UNCERTAINTY, IRREVERSIBILITY, AND INVESTMENT IN SECOND-GENERATION BIOFUELS

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ABSTRACT

The present study formalizes and quantifies the importance of uncertainty 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 calculate the portion of that entry trigger price required to cover cost and the portion that corresponds to risk premium. We then discuss the effect of managerial flexibility on the entry risk premium and the prices of gasoline that would trigger mothballing, reactivation, and exit. Results show that the risk premium required by plants to enter the second-generation biofuel market is likely to be substantial. The analysis also reveals that a break-even approach (which ignores the portion of entry price composed of risk premium) would significantly underestimate the gasoline entry trigger price and the magnitude of that underestimation increases as both volatility and mean of gasoline prices increase. Results also uncover a great deal of hysteresis (i.e. a range of gasoline prices for which there is neither entry nor exit in the market) in entry/exit behavior by plants. Hysteresis increases as gasoline prices become more volatile. Hysteresis suggests that, at the industry level, positive (negative) demand shocks will have a significant impact on prices (production) and a limited impact on production (prices). In combination all of these results suggest that policies supporting second generation biofuels may have fallen short of their targets because of their failure to alleviate uncertainty.

1 INTRODUCTION

While analyses of the economic viability of cellulosic biofuels suggest a positive net present value of such investments, entry into the market has not occurred at the pace set by the Renewable Fuel Standard (RFS). The present study quantitatively evaluates the hypothesis that, due to the uncertain and irreversible nature of investment in this industry, investors require a non-trivial premium on expected profitability to enter the market. We also hypothesize that managerial flexibility (the possibility of mothballing and reactivation) may reduce such premium. Results from a parameterized real options analysis suggest a premium of72% in expected profitability revealing that uncertainty creates a significant barrier to entry. Managerial flexibility does not have a significant (negative) effect on entry trigger price but, it does have a slightly more important (negative) effect on exit trigger price. Moreover, results also suggest a potential for significant hysteresis once investments have been made; i.e. plants will require larger losses before shutting down operations. Hysteresis is aggravated by higher levels of uncertainty and irreversibility. We argue that renewable fuel standards are not effective in addressing uncertainty and that alternative or complementary policy instruments may be required to induce the level of investment mandated by RFS2. Alternative policy options are discussed.

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 many positive projections, cellulosic biofuel production has continually fallen well short of mandates set forth by RFS2. In 2013, cellulosic biofuel production totaled six million gallons. This falls

994 million gallons below the target goal of 1 billion gallons for the year set by the Second Renewable Fuel Standard (Schnepf and Yacobucci, 2010).

Numerous studies, in both business and academic realms, have used a net present value (NPV) and/or break-even analysis to predict the price required to make cellulosic biofuel profitable. Using this approach, these studies routinely find that a cellulosic biofuel plant built today should have a positive return on the investment (Anex et al., 2010, Brown et al., 2013, Gonzalez et al., 2012b, Brown and Brown, 2013b, Tyner and Petter, Cannon, 2012, Jones et al., 2009). Without accounting for risk it is hard to reconcile the reality of biofuel production with predictions of profitability by economic studies. We hypothesize that the inconsistency between theoretical predictions and empirical observations is the systematic underestimation, by the former, of the role of uncertainty as a barrier to investment. It does not appear that cellulosic biofuel production will meet the 16 billion gallons required by 2022.

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 since they are produced from cellulosic plant matter such as corn stover, switch grass, or trees rather than sugar (EIA, 2013, Energy). 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. Most existing second generation plants do produce ethanol, however, since converting biofuels to "drop in" is a recent development (EIA, 2013). 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).

Typically large-scale investment projects such as second generation biofuel refineries must pass some kind of cost-benefit analysis to judge the profitability of the investment before construction can be started. Usually, a net present value analysis is used. While this can be useful in established stable industries, evaluating investment in a new industry that experiences large amounts of uncertainty from both technical and market sources requires consideration of the effects of uncertainty on entry and exit behavior (Dixit, 1994, Gonzalez et al., 2012a). This uncertainty translates into a value, for having the option to wait to make a decision. Waiting allows the decision maker to observe the evolution of random variables and re-assess the risk associated with the investment.[1]

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, Burke, 2012, Song et al.2010, Pederson and Zou, 2009) 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.

In particular, the difference in trigger prices between the break-even approach and real options without considering mothballing and reactivation permits quantification of the effect of uncertainty on entry trigger price. In turn this will reveal the magnitude of the

[1] It is important to note that it is possible to build uncertainty into an NPV analysis. More specifically one can specify a percent chance of economic loss that is acceptable and build that into the trigger price for entry. This will yield a positive NPV. This qualification will create a trigger price for entry that is higher than the break-even price. In this paper, unless otherwise specified, we compare real options trigger price for entry (exit) to break-even and (Marshallian exit prices). We also create a situation with an 80% chance of economic gain to be compared to the break even and real option scenarios; this will be discussed later.

underestimation of uncertainty, embedded in the break-even approach which may explain the puzzling difference between predictions of profitability and absence of entry into the industry. On the other hand the difference in trigger prices between real options with mothball and reactivation and real options without these intermediate states permits quantification of the effect of managerial flexibility, given uncertainty and irreversibility, on the risk premium that investors require to enter the market.

2 METHODS

As mentioned earlier, this paper compares the entry and exit trigger prices for a real options framework to an NPV break-even framework to come up with a price premium for uncertainty. The break-even model is centered on standard discounting. Revenue and costs are discounted for the future at a pre-specified discount rate. The summation of all of these expected discounted values are put together to come up with the value of a project in today's dollars. Under NPV break-even assumptions a firm will enter the market if their discounted price is greater than or equal to their discounted operating cost plus capital expenditure. This equality is written as $\frac{W_h}{\delta-\mu} \geq \frac{w}{\delta} + k$. W_h denotes the trigger price per gallon for entry, δ the discount rate, μ the drift rate in price, w the operating cost per gallon, and k the capital cost per gallon of plant capacity. A firm will exit the market if the discounted price falls below discounted operating cost plus the net scrap value of selling the plant. This exit price is consistent with the Marshallian exit price of a firm exiting an industry. In other words a firm will leave in the long run if its average revenue cannot cover its average cost. This equality is written as $\frac{W_l}{\delta-\mu} \leqq \frac{w}{\delta} + l$. W_l denotes the trigger price per gallon for exit and l the net scrap value of selling the plant.

2.1 Real Options Defined

The real options analysis and corresponding intuition used in this paper is taken from (Dixit, 1994). The process has already been developed but the rest of this chapter is dedicated to explaining and showing how real options affect trigger prices for entry and operation. Real options are to project investment, what financial options are to stock or commodity investment. Both of these options give the right but not the obligation to make a decision in the future. This right without obligation mitigates the downside risk associated with an investment project while still allowing to capitalize from the upside. The value of this option is captured and quantified in a real options analysis. For the option to invest to have value (i.e. for the real options approach to differ from the break-even approach), three conditions must hold:

1. Investment cost is either fully or partially irreversible.
2. The future evolution of one of the variables in the model is uncertain.

3. Timing of the investment can be controlled.

Biofuel plants are large investments that have little reversibility. Much of the equipment is specific to the industry. 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. For instance 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 are also experiencing low prices and as a result are in a similar position.

Wholesale gasoline price per gallon is used as a proxy for the price received for a gallon of drop in biofuel. Using, converting, and logging monthly data covering the past five years from the EIA, the average annual standard deviation for a percentage change in wholesale gasoline selling price was found to be .209. Such deviations would cause drastic swings in a biofuel producer's revenue. An increase or decrease in prices by even a portion of the standard deviation could make or break a plant. This standard deviation in price satisfies the uncertainty requirement for real options. Finally, the timing of an investment in a second-generation corn stover fed bio-gasoline plant is fairly flexible.

There are no real barriers to entry other than the high capital cost associated with commercial scale plants and preliminary pilot plants, which is not timing sensitive. The only time sensitive variable in a second generation bio-fuel plant is the potential change in tax policy. If subsidies and tax credits continue to change they may shut the window on entry.

There is one additional assumption that must hold within the model. It was not mentioned earlier since it has to do with the way the model is set up and not with how the variables and parameters exist in the real world. The project must be assumed to have an infinite life. This assumption must hold to satisfy the smooth pasting conditions of the equalities. This assumption is accounted for by replacing capital as quickly as it depreciates. This replacement cost gets built into operating cost. This infinite project life, while necessary, has two offsetting effects compared to a traditional break-even analysis. Building in capital depreciation costs into operating costs will raise the trigger price since it essentially doubles capital cost. A producer must pay capital cost to start the plant and then an annual payment of capital cost for the infinite life of the plant. The infinite life also lowers the trigger price in the sense that price has a positive trend, costs do not. Getting higher prices for an infinite life compared to say 20 years will decrease the trigger price.

2.2 Decisions for Entry, Mothball, Reactivation, and Exit

There are three different states a plant can be in: idle, active, or mothballed. In an idle state, a plant is not paying either fixed 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, every period, pays operating costs w, and, earns revenue P. An active plant also has the option of converting to a mothballed state. 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 to active 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. It also loses its option to reactivate. The ability to switch between these different states is represented in table 2.1. X is possible, - is not.

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

There are several assumptions that must hold for this model to function. We assume $l < k$. We also assume that $w < m$,otherwise the firm will never mothball (Schmit et al., 2009). Similarly, it is necessary for $r < k$, otherwise it would never be optimal to mothball and reactivate later since it would always be cheaper to exit and then enter again.

The output prices that trigger entry, mothball, exit, and reactivation when the option of waiting to make the investment is factored (real options) in are denoted by P_h, P_m, P_r, and P_l respectively.. The output prices that trigger entry and exit when waiting is not an option (break-even) are denoted by W_h and W_l respectively.

Price per gallon P is the wholesale price of a gallon of bio-gasoline. This price is assumed to change over time according to a Geometric Brownian Motion (GBM) process.[2] This process not only changes over time but is also continuous in time. In other words decisions can be made at infinitesimally small units of time. GBM is a stochastic process that incorporates both a drift parameter and a variance parameter for making predictions in future prices. The equation for this is denoted as $dP = \mu P dt + \sigma P dz$. A change in price (dP) is dependent upon its drift rate and its variability. Drift rate grows over a time increment (dt). The standard deviation is tied to the increment of a Weiner process denoted by dz, which is a function of time and variability, $= \varepsilon_t \sqrt{dt}$. The factor ε_t is a normally distributed random variable with a mean of zero and a standard deviation of 1, so the expected value of $dz = 0$. P follows a normal distribution. Gasoline prices have typically been characterized by log-normal distributions (Dixit and Pindyck 1994)). Gasoline prices enter our model in log form. Given log-normality of gasoline price, the log of gasoline price is characterized by a normal distribution. It is also assumed that the discount rate δ is greater than the drift rate μ. This must hold otherwise it would never be optimal to invest since the growth rate would outpace the discount rate. It would always be possible to do "better" by waiting longer.

2.3 The Decision to Enter

Let us denote an idle project's discounted expected value by $V_0(P)$. For an idle plant, this value is completely based off of the option for the firm to enter the industry in the future. An idle plant has no revenue or expenses, but has the option of earning a profit in the future if the option is exercised and the plant is brought to an active state. An investor that owns a plant in an idle state could do one of two things, hold onto the option and

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[2] This assumption is supported by statistical tests conducted with historical gasoline price data. Tests will be presented and discussed in detail in Section 3.1.

activate the plant if prices are sufficiently high or sell the option to someone else and invest the proceeds. The former is represented by the equation $E_t[dV_0(P)]dt^{-1}$, where ε_t is the expected value of the project at time t. The latter is represented by the function $\delta V_0(P)$. Think of the left hand side as the return generated from selling the project and investing the proceeds. The right hand side is the expected capital gain of the project. Arbitrage in efficient markets would set these two returns equal:

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

Equation one is a Bellman equation and it must hold under efficient markets. Equation (1) implicitly defines the entry trigger price (i.e. the price at which the investor is indifferent between entering the market and staying out). To solve for this price we first need to find an expression for $dV_0(P)$. This expression reveals that the value of the project is a function of gasoline price which is, in turn, a random variable following a geometric Brownian motion process. To obtain an expression for solve this we make use of Ito's Lemma. Ito's Lemma is, in essence, a Taylor series expansion $dV = \sum_{i=1}^{\infty} \frac{1}{i!} \frac{\partial^i V}{\partial P^i} (dP)^i$, where $dP = \mu Pdt + \sigma Pdz$. The second order term is $(dP)^2 = (\mu P)^2 (dt)^2 + 2(\mu P)(\sigma P)(dt)^{\frac{3}{2}} + (\sigma P)^2 dt$ which simplifies to $(\sigma P)^2 dt$ since $(dt)^2$ and $(dt)^{\frac{3}{2}}$ go to zero faster than dt as dt approaches zero. Higher order terms vanish as $(dP)^3$ and $(dP)^4$ will have all of their associated dt terms taken to a power higher than one and as a result will simplify to zero. After using Ito's Lemma we are left with:

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

Substituting dP into (2) yields:

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

We then substitute (3) into (1) and get:

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

Given that $E_t[dz] = 0$, 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 and Pindyck 1994 p. 213-235):

$$V_0 = A_0 P^{-\alpha} + B_0 P^{\beta} \tag{6}$$

Where α and β are parameters that 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 prices increase. For an idle plant we drop $A_0 P^{-\alpha}$ since an idle project has no value if price approaches zero. If $A_0 P^{-\alpha}$ approaches zero the first term vanishes rendering the following solution to the differential equation:

$$V_0 = B_0 P^{\beta} \tag{7}$$

We now turn our attention to the decision to mothball the plant after entry has occurred.

2.4 The Decision to Mothball

Now that we have solved for the value of a plant in an idle state V_0, we look at a plant in an active state V_1. A plant in an active state is producing biofuel and earning an ongoing net revenue stream equal to $(P - w)$. Equilibrium in the market requires:

$$\delta V_1 = (P - w) + E_t[dV_1(P)]dt^{-1} \tag{8}$$

Notice the similarities of the Bellman equation for an active plant equation (8) to the Bellman equation for an idle plant equation (1). Like equation (1), equation (8) has an option value of being able to change states but it also contains a term for both price and operating cost to denote operating revenue. The value function V_1 is derived following the same procedure by which we derived V_0. Such procedure results in:

$$V_1(P) = P(\delta - \mu)^{-1} - w\delta^{-1} + A_1P^{-\alpha} + B_1P^{\beta} \tag{9}$$

Where A_1 and B_1 are unknown constants, $A_1P^{-\alpha}$ and and B_1P^{β}which capture the option value of mothballing the plant if output price decreases and the option value of mothballing if the output price increases respectively. If the output price is sufficiently high to induce the firm to keep the plant active, further increases in output price will make the value of mothball vanish; i.e. B_1P^{β}=0. Therefore equation (9) simplifies to:

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

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

2.5 The Decision to Reactivate or Exit

Now think of a plant that is currently in a mothball state. It is experiencing an ongoing maintenance cost of m. The bellman equation for a plant in a mothballed state is:

$$\delta V_m = E_t[dV_m(P)]dt^{-1} - m \tag{11}$$

Once again, the left hand side represents the return from selling the plant and investing the proceeds. The right hand side represents the expected value of keeping the project. By using the same process that was used for equations (1) and (8) this equation 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, $m\delta^{-1}$ 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. This is why each option only has one term associated with it.

2.6 Deriving the trigger prices

Our representative plant has the option to switch from idle to active, active to mothballed, mothball 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_r, and P_l, 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 states that switching from one state to another occurs when the value of the current state becomes lower than the value of the project under the state to which the firm would like to switch minus the fixed exercise price (or switching cost) which we denote by k, E_m, r, and l when the firm switches to active, mothball, reactivation, and 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 value of P_h that sets the value of the option to enter equal to 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 both 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 four unknown constants associated with the option value of switching states (A_1, A_m, B_0, and B_m):

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

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

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

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

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

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

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

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

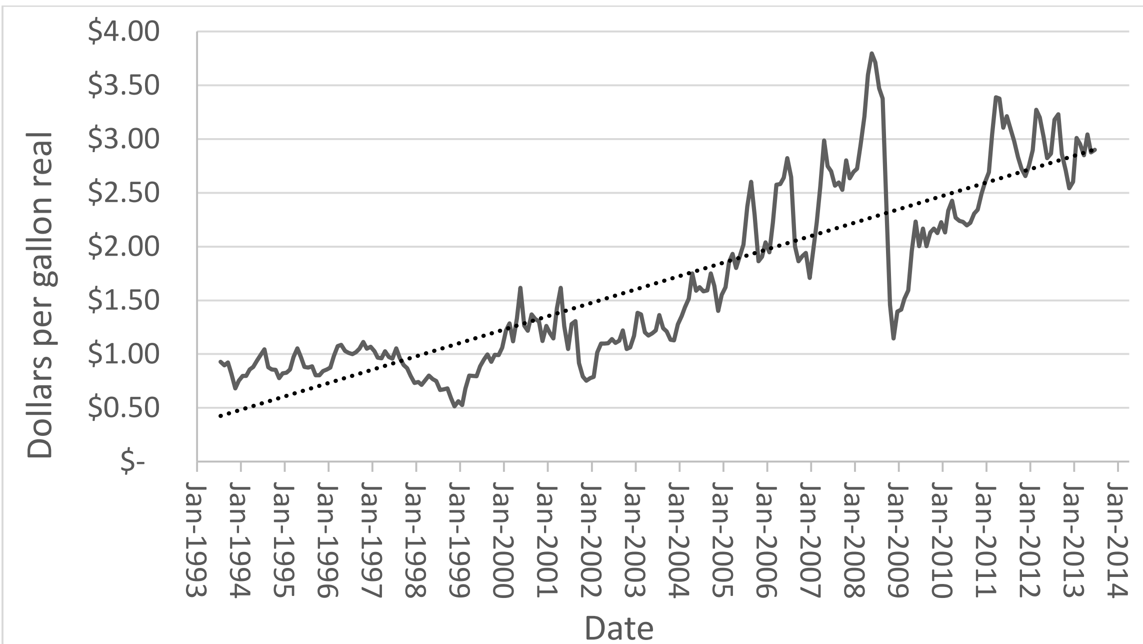
The first four equations constitute direct corollaries of the value matching conditions and the next four equations are derived from the smooth pasting conditions. This system is solved numerically in Matlab using the code presented in Appendix 1. Solution of the system without managerial flexibility (i.e. without the option to mothball and re-entry) is, in turn, presented in Appendix 2.

3 PARAMETERS AND ESTIMATION

3.1 Variable of Interest

In order to identify the stochastic process followed by gasoline price and whether that stochastic process warrants the use of a real options approach we looked at average monthly wholesale gasoline prices in the Midwest for the past twenty years. This data is shown in Figure 3.1.

Figure 3.1: History of the average real wholesale gasoline price in the Midwest (PADD area 2) (EIA, 2013)



Gasoline prices seem to have followed an upward trend in this period. In other words there is a positive drift rate which we denote by μ. The average monthly percent change in price in these series results in a drift rate of 0.48%. Converted to annual this term becomes 5.7%. Despite our calculations this drift rate seems overly ambitious. It is unlikely that this growth in wholesale gasoline prices will continue at this rate into the future. We chose a more modest rate based off of the EIA's (U.S. Energy Information Administration) 30 year projections for wholesale gasoline prices. This gives us a drift rate of 1.85%.

The monthly and yearly standard deviation in for a one percent change in gasoline price over the past 20 years are .1 and .35 respectively. The standard deviation over the last five years was .06 and .21 for monthly and yearly calculations respectively. For our base case analysis we use the more conservative estimate of yearly standard deviation equal to .21. The dramatic spikes in prices experienced in years 2004-2007, and the subsequent crash in 2008 may overestimate the variance for future gasoline prices.

The equation used to calculate drift and standard deviation is $dt = \ln(\frac{P_t}{P_{t-1}})$. The data is logged since wholesale gasoline prices are assumed to be log normally distributed (Schmit et al., 2009, Dixit, 1994). Taking logarithm of prices converts this log normal distribution into a normal distribution, which is consistent with GBM assumptions. The interpretation of this logging in respect to the drift and standard deviation are the drift is considered the average percentage change in gasoline price in a year. The standard deviation can be interpreted as the standard deviation of a one percent change in price. We chose to use prices in the Midwest since a stover fed plant would most likely locate and sell there, due to the relatively high corn yields and low transportation cost to local markets.

There is significant variation in P from year to year. This variation in P, with respect to 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 process respectively (Dixit and Pindyck 1994). Brownian motion behaves randomly and the price at time t depends only on the price in $t-1$, the drift rate, and the stochastic term. Mean reversion behaves similarly except that it has an additional term that drags future values back to a given mean or trend. This can be thought of as prices reverting to the cost of production in the long run (Dixit and Pindyck 1994). Brownian motion is modeled as $dP = \mu dt + \sigma dz$. Where μ is the drift rate of P, σ is the standard deviation of a percentage change in P, dt is the change in time, and *dz* is the increment of a Weiner process. On the other hand, a mean reversion process is modeled as $dP = \eta(\bar{P} - P)dt + \sigma dz$, where $\bar{P}$ represents the mean value which P tends to revert to and η is the speed at which this reversion occurs.

For Brownian motion, the price in the current period P_t is a function of the price in the preceding period P_{t-1}, the variability of price σ, and the drift rate μ. The validity of assuming a Brownian motion as the data generating process (DGP) of gasoline prices is evaluated by conducting a unit root test for non-stationarity/autocorrelation of the price series. If the price in any given period depends on the price in the previous period, then a Dickey Fuller unit root test will fail to reject the null hypothesis of non-stationarity (Wooldridge, 2012). Mathematically this explanation is modeled as $P_t - P_{t-1} = a + b(P_{t-1}) + e$, P_t=a+b($P\_$(t−1))+cµ+e where P_t is the price in this period, P_{t-1} is the price lagged by one period, a is the intercept, e is the residual, and $b = either\ 0\ or\ 1$. If $b = 1$ non-stationarity exists within our data set. If b=0 the data is stationary.

Non-stationarity would mean that correlation between the two periods cannot be statistically rejected and it would legitimize the use of Brownian motion over a mean reverting process. If correlation between prices in last period and this period can be rejected, the unit root test will reject the null. In this case the mean reverting process is the preferred assumption.

We conducted two unit root tests.[3] We first conducted a Dickey Fuller test based on a specification where only lagged wholesale gasoline real price was included as an explanatory variable of gasoline wholesale real price at time t. We then conducted another Dickey Fuller test on a specification where wholesale gasoline price at time t is regressed on lagged real prices at time $t-1$ and drift. The null hypothesis was that the data followed a non-stationary process and that the price in this period was perfectly correlated with the price last period. The test fails to reject nonstationarity with the first specification (test statistic of -1.48) but the test rejects nonstationarity under the second specification (test statistic of -3.50). These answers give conflicting results. Failing to reject nonstationarity would suggest that Brownian motion would be an appropriate approximation to the DGP butrejecting nonstationarity would favor approximation with a mean reversion process.

Dixit and Pindyck argue that prices of commodities such as oil follow a mean reverting process. Under this assumption, prices below the projected level have a tendency to increase and prices above the projected level have a tendency to decrease. They assert that testing for autocorrelation should be done over the largest time period possible (Dixit, 1994). While this adds robustness to a unit root test, and data for the past hundred years is available, the market structure for gasoline has drastically changed in the

[3] Dickey Fuller tests were run with STATA based on historical gasoline prices displayed in Figure 3.1

past decade and incorporating too many years detracts from the legitimacy of modeling the current market.

Despite these conflicting results, a strong case for using the Brownian motion form can be made. There has been a large amount of debate in the literature over the similarity in results given by models using Brownian motion assumptions and those resulting from use of mean reversion assumptions (Pindyck, 1999, Sarkar, 2003, Metcalf and Hassett, 1995). Specifically the debate has been on whether Brownian motion can be used as an approximation for a mean reversion process without compromising the reliability of results. Mean reversion has the advantage of being a more reasonable assumption in many markets due to economic factors working to bring the price of a product back to its marginal cost of production. An example of this would be additional plants entering the industry under high prices or plants leaving the industry under low prices. The problems are that these marginal costs sometimes shift confounding predictions made by mean reversion, and calculations for trigger prices under mean reversion assumptions can be cumbersome (Metcalf and Hassett, 1995). Brownian motion has the advantage of analytical tractability (Dixit, 1994). In other words, problems modeled using Brownian motion can be solved by solving formulas and give actual answers rather than forcing data through a program that gives approximations.

A mean reverting process converges asymptotically to a Brownian motion process as the rate of mean reversion tends to zero. If the speed of reversion, η, equals zero then a mean reversion process and a Brownian motion process will give the exact same answer (Sarkar, 2003, Pindyck, 1999, Metcalf and Hassett, 1995). Therefore Pindyck and Metcalf 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 (Pindyck, 1999, Metcalf and Hassett, 1995). Moreover, volatility also affects the appropriateness of using GBM to approximate the DGP (Pindyck, 1999, Metcalf and Hassett, 1995). Results from a GBM approximation to the DGP are less reliable, the higher the volatility σ of the random variable. Metcalf and Hassett (1995) conducted sensitivity analysis and found that under a volatility similar to this paper yearly ($\sigma = .25$) and a mean-reversion coefficient of η=.09, a GBM approximation results in trigger prices that deviate from those of mean reversion by only 2% (Metcalf and Hassett, 1995).

Since we have calculated volatility in our DGP, we now proceed to calculate the rate (if any) of mean reversion to determine the appropriateness of a GBM as an approximation to the DGP. To determine the reversion speed of P we regressed gasoline wholesale prices over the past twenty years on its lagged price and drift rate; i.e. $P_{t+1} - P_t = \beta_0 + \eta(\overline{(P\mu_t)} - P_t)$. Where $P_{t+1} - P_t$ is the annual change in price, β_0 is the intercept of the equation, $(\overline{(P\mu_t)} - P_t)$ is the difference in mean price and actual price, and η is the reversion speed. Estimation results in yearly $\eta = .66$

3.2 Technology and Pathways

Before getting into cost estimation it is important to note that there are multiple pathways to producing second generation biofuel and that different pathways can have very different costs and yields. This section explains the different pathways that exist and why we pick the pathways that we do. 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). There have been numerous variations of these three base technologies in small scale pilot plants but they still are primarily based off one of these three technologies. Gasification uses high heat and low oxygen to turn the feedstock into syngas, it then adds catalysts to this syngas to convert it to liquid fuels (Brown and Brown, 2013b). Hydrolysis converts plant cellulosic material to sugars after the material is broken down through either enzymes, chemicals, or pressure. These sugars are then turned into fuel through a fermentation process that is typically driven by E. coli and S. cerevisiae bacteria (Hughes et al., 2013).

The final technology, and the one used in this paper, is fast pyrolysis. This process can be roughly simplified into five steps.

1. Biomass pre-treatment
2. Fast Pyrolysis
3. Solids Removal
4. Oil Collection
5. Oil Upgrading

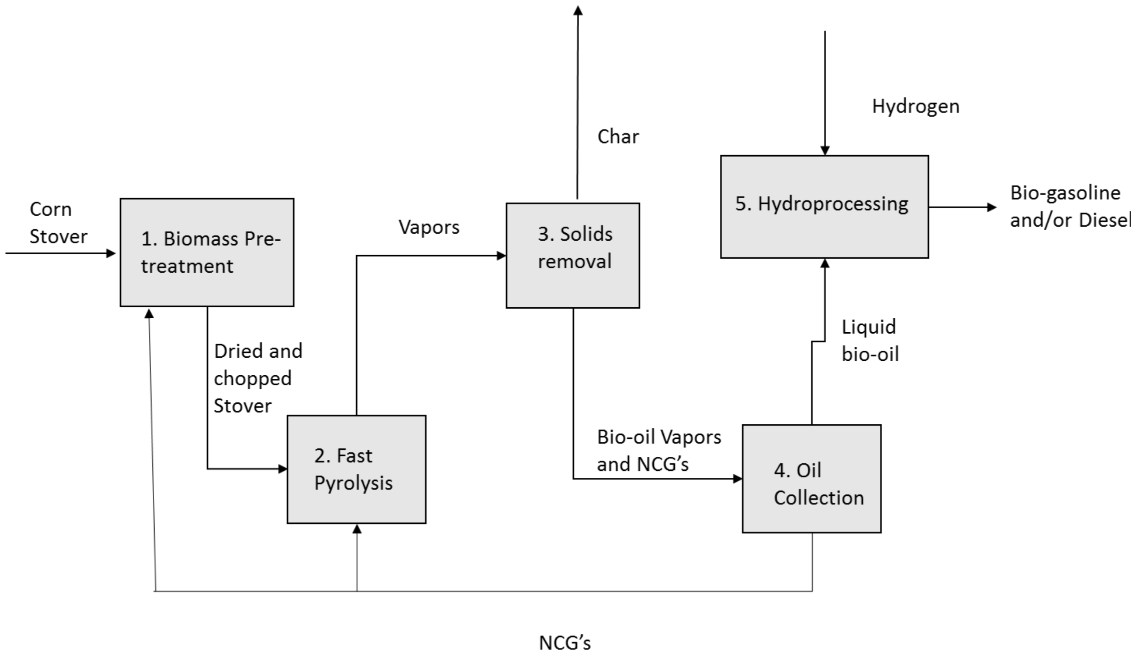


Figure 3.2: Steps of Converting Corn Stover to Bio gasoline using Fast Pyrolysis, taken and modified from Wright et al. (2010).

The first step of fast pyrolysis is the pretreatment process. Stover is collected and ground to pieces that are 10 mm in diameter which makes them easier to dry. The stover is then dried to a moisture content of 7%. It is then ground again to pieces that are only 3mm in diameter. This small diameter assures that the stover will be efficiently used by the equipment.

The second step is the pyrolysis itself, more specifically fast pyrolysis. In this process the pre-treated biomass is sent to a pyrolysis reactor. This reactor rapidly heats stover to approximately $480^{o}\ C$. This rapid heating converts the biomass to a gaseous state. This gas contains char, bio-oil, and non-condensable gases (NCG's) such as carbon monoxide and methane.

During the third step these gases evaporate from the pyrolysis reactor and are sent through cleaning equipment (either a turbine or filter) to separate the char from the gas. The char must be collected due to its high carbon and ash content which would harm the process to further refine the bio-oil. This collected char is then either sold as a marketable co product or can be combusted and its heat is used to assist both steps one and two for drying and pyrolysis respectively. Some plants also use this char to also produce electricity which is then used to run the plant and/or sold to the grid.

The forth step of this process is oil collection. During this step, the remaining gas net of the char is sent through an indirect heat exchanger. This rapidly cools that gas to $150^0\ C$. Bio-oil becomes liquid at these lower temperatures and is collected. Like their name would imply NCG's stay in their vapor form, this vapor is collected and combusted along with the char to provide heat for pyrolysis and drying.

During the fifth step the bio oil then can go through one of two processes to further reduce the oxygen content and refine it to a usable fuel, bio-gasoline or bio-diesel. The first option is fluid catalytic cracking (FCC). In FCC the bio-oil gets depolymerized and further deoxygenated. This creates hydrocarbons which can then be blended with existing hydrocarbon-based biofuels (Brown and Brown, 2013a). The second option is hydrotreatment. Hydrotreatment further reduces the oxygen content, and stimulates the depolymerization of bio-oil by adding hydrogen and refines it into a useable fuel such as bio-gasoline or bio-diesel. This paper assumes a hydrotreatment process for the refining of bio oil. Hydrotreatment is chosen as the process of converting bio-oil to bio-gasoline since has higher yields and more favorable economics than FCC (Brown and Brown, 2013b).

Hydroprocessing is a general term that includes two separate processes, hydrotreatment and hydrocracking. During hydrotreatment bio-oil is subjected to high pressure (1000-1500psi), and temperatures ($300^0 - 400^0 C$). There is also large amounts of hydrogen added to the bio-oil during this step. This combination of temperature, pressure, and hydrogen removes impurities such as nitrogen and sulfur from the bio-oil.

The second step of hydroprocessing is hydrocracking. During this step even higher pressures and temperatures, $400^0 - 450^0\ C$ and $1500 - 2000\,psi,$ are used to depolymerize the molecules found in bio-oil into shorter chains which are chemically similar to fossil fuel based gasoline. Both of these processes further reduce the oxygen content found in the bio-oil until it is at a point low enough where the upgraded product can be used as a drop in fuel, in our case bio-gasoline. Once hydroprocessing is complete we are left with our drop in biofuel, which is ready to be blended or directly sold.

Choosing a pathway for biofuel production is challenging. The estimates for yield and cost of different technologies change every few months. This paper attempted to use the timeliest numbers possible for the existing technologies but even these are subject to change at a moment's notice. The technology evolves very rapidly. Potentially hydrolysis is just one new bacteria strain away from becoming the least attractive to the most attractive second-generation technology. Having said this, there are several arguments for assuming a fast pyrolysis with hydrotreatment as the pathway of choice. The only existing large scale plant has adopted a variation of this technology so there is a precedent for it. A corporation's job is to maximize its profits, this can only be done with the most cost effective technology. Another argument is that currently hydrolysis is a fairly outdated technology that is better suited for ethanol production. Hydrolysis makes sugars which work well for refining into ethanol but are harder to refine into a drop in. Currently, there are no planned drop-in plants that use hydrolysis as a pathway (Brown and Brown, 2013a). The economics and chemistry do not line up. Gasification also experiences the unfavorable economics compared to fast pyrolysis. In a Techno Economic Analysis (TEA) study, conducted by Tristan Brown and Robert Brown at Iowa State University, fast pyrolysis was found to be considerably more cost effective than both hydrolysis and gasification. The lowest minimum fuel selling price (MFSP) for Fast Pyrolysis was found to be under half that of both hydrolysis and gasification pathways. The MFSP for a gallon of biofuel on these processes were \$2.00, \$5.00, and \$4.50 respectively (Brown and Brown, 2013a).

3.3 Fixed and Operating Costs

Now that the pathway is known it is possible to parameterize our costs. This paper, unless otherwise noted takes its assumptions for fixed and operating costs from (Brown et al., 2013). These costs are summarized at the end of the section in table 3.3. Brown's paper does an NPV analysis for a second generation drop-in biofuel plant over different regions; Brown models a plant that processes 2000 dry tons of stover a day. This paper takes Brown's numbers for cost and converts them into a per gallon basis. The operating cost w, is calculated by taking Brown's estimation of yearly operating cost plus our calculations for capital replacement and federal tax. Capital replacement is added into w to replace capital at the rate it is used up to ensure an infinite life of the plant; this infinite life assumption is required for real options analysis. Federal tax is added to keep the project more realistic for our analysis. This 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, cost of replacing capital, and miscellaneous.

This paper calculates the cost of replacing capital by annualizing capital cost and converting it to a per gallon basis. This model also attempts to incorporate corporate income tax into its operating cost expense. For this to work with a real options model, a conversion is necessary to keep the tax constant and in per gallon terms. Traditional income taxes overcomplicate the real options model and cause it to break down (Niemann and Sureth, 2004). We assume an effective tax rate on net income to be 20%, that 20% will be levied on the predicted taxable net revenue over the twenty year period, and converted to a per gallon basis. We then take the NPV of these and annualize it to come up with a constant tax that is paid every year. This paper also assumes that a company can pay negative tax. We assume the plant is part of a larger company and that a negative tax owed within the biofuel plant can be sent to another part of the company to cancel out that tax; this is relevant for early years when the plants costs are higher than its revenue.

There are several subsidies and tax breaks currently in the industry. However, due to their uncertain future this paper omits all of them and looks at trigger prices free of policy.

As previously mentioned most of this paper's operating costs come from the predictions in Brown's paper "Regional Differences in the Economic Feasibility of Advanced Biorefineries: Fast Pyrolysis and Hydroprocessing," (Brown et al., 2013). One exception to this is the cost of corn stover. The literature gives a wide range of predictions on the cost of corn stover. The predicted cost for one dry metric ton of stover delivered to plant ranges from approximately \$16 to \$112. (Gallagher et al., 2003, Fiegel et al.). Other predictions fall into a range between \$40 to \$101 (Brechbill et al., 2011, Perrin et al., 2012, Brown et al., 2013, Gonzalez et al., 2012b).

These discrepancies in predicted cost exist since the corn stover market remains largely undeveloped and on a very small scale. Due to this infancy in the industry, assumptions for the impact of stover harvest on next year's crop yield, the amount of fertilizer required to replace the nutrients lost from stover harvest, and the price required to induce enough farmers to collect stover to supply a biofuel plant are challenging. The fact that these impacts are experienced differently across areas with disparate corn yields, weather, tillage, and soil type compounds the prediction problem (Wilhelm et al., 2004).

These things can be asymmetrical in different parts of the same field, let alone across an entire region.

The assumption made in Brown's previously mentioned paper is $101 per dry ton of stover. This seems to be on the high end of most of the predictions. The assumption made in this study is that a refinery can buy a ton of stover at $83 a dry ton. This assumption is used since it falls towards the middle of the other predictions. It is also the assumption used in another of Brown's papers "Techno-Economic Analysis of Biomass to Transportation Fuels and Electricity via Fast Pyrolysis and Hydroprocessing," (Brown and Brown, 2013b) as well as a (Wright et al., 2010). While $83 a ton may seem conservative compared with other $100 plus predictions, this paper contests that any second-generation biofuel plants that come online in the near future will likely pick a location that has favorable conditions for collecting stover, conditions that keep both the opportunity and monetary cost of stover harvest low.

There was also disagreement on the yield of bio-gasoline per dry ton of feedstock. The predictions were, 72 gallons of bio-gasoline per dry ton and 85 gallons of bio-gasoline per dry metric ton, made by Kior and Brown, respectively (Biofuels Digest, 2013; Brown et al., 2013). Kior's assumption is used in this paper. As of right now, they are the only commercial scale cellulosic biofuel drop-in plant. They would know what their own yields are. It is important to note that some studies suggest up to a ten percent yield reduction converting from yellow pine to corn stover for a feedstock (Demirbas, 2011, Brown et al., 2013). Kior's primary feedstock is yellow pine but they claim they can use stover just as easily without mentioning a yield loss so this is the number that will be used. With these assumptions in mind the cost of corn stover per gallon of biofuel is projected to be $1.15 per gallon in real terms.

Table 3. illustrates the calculated components that make up this models operating cost. All these components, with the exception of capital replacement cost, were calculated from Brown's paper. In Brown they were listed as yearly costs but this paper converted them to a per gallon basis for the model. These individual values only have a direct importance to our analysis in how they affect w. It is however interesting to include them to illustrate what w is actually composed of. Almost half of w comes from stover cost, approximately one third comes from capital replacement, and about a fifth comes from

hydrogen. These three expenses drive the operating cost for cellulosic bio gasoline production. A plants operating cost is very sensitive to these two inputs.

It should be noted that part of the costs in the miscellaneous category are negative. This model assumes that the char left over from pyrolysis is burnt and converted to electricity. This electricity runs the plant and the excess is sold to the grid. Building electricity into the operating cost is required for our model, but it does understate miscellaneous cost by about $.20 a gallon.

Table 3.1: Operating costs per gallon for project.

Stover	$	1.15
Hydrogen	$	0.51
Depreciation upkeep	$	0.79
Misc	$	0.11

Total investment cost is calculated to be $429,000,000 and total yearly operating cost is $121,491,887. After calculating and converting the cost variables found in the literature, operating cost (including stover cost) is equal to $w = \$2.56$ per gallon and capital cost is equal to $k = \$9.91$ per gallon of plant capacity. Typically a plant pays its capital costs fully or partially with financing which would be spread out over a number of years. Real options does not allow for this, and k must be paid all at once. 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 output per year to get k. Notice that the financing assumption was only used to calculate the principal, it was not assumed to be paid back over twenty years.

In this paper, capital cost k, is calculated as the present value of investment cost. The construction period is three years. The plant pays back the investment cost with interest in full after three years of construction. This cost is then divided by the total number of gallons produced in a year to get k. Think of k as the capital cost per gallon of plant capacity. Investment cost parameters are summarized in the following table

Table 3.2 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	4744800 gallons	author's calculation

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 literature on the costs associated with mothballing and reactivation for second generation drop in biofuel plants. Our assumptions reflect those of Schmitt's paper which models a real options analysis for a first generation corn ethanol plant. Using these assumptions m was calculated as .025k and l was calculated as 0.25k (Schmit et al., 2009). This paper made slight modifications for Schmitt's assumptions for E_m and r. Schmitt assumes that E_m=.05k and that r=0.1k. These numbers are taken from the calculated E_m equaling .03k for a methanol facility. They increase E_m to .05k due to their smaller plant sizes. r is equal to $2E_m$ (Schmit et al. 2009). These numbers seem overstated since our paper looks at plants that are both larger and have a higher proportion of total spending sunk into capital. Our plant is approximately four times larger than even the largest ethanol plants in Schmitt's study. A first generation plant has a discounted operating to capital cost ratio of just over five and a half to one. In other words, over a plant's life they will pay five and a half times as much for operating expenses as they do for capital in present value terms. The assumptions made in this paper put this ratio of discounted operating costs to capital at just over two and a half to one. These plants have so much more capital than first generation plants that it makes sense that there would be economies of scale in both reactivation and in mothballing fixed cost. With this in mind we set E_m=0.025k and r=0.05k.

Table 3.1: 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

4 RESULTS

Trigger prices resulting from numerical solution of the system (22)-(29) are reported in Table 4.1. 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 2 are also reported in Table 4.1 and denoted as $\hat{P}_h\, and\, \hat{P}_l$. Entry and exit trigger prices under break-even and Marshallian exit assumptions are also calculated and reported in Table 4.1 for comparison with real options. The break-even price for entry, W_h occurs when $\frac{W_h}{\delta-\mu} \geq \frac{w}{\partial} + k$. The trigger price for Marshallian exit W_l occurs when $\frac{W_l}{\delta-\mu} \leq \frac{w}{\partial} + l$. W_l stands for price per gallon, δ the discount rate, μ the drift rate, and *w* the operating cost per gallon. We also calculate an NPV entry price that demands an 80% chance of economic profit when our risk level is considered NPV_h. This illustrates the difference in an NPV break-even analysis and what is the case for real life investment. Investors would want better than a fifty percent chance of making money.

Table 4.1: Trigger prices in dollars per gallon for our Break-even, **Marshallian** exit, NPV, real options with managerial flexibility, and real options without managerial flexibility analysis.

Trigger price	Price trigger occurs	Definition
W_h	$ 2.89	Break-even price
W_l	$ 1.88	Marshallian exit price
P_h	$ 4.97	RO entry price with managerial flexibility
P_l	$ 1.91	RO exit price with managerial flexibility
P_m	$ 1.91	RO mothball price with managerial flexibility
P_r	$ 2.89	RO reactivation price with managerial flexibility
$\hat{P}_h$	$ 4.98	RO entry without managerial flexibility
$\hat{P}_l$	$ 1.90	RO exit without managerial flexibility
NPV_h	$ 3.51	NPV entry price with 80% chance of econ. profit

It can be concluded from the table 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 was 72% above the break-even price W_h. Real option exit trigger price P_l was about the same as the Marshallian exit price W_l for our level of uncertainty, a gap did form however for higher levels of uncertainty. The uncertainty combined with irreversibility within our real options analysis caused plants to demand a higher price to invest and accept a lower price before exiting compared to traditional approaches. For our given level of uncertainty and drift rate it appears that break even greatly underestimates the price at which a firm will enter for a second generation drop in biofuel plant. It however does not cause firms to accept lower prices for exit until higher levels of uncertainty. Managerial flexibility has very little impact. Having the decision to mothball and reactivate later affects entry price by $.01 per gallon. The effects on exit trigger prices are more pronounced for higher levels of uncertainty. At our base levels however P_l is actually $.01 more than $\hat{P}_l$. A plant with the ability to reduce economic losses while waiting for conditions to improve will have no effect until standard deviation reaches .25 which will be discussed later. For levels higher than this it will allow plants to stay in business longer than one that cannot.[4]

Figure 4.1 shows how uncertainty affects the trigger price for entry at different levels. This graph uses $\hat{P}_h$ (which ignores the options of mothball and reactivation) so that the effect of uncertainty is not confounded with managerial flexibility. The difference between P_h and $\hat{P}_h$ is minimal. This is due to the fact that the value of the option to mothball is very low at entry trigger prices. P_h was omitted to keep the graph cleaner and not be redundant. The gap between W_h and $\hat{P}_h$ is very low when $\sigma = 0$. (The difference at 0% is caused by the drift rate, which will be discussed further in graph 4.3.) Increasing the uncertainty has no effect on break even W_h since break even only considers the expected value. $\hat{P}_h$ however, continually increases with uncertainty. Higher uncertainties increase the option value of waiting to invest, which in turn cause the firm to demand a higher

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[4] Our results comparing P_l to W_l and P_h to $\hat{P}_h$ initially appears at odds with what the literature would suggest. There is however nothing intuitively incorrect with our assumptions. Both of these comparisons yield expected results with higher levels of uncertainty. For low levels of uncertainty they give conflicting results because of the drift rate more strongly affecting W_l than P_l. For low levels of uncertainty, the mandatory mothball state costs more than it is worth. This makes the firm want to exit before it mothballs. Both of these situations will be discussed in more detail.

premium for entry. When σ reaches 60% the firm requires, to enter the market, a price more than 2.5 times higher than the break-even price under NPV.

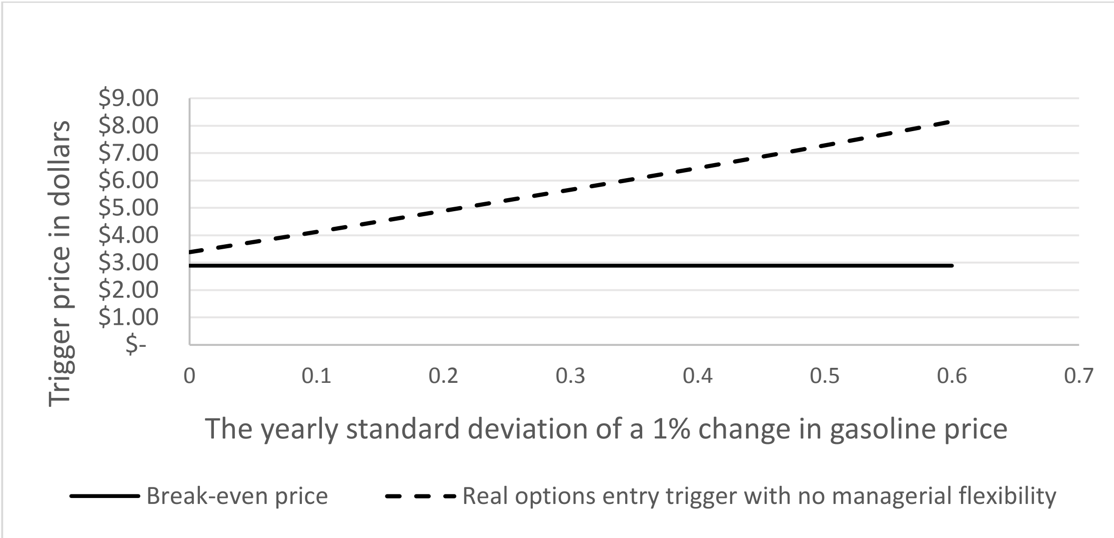

Figure 4.1: Entry trigger prices over different levels of uncertainty

Uncertainty and irreversibility in investment may result in hysteresis in firm behavior. Hysteresis may be thought of as inaction. Firms are less responsive to profitability signals because they are anticipating potential changes in these signals in the future. We now explore hysteresis in the case of biofuel firms that have the option to mothball and reactivate. In particular Figure 4.2 illustrates the link between uncertainty and hysteresis. The gap between P_h and P_l in Figure 4.2 can be thought of as a firm's limited response zone. An idle firm will not enter the market until gasoline price becomes greater than or equal to P_h. If a firm is already active, it will not exit the market until gasoline price falls below P_l. Therefore if the price of gasoline is between P_h and P_l no entry or exit will occur in this market. The main insight provided by Figure 4.2 is that 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 and it makes exit of firms already in operation also 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.

The inactivity zone under breakeven and Marshallian analysis is constant for all levels of uncertainty. Using break-even a firm will enter if $\frac{P}{\delta-\mu} \geq \frac{w}{\delta}+k$. Once entered that same firm would only leave if $\frac{P}{\delta-\mu} \leq \frac{w}{\partial} + l$. This exit trigger price is calculated as a Marshallian exit price. If a firm cannot cover their average cost in the long run they will exit. A firm will enter the industry if their discounted price covers their discounted operating costs and lump sum capital cost. They will leave once their discounted price falls below their discounted operating costs plus the lump sum value the firm receives for selling their plant upon leaving the industry. For NPV analysis the zone of inaction is the difference between k and l which, under our assumptions, is equal to $0.1.01 per gallon. Real options analysis, on the other hand, has more flexibility. Its inaction zone is between mothballing and reactivation trigger prices. In real options the wedge between entry and exit is known as the firm's limited response zone, this zone increases with uncertainty and is considerably larger than its break-even/Marshallian exit counterpart. Under our assumptions of σ=.209 and μ=1.85% the inaction zone between P_h and P_l is $3.06.

In this paper our break-even is slightly modified from a traditional break-even. A standard break-even analysis would not include a yearly cost to replace capital. It would instead have a finite project life and only calculate depreciation for tax purposes. This modification was made to make our comparison consistent with real options, even if it does diverge from a traditional NPV break-even analysis. The same is true for the Marshallian exit price.

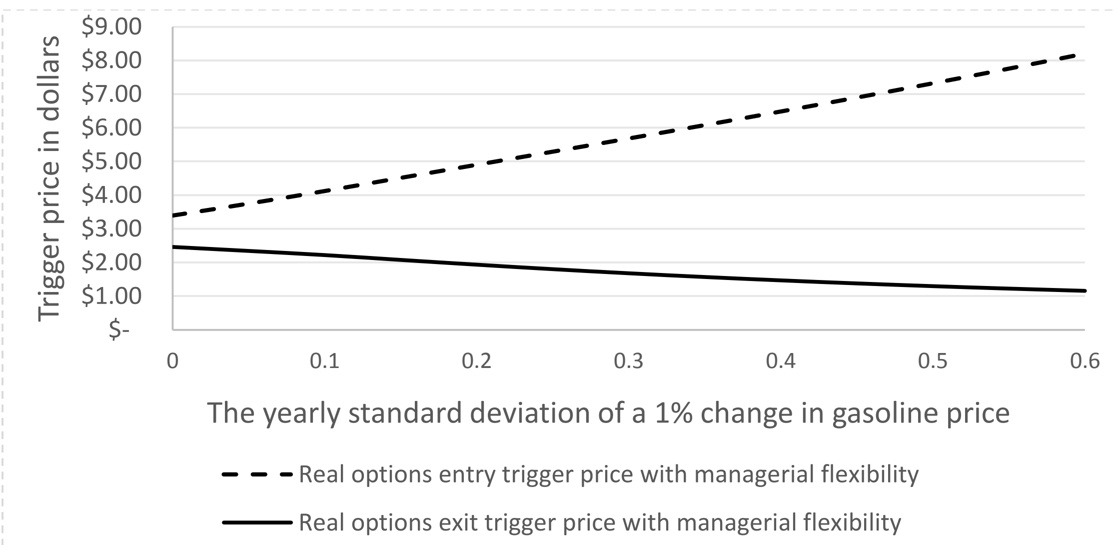

Figure 4.2: The effect of uncertainty on the wedge between P_h and P_l.

Figure 4.3 additionally incorporates the trigger prices for mothball and reactivation over different levels of uncertainty. These interactions between entry, mothballing, reactivation, and exit, show us how a plant will respond to different bio gasoline prices at different levels of uncertainty. There is a hysteresis between the mothball and reactivation price that grows with uncertainty. An active firm will wait longer to mothball under higher levels of uncertainty and a mothball firm will wait longer under higher levels of uncertainty to reactivate. Figure 4.3 shows some interactions between trigger prices that may seem counter intuitive for low levels of variability (levels below .30). The first of these is P_m converging to P_l. This is a function of how the equations are forced to interact in Matlab. A firm must mothball before it exits. For low levels of uncertainty, there is little value to the options that arise from being in a mothballed state, since prices are unlikely to change enough to induce a state change. There is however a maintenance cost m that must be paid to stay in this state and a fixed cost E_m to get to this state. This additional cost paired with a low option value means that it would never be optimal for a firm to mothball. It would always exit before it considered mothballing. For a similar reason P_r converges to P_l for low levels of uncertainty. A firm would not spend any time in the mothballed state and would exit immediately. It would never have a chance to reactivate. $P_m$and P_r are trivial under low levels of variability. For these low levels there is a mandatory fixed cost to change states, and for a mothballed state an operating cost; this is paired with these options having little value. In reality a firm would never consider mothballing for uncertainty below .30 and as a result never would consider mothballing. Because of the previously stated argument, we set P_r and P_m equal to W_h for levels of uncertainty that would have yielded a result of a lower trigger price for them than the Marshallian exit price.

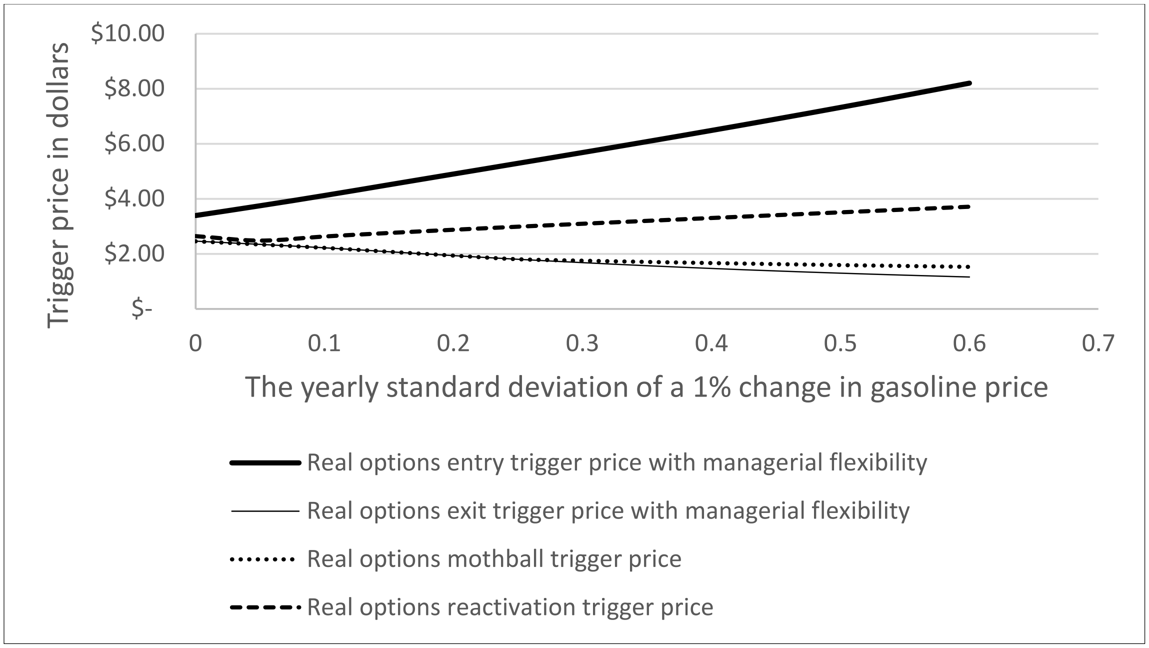

Figure 4.3: The impact of uncertainty on hysteresis

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. As expected, increases in the drift rate reduce entry trigger prices. As the prospects of the investment improve, plants require a lower price to invest without delay. Figure 4.4 also reveals that uncertainty and irreversibility soften the effect of an increase in the drift rate on entry trigger price; i.e. on Figure 4.4the slope for $\hat{P}_h$ is less steep than W_h. The effect of an increased drift has conflicting effects on $\hat{P}_h$. Like break-even, a project that trends towards increasingly favorable situations makes investment now more attractive since it lowers the likelihood of negative outcomes, but it also increases the value of waiting. Waiting with a positive drift rate becomes more valuable, because future prices are now discounted by $(\delta - \mu)$ instead of just δ. This explains why P_l and $\hat{\bar{P}}_l$ are higher than W_l for low levels of uncertainty. In these instances the impact of drift is stronger than the impact of uncertainty for real option exit prices. In other words the positive drift rate decreases W_l more than the combination of uncertainty and drift rate decreases real option exit, due to drifts reduced affect on real options compared to break-even/Marshallian assumptions.

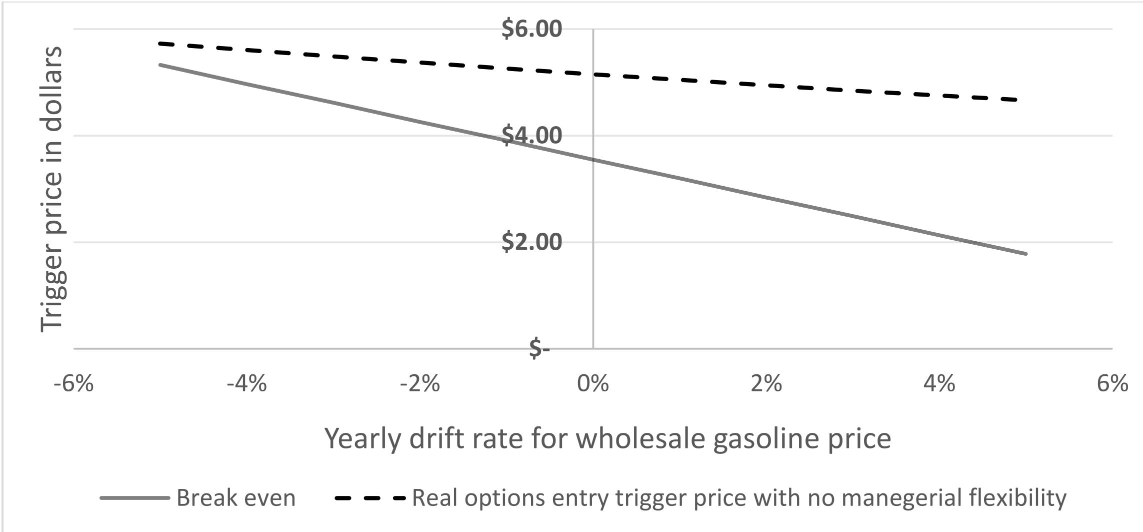

Figure 4.4: The comparison of W_h and $\widehat{\boldsymbol{P}}_{\boldsymbol{h}}$ over different drift rates

We explore the sensitivity of hysteresis (the range of inaction) to the drift rate. Results are displayed in Figure 4.5. Increases in drift rate have a close to proportional effect on entry and exit trigger prices. Specifically, they decrease at a modest rate as the drift rate increases. This furthers the argument that uncertainty and irreversibility are the important drivers of hysteresis within the biofuel industry.

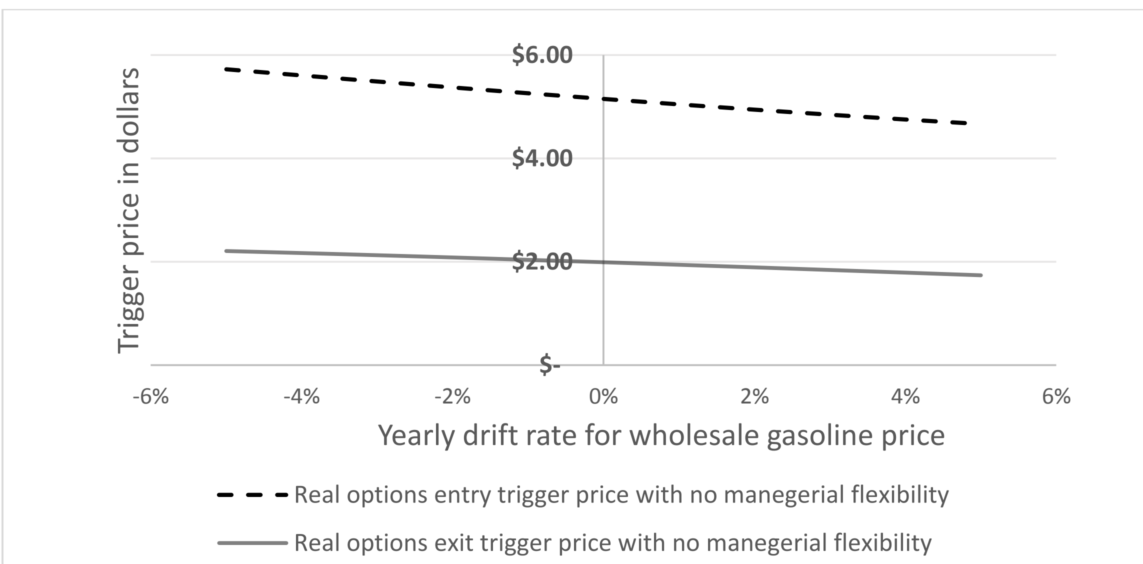

Figure 4.5: The effect that yearly drift rate has on the hysteresis between $\widehat{\boldsymbol{P}}_{\boldsymbol{h}}$ and $\widehat{\boldsymbol{P}}_{\boldsymbol{l}}$

Figures 4.6 and 4.7 show how much of the gap between W_h (W_l) and real P_h (P_l) is explained by uncertainty, and how much comes from the additional flexibility in decision making our model adds that break-even and Marshallian theory do not account for. In other words, the option to mothball and reactivate make the plant more realistic but it makes the trigger price for exit lower than it would be if we were to compare NPV entry and exit to a real options analysis that only had options for entry and exit. This is due to being able to mothball to reduce losses in the event that conditions become unfavorable and reactivate it if conditions improve later for a reactivation price less than k. In other words it gives an additional value to waiting that doesn't have a counterpart inbreak-even. When doing a real options analysis that modeled just idle and active states the $\hat{P}_h$ and $\hat{P}_l$ under the same parameters as our previous analysis, yielded prices of $4.98 and $1.90 respectively. P_h and $\hat{P}_h$ hardly differ since P_h is much higher than P_m; with our given level of variability and positive drift it is unlikely that a price would fall far enough to mothball. Since this is unlikely the option value to mothball when a firm is experiencing P_h is very low, it would not outweigh the fixed and operating cost of mothballing.

The impact that managerial flexibility has on P_l is clear. A firm will wait longer to exit if it has the option to reduce its losses and reactivate in the future. This lowering of the exit trigger price will increase the hysteresis between entry and exit. In our analysis this holds true for any standard deviation greater than .22. The reason this is not the case for all levels of uncertainty is that for low levels of uncertainty the cost of mothballing does not outweigh the option value of being able to reactivate in the future. The impact that managerial flexibility has on P_h is less clear. It has very little effect on it which makes sense given how unlikely it is at high prices, that mothballing would be used.$P_h P_h \hat{P}_h P_l \hat{P}_l$ Overall the effect that managerial flexibility has on P_h is trivial but it is important to explain why it changes.

Figure 4.6 shows how small of an effect that managerial flexibility actually has on the decision to enter for different levels of uncertainty. The lines for $P_h\ and\ \hat{P}_h$ fall right on top of one another. Uncertainty affects the decision to enter for a plant with, and a plant without managerial flexibility the same. This furthers the argument that at the high prices required for entry $P_h\ and\ \hat{P}_h$ are so far away from P_m that the option has no value at this point.

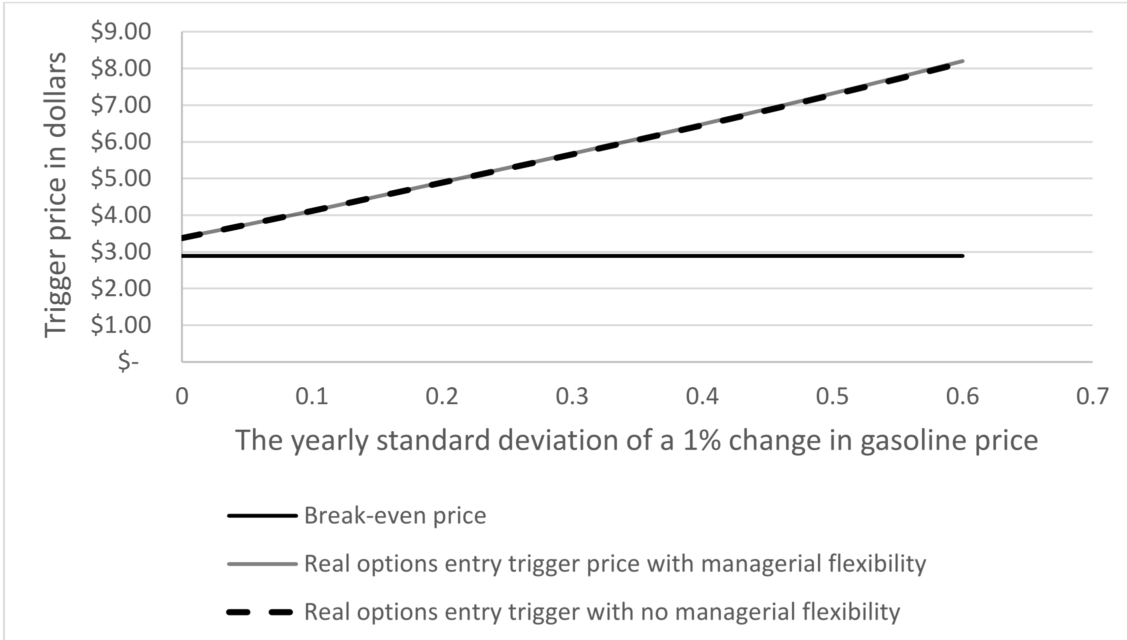

Figure 4.6: Effect of managerial flexibility on the decision to enter.

$P_l P_m P_l P_h$Figure 4.7 shows how managerial flexibility effects exit. In figure 4.6 we saw that flexibilities affect on entry is negligible. For our given level of uncertainty Managerial flexibility has no meaningful effect on P_l either. Managerial flexibility does however have an impact on P_l for higher levels of uncertainty. For a standard deviation of .6 a firm will leave the industry $.36 sooner if they do not have the option to reduce their variable costs until market conditions improve to a point where they can reactivate. This makes sense since P_m is much closer to P_l than it is to P_h. The value option to mothball has an inverse relationship with price.

$P_l \hat{P}_l$ Plants are willing to stay in the market and bear higher losses if they have the option to mothball which reduces these losses to only *m* per gallon instead of *P-w* per gallon, and reactivate in the future if prices improve. This explanation is apparent anywhere between .22 to .6 standard deviation. From 0% to .22 however there is another affect that outweighs the option value of mothballing which causes P_l to actually be greater than $\hat{P}_l$. Option values increase with higher amounts of uncertainty. Under relatively low levels of uncertainty the option does not hold much value. In addition to this our Bellman equations are set up in a way that requires a firm to mothball before it exits. In the situation with managerial flexibility, if a plant decides to exit it must pay fixed cost E_m before it can leave even if it goes directly from active to idle. This low option value paired with what is essentially an additional cost to exit causes the firm to leave earlier in the situation where it has flexibility than one where it does not.

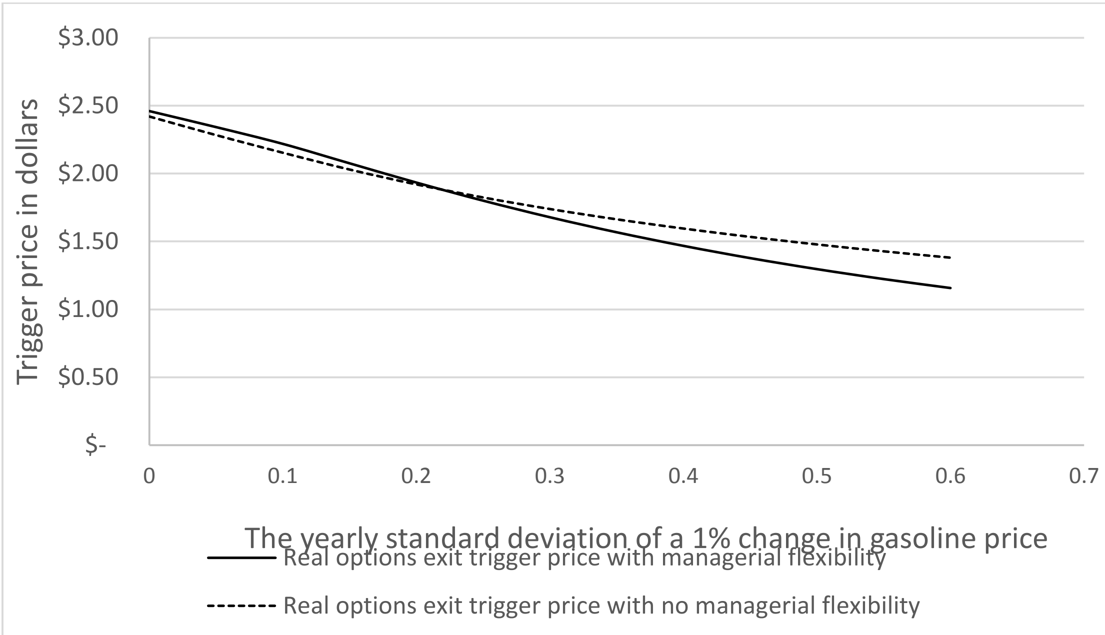

Figure 4.7: The effect of managerial flexibility on the decision to exit.

5 CONCLUSIONS

The large amount of existing literature puts the break-even entry price of a second generation drop in biofuel plant anywhere between $2.00 to $2.70 a gallon for a commercial scale plant (Anex et al., 2010, Wright et al., 2010, Brown et al., 2013, Tyner and Petter, Cannon, 2012, Jones et al., 2009). If we assume a biofuel selling price equal to that of wholesale gasoline price, which is currently $2.79 a gallon, one would expect that, even under the least promising break-even analysis, NPV for a second generation biofuel plant would be greater than zero (EIA, 2014). It is important to note that a positive NPV does not guarantee investment in the real world, if these NPV's required an economic gain with greater than 50% probability then this would not be the case. By definition though this would require accounting for and building risk into the model. Despite this positive NPV, the United States is in a situation where it is well short of its Renewable Fuels Mandate for cellulosic biofuels every year. This shortfall has been considerable. In 2013, cellulosic biofuel production totaled six million gallons. This falls 994 million gallons below the target goal of 1 billion gallons set by the Renewable Fuel Standard (Schnepf and Yacobucci, 2010). This gap between the break even and actual price is caused by uncertainty.

This chronic shortfall in investment in cellulosic biofuel plants is easily rationalized when uncertainty and irreversibility, two distinctive features of this industry, are considered. The market for gasoline has been known to be volatile. Using wholesale monthly data over the last twenty years we calculated a yearly standard deviation of gasoline price of just under .21. This volatility has a large effect on the option value of waiting and gives us an entry trigger price of $4.98 per gallon as opposed to $2.89 per gallon, which emerges under conventional microeconomic theory (i.e. when uncertainty and irreversibility are ignored). In other words gasoline prices have been high enough to induce investment under a break-even model that ignores uncertainty. Once uncertainty and irreversibility are added into the calculation, prices fall well short of the trigger price for entry. It then follows that uncertainty constitutes a significance barrier to meeting the Renewable Fuel Standard for cellulosic biofuel.

Another conclusion to be drawn from the data is that once firms are in the industry they will stay in longer before exiting under a real options analysis than they would under an break-even/Marshallian analysis for moderate to high levels of uncertainty. Hysteresis between entry and exit increases with higher levels of uncertainty. Drift rates also cause effect real options differently than beak-even/Marshallian assumptions. They have a more modest effect on real options due to the conflicting effect on the expected value and option value.

Using the insights from this study, this paper makes several recommendations that could allow for meeting the Renewable Fuel Standard in a more cost effective way. Since the RFS was started for cellulosic biofuels policies primarily have been designed to address expected value, lowering costs, or offering attractive financing that improves NPV. All of these policies will lower trigger price but none of them address uncertainty. Results in this paper suggest that using government subsidies to reduce uncertainty may be more effective than policies aimed at affecting mean return on investment. Some ideas for reducing uncertainty have been developed in the literature. They include government subsidized insurance that guarantees a minimum price and forward contracts that lock the producer into a specific price in the future regardless of what the market does (Tyner et al., 2010, Song et al.). In theory these policies could dramatically reduce uncertainty inherent within the cellulosic biofuel industry. It would be possible to adapt this RO analysis to these policies by adding in parameters associated with a given policy and then resolving the equations in Matlab. This is a topic of future research.

Following the same logic, the government could reduce the perceived risk in the industry if they enforced existing mandates. The EPA waives the RIN mandate every year. Every year congress debates what subsidies for biofuels they will cut. This uncertainty involved within these already inefficient price subsidies makes them even less efficient to address uncertainty. If the goal is to induce investment into cellulosic biofuel production, the government could reduce the uncertainty involved in policy. While these previously mentioned policies for reducing uncertainty are important, and finding a most cost effective one would require looking at them in a vacuum as I have discussed, this is not the whole story. The reality is that for any producer to get financing, they need to be locked into a long term offtake contract. This reality does not detract from the legitimacy of this paper or looking at other policy options but it is something that should be considered when thinking about second generation biofuel plant investment.

All of the assumptions for costs, prices, and technology where the most sensible under current information; these can however change as technology and markets evolve and could significantly affect trigger prices. Stover accounts for about half of a biofuel plants operating cost. Yet there is considerable uncertainty surrounding this coefficient as well. Moreover the hydrogen being used in these plants comes from natural gas. Natural gas prices have historically been even more volatile than gasoline. Prices for natural gas could, and probably will change in the future. This would affect trigger prices. Currently Pyrolysis is the most promising technology but a single innovation in an existing or new technology could completely turn the tables, and alter the cost projections.

This paper modeled how changes in price can effect entry and exit into an industry. While literature suggests that price is the largest determinant for entry. It is not however the only determinant. Costs, yields, and government policy all carry with them a degree of uncertainty for this new industry. An analysis done that incorporates the uncertainty experienced by all of these variables would go a long ways in furthering the literature on second generation drop in biofuel plants.

This study is not without limitations. While the study does account for uncertainty in price, it 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 uncertainties full effect on entry trigger price would also incorporate the uncertainty on the production side of cellulosic biofuels. This additional uncertainty would likely compound the already large amount of hysteresis within the industry. This limitation could be overcome by modeling a real options analysis for cellulosic biofuels using two stochastic variables, one for price and one for cost. The purpose of this study, however, was to determine the effect of uncertainty on output, arguably the main source of uncertainty, on firm behavior.

Another limitation of this study is that numbers for plant cost, capacity, and output are speculative. Our study gathered numbers from the most reliable sources possible but the fact of the matter is that, at the moment, only one large scale plant with this technology exists (KIOR) and even it is running well under capacity. All of our information was taken from pilot plants, TEA's, and modifications from cellulosic ethanol plants. These numbers are the best estimations possible but they may change once data from actual large scale plants becomes available. This could be remedied by re-doing this analysis in several years when the technology is more proven and more reliable numbers exist.

The next logical step for this research would be to model government policy into it. The study has already quantified the impact that uncertainty has on entry and exit from the industry, it would be interesting to see the impact that each government policy, both in place and proposed, would have on entry into the industry. More specifically the different magnitudes that a fixed subsidy, variable subsidy, financing, futures contract, and the RFS would have on trigger prices. (Tyner et al., 2010, Song et al. 2010) This would be done by modifying the Bellman equations, specifically adding additional terms and parameters to model the incentive being considered. Furthermore, these policies could be compared on a cost effectiveness basis i.e. for every million dollars spent through a specific policy how much does the trigger price decrease? Judging by our results for this study, a policy that addresses uncertainty may be more cost effective than one that simply tries to increase the expected price.

Another option for future research would be to model the externalities of cellulosic biofuel production into the cost. More specifically if one could retrieve a value for the amount of carbon reduced, domestic job creation, etc. from a gallon of biofuel it would be possible to come up with a social trigger price for entry and exit that would reflect its social value. The hypothesis would be that a gallon of drop in biofuel would have a different value to society than a gallon of petroleum based fuel. This value could then be used to justify the economically efficient level of government incentives to be used in the cellulosic biofuel market.

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7 APPENDIX

Appendix 1: 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 2: 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)
```