Uncertainty, Irreversibility, and Investment in Second-Generation Biofuels

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Abstract

The present study formalizes and quantifies the importance of uncertainty, irreversibility, and managerial flexibility for investment in a corn-stover based cellulosic biofuel plant. Using a real options model, we recover prices of gasoline that would trigger entry into the market and compare it to breakeven entry price (long run average cost). Our analysis shows that the price premium (above breakeven) likely to be required by investors to enter the market due to the uncertain and irreversible nature of investment is substantial. Managerial flexibility (embedded by the option of mothballing and reactivating the plant) does not sensibly reduce the entry premium. Results also suggest that price volatility may greatly increase hysteresis (i.e. a range of gasoline prices for which there is neither entry nor exit in the market) in firm behavior and decrease supply elasticity. In combination all of these results suggest that, 1) policies supporting second generation biofuels may have fell short of their targets because of their failure to alleviate price uncertainty, and 2) the use of price-based instruments such as reverse auctions, either in isolation or in combination with mandates, may be warranted.

1 Introduction

Over the past decade, the United States has increasingly pushed for the development of economical forms of renewable fuels. This is due to increased concerns over climate change, energy security, and the desire for domestic job creation. Biofuels in particular, and lately cellulosic biofuels, have received a large amount of attention due to their potential benefits in addressing these problems. The first renewable fuel standard was established in 2005, and expanded to the form used today with the passage of the second renewable fuel standard in 2007 (RFS2). The RFS2 requires by the year 2022, 36 billion gallons of biofuel (ethanol equivalent) to be used annually within the United States, 16 billion of which must come from cellulosic sources. It also sets a cap on the maximum amount of biofuel from corn ethanol at 15 billion gallons.

Despite policy support and high gasoline prices, cellulosic biofuel production has continually fallen well short of mandates set forth by RFS2. In 2013, cellulosic biofuel production totaled six million gallons, 994 million gallons below the target goal of 1 billion gallons for the year set by the RFS2 (Schnepf and Yacobucci, 2010). Numerous studies, in both business and academic realms, have routinely found that a cellulosic biofuel plant built today could have a positive *mean* return on the investment (Anex et al., 2010; Brown et al., 2013; Gonzalez et al., 2012b; Brown and Brown, 2013b; Petter and Tyner, 2014; Jones et al., 2009). However, they have also found that there is significant uncertainty around that mean. For instance Petter and Tyner (2014) found that the probability of economic loss is almost 50%.

Unfortunately the approach used by these studies (net present value of investment) does not allow calculation of an entry trigger price and, consequently, precludes quantification of the role of uncertainty on behavior. The present study applies real options analysis to quantitatively evaluate the hypothesis that, due to the uncertain and irreversible nature of investment in this industry, investors in second-generation biofuels require a substantial premium, above and beyond breakeven gasoline price, that is not covered by currently observed prices. We also hypothesize that managerial flexibility (the possibility of mothballing and reactivating the plant) may reduce such premium. Our results offer insights into the inability of the RFS2 to trigger investment and discusses alternative or complementary policy instruments that can be more effective in addressing uncertainty.

2 Methods

Biofuels are defined as "transportation fuels like ethanol and diesel that are made from biomass materials" (EIA, 2013). Currently there are three main types (generations) of biofuels. First generation biofuels are produced from the sugars found in crops such as corn or sugar cane. These sugars are processed through various pathways to produce ethanol which is then blended with gasoline. Second generation biofuels differ from first generation in that they are produced from cellulosic plant matter such as corn stover, switch grass, or trees rather than sugar (EIA, 2013). They have also recently advanced to the point where the process produces a gasoline or diesel equivalent fuel referred to as a "drop in" instead of ethanol, which is subject to blending limits. Third generation biofuels typically use algae or bacteria to break down a cellulosic feedstock to produce biodiesel (Carere et al., 2008).

This paper focuses on second-generation drop-ins. The advantage of a drop in is that existing combustion engines can burn it without any modifications. This chemical similarity to petroleum-derived fuels gives second-generation biofuels an advantage over ethanol as it eliminates constraints on blending (Tyner et al., 2011). Nine trillion dollars' worth of transportation infrastructure exists in the United States to handle petroleum-based products (Halog and Bortsie-Aryee, 2013). Pipelines cannot transport ethanol and most cars cannot burn a mixture that contains more than ten to fifteen percent ethanol without damaging the engine (Blanco and Isenhouer, 2010; Tyner and Taheripour, 2014). Wholesale gasoline price per gallon is used as a proxy for the price received for a gallon of drop in biofuel as they are, by their chemical nature, perfect substitutes.

Investment in second generation biofuels is subject to a great deal of uncertainty and irreversibility. There are many sources of uncertainty affecting investment in a biofuel plant (Petter and Tyner, 2014). First, there is market uncertainty. The price of gasoline, the cost of stover, hydrogen, even equipment can vary over time. There is also uncertainty inherent within production; i.e. the amount of biofuel that can be produced per ton of biomass processed. In this study we focus on uncertainty caused by volatility in output price; i.e. gasoline price. Several reasons motivate this choice. First, biofuel price is perhaps the most important determinant of plants net revenue (Petter and Tyner, 2014). Second, once a biofuel market is well established technical uncertainty and feedstock price uncertainty will likely diminish, whereas gasoline price uncertainty will remain substantial. Finally, volatility in gasoline price, in contrast to other sources of uncertainty, can be measured and its evolution over time can be modeled and quantified based on historical data.

In addition to being subject to a great deal of uncertainty, investment in a biofuel plant is also largely irreversible. Much of the equipment is specific to the industry. For instance, a tank used for pyrolysis may cost millions of dollars by the time it is installed but if the industry becomes unprofitable it does not have many other uses. If one plant becomes unprofitable due to a systemic risk in the industry, such as low gasoline prices, the only other firms that would be interested in purchasing a pyrolysis tank would be firms in the same industry. They however would not buy it upon the initial plant's exit for anywhere near its purchase price since they would also be in a similar position.

2.1 Real Options Defined

Large-scale investment projects such as second generation biofuel refineries have been evaluated from a Net Present Value (NPV) point of view. The NPV model is centered on standard discounting. Projected revenue and costs are discounted from the future at a pre-specified discount rate. The summation of all of these expected discounted values are combined to compute the expected value of a project in the current period. An NPV analysis of biofuel plants can, and has, incorporated risk. An NPV that incorporates risk by modeling the probability distribution of stochastic variables over the life time of the project allows calculation of a probability distribution of NPVs (Petter and Tyner, 2014). Such analysis allows recovery of conditions under which the probability of a negative NPV is below some threshold.

Unfortunately an NPV approach is not designed to provide estimates of entry (or exit) trigger price. The breakeven price of output (i.e. the price that would result in zero NPV) can be calculated and used as a reference but previous literature (Dixit, 1994) has convincingly argued that such measure greatly underestimates entry prices when investment is subject to substantial uncertainty and irreversibility. Such underestimation comes from the fact that a breakeven price based on present value of future cash flows, ignores the investors' option to wait and invest in the future. In other words, the price at which an investor, operating under rational expectations in an uncertain environment, is indifferent between investing and waiting cannot be recovered from an NPV.

One way of formalizing and quantifying the value of waiting and, consequently, the role of uncertainty in entry trigger prices is using a real options analysis. Factoring uncertainty into the cost/benefit analysis for entry into the biofuel supply chain has recently gained popularity (Schmit et al., 2009; Brandão et al., 2009; Song et al., 2011; Pederson and Zou, 2009; Gonzalez et al., 2012a) but this approach has not been applied to the analysis of investment in a second generation drop-in biofuel plants. This paper fills this gap by developing a real options model of a plant's decision making for optimal entry, exit, mothball, and reactivation trigger prices for a second-generation corn stover fed biofuel plant. Moreover, we calculate entry and exit trigger prices with a real options model that ignores the managerial flexibility embedded in mothball and reactivation. Solving a real options model with and without mothball and reactivation, allows identification of the risk premium required by investors to enter the market and the offsetting effect of managerial flexibility.

2.1.1. Investment States and Transitions

There are three different states a plant can be in: idle, active, or mothballed. In an idle state, a plant is not paying variable or capital costs since it has not been built yet. It is also not receiving income but has the option of activating in the future. An active plant pays an investment cost k to enter the market and then pays, every period, operating costs w, and earns revenue, P. An active plant also has the option of converting to a mothballed state in which the plant is not producing, but it is kept ready for potential reactivation.

To get to a mothballed state an active plant must pay a fixed cost of E_m and pays an ongoing operating mothball maintenance cost m to keep the plant in working order should it decide to use its option of reactivating in the future for a fixed cost r. In a mothballed state a plant also has the option of exiting the industry. In the event that the firm decides to exit the market, it forfeits its mothball maintenance cost, and gets a fraction of the initial capital, l, back. The plant would incur some costs for exiting but after combining them with the value it gets for selling the plant we assume l to be positive. By exiting, a plant also loses its option to reactivate. The ability to switch between these different states is represented in Table 1, where an X (-) indicates that transition from the state indicated in the row to the state indicated in the column, is (not) possible.

Table 1. States and Transitions

	Idle	Active	Mothballed
Idle	-	X	-
Active	-	-	X
Mothballed	X	X	-

We denote output prices that trigger entry, mothball, exit, and reactivation under real options by P_h, P_m, P_l, and P_r respectively. The output prices that trigger entry and exit under Marshallian behavior (waiting is not an option and expectations are myopic) are denoted by W_h and W_l respectively. The wholesale price of a gallon of bio-gasoline is denoted by P. This price is assumed to be log-normally distributed and, consequently, its change over time is modeled according to a Geometric Brownian Motion (GBM) process.[1]

GBM is a stochastic process that allows incorporation of a drift parameter and a random parameter governing the evolution of gasoline price. The GBM process is depicted as $dP = \mu P dt + \sigma P dz$. A change in price ($dP$) is dependent upon a combination of the drift rate (μ) and the passage of time (dt). The change in price is also determined by a random shock (dz) in combination with the standard deviation, σ. The shock is a function of random noise and time,

[1] This assumption is consistent with statistical tests conducted with historical gasoline price data. Tests will be presented and discussed in detail in Section 2.2.

$dz = \varepsilon_t \sqrt{dt}$. The factor ε_t is a random variable distributed standard normal, so the unconditional expectation of dz is equal to zero.

2.1.2. Value of an idle investment

Let us denote an idle project's discounted expected value by $V_0(P)$. An idle plant has no revenue or expenses, but can earn profits in the future if the option to enter is exercised and the plant is brought to an active state. As shown elsewhere (Dixit, 1994) the Bellman equation describing optimal behavior of a firm holding the option to invest in a project is:

$$\delta V_0(P)dt = E_t[dV_0(P)] \tag{1}$$

where δ is the discount rate dt is an infinitesimal time period, and the rest is as defined before.

Equation (1) simply states that the expected return on the investment opportunity over a time interval dt is equal to the project's expected rate of capital appreciation.

The value of the idle project, $V_0(P)$, is a function of gasoline price which is, in turn, a random variable following a geometric Brownian motion process. Applying Ito's Lemma yields:

$$dV = \frac{\partial V}{\partial P} dP - \frac{\partial^2 V}{2\partial P^2} dP^2 \tag{2}$$

Substituting dP (the GBM defined before) into (2) yields:

$$dV = \frac{\partial V}{\partial P}(\mu P dt) + \frac{\partial^2 V}{\partial P^2}\left(\frac{1}{2}\sigma^2 P^2 dt\right) + \frac{\partial V}{\partial P}\ (\sigma P dz) \tag{3}$$

Substituting (3) into (1), dividing both sides by dt, and taking expectations results in:

$$\delta V_0(P) = \ E_t\left[\frac{\partial V}{\partial P}(\mu P) + \frac{\partial^2 V}{\partial P^2}\left(\frac{1}{2}\sigma^2 P^2\right)\right] + E_t\left[\frac{\partial V}{\partial P}\sigma P dz(dt^{-1})\right] \tag{4}$$

Given that dz is proportional on ε_t which is distributed standard normal, $E_t[dz] = 0$.

Hence, equation (4) is simplified to:

$$\delta V_0(P) = \frac{\partial V}{\partial P}(\mu P) + \frac{\partial^2 V}{\partial P^2}\left(\frac{1}{2}\sigma^2 P^2\right) \tag{5}$$

Equation (5) constitutes a second order homogenous ordinary differential equation. As such, it has the solution (Dixit, 1994, p. 213-235):

$$V_0 = A_0 P^{-\alpha} + B_0 P^{\beta} \quad (6)$$

Parameters α and β capture and incorporate the uncertainty modeled by GBM into the model:

$$-\alpha = 0.5[(1 - 2\mu\sigma^{-2}) - ((1 - 2\mu\sigma^{-2})^2 + 8\delta\sigma^{-2})^{.5}] < 0$$

$$\beta = 0.5[(1 - 2\mu\sigma^{-2}) + ((1 - 2\mu\sigma^{-2})^2 + 8\delta\sigma^{-2})^{.5}] > 1$$

where A_0 and B_0 are unknown constants. The term $A_0 P^{-\alpha}$ represents the option value of changing states if output price decreases, and $B_0 P^{\beta}$ represents the option value of switching to another state if output price increases. The term $A_0 P^{-\alpha}$ vanishes when the project is idle as there is no value to the project when output price approaches zero. Therefore:

$$V_0 = B_0 P^{\beta} \quad (7)$$

2.1.3. Value of an active investment

We denote an active project's discounted expected value by $V_1(P)$. A plant in an active state is producing biofuel and earning an ongoing net revenue stream (per liter) equal to $P - w$. The Bellman equation in this state is depicted by:

$$\delta V_1 dt = (P - w)dt + E_t[dV_1(P)] \quad (8)$$

The value function V_1 is derived following the same procedure by which we derived V_0. Such procedure results in:

$$V_1(P) = P(\delta - \mu)^{-1} - w\delta^{-1} + A_1 P^{-\alpha} + B_1 P^{\beta} \quad (9)$$

where A_1 and B_1 are unknown constants, $A_1 P^{-\alpha}$ and and $B_1 P^{\beta}$ capture the option value of mothballing the plant if output price decreases and the option value of mothballing if the output price increases respectively. When the output price is sufficiently high to induce the firm to keep the plant active, B_1P^{β} converges to zero. Therefore:

$$V_1(P) = P(\delta - \mu)^{-1} - w\delta^{-1} + A_1P^{-\alpha} \tag{10}$$

We now look at a situation where a firm that has a mothballed plant, has the option to reactivate or exit the market altogether.

2.1.4. Value of a mothballed investment

A firm with a plant in a mothballed state is experiencing an ongoing maintenance cost of m. The Bellman equation for a plant in a mothballed state is:

$$\delta V_m dt = E_t[dV_m(P)] - m(dt) \tag{11}$$

By using the same procedure used for equations (1) and (8) this expression converts to:

$$V_m(P) = A_mP^{-\alpha} + B_mP^{\beta} - m\delta^{-1} \tag{12}$$

where A_m and B_m are unknown constants, $A_mP^{-\alpha}$ represents the option value of being able to exit, B_mP^{β} represents the option value of being able to reactivate, and $m\delta^{-1}$ represents the present value of maintenance cost if the plant never changes states. The option value to exit is positive only if the price decreases, and the option value to reactivate is positive only if the price increases which is why each option has only one term.

2.1.5. Deriving the Trigger Prices

Our representative plant has the option to switch from idle to active, active to mothballed, mothballed to exit, and mothballed to active at any given point in time. Each of these options will be exercised at a specific price which we denote by P_h, P_m, P_l, and P_r respectively. These prices are referred to as trigger prices. Trigger prices are characterized by two conditions known as the value matching condition and the smooth pasting condition at each switching point. The value matching condition depicts the output price at which the firm is indifferent between two states. Switching occurs when, due to a change in output price, the value of the project under the current state becomes lower than the value of the project under the state to which the firm would like to switch minus the switching cost. Switching costs are denoted by k, E_m, r, or l when the firm switches to from idle to active, active to mothball, mothball to reactivation, and mothball to exit respectively. The smooth pasting condition requires these value functions to be tangent to one another at the trigger price.

We start by looking at the trigger price for switching a biofuel plant from an idle state to an active state. The value matching condition occurs between these two states at a gasoline price we denote by P_h. At this price, the value of the option to enter equals the value of an active project minus the fixed cost of switching states k:

$$V_0(P_h) = V_1(P_h) - k \tag{13}$$

The corresponding smooth pasting condition between these two states is:

$$V'_0(P_h) = V'_1(P_h) \tag{14}$$

The value matching condition corresponding to the transition from active to mothball can be denoted by:

$$V_1(P_m) = V_m(P_m) - E_m \tag{15}$$

where P_m represents the trigger price that will take a plant from an active state to a mothballed state and E_m denotes the fixed cost of mothballing. The corresponding smooth pasting condition between active and mothballed states is:

$$V'_1(P_m) = V'_m(P_m) \tag{16}$$

A mothball state has two options for switching states. It can change back to an active state for a fixed reactivation cost of r. It could also change back to an idle state and receive a net scrap value l. Since there are two options for this state there needs to be two value matching conditions and two smooth pasting conditions satisfied. The decision to move from a mothballed state to an active state occurs at P_r. The value matching condition for this is:

$$V_m(P_r) = V_1(P_r) - r \tag{17}$$

The corresponding smooth pasting condition is:

$$V'_m(P_r) = V'_1(P_r) \tag{18}$$

The value matching condition between a mothballed state and an idle state is:

$$V_m(P_l) = V_0(P_l) - l \tag{19}$$

The corresponding smooth pasting condition is:

$$V'_m(P_l) = V'_0(P_l) \tag{20}$$

We now substitute value functions (7), (10), and (12) into their corresponding value matching equations (13), (15), (17), and (19) at their designated trigger prices and the derivative of the value functions with respect to P into the smooth-pasting equations (14), (16), (18), and (20). These substitutions result in a nonlinear system of eight equations in eight unknowns. Four of these unknowns are trigger prices (P_h, P_m, P_r, P_l) and the other four are constants associated with the option value of switching states (A_1, A_m, B_0, and B_m):

$$B_0 {P_h}^{\beta} = P_h(\delta - \mu)^{-1} - w\delta^{-1} + A_1 {P_h}^{\alpha} - k \tag{21}$$

$$P_m(\delta - \mu)^{-1} - w\delta^{-1} + A_1 {P_m}^{\alpha} = A_m {P_m}^{\alpha} + B_m P^{\beta} - m\delta^{-1} - E_m \tag{22}$$

$$A_m {P_r}^{\alpha} + B_m {P_r}^{\beta} - m\delta^{-1} = P_r(\delta - \mu)^{-1} - w\delta^{-1} + A_1 {P_r}^{\alpha} - r \tag{23}$$

$$A_m {P_l}^{\alpha} + B_m {P_l}^{\beta} - m\delta^{-1} = B_0 {P_l}^{\beta} - l \tag{24}$$

$$\beta B_0 {P_h}^{\beta - 1} = -P_h(\delta - \mu)^{-2} + \alpha A_1 {P_h}^{\alpha - 1} \tag{25}$$

$$-P_m(\delta - \mu)^{-2} + w\delta^{-2} + \alpha A_1 {P_m}^{\alpha - 1} = \alpha A_m {P_m}^{\alpha - 1} + \beta B_m P^{\beta - 1} \tag{26}$$

$$\alpha A_m {P_r}^{\alpha - 1} + \beta B_m {P_r}^{\beta - 1} + m\delta^{-2} = -P_r(\delta - \mu)^{-2} + \alpha A_1 {P_r}^{\alpha - 1} \tag{27}$$

$$\alpha A_m {P_l}^{\alpha-1} + \beta B_m {P_l}^{\beta-1} = \beta B_0 {P_l}^{\beta-1} \tag{28}$$

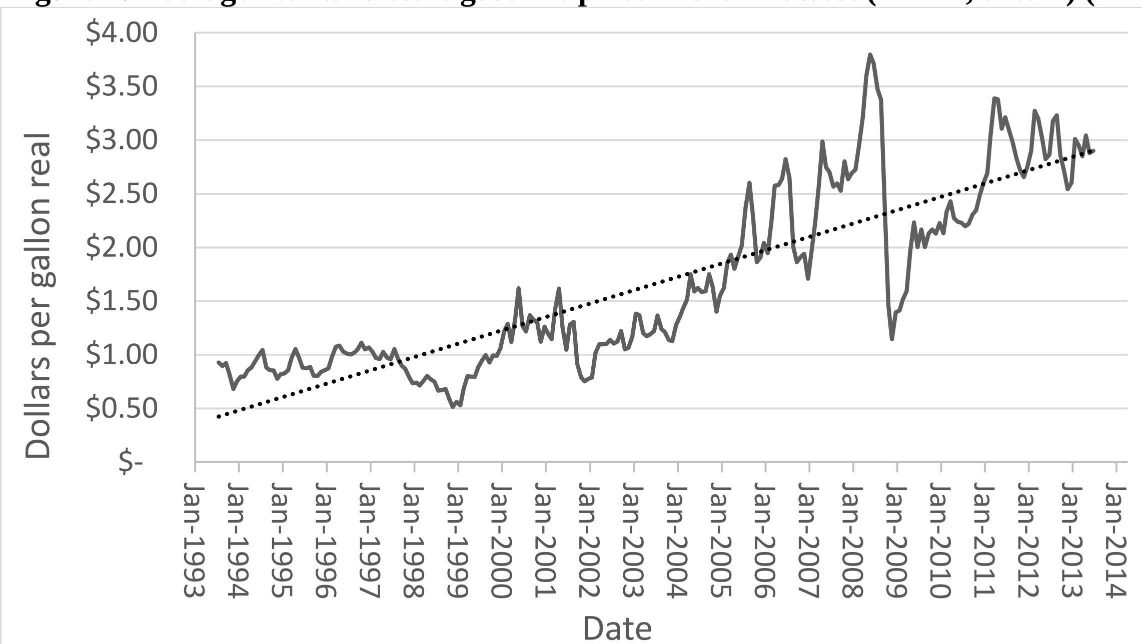
The first four equations constitute direct corollaries of the value matching conditions and the next four equations are derived from the smooth pasting conditions. This system is solved numerically in Matlab using the code presented in Appendix A. Solution of the system without managerial flexibility (i.e. without the option to mothball and re-entry) is, in turn, presented in Appendix B.

2.2 Price of Gasoline: Identification of the Stochastic Process

There is significant variation in gasoline price (P) from year to year. This variation in P over time, can either evolve following a stationary or a non-stationary process. These processes are most simply and commonly modeled using a mean reversion or Brownian motion (including GBM) process respectively (Dixit, 1994). Therefore the validity of assuming a GBM as the data generating process (DGP) of gasoline prices is evaluated by conducting a unit root test for non-stationarity of the price series. If the change in price between two periods is not a function of the price in the first period, then a Dickey Fuller unit root test will fail to reject the null hypothesis of non-stationarity (Wooldridge, 2012) and a GBM is more appropriate than a mean reverting process.

Mathematically this explanation is modeled as $P_t - P_{t-1} = a + b(P_{t-1}) + e$ or, including a drift, $P_t - P_{t-1} = a + b(P_{t-1}) + c\mu + e$, where P_t is the price in period t, P_{t-1} is the price lagged by one period, a is the intercept, e is the residual, and b is the slope which is the parameter to be tested. If $b = 0$ (null hypothesis), the data is non-stationary and a GBM is an appropriate specification of gasoline prices. We conducted unit root tests under both specifications; i.e. with and without a drift. Dickey-Fuller tests were run with STATA based on average monthly wholesale gasoline prices in the Midwest for the past twenty years (Figure 1). The test fails to reject nonstationarity with the first specification (test statistic of -1.48) but rejects nonstationarity under the second specification (test statistic of -3.50). These answers give conflicting results.

Figure 1. Average real wholesale gasoline price in the Midwest (PADD, area 2) (EIA, 2013)



There has been a large amount of debate in the literature over the similarity in results given by models using GBM and those resulting from use of mean reversion assumptions (Pindyck, 1999; Sarkar, 2003; Metcalf and Hassett, 1995). Based on that literature a case for using a GBM process to model gasoline prices can be made despite these conflicting results. First, GBM has the advantage of analytical tractability (Dixit, 1994). Secondly, a mean reverting process converges asymptotically to a GBM process as the rate of mean reversion tends to zero (Sarkar, 2003; Pindyck, 1999; Metcalf and Hassett, 1995). Pindyck (1999) and Metcalf and Hassett (1995) argue that a Brownian motion is a good approximation even if the true DGP is a mean-reverting one as long as the speed of reversion is low.

We have estimated the rate of mean reversion to determine the appropriateness of a GBM as an approximation to the data generating process. In particular we regressed the change in gasoline wholesale prices on its lagged price, with and without drift rate. Estimates of mean reversion, η, are highly sensitive to the period of time considered (subsets of the last twenty years) and range from zero to 0.66. Again, these estimates offer conflicting views. Henceforth, with the caveat that there is significant uncertainty on reversion speed, we assume gasoline prices follow a GBM process.

Given recent potential structural changes in the oil and gasoline markets, instead of extrapolating past price trends to the future, we use the U.S. Energy Information Administration (EIA, 2014) 30 year projections for wholesale gasoline prices. This gives us a drift rate of 1.85%. Unfortunately, the EIA offers no projections for standard deviation so extrapolation of past standard deviation is our only option. The yearly standard deviation in percentage changes in gasoline price over the past five years was 0.21 (0.35 over the last twenty years). For our base case analysis we use the more conservative estimate since dramatic spikes in prices during 2004-2007, and the subsequent crash in 2008, may result in overestimation of past, and consequently future, standard deviation of gasoline prices.

Consistently with the assumption of GBM for gasoline prices, we have calculated the standard deviation of $\ln(\frac{P_t}{P_{t-1}})$ as prices are assumed to be log-normally distributed (Schmit et al., 2009; Dixit, 1994). The standard deviation can be interpreted as the standard deviation of a one percent change in price. We use prices in the Midwest since a stover fed plant would most likely locate and sell there, due to high corn density and low transportation cost to local markets.

2.3 Fixed and Operating Costs

There are three main types of second-generation technology that converts cellulosic biomass into biofuels. These technologies are gasification, hydrolysis, and fast pyrolysis (Hughes et al., 2013; Brown and Brown, 2013a). We analyze the case of fast pyrolysis as it has been found to be the most cost-competitive process to produce drop-in biofuels (Wright et al., 2010; Brown and Brown, 2013a; Petter and Tyner, 2014).

Unless otherwise noted we use fixed and operating costs reported by Brown et al. (2013). These costs are summarized in Table 2. The operating cost w, is calculated by combining yearly operating cost in Brown et al. (2013), our calculations for capital replacement, and federal tax. Capital replacement is added into w to ensure an infinite life of the plant.[2] The cost of replacing capital is calculated by annualizing capital cost. We assume a 20% effective tax rate on net income. Yearly operating cost is then divided by the number of gallons of biofuel the plant produces a year. This paper breaks operating cost into four categories, stover cost, hydrogen cost, capital replacement cost, and miscellaneous. These costs are reported in Table 2 and were obtained from Brown et al. (2013) with the exception of feedstock cost. Total yearly operating cost per gallon (for a plant producing 47.4 million gallons per year) is equal to $w = \$2.56$.

Table 2. Operating costs per gallon for project

Stover	$1.15
Hydrogen	$0.51
Depreciation upkeep	$0.79
Miscelaneous	$0.11
Total	**$2.56**

Regarding the cost of feedstock, the literature offers a wide range of estimates. The predicted cost for one dry metric ton of stover delivered to the plant ranges from approximately $16 to $112. (Gallagher et al., 2003; Fiegel et al., 2012). Most predictions fall into a range between $40 and $101 (Brechbill et al., 2011; Perrin et al., 2012; Brown et al., 2013; Gonzalez et al.,

[2] The assumption of infinite horizon greatly simplifies the problem. On the other hand, this assumption may overestimate the entry trigger price. However the upward bias generated by the infinite horizon assumptions has been found to become very small when time to maturity is 20 years (Grasselli, 2011). Since cellulosic biofuel plants are typically assumed to operate for 20 years (e.g. Petter and Tyner, 2014; Brown et al. 2013), we assume an infinite horizon.

2012b). These discrepancies in predicted cost exist due to the fact that the corn stover market remains largely undeveloped and assumptions on nutrient replacement, soil effects of removal, corn yields, weather, and tillage vary widely across studies (Wilhelm et al., 2004). In this study we assume that a refinery can purchase a ton of stover at \$83 a dry ton, which seems a reasonable central tendency of previously reported estimates. Finally, while Brown et al. (2013) assumed that 85 gallons of bio-gasoline can be obtained per metric dry ton of stover processed, Kior, which is currently the only commerical scale cellulosic biofuel drop-in plant reported a yield of 72 gallons per metric dry ton (Biofuels Digest, 2013). Kior's reported value is used in this study.[3]

In this paper, capital cost k, is calculated as the present value of investment cost. The assumptions under which capital cost is calculated are reported in Table 3. The construction period is three years. The plant pays back the investment cost with interest in full after three years of construction. Our model assumes 100% loan financing for only the three years of construction. We then took the principal of this loan after three years, paid it all at once, and divided by capacity to obtain k. Notice that the financing assumption was only used to calculate the principal. This cost is then divided by the total number of gallons produced in a year to get $k = \$9.91$ per gallon of plant capacity.

Table 3. Assumptions for Financing

Parameter	Value	Source
Investment cost	\$429,000,000	Brown et al. 2013
Construction time	3 years	Wright et al. 2010
% of investment in year one	8%	Wright et al. 2010
% of investment in year two	60%	Wright et al. 2010
% of investment in year three	32%	Wright et al. 2010
Interest rate	7.5%	Wright et al. 2010
PV of investment cost (after interest)	\$470,350,236	author's calculation
Gallons of bio-gasoline produced per year	47,448,000 gallons	author's calculation

[3] A note of caution is in place here. Kior's primary feedstock is yellow pine and previous studies suggest that there could be a yield reduction when converting from yellow pine to corn stover (Demirbas, 2011; Brown et al., 2013).

The parameters E_m, $r, l,$ and m are all calculated as percentages of k. Due to the infancy of this industry, there is little information on the costs associated with mothballing and reactivation for second generation drop in biofuel plants. Following Schmit et al. (2009), who conducts a real options analysis for a first generation corn ethanol plant, m was calculated as $0.025k$ and l was calculated as $0.25k$. Slight modifications were introduced to E_m and r relative to Schmit et al. (2009). Schmit et al. (2009) adjust pre-existing estimates based on the scale of production of the plant they are analyzing and find that $E_m = 0.05k$ and $r = 0.1k$. We follow this procedure and adjust these figures to our plant which is approximately four times larger than the largest ethanol plant in Schmit et al. (2009). The adjustment results in $E_m = 0.025k$ and $r = 0.05k$. All parameter values used in our analysis are summarized in Table 4.

Table 4. Assumptions of all parameters used in this study.

Parameter	Definition	Value	Scale	Source
μ	Drift rate	1.85%	per year	EIA 2014
σ	Standard deviation	20.92%	per year	EIA 2014
δ	Discount rate	10.00%	per year	Brown et al. (2013)
i	Interest rate	7.50%	per year	Brown et al. (2013)
w	Operating cost	\$2.56	per gallon produced	Brown et al. (2013)
m	Mothball maintenance cost	\$0.25	per gallon produced	Schmit et al. (2009)
k	Capital cost	\$9.91	per gallon of total capacity	Brown et al. (2013)
l	Scrap value	\$2.48	per gallon of total capacity	Schmit et al. (2009)
Em	Mothball fixed cost	\$0.25	per gallon of total capacity	Schmit et al. (2009)
r	Reactivation cost	\$0.50	per gallon of total capacity	Schmit et al. (2009)

3 Results and Discussion

Trigger prices resulting from numerical solution of the system (21)-(28) are reported in Table 5. Trigger prices of entry, mothball, reactivation, and exit are denoted by P_h, P_m, P_r, and P_l

respectively. Entry and exit trigger prices calculated without managerial flexibility (without mothballing and reactivation) were obtained from value matching and smooth pasting conditions depicted in Appendix B, and are also reported in Table 5 and denoted as $\hat{P}_h$ and $\hat{P}_l$. The Marshallian entry trigger price, W_h, is the long run average cost, composed of operating cost and the interest on the sunk cost of investment, $W_h = w + ik$ (Dixit, 1994, pp 219). This is, essentially, the price at which the firm breaks even. The Marshallian exit trigger price, W_l, is the average variable cost plus the interest on scrap value, $W_l = w + il$ (Dixit, 1994, pp 219), and the rest is as defined in Table 4. Entry and exit trigger prices under Marshallian behavior (which assumes static expectations, as opposed to rational expectations assumed by real options) are also calculated and reported in Table 5 for comparison with real options.

Table 5: Marshallian trigger prices and real options trigger prices

Trigger price	Price trigger occurs	Definition
W_h	$0.87	Marshallian entry trigger price
W_l	$0.73	Marshallian exit trigger price
P_h	$1.29	RO entry price with managerial flexibility
P_l	$0.51	RO exit price with managerial flexibility
P_m	$0.51	RO mothball price
P_r	$0.76	RO reactivation price
$\hat{P}_h$	$1.29	RO entry without managerial flexibility
$\hat{P}_l$	$0.51	RO exit without managerial flexibility

Under parameter values in Table 4, results suggest that uncertainty plays a major role in both the decision to enter and the decision to exit. The real options entry trigger price, P_h, is 50% above the Marshallian entry trigger price, W_h. Real option exit trigger price, P_l, is 30% lower than the Marshallian exit trigger price, W_l. Our results demonstrate that, under our assumed level of uncertainty and drift rate, a Marshallian approach would greatly underestimate the price of gasoline that would trigger entry into the market. This, in turn, shows the importance of using real options to evaluate entry into the second generation biofuel industry. Moreover, our results indicate that managerial flexibility has almost no impact on entry behavior. Having the option to mothball and reactivate later does not reduce entry trigger price (as conceptually expected). Similarly, managerial flexibility has no effect on exit trigger prices.

Volatility and drift rate of gasoline price are not only critical drivers of these results but also highly uncertain parameters. Therefore it is important to conduct sensitivity analysis to evaluate the robustness of our results to changes in those parameters. Results from such sensitivity analysis are reported in Figures 2-5. We will discuss each in turn. Figure 2 shows how changes in volatility of gasoline price affects the trigger price for entry. This graph compares the real option entry price (the price $\hat{P}_h$ is used so that the effect of uncertainty is not confounded with managerial flexibility) with Marshallian entry price.

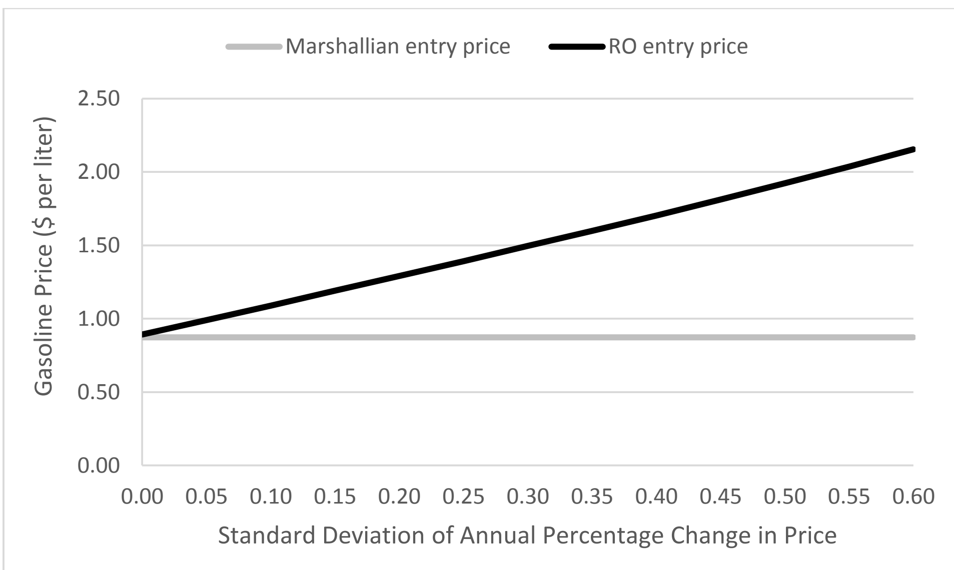


Figure 2. Entry trigger prices over different levels of uncertainty

As revealed by Figure 2, the gap between W_h and $\hat{P}_h$ vanishes under certainty; i.e. when $\sigma = 0$. Increased uncertainty has no effect on Marshallian entry trigger price as this value assumes static expectations, so that a more volatile gasoline price in the future is not incorporated into current behavior. The real option entry trigger price raises with increased gasoline price volatility as the real options framework considers rational expectations (Dixit, 1994). Results show that investors will ask for a higher price premium to enter the market as gasoline price volatility increases. The real option entry trigger price seems quite sensitivity to changes in volatility. It is worth noting that even if gasoline price volatility is halved (from currently observed 20% to 10%), the real option entry price is still 25% higher than the breakeven price.

Uncertainty and irreversibility in investment may result in conservative firm behavior. Firms are less responsive to profitability signals because they are anticipating potential changes in these signals in the future. Technically, this inaction is called hysteresis and it denotes a situation in which firms tend to maintain the status quo and avoid switching to other states. **Error! Reference source not found.** illustrates the link between uncertainty and hysteresis. If gasoline price varies within the entry and reactivation boundaries in **Error! Reference source not found.**, idle plants will not be activated and active plants will not be mothballed. If gasoline price varies between the reactivation and mothball boundaries, idle plants will not be activated, mothballed plants will not be reactivated, and active plants will not be mothballed. Moreover, if gasoline price varies between the exit and mothball boundaries idle plants will not be activated, and mothballed plants will not be reactivated or sold. Figure 3 reveals that these zones of hysteresis widen as gasoline price volatility increases.

The positive link between uncertainty and hysteresis has important policy implications. First, an increase in gasoline price volatility, which has been the case over the past decade (EIA 2014), makes firm entry into the market more unlikely. This result suggests that, if policies designed to support biofuels remain unadjusted, recent increases in gasoline price volatility may have greatly diminished their effectiveness, and their likelihood of success. Second, the volatility in gasoline price is associated with volatility in oil prices. Therefore as volatility of oil price raises, hysteresis in the biofuel market will increase (as indicated by a widening of the vertical distance between lines) resulting in an increasingly inelastic industry supply. The inelastic nature of supply may generate large swings in bio-gasoline prices as production levels adjust lethargically to demand shocks. Therefore supply inelasticity exacerbates the volatility of bio-gasoline prices relative to oil and regular gasoline, reducing even more the effectiveness of biofuel policies.

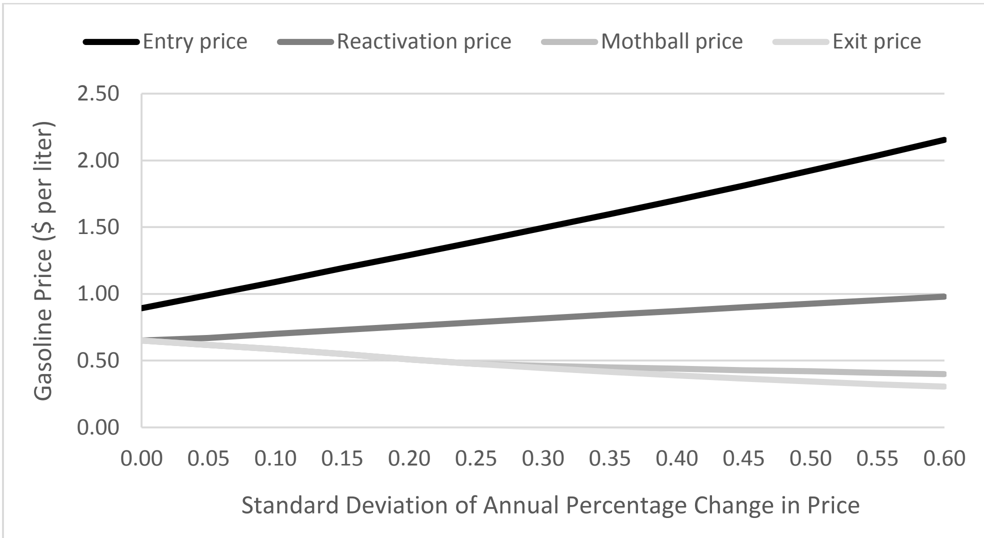


Figure 3. The impact of uncertainty on hysteresis

Figure 3 also reveals that mothball and exit trigger prices converge at 25% volatility. This means that firms will not be interested in mothballing the plant at low prices for levels of price volatility of 25% or lower. At these levels of uncertainty, if the price drops significantly the firm will exit the market without mothballing the plant first. When uncertainty is low enough, profitability signals embedded in gasoline price are taken with certain degree of confidence; i.e. they are not expected to change significantly in the future. This makes firms less likely to switch to intermediate states such as mothballing. A high cost of mothballing, all else constant, will also make firms less likely to switch to that state. Therefore for a given vector of costs associated with entry (k), mothball (m and E_m), reactivation (r), and exit (l), there will be a level of uncertainty that is low enough to reduce the value of mothballing to zero. Figure 3 reveals that, given our estimated costs, that level of uncertainty is 25%. Note, finally, that under 25% volatility the reactivation trigger price is trivial since that plant will never be mothballed and, as a result, will not be reactivated.

It is important to compare, at our assumed levels of volatility and drift rate, the inactivity zone under real options to the inactivity zone under Marshallian entry and exit trigger prices. The difference reveals the importance of firms' expectations formation process on behavior. With a 20% volatility in gasoline price and 1.85 drift rate, no entry or exit occurs under myopic expectations (Marshallian prices) between \$0.87 per liter and \$0.73 per liter. Under the same volatility and drift rate, the range of inaction under rational expectations (real options prices) takes place between \$1.29 and \$0.51. This demonstrates that, under rational expectations, firms incorporate future potential changes in profitability signals and, consequently, behave much more conservatively. This suggests that using breakeven analysis or NPV, even incorporating risk, may greatly overestimate firms' reactions to changes in prices driven by policy or market conditions due to their failure to incorporate rational expectations.

The positive drift rate calculated for wholesale gasoline price reveals an expected improvement in profitability. We explore whether such expected improvement in future profitability affects entry trigger price and to what extent that effect is magnified or softened by uncertainty and irreversibility. Figure 4 displays the relationship between drift rates and entry trigger prices under real options and Marshallian behavior.

An increase in drift rate has conflicting effects on real option entry trigger price.[4] On one hand, a higher drift increases the value of waiting since profitability conditions become more favorable in the future (i.e. because future prices are discounted by $\delta - \mu$). On the other hand a

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[4] This figure uses real options entry and exit trigger prices without managerial flexibility so that the effects of such flexibility are not confounded with those of uncertainty and irreversibility. It is worth noting, however, that prices with and without managerial flexibility are virtually the same.

higher drift lowers the likelihood of negative outcomes in the short run, making investment now more attractive. The latter effect dominates the former so that increases in the drift rate reduce entry trigger prices under rational expectations. Since Marshallian behavior assumes myopic expectations, the Marshallian entry price is not affected by the future trajectory of gasoline price. Therefore increases in the drift rate decrease the price premium required by investors to enter the market above and beyond the breakeven price (i.e. long term average cost).

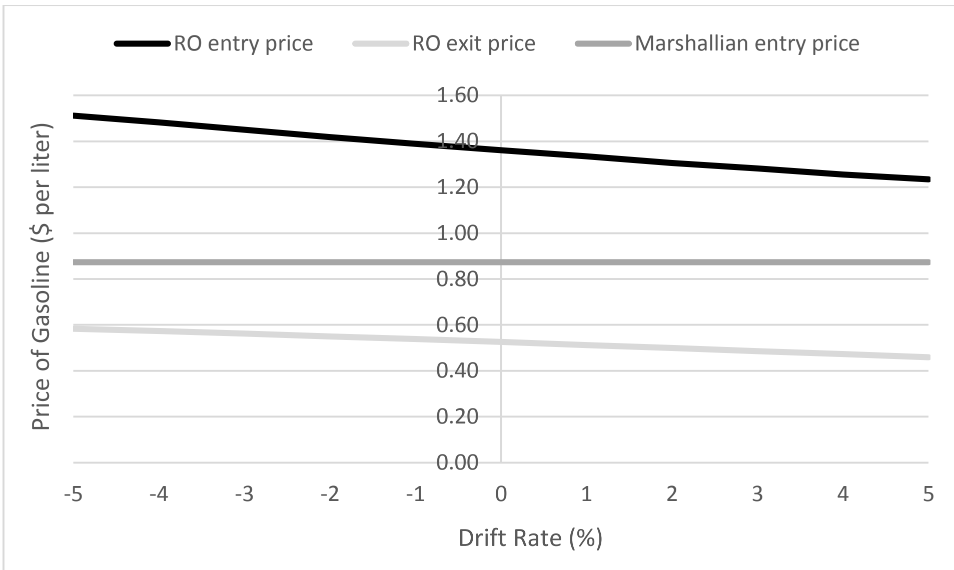

Figure 4. Drift Rate and Entry Trigger Prices

Results in Figure 4 suggest that policies aimed at increasing the future price of bio-gasoline without substantially reducing uncertainty may not be very effective at inducing entry into the market. As shown in Figure 4, while increases in drift rate are associated with lower entry trigger price, the reduction in such price is very modest. Therefore these results may offer an explanation to the fact that quantity instruments, namely the RFS2, have not been very effective. On the other hand, price instruments, which by design reduce price uncertainty, may be much more effective as suggested by results in Figure 3.

Figure 4 also displays the real options exit trigger prices so that we can explore the sensitivity of hysteresis (the range of inaction) to the drift rate. While higher drift rates slightly decrease hysteresis (i.e. the distance between entry and exit frontiers), they do so at a small rate. In fact the drift rate has a close to proportional effect on entry and exit trigger prices. Hence uncertainty and irreversibility, as opposed to drift rates, are the main drivers of hysteresis within the biofuel industry. Therefore, this furthers the argument that policies that increase drift rate, in addition to being relatively ineffective at inducing entry, may also be ineffective at increasing the elasticity of aggregate bio-gasoline supply.

The cost or even the possibility of mothballing and reactivation assumed in this study are highly uncertain, as there are no market observations based on which these can be assessed. It is then important to understand entry and exist behavior when such flexibility is not available to firms. Managerial flexibility enhances the profitability of plants facing random prices. Therefore it is expected that managerial flexibility will alleviate uncertainty and reduce the price premium required by investors. Consequently, the absence of managerial flexibility should raise the price premium required by investors but the magnitude of such increase is unknown.

Fortunately our framework allows calculation of trigger prices without managerial flexibility as well as with flexibility. This allows us, not only to determine the price premium for entry without flexibility but also the magnitude of the offsetting effect of flexibility on uncertainty and irreversibility. Real options entry trigger prices with and without flexibility and Marshallian entry trigger price are plotted in Figure 5. The price premium required for entry is depicted by the vertical distance between these lines. Results in Figure 5 suggest that managerial flexibility has virtually no effect on the price premium required by investors at all levels of uncertainty. Therefore, the absence of flexibility would not worsen the prospects of entry into the industry. In other words, our results in terms of price premiums for entry are robust to the assumption of flexibility held in this study.

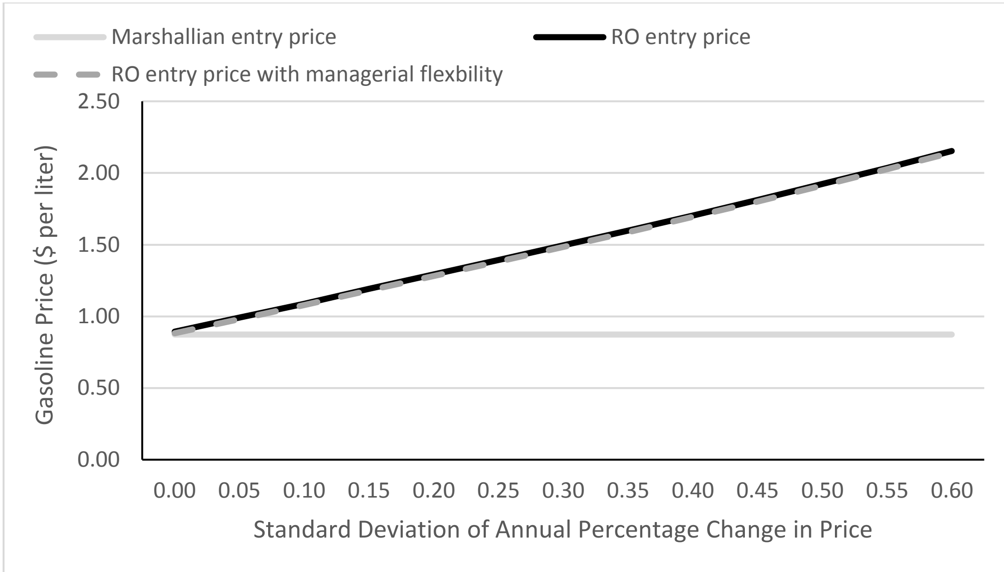

Figure 5. Volatility and Entry Trigger prices

4 Conclusion and Policy Implications

This study has used a real options approach to compute the premium (above and beyond breakeven price) that investors would require on the price of gasoline to enter the biofuel market. It has also computed mothball, reactivation, and exit trigger prices for a range of uncertainty levels, captured by the volatility of percentage changes in gasoline price.

Our analysis reveals that uncertainty is likely a significant barrier to market entry in the cellulosic biofuels industry. It also reveals that managerial flexibility, if technologically viable, does not alleviate the effect of uncertainty on the price premium required for entry. Moreover there seems to be significant potential for hysteresis in this market which will greatly inhibit supply response to demand shocks, magnifying price volatility. Hysteresis is positively associated with gasoline price volatility. Expectations of future increases in gasoline price (positive drift rate) help the prospects of the cellulosic biofuel industry only to a small degree.

The US government has, so far, implemented a quantity-based policy (RFS2), by which gasoline blenders are forced to purchase a minimum amount of biofuels. Yet, this policy has failed to achieve the stated targets. Our analysis may offer some insights into the failure of the RFS2.

Mandates impose a lower bound on demand. This demand level would, in theory, intersect supply at a price that is high enough to induce the desired production. However, an aggregate supply does not currently exist in the cellulosic biofuel industry, so the price that would result from the intersection of supply with the government mandated demand is unknown. Therefore this policy fails to address price uncertainty which, according to our analysis, may severely dampen its effectiveness. Other policies that have been implemented alongside the RFS2 are subsidies to lower production cost (e.g. biomass crop assistance program), and programs that enhance financing conditions. While both policies may result in a reduction of entry premiums (by reducing w and k respectively), they also fail to address the price uncertainty that introduces a wedge between breakeven price (Marshallian entry price) and real options entry trigger price.

These insights suggest that price-based policy instruments, by directly hindering output price volatility, may be more effective than renewable fuel standards. Therefore policy instruments such as reverse auctions or minimum prices could be viable avenues to end with the chronic production shortage that has forced the government to repeatedly waive the RFS2. Our analysis demonstrated that reductions in price volatility, even if leaving future trend of gasoline price unaffected, can substantially reduce the price premium required by investors to enter the market.

However, under zero bio-gasoline price volatility, the entry trigger price is reduced to \$0.89 per liter while the wholesale price of gasoline has hovered around \$0.79 in the last year. This suggests that uncertainty-reducing policies may not be sufficient by themselves to increase biofuel production. Similarly, our analysis indicates that policies that increase expected price but do not reduce uncertainty would require a subsidy that is approximately 50% of current price. This seems too costly to be implemented by the government. Therefore an instrument capable of reducing uncertainty and increasing the mean of bio-gasoline price simultaneously, seems warranted if the cellulosic biofuel industry is to fulfill the mandate embedded in the RFS2. Some instruments previously discussed in the scholarly literature (e.g. Tyner et al., 2010; Petter and Tyner, 2014; Song et al., 2011) like reverse auctions or minimum price entail such combination.

A reverse auction is a contract by which the government guarantees the producer the purchase of a given volume of biofuels at a contract price. If the market price is lower than the contract price the government makes the purchase. Otherwise, the producer sells the fuel in the market. Hence reverse auctions work, in effect, as a minimum price. This policy has two effects. It reduces downside risk without curtailing upside outcomes. This results in reduced price volatility and increased drift rate. Both effects, but particularly the former, would reduce the price premium required by investors to enter which enhances the effectiveness of the policy.

Another option is to combine price and quantity-based policy instrument to achieve stated biofuel inclusion targets. For instance, a mandated volume can be maintained through the RFS2 but combined with a reverse auction or forward contract. A reverse auction can be used so that entry price is reduced and an aggregate supply developed. Mandates can then be established in accordance with built capacity which makes the mandate easier to enforce. As the industry develops price instruments can be phased out and the mandate can be maintained. The framework used in this study can be adapted to model and quantify the effect of these policy instruments. In addition the cost at which each instrument can reduce entry price to a certain target can be calculated so that alternative instruments are evaluated based on cost-effectiveness. This seems like a promising avenue for future research.

There is also a dynamic dimension to policy design whose importance is underscored by our results. Our analysis indicates that policy interventions that do not adjust to changes in market conditions may fail to deliver the desired goal. Empirical evidence shows that volatility in oil markets has undergone structural changes in the recent past (e.g. Salisu and Fasanya, 2013). Structural changes that increase volatility of oil and gasoline prices (Salisu and Fasanya, 2013 found evidence of such increase in 2008) call for more aggressive biofuel policies, as investors will require a higher premium in response to increased uncertainty.

This study is not without limitations. The study focuses on gasoline price uncertainty and does not account for the uncertainty inherent within production. The cost of stover, hydrogen, even equipment can all vary over time. A model that accounts for multiple sources of uncertainty may provide information as to whether these sources operate linearly on entry price, or they interact to produce non-proportional effects on the entry premium (Schmit et al., 2011). Another limitation of this study, and one shared with other studies in this literature, is the uncertainty surrounding parameter values such as plant cost and its relationship with scale of production. While all sources of information have been documented here, only one large scale plant with this technology exists (KIOR), limiting the reliability of these figures. However, these analysis could (and should) be re-run once new information arrives. Our framework easily allows for such exercise.

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Appendix A: Numerical analytical approach in MatLab

Code

```
function F = ROA(x)
alpha=-2.0628;
beta=2.2155;
delta=0.1;
mu=.01854;
w=2.56;
k=9.91;
m=0.25;
em=0.25;
r=0.50;
l=-2.48;

F = [x(7)*(x(1)^beta)-x(1)*((delta-mu)^-1)+w*(delta^-1)-x(5)*(x(1)^alpha)+k;
      x(3)*((delta-mu)^-1)-w*((delta)^-1)+x(5)*(x(3)^alpha)-
x(6)*(x(3)^alpha)-x(8)*(x(3)^beta)+m*(delta^-1)+em;
      x(6)*(x(4)^alpha)+x(8)*(x(4)^beta)-m*(delta^-1)-x(4)*((delta-mu)^-
1)+w*(delta^-1)-x(5)*(x(4)^alpha)+r;
      x(6)*(x(2)^alpha)+x(8)*(x(2)^beta)-m*(delta^-1)-x(7)*(x(2)^beta)+l;
      beta*x(7)*(x(1)^(beta-1))-((delta-mu)^-1)-alpha*x(5)*(x(1)^(alpha-1));
      ((delta-mu)^-1)+alpha*x(5)*(x(3)^(alpha-1))-alpha*x(6)*(x(3)^(alpha-
1))-beta*x(8)*(x(3)^(beta-1));
      alpha*x(6)*(x(4)^(alpha-1))+beta*x(8)*(x(4)^(beta-1))-((delta-mu)^-1)-
alpha*x(5)*(x(4)^(alpha-1));
      alpha*x(6)*(x(2)^(alpha-1))+beta*x(8)*(x(2)^(beta-1))-
beta*x(7)*(x(2)^(beta-1))];
```

Steps for solving

```
options = optimset ('MaxFunEvals',10000,'MaxIter',10000)


x0 = [5;1;1;2;1;1;1;1];  % Make a starting guess at the solution
[x,fval] = fsolve(@ROA6,x0,options)
```

Appendix B: Equations defining value matching and smooth pasting conditions without the managerial flexibility to mothball or reactivate

Code

```
function F = ROA5(x)
alpha=-2.0628;
beta=2.2155;
delta=0.1;
mu=.01854;
w=2.2.56;
k=9.91;
l=-2.48;

F = [x(4)*(x(1)^beta)-x(3)*(x(1)^alpha)-x(1)*((delta-mu)^-1)+w*(delta^-1)+k;
    beta*x(4)*(x(1)^(beta-1))-alpha*x(3)*(x(1)^(alpha-1))-((delta-mu)^-1);
    x(3)*(x(2)^alpha)+x(2)*((delta-mu)^-1)-w*((delta)^-1)-
x(4)*(x(2)^(beta))+l;
    alpha*x(3)*(x(2)^(alpha-1))+((delta-mu)^-1)-beta*x(4)*(x(2)^(beta-1))];
```

Steps for solving

options = optimset ('MaxFunEvals',10000,'MaxIter',10000)

```
x0 = [4;1;1;1];  % Make a starting guess at the solution
[x,fval] = fsolve(@ROA5,x0,options)
```