REAL OPTIONS FOR AGRICULTURE TECHNOLOGY: A VENTURE CAPITAL VALUATION APPROACH

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Real Options for Agriculture Technology: A Venture Capital Valuation Approach

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ABSTRACT

For startups and young companies, there is significant uncertainty and managerial flexibility within a company's business model, research and development (R&D) processes, and commercialization strategy. These characteristics make early stage companies difficult to value. While the predominant valuation tools used include discounted cash flow and multiples analysis, their fixed assumptions and improper risk adjustment tend to undervalue startups with managerial flexibility, uncertainty, and high growth potential. This thesis utilizes stochastic real options to assist with the valuation process for agricultural technology startups in order to better reflect uncertainty, managerial flexibility, and asymmetric growth that is existent. The stochastic real options are integrated into decision trees to account for uncertainty and the two types of risk, being private and market risk. While this application is used for two case studies of startups in agricultural technology, the method can be applied to different startups with varying scenarios and industries.

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CHAPTER 1. INTRODUCTION

1.1. Overview

The agricultural technology sector has seen rapid progress with investment, corporate acquisition, and startup companies. Much of this recent investment rise can be attributed to (a) a growing population and decreasing arable farmland acres, (b) concerns about the environmental effect of agriculture, and (c) a realization about the minimal digitization relative to other industries. The field of venture capital investments in agriculture technology (AgTech) has been popular in recent years. This rise for AgTech has made valuation in the sector an important challenge to consider. With an industry that is challenged by risk and uncertainty, consolidation, and growth, different valuation approaches outside the mainstream methods need to be considered in order to account for managerial flexibility.

Difficult investment environments, such as historic lows for U.S. interest rates and negative interest rates across the globe, have placed attention on new strategies to increase the return on investment. While public securities, such as equities, provide a way to generate fair investment returns, underfunded pension funds across the globe have searched for ways to receive a higher return than traditional public market rates in an attempt to play catch up with pension funding. This route has led institutional and high net-worth investors to seek additional allocation in areas such as leveraged-buyout private equity and venture capital. On average, the latter alternatives offer higher returns for investors while carrying greater risk and uncertainty. Leveraged buyouts require an ample amount of debt to fund the purchase, usually around 70% debt and 30% equity. Venture capital typically does not include any debt but holds investments in early stage companies with vast risk and uncertainty for product or service offerings, go-to-market strategies, and funding viability. Given the interest in higher potential returns and the low cost of debt via leveraged buyouts, private equity and venture capital have received record funds from investors. Specifically, venture capital (VC) has stolen much attention in the investment industry because of the number of notable initial public offerings (IPOs) and record unicorn companies (>$1 billion valuations). Teare (2019) reported that 2018 saw a record of 151 new unicorn startups. In 2019, there were 452 unicorn companies that raised $345.1 billion, for a total valuation of $1.6 trillion. Specifically, agriculture technology has seen an uptick in VC investment with nearly $20 billion in 2019. While venture capital can be a method for delivering strong investment returns, the approach carries significant risk and uncertainty. The traditional industry of venture capital holds a “home-run” investment philosophy, meaning that, while most portfolio companies are likely to fail, just one or two companies make up the entirety of a portfolio’s return. This concept is based on pure probability standards because most startups fail. One or two startups may hold a higher probability of becoming a $1+ billion company, which can make up the entire portfolio’s return given the magnitude. With all the uncertainty placed into the future of these startups, one of the only things an investor has control over is the price paid or the valuation. While creating an accurate valuation for a startup is nearly impossible, a model must host flexibility given the optionality that takes place over the evolution of startups. Traditionally, most valuations are produced via discounted cash flow or market multiples. In many cases, these methods include fixed assumptions that lack managerial flexibility, proving to be unfit for the vast risk and uncertainty of startups.

This study’s purpose is to develop alternative valuation approaches that account for risk and uncertainty, allowing managerial flexibility as the startup evolves in different stages of expansion and applying that valuation to AgTech startups. This alternative approach includes binomial and decision trees, real options, and stochastic simulation that are applied to two different AgTech startup case studies. The stochastic nature of inputs allows for probability distributions which can incorporate better uncertainty versus fixed assumptions. Real options allow for managerial flexibility to be present in the model, while the combination of binomial and decision trees account for the two main risk types, private and market.

This chapter introduces the background of venture capital investment in agricultural technology and the evolution in that space. The chapter also touches on the mainstream valuation methodologies used among investors for negotiations between startups and venture capital firms. Throughout the chapter, industry trends and methodologies are discussed to establish the foundation in this thesis in order to better understand the relevance of utilizing valuation alternatives.

1.2. Evolution of AgTech Funding

There has been a significant uptick in capital investment towards the agriculture industry in recent years; this money largely focuses on agriculture technology (AgTech). While publicly traded securities and leveraged buyout private equity have been a source of this investment, most investments have been established via venture capital. Because venture capital (VC) is often used to fund solutions for emerging problems, it is intuitive to understand the interest in agriculture. “The 9 Billion” (2011) identifies one problem in agriculture as the 9-billion people problem. The United Nations estimates that there will be approximately 9.7 billion humans globally by 2050. The combination of decreasing total farmland and increasing demands for food, specifically protein, creates a significant need for problem solving. In addition, developing nations and a rising middle class are demanding higher-quality food with sustainability driving the conversation. The ability to innovate is not new for the industry because combinations of mechanical and chemical technologies have allowed productivity gains to double in the last 50 years with little change in the aggregate quantity of inputs (Alston, Andersen, James, & Pardey, 2010). While innovation has persisted, global agriculture is estimated to contribute about one-fourth of the world's carbon emissions, making sustainable agriculture an important factor in this era that seeks to increase production. Hence, one must produce more with less.

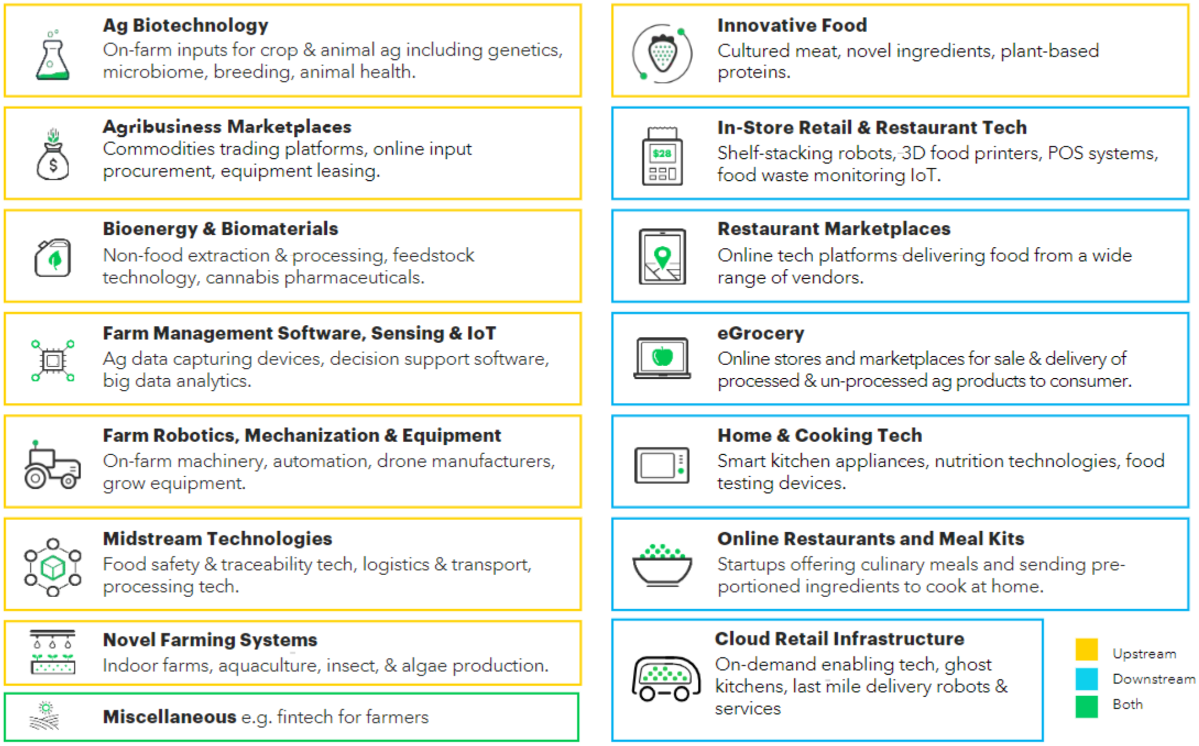
Agricultural has been encouraged for years as a viable investment candidate (Food and Agriculture Organization [FAO] of the United Nations, 2012; Hancock Investment Group, 2009; Kleinwot Benson Investors, 2010). During the early 2000s, agriculture was perceived to be attractive given the negative correlation to equities and the relation to inflation. By 2016, thirteen different agricultural firms had raised more than $1 billion in assets under management. In recent years, AgTech has been viewed as attractive because of the strong investment-return potential that it can produce. While some AgTech funds began to appear in the early 2000s, an acceleration came after the 2013 Monsanto acquisition of Climate Corp for $1.1 billion. According to AgFunder (2018), global AgTech had an increase in deal value from $309 million to $1.3 billion between 2013 and 2017. By 2017, there were 76 different VC and private equity (PE) firms involved with agriculture. Following the increased funding by VC and PE during the period, corporate ventures also sought interest in the space. These new endeavors largely existed as current agriculture and food operators that were willing to invest corporate cash into innovative technologies. Examples included Monsanto Growth Ventures and Syngenta Ventures; these companies hoped to increase their presence in biologics and yield-boosting biotechnology. Food companies such as General Mills and Kellogg also followed this strategy to diversify into the growing market created by health-conscious consumers. The common purposes for these corporate ventures seemed to be (a) facilitating the best technology, (b) offsetting the fear of being left behind, (c) leveraging capital, (d) diversifying portfolios, and (e) forming new partnerships (Wilson & Vetsch, 2020).

In 2019, there was a total of $19.8 billion of global AgTech investments across 1,858 deals and 2,344 unique investors (AgFunder, 2020). This investment amount is down slightly from the 2018 investment of $20.8 billion. The largest transition of capital inflow took place between 2017 and 2018, with an increase of $9.3 billion. In the past 5 years from 2015 to 2019, there has been a 250% growth for investment towards AgTech. In the same AgFunder (2020) report, downstream AgTech dominated much of the overall investment: nearly 50% of the money was contributed to the sectors of eGrocer, cloud retail infrastructure, and restaurant marketplaces. This asymmetric allocation to downstream versus upstream and midstream may be attributed to larger addressable markets as well as the complexity of upstream or midstream technology. In 2019, California hosted the majority of the total AgTech investment, with $4.9 billion allocated to startups within the state; Massachusetts was in second place with $1.1 billion.

AgTech continues to grow as the space becomes a notable area to sustain the planet and keep climate change in check. Figure 1.1 illustrates the sizeable opportunities that are possible in the trillion-dollar agriculture industry. Outside regenerative agriculture and biologics, innovative food technology has been distinguished as another factor for opposing carbon emissions. This interest in food technology was represented by the 2019 IPO of plant-based Beyond Meat; the company's market cap rose more than 250% in the months following the offering. Additionally, plant-based Impossible Foods had a 2020 capital raise of $500 million, and Memphis Meat, a cultured-meat startup, raised $161 million the same year (Min, 2019; Rowland, 2020; Shieber, 2020).

Figure 1.1

Agri-FoodTech Category Definitions (AgFunder 2020, p. 21)



1.3. Valuation Methodologies

Investors and institutions across the investment horizon share similar tools and processes to measure investment potential. While assumptions, trends, and dynamics vary across industries, assets, and scope, the valuation procedures are consistent. A startup's stage and financial positioning determine the type of valuation procedure to use. In the case of pre-revenue or very early stage startups, methodologies including risk-factor summation, the venture-capital method, or scorecard valuation are commonly utilized. If the startup is later in its development and produces income, a discounted cash flow or market multiples valuation is used. Even if revenue or a profit is not present or soon to be, a discounted cash flow model may still be used to generate a value.

Two predominantly utilized tools for valuation are discounted cash flows and market multiples (Holthausen & Zmijewski, 2012). Although the situation matters regarding how or which one to use, these two methodologies can be applied to different asset types, such as public equities, private equities, or real estate. These tools have been promoted for many years and continue to be the desired options for valuation. However, the techniques also carry fixed assumptions that lack the flexibility and randomness which venture capital has to offer. Alternative methodologies, including stochastic real options and decision trees are introduced in this study in order to discuss the benefits and apply all tools to the process of valuation given extreme risk and uncertainty.

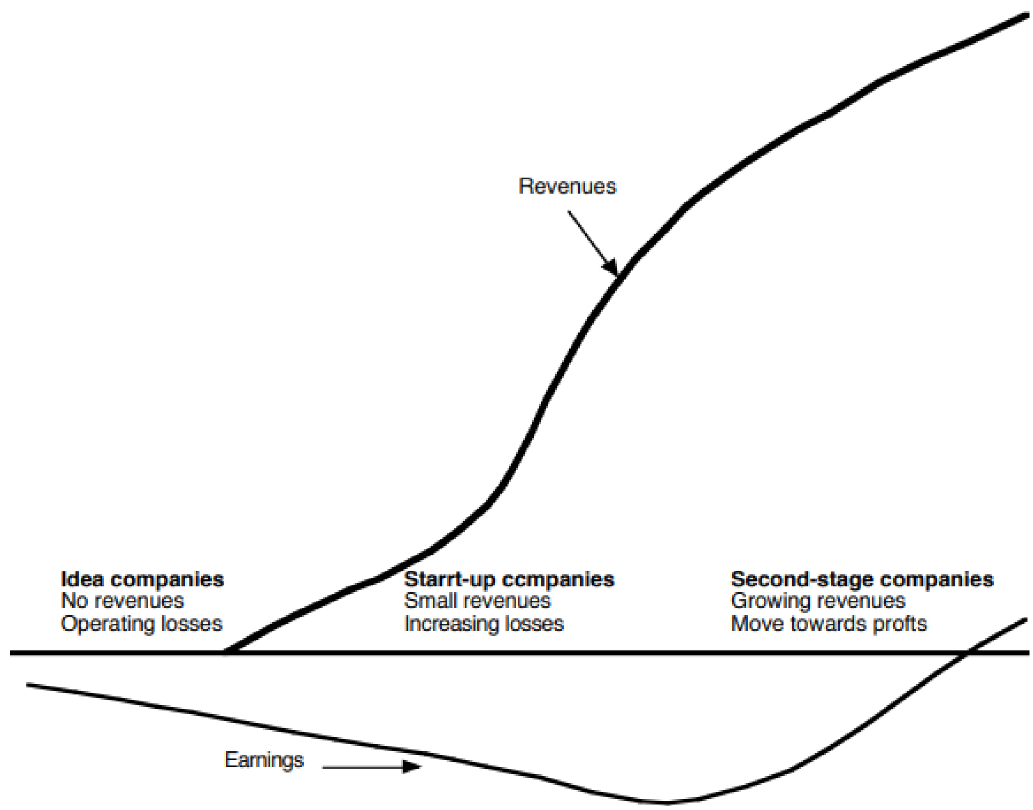
1.4. Problem Statement

As an early stage investor, there is significant risk and uncertainty for an investment; the valuation is the one thing that an investor can control. By overpaying for a company, the investor already sets up the opportunity for failure because the chances of fulfilling a higher valuation go down immensely. Because VC is largely a process of a single company fulfilling the portfolio's return, an overvalued investment makes the entire return much harder to achieve. Likewise, undervaluing a company can also be detrimental to VC. When an investor undervalues a startup that becomes a 10x return on investment, the investor loses a significant opportunity cost. Therefore, the chance of missing out becomes a substantial risk that is not typically considered.

In many cases, common valuation methodologies provide a good means for investment analysis. However, these methodologies lose effectiveness as uncertainty increases. Figure 1.2 illustrates the theoretical life cycle of an early stage company through years of existence. In this illustration, it is evident that there are many different avenues the company may decide to take, which can be represented as options or alternative paths. Additionally, methodologies that rely on forecasting cash flows for valuation (DCF) can prove difficult given the trailing time period of negative earnings. As a startup begins its life cycle, there is no revenue and only cash burn as significant spending in research and development (R&D) is performed. Even while revenue begins to see generation, the acceleration of growth requires even more spending to fulfill the demand. Hence, the startup can go years without seeing profitability and positive cash flow.

Figure 1.2

Early Stages of a Company's Life Cycle (Damodaran, 2009, p. 4)



Illustrating the concept of managerial flexibility, the startup may decide to move into additional industries and to increase the total addressable market. This action drastically changes the startup's value and the potential future value. Another example is the range of costs that a startup may have, such as research and development, or marketing. While the startup would hope to scale costs, competition or struggles may prevent the company from doing so. This assumption is critical for the startup to reach profitability and has a huge effect on both valuation and operational strategy. These examples are just a few of the critical variables that influence viability and strongly indicate the need to introduce flexibility into the model. Because both the discounted cash flow and multiples methodologies cannot offer this notion, additional options must be considered for improved deal negotiation in order to benefit both parties.

After discussing the pitfalls for discounted cash flow and multiples valuation, these traditional methods place skepticism in the practice of VC investments. However, these are still the dominant tools for valuing startups in today's environment. In this case, an assumption can be made that most deal negotiation that is based on valuing venture capital is improperly structured given the true risk and return. To tie this problem into agriculture, the lack of public AgTech companies (excluding legacy firms such as BASF, Bayer, etc.) and the increased funding only in recent years have made the past paths to follow non-existent. In addition, agriculture is a volatile industry (Wilson & Vetsch, 2020) that is largely dominated by a few corporate players. With the industry subject to minority rule by many investors (especially in upstream and midstream agriculture), valuations can be misunderstood and misrepresented. With the extra tailwind of uncertainty in agriculture, valuation methodologies that include managerial flexibility are important for the growing field of AgTech VC.

1.5. Objectives, Procedures, and Hypothesis

This study's purpose is to apply alternative valuation approaches that better account for risk and uncertainty with AgTech startups by using stochastic real options and decision trees all in one framework. The specific objectives include (a) applying the decision tree and binomial lattice to consider private and market risk, (b) utilizing real options to value managerial flexibility, and (c) valuing the entire startup. This application is demonstrated on two AgTech startups that feature different industry dynamics (e.g., biotechnology and plant-based meat). Discounted cash flow models are first constructed to find the underlying net present value (NPV) for the company products. To consider both private and public risks, real options are integrated into decision trees to map potential options for the startups during discrete periods. Finally, stochastic simulation through Monte Carlo is applied to variables within the models in order to account for randomness and to display the valuation's sensitivity. This entire procedure allows the valuation model to host managerial flexibility, properly represent risk, and provide a strategic map in evaluating optionality. With the addition of stochastic real options and decision trees, the valuation models can be better exploited for risk analysis and investment decisions under uncertainty. Not only does this add to a more precise valuation of real-world risks, but the approach also corresponds with a stronger deal negotiating power. Because this strategy places more power in flexibility than fixed assumptions, the ability to defend and to articulate deal negotiation is improved and expedited for both parties.

1.6. Organization

The study is organized as follows: Chapter 2 reviews previous studies and research performed on this topic. With the real option procedure popular among academia, the literature is rich but limited in the terms of agriculture and venture capital. Chapter 3 explores the theory behind valuation tools such as DCF, multiples, real options, and more. The chapter explains the pros and cons as well as outlining a theoretical framework that leads to the applied case studies. Chapter 4 introduces the first case-study startup and applies the model while summarizing the results. Chapter 5's case study takes a similar structure to Chapter 4 but with the second company. Finally, Chapter 6 summarizes the entire study along with limitations, literature contributions, and further research suggestions.

CHAPTER 2. BACKGROUND AND RELEVANT STUDIES

2.1. Scope of Background and Studies

The sections in this chapter focus on industry dynamics and the previous studies related to this study's topic. Research and the background literature are complemented by both academic and industry studies. The mixture of these draws out interesting results because academia tends to focus on the methodology and theoretical uses of modeling while industry attempts to apply them to case studies and deal-making. The sections included below are characterized by similar goals and purposes for the past studies which focused on multiple themes, such as agriculture as an asset class, AgTech funding, and valuation methodologies using real options and stochastic simulation. Overall, there is little work that combines the emerging growth in AgTech investment with flexible risk-adjusted valuation. The chapter closes with a discussion about why this study is different and the valuable extensions that it brings to past work.

2.2. Investment in Agriculture

There has been a 20-year evolution within agricultural investment. Until 2015, participation in agricultural investment was primarily public securities or farmland (Wilson & Vetsch, 2020). Since then, industry investment has moved to AgTech venture capital. Major AgTech acquisitions such as Blue River Technology (John Deere acquirer for $305 million in 2017) and Climate Corp (Monsanto acquirer for $1.1 billion in 2013) have driven investor interest for firms with similar goals of significant investment returns (Ag Professional, 2017; Schwartz, 2013). Other motives for investing in AgTech include the need to feed a growing population while faced with declining arable farmland. According to FAO of the United Nations (2012), the year 2050 should see the world's population reach 9 billion people, implying a need for 70% food-requirement increases. Agriculture's influence on climate change and capabilities to mitigate climate change (e.g., regenerative farming and biologics) have driven environmental-social-governance (ESG) investing interest. Finally, the farming industry is viewed as being ripe for disruption (Sousa, 2019). The combination of non-digitized farming techniques and the domination of legacy players throughout the supply chain are signs of potential industry disruption.

The following sub-sections explain this evolution and provide the background for the amount of investment that has taken place in this space. First, agriculture as a form of asset classes is introduced, followed by AgTech funding. This section is finished by summarizing the characteristics and dynamics within AgTech venture capital.

2.2.1. Agriculture as an Asset Class

Agriculture has been described as the perfect investment given favorable returns, the relationship to inflation, low risk, and a negative correlation to equities (Hancock Agricultural Investment Group, 2009). Macquarie Agriculture Funds Management (2012), German and Martin (2011), and Martin (2011) all suggested that farmland should be included in a diverse portfolio. Malloy (2019) described the motivation for growth in farmland investment, which is largely influenced by a double tailwind of rent and appreciation. The same authors suggested little or no correlation for other asset classes, pushing the idea of great diversification.

While farmland is certainly a large part of agriculture, capital allocation in the entire value chain is something that has been less popularized. Kleinwot Benson Investors (2010) proposed that a suggested agriculture portfolio should be comprised of agri-processors, agri-service suppliers, and producers. Chen, Wilson, Larsen, and Dahl (2015) studied the value chain using a mean-value at risk with a copula portfolio. Results pointed to farmland as an important asset, but there was an allocation shift to other agriculture assets with greater returns as risk tolerance increased. In a revisited topic, Wilson and Vetsch (2020) studied the wide variety of sectors in the entire agriculture value chain and concluded that there was a strong absolute return between 2005 and 2019, receiving better cumulative gains than the S&P 500. The mean-conditional value at risk model proposed maximum allocations for most AgTech firms, such as Raven Industries, Trimble, and Renewable Energy Group.

While broad agriculture as an asset class morphs into a larger focus on AgTech, specific VC funds in this space can drive this concept further. With the industry's unique traits, it is valid for investors to view these assets as a separate entity.

2.2.2. Agricultural Technology Funding

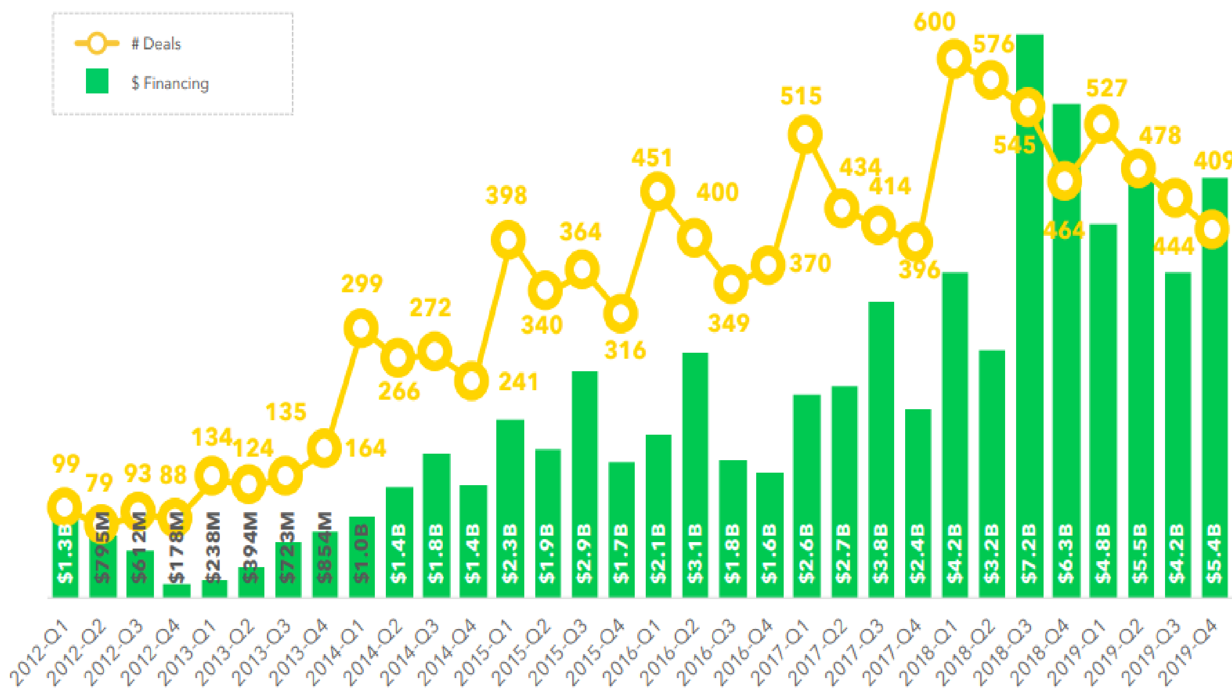
When discussing the environment of funding in AgTech, the focus is on venture capital. Because this topic is more applicable to industry, we would expect most of the research to be performed by industry. AgFunder, an AgTech VC with a proprietary database ecosystem of AgTech startups, reported tremendous growth for global AgTech VC funding: 250% growth from 2014 and 2019. AgFunder (2020) reported a total global investment of $19.8 billion in 2019, up from $2.9 billion in 2012. While upstream agriculture still receives good representation, downstream tends to generate more funding with nearly double the capital of $12 billion. Based on 2019 results, the category of bioenergy and biomaterials generated the largest median deal size of $3.5 million per deal, followed by eGrocer and restaurant marketplaces, both drawing $3.4 million. Other categories above the $3.0 million median deal size included biotechnology, innovative food, and midstream technologies.

Deal volume and activity by stage play a large factor in the funding dynamics. In VC, there is common jargon that refers to the different funding stages. The first official round of funding is a seed stage followed by series A, series B, etc., until the company either becomes profitable, enlists on an exchange, or is acquired. In 2019, seed stage earned a total of 1,090 deals, for a total of $859 million, while the late stages (series E and later) received $7.0 billion with just 119 deals. The next-largest stage was series B with a total of $3.8 billion across 169 deals. As discussed in Chapter 1, VC is a “homerun”-like process. This is evident given deal averages and medians by stage, with series D having average and median deal sizes of $78 million and $35 million, respectively. Similarly, the late stage saw the same effect, with average and median sizes of $80 million and $22 million across the globe. (AgFunder, 2020). Interestingly, the later stage’s average size was barely higher than series D funding while the median size was significantly lower versus the series D. This explains that, after series D, valuation and capital raising become difficult, and the startups do not see much of a valuation increase. From a geographic standpoint, the United States has the largest allocation of total funding: $8.7 billion across 653 deals. China follows the U.S. with $3.2 billion from 181 deals. Thereafter, funding drops significantly, with only India, the United Kingdom, and Columbia having greater than $1.0 billion in funding. Figure 2.1 illustrates the growing volume, in terms of the number of deals and size, over time. Although 2019 saw a small decline, the overall trend has increased.

In high-income, developed countries, government funding for agricultural research and development (R&D) has seen deceleration while investment within the industry has steadily increased (Fuglie et al., 2011). In the past, the government has been an essential player for R&D through funded research stations and universities, hoping to increase a strong and safe domestic food supply. Historically, private R&D has been less in emerging countries. However, these same low- to middle-income countries are now becoming large players in private R&D.

Figure 2.1

Quarterly Deal Volume and Activity (AgFunder, 2020, p. 15)



Silva, Graff, and Zilberman (2020) attempted to understand the motives behind the increased VC funding for AgTech. They used regression analysis on AgTech investment against commodity prices to test whether commodity prices have a factor with the increased investment for AgTech. They also regressed exit events to AgTech investment to test if there were a herding effect on large exit events and increased investment. There is thought that, when commodity prices increase, the broad industry of agriculture becomes more attractive, hence the inflow of VC investment. This concept does host a trickle-down effect because high commodity prices not only positively affect producers, but also distributors and manufacturers. The success of large agricultural companies allows corporations to increase cash flow and incorporate internal investment. While this investment can be internal R&D, the increase in AgTech mergers and acquisitions (M&A) explains that corporate R&D can be better achieved through AgTech acquisitions or licensing. Silva et al.'s model suggested that increased commodity prices and larger exits (liquidity events such as IPOs or acquisition) do increase VC investment in AgTech. Using dummy variables to represent location, the team also concluded that U.S.-based startups receive greater funding than non-U.S.-based startups. The academic literature's results are consistent with what has been seen in the private-sector reporting.

2.2.3. Characteristics of Agriculture Venture Capital

The agricultural industry features a few big companies which tend to have strong brand name and supply chain control of the industry. Because of this strong foothold, startups have turned from a disruption strategy only to one that works in conjunction with legacy companies to commercialization products and illustrate go-to-market strategies. While legacy products and applications continue to exist, new forms of technology within the supply chain have caused innovative methods to evolve.

The AgTech industry is broad and is broken down by upstream, midstream, and downstream classifications. The upstream category refers to the agriculture inputs. Popular upstream technologies include biotechnology, equipment robotics and mechanization, novel farming systems (e.g., indoor farms, aquaculture, and insect productions), farm-management software, sensing, and the internet of things (IoT). In terms of funding, biotechnology and innovative food garner over $1 billion each (AgFunder, 2020). These areas, largely focusing on biologics and plant-based meats, can be motivationally driven by climate-change efforts. The total space for upstream agriculture received $5.5 billion (excluding midstream) in 2019.

Midstream agriculture is the point where the upstream meats the downstream to make the holistic value chain viable. Scott (2015) defined the midstream sector as being food production such as meat, fish, animal feed, and dairy. This is, of course, the traditional concept of a midstream. AgFunder (2020) classified midstream technologies, perhaps a better, updated view of the category, as food safety and traceability tech, logistics and transport, and processing. In recent years, varieties for this midstream technology have taken the form of blockchain traceability or online marketplaces. The midstream category received the least amount of funding, relative to all three categories, in 2019, for a total of $2.1 billion.

The downstream agriculture sector is referred to as food processing (Scott, 2015). Like the midstream classification, this category's definition has expanded over time as technology became more prominent. AgFunder (2020) includes fewer conventional businesses in the downstream group such as food delivery, meal kits, restaurant marketplaces, and food-waste monitoring. The downstream classification has received more funding and larger deal values relative to other categories: $12 billion in 2019 with the largest deal being $1 billion. The potential reasoning may be the larger total addressable market that downstream corporations can receive. While the upstream and midstream categories typically just see exposure to producers and manufacturers, the downstream companies can, theoretically, touch every individual on the globe.

The agriculture industry has long been dominated by big corporations, commonly called "big ag." This dynamic has been largely true for specific sectors such as seed and chemicals, machinery, and processing. MacDonald (2019) reported the six major seed and chemical firms of 2015 as BASF, Bayer, Dow Chemical, DuPont, Monsanto, and Syngenta. In 2000, the four largest agribusiness companies combined for 51% of U.S. soybean seed sold. In 2015, those same companies increased their total share to 76% (Moon, 2019). Since 2015, there have been three major acquisitions that raised antitrust issues: ChemChina's acquisition of Syngenta, the Dow Chemical-DuPont merger, and the Bayer-Monsanto merger. The U.S. Department of

Agriculture (USDA) recognized antitrust concerns with two broad issues: (a) high price floors for farmers and (b) reduced R&D expenditures and a lack of future innovation incentives.

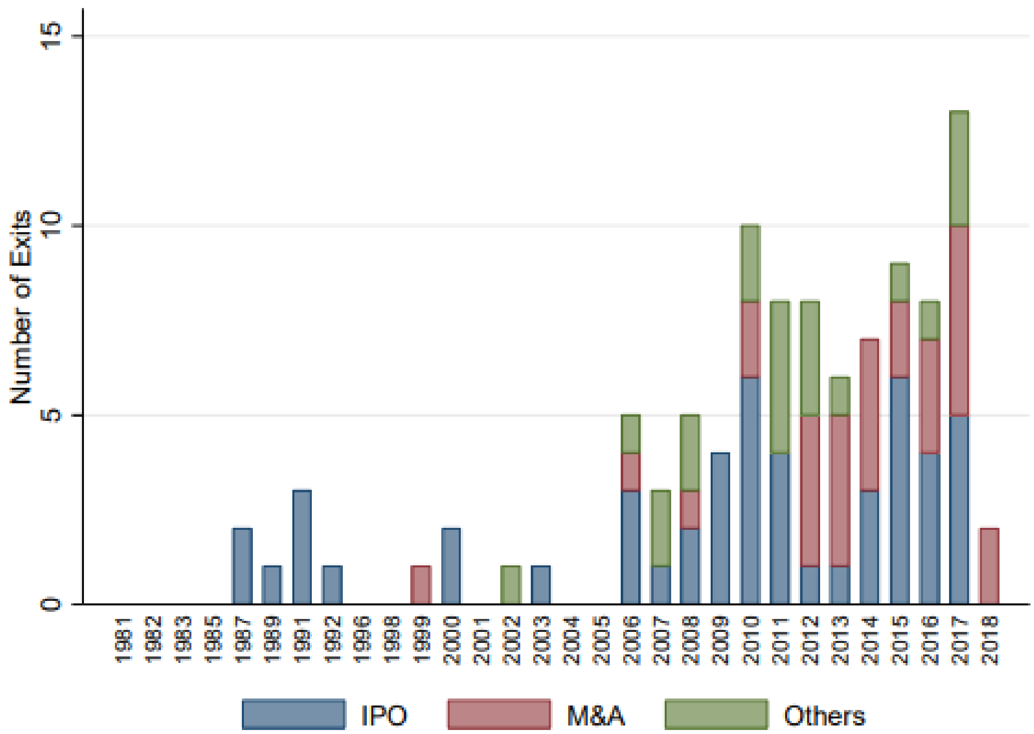
The processing industry has also seen lawsuit allegations among the "big four," referring to Tyson Foods, JBS, Cargill, and National Beef Packing. These four processers collectively purchase and process over 80% of the U.S.-fed cattle annually (Welshans, 2019). Recent lawsuits point to the allegations of conspiring to depress prices for cattle purchased from American ranchers from 2015 to the present day.

While big ag may have been a bottleneck for agricultural startup innovation, depressed farm income has forced producers to find alternatives to earn a premium. Excluding federal support, 2019 featured the second-lowest net farm income since 2010 (Farm Bureau, 2019). The popularization of agriculture technology creates many different ways in which this trend can be reversed. For example, biologics have allowed integrated pest management (IPM) programs to grow and to gain efficacy. Online marketplaces allow more producers to sell and source products directly with the other parties, avoiding middleman costs. This new interest has forced big ag to partner with AgTech startups to create better products and produce more with less.

With a long-practiced agriculture industry that is prime for technological advancements, startups have three primary options: to compete among legacy ag companies, license technology, or become acquired. Verdant Partners (2020) recorded nearly 20 M&A deals (excluding 10 animal-tech deals) in 2019, down slightly from 2018. However, the long-term trend has been strong since 2012 when there were deals in the low single digits. Since 2012, there have been only two years with a decreased deal count. Silva et al. (2020) showed similar results, with a significant uptick in the overall exit activity starting in 2006. Given the data for startups that reported an exit, both IPOs and M&As exhibited encouraging activity. Figure 2.2 illustrates the previous comments. It also presents that different exit types do not carry a clear trend. Combinations of IPO, M&A, and others vary significantly from year-to-year. This unclear trend strengths prior comments made of historic path dependency being difficult for AgTech given the novelty today.

Figure 2.2

Exit Events Over the Period 1981-2018 (Silva et al., 2020, p. 18)



While the number of exits gained traction, the deals' value did as well. While the IPO valuations consistently remain below the $1-billion mark, M&A has significant spikes in total valuation. For example, in 2013, M&A deals contributed almost $6 billion in value. Likewise, 2018 saw over $4 billion of value from M&A (Silva et al., 2020; Verdant Partners, 2020). While M&A has played an important role in strategic directions for AgTech startups, the accelerated capital in the industry may be able to sustain these startups longer in order to disrupt the industry as a standalone enterprise, perhaps reaching IPO status. This is yet to be determined.

2.3. Conventional Methods for Venture Capital Valuation

The evolution of valuation has, accordingly, brought different tools and processes to value an asset. No method is perfect, especially for venture capital where startups do not have established financials or, many times, a thorough business plan. Many valuation practices become a derivative of the investor's philosophy. Some approaches are rather scientific while other approaches lack scientific rigor. Although much of the valuation procedure depends on the investment's specifics, an agreement among all is that some sort of price must be established to have a starting point for party negotiation. The following subsections describe different models that are used for general valuation but are focused on VC. While discounted cash flow and market multiples are common approaches to value other forms of asset classes (e.g., public equities or real estate), the remaining tools are predominantly used with venture capital only.

2.3.1. Discounted Cash Flow (DCF)

The most common, and intuitive, approach for valuing an asset is the discounted cash flow model. With this form, the forecasted cash flows to be produced by a given asset are discounted by a risk-adjusted rate to achieve the present-day value. The DCF technique requires an understanding of compound interest and the ability to forecast cash inflows and outflows for an investment (Parker, 1968). While DCF has been modified for better use, the concept of compound interest traces back to at least 1800-1600 B.C. in Mesopotamia. Another important framework in the underlying model is time-value-of-money, with an assumption that a dollar amount today is more valuable than a dollar amount in the future if there is the ability to invest and to achieve a return on that original dollar. Parker (1968) elaborated that this present-value approach became evident in financial investment as early as 1582. However, the DCF model did not become widespread until the 1960s.

While DCF valuation leads to the asset's intrinsic value, many assumptions must be evaluated and used to achieve the outcome. Damodaran (2009) point to four pieces that make up this intrinsic value: (a) cash flows from existing assets, (b) expected growth from new investments and improved efficiency for existing assets, (c) the discount rates from an assessment of risk with both business and equity, and (d) an assessment of when the firm would become a stable growth company (to estimate terminal value). With this outcome, the valuation is only as good as the defined assumptions.

A DCF model has and continues to be a great tool to value opportunity and investment; however, the standalone model presents problems when assigning uncertainty. The lack of flexibility for time and opportunities can create problematic valuations. Keeley, Punjabi, and Turki (1996) found that, when valuing venture capital startups, the DCF method underestimated the value compared to the real option models. In a comparative study, DCF offered a negative net present value for all three case studies while the real options model provided all positive values. Keeley et al. noted that the weaknesses for DCF reside in the assumption of follow-on investments being made, regardless of the venture's interim performance. Similarly, Damodaran (2001) expressed his concern about DCF for early stage technology companies, with the model ignoring the potential markets that companies can disrupt. Instead, Damodaran argued that a premium can be added to the standalone DCF value given the optionality which the future may have on high, scalable growth potential.

For additional criticism about DCF use with young companies, Damodaran (2009) illustrated that the four main pieces of intrinsic value are also the problem with the model's faults for uncertainty. First, a startup's existing assets are limited. The growth of assets, both for existing and future investment, is unclear in what the actual business model or strategy may evolve with no promise that the startup continues as a viably funded business. The discount rate, for risk consideration, is often drawn from the availability of market prices, making it difficult for privately traded companies. Finally, it is not unusual that the terminal value may account for 90-100% of the total company value. Without knowing when the company would reach stable growth so early in the life cycle, the terminal value becomes a guessing game.

2.3.2. Market Multiples

Another commonly used valuation tool is the market multiples approach, which is also known as relative valuation or comparable company analysis. With this method, the objective is to price an asset relative to peers instead of discovering the asset's intrinsic value. From the given asset, similar peers are identified and compared to different metrics to form a relative value for the asset. A significant benefit of this procedure versus the discounted cash flow is the diminishing need for assumptions. While operational forecasts must still be made, additional assumptions about working capital, investing activities, and financing activities can be ignored. Depending on the type of multiple used, the financial metric is either applied to a multiple that the individual asset contains or to the average (or median) multiple of the peer group.

Although market multiple valuation is straightforward, the outcome is largely defined by the peers used in the analysis and the multiple being applied. The first step is to form a group of peer companies that are similar to the target company. Some comparable attributes to screen for include industry classification, geography, size, growth rate, and profitability (Corporate Finance Institute, n.d.). The technical explanation for multiples is that of a ratio. The numerator for most multiples is based on the enterprise value or equity value while the denominator is usually related to cash flow, earnings, revenue, or book value (Holthausen & Zmijewski, 2012). In the late 1990s, while the internet market began to materialize, these young companies had negative profits, little revenue, or negligible book values. Damodaran (2001) noted that a new standard to fight this unconventional problem was to use novel metrics, such as customer acquisition cost, customer retention, lifetime value per customer, and multiples for website hits or subscribers, in the denominator. Although not proven, these latter methods may also have been a reason for the internet bubble that was seen in the late 1990s and early 2000s. Ultimately, the right kind of multiple to use is dependent on the scenario. A price-to-earnings (PE) ratio is one of the most-utilized multiples; however, capital structure and deprecation measures can create a bias for a consistent comparison among different companies. The enterprise value-to-earning before interest, tax, depreciation, and amortization (EV/EBITDA) multiple does not have the same problems as the PE ratio and can be a better proxy for a true cash flow comparison. For this reason, EV/EBITDA has gained traction in the industry. For early stage companies, these two popular multiples may not suffice because it takes positive earnings to use them. Therefore, EV/revenue is popular if the company has negative earnings. Still, the startup may be pre-revenue, making an EV/revenue unattainable. Figure 2.3 exemplifies the attractiveness of EV/EBITDA multiples because one can simply compare different industries. Since mid-2018, both agricultural products and services, and producers have traded lower than the broad S&P 500 index (a good market barometer). These multiples help to put valuations into perspective for different industries, such as agriculture, and where the industry trades relative to the market. While this example illustrates multiples use among sectors, the same format can be done for separate companies to compare valuations.

Figure 2.3

Public Market Multiples Comparison (Moss Adams, 2020, p. 4)

Holthausen and Zmijewski (2012) described the importance of performing thorough due diligence regarding the proposed peer group versus simply calculating a mean or median multiple for companies in a particular Standard Industrial Classification (SIC) code or industry. They found that value drivers, such as cost structure, working capital, and capital expenditure requirements, were important when deriving an accurate assessment of market multiples.

A popular strategic direction for startups is acquisition. A way to determine the valuation for M&A activity is precedent transactions or multiples at the purchase price. This offers guidance about profiles of past sales and how relevant the information could be to an upcoming acquisition. Table 2.1 shows multiple large transactions that took place within the agriculture industry. Although specific functions for these companies are different, a range of nearly a 10x multiplier exists between the EBITDA multiples. In precedent transaction multiples, it is common to see a premium from market-trading multiples because an acquisition offer typically needs to be at a premium in order to encourage a vote for a sale from the selling company.

Table 2.1

List of Agriculture Transaction Multiples

Total Sales Price	Historic EBITDA	EBITDA Multiple	Transaction
$240,000,000	$40,000,000	6.00x	Dakota Growers Pasta to Viterra
$330,000,000	$42,000,000	7.86x	Viterra to Glencore
$370,000,000	$44,000,000	8.41x	Glencore to Post Holdings
$4,600,000,000	$650,000,000	7.08x	Gavilon to Marubeni
$43,000,000,000	$2,700,000,000	15.93x	Syngenta to ChemChina

Like the DCF, market multiples also pose problems with valuation proxies for early stage companies, including venture capital. Damodaran (2009) lays out five critical problems that a multiples approach has for these companies. One problem is a lack of conventional financials to attach a multiple to because the firms may be unprofitable, have limited or no revenue, and have little tangible book value. A second problem is limitations on comparable companies as fellow private companies are not publicly traded and have opaque financials for comparison. Public-company comparison offers a bad alternative because the firms have different risk traits and characteristics. A third problem is no good proxy for risk. The consideration of risk used with multiples is typically market based. A short existence period and firm privatization make strong peer multiples hard to determine. The fourth problem is the inability to control for the firm's survival, given that market multiples assume an ongoing operation. The fifth and final issue is that market multiples cannot be easily adjusted for equity claims and illiquidity.

2.3.3. Scorecard Valuation

A less robust, yet popular, option among venture capital is the scorecard methodology. This approach is more prevalent with pre-revenue startups. An investor begins by determining the average pre-money valuation among the target company's similar peers. Seedrs (n.d.) determined that there is an average pre-money valuation of £750,000 to £2 million for seed-stage, pre-revenue companies. The next step compares the target company to similar deals done in the given industry by considering multiple facets. These facets can include the strengths of management, market size, product or service, and sales channel. For each available factor, a score is given. In addition to the score, there is also a weight on each factor; some factors carry more weight than others. The factors' total weighted average is then multiplied by the industry's average pre-money valuation, determining the total estimated value. A critical downfall of this method is the subjectivity in weighting these different facets.

2.3.4. Venture Capital Method

According to Payne (2011), the Venture Capital Method (VC Method) was first described by Harvard professor Bill Sahlman in a 1987 case study and has been revised since then. This method works backward to first determine a post-money valuation to calculate pre-money valuation. The VC Method states that return on investment (ROI) is a determinant of terminal value (anticipated selling price) and post-money valuation (the valuation after investment).

Seedrs (n.d.) uses the following example to solidify the theory: A software-as-a-service (SaaS) startup with revenues of $20 million upon exit is expected to have post-tax earnings of 15%, or $3 million. Assuming the industry-specific price-to-earnings (PE) ratio is 15x, the SaaS startup reckons a terminal value of $45 million. Now, the investor must establish the desired ROI (anticipated ROI). With an assumption that the investor anticipates 25x, the post-money valuation is $1.8 million. However, the cash investment for the SaaS startup must be considered to reach the pre-valuation amount. If the startup receives $500,000 in cash financing, the pre-money valuation equates to $1.3 million. The example is written as follows:

Post-Money Valuation: $45 million ÷ 25x = $1.8 million

Pre-Money Valuation: $1.8 million - $500,000 = $1.3 million

2.3.5. Cost-to-Duplicate

There is a substantial amount of both industry and academic literature about the valuation practices for venture capital. One unconventional method is known as cost-to-duplicate. This approach is used by calculating the cost of building a similar company from scratch. This method often looks at the physical assets to determine the fair-market value (McClurse, 2020). Unfortunately, this method lacks the forward-looking potential for future sales and profits. Also, this technique does not capture intangible assets, such as brands. These issues are very problematic because two important concepts of venture capital are hopeful growth and high-value assets that are intangible.

2.3.6. Risk-Factor Summation

With the risk-factor summation approach, an estimated initial value is calculated by utilizing one of the previous methods. From there, different types of business risks are quantified, and either added to, or deducted from the initial valuation. The summation of the initial value, any additions, and any deductions become the final valuation. Some popular risks that are considered include management, political, manufacturing, market competition, investment, capital accumulations, technological, and legal risk (Corporate Finance Institute, n.d.) As Seedr (n.d.) represents, a range of -2 to +2 is assigned to the risks with every 1-point score (positive or negative) serving as a $200,000 value. A score of 0 is assigned as neutral. Understandably, one of this approach's downfalls is the subjective scoring of risk.

2.3.7. Dave Berkus Method

The Dave Berkus approach, named after an American venture capitalist and angel investor, assesses five key success factors: (a) basic value, (b) technology, (c) execution, (d) strategic relationships in core markets, and (e) production and consequent sales. The five separate factors are measured quantitatively, with the total equaling the final valuation. This approach is sometimes referred to as the Stage Development Method or the Development Stage Valuation Approach (Corporate Finance Institute, n.d.) The Dave Berkus method is traditionally used in the earliest stages, if at all, as a starting point for the company's valuation.

2.3.8. Software-as-a-Service (SaaS) Valuation

SaaS is a business model where software is licensed and delivered through a subscription channel and is centrally hosted by the seller. SaaS has become a popular business model for technology, including AgTech. Popular use cases for AgTech SaaS include precision agriculture, imagery, online marketplaces, and digital farm management. The concept of SaaS valuation is not a methodology but is an additive to the process. While a SaaS company may be valued through a DCF, there are concepts worth noting that make analysis different than with other business models. According to Smale (2018), key metrics include customer churn, customer acquisition cost (CAC), customer lifetime value (CLTV), monthly recurring revenue (MRR), and annual recurring revenue (ARR). These metrics are critical when modeling cash flow to determine if a SaaS startup can afford to capture customers with retention in modest cash-burn procedures. They are also prominent in setting quantitative goals to reach scalable profitability.

2.4. Real Options in Venture Capital

Real options have similar traits as financial options where both grant the holder a right, but no obligation, to exercise a decision. The difference takes place in the underlying assets being valued. While financial options focus on a financial asset, such as a stock, real options account for real assets. A real asset can be items such as real estate, technology, machinery, or other capital expenditures that require investment. Real option analysis (ROA) can be a supplement to DCF valuation when optionality is in play. The benefit of ROA lies in the managerial flexibility for alternative paths that an investment may take. As time increases, uncertainty does as well. Instead of the fixed assumptions featured in DCF or multiples, ROA provides a way to value different decisions that may occur during the option's life. If a project is extremely unattractive or attractive, the practicality of using ROA would not provide additional value. However, ROA is best used in situations where the initial NPV is in a gray area, or controversial, for positive or negative outcomes. The option value can be added to the NPV calculation, leading to a total value. Therefore, even if the NPV is negative, a positive real-option value can enhance the overall valuation to be positive as well.

A handful of input parameters are needed to calculate a real option. Kodukula and Papudesu (2006) summarized these inputs where S_0 is current asset value, X is a strike price, σ is volatility, r is the risk-free rate, and T is time to expiration.

While there are only five inputs needed for an option valued via the Black-Scholes method, there is an additional input needed for a value with the binomial method because the binomial method utilizes discrete time periods, hence there is a need for incremental time steps represented as δt.

There are numerous types of real options for different scenarios. Table 2.2 lists the generic types of real options that can be utilized, specifically for venture capital. Given the R&D phases involved with many early stage technology companies, the options to expand, defer, and abandon are important when valuing the managerial flexibility involved with the R&D learning curve. There must be dimensions of flexibility for uncertainty and time factors. Without this, traditional valuation methods, such as DCF or multiples, can either overvalue or undervalue a startup's potential.

Table 2.2

Generic Real-Option Types

Option Type	Description
Expand	Expansion of a new or existing product line; entrance into new geography, demographic, or other segments.
Abandon	Abandon a project or company via liquidating assets or selling the company. Abandonment is especially helpful in R&D processes.
Delay	Wait to pursue an action by allowing uncertainty to clear. Negotiation or significant investment in new items may require delays to process information.
Contract	Outsource an action to reduce costs or simply the business model. This leads to a monetary saving or re-focused offering.
Choose	Choose between different option types listed above. The option leading to the best return on investment is pursued.
Sequential	Staged options are dependent on each other such as an expansion project. For example, regulatory approval may be needed before infrastructure projects.

Damodaran (2001) provided numerous real-option types to supplement the valuation of technology companies. He used the delay option type in order to find the option value for acquiring technology rights to improve service. Before the ROA, the decision's net present value was negative. However, after applying the option to delay, the NPV became positive in over $10 million. Another ROA was performed with the option to expand into new geography. Before ROA, the risk-adjusted NPV offered a -$200 million loss for the expansion, signaling a stop to the project. However, considering this option to expand creates approximately $528 million in potential cash flow, leading to a final NPV of $328 million. Adding ROA makes the expansion project appear attractive on the monetary upside.

In more specific cases with venture capital, Amram and Kulatilaka (1999) utilized case studies to represent situations of valuing and investing in a startup. To value a startup, the Black-Scholes formula was used to price a growth option (options to expand) for the startup to achieve a larger market share in future years with additional capital. Because this startup is an early stage with no near-term revenues, an imprecise DCF calculation produces a negative NPV to expand

and to compete for a higher market share. After applying the growth option for additional investor capital two years later, the startup value becomes over $1 million. In the same example but modified for the option to abandon the investment to grow, the startup presented a value of $1.74 million.

Fazekas (2016) said that real options can present the increased business value that is generated by the startups' learning curve. Instead of applying real option pricing with techniques for continuous variables, a common approach used with pure traded financial options, integrating decision trees into real options may offer additional flexibility for VC. The multi-stage process of VC funding and startup decision making makes continuous option pricing a problem, hence the importance of decision tree analysis. Because there is a learning curve for startups changing strategy and alternating options, Fazekas argued that time must be represented as discrete. The reasoning for this is that startups and investors can pursue various actions, such as abandoning the project, market expansion, or delaying a project, at different stages.

Keeley et al. (1996) also recognized the need for multi-stage consideration in discrete periods because the real option method recognizes that follow-on investment is only made if the startup is performing well. In this study, real-option values provided positive NPVs for all case studies while the traditional DCF provided all negative NPVs. Not only did the options approach achieve a positive value, but also added a premium of $13-18 million to the baseline DCF values.

In research focused on encouragement versus application, Wang and Tang (2010) wrote about the importance of investment evaluation for agriculture VC projects using real-option analysis versus DCF. The authors said that applying real options in agriculture VC can help the government, investors, and operators obtain ideal benefits while reducing the maximal risks.

Both the Black-Scholes and binomial pricing models were shown with an emphasis on binomial option-pricing due to the discrete movements that the project exhibits over time.

An area where real-option valuation has become popular is biotechnology. As Kellogg and Charnes (2000) noted, the biotechnology industry had significant valuations despite limited or no product revenue. This situation should not be surprising because, in the biotechnology space, it can take many years to commercialize a product, if such commercialization happens. While many resources must be obtained to achieve such an accomplishment that has a small probability, there can be an enormous upside (e.g., an Alzheimer's drug). In this scenario, a real option can be valuable because it is a right, not an obligation, to acquire a business asset or opportunity with its associated physical and intellectual capital assets (Razgaitis, 2003). In the biotechnology example, an investor may exercise a real option to own the biotech firm, or the product itself once a drug is commercialized.

Considering different real options for high-growth, emerging technology companies is important. A DCF that builds into future expectations of a young company can already be said to host potential upside already being reflected in the value. However, a counterargument is that one success in a business or market can create a stepping stone for additional markets (Damodaran, 2009). Sometimes, startups may start small, but they have the ability or goals to disrupt something bigger than what is attainable in the short term. If the startup is successful with this measure, the investor would, ultimately, undervalue the startup by ignoring the additional premiums that the company can earn. This may be a reason why fast-scaling technology companies tend to trade at higher valuations versus other industries. Damodaran used Apple and Microsoft as examples to solidify the real option’s importance. For Apple, the introduction of the iPhone's customer base led to the development of the iPod. Microsoft's creation of operating systems (MSDOS and Windows) was further extended to build Microsoft Word.

2.5. Stochastic Simulation in Valuation

Part of this study's framework is to add randomness to an outcome given the uncertainty of startups. Monte Carlo simulation is a stochastic process that randomly selects values to create scenarios (Schumann, 2006). Stochastic simulations capture risk with input variables which affect the risk for the output variables. Through stochastic simulation, one can derive probability distributions for the output variables. These randomly selected values are taken from a fixed range in order to fit a handpicked probability distribution. The Monte Carlo technique is inserted within the assumptions to help reduce uncertainty and bias through simulating many possible results. Therefore, instead of having a single result, there is a range of high probabilistic results. To insert the Monte Carlo technique within a DCF, distinct variables with high influence and high uncertainty can be stochastically simulated to improve the alternate paths versus the original DCF's fixed assumption. While it matters for the variable being selected, a popular probability distribution is taken to include normal, triangular, uniform, and lognormal distributions (Razgaitis, 2003; Schumann, 2006).

Lifland (2015) used an applied case study to compare standalone DCF versus DCF with a Monte Carlo simulation. The standalone DCF offered a positive NPV, which would ordinarily receive approval from the decision maker. However, the DCF with Monte Carlo results shed the realism on the probabilistic negative NPV that can take place. Lifland argued that the Monte Carlo method should be applied with DCF for a more thorough review because the absolute acceptance of projects where the NPV is greater than zero does not shine a light on the holistic view.

2.6. AgTech Valuation Techniques and Relevant Studies

There is little-to-no literature about the techniques for valuing AgTech startups. However, there is literature on valuing single technologies that are applied to agriculture. Wynn, Spangenberg, Smith, and Wilson (2020) utilized real options to estimate the pre-commercialization value of a drought-tolerant wheat-trait technology. Because developing a trait via gene editing has uncertainties that cannot be accounted for, corporate NPV analysis is a poor valuation method. A large factor that must be considered during the development phases is the project's abandonment. In this study, the option to abandon is used in different phases as salvage values that are an alternative for continuing the project. The framework used binomial option trees and discrete-event simulations with the Monte Carlo technique to model the investment's option values. The model's random variables are fit to an appropriate distribution, accounting for uncertainty with the inputs. The model calculated the option value at each tree node, starting with the NPV of the projected revenue after commercialization and using backward induction for each phase of the R&D process. The binomial option tree at the five project phases included options to continue, postpone, or abandon the trait investment. This option inclusion offered the managerial flexibility that early stage projects (or startups) carry under uncertain conditions. The model's conclusion shows that six countries were selected as having agronomic, regulatory, and market conditions that were conducive for commercializing a new trait. Few models would have been able to establish this conclusion.

In a similar application, Shakya, Wilson, and Dahl (2013) applied real option analysis and stochastic dominance to drought-tolerant (DT) corn with gene-modification technology. Option values were derived at decision-tree nodes throughout the R&D phases with options to continue, to wait, or to abandon the investment project. Proper risk analysis for these projects is important because such an internal project can cost over $130 million in a ten to twelve-year period. The results showed that the Prairie Gateway and Northern Great Plains regions would host the greatest value for DT corn given the end-market dynamics. At every phase of the development process, the real options had a positive value. Without the potential for an out-of-the-money option value during the discovery phase, the base-case scenario was in-the-money for the expected value for all other phases. With a discounted cash flow analysis, it's possible that the NPV would have discouraged the same project.

In an attempt to compare the economics of gene editing (GE) versus gene modification (GM), Bullock, Wilson, and Neadeau (2021) applied decision trees with a binomial lattice to determine the valuation of an abandonment real option on a new crop technology. The combination of a decision tree and a binomial lattice accounted for the private and market risks that internal R&D and commercialization would cause. Because the two R&D technologies have different technical costs, time requirements, and processes, trait developers had a pertinent interest in which method is a better option. Using a real option valuation, the literature proved that, from a cost perspective, GE is significantly less burdensome than GM. Assuming a $25-acre trait value, the number of acres needed to break even was 2.3 million acres for GE and 62 million acres for GM. This 96.3% lower acreage amount makes GE a dominant method in R&D and dramatically reduces the product's risk.

Ehmke, Golub, Harbor, and Boehlje (2004) implemented real option analysis to value the investment opportunity for organic wheat and barley production for farmers who were using precision-agricultural technology. A farmer's transition from conventional to organic farming must offer financial incentives to lessen the risk of change. In addition, the use of precision technology must show a value enhancement to make the logistics and expense worth it. In this study, the option to delay was used for the farmer to delay the investment in organic production until there were increased precision data and a better understanding of the information at hand. The study found that this option had exceptional value where, mattering on the level of uncertainty, ranged between $10,991 and $13,636. The combination of NPV and the real option value to enter organic production with precision agriculture resulted in total values ranging from $54,839 to $57,484. Hence, the option value to delay added 20-23% of the overall value.

In a different use case for greenhouse construction, Tzouramani and Mattas (2004) utilized a discounted cash flow analysis to decide the feasibility of a modern versus a traditional greenhouse. Although the resulting DCF indicated that a modern greenhouse was feasible, there was limited uncertainty and irreversible action methodology used with the model. This led to a stochastic real option approach to validate the analysis. The study used Monte Carlo simulation to account for commodity price uncertainty and real option analysis with the construction project. The study's outcome was to demonstrate the need to embrace uncertainty and flexibility in the model; otherwise, the farmers would make faulty decisions.

2.7. Extensions and Conclusion

This study strives to draw and to combine the previously mentioned concepts. Through the literature review, it is clear that the traditional methods of DCF or multiples alone cannot offer the proper flexibility and risk incorporation within a valuation. With the large addressable market of agriculture, a limited history with IPOs and M&A, and industry volatility, the increasing AgTech investment presents a great opportunity to apply stochastic real options and to the valuation procedure. The following chapters move into valuation theory and the applied tools for valuation in the scope of the following case studies of Chapters 4 and 5.

CHAPTER 3. THEORETICAL MODEL

3.1. Introduction

The model included in this study is a combination of several distinct elements. This study's model builds on a DCF while introducing uncertainty and managerial flexibility through stochastic real options integrated into decision trees. DCF defines the value of an asset or company. However, given the lack of managerial flexibility and fixed assumptions, DCF tends to undervalue the asset due to a lack of optionality consideration. Therefore, real options (e.g., expand, abandon, delay) must be included with DCF value to account for the flexibility and optionality in the business. Hence, the total value of a company is derived from combining DCF value and real option value. However, Chapter 4's case study introduces the application of using real option valuation as the sole tool to value a company.

The DCF is first reviewed along with the important components that make up the DCF model. The real option value is then discussed by showing the different kinds of possible options and the methodologies of calculating them. Finally, stochastic simulation, decision trees, and binomial lattice are discussed to provide insight into the private and market risks faced by young companies. The theory of these models is explained in an effort to lead up to the empirical model introduced in Chapters 4 and 5.

3.2. Problems with AgTech Valuation

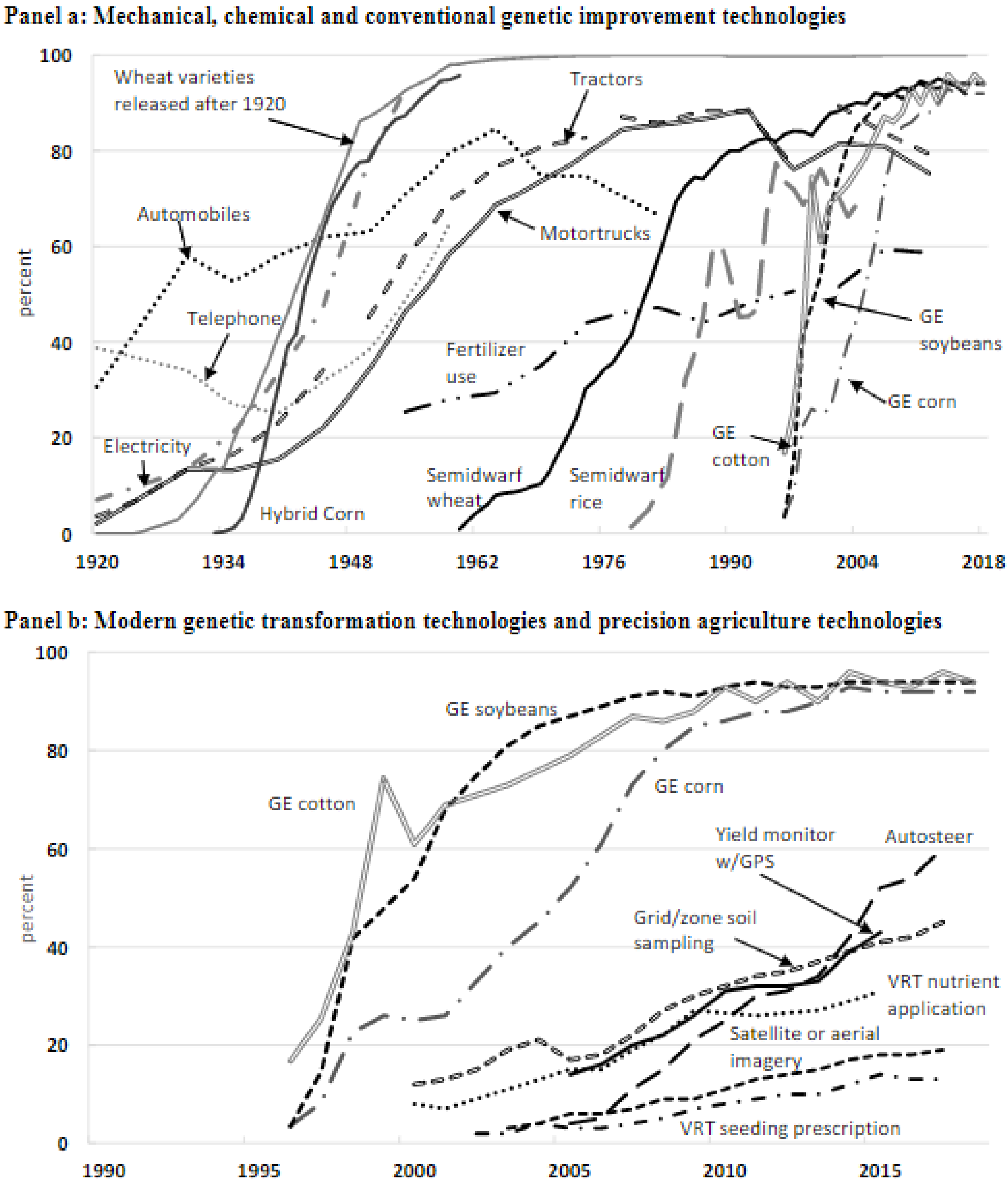
Since AgTech is still early in the evolutionary stage, valuation among startups remains difficult. Merger and acquisition data are not plentiful, creating uncertainty around exit multiples and terminal value. Additionally, adoption of AgTech from farmers can be difficult to predict given slow adoption on some technology but high off-take adoption on others. Finally, the lack of intangible assets (intellectual property, trade secrets, etc.) makes liquidation values largely unknown for many.

While there are publicly traded agricultural companies (e.g., John Deere, Marrone Bio Innovations, etc.), mergers and acquisitions (M&A) of new technologies developed within the past five years have not seen much acquisition data. M&A is a significant way to generate multiples valuation on comparable firms since it can be claimed with certainty that similar companies have been sold at a given price. Without this information, it becomes difficult in relying on this methodology. Therefore, exit values received in the markets make terminal value hard to determine.

For many AgTech products, the adoption rate tends to also be slower in production agriculture (Fitch Solutions, 2019). However, some past technologies have proven this wrong given the high offtake adoption to quickly reach maximum penetration. Therefore, adoption has significant uncertainty in the commercialization of new technology. The variability of adoption tends to be based on yield or cost-cutting enhancements produced by the technology. Figure 3.1 illustrates a historic adoption model of influential technologies in U.S. agriculture. This is proof that strong AgTech adoption cannot only occur but reach very high penetration rates of nearly 100% maximum capacity. Certainly, this feature of technology to cover nearly the entire addressable market is absent from other technologies outside of few revolutionary products such as smartphones or electricity.

Figure 3.1

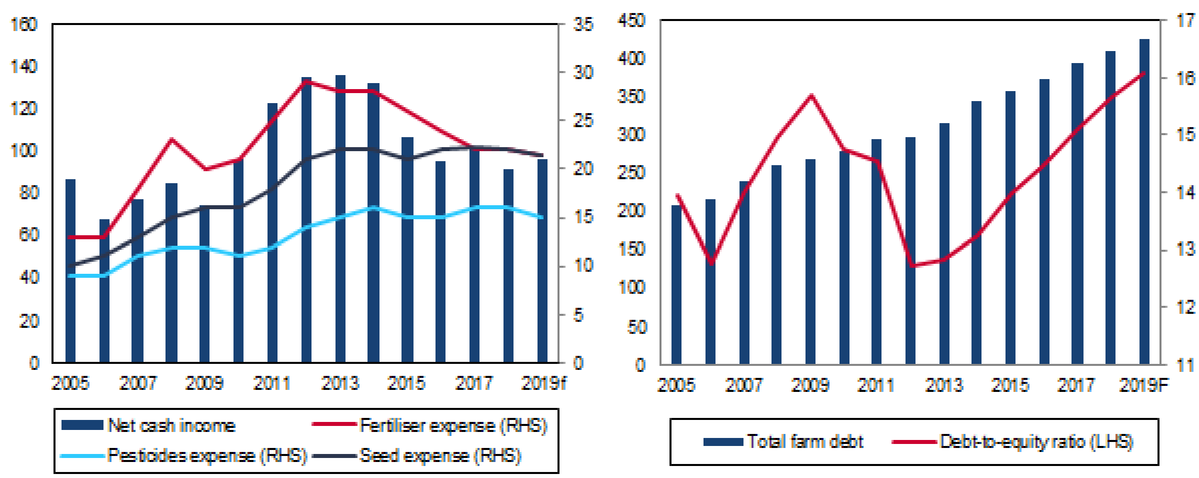
Waves of Technology Adoption in U.S. Agriculture (Alston & Pardey, 2020)



In further discussion of slow AgTech adoption, certain contributions include a producer profile that tends to be older and act in more caution towards technology changes. Another significant issue that has contributed to a naturally slow adoption rate among the industry is financial distress among producers represented in Figure 3.2. As shown, while crop inputs of fertilizer, pesticides, and seed have seen an increase or stagnant rise in costs, income has declined with total farm debt steadily increasing. In any case of technology, the speed at which adoption occurs will be slow and difficult given the user profiles are similar to Figure 3.2's circumstances. However, technology implementation offers the ability to reverse this trend but is exercised with caution given the small margin of error available. This is due to the slow feedback loop of only a single crop per year to demonstrate effectiveness.

Figure 3.2

U.S. Farm Income, Expense, & Debt, USD Billions (Fitch Solutions, 2018)



Intuitively, struggling end markets create slower adoption that's exercised with caution. A relevant point to AgTech is that it's not consumer technology (Harris, 2018), at least in upstream and midstream. Much of this technology does not have to be design-focused, but simply work well. A dynamic that may come into play with engineering and funding AgTech is the minority rule. Being much of it is not consumer technology, it is difficult to know the most relevant keys in making products and services work for producers. If not significantly involved at the producer level, technologies may not be appropriate for practical use and therefore limit adoption rates via reputation. In a comprehensive 2013 USDA survey to farmers, 90,361 of

229,327 respondents said irrigation decisions are made by “the feel of the soil”. Less than 10% used soil moisture sensors and less than 1% used computer simulation programs. Since this time, there has been increased adoption, but still slower than most industry adoption rates. Note that this rhetoric does not necessarily apply the same to consumer-facing AgTech (e.g., plant-based meat or meal kits).

In a final point of discussing AgTech’s valuation problems, asset valuation is hard with technology startups. Since technology companies can be less capital intensive than more tangible industries, most assets can be derived from intangible assets such as intellectual property and network effects. This makes liquidation value low and difficult to consider in worst-case scenario valuations. As discussed above, AgTech adoption can be uncertain and hard to estimate for the future growth of tech providers. Therefore, revenue growth and in turn, eventual cash flow becomes nearly impossible to accurately measure. This is significant if the startups feature high rates of cash burn that eats into valuation and potential dilution. If these AgTech companies feature slow adoption and high cash burn, the ultimate value of the startup becomes the terminal value typically discovered by averages of previous exits on comparable companies. This, of course, poses problems in an industry that lacks enough comparable exits to apply terminal value to and of course the assumption that the startup survives to terminal value. This latter point can be a bad assumption given the high failure rate of startup companies.

While it is difficult to apply valuation procedures to startups in general, agriculture technology startups offer additional uncertainty given the lack of data and adoption curves featured in the industry. Therefore, there is a need for other methods to help provide color to this problem.

3.3. Discounted Cash Flow (DCF) Model

A DCF is a widely used application for valuing an asset from its intrinsic value. Estimated cash flows generated by an asset are discounted to present-day value to achieve an intrinsic valuation. Each cash flow that occurs farther from the present-day becomes less valuable given the concept of time-value-of-money (TVM). A formalized DCF model can be summarized as:

$$DCF = \sum_{t=0}^{\infty} \frac{E(CF_t)}{(1+R)^t}$$

Where CF_t is the after-tax cash flow at time t and R is the cost of capital adjusted for risk. The sum of discounted after-tax cash flow is the value of the DCF.

3.3.1. Cash Flows and Terminal Value

Since a DCF incorporates TVM, the periods in which cash flows are received are critical attributes of the final valuation. For young companies that are pre-revenue, there is likely no cash flow generated for many years. Therefore, it is not uncommon for terminal value (value of the asset beyond the forecast period) to account for 90%, 100%, or more than 100% of present value (Damodaran, 2009). The assumption of when a company reaches stable growth is an important factor. However, many times startups do not even reach the point of stable growth to derive terminal value given the high failure rate.

Two common approaches that determine terminal value include a terminal growth rate via the Gordon Growth method (not the only formula to use) or exit multiple. A terminal growth rate is derived by the formula:

$$Terminal\ Value = \frac{(FCF \times [1+g])}{(R\text{-}g)}$$

Where FCF is free cash flow, g is the expected terminal growth rate of the asset, and R is the cost of capital adjusted for risk.

The exit multiple approach is not necessarily consistent with DCF given the market pricing framework versus intrinsic form. However, it may be a more appropriate procedure in venture capital valuation given that in an acquisition scenario, the company would likely be matched to past transactions with similar multiples. A terminal value via exit multiple is constructed by multiplying the final forecasted period EBITDA (earnings before interest, tax, depreciation, and amortization) and an EBITDA multiple discounted to present value (Corporate Finance Institute, n.d.a.).

Because each company is at a different stage in its growth cycle and has different assumptions, terminal growth periods vary. For a low growth, mature company, terminal growth may have already been achieved. For an early stage startup, this stability may still be decades away. Product and service, geography, and business model are all important considerations when assuming time to stability.

3.3.2. Cost of Capital

The cost of capital can be derived from two distinct capitalization structures: the cost of equity and the cost of debt. Expressed by Jennergren (2006) the weighted average cost of capital, or WACC, is further defined as:

$$WACC = r_E \frac{E}{D+E} + r_D(1-\tau)\frac{D}{D+E}$$

Where E is the market value of equity, D is the market value of debt, r_E is the nominal required rate of return on equity, r_D is the nominal cost of debt, and τ is the tax rate.

WACC acts as the proxy for risk within expected cash flows. Mathematically, WACC and NPV have an inverse relationship. A higher WACC, emulating risk, produces a lower NPV.

Likewise, a lower WACC creates a higher NPV. While the cost of debt is rather straightforward given the borrowing rate of debt, the cost of equity is not as intuitive. The most common method to deriving the cost of equity is a capital asset pricing model (CAPM).

The cost of capital in venture capital (VC) contrasts with traditional WACC used among other applications. Most likely, the startup does not have debt. Therefore, the cost of capital becomes a focus on the cost of equity solely. Because of this reason, CAPM results are the outcome of the discount rate used within the model. By definition, the CAPM model can be illustrated as:

$$E(R_i) = R_f + \beta_i(R_M - R_f)$$

Where $E(R_i)$ is the expected return on asset i, R_f is the risk-free rate, β_i is the beta of asset i, and R_M is the market return.

The results, $E(R_i)$, is the CAPM result and hence the cost of equity. If there is additional risk to be considered that CAPM doesn't capture, an additional risk premium can be added to the cost of equity to better compensate an investor for high-risk assets. A startup holds high risk and uncertainty that is difficult to be accounted for by traditional discount rate measures. Fazekas (2016) explains that young companies pose estimation challenges of discount rates given the beta element within CAPM and its reliance on historic data not readily available for private young startups. He emphasizes that it was for this reason real options were conceived in valuation to better reflect the uncertainty of investments and coinciding risk.

3.4. Real Option Analysis (ROA)

Startup companies, especially ones involved in R&D projects, typically have embedded options in the project development phases (Dixit & Pindyck, 2012). Valuation that accounts for embedded real options is advantageous relative to standard DCF valuation. The DCF's inability to capture managerial flexibility and influential strategic decisions early in the company's life lead to underestimating the value of startups by failing to consider the ability to defer or abandon decisions to later dates (Trigeorgis, 1995). ROA considers different time nodes throughout the young company's life, offering optionality at each node to pivot decisions. This differs from a DCF which assumes a committed decision and strategy without flexibility to evolve or pivot.

Option-pricing was first developed for the use in financial instruments used in markets. However, the application spread to the use of real options, accounting for option valuation on real assets. To this day, real options analysis (ROA) has seen limited use to practical problems given the mathematical complexity, theoretical assumptions required, and lack of intuitive appeal (Brandao, Dyer, & Hahn, 2005). While this is the case, real options can be beneficial to valuation applications. Real options allow for viable investment decisions that carry high uncertainty and management flexibility. The rise of uncertainty increases the value of an option. Table 3.1 visualizes the relationship between the value of options relative to uncertainty and managerial flexibility. Since real options can account for these two non-fixed elements, the option value is high when both uncertainty and managerial flexibility is high. Likewise, when these two elements are low, the option value is low.

Table 3.1

Value Chart for Real Options

		Uncertainty	
		High	Low
Managerial Flexibility	High	High Option Value	Medium Option Value
	Low	Small Option Value	No Option Value

Though real options have similarities to financial options, there are some differences where the option value is derived from real assets (e.g., equipment or property) versus financial assets. Also, real options are based on multistage investments that account for decisions at each discrete stage. This is where managerial flexibility is fulfilled.

Real options can apply to technology valuation but in a much less known way. Damodaran (2001) describes real options as a great method to account for upside opportunities not always immediately recognized. He provides the use of real options on patent valuations that not only allow for a premium valuation given the intended market the patent is to serve, but also additional expansion the patent might allow the company to enter. Kodukula and Papudesu (2006) also find applying different types of real options a handy tool for discovering the value of startups. Razgaitis (2003) pushes the motive of using ROA in valuation to achieve favorable negotiation in deal-making. Since ROA considers uncertainty and managerial flexibility, it best reflects defensible analysis to reach decision making.

Figure 3.3 summarizes the approaches aimed at option pricing methods for valuation. In different approaches, it is important to consider that only some of the uncertainties within real assets can be considered market-priced risk while others may be only assessed via subjective methods. The approach is largely determined by risk profiles of the investment and the extent to which decisions made during the life are project-specific uncertainties versus risks of objective measurement through benchmarking (Fazekas, 2016). An example of this is a startup’s stage of progress. For R&D, the risk is primarily internal since major risks deal with technology and execution risk of the startup team. For commercialization, the risk is less of private and more of market. Pricing, penetration, and demand are now the highest risks of the startup, all of which are market driven.

The use of Figure 3.3's option will be driven by the different circumstances at hand for the company and the technological evolution of their progress and stage.

Figure 3.3

Option Pricing Valuation Approaches (Fazekas, 2016)

	Assumption	Valuation model	Applicability:
The classic approach (Amram – Kulatilaka 1999)	Replicating portfolios can be constructed from traded products; i.e. the existence of a replication security is assumed that correlates perfectly with the investment and moves closely together with a geometric Brownian motion; consequently the no-arbitrage argument is sound.	A method applied for the valuation of financial options such as the BS or the CRR model based on the market data of the replication security.	Conditions for the classic approach are rarely given. It can be applied if an adequate traded replicating security exists. In the lack of such instrument, however, if project-specific idiosyncratic risks are determinant, the method cannot be applied.
Subjective approach (Luehrman 1998)	It assumes the existence of a replicating portfolio and therefore the applicability of no-arbitrage arguments. It also assumes the portfolio's co-movement with a geometric Brownian motion.	A method applied for the valuation of financial options such as the BS or the CRR model based on the 'price' derived from the DCF-based valuation of the project and estimated volatility.	While the data of the replicating portfolio do not play a key role in the valuation, the reliability of subjective data is questionable. For lack of a replicating portfolio, the application of a valuation method founded on the no-arbitrage argument is inconsistent.
Marketed asset disclaimer (MAD) approach (Copeland – Antikarov 2001)	The replicating security is the project's NPV itself, without flexibility; therefore, the assumptions are the same as those applicable to the use of NPV: the computation of expected returns is based on the existence of (replicating) securities of similar risk. Asset price movements can be described by geometric Brownian motion.	Valuation with a binomial tree method. A CAPM-based discount rate is applied for the calculation of the project's NPV. A subjective estimate of cash flows and volatility.	There is no need for a replicating portfolio. Owing to the subjectivity of the data, assets and options might be mispriced. Estimating subjective data is problematic. A security of similar risk is required for proper NPV calculation.
Revised classic approach (Amram – Kulatilaka 2000)	The model supplements the classic approach, given that the classic approach is based on fairly restricting assumptions. It cancels the assumptions of the former.	Application of decision trees. Allocation of subjective odds to individual outcomes. Subjective estimate of cash flows. NPV calculation by using the appropriate WACC discount rate.	Its application is justified when project-specific risks dominate instead of the risk priced in by the market. Due to the subjectivity of data, mispricing can occur.
The integrated approach (Smith – Nau 1995)	Partially complete market: complete market in terms of market risks, but incomplete market in terms of project-specific (private) risks.	The option pricing model is applied to risks that can be hedged by traded securities and decision trees are applied to project-specific risks.	Due to the integration of the decision tree and the option pricing methods, this approach can be universally applied. Market risks and project-specific risks need to be separated. The perception of project-specific risks is subjective.

3.4.1. Types of Options

In ROA, there are different types of options that can be considered, simple and compound. While there are nearly a dozen types of options, certain types are more relevant to venture capital and associated valuation. Table 3.2 lists various real option types which can be referred to via Kodukula and Papudesu (2006).

Table 3.2

Different Option-Type Descriptions

Option Type	Characterization	Effect	Description
Expand (Growth)	Simple	Call	To expand a product or project with high growth potential.
Defer	Simple	Put	To wait or delay a decision until uncertainty fades or markets become favorable.
Abandon	Simple	Put	To abandon a project and walk away with the salvage value if the project becomes unattractive.
Contract	Simple	Put	To contract or outsource company costs for potential changes in market conditions.
Chooser	Simple	Call & Put	Ability to choose options to expand, contract, abandon, or delay. The option that offers the highest value is the type to choose.
Barrier	Simple	Call & Put	Transforms the above option types with a predefined price to avoid any psychological bias in making option decisions.
Sequential	Compound		Options are provided in multi-stage phases where option values are reliant on previous options in an ordering.
Parallel	Compound		Multiple options that are active simultaneously.
Rainbow	Compound		The option or options host numerous sources of uncertainty.
Learner	Compound		Different options can resolve uncertainty and increase the effectiveness of other options.

A simple option is a single option and is mostly used in explaining the alternate option types available. Simple options are based on the underlying value of an asset and are independent of each other. Though there are a half dozen different kinds of simple options, common ones for startups include options to expand, defer, abandon, and contract.

An option to expand is common for growing businesses. This may take place in different ways, but two common approaches would be to acquire assets to enter new markets or to reinvest internally for expansion. Given the success of a project, management has the option to invest additional capital to grow scale and value (Schwartz & Trigeorgis, 2001). Certainly, this process is relevant to later stage startups as they pursue ramp up in areas outside of their initial product or service. The option to expand can be expressed as a call option.

The abandonment option becomes useful in efforts to fund initiatives. Whether from a VC or a startup decision making process, abandoning projects or investments must be considered. For a young company, this may the ability to liquidate assets or place a strategic exit to an acquirer. This concept is commonly used in the world of biotechnology where many phases of investments may be needed to pursue commercialization. The abandonment option is synonymous with a put option.

Two additional put options important to startups include the option to delay and the option to contract. There are situations when there are poor times to decide given residing uncertainty. The option to defer can create value by allowing uncertainty to proceed and become more certain, offering a different value proposition. From both a venture capitalist and startup standpoint, this option to defer can be of interest as new industries or concepts become tested. Schwartz and Trigeorgis (2001) also highlight the decision to license technologies very relevant in the option to delay. Likewise, the option to contract can navigate uncertainty by allowing the right to sell or outsource part of operations or assets while market conditions or costs are unfavorable.

A chooser option, also known as an exotic option, takes on a bit more complexity than the previous types given the chooser option itself has several option alternatives. With the right to choose, a decision can be made between deferral, expansion, contraction, or abandonment. The chooser option is valuable in the sense that it offers a choice with a potential call or put option (Kodukula & Papudesu, 2006). In situations where alternative paths are possible, chooser options can be optimal as it exercises the highest option type available. This is important for young companies as management navigates R&D and commercialization of products and business models.

A compound option is a more advanced option that is dependent on the underlying values of other options. Simply stated, a compound option is "an option on an option" (Sereno, 2007). Because of this, they carry multiple strike prices and expiration dates. An important compound option for young companies is the sequential option. This option considers multiple stages where each stage itself is an option. Hence, the multi-stage option can become a call, put, or combination of both (Damodaran, 2001). The first stage of the option begins with the longest exercise time. It then works backward until the shortest timed exercise option to derive the final value. Since the length and layers of options in compound options can become complex, it may better to utilize a simpler valuation model less prone to estimation error and assumptions (Damodaran, 2001).

Real Options to value R&D is rich in literature (Brach & Paxson, 2001; Jensen & Warren, 2001; Luehrman, 1998; Morris, Teisberg, & Kolbe, 1991; Seppä & Laamanen, 2001). Dixit and Pindyck (2012) identify that most project development hosts embedded options at each phase of the R&D process. A common real option in most R&D includes the option to abandon (Berger, Ofek, & Swary, 1996; Bullock et al. (2021); Dixit & Pindyck, 2012; Kodukula & Papudesu, 2006). The intuitive appeal for this type of option is the flexibility to abandon an R&D project if it becomes unappealing at different phases as the process proceeds. In turn, management is always left with the option to abandon the project and walk away with the salvage value. Likewise, an option to expand is pertinent to high growth companies where there is significant upside potential. Similar to a call option, the option to expand can be exercised as the proposed expansion project becomes attractive relative to the cost of expansion.

Sereno (2007) explains the relevance of sequential compound options in technology and venture capital. Since many technology creations include multiple stages of investment, the technology itself is seen as compound options for successful investment. Aside from investment, R&D also has multiple phases with dependency on previous phases. For example, the option of FDA submission is reliant on the previous staged option of successful trials.

The different types of real options serve as natural call and put options that are common in young companies. As managerial flexibility is present in most scenarios, real option types can serve as a hedge against failure and be a strategic guide in weighing alternatives.

3.4.2. Option Pricing Methods

There are four categories of pricing or valuing options that carry similar results but different intuition being (1) closed-form equation models (2) lattice-based models, (3) Monte Carlo models and (4) decision tree models. Two very common methods are Black-Scholes and binomial lattice. Choosing between the two methods matters largely on the option being valued and the explanation of results. Since technologies and young companies host managerial flexibility, discrete time periods (or nodes) are important in considering potential options. These characteristics make American-style options more appropriate, where one can exercise options before expiration. For this reason, this section focuses more on the binomial method versus Black-Scholes.

The most well-known option-pricing method in finance is the Black-Scholes option pricing model developed by Nobel Prize winner Myron Scholes and Fischer Black. This method is popular for valuing financial options (particularly on non-dividend stocks) and serves as the underlying basis for real options. Through an option, the holder has the right but not the obligation to execute the option. For a call option holder, the hope is for an underlying asset value to increase as the holder can buy the asset at a lower price than a listed price. On the other hand, a put option holder benefits when the asset value decreases as they can sell the asset at a higher price than the listed price. The Black-Scholes model can be defined as:

$$Call\ Option = N(d_1)P_0 - N(d_2)Xe^{-r*T}$$

$$Put\ Option = N(-d_2)Xe^{-r*T} - N(-d_1)P_0$$

Where,

$$d_1 = \frac{ln\left(\frac{P_0}{X}\right) + (r + \frac{\sigma^2}{2})t}{\sigma\sqrt{t}}$$

$$d_2 = d_1 - \sigma\sqrt{t}$$

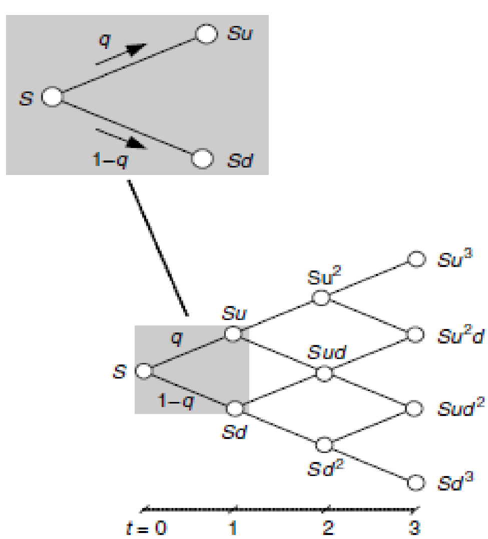
Where *N* is distribution functions, P_0 is the current price of the underlying asset, *X* is the strike price, *r* is the risk-free rate, *t* is time to maturity, and *σ* is the implied volatility.

Two downfalls of using the Black-Scholes option-pricing model for managerial flexibility is it is subject to European options. With European options, an option cannot be exercised before the determined expiration date along with only accounting for continuous time. This varies from an American option where each option node can be exercised before an expiration date. American options are pertinent in modeling VC investments and technology. This is because the real options of management flexibility do not have an expiration-only time of being exercised. Though Black-Scholes provides helpful tools in option-pricing, specifically financial assets, the following method offers a better alternative to price options.

The binomial options-pricing model was first developed after the Black-Scholes by Cox, Ross, and Rubinstein (1979). The binomial method considers option values at discrete time periods, making it an obvious attraction to the venture capital world where there is strong managerial flexibility of financing, business models, and M&A. The projection lattice represents a discrete analog to an underlying continuous stochastic process (often Geometric Brownian Motion) In the binomial option-pricing model, an asset's price can move to one of two possible prices at a discrete period. The original asset value, *S*, can either move to *Su* or *Sd* at a probability of *q* and *1-q*, respectively. *Su* represents an "up" move and is generally greater than 1 while *Sd* is a "down" move and less than 1. The size in the step is reliant on the volatility of the option at hand. This binomial step process is illustrated in Figure 3.4 where an initial step movement can compound into multiple steps. As the procedure expands into more periods, the process takes on a binomial lattice or probability tree with binary branches.

Figure 3.4

Recombing Binomial Lattice (Brandao, Dyer, & Hahn, 2005)



The behavior of Figure 3.4 assumes the underlying state variable in a risk-neutral world. This assumption is necessary to eliminate arbitrage opportunities for riskless profit (Cox et al. 1979). The risk-neutral probability is not the same as objective probabilities. Risk-neutral probability is just a mathematical intermediate to enable the discounting of cash flows using a risk-free rate (Kodukula & Papudesu, 2006). For this concept to hold, three conditions must be met.

As Klebe (2019) describes the conditions, the first condition is the expected return in risk-neutral environments and the average return of the underlying variable is equal. Therefore, the expected return is equivalent to the risk-free rate and the condition equation can be expressed as such:

$$Se^{r_f \Delta t} = pSu+(1-p)Sd$$

Where S is the present value of the underlying asset value, r_f is the risk-free rate, Δt is the time interval, $e^{r_f \Delta t}$ is a growth factor, p is the probability of an up move, u is an up factor, and d is a down factor.

The second condition relates to the variance of S. Variance of variable S is equal to $E(S^2)-E(S)^2$ and can be expressed mathematically as:

$$\sigma^2 \Delta t = pu^2+(1-p)d^2-[pu+(1-p)d]^2$$

Where σ^2 is the variance of S.

The third and final condition is that u and d factors must be inverse such that:

$$u = \frac{1}{d}$$

Conditions for a small Δt are then satisfied as to the following:

$$u = e^{\sigma \sqrt{\Delta t}},$$

$$d = e^{-\sigma\sqrt{\Delta t}} = \frac{1}{u}$$

$$p = \frac{e^{r \cdot \Delta t} - d}{u - d}$$

With the above equations, parameters of *p, u,* and *d* can be derived. The next step is to calculate each node until the binomial lattice is complete. The number of nodes and discrete time periods are determined on the application and implied decision making. Hull (2008) states that increased decision nodes result in more robust option valuation due to smaller time step size.

Backward induction, the process of evaluating each terminal node during time *T* and working backward in time, is the correct framework in modeling binomial lattice. As the evaluator proceeds backward, the option values are discounted for time. The mathematical representation of the call option value at its terminal node is:

$$max(S_T - K, 0)$$

and the put option value at its terminal node is:

$$max(K - S_T, 0)$$

Where S_T is the value of the variable at a terminal node during time *T, T* is the total life of the option, and *K* is the strike level.

The entire options life, *T*, is broken into *N* subintervals of length to reflect the discrete time periods, or Δt. At time $i\Delta t$, the *j*th node is referred to as the (*i, j*) node. After *N* subintervals, the call option value at each terminal node is distinguished as:

$$f_{N,j} = max(S_0 u^j d^{N-j} - K, 0)$$

As one works backward through the binomial lattice, the American-style option must consider the early exercise at each node. Therefore, the option premium, $f_{i,j}$ is compared with the option's intrinsic value at each (*i, j*) node (Klebe, 2019). Hence, the American call option valuation at each node is:

$$f_{i,j} = max(S_0 u^j d^{i-j} - K, e^{-rf\Delta t}[pf_{i+1,j+1} + (1-p)f_{i+1,j})$$

3.4.3. Decision Tree and Binomial Lattice Integration for Risk

The main component of utilizing real options in a decision and binomial lattice framework is to better measure risk and embrace uncertainty. Since DCF and multiples hold fixed assumptions, they fail in proper risk measurement. The most common method of measuring risk in investment analysis is through a discount rate derived by the weighted average cost of capital. Since a startup is typically structured as equity only, the cost of equity is the primary catalyst for the discount rate. The cost of equity determined by the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964) is typically applied. However, CAPM hosts major estimation challenges as beta, the relative risk ratio, plays a pivotal role in the model. Beta is estimated through historical data that is not readily available for private startup enterprises. Also, CAPM assumes that only undiversifiable market risks are relevant to investors. As Fazekas (2016) explains, this is not the case in early companies where founders or employers are not diversified with their wealth and the largest risk becomes idiosyncratic. Therefore, idiosyncratic risk plays a dominant role in measuring total risk as opposed to systemic risk (Cochrane 2005, Ewens et al. 2013) for early companies. This results in CAPM's exclusive systemic risk focus disadvantageous for VC.

Fazekas (2016) implies how multiple valuations are also poor in risk assessment as young, innovative companies do not have strong relative competitors given the unique characteristics of such firms and opaque financial metrics to compare. This leads to a peer group that is publicly traded. However, the aspect of being a liquid investment makes accurate comparable measurements inaccurate given vastly different risks and growth features. There is also no controlling effect on the low survival rate of startups becoming viable companies.

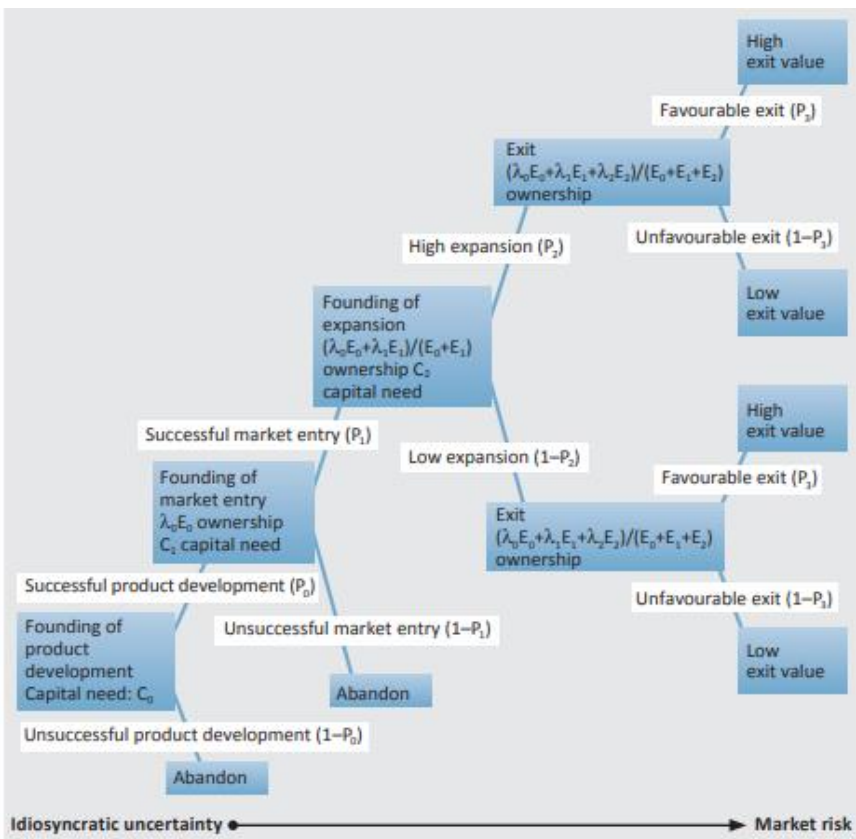
Venture capital financing is full of embedded optionality through a continuous learning process within startups and potential pivots that arise. Pro-rata participation warrants issued, or abandonment options are risk tools commonly utilized by VC to manage risk in the continuous learning process of uncertainty. Whether these arrangements are structured as real options or not, the framework of real options is present in VC.

Unlike traded financial products, the unique characteristics of VC investments restrict valuation procedures applied in replicating securities as the basis of methods cannot be found. Due to this, allocation weights of specific outcomes cannot be defined to ensure reliable risk-neutral valuation. As a result, techniques must implement additional methods like decision trees into ROA to capture flexibility. Decision alternatives throughout the startup's life include multi-stage financing, product development, entry and exit, and others. These elements succumb to both market and private-based risks that melt together given the relatedness. The uncertainty related to technology R&D and the potential of commercial success emphasize this (Kodukula and Papudesu, 2006; Guthrie, 2009; Brandao, Dyer, Hahn, 2005). Dotta (2018) uses Airbnb as an example for this as the company's business model and product value proposition (private risks) clash with prices to stay at one's place (market risk). Market risks can be hedged by trading securities and private uncertainties whereas similar hedging is not an option. Copycat portfolios may be constructed to achieve risk-neutral weights. For private risk, the risk factors are company-specific where subjective odds are estimated and allocated to individual outcomes to analyze probabilistic chance. These two important risk distinctions occur throughout a startup's life cycle from private risk in R&D to market risk in commercialization and adoption. During

R&D, one must lean away from a random walk assumption since the nature of the assets cannot be shaped on a normally distributed curve (Dotta, 2018). Hence, the solution of risk management and uncertainty is integrated into probability nodes of a decision tree versus standard deviation. Figure 3.5 shows the alternative paths that may arise during a VC investment life. As represented, the initial tree nodes become a subject of product development. In the case of a positive product founding, market-entry becomes the next node. This is followed by expansion and later exits. At any given node, there is the option of abandoning or exiting, creating the flexibility factor in the model.

Figure 3.5

Decision Tree of VC Options (Fazekas, 2016)

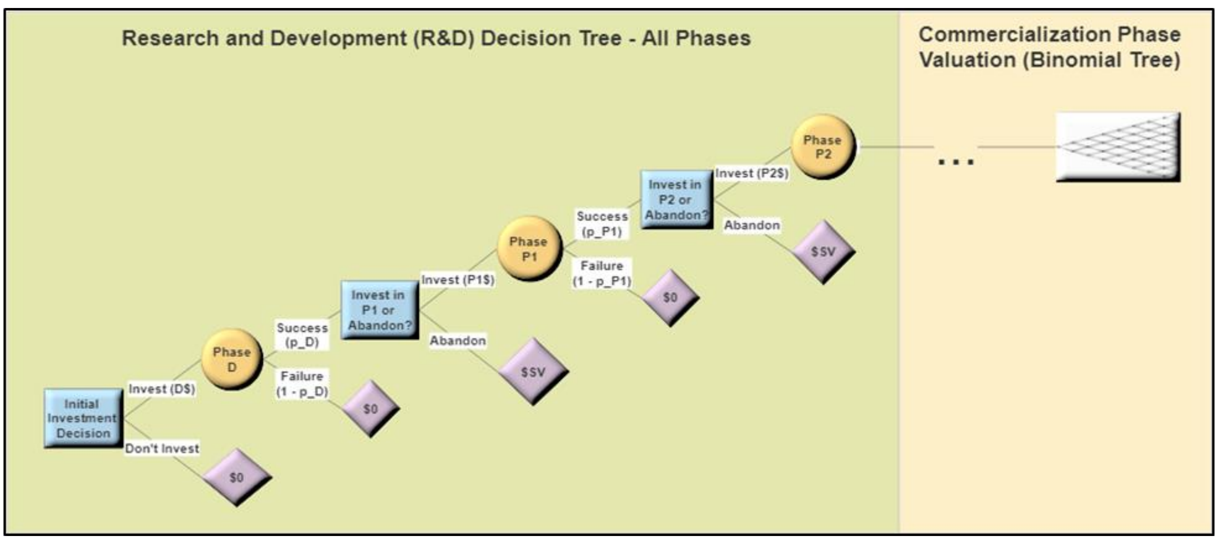


Implementation of decision trees is important in estimating private, company-specific risks. This is done through the subjective probability estimation of successes at each node.

However, market risk eventually becomes a factor as the idiosyncratic risk of internal action disappears when commercialization and product sales become the company cycle. Figure 3.6 shows this transition of risk type through product R&D. Once market risk appears, a binomial lattice (or tree) is illustrated to understand the backward induction of real option value. An important characterization of the two tree forms is the probability. A potential downfall of decision trees is that the probability must be estimated with potential induction of subjectivity while lattice outcomes are driven by stochastic processes. In addition, there is no settled agreement on an appropriate discount rate used in decision tree analysis while binomial lattices are driven by stochastic processes (Bullock, Wilson, Neadeau, 2021).

Figure 3.6

Decision-Theoretic Schematic of Model (Bullock, Wilson & Neadeau, 2021)



This inclusion of decision tree and binomial lattice into real options modeling accommodates the different types of risk (Smith and Nau, 1995). Also, the decision flexibility of a learning curve as uncertainty unfolds adds depth to the model with realistic case scenarios encountered in VC. This integration makes the empirical form preferable over different methodologies used such as sole real options, DCF, or multiples analysis.

3.5. Financial Modeling of Technology Firms

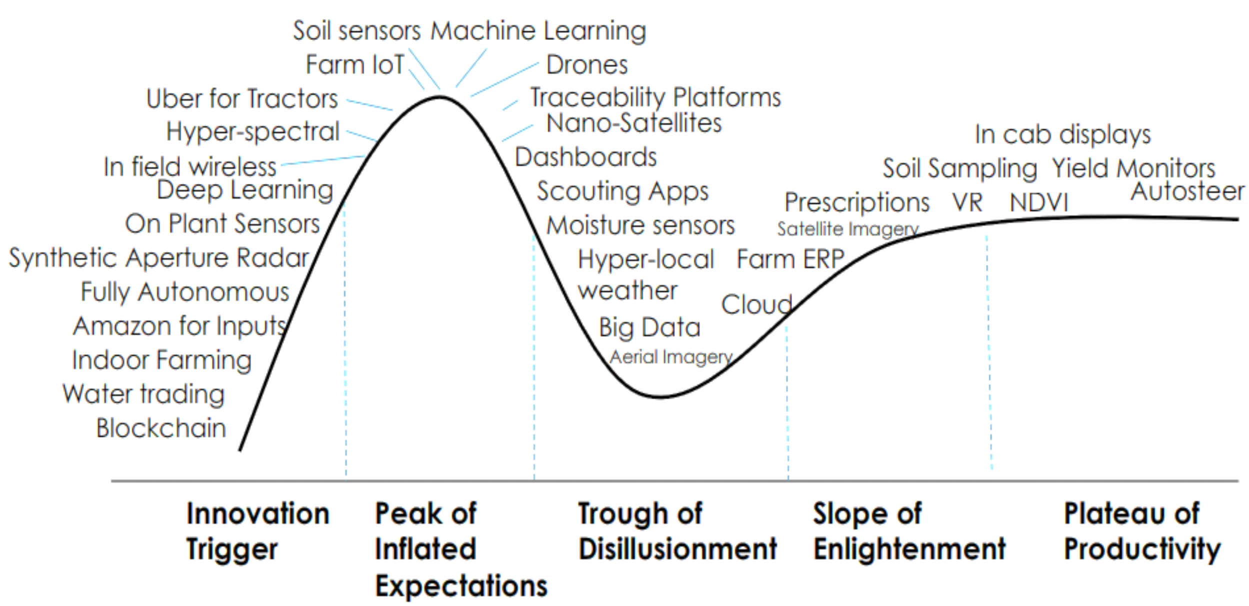
In this section, some evolution is explored on how technology creates unexpected externalities and leads to new markets. This idea is one of the main attributes of how traditional valuation of DCF or multiples fails to consider upside opportunities in valuing technology.

3.5.1. Dynamics of Technology

The definition of technology can change among individuals, firms, and investors. For some, it's commonly thought of as computerized innovation such as software or hardware tools. For others, it may be broader to include anything progressive in nature. Regarding AgTech, Figure 3.7 depicts Monsanto's version of the Gartner Hype Cycle applied to agriculture. This illustration shows various AgTech of both past and future and where they stand in their cycle. In a presentation during 2020, Better Food Ventures updated their perspective on the curve with technologies in peak expectations now moving to a trough of disillusionment. Likewise, with the shift, big data is now beginning to near the plateau of productivity.

Figure 3.7

AgTech Innovation Curve (Monsanto Presentation, 2016)



At the beginning of the technology's life, early proof-of-concept stories and media interest create publicity on the technology. From there, interest peaks as there become few success stories and many failures. This peak leads to a trough where interest wanes and the technology's viability is questioned. Through a few early adopters, the technology begins to shed benefit and prove itself from a commercial standpoint. At this point, the technology becomes well understand with data to support the growth trajectory. Finally, the technology enters a plateau when it is or has entered mainstream markets with relevance paying off.

Technology can be characterized as a blanket statement of knowledge applied to an area for progress. In agriculture, the field of technology is hosted in many things such as biotechnology, precision ag and digitization, controlled environment agriculture, and innovative foods to name a few. Something that technology has brought to the public is the idea of growth externalities. For example, the development of the internet created an opportunity for smartphones to thrive. In the development of smartphones and their eventual saturation of populations, multi-billion-dollar industries arrived to cater to new platforms. These platforms included social media and games among all. This then led to hundreds of billions in annual advertising investment across platforms. Numerous things can be accrued through this brief explanation of innovations which are (1) almost no one envisioned these opportunities until it was obvious and (2) there was no way to properly value or judge these new markets.

Over the last two decades, technology has had a profound impact on creating monetary and societal value. Participants that were not involved in the financial upside of this rise missed substantial opportunity cost. According to Damodaran (2001), technology-focused companies tend to obtain higher valuations than their counterparts. For many, this high valuation relative to other competing industries may prevent someone from investing in such companies. However, he also mentions that these same investors may fail to consider the value upside of technology companies. Technology companies tend to be at the forefront of innovation, prompting rapid growth of revenue and adoption. A common characteristic among certain technologies is that they can be scalable and require little capital investment. This in return, creates margin expansion and booming cash flows for businesses to reinvest in even more technological growth. Another characteristic, though less common, can be network effects that create substantial value for user bases. These technological developments have been known to lead to externalities most valuations cannot account for.

3.5.2. Multiples for Technology Valuation

Successful technology tends to lead to upside externalities that cannot be easily considered in DCF or multiples. Nonetheless, these tools do still get commonly used to derive values. While a DCF cannot be modified to fit much change, multiples can have a bit more flexibility. Emerging out of the momentum leading up to the Dot.com bubble, the valuation of technology startups became more creative through multiples valuation. Derivatives of early stage technology are usually characterized by either pre-revenue or negative profits, leading to large cash burn. Since the most popular multiples include data of revenue, EBITDA, and net income, applying these to startups can be impossible to do. Therefore, alternative multiples were established in considering new and relevant metrics.

Damodaran (2001) describes that analysts began dividing market value by the number of hits generated for a firm's website. Different business models of technology companies required modified versions of this new denominator in multiples. While the following multiples were first used for internet and social media companies, they've grown to include software-as-a-service

(SaaS) companies too. Given SaaS's popular and unique business model of service platforms, customer and subscriber growth is key in determining value.

As SaaS models grew, new philosophical valuations gained footing to adapt to bottom-up revenue generation. Three multiples for these common business models include:

$$\textit{Value per Subscriber} = \frac{\textit{(Market Value of Equity + Market Value of Debt)}}{\textit{Number of Subscribers}}$$

$$\textit{Value per Customer} = \frac{\textit{(Market Value of Equity + Market Value of Debt)}}{\textit{Number of Customers}}$$

$$\textit{Value per Visitor} = \frac{\textit{(Market Value of Equity + Market Value of Debt)}}{\textit{Number of Visitors to Site}}$$

While the above multiples look a bit different than traditional types, the determinants of value are the same which are cash flows, growth, and risk but with a more complex relationship. In searching for more rigorous relationships of value attachment, the DCF of customers is considered with the following equation:

$$\textit{Value per Customer} = VX = \sum_{t=1}^{t=n} \frac{CFX}{(1+r)^t}$$

Where n is years, CFX is the net present value of a customer (revenue minus cost to serve the customer), and r is the discount rate.

A discount rate can be comparable to a riskless rate if a customer has signed a contract to remain a subscriber for the next n years. However, given a customer would always have the likelihood of opting out of subscriber contracts, there should be a risk premium to adjust for this which can be done via a higher discount rate. In continuation of the value per customer equation derived above, the value of the firm can now be estimated. If the company is assumed to continue to add new subscribers in future years, the following equation can be solved to find value.

$$Value\ of\ Firm = NX \times VX + \sum_{t=1}^{t=\infty} \frac{\Delta NX_t (VX_t - C_t}{(1+k_C)^t}$$

Where NX is the number of existing subscribers, C_t is the cost of each new subscriber added in period t, ΔNX_t is the change in new subscribers, VX_t is the value per subscriber in period t, and k_C is the discount rate.

If both sides of the equation are divided by NX, the value of a firm per subscriber base is both a function of expected value generated by existing subscribers and also potential value creation of subscriber base growth. To reflect a competitive market where C_t converges to value generated by customers, the value per subscriber becomes the present value of cash flows generated by each subscriber:

$$Value\ per\ Existing\ Subscriber_{C=VX} = VX$$

This same customer value process can be done for other technology companies but vary on accurate forecasts as it is harder to estimate customer value where a fixed price doesn't hold, such as that of a subscription.

3.6. Conclusion

In this chapter, the theoretical models are introduced which began with DCF and included real option valuation. Though real options are not the most intuitive technique in valuation, they provide a means for valuing managerial flexibility and high growth opportunities in startups. Additionally, the stochastic real options integrated into decision trees allow for both private and market risk to be represented in the model.

The most popular forms of valuation (DCF and multiples) are commonly used for technology valuation. While the DCF process does not experience much modification, multiples have seen an evolution over the years of technology change in which different denominators have become used to substitute for traditional financial metrics. While an answer to value can be derived from this route, it can become difficult to contrast comparable firms and ensure smart valuation. With evident problems in both methodologies used as standalone tools, real options can be instrumental in adding strength to the process.

In Chapter 4, the case study applies an empirical model built from the theory discussed in this chapter. A DCF is constructed to assume a starting net present value for the valuation tree in the binomial lattice. Stochastic real options are utilized for the given strategic nature of the startup while being integrated into a decision tree that considers the marginal probabilistic success of the startup.

CHAPTER 4. AG BIOTECH STARTUP CASE STUDY

4.1. Introduction

AgTech startups can be broad and come from different areas within the entire agricultural industry. These different areas of the industry host varying dynamics such as end market customers, regulation, intellectual property, and profitability. With that consideration, optionality (hence real options) changes between young companies. Since startups host uncertainty (given the limited operational history) and managerial flexibility, a valuation model must cater to that. DCF methods with fixed assumptions do not capture the potential upside of additional growth opportunities. In addition, DCF assumes a company project will continue as implemented, limiting the managerial flexibility in opting out of certain project scenarios. Real options for startup valuation fix these problems as growth opportunities or managerial flexibility (such as abandoning a project) can be quantified. These lead to a more accurate valuation accounting for characteristics that DCF fails to consider.

This chapter applies an empirical model to a real case study to quantify the value of a startup using stochastic real options and decision trees. The model results are compared to a traditional DCF analysis to provide insight into the outcome difference. The model applies two separate real options, an abandonment, and a sequential compound option. The abandonment option is the value of the startup's first product while the sequential option considers the value of the second product in the pipeline. Since these are the only products of the startup, combining real option values for both products becomes the base valuation of the startup. This varies to traditional use of real options in valuation as typically, a real option value is added to an existing valuation of a company, equating the total valuation. Since this startup does not have operational history or a previous valuation, the real option values are the only values existent for the startup.

4.2. Conceptual Case

The empirical model is applied to an AgTech startup operating in agriculture biotechnology. Agriculture biotech is a popular segment within AgTech dating back for decades. Legacy ag biotech such as Monsanto-Bayer, FMC, Corteva, and BASF have strong positioning in the market for crop protection (e.g., pesticides and herbicides), seed and seed treatment, and stimulants. Most of these products are synthetic, pointing to much of today's criticism for agriculture's impact on human health and climate change. As these legacy companies continue to dominate the market, there is a growing market share for biological representation as more farmers and consumers push for organic production and food. Biologics are derived from biological sources, making their crop input use acceptable for organic production. While biologics are one form of crop management control, additional methods such as pheromones, volatile organic compounds, and sterile insect technology also participate in the growing effort of non-synthetic food production. The aggregate technologies described can be incorporated into integrated pest management (IPM) programs to decrease input costs and increase the effectiveness of treatment results. The increased rate of pest resistance to common synthetic inputs has led to the interest in IPM, allowing farmers to incorporate both synthetic and biologic practices for the most efficient cost and efficacious outcome.

Due to the upstream dynamics of ag biotech, there are embedded optionality within this startup such as R&D pipelines, synergistic products, commercialization strategies, distribution modes, and business models. For example, a finished technology may apply to fixing an additional problem utilizing a similar technology, opening a new addressable market and an expansion opportunity. In addition, an R&D pipeline may prove to be unattractive in both probability of success or commercialization opportunities where management may decide to abandon the project for something of higher value. These characteristics offer a need for managerial flexibility and embracement of uncertainty where stochastic real options thrive.

A non-disclosure agreement (NDA) was signed with the management of this startup to utilize their assumptions but not disclose their company name, any financial information, and intellectual property. Hence, details are laid out best as can be given circumstances.

The ag biotech startup operates in the sterile insect technology industry, utilizing gene-editing tools to sterilize male insects. The startup hosts large risks as they are pre-revenue with no finished product yet. Therefore, there is both private and public risk existent. This first patented product is important to further product development as the patent can drive further products with lesser additional cost. The first product modeled through the abandonment option is a sterile insect, made possible through gene-edited sterile insect technology, applied to certain fruit and berry crops as part of an IPM program for crop protection. The second product is a similar application but of a different insect type, tailored towards different targeted crop types. The goal of the sterile insects is to naturally produce unfertilized eggs with female insects in the field, suppressing the overall pest population among high value fruit crops.

If the new product is approved and enters commercialization, the offering is novel with limited prior technologies to use for interpretation of market demand and penetration. Due to this feature, the stochastic nature of the model is necessary for evaluating a range versus fixed inputs.

4.3. Empirical Model

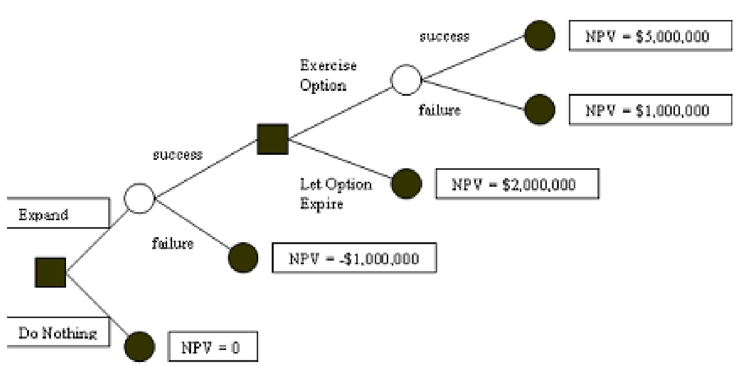
The model to value the ag biotech startup incorporates stochastic real options integrated into decision trees. These different elements bring complimentary risk analysis to what would be a standalone DCF model. The model incorporates two different real options. One option, an abandonment option, is a simple option that values the ability for management to abandon their first product in development and take an exit value (M&A transaction buyout) in exchange. The other option, a sequential compound option, is an advanced option that values the different phases of a second product with dependency on the regulatory approval of the first. The combined option value of these two products is equivalent to the startup valuation since these two pipeline products do make up the entire company and there are no existing product lines.

Since R&D phases build on each other's progress, there is a marginal probability of as the company continues to evolve. At every new phase, the marginal probability of success accounts for the previous success probabilities and applies them to the new phase's success. Hence, by the time the commercialization phase is reached, the marginal probability of success is far from 100% for high-risk R&D projects with a high probability of failure. Since there is private risk in R&D and product development, the model must incorporate decision tree analysis to account for this probability of success.

Figure 4.1 displays an example of the empirical model features. The tree combines decision and chance nodes as the project (or startup) advances through time. First, a decision must be made, followed by a chance node of success and failure of the decision. The optimal decision is either to continue the project or exercise the option. This decision is dependent on the expected value of the outcome.

Figure 4.1

Binomial Tree Model (Pinkasovitch, 2020)



A distribution of inputs is needed to incorporate the risk of assumptions. Because there is a limited operating timeline for startups, the time and cost to achieve success can be very inaccurate. In addition, the probability of success exists at different stages of R&D given the different risk profiles of each. The distribution used to model R&D phase's time and the cost is a PERT distribution. PERT uses a minimum, likely, and maximum input range obtained from expert estimation (e.g., management, consultants, etc.). Hence, the distribution is described as *PERT(minimum, likely, maximum)*. This input range allows for stochastic Monte Carlo simulation to consider the randomness and uncertainty within the assumptions. PERT derives its shape from a parameterized Beta distribution which facilitates a range of skewness and kurtosis estimates, as illustrated in Figure 4.2. Based on the range assumptions, the distribution can hold different forms which include both normal and asymmetry.

While R&D phase time and cost utilize PERT, the probability of success for each phase uses a uniform distribution such *as Uniform(minimum, maximum)*. A uniform distribution, shown in Figure 4.3, assigns equal probability weight to all values within the range of minimum and maximum assumptions. The uniform distribution provides an estimation when little or no data is available, making it strong for parameters with uncertainty.

The following sections of the chapter discuss data and assumptions, stages of the abandonment option, and phases of the sequential option. For the use of Monte Carlo and decision tree analysis, Palisade Software excel add-ins of *@Risk*™ and *PrecisionTree*™ are used. The Monte Carlo analysis utilized 10,000 simulations of input distributions to derive statistical analysis on the input and output variables.

Figure 4.2

PERT Distribution Example (Vose Software)

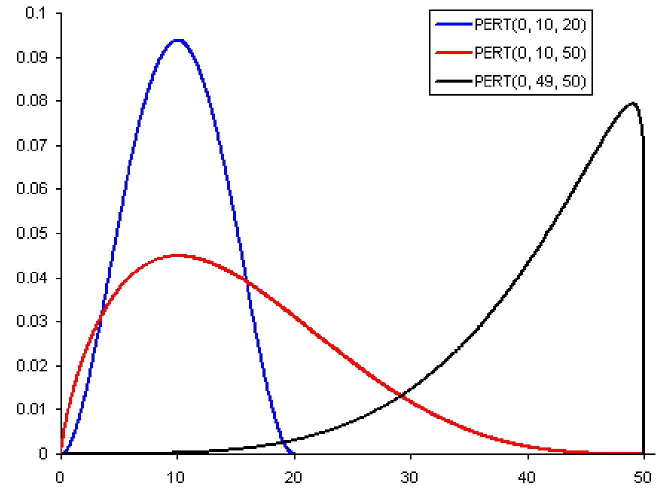
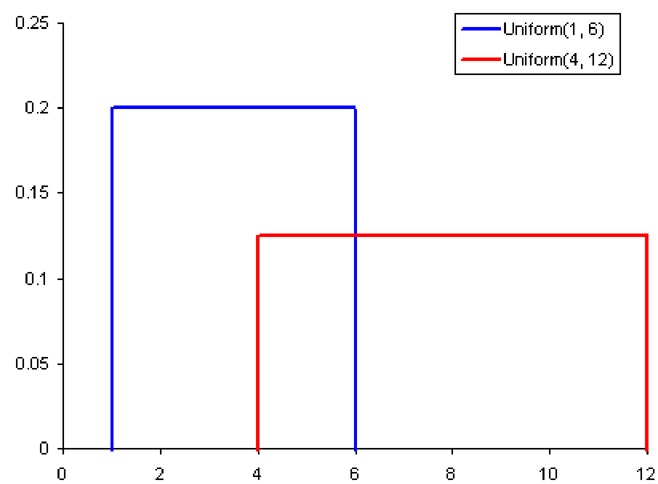


Figure 4.3

Uniform Distribution Example (Vose Software)



4.4. Data and Assumptions

Model inputs are derived from interviewing the startup's management team including the CEO (chief executive officers) and CBO (chief business officer). This includes the different ranges of time, cost, and probability of success in different R&D phases. Likewise, market penetration and unit economics such as manufacturer suggested retail price (MSRP) per acre and margin were also collected via management. These distribution assumptions are represented in their respective sub-chapters. The assumptions gathered by management for a PERT and Uniform distribution are known as expert opinion. While most of internal R&D efforts and some commercial assumptions are expert opinion, there are additional input parameters that were obtained via other sources. The combination of management's expert opinion and other assumptions made are incorporated into a model to derive the DCF value per product which serves as the starting NPV for the real option analysis.

Both products are forecasted for 15 years of commercialization. Since the products are being used to value the entire startup, a terminal value must be applied. The terminal value is calculated as a random parameter with features detailed in Table 4.1. The historic 20-year U.S. GDP growth is used as a proxy for terminal growth with Uniform stochastic simulation between the 25th and 75th percentile of GDP. Both the abandonment and sequential option apply a terminal value which is calculated with the same following formula:

$$\textit{Terminal Value} = \frac{(FCF \times [1+g])}{(R-g)}$$

Where *FCF* is the last forecasted period's free cash flow (15 years in this case), *g* is the 20-year U.S. GDP growth, and *R* is the cost of capital adjusted for risk. This cost of capital calculation is discussed later in the chapter.

Table 4.1

Terminal Growth Parameter for Both Products

Parameter	**Min**	**Max**	**Source**	**Comments**
Terminal Growth Rate	1.7%	2.9%	Macrotrends	25th and 75th percentile of historic US GDP growth.

There are non-random parameters applied to both abandonment and sequential options including risk-free rate, discount rate, and inflation factor which can be found in Table 4.2. The risk-free rate for the model is the 20-year U.S. Treasury yield. Since the startup is not capitalized with any debt, the discount rate is calculated using the CAPM approach to derive a cost of equity. Beta is derived by finding the weekly price volatility of twelve publicly traded ag biotech companies between October 2015 to October 2020 against the S&P 500 index. To incorporate risk premium, the 10-year average return of the S&P 500 is applied as market return in the CAPM equation. The CAPM equation applied to both options is written as:

$$E(R_i) = R_f + \beta_i (R_M - R_f)$$

Where $E(R_i)$ is the applied discount rate or cost of equity, R_f is the 20-year U.S. Treasury yield, β_i is the raw beta for 12 publicly traded agricultural biotechnology companies, and R_M is the 10-year average S&P 500 return.

The inflation factor applied to the forecast is 2.0%. This is based on the Federal Reserve's expectations of obtaining a 2.0% inflation target of the U.S. economy. Although the inflation factor is not a crucial assumption to the model, it's necessary for realistic inflation in agriculture. Table 4.2 displays the non-random parameter details utilized in both product calculations.

Table 4.2

Non-Random Parameters for Both Products

Parameter	**Value**	**Source**	**Comments**
Risk-Free Rate	1.34%	Macrotrends	20-year treasury yield October 5th, 2020.
Discount Rate	11.0%	Calculations, Bloomberg, and Macrotrends	Cost of equity utilizing public ag biotech volatility and S&P 500 returns.
Inflation Factor	2.00%	Federal Reserve	Federal Reserve Target.

The option models for commercialization utilize a market penetration model, similar to previous genetically modified crop studies (Bullock et al., 2021; Wilson et al., 2015; Shakya et al., 2014; Wynn et al., 2018). Penetration, measured as a percent of total addressable acres, is stochastic and modeled on management assumptions of an initial, peak, and final penetration percent expectations. Ranges of years before and after peak year are modeled via linear interpolation using the simulated penetration values.

The calculated market penetration percent is used to project the total acres that the startup's products are sold on. To obtain the projected acres, the total addressable acres is multiplied by penetration percent such that:

$$P_A = T_A * \propto$$

Where P_A is the total projected acres the products are sold on, T_A is the total addressable acres the product can be applied to and $\propto$ is the penetration percent of addressable acres the products obtain.

Revenue considers market penetration, manufacturer suggested retail price (MSRP), and inflation. MSRP is modeled in a distribution that considers a relative product pricing range to the farmer. The revenue equation can be written as:

$$R = (P_A * \tau) * (1+\varsigma)^t$$

Where P_A is the total acres the product is sold on, τ is the MSRP per acre, ς is the inflation factor, and t is the discounted time period.

The profitability of the product is simply a function of profit margin. Profit margin considers all cost of goods and operating expenses necessary in providing the product. Since the model assumes no working capital, limited capital expenditures, and no non-cash expense, the profit serves as a proxy for free cash flow. Hence, the profitability equation is such:

$$\pi = R * \omega$$

Where R is the revenue obtained and ω is the profit margin of the product.

The commercialization forecast begins at the simulated value in which accumulated R&D time ends to ensure correct discount periods. Profit, π, is discounted to obtain an NPV of cash flows. The sum of cash flows for the 15 commercial years and terminal value equates to the starting NPV for the options.

The following sub-sections focus on specific inputs and outputs to the abandonment and sequential options. Aside from the terminal growth rate, risk-free rate, discount rate, and inflation factor, all other model inputs are tailored towards the specific option type and product modeled.

4.5. Abandonment Option of Product 1

The first option applied to the startup is an abandonment option on their first ever product. With this option, management has the flexibility to abandon the product development and walk away with the salvage value in exchange for continuing to commercialization. Since this is a pre-revenue startup, there is no existing commercial work in place. Hence, the first product must go through the R&D process first in order to enter commercialization multiple years later.

During the R&D phases, management is faced with success and failure probabilities which incur at different discrete time periods. Until the commercialization phase, the salvage value that can be exercised is a percent of total sunk R&D costs such as plant, property, equipment, and intellectual property. As the company enters commercialization, the salvage value instead becomes the exit value, meaning the acquisition price if a firm is to buy the startup.

The exit value within the model can be calculated using the forecasted annual revenue multiplied by an acquisition multiple (or exit multiple) of the revenue. This is expressed as:

$$Exit_S = R_T * \emptyset$$

Where $Exit_S$ is the startup's acquisition sale price and the exercise price, R_T is the startup's revenue at time *T*, and $\emptyset$ is the exit multiple paid for the startup by an acquirer.

The exit revenue multiple is derived on past merger and acquisition (M&A) transactions in the ag biotechnology sector between 2015-2020 in North America with acquisitions between $0-10 billion. The minimum and maximum multiples are used in a Uniform distribution and are shown in Table 4.3.

Table 4.3

Revenue Multiple Parameter for Product 1

Parameter	Mix	Max	Source	Comments
Exit Revenue Multiple	0.3x	3.9x	Bloomberg Terminal	8 ag biotech M&A transactions in North America between 2015-2020 between $0-10 billion value.

4.5.1. R&D Phases

With this genetic engineering startup, there are multiple critical R&D phases to complete in order to take the first product to commercialization. These phases are summarized by discovery and technology implementation, efficacy trials, regulatory approval, and distribution plan. These different phases are each characterized by separate time to completion, cost, and probability of success. A range of these variables for all different phases was collected by the management team to derive a distribution of inputs.

Table 4.4 displays the *PERT(min, likely, max)* and *Uniform(min, max)* distribution assumptions concluded by management for the four different phases of R&D. Phases of regulation and distribution plan are distinguishable from others for their significant range of time and cost between the minimum and maximum assumptions.

Table 4.4

R&D Phase Distribution Assumptions for Product 1

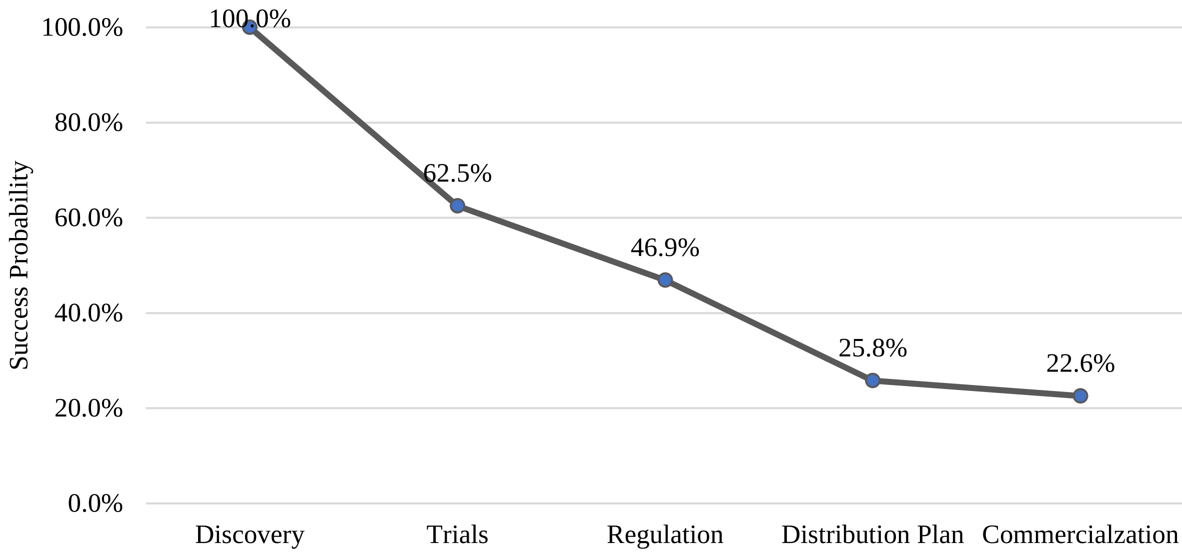
Phase	Time (Years)			Cost (Thousands $USD)			Probability of Success	
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Max**
Discovery	1.0	2.0	3.0	$500	$1,000	$1,500	25.0%	100.0%
Trials	1.0	2.0	4.0	$750	$1,500	$3,000	50.0%	100.0%
Regulation	1.5	2.0	5.0	$750	$100	$3,000	10.0%	100.0%
Distribution Plan	1.0	2.0	4.0	$5,000	$8,000	$16,000	75.0%	100.0%

Source: Management estimates (as described below).

The distribution assumptions in Table 4.4 are simulated 10,000 iterations with Monte Carlo using *@Risk* excel add-in, provided by Palisade Software. Since each phase is dependent on its predecessors, a marginal probability of success can be calculated given the success probability of each phase. Figure 4.4. illustrates this outcome as each additional phase lowers the probability of the final outcome, being commercialization. Before any phase is complete, there is a 100% probability of success. However, further succession of phases lowers the probability of successful commercialization after each phase. In the final phase of commercialization, there is only a 22.6% mean marginal probability of success.

Figure 4.4

Mean Marginal Probability of Success through Phases for Product 1



4.5.2. Commercialization

Commercialization is the final phase of the business after product R&D is accomplished and market risk begins. Since the commercialization phase is subject to market dynamics (e.g., price, penetration, demand) of the product, the binomial lattice is applied to calculate the abandonment option. To calculate the starting net present value for the product, a DCF is constructed which includes both random and fixed input parameters. The random input parameters used a Uniform distribution to consider uncertainty in important variables such as price, margin, and penetration.

Tables 4.5 and 4.6 show both random and fixed parameters used to calculate the product NPV. For initial market penetration, the range is 3% to 10% with peak penetration of 20% to 50%. By the final year, the range is just 15% to 30%, implying an “S-like” growth curve. MSRP ranges between $200 and $750 per acre with the final profit margin being 10% to 30%. If the startup is to abandon the R&D of their first product, the salvage value percentage they would obtain is between 15% and 25% of sunk R&D costs.

Based on the identified specialty crops that the startup's first product could be applied to, the total addressable acres available include 350,000 acres across multiple different fruit types. Therefore, there is a fixed addressable market that the product can target and market to.

Table 4.5

Random Parameters of DCF for Product 1

Variable	Minimum	Maximum
Peak Market Penetration	20.0%	50.0%
Initial Market Penetration	3.0%	10.0%
Final Year Market Penetration	15.0%	30.0%
MSRP per Acre	$200.00	$750.00
Profit Margin	10.0%	30.0%
Salvage (% Sunk R&D Cost)	15.0%	25.0%

Source: Management estimates (as described below).

Table 4.6

Fixed Parameters of DCF for Product 1

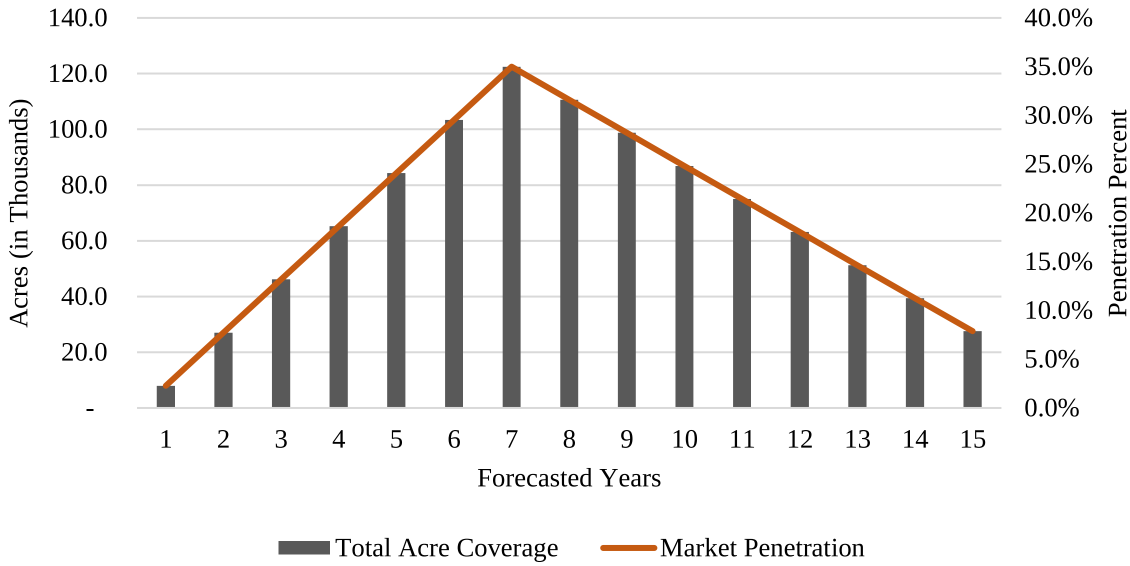
Variable	Assumption
Total Addressable Acres	350,000
Years of Commercialization	15

Source: Management estimates (as described below).

Based on management assumptions, the commercial life forecasted is fifteen years and utilizes a market penetration model. Given the increased competition and changing technology dynamics, management assumes peak market penetration in the seventh year. Figure 4.5 shows the projected mean market penetration of acres sold to. The penetration model realistically features a peak year in which it then tapers off as increased competition enters the market and the startup's product loses market share. At the product's peak share of 35%, the product is applied to approximately 120,000 acres within the United States.

Figure 4.5

Mean Market Penetration for Product 1



The resulting fifteen years of simulated discounted cash flows are the initial NPV for the real option. The up and down step needed for stochastic movement is provided by the volatility of the forecasted cash flow's logged returns. During the 15-year option life, management can weigh the option to either continue operations or abandon the commercialization effort via exit opportunity (acquired) based on the forecasted revenue and stochastic exit revenue multiple. Table 4.7 features all the parameters for the abandonment option calculation.

Table 4.7

Abandonment Option Parameters

Variable	**Notation**	**Explanation**	**Model Input**
Underlying Price (NPV)	S_0	NPV of commercialization cash flows.	Mean NPV
Volatility	σ	Standard deviation of forecasted cash flows.	Mean Volatility
Time to Maturity	T	15-year commercialization life.	15
Time Increment	δt	Discrete time step by 1 year.	1
Risk-Free Rate	R	20-year U.S. Treasury yield.	1.34
Strike Price	X	Exit value based on revenue multiple.	Mean Exit Value

4.5.3. Decision Tree Analysis

The integration of decision trees in the model creates a robust structure that considers the private risk associated with internal company R&D and market risk associated with commercialization efforts. The decision tree hosts both decision and chance nodes. It begins with a decision node that simply evaluates whether to proceed with a certain action (e.g., initiate project, continue to phase 2, etc.). If the decision node is false, the project is abandoned, or the company is liquidated. If the node is true, the tree leads to a chance node where probabilistic outcomes are compared on the likelihood of success and failure. The tree continues to go through these series until all R&D efforts are complete. In the final decision node, the decision to commercialize is considered with the value of the node being the real option value obtained in the commercial abandonment option. Since the probabilities, salvage values, and commercialization option value is integrated with the decision tree, the outcome of the tree itself is stochastically derived. Figure 4.6 visualizes the five decision nodes of the model's decision tree. At each of the decision nodes, a "yes" or no" decision must be made to move onto the next phase. Each decision node is followed by a chance node where marginal probabilities are weighted amongst the market value to continue to the final phase of commercialization.

Figure 4.6

Evolving Decision Nodes of Product 1

4.5.4. Base Case Results

The model's results include the real option value at each stage of the decision tree. Since these phases occur at discrete periods, a new ROV is calculated as the progress and probability of success adapt to new circumstances. Figure 4.7 displays the conditional mean ROV at these different discrete phases of progress. The initial project ROV assumes the option value before any phases are completed. Therefore, the initial project ROV would intuitively have the lowest ROV of any stage, resulting in a total $30.2 million value. The following phase's ROV builds on the progress as they assume successful completion which increases the value at every occurrence. For example, the successful completion of the discovery phase leads to an ROV of $49.1 million.

Figure 4.7's progressing real option values provide a means to understand where significant value creation takes place. Noticeably, ROV jumps significantly after the trial completion. Since the distribution plan is the final phase before commercialization, the success of this phase is equivalent to the expected value of commercialization. Hence, the value of the startup's first product has a valuation of $141.7 million. To relatively compare among the DCF values, the $141.7 million valuation at commercialization is used.

Figure 4.7

Conditional Mean ROV at Each Phase for Product 1(Thousands $USD)

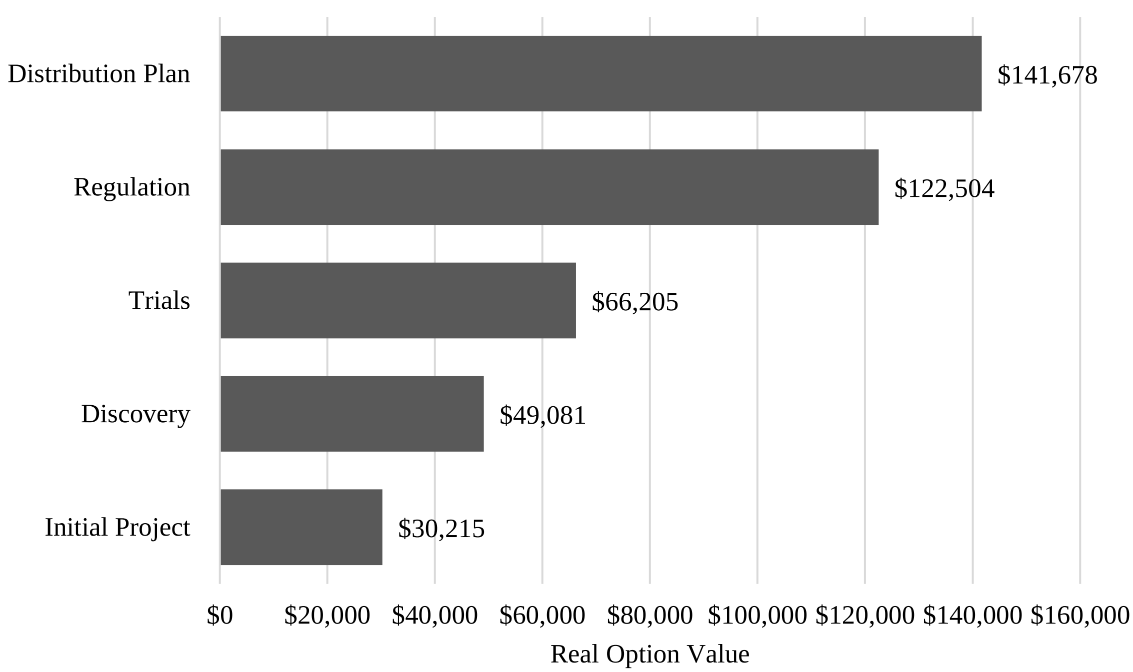
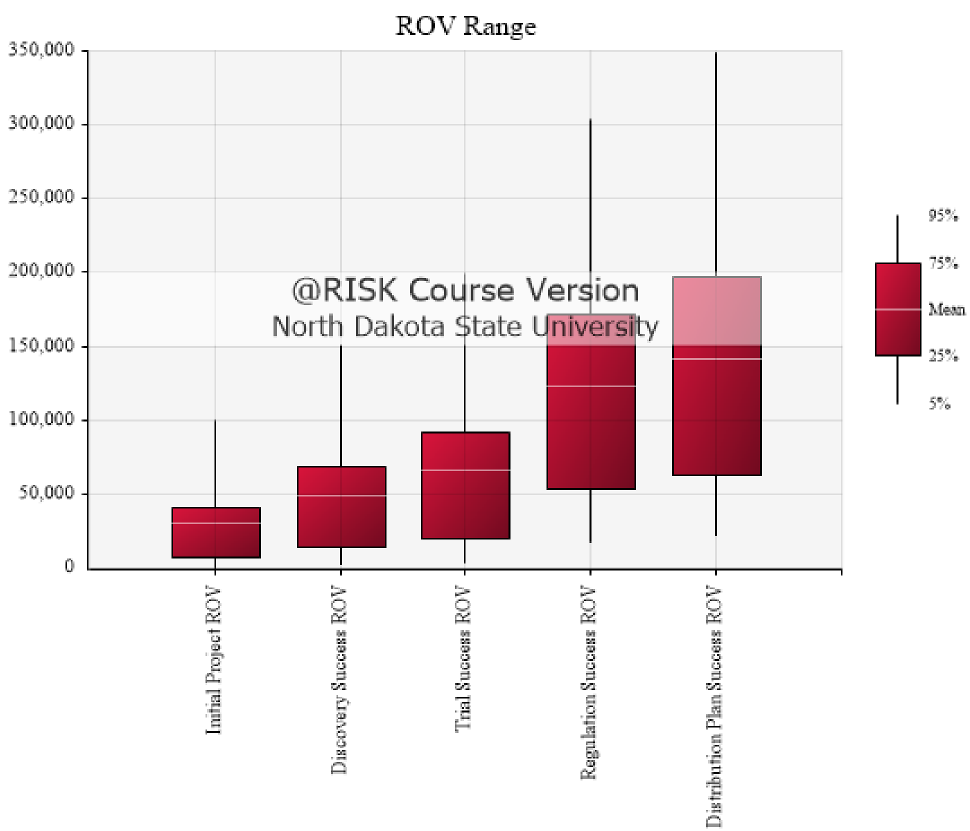


Figure 4.8 exhibits the same conditional ROV of phases from Figure 4.7, but with inclusion of the range. The range of the red surface embodies the 25th to 75th percentile with the extended black lines ranging from the 5th to 95th percentile. As each phase is passed, the asymmetric upside grows, reaching $348.5 million in ROV in the successful distribution phase at the 95th percentile.

Since there is managerial flexibility of a high growth opportunity present in the model, the valuation is heavily skewed to the upside versus a limited downside value. At the initial onset of the project, there is only a 3.6% probability of negative ROV with a 96.4% probability of positive ROV. That probability of positive value only increases with the successful progress of phases. By the final distribution plan phase, there is just a 0.1% probability of negative ROV.

Figure 4.8

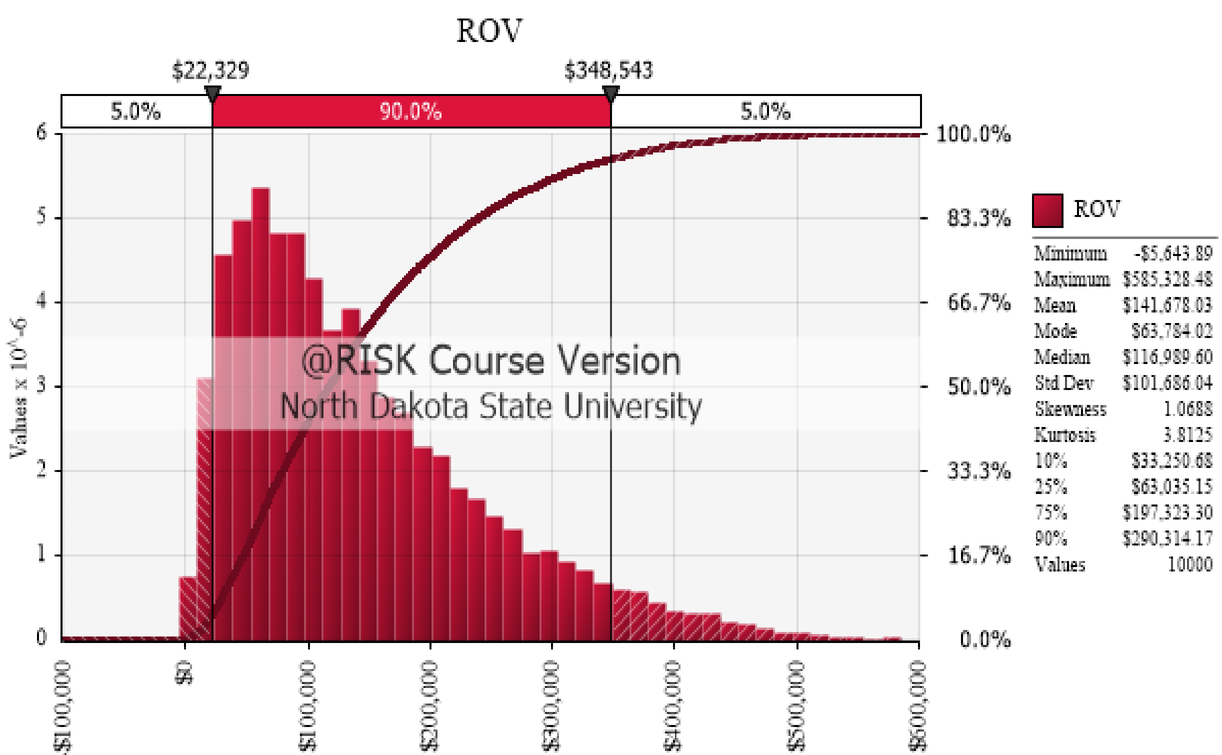
Box-and-Whisker Plot of Conditional ROV Phases for Product 1(Thousands $USD)



As mentioned previously, the base case results found the startup's first product to be valued at $141.7 million using real option value. Figure 4.9 displays the stochastic simulation output, utilizing 10,000 simulations. The distribution reports a 90% confidence interval of ROV between $22.3 million and $348.5 million with a standard deviation of $101.7 million. As quantified through a skewness of 1.07, there is asymmetric upside accounted for with tail simulations, such as the maximum value of $585.3 million. Even at just the 10th percentile, the value is $33.3 million. The kurtosis of the distribution is 3.8, indicating more weight to the tail than what a normal distribution would offer. Figure 4.9's output validates the benefit of using stochastic real options for startup valuation as the tool strongly considers the valuation asymmetry that can occur within successful startups that exhibit the "home-run" capabilities as exemplified in Chapter 1.

Figure 4.9

ROV Simulation Results of Product 1(Thousands $USD)



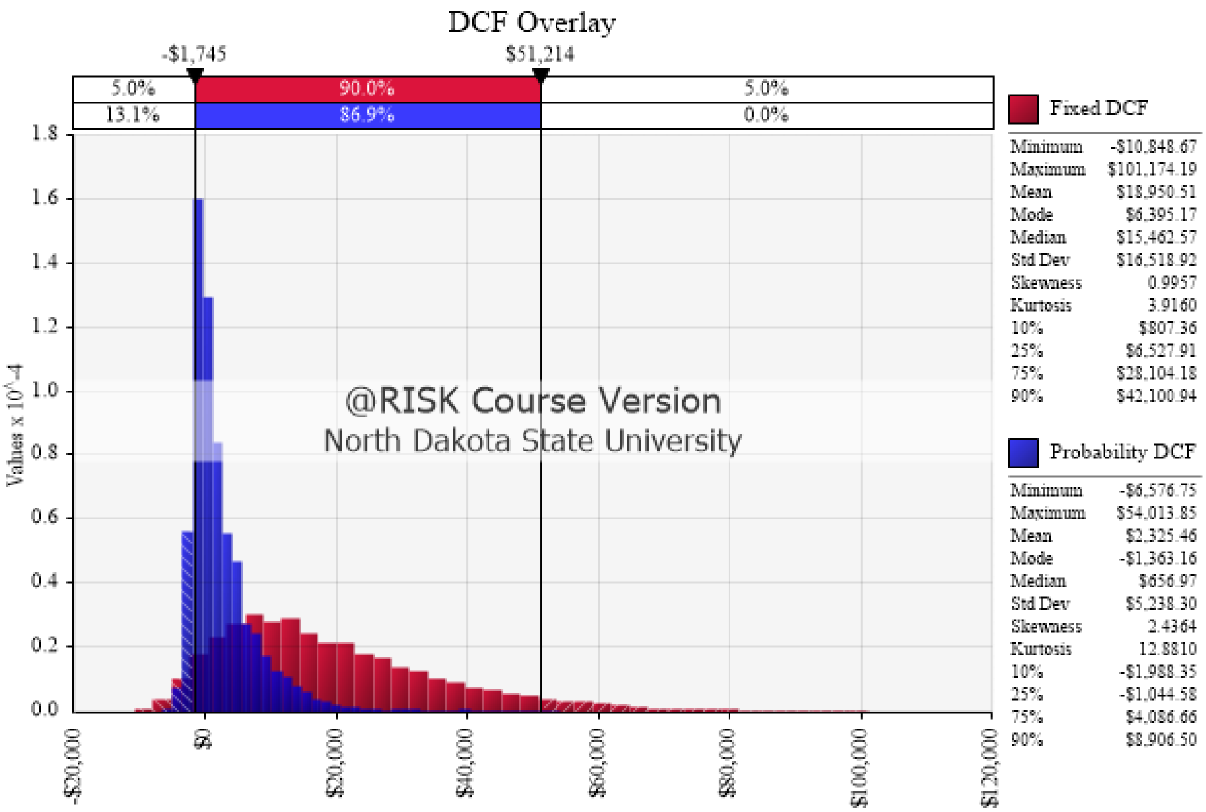
For a relative comparison with DCF approaches, Figure 4.10 features an overlay distribution of 10,000 iterations of a fixed and probability DCF. The fixed DCF approach assumes no marginal probability of success within the calculation. Therefore, the NPV is not risk-adjusted for the probability of failure as the startup attempts to reach commercialization through the different phases. The probability DCF does consider the marginal probability of success which is significant in the case of low probabilistic phase completion. As reviewed prior, there is only a 22.6% probability of success the startup reaches commercialization with the first product. Therefore, the fixed DCF can dramatically overvalue the business without this consideration. Since most DCF valuations do not consider the marginal probability, it’s helpful to compare both fixed and probabilistic DCF values to drive the concept.

For the fixed DCF, the mean value is $18.95 million with a standard deviation of $16.5 million. While the value output is strongly positive for a pre-revenue startup, the asymmetry is not nearly as high relative to the ROV output, represented by the maximum value of $101.2 million versus $585.3 million of maximum ROV. In addition, it’s more normally distributed versus the ROV output, proven by the skewness of 0.996. Based on the output, there is a 92% probability of positive value and an 8% probability of negative value.

The probability DCF shows a stark result as the mean value is just $2.3 million with much larger downside risk in negative value. In fact, there is just a 59% probability of positive value versus a 41% probability of negative value. Additionally, there is less asymmetric upside versus both the fixed DCF and ROV results. This is proven through the high kurtosis of 12.9, which is easily visualized as most of the distribution revolves around the near zero value range.

Figure 4.10

DCF Overlay Simulation Results of Product 1(Thousands $USD)



The contrasts between the two DCF methods and ROV are consistent with the claim that DCF tends to undervalue companies by not capturing the managerial flexibility. Because the ROV method allows the option to abandon the development and commercialization of the product for either a salvage value or exit value, material value is provided that cannot be captured in the inflexibility of a DCF assumptions whether it is fixed or probabilistically derived.

This relative comparison of methods validates the reasoning of using real options to value startups given the significant uncertainty and flexibility in a business. The failure to consider the real option value on the startup’s first product would prevent the venture capitalist from appreciating the true asymmetric upside in the investment opportunity and missing a potential “home-run” for the portfolio.

4.5.5. Sensitivities and Scenarios

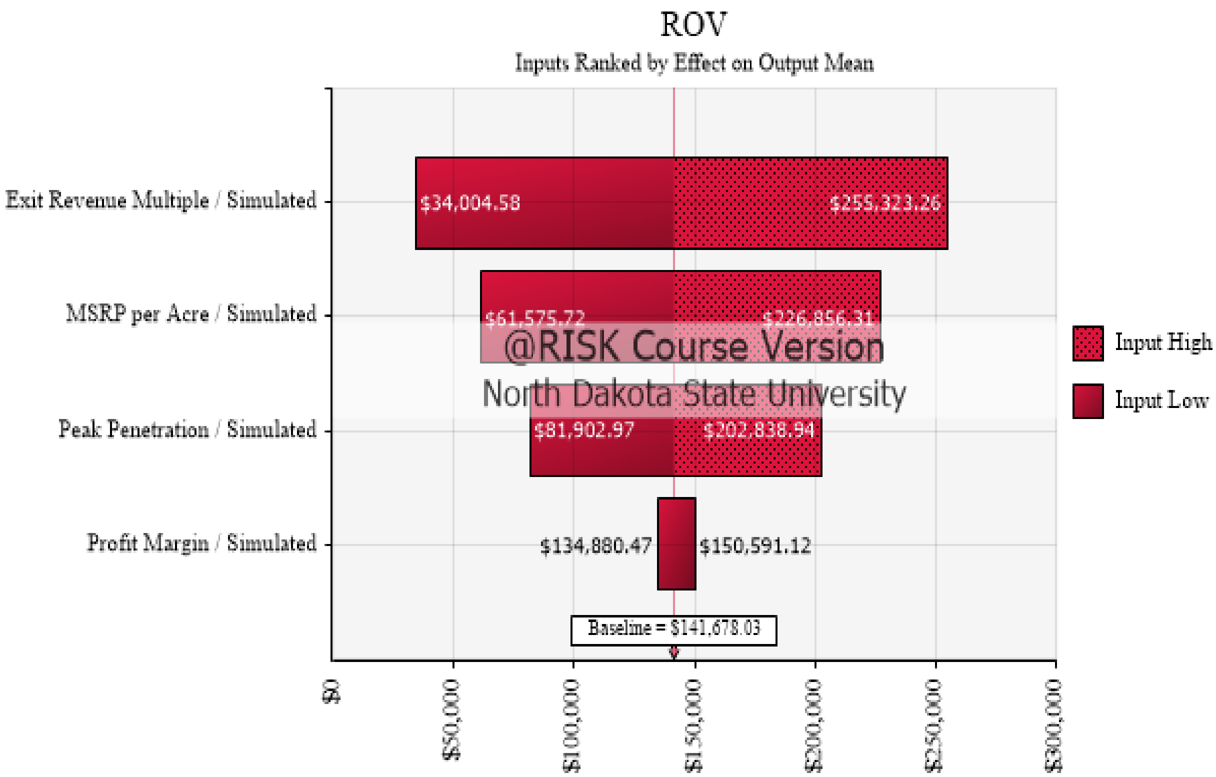
The previous section focused on the base results of the model. However, a model's results are only as good as the inputs involved. Inputs can, and likely will, be wrong. This is especially true for a startup that does not have certain costs and commercialization information. Therefore, it is necessary to analyze sensitivities and alternative scenarios via stress testing to understand what influences the outcome most. Since this study argues for the consideration of real option valuation, this exercise allocates most energy to the ROV output versus the DCF results. For the ROV output, the top four sensitivities are analyzed throughout different sensitivity forms such as correlations, tornado graphs, and spider graphs.

Figure 4.11 presents a tornado graph of the four most influential inputs to the dollar change in the output mean, being $141.7 million. The top bar features the most sensitive input which carries the highest range, followed consecutively by the next most sensitive inputs. The dark shaded side (left) of the chart implies the lower 10th percentile of distribution results while the light shaded side (right) implies the upper 10th percentile of results. As demonstrated in Figure 4.11, the exit revenue multiple (acting as the exercise price in the abandonment option) holds the highest sensitivity out of all inputs in the model. From the baseline mean value of $141.7 million, the lower bound range of the input implies a low output of just $34.0 million in value versus the higher bound of $255.3 million. It shouldn't come as a surprise that the exit multiple is this influential on the change in mean value as it dictates the action to exercise or not exercise the option.

While not as influential as the exit multiple, other inputs of highest sensitivity included are MSRP per acre, peak market penetration, and profit margin. MSRP and peak market penetration are critical variables in translating revenue and net present value for the product, hence the initial NPV for the stochastic process. In the lowest 10th percentile, MSRP per acre leads to just $61.6 million in ROV versus the top 10th percentile of $226.9 million in value. Though profit margin is the fourth most sensitive to change in ROV, it's not nearly as critical as others given the lower and upper range is only $15.7 million in the delta.

Figure 4.11

Change in ROV Output Mean of Product 1(Thousands $USD)



Since the exit multiple is critical in sensitivity to the output, further analysis is provided. Figure 4.12 displays a colored scatter plot of the entire distribution. The plot is made up of the lowest 10th percentile (blue), highest 10th percentile (green), and remaining percentile (red). As the exit multiple increases, ROV variation increases dramatically, offering the asymmetric upside previously analyzed in Figure 4.9. The quadrants are subdivided at the mean ROV and exit multiple. The percentage within the quadrants describes the probability of the specific percentile's outcome within the quadrant. Noticeably, if the scatter point lands in quadrant II where the exit multiple and ROV are greater than the mean, 83.0% of the scatter points are in the 10th percentile. Interestingly, 100% of the lower 10th percentile resides in quadrant IV. This quadrant only carries a mean 0.44x exit multiple with a maximum of approximately 0.7x. This implies that to obtain an ROV greater than the lowest 10th percentile, an exit multiple greater than 0.7x is needed while holding all else constant.

Figure 4.12

Scatter Plot Relationship of Exit Value and ROV (Thousands $USD)

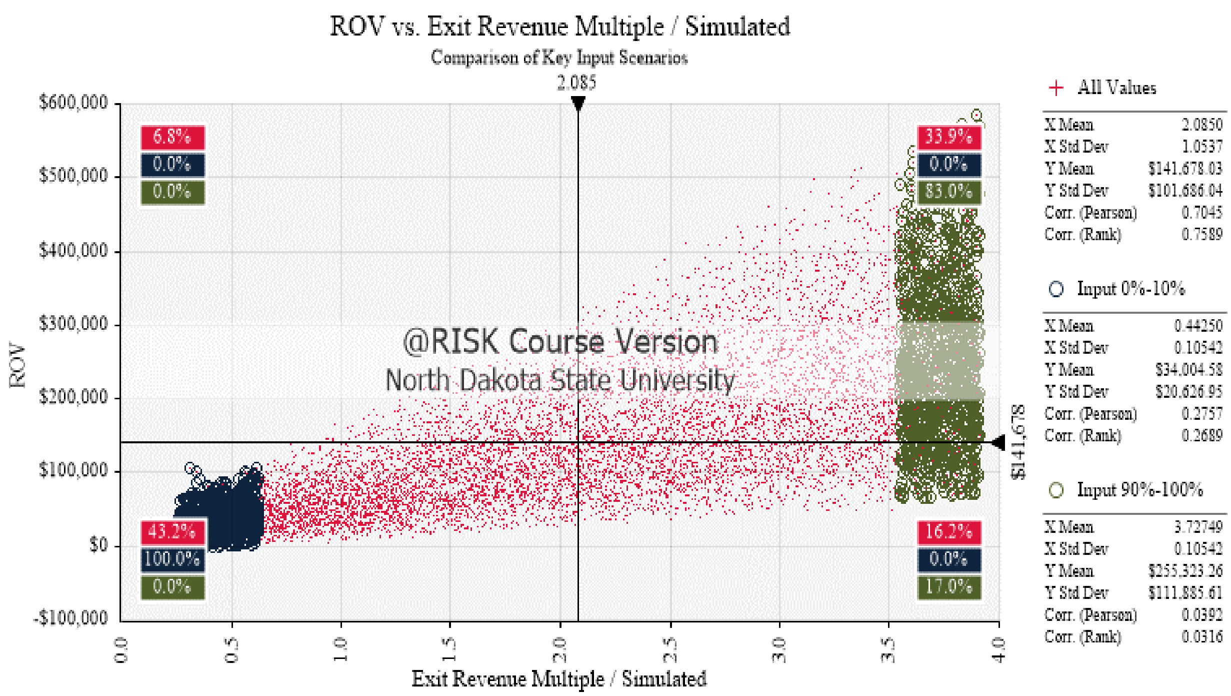


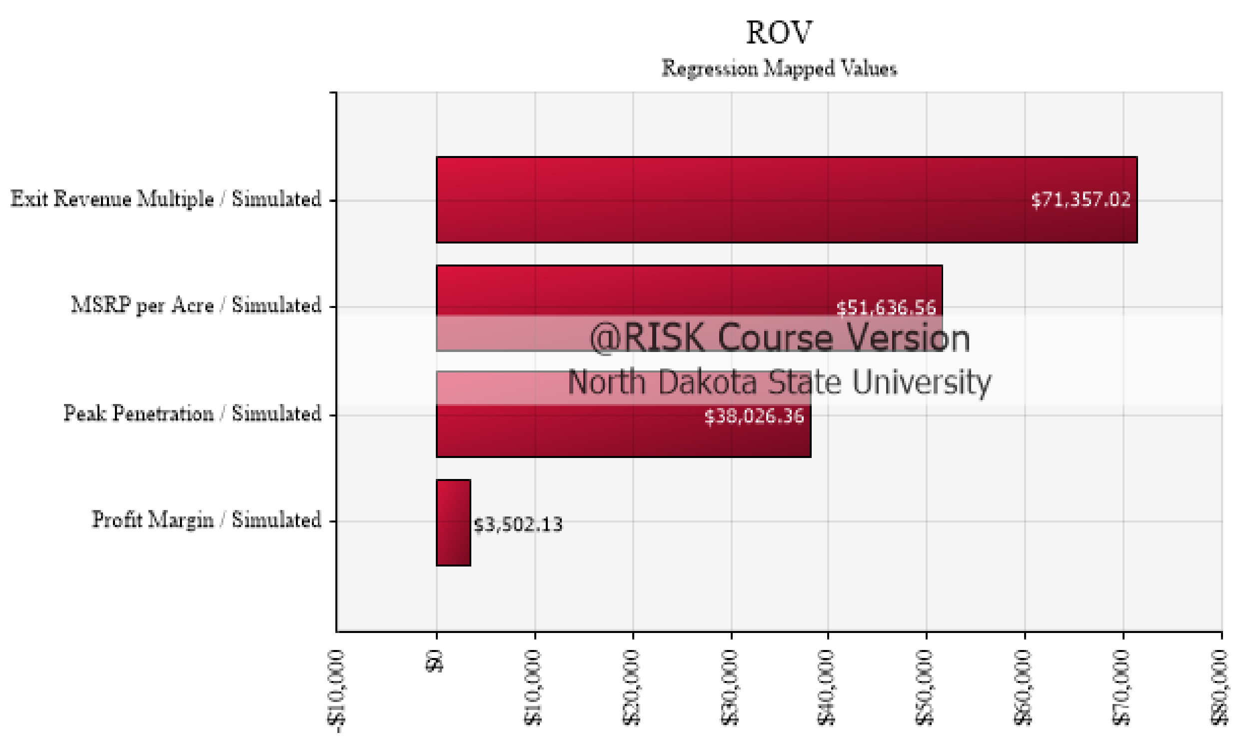
Figure 4.13 is a viewpoint of the regression mapped sensitivity results. Here, the variance of the ROV is expressed as a dollar amount per one unit of standard deviation change in the input. For example, with a one standard deviation increase for the exit multiple, ROV increases by $71.4 million. This output has implications for both the investor and the management team as it shows what specific inputs can cause a material increase on the ROV, hence the important actions that would lead to value creation. Unfortunately, the three most material inputs in Figure

4.13 are largely driven by the market versus management's control and execution. Therefore, the importance of a sound understanding of the startup's market is crucial to success.

A Spearman rank correlation is also analyzed among the inputs. Spearman rank differs from Pearson correlation as the latter assumes normality while Spearman can correlate non-normal distributions. It is important to note that each coefficient is measured by itself in relation to the dependent variable. The exit multiple, which has a 0.76 coefficient, is said to explain 76% of the ROV's variation. Therefore, 24% of the remaining variation is explained by other inputs outside of exit multiple. MSRP per acre and peak penetration have coefficients of 0.50 and 0.35, respectfully. The profit margin only carries a 0.04% Spearman rank correlation, validating previous comments as to its lesser significance versus other input assumptions.

Figure 4.13

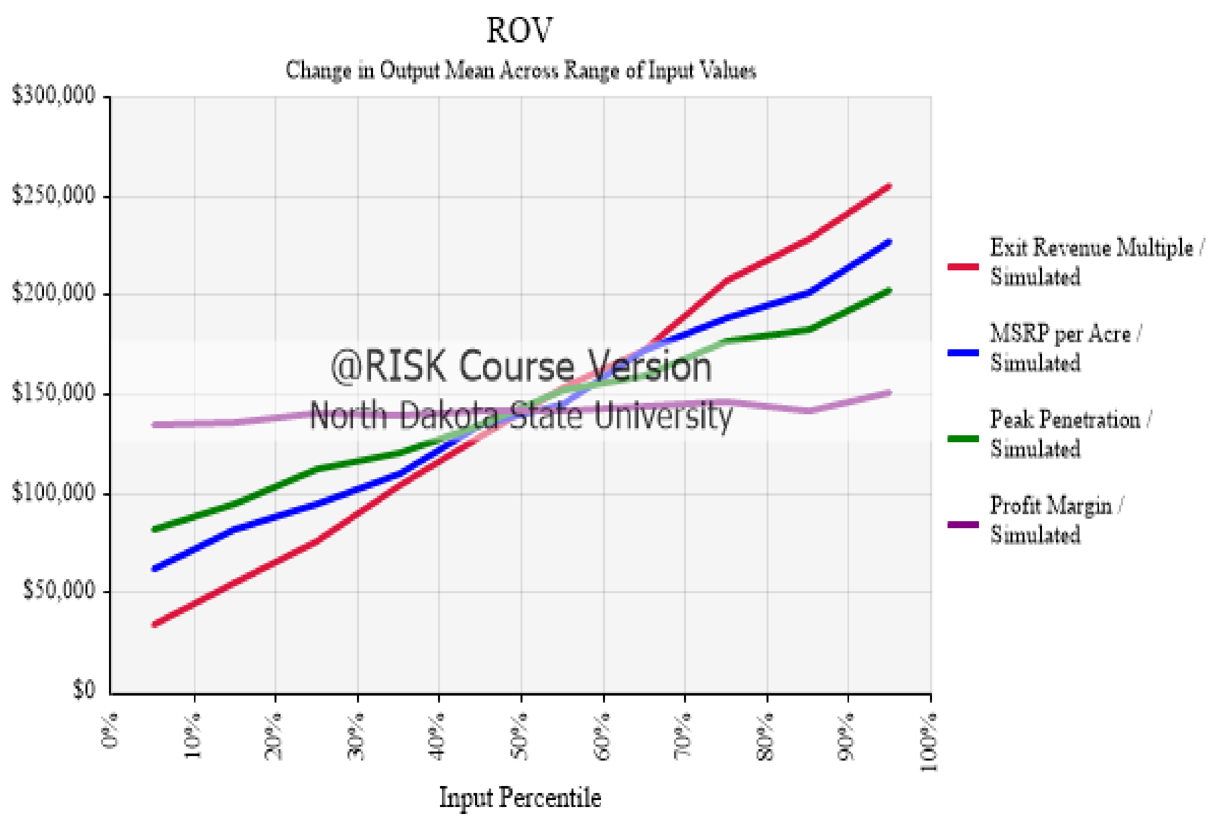
Regression Mapped Values of Product 1(Thousands $USD)



In a final illustration of input sensitivity to ROV output, Figure 4.14 features a spider graph that visualizes the dollar change in ROV output to a different percentile of inputs. Slope is the most important attribute in analyzing the change relative to input percentile. Similar to the prior sensitivity analysis, exit multiple displays the most influential change in ROV at each percentile. Though all inputs are rather constant through the various percentiles, the MSRP per acre, peak penetration, and profit margin all become increasingly critical at the 85th percentile as slope increases relative to other percentile ranges. This implies that the upper 15th percentile is those three inputs that have the ability to asymmetrical affect the ROV in a positive way relative to the bottom 85th percentile of input.

Figure 4.14

Spider Graph of Product 1



Without applying detailed sensitivity analysis on these critical variables, it would be very difficult to deal with input uncertainty in valuing the startup and understanding material drivers of value. Therefore, the sensitivity exercise is insightful in ascribing to critical components that create value and investment return for the startup and the venture capitalist. Most importantly, the operator can prioritize and hone in on the most important variables that are to offer value creation long term.

Aside from just sensitivity analysis, a scenario analysis is also conducted on the outputs to understand the critical inputs under certain stress testing scenarios. Figure 4.15 expresses the results of key inputs that contribute to the product's ROV above the 90th percentile. The resulting statistic is measured by the median change of input divided by standard deviation. For example, the median exit multiple in the subset is 1.2094 standard deviation above the median exit multiple in the entire simulation. The percentage is the percentile in which the median input in the subset is of the median input of the entire simulation. Hence, 84.9% represents the median exit multiple in the subset being the percentile of the median exit multiple within the entire simulation. The three inputs listed (exit multiple, MSRP per acre, peak penetration) are the only inputs that are significantly larger in the scenario when ROV is greater than the 90th percentile.

Likewise, similar scenario analysis can be performed on the lower percentile of ROV results. Figure 4.16 expresses the scenario results at the bottom 25th percentile of ROV. Here, the inputs are the same as before, except their effect is different. Exit multiple, MSRP per acre, and peak penetration are the only significant inputs affecting the bottom 25th percentile of ROV. The subset ratio of median to standard deviation in inputs is now below the median input of the entire simulation.

Figure 4.15

Scenario Analysis >90th percentile of Product 1

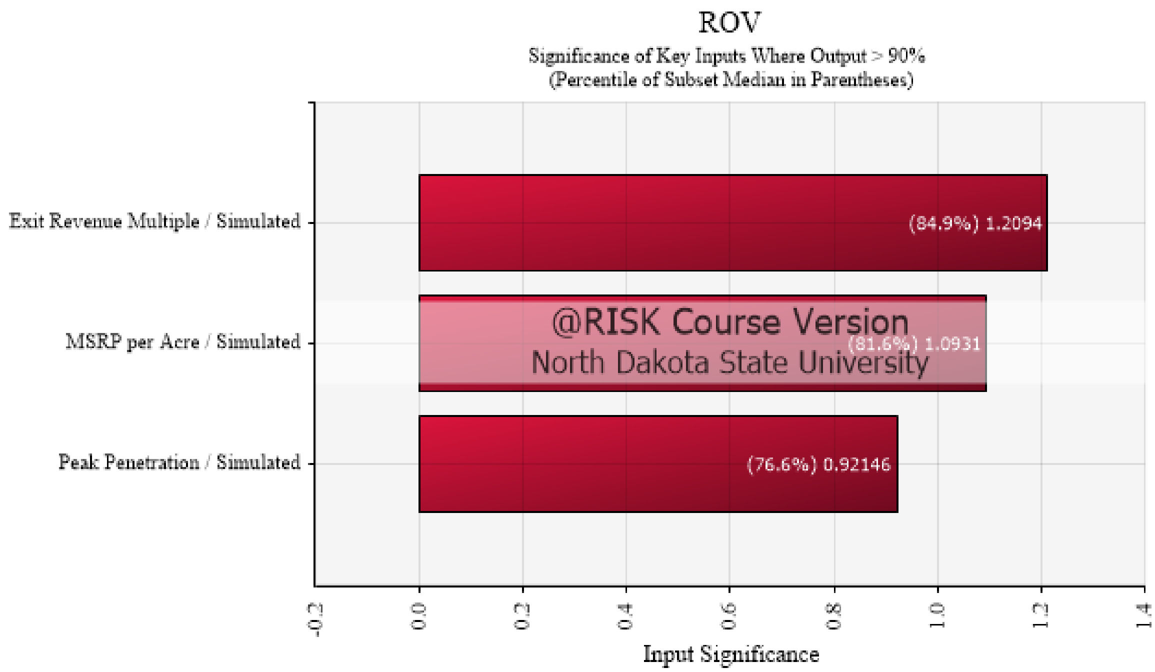
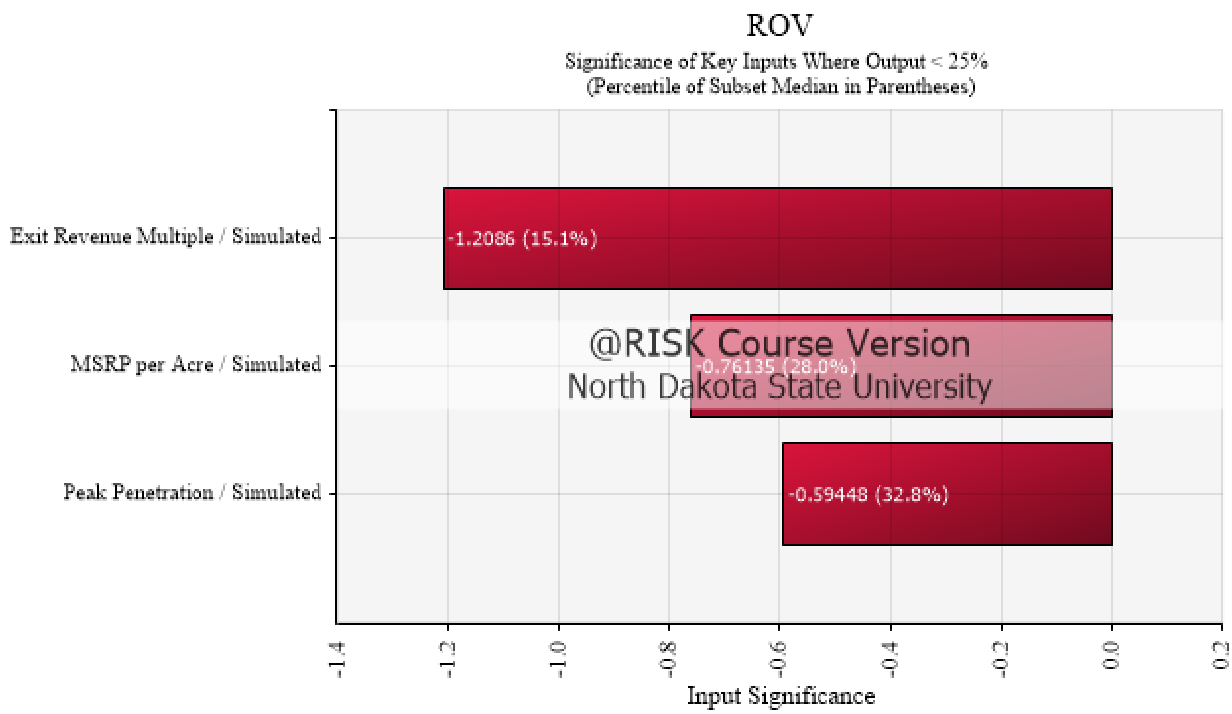


Figure 4.16

Scenario Analysis <25% of Product 1



Appendix A through D features the ranked effect on output mean and regression mapped values sensitivity results for both the fixed and probability DCF. For a sense of relativity, there are both similarities and differences in their most sensitive inputs versus the ROV results. For the fixed DCF, the MSRP per acre is of highest sensitivity followed by profit margin, peak penetration, and regulatory cost. Though three of four inputs are the same as in the ROV inputs, the rank and range of variability are large. The same most sensitive inputs of the fixed DCF are also the same four inputs for the probability DCF. However, the ordering was changed with regulatory success being of highest sensitivity. This intuitively makes sense since the probabilistic DCF considers the marginal probability of success in phases while the fixed DCF does not. Since the regulation phase has the lowest minimum probability range (10%) of success, it's understandable why this is material to the valuation.

Though there are material sensitivities that must be considered in the ROV model output, it's evident that the valuation procedure using ROV versus the DCF methodologies is robust in accounting for asymmetric upside and uncertainty, a key downfall of DCF valuation. While the sensitivities and scenarios offer insight into the influences of valuation, they are also useful in assessing the legitimate drivers of creating or destroying value for the startup, something important to both investors and managers.

In the next chapter subsection of 4.6, the startup's second product will be valued, compared, and analyzed similarly to the first product previously reviewed. For the ease of information flow, the style and analysis will follow a similar order. Additionally, there will be less explanation of illustration criteria and methodology used since much of that is covered prior.

4.6. Sequential Option of Product 2

A sequential compound option is a complex option type that is essentially an “option of an option”. The sequential option is comprised of multi-stages that can include a call on a call, call on a put, put and a put, and put and a call. The sequential real option analysis first begins with the longest dated phase (or stage) and works backward to the shorted dated phase. This is because the longest dated phase must be exercised first in order to achieve the final result of a project.

For this sequential option, the startup’s second product is valued based on a multi-stage R&D process leading up to commercialization. The three phases used are critical components to the second product’s success which includes technology development, trial performance, and regulatory approval. To illustrate, the startup must decide to either continue (put) or abandon (call) the entire project at every one of those sequential three phases.

In addition to the second product’s success at the different sequential phases, there is dependency on the first product’s regulatory approval. Though this second product is lesser in the priority pipeline versus the first product, there is an obvious interest for management to be simultaneously working on the second product to offer near term growth after the launch of the first product. However, this continuation of the second product’s development is only up to a certain point to which management will wait to confirm the regulatory approval of the first product before continuation of the sunk R&D cost into the second product’s development. Therefore, this additional component is modeled in both the discovery R&D phase of the second product, along with using a logic node in the decision tree.

The following sub-sections explain the details and inputs of the sequential option. The three different stages are discussed, followed by the results and sensitivities of the option.

4.6.1. R&D and DCF

Like for the abandonment option, there is an underlying NPV assigned to the sequential option. This NPV is a by-product of the probabilistic DCF output of the second product. Table 4.8 represents the PERT and Uniform distributions assumptions derived through expert opinion by management. Since the second product is similar to the first, the R&D phases are the same. While the majority of phases take similar time and cost as the first product, the probability of success is noticeably higher since a similar version of gene editing has been done previously in the first product. Hence, there is greater certainty in what can and cannot be done via technological capabilities.

Table 4.8

R&D Phase Distribution Assumptions for Product 2

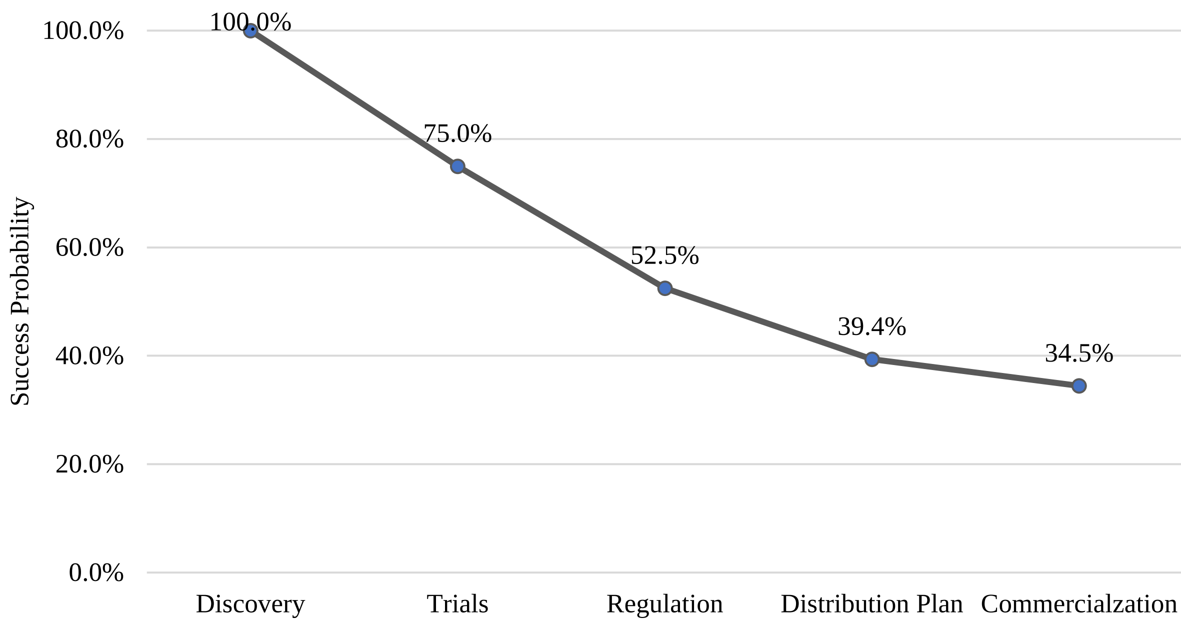
Phase	**Time (Years)**			**Cost (Thousands $USD)**			**Probability of Success**	
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Max**
Discovery	1.0	2.0	3.0	$500	$1,000	$1,500	50.0%	100.0%
Trials	1.0	2.0	4.0	$1,000	$2,500	$4,000	40.0%	100.0%
Regulation	1.5	2.0	5.0	$750	$1,000	$3,000	50.0%	100.0%
Distribution Plan	1.0	2.0	4.0	$4,000	$6,000	$10,000	75.0%	100.0%

Source: Management estimates (as described below).

Figure 4.17 features the consecutive phases in a marginal success format. Before anything is completed, the starting probability of success is 100%. After considering the marginal probability of success, there is a 34.5% mean success probability of reaching commercialization. Recalling that the first product only had a 22.6% probability of reaching commercialization, the second product has increased certainty of success by over 12%. It's important to take note of the declining slope of probability with each additional phase. While consideration of the discovery phase decreasing the end success by 25%, the following phases have a lesser effect on the ending probability of commercialization.

Figure 4.17

Mean Marginal Probability of Success through Phases for Product 2



Similar to the first product's commercialization, the second product also features a market penetration model with a Uniform distribution of random and fixed inputs represented in Tables 4.9 and 4.10. While the second product's R&D and commercial strategy are similar, different product dynamics create altering unit economics and market demand. For example, the first product had 350,000 total addressable acres while the second product only carries 50,000 acres due to the smaller target market the product can be applied to. However, the second product has a significantly higher manufacturer's suggested retail price (MSRP) and peak market penetration. In other words, while the product cannot be applied to as large of an addressable market as the first product, the second product can achieve higher value per acre and penetrate a larger percentage of the market. The profit margin and salvage value range remain the same as in the first product.

Table 4.9

Random Parameters of DCF for Product 2

Variable	Minimum	Maximum
Peak Market Penetration	30.0%	70.0%
Initial Market Penetration	5.0%	10.0%
Final Year Market Penetration	10.0%	25.0%
MSRP per Acre	$500.00	$1,500.00
Profit Margin	10.0%	30.0%
Salvage (% Sunk R&D Cost)	15.0%	25.0%

Source: Management estimates (as described below).

Table 4.10

Fixed Parameters of DCF for Product 2

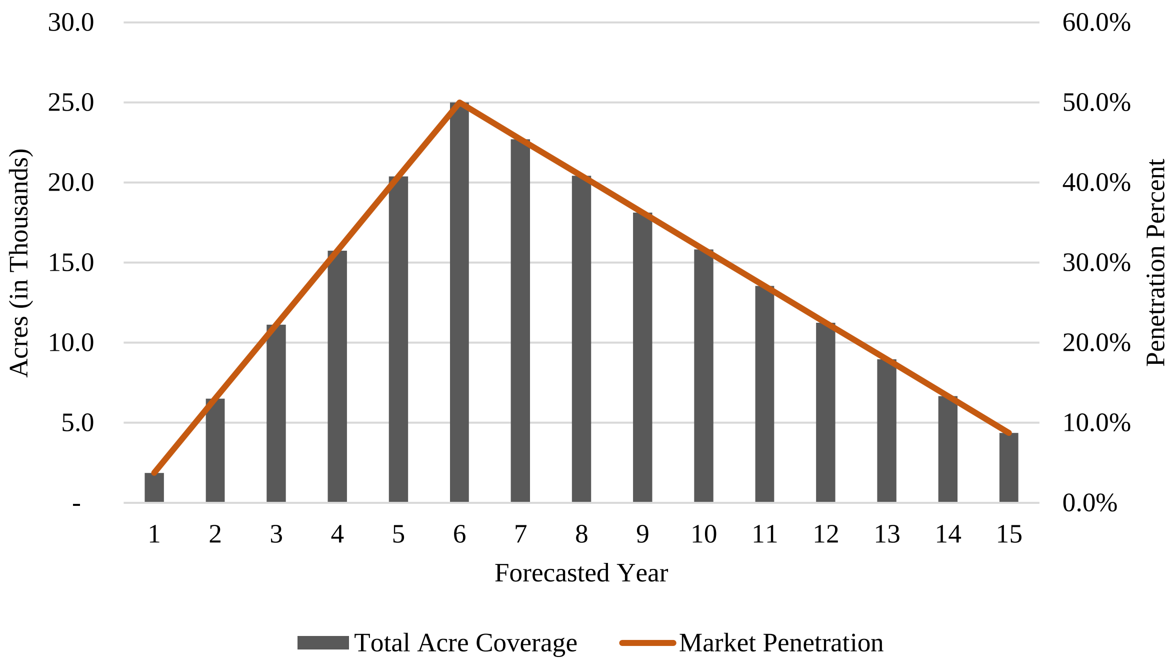
Variable	Assumption
Total Addressable Acres	50,000
Years of Commercialization	15.0

Source: Management estimates (as described below).

The second product hosts a 15-year commercialization life. Based on management assumptions, the peak year takes place in the sixth year of commercialization before tapering off in market share. While the second product does not cover as many acres, the penetration rate of initial and peak penetration is considerably higher than in the first product’s forecast. This market penetration model forecast is displayed in Figure 4.18. In the sixth year, the product is estimated to achieve approximately 50% of the total addressable acres, translating into 25,000 acres. By the final year of commercialization, the startup’s market share of the second product is expected to be under 10%, realizing the realistic nature of competitive entrance and deteriorating market share positions.

Figure 4.18

Mean Market Penetration for Product 2



4.6.2. Sequential Phases I, II, III

Phase I of the product development begins with the genetic editing discovery and technicalities. Though the second product concept has been targeted, there are multiple years needed to create the edit lines and perform lab validations before the continuation of the next sequential phase. Being this comes first before any other process in the development, it is the shortest among all phases with an estimated timeline of two years. The estimated cost for the phase I option uses the distribution range from the R&D discovery phase.

Phase II, the trials stage, is the second longest stage of two years. While this is the same time length as phase I, the trial stage is sequential of technicality success. In addition, the expert opinion distribution of estimated phase time consists of a longer maximum tail for trials, making it the dominant phase II stage. This phase serves as either a call or put option of Phase I's success. For example, if phase I goes according to plan and is successful, management would choose to exercise phase I and move to phase II. Likewise, they can do the opposite to not continue to further phases and incur more time and cost. Trial estimates include approximately two years; hence the total option life of phase II is 4 years since this includes Phase I's estimated time of two years.

Phase III, the last phase of the sequential option, is the regulatory approval process. Hence, to fulfill the entire sequential option, phase III must be exercised. With an estimated time of three years, the total option life of Phase III is seven years which includes the prior phase times. Since phase III is the last of the option stages, the sequential option in its entirety is seven years in length. This accumulated time is represented in Table 4.11. In addition to time, the cost distribution is a critical element modeled as a PERT distribution. If the cost exceeds the opportunity, the call option to enter the next phase is not exercised and management would abandon the second product's development.

Table 4.11

Sequential Phase Parameters for Product 2

Phase	Description	Cost Distribution (Thousands $USD)	Time to Completion	Accumulated Option Life
Phase I	Technology	PERT($500,$1,000,$1,500)	2	2
Phase II	Trials	PERT($1,000,$2,500,$4,000)	2	4
Phase III	Regulatory	PERT($750,$1,000,$3,000)	3	7

Source: Management estimates (as described below).

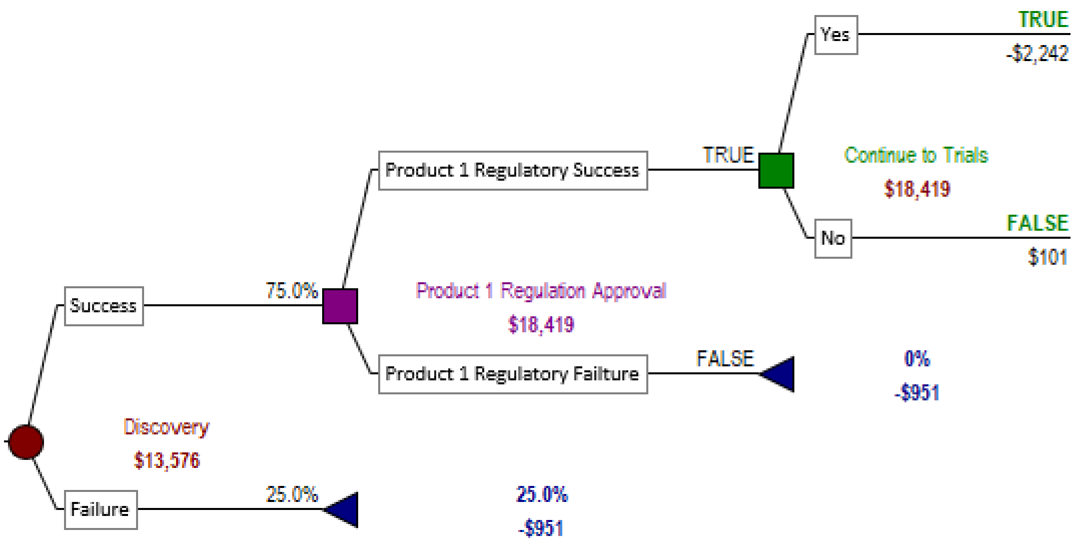
As mentioned, the longest duration phase must be calculated first and proceed backward to the shortest duration phase. The calculated DCF value is the starting NPV for the first sequential option of the, being regulatory phase since it's the longest duration. The volatility applied is derived from the volatility of the forecasted cash flow's logged returns of the second product. However, after the regulatory option is calculated, the resulting ROV becomes the underlying NPV for the next option in order, being trials. Likewise, the second calculated ROV becomes the starting NPV for the third and final option of the technology phase, which has the shortest duration. The resulting ROV of the final option calculated is the ROV of the entire sequential option. This final ROV is the value that is placed into the decision tree as the commercialization value, which is the last node, of the second product.

4.6.3. Decision Tree Analysis

The decision tree of the second product follows a similar path as the first product. Although the decision and chance nodes are the same, there is an important logic node inserted into the decision tree. The logic node, shown in Figure 4.19, takes place after the second product's discovery phase completion. Instead of immediately incurring significant costs in the trial and regulatory phases, management will wait for certainty in regulatory approval of the first product before proceeding with additional R&D phases of the second. Therefore, this logic node extends the commercialization time for the second product with the tradeoff become of not burdened additional sunk cost if the first product is to fail regulatory approval.

Figure 4.19

Implementation of Discrete Node for Product 2



4.6.4. Base Case Results

The base case results for the sequential option take on a similar format as the abandonment option. Figure 4.20 displays the resulting conditional real option values at the various stages of R&D. Before any success of phases is completed, the initial ROV of the second product is $13.6 million. The distribution plan is the final phase before commercialization, therefore, the success of this phase is equivalent to the expected value of commercialization. For the second product, commercialization value can be inferred as $45.2 million. With using ROV as the methodology for valuation, the startup's second product is valued at $45.2 million. This value, as in the previous abandonment option, is compared relative to the DCF results.

Figure 4.20

Conditional Mean ROV at Each Phase for Product 2 (Thousands $USD)

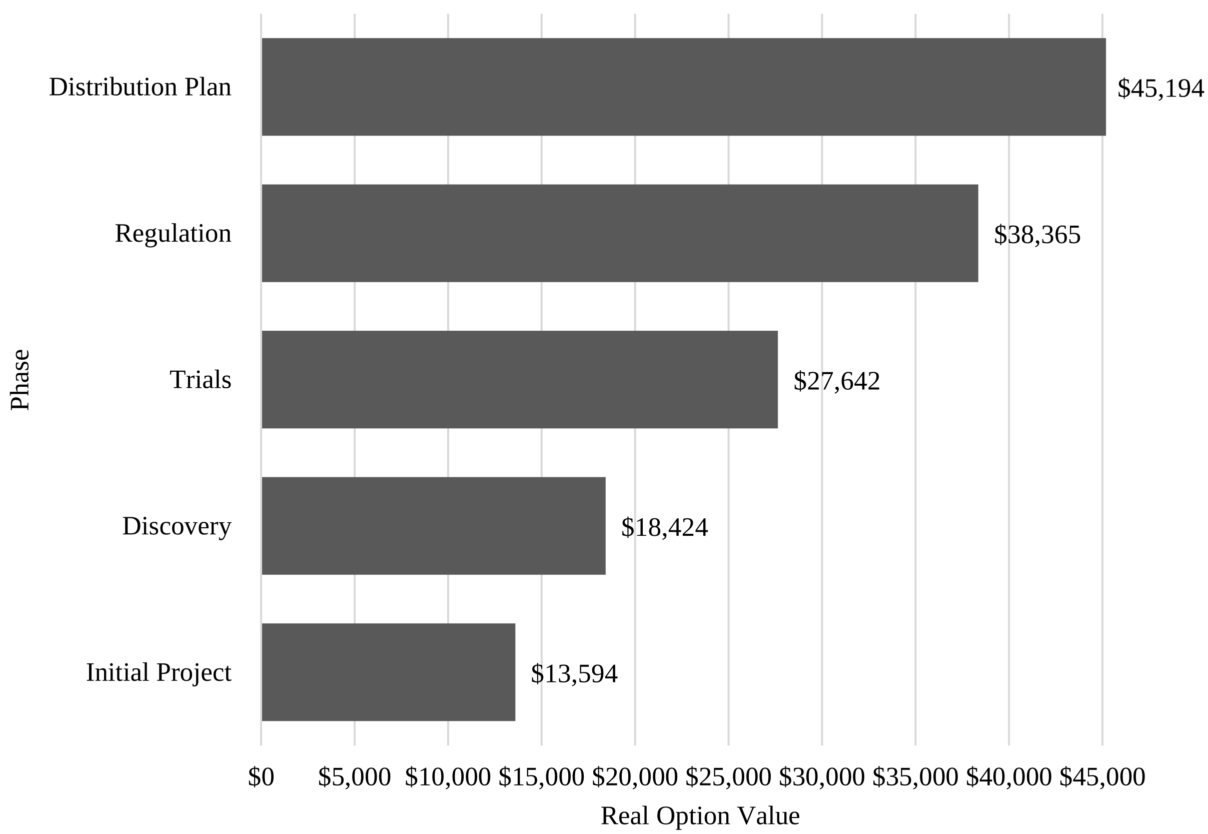


Figure 4.21 shows the conditional ROV range for the discrete phases via a Box-and-Whisker graph. In the 95th percentile of value, the ROV exceeds $109.6 million, offering evident asymmetric upside like in the abandonment option. As noticed in the prior option, there is a significantly higher upside than downside, expressed through the tails of 5th versus 95th percentiles.

For the completion of each phase, the probability of positive value increases. At the initial onset of the second product's development, there is a 6.9% probability of negative ROV. With the progression of phases, there is just a 1.7% probability of negative ROV by the time commercialization is reach, leaving a solid 98.3% probability of positive value.

Figure 4.21

Box-and-Whisker Plot of Conditional ROV Phases for Product 2

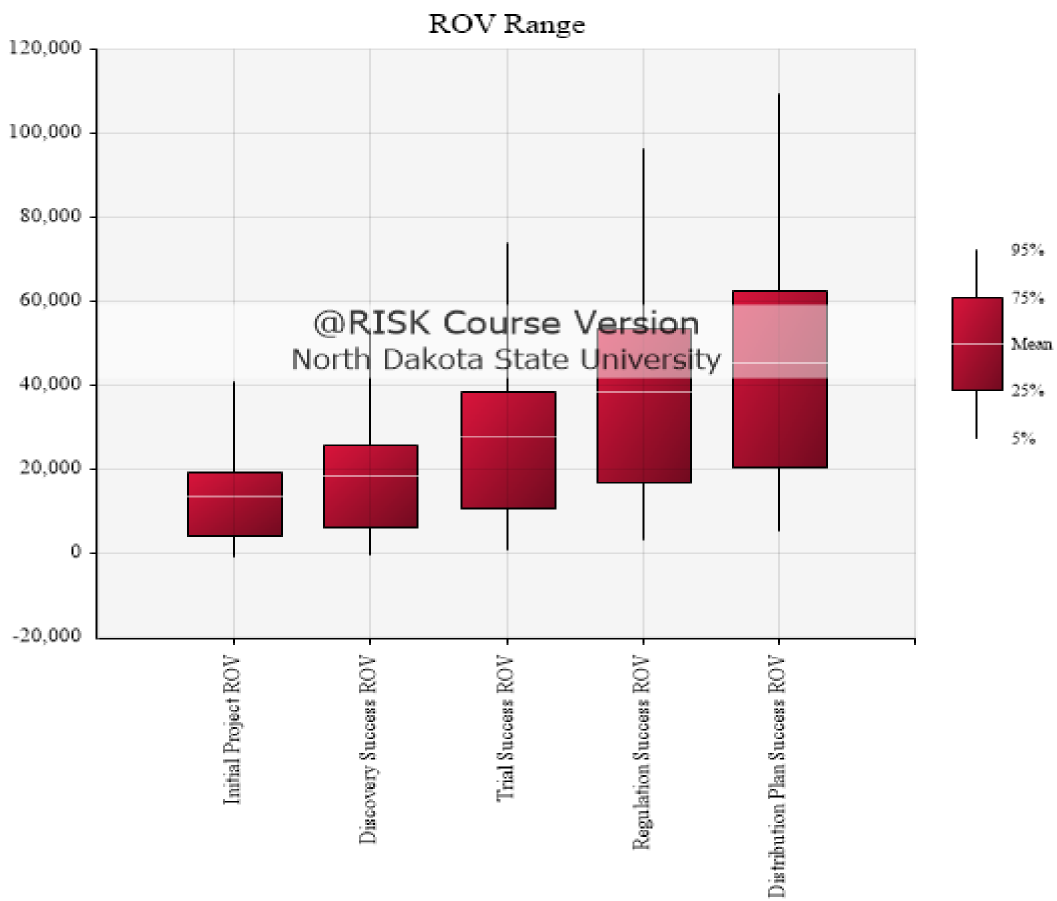
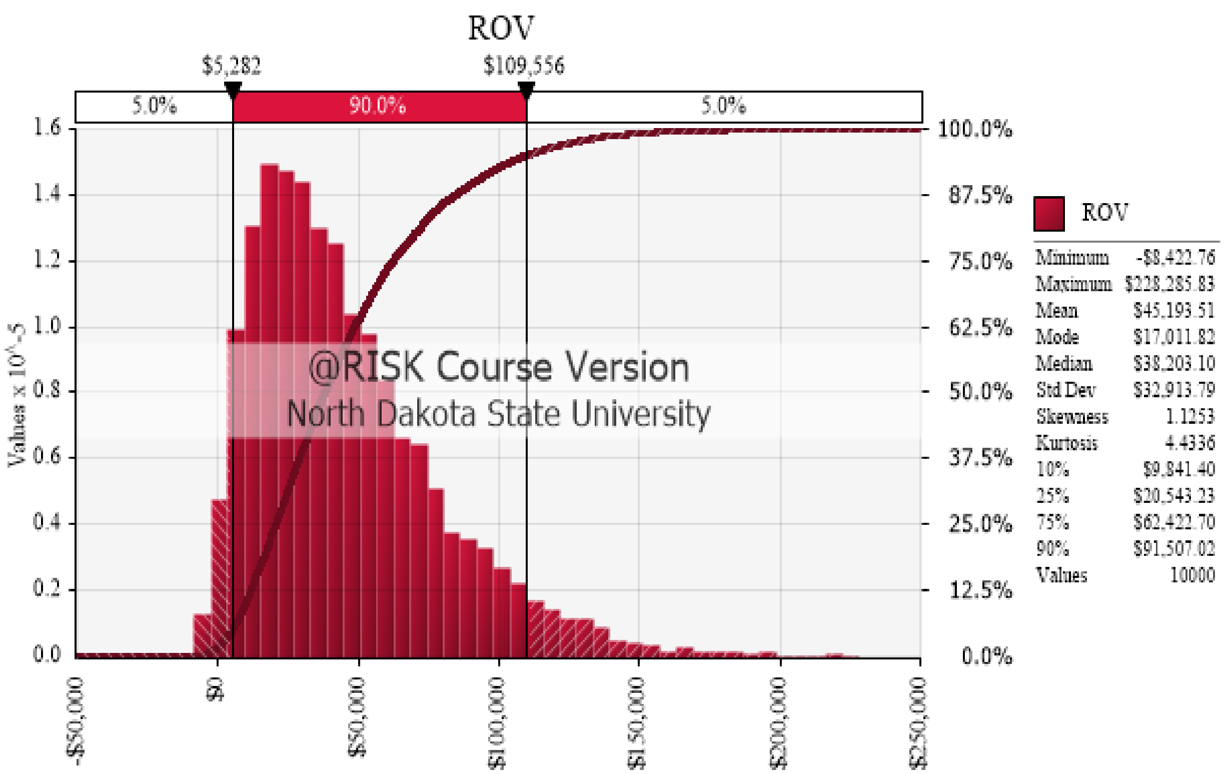


Figure 4.22 shows the second product's ROV distribution results. Here, it is quantified that there is a right-skewness of value with a skewness statistic of 1.1. The mean ROV is $45.2 million with a standard deviation of $32.9. Similar to the abandonment option, the sequential option provides material asymmetric upside given the minimum value of only -$8.4 million and the maximum is $228.3 million. In addition, the 10th percentile still has a strong positive ROV of $9.8 million with the 90th percentile reflecting a value of $91.5 million. While the second product's value is only approximately a third of the first product's value, $45.2 million still offers strong additional contribution to the startup's overall valuation given the longer discounted timeline of the product development.

Figure 4.22

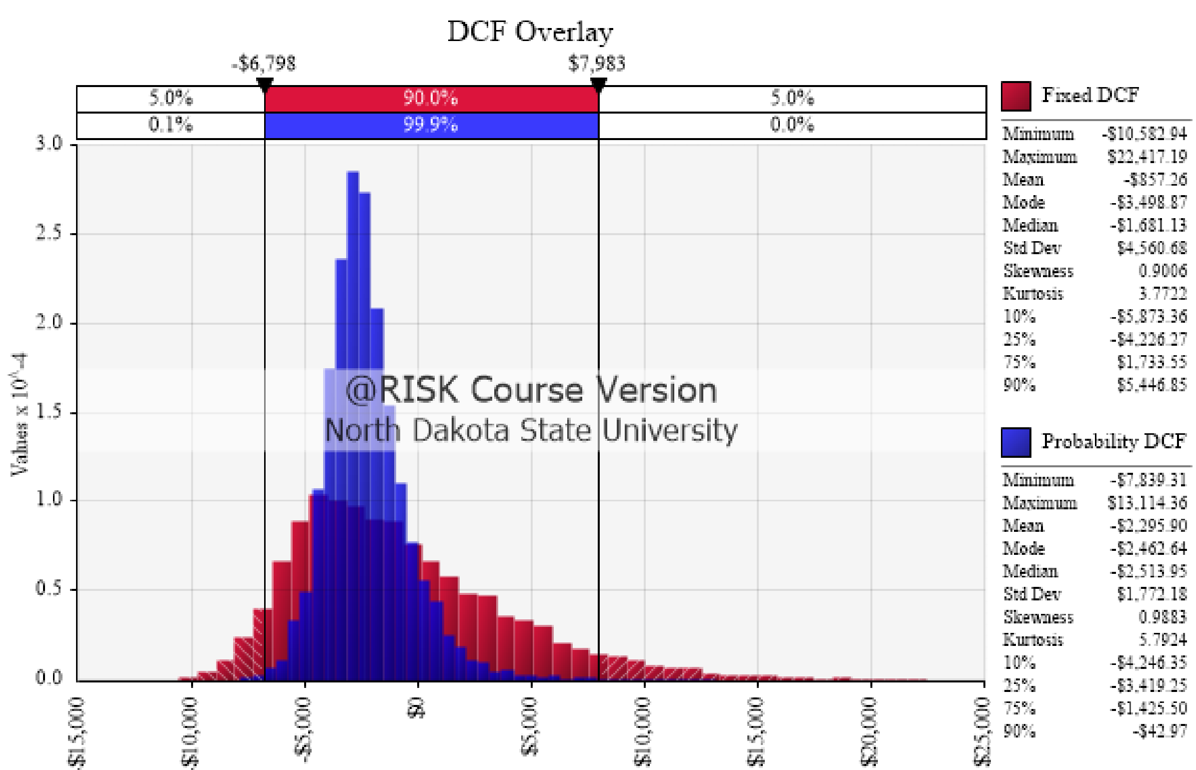
ROV Simulation Results of Product 2 (Thousands $USD)



Figures 4.23 illustrates the overlay of the fixed and probability DCF method distributions. The fixed DCF doesn't consider marginal probability while the probabilistic DCF does. It can be noted that both take on a near normal distribution, expressed by skewness statistics of 0.90 and 0.99 for fixed and probability DCFs, respectively. Both methods have negative mean ROVs of -$857,000 and -$2.3 million for fixed and probability, respectively. These latter values are significantly less than the mean ROV of $45.7 million. In addition, the downside symmetry is much worse for both DCFs. While the fixed DCF carries a minimum value of -$10.6 million, the probability DCF has a minimum of -$7.8 million. This latter value is near the same for the ROV minimum, but without the maximum upside in higher percentiles. When analyzing the distribution for both DCFs, it is discovered that there is a 64% probability that the fixed DCF produces a negative value while the probabilistic DCF has a 90% probability of negative value.

Figure 4.23

DCF Overlay Simulation Results of Product 2 (Thousands $USD)



This delta in DCF outputs to ROV output can be contributed to the lack of managerial flexibility that the DCFs hold. While both DCF methods assume a fixed assumption of all R&D phases and commercialization execution, the sequential ROV considers the important value of staged call options. Instead of following through with the entire development of the second product, management can either exercise their option to continue operations or avoid the development of a product that may not deem worth it after increasing their information.

As R&D success and market dynamics unfold, management has the flexibility to utilize the different options on continuing to the next stage. This managerial flexibility in staged processes is what creates the substantial value of the sequential option to grow, offering the upside that the DCF methodologies cannot. Like the first product's abandonment option, the second product's sequential option confirms the value of utilizing real options to value startups.

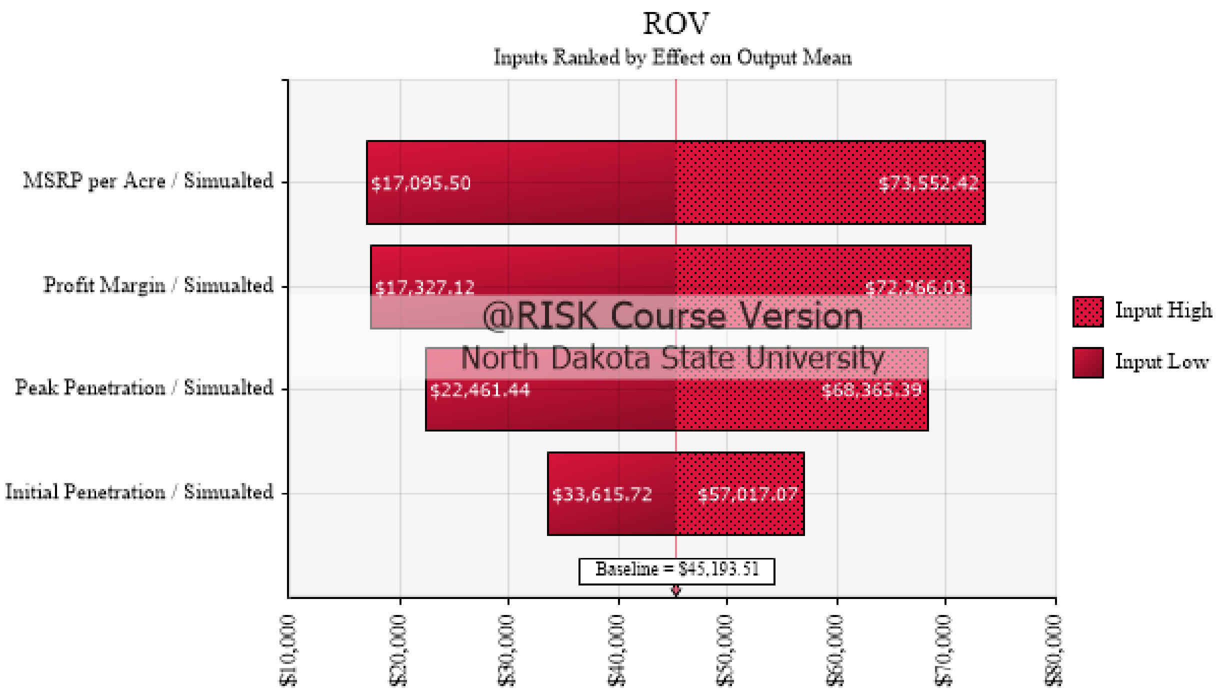
4.6.5. Sensitivities and Scenarios

Sensitivity and scenario analysis is performed on the sequential option, like the abandonment option. Figure 4.24 features a tornado graph of the change in output mean for the top four sensitivities to the second product. MSRP per acre, profit margin, peak penetration, and initial penetration are of highest influence. The most sensitive input, MSRP per acre, contributed to a low and high ROV of $17.1 million and $73.6 million. Profit margin had a similar influence as MSRP with a low and high value of $17.3 million and $72.3 million. Peak and initial penetration had a lesser degree of influence, but still relevant to product 2's ROV sensitivity.

Interestingly, the second product's most sensitive inputs are similar to the first product's inputs. MSRP per acre, profit margin, and peak penetration are both existent in the two different products. However, they contribute different values and different orders of magnitude relative to each other. This crossover in sensitive inputs allows the startup's management team and venture capital investors reflection over significant drivers of a value path. Knowing these same inputs are dramatically important among both products as prioritization and focus can be placed on strongly understanding the marketplace and preparation for penetration of market share.

Figure 4.24

Change in Output Mean of Product 2 (Thousands $USD)



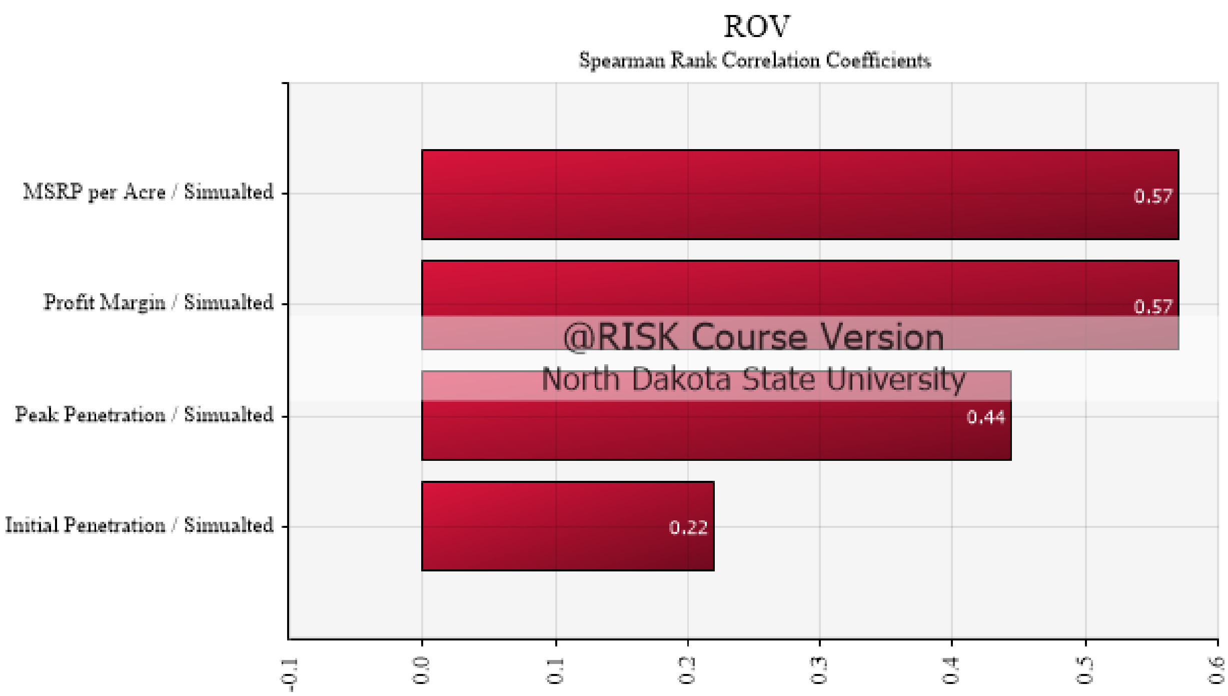
A regression mapped value sensitivity was also performed. The exercise found that one standard deviation increase in MSRP per acre contributes over $17.7 million in ROV. The same standard deviation increase of profit margin allows for $17.7 million in ROV increase too. While still important in driving value, standard deviation increases in penetration can drive value of $14.2 million and $7.2 million among peak and initial penetration rates, respectively.

Figure 4.25 features the Spearman rank correlation coefficients. Following a similar suit, the same inputs as described above are most correlated to the change in ROV. Both MSRP per acre and profit margin have a 0.57 coefficient, implying that each input explains the change in

ROV by 57% as a standalone variable holding all else constant. Peak penetration carries a coefficient of 0.44 and initial penetration has a 0.22 coefficient.

Figure 4.25

Spearman Rank Correlation of Product 2



Though not shown, a spider graph sensitivity analysis is consistent with the discussed inputs above. While nearly all slopes are constant among the varying percentiles, there is a notable slope increase for the initial penetration input at the 75th percentile. Between the 75th and 95th percentile, an approximate $7.5 million increase in ROV is expressed which is occurs at a much higher rate of change versus the remaining percentiles. This implies that the 75th and above percentile for initial penetration rate is important increasing value for the second product.

Scenario analysis is featured in Figures 4.26 and 4.27. In Figure 4.26 where the scenario is greater than the 90th percentile ROV, profit margin, MSRP, peak, and initial penetration all prove significant in generating the upper 10th percentile of ROV results. However, in Figure 4.27, only three of the four same variables are significant to the lower 25th percentile.

Figure 4.26

Scenario Analysis >90% of Product 2

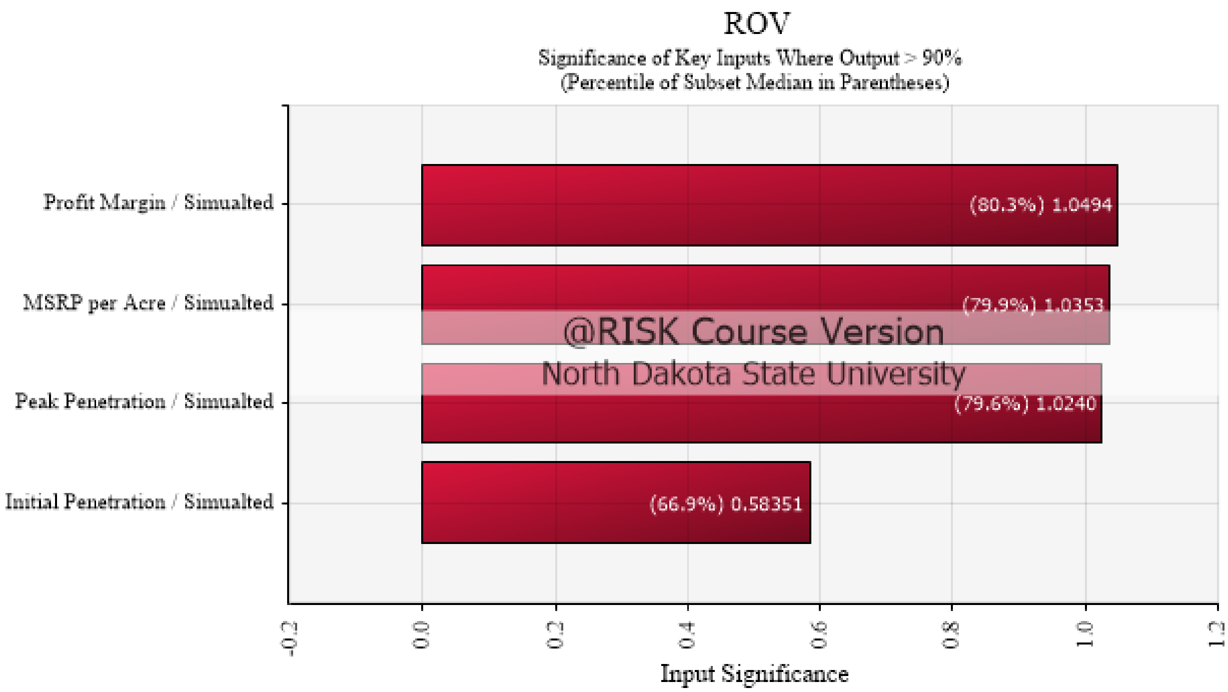
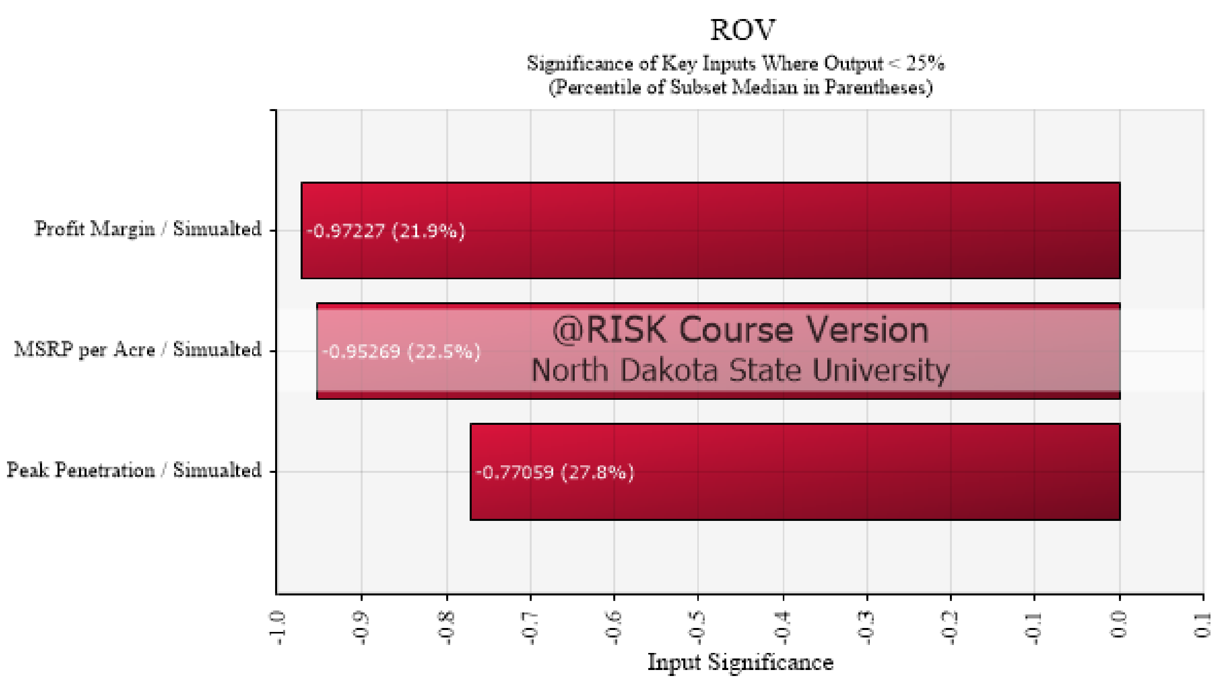


Figure 4.27

Scenario Analysis <25% of Product 2



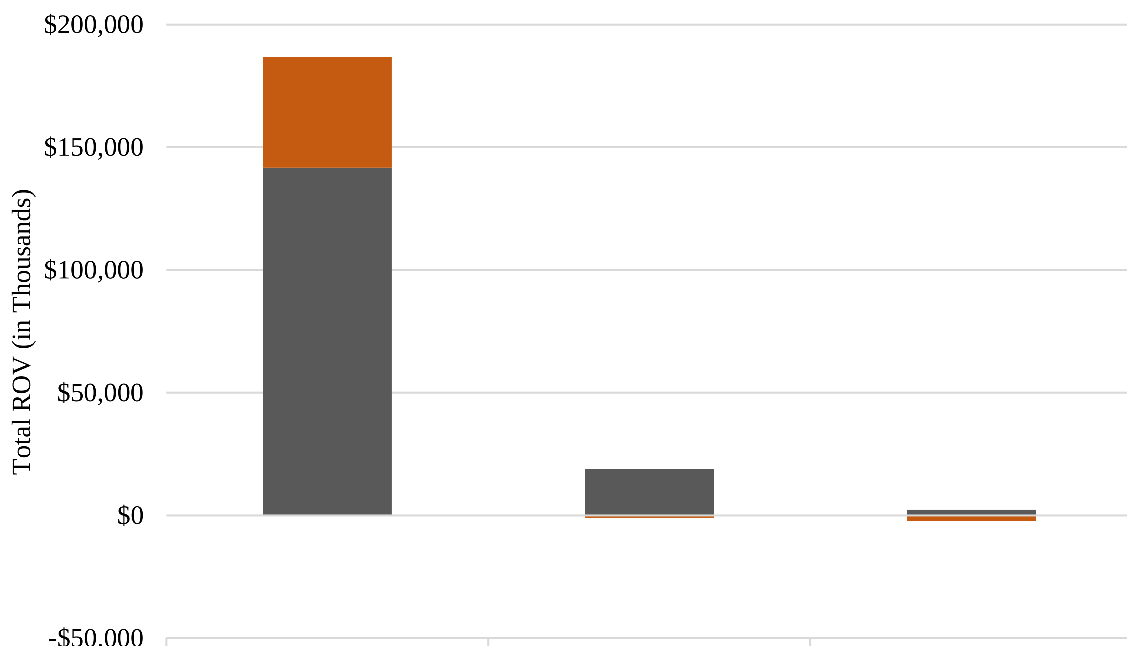
4.7. Aggregate Valuation

DCF is a popular method to value assets. However, in the presence of uncertainty and management flexibility, DCF tends to undervalue growth companies (Damodaran, 2001; Keeley et al., 1996; Trigeorgis, 1995). Similarly, the aggregate model results shown in Figure 4.28 support past claims as ROV captures the material upside on the valuation of the startup, made possible through the managerial flexibility and growth potential of both upcoming products.

The first product, valued via the abandonment option, has a real option value of $141.7 million versus the fixed and probabilistic DCFs of $18.95 million and $2.3 million, respectively. Likewise, the second product, valued with the sequential option, has a real option value of $45.2 million while the fixed and probabilistic DCFs are both negative in value.

Figure 4.28

Valuation Method Comparison (Thousands $USD)



	ROV	Fixed DCF	Probability DCF
Product 2	$45,194	-$857	-$2,296
Product 1	$141,678	$18,951	$2,325

Product 1 Product 2

Since the startup only has near term intentions of creating and commercializing the two products described, the combination of the products makes up the startup in its entirety. Therefore, the combining valuation of the two products can be stated as the overall valuation of the startup since terminal value and all relevant costs are incorporated into the separate product valuations. As a result, the startup's total valuation is $186.9 million using ROV methodology while the fixed and probabilistic DCF valuations are just $18.1 million and $29,000, respectively. Therefore, the use of real options value the startup 933% (10.3x) higher than the fixed DCF and 632093% (644.5x) higher than the probabilistic DCF. In terms of product contribution, the first product (abandonment option) equates to 76% of the total company value with the remaining 24% from the second product (sequential option). Results are presented in Table 4.12.

Table 4.12

Total Valuation Comparison and Contribution (Thousands $USD)

Different Valuation Methods			
Product	Real Option Value	Fixed DCF	Probability DCF
Product 1	$141,678	$18,951	$2,325
Product 2	$45,194	-$857	-$2,296
Total	$186,872	$18,093	$30
Delta		-933%	-632093%

Product Contribution			
Product 1	76%	105%	7867%
Product 2	24%	-5%	-7767%
	100%	100%	100%

4.8. Conclusion

Literature is rich proving that DCF valuations tend to undervalue companies with managerial flexibility and growth opportunities. The startup's valuation derived in Chapter 4 supports previous literature with real option value showing significant valuation increase versus fixed and probabilistic DCFs. With the combination of the abandonment and sequential options, the real option value methodology values the startup at nearly $186.2 million. Relatively speaking, the fixed and probabilistic DCFs valued the startup at $18.1 million and $29,000, respectively. Hence, both DCF methods failed to consider the managerial flexibility in abandoning the first product and expanding into a second product via stages. Therefore, it can be concluded that real option valuation is a robust methodology in startup valuation. Unlike the DCF approach, real options consider the asymmetric upside in growth and host the flexibility for management to abandon or pivot projects and decisions.

Implications of the results are important for venture capitalists and investors. Since investing in startups has much uncertainty, stochastic outputs and assumptions need to be considered given the limited historical data to use. Passing on an investment that turns out to be extremely successful is also of high risk for early stage investors. A main reason why investors pass on startups that turn out to be successful is the lack of quantifying the upside potential with the investment. Real options allow for investors to value the additional upside of startups, allowing for a more accurate investment that reflects on the true nature of startups. The implications are also important for the startup's founders or management teams. In the negotiation process for valuations, management can better express and quantify their potential upside to investors for more favorable terms. From an internal use case, management can also value the flexibility of their decision making, ensuring efficient use of capital and value creation.

CHAPTER 5. BEYOND MEAT CASE STUDY

5.1. Introduction

In Chapter 4, a valuation using real options is applied to a pre-revenue AgTech startup using gene editing in agricultural biotechnology. The startup is valued on two products, the second being a pipeline product to follow the first. Since these two products made up the entirety of the startup, the aggregate ROVs for both products equaled the entire valuation for the startup.

In Chapter 5, real options are again used for valuation purposes. However, the real options applied in Chapter 5 contribute to a current valuation of a company versus valuation in its entirety. Therefore, the valuation procedure in Chapter 5 can be written as:

$$\sum V = NPV_0 + ROV_1 + \ldots ROV_y$$

Where $\sum V$ is the sum of company value, NPV_0 is the net present value in time zero, ROV_1 is the first real option value, and ROV_y are additional real option values. Whether the company is a pre-revenue startup or a young incumbent, high growth firms have options. In some cases, there may be many options at hand, likely to do with expansion opportunities. Ignoring the value of these options means undervaluing the company. Hence, there is importance in developing the appropriate models to determine this real option value and obtain a more reflective valuation of a high growth company. Additionally, DCFs alone cannot account for this procedure due to their fixed assumptions. Since the DCF cannot incorporate managerial flexibility and uncertainty into the model, they tend to understate the value of companies with high growth.

The model in Chapter 5 utilizes two sequential compound options where growth opportunities are analyzed based on a “call” or “put” action at specific phases. These sequential compound options are similar to Chapter 4’s case study of the startup’s second product. In this chapter, the two sequential option values are applied to an existing valuation to reach an aggregate value of the young AgTech company, Beyond Meat. The two options analyze the growth opportunities of expanding into China with plant-based beef and product expansion of plant-based chicken in the United States.

5.2. Conceptual Case

The real option valuation case study applied in this chapter is on the young, plant-based meat AgTech company of Beyond Meat. Unlike the startup in Chapter 4, Beyond Meat is a publicly traded company (NASDAQ: BYND). Therefore, financial information is public and accessible. BYND is based in Los Angeles, CA and is a producer of plant-based meat products which currently includes beef, pork, and to a small extent chicken. The company was founded in 2009 and had an initial public offering (IPO) in 2019. Since then, BYND has been a sought-after investment, souring 163% on the first session of trading. This made BYND the biggest-popping U.S. IPO since 2000 (Murphy, 2019).

The success in BYND stock signaled public investor interest in sustainable AgTech as the company became a modern “poster child” for successful AgTech investment. AgFunder (2020) reported that 2019 global investment in innovative food (e.g. plant-based food) doubled from 2018 with an aggregate of $1 billion in funding across 158 deals. Impossible Foods, a direct competitor of BYND, raised $700 million in investment during 2019-2020 with a valuation of $2 billion (CBI Insights, 2019). Aside from Impossible’s plant-based meat, a 2020 press conference unveiled a prototype of plant-based milk product development (Temple, 2020). This is just one example of the growth optionality of young, innovative companies in this sector.

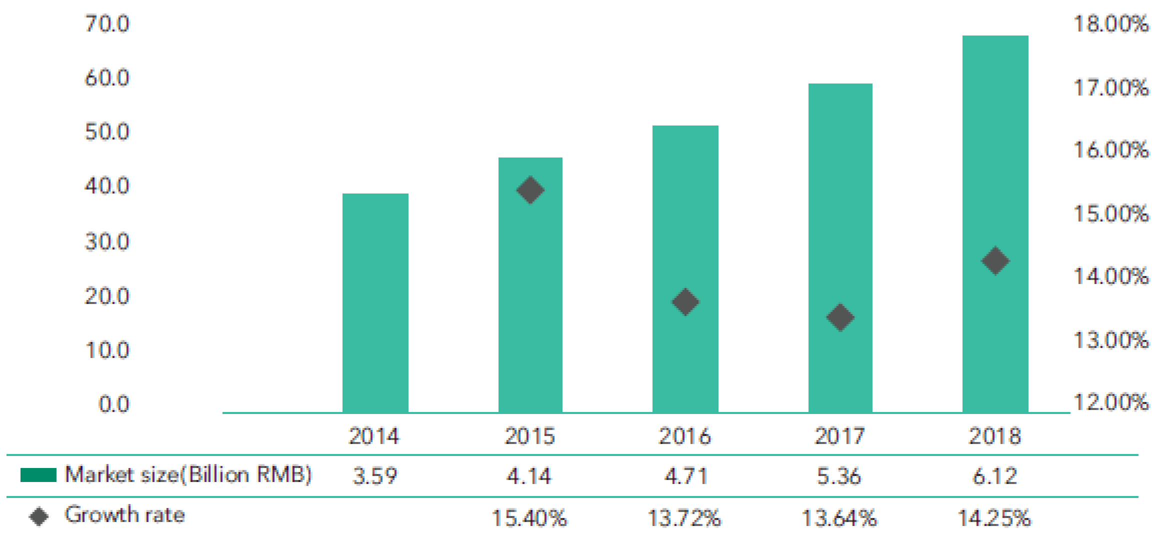
Specifically, for Asia-Pacific based startups, over $230 million in funding has been raised for alternative protein such as plant-based meat. Popularity in this trend can be awarded to rising fear of animal-born disease and demand for natural production of food (Huling, 2020). Another significant driver of plant-based meat adoption is animal agriculture's impact on environmental sustainability (The Good Food Institute, 2018). China is a leader in world meat consumption, making up 28% of total consumption which is 2x the United States consumption. Due to population growth and a 70% demand increase for animal-based protein, China is influential to animal agriculture's impact on climate change.

While plant-based meat is largely in its infancy, the growth among plant-based dairy customers can be a proxy of expectations in plant-based meat. According to The Good Food Institute (2018), plant-based protein drinks in China grew sevenfold from $2.5 billion in 2007 to $18.25 billion in 2016. Figure 5.1 represents the volume and market size growth of plant-based meat in China. 2018 featured an estimated market size of 6.1 billion yuan, equivalent to USD 910 million which reflects a 14.2% year-over-year growth rate. In the same report, a consumer insights study found that 90% of all plant-based meat-eating participants (5,689 valid participant responses) were non-vegetarian. Hence, the growth of plant-based meat products is not only a function of increasing market share within an already vegetarian market but expanding the reach to everyone who consumes meat.

For plant-based meat ingredients, China feels positioned to produce large volumes of prominent raw materials for use such as rice, wheat, peas, and potatoes. Pea protein, an important ingredient for Beyond Meat's product, has especially gained momentum as a processed protein in China growing from 67,453 tons of capacity in 2017 to 146,313 tons in 2019 (Huling, 2020; The Good Food Institute, 2020).

Figure 5.1

Plant-based Meat Production Volume and Growth Rate (Good Food Institute, 2018)



While BYND has had success in plant-based meat (largely beef) within the U.S., there is much growth potential in additional products and geographic expansion. This case study's model develops two real option values to BYND including sequential options of an additional product of plant-based chicken in the U.S. market and the international expansion of plant-based beef into China.

Beginning in 2020, Beyond Meat had achieved both of these significant milestones with the regulatory approval of Chinese expansion and also the launching of plant-based chicken in select Kentucky Fried Chicken (KFC) restaurants in the U.S. For the sake of this study, it is assumed that neither action has yet occurred and that the expansion projects are being determined.

As venture capitalists focus on private markets and public investment managers focus on young public growth companies (e.g. Beyond Meat) in innovative foods, the same applications are of high relevance. Since these two components are significant in increasing value and growing revenue for plant-based protein companies, the valuation of these growth opportunities is important and of high relevance.

5.3. Sequential Options

Sequential options are important when valuing a staged investment process with optionality, as in Chapter 4's case study. Startups and young companies have critical milestones that must be met in order to raise capital and increase valuation. Given these milestones are commonly attached to capital that is callable or puttable (though VC funding rounds or capital market stock options), the value of growth opportunities through sequential phases are important. Given the relevance to high growth, both Sereno (2007) and Damodaran (2001) utilize sequential options in the valuation of technology.

A sequential option is a compound option type where multi-phase projects lead to various options in the entire project. The sequential option can become a call or put option as different phases are processed. Sequential options can contain both calls and puts such as a call on put or put on call. For example, if a construction project is to be planned, there are multiple phases involved. One of the phases may be developing a blueprint design, followed by the land purchase, and finished through construction. In that case, the project holds three real options that are contingent upon prior completion. The project manager could decide to utilize a put or call option on the ongoing phases depending on the success of the prior phase. The benefit of quantifying this is the managerial flexibility in strategic decisions. Instead of assuming a continuation of sunk cost and time, management can change direction or utilize saved cost on different projects of higher value creation.

The construction example described above is like Beyond Meat's strategy of geographic expansion projects or expanding product lines. China, a population of over 1.4 billion people, is an important market for Beyond Meat to enter commercialization with. This is particularly true for plant-based beef where rising incomes and beef protein have become a growing trend among Chinese. Additionally, the expansion of plant-based chicken (solely in the U.S. to start) is an important growth option for the company if they are to establish a strong brand in the entire plant-based meat market versus single meats alone.

For the sequential options of Chapter 5, Beyond Meat's expansion into China for plant-based beef is valued to estimate the expansion optionality of increasing their addressable market. The two important phases evaluated are regulation and infrastructure. The regulatory stage consists of obtaining regulatory approval of their plant-based beef in China while the infrastructure stage makes up the construction and implementation of large processing and logistics facilities to supply grocers, restaurants, and consumers internationally.

The company's plant-based chicken product is valued to estimate the growth upside in creating and commercializing it in the United States. The important phases in this opportunity are classified as the product creation and regulatory approval. The aggregate value of these two sequential growth options can be added to the existing Beyond Meat valuation (assuming valuation is based on current product lines and geography) to reach a total company valuation. Therefore, the upside optionality in the high growth company is recognized. Without considerations of these options, the company would be undervalued among investors.

5.4. China Expansion with Plant-Based Beef

Whether the purpose is for conducting a study, market research analysis, or valuation analysis, there are many parameters of valuation not known given the limited history or relevant examples of new markets. For plant-based meat, the product and industry are new, creating parameters that are largely unknown to date. Hence, the appropriate practice is to derive representative distributions using expert judgment.

There are different research and development (R&D) phases Beyond Meat must face in order to enter commercialization with plant-based beef in China. The two critical phases are summarized by regulation and infrastructure. In order to enter China with plant-based beef, the Company must ensure ingredients and labels meet Chinese regulatory standards which can become a lengthy and costly process. Once, regulation is approved, Beyond Meat must establish infrastructure to process their product at scale across China. The following sub-sections describe the various R&D stages and lay out the two phases critical in the sequential option.

5.4.1. R&D of Chinese Expansion

Table 5.1 features the PERT and Uniform distribution assumptions to model the stochastic inputs of phase time, cost, and probability of success. This stochastic nature is essential in accounting for uncertainty in assumptions that typically come with multi-year phase projects where delays and budgeting implode on initial estimations and success.

Table 5.1

R&D Phase Distribution Assumptions for Chinese Expansion

Phase	**Time (Years)**			**Cost (Thousands $USD)**			**Probability of Success**	
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Max**
Regulation	0.6	1.0	2.0	$5,000	$19,000	$50,000	70.0%	100.0%
Infrastructure	0.6	2.0	3.0	$75,000	$125,000	$300,000	90.0%	100.0%

Source: Author estimates based on review of industry studies and firm information (as described below).

According to the Food and Drug Administration (FDA), there are two primary timelines in granting regulatory approval. The standard review has a goal of a ten-month review while the priority review targets six months. Since Beyond Meat's product likely doesn't garner the need for high priority, the likely targeted time for regulatory approval is estimated at one year. While this can take a shorter time, there is a much longer tail of a maximum time period which compromises delays and problems featured along the way. While the FDA's standards can be a proxy for estimated regulatory time, it doesn't dictate the same standards as China's process. The Good Food Institute (2018) reports that the National Health Commission (NHC), the governing body for regulatory novel food ingredient approval in China, classifies the approval process into Non-GMO food ingredients and GMO ingredients. Since Beyond Meat's products are non-GMO, the timeframe for approval is much quicker being 1-2 years versus 5-7 years for GMO.

Johns Hopkins Bloomberg School of Public Health (2018) finds that the general median cost figure for trialing new drugs through regulation is \$19 million. Their studies found half of the regulatory trials were between \$12 million and \$33 million with the lowest cost of \$2 million and the highest of \$347 million. Since the primary trials included drugs for disease and sickness treatment, Beyond Meat's regulatory approval for food is not expected to be as high as the maximum outliers. Therefore, \$19 million is estimated for the likely cost of China's regulatory phase with a minimum and maximum range of large variation given the uncertainty.

In Beyond Meat's quarterly filing (10-Q) for the period ending September 26, 2020, the company reported the acquisition of certain assets including land, building, vehicles, machinery and equipment, and certain workforce from one of their co-manufacturers for cash of \$14.5 million. In this announcement, the company mentioned the facility intends to manufacture the production of finished goods. In the same SEC filing, Beyond Meat agreed to a \$10 million investment in an international facility to renovate and lease the property for production use with an expectation of full-scale production in early 2021. In another phase of the same facility contract, Beyond Meat can proceed with a \$30 million land investment to build a new additional production facility. In a final element to the contract, Beyond Meat can purchase another piece of land for $10 million for the development of an additional facility. Hence, the aggregate investment in an international facility of scalable production is approximately $50 million which includes renovation of an existing facility and two land purchases for facility expansion. Based on the company's revolving credit facility's capacity of $150 million, it is assumed that most borrowed capital would go towards the infrastructure of production. Therefore, it is estimated that there would be another $75 million of required investment for Beyond Meat to build the necessary facilities on the purchased land. In aggregate, this assumes a total investment in Chinese infrastructure of $125 million. To reach full-scale production on the facility, it's estimated that two years is likely in achieving this in meaningful commercialization ways. However, there are wide variations in distribution to consider the probability of different times and costs outside of the estimated likelihood.

5.4.2. Chinese Market Adoption and Commercialization

Being plant-based meat is in its infancy, market penetration is uncertain and complex, making stochastic simulation within probability distributions essential. Additionally, the growing number of competitors in the industry makes market share expectations difficult. According to The Good Food Institute (2018), domestic Chinese plant-based meat companies are primarily medium-size companies with fragmented market share of most brands less than 3%. It is believed and modeled that Beyond Meat would have significant market share over many of these private, medium-size companies when entering the market given their brand presence and larger scale of shelf-space and distribution capabilities (e.g., retail, restaurants, direct-to-consumer). Beyond Meat has been benefiting the greatest of all players in the growing plant-based meat market. According to Cheng (2020), Beyond Meat holds 10% market share, ranking third among industry competitors. Morningstar Farms, a Kellogg brand, holds 41% market share with Conagra’s Gardein at 14%.

Chapter 5’s study uses a similar market adoption model as Chapter 4 for plant-based beef demand in China. The market penetration model utilizes an initial and final year penetration rate stochastically simulated for adoption of plant-based beef within the animal-beef market. The market penetration derived is a function of multiple items which include stochastic penetration rates, Chinese population growth, and China’s per capita beef consumption.

Table 5.2 illustrates the random variables used for a PERT distribution of both plant-based beef penetration into the animal-beef market and Beyond Meat’s market share expectations. The relative growth in plant-based dairy is key in determining assumptions of penetration rates for plant-based beef. Since plant-based meat is in its infancy, adoption is difficult to measure and compare. However, plant-based milk can be used as a potential proxy of adoption. Plant-based milk is estimated to have 13% of the U.S. milk market (Mintel, 2018). Stephens (2020) suggests the potential of plant-based meat to reach 20% penetration in the meat industry by 2030. These various data points for penetration are used in a PERT distribution to account for the adoption uncertainty in these novel products.

Table 5.2

Probability Distribution of Market Adoption and Market Share of Chinese Beef

Variable	Minimum	Likely	Maximum
Initial Plant-Based Beef Penetration	1.0%	3.0%	5.0%
Final Year Plant-Based Beef Penetration	5.0%	13.0%	20.0%
Beyond Meat Initial Market Share	3.0%	5.0%	10.0%
Beyond Meat Peak Market Share	15.0%	40.0%	50.0%
Beyond Meat Final Market Share	10.0%	30.0%	40.0%

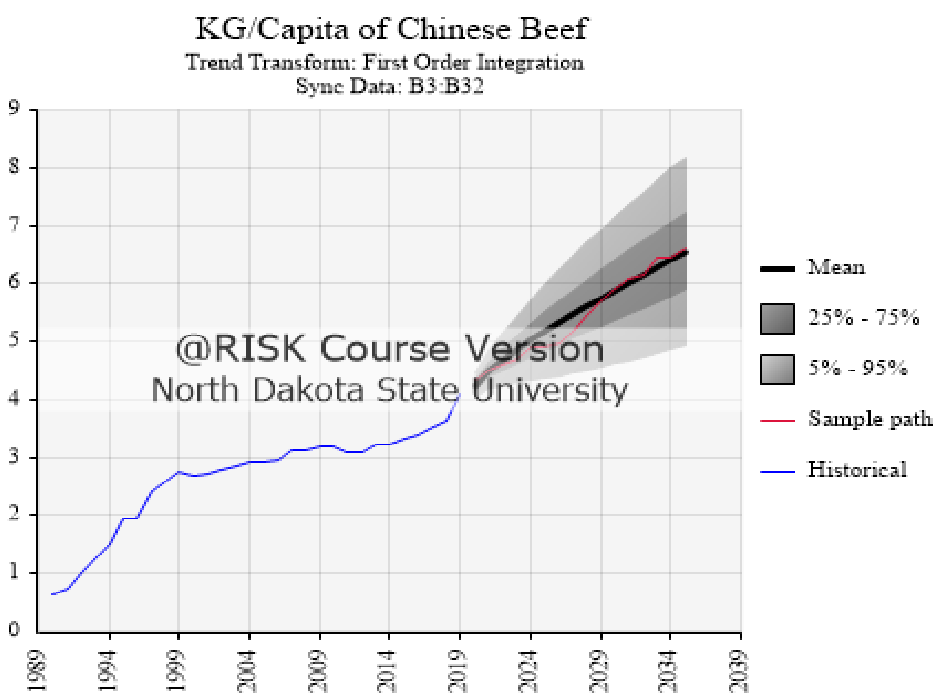
Source: Author estimates based on review of industry studies and firm information (as described below).

Additional important data in forecasting plant-based penetration includes the population growth of China and their projected beef consumption. The United Nations forecast of global population is used as the basis for forecasting China's population growth. Beginning in 2023, China's population is expected to be 1.45 billion and grow to 1.46 billion a decade later. This forecast experiences a peak population taking place in 2032 and declining afterward.

To project per capita plant-based beef consumption, animal-based beef consumption must first be forecasted. Historical China beef consumption was collected from OECD to forecast future consumption demand using first order integration. In 1990, beef consumption per capita was just 0.64 kilograms while 2019 was 4.09 kilograms. As mentioned earlier, this trend is expected to continue with 2033 per capita demand of 5.56 kilograms. This trend is depicted in Figure 5.2 with the blue line as the historical demand and the dark black line as the mean forecast through 2035. The shaded gray indicates the probability range.

Figure 5.2

Historic and Forecasted Trend of per Capita Animal-Beef Consumption (in Kilograms)



The animal-beef demand is forecasted prior to plant-based demand with an equation expressed as:

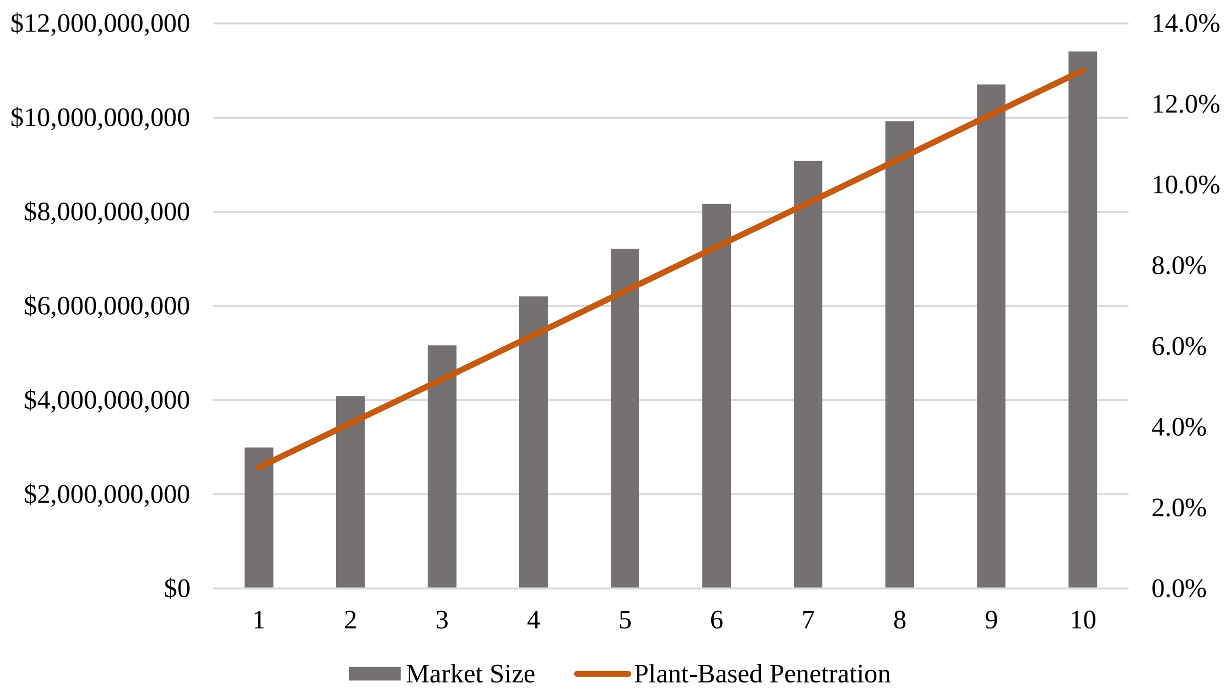
$$B_D = E * C_{KG} * Ib_C$$

Where B_D is the total demand for beef in pounds, E is the estimated Chinese population, C_{KG} is per capita beef consumption in kilograms, and Ib_C is the conversion of kilograms to pounds. Utilizing the equation and the stochastic probability distribution of plant-based beef penetration and Beyond Meat market share, a forecast of China's demand for plant-based beef demand can be estimated and is shown in Figure 5.3.

While China's population is estimated to decline (according to United Nations), beef consumption is expected to increase to record levels while plant-based beef increases penetration into the animal-based market. Hence, the market of plant-based beef sees approximately 3% penetration and increases to around 13% a decade later.

Figure 5.3

Chinese Plant-Based Beef Market Size and Penetration



After total animal and plant-based beef demand are estimated, the stochastic market penetration model is applied to Beyond Meat's market share within the plant-based market. This plant-based demand is multiplied by Beyond Meat's stochastic market share and average selling price per pound to equate to revenue such as:

$$R = P_D * BYND_{MS} * P_P$$

Where R is revenue, P_D is plant-based demand, $BYND_{MS}$ is Beyond Meat's market share, and P_P is the selling price of plant-based beef in pounds.

Because plant-based products currently cater towards a smaller subset of consumers and are more expensive to produce without significant scale, price per pound is at a premium to traditional meat presently. According to Piper (2020), the average price of meat alternatives sold in U.S. grocery stores in 2019 was $9.87 per pound. This compares to an average beef price between January 2017 to April 2020 of $4.47 per pound.

Beyond Meat's chief growth officer, Chuck Muth, highlighted price and cost decreases as one of three main priorities of the company, noting the goal of becoming similar priced as animal ground beef. Due to scale and increased R&D efficiency, Beyond Meat claims to have a cost of production of $3.50 per pound in 2020, compared to $4.50 per pound in 2019 (Piper, 2020). It's also important to take note that Beyond Sausage Sandwich, a Dunkin' sausage breakfast sandwich using Beyond Meat's sausage, sells for the same price as meat sausage sandwiches. Beyond Meat has committed to sell at least one product of the same or cheaper price than animal-based meat by 2024. For these reasons, the selling price of Beyond Meat's product is modeled with an initial and final ending price, assuming a decreasing price over the forecast. Initial, the price is expected to have a likely $6.00 target with a minimum and maximum price of $4.47 (same as animal beef) and $10.00, respectively. The final price point at which the model ends holds a minimum, likely, and maximum range of $2.94, $4.47, and $6.00, respectively which reflects price parity with animal-based beef.

Net profit can be estimated by multiplying revenue and net profit margin. Since the company is likely to decrease its cost of production as operations scale, profit margin will increase over time. Based on analyst estimates of equity research reports, it’s likely that a profit margin of 2.5% is achievable near-term with a high 5% margin. Since the company is not profitable in 2020, a minimum margin is estimated at 0% for the PERT distribution. While these are estimates in the early years of the forecast, final year margin ranges are modeled to account for the increase in profitability. For a final year margin, a minimum, likely, and maximum input of 2.5%, 5.0%, and 15.0% is modeled, respectively. The 15% is in line with peer groups in processed meat and ingredients.

This aggregate profit is discounted using the weighted average cost of capital (WACC). With a 99.3% equity composition and 0.7% debt structure, the estimated WACC for Beyond Meat is 13.6%. This is derived through a Bloomberg terminal which considers relative return among the S&P Index and risk-free rate of the U.S. ten-year treasury. The forecast using a ten-year commercialization period in which the accumulated discounted cash flow is the starting NPV for the sequential option.

5.4.3. Sequential Phase I and II for China

There are two important sequential investment options identified in a Beyond Meat expansion into China. Since plant-based beef technology is already established, patented, and proven safe, the initial technicalities and trials are a non-factor. However, there is a separate regulatory process the company must complete within China to sell product. After the regulatory hurdle which consumes large costs and lengthy time, infrastructure investment is needed.

Because infrastructure for processing and logistics is extremely expensive, Beyond Meat would likely not pursue the project until regulatory certainty is completed. Hence, there are sequential investment phases that act as an “option on an option”. For this situation, management can perform multiple decisions which include different combinations of puts and calls such as a call on the regulatory option but a put on infrastructure if regulation is not successful. Likewise, management can place a call option on regulation and a call option on infrastructure if regulation is successful and the market environment is opportunistic.

Table 5.3 displays the details of the two sequential phases which are modeled as a stochastic cost distribution. The regulation phase has an estimated time to completion of one year while the infrastructure timeframe is two years until completion. Hence, the entire option life of the combined compound option is three years. This sequential option can be interpreted similarly to a call option since management can proceed to the following phase with successful completion and interest of the previous phase,

Table 5.3

China Expansion Sequential Phase Parameters

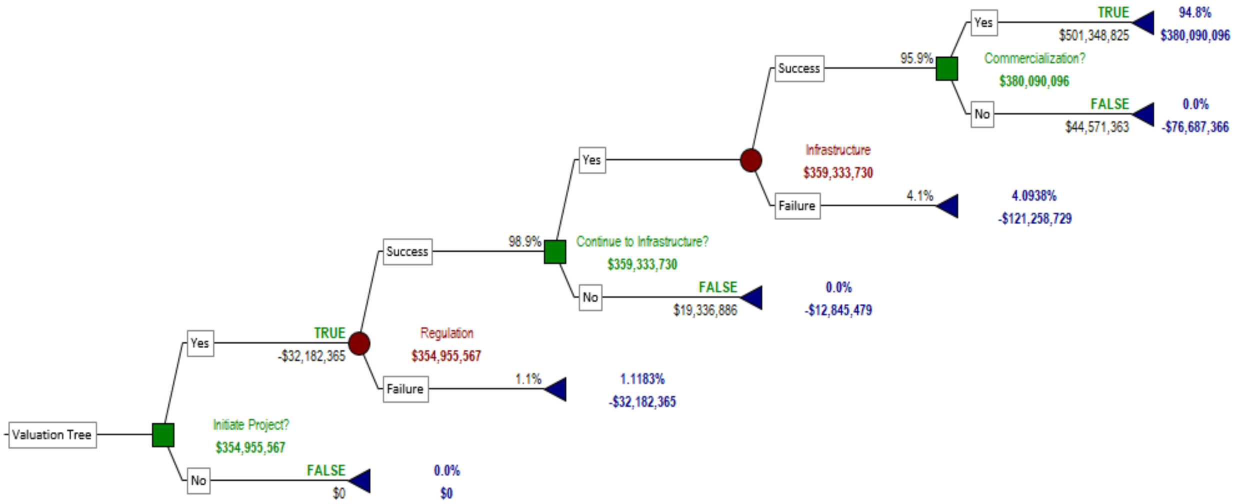
Phase	Description	Cost Distribution (Thousands USD)	Time to Completion	Accumulated Option Life
Phase I	Regulation	PERT($5,000, $19,000, $50,000)	1	2
Phase II	Infrastructure	PERT($75,000, $125,000, $300,000)	2	3

Source: Author estimates based on review of industry studies and firm information (as described below).

A decision tree is applied to the model, similar to Chapter 4, where different decision nodes are followed by probability nodes to measure the expected value of successful stages. As mentioned prior, the two critical phases of private risk in R&D include regulation and infrastructure. Therefore, these two phases must be successful in order to move to the commercialization of plant-based beef in China. Figure 5.4 illustrates these decision and chance nodes modeled in *PrecicionTree* Excel.

Figure 5.4

Evolving Decision Nodes of Chinese Expansion



5.4.4. Base Case Results: Chinese Expansion

The base case results of the Chinese expansion revolve around the initial project real option value. This ROV assumes the beginning value of the project before phases are completed, hence there are no assumptions of successful commercialization. This contrasts with Chapter 4's case study where the ROV used to value the startup assumed the last node of the decision tree, being successful commercialization. This initial project ROV is one of two ROV's added to the existing Beyond Meat valuation to consider the upside in the sequential growth options.

Figure 5.5 displays the simulation results of the initial project ROV for the Chinese expansion. The mean value is $218.3 million with significant right-skewness, illustrated by the skewness statistic of 1.0 and maximum value of $1.4 billion. Based on the results, there is only a 6% probability that the ROV enters negative value with 94% probability of positive value. Even in just the 10th percentile, the value is $24.6 million. Given the distribution, there is a 90%

confidence the value falls between $0 and $529 million. As the positive fat-tail distribution represents, this optionality is important for investors to consider as the opportunity cost is high if one is to not consider this potential growth and not invest. As mentioned prior, Figure 5.5 only shows the initial project ROV before successful phase completions. While this would be the appropriate value to add to an existing valuation, it's important to understand the change in ROV as the critical R&D and commercial phases are completed.

Figure 5.5

ROV Simulation Results of Chinese Expansion (Thousands $USD)

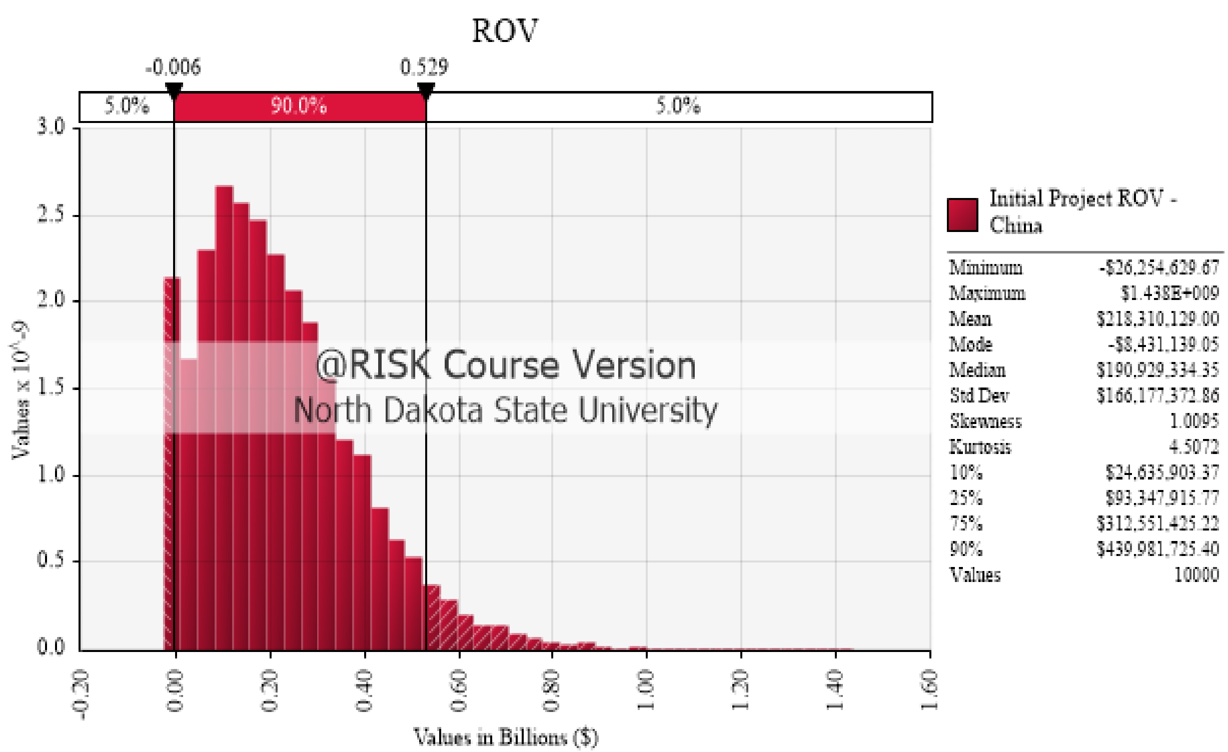
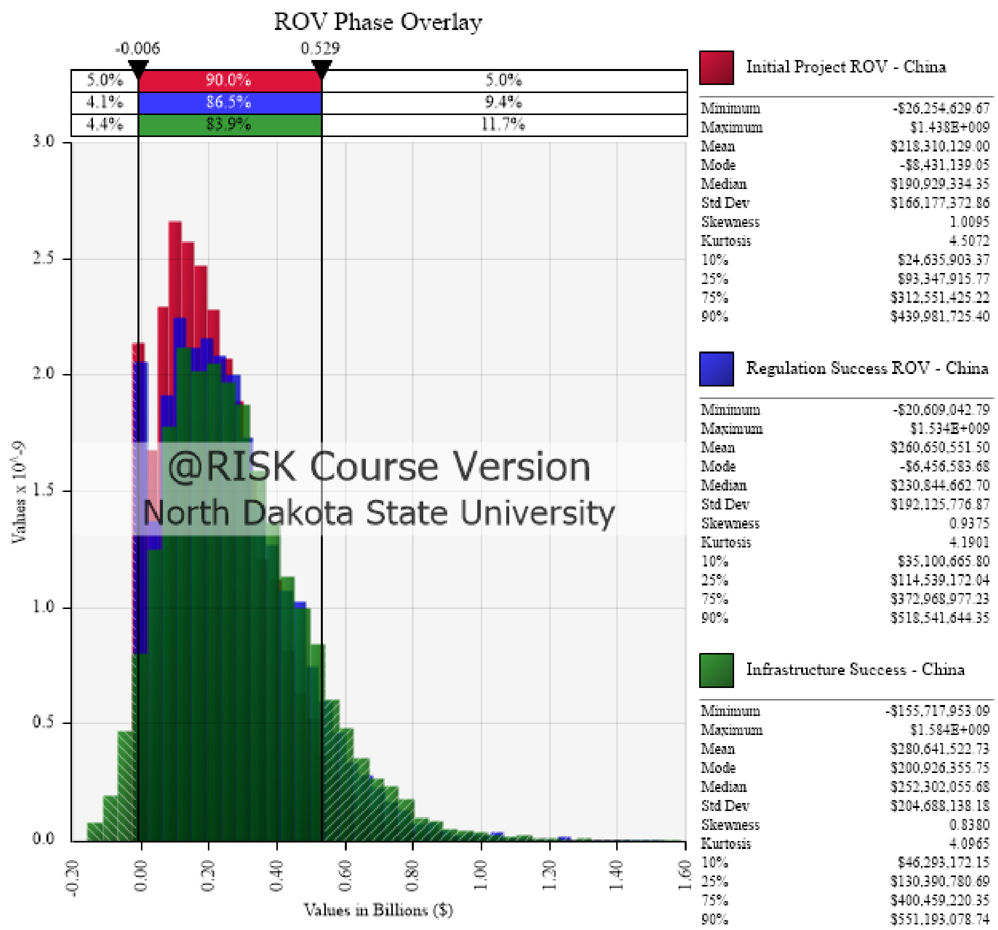


Figure 5.6 presents an overlay of the ROV distributions at the discrete stages of success. The initial project ROV, colored in red, is simply the same distribution represented in Figure 5.5. The ROV assuming a successful regulatory approval in China is colored in blue. Given the increased certainty of success, the mean ROV is $260.7 million with an upward shift in percentile values as well. The ROV assuming successful infrastructure completion is equivalent

to the commercialization value and is valued at $280.6 million. Therefore, it can be inferred that if all phases are complete and commercialization is successful, the total ROV of Chinese expansion of plant-based beef is $280.6M. As the phases are completed, the probability of positive ROV also increases with offering a 95% chance of positive value after the infrastructure success. Based on the marginal probability of success among the two critical phases, there is a 72.9% probability that Beyond Meat reaches commercialization of Chinese plant-based meat. Since there is more certainty among the various steps to reach commercialization, the change in real option value across the different phases is not as significant as in the Chapter 4 case study where a greater probability of failure was present.

Figure 5.6

Overlay of ROV Phases of Chinese Expansion (Thousands $USD)



For relativity in different methodologies, one can compare a fixed and probabilistic DCF valuation as Chapter 4 did. The fixed DCF produced a mean value of $273.2 million and the probability DCF had a $210.4 million mean valuation. For ROV, the commercialization success phase is used to compare instead of the initial project ROV as in Figure 5.5. The commercial success phase is compared to the DCF methods because all scenarios assume successful R&D phases and a full commercialization period. Hence, the ROV of $280.6 million can be relatively compared to the $273.2 million and $210.4 million valuations. While the fixed DCF is nearly the same value as ROV, it's also not risk-adjusted for marginal probability of success such as the probability DCF. When comparing the latter, there is a significant delta in the difference of approximately $70 million which is 25% more total value. Based on this assessment, it can be again concluded that DCF methods tend to undervalue high growth opportunities and companies.

5.4.5. Sensitivities and Scenarios

Since there is vast uncertainty in the evolution of plant-based beef demand, market pricing, and market share dynamics, sensitivity and scenario analysis are crucial to the study. A probability distribution for most of the assumptions is used to stochastically derive results under uncertainty. Figure 5.7 illustrates a tornado graph of the change in mean ROV of the China expansion project. Within the upper and lower 10th percentiles of the distribution, the final market penetration of plant-based beef has the highest sensitivity with a minimum value of $90.5 million and maximum of $346.7 million. Beyond Meat's peak market share is the second highest sensitivity which has a long negative tail to the mean versus the final market penetration input, meaning there is more downside versus upside expected value. The final profit margin of the company and per capita beef consumption remain as the other most sensitive inputs.

Figure 5.7

Change in Output Mean of Chinese Expansion ROV

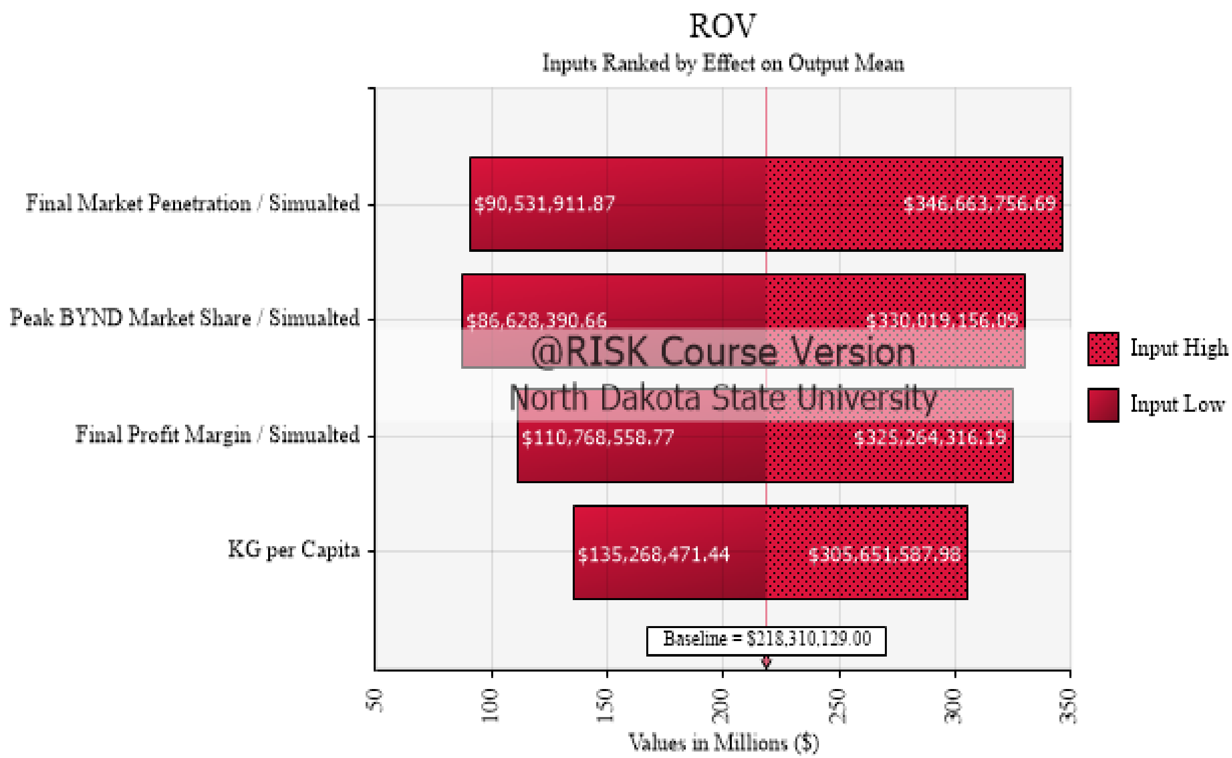
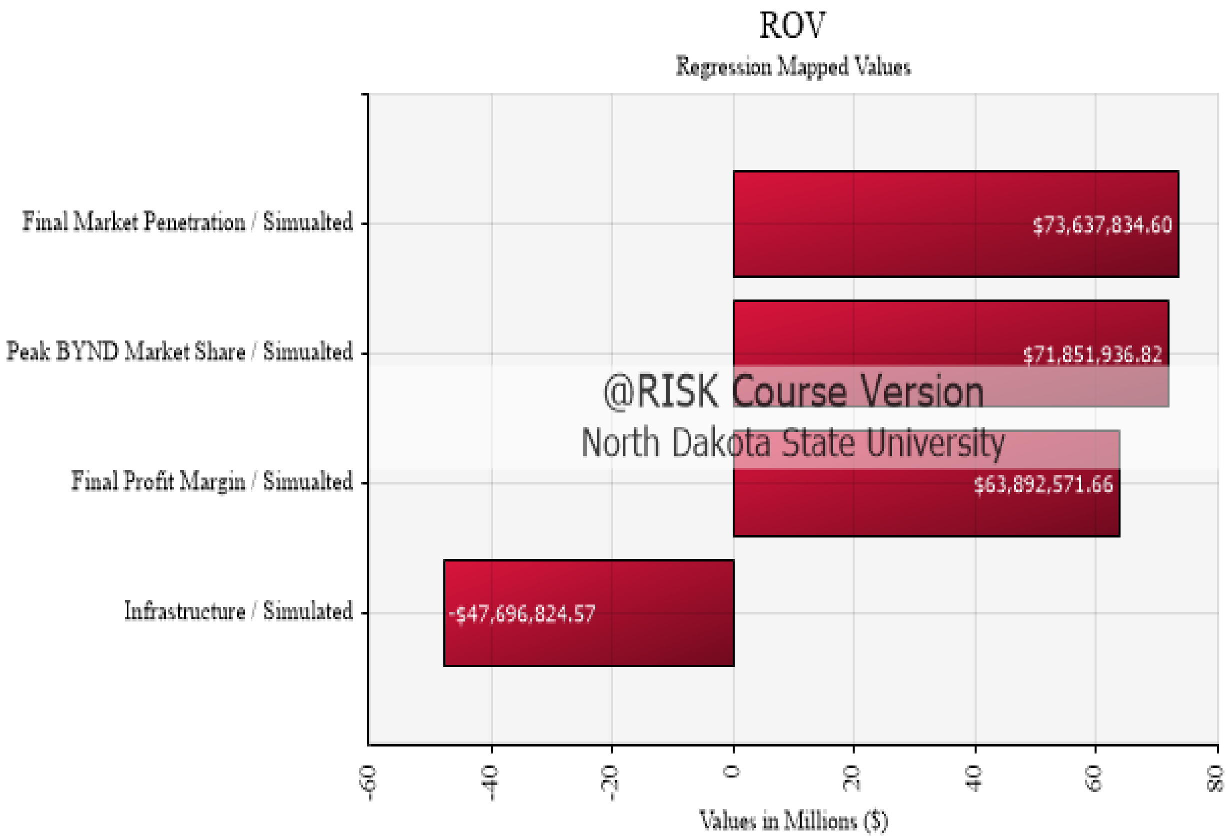


Figure 5.8 is also a sensitivity output but conveys the information differently. In a regression mapped value analysis, the variable represents the change in ROV output per one standard deviation increase in the input. Hence, for one standard deviation increase of final market penetration of plant-based beef, Beyond Meat’s ROV increases by $73.6 million. Likewise, Beyond Meat’s peak market share shows a similar change with a $71.9 million in ROV increase. For this sensitivity exercise, the first three sensitivities are the same as in Figure 5.7, but for the final variable. In regression mapped values, the infrastructure cost is important. This variable shows that one standard deviation increase in infrastructure costs result in a -$47.7 million decrease for Beyond Meat’s ROV.

Figure 5.8

Regression Mapped Value of Chinese Expansion



When analyzing the correlations of the inputs to ROV's change, the final market penetration has a Spearman rank coefficient of 0.46 implying that the input explains 46% of the ROV change holding others constant. The peak market share of BYND has a coefficient of 0.43, followed by final profit margin and infrastructure coefficients of 0.39 and -0.31, respectively.

In an analysis that studies the input's contribution to variance, the top four sensitivities together result in 62.3% of the ROV's variance. Contrasting from the Spearman rank correlation, the contribution to variance includes the relative effect of the combined inputs versus the inputs on a standalone basis while holding others constant. Of that contribution, the final market penetration makes up 20.3% with a peak Beyond Meat market share of 18.1%.

5.5. Plant-Based Chicken Product Expansion in U.S.

As described at the beginning of 5.4, the plant-based meat market is very new. Therefore, the limited history of relative companies or industry examples makes many valuation parameters unknown. In this case, deriving representative distributions through expert judgment is appropriate in valuing a novel industry and product. Like the Chinese expansion, the following sub-sections highlight the areas of importance for plant-based chicken expansion including R&D, commercialization, and sequential phases.

5.5.1. R&D of Chicken Product Expansion

There are R&D phases Beyond Meat must perform to expand its product line. The first obvious phase is the creation of plant-based chicken and the efficacy of its protein and nutritional studies. Though the company has created plant-based beef and pork, there are large alterations that must be done to create a product for chicken. Once created, there is then the process of regulatory approval to ensure nutritional and health safety for consumers. The inputs for the PERT distribution of these phases include time to completion, cost, and the probability of success and are shown in Table 5.4.

Table 5.4

R&D Phase Distribution Assumptions for Chicken Expansion

Phase	**Time (Years)**			**Cost (Thousands $USD)**			**Probability of Success**	
	Min	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Max**
Protein & Nutrition Studies	1.0	2.0	4.0	$10,000,000	$42,000,000	$100,000,000	50.0%	100.0%
Regulation	0.6	1.0	2.0	$5,000,000	$19,000,000	$50,000,000	75.0%	100.0%

Source: Author estimates based on review of industry studies and firm information (as described below).

It is uncertain what the time and cost to create plant-based chicken is. However, the past creations of beef and sausage can be utilized as a proxy to determine these factors of chicken. After the company's 2009 founding, 2014 was the first year in which the company began selling plant-based beef. While this process took five years, plant-based sausage began being marketed in 2017. With expectations of synergies, increased learning curves, and development processes improving for each product, plant-based chicken would constitute an even shorter time frame to establish. In addition, historic spend on research and development can help determine an approximate cost range of creating and testing plant-based chicken. Between 2016 and 2019, the company had spent a total of $41.8 million on R&D. Therefore, it is assumed that most of this historic R&D is attributable to extensions of product creation with decreasing timeframes of completions.

Like the China expansion option featured, this option also has regulation as a major phase to overcome. Utilizing the FDA's framework outlined previously, the regulatory inputs are similar to the China regulatory inputs.

5.5.2. U.S. Market Adoption and Commercialization

As mentioned in the discussion on China's adoption, the entire market of plant-based meat is early and uncertain. Hence, a distribution range of inputs is necessary to account for the uncertainty at hand. For plant-based chicken, there are no major players which leave the market fragmented. Given Beyond Meat's U.S. dominance in plant-based meat via brand recognition, distribution capabilities, and shelf space, it is assumed they can hold a dominant position in the plant-based chicken market as well.

The market penetration model for U.S. adoption takes the same procedural process as modeling Chinese penetration via an initial and final year penetration rate. Resulting penetration utilizes stochastic penetration rates, U.S. population growth, and per capita chicken consumption among the American population. Table 5.5 represents the inputs for a PERT distribution of plant-based chicken penetration of animal-based chicken and Beyond Meat's market share within that specific market. Like adoption for plant-based beef, plant-based chicken adoption is modeled to reflect the plant-based dairy industry's growth adoption. Data for U.S. population growth and per capita chicken consumption are derived from the same sources as in China's option, being the United Nations and OECD.

Table 5.5

Probability Distribution of Market Adoption and Market Share of U.S. Chicken

Variable	**Minimum**	**Likely**	**Maximum**
Initial Plant-Based Chicken Penetration	0.0%	0.5%	2.0%
Final Year Plant-Based Chicken Penetration	1.0%	13.0%	20.0%
Beyond Meat Initial Market Share	3.0%	5.0%	10.0%
Beyond Meat Peak Market Share	15.0%	40.0%	50.0%
Beyond Meat Final Market Share	10.0%	30.0%	40.0%

Source: Author estimates based on review of industry studies and firm information (as described below).

The estimated animal-based chicken demand for the United States can be written as such:

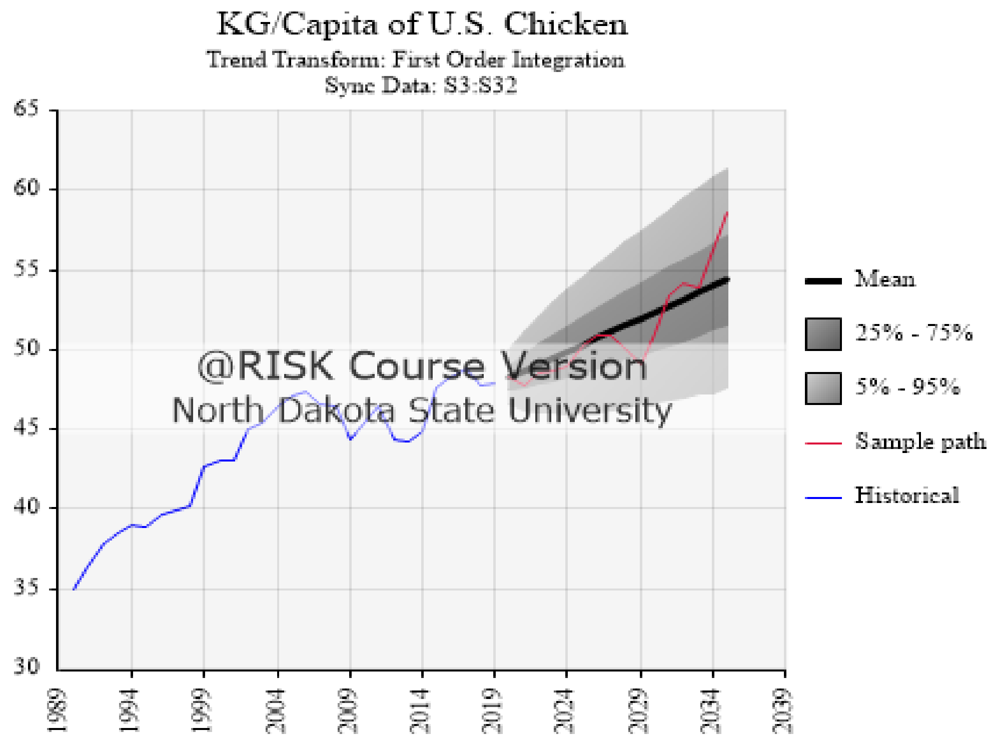
$$C_D = E * C_{KG} * Ib_C$$

Where C_D is the total demand for chicken in pounds, E is the estimated U.S. population, C_{KG} is per capita chicken consumption in kilograms, and Ib_C is the conversion of kilograms to pounds.

Figure 5.9 illustrates the forecasted per capita chicken consumption of the U.S. derived using first-order integration. The demand for chicken within the U.S. has increased majorly with a clear trend line of continuation. In 1990, per capita consumption was 34.97 kilograms and rose to 47.76 kilograms by 2019. By 2032, the expected per capita chicken consumption of the U.S. is forecasted to be 49.62 kilograms.

Figure 5.9

Historic and Forecasted Trend of per Capita Animal-Chicken Consumption (in Kilograms)



Demand for plant-based chicken is modeled via the stochastic probability distribution of penetration growth to the forecasted animal-based chicken market. Revenue for Beyond Meat's chicken is a function of the company's market share within plant-based chicken and the average selling price per pound to equate to revenue such as:

$$R = P_D * BYND_{MS} * P_P$$

Where R is revenue, P_D is plant-based demand, $BYND_{MS}$ is Beyond Meat's market share, and P_P is the selling price of plant-based chicken in pounds.

Reiterating the prior comments of price and cost expectations, Beyond Meat expects to eventually achieve price parity, or even less, than animal-based protein. For now, plant-based chicken is a niche and not at significant scale. Hence, the market price and cost of production are still high relative to animal-based chicken meat. The average historic chicken price between January 2017 to April 2020 is $2.09 per pound. To start, the expected selling price per pound of Beyond Meat's chicken is estimated in a PERT distribution of $2.09, $6.00, and $10.00 for minimum, likely, and maximum assumptions. As efficiencies are gained, the final ending prices are expected to host a distribution of $2.00, $2.09, and $6.00, reaching price parity given the likely price.

Profit margin is modeled as a PERT distribution with the same input range as the previous option exercise. Additionally, WACC is the same of 13.6% with a ten-year pro forma. The calculated NPV is the starting value for the sequential options underlying NPV.

5.5.3. Sequential Phase I and II of U.S.

The two important sequential investment phases identified for the company's expansion into chicken within the U.S. include the product creation and FDA regulatory approval. Though Beyond Meat already has existing beef and pork products, their chicken production must also exhibit safe and sound results to achieve regulatory approval. In the first sequential phase required, Beyond Meat must create the product and also validate its efficacy in protein, health, and nutritional value so marketing efforts can be established. This first creation phase is expected to last two years with the regulatory phase to follow with one year. However, since a sequential option is calculated backward from longest period to shortest, product creation is calculated first with the resulting ROV becoming the starting NPV for the regulatory option.

Table 5.6 displays the details of the two sequential phases, modeled as a stochastic cost distribution. Given the accumulated life of both options, the entire option life of the combined compound option is three years.

Table 5.6

Chicken Product Expansion Sequential Phase Parameters

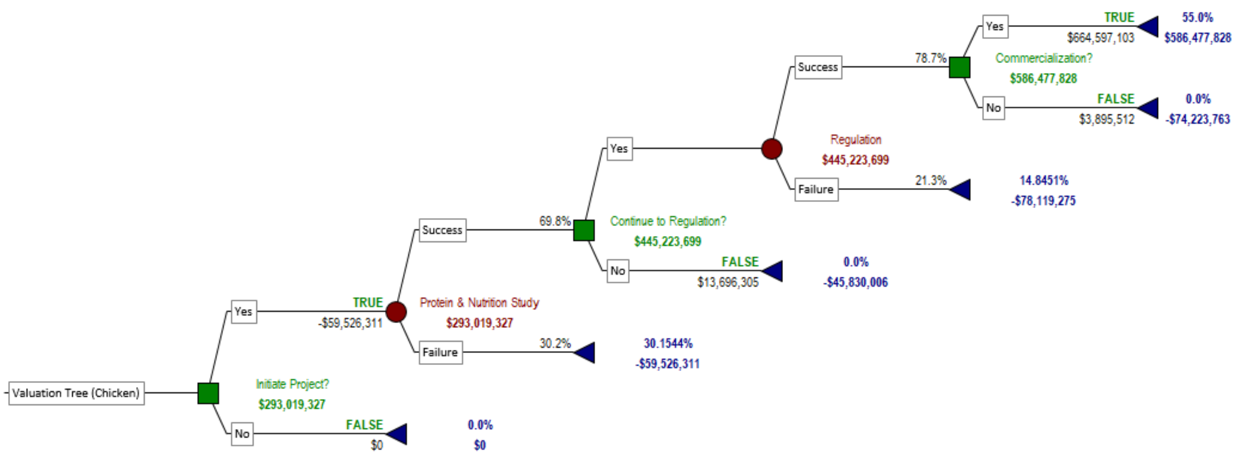
Phase	Description	Cost Distribution (Thousands USD)	Time to Completion	Accumulated Option Life
Phase I	Protein & Nutrition Studies	PERT($10,000, $42,000, $100,000)	2	2
Phase II	Regulation	PERT($5,000, $19,000, $50,000)	1	3

Source: Author estimates based on review of industry studies and firm information (as described below).

Figure 5.10 displays the decision nodes as Beyond Meat begins the chicken R&D process and evolves to commercialization. To start, the first R&D procedure is the initiation of the project via undertaking the protein and nutritional studies. This includes the optimization of ingredient mix with providing data of efficacy in the product. From there, regulatory approval must be met in order to approach commercialization. At each node, the marginal probability of success is assessed and modeled for an expected value.

Figure 5.10

Evolving Decision Nodes of Chicken Product Expansion



5.5.4. Base Case Results

As in the Chinese expansion option, the chicken product expansion uses the initial project ROV to add to the existing valuation. Figure 5.11 shows the simulation results of the initial project ROV which has a mean value of $274.3 million. Surprisingly, this mean ROV is higher than the Chinese expansion even though the population is significantly less. However, the per capita demand for chicken in the U.S. is exceptionally high, rewarding a product that is targeting the growing demand for chicken protein in a developed country.

Similar to the China expansion, the results for plant-based chicken show an asymmetric positive skewness marked by a maximum value of $1.3 billion. The 10th percentile exhibits $77.4 million with the 90th percentile of $510.1 million. Another notable point relative to the Chinese expansion is the probability of positive and negative ROV. For plant-based chicken in the U.S., there is just a 1.4% probability of negative ROV to almost 99% positive value. This compares to 6% probability of negative ROV for China.

Figure 5.11

ROV Simulation Results of Chicken Product Expansion

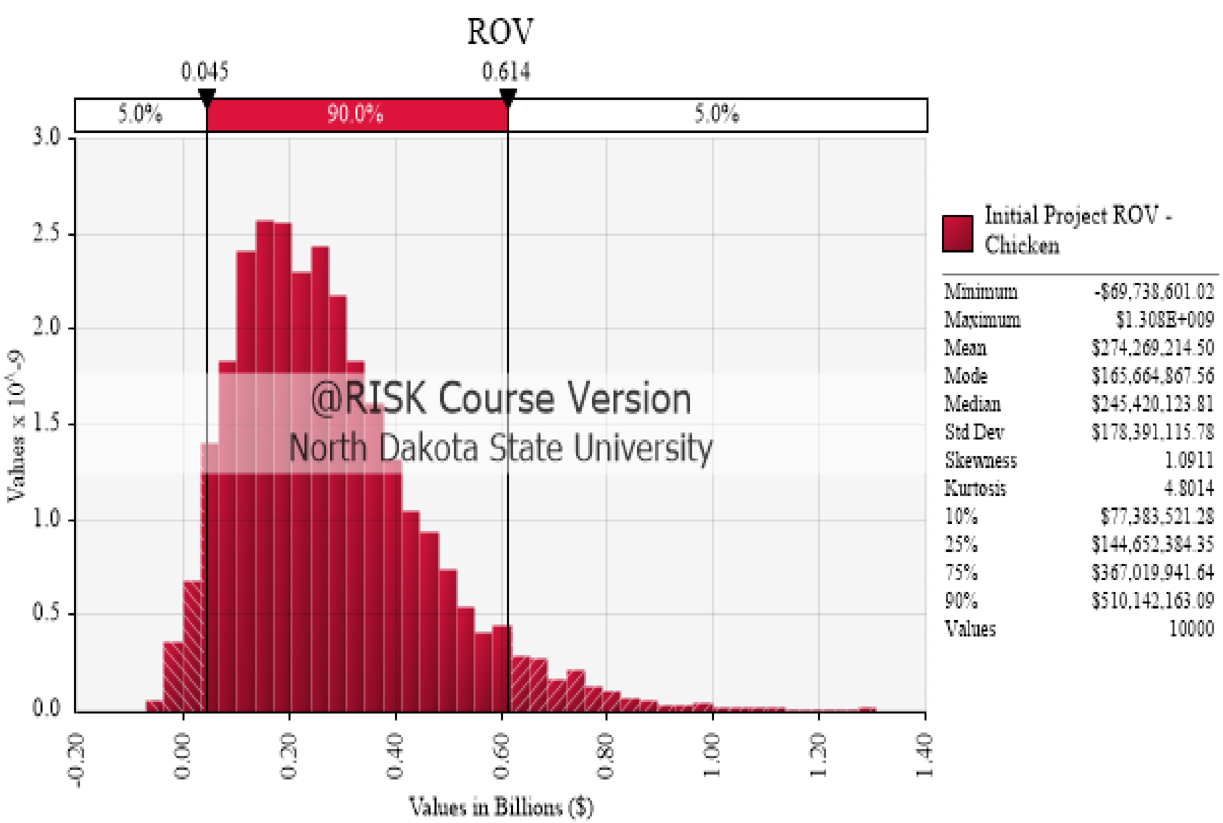
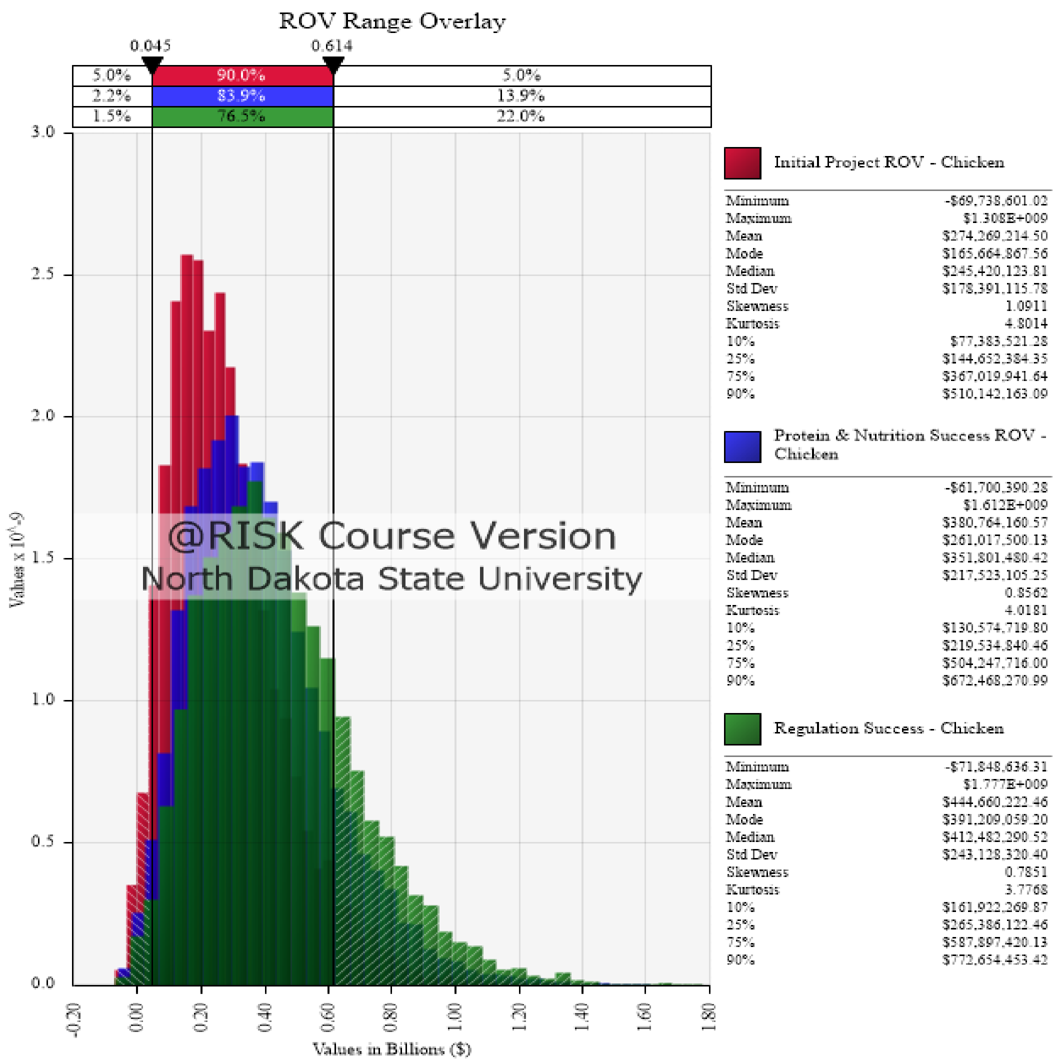


Figure 5.12 displays ROV overlay at the different phases of success. The initial ROV, as the red distribution, is the same as featured in Figure 5.11 with a mean value of $274.3 million. As the different stages move to successful completion, the ROV for chicken increases. Assuming successful completion of product creation and nutritional studies, the mean ROV increases to $380.8 million. In the next regulation phase, the approval of plant-based chicken in the U.S. increasing the mean ROV to $444.7 million. Therefore, the execution of the multi-phase completion is critical in materially increasing the ROV of Beyond Meat's expansion efforts.

Figure 5.12

Overlay of ROV Phases of Chicken Product Expansion (Thousands $USD)



Using the commercialization ROV as a relative comparison among DCF methodologies, the mean ROV of $444.7 million is almost the same as the $498.6 million fixed DCF value and significantly higher than the $309.7 million probabilistic DCF value. As mentioned in the Chinese expansion, the fixed DCF does not consider the risk-adjustment for marginal success which is a critical component in real world risk quantification. Hence, the probabilistic DCF is the best method to compare the ROV to. It can be concluded that the DCF method does not capture the full value of managerial flexibility in staged phase options or the asymmetric upside with a higher percentile probability of success.

5.5.5. Sensitivities and Scenarios

The sensitivities most critical to Beyond Meat's product expansion into U.S. chicken include penetration dynamics as seen in the Chinese option. Figure 5.13 displays the Spearman rank correlation of top sensitivities. The final market penetration of plant-based meat into animal-based meat has a 61% correlation to the change in ROV, assuming no other variables. Peak market share, creation and nutritional studies, and final profit margin are also influential with a 32% to 35% correlation to ROV change.

Figure 5.14 is a spider graph view of the ROV change relative to the different input percentiles. While the inputs are the same as featured in Figure 5.13, the final market penetration is interesting to note in terms of percentile change. While the slope is dramatically higher than any other input, the increase is noticeably accelerated around the 85th percentile. This 85th to 95th percentile range of final market penetration increases the ROV by approximately $70 million.

Figure 5.13

Spearman Rank Correlation of Chicken Product Expansion

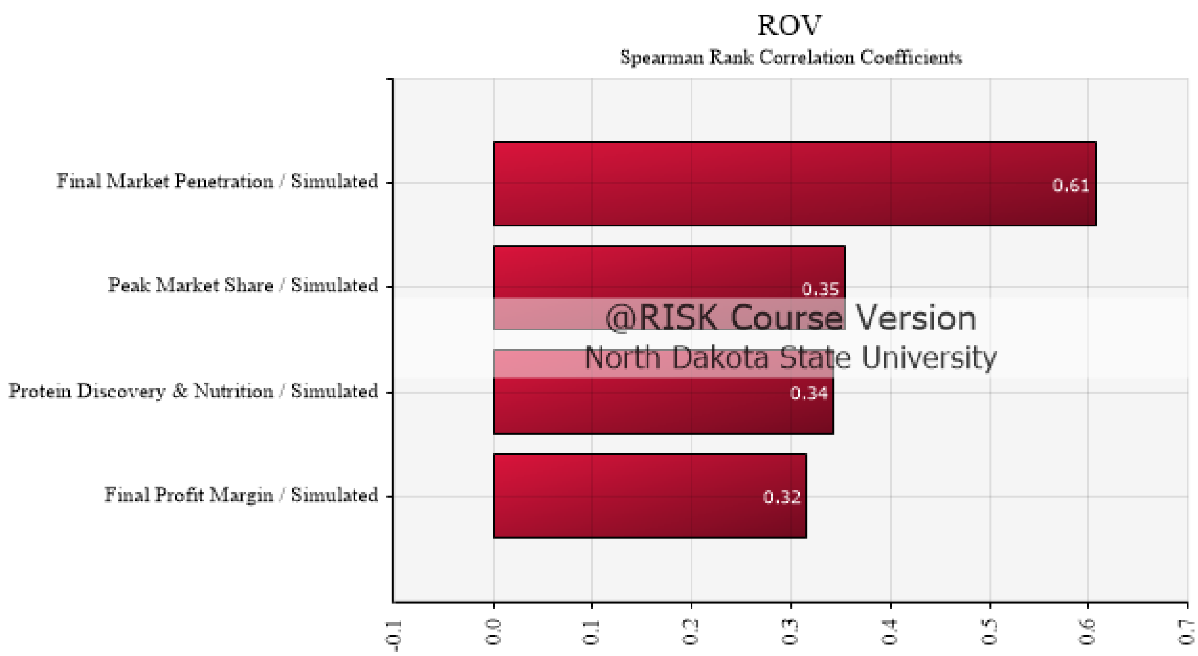
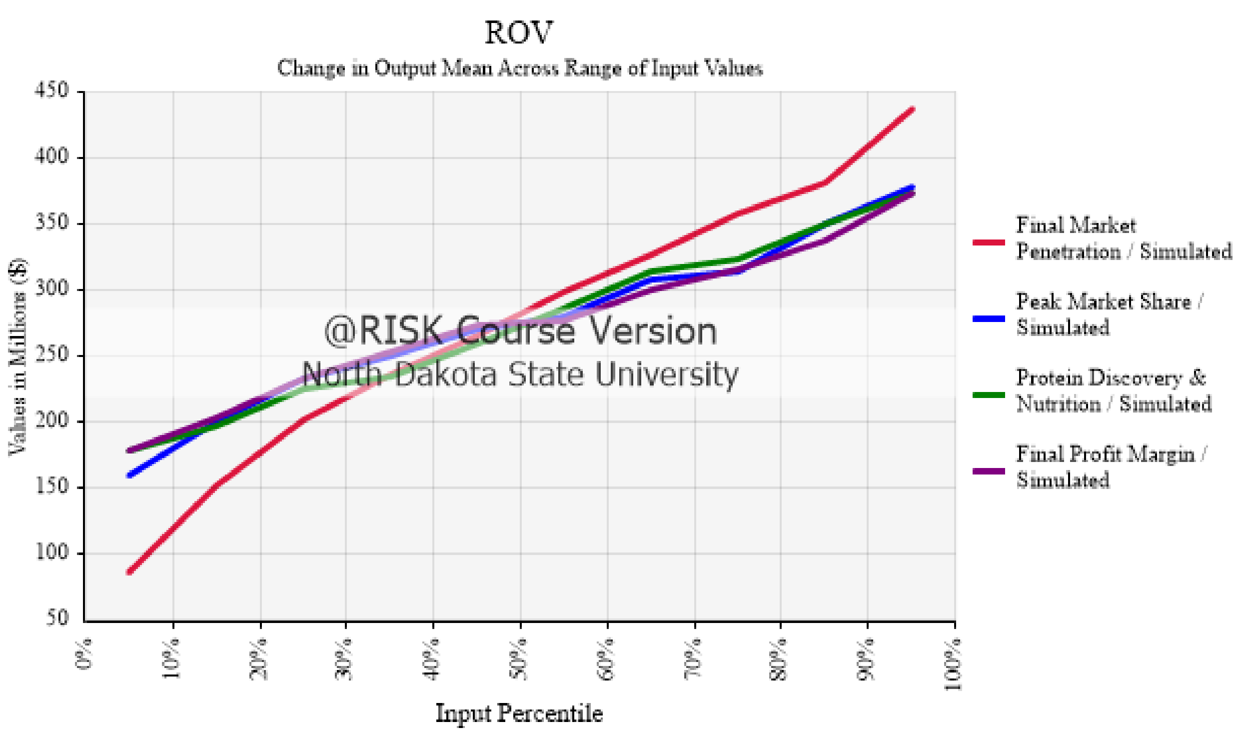


Figure 5.14

Spider Graph of Chicken Product Expansion (Thousands $USD)



Interpreting the change in output mean, the lower and upper 10th percentiles of ROV to final market penetration input have a lower and upper calculation of $86.3 million and $438.0 million, respectively. To a lesser extent, peak market share is also important which has a lower and upper bound of $159.3 million and $378.3 million. Through regression mapped values, results show that one standard deviation increase in the final market penetration increases ROV by $101.2 million. This increase is nearly 40% of the baseline mean ROV.

Knowing that these two characteristics are so influential in driving the sensitivity of ROV, a thorough market analysis can be demonstrated by Beyond Meat to best position the company within the market and truly understand the expected growth emerging from plant-based chicken.

5.6. Aggregate ROV and Existing Valuation

One of the main contrasts of Beyond Meat's case study versus the startup from Chapter 4 is how the real option value is compared and aggregated to determine the value of the companies. The startup in Chapter 4 uses the commercial success ROV as the option value to determine company value, compared to using the initial project ROV for Beyond Meat. In addition, the startup's value is solely derived from the aggregate ROV while Beyond Meat's ROV is combined with an existing valuation to reach a total value. This difference in ROV use is simply due to the different stages the two young companies are at. Unlike the startup, Beyond Meat has an existing product generating revenue and creating value. Therefore, the appropriate method in using ROV is to add it to the current valuation.

Since the calculated ROV must add to an existing valuation, it then becomes a question of what the appropriate existing valuation is. The purpose of this study is not to determine what that existing valuation is. However, it can be discussed in a way in which to think about the aggregation of the ROVs discovered in this chapter and existing valuation.

Figure 5.15 displays the historic stock price of Beyond Meat from the IPO in early May 2019 to December 15th, 2020. The stock price is simply the market cap divided by the number of outstanding shares. As of December 15th, 2020, Beyond Meat's stock price insinuated a market cap of $8.62 billion. In other words, the market was valuing Beyond Meat at $8.62 billion on that specific date. While this is the market value of the company, other investors may have a different valuation for the company. Hence, the purpose of this study is not to subjectively determine what the existing valuation of Beyond Meat is.

Figure 5.15

Beyond Meat's Historic Stock Price (CNBC)

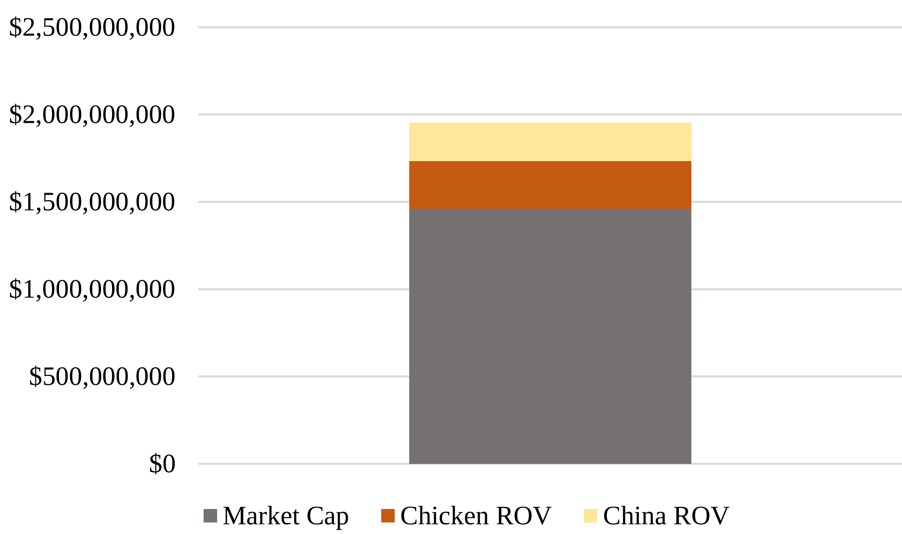
In the process of valuing Beyond Meat, one would calculate their existing valuation of Beyond Meat and add the ROVs of this study to that valuation for the total value of the company. An important limitation, however, is that the existing valuation cannot contain synergies of the ROVs in this study. Otherwise, the total company valuation would be overvalued due to double counting.

For the sake of illustration in an example of aggregate valuation, the current market value of $8.62 billion is used. For disclosure, it is assumed that this market value does not contain any expected value from U.S. chicken product expansion or Chinese expansion of beef. Though it's likely this value does contain these forward-looking items, this example is for illustration purposes and not accuracy. The existing valuation of $8.62 billion is combined with the calculated ROVs to accumulate a total company valuation of $9.11 billion. With the Chinese expansion ROV of $218.3 million and the chicken expansion ROV of $274.3 million, the two combined ROV make up approximately 5% of the overall value.

Note that since the existing valuation of $8.62 billion likely includes forward-looking expansion into these two markets, the example is overvalued. In Figure 5.16's case of the existing valuation being less, the ROV would contribute a much larger part to the overall valuation. For example, at the IPO in May 2019, the implied market valuation of Beyond Meat was just $1.46 billion (Wang & Picker, 2019). In this situation, where one can argue this study's ROV markets are not priced in, the combined ROVs would contribute 25% of the total value.

Figure 5.16

Example of Beyond Meat's Aggregate Valuation at IPO



5.7. Conclusion

This chapter features a case study of applying ROVs to the young, publicly traded AgTech company, Beyond Meat. The purpose of applying ROV is to consider growth options at stake for a young, high growth company. Without consideration of ROV to growth opportunities, an investor is likely to undervalue Beyond Meat, potentially missing out on returns.

This case study uses sequential options to derive ROVs for two growth opportunities of Beyond Meat. The first opportunity is the option to expand into China with plant-based beef in consideration of two important phases being regulatory approval and infrastructure completion. With an accumulated option life of three years, results found an ROV of $218.3 million. The second opportunity is the option to expand with the creation of plant-based chicken in the United States with sequential phases of creation and regulatory approval. The value (ROV) of chicken product expansion is $274.3 million ROV. Hence, the aggregate ROV for sequential growth options into the two markets is $492.6 million.

The most sensitive inputs to ROV output revolve around penetration dynamics in both plant-based penetration to animal-based meat and market share of Beyond Meat. Interestingly, these sensitivities are critical to both the Chinese expansion and the U.S. chicken expansion. Therefore, for an investor, it is important to keep close attention to what takes place in the evolution of plant-based meat. If penetration and demand continue to see strong growth, higher percentile values of company valuation can be expected whereas if the market does not expand as projected, Beyond Meat will be far less attractive.

Since this is an overall theme discussion at the beginning of the chapter, these market implications are important for venture capitalists and startups participating in the plant-based meat market (and alternative proteins in general). Emerging competition and technologies are likely to face similar phases, barriers, and risks, making this study relevant to all market participants.

For the $492.6 million in aggregate ROV, that value must be added to an existing valuation. Since the purpose of this study isn't to value the existing value of Beyond Meat, the reader must determine the appropriate value. Hence, the combination of existing value and ROV would be the total value of Beyond Meat. This application can be utilized among other companies of different stages and industries to quantify the growth opportunities in an emerging market.

CHAPTER 6. CONCLUSION

This chapter summarizes the entire thesis. First, the purpose and objective of the problem is discussed with reasoning for alternative solutions. Next, the methodologies used to create an alternative solution is framed. The results of both case studies from Chapters 4 and 5 are reviewed and highlighted. This is followed by an explanation of the results and methodology's contributions to the existing literature, including the limitations involved and a summary of where further research can take the existing conclusion.

6.1. Purpose and Objectives

Startups and early stage companies hold extreme uncertainty and managerial flexibility. Since there is little operating history and novel products at stake, there is limited prior knowledge or expectations on how the startup may perform or the business model chosen to execute on performance. Since this uncertainty lies at the heart of startups, traditional methods of valuation such as discounted cash flow and multiples are challenging tools to use. Discounted cash flow assumptions are fixed and assume an ongoing operation of products, strategies, and unit economics. However, the reality of startups is the opposite of all of these where often there is managerial flexibility to change product lines, strategic business models, and commercialization timelines. In addition, discounted cash flows fail to account for the upside optionality in product expansion and externalities that are positive for startups, ultimately undervaluing the high growth in startups. Likewise, multiples also have flaws since comparable startups typically do not have financial data existent given the limited operating history. Even if there is financial data present (e.g. revenue), the data is private and cannot be used in an analysis. To use publicly traded companies where data is public is not a good proxy for comparison since public companies host a longer operating history and also have different risk profiles than private startups. Given these problematic methods commonly used for startup valuation, different alternatives should be considered.

Stochastic real options provide a means to value startups that thrive on uncertainty and managerial flexibility. The stochastic nature of inputs provides a probability distribution that considers the range of input versus a fixed input assumption. The ability to simulate the range also provides a likelihood path of law of large numbers where inputs can be better analyzed for risk. Real option value increases with volatility and uncertainty. Hence, the method can quantify the upside value in managerial flexibility of startups. inclusion of decision trees also adds an extra element of risk management as private risk is considered given the probability of success. The combination of these valuation characteristics offers an alternative to discounted cash flow or multiples valuation for startups that may pose more accurate results of valuation.

The objective of this thesis is to utilize stochastic real options and decision trees to value agricultural technology. The first case study presented in Chapter 4 uses these methods to value an agriculture biotechnology startup solely using real options. Chapter 5 uses these same methods to value upside optionality in the publicly traded company, Beyond Meat. Through the use of these methodologies, the goal is to quantify and prove the application in valuing early stage companies which host uncertainty and flexibility, and to value upside optionality in young growth companies within AgTech.

6.2. Methodology and Explanation

The methodology used in both Chapter 4 and 5 uses stochastic real options and decision tree integration for valuation. Chapter 4 is a case study of a private AgTech startup operating in the agricultural biotechnology sector. A real options valuation is used on the first product currently being developed along with the second product of similar characteristics. Since the startup does not have existing products, the aggregate real option value of the two products in development equates to the entire startup valuation. The first product is valued via an abandonment option which quantifies the option to continue operations or exit through merger and acquisition. The second product is valued via a sequential option which quantifies the option to proceed to the product development stages in multiple phases, ultimately being dependent on the first product's success in regulatory approval. The aggregate value of these two options, hence the startup's value in its entirety, quantifies the upside opportunity in the startup's ability to have managerial flexibility and uncertainty in product development and commercialization.

Chapter 5's case study uses the same methodology to value upside growth options for the publicly traded plant-based meat company, Beyond Meat. Unlike using real options to value the entire company, this application uses real options to value potential growth opportunities for Beyond Meat. The first option is a sequential option that values the ability to enter the Chinese market with plant-based beef. The second option is another sequential option that values the ability to create and commercialize plant-based chicken efforts in the United States market. The aggregate value of these two options is added to the existing value of Beyond Meat. Hence, they do not equal the entire company valuation like in Chapter 4 but provide upside value in Beyond Meat's flexibility to enter new markets.

6.3. Result Review

This subsection reviews the results of the thesis. The review is broken into two smaller subsections of the agricultural biotechnology startup case study from Chapter 4 and the Beyond Meat case study in Chapter 5. In both studies, the utilization of real option values are significant in increasing the overall value of both companies and quantifying the managerial flexibility and growth opportunities.

6.3.1. Agriculture Biotech Startup Case Study: Chapter 4

Stochastic real options integrated with decision trees is the methodology used to value the startup from Chapter 4. The entire valuation is a combination of two different products, both being valued with real options but different option types. Product 1 is valued via an abandonment option that considers the startup's ability to continue R&D and commercialization or abandon the efforts and take either a salvage value during the R&D or an exit value during commercialization. By using a DCF to value the startup, one could not incorporate this described managerial flexibility within the model or account for the stochastic uncertainty of assumptions. Therefore, the valuation would likely be understated.

Critical R&D and commercialization assumptions utilized probability distributions to account for the uncertainty in the inputs and their effect on the output. The resulting valuation of the stochastic real option valuation is compared to fixed and probability-weighted discounted cash flow valuations. The analysis found the ROV to value the startup at a significantly higher valuation versus the two DCF methods. Using ROV, the startup is valued at over $186 million versus the fixed DCF value of $18 million and probability DCF value of $30,000. The ROV methodology values the startup over 10x higher than fixed DCF and 644x higher than probability DCF. This additional upside can be contributed to the quantification of the startup's ability to abandon the first product if it becomes attractive or exit via M&A if the offer supersedes the valuation of continuing operations. Hence, this managerial flexibility for the startup to pivot and make decisions in real-time has enormous value upside. Additionally, the stochastic nature of inputs allows for proper risk analysis versus alternative methods like discount rates.

The results of comparative valuations are consistent with previous literature which claims that DCFs tend to undervalue companies with high growth potential and managerial flexibility.

Therefore, the ability to quantify these aspects in a valuation has huge implications for both sides of a deal negation. For a startup, the management team can properly assess the risk and opportunity in their company's different strategic paths and quantify the alternative decisions for optimum value creations. Likewise, the venture capital investor can quantify the upside opportunities in an investment and better compare various deals based on expected value versus stationary values among investments. Additionally, opportunity cost can be better represented as one of venture investors' largest reoccurring mistakes include not investing in a company that becomes good investments due to a narrowed vision of optionality and managerial flexibility and how it is quantified.

6.3.2. Beyond Meat Case Study: Chapter 5

This case study of Beyond Meat utilizes the same stochastic real option and decision tree integration methodology as in the prior case study. However, instead of using the ROV to value the entire company, the two ROVs calculated are added to an already existing valuation of the company. Unlike the pre-revenue startup from Chapter 4, Beyond Meat has existing product lines and revenue being generated. Hence, there is an existing valuation of the company based on those characteristics. However, the ROVs in the study quantify additional expansion opportunities that can emerge from the company. By ignoring the ROV, Beyond Meat would be undervalued using DCF alone. The two expansions identified are geographic growth into China with plant-based beef and the creation of plant-based chicken for the U.S. market. With high probabilities of both opportunities taking place in the future, an investor would undervalue Beyond Meat without considering the managerial flexibility of entering these markets.

The results of Chinese expansion with plant-based beef include \$218.3 million of ROV. Likewise, the ROV of plant-based chicken is \$274.3 million. Hence, the aggregate ROV of

Beyond Meat is $492.6 million. This ROV is then added to an existing company valuation. This study does not determine what the existing valuation of Beyond Meat is as that is left to the subjective nature of the reader. However, caution is provided as to be aware of what existing valuation is made of. By using the publicly traded market value, it must be ensured that none of that value is part of the two markets the ROVs in this study identified. Since it is impossible to know if that is the case, the reader must assess and provide their own existing valuation of Beyond Meat in ensuring there is no value overlap between growth opportunities. Therefore, the contribution of ROV to the total valuation will depend on the reader's existing valuation. To illustrate, with a December 15, 2020 market value of $8.62 billion, ROV is just 5% of the total value. However, if the initial IPO value of $1.46 billion is implied, the ROV contributes 25% to the total value. As mentioned, since these existing values are dependent on market values (which considers many investor's theses on Beyond Meat), it cannot be determined that this is the appropriate existing valuation to utilize. This is left to the reader to decide.

The final important takeaway from Chapter 5 is the consistency of DCF methodologies undervaluing high growth opportunities that host managerial flexibility. The commercial success phase of ROV in the China expansion is over $70 million higher than the probabilistic DCF output, adding an additional 25% of the total value. Likewise, the chicken product expansion's commercial ROV is more than 43% higher than probabilistic DCF. These results are reiterative of both Chapter 4 results and academic literature claiming DCFs undervalue companies of high growth.

6.4. Contribution to Literature

Existing literature is rich in real options, stochastic processes, and decision trees as sole components of valuation. However, there are few studies that incorporate the combination of them together into a comprehensive valuation methodology. In addition, there is little valuation literature available of agricultural technology, an industry that has and will likely continue to compound in relevance. Most importantly, there is not to the knowledge any existing published literature that uses real options solely to value startups. This application, featured in Chapter 4, lays the first groundwork to utilize this approach for startup valuation. This differs from previous real option valuation that values technology as a part of a company versus the entire company itself. Therefore, there are three significant components to this study that contribute to existing literature which are summarized by the integration of methodologies, application to AgTech startups, and valuation of an entire company solely using real options.

6.5. Limitations

A study is not complete without disclosure of important limitations that may alter its effectiveness in industry use. First, the real option valuation is determined through a stochastic process that features valuation steps based on cash flow volatility. While this may be the case at times, valuation can take on different philosophical forms in the market which include intrinsic, momentum, relative, and other valuation philosophies.

The data obtained for both case studies require expert opinion from management teams, investor relations, and the author. Therefore, assumptions such as pricing, adoption, and strategic procedures are driven by subjective inputs versus sole objective assumptions. Alternative expert opinion or experiences may derive different inputs which would change valuation output results.

An additional limitation to realistic industry application is the common use of well-known valuation techniques versus the lack of knowledge behind real option valuation. Therefore, negotiation and interpretation with startup executives, existing or additional investor bases, and audit committees will likely prove difficult given the newness of the methodology among most. Compared to DCF or multiples, ROV is not as intuitive and easily calculatable.

6.6. Suggestions for Further Research

This study provides a framework for applying stochastic real options and decision tree integration for valuations in startups. Extension of this research could include the comparison of multiples as a relative valuation comparison among DCF and ROV methodologies. This additional work would enhance the thorough analysis of comparing different valuation strategies on the primary differences of each.

An additional extension of research is comparing the binomial ROV methodology to the Black-Scholes option pricing model. This would essentially compare results of an American versus European style ROV and whether results differ.

Finally, utilizing alternative distributions outside of the PERT and uniform methods may provide different results outside of the current format. Distributions that consider both upside and downside tail risks can increase the robustness of the study and add efficacy to the process. While this study uses expert opinion, potential datasets on success probability and market dynamics may be more objective in the analysis.

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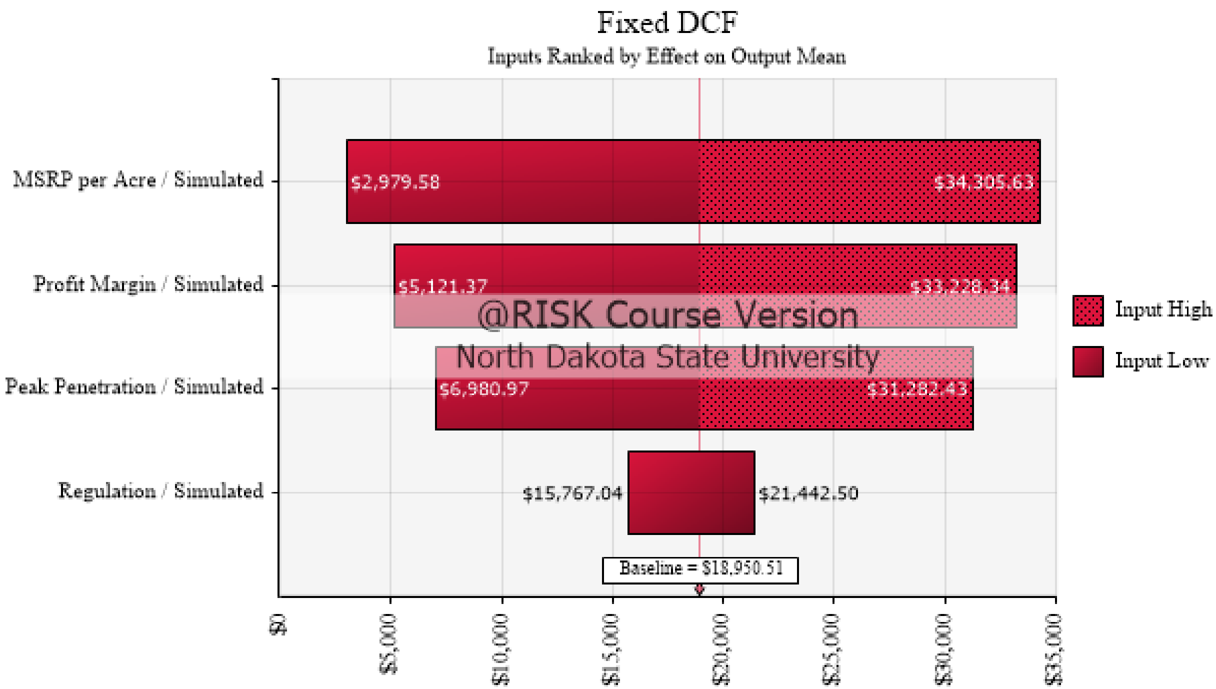
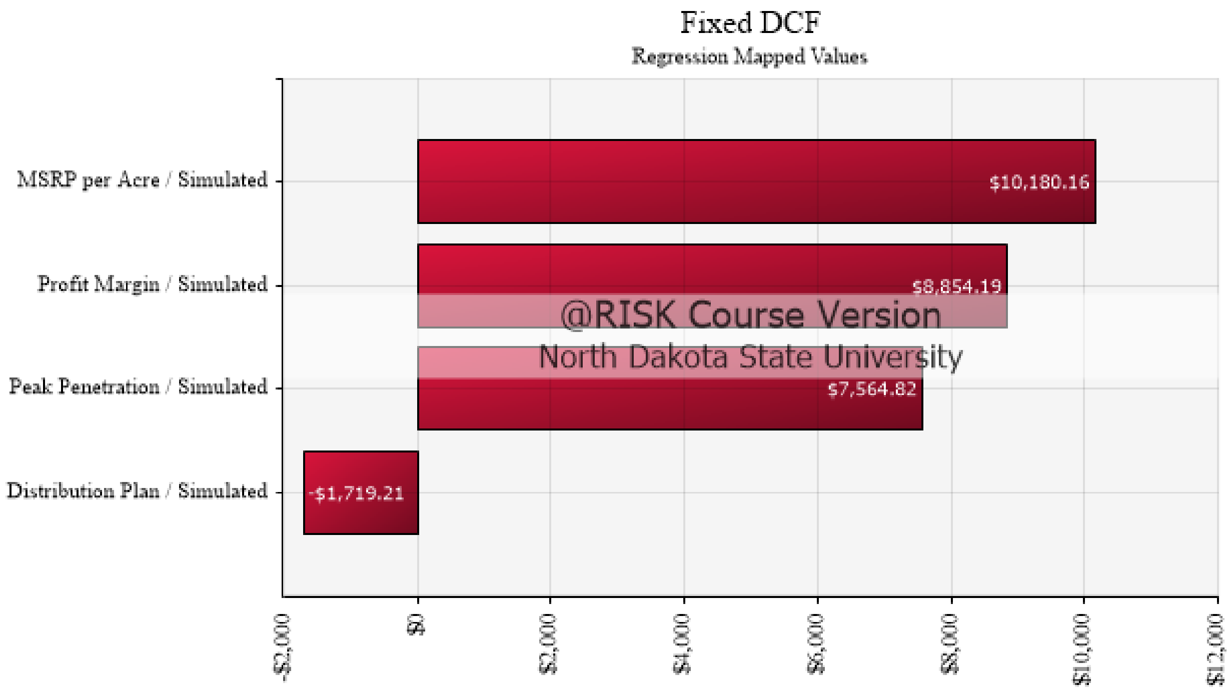
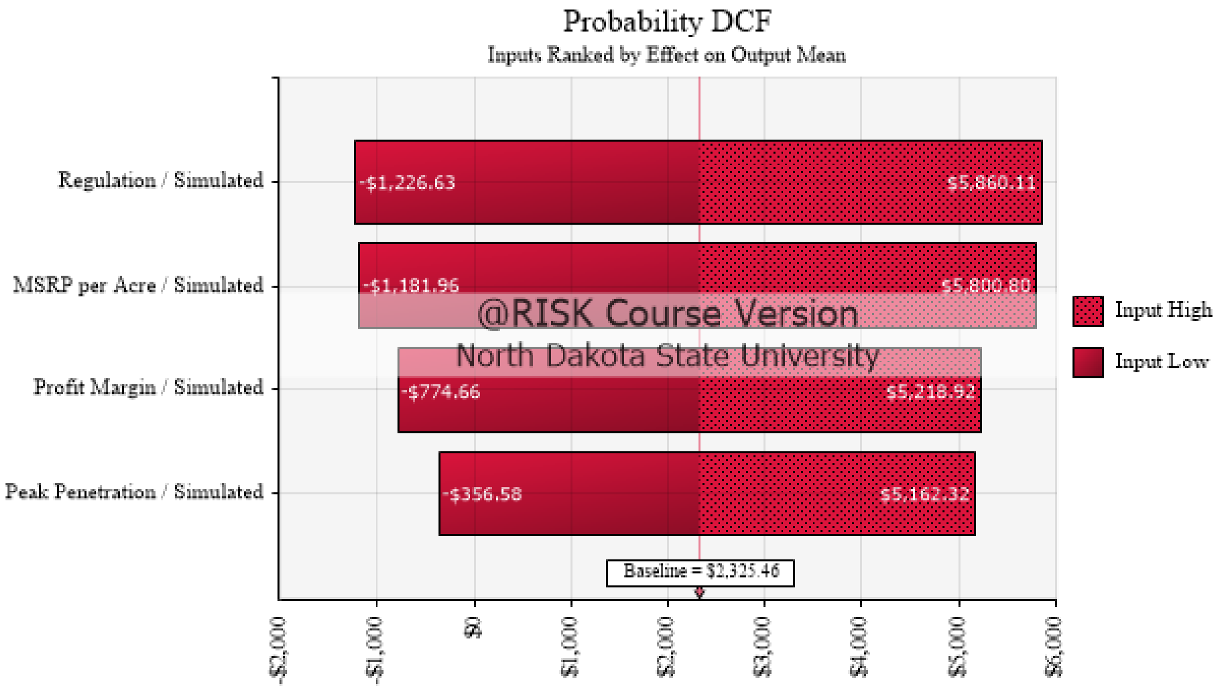
APPENDIX A. FIXED DCF EFFECT ON OUTPUT MEAN OF PRODUCT 1



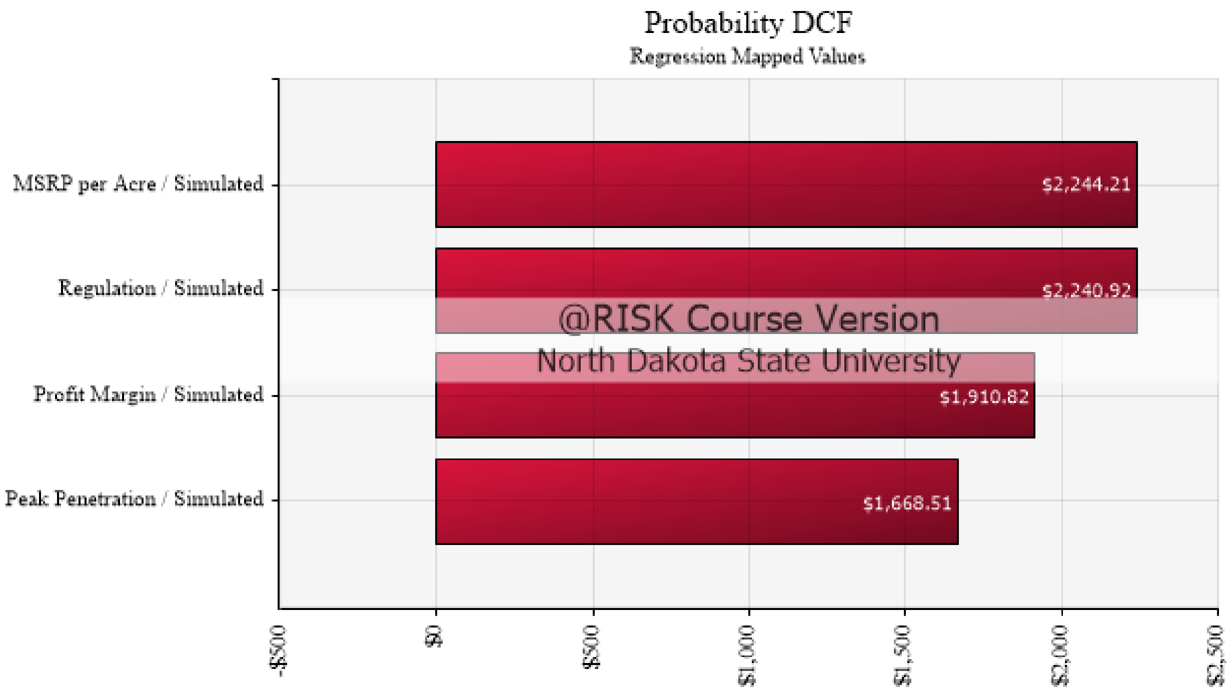
APPENDIX B. FIXED DCF REGRESSION MAPPED VALUE OF PRODUCT 1



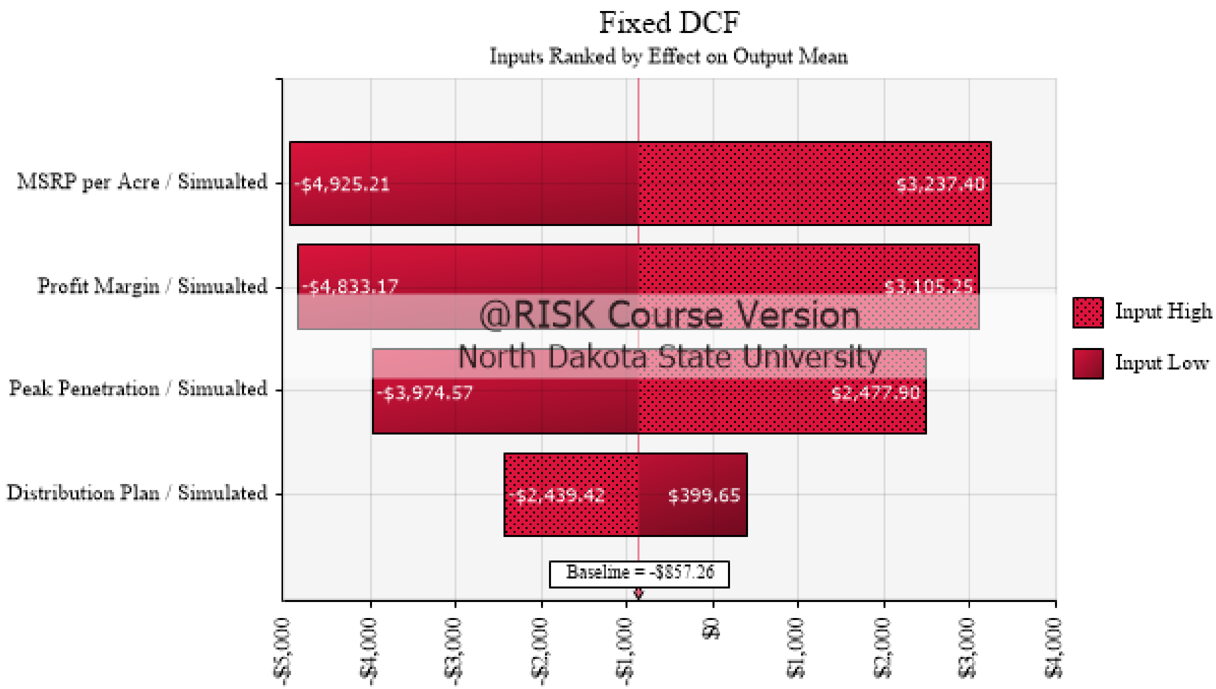
APPENDIX C. PROBABILITY DCF EFFECT ON OUTPUT MEAN OF PRODUCT 1



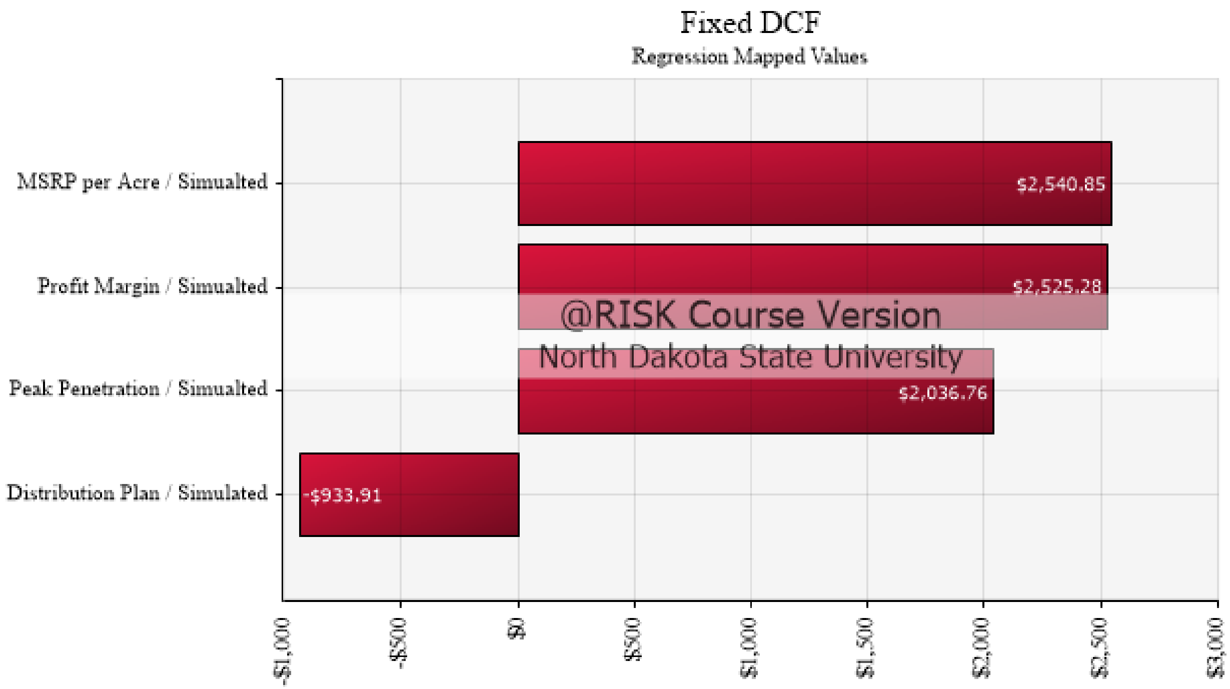
APPENDIX D. PROBABILITY DCF REGRESSION MAPPED VALUE OF PRODUCT 1



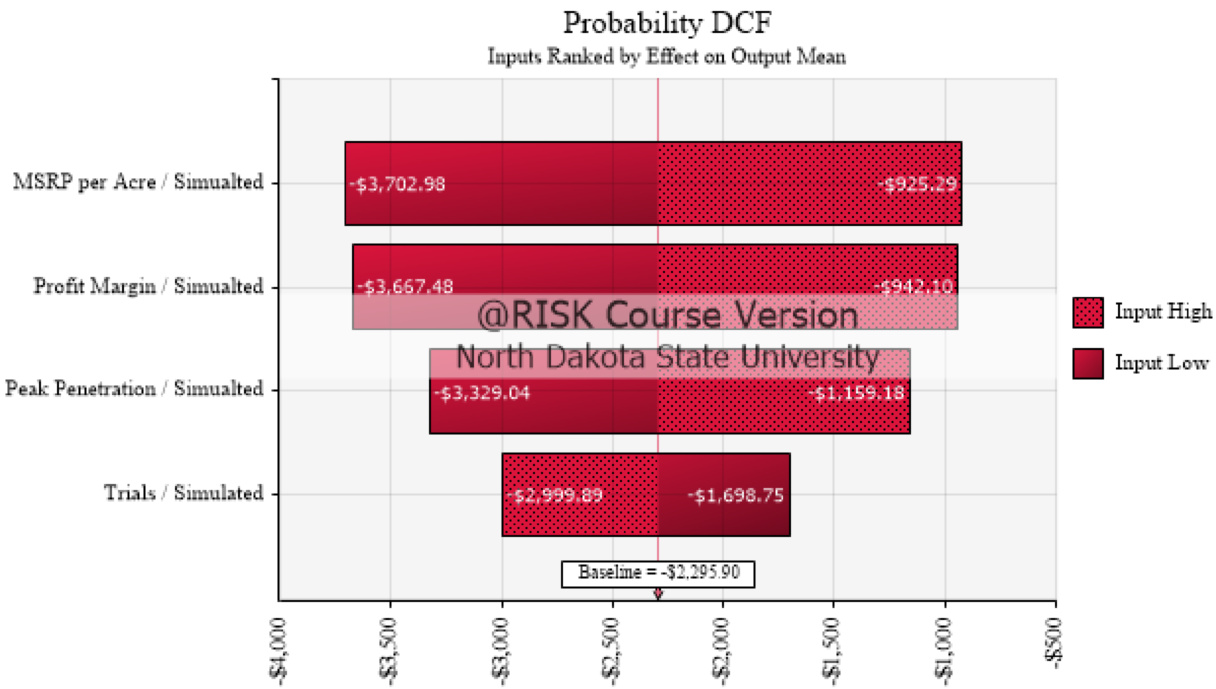
APPENDIX E. FIXED DCF EFFECT ON OUTPUT MEAN OF PRODUCT 2



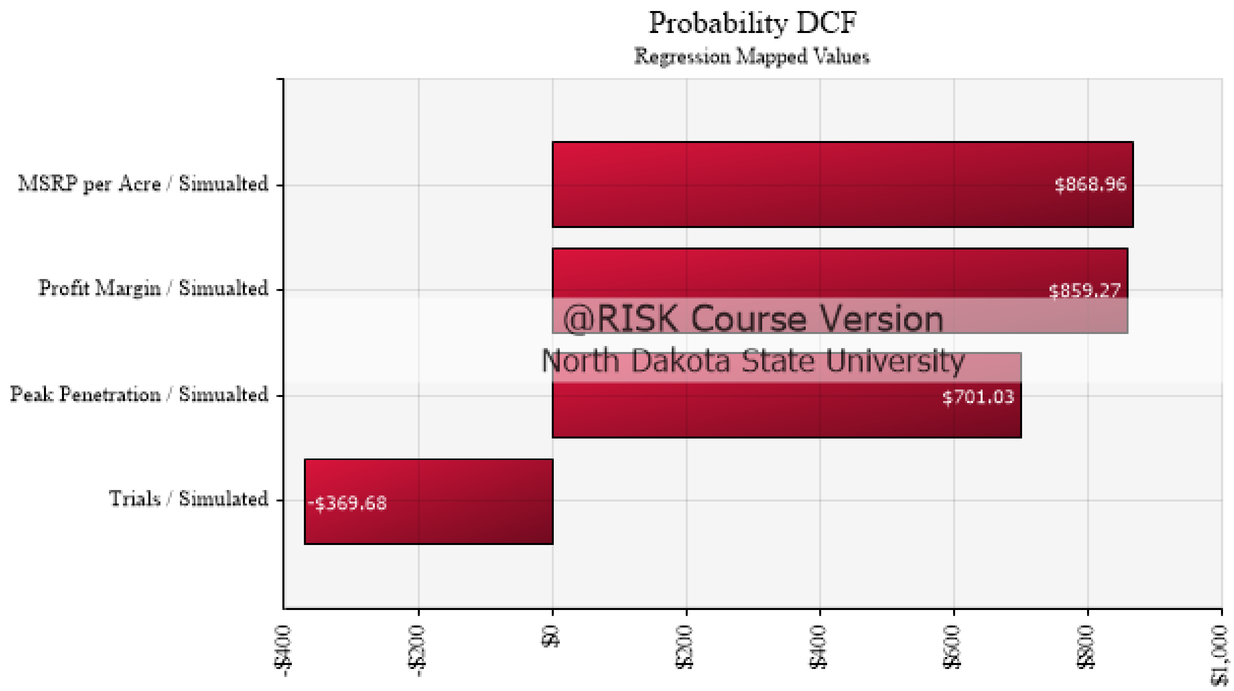
APPENDIX F. FIXED DCF REGRESSION MAPPED VALUE OF PRODUCT 2



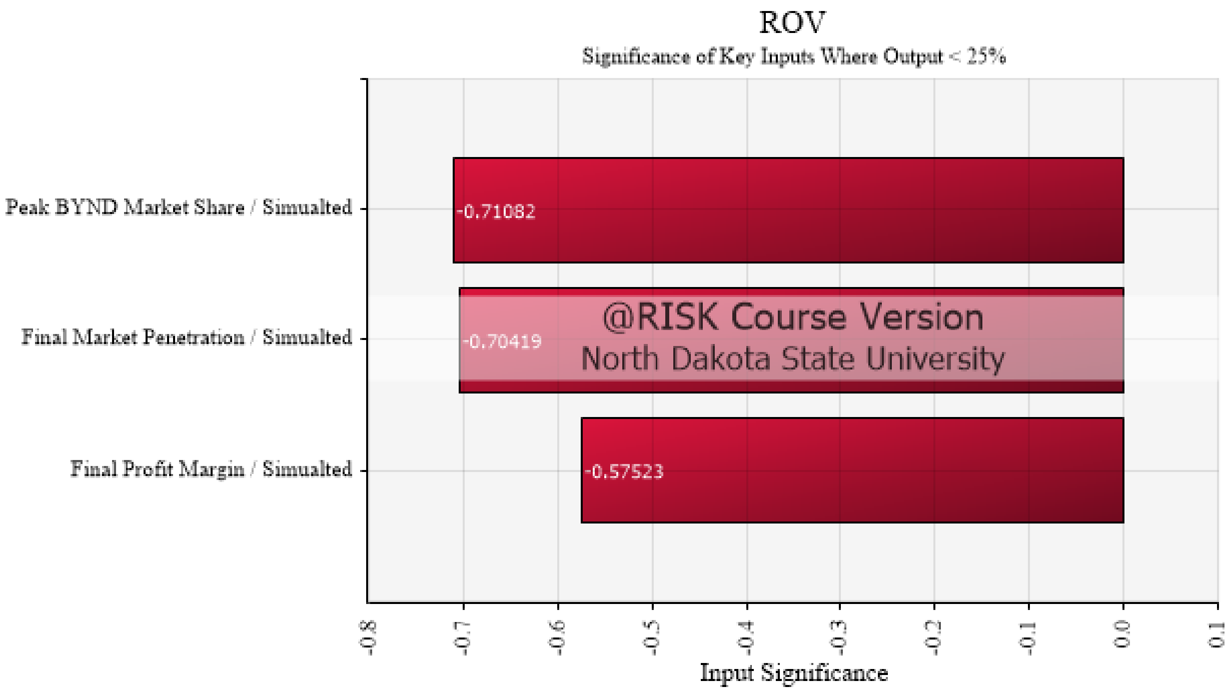
APPENDIX G. PROBABILITY DCF EFFECT ON OUTPUT MEAN OF PRODUCT 2



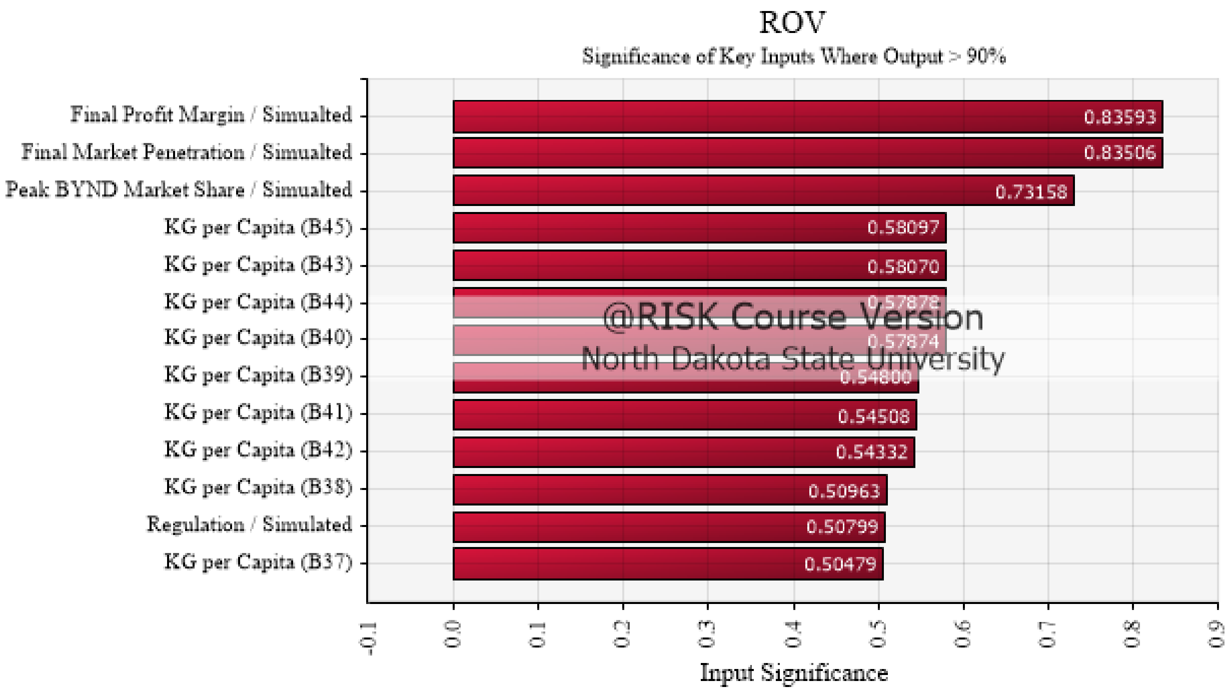
APPENDIX H. PROBABILITY DCF REGRESSION MAPPED VALUE OF PRODUCT 2



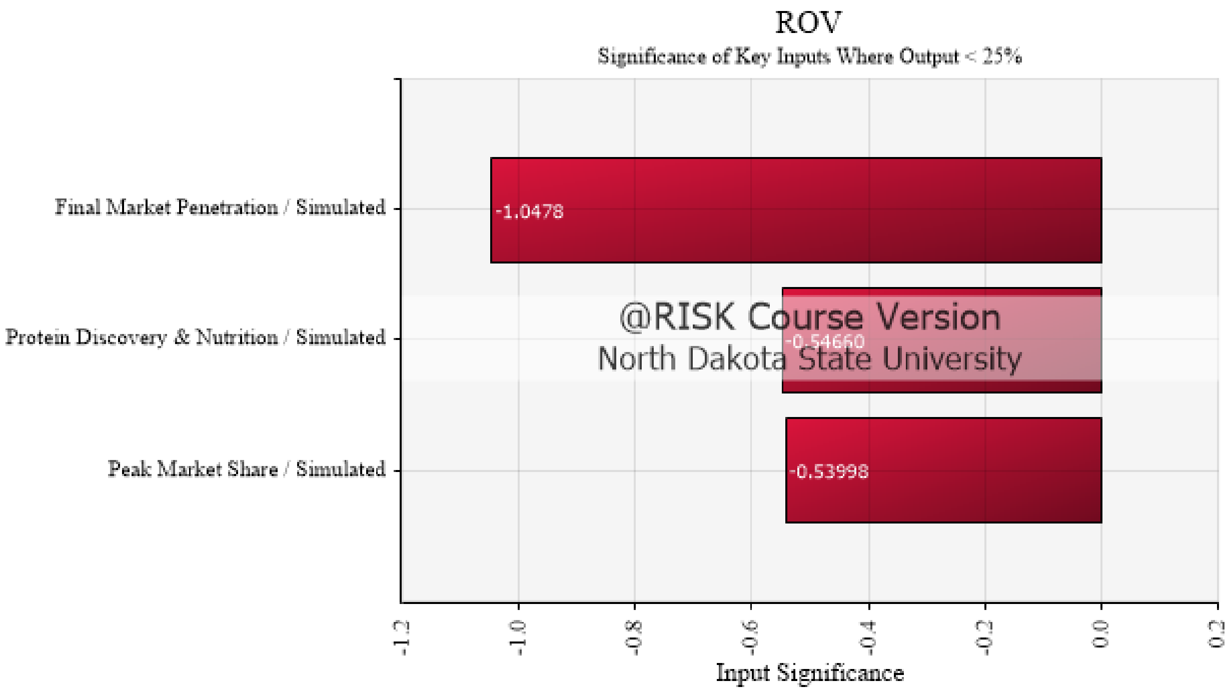
APPENDIX I. CHINA EXPANSION <25TH PERCENTILE SCENARIO RESULTS



APPENDIX J. CHINA EXPANSION >90TH PERCENTILE SCENARIO RESULTS



APPENDIX K. CHICKEN EXPANSION <25TH PERCENTILE SCENARIO RESULTS



APPENDIX L. CHICKEN EXPANSION >90TH PERCENTILE SCENARIO RESULTS