A Stochastic Techno-Economic Comparison of Alternative Jet Fuel Production Pathways

by

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Submitted to the Institute for Data, Systems, and Society
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Abstract

This study quantifies and compares the costs of production for six alternative jet fuel pathways using consistent financial and technical assumptions. Uncertainty was propagated through the analysis using Monte Carlo simulations. The six processes assessed were hydroprocessed ester and fatty acids (HEFA) using soybean oil, yellow grease, and tallow; advanced fermentation (AF) using corn grain, sugarcane, and herbaceous biomass; conventional gasification and Fischer-Tropsch (FT) using municipal solid waste; aqueous phase processing (APP) using woody biomass; hydrothermal liquefaction (HTL) using woody biomass; and fast pyrolysis and hydroprocessing (FPH) using corn stover. The results indicate that none of the six processes would be profitable in the absence of government incentives, with HEFA using yellow grease, HEFA using tallow, and FT revealing the lowest mean jet fuel prices at \$0.91/liter (\$0.66/liter to \$1.24/liter), \$1.06/liter (\$0.79/liter to \$1.42/liter), and \$1.15/liter (\$0.95/liter to \$1.39/liter), respectively. The highest mean NPV was the NPV calculated for HEFA yellow grease with a mean value (in \$B) of -0.112 (95% range of -0.412 to 0.179), followed by HEFA tallow with -0.202 (-0.517 to 0.100) and FT with -0.210 (-0.424 to 0.033). This study also quantifies plant performance in the United States with a policy analysis. The alternative fuel production models were used to examine the economic viability of each pathway under a variety of existing and potential regulatory scenarios. Results indicate that some pathways could achieve positive NPV with relatively high likelihood under existing policy supports, with HEFA and FPH revealing the highest probability of positive NPV at 94.9% and 99.7%, respectively, in the best-case scenario.

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Chapter 1

Introduction

1.1 Background

Aviation currently contributes 2% to anthropogenic GHG emissions (ICAO, 2010). The impact is expected to grow in the absence of mitigation measures, due in part to a projected annual industry growth (measured in revenue passenger kilometers) of approximately 5% out to 2034 (Boeing, 2015). The aviation industry's CO_2 emissions have grown by 3.6% per year since 1980, or approximately double the current world growth rate of CO_2 emissions from energy consumption, prompting attention from numerous international and domestic regulatory authorities (Schäfer, 2014). The International Air Transport Association (IATA), for example, targets carbon-neutral growth from 2020 onward and a 50% reduction in net emissions by 2050 compared to 2005 levels (IATA, 2009). Alternative jet fuels produced from biomass have received considerable attention from policy-makers and academia as a potential means to significantly reduce greenhouse gas emissions attributable to aviation (ICAO, 2016). The United States Federal Aviation Administration (FAA), for example, sets an aspirational consumption target of 1 billion gallons of alternative jet fuel by 2018, and alternative jet fuel can qualify under the second iteration of the Environmental Protection Agency's (EPA) Renewable Fuel Standard (FAA, 2012). Emissions savings attributable to alternative jet fuels have been well-documented in several pathway- and feedstock-specific life cycle GHG emission analyses (Seber et al., 2014; Staples et al., 2014; Suresh, 2016).

One of the main challenges for alternative aviation fuels is the economic feasibility of converting biomass or other feedstocks into liquid fuel that meets current jet fuel specifications. Five pathways have been approved by ASTM International as drop-in alternative jet fuels: Fischer-Tropsch Synthetic Paraffin Kerosene (FT-SPK), Fischer-Tropsch Synthetic Kerosene with Aromatics (FT-SKA), Hydroprocessed Esters and Fatty Acids (HEFA), Synthetic Iso-Paraffins from fermented hydroprocessed sugar (SIP), and Alcohol-to-Jet SPK (ATJ-SPK). Sixteen additional pathways are under review (CAAFI, 2016). ASTM certification associated with fuels produced from these pathways allows up to 50% blending by volume in current aircraft engines, and some of these pathways, as a result, have been implemented in commercial scale production facilities (ICAO, 2016).

This thesis describes a techno-economic study that used harmonized assumptions for six different alternative jet fuel pathways and incorporated uncertainty throughout the analysis. Existing studies estimated costs of production for specific pathways or feedstocks through detailed techno-economic analyses (TEA) that evaluated pathway performance by calculating the breakeven price of fuel or the net present value of the plant over the modeled refinery's lifetime (Bittner et al., 2015; Bond et al., 2014; Niziolek et al., 2015; Pearlson et al., 2013; Staples et al., 2014; Zhu et al., 2014). Although considerable uncertainty surrounds critical variables such as fuel prices, conversion yield, and capital expenditures, few studies to date have incorporated stochasticity in the modeled pathways or have examined the diesel and jet fuel industry specifically (de Jong et al., 2015). This paper incorporates both harmonized assumptions and stochasticity in critical inputs and accounts for different policy scenarios in a harmonized comparison of jet fuel production techniques.

1.2 The Renewable Fuel Standard

From a technical standpoint, this study primarily focuses on probabilistic models for alternative jet fuel production pathways. Existing U.S. policy, however, allows for the characterization of the private costs of these pathways within the context of supports and subsidies created under the Renewable Fuel Standard (RFS). This framework, created as an expansion to the Clean Air Act (CAA) under the Energy Policy Act of 2005, incentivizes the use of alternative fuels provided those fuels meet certain greenhouse gas reduction targets. The Environmental Protection Agency (EPA) oversees the execution of the RFS along with the Department of Agriculture and the Department of Energy. The most relevant function of the RFS in the context of this study is the creation of yearly alternative fuel mandates as dictated by Renewable Volume Obligations (RVOs). These are targets that require replacement of conventional petroleum fuels with alternative fuels in increasing amounts. As of 2017, the EPA has dictated four renewable fuel categories with separate obligations for each: biomass-based diesel, cellulosic biofuel, advanced biofuel, and renewable fuel. The program was amended with the Energy Independence and Security Act of 2007 (or RFS2) which expanded the RVO requirement to 36 billion gallons of alternative fuel through 2022. The RVO categories are listed in Table 1.1 along with their corresponding GHG intensity reduction requirement. Note that this intensity reduction is compared to 2005 measures of conventional petroleum-based fuel emissions intensities.

Figure 1-1 demonstrates the evolution of these blendstock requirements over time– note that the proportion of cellulosic biofuel, advanced biofuel, and biomass-based diesel grows relative to the renewable fuel requirement. The growing requirements for cellulosic biofuel, a fuel for which most conversion pathways are technically immature, corresponds with a growing value assigned to cellulosic fuels. Appendix D expands upon the value of RINs in greater detail.

Table 1.1: RVO fuel categories and feedstock/pathway examples

Fuel Category	GHG Intensity Reduction	Feedstock Examples	Pathway Examples
Renewable Fuel	20%	Corn starch	Dry mill process, fermentation
Advanced Biofuel	50%	Sugarcane, corn stover, soybean oil	HEFA, AF
Biomass-based Diesel	50%	Sugarcane, corn stover, soybean oil	HEFA, AF
Cellulosic biofuel/biodiesel	60%	Woody biomass, switchgrass	FPH, HTL

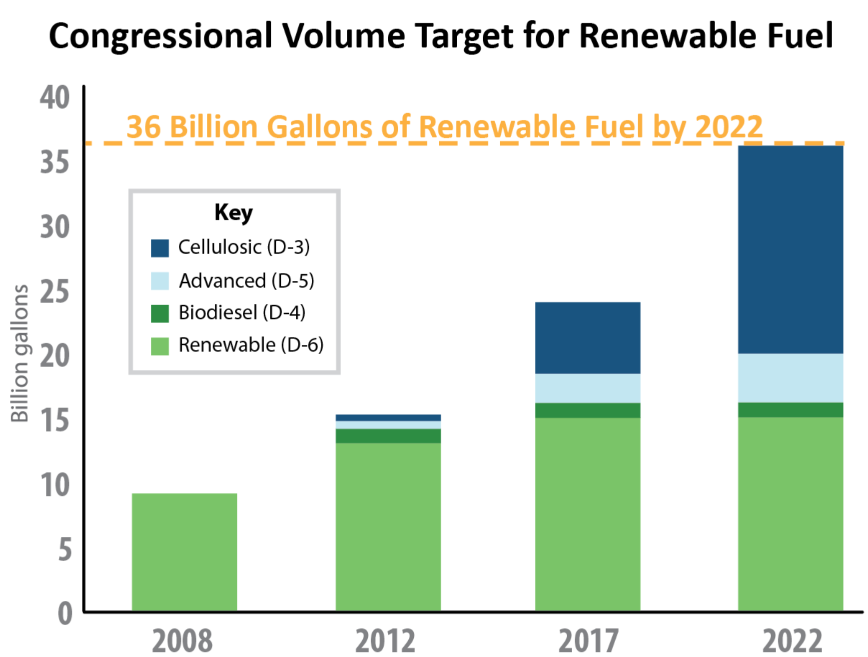

Figure 1-1: EPA Renewable Volume Obligations dictated by the RFS (EPA, 2016)

Chapter 2

Materials and Methods

2.1 Alternative Jet Fuel Pathway Modeling

This study compared six alternative jet fuel pathways for which data is available in peer-reviewed studies: HEFA, fermentation and advanced fermentation (AF), aqueous phase processing (APP), conventional gasification and Fischer-Tropsch (FT), hydrothermal liquefaction (HTL), and fast pyrolysis and hydroprocessing (FPH). The source literature and information regarding the feedstocks and liquid fuel products for each pathway is found in Table 2.1. A technical survey of each pathway can be found in Appendix A and the technical assumptions used in the original literature sources can be found in Appendix B. In every case, the products are chemically equivalent to conventional products of petroleum refining, with the middle distillate fraction composed of renewable or "green" diesel and kerosene-type jet fuel.

The surveyed pathways are at various stages of technical maturity, and discrepancies in commercialization were accounted for with a n^{th} plant analysis that assumes construction in 2015 and plant operation beginning in 2018. The design bases for the pathway models, however, varied with the availability of bench-, pilot- or commercial-scale process data, with some models constructed using industry data and others constructed using computer-simulated results. Although the HEFA pathway is modeled by Pearlson et al. using Aspen Plus chemical process software, the material and energy balances were confirmed against commercial-scale values from

Table 2.1: The six alternative jet fuel production pathways evaluated in this study

Pathway	Feedstock	Fuel Products	Source
HEFA	Soybean oil, tallow, yellow grease	LPG, naphtha, middle distillates	Pearlson et al., 2013; Seber et al. 2014
AF	Corn grain, sugarcane, herbaceous biomass	LPG, naphtha, middle distillates	Staples et al., 2014
APP	Woody biomass	LPG, naphtha, middle distillates	Bond et al., 2014
HTL	Woody biomass	Gasoline, heavy oil, middle distillates	Zhu et al., 2014
FT	MSW	Gasoline, middle distillates	Niziolek et al., 2015; Suresh, 2016
FPH	Corn stover	Gasoline, middle distillates	Bittner et al., 2015; Brown et al., 2013

the UOP-Honeywell Ecofining process (Pearlson et al., 2013). The Fischer-Tropsch process, a reaction that converts a syngas intermediate into liquid hydrocarbons, is well-understood from nearly a century of research at varying scales, but the plant design presented by Niziolek et al. incorporates a novel nonlinear optimization model that integrates both simulation results and industry-created sub-processes (Niziolek et al., 2015). Similarly, the AF pathway modeled by Staples et. al. relies heavily on industry heuristics and commercial-scale plant data when replicating the material and utility requirements for various process steps (Staples et al., 2014). Zhu et al. models the HTL process using bench-scale data from the Pacific Northwest National Laboratory (PNNL) (Zhu et al., 2014). Bittner et al. and Bond et al. rely on a combination of experimental data and simulation results for the APP and FPH processes, respectively (Bittner et al., 2015; Bond et al., 2015). This study assumed equivalent fuel yields at scale in each case.

This study compared each pathway using material and energy balances from the sources found in Table 2.1, but the original TEAs of the pathways relied on deterministic fuel yields and capital cost estimates as well as historical averages for input and output prices. Point values for these model components were then used in a

Discounted Cash Flow Rate of Return (DCFROR) model that was used to determine either the net present value (NPV) of the plant assuming market fuel prices or the minimum middle distillate selling price (MSP) such that the NPV was positive. Assuming that prices for inputs and outputs were certain throughout a plant's lifetime, however, does not account for fluctuations in the costs of key inputs or the prices of fuel products. The original TEA studies associated with each pathway used DCFROR variables with deterministic values, but in reality these variables change stochastically such that sampling values from probabilistic models provided a better model for input value fluctuation over a plant's lifetime.

Blazy et al. used the example of diesel fuel price, which can be affected by a multitude of external forces such as supply shocks, changes in demand, or adjustments to domestic policy (Blazy et al., 2016). Using a single value for the price of diesel ignored these fluctuations. Instead, correlating the price of diesel to stochastic variations in the projected price of gasoline provided a more robust description of how this input changed over time. Instead of varying independently with time, other fuel products were also correlated to the stochastically projected price of gasoline. This study implemented stochasticity using a Monte Carlo simulation that sampled values from probability distributions assigned to critical inputs. A MATLAB model sampled values from each probability distribution, computed either MSP and NPV over 10,000 iterations, and stored the results for each iteration such that each iteration was a discrete 20-year plant lifetime.

2.2 Financial Model

This study employed a MATLAB version of the DCFROR model from Pearlson et al. in order to quantify pathway performance in terms of MSP and NPV (Pearlson et al., 2013). Financial assumptions were harmonized for each pathway assuming a 20-year plant lifetime with 20% equity financing and a 10-year loan with 10% interest. Each plant was assumed to operate for 8400 hours, or 350 days, per year. The income tax rate was assumed to be 16.9% based on the value for the average effective corporate tax rate from the United States Government Accountability Office (GAO, 2013). Other financial assumptions were drawn from Blazy et al.'s research on bio-process commercialization (Blazy et al., 2016). All costs and prices were expressed in 2015 USD. The critical inputs for the DCFROR model were assessed using the relevant studies associated with each pathway, and probability distributions were assigned to each input given the availability of relevant data. The complete table of parameters, their distributions, and the references associated with the data underlying each distribution was included in the Appendix B. Probabilistic inputs that were common between pathways include capital expenditures, fixed operating costs, feedstock costs, and fuel prices. The parameter distributions were primarily dependent on the available data: uniform distributions were used in cases where data values were equally likely and triangular or beta PERT distributions were used when minimum, maximum, and most likely values were known. In cases of statistical uncertainty arising from descriptive data sets, such as historical commodity prices or price projections, the probability distributions were developed from the samples themselves. The fit of these distributions was confirmed using the Anderson-Darling test (Stephens, 1974).

The feedstock input quantities and associated maximum fuel outputs can be found in Appendix B. Due to the price parity between diesel and jet fuel the model solved for the MSP of middle distillates (i.e. jet and diesel). The MSP for middle distillate fuels was calculated as the price for middle distillates such that the refinery has an NPV of zero. The MSP thus represents the price for middle distillates that a producer must demand in order to achieve a target rate of return. All other products, such as naphtha or LPG, were sold at the sampled market price and not at a correlated premium, a method used in previous TEA studies (Pearlson et al., 2013). The costs of transportation from the plant to the retail location were not considered, nor were additional fuel taxes, so the MSP and other product prices are the "gate price" of the fuel and not the at-pump price. The DCFROR model was also used to calculate the NPV of each pathway assuming market prices for all fuel products. A positive NPV implies that a producer can expect profits above the target rate of return, while a negative NPV implies net losses below a target rate of return. MSP and NPV calculations were chosen as metrics for plant performance due to literature precedent and due to ease of visual comparison.

2.3 Technical Uncertainty

2.3.1 Capital Investment and Fixed Operating Cost Uncertainty

The capital cost estimates for each refinery model were obtained from the literature studies used to determine the mass and energy balances for the pathways examined in this study. The deterministic pathway capacity was fixed to 111.3 million liters/year (2000 barrels/day) a reference capacity used for many of the original case processes (Pearlson et al., 2013; Staples et al. 2014; Niziolek et al. 2015). This output capacity varied, however, with stochastic changes in fuel yield. Plant utility requirements, feedstock inputs, and product slates were normalized to a 111.3 million liters/year output capacity in cases where the reference pathways produced greater volumes of liquid fuels (Bond et al. 2015; Zhu et al. 2014; Bittner et al. 2015). This study assumed greenfield plants with onsite hydrogen production, and it is noted that capital and operating costs might be reduced with brownfield sites purchasing offsite hydrogen. The feedstock inputs and fuel outputs for each pathway are summarized in Appendix B. Where data availability allowed, plant component cost estimates and fuel yields were harmonized between pathways. Due to diverse simulation techniques (using Aspen Plus™, ChemCAD©, or mathematical models) and conversion data sources (bench tests, industry heuristics), this study assumed that the deterministic capital expense values accurately reflect the investment requirements for each process. Because this study further assumed that construction for each plant begins in 2015, the capital costs were adjusted to 2015 USD using the Chemical Engineering Plant Cost Index (Chemical Engineering, 2016).

In order to incorporate uncertainty into the capital cost figures, the error associated with deterministic cost estimates was assumed to be 20% (Gary et al., 2007). A review of other biomass-to-jet fuel studies revealed that the capital costs for similar plant components fall within this range. Previous studies employed a triangular or beta PERT distribution given mode, minimum, and maximum values, and a beta PERT distribution was employed in this case (Bittner et al., 2015; Blazy et al., 2016; Zhao et al., 2015). Brown found that an asymmetric probability distribution with positive skewness best represented current capital expenditures, and a 5% mean cost overrun was assumed based on a survey of the literature for a variety of industrial plants and construction projects (Brown, 2015). As a result, a beta PERT distribution for fixed capital investment (FCI) that varies between 80% and 150% of the deterministic value was used in order to replicate these conditions. Following an assumption found in several preceding TEA studies for these pathways, working capital (WC) was assumed to be 5% of the FCI, and the sum of these two values was the total capital investment (TCI) (Peters et al., 2003; Pearlson et al., 2013; Staples et al. 2014; Bond et al., 2014).

Fixed operating costs (FOC) was determined as a percentage of the capital costs, but each pathway cited widely varying deterministic values that correspond with differences in estimates of yearly expenses such as labor and maintenance. Insurance, local taxes, maintenance, and contingency costs for each pathway were estimated using guidance from the petroleum refining industry, and the literature FOC as a percentage of FCI was selected as the mode for a positively-skewed beta PERT distribution with harmonized parameters (Gary et al., 2007). Each pathway's FOC was varied by 50% and values beyond the bounds of this distribution were investigated in the sensitivity analyses.

2.3.2 Fuel Yield Uncertainty

The conversion efficiency of each pathway was described by assigning a probability distribution to fuel yield in terms of liters of gasoline equivalent (LGE) per metric ton of feedstock. The energy shares of each fuel product, expressed as the energy content of each fuel product (in MJ) divided by the total energy content of the product slate (in MJ), was assumed to remain constant for each pathway. In literature refinery models where diesel was the only middle distillate product, this study followed Bittner et al. and assumed that this stream was 50% jet fuel and 50% diesel by volume when calculating NPV (Bittner et al., 2015). Previous studies that incorporated fuel yield uncertainty employed a variety of probability distributions based on bench-scale data or simulation results including beta general distributions, beta PERT distributions, and triangular distributions (Zhao et al., 2014; Petter and Tyner, 2014; Zhu et al., 2003). In this case, a lack of fuel yield data dictated the use of a beta PERT distribution with some minimum, maximum, and mode value using the method employed by Suresh and Petter and Tyner (Suresh, 2016; Petter and Tyner, 2014). Following Zhao et al., a negatively-skewed beta PERT distribution was assumed based on pathway-specific supporting data. In pathway cases with only one supporting study, such as HEFA, AF, and APP, the deterministic value was used as the maximum fuel yield value. Because of the negative skewness, the distribution mean was lower than the deterministic value. In order to illustrate the different fuel yield scenarios, the upper and lower bounds of this distribution were investigated in the sensitivity analyses with the original literature value used as the upper input. The distribution parameters and their references can be found in Appendix B.

2.4 Fuel and Utility Price Uncertainty

In order to project the prices of natural gas, electricity, and gasoline from the analysis start point in 2018 through the plant's 20-year lifetime, Geometric Brownian Motion (GBM) was applied according to the method described in Zhao et al. as shown in Equation 1:

$$P_t = P_{t-1} \times e^t + \epsilon \tag{2.1}$$

where P_t is the price at time t, $P_t - 1$ is the previous year's price, r is the growth rate, and ϵ is the yearly price variation (Zhao et al., 2014). The Energy Information Administration (EIA) Annual Energy Outlook (AEO) 2015 provides projected price data in the analysis start year (2018) as well as real price growth rates from 2018 to 2038, with low, reference, and high oil price scenarios describing the behavior of these prices over time (EIA, 2015). Uncertainty was incorporated in the gasoline growth rate and the 2018 start price by assigning a beta PERT distribution to both parameters using the oil price scenarios as low, mode, and high values. The starting prices and growth rates for natural gas and electricity were then correlated with the selected gasoline values (EIA, 2016a,e). The 2018 prices of gasoline, natural gas, and electricity from the AEO reference case projections are \$0.58/liter, \$5.02/GJ, and \$0.07/kWh, respectively (2015 USD). The yearly price variation term, , was selected from a normal distribution of the year-to-year variations in prices from the past 15 years from 2001 to 2015. Although the MATLAB model was constructed to ensure that prices remain positive, values selected from the outer bounds of the variation distribution can result in prices far above or far below prices seen in historical or projected datasets. Prices were prevented from dropping below 75% of the lowest forecasted value or rising above 125% of the highest forecasted value in order to correct for this error.

The prices of other fuel products, such as LPG, jet, and diesel, were correlated with the gasoline price using historical price data from the EIA (EIA 2016b,c,d,f). Following Pearlson et al. and Staples et al., the propane spot price was used as a surrogate for both light ends and LPG and the gasoline price was used as a surrogate for naphtha (Pearlson et al., 2013; Staples et al., 2014). The correlation functions for these fuels were based on their historical regression relationship and can be found in Appendix B.

2.5 Policy Uncertainty

In order to quantify uncertainty under various policy scenarios including the Renewable Fuel Standard (RFS2), this study modeled the price behavior of fuel credits called Renewable Identification Numbers (RINs) using probability distributions and incorporated various tax credit scenarios as sensitivity analyses. Under RFS2, blenders and refiners are required to incorporate a certain quantity of biofuels in their annual supply in order to meet their Renewable Volume Obligation (RVO). Renewable fuels generate RIN certificates, which can be bought and sold to help blenders and refiners achieve their RVO; as a result, RINs represent a source of additional revenue for biofuel producers (ICCT, 2014). The nationwide RVO increases every year up to 36 billion gallons in 2022. At the conclusion of 2022, the RVO could be extended, increased, or reduced with the passage of a new RFS, thus changing the RIN market substantially (Winchester, et al., 2013). Information regarding the implementation of RINs for each fuel product and the calculation of stochastic RIN prices can be found in Appendix D.

The Biodiesel Mixture Excise Tax Credit, which can be applied to both biodiesel and renewable diesel mixtures, is a $1.00/gallon ($0.26/liter) credit applied to conventional and alternative diesel blends (DOE, 2016). This credit is often instated retroactively, so the existence of the credit from year to year is the subject of considerable uncertainty. Blenders arrange sharing provisions with alternative fuel producers in order to compensate biofuel production (Irwin, 2015). Various sharing agreements between producers and blenders including 25%, 50%, 75%, and 100% of the $1.00/gallon ($0.26/liter) given to producers were explored. Blenders and producers were assumed to share the additional revenue from these credits according to such sharing contracts. A producer's credit, or a credit given directly to producers instead of blenders, is the subject of current legislation in the U.S. Senate (Swoboda, 2016). If passed, this new credit would be paid to producers but would also likely be shared via market mechanisms. Thus, the $1.00/gallon ($0.26/liter) credit represents an upper-limit value for a credit given to producers. Because the FT MSW feed composition contains unseparated biogenic and non-biogenic components, it was ineligible for the blender's or producer's credits.

Six different scenarios were examined in this study to reflect future legislative uncertainty: a case in which the pathways were evaluated without the benefit of policy supports; a case in which the blender's credit was not renewed at the conclusion of 2016 and the RVO falls to zero at the conclusion of 2022; and four different sharing arrangements with 25%, 50%, 75%, and 100% of a $1.00/gallon ($0.26/liter) excise tax credit given to producers along with a perpetual RIN market. Note that a zero RVO eliminates the demand for RINs, thereby removing the RIN revenue stream.

Chapter 3

Results and Discussion

3.1 MSP and NPV

The MSP and NPV were first calculated without the addition of policy supports or financial incentives. Box-and-whisker comparisons of each pathway's MSP and NPV results are shown in Figures 3-1 and 3-2, with the limits of each pathway result representing the middle 95% of values. The lowest mean MSP was that of HEFA yellow grease with a value of \$0.91/liter (95% range of \$0.66/liter to \$1.24/liter), followed by HEFA tallow with a mean MSP value of \$1.06/liter (\$0.79/liter to \$1.42/liter), FT with \$1.15/liter (\$0.95/liter to \$1.39/liter), HEFA soybean oil with \$1.19/liter (\$0.87/liter to \$1.60/liter), AF sugarcane at \$1.47/liter (\$1.10/liter to \$1.96/liter), FPH with \$1.52/liter (\$1.02/liter to \$2.10/liter), AF corn grain with \$1.66/liter (\$1.30/liter to \$2.10/liter), APP with \$2.07/liter (\$1.73/liter to \$2.48/liter), AF herbaceous biomass with \$2.51/liter (\$2.16/liter to \$2.92/liter), and HTL with \$2.78/liter (\$2.09/liter to \$3.58/liter). None of the MSP results approached the 5-year average conventional jet fuel price of \$0.64/L, even at the lower-bound values (EIA, 2016d).

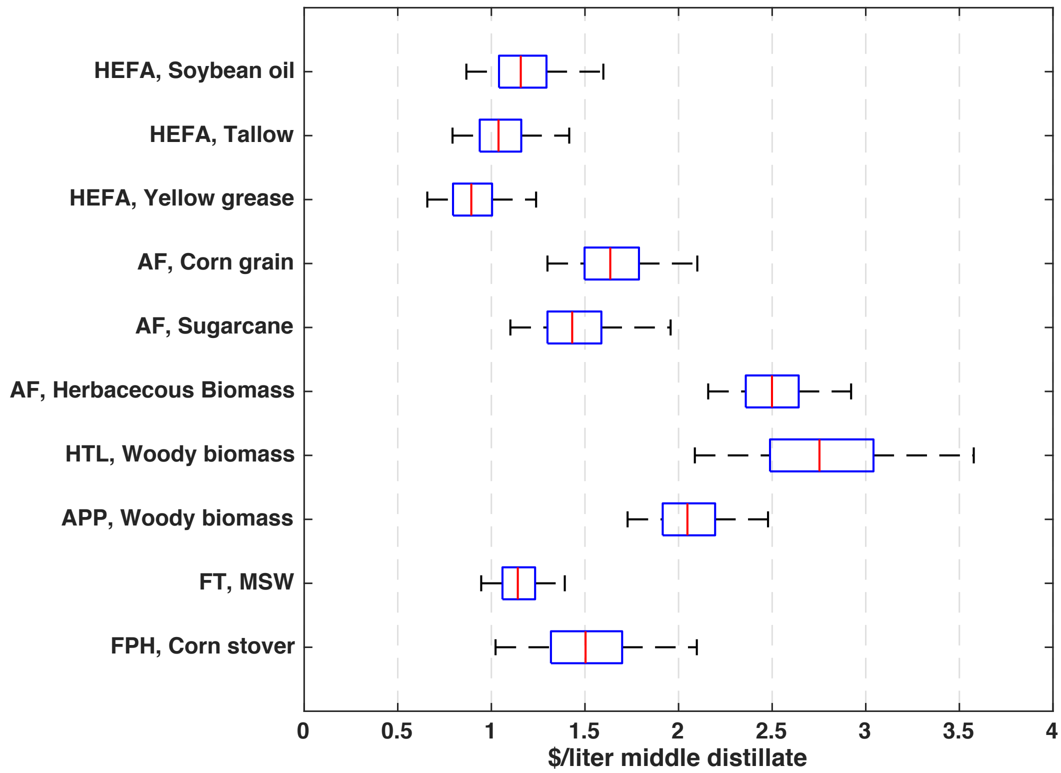

Figure 3-1: Box-and-whisker plot of the MSP results for each pathway evaluated in this study

The mean future middle distillate prices were subject to considerable uncertainty over time, and the volatility of price behavior was accounted for with NPV calculations that incorporated projected prices of middle distillate fuels. None of the pathway simulations resulted in positive mean NPV values, although HEFA and FT exhibited positive NPV values at the upper bound of the results distribution. The highest mean NPV was that of HEFA yellow grease with a mean value (in $B) of -0.112 (95% range of -0.412 to 0.179), followed by HEFA tallow with -0.202 (-0.517 to 0.100), FT with -0.210 (-0.424 to 0.033), HEFA soybean oil with -0.281 (-0.625 to 0.049), AF sugarcane with -0.420 (-0.775 to -0.099), AF corn grain with -0.552 (-0.905 to -0.216), FPH with -0.344 (-0.583 to -0.070), APP with -0.716 (-1.005 to -0.408), HTL with -0.854 (-1.120 to -0.560), and AF herbaceous biomass with -1.036 (-1.336 to -0.716).

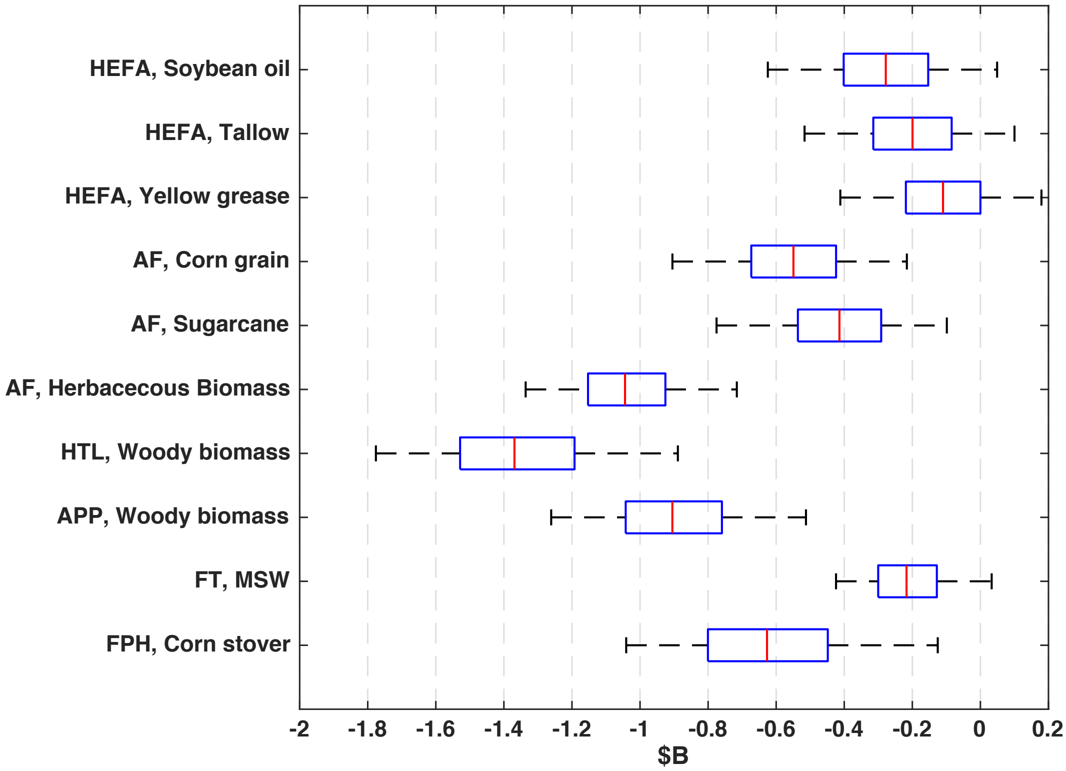

Figure 3-2: Box-and-whisker plot of the NPV over the 20-year lifetime for each pathway evaluated in this study

The cumulative density functions of the NPV results are shown in Figure 3-3 and the baseline probabilities of positive NPV over each plant's lifetime are shown in Figure 3-7 (in the "No Policy" case). HEFA demonstrated the highest probability of positive NPV with a 27.7%, 14.8%, and 8.6% chance of positive NPV for yellow grease, tallow, and soybean oil, respectively. HEFA and FT exhibited the lowest mean MSP and the least negative NPV due to a combination of factors: in the HEFA case, low capital investment requirements and high fuel yields outweighed relatively high feedstock costs. In the case of FT, these results stemmed from high fuel yields, no-cost feedstock, and comparatively low capital investment.

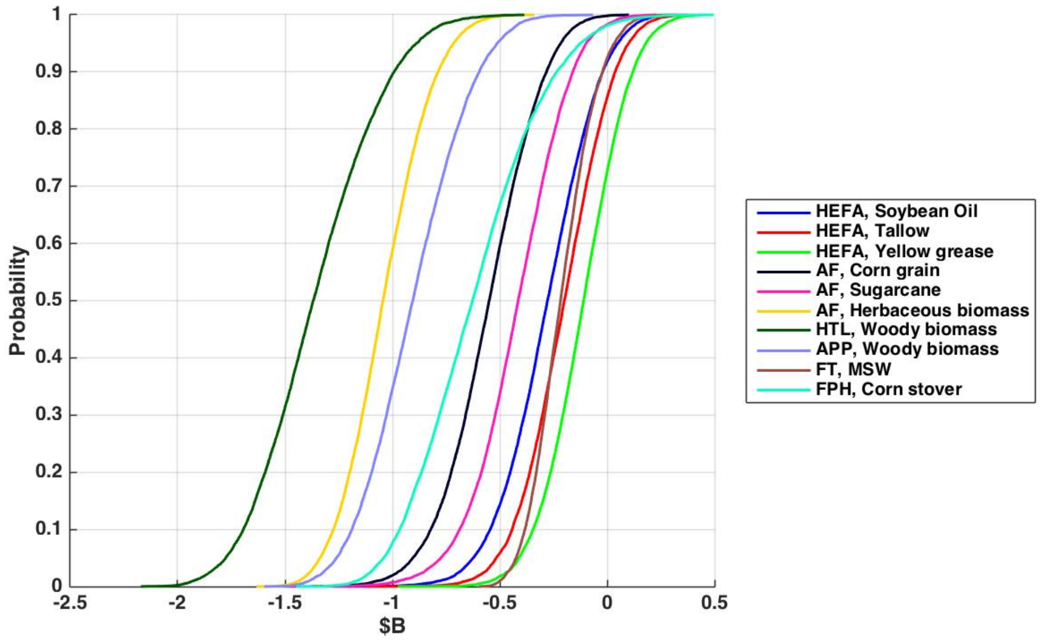

Figure 3-3: The cumulative density function (CDF) for the NPV results for each pathway

An evaluation of the NPV contributors to variance revealed that yearly fuel price deviations primarily explained the variance in the NPV results for AF herbaceous biomass, APP, FT, HTL, and FPH, at 39%, 48%, 49%, 64%, and 56%. The primary contributor for HEFA, AF corn grain, and AF sugarcane was feedstock cost. The feedstock cost distribution was negatively skewed which explains the negative skewness of the NPV distributions for these pathways. More information regarding the skewness and kurtosis of distributions fit to the Monte Carlo results can be found in Appendix C. Note that the variance for each pathway was influenced by the availability of data for the underlying distributions. In some cases, feedstock prices were based off of industry heuristics rather than historical price behavior. The price for herbaceous or woody biomass, for example, relied on low, mode, and high values from relevant literature sources surveying similar cellulosic biofuel refineries. The price for soybean oil and slaughtering byproducts, meanwhile, was described by a lognormal distribution derived from historical commodity prices. A survey of the contributors to variance for each pathway can be found in Appendix C. The MSP and NPV results for each pathway were separated into their constituent cost and revenue streams as shown in Figure 3-4 and 3-5. Only the mean values were reported in this figure, and the median and standard deviations for each component can be found in Appendix C. For NPV, the revenue stream components were separated into gasoline/naphtha, middle distillate fuels, other co-products, and scrap materials. Due to the sorting requirement during the MSW pre-processing stage, only the FT pathway collected revenue from scrap materials. The cost stream components were separated into capital costs, fixed operating expenditures, non-feedstock variable operating expenditures, feedstock expenditures, and income tax.

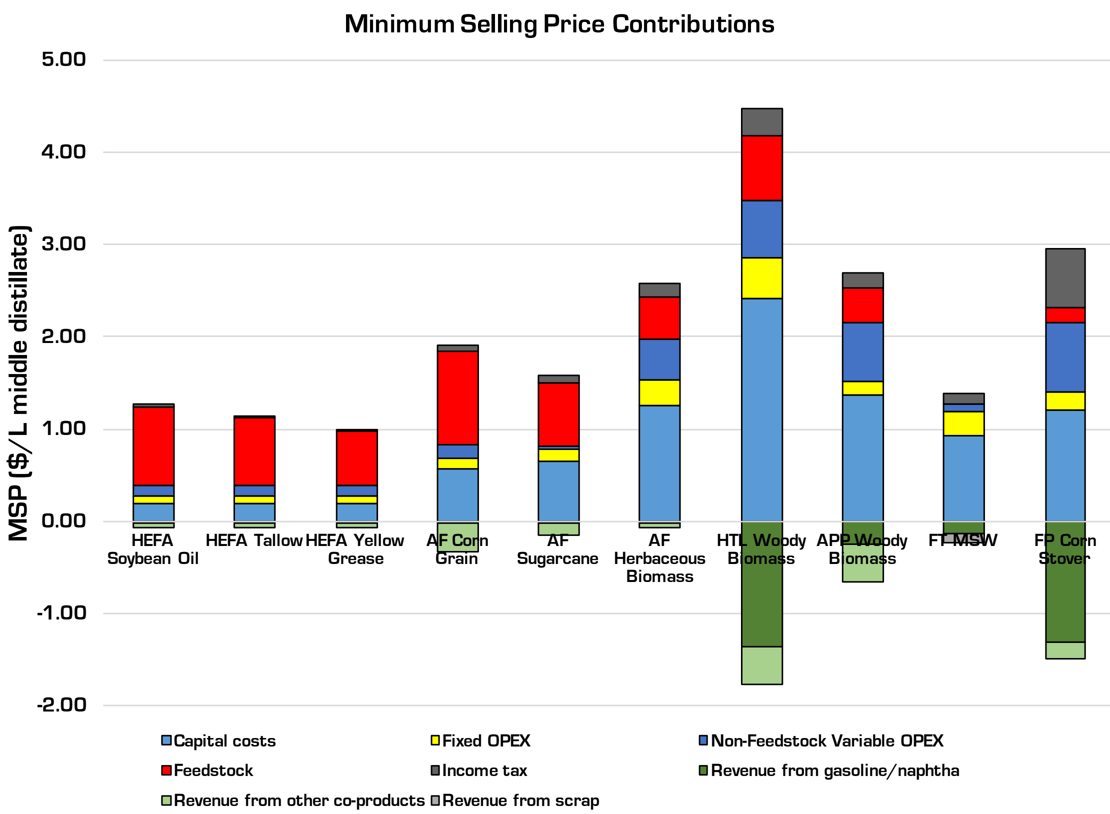

Figure 3-4: Mean MSP ($/liter) results breakdown by cost and revenue contributions

Although plant capacities were harmonized, the product distribution varied based on the literature material balances, with HEFA, AF, APP, and FT pathways optimized for middle distillate production and HTL and FPH optimized for total fuel production. In the cases of HEFA, AF, APP, and FT, middle distillate fuels comprised the largest portion of the revenue stream. Because HTL and FPH produce more gasoline then middle distillates, the largest contributor to the revenue stream for those pathways was gasoline.

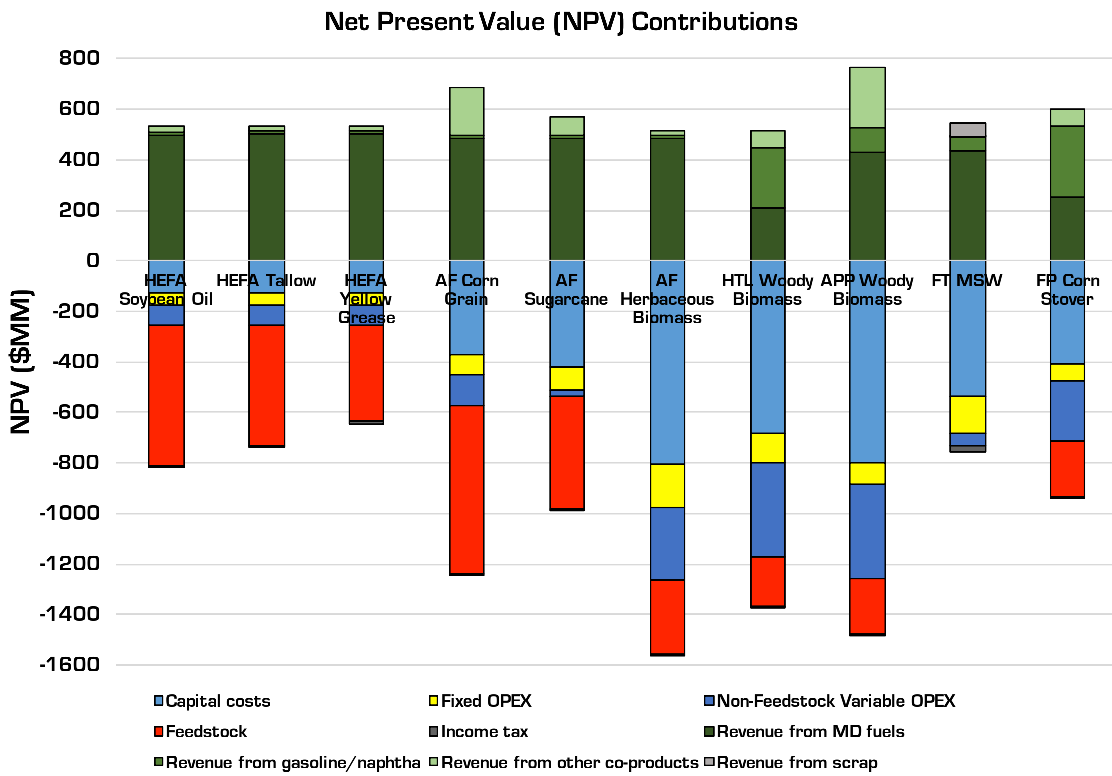

Figure 3-5: Mean NPV ($B) results breakdown by cost and revenue contributions

The revenue contributions to NPV for each pathway were larger in cases where pathways produce additional non-liquid-fuel products. This was true for AF corn grain, a byproduct of which is distiller's dried grains with solubles (DDGS); AF sugarcane, a byproduct of which is sugarcane bagasse used to generate power; APP, a byproduct of which is hydroxymethylfurfural (HMF) and acetic acid; FT, a byproduct of which is scrap materials; and FPH, a byproduct of which is generated electricity from the heat of the pyrolysis reaction. The price of feedstock was the primary cost contributor to MSP and NPV for HEFA, AF corn grain, and AF sugarcane, and capital investment was the largest cost contributor to MSP and NPV for AF herbaceous biomass, HTL, APP, FT, and FPH. Fixed operating expenditures, which include maintenance, labor, and other yearly cost requirements, contributed an average of 9% and at most 20% to the cost stream for each pathway. Non-feedstock variable operating expenses, such as wastewater treatment, catalyst costs, and other utilities, comprised an average of 15% and at most 27% of the cost stream for each pathway.

The impact of different critical variables on MSP were examined with a sensitivity analysis for each pathway, quantifying the impact of adjustments to fixed operating costs, capital investment, fuel yield, income tax rate, feedstock costs, and the discount rate. The results are shown in Figure 3-6. The discount rate, which resulted from the rate of required return for equity and loan interest rate for debt, had the largest impact on MSP for every case except for the HEFA pathway, which required the lowest capital investment among all pathways and was therefore less sensitive to rate of return assumptions. The discount rate had a larger impact for pathways with a larger capital investment requirement because higher discount rates minimized the value of future cash flows, thus increasing the price of middle distillates required to set NPV equal to zero over the plant's 20-year lifetime. The upper-bound discount rate test value of 22% was taken from Blazy et al., who suggested that the discount rate could be this high in order to offset the risks associated with investment in alternative fuel production technologies (Blazy et al., 2016). This can increase the MSP by up to 40%. The lower-bound discount rate value of 3.2% came from the social opportunity cost of capital based on long-term treasury bond rates from the U.S. Office of Management and Budget (U.S. OMB, 2015). Use of this value can decrease MSP by up to 60%. The pathways with the lowest mean MSP under the social opportunity cost of capital were FT and FPH with a mean MSP of \$0.58/L and \$0.61/L, respectively.

The fuel yield sensitivity analysis tested the outer bounds of the beta PERT distributions used for each pathway. Since the distributions were skewed negatively, the mode fuel yield value was close to the maximum so increases in fuel yield fail to lower mean MSP more than 20%. Similarly, varying fixed operating costs to extreme values changed the mean MSP only up to 14%. Although decreasing capital costs to 80% of the deterministic value improved mean MSP results, increasing those costs to

150% of the deterministic value increased mean MSP values by up to 50%, indicating that cost overruns inhibited the economic viability of a given pathway. In order to explore the impact of feedstock cost on the FT pathway, which owed its probability of positive NPV and low mean MSP in part to a zero feedstock cost, the cost was varied by $55/MT both positively and negatively to reflect average landfill tipping fees. Although this could be a source of revenue in the short run, this tipping fee could become a cost if MSW is increasingly used as a feedstock for fuel production. Both cases adjusted the mean MSP by 15% positively or negatively. The income tax rate was varied between 0% and 39% with the upper bound chosen to reflect the 2015 U.S. combined corporate income tax rate (OECD, 2016). This value increased the mean MSP by up to 20%.

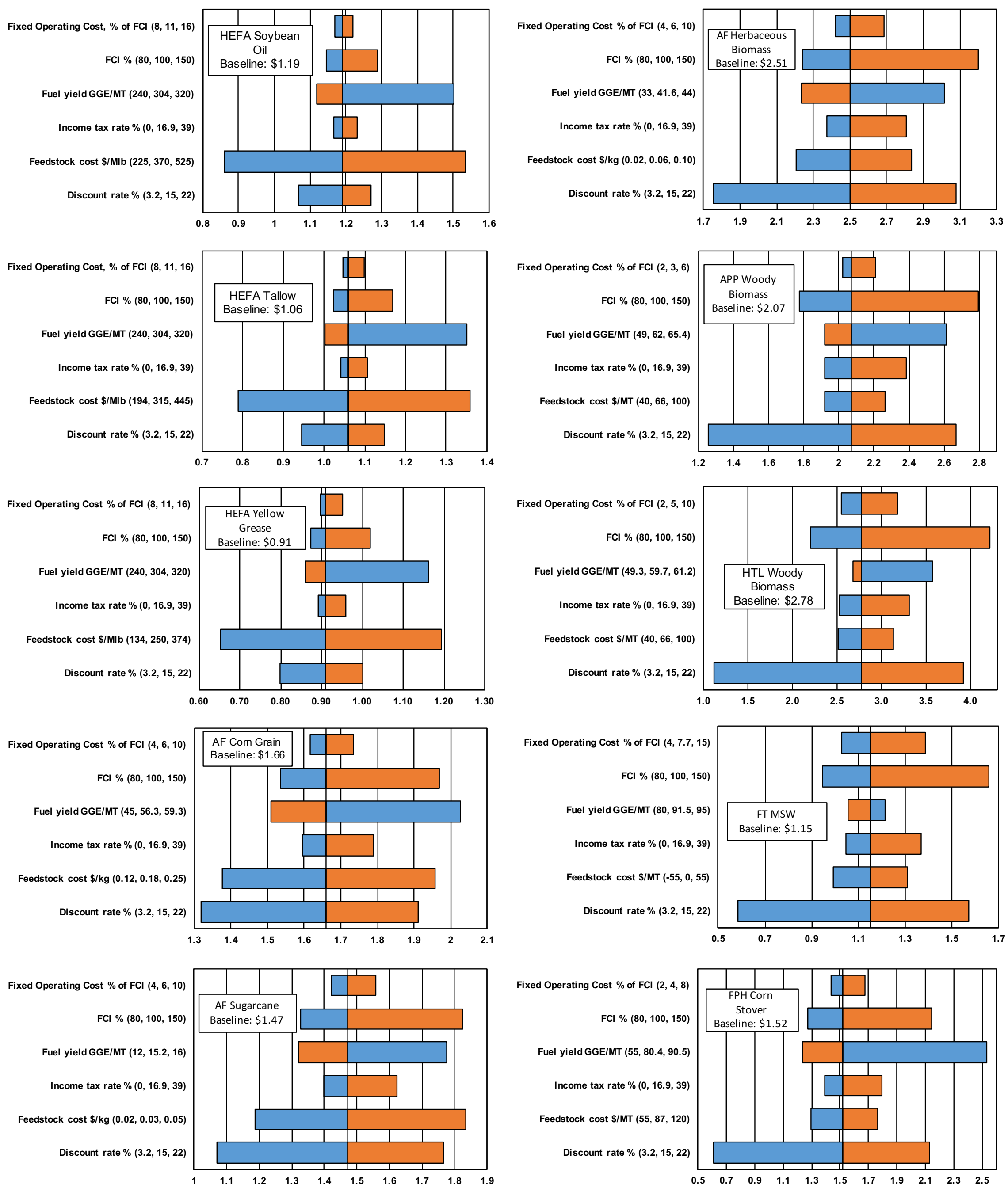

Figure 3-6: MSP sensitivity results for each pathway. All values expressed are mean values in units of $/liter. The variables and associated test inputs are listed on the left axis (low, baseline, high)

3.2 Policy Scenario Analysis

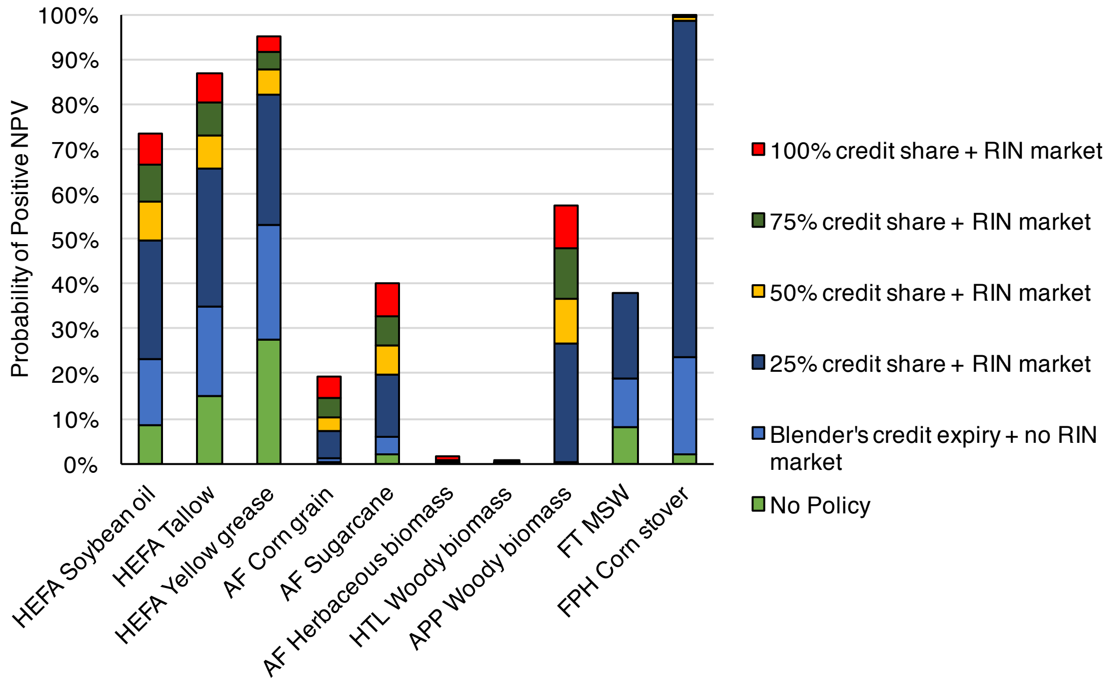

Figure 3-7: The probability of positive NPV over each pathway's 20-year plant lifetime under various policy scenarios. The "No Policy" case describes the results presented in section 3.1

To quantify the impact of different policy environments on the economic viability of alternative fuel production techniques, the NPV for each pathway was calculated and the cumulative density distribution was used to find the probability of positive NPV. The results of this analysis are shown in Figure 3-7. The HEFA pathway showed the highest likelihood of positive NPV in a case with no policy supports for alternative fuels, with each of the three evaluated feedstocks outperforming the other pathways (27.7% for HEFA yellow grease, 14.8% for HEFA tallow, and 8.56% for HEFA soybean oil). Under the policy case with no blender's credit and a zero RVO, HEFA yellow grease, HEFA tallow, and FPH had the highest probability of positive NPV at 53.2%, 34.9%, and 23.5%, respectively. The probability of positive NPV for FPH is higher under this scenario because the pathway used corn stover, a cellulosic feedstock, and therefore earned higher-value D3 and D7 RINs. HEFA, meanwhile, earned D4 and D5

RINs because it uses soybean oil and animal fats as feedstocks. Under the 50% credit-share and RIN market policy case, FPH, HEFA yellow grease, and HEFA tallow had the highest probability of positive NPV at 99.2%, 87.7%, and 73.1%. This was due to the higher value of D3 and D7 RINs relative to D4 and D5 RINs. Although FT had a 7.87% probability of positive NPV under the "No Policy" case, fuels produced from MSW only earned a D5 Advanced Biofuel RIN and were not subject to blender's credits, so the maximum probability of positive NPV for FT was only 37.8%. Under the 100% credit-share case, five of the 10 feedstock-pathway combinations resulted in a 50% chance of positive NPV or higher: FPH, HEFA yellow grease, HEFA tallow, HEFA soybean oil, and APP have positive NPV probabilities of 99.7%, 94.9%, 86.6%, 73.4%, and 57.6%, respectively.

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Chapter 4

Conclusions

This thesis illustrates a harmonized comparison of U.S. alternative jet fuel production that used stochasticity in key variables. By fitting probability distributions to input parameters such as fuel yield, capital expenditures, or fuel prices, the costs of production for each pathway and feedstock could be expressed as a range of potential values under a variety of scenarios. For the first time, the use of Monte Carlo simulations allows for the capture of uncertainty in alternative jet fuel production MSP and NPV results. This thesis demonstrates the value of uncertainty inclusion in energy conversion models and presents a rigorous method for conducting policy analyses. In the baseline scenario, the lowest mean MSP was that of HEFA yellow grease with a value of $0.91/liter (95% range of $0.66/liter to $1.24/liter), followed by HEFA tallow with a mean MSP value of $1.06/liter ($0.79/liter to $1.42/liter) and FT with $1.15/liter ($0.95/liter to $1.39/liter). None of these results approach the March 2017 conventional U.S. jet fuel price of $0.40/L, although the EIA indicates that these prices could rise above $1.08/L over the next 20 years. Similarly, the highest mean NPV was the NPV calculated for HEFA yellow grease with a mean value (in $B) of -0.112 (95% range of -0.412 to 0.179), followed by HEFA tallow with -0.202 (-0.517 to 0.100) and FT with -0.210 (-0.424 to 0.033). In each case, the probability of positive NPV is 27.7%, 14.78%, and 7.87%, respectively. These results suggest that current alternative jet fuel production pathways are not cost-competitive with conventional petroleum refining.

The models also apply existing United States policy incentives under the Renewable Fuel Standard.The results suggest that although no pathway is economically viable without policy supports, regulations can improve the possibility of alternative jet fuel competition in the market. In the policy case with no RIN market and blender's credit expiration, the highest probability of positive NPV is for HEFA yellow grease at 53.2%; in the policy case with 100% credit share and a continual RIN market, the highest probability of positive NPV is for fast pyrolysis and hydroprocessing at 99.9%. These results suggest that current policy supports can incentivize investment in alternative jet fuels, although some pathways may be incentivized more than others depending on the structure of the regulations. For example, increasing Renewable Volume Obligations for cellulosic biofuels drives higher demand–and higher value–for cellulosic biofuel RINs, which in turn improves the economic outlook for pathways that use feedstocks such as corn stover or sugarcane. The results for each pathway can be used by regulatory agencies such as the EPA, USDA, or DOE to craft policies that favor alternative jet fuel production and can be leveraged by investors to target promising feedstock conversion technologies. The results in this thesis, moreover, can be broadly applied to international efforts seeking a framework for regulations that support alternative fuels.

Appendix A

Pathway Descriptions

The following process overviews for each pathway come from the sources that supply the mass and energy balances for the techno-economic evaluation models. Figure A-1 displays each the pre-treatment and intermediate steps required for the production of drop-in transportation fuels.

A.1 Hydroprocessed esters & fatty acids (HEFA)

The HEFA process uses vegetable or slaughtering byproduct oils such as soybean oil, tallow, and yellow grease as feedstocks. Hydrogen gas is fed into the feed stream in a hydrotreator, which deoxygenates the oil. After cooling, the effluent is sent to an isomerization unit which produces select hydrocarbons of various carbon chain lengths. Mixed paraffin gases, carbon dioxide, and excess hydrogen are separated out in a series of separation columns, with paraffin gases and hydrogen recycled to the hydrotreator and wastewater separated for treatment. The liquid products stream is then separated into LPG, naphtha, jet, and diesel (Pearlson et al., 2013; Seber et al., 2014).

A.2 Advanced fermentation (AF)

Fermentation and advanced fermentation (AF) technologies encapsulate multiple production pathways that incorporate the micro-organic metabolism of biomass-derived sugars. Staples et al. examines three different feedstocks, including corn grain, sugarcane, and herbaceous biomass, each with different process steps. Corn grain is dry milled and ground into corn flour prior to liquefaction with process water and high pressure steam. Sugarcane is cleaned, chopped, shredded, and crushed to extract sucrose. A byproduct of this process is sugarcane bagasse, which is used to co-generate power and heat to meet the utility requirements for the refinery. Herbaceous biomass, or switchgrass in this case, is subjected to dilute acid treatment to extract the sugar prior to fermentation. After the extraction process for each feedstock, polymeric sugars are broken down via saccharification into glucose, fructose, and xylose using enzymatic hydrolysis. Depending on the microorganism used, these sugar products can be metabolized into a variety of platform molecules including triacylglycerides (TAGs), fatty acids, alkanes, isobutanol, and ethanol. Although Staples et al. considers each platform molecule, this study uses the baseline mass and energy requirements which correspond with the fatty acids intermediate. In order to extract these platform molecules, centrifugation, hexane solvent extraction, potassium hydroxide lysing, and distillation are explored, although centrifugation is used as the baseline process. The platform molecules are then upgraded to LPG, naphtha, jet, and diesel via the HEFA process used by Pearlson et al. (Staples et al., 2014).

A.3 Aqueous phase processing (APP)

This process uses woody biomass as a lignocellulosic feedstock, which is subjected to hot water extraction pretreatment to extract hemicellulose sugars in one stream and cellulose and lignin in the other. The hemicellulose stream is hydrolyzed into xylose and other monomeric sugars which are then dehydrated to form furans. Furfural and acetic acid are recovered via xylose and arabinose dehydration. The furfural is then upgraded to straight-chain and branched alkanes after deoxygenation. Separated furfural and acetic acid streams can be sold in the chemical industry. After pretreatment, the cellulose and lignin stream is treated with sulfuric acid to produce levulinic acid and formic acid. Residual lignin is combusted in a boiler generator for heat and power. Levulinic acid is then converted to -valerolactone (GVL), which itself is converted to branch-chain alkanes. Products include LPG, naphtha, jet, and diesel (Bond et al., 2014).

A.4 Hydrothermal liquefaction (HTL)

This process uses woody biomass as a feedstock. The inlet pellets are first ground and softened with hot water to form a slurry. After pre-heating, the slurry is fed to the HTL reactor which converts the slurry into bio-oil. Solid wastes, such as ash and other inorganic solids, as well as an aqueous phase consisting of dissolved organics are water, are removed from the reactor. The aqueous phase is either sent to heat the reactor inlet stream or separated for waste treatment. The bio-oil, which can be sold as a crude oil substitute, is upgraded via hydtrotreating to remove oxygen. These hydrocarbon products are then cooled and separated via distillation into gasoline, diesel, and heavy oil. Although the process requires hydrogen, the refinery design includes a steam reforming process onsite, so the cost of hydrogen is subsumed in the capital cost of the reforming units (Zhu et al., 2014).

A.5 Conventional gasification and Fischer-Tropsch (FT)

This process uses municipal solid waste (MSW) as a feedstock, which undergoes considerable sorting and processing prior to any reaction stages. The MSW composition, which uses the US Environmental Protection Agency's composition values from 2013, which includes food waste, metals, paper, and other materials. Non-combustibles and other inorganics must be sorted out via a system of conveyors, shredders, and other separators called a Refuse Derived Fuel (RDF) facility. The prepared feed is then gasified, or partially oxidized, at high temperatures to produce syngas, a mixture of carbon monoxide and hydrogen. The syngas is cooled, conditioned, and converted to fuels and paraffinic wax via the Fischer-Tropsch catalytic reaction. These products are separated into naphtha, jet, and diesel streams, with naphtha further reformed into gasoline (Niziolek et al., 2015; Suresh, 2016).

A.6 Fast pyrolysis and hydroprocessing (FPH)

Fast pyrolysis is a rapid thermal conversion process that produces three products including char, gas, and bio-oil. Corn stover, the feedstock input evaluated for this pathway, is subjected to drying, grinding, and chopping pre-treatment steps. The pyrolysis reactor then converts the pre-treated corn stover into bio-oil through anaerobic treatment at high temperatures. Due to the high oxygen content of bio-oil, hydroprocessing and catalytic upgrading via hydrotreating and hydrocracking is then used to produce a variety of deoxygenated products including gasoline and diesel (Bittner et al., 2015).

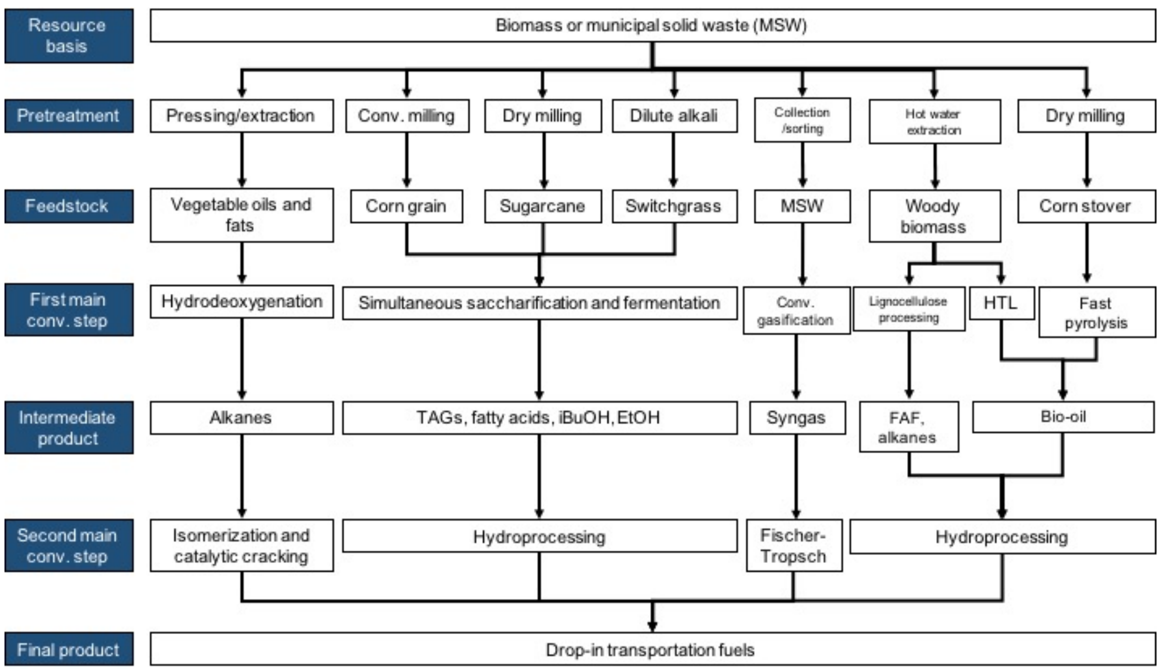

Figure A-1: Process overview for each pathway includes feedstocks, pretreatment steps, critical conversion steps, and intermediate and final products

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Appendix B

Fuel Production Model Parameters

B.1 Model Parameters

Table B.1: Financial assumptions

Parameter	Assumption
Loan Interest	10%
Loan Term	10
Working Capital (% of FCI)	5%
Type of Depreciation	Variable Declining Balance
Depreciation Period (years)	10
Construction Period (years)	3
Discount Rate	15%
Income Tax Rate	16.90%
Operating Hours per Year	8,400
Construction year	2015
Operation start year	2018
Inflation	2%
Year 1 production capacity	75%

Table B.2: HEFA Monte Carlo variables and distribution parameters

Variable	Nominal Range[a]	Units	Distribution
Material and energy process outputs			
Fuel yield[32]	[240, 304, 320]	GGE/MT	Beta PERT
Material and energy prices			
Process water[23, 31, 32]	[0.379, 2.16, 2.76]	$/Mgal	Triangular
Hydrogen[48]	[1.08, 1.55, 2.03]	$/lb	Beta PERT
Soybean oil[10]	[5.8822,0.2589]	$/Mlb	Lognormal
Tallow[b, 45]	0.838x + 5.61	$/Mlb	N/A
Yellow grease[b, 45]	0.799x - 45.7	$/Mlb	N/A
Gasoline price in analysis start year (2018)[13]	[1.68, 2.18, 3.53]	$/gal	Beta PERT
Gasoline price growth rate projection[13]	[0.85, 2.11, 2.33]	%	Beta PERT
Gasoline price yearly deviations[20]	[0, 0.3547]	$/gal	Normal
Electricity price yearly deviations[14]	[0, 0.00295]	$/kWh	Normal
Natural gas price yearly deviations[18]	[0, 72.99]	$/MT	Normal
D4 RINs[3]	[-0.3441, 0.2262]	$/RIN	Lognormal
Capital and fixed costs			
FCI[32]	[50.0, 62.5, 93.7]	$M	Beta PERT
Fixed operating expenses[32]	[8.75, 10.5, 15.75]	% of FCI	Beta PERT

[a]Note: in the tables that follow, the parameters in the Nominal Range column will adhere to the following format: Lognormal distributions: log mean, log standard deviation) Normal distributions: mean, standard deviation) Triangular/Beta PERT distributions: low, mode, high) Uniform distributions: low, high)

[b]Note: prices for tallow and yellow grease correlate closely with soybean oil, so the equations in the Nominal Range column represent the results of a linear regression between the historical prices for tallow/yellow grease and the historical prices for soybean oil.

Table B.3: AF Monte Carlo variables and distribution parameters

Variable	Nominal Range	Units	Distribution
Material and energy process outputs			
Fuel yield, Corn grain[40]	[44.5, 56.3, 59.3]	GGE/MT	Beta PERT
Fuel yield, Sugarcane[40]	[12.0, 15.2, 16.0]	GGE/MT	Beta PERT
Fuel yield, Herbaceous biomass[40]	[32.8, 41.6, 43.7]	GGE/MT	Beta PERT
Material and energy prices			
Process water[23, 31, 32]	[0.379, 2.16, 2.76]	$/Mgal	Triangular
Corn grain[46]	[-1.732, 0.2696]	$/kg	Lognormal
Sugarcane[9]	[3.4574, 0.3210]	$/kg	Lognormal
Herbaceous biomass[40]	[0.030, 0.059, 0.089]	$/kg	Triangular
Gasoline price in analysis start year (2018)[13]	[1.68, 2.18, 3.53]	$/gal	Beta PERT
Gasoline price growth rate projection[13]	[0.85, 2.11, 2.33]	%	Beta PERT
Gasoline price yearly deviations[20]	[0, 0.3547]	$/gal	Normal
Electricity price yearly deviations[14]	[0, 0.00295]	$/kWh	Normal
Natural gas price yearly deviations[18]	[0, 72.99]	$/MT	Normal
DDGS[c, 47]	0.694x + 0.0162	$/kg	N/A
D4 RINs[5]	[-0.3441, 0.2262]	$/RIN	Lognormal
Capital and fixed costs			
FCI, corn grain[40]	[143, 179, 268]	$M	Beta PERT
FCI, sugarcane[40]	[163, 204, 306]	$M	Beta PERT
FCI, herbaceous biomass[40]	[312, 389, 584]	$M	Beta PERT
Fixed operating expenses[40]	[5.08, 6.09, 9.14]	% of FCI	Beta PERT

[c]Note: the historical prices for DDGS correlate closely with the price for corn grain, so the equation in the Nominal Range column represents a linear regression between the historical price of DDGS and the historical price of corn grain.

Table B.4: APP Monte Carlo variables and distribution parameters

Variable	Nominal Range	Units	Distribution
Material and energy process outputs			
Fuel yield[4]	[49.0, 62.1, 65.4]	GGE/MT	Beta PERT
Material and energy prices			
Woody biomass[4, 25, 49]	[51.89, 66.05, 78.69]	$/MT	Triangular
Sodium chloride[4, 44]	[35.6, 55]	$/MT	Uniform
Acetone[4, 22]	[772, 1121.21]	$/MT	Uniform
Tetrahydrofuran[4, 22]	[3364.6, 3476.6]	$/MT	Uniform
Sulfuric acid[5, 22]	[80, 103.4]	$/MT	Uniform
Hydrochloric acid[4, 22]	[90, 254.4]	$/MT	Uniform
Acetic acid[4, 5]	[745.9, 1181.4]	$/MT	Triangular
HMF[4]	1607.5	$/MT	Non-variable
SBP[4]	50.9	$/MT	Non-variable
Process water[23, 31, 32]	[0.10, 0.57, 0.73]	$/MT	Triangular
Gasoline price in analysis start year (2018)[13]	[1.68, 2.18, 3.53]	$/gal	Beta PERT
Gasoline price growth rate projection[13]	[0.85, 2.11, 2.33]	%	Beta PERT
Gasoline price yearly deviations[20]	[0, 0.3547]	$/gal	Normal
Electricity price yearly deviations[14]	[0, 0.00295]	$/kWh	Normal
Natural gas price yearly deviations[18]	[0, 72.99]	$/MT	Normal
D4 RINs[3]	[-0.3441, 0.2262]	$/RIN	Lognormal
Capital and fixed costs			
Fixed capital investment[4]	[388, 485, 727]	$M	Beta PERT
Fixed operating expenses[4]	[2.5, 3.0, 4.5]	% of FCI	Beta PERT

Table B.5: HTL Monte Carlo variables and distribution parameters

Variable	Nominal Range	Units	Distribution
Material and energy process outputs			
Fuel yield[49]	[49.3, 59.7, 61.2]	GGE/MT	Beta PERT
Material and energy prices			
Woody biomass[4, 25, 49]	[51.89, 66.05, 78.69]	$/MT	Triangular
Catalyst costs[49]	[6.27, 1.04]	$M	Normal
Wastewater treatment[49]	[28.6, 4.76]	$M	Normal
Gasoline price in analysis start year (2018)[13]	[1.68, 2.18, 3.53]	$/gal	Beta PERT
Gasoline price growth rate projection[13]	[0.85, 2.11, 2.33]	%	Beta PERT
Gasoline price yearly deviations[20]	[0, 0.3547]	$/gal	Normal
Electricity price yearly deviations[14]	[0, 0.00295]	$/kWh	Normal
Natural gas price yearly deviations[18]	[0, 72.99]	$/MT	Normal
D4 RINs[3]	[-0.3441, 0.2262]	$/RIN	Lognormal
Capital and fixed costs			
Fixed capital investment[49]	[418, 523, 785]	$M	Beta PERT
Fixed operating expenses[49]	[4.08, 4.89, 7.34]	% of FCI	Beta PERT

Table B.6: FT Monte Carlo variables and distribution parameters

Variable	Nominal Range	Units	Distribution
Material and energy process inputs			
Utility for MSW pre-processing[8, 35, 36]	[0.06, 0.13, 0.15]	MJ/kg_{MSW}	Triangular
Natural gas[27]	[6, 0.6]	g/kg_{PMSW}	Normal
Petroleum coke[27]	[50, 5]	g/kg_{PMSW}	Normal
Olivine[11, 23, 28]	[1.37, 2.07, 4.96]	g/kg_{PMSW}	Triangular
Tar reforming catalyst[11, 12, 28]	[0.005, 0.006, 0.045]	g/kg_{PMSW}	Triangular
Material and energy process outputs			
Fuel yield[30, 36, 42, 43]	[79.8, 91.5, 95]	GGE/MT	Beta PERT
Scrap aluminum[21]	[5.9, 14.1, 15.1]	g/kg_{MSW}	Triangular
Scrap iron and steel[21]	[3.2, 3.6, 26.7]	g/kg_{MSW}	Triangular
Scrap glass[21]	[29.6, 32.9, 45.2]	g/kg_{MSW}	Triangular
Material and energy prices			
Gasoline price in analysis start year (2018)[13]	[1.68, 2.18, 3.53]	$/gal	Beta PERT
Gasoline price growth rate projection[13]	[0.85, 2.11, 2.33]	%	Beta PERT
Gasoline price yearly deviations[20]	[0, 0.3547]	$/gal	Normal
Natural gas price yearly deviations[18]	[0, 72.99]	$/MT	Normal
Electricity price yearly deviations[14]	[0, 0.00295]	$/kWh	Normal
Higher alcohols[6, 34, 37]	[1.28, 2.00, 3.00]	$/gal	Triangular
Petroleum coke[2]	[4.1046, 0.1886]	Based on $/MT	Lognormal
Sulfur[44]	[4.5898, 0.3407]	Based on $/MT	Lognormal
Scrap aluminum[23, 26, 29, 39, 39]	[772, 1858, 2457]	$/MT	Triangular
Scrap iron and steel[23, 26, 29, 39, 39]	[136, 342, 492]	$/MT	Triangular
Scrap glass[24, 29]	[7, 22, 30]	$/MT	Triangular
Construction aggregates[44]	[7.82, 10.21, 18.36]	$/MT	Triangular
Olivine[23, 34, 50]	[235, 255, 332]	$/MT	Triangular
Tar reforming catalyst[23, 34, 50]	[12670, 15130, 20812]	$/MT	Triangular
Alcohol synthesis catalyst[23, 34, 50]	[12915, 14244, 15696]	$/MT	Triangular
Process water[23, 31, 32]	[0.10, 0.57, 0.73]	$/MT	Triangular
D4 RINs[3]	[-0.3441, 0.2262]	$/RIN	Lognormal
Capital and fixed costs			
Fixed capital investment[30]	[206, 258, 387]	$M	Beta PERT
Fixed operating expenses[41]	[6.4,7.7,11.6]	% of FCI	Beta PERT

Table B.7: FPH Monte Carlo variables and distribution parameters

Variable	Nominal Range	Units	Distribution
Material and energy process outputs			
Fuel yield[1]	[57.9, 80.4, 90.5]	GGE/MT	Beta PERT
Material and energy prices			
Corn stover[46]	[57.95, 87.46. 115.91]	$/MT	Beta PERT
Catalyst costs[7]	[1.87, 0.31]	$M	Normal
Hydrogen[46]	[2.37, 3.42, 4.48]	$/kg	Beta PERT
Gasoline price in analysis start year (2018)[13]	[1.68, 2.18, 3.53]	$/gal	Beta PERT
Gasoline price growth rate projection[13]	[0.85, 2.11, 2.33]	%	Beta PERT
Gasoline price yearly deviations[20]	[0, 0.3547]	$/gal	Normal
Electricity price yearly deviations[14]	[0, 0.00295]	$/kWh	Normal
Natural gas price yearly deviations[18]	[0, 72.99]	$/MT	Normal
Capital and fixed costs			
Fixed capital investment[7]	[284, 355, 532]	$M	Beta PERT
Fixed operating expenses[7]	[3.56, 4.27, 6.41]	% of FCI	Beta PERT

Table B.8: Source literature plant designs and assumptions

	HEFA	AF Corn grain	AF Sugarcane	AF Herbaceous biomass	APP	HTL	FT	FPH
Source	Pearlson et al., 2013; Seber et al., 2015	Staples et al., 2014	Staples et al., 2014	Staples et al., 2014	Bond, et al., 2014	Zhu et al., 2014	Suresh, 2016; Niziolek et al., 2015	Bittner et al., 2015; Brown et al., 2013
Cost basis	2010	2012	2012	2012	2010	2007	2014	2011
Feedstock (MT/day)	285	1534	5684	2078	1757	2000	864	2000
Feedstock	Soybean oil, tallow, yellow grease	Corn grain	Sugarcane	Herbaceous biomass	Woody biomass	Woody biomass	MSW	Corn stover
Literature capacity (bpd)	2000	2000	2000	2000	2600	3200	2000	3600
Fuel product energy share (MJ/MJ liquid fuel products)								
LPG	7%	7%	7%	7%	2%	0%	0%	0%
Naphtha	2%	2%	2%	2%	18%	0%	0%	0%
Gasoline	0%	0%	0%	0%	0%	53%	11%	52%
Jet	14%	15%	15%	15%	72%	0%	13%	0%
Diesel	77%	76%	76%	76%	8%	47%	76%	48%
Hydrogen requirement (kg/day)	7,674.2	0	0	0	0	0	0	48,581.3
Natural gas requirement (MMBTU/year)	245,247	1,198,317	318,758	318,758	0	532,951	0	0
Electricity requirement (MWh/year)	8,212	68,507	0	62,705	17,086	110,818	80,991	0
Heavy oil production (MGY)	0	0	0	0	0	7.5	0	0
Project life	20 years	20 years	20 years	20 years	20 years	22 years	20 years	22 years
Construction time	3 years	3 years	3 years	3 years	3 years	2 years	3 years	2 years
% Spent in Year 1	8%	8%	8%	8%	8%	8%	8%	8%
% Spent in Year 2	60%	60%	60%	60%	60%	60%	60%	60%
% Spent in Year 3	32%	32%	32%	32%	32%	32%	32%	32%
Startup Period	0.5 years	0.5 years	0.5 years	0.5 years	0.5 years	0.5 years	0.5 years	0.5 years
Startup Production Rate	50%	50%	50%	50%	50%	50%	50%	50%

Table B.9: Input feedstock rates and maximum fuel product outputs

	HEFA	**AF Corn grain**	**AF Sugarcane**	**AF Herbaceous biomass**	**APP**	**HTL**	**FT**	**FPH**
Feedstock (MT/day)	285	1534	5680	2080	1330	1240	860	940
Feedstock	Soybean oil, tallow, yellow grease	Corn grain	Sugarcane	Herbaceous biomass	Woody biomass	Woody biomass	MSW	Corn stover
Maximum product output (MGY)								
LPG	2.79	3.04	3.04	3.04	0.60	--	--	--
Naphtha	0.68	0.68	0.69	0.69	5.65	--	--	--
Gasoline	--	--	--	--	--	13.5	3.24	15.8
Jet	4.36	4.41	4.41	4.41	20.8	5.67	3.52	6.80
Diesel	22.9	22.6	22.6	22.6	2.33	5.67	20.7	6.80
Heavy oil	--	--	--	--	--	4.61	--	--

Table B.10: Fuel price correlations from historical U.S. Energy Information Administration (EIA) data

Fuel price	**Correlation with gasoline price, *x***
Propane	$0.3762x + 0.0476$
Heavy oil	$0.8683x – 0.0330$
Jet fuel	$1.1698x – 0.0906$
Diesel	$1.1798x – 0.0786$

B.2 Model Parameter References

1) Bittner, A., Tyner, W.E., Zhao, X., 2015. Field to flight: A techno-economic analysis of the corn stover to aviation biofuels supply chain. Biofuels, Bioproducts, & Biorefining. 9, 201-210. doi: 10.1002/bbb.1536

2) Bloomberg L.P., 2016a. Price graph for ACFFPCDT, Average Cost of Fossil Fuels Pet Coke Dollars per Ton - US DOE source, 2006 - 2015. Bloomberg database. Massachusetts Institute of Technology Information Systems & Technology.

3) Bloomberg L.P., 2016b. Price graph for RINSET15 10/2/14 to 12/31/15. Bloomberg database. Massachusetts Institute of Technology Information Systems & Technology.

4) Bond, J.Q., Upadhye, A. a., Olcay, H., Tompsett, G. a., Jae, J., Xing, R., Alonso, D.M., Wang, D., Zhang, T., Kumar, R., Foster, A., Sen, S.M., Maravelias, C.T., Malina, R., Barrett, S.R.H., Lobo, R., Wyman, C.E., Dumesic, J. a., Huber, G.W., 2014. Production of renewable jet fuel range alkanes and commodity chemicals from integrated catalytic processing of biomass. Energy Environ. Sci. 7, 1500-1523. doi:10.1039/C3EE43846E

5) Brennan, D.J., 1998. Process Industry Economics: an Industrial Perspective. Institute of Chemical Enginers.

6) Brown, R., 2003. Phenol demand is stable while acetone firms. Chemical Market Reporter. 264, 22.

7) Brown, T.R., Thilakaratne, R., Brown, R.C., Hu, G., 2013. Techno-economic analysis of biomass to transportation fuels and electricity via fast pyrolysis and hydroprocessing. Fuel 106, 463-469. doi:10.1016/j.fuel.2012.11.029

8) Caputo, A.C., Pelagagge, P.M., 2002. RDF production plants: I. Design and costs. Appl. Therm. Eng. 22, 423-437. doi:10.1016/S1359-4311(01)00100-4

9) CME Group, 2016. No. 11 Sugar Futures End of Day Settlement Price. Index Mundi.

10) CME Group, 2016. Soybean oil futures settlements. Index Mundi.

11) Dutta, A., Phillips, S.D., 2009. Thermochemical Ethanol via Direct Gasification and Mixed Alcohol Synthesis of Lignocellulosic Biomass. doi: NREL/TP-510-45913

12) Dutta, A., Talmadge, M., Hensley, J., Worley, M., Dudgeon, D., Barton, D., Groenendijk, P., Ferrari, D., Stears, B., Searcy, E., Wright, C., Hess, J.R., 2012. Techno-economics for conversion of lignocellulosic biomass to ethanol by indirect gasification and mixed alcohol synthesis. Environ. Prog. Sustain. Energy 31, 182-190. doi:10.1002/ep.10625

13) EIA, 2015. Annual Energy Outlook, vol. 2015.

14) EIA, 2016a. Average Industrial Retail Price of Electricity, vol. 2016.

15) EIA, 2016b. Cushing, OK WTI Spot Price FOB, vol. 2016.

16) EIA, 2016c. Mont Belvieu, TX Propane Spot Price, vol. 2016.

17) EIA, 2016d. U.S. Kerosene-Type Jet Fuel Wholesale/Resale Price by Refiners, vol. 2016.

18) EIA, 2016e. U.S. Natural Gas Industrial Price, vol. 2016.

19) EIA, 2016f. U.S. No. 2 Diesel Wholesale/Resale Price by Refiners, vol. 2016.

20) EIA, 2016g. U.S. Total Gasoline Wholesale/Resale Price by Refiners, vol. 2016.

21) EPA, 2015. Advancing Sustainable Materials Management: Facts and Figures 2013.

22) ICIS Chemical Business, 2015. Chemical price reports.

23) Jones, S.B., Zhu, Y., Valkenburg, C., 2009. Municipal Solid Waste (MSW) to Liquid Fuels Synthesis, Volume 2: A Techno-economic Evaluation of the Production of Mixed Alcohols. Report PNNL-18482, Pacific Northwest National Laboratory.

24)Kessler Consulting Inc., 2009. Materials recovery facility feasibility study. Pinellas County Department of Solid Waste Operations.

25)Li, B., Ou, L., Dang, Q., Meyer, P., Jones, S., Brown, R., Wright, M., 2015. Techno-economic and uncertainty analysis of in situ and ex situ fast pyrolysis for biofuel production. Bioresour. Technol. 196, 49-56. doi:10.1016/j.biortech.2015.07.073

26)Metalprices.com, 2016. Aluminum Cans (UBC).

27)Motycka, S. A., 2013. Doctor of Philosophy thesis, George Washington University.

28) Mu, D., Seager, T., Rao, P.S., Zhao, F., 2010. Comparative life cycle assessment of lignocellulosic ethanol production: Biochemical versus thermochemical conversion. Environ. Manage. 46, 565-578. doi:10.1007/s00267-010-9494-2

29) Nishtala, S., Solano-Mora, E., 2016. Description of the Material Recovery Facilities Process Model Design, Cost, and Life-Cycle Inventory for the MSW-DST Tool. Research Triangle Institute.

30) Niziolek, A.M., Onel, O., Hasan, M.M.F., Floudas, C.A., 2014. Municipal solid waste to liquid transportation fuels - Part II: Process synthesis and global optimization strategies. Comput. Chem. Eng. doi:10.1016/j.compchemeng.2014.10.007

31) Organisation for Economic Co-operation and Development (OECD), 1999. Industrial Water Pricing in OECD Countries. Report ENV/EPOC/GEEI(98)10/FINAL.

32) Pearlson, M., Wollersheim, C., Hileman, J., 2013. A techno-economic review of hydroprocessed renewable esters and fatty acids for jet fuel production. Biofuels, Bioproducts, & Biorefining. 7, 89-96. doi: 10.1002/bbb.1378

33) Peters, M.S., Timmerhaus, K.D., West, R.E., 2003. Plant design and economics for chemical engineers. McGraw-Hill Higher Education: New York, New York. 5th edn.

34) Phillips, S., Aden, A., Jechura, J., Dayton, D., Eggeman, T., 2007. Thermochemical Ethanol via Indirect Gasification and Mixed Alcohol Synthesis of Lignocellulosic Biomass. Contract 1-132. doi:NREL/TP-510-41168

35) Pressley, P.N., Levis, J.W., Damgaard, A., Barlaz, M.A., DeCarolis, J.F., 2015. Analysis of material recovery facilities for use in life-cycle assessment. Waste Manag. 35, 307-317. doi:10.1016/j.wasman.2014.09.012

36) Pressley, P.N., Aziz, T.N., Decarolis, J.F., Barlaz, M.A., He, F., Li, F., Damgaard, A., 2014. Municipal solid waste conversion to transportation fuels: A life-cycle estimation of global warming potential and energy consumption. J. Clean. Prod. 70, 145-153. doi:10.1016/j.jclepro.2014.02.041

37) Ramey, D., 2004. Production of Butyric Acid and Butanol from Biomass. Biomol. Eng. Size: 3.9. doi:10.2172/843183

38) Scrap Register Prices, 2016. United States Scrap Metal Prices.

39) Southern Resources, 2016. Scrap Prices.

40) Staples, M.D., Malina, R., Olcay, H., Pearlson, M.N., Hileman, J.I., Boies, A., Barrett, S.R.H., 2014. Lifecycle greenhouse gas footprint and minimum selling price

of renewable diesel and jet fuel from fermentation and advanced fermentation production technologies. Energy Environ. Sci. 7, 1545. doi:10.1039/c3ee43655a

41) Suresh, P., 2016. Environmental and economic assessment of transportation fuels from municipal solid waste. Thesis for Master of Science in Aeronautics and Astronautics at the Massachusetts Institute of Technology.

42) Swanson, R.M., Platon, A., Satrio, J.A., Brown, R.C., 2010. Techno-economic analysis of biomass-to-liquids production based on gasification. Fuel 89. doi:10.1016/j.fuel.2010.07.027

43) Unruh, D., Pabst, K., Schaub, G., 2010. Fischer-Tropsch synfuels from biomass: maximizing carbon efficiency and hydrocarbon yield. Energy & Fuels. 24, 2634-2641. doi:10.1021/ef9009185.

44) USGS 2016. Mineral Commodity Summaries 2016.

45) USDA Agricultural Marketing Service, 2016. Livestock, Poultry & Grain Market News. LS179A: Tallow, grease, lard, & protein (Da/Wk/Mo) wtd w/Loads.

46) USDA Agricultural Marketing Service, 2016. Livestock, Poultry & Grain Market News. U.S. No. 2 Yellow Corn, FOB Gulf of Mexico.

47) USDA Economic Research Service, 2016. Dried distillers grain with solubles price.

48) Zhao, X., Brown, T.R., Tyner, W.E., 2015. Stochastic techno-economic evaluation of cellulosic biofuel pathways. Bioresour. Technol. 198, 755-763. doi:10.1016/j.biortech.2015.09.056

49) Zhu, Y., Biddy, M.J., Jones, S.B., Elliott, D.C., Schmidt, A.J., 2014. Techno-economic analysis of liquid fuel production from woody biomass via hydrothermal liquefaction (HTL) and upgrading. Appl. Energy 129, 384-394. doi:10.1016/j.apenergy.2014.03.053

50) Zhu, Y.,Tjokro Rahardjo, S.A., Valkenburg, C., Snowden-Swan, L.J., Jones, S.B., Machinal, M.A., 2011. Techno-economic Analysis for the Thermochemical Conversion of Biomass to Liquid Fuels. Report PNNL-19009, Pacific Northwest National Laboratory.

Appendix C

Detailed MSP and NPV Results

C.1 MSP and NPV Monte Carlo Data

Table C.1: MSP ($/L) results for each pathway

Pathway	Median	Mean	Std. Dev.	Lower 5%	Upper 5%
HEFA, Soybean oil	1.16	1.19	0.22	0.87	1.60
HEFA, Tallow	1.04	1.06	0.19	0.79	1.42
HEFA, Yellow grease	0.89	0.91	0.18	0.66	1.24
AF, Corn grain	1.64	1.66	0.25	1.30	2.10
AF, Sugarcane	1.43	1.47	0.26	1.10	1.96
AF, Herbaceous biomass	2.50	2.51	0.23	2.16	2.92
APP	2.05	2.07	0.23	1.73	2.48
HTL	2.75	2.78	0.45	2.09	3.58
FT	1.14	1.15	0.14	0.95	1.39
FPH	1.50	1.52	0.33	1.02	2.10

Table C.2: NPV ($B) results for each pathway

Pathway	Median	Mean	Std. Dev.	Lower 5%	Upper 5%
HEFA, Soybean oil	-0.278	-0.281	0.205	-0.625	0.049
HEFA, Tallow	-0.199	-0.202	0.188	-0.517	0.100
HEFA, Yellow grease	-0.110	-0.112	0.181	-0.412	0.179
AF, Corn grain	-0.549	-0.552	0.209	-0.905	-0.216
AF, Sugarcane	-0.414	-0.420	0.209	-0.775	-0.099
AF, Herbaceous biomass	-1.044	-1.036	0.188	-1.336	-0.716
APP	-0.863	-0.854	0.171	-1.120	-0.560
HTL	-0.721	-0.716	0.181	-1.005	-0.408
FT	-0.217	-0.210	0.139	-0.424	0.033
FPH	-0.351	-0.344	0.157	-0.583	-0.070

Table C.3: MSP ($/L) contribution results for HEFA and AF

	HEFA Soy			**HEFA Tallow**			**HEFA Yellow Grease**			**AF Corn Grain**			**AF Sugarcane**			**AF Herbaceous Biomass**		
	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.
Capital costs	0.19	0.19	0.02	0.19	0.19	0.02	0.19	0.19	0.02	0.57	0.58	0.07	0.65	0.66	0.09	1.24	1.26	0.16
Fixed OPEX	0.07	0.07	0.01	0.07	0.07	0.01	0.07	0.07	0.01	0.12	0.13	0.02	0.14	0.14	0.02	0.27	0.27	0.03
Variable OPEX	0.12	0.12	0.01	0.12	0.12	0.01	0.12	0.12	0.01	0.17	0.17	0.01	0.03	0.03	0.00	0.44	0.44	0.02
Feedstock	0.81	0.83	0.22	0.69	0.71	0.19	0.54	0.56	0.18	1.01	1.04	0.29	0.66	0.70	0.24	0.46	0.46	0.10
Income tax	0.02	0.02	0.00	0.02	0.02	0.00	0.02	0.02	0.00	0.07	0.07	0.01	0.07	0.08	0.01	0.14	0.14	0.02
Revenue from gasoline/naphtha	-0.02	-0.02	0.00	-0.02	-0.02	0.00	-0.02	-0.02	0.00	-0.02	-0.02	0.00	-0.02	-0.02	0.00	-0.02	-0.02	0.00
Revenue from other co-products	-0.04	-0.04	0.01	-0.04	-0.04	0.01	-0.04	-0.04	0.01	-0.30	-0.31	0.07	-0.13	-0.13	0.01	-0.04	-0.04	0.01

Table C.4: MSP (\$/L) contribution results for APP, HTL, FT, and FPH

	HTL			APP			FT			FPH		
	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.
Capital costs	2.39	2.41	0.30	1.37	1.38	0.18	0.92	0.93	0.12	1.19	1.21	0.18
Fixed OPEX	0.44	0.44	0.08	0.15	0.15	0.02	0.26	0.26	0.03	0.18	0.19	0.03
Variable OPEX	0.62	0.62	0.08	0.65	0.65	0.05	0.08	0.08	0.01	0.75	0.76	0.10
Feedstock	0.70	0.70	0.06	0.38	0.38	0.04	0.00	0.00	0.00	0.15	0.15	0.02
Income tax	0.29	0.29	0.04	0.16	0.16	0.02	0.11	0.11	0.01	0.64	0.65	0.10
Revenue from gasoline/naphtha	-1.36	-1.36	0.14	-0.25	-0.25	0.03	-0.13	-0.13	0.02	-1.31	-1.31	0.14
Revenue from other co-products	-0.41	-0.41	0.05	-0.41	-0.42	0.04	0.00	0.00	0.00	-0.19	-0.19	0.02
Revenue from scrap	0.00	0.00	0.00	0.00	0.00	0.00	-0.10	-0.10	0.02	0.00	0.00	0.00

Table C.5: NPV ($B) contribution results for HEFA and AF

	HEFA Soy			HEFA Tallow			HEFA Yellow Grease			AF Corn Grain			AF Sugarcane			AF Herbaceous Biomass		
	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.
Capital costs	-0.128	-0.129	0.016	-0.127	-0.129	0.016	-0.128	-0.129	0.016	-0.366	-0.369	0.044	-0.416	-0.421	0.051	-0.796	-0.803	0.096
Fixed OPEX	-0.048	-0.048	0.005	-0.048	-0.048	0.005	-0.048	-0.048	0.005	-0.080	-0.081	0.009	-0.091	-0.092	0.010	-0.173	-0.175	0.020
Non-Feedstock Variable OPEX	-0.080	-0.080	0.008	-0.080	-0.080	0.008	-0.080	-0.080	0.008	-0.119	-0.121	0.012	-0.023	-0.023	0.003	-0.284	-0.285	0.004
Feedstock	-0.532	-0.552	0.145	-0.456	-0.472	0.121	-0.360	-0.375	0.118	-0.641	-0.666	0.182	-0.424	-0.446	0.147	-0.291	-0.291	0.059
Income tax	0.000	-0.005	0.010	0.000	-0.007	0.013	-0.003	-0.013	0.018	0.000	-0.002	0.006	0.000	-0.007	0.012	0.000	0.000	0.002
Revenue from MD fuels	0.486	0.500	0.146	0.489	0.502	0.147	0.489	0.501	0.149	0.469	0.483	0.142	0.470	0.482	0.142	0.469	0.484	0.141
Revenue from gasoline	0.011	0.012	0.003	0.011	0.012	0.003	0.011	0.012	0.003	0.011	0.012	0.003	0.011	0.012	0.003	0.011	0.012	0.003
Revenue from other co-products	0.021	0.021	0.005	0.021	0.021	0.005	0.021	0.021	0.005	0.186	0.191	0.041	0.075	0.075	0.006	0.022	0.023	0.005

Table C.6: NPV ($B) contribution results for APP, HTL, FT, and FPH

	HTL			APP			FT			FPH		
	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.	Med.	Mean	Std. Dev.
Capital costs	-0.675	-0.682	0.083	-0.789	-0.798	0.096	-0.527	-0.533	0.064	-0.405	-0.410	0.050
Fixed OPEX	-0.118	-0.119	0.013	-0.084	-0.085	0.010	-0.147	-0.149	0.017	-0.062	-0.063	0.007
Non-Feedstock Variable OPEX	-0.372	-0.372	0.026	-0.375	-0.375	0.024	-0.049	-0.049	0.003	-0.242	-0.242	0.025
Feedstock	-0.197	-0.196	0.016	-0.218	-0.218	0.018	0.000	0.000	0.000	-0.218	-0.218	0.027
Income tax	0.000	-0.001	0.003	0.000	-0.005	0.009	-0.022	-0.026	0.021	-0.001	-0.008	0.013
Revenue from MD fuels	0.204	0.210	0.063	0.415	0.427	0.129	0.422	0.433	0.129	0.246	0.254	0.078
Revenue from gasoline	0.231	0.237	0.064	0.097	0.100	0.027	0.053	0.055	0.015	0.271	0.280	0.078
Revenue from other co-products	0.068	0.070	0.020	0.239	0.239	0.018	0.002	0.002	0.001	0.064	0.064	0.005
Revenue from scrap	--	--	--	--	--	--	0.057	0.057	0.014	--	--	--

Table C.7: Skewness and kurtosis results for baseline MSP and NPV kernel distributions

	MSP		NPV	
	Skewness	Kurtosis	Skewness	Kurtosis
HEFA Soybean oil	0.771	4.022	-0.202	3.142
HEFA Tallow	0.772	3.957	-0.145	3.071
HEFA Yellow grease	0.772	4.146	-0.096	3.005
AF Corn grain	0.711	4.036	-0.183	3.067
AF Sugarcane	0.838	4.186	-0.297	3.378
AF Herbaceous biomass	0.391	3.030	0.170	2.812
HTL	0.283	2.797	0.218	2.785
APP	0.418	2.932	0.133	2.712
FT	0.337	2.753	0.259	2.816
FPH	0.381	3.196	0.300	2.778

Note: The MSP and NPV results were fit to kernel distributions, a distribution used in cases when parametric distributions fail to properly describe the dataset. The positive skewness of the MSP results can be observed in the difference between the median and mean MSP for each case, with the median MSP slightly less than the mean MSP by \$0.01/L - \$0.04/L. The positive skewness of the capital investment distribution imposes the greatest influence on the positive skewness of the MSP distributions, and none of the pathways reveal symmetrical skewness results (skewness less than 0.25). A test for normality (kurtosis of 3) reveals that none of the MSP results can be described accurately by a normal distribution. Conversely, the NPV results demonstrate kurtosis values that conform closely with a normal distribution, with all values falling within 15% of 3. The NPV distributions reveal more varied skewness results, with AF from herbaceous biomass, HTL, APP, and FPH skewed positively due to the dominance of capital costs among contributors to variance and HEFA, AF from corn grain, and AF from sugarcane skewed negatively due to the dominance of feedstock among contributors to variance

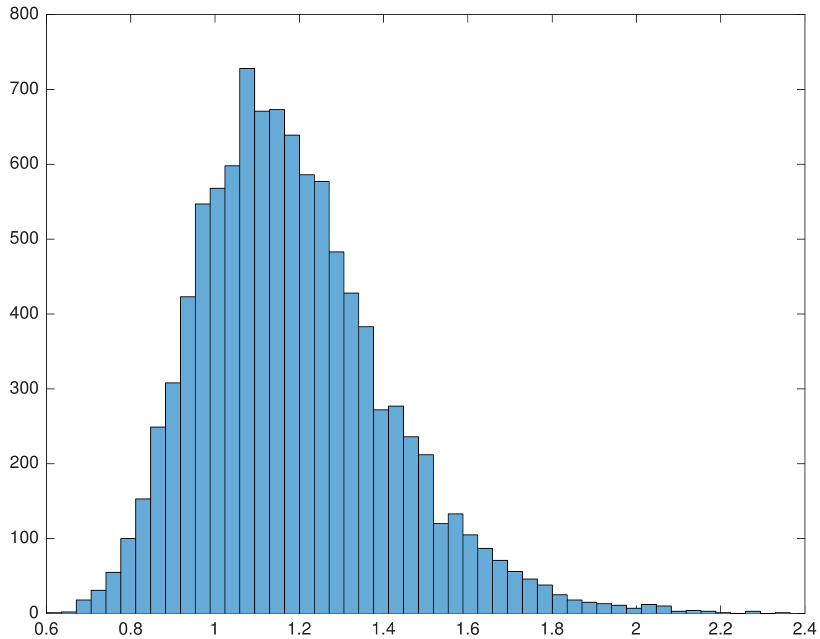

Figure C-1: HEFA soybean oil MSP histogram ($/L)

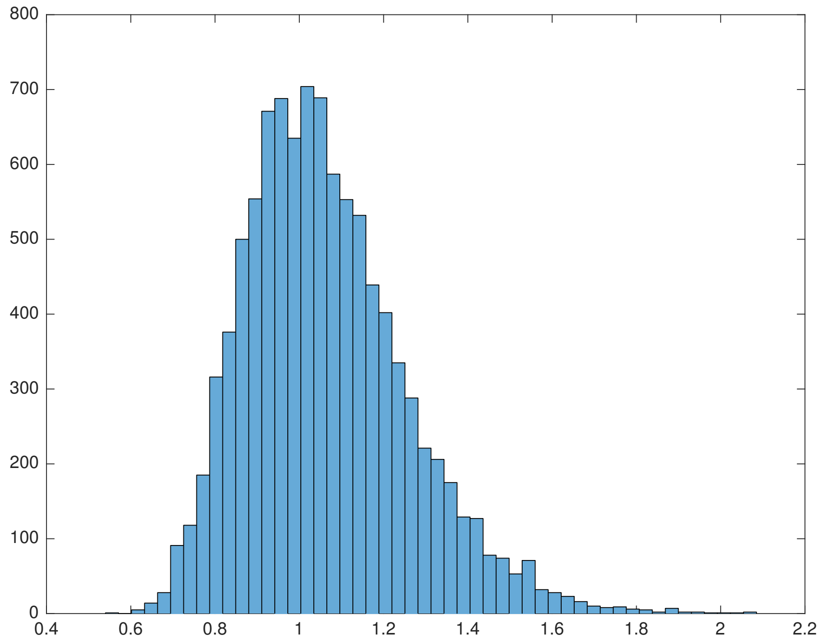

Figure C-2: HEFA tallow MSP histogram ($/L)

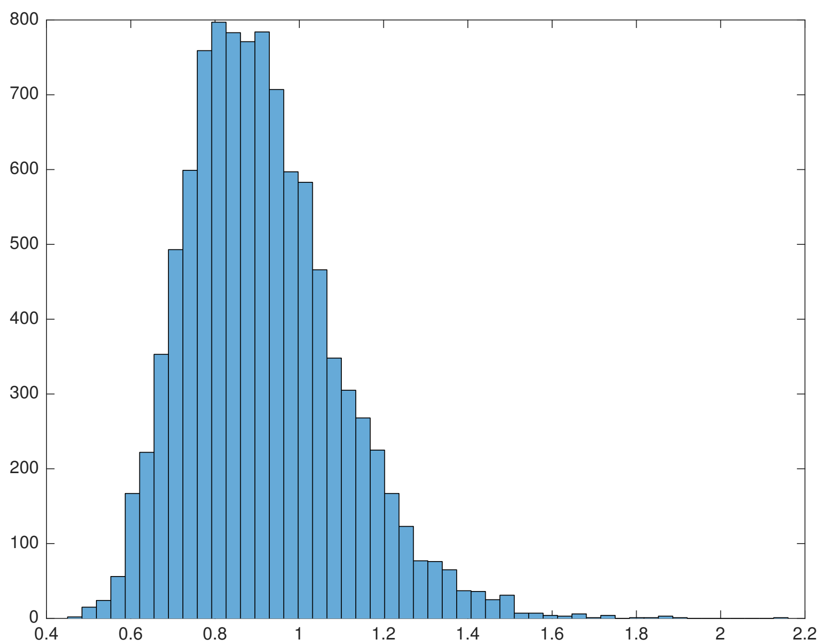

Figure C-3: HEFA yellow grease MSP histogram ($/L)

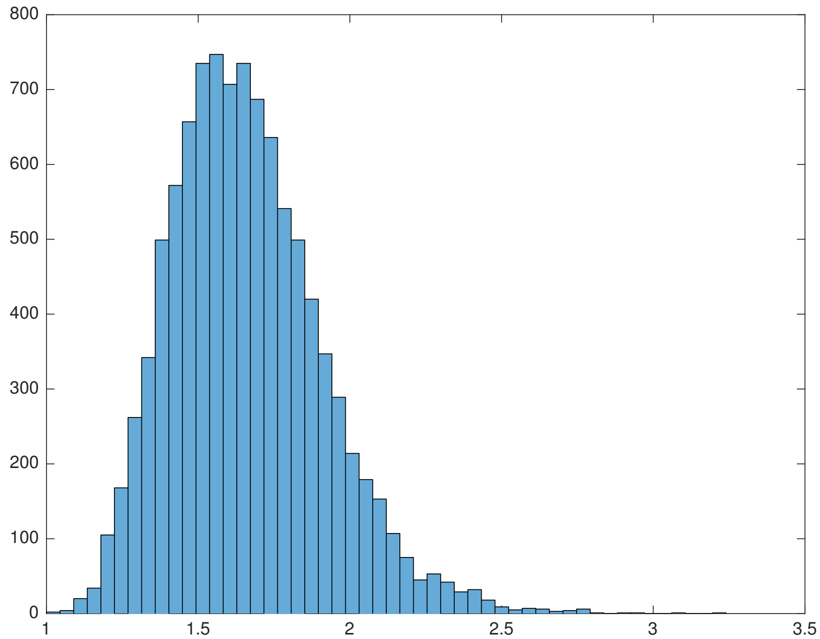

Figure C-4: AF corn grain MSP histogram ($/L)

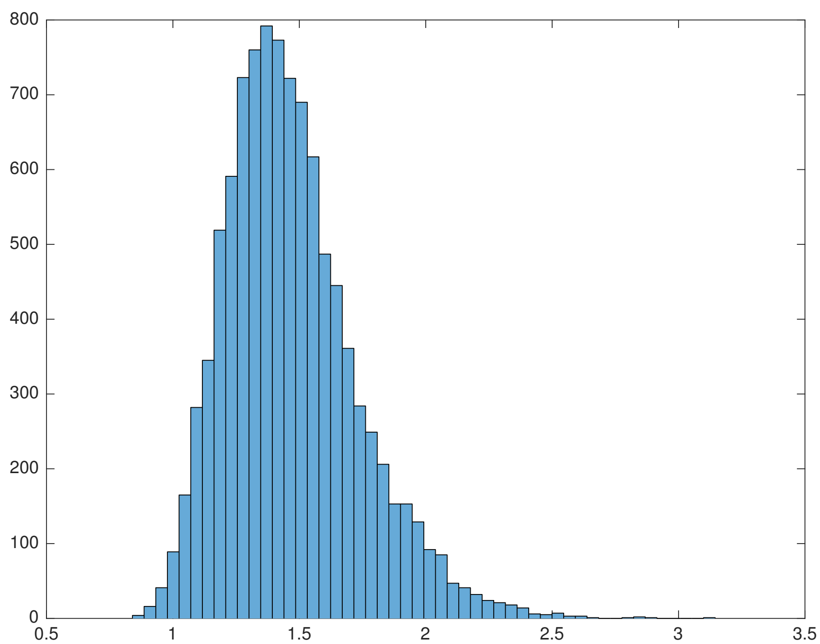

Figure C-5: AF sugarcane MSP histogram ($/L)

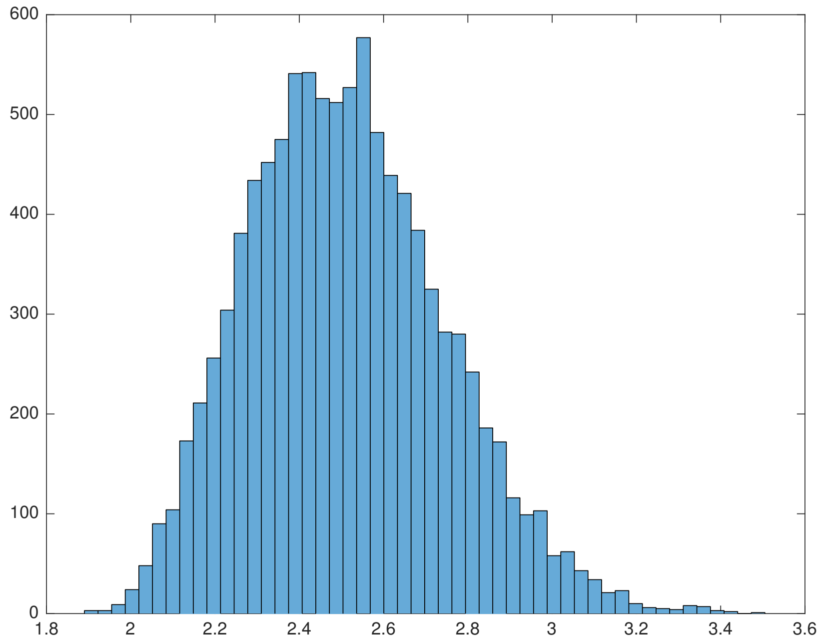

Figure C-6: AF herbaceous biomass MSP histogram ($/L)

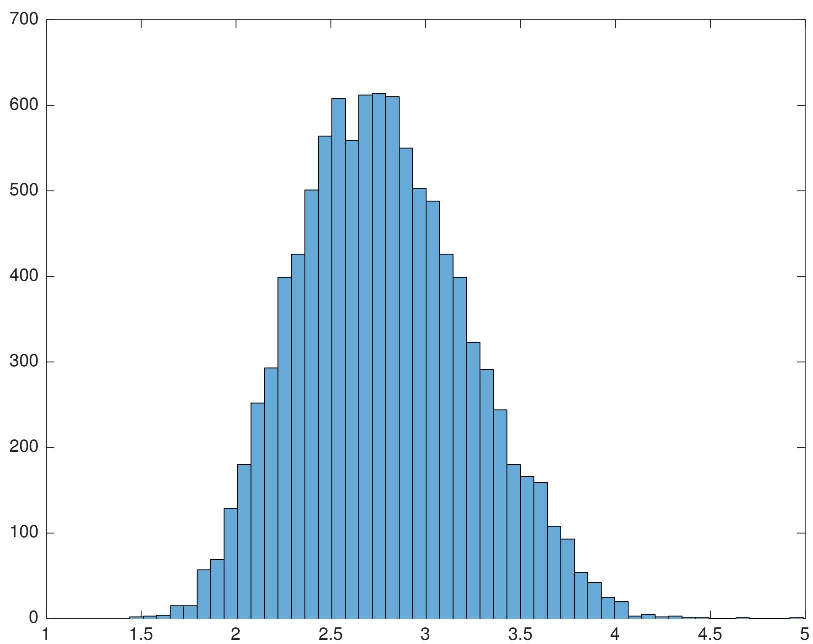

Figure C-7: HTL MSP histogram ($/L)

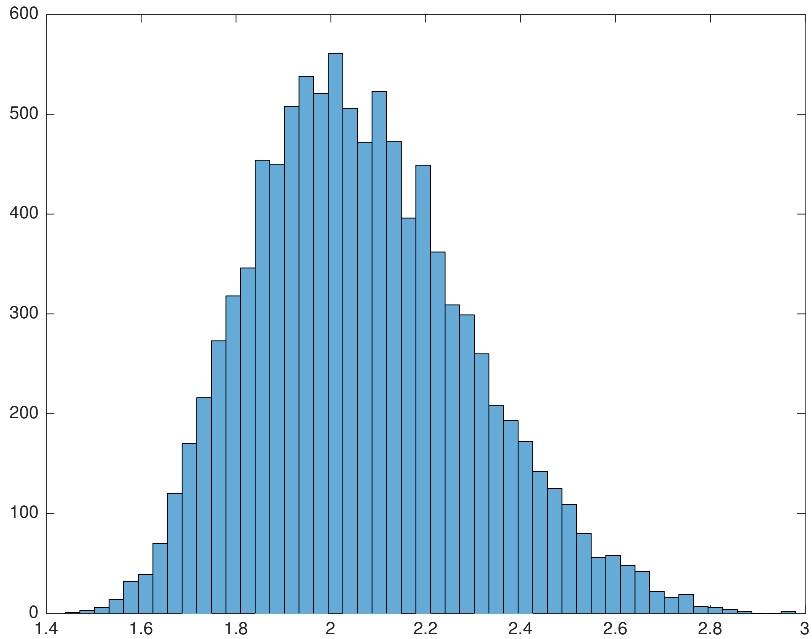

Figure C-8: APP MSP histogram ($/L)

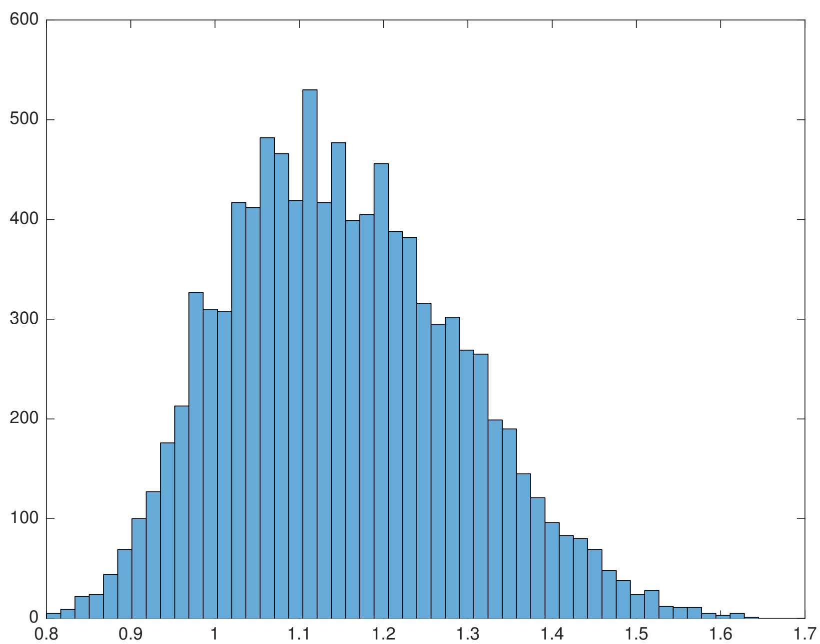

Figure C-9: FT MSP histogram ($/L)

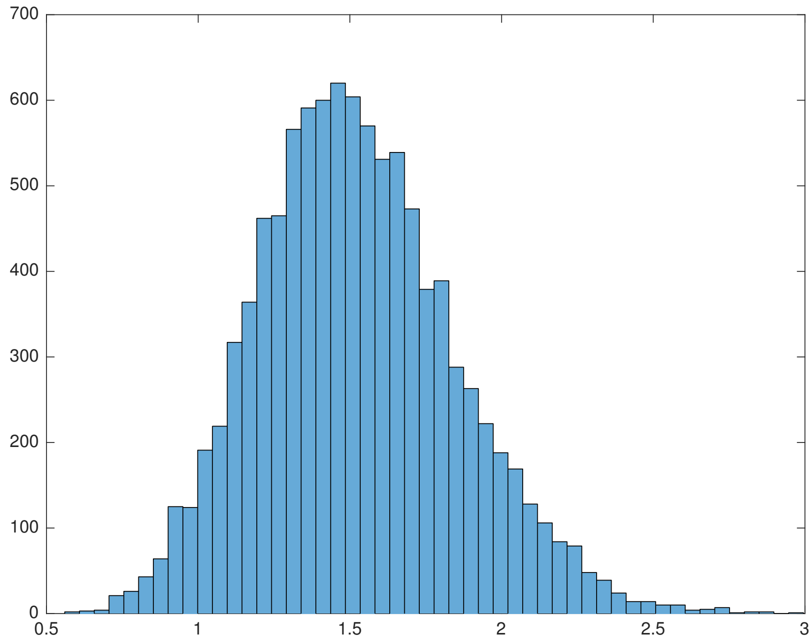

Figure C-10: FPH MSP histogram ($/L)

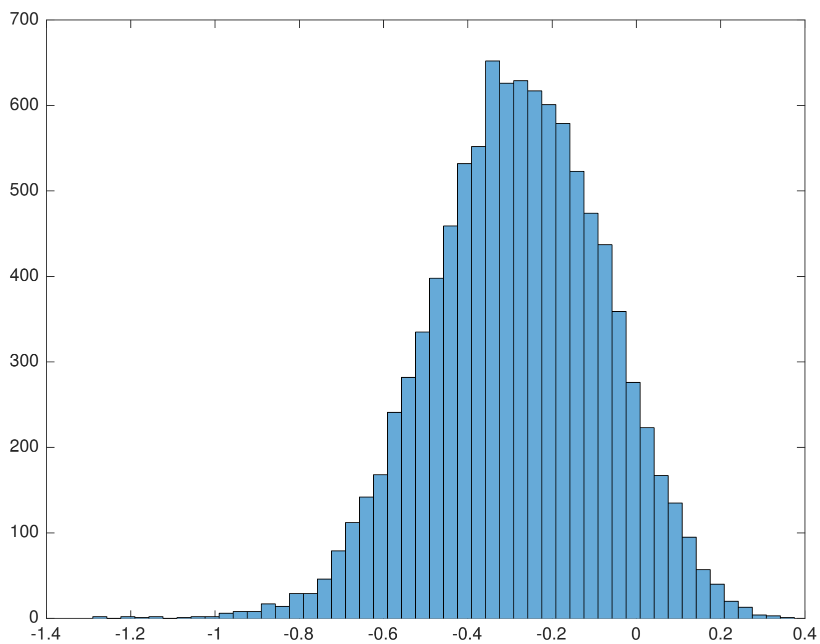

Figure C-11: HEFA soybean oil NPV histogram ($B)

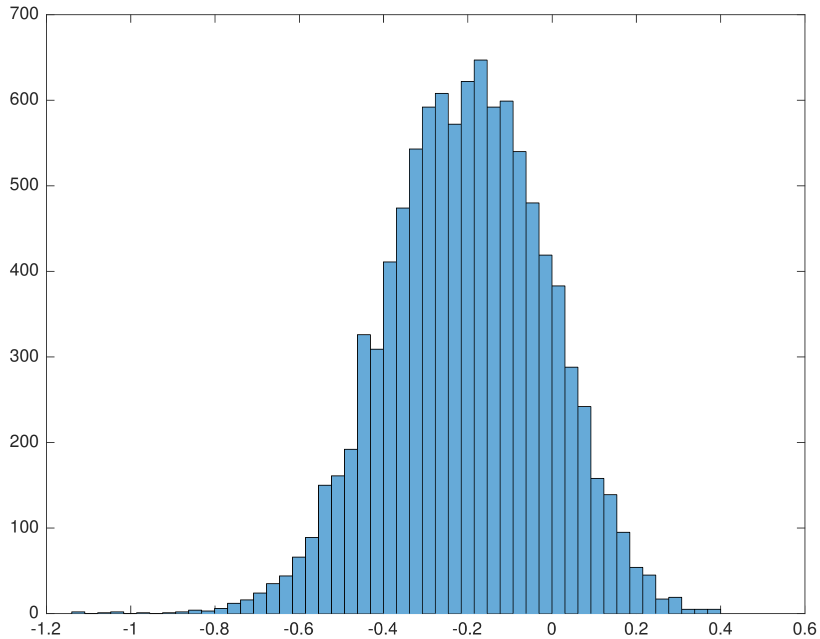

Figure C-12: HEFA tallow NPV histogram ($B)

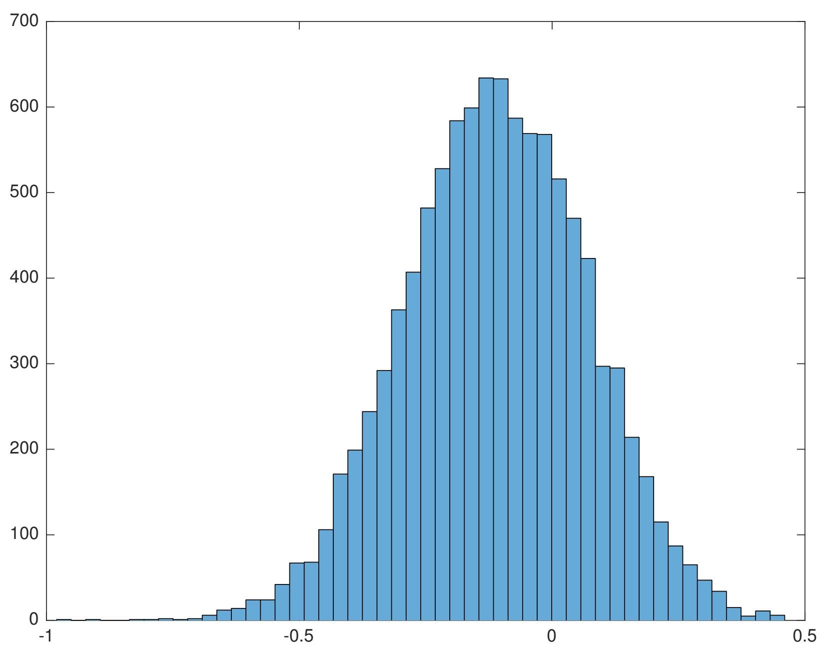

Figure C-13: HEFA yellow grease NPV histogram ($B)

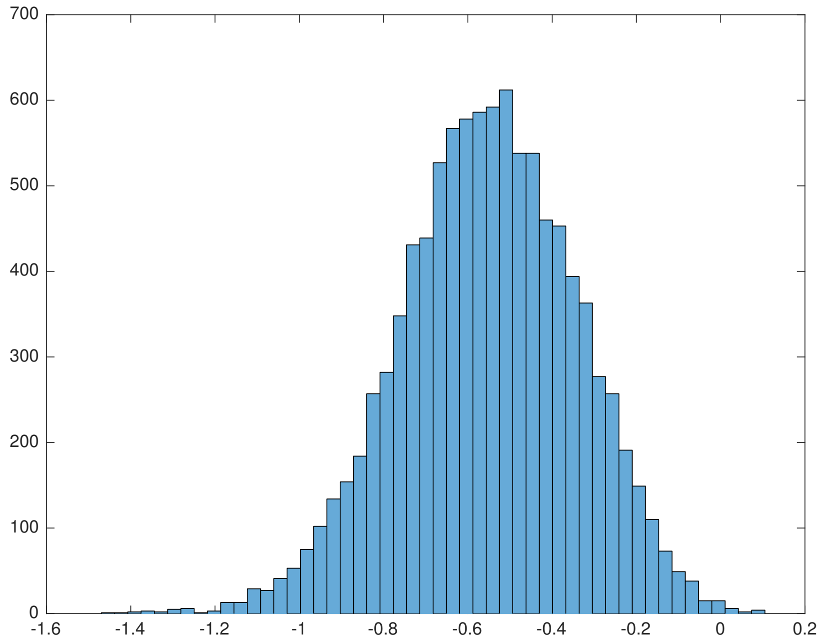

Figure C-14: AF corn grain NPV histogram ($B)

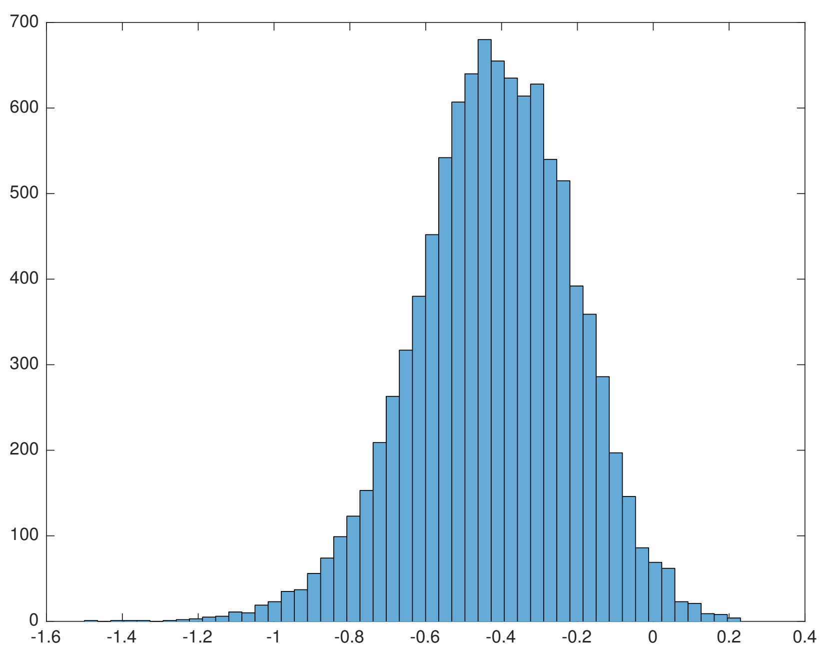

Figure C-15: AF sugarcane NPV histogram ($B)

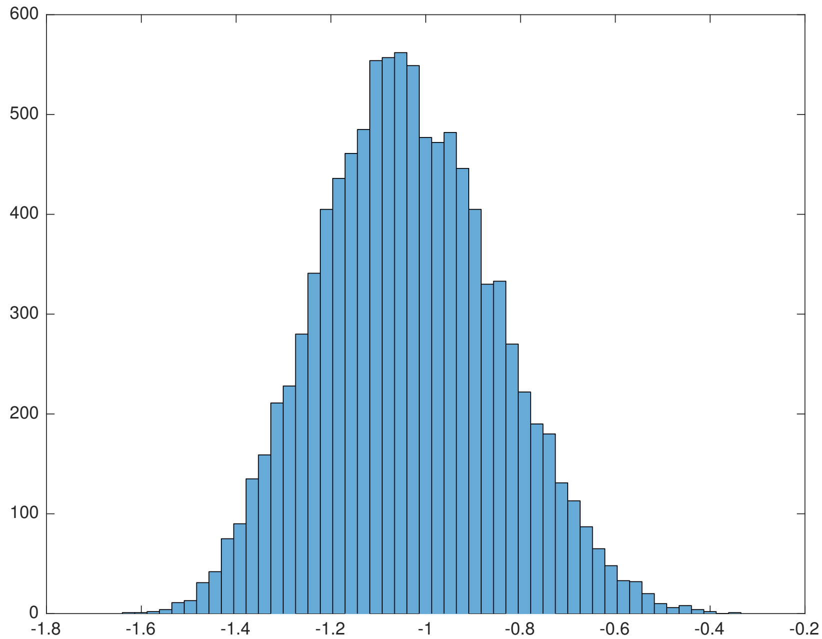

Figure C-16: AF herbaceous biomass NPV histogram ($B)

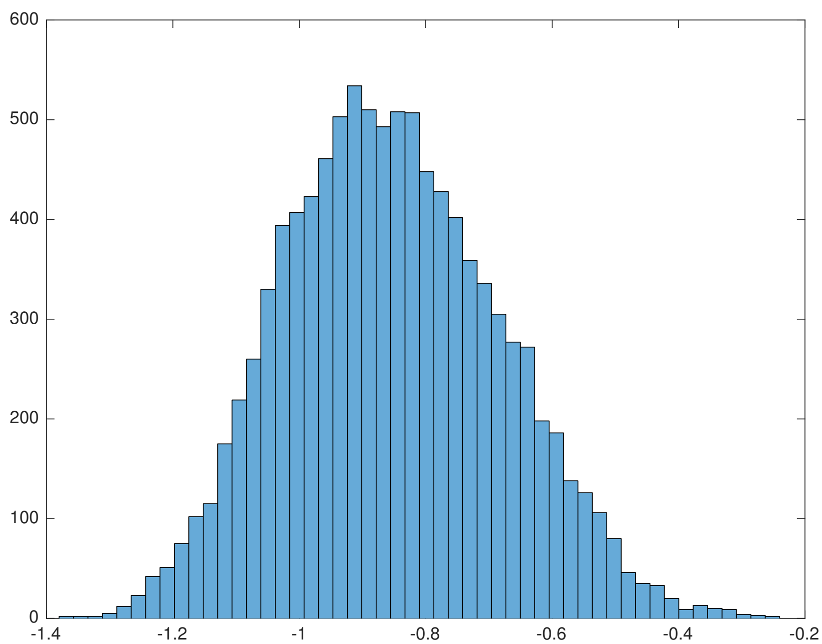

Figure C-17: HTL NPV histogram ($B)

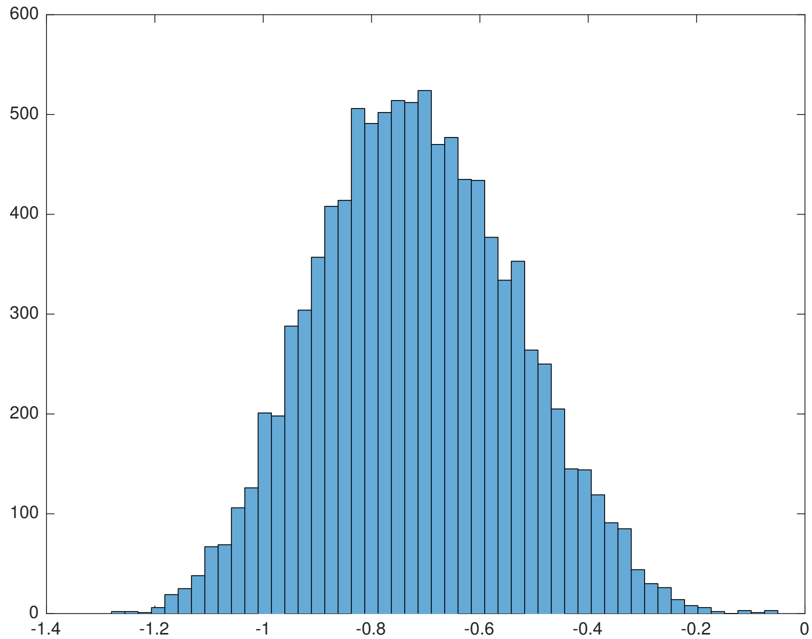

Figure C-18: APP NPV histogram ($B)

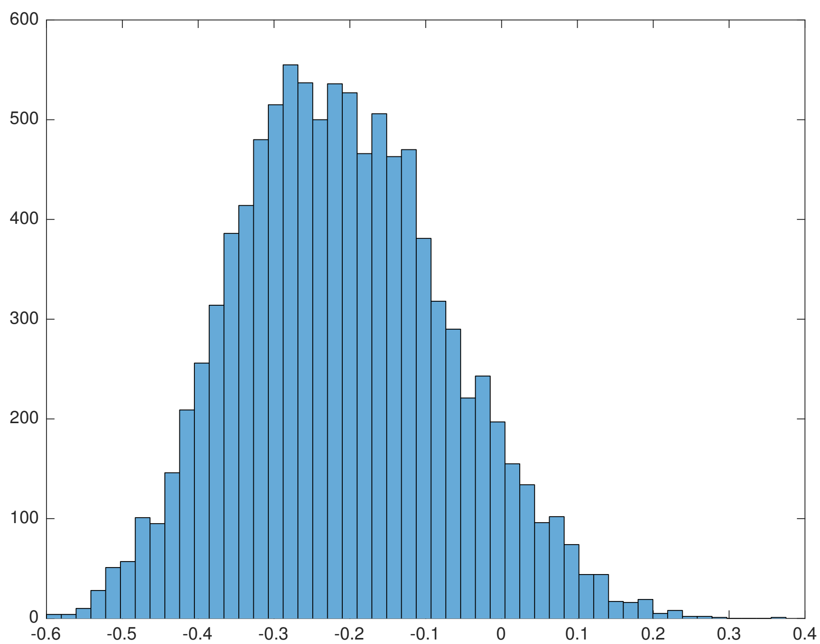

Figure C-19: FT NPV histogram ($B)

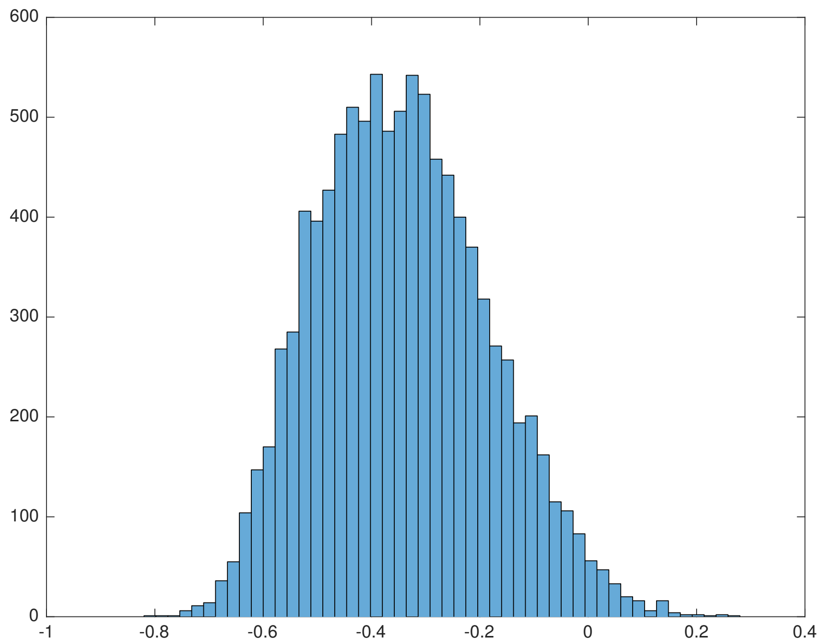

Figure C-20: FPH NPV histogram ($B)

C.2 Contribution to Variance

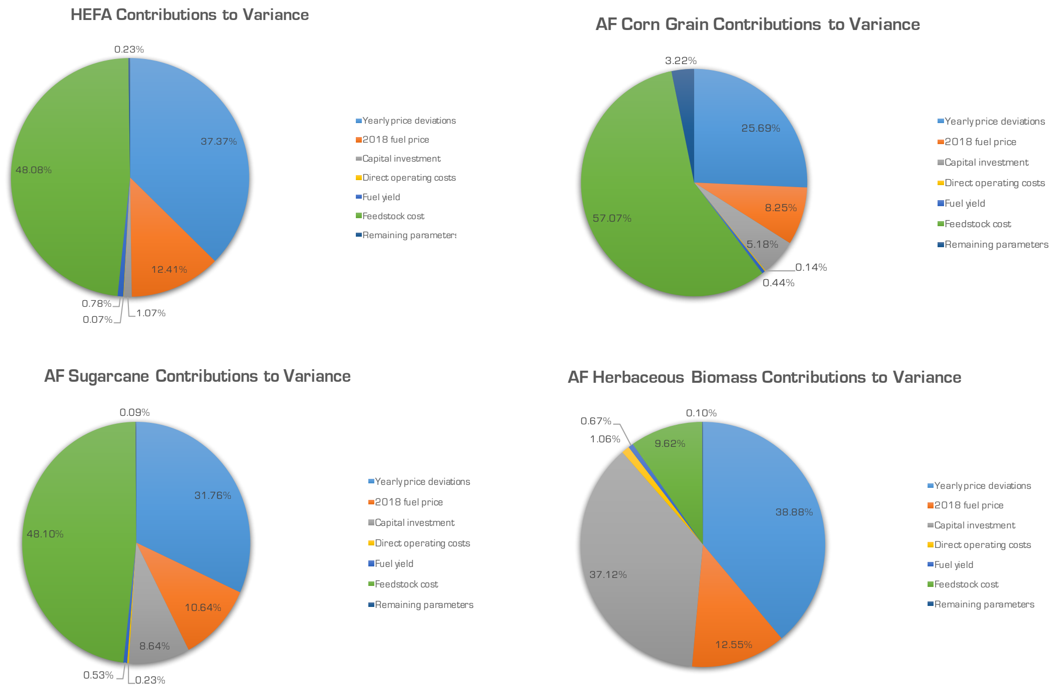

Figure C-21: Contributions to variance for HEFA and AF pathways

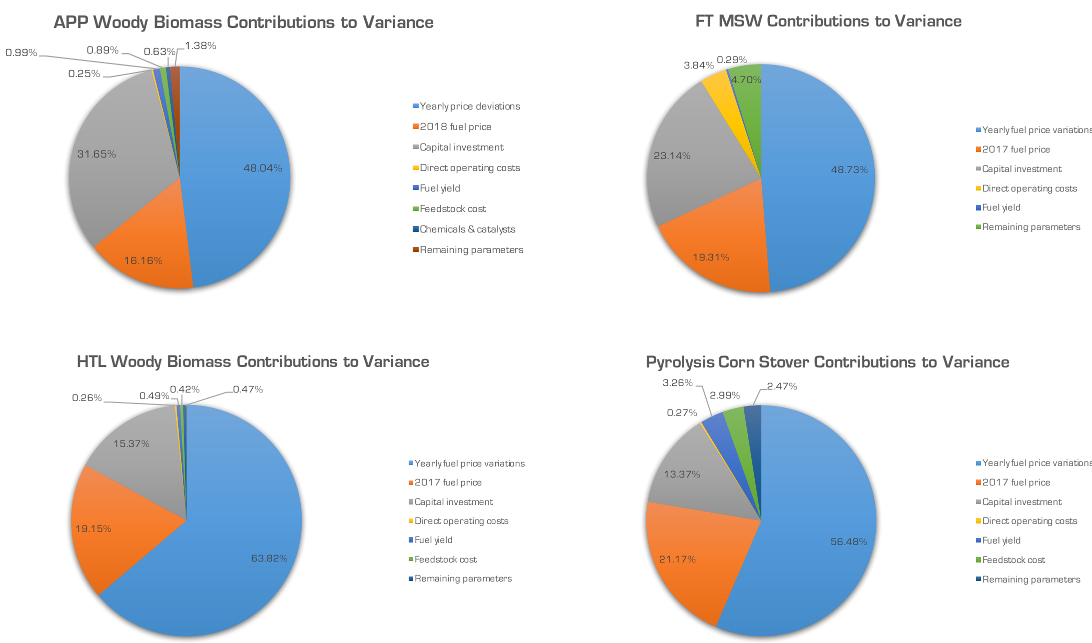

Figure C-22: Contributions to variance for APP, FT, HTL, and FPH

Table C.8: NPV contributions to variance for each pathway

	HEFA	AF Corn	AF Sugarcane	AF Herbaceous Biomass	APP	HTL	FT	FPH
Yearly price deviations	1.62E+16	1.49E+16	1.44E+16	1.45E+16	2.80E+16	7.87E+16	8.56E+15	4.56E+16
2018 fuel price	5.39E+15	4.78E+15	4.82E+15	4.69E+15	9.41E+15	2.36E+16	3.39E+15	1.71E+16
Capital investment	4.65E+14	3.00E+15	3.92E+15	1.39E+16	1.84E+16	1.89E+16	4.06E+15	1.08E+16
Direct operating costs	2.90E+13	8.18E+13	1.06E+14	3.97E+14	1.48E+14	3.19E+14	6.74E+14	2.16E+14
Fuel yield	3.37E+14	2.56E+14	2.41E+14	2.50E+14	5.78E+14	6.07E+14	5.07E+13	2.63E+15
Feedstock cost	2.09E+16	3.31E+16	2.18E+16	3.60E+15	5.16E+14	5.23E+14	--	2.41E+15
Remaining parameters	9.97E+13	1.87E+15	4.30E+13	3.81E+13	1.17E+15	5.81E+14	8.26E+14	2.00E+15

C.3 Detailed Sensitivity Analysis Results

Table C.9: Sensitivity analysis for HEFA soybean oil MSP and positive NPV probability

HEFA Soybean Oil						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	1.07	1.27	1.19	21.8%	8.6%	3.5%
Feedstock cost $/Mlb (225, 370, 525)	0.86	1.53	1.19	27.4%	8.6%	0.1%
Income tax rate % (0, 16.9, 39)	1.16	1.23	1.19	8.7%	8.6%	6.8%
Fuel yield GGE/MT (240, 304, 320)	1.50	1.12	1.19	2.2%	8.6%	12.2%
FCI % (80, 100, 150)	1.14	1.29	1.19	10.4%	8.6%	5.1%
Fixed Operating Cost, % of FCI (8, 11, 16)	1.17	1.22	1.19	9.1%	8.6%	6.9%

Table C.10: Sensitivity analysis for HEFA tallow MSP and positive NPV probability

HEFA Tallow						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	0.95	1.15	1.06	31.2%	14.8%	6.6%
Feedstock cost $/Mlb (194, 315, 445)	0.79	1.36	1.06	36.8%	14.8%	0.7%
Income tax rate % (0, 16.9, 39)	1.04	1.11	1.06	15.5%	14.8%	10.8%
Fuel yield GGE/MT (240, 304, 320)	1.35	1.00	1.06	3.7%	14.8%	17.8%
FCI % (80, 100, 150)	1.02	1.17	1.06	16.4%	14.8%	8.4%
Fixed Operating Cost, % of FCI (8, 11, 16)	1.05	1.10	1.06	14.4%	14.8%	11.2%

Table C.11: Sensitivity analysis for HEFA yellow grease MSP and positive NPV probability

HEFA Yellow Grease						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	0.80	1.00	0.91	44.8%	27.7%	14.0%
Feedstock cost $/Mlb (134, 250, 374)	0.65	1.19	0.91	57.6%	27.7%	3.3%
Income tax rate % (0, 16.9, 39)	0.89	0.96	0.91	28.4%	27.7%	19.7%
Fuel yield GGE/MT (240, 304, 320)	1.16	0.86	0.91	9.6%	27.7%	31.5%
FCI % (80, 100, 150)	0.87	1.02	0.91	29.8%	27.7%	16.6%
Fixed Operating Cost % of FCI (8, 11, 16)	0.90	0.95	0.91	26.6%	27.7%	21.5%

Table C.12: Sensitivity analysis for AF corn grain MSP and positive NPV probability

AF Corn Grain						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	1.32	1.91	1.66	1.3%	1.9%	0.2%
Feedstock cost $/kg (0.12, 0.18, 0.25)	1.38	1.96	1.66	1.4%	2.0%	0.0%
Income tax rate % (0, 16.9, 39)	1.60	1.79	1.66	1.6%	1.8%	1.4%
Fuel yield GGE/MT (45, 56.3, 59.3)	2.03	1.51	1.66	2.0%	1.5%	2.4%
FCI % (80, 100, 150)	1.53	1.97	1.66	1.5%	2.0%	0.3%
Fixed Operating Cost % of FCI (4, 6, 10)	1.62	1.74	1.66	1.6%	1.7%	1.1%

Table C.13: Sensitivity analysis for AF sugarcane MSP and positive NPV probability

AF Sugarcane						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	1.07	1.76	1.47	26.9%	1.8%	2.6%
Feedstock cost $/kg (0.02, 0.03, 0.05)	1.19	1.83	1.47	6.1%	1.8%	0.0%
Income tax rate % (0, 16.9, 39)	1.40	1.62	1.47	3.7%	1.8%	1.9%
Fuel yield GGE/MT (12, 15.2, 16)	1.78	1.32	1.47	0.1%	1.8%	8.3%
FCI % (80, 100, 150)	1.33	1.83	1.47	6.9%	1.8%	2.8%
Fixed Operating Cost % of FCI (4, 6, 10)	1.42	1.56	1.47	3.6%	1.8%	1.9%

Table C.14: Sensitivity analysis for AF herbaceous biomass MSP and positive NPV probability

AF Herbaceous Biomass						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	1.75	3.08	2.51	0.8%	0.0%	0.0%
Feedstock cost $/kg (0.02, 0.06, 0.10)	2.20	2.84	2.51	0.0%	0.0%	0.0%
Income tax rate % (0, 16.9, 39)	2.37	2.81	2.51	0.0%	0.0%	0.0%
Fuel yield GGE/MT (33, 41.6, 44)	3.02	2.24	2.51	0.0%	0.0%	0.0%
FCI % (80, 100, 150)	2.24	3.20	2.51	0.0%	0.0%	0.0%
Fixed Operating Cost % of FCI (4, 6, 10)	2.42	2.68	2.51	0.0%	0.0%	0.0%

Table C.15: Sensitivity analysis for HTL MSP and positive NPV probability

HTL Woody Biomass						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	1.11	3.92	2.78	54.6%	0.0%	3.1%
Feedstock cost $/MT (40, 66, 100)	2.51	3.13	2.78	11.9%	0.0%	3.2%
Income tax rate % (0, 16.9, 39)	2.52	3.32	2.78	11.2%	0.0%	3.2%
Fuel yield GGE/MT (49.3, 59.7, 61.2)	3.57	2.69	2.78	1.2%	0.0%	11.3%
FCI % (80, 100, 150)	2.20	4.22	2.78	18.0%	0.0%	4.0%
Fixed Operating Cost % of FCI (2, 5, 10)	2.55	3.19	2.78	11.3%	0.0%	3.4%

Table C.16: Sensitivity analysis for APP MSP and positive NPV probability

APP Woody Biomass						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	1.26	2.67	2.07	11.6%	0.0%	0.0%
Feedstock cost $/MT (40, 66, 100)	1.92	2.26	2.07	0.0%	0.0%	0.0%
Income tax rate % (0, 16.9, 39)	1.92	2.38	2.07	0.0%	0.0%	0.0%
Fuel yield GGE/MT (49, 62, 65.4)	2.61	1.92	2.07	0.0%	0.0%	0.1%
FCI % (80, 100, 150)	1.78	2.79	2.07	0.1%	0.0%	0.0%
Fixed Operating Cost % of FCI (2, 3, 6)	2.02	2.21	2.07	0.0%	0.0%	0.0%

Table C.17: Sensitivity analysis for FT MSP and positive NPV probability

FT MSW						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	0.58	1.57	1.15	65.8%	7.9%	0.0%
Feedstock cost $/MT (-55, 0, 55)	0.99	1.31	1.15	9.4%	7.9%	0.8%
Income tax rate % (0, 16.9, 39)	1.05	1.37	1.15	5.9%	7.9%	0.8%
Fuel yield GGE/MT (80, 91.5, 95)	1.21	1.05	1.15	1.0%	7.9%	7.4%
FCI % (80, 100, 150)	0.95	1.66	1.15	13.7%	7.9%	0.0%
Fixed Operating Cost % of FCI (4, 7.7, 15)	1.03	1.39	1.15	7.4%	7.9%	3.3%

Table C.18: Sensitivity analysis for FPH MSP and positive NPV probability

Pyrolysis Corn Stover						
	$/L MD			P(NPV>0)		
	Low	High	Baseline	Low	Baseline	High
Discount rate % (3.2, 15, 22)	0.61	2.13	1.52	33.2%	2.1%	0.1%
Feedstock cost $/MT (55, 87, 120)	1.30	1.76	1.52	4.8%	2.1%	0.7%
Income tax rate % (0, 16.9, 39)	1.39	1.79	1.52	3.1%	2.1%	1.1%
Fuel yield GGE/MT (55, 80.4, 90.5)	2.53	1.24	1.52	0.0%	2.1%	7.4%
FCI % (80, 100, 150)	1.28	2.15	1.52	6.2%	2.1%	0.1%
Fixed Operating Cost % of FCI (2, 4, 8)	1.43	1.67	1.52	3.2%	2.1%	1.2%

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Appendix D

Policy Analysis Methods

D.1 Equivalence Value Assignment

To demonstrate compliance with the RVO, blenders and refiners buy and sell 38-digit RIN codes assigned to each gallon of biofuel. These RINs have different D-Code designations associated with the emissions mitigation potential of different biofuel production pathways. As the RVO increases, RINs for fuels produced from pathways that abate greater quantities of greenhouse gases become more valuable. D3 Cellulosic Biofuel RINs, for example, can only be earned by pathways that use a cellulosic feedstock and emit 60% fewer greenhouse gases than conventional fuels. As a result, D3 RINs are more valuable on a $ per RIN basis than D5 Advanced Biofuel RINs, which have a less stringent feedstock requirement and require a 50% greenhouse gas reduction (ICCT, 2014). Where life-cycle emissions data is not available, this thesis refer to D-Codes assigned to these pathways by the EPA.

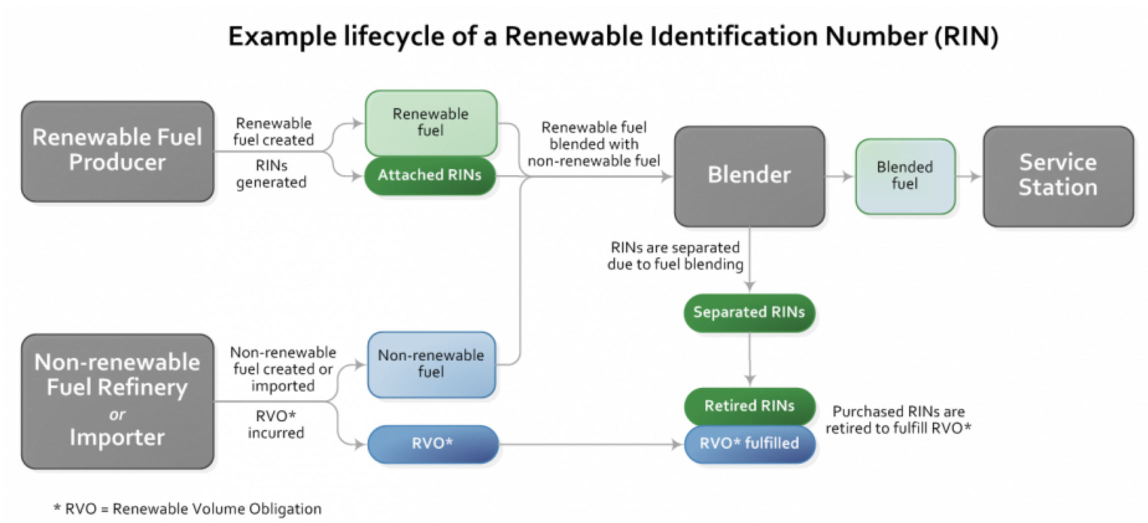

Figure D-1: RIN lifecycle from fuel production to purchase points (EPA, 2016)

Under the Renewable Fuel Standard (RFS), renewable fuel products are eligible for equivalence multipliers that increase the number of RINs earned per gallon. For example, depending on the LHV of the fuel, diesel could earn an equivalence value multiplier of 1.7. The number of RINs earned would then be subject to multiplication by 1.7. We assume that the proprietors of each pathway would apply for and earn the equivalence values commensurate with the LHV of each fuel product, according to the following equation:

$$EV = \frac{R}{0.972} \times \frac{EC}{77,000} \tag{D.1}$$

where EV is the equivalence value rounded to the nearest tenth, R is the renewable content of the fuel (assumed to be 1 for each pathway) and EC is the energy content of the renewable fuel in Btu per gallon (LHV). Table D.2 provides the assumed LHV for each fuel product and the associated equivalence value. In general, any pathway that converts a cellulosic feedstock into fuel earns a D7 RIN for middle distillates and a D3 RIN for other fuels. Commercial HEFA plants that use oil feedstocks earn D4 RINs for middle distillates and D5 RINs for other fuels, and MSW conversion pathways with non-cellulosic feedstocks earn D5 RINs (EPA, 2016).

Historical price values for D4 and D5 RINs were collected from Bloomberg commodity datasets (Bloomberg, 2016a,b). D4 and D5 RINs correlate closely over time, so the price of D5 RINs in any given year was dictated by the following equation using the random result of a kernel distribution applied to D4 RIN price data:

$$Price_{D5} = 0.813 \times Price_{D4} + 0.0811 \tag{D.2}$$

Because D3 and D7 RINs only comprise 0.8% of the RINs generated in 2015, price data is less readily available (EPA, 2015b). As a proxy, we follow Stock's method of estimating D3/D7 RIN prices by adding the D5 RIN price to the Cellulosic Waiver Credit (CWC), an EPA price support for cellulosic fuels that equates to \$0.25 in real terms or \$3.00 in real terms minus the average yearly wholesale price of gasoline, whichever is higher (EPA, 2015a; Stock, 2015). We apply this method on a year-to-year basis, combining the stochastic D5 RIN value with the CWC determined from the GBM-estimated gasoline price. Equivalence values, which are RIN multipliers attached to each gallon of fuel, are calculated based off of the assumed energy content (LHV) of each product using the equation found in RFS2. The distributions for each RIN type based on the Bloomberg commodity data are shown in Figure D-2.

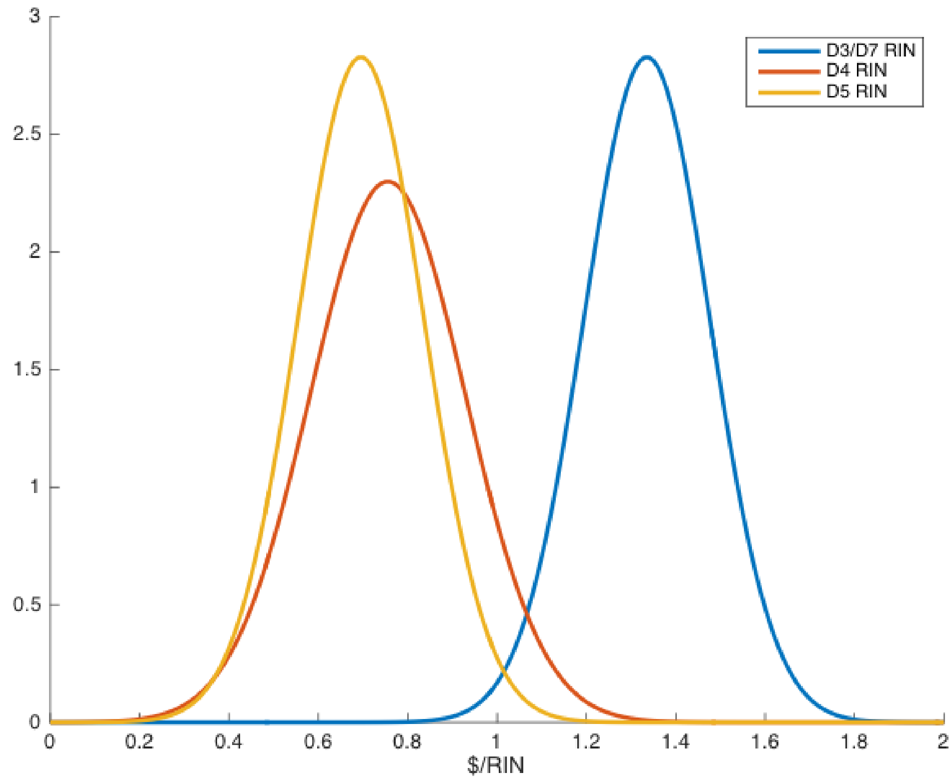

Figure D-2: RIN price distributions ($/RIN)

Table D.1: Earned RINs for each pathway and feedstock

Pathway	Fuel product	Earned D-Code	D-Code Classification
HEFA	LPG	D5	Advanced biofuel
	Naphtha	D5	Advanced biofuel
	Jet	D4	Biomass-based diesel
	Diesel	D4	Biomass-based diesel
AF	LPG	D5/D3*	Advanced biofuel/Cellulosic biofuel
	Naphtha	D5/D3*	Advanced biofuel/Cellulosic biofuel
	Jet	D4/D7*	Biomass-based diesel/Cellulosic diesel
	Diesel	D4/D7*	Biomass-based diesel/Cellulosic diesel
APP	LPG	D3	Cellulosic biofuel
	Naphtha	D3	Cellulosic biofuel
	Jet	D7	Cellulosic diesel
	Diesel	D7	Cellulosic diesel
HTL	Gasoline	D3	Cellulosic biofuel
	Jet	D7	Cellulosic diesel
	Diesel	D7	Cellulosic diesel
FT	Gasoline	D5	Advanced biofuel
	Jet	D5	Advanced biofuel
	Diesel	D5	Advanced biofuel
FPH	Gasoline	D3	Cellulosic biofuel
	Jet	D7	Cellulosic diesel
	Diesel	D7	Cellulosic diesel

*D3/D7 RINs only earned for herbaceous biomass feedstock in the AF case.

Table D.2: Assumed LHV and equivalence value for each fuel product

Fuel product	LHV (Btu/gallon)	Equivalence value
LPG	84,950	1.1
Naphtha	111,520	1.5
Gasoline	115,983	1.5
Jet	125,800	1.7
Diesel	128,450	1.7

D.2 Policy Analysis References

1) Bloomberg L.P., 2016a. Price graph for RINSEA15 10/1/14 to 6/10/15. Bloomberg database. Massachusetts Institute of Technology Information Systems & Technology.

2) Bloomberg L.P., 2016b. Price graph for RINSET15 10/2/14 to 12/31/15. Bloomberg database. Massachusetts Institute of Technology Information Systems & Technology.

3) Chevron Products Company, 2007. Aviation Fuels Technical Review.

4) Code of Federal Regulations, 2014. 40 CFR §80.1415: How are equivalence values assigned to renewable fuel? Legal Information Institute, Cornell University Law School.

5) EPA, 2015b. Cellulosic Waiver Credit Price Calculation for 2016.

6) EPA, 2015a. RIN Generation Summary, vol 2015.

7) EPA, 2016. Approved Pathways for Renewable Fuel, vol. 2016.

8) GREET, 2016. The Greenhouse Gases, Regulated Emissions, and Energy Use in Transportation Model, GREET 1.8d.1. Argonne National Laboratory: Argonne, IL.

9) International Council on Clean Transportation, 2014. A conversational guide to Renewable Identification Numbers (RINs) in the U.S. Renewable Fuel Standard.

10) Stock, J.H., 2015. Administering the cellulosic requirements under the Renewable Fuel Standard with increasing and uncertain supply. Harvard University Department of Economics.

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Bibliography

[1] Air Transport Action Group, 2013. Reducing emissions from aviation through carbon-neutral growth from 2020. Working Paper Developed for the 38th ICAO Assembly.

[2] Bittner, A., Tyner, W.E., Zhao, X., 2015. Field to flight: A techno-economic analysis of the corn stover to aviation biofuels supply chain. Biofuels, Bioproducts, & Biorefining. 9, 201-210. doi: 10.1002/bbb.1536

[3] Blazy, D., Pearlson, M.N., 2016. A Monte Carlo-based Methodology for Valuing Refineries Producing Aviation Biofuel. doi:10.1039/9781782622444-00336

[4] Boeing, 2015. "Long Term Outlook" Current Market Outlook: 2015-2034, 7-9.

[5] Bond, J.Q., Upadhye, A. a., Olcay, H., Tompsett, G. a., Jae, J., Xing, R., Alonso, D.M., Wang, D., Zhang, T., Kumar, R., Foster, A., Sen, S.M., Maravelias, C.T., Malina, R., Barrett, S.R.H., Lobo, R., Wyman, C.E., Dumesic, J. a., Huber, G.W., 2014. Production of renewable jet fuel range alkanes and commodity chemicals from integrated catalytic processing of biomass. Energy Environ. Sci. 7, 1500-1523. doi:10.1039/C3EE43846E

[6] Brown, T.R., 2015. A critical analysis of thermochemical cellulosic biorefinery capital cost estimates. Biofuels, Bioproducts, & Biorefining. 9, 412-421. doi: 10.1002/bbb.1546

[7] Brown, T.R., Thilakaratne, R., Brown, R.C., Hu, G., 2013. Techno-economic analysis of biomass to transportation fuels and electricity via fast pyrolysis and hydroprocessing. Fuel 106, 463-469. doi:10.1016/j.fuel.2012.11.029

[8] CAAFI Commercial Aviation Alternative Fuels Initiative, 2016. Opening remarks by Steve Csonka, 5th Biennial General Meeting, Oct 25 2016. (accessed Dec 5 2016)

[9] de Jong, S., Hoefnagels, R., Faaij, A., Slade, R., Mawhood, R., Junginger, M., 2015. The feasibility of short-term production strategies for renewable jet fuels - a comprehensive techno-economic comparison. Biofuels, Bioprod. Biorefining 9, 778-800. doi:10.1002/bbb.1613

[10] DOE, 2015. U.S. Department of Energy Loan Programs Office: Investing in American Energy.

[11] DOE, 2016. Alternative Fuels Data Center: Biodiesel Mixture Excise Tax Credit.

[12] Economic Indicators, 2016. Chemical Engineering. 123, 68.

[13] EIA, 2015. Annual Energy Outlook, vol. 2015.

[14] EIA, 2016a. Average Industrial Retail Price of Electricity, vol. 2016.

[15] EIA, 2016b. Cushing, OK WTI Spot Price FOB, vol. 2016.

[16] EIA, 2016c. Mont Belvieu, TX Propane Spot Price, vol. 2016.

[17] EIA, 2016d. U.S. Kerosene-Type Jet Fuel Wholesale/Resale Price by Refiners, vol. 2016.

[18] EIA, 2016e. U.S. Natural Gas Industrial Price, vol. 2016.

[19] EIA, 2016f. U.S. No. 2 Diesel Wholesale/Resale Price by Refiners, vol. 2016.

[20] EIA, 2016g. U.S. Total Gasoline Wholesale/Resale Price by Refiners, vol. 2016.

[21] EPA, 2016. Program Overview for Renewable Fuel Standard Program.

[22] Federal Aviation Administration, 2012. Aviation Greenhouse Gas Emissions Reduction Plan.

[23] Gary, J.H., Handwerk, G.E., Kaiser, M.J., 2007. Petroleum Refining: Technology and Economics. Taylor & Francis: Basel, Switzerland. 5th edn.

[24] International Air Transportation Authority, 2009. Carbon Neutral Growth by 2020. Press Release no. 26.

[25] International Civil Aviation Organization, 2010. Aviation's Contribution to Climate Change. ICAO Environmental Report, 38-41.

[26] International Civil Aviation Organization, 2016. Chapter 4: Global Emissions: Sustainable Alternative Fuels. ICAO Environmental Report, 153-177.

[27] International Council on Clean Transportation, 2014. A conversational guide to Renewable Identification Numbers (RINs) in the U.S. Renewable Fuel Standard.

[28] Irwin, S., 2015. Why do blenders share retroactively reinstated tax credits with biofuel producers? Farmdoc Daily. University of Illinois at Urbana-Champaign Department of Agricultural and Consumer Economics.

[29] Niziolek, A.M., Onel, O., Hasan, M.M.F., Floudas, C.A., 2014. Municipal solid waste to liquid transportation fuels - Part II: Process synthesis and global optimization strategies. Comput. Chem. Eng. doi:10.1016/j.compchemeng.2014.10.007

[30] Organisation for Economic Co-operation and Development (OECD), 2016. Tax database, Table II.1: Corporate income tax rate.

[31] Pearlson, M., Wollersheim, C., Hileman, J., 2013. A techno-economic review of hydroprocessed renewable esters and fatty acids for jet fuel production. Biofuels, Bioproducts, & Biorefining. 7, 89-96. doi: 10.1002/bbb.1378

[32] Peters, M.S., Timmerhaus, K.D., West, R.E., 2003. Plant design and economics for chemical engineers. McGraw-Hill Higher Education: New York, New York. 5th edn.

[33] Petter, R. Tyner, W.E., 2014. Technoeconomic and policy analysis for corn stover biofuels. ISRN Economics. 2014, 1-13. doi: 10.1155/2014/515898

[34] Schäfer, A.W., Evans, A.D., Reynolds, T.G., Dray, L., 2015. Costs of mitigating CO2 emissions from passengerăaircraft. Nat. Clim. Chang. 6, 2011-2014. doi:10.1038/nclimate2865

[35] Seber, G., Malina, R., Pearlson, M.N., Olcay, H., Hileman, J.I., Barrett, S.R.H., 2014. Environmental and economic assessment of producing hydroprocessed jet and diesel fuel from waste oils and tallow. Biomass and Bioenergy 67, 108-118. doi:10.1016/j.biombioe.2014.04.024

[36] Staples, M.D., Malina, R., Olcay, H., Pearlson, M.N., Hileman, J.I., Boies, A., Barrett, S.R.H., 2014. Lifecycle greenhouse gas footprint and minimum selling price of renewable diesel and jet fuel from fermentation and advanced fermentation production technologies. Energy Environ. Sci. 7, 1545. doi:10.1039/c3ee43655a

[37] Stephens, M. A., 1974. EDF Statistics for goodness of fit and some comparisons. Journal of the American Statistical Association. 347, 730-737. doi: 10.1080/01621459.1974.10480196

[38] Suresh, P., 2016. Environmental and economic assessment of transportation fuels from municipal solid waste. Thesis for Master of Science in Aeronautics and Astronautics at the Massachusetts Institute of Technology.

[39] Swoboda, R., 2016. Iowa Senators support biodiesel tax credit extension. American Agriculturist.

[40] United States Government Accountability Office, 2013. Corporate Income Tax: Effective Tax Rates Can Differ Significantly from the Statutory Rate, Report GAO-13-520.

[41] U.S. OMB, 2015. Discount rates for cost-effectiveness, lease purchase, and related analyses. Circular A-94 Appendix C.

[42] Winchester, N., McConnachie, D., Wollersheim, C., Waitz, I.A., 2013. Economic and emissions impacts of renewable fuel goals for aviation in the US. Transp. Res. Part A Policy Pract. 58, 116-128. doi:10.1016/j.tra.2013.10.001

[43] Zhao, X., Brown, T.R., Tyner, W.E., 2015. Stochastic techno-economic evaluation of cellulosic biofuel pathways. Bioresour. Technol. 198, 755-763. doi:10.1016/j.biortech.2015.09.056

[44] Zhu, Y., Biddy, M.J., Jones, S.B., Elliott, D.C., Schmidt, A.J., 2014. Techno-economic analysis of liquid fuel production from woody biomass via hydrothermal liquefaction (HTL) and upgrading. Appl. Energy 129, 384-394. doi:10.1016/j.apenergy.2014.03.053