Algae-based two-stage supply chain with co-products

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Abstract

The last years have seen the emergence of the bioeconomy. Assessment of these new technologies is a significant challenge. We develop a unique dynamic programming framework to assess the value of the investment in a multi-stage supply chain with the production of bio-feedstock and its processing into multiple outputs. The system allows for adaptive learning in all supply chain stages, which creates a positive learning effect of co-outputs. We apply the framework to macroalgae (seaweed) farming and biorefinery processing into proteins and sugars for the Philippines and Ireland as representatives of developing and developed economies with emerging supply chains. We run Monte Carlo simulations to analyze the uncertainty of learning and prices. The key results indicate that the macroalgae sector that builds on traditional technologies is quite viable. Developing a new algae industry that generates proteins and other high-value products requires significant investment and depends on the dynamics of learning and prices. Even though the production of high-value chemicals is not yet viable, it gains profitability potential from learning of feedstock farming that is currently produced for the lower value application. The learning is much more valuable in feedstock production and processing into proteins than low-value chemicals currently produced (carrageenan).

Highlights

- Original dynamic, two-stage supply chain model with non-linear cost functions, learning in each stage, and heterogenous coproducts.
- Analysis of impact of learning effects and prices on investment decision in a supply chain of aquaculture.
- Theoretical and empirical confirmation of the importance of learning and co-production in multi-stage supply chains. The co-production allows financing

learning in both stages of the supply chain that may transform the presently non-viable product into a profitable in the long run.

- If the combined impact of learning is greater than the discount effect, than the investment in a technology is likely to be profitable even if prices decline.
- Monte Carlo simulations for the Philippines and Ireland indicate that learning at the stage of the cultivation and biorefining into proteins is currently more important that processing into carrageenan (sugars).
- The payback period for the industry in the Philippines is up to 3 years, while western financiers should plan for a long-term investment and maintain high learning rates to reach profitable commercialization

Keywords: *non-linear dynamic optimal control, two-stage production, learning, multiple co-outputs*, *biorefinery, seaweed, Monte-Carlo simulations*

JEL Classification Numbers: Q12, Q16, Q22, Q57, C61

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1. Introduction

The concept of bioeconomy refers to sectors of the economy that are using biological resources to produce renewable products (NAS, 2020; European Commission, 2018; Pyka, Cardellini, van Meijl, & Verkerk, 2022). More specifically, the bioeconomy utilizes new life sciences knowledge to produce a wide range of products from living organisms and the waste they generate (Zilberman, Gordon, Hochman, & Wesseler, 2018). As new biotechnologies emerge, a significant challenge is developing economic decision-making tools for ex-ante assessment that incorporate the complex supply chains and multi-level systems of feedstock production, refining technologies, markets, environmental externalities, and policies (Ramcilovic-Suominen & Pülzl, 2018; Wesseler & von Braun, 2017). Much of the literature on the economics of technological change in the bioeconomy is an ex-post assessment of the rate of return to research or the adoption of new technologies (Antle, 2019; Zilberman, Gordon, Hochman, & Wesseler, 2018; Alston, Pardey, & Rao, 2021). However, to address the challenges of introducing innovations, ex-ante analysis of their design and implementation is essential (Van Eenennaam, De Figueiredo Silva, Trott, & Zilberman, 2021).

The research was motivated by conversations with industry stakeholders. Inspired by the spike in demand for plant-based milk products, the industry believes that macroalgae (seaweeds) have potential (van den Burg, 2019; GFI, 2021). Plant-based milk has grown from a niche product to a business worth USD 20bn a year worldwide (The Economist, 2021). The accelerated growth of plant-based meat, eggs, and dairy signals a growing global demand for more-sustainable alternatives to conventional products. The macroalgae-based bioeconomy can play a vital role in providing sustainable food (Cai, et al., 2021), animal feed (Seghetta, et al., 2017), pharmaceuticals, fertilizers (Seghetta, Hou, Bastianoni, Bjerre, & Thomsen, 2016) and hydrocolloids (alginates, agar and carrageenan) (Alba & Kontogiorgos, 2019). The comparative advantages of macroalgae are the much higher biomass productivity than that of terrestrial plants (Casoni, Ramos, Estrada, & Diaz, 2020), while not competing for land or freshwater (Golberg, et al., 2020), with a potential for carbon sequestration (Krause-Jensen & Duarte, 2016).

There is a long tradition of cultivating seaweeds in East Asia and wild harvesting in the West for low-value applications like food and carrageenan (Araújo, et al., 2021; Cai, et al., 2021). New developments in biorefineries create an opportunity to shift from low-value commodities toward higher-value products in the cosmetics, functional food, nutraceutical, and pharmaceutical markets (Golberg, et al., 2020). These innovations are at the stage of initial commercialization, which includes the testing of the product. Accordingly, our analysis focuses on testing products prior to commercialization, assessing how profitable they are and to what extent the macroalgae-based supply chain should be commercialized.

Zilberman, et al., (2022) distinguish between the innovation supply chain (ISC) and the production supply chain (PSC). In the ISC the innovative ideas developed by research units are transformed into inventions, upscaled, and tested for efficacy and profitability. The last stage of ISC involves experimenting with the PSC design. The PSC is built on ISC as the innovating firm designs and implements a multistage supply chain where feedstocks are supplied to a biorefinery to be processed into commodities. The biorefinery approach is a means to increase the environmental sustainability and economic feasibility of industrial processes (Araújo, et al., 2021). Advanced macroalgae-based technologies, which aim to produce higher value products, tend to be in the upscaling and early production stages in the cleavage between the ISC and PSC.

The transition from the ISC to the PSC may not be distinct. The relationship between the ISC and PSC is symbiotic and synergetic, with a lot of feedback. For example, Pure Ocean Algae, a macroalgae-based biotechnology company in Ireland, has successfully completed a seed funding round which will see it invest more than €3 million to develop the existing land-based facilities to sea site production and expand

R&D and implementation teams (TheFishSite, 2022). SEAKURA cultivates seaweed to produce low-value food additives (Seakura, 2022). Operating on the edge of profitability, it is constantly engaged in R&D for adding fine chemicals to its product line.

The traditional approach is to select investment in innovative products and supply chains based on the rate of return (ROR) and NPV (Norton & Davis, 1981). Dixit & Pindyck (1994), introduce the Real Option (RO) approach for project assessment, emphasizing that timing is a crucial element of investment decisions. Thus, the evaluation of projects needs to determine when to introduce new technology, not only if to introduce it. While the RO approach has been widely applied in the natural resource evaluation (Deeney, Cummins, Heintz, & Pryce, 2020), we deal with cases where the key question is not when but how to develop and produce a product. The entrepreneur controlling the technology is constrained by the availability of specialized personnel that can manage production and learning. So, they aim towards early implementing testing. A delay of introduction of a technology might be costly also because of intellectual property rights (IPR) considerations. If, for instance, researchers developed a product, they built a team that can carry it forward. But the availability of key personnel is limited, and others may catch up and gain patents and technological edge. Therefore, even if the technology is in the stage of development with only the general features known, the innovator might seek immediate implementation, otherwise, the momentum is gone (Mayer, 2022). This is relevant especially to startups and biotechnologies addressing climate changes that do not leave time to procrastinate. Innovators must start applying the lab-based technology even if it is not yet profitable to learn, improve and evaluate the profitability (Bergemann & Hege, 2005). Thus, in the transition from innovation to production, it is important to improve the technology through learning by doing (LBD) to have a better assessment of the profit potential. Once a technology is established, the timing of testing technology commercialization should be considered for economic analysis. Generating new information for stimulating private sector investment is the argument for immediate investment by the public sector or public sector support. This investment can be evaluated by NPV since timing is not an issue, and the RO approach is not applicable.

There is a new wave of economic literature that emphasizes that the multiple stages of bioeconomy supply chains cannot be viewed in isolation because they are managed in an integrated manner. The relationship between feedstock and the biorefinery are symbiotic (Barrett, Reardon, Swinnen, & Zilberman, Forthcoming). The vast literature emphasizes that in developing a new product, the two stages of feedstock production and its further processing are linked (Zilberman, Lu, & Reardon, 2019). The same financier invests in both stages. This is the case in biofuels (Antràs & Zilberman, 2022), food (Macchiavello, Reardon, & Richards, 2022), and natural resources (Zilberman, Reardon, Silver, Lu, & Heiman, 2022). In the case of seaweeds, which is used as feedstock to producing proteins and other outputs in the biorefibnery, entrepreneur needs to determent how to allocate resources between the different stages of the supply chain.

The literature contains different elements of the supply chain: multiple stage supply chain with homogeneous output (Spiegel, Britz, Djanibekov, & Finger, 2020; Chen, Khanna, & Yeh, 2012), static models for contracting decision (Du, Lu, Reardon, & Zilberman, 2016), dynamic models with linear cost functions, or single stage models with learning (Chen, Zhang, Fan, Hu, & Zhao, 2017). Investigation of learning is commonly done in single output or single stage dynamic models (Deeney, Cummins, Heintz, & Pryce, 2020). Our study presents the first model that combines the essential elements for initial supply chain profitability and design analysis. We develop the dynamic optimal control model with multistage supply chain, coproduction, non-linear costs and learning.

Having two-stage dynamic model with learning in each of the stages, and coproduction of diversified products, allows investigating the real-world situation that follows the intuition of the industry (Zeichner, 2020; Argaman, 2020). The key questions of the investor are: in which stage of supply chain investment is more important for developing the innovation, what is the importance of learning vs prices, and to what extent the investment in macroalgae supply chain can be profitable in the short-run vs. long run. Our approach can contribute to decision-making regarding early-stage investment in innovations on the edge of commercialization.

The model parameters are collected from a variety of sources: the literature, interviews with industry stakeholders, as well as data on the international trade of seaweed, thickeners, and proteins. The model is validated for the case of the Philippines, a developing economy with a traditional seaweed harvesting industry with low-value applications. We also examine the case for Ireland, a developed economy with an emerging macroalgae-based industry. Finally, we perform stochastic modeling analysis, including Monte Carlo simulations, to investigate the impact of uncertainty in prices and learning on profitability.

The major results shed the light on the variation in payback period in developed and developing countries and the stages of the supply chain where the learning is most crucial. First, if for investment in the macroalgae-based experimental activity to pay for itself it will be more likely to become profitable even for low learning rates in the Philippines and within shorter payback period than in Ireland. The production of seaweed feedstock is projected to start with supporting the low-value commodity (carrageenan). It allows gaining learning on feedstock and reaching profitability of coproducing the high value chemical (proteins) in the later stage. In Ireland, the probability for profitability requires higher learning rates and investment horizon for at least 10 years.

Second, the results identify the weak points of the system: high uncertainty of yields in seaweed production and productivity of biorefining into proteins. Accordingly, investment in activities with higher LBD potential (macraolgae farming and processing into high-value chemicals) should be prioritized. Even though the production of high-value chemicals is not yet profitable, it gains profitability potential from learning of feedstock farming that is currently produced for the lower value application. Once the co-production becomes viable, the profitability of the entire supply chain is enhanced.

2. Macroalgae bioeconomy in a nutshell

Macroalgae have been popular in Asian cuisine for centuries. Their high biomass growth rates, and the high content of organic compounds such as polyunsaturated fatty acids, led to an increase in consumer demand for algae products and the commercial interest in seaweed production during the last several decades (Hochman & Palatnik, 2022). Seaweed farms bring benefits beyond the immediate value of their crop. Advancements in science and technologies led to the diversifying of macroalgae applications in food and beverages (Torres, Kraan, & Domınguez, 2019), pharma products (Golberg, et al., 2020), wastewater treatment (Wang, et al., 2020), bio-refining (Prabhu, Israel, Palatnik, Zilberman, & Golberg, 2020; Seghetta, Hou, Bastianoni, Bjerre, & Thomsen, 2016), dietary supplements (Peñalver, et al., 2020), cosmetics (Pereira, 2018), animal feed (Morais, et al., 2020), and other intermediate factors of production (Janarthanan & Senthil Kumar, 2018).

One leading example is the use of seaweed-based hydrocolloids such as carrageenan as natural binders and emulsifiers employed in foods, cosmetics, and drugs (Duarte, et al., 2020). The annual global growth rate of carrageenan was 2% between 2009 and 2015, valued in 2015 at more than half a U.S. billion dollars (Ferdouse, Holdt, Smith, Murúa, & Yang, 2018). The Philippines are one of the largest producers of cultivated macroalgae in the world (FAO, 2022), while Ireland is the leading EU seaweed producer in terms of biomass volumes and in a number of macroalgae production companies that reached about 20 units by 2019 (Araújo, et al., 2021).

The very few economic studies on macroalgae utilization find that the production is currently profitable if cultivated in developing countries (e.g. Philippines, Tanzania, Indonesia) and if processed for food (Cai, et al., 2021). Cultivation in developed countries and processing for fuels and high-value commodities are not yet economically viable (Hochman & Palatnik, 2022). The main reasons are relatively low prices of substitutes (such as corn bioethanol), and immature technologies of industrial, autonomous cultivation, and biorefining (Palatnik & Zilberman, 2017). For example, the rate of macroalgae growth and the conversion factors – two key parameters in productivity- show a wide range and may be subject to even higher variation due to climatic changes. Macroalgae growth depends on saturation kinetics by light intensity, ambient dissolved inorganic nutrient concentrations, and temperature (Buschmann, et al., 2004). Cultivation uncertainty is exacerbated by stochastic weather and seasonal variability between regions, within years, and between years (Lehahn, Ingle, & Golberg, 2016). This variation in the product might have a major effect on the cost-effectiveness of the technology. Growth and conversion parameters may evolve with learning. The variability of technology parameters, as well as prices of inputs and outputs, impact profitability over time.

In addition, the biorefinery process has not fully entered commercial production, but laboratory-based conversion technology is about to be scaled up to industrial-scale facilities for fermentation-derived products. The transition from lab to large-scale macroalgae cultivation is also expected to reduce costs as producers learn the environment, and detect optimal conditions for maximum yield, as happened previously in corn and sugarcane ethanol, where the cost and economic viability have improved because of learning in processing as well as feedstock production (Khanna & Crago, 2012; Chen & Khanna, 2012).

The seaweed supply chains consist of upstream aquafarmers, midstream processors and wholesalers, and downstream retailers. Our framework which is designed to reflect these features may apply to any supply chain or production process that includes at least two stages of production. Considering the industrial application, we develop a mathematical model as a decision support tool for strategic planning. This model aims at aiding stakeholders in optimizing the macroalgae-based bioeconomy, by integrating the decisions at the cultivation and biorefinery stages while considering variability in costs, different shares of biorefinery outputs, and maximizing the expected net present value of profits of the two-stage production over time.

3. State of the art

This review is structured around two main bodies of multidisciplinary literature that are related to our research. The first is the literature on learning implemented in the bioeconomy. The second is the literature on supply chain management. We discuss each of these research areas, identify the gaps, and highlight the contribution of this article.

Novel technologies are often expensive at the point of their market introduction but become cheaper due to the process of technological learning (Weiss, Junginger, Patel, & Blok, 2010). Unit costs of innovative technologies have been observed to decline rapidly with the accumulation of production experience/knowledge, measured by cumulative production (McDonald & Schrattenholzer, 2002). Technological learning, or LBD, —or the learning effect—is a concept, which permits the evaluation of the decrease in unit production costs when cumulative production increases. LBD was explicitly introduced into economic analysis by Arrow (1962). The literature identifies several major drivers of technological learning: learning-by-doing, learning-by-researching, learning-by-using, learning-by-interacting, and economies of scale (Arrow, 1962; Landes, 1969; Kahouli-Brahmi, 2008; Goodwin, Featherstone, & Zeuli, 2002; Li & Ni, 2016). All these mechanisms reflect the fact that technologies may experience declining costs because of their increasing adoption due to the accumulation of knowledge through, among others, these drivers of technological learning (Kahouli-Brahmi, 2008).

In the case of biofuels, studies show that LBD measured by cumulative production played a significant role in reducing the unit industrial processing costs of corn ethanol over the period 1983–2005 (Chen & Khanna, 2012; Hettinga, et al., 2009). Due to the wide range of macroalgae growth rates and biorefinery conversion factors the notion of LBD is especially relevant in the context of macroalgae.

Several functional forms of an experience curve have been used in the economic literature to represent the LBD effect. Kahouli-Brahmi (2008) provides a comprehensive review of the literature on technological learning in energy–environment–economy modeling. The most common format, which is also usually employed for bioeconomics (Deeney, Cummins, Heintz, & Pryce, 2020) and biofuel technologies (Chen, Khanna, & Yeh, 2012), is the original form of learning function (Verdoorn, 1956; Hirsch, 1952) that served as the starting point in Arrow (1962):

(1) $C = JXcum^{-\mu}$

Where C is the unit cost of production, investment, or capital, J is the initial production cost of the first unit, $Xcum$ is the cumulative production of a product, and μ is a parametric constant capturing the rate of cost reduction. In other words, μ is the elasticity of LBD, which defines the effectiveness with which the learning process takes place. The learning rate (LR), or 1-progress ratio (PR), defined as 2^{μ}, is the rate at which the unit cost of technology is expected to decline with every doubling of cumulative production (Rivers & Jaccard, 2006).

Chen et al., (2017) review empirical studies on LRs in the biofuels industry. They show an evaluated cost reduction in the range of 13%-35% as the cumulative production of biofuels doubles. Chen et al., (2017), like many other studies that incorporate learning effects in the cost function, present a single-stage dynamic programming framework for investigating time-dependent and adaptive decision-making processes to develop advanced fuel technologies. It appears that existing literature has seldom addressed the dynamic role of LBD, which affects multiple stages of the process and product innovation (Li & Ni, 2016).

The two-stage supply-chain literature focuses mainly on the following major challenges: inventory optimization, location planning, and feedstock uncertainty. A significant branch of the two-stage production models encompasses inventory optimization models, where the decision about the optimal inventory of feedstock size or quality affects the second stage of production (Wu & Wang, 2015). Enders et al. (2014) model a single-item inventory system with a high priority lost sales, customer class, and a lower priority backordering class. They propose a critical level policy and develop a procedure to determine its average performance. Isotupa (2015) analyzes a lost-sales inventory system with two classes of goods and shows that there is a sub-optimal policy under certain conditions. Xu, Serrano, and Lin (2017) employ the dynamic programming approach to investigate the inventory-rationing problem in a two-product tandem make-to-stock production/inventory system. The model proposed in our study introduces a more dynamic approach where instead of a given amount of feedstock inventory, the production of feedstock at the first stage is directly impacted by the production of a variety of second-stage outputs. In our model, the non-linear costs are affected by learning in terms of accumulated production of feedstock.

Another stream of research models multi-stage production with the uncertainty that reflects the renewable energy volatility in power generation. Those studies specify in detail the characteristics of renewables such as wind (Wang & Guan, 2013), solar (Torani, Rausser, & Zilberman, 2016), and municipal solid waste (Wu, Huang, Li, Xie, & Xu, 2015) in the power supply or carbon sequestration (Deeney, Cummins, Heintz, & Pryce, 2020). Here, the second stage output – electricity – is a homogeneous good, whereas our analysis provides an additional decision parameter that affects the profitability – the output bundle might be constructed of two (or more) goods that vary with both costs of production and output prices.

Deeney et al., (2020) present a real option evaluation of production with learning. The model represents single stage production and a single output (applied to CO_2 recycling technology). Importantly, the authors separate the learning at the stage of R&D from the early stage of commercialization and production. In their framework the learning ends at the stage of product development. From Arrow (1962) we know that learning is essential especially in the early stage of production. We follow the classical (Arrow, 1962) and the recent literature on the supply chain (Zilberman, Reardon, Silver, Lu, & Heiman, 2022) that indicate that in the early stage of production the learning continues and is highly important. Therefore, our framework complements the approach presented by Deeeney et al., (2020).

A large body of literature assesses the economics of corn and sugarcane-based ethanol and biodiesel (Babcock, Bruce, Stephan, & David, 2011; Crago, Christine, & Madhu, 2014; Jain, Atul, Madhu, Matthew, & Haixiao, 2010). Osmani and Zhang (2013) present the two-stage supply chain analysis of bioethanol. Muth, et al., (2014) investigated the agricultural production of feedstock that varies widely across the landscape according to site-specific characteristics such as topography and soil biogeochemistry. In both studies, the multi-feedstock decision is made at the first stage of linear cost functions.

Palatnik and Zilberman (2017) report that although the literature on economic analysis of macroalgae utilization is rapidly increasing, it lacks an established cost function. Most of the studies employ a linear approximation for National Renewable Energy Laboratory (NREL) costs module for corn-stove biorefinery (Konda, Singh, Simmons, & Klein-Marcuschamer, 2015; Korzen, Peled, Zemah Shamir, Shechter, & Gedanken, 2015; Seghetta, Hou, Bastianoni, Bjerre, & Thomsen, 2016).

The economic analysis of agriculture has a long history of applicating mathematical programming approaches to multi-stage supply chains for homogeneous final output (Hazell & Norton, 1986; Berg, 1987; Spiegel, Britz, Djanibekov, & Finger, 2020). Some studies included also sensitivity analysis for learning (Acs, Berentsen, Huirne, & Van Asseldonk, 2009). Several recent studies have addressed the questions of agricultural ISC (Du, Lu, Reardon, & Zilberman, 2016; Lu, Reardon, & Zilberman, 2016; Zilberman, Lu, & Reardon, 2017). These studies focused on the decision of contracting the production of feedstock versus self-production under various conditions. Lu, Reardon, and Zilberman (2016) investigated the impact of technology adoption on supply chain design. Yet the studies investigate static models and lack an explicit investigation of learning and its role in investment decisions in a multi-stage supply chain with co-production. Zilberman, et al., (2022) present a stylized dynamic model, without a real-world application.

To summarize, for an accurate representation of the ISC of the macroalgae-bioeconomy, the analytical methodology should incorporate the key features of the multiple-stage production process: farming of the feedstock and biorefining of the feedstock into multiple outputs. Another crucial feature is for the cost function to allow for non-linearities and the possibility for costs to decline through LBD. The important prior works set the stage for ISC analysis by investigating its distinct features. The present article contributes to the literature by designing the first dynamic optimal control model for a two-stage supply chain with co-production, incorporating the variation in yields and conversion factors through LBD elasticities in non-linear cost functions.

4. Materials and methods

To analyze the potential of investment in the seaweed-based supply chain, the following procedure was applied (Figure 1. Scientific procedure

): we develop a dynamic conceptual framework with two stages of the supply chain – feedstock cultivation and processing into multiple outputs. Next, parameters of the cost function in the macroalgae-based industry are calculated, and the model is validated for the case of the Philippines. Finally, the application for two case studies (the Philippines and Ireland) is evaluated using Monte-Carlo simulations to quantify uncertainties based on random experiments to estimate possible ranges and distributions of prices and LBD elasticities.

Table 1 is about here

This section briefly presents the optimal control model of the supply chain, consisting of the feedstock cultivation in the first stage of production, which is the input for biorefinery that processes the feedstock into outputs *a* and *b* in the second stage. At each stage of production and for each output, we assume non-linear cost functions with LBD. Denote the cumulative production of feedstock by X_{cum}, then x is the production of feedstock (macroalgae or other) at this particular moment so that the state equation is:

(2) $x(t) = \frac{dX_{cum}}{dt}$

Define *a(t)* as the share of feedstock used for the production of output a (e. g. proteins) at time t (assuming 1 to 1 conversion), and x_a as the production of proteins at this particular moment. Hence, $x(t)a(t) = x_a$. Then, denote for all $t, s \in T$:

(3) $X_{a,cum} = \int_0^t x(s)a(s)ds,$

Where $X_{a,cum}$ is the cumulative production of proteins by time *t*. Similarly, $X_{b,cum} = \int_0^t x(s)b(s)ds$, where $X_{b,cum}$ is the cumulative production of output *b* (e. g. sugars - carrageenan), *b(t)* is the share of feedstock at time *t* used for the production of sugars and x_b is the production of sugars at this particular moment. In what follows each equation applies to time *t*. We eliminate the time argument for readability.

For simplicity, assume that $X_{cum} = X_{a,cum} + X_{b,cum}$ and $x = x_a + x_b$ meaning no waste or residuals occur in the production process. The definition implies that X_{cum}, $X_{a,cum}$, and $X_{b,cum}$ are state variables and x, x_a, x_b are non-negative control variables.

Next, we assume non-linear production costs of proteins (*Ca*), sugars (*Cb*), and feedstock (*C*) that decline with LBD:

(4) $C_a = \frac{A x_a^{\phi}}{X_{a,cum}^{\psi}}$; $C_b = \frac{B x_b^{\xi}}{X_{b,cum}^{\zeta}}$; $C = J \frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu}}$

Where $\mu, \zeta, \psi > 0$ are the elasticities of LBD that define the effectiveness with which the learning process takes place in the processing of seaweed into proteins and sugars, and seaweed farming, respectively. The parameters $\phi, \xi \geq 1$ indicate the marginal cost growth rate. Thus, unlike most previous studies, we allow for the more general form of the production costs at the second stage of production. For example, if $\phi, \xi = 1$, all the production costs follow the standard (linear) form with LBD (Arrow, 1962; Chen, Khanna, & Yeh, 2012). Whereas for $\phi, \xi = 2$, the cost function of the second stage of production is of quadratic form incorporating LBD.

The parameters *A, B,* and *J* are costs of the first unit produced that may be calculated using one given point of the curve, usually the starting point (Kahouli-Brahmi, 2008), for example:

(5) $J = \frac{C_0}{X_{cum0}{}^{\mu}}$

Now, denote by $P_a(t)$ and $P_b(t)$ the prices of outputs a and b respectively. Let the discount factor be r, then e^{-rt} is the continuous time discounting factor. Then, the investor in ISC maximizes the present discounted value of expected lifetime profits:

(6) $\max_{x_a, x_b} \pi = \int_T^{\infty} \left(P_a\, x_a + P_b\, x_b - A \frac{x_a^{\phi}}{X_{a,cum}^{\psi}} - B \frac{x_b^{\xi}}{X_{b,cum}^{\zeta}} - J \frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu}} \right) e^{-rt} dt$

The framework allows the revenue and cost functions to decline over time due to dynamic processes of learning. If potential revenues increase over time and costs of cultivation and/ or processing decline, production will increase. First order conditions are developed and proved in Appendix A.

Rearranging F.O.C. allows investigating the factors that impact the growth of output:

$$(7)\ \left(\dot{x}_a/x_a\right) = \frac{P_a X_{a,cum}^{\psi}}{\phi A(\phi-1)}\left[\left(\frac{\dot{P}_a}{P_a} - r\right) + \frac{\psi A(\phi-1)x_a^{\phi}}{P_a X_{a,cum}^{\psi+1}} + r\phi A\frac{x_a^{\phi-1}}{P_a X_{a,cum}^{\psi}} + \frac{Jr}{(X_{a,cum}+X_{b,cum})^{\mu}}\right]$$

Where $\dot{x}_a$ is a time derivative of output x_a and $\dot{P}_a$ is a time derivative of price of a. As the cost function for output *b* is symmetrical to *a*, similar rules apply. From Equation (7) we identify the key effects driving the dynamics of the supply chain, presented here for output *a* and symmetric for output *b*:

1. The **price dynamics effect** $\left(\frac{\dot{P}_a}{P_a} - r\right)$**,** is the relative price growth comparing to the discounted rate.
2. The **learning effect** $\left(\frac{\psi}{X_{a,cum}^{\psi+1}} * \frac{A(\phi-1)x_a^{\phi}}{P_a}\right)$, is the joint contribution of learning and cost.
3. The **discount effect** $r\left(\frac{\phi A x_a^{\phi-1}}{P_a X_{a,cum}^{\psi}} + \frac{J}{(X_{a,cum}+X_{b,cum})^{\mu}}\right)$, reflects discount cost saving for cultivation and processing as a result of learning.

From the F.O. C. the following propositions are derived (find the proof in Appendix B**: Propositions and proofs**):

Proposition 1. *The expected output of the innovative technology increases, if the learning effect is greater than the price effect when prices decline.*

As long as prices of output increase, the production is profitable. But, the prices of novel technologies usually follow a downward trajectory: as the production expends, the prices decline if demand is not perfectly elastic. Therefore, *Proposition 1* identifies condition whether production remains profitable when prices decline. If the price is decreasing over time, the output increases if the learning effect and the discount effect are greater than the price effect, i. e. if the sum of the learning and discount effects is greater than the decline of discounted price growth (Equation 7). The cost function implies there may be an increase in the volume of production <u>and</u> a reduction in price.

The next propositions describe the comparative statics of the profit function.

Proposition 2*. Production of one or both co-outputs may occur in the early period even if at least one of them is not profitable, to accumulate learning of feedstock that will result in a profitable supply chain in the longer term.*

The more profitable output of the second stage of the supply chain contributes to the increase in productivity in the first stage of ISC (cultivation) that serves as input also to the less profitable output of the second stage (processing). The feedstock accumulates faster, resulting in cheaper unit costs to the benefit of all co-produced outputs of a biorefinery. The economic meaning is that co-production has a positive complementarity effect of learning.

Proposition 3a*. The output growth rate is non-decreasing in output price growth and increases, if its price growth is higher than the interest rate.*

This result is particularly interesting. Time derivatives of outputs, which are equal to growth rates for small changes, clarify that the growth rate of output is smaller than the growth rate of prices. Yet if the price increases over time, the output also grows. The dynamic nature of the model clarifies the intuition that if prices grow less than the discount rate, the growth rate of output declines, as the investor may choose the alternative of a 'risk-free' bank return.

Proposition 3b*. If learning is faster than the increase in costs, then output grows faster than prices.*

The result implies from time derivatives of output with respect to the time derivative of own price.

In the following sections, the key parameters are evaluated and the profitability conditions of the proposed optimal-control supply-chain design model are demonstrated.

To summarize, the conceptual model emphasizes the importance of learning effect, interest rate and price dynamics. More elastic demand would require slower reduction of outputs. Low interest rates and high learning increase profitability and the rate of growth of second stage co-outputs. The concept applies to the final stage of ISC where the initial pre-commercialization investment in the innovative technology is checked for profitability.

5. Application to macroalgae

Several organizations try to decide whether they build an experimental farm and learn about profitability in production (Zeichner, 2020). For example, Norway is encouraging research institutions, industries, and public authorities to develop a bioeconomy based on the production and processing of cultivated seaweeds (Stévant, Rebours, & Chapman, 2017). The targeted production potential has not been reached yet since only part of the companies that received a permit for seaweed cultivation, and processing since 2014 are currently in operation and most have still reduced production capacity (Broch, et al., 2019). AKUA is a Meat-alt company based in the US making plant-based foods from seaweeds. It has successfully completed a recent fund-raising round to create a platform of clean-label (Republic, 2022). Those are few of the many examples to the macroalgae industry in the stage to decide on the commercialization of the new technologies.

We apply the theoretical framework to farm-level decisions regarding investment in innovative technologies in the cultivation and biorefining of seaweeds. Following Ingle, et al. (2017), we consider investments into Red macroalgae (*Kappaphycus alvarezii*) production (first stage of ISC) and processing into two outputs: industrial proteins and unique polysaccharides - carrageenan (second stage). The macroalgae-based industry is characterized by traditional methods of cultivation and drying in Asia, and by the developing novel technologies of cultivation and processing in developed countries (Hochman & Palatnik, 2022). Accordingly, we apply the model to two case studies: the Philippines, as the representative of the world leader with traditional macroalgae economy in East Asia with low-value applications (Cai, et al., 2021), and Ireland, as the representative of the developed economy that promotes advances in macroalgae-based bioeconomy (Araújo, et al., 2021).

The actual data on model parameters is collected to provide insights into the true profitability of macroalgae utilization to proteins and carrageenan. A major effort to collect consistent data on the seaweed industry and derivatives by countries over time was performed. The most detailed and consistent dataset was identified in UN COMTRADE. Monthly trade value (in USD) and net weight (kg) for seaweeds, thickeners derived from vegetable products (including Carrageenan) and textured protein substances allowed for calculating the average monthly prices of the traded commodities.

Even though the trade volumes of seaweed in the reported period are of a similar scale, the two countries chosen for case studies represent very different industries for macroalgae-based commodities. The volume of trade in carrageenan is much larger, and the prices are on average lower in the Philippines than in Ireland. The volume and the prices of protein substances exported from Ireland are by merit of order higher than those of the Philippines. This can be partly explained by the fact that the quality of proteins exported from the Philippines is on average lower than that of Ireland (FAO, 2019).

Table 1 is about here

To base the estimation of the profitability of the macroalgae industry on cost parameters that reflect its specifications, we reviewed the LBD estimations available in the literature.

Table 1 reports for each model-parameter: its description, average value and range, setup values for Monte Carlo analysis for the Philippines and Ireland, and the source.

6. Results

To illustrate the outcomes of the dynamic optimal control model, we first validate the consistency for the case of the Philippines. Next, the stochastic modeling analysis including Monte Carlo simulations of profitability for the two case studies is performed.

6.1. Model verification

For validation, we apply the modeling framework to the mean values of all the parameters of the case of the Philippines (Table 1): $P_a = 5000\ \$/\text{ton}; P_b = 5500\$/\text{ton}; A = 4200\$/\text{ton}; B = 4500\$/\text{ton}; J = 1600\$/\text{ton}; \psi = 0.19; \zeta = 0.35; \mu = 0.42$. The result is positive production of the feedstock and both outputs with NPV of about USD 220M in 2016 values (Figure 2). The accumulated production doubles 3 times within the period of 10 years, implying much room for learning.

Moreover, the marginal profits (marginal revenue minus marginal costs) for both goods are negative at the beginning but become positive after some point. The profitability of producing output *b* (*carrageenan*) is higher, and it grows relatively faster in the beginning due to the higher LBD and initial price. However, over time, the accumulation of feedstock production (and therefore knowledge and experience) reduces the costs of the first stage for output *a* (protein) as well. This result reinforces the positive complementarity effect of learning expressed in *Proposition 2*.

In addition, the higher price growth for output *a* ultimately leads to higher profitability of protein over carrageenan. This result supports the intuition that even though the production of high-value chemicals in East Asia is not well-established and the industry is still centered around traditional technologies, the knowledge gained in cultivation of feedstock and the processing of complementary low-value outputs can facilitate the profitable production of high-value chemicals that ultimately increase the profitability of the entire supply chain.

Figure 2 *about here*

Increasing first unit cost of the first stage to $J = 4000$ \$/ton reduces the optimal production plan to zero at the average learning rates. However, if we change the learning rates to the upper bound, we observe the positive production plans and profitable production from the very beginning. Hence, there is a substitution between the learning effect and first-unit costs. Note that the FAO (2013) report of observed costs of *K. alvarezii* cultivation in developing countries indicates that most of the investment and capital costs (*i.e.* first unit costs- *J*) of seaweed are within the range of USD 600- 1600 per ton. The USD 4000 per ton simulated here is the far-end outlier. Therefore, supporting Proposition 2 the results show that LBD reverses non-profitable production, even for the relatively high costs of cultivation that usually characterize aquafarms in developed countries.

Following the above verification of the developed dynamic optimal control model, we continue investigating the impact of uncertainty in prices and yields on profitability of ISC using Monte Carlo simulations.

6.2. Monte Carlo simulations

We continue the analysis with Monte-Carlo simulations (Boyle, 1977) to obtain possible distributions for the economic return of macroalgae-based ISC for two representative case studies: the Philippines and Ireland. Our investigation focuses on prices and learning elasticities due to the high variation of observed prices of outputs and the uncertainty in yields in all stages of the supply chain.

For the following Monte Carlo simulations of profitability, the common setup includes the growth rates of marginal costs of outputs a (protein) and b (carrageenan) that are held constant over all the scenarios and equal to ϕ=1.05 and ξ= 1.1 respectively. The price growth rates are kept constant to the estimated average level inferred from the 7% price growth rate for output *a*, and 4% for output *b*. The discount rate is fixed to r=4%. Other parameters are specific for the Philippines and Ireland as presented in Table 1.

Before each simulation, we determine the 7-dimensional vector of parameters (for prices, prices growth rates, and LBD elasticities), which completely parametrize the intertemporal optimization problem. LBD elasticities are assumed to be normally (independently) distributed between the estimated lower and upper bounds.

The price related parameters are randomly drawn from the database for Ireland and for the Philippines. We consider the joint distribution of the prices and price growth rates for both outputs. This assumption is necessary to account for potential correlations between prices and changes in the prices of outputs.

We consider time horizons of 3 and 10 years to identify the payback time widely used in agricultural investment planning (Brandes, Budde, & Sperling, 1980). This is the time needed to recover a given investment outlay, including compound interest through future revenues (Zweifel, Praktiknjo, & Erdmann, 2017). For each time period, 1000 Monte Carlo simulations are conducted by drawing a random vector of parameters (given the distributions above) and solving the intertemporal profit maximization problem.

The general observation from the simulations refers to the production plans for both cases. The results indicate that the production can be split into phases of (1) learning (2) exploitation. In the learning period, the firm focuses on the production of feedstock and processing it into single output that has a comparative advantage, rarely switching between the outputs. LBD stimulates producing more of the output given that the more of the good is generated the cheaper it becomes to produce it. The second phase is the exploitation period. In this phase parallel to exploiting the profit from the good that the firm has learned to produce it also learns to produce the complementary output of processing. Given that the first-stage good has already become profitable the firm learns to produce the second good much more aggressively than it used to with the first output. This outcome reinforces the results from optimization analysis for the Philippines and yet again supports the theoretical intuition of *Propositions 2 -3*.

6.2.1. The Philippines

Figure 3 presents the impact of learning effect of each of the stages of ISC on the profitability within three years for the case of Philippines. Evidently, reaching profitability within 3 years for the range of LBD elasticities reported in the literature is plausible but not certain. The simulations confirm the observed stage of the industry in the Philippines, where for current rates of LBD elasticities the supply chain of seaweed cultivation and processing to carrageenan is mostly profitable within a short period of time, while profitability of processing to high value output is not certain. For the time horizon of 3 years, the LBD and first-unit cost parameters play the prevalent role over the prices in the decision of what to produce. The NPV is the most sensitive to ψ -the LBD elasticity of the output a (proteins), while second correlate is μ - the LBD of feedstock cultivation.

Figure 3 about here

Figure 4 investigates the substitutability of LBD elasticities for profitable production. It plots the results of NPV given different LBD rates using Support Vector Machine (SVM) (Chapelle, Vapnik, Bousquet, & Mukherjee, 2002). SVM is the supervised machine learning classification technique, which identifies the separating hyper-curve using the labeled data. Here, instead of a simple linear estimator, the nonlinear SVM is implemented using the “kernel trick”. The highlighted SVMs are those defining the separating curve. This analysis supports previous results in identifying the sensitivity of profitable ISC to LBD elasticities with ψ as the most important, then μ followed by ζ. Moreover, the results reveal a constrain of at least 0.1 for ψ to insure profitable ISC, no matter what learning elasticities are in the other stages. In other words, a learning rate of about 7% in processing macroalgae into proteins is required to reach profitability within 3 years.

Figure 4 about here

Importantly Figure 4 demonstrates by reconstructing the separating hyperplane using SVM that to keep the profitability of the ISC a change of 0.1 in ψ is corresponding to about 0.2 change in μ. The economic meaning is that to maintain profitability, a reduction of 7% in costs of processing macroalgae into proteins is equivalent to 13% decline in costs of seaweed farming for each doubling of cumulative production.

Figure 5 presents the results of the simulations for the horizon of 10 years.

Figure 5 about here

The profitability in this case is almost always positive implying that high pace of learning is less critical. However, ψ remains the primary correlate to profitability, although the spread for other learning elasticities is reduced. Therefore, the relative importance of learning in the longer horizon is reduced reflecting opportunities to exploit the output with lower LBD as well.

6.2.2. Ireland

Figure 6 presents the results for profitability of macroalgae-based ISC over 3 years in Ireland. We observe that reaching payback period for the ISC in the developed country is highly unlikely within the range of LBD elasticities reported in the literature.

Generally, the probability for profit in the short run is low. Both ψ and μ might affect profitability, while the impact of ζ is negligible. The major reason for this is that J – the first unite cost of farming - is relatively larger in Ireland comparing to the Philippines.

Figure 6 about here

Figure 7 presents the results of the simulations for the horizon of 10 years. The probability of profitability increases but is not very high even in the long run. The impact of LBD elasticities is increased, with the general ordering remaining similar to the Philippines. Yet again, ψ is the primary correlate to profitability, and the overall impact of LBD outweighs the effect of prices.

Figure 7 is about here.

The outcomes for Ireland indicate that to ensure profitable investment in developed countries, either a high pace of learning over a long term horizon or a technological breakthrough is essential.

7. Discussion and conclusion

There is a growing interest in the assessment of bio-based supply chains. As macroalgae cultivation and utilization technologies are under development, this study focuses on assessing the profitability of investment in testing and initial commercialization of the technology, taking into account the potential gain from learning at different stages of the production process. We focus on the investment in innovative technologies when the uncertainty in yields and outputs requires further learning during application that validates the team's expertise and the technology's viability. This phase is the borderline between ISC and PSC when the initial model for a PSC is assessed. Following the initial learning and refinement analyzed here, the tactical timing decision might be considered using the RO approach.

The contribution of this article to the literature on the assessment and implementation of innovations is by developing a dynamic model of the two-stage supply chain with non-linear cost functions, learning and heterogeneous co-outputs. The modeling framework addresses the main challenges of the seaweed-bioeconomy, taking into consideration the main characteristics of natural resource utilization: the ability for multi-output production at the biorefinery; and uncertainly of yields and prices. The article incorporates non-linear profitability impacts and explicitly evaluates LBD dynamics.

The theoretical contributions are illustrated using a numerical simulation calibrated with real data and providing solutions to production choice problem. The ISC starts with cultivation of *Kappaphycus* that is utilized as the feedstock to the bio-refinery; the two simultaneous co-outputs of the bio-refinery are industrial protein and carrageenan. Next, Monte Carlo simulations reflect the impact of prices, learning rates and ISC horizon on the profitability for two representative case studies: Ireland and the Philippines. This work comes in response to the needs of decision makers in the governance of bioeconomy to evaluate emerging technologies with the aim of utilizing renewable natural sources for sustainable economic growth.

Investigating the profitability of the supply chain in different time horizons allows evaluating the time to profitable commercialization. Importantly, the results reveal that the probability for profitable investment in the developed countries with emerging macroalgae-based ISC in the short-run is low. Yet, for the 10 years planning horizon the likelihood of profitable production sharply increases. In developing countries with traditional technologies of seaweed farming, the probability of reaching profitable production is high even in the short run. Accordingly, the results show that given the learning rates from the literature and the actual costs and prices for developed and developing countries, the payback period for the industry in the Philippines is up to 3 years, while western financiers should plan for a long-term investment and maintain high learning rates to reach profitable commercialization.

Interesting results for the Philippines show the potential to diversify investment strategy by adding utilization of seaweed into proteins in coproduction with low value application (e.g. carrageenan).

The results indicate the significance of the LBD as an indicator of the profitability of novel technologies. Empirical results highlight that a relatively high learning rate of 7% in biorefining of seaweed to proteins is required for a profitable production. Gaining knowledge and experience in best offshore cultivation practices is also important to boosting the mass utilization of the renewable resource – macroalgae. Stakeholders from the industry confirmed these results.

Moreover, the simulations indicate that production costs in developed countries can be sensitive to the learning effect. The first unit cost of cultivation of USD 4000 per ton (in 2016 prices) appears to be the threshold where LBD can reverse non-profitable production.

The results emphasize that the value of a technology depends on the initial (fixed) costs, output prices and learning. Of major importance is the early period learning, when the entrepreneur absorbs losses for the sake of future profits. We show that for every learning rate, the time to maturity of the technology declines with the increase in output prices, output of the co-product, but increases with first unit costs.

The empirical results for both countries stress the importance of the investment in R&D in the production of algae and in the purification of protein in order to reduce the costs of natural resource utilization and increase the overall profitability of the supply chain. Naturally, prices change and once the technology is mature timing considerations should be introduced.

Our focus on macroalgae is driven by high yields of this renewable natural resource, which does not compete with food crops for arable land or potable water, and is a potential feedstock for sustainable food, high value chemicals and biofuels, allowing also for carbon sequestration. Carbon pricing can increase the demand for the outputs of biorefinery while reducing costs seaweed farming leading to the adoption macroalgae-based bioeconomy (Zilberman, Reardon, Silver, Lu, & Heiman, 2022). Developing novel uses to proteins and sugars and other unique chemicals extracted from macroalgae at the biorefinery can boost the viability of the utilization. To generalize, rather than competing with existing goods, the scientific challenge can be the investigation of the potential to utilize macroalgae for unique foods, high value chemicals and fuels.

This work can be extended in several directions. First, incorporating entrepreneurs' attitudes toward risk considerations (Zilberman, Lu, & Reardon, 2017). The reliability of the volume, timing, and intermediary input quality may be uncertain (Zilberman, Reardon, Silver, Lu, & Heiman, 2022). Risk aversion will lead to producing less total output. Similarly, riskier processing of the intermediary input is likely to lower production (Lu, Reardon, & Zilberman, 2016). Over time, learning and adaptation may reduce the risk of supply and processing activities and increase overall production. In practice, entrepreneurs operate under credit constraints, which are more restrictive in developing countries and reflect asymmetric information between borrowers and lenders (Stiglitz & Weiss, 1986). Furthermore, entrepreneurs need opportunities to invest in protective measures to increase resilience of their supply chains to extreme weather risks.

Another conceivably important aspect that was beyond the scope of this article is the innovation spillover. As proteins and sugars are produced simultaneously from a given quantity of the seaweed, the accumulation of R&D and experience in processing seaweeds into proteins can stimulate the efficiency in production of sugars, and vice versa. Therefore, the possibility of correlation between learning rates of co-outputs of the biorefinery should be investigated.

Finally, the present article evaluated the profitability of natural resource utilization without considering the environmental and social externalities. Large-scale macroalgae cultivation involves direct and external effects on marine environment, carbon absorption, potable water, land use and employment. If macroalgae-based products, e.g. biofuels, proteins and sugars, crowd-out the use of substitutes, the negative effects of fossil and crop-based energy might be mediated (Zilberman, Rajagopal, & Kaplan, 2017). Further analysis on macroalgae external costs and benefits, as well as social welfare analysis, is required for an accurate policy intervention**.** The analysis on the technological prospects of macroalgae biorefinery should evaluate the social net benefit too. Consequently, the recommendation upon optimal mix of outputs is to be based on social (versus private) costs.

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Table 1: Model Parameters, Value, Range and Source

Para-meter	Description	Mean Value	Monte Carlo Setup		Notes
			Philippines	Ireland	
A	First unit cost of output *a* (protein) USD 2016 per ton	4,200	6,000	5,500	Self-calculated based on the price
B	First unit cost of output *b* *(carrageenan)* USD 2010 per ton	4,500	6,500	5,000	(Brown, 2015)
		Range	4,000-6,500		
J	First unit cost of feedstock (seaweed) USD 2010 per ton	1,600	2,200	3,600	(Buck & Buchholz, 2004; Valderrama, eds. 2013)
		Range	600-7,000		
$\boldsymbol{\phi}$	Marginal cost growth of *a*	5%	5%	5%	Assumed based on experts' evaluation
		Range	0-20%		

$\boldsymbol{\xi}$	Marginal cost growth of *b*	5%	5%	5%	Assumed based on experts' evaluation
		Range	0-45%		
Pa	Price of output *a* (protein) USD per ton	10,000	3,031	4,200	Prices calculated from value and quantity of the corresponding exporters *Source:* UN COMTRADE; commodity 210610 protein; concentrates and textured protein substances
		Range	1,000-11,000	4,000-26,000	
$\dot{\boldsymbol{P}}_{\boldsymbol{a}}$	Annual growth of Price output *a* (protein)	4%	4%	4%	Price growth rates own calculations based on: UN COMTRADE; commodity 210610 protein; concentrates and textured protein substances
		Range	-43% to 92%		
Pb	Price of output *b* (*carrageenan*) USD per ton	11,000	5,852	3,123	Prices calculated from value and quantity of the corresponding exporters *Source:* UN COMTRADE; commodity HS130239 (mucilages and thickeners).
		Range	5,000-48,000	3,000-61,000	
$\dot{\boldsymbol{P}}_{\boldsymbol{b}}$	Annual growth of Price output *b* (*carrageenan*)	4%	4%	4%	Price growth rates own calculations based on: UN COMTRADE; commodity HS130239 (mucilages and thickeners).
		Range	-11% to 53%		

ψ	elasticity of LBD in processing of seaweed to proteins	0.19	0.25 (0.23)	0.39 (0.4)	(Weiss, Junginger, Patel, & Blok, 2010)
		Range	0.10 - 0.36		
ζ	elasticity of LBD in processing of seaweed to sugars - *Carrageenan*	0.35	0.29 (0.14)	0.41 (0.21)	(Chen, Zhang, Fan, Hu, & Zhao, 2017)
		Range	0.29-0.41		
μ	elasticity of LBD in seaweed farming – Kappaphycus	0.42	0.45 (0.27)	0.38 (0.4)	(Weiss, Junginger, Patel, & Blok, 2010)
		Range	0.15-0.69		
r	Annual discount rate	4%	4%	4%	interest rate for mid-term loans
		Range	0-10%		

Figures

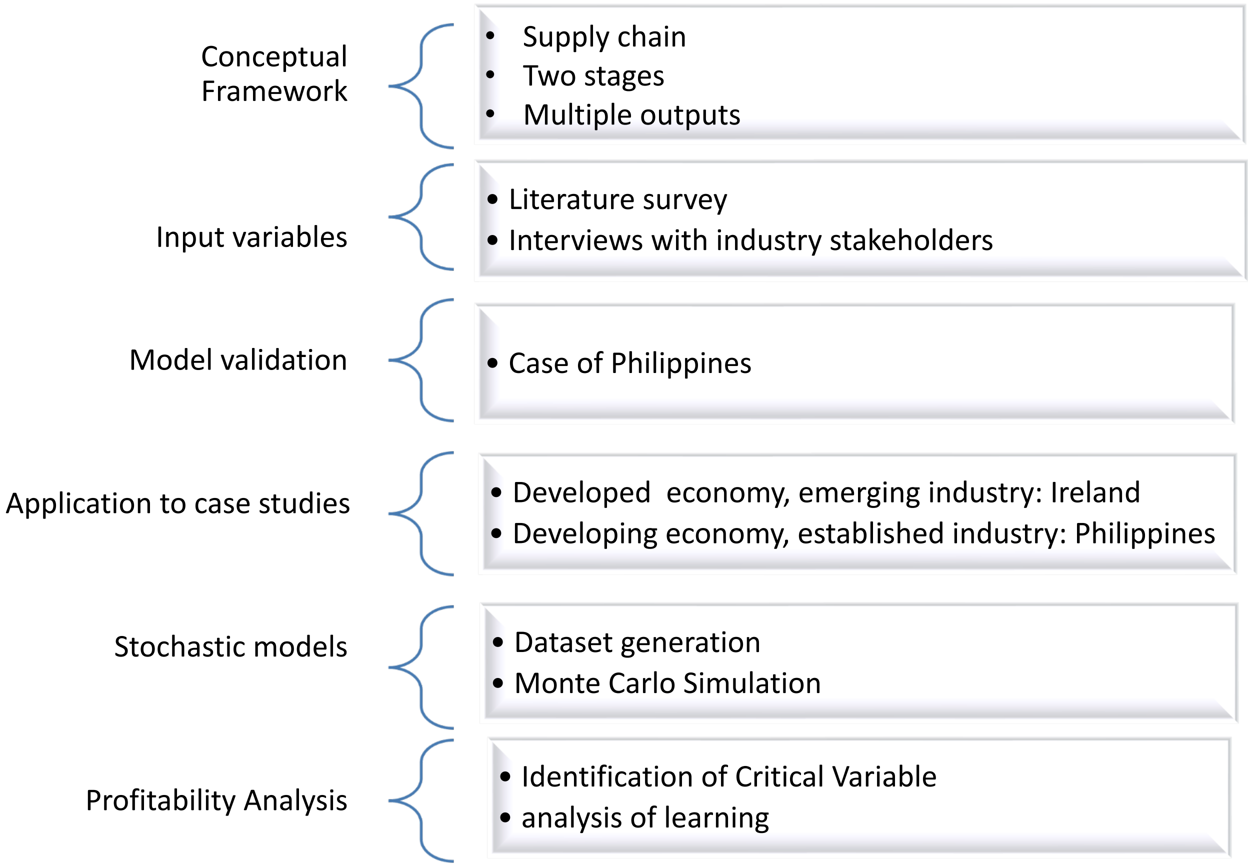

Figure 1. Scientific procedure

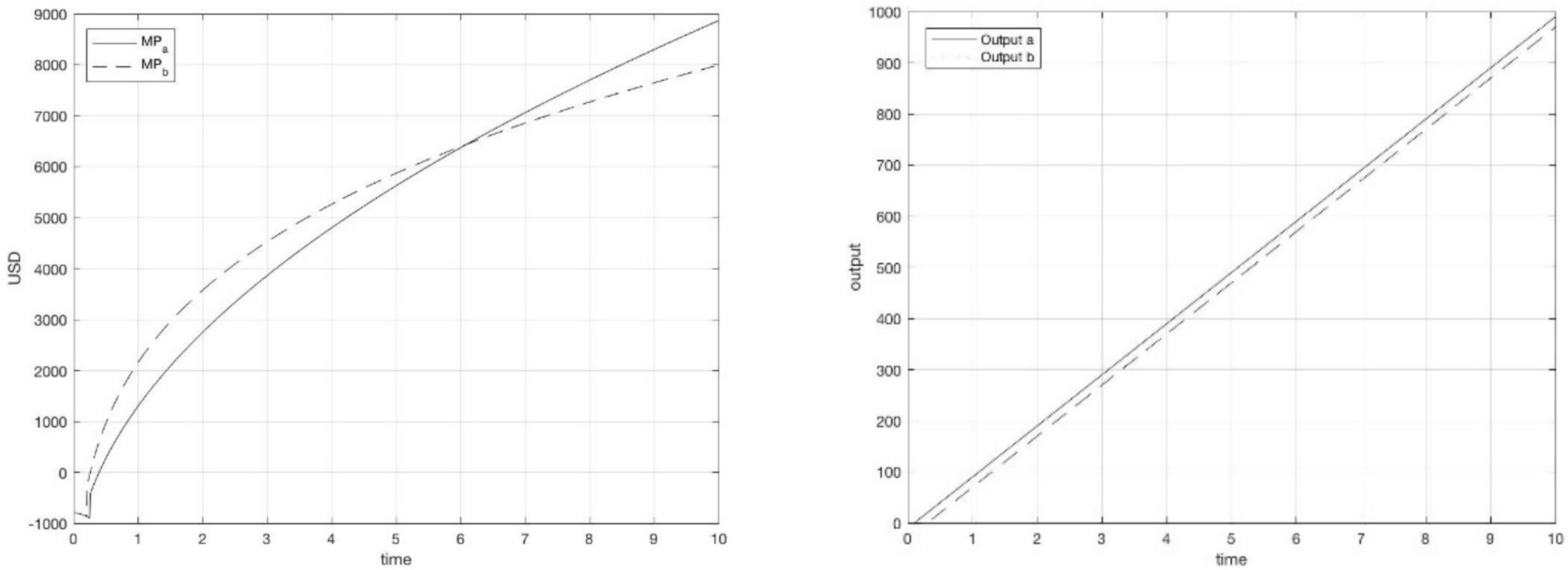

Figure 2. Co-outputs a and b Marginal profit (MP in USD per ton) and production (ton per year) in the average scenario

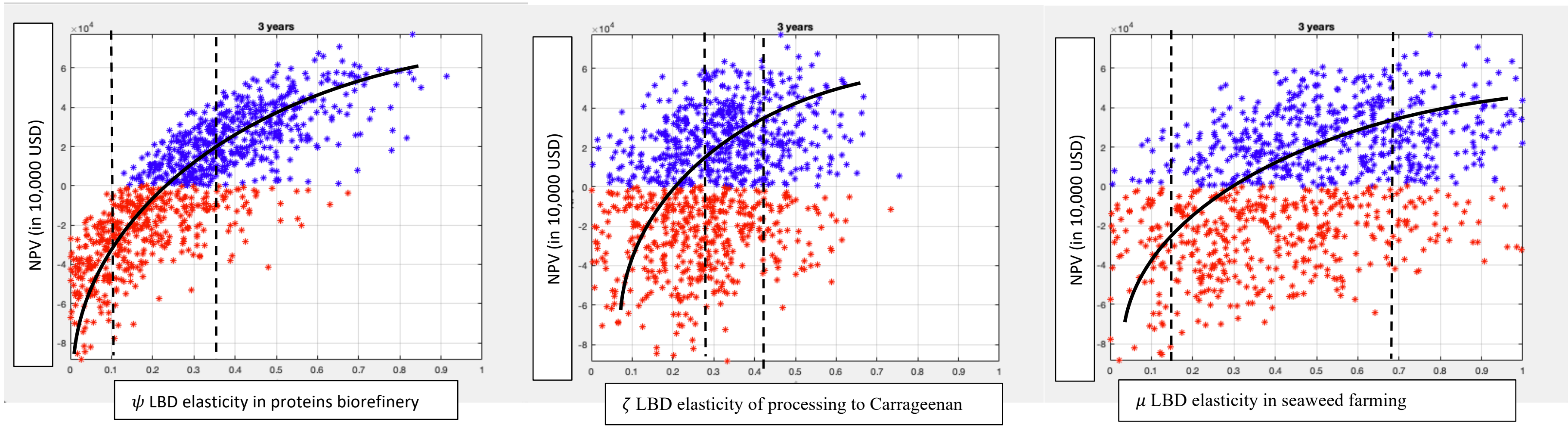

Figure 3: Profitability of the supply chain in the Philippines for 3 years as a function of LBD elasticities.

Blue dots represent positive profit while red indicate negative NPV. Black lines draw the trend and dashed lines show the range of LBD elasticities.

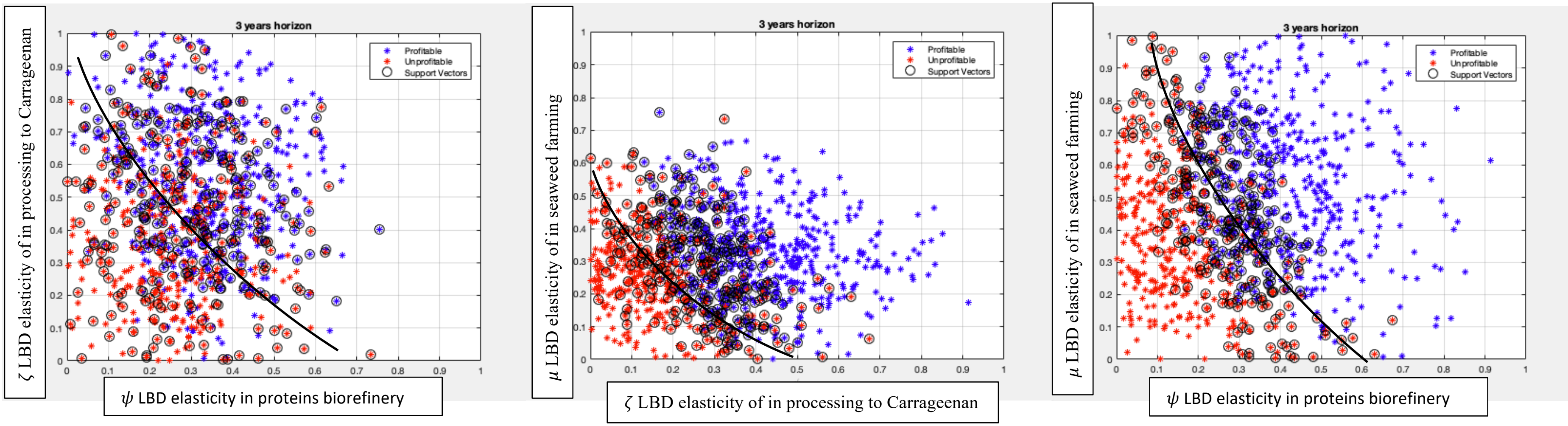

Figure 4: Substitutability between LBDs for Profitable supply chain in the Philippines (3 years).

Legend: Blue dots represent positive profit while red indicate negative NPV. Circled dotes indicate support vector.

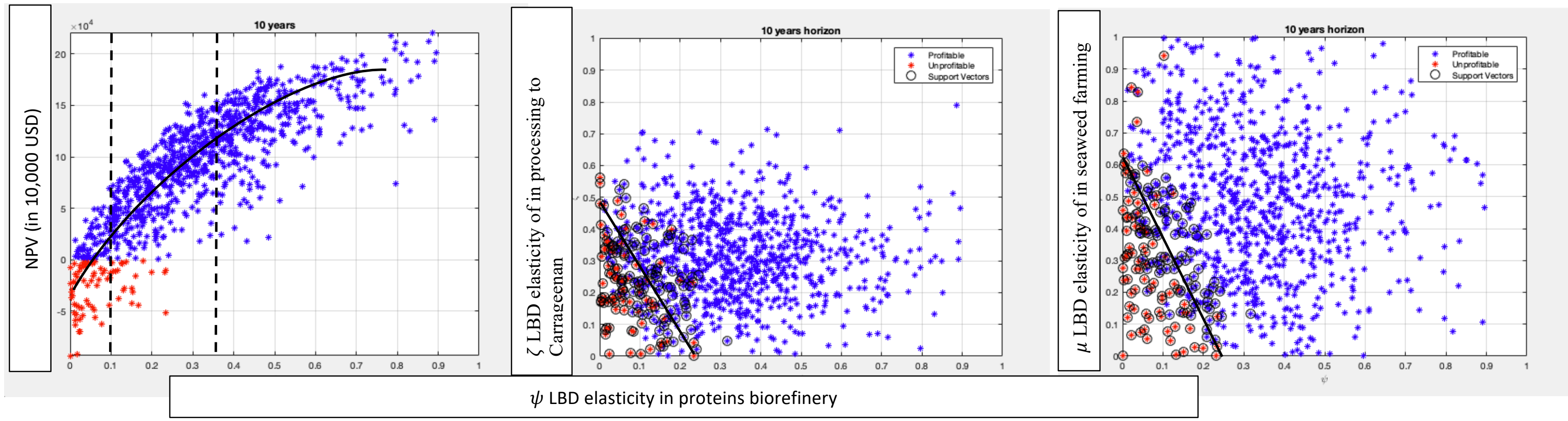

Figure 5: Profitability and Substitution between LBDs in the Philippines (10 years).

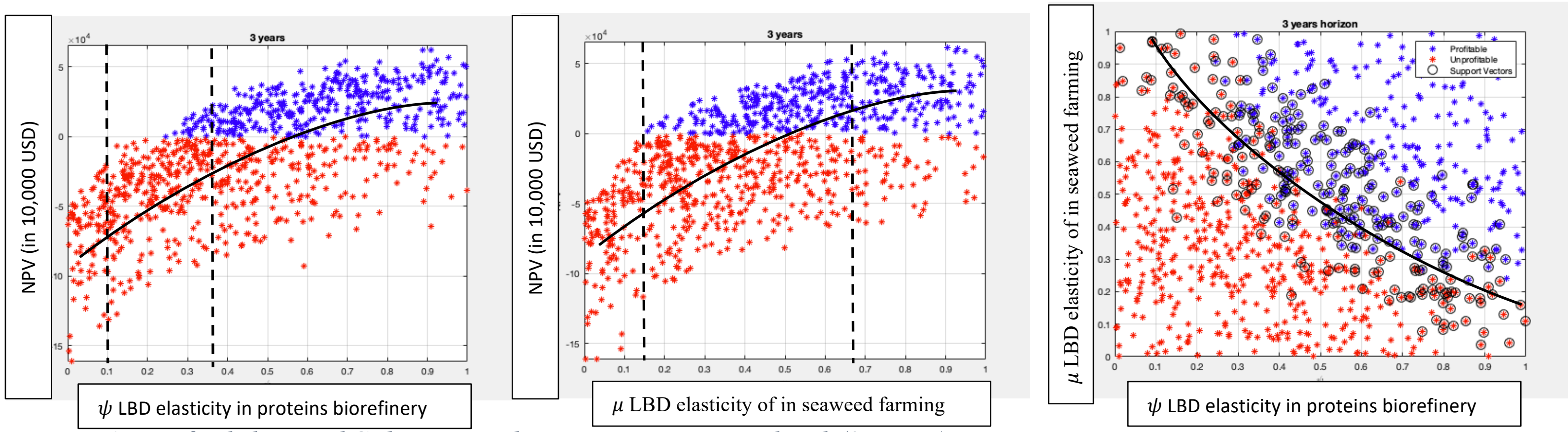

Figure 6: Profitability and Substitution between LBDs in Ireland (3 years).

Blue dots represent positive profit while red indicate negative NPV. Black lines draw the trend and dashed lines show the range of LBD elasticities. Circled dotes indicate support vector.

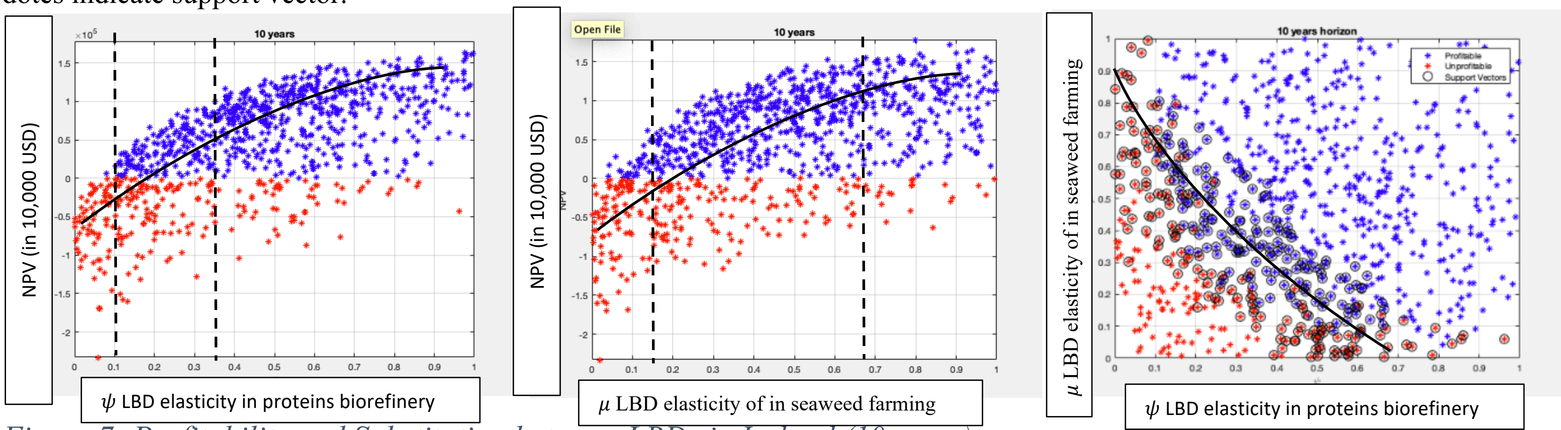

Figure 7: Profitability and Substitution between LBDs in Ireland (10 years).

Blue dots represent positive profit while red indicate negative NPV. Black lines draw the trend and dashed lines show the range of LBD elasticities. Circled dotes indicate support vector.

Appendix A: First order conditions

Let H to define the temporal Hamiltonian:

A. 1 $$H = \left(P_a\, x_a + P_b\, x_b - A\frac{x_a^{\phi}}{X_{a,cum}{}^{\psi}} - B\frac{x_b^{\xi}}{X_{b,cum}{}^{\zeta}} - J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu}}\right)e^{-rt}$$

and apply the *Hamiltonian* equation as a first order condition for the optimization problem:

A. 2 $$\frac{\partial H}{\partial X_{a,cum}} = \left[\psi A\frac{x^{\phi}{}_a}{X_{a,cum}{}^{\psi+1}} + \mu\, J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}}\right]e^{-rt};$$

A. 3 $$\frac{\partial H}{\partial X_{b,cum}} = \left[\zeta B\frac{x^{\xi}{}_b}{X_{b,cum}{}_b^{\zeta+1}} + \mu\, J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}}\right]e^{-rt};$$

A. 4 $$\frac{\partial H}{\partial x_a} = [P_a - \phi A\frac{x_a^{\phi-1}}{X_{a,cum}{}^{\psi+1}} - \frac{J}{(X_{a,cum}+X_{b,cum})^{\mu}}]\, e^{-rt};$$

A. 5 $$\frac{\partial H}{\partial x_b} = [P_b - \xi B\frac{x_b^{\xi-1}}{X_{b,cum}{}^{\zeta+1}} - \frac{J}{(X_{a,cum}+X_{b,cum})^{\mu}}]\, e^{-rt};$$

A. 6 $$\frac{d}{dt}\left[\frac{\partial H}{\partial x_a}\right] = -re^{-rt}\,\frac{\partial H}{\partial x_a} + e^{-rt}\left[\dot{P}_a + \mu J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}} - \phi A\,\frac{(\phi-1)\,x_a^{\phi-2}\dot{x}_a X_{a,cum} - \psi\, x_a^{\phi}}{X_{a,cum}{}^{\psi+1}}\right];$$

A. 7 $$\frac{d}{dt}\left[\frac{\partial H}{\partial x_b}\right] = -re^{-rt}\,\frac{\partial H}{\partial x_b} + e^{-rt}\left[\dot{P}_b + \mu J\frac{x_a + x_b}{(X_{a,cum}+X_{b,cum})^{\mu+1}} - \xi B\,\frac{(\xi-1)\,x_b^{\xi-2}\dot{x}_b X_{b,cum} - \zeta\, x_b^{\xi}}{X_{b,cum}{}^{\zeta+1}}\right].$$

Where $\dot{x}_a, \dot{x}_b$ are time derivatives of outputs x_a and x_b respectively, which are equal to growth rates for small changes. Accordingly $\dot{P}_a, \dot{P}_b$ are time derivatives of prices. To find the solution, we solve the system of equations (A.8):

A. 8 $$\begin{cases} \dfrac{\partial H}{\partial X_{a,cum}} - \dfrac{\partial}{\partial t}\left[\dfrac{\partial H}{\partial x_a}\right] = 0 \\ \dfrac{\partial H}{\partial X_{b,cum}} - \dfrac{\partial}{\partial t}\left[\dfrac{\partial H}{\partial x_b}\right] = 0 \end{cases}$$

Then we obtain the following first order conditions (FOCs):

$$\text{A. 9} \quad \begin{cases} \psi A \frac{x_a^{\phi}}{X_{a,cum}{}^{\psi+1}} + \phi A \frac{(\phi-1)x_a^{\phi-2}\dot{x}_a X_{a,cum} - \psi x_a^{\phi}}{X_{a,cum}{}^{\psi+1}} - r\phi A \frac{x_a^{\phi-1}}{X_{a,cum}{}^{\psi}} - \frac{Jr}{(X_{a,cum}+X_{b,cum})^{\mu}} - \dot{P}_a + rP_a = 0 \\ \zeta B \frac{x_b^{\xi}}{X_{b,cum}{}^{\zeta+1}} + \xi B \frac{(\xi-1)x_b^{\xi-2}\dot{x}_b X_{b,cum} - \zeta x_b^{\xi}}{X_{b,cum}{}^{\zeta+1}} - r\xi B \frac{x_b^{\xi-1}}{X_{b,cum}{}^{\zeta}} - \frac{Jr}{(X_{a,cum}+X_{b,cum})^{\mu}} - \dot{P}_b + rP_b = 0 \end{cases}$$

Lemma: The solution to *FOCs* is a global maximum of the firm problem.

Proof. Let us check that strict globalized version of Legendre condition is satisfied, since the second derivative $\nabla_{xx} H$:

$$\text{A. 10} \quad \nabla_{xx} H = \begin{bmatrix} -A\phi(\phi-1)\frac{x_a^{\phi-2}}{X_{a,cum}{}^{\psi}} e^{-rt} & 0 \\ 0 & -B\xi(\xi-1)\frac{x_b^{\xi-2}}{X_{b,cum}{}^{\zeta}} e^{-rt} \end{bmatrix}$$

$\nabla_{xx} H$ is negative definite whenever $\xi, \phi > 1$. Therefore, we can apply the strict Weierstrass condition and guarantee that the obtained solution is a strong local maximum. Note as well, that since $\pi(x_a, x_b)$ is a concave function, then the second variation would be negative, therefore, the local maximum is also a global one.

Appendix B: Propositions and proofs

Propositions B1 and *B2* are validating the economic intuition of the model:

Proposition B1. The present discounted value of expected life-time profit is increasing in prices P_a, P_b and the elasticities of learning by-doing ψ, ζ, μ.

Proof. This statement is evident from *FOCs* (Equation A.9, Appendix A).

Proposition B2. The profit is decreasing in first-unit costs *A, B, J*, and marginal cost growth of output φ and ξ.

Proof. Propositions B1 and B2 can be proven by taking the derivatives of profit function with respect to the corresponding parameters. Note that none of the parameters depends on time. Therefore, taking the derivative of the integral functional is the same as taking the derivative of the functional under the integral sign.

Proposition 1. The expected output of the innovative technology increases, if the learning by doing effect is greater than the price effect when prices decline.

Proof. Rearranging F.O. C. (Equation A.9, 0Appendix A) we can derive:

B. 1 $$\frac{\dot{P}_a}{P_a} - r = \frac{\psi A(1-\phi)x_a^{\phi}}{P_a X_{a,cum}^{\psi+1}} - r\phi A \frac{x_a^{\phi-1}}{P_a X_{a,cum}{}^{\psi}} - \frac{Jr}{(X_{a,cum}+X_{b,cum})^{\mu}} + \frac{\phi A(\phi-1)x_a^{\phi-1}\left({}^{\dot{x}_a}/_{x_a^{\phi}}\right)}{P_a X_{a,cum}^{\psi}}$$

We can further rearrange the term:

B. 2 $$\left({}^{\dot{x}_a}/_{x_a}\right) = \frac{P_a X_{a,cum}^{\psi}}{\phi A(\phi-1)}\left[\left(\frac{\dot{P}_a}{P_a} - r\right) + \frac{\psi A(\phi-1)x_a^{\phi}}{P_a X_{a,cum}^{\psi+1}} + r\phi A \frac{x_a^{\phi-1}}{P_a X_{a,cum}^{\psi}} + \frac{Jr}{(X_{a,cum}+X_{b,cum})^{\mu}}\right]$$

Where the left hand side is the growth of output and the right hand side (RHS) denotes affecting it factors.

As $\phi \geq 1$, the first three terms on the right hand side of Equation (B.2), which represent learning effect on the marginal cost, are negative. The last term, representing production growth effect, can be positive or negative depending on the growth rate of output *a*. Therefore, the cost function implies there may be an increase in volume of production and a reduction of price. Equation B.2 states that even if prices decline over time, production indeed remains profitable. As the cost function for output *b* is symmetrical to *a*, similar rule applies.

The next propositions describe the comparative statics of the profit function.

Proposition 2. *Production of one or both co-outputs may occur in early period even if at least one of them are not profitable, to accumulate learning of feedstock that will result in profitable supply chain in the longer term.*

Proof: From *Equations A.6* and *A.7*, it is evident that the more feedstock is produced in the first stage (macroalgae cultivation), the faster is learning at the first stage of production, and the unit production costs decrease, no matter whether the feedstock is mainly processed into output *a* or *b*. The economic meaning is that co-production has a positive complementarity effect of learning. The more profitable output contributes to the increase in productivity in the first stage of ISC (cultivation) that serves as an input also to the less profitable output of the second stage (processing). The feedstock accumulates faster, resulting cheaper unit costs to the benefit of all co-produced outputs a biorefinery.

Proposition 3a*. The growth rate of output is non-decreasing in output price growth and increasing if its price growth is higher than the interest rate.*

Proof. Derive $\dot{x}_a$ or $\dot{x}_b$ (time derivatives of outputs *a* and *b* which are equal to growth rates for small changes) from *F.O.C.* (Equation A.9):

B. 3 $$\dot{x}_a = \frac{{X_{a,cum}}^{\psi}}{A\phi(\phi-1)x_a^{\phi-2}} P_a \left(\frac{\dot{P}_a}{P_a} - r\right) \; and \; \dot{x}_b = \frac{{X_{b,cum}}^{\zeta}}{B\xi(\xi-1)x_{ab}^{\xi-2}} P_b \left(\frac{\dot{P}_b}{P_b} - r\right)$$

Evidently the growth rate of output is smaller than the growth rate of prices. Yet if price increases over time, the output increases over time too.

The dynamic nature of the model clarifies the intuition that if the price growth is higher than the discount rate, then increasing production is profitable.

Proposition 3b. *If learning is faster than the increase in costs, then output grows faster than prices.*

The output growth is non-decreasing in output price growth, and non-increasing in output price level.

Proof: The time derivatives of output with respect to the time derivative of own price is (for output *a*, since for *b* they would look symmetric):

B. 4 $$\frac{\partial \dot{x}_a}{\partial \dot{P}_a} = \frac{{X_{a,cum}}^{\psi}}{A\phi(\phi-1)x_a^{\phi-2}} \geq 0$$

Keeping in mind that the numerator in *Equation B.4* represents learning and the denominator represents costs of the second stage of production, the result indicates that if learning is faster than the increase in costs, output grows faster than prices.