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Dynamic Modeling of Learning in Emerging Energy Industries: The Example of Advanced Biofuels in the United States

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Abstract

This paper (and its [supplemental model](#)) presents novel approaches to modeling interactions and related policies among investment, production, and learning in an emerging competitive industry. New biomass-to-biofuels pathways are being developed and commercialized to support goals for U.S. advanced biofuel use, such as those in the Energy Independence and Security Act of 2007. We explore the impact of learning rates and techno-economics in a learning model excerpted from the Biomass Scenario Model (BSM), developed by the U.S. Department of Energy and the National Renewable Energy Laboratory to explore the impact of biofuel policy on the evolution of the biofuels industry. The BSM integrates investment, production, and learning among competing biofuel conversion options that are at different stages of industrial development. We explain the novel methods used to simulate the impact of differing assumptions about mature industry techno-economics and about learning rates while accounting for the different maturity levels of various conversion pathways. A sensitivity study shows that the parameters studied (fixed capital investment, process yield, progress ratios, and pre-commercial investment) exhibit highly interactive effects, and the system, as modeled, tends toward market dominance of a single pathway due to competition and learning dynamics.

Keywords

Biomass, Biofuel, Learning, Learning Curve, Experience Curve, Policy, Renewable Fuels Standard, System Dynamics

Introduction

Modeling the emergence of an industry presents challenges in assessing the dynamic interactions among investment decisions, cost reductions during development (e.g., due to industrial learning and economies of scale), and levels of utilization and associated production. The Biomass Scenario Model (BSM) uses novel approaches to address several of these challenges. It was developed by the U.S. Department of Energy (DOE), partnering with the National Renewable Energy Laboratory (NREL), in an effort to reduce ambiguity about potential futures and to improve understanding of the role of policy in industry development (Bush, 2011; Bush *et al.*, 2008; Newes *et al.*, 2011; Lin *et al.*, 2013; Peterson *et al.*, 2013; Inman *et al.*, 2014). Developed in ISEE system's STELLA®¹, the model uses a system of coupled ordinary differential equations and integrates these forward in time. This links variables that represent physical, technical, economic, and behavioral features of the biofuels supply chain through interdependent rates of change and feedbacks. The BSM has been extensively validated; in particular, the learning curves which are used here are based on historical data on learning in ethanol and related industries (McCurdy *et al.*, n.d.). The BSM is an analysis platform that is designed to explore the impact of biofuel policy on the evolution of the biofuels supply chain. It includes modules representing the U.S. agricultural system; pathways that convert starch, cellulosic, oil crop, and algal feedstocks into liquid fuels; and downstream distribution and dispensing of fuels.

Today's biofuels industry includes mature commercial enterprises, such as starch-to-ethanol, sugarcane-to-ethanol, and biodiesel. Other emerging technology pathways convert cellulosic and bio-oil feedstocks to ethanol, butanol, or other hydrocarbons; they could develop substantially in the future but are not yet mature at industrial scales. These biomass-to-biofuel conversion technology pathways have potential to reduce carbon emissions, to enhance U.S. energy security, and to increase the degree to which non-food biomass resources supplement or displace corn-based fuel ethanol production. The Energy Independence and Security Act of 2007 (EISA) mandates 36 billion gallons of renewable transportation fuel in the U.S. marketplace by the year 2022 (Energy Independence and Security Act of 2007), and includes targets for growth of advanced biofuels (cellulosic biofuels, biomass-based diesel, and other biofuels that meet threshold greenhouse gas emissions reductions of 50%). In response to this mandate, successive U.S. administrations have provided incentives for advanced biofuels development.

In developing the BSM, we sought to provide a simple representation of the mechanisms, constraints, and trade-offs associated with supply chain evolution based on the physical features and relationships of the biomass-to-biofuels industrial system. We drew from a broad set of information sources in order to incorporate data about today's industry, assess the current status of less mature pathways, estimate the economic and technical performance of prospective pathways, characterize relationships and constraints, and represent the effects of choices by key decision makers. A central feature of the BSM is a dynamic framework that integrates investment, production, and industrial learning among competing biofuel conversion options.

In this paper, we focus on a subset of the BSM by addressing learning and associated investment in conversion pathways that are in early stages of development and whose mature techno-economic performance is unknown—not the mature, established conversion pathways that dominate current production of biofuels in the United States. We show how the model represents

¹ <http://www.iseesystems.com>

learning concepts and highlight how our approach differs from the approaches commonly used in other energy models. We then explain how the BSM couples together investment, production, and learning processes in the context of competing biomass-to-biofuel conversion technology pathways. A sensitivity analysis of the simplified model is used to derive insights into the role of pre-commercial investment, learning rates, mature-technology capital costs, and mature-technology yields in the competition among pathways for investment and in overall stimulation of industry development.

Applying learning curve concepts in the BSM

Cost reduction through learning-by-doing is a prominent feature of many analyses of the energy sector (Junginger *et al.*, 2010). Learning curves (also known as experience curves) are based on the empirical observation that in many industries' unit cost declines along with increases in production experience. This finding was documented in the 1930s for labor input for airframe manufacture (Wright, 1936). Beginning in the mid-1960s, analyses used the experience curve concept to explain the cost behavior and the resultant market share dynamics in competitive industries (Hax and Majluf, 1982; Kouvaritakis *et al.*, 2000). In the energy sector, empirical observation has also supported a learning curve approach. For example, endogenous learning is a component in studies focusing on ethanol production in Brazil (Van den Wall Bake *et al.*, 2009) and the United States (Chen and Khanna, 2012; Chum *et al.*, 2013) and in studies focusing on electricity generation, including nuclear, coal, hydropower, wind, and solar photovoltaics (McDonald and Schrattenholzer, 2001).

The system dynamics literature describes the use of learning curves in models of strategy dynamics, technological development, industry growth, and investment decision-making. For example, Naim and Towill (1994) present various learning curve formulations and their application in system dynamics models. Fiddaman's work on integrated climate-economy system dynamics models (1997) explicitly accounts for learning-by-doing. Morrison (2005) uses an extension of learning curve theory to show the potential emergence of positive feedbacks in productivity in the context of throughput constraints. Sterman *et al.* (2007) describe a system dynamics model with learning curves that is used to explore "get big fast" strategies under conditions of bounded rationality for actors in the system. Learning curves are also a prominent feature of a system dynamics model of the photovoltaic industry (Jeon and Shin, 2014). This model uses system dynamics and Monte Carlo analysis to examine how the value of PV technology varies over time in response to uncertainty and volatility in 11 key input drivers.

A single-factor learning curve is commonly used for analyses in the energy sector. Less commonly used are multiple-factor learning curves that incorporate, for example, research and development investment (Junginger *et al.*, 2010). In the single-factor formulation, each doubling of experience yields a constant percentage decrease in unit costs. The relationship is often expressed as a power law:

$$Y = aX^b \tag{1}$$

Y current unit cost
 X cumulative production
 a unit cost of initial unit
 b slope of the function when plotted on a log-log scale

$$PR = 2^{-b} \tag{2}$$

$$LR = 1 - PR \tag{3}$$

PR is the progress ratio, the relative cost after each doubling of cumulative production
 LR is the learning rate, the relative cost reduction after each doubling of cumulative production

A single-factor learning curve yields results such as those shown in Figure 1.

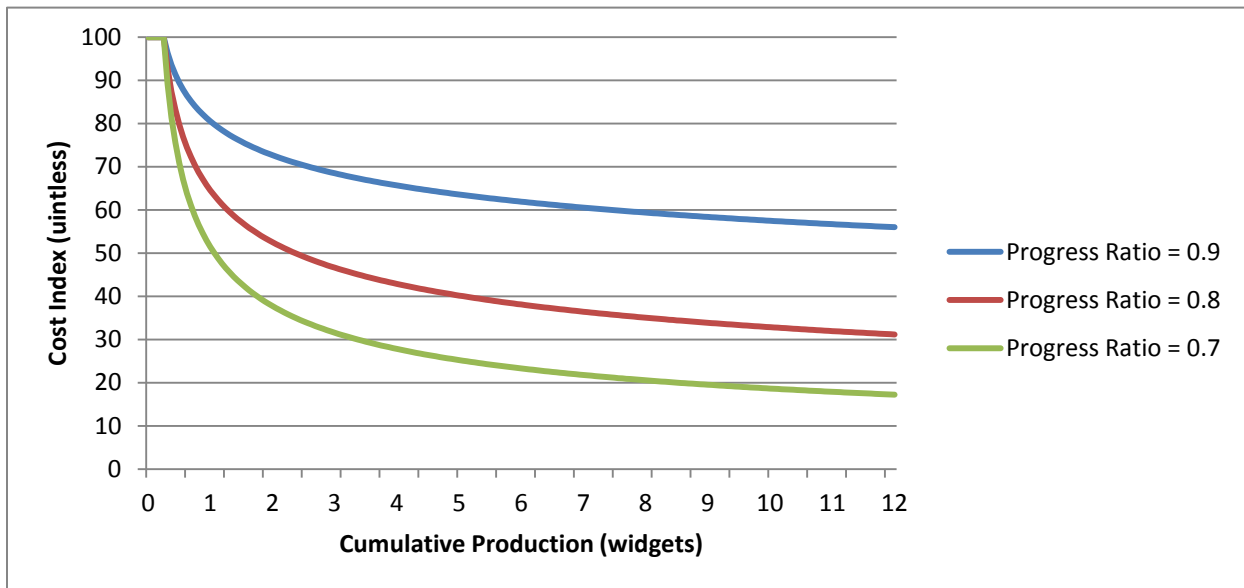


Figure 1. The chart illustrates a single-factor learning curve relationship under three different progress ratios. With each doubling of cumulative production, the cost index is reduced by a constant percentage based on the progress ratio.

The learning curve approaches in the literature generally observe a historical progress ratio, which may then be extrapolated to the future. For a single factor learning curve for unit cost, this would result in an implicit ultimate cost of near zero. In the BSM, we use a learning curve approach to enable us to interpolate between the characteristics of current and future technology for each technology pathway under consideration. In doing so, we have adapted the single-factor learning curve in several ways. First, instead of using an implicit asymptote of zero for unit cost, in the BSM we define an explicit asymptote of a “mature technology.” As discussed in Newes *et al.* (2011), we introduce a variable called maturity, M :

$$M = \begin{cases} 1 - (1 - M_0) \left(\frac{L^*}{E} \right)^{\left(\frac{1-PR}{\ln 2} \right)} & \text{for } E \geq L^* \\ M_0 & \text{otherwise} \end{cases} \quad (4)$$

$$L^* = \max\{L, E_0\} \quad (5)$$

M_0 is initial maturity
 L is the minimum experience for learning
 L^* is the effective minimum experience for learning
 E is the cumulative experience
 E_0 is the initial cumulative experience
 PR is the progress ratio

From Newes *et al.* (2011).

Second, we adapt the single-factor learning curve approach that typically is connected to a single technical attribute (unit cost). Instead of a single measure, we define a vector of technical attributes that are assumed to depend on industry maturity. This vector includes the following attributes, each of which has a mature value input and a current state-of-industry value that is calculated. As the industry matures, each value is assumed to approach the mature value or n^{th} plant characteristics.

- Process yield
- Feedstock throughput capacity—the degree to which facilities are able to perform at nameplate capacity
- Capital cost—the premium in capital cost, beyond the n^{th} plant estimate, which would be observed if development of a facility was begun today
- Investor risk premium—the additional premium, beyond normal hurdle rate, that investors would require for investment in the facility
- Access to debt financing—the portion of the expected facility capital cost that would be financed via borrowing (as contrasted with equity investment).

Accordingly, we define a multiplier m that is arrayed by technical attribute i , where n denotes input n^{th} plant values. This multiplier is a function of maturity, as described next. Generally, the value of the technical attributes A in any simulated year is calculated as:

$$A_i = m_i A_{i,n} \tag{6}$$

A is a vector of technical attributes (various units)
 m is a multiplier (unitless)
 i is the index of technical attributes
 n is the ultimate nth plant attributes

$$0 < m_i \tag{7}$$

Figure 2 summarizes these interactions in a causal loop diagram.

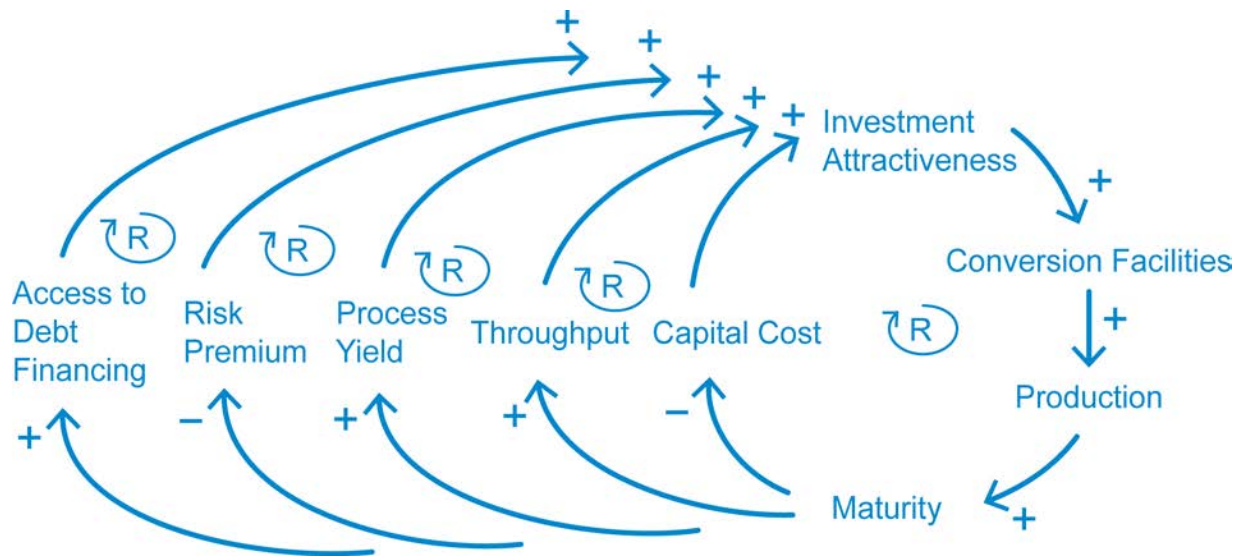


Figure 2. A causal loop diagram summarizing the interactions of maturity, the vector of technical attributes, investment attractiveness, conversion facilities, and production.

Third, instead of a single learning curve metric, we have applied learning curves in a cascading fashion to multiple industry development scales (pilot, demonstration, pioneer, and commercial). Pilot and demonstration facilities are constructed without the intention of producing fuel for commercial sale. For most technologies in the BSM, commercial scale is over 2,000 short tons per day throughput capacity. Pioneer scale refers to the early commercial developments that are assumed to be approximately one-third the scale of commercial facilities and to have higher capital costs. As a result, at any point in simulated time, the performance and cost characteristics of a pioneer or commercial-scale facility are estimated and used to inform the model’s investment allocation. To accomplish this, maturity is calculated at each developmental scale, and the multiplier m in the equation above is calculated based on the impact of each development scale:

$$m_i = C_i M_C + [D_i M_D + P_i (1 - M_D)] \times (1 - M_C) \quad (8)$$

$$0 < M \leq 1 \quad (9)$$

MC is commercial maturity and MD is demonstration maturity

C is the vector of mature commercial multipliers

D is the vector of mature demonstration multipliers

P is the vector of mature pilot multipliers

Mature multipliers at commercial, demonstration, and pilot scale (C , D , and P) define the maximum performance on each technical attribute that can be achieved through experience at that scale.

With these three modifications to the single-factor learning curve, we have developed a novel modeling approach to modeling learning that accounts for performance in multiple technical attributes that approach non-zero ultimate values through development at multiple scales. This approach is best suited to situations wherein the modeler can readily assume knowledge of the ultimate technical attributes of the technology and the mature technology characteristics, and would like to explore scenarios for the rate at which current technology approaches this mature performance. We are not aware of other literature describing this application of learning curves. In situations where mature technology characteristics can be estimated, this approach replaces the implicit assumption in much of the literature of ultimate near-zero cost (if unit cost is the attribute). For the BSM, we operationally define “mature technology” by drawing from engineering design studies that estimate capital investment, process yield, and fixed and variable operating costs for the “ n^{th} plant” (where n is a large number) of a given pathway. Because the BSM relies on design studies to provide estimates for n^{th} plant techno-economics, its results are subject to uncertainties in yield and cost estimates as well as scale effects of assumed commercial plant sizes.

Figure 3 shows an illustrative example of the correspondence between production (or experience), maturity, and values of technical attributes over the simulated time. We use different units of experience at different scales, as shown in panel a. As shown in panel b, the maturity multipliers include experience at each scale, increasing as cumulative production grows over time and asymptotic to one. Panel c illustrates how current (or state-of-industry) values for two of the technical attributes change as they approach mature values as cumulative production increases over time.

Because the BSM is a forward-looking simulation model of technologies that are not yet commercialized, there is no empirical data from which to estimate many of the progress ratios that we use. Instead, it uses assumed values that are informed by statistically estimated values for progress ratios from the literature about related technologies, such as starch ethanol production and, more generally, the chemical process industry. In their review of retrospective studies of learning in the energy sector, McDonald and Schrattenholzer (2001) identify a high degree of variability in estimates for learning rates—both within a given technology and across differing energy technologies. They suggest that modelers should consider the uncertainty in the value of learning rates (McDonald and Schrattenholzer, 2001). For the BSM, this points to the importance of including sensitivity analysis of learning rates in this paper. Model results are not predictions, but should be viewed as plausible scenarios subject to uncertainties in model structure and data inputs.

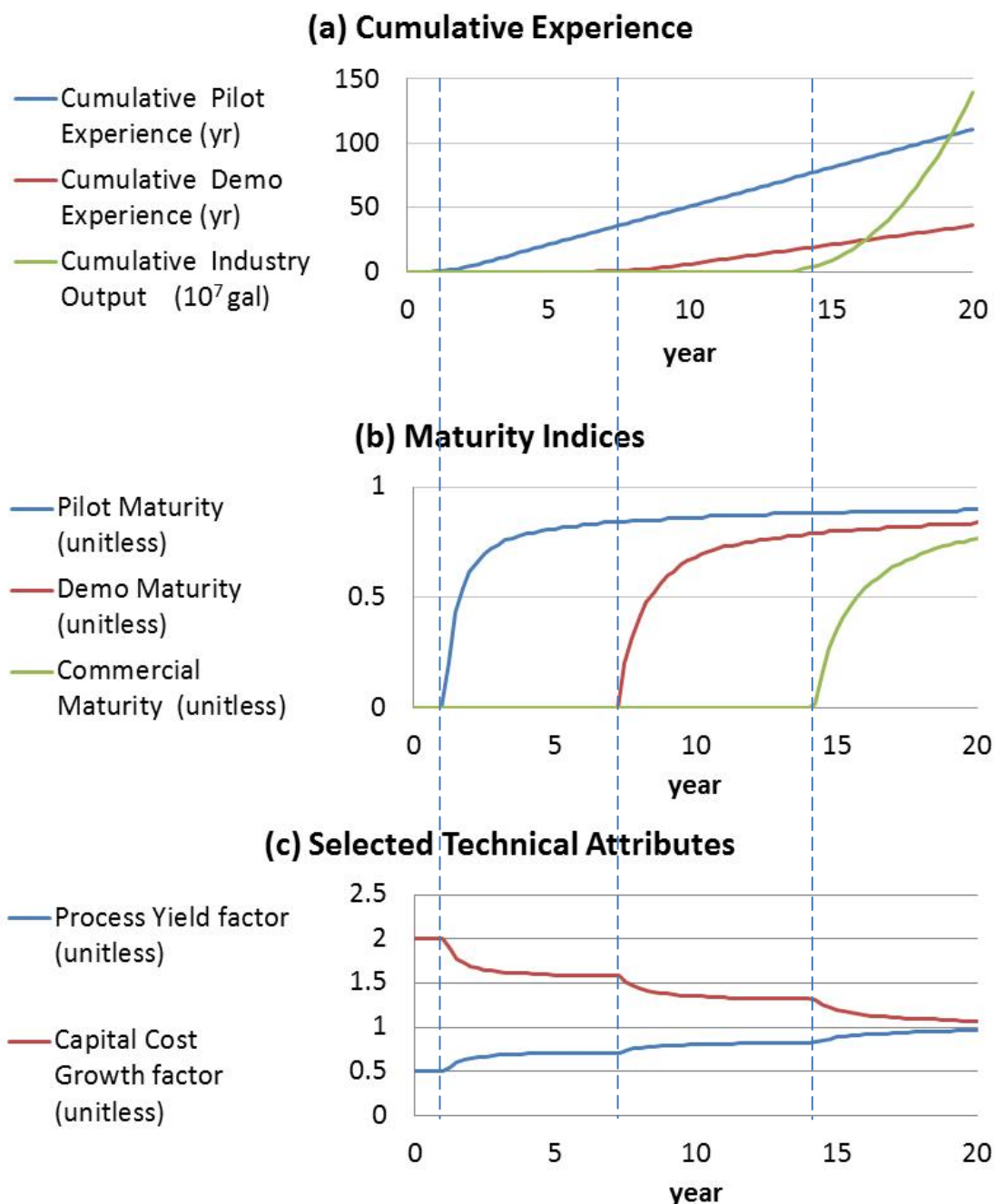


Figure 3. (a) The first panel illustrates experience profiles at pilot and demo scales, as well as commercial scale (measured in industry output). Pre-commercial curves are based on accumulation of operating time at pilot and demo scales. Cumulative industry output grows as a quadratic, reflecting constant linear growth in annual industry output beginning in year 14. (b) The second panel shows change in maturity index with increasing cumulative pilot experience, demonstration experience, or commercial production over time. The corresponding experience or production curves are shown in panel a. Pilot experience precedes demonstration experience, which precedes commercial production. Maturity is correlated with doublings of experience at each scale. The maturity index is an abstract, unitless multiplier that is multiplied by metrics of mature technological performance to estimate the state of the industry. (c) The third panel illustrates a cascading effect of maturation on selected technical attributes. Technical attributes improve with maturity, based on a distinct calculation for each measure. The technical attributes shown are a subset of those used for commercial biorefineries. At a given year in simulated time, investment techno-economics will reflect the cumulative effect of pilot, demo, and commercial maturity levels. Technical attributes progress differently at different industry-development scales.

Coupling learning, production, and investment in the BSM

Production and investment in the BSM depend upon performance in each technical attribute, as calculated in the learning process. In the BSM, techno-economic information drawn from design reports and engineering studies is used to select the input assumptions for the initial and mature industry (or n^{th} plant) technical attributes vector (listed above), the financial and performance characteristics for different biomass-to-biofuel conversion technology pathways. Over simulated time, the model's learning curve logic determines how the state of each pathway moves from today's characteristics toward n^{th} plant maturity. Together with other inputs, notably feedstock cost and product price, the state of each pathway defines streams of expected costs and revenues associated with a prospective project investment based on costs and revenues in the simulated year, without investor foresight. In the BSM, we discount these expected costs and revenues streams to the current simulated year to calculate the net present value (NPV) of the prospective investment, as follows:

$$NPV_j = R_j - [I_j + C_j + T_j] \quad (10)$$

NPV is the net present value of investment in a biorefinery of technology i
 R is the NPV of expected revenue less expected operating costs for technology j
 T_j is the initial equity investment for technology j
 C is the present value of the debt for technology j
 T is the net present value of the taxes less tax credits for technology j

The net present value calculation uses the required rate of return, which changes with maturity, and is calculated according to:

$$R_{d,n} = \sum_{t=0}^n \frac{R_t}{(1+d)^t} \quad (11)$$

$R_{d,n}$ is the expected revenue less expected operating cost, discounted by the required rate of return d over n time periods
 R_t is the net revenue in time period t
 d is the required rate of return
 t is the current time period
 n is the final time period

Then, we use a logistic function to allocate investment among different conversion pathway options or non-biofuels options based on the relative financial attractiveness of each. This approach is often used to model consumer choice situations (Train, 2009); in the BSM, we use logistic formulations to allocate limited resources, such as plant construction capacity, among competing uses.

$$S_j = \frac{e^{(k+cNPV_j)}}{\sum_j e^{(k+cNPV_j)}} \quad (12)$$

S is the share construction capacity allocated to pathway j
 k is a constant
 c is a constant scaling factor

As suggested in Figure 4, reinforcing feedbacks (also called “positive” feedbacks) emerge from the coupling of investment, production, learning, and the maturation of a set of performance attributes.

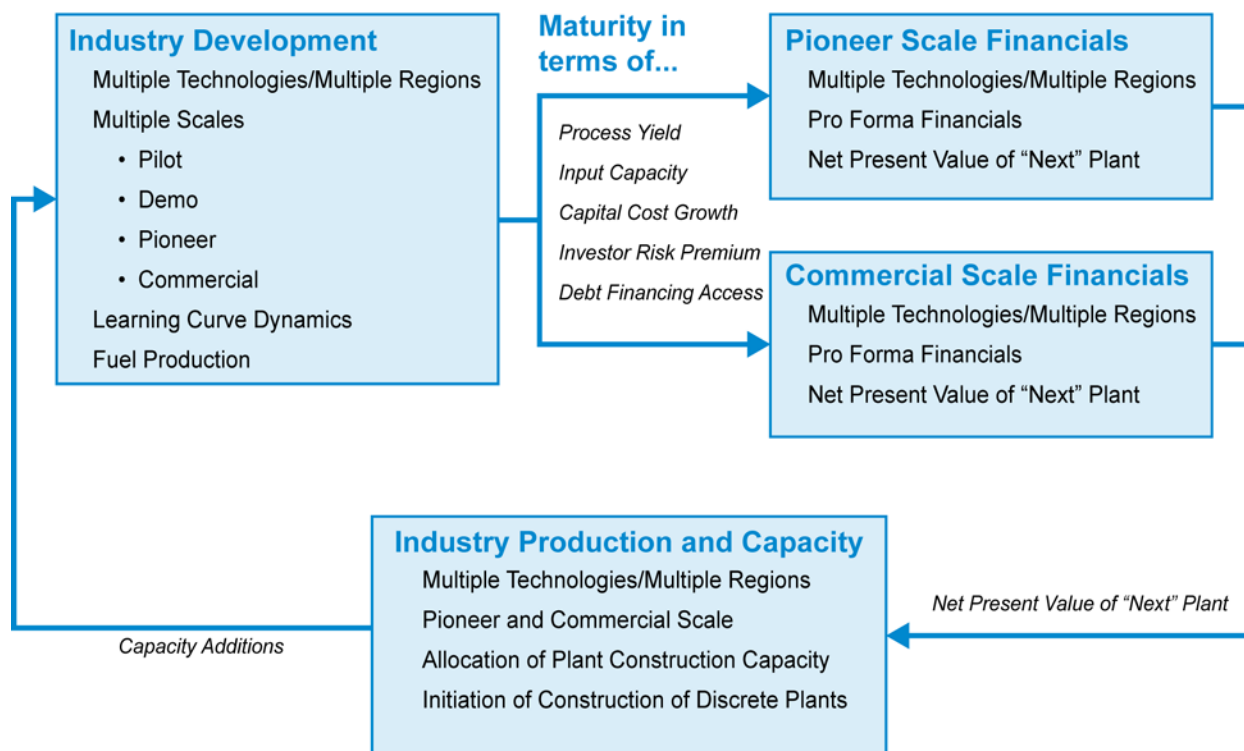


Figure 4. The chart is an overview of key concepts, mechanisms, and processes in the BSM. Reinforcing feedbacks around investment, production, and learning drive biomass-to-biofuel conversion technology pathway and industry evolution.

Sensitivity study design

The BSM is a dynamically complex model that is rich in feedback and nonlinearities (Peterson *et al.*, 2013). To investigate the impact of learning, investment, and techno-economic inputs on biofuel industry development, we extracted from the BSM a simplified model, focusing on biomass-to-biofuel conversion processes that occur at biorefineries. While the BSM considers ten U.S. regions, this simplified model considers only one region and only three conversion technology pathways (labeled “A,” “B,” and “C”), as opposed to more than ten conversion technology pathways in the larger model. Costs of feedstocks entering the biorefinery and prices of products that the biorefinery produces are defined as scenario inputs. The model is configured such that the three hypothetical pathways under consideration differ in their n^{th} plant techno-economic characteristics, their initial levels of maturity, and their pre-commercial investment profiles. These baseline conditions serve as a springboard for a sensitivity analysis in which we vary select techno-economic attributes, learning rates, and pre-commercial investment scenarios (Table 1). The sensitivity ranges are relatively narrow (McDonald and Schrattenholzer, 2001), but sufficient to cause substantial variation in the key result, technology market share.

The techno-economic attributes were selected to mimic real trade-offs among capital, feedstock, and other operating costs, without specifically representing existing technologies. For example, there are actual technologies with higher first-costs and lower operating costs, higher feedstock costs and higher co-product sales, lower operating costs and lower yield, and lower maturity and lower expected future performance. In the baseline condition:

- Pathway A: This conversion technology pathway represents an extremely promising pathway that is very early in its development.
- Pathway B is quite promising as well (although its expected yield at maturity is lower than A) and is closer to commercialization than A.
- Pathway C is very close to commercialization but has a very high capital cost and significantly lower yields. On the other hand, pathway C appears to have a favorable variable cost structure relative to the other two options.

The sensitivity variations perturb the attractiveness of the pathways along one or more dimensions. Initial technical maturity (M_P , D , or C) and progress ratio (PR) are the learning attributes in the sensitivity variation. Initial technical maturity is the initial value of the maturity index that was described in the learning section. It has a value between 0 and 1, where 1 represents full n^{th} plant maturity and associated performance. The selected progress ratio value of $PR = 0.75$, and the sensitivity value of $PR = 0.79$ are within the range of historical progress ratios for starch ethanol and chemical processes. Pre-commercial investment projects at pilot and demonstration scales are projects not intended for commercial production that contribute to the initial learning of each pathway, as described above. Simulations are conducted against a policy backdrop designed to stimulate initial take-off of all pathways. Policies consist of loan guarantees and capital cost grants for pioneer-scale facilities that expire in 2022. An initial product subsidy applies to each gallon of production, up to the first 1 billion gallons of industry output; this is reduced to a nominal amount for the duration of the simulation. It is important to note that this is a hypothetical policy set. The policies are derived from a scenario library developed elsewhere in the BSM project. For details on these scenarios, see Inman *et al.* (2014).

Table 1. Conditions for baseline simulation.

		Pathway A Baseline	Pathway B Baseline	Pathway C Baseline	Sensitivity Variation
Mature Industry Techno-economics	Feedstock Input (dry short ton/day)	2,000	2,000	2,000	
	Fixed Capital Investment (\$)	300,000,000	300,000,000	400,000,000	1.15 × baseline
	Fixed Operating Cost (\$/yr)	15,000,000	15,000,000	15,000,000	
	Other (non-feedstock) Variable Operating Cost (\$/yr)	50,000,000	40,000,000	5,000,000	
	Co-Product Sales Revenue (\$/yr)	5,000,000	16,000,000	10,000,000	
	Process Yield (gal/dry short ton)	100	90	66	0.85 × baseline
Initial Technical Maturity (unit-less)	Pilot	0.1	0.5	0.85	0.85 × baseline (pathway “B” only)
	Demonstration	0	0.5	0.75	
	Commercial	0	0	0	
Progress Ratio (1/doubling)	Pilot	0.75	0.75	0.75	1.05 × baseline
	Demonstration	0.75	0.75	0.75	
	Commercial	0.75	0.75	0.75	
Pre-Commercial Investment (projects/yr)	Pilot	pre-2012: 2 2012: 4 2013: 4 2014: 4	pre-2012: 2 2012: 4 2013: 4 2014: 4	pre-2012: 2 other yrs: 0	
	Demo	pre-2012: 0 2014: 4 2015: 4 2016: 4	pre-2012: 0 2014: 4 2015: 4 2016: 4	pre-2012: 0 other yrs: 0	

For the sensitivity study, baseline conditions are modified as shown in the final column. Each combination of conditions was simulated, resulting in two conditions each for three parameters (fixed capital investment, process yield, and progress ratio) for each of three pathways and two conditions of a fourth parameter (initial pre-commercial maturity) for pathway B only.

Results and insights

Figure 5 shows simulation results under baseline conditions. With this set of baseline policy conditions and input values for feedstock cost and product price, the model generates a phased evolution in which pathway C is first to mature. Over time, growth in pathway C stabilizes, while pathway B, and then pathway A, grow to significant volumes (Figure 5).

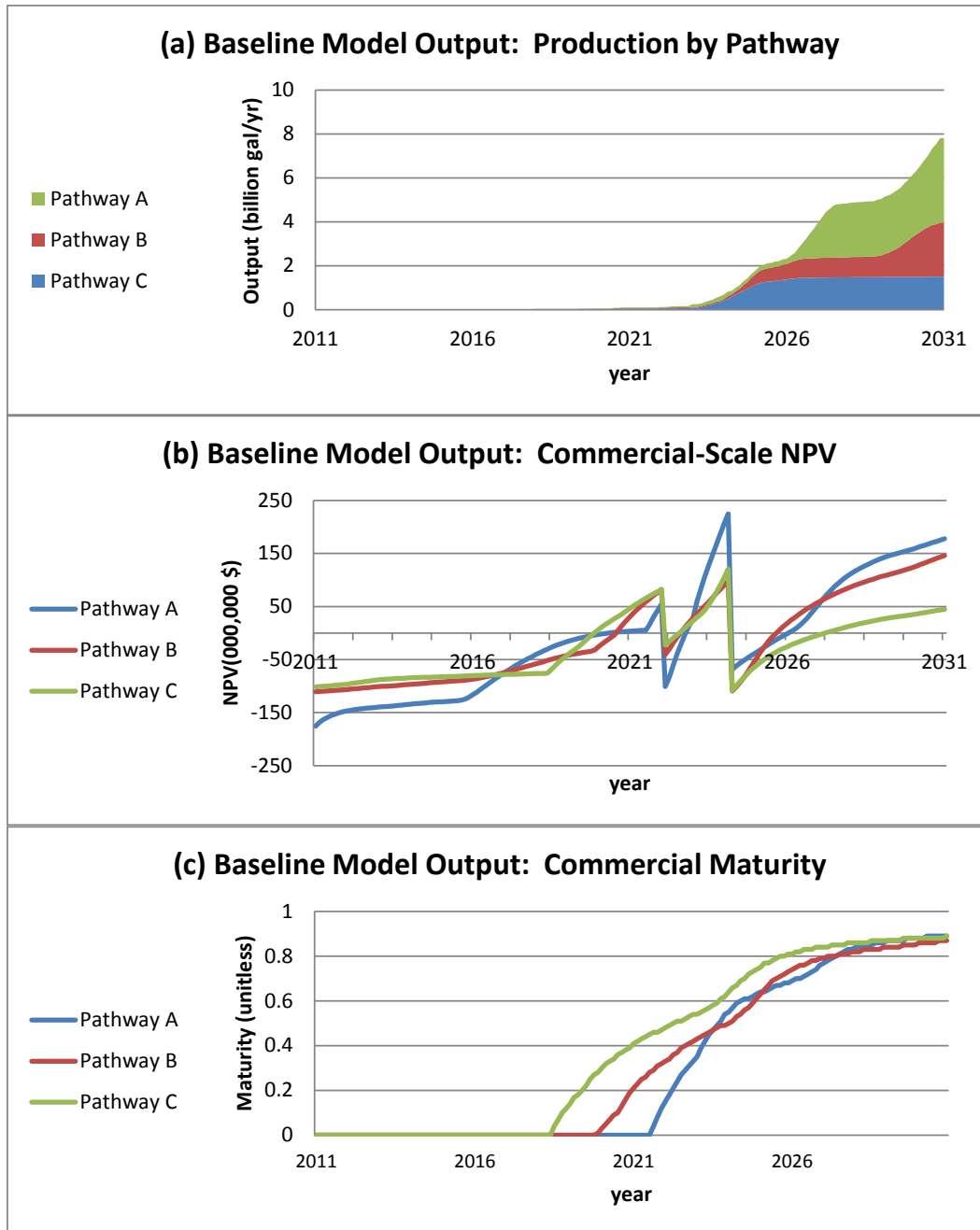


Figure 5. The figure shows baseline results by conversion technology pathway. (a) The first panel shows baseline production. For the purposes of this study, pathway characteristics were selected to show industry growth for all three pathways under the background policy conditions that were modeled. (b) The second panel shows baseline results for commercial-scale NPV by conversion technology pathway. Modeled decisions to invest in commercial-scale facilities are based on NPV for a new commercial facility constructed in each year. NPV is calculated based on capital costs, operating expenses, revenue from product sales, and effects of incentives, all of which change over time. Positive NPV in Figure 8 corresponds with early industry growth in Figure 7. There are 2 discontinuities in each NPV trace. The first is the result of expiration of FCI loan guarantees. The second is the result of expiration of fuel product startup subsidies that applies to the first 1 billion gallons of industry output. (c) The third panel shows baseline results for commercial maturity by conversion technology pathway. The chart shows that pathway C is initially more mature and obtains early investment that advances its maturity. Pathways A and B are able to compete sufficiently such that they also mature.

The results from this sensitivity study (see Figure 6) illustrate competition among biomass-to-biofuel conversion technology pathways, interaction among the sensitivity parameters studied, and a tendency for a single pathway to gain most of the technology market share. Each horizontal, colored line represents a different amount of biofuel production in the year 2030 from one of the conversion technology pathways. The numerical x -axis labels indicate simulation condition values that are held constant within that column while other sensitivity parameters are varied. In any given column, there are many different year 2030 production levels for each pathway. These represent results of different simulations for sensitivity parameters other than the one for which the column is labeled.

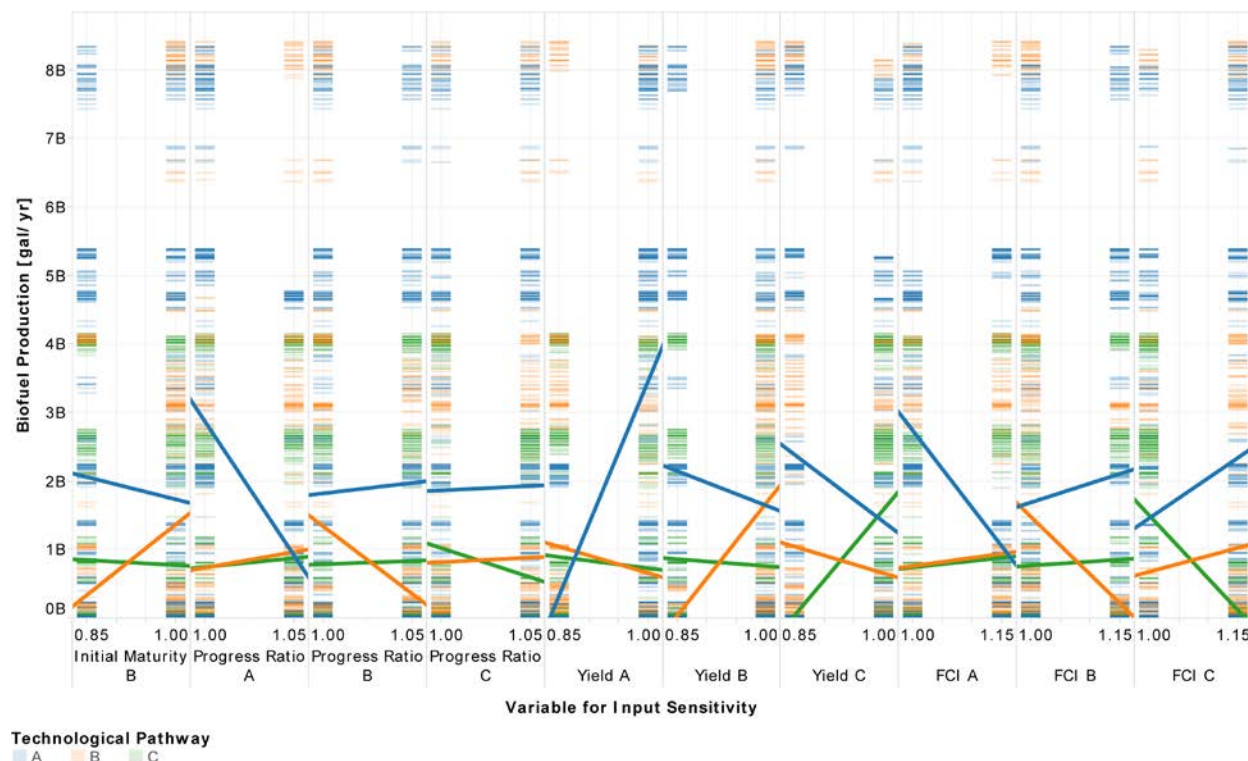


Figure 6. The chart is a summary of sensitivity study results. Interpretation of this chart is discussed in the text. In each column the baseline case is at 1.00 on the x axis. Each horizontal bar in the chart represents the biofuel production for one of the three pathways (indicated by the color or the bar) in the year 2030 under one set of conditions in the sensitivity study. Each of the 10 columns labeled with a sensitivity variable name at the bottom separates the simulation results for a low value of that input variable from those for a high value of that variable, such that all of the simulations in the study are shown once in each of the 10 columns. The slanted lines indicate how the mean output of each pathway varies as a function of the sensitivity variable for that column.

Competition

Competition among the pathways shapes results of the sensitivity study. In general, sensitivity cases that reduce the performance of a given conversion technology pathway affect fuel production from that pathway the most, and the other pathways tend to benefit. Conversely, improved performance primarily increases production from the improved pathway, with secondary effects decreasing production from the other pathways. The examples below give trends in one direction only, but each of these could be expressed either as an increase or a decrease.

- See Figure 6, column 1, “Initial Maturity B.” Sub-column labeled “0.85” has lower initial maturity than sub-column labeled “1.00.” Production in “0.85” is lower on average than production in “1.00” as indicated by the slope and endpoints of the orange line. Production from conversion pathway B drops dramatically if its initial maturity is lowered, and production from conversion pathways A and C increases modestly on average.
- See Figure 6, columns 2–4, “Progress Ratio A, B, or C.” Sub-columns labeled “1.04” have higher progress ratios than sub-columns labeled “1.00” for pathway A, B, or C, respectively. An increase in progress ratio for pathway A, B, or C causes production for that conversion pathway to plummet, as indicated by the slopes and endpoints of the blue line in the column “Progress Ratio A,” by the orange line in the column “Progress Ratio B,” and by the green line in the column “Progress Ratio C.” The other pathways increase production slightly in each case, as shown by the other two line colors. Pathway A is more sensitive to changes in its progress ratio than the other pathways, primarily because of its initial immaturity, as indicated by the steeper slope of the blue line in the column “Progress Ratio A” relative to the slopes of the orange line in pathway B and green line in pathway C.
- See Figure 6, columns 5–7, “Yield A, B, or C.” Sub-columns labeled “0.85” have a lower yield than sub-columns labeled “1.00.” A drop in yield results in a dramatic loss in production capacity for the affected conversion pathway, shown by the slopes and endpoints of the blue line in the “Yield A” column, the orange line in the “Yield B” column, and the green line in the “Yield C” column. The drop in yield in a given conversion pathway generally increases the capacity of the other pathways. This is shown in the figure because the slopes of the two lines for the unaffected pathways are negative, but the slope for the affected pathway is positive. For example, in the “Yield A” column, production for pathway B (orange) and pathway C (green) is higher in sub-column “0.85” than in sub-column “1.00.” The increase may or may not be sufficient to make up the production capacity loss. For example, a drop in yield in pathway A or C could cause an increase in pathway B that is sufficient to make up the overall production loss because production from pathway B generally can increase more rapidly and attain higher levels than from pathways A and C.
- See Figure 6, columns 8–10, “FCI A, B, or C.” Sub-columns labeled “1.15” have a higher capital cost than sub-columns labeled “1.00.” An increase in the capital cost of pathway A causes much lower production capacity from pathway A, as shown by the negative slope of the blue line in the “FCI A” column. Pathways B and C only increase their production capacity a little in response, with the orange and green lines having a small positive slope. Conversely, the production capacity of conversion pathway A benefits greatly from increases in the capital cost of the other pathways, especially for increases in FCI C, as shown by the relatively large positive slope of the blue lines (for pathway A) in column “FCI C.” Pathways B and C show drastic loss in production at higher capital costs, with large negative slopes for the orange (B) and green (C) lines in columns “FCI B” and “FCI C,” respectively. Pathway B, and especially pathway C, are less influenced by increased capital costs in the other conversion pathways, as shown, for example, by the relatively low positive slope of the green lines (for pathway C) in the “FCI A” and “FCI B” columns.

Note that this simple model does not include competition among pathways for feedstock or for end users. Studies with the BSM have indicated that these can be significant factors under some scenario conditions.

Interaction

The input parameters exhibit interacting effects. Every combination of input parameters (fixed capital investment, process yield, progress ratios, and pre-commercial investment) shows interaction in its effects on simulation results. These interactions are not simple linear relationships, but rather, nonlinear dependencies rooted in the feedback mechanisms inherent in the dynamics of coupled learning and investment. Small differences in progress ratio, cost, and yield shape the evolution of the system through the feedback structure of the model in a complex and nonlinear manner.

Reducing a pathway's assumed performance does not necessarily lead to increased production capacity for competing pathways, but in certain situations, an increase may be dramatic. For example, Figure 6 shows a small subset of the sensitivity studies in which dramatic changes may be observed. These situations are likely conditions that are favorable for industry growth, such that the growth opportunity will be met by the most competitive pathway, and lower performance of one pathway will open an opportunity for another.

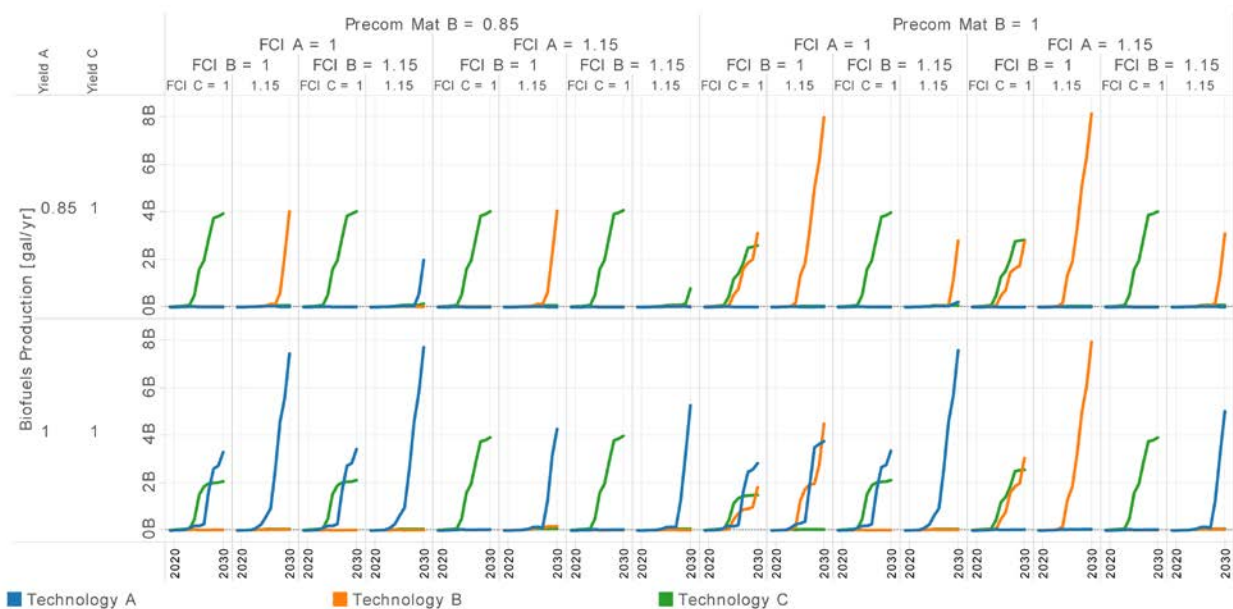


Figure 6. The chart is a subset of sensitivity analysis results showing examples of significant change with change in pathway performance.

Market dominance

In our sensitivity analysis, the case where all three pathways exhibit high output is the base case, which was selected with that goal. There are only a handful of cases where two exhibit high output. In the cases where two pathways exhibit high output, each pathway must remain sufficiently competitive with the other to attract investment during key periods of market development. This tendency toward market dominance is a key feature of the behavior of this model, given the reinforcing feedback as encoded in the logistic, techno-economic, and learning

parameters used in this study. In Figure 7, points at the vertices of the triangle are dominated by a single pathway. The figure 7 shows that many of these single-pathway simulations are also those with higher biofuels production output (shown by larger, darker blue circles). A few of the high-output cases have high production from 2 pathways (points along one of the sides of the triangle). High output cases do not have pathway C as the largest-producing pathway, but include cases with dominance from A, from B, or combined production with either A or B having the largest production. Figure 8 zooms in on a small subset where more than one pathway develops.

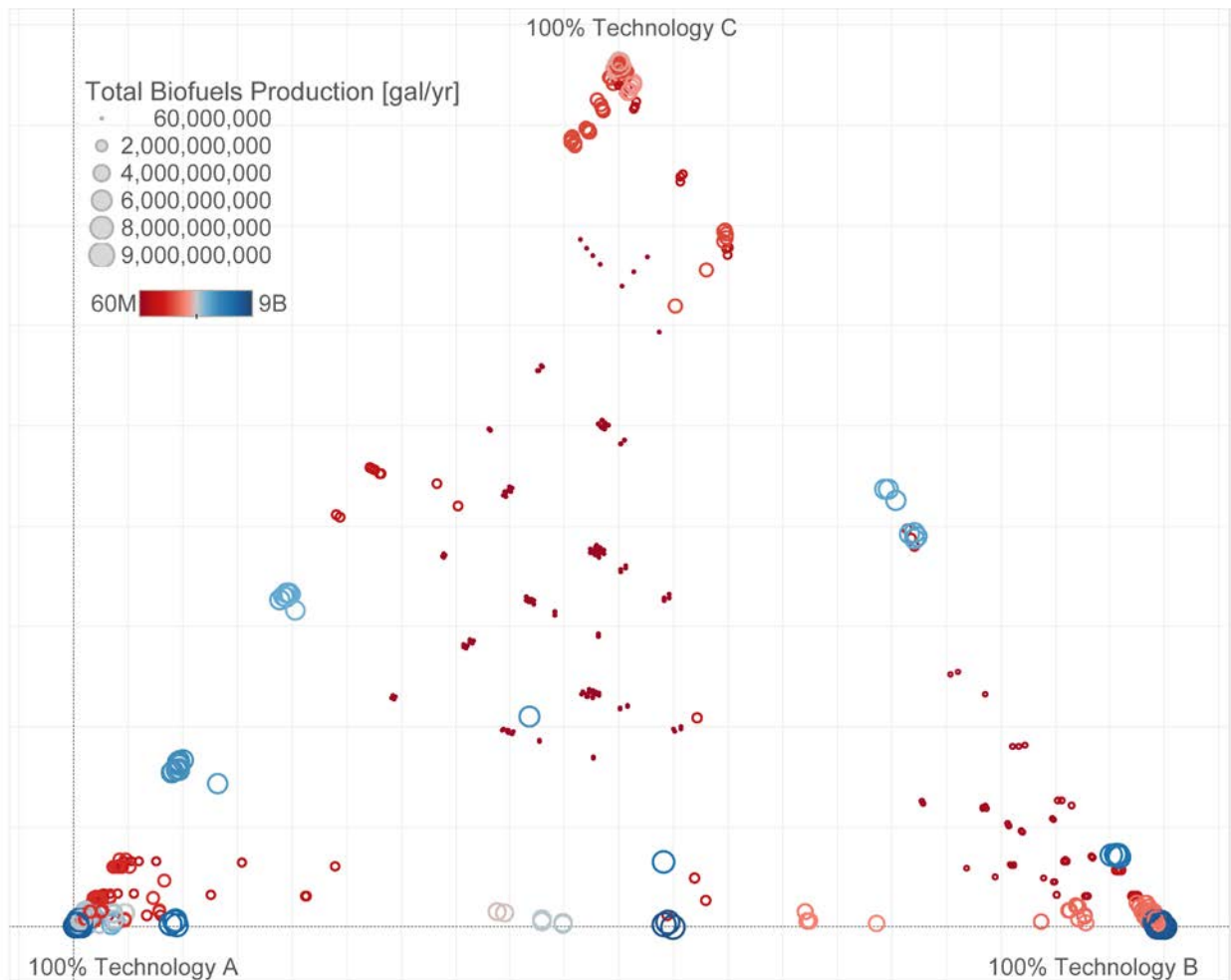


Figure 7. This figure shows total biofuels production in 2030 and the distribution of biofuels production among pathways. The points that fall at the vertices show dominance by a single pathway; points that fall along a side have production from the two pathways corresponding to the two adjoining vertices; and points in the middle share production among all three pathways.

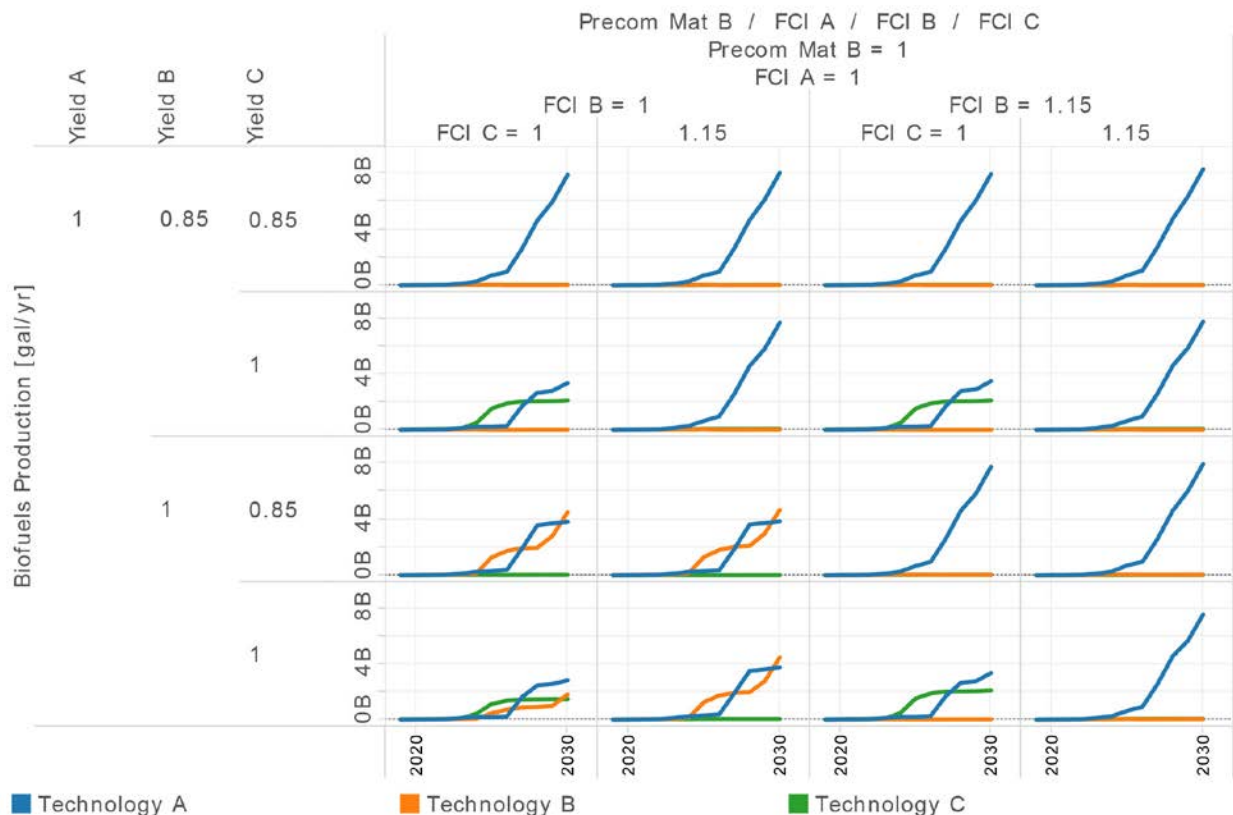


Figure 8. The chart is a subset of sensitivity analysis results showing examples of multiple pathways increasing production.

In this discussion, market dominance refers to dominance of a technology, not dominance of a single firm. This conceptualization of market dominance is consistent with a competitive market. This is application of the “competitive exclusion principle” (Meadows, 2008) and an example of the “success to the successful” system archetype as described in Senge (1990). Figure 9 shows this as a causal loop diagram, illustrating in greater detail the reinforcing feedback shown in Figure 2. Pathways can dominate through combinations of superior mature techno-economics, higher learning rates, and greater initial maturity. This is one of the fundamental mechanisms by which a pathway that initially attracts slightly more investment could develop more rapidly and ultimately dominate the market. The pathway that initially attracts more investment develops more biorefineries, produces more fuel, and advances down the learning curve through these experiences. This increase in maturity, translated into more favorable cost and performance, makes it even more attractive to future investment. Annual investment in construction of new biorefineries is assumed to be constrained. Pathways compete directly for this investment, so the reinforcing feedback can cause favorable pathways to attract most of the investment and dominate the market. Even without complete market dominance, successful pathways have a tendency to suppress less favorable ones, so it is rare that all pathways succeed equally well. This can only happen in the unlikely situation where technological parameters are tuned to maintain sufficient competitiveness among all pathways.

The implications of the tendency toward market dominance of one or two pathways for actual industry development are challenging to assess. In this simple model, the tendency for market

dominance may occur in part because of the small number of pathways considered, and perhaps also because the model does not sufficiently represent details of different market segments, which might provide competitive advantage to multiple pathways, each in its respective niche.

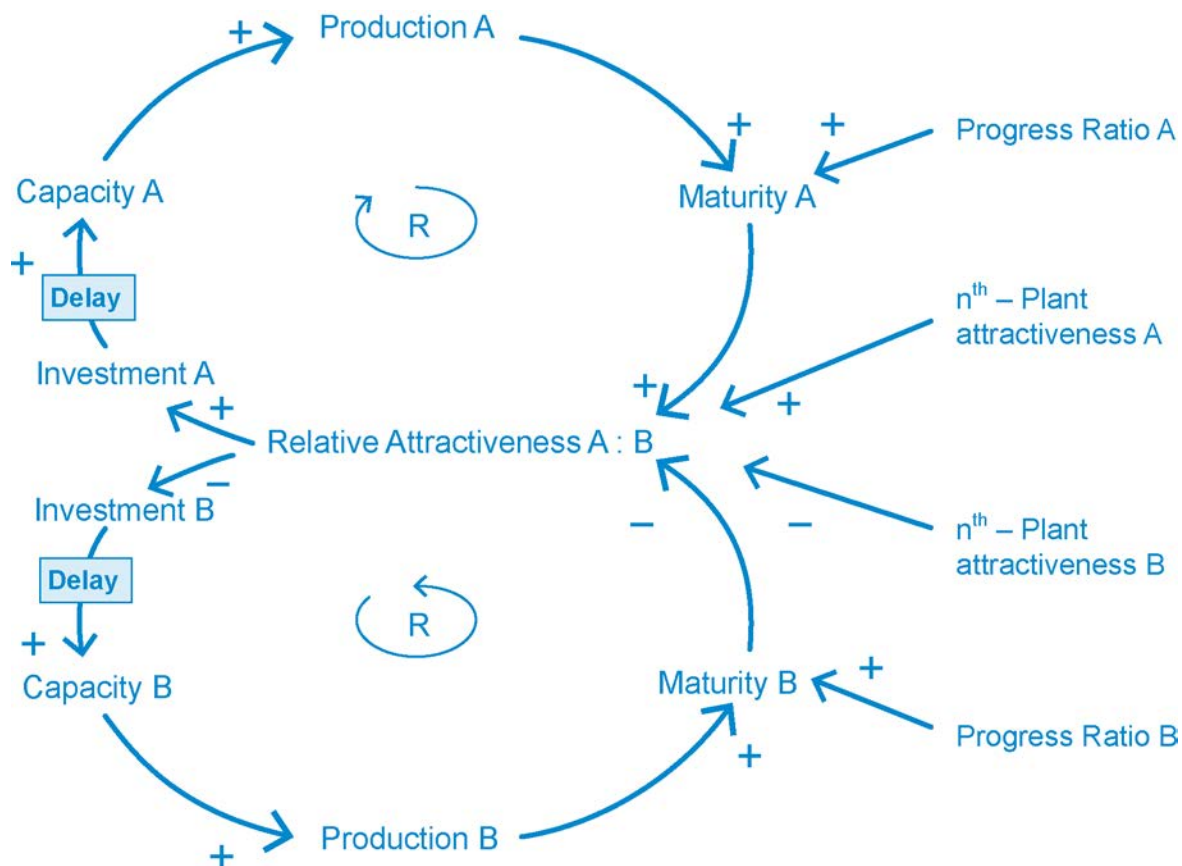


Figure 9. The chart shows key factors in the competition between pathways for investment. Attractiveness of investment in a given pathway is determined by mature industry techno-economics, as modified by current state of maturity. Progress ratio governs the speed by which production translates into increases in maturity. Lock-in dynamics can result from differences in (1) initial maturity, (2) progress ratios, or (3) n^{th} plant techno-economics such as capital cost or yield.

The converse of market dominance—pathway failure—is also common. If a pathway does not reach some minimal level of learning-based feedback, it is unable to attract sufficient investment and therefore fails to develop. There are thresholds for progress ratios, and to a lesser extent, for techno-economics and initial maturity, in their contribution to this reinforcing feedback between industry development and learning-based cost reductions.

Production capacity and maturity both contribute to learning, but on different timescales, resulting in a sequence of feedback responses. Production capacity, when utilized, directly and immediately increases learning from experience, a function of production. This is especially influential in the early years of pathway growth. Maturity influences learning; increased maturity facilitates investment in new plants, but guarantees neither production capacity construction nor production of biofuels due to external conditions and competition between pathways.

Limitations

This analysis has several important limitations. First, the learning model boundaries include only the biomass-to-biofuels conversion portion of the supply chain, eliminating interactions with feedstock supply and fuel demand. This portion of the supply chain is illustrative of the interplay between investment, technology development, and production. Second, the concept of n^{th} plant performance is not grounded in purely physical limitations, so quantitative values for n^{th} plant performance are uncertain. Third, learning rates (or progress ratios) are highly uncertain, and the full range of possibilities is not explored here. Fourth, learning rates may not reflect omitted variables. Fifth, modeled markets are simplified, eliminating niches that may counteract the tendency to market dominance. Sixth, this novel formulation of learning curves is not validated elsewhere in the literature. Despite these limitations, we offer this paper and the associated model as a potentially valuable approach to understanding emerging industry development.

Conclusions

The simplified learning model illustrates implementation of the novel approach to learning that is used in the full BSM model. This approach contrasts with the single factor learning model in (1) progress toward mature performance instead of an implicit zero asymptote of (2) multiple technical attributes instead of only unit cost at (3) multiple development scales. The sensitivity study shows that the parameters studied (fixed capital investment, process yield, progress ratios, and pre-commercial investment) exhibit highly interactive effects. The system tends to show market dominance of a single pathway due to competition and learning dynamics. While these results do not predict biofuels industry development, they illustrate the types of behavior that could occur for different combinations of techno-economic and learning parameters for biomass-to-biofuel conversion technology pathways. This modeling approach could be broadly useful in representing the interactions among investment decisions, cost reductions during development, and utilization and production in the emergence of other industries. The results could inform future analytic work to explore the robustness of the finding of a tendency toward market dominance, and the policy implications of this kind of system behavior could be considered.

The coupling of learning and investment, within the context of a dynamic model, can generate results that show a variety of potential behaviors of the system. These may inform the development of a shared understanding among stakeholders of possible effects of policy, external factors, decision making (e.g., by investors, growers, and consumers), infrastructure constraints, and learning on the development trajectory of the domestic biofuels industry. Exploration of learning and investment scenarios for biofuels industry development could help inform consideration of biofuels as part of U.S. energy and climate strategy. For example, the system behavior showing a tendency toward dominance of single pathways could prompt discussion about whether this outcome appears likely or is an artifact of the model formulation, how mitigating circumstances (e.g., more detailed representation of different market segments) could overcome this tendency, and social costs or benefits of such an outcome. Similarly, the wide range of potential learning rates could focus discussion on rates of progress that are or are not conducive to further public or private investment. Through its uses as an analysis platform and scenario generator, the BSM can inform the pursuit of these biofuels goals.

Appendix

Table A1. Indices for Equations

Index Symbol	Definition	Variables Using Index
0	Initial value	M
n	Ultimate value	A
i	Attributes of technologies	A
C, D, P	Scale (Commercial, Demo, Pilot)	M
j	Technology pathways	NPV, S

Table A2. Selected Equations

Eq. No. or Symbol	Equation and Variable Name in Model	Units	Variable Name in Paper
4	$M = \begin{cases} 1 - (1 - M_0) \left(\frac{L^*}{E} \right)^{\left(\frac{1-PR}{\ln 2} \right)} & \text{for } E \geq L^* \\ M_0 & \text{otherwise} \end{cases}$		
$0 \leq M \leq 1$	Pilot Maturity Demo Maturity Commercial Maturity	Unitless	Pilot maturity Demonstration maturity Commercial maturity
L	Min Pilot Experience for Learning Min Demo Experience for Learning Min Cume Industry Output for Learning	year	Minimum experience for learning
$0 \leq PR \leq 1$	Pilot Progress Ratios, Demo Project Ratios, Project Ratios Commercial	1/doubling	Progress ratio
E	Cumulative Pilot Experience Cumulative Demo Experience Cumulative Industry Output	year year billion gallons	Cumulative experience
6	$A_i = m_i A_{i,n}$		
A	State of Industry Process Yield FS Throughput C, FS Throughput P	gal/short ton short ton/day	Process yield Feedstock throughput capacity

Eq. No. or Symbol	Equation and Variable Name in Model	Units	Variable Name in Paper
(vector of technical attributes)	Expected FCI C, Expected FCI P Req'd Rate of Return as % Expected Equity Fraction	\$	Capital cost growth Investor risk premium Access to debt financing
$0 < m_i$	State of Industry Multipliers (one for each technical attribute A)	unitless	multiplier
8	$m_i = C_i M_C + [D_i M_D + P_i (1 - M_D)] \times (1 - M_C)$		
C D P	Mature Commercial Multipliers Mature Demo Multipliers Mature Pilot Multipliers (one for each technical attribute A)	unitless unitless unitless	Mature commercial multiplier Mature demonstration multiplier Mature pilot multiplier
10	$NPV_j = R_j - [I_j + C_j + T_j]$		
NPV R I C T	NPV Investment C NPV Revs Net of Op Cost C Initial Equity Investment C PV Loan Payment C NPV Taxes C	\$ \$ \$ \$ \$	Net present value Expected revenue – operating costs Initial equity investment Present value of debt NPV of taxes – tax credits
12	$S_j = \frac{e^{(k+cNPV_j)}}{\sum_j e^{(k+cNPV_j)}}$		This equation summarizes several calculations in the model.
S k c	share to biofuels offset for attractiveness weighting invest attractiveness weighting	Unitless unitless unitless	Share of construction capacity Constant Constant scaling factor

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