 (Gas. substitute): $error_t = EthanolMktPrice_t - (\frac{GasPrice_t}{1.25} + BlendCredit_t)$

$X(t) = GasolinePrice_t/1.25 - 0.28\,CornPrice_t$

$\alpha = FixedCost - BlendCredit_t$

	Jan. 2000 - Dec. 2007			Jan. 2008 - Sept. 2017		
	Model 1	Model 5	Model 6	Model 1	Model 5	Model 6
$X(t) > \alpha$: RMSE	0.34	0.72	0.34	0.29	0.42	0.29
$X(t) > \alpha$: N obs.	76	76	76	64	64	64
$X(t) < \alpha$: RMSE	0.23	0.23	0.22	0.17	0.17	0.29
$X(t) < \alpha$: N obs.	20	20	20	53	53	53

Table 4: Performance of ethanol pricing models conditional on gasoline and corn prices.

performance and supports the substitution effect. Based on engineering considerations we have used 65 cents as our best estimate of non-corn costs in the production of a gallon of ethanol. The empirical performance of the theoretical model is robust to fixed costs within a range from 50 to 80 cents, which would have been plausible as well.

3.3. Gasoline, corn, and ethanol production

The ethanol capacity utilization rate is defined as the ratio between monthly industry production $Q(t)$ and installed capacity $K(t)$. The model in section 2 predicts, through its equilibrium, a non linear relationship between the market prices for gasoline and corn, and the ethanol capacity utilization rate:

$$\frac{G(t)}{1.25} - 0.28C(t) > \alpha \iff Q(t)/K(t) = 1$$

$$\frac{G(t)}{1.25} - 0.28C(t) = \alpha \iff Q(t)/K(t) \in (M(t)/K(t), 1)$$
$$\frac{G(t)}{1.25} - 0.28C(t) < \alpha \iff Q(t)/K(t) = M(t)/K(t)$$

Ethanol production, the government imposed mandate, and installed capacity are time dependent and evolved between 2000 and 2017 as shown in figure 1. We interpret the instances in which production or the mandate were above monthly installed capacity as measurement error of actual production and of installed capacity (only available with yearly frequency and made monthly by interpolation). We set the corresponding ratios equal to one in empirical testing. According to the model the capacity utilization rate should be increasing in the spread given by $\frac{G(t)}{1.25} - 0.28C(t)$.

The mandate to capacity ratio was effectively zero from 2000 until the Energy Policy Act of 2005, and close to 0.75 in 2006-2007, prior to the Energy Independence and Security Act. The upper panel in table 5 displays empirical and theoretical utilization ratios for the period before the full effect of the RFS mandate. Empirical results in table 5 show increasing utilization ratios as function of the spread between gasoline and corn, as predicted by the model. However, under a zero mandate, the model predicts an extreme range of theoretical output (from zero output to full capacity). This is unlikely to be observed in the data because of the possibility of storage and other sources of ethanol demand, not considered in our model, that are likely to keep some firms active. We attribute the quantitative mismatch between the model and historical data, displayed in the fourth column of the bottom panel of table 5, to the limited scope of our model.

The interplay between installed capacity, mandates, gasoline and corn prices was significant in the period from January 2008 to September 2017. This is from the start of the RFS mandate being fully in place to the latest month for which production data was available at the time of writing. Results are shown in the bottom panel of table 5. We evaluate capacity utilization statistics decomposing the sample in three sets determined

Capacity utilization conditional on the spread $X(t)$ between gasoline and corn. Prior to the full effect of the RFS mandate. Monthly data, Jan. 2000 - Dec. 2007. Mean $\alpha = 0.12$.

Production / capacity	$X(t) > 0.24$	$0.0 < X(t) \leq 0.24$	$X(t) \leq 0.0$
Historical mean	0.97	0.92	0.83
	(0.01)	(0.01)	(0.04)
Model w/ final mandate: mean	1	0.60	0.0
	(0.00)	(0.08)	(0.00)
Model w/ law mandate: mean	1	0.60	0.0
	(0.00)	(0.08)	(0.00)
N obs.	51	40	4

Capacity utilization conditional on the spread between gasoline and corn. Under the full effect of the RFS mandate. Monthly data, Jan. 2008 - Sept. 2017. Mean $\alpha = 0.46$.

Production / capacity	$X(t) > 0.6$	$0.3 < X(t) \leq 0.6$	$X(t) \leq 0.3$
Historical mean	0.98	0.95	0.91
	(0.01)	(0.01)	(0.02)
Model w/ final mandate: mean	1	0.96	0.90
	(0.00)	(0.01)	(0.02)
Model w/ law mandate: mean	1	0.97	0.92
	(0.00)	(0.01)	(0.02)
N obs.	51	48	18

Table 5: Historical and theoretical capacity utilization ratios.

by the proximity of the spread to the mean value of α, at 0.46 during that period. We consider the government mandate as stipulated by law in 2007 and, alternatively, as modified by the EPA in its subsequent rulings. The model implies that, in the event of gasoline being expensive relative to corn, the production to capacity ratio should be equal to 1 and independent from the ethanol mandate. This agrees qualitatively with the second column in table 5 that shows a relatively high historical capacity utilization at 0.98. The third column corresponds to the case of a spread relatively close to α. In this case the utilization ratio is predicted to be between full capacity and that determined by the mandate. The fourth column corresponds to instances with inexpensive gasoline relative to corn. The model implies, in this last case, that the capacity utilization ratio should be close to that dictated by strict compliance with the mandate. Empirical results in all the columns in the bottom panel of table 5 are in close agreement with the model.

It is also informative to compute the time series of capacity utilization ratio as predicted by the model in terms of historical corn and gasoline prices, and compare it with historical utilization ratios. Figure 6 displays such series with two notorious instances of low capacity utilization (in 2009 and 2012) partially reproduced by the model.

3.4. Valuation of Green Plains

In section 2 we valued an ethanol producer of unit size as a portfolio of European call options on the spread $X(t)$, with weights for gasoline and corn at 1/1.25 and -0.28 respectively. This is (10), where the options have their strike at $\alpha = F - b$, namely the difference between the fixed cost and blending tax credit per gallon of ethanol. Therefore the first and second derivatives of the value of the firm with respect to the spread are positive in the model. The firm's value derivative with respect to the implied spread volatility is also positive. In this section we test these predictions on data from Green Plains, the largest firm that satisfies the rare condition of being publicly traded and

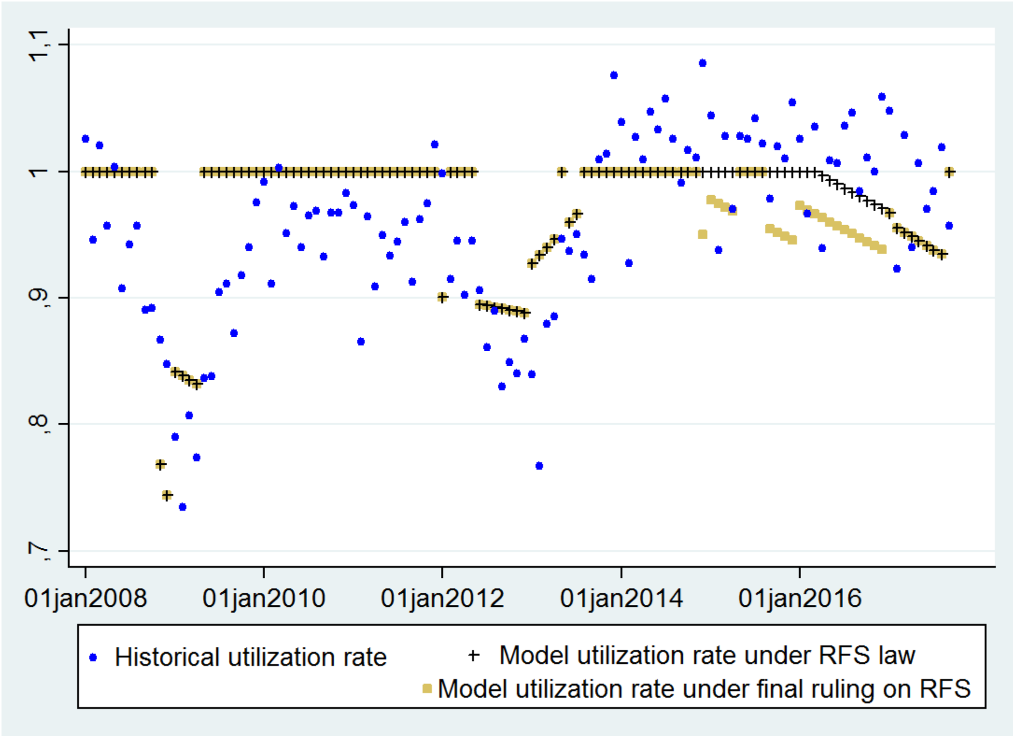

Figure 6: Theoretical and actual capacity utilization ratios.

focused solely on ethanol as seen in table 2. Unfortunately, a larger set of sizable firms that are both publicly traded and focus almost exclusively on ethanol is not available. Figure 7, based on monthly observations of the spread and the share price of Green Plains between January 2012 and September 2017, suggests strong comovement between these two quantities. Figure 8 also suggests an increasing slope for the share value as a function of the spread beyond the value of $\alpha = 0.65$ in this period.

We postulate that our theory provides a framework for computing the total value of the firm, also called the enterprise value in the finance literature. This is the sum of equity and outstanding debt. Hence,

$$N_{shares} * SharePrice(t) + Debt_{firm} = K_{firm} * V(X(t)), \tag{11}$$

where K_{firm} is the installed capacity of the firm, N_{shares} is the number of outstanding

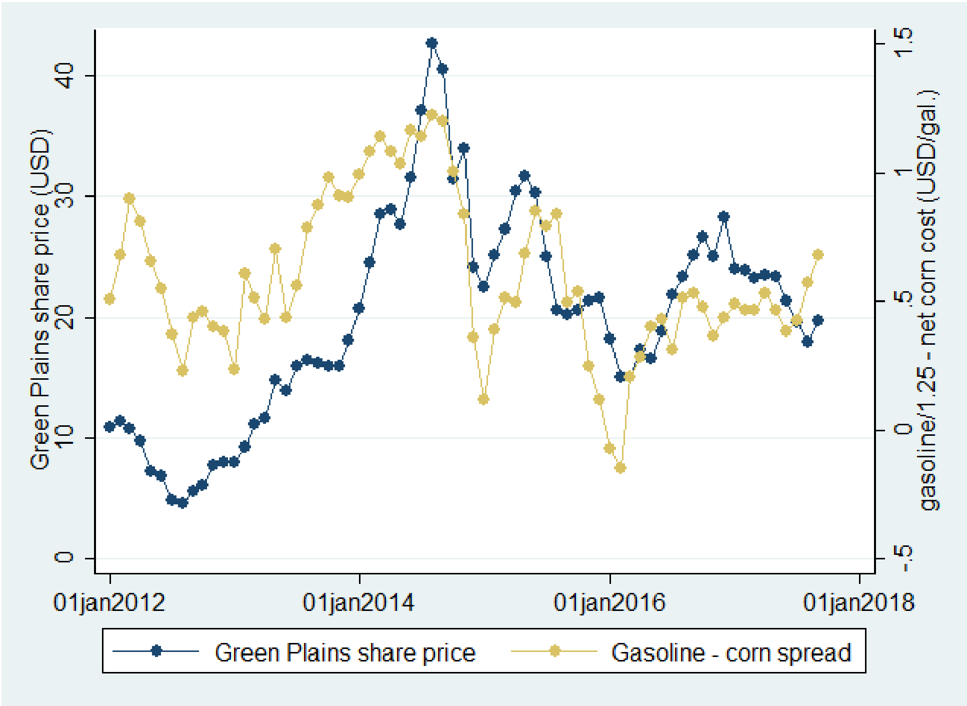

Figure 7: Green Plains share price, and gasoline price - production cost spread.

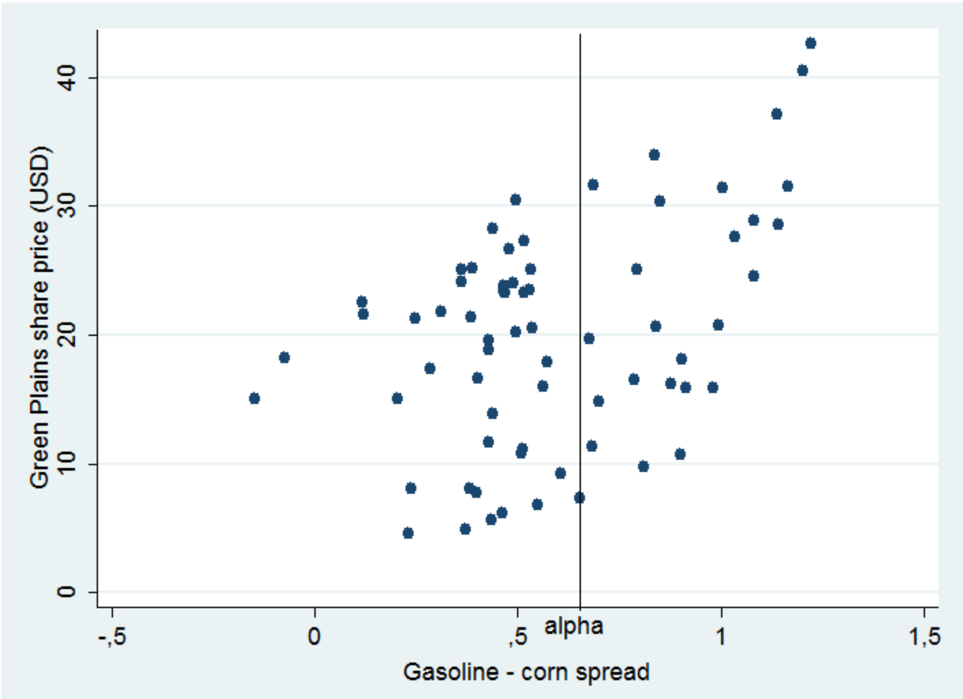

Figure 8: Green Plains share price vs. gasoline price - production cost spread.

shares and $Debt_{firm}$ is the outstanding debt of the firm. $V(X(t))$ is the value function derived in section 2 for an ethanol producer of unit size, which is a function of prevailing market conditions in the gasoline and corn markets through the spread $X(t)$. From (11), the share price is

$$SharePrice(t) = \frac{K_{firm} * V(X(t))}{N_{shares}} - \frac{Debt_{firm}}{N_{shares}}. \tag{12}$$

In our regression analysis we avoid choosing a parametric form the dynamics of $X(t)$ in (8) (hence for $V(X(t))$) and rely instead on the fact that the value of a European call option is a convex and increasing function of the underlying. In our application, the strike of the European call options in (10) is given by α. Hence we approximate the non linear behavior of $V(X(t))$ by the sum of linear and quadratic terms on $X(t) - \alpha$. Motivated by (12) we regress

$$\begin{aligned} SharePrice(t) &= \beta_0 + \beta_1 \frac{Capacity(t)}{N_{Shares}(t)}(X(t) - \alpha) + \beta_2 \frac{Capacity(t)}{N_{Shares}(t)}(X(t) - \alpha)^2 + \\ &+ \beta_3 \frac{Debt(t)}{N_{Shares}(t)} + controls(t) + \epsilon(t), \end{aligned} \tag{13}$$

in monthly levels and in monthly differences with data between January 2012 and September 2017. We also display coefficients for standard Fama-French factors, which are controls in our regressions, in either level or first difference form. In unreported results, the 10y USD interest rate and the VIX index, controlling for the prevailing discount factor and risk aversion, had no significant effects on the price of Green Plains.

Results are presented in table 6. We focus first on the second and fourth columns. Although casual inspection of the spread suggests mean reverting behavior, the high adjusted R-square of the regression in levels in the second column might be due to the relatively persistent nature of the variables under study even after controlling for a trend.

To alleviate this concern we also display in the fourth column results for a regression based on first order differences. In both types of regressions we find strongly significant and positive effects for the linear and quadratic spread terms in explaining levels and monthly changes in the value of the ethanol producer. For instance, a 50 cent increase in the value of the spread from an initial value of 65 cents, which is in line with recent history shown in figures 7 and 8, should be multiplied by the linear and quadratic coefficients on spread in the second or fourth columns and properly adjusted by installed capacity (1,461 million gallons per year in 2017) and number of outstanding shares (46 million in 2017). Such change in the gasoline/corn markets leads to an estimated increase of approximately 12 dollars in the share price of Green Plains. About 8 dollars arise from the linear effect of spread on firm valuation and 4 dollars are due to the quadratic contribution related to the convexity of option value. This is economically important. The positive estimates for the quadratic term in the regressions are in line with the convexity of the theoretical value function derived from the option payoff. The effect of debt, both in levels and in changes, is negative and significant in the share price as expected. Evidence for the impact of the Fama-French factors is mixed.

Results in the second and fourth columns of table 6 arise from regressions on a spread with weights dictated by the model (1/1.25 and -0.28 for gasoline and corn respectively). Therefore the spread coefficient in the second column can simply be divided by 1.25 and multiplied by (-0.28) to derive implicit coefficients for gasoline and corn on the share price, equal to 377,440 and -132,104 respectively. It is informative to explore the ability of this model to fit share prices by comparing its performance with that of a purely econometric framework in which gasoline and corn are allowed to be weighted independently. In this comparator case we do not let the theory in section 2 inform us about the relative weighting of these two variables. Results of this exercise, in levels, are presented in the third column of table 6 where the gasoline and corn coefficients are 326,481 and -185,340, Newey-West regression with 3 lags for

$$\begin{aligned} SharePrice(t) &= \beta_0 + \beta_1 \frac{Capacity(t)}{N_{Shares}(t)}(X(t)-\alpha) + \beta_2 \frac{Capacity(t)}{N_{Shares}(t)}(X(t)-\alpha)^2 + \\ &+ \beta_3 \frac{Debt(t)}{N_{Shares}(t)} + controls(t) + \epsilon(t). \end{aligned}$$

$$\begin{aligned} SharePrice(t) &= \beta_0 + \beta_1 \frac{Capacity(t)}{N_{Shares}(t)} Gasoline(t) + \beta_2 \frac{Capacity(t)}{N_{Shares}(t)} Corn(t) + \\ &+ \beta_3 \frac{Capacity(t)}{N_{Shares}(t)}(X(t)-\alpha)^2 + \beta_4 \frac{Debt(t)}{N_{Shares}(t)} + controls(t) + \epsilon(t). \end{aligned}$$

Sample: 69 monthly observations between January 2012 and September 2017. *, ** and *** indicate significance at the 10%, 5% and 1% levels. Capacity in million of gallons per year.

	GP price level	GP price level	GP price diff.	GP price diff.
K/N spread (level or diff)	471,800***		377,667***	
K/N gasoline (level or diff)		326,481***		291,931**
K/N corn (level or diff)		-185,340***		-125,178**
K/N spreadSq (level or diff)	544,081***	422,342***	417,415**	402,841**
1/N debt (level or diff)	-1.08***	-0.88**	-0.49***	-0.62***
MKT factor (level or diff)	0.08	0.08	0.06**	0.06**
SMB factor (level or diff)	-0.36**	-0.41***	-0.19	-0.19
HML factor (level or diff)	0.23**	0.30***	0.12	0.13*
Trend	0.06	-0.07		
Constant	0.15	26.02	-0.10	-0.14
Adj-R squared	0.81	0.83	0.23	0.22
N obs	69	69	68	68

Table 6: Regression of Green Plains share price on fundamental variables.

in economic proximity to the coefficients for gasoline and corn derived above under the model-based restriction. A similar agreement is apparent by comparing the gasoline and corn coefficients implied by the spread coefficient in the fourth column (302,133 and -105,747) with those in the fifth column (291,931 and -125,178), based in both cases on first differences. Moreover, independently estimating the weights of gasoline and corn does not increase the associated R-squared. Therefore, a regression analysis of the fundamental exogenous factors (gasoline and corn) driving the changes in the value of Green Plains rediscovers the relative weighting for gasoline and corn implied by the theoretical model. In all of our analyses we are making the plausible assumption that variations in the right hand side variables in our regressions are not endogenous in the short term to the value of the ethanol producer.

We also intended to test the sensitivity of firm value with respect to the relevant spread volatility, which is positive within the model. However, this is unfeasible in a direct manner because the expected long term volatility of the spread is not observable in the market. A synthetic substitute would depend on estimates of changes in the long term correlation between corn and gasoline, which are unavailable as well. In unreported tests we estimated the response of the Green Plains share price to changes in short term realized spread volatility, with no significant effects. This might be due to the fact that the value of the firm is equivalent to a portfolio of long dated options and volatility expectations change mostly for short horizons.

3.5. Switching costs

The model in section 2 assumes zero switching costs in a simplification of reality that allows us to derive testable closed form solutions. In the presence of switching costs, the operation policy for a producer is not determined solely by the instantaneous value of the spread $X(t)$ as in section 2. In this case, it is sub-optimal for an initially inactive ethanol producer to start production if $X(t) < \alpha + \epsilon_u$ for some positive ϵ_u. It is also sub-optimal to turn off production for $X(t) > \alpha - \epsilon_d$ for some positive ϵ_d. There is a range $(\alpha - \epsilon_d, \alpha + \epsilon_u)$ for $X(t)$ in which the producer might be active or inactive depending on its recent behavior. Schmit et al. (2009) show that the gap between trigger points to mothball or reactivate an ethanol plant is between 0.5 and 1 US dollars per gallon. The fact that this gap is smaller than the standard deviations of gasoline, corn and ethanol prices implied by figure 3 serves as justification for our zero switching cost assumption in section 2. Under non zero switching costs, as in Brennan and Schwartz (1985), the value function for an inactive producer has a smaller sensitivity with respect to X than the value function for an active producer.

The formulation and empirical testing of a fully developed model with switching costs is beyond both the scope of this paper and of available data. However, in this section we run preliminary tests for the presence of switching costs based on the general remarks made above. We search for evidence of switching costs in the statistics of capacity utilization and in the behavior of Green Plains prices.

We define the excess utilization ratio as the difference between actual capacity utilization ratio and the capacity utilization ratio prescribed by the model with no switching costs. Positive real switching costs would lead to positive excess utilization for $\alpha - \epsilon_d < X(t) < \alpha$ (as firms remain active to avoid immediate payment of switching cost). Switching costs would also lead to negative excess utilization for $\alpha < X(t) < \alpha + \epsilon_u$.

Results in table 7 are mildly consistent with switching costs. Mean estimates for excess utilization ratio are positive and negative for $X(t) \leq \alpha$ and $X(t) > \alpha$ respectively, but with no strong statistical significance. The last two rows in table 7 show excess utilization ratios conditional on $X(t)$ crossing α. Only a few events of this kind are available in our data set. In particular, a decrease in the spread across α leads to a positive excess utilization ratio. This is consistent with a delay in turning production off, Excess capacity utilization conditional on the spread $X(t)$ between gasoline and corn. Monthly data, Jan. 2008 - Sept. 2017.

	Mean excess utilization	N obs
$X(t) \leq \alpha - 0.25$	0.017	27
	(0.013)	
$\alpha - 0.25 < X(t) \leq \alpha$	0.021*	26
	(0.012)	
$\alpha < X(t) \leq \alpha + 0.25$	-0.019	14
	(0.018)	
$\alpha + 0.25 \leq X(t)$	-0.039**	50
	(0.007)	
$X(t) \leq \alpha$ and $X(t-1) > \alpha$	0.08**	5
	(0.02)	
$X(t) > \alpha$ and $X(t-1) \leq \alpha$	-0.06	4
	(0.04)	

Table 7: Historical excess utilization ratios.

relative to the operating policy in a model with no switching costs.

We also test for an indication of switching costs in the behavior of Green Plains' share price. Switching costs imply a range $(\alpha - \epsilon_d, \alpha + \epsilon_u)$ for $X(t)$ in which the producer might be active or inactive depending on its recent behavior. Two value functions coexist in this range. Motivated by Brennan and Schwartz (1985) we test for switching costs indirectly by comparing the slope of the value functions in periods in which the firm was likely active with those periods in which the firm was likely inactive. We associate rising (decreasing) spread episodes with periods of initial inactivity (activity).

We take $\alpha - 0.5 < X(t) < \alpha + 0.5$ as a plausible range in which Green Plains can be active or inactive. Our results in the fourth column in table 8 show a strongly positive coefficient for the spread in the value function after conditioning for decreasing spreads. For rising spreads, in the fifth column, the sensitivity of the value function with respect to the spread is not significantly different from zero. A t-test for the difference of these slope coefficients is significant at the 95% confidence level. Hence, the behavior of Green

OLS regression

$$SharePrice(t) \;=\; \beta_0 + \beta_1 \frac{Capacity(t)}{N_{Shares}(t)}(X(t) - \alpha) + controls(t) + \epsilon(t).$$

Sample: 69 monthly observations between January 2012 and September 2017. *, ** and *** indicate significance at the 10%, 5% and 1% levels. Inner range defined as $\alpha - 0.5 < X(t) < \alpha + 0.5$. Fourth and fifth columns are conditional on rising and decreasing spreads, respectively.

	GP price diff. full sample	GP price diff. inner range	GP price diff. inner range $X(t) - X(t-1) > 0$	GP price diff. inner range $X(t) - X(t-1) < 0$
K/N spread (diff)	216,742***	215,615**	40,324	622,397**
	(77,845)	(80,376)	(137,907)	(227,098)
1/N debt (diff)	-0.1	-0.2	-0.6	1.3
	(0.3)	(0.6)	(0.6)	(1.1)
MKT factor (diff)	0.04	0.02	0.05	-0.05
	(0.03)	(0.03)	(0.04)	(0.07)
Constant	0	0	0.3	1.6
	(0.3)	(0.4)	(0.6)	(1.0)
Adj-R squared	0.13	0.09	0.01	0.14
N obs	68	62	34	28

Table 8: Regression of Green Plains share price on fundamental variables.

Plains' price with respect to $X(t)$ in the vicinity of α is consistent with the presence of switching costs.

4. Conclusions

We have developed and tested a stylized equilibrium model for producers and blenders of ethanol. Producers have the option to turn off unprofitable plants. Blenders choose the composition of fuel by adding ethanol to gasoline while satisfying the minimum government mandate. The cost of corn and the price of gasoline are the fundamental dynamical inputs to the model, which also incorporates engineering settings, industry capacity, government incentives and mandates as external parameters. The model makes several quantitative predictions in analytical form. First, the price of ethanol is the maximum of properly scaled gasoline and corn prices as a consequence of the possibility of substitution between gasoline and ethanol. This observation is supported in the data. We found empirical evidence that between 2008 and 2017 ethanol was alternatively priced as gasoline or as corn with similar frequency. Therefore, we find that models in the literature that fail to account for one of these two drivers are incomplete.

Second, the volume of ethanol production is determined in the model by the relative price of ethanol and gasoline. Production reaches full capacity utilization when gasoline is sufficiently expensive relative to corn and demand for ethanol is high. Production is as low as the government imposed mandate when corn is sufficiently expensive relative to gasoline. We also found empirically that after the RFS was under full effect, industry output largely fluctuated between the minimum level mandated by the government when the production of ethanol was relatively expensive, and its maximum installed capacity when ethanol was relatively cheap. Therefore, we confirmed that the government mandate and installed capacity are quantitatively important in a proper description of the ethanol market.

Third, the value of a producer in the model is that of portfolio of European call options on the gasoline-corn spread. Using data from Green Plains, a major ethanol producer, we confirmed empirically that its share price between 2012 and 2017 was an increasing and convex function of the spread between gasoline and corn, as in the real option derived from the model. We could not properly test volatility dependence for the market value of Green Plains because data for the relevant long term volatility of the gasoline-corn spread was not available. Measures of short term volatility were not significant in their impact on Green Plains. The empirical behavior of Green Plains also suggests the presence of switching costs, which are not accounted for in our model.

Therefore, most pressing among the avenues for future research is the need to model and test the endogenous growth, entry, and exit of ethanol producers under stochastic corn and gasoline prices, and various policies. At the aggregate level we have not considered the interplay between the possibility of ethanol storage, and ethanol, gasoline and corn prices. Finally, the valuation of blenders as large, diversified fuel companies that hold the option to choose the fuel mix, is also left for future research.

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