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Valuing Circularity: Sustainable Finance with Real Options methodology

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Valuing Circularity: Sustainable Finance with Real Options methodology

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Abstract

This thesis presents an enhanced framework for valuing circular investments based on the Value Hill model using real options analysis. We propose a new flexible numerical methodology for valuing circularity using the Least Squares Monte Carlo simulation (LSMC) method of Longstaff and Schwartz (2001). The Value Hill model of circularity represents the course followed by the value of an asset, specifically after primary use. To validate the efficiency of our model, we conduct an empirical study on the smartphone business using the case of Apple. Results of our empirical analysis show that investing in circularity enhances financial value. Our model enables analysts, managers, and sophisticated investors to make more informed decisions when assessing such projects.

Keywords: Sustainability, Circular Economy, Real options, American-style options, Least Squares Monte Carlo, Dynamic Programming

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Introduction

Over the last decades, rivalry over the world's most valuable resources has become extremely fierce. The competition for materials and resources is getting sharper over time due to several factors, such as the rising population growth and urbanization rates, consumption and waste generation, and the fear of climate change. The world's population will be more than double in 2100 compared to 1990, thus increasing urbanization and competition for resources. Studies conducted by the United Nations suggest that the urbanization rate will be around 68% in 2050. Consequently, the sustainability of natural resources has become one of the main concerns of governments to protect the environment and achieve sustainable development. The United Nations (UN) has established a framework for international commitment to develop policies focused on the long-term impacts of economic activity known as the Sustainable Development Goals (SDGs). Sustainable finance is one of the most important tools that helps achieve the SDGs and encourages the financial system to make positive changes and to take social, environmental and governance (ESG) factors into financial decision-making.

The circular economy (CE) concept has gained significant attention among scholars, professionals, and policymakers as it helps preserve natural resources for future generations and slows down the impact of climate change. The European Commission (2014) defines the circular economy as an economic system that aims to create additional value from a product after primary use by creating a closed loop of resources. See Figure 1. In general, circular economy entails the extraction and transformation of resources and the distribution, use, and recovery of goods and materials. The Value Hill framework is a business strategy tool that proposes the categorization of the lifecycle of a product into phases: pre-use, use, and post-use. This tool enables businesses to position themselves on Value Hill to determine their position in terms of circularity. It helps corporations implement the most suitable circular strategies in their case and determine the missing patterns in their circular models. The model suggests implementing life extension strategies, like reuse, refurbishing, remanufacturing, and recycling. Additionally, such a transition requires corporations to rethink their visions and strategies to ensure survival and future environmental sustainability, which will require significant changes in their strategies and policies. (Achterbeg et al., 2016; Gonzalez et al., 2021).

There are several drivers for businesses to shift towards circularity. For example, circularity can help companies improve their profit margins by reducing energy and material costs. Circularity enables companies to enhance their brand equity and improve their customer satisfaction by creating products of higher quality. In addition, it allows companies to gain competitive advantage by locking into more innovative models and achieving organizational synergies. Finally, circularity can help institutions hedge against the increased volatility in raw materials prices over the long-run (Tura et al., 2019; Mallick et al., 2023).

In contrast, the traditional (linear) economy model assumes a linear flow of resources from extraction until divestment, implying that additional value cannot be captured from the product after use. See Figure 2. This model presumes the producer has no control over the product once it is with the final consumer (Sauve et al., 2016). Maximizing profit by selling products that have a short lifespan while ignoring environmental externalities is the premise of the linear economy. It assumes resources are abundant, easy sourcing, and cheap disposal of resources and production materials. The Finance Working Group (2016) suggests that such a production model could lead to shortages and increased price volatility over the long-term.

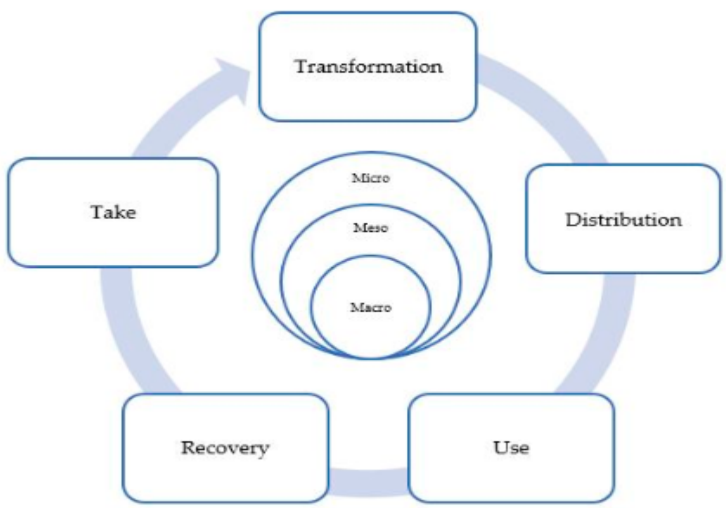

Figure 1: Flows of resources in a circular economy (Gonzalez et al., 2021).

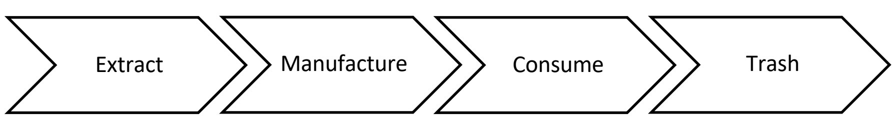

Figure 2: Flow of resources in a Linear economy (Gonzalez et al., 2021).

A primary challenge confronting organizations in implementing circularity is the inability to value projects using the classical capital budgeting approaches due to the high level of uncertainty. Classical capital budgeting approaches, such as the net present value (NPV), have several limitations in valuing circular projects. Those limitations include the lack of managerial flexibility to either reverse or postpone an investment decision as it treats it as a "Now or Never" decision. Another limitation is the loss of potential competitive position that can negatively affect the value of the business (Trigeorgis, 1993a). Moreover, it assumes the project will operate and generate fixed cash flows in each year of the project's lifetime, ignoring uncertainty and potential changes in the external environment. To overcome the shortcomings of the classical investment valuation approaches, Weskamp et al. (2015) and Gonzales et al. (2021) suggest using real options analysis to value circularity. Real options analysis is a numerical approach for valuing investments that bear a high degree of uncertainty. It gives the decision-maker the right but not the obligation to invest in a real asset on a future date, contingent on the price of the underlying asset and market conditions. Unlike financial options, real options derive their value from a real asset (i.e., project, land or new technologies) rather than a financial asset (i.e., stock, bond or FX). When decision-making is complex, real options provide decision-makers with the flexibility to make major managerial decisions in the future based on new information that emerges (Alexander & Chen, 2021).

In this thesis, we aim to extend the work of Gonzales et al. (2021) by providing an enhanced model for valuing circular investments. We develop a numerical methodology for valuing circularity by applying real options analysis. We attempt to solve the real options using the Least Squares Monte Carlo (LSMC) simulation method of Longstaff and Schwartz (2001). LSMC is a numerical approach for valuing American-style options that alternates between Monte Carlo simulation, dynamic programming, and ordinary least square regression to determine the optimal time to exercise the option and the expected value of the option contract. Then, we present a numerical investigation using hypothetical figures to explain and test our algorithm. To validate the practical application of our model, we conduct an empirical study to value the implementation of circularity in the smartphone business using the case of Apple.

The remainder of this thesis is structured as follows. Section 2 provides a literature review. Section 3 describes the methodology. Section 4 presents our numerical investigation, while Section 5 covers an empirical study of the smartphone business. Finally, Section 6 concludes our research.

I. Literature Review

1. Circularity: Design, complexity and challenges

1.1. Design

Kircher et al. (2017), Noman and Amin (2017), Ellen MacArthur (2013) and Potting (2017) cite the 9Rs framework that includes nine generic circular strategies. Circular strategies suggested in the 9Rs framework are further categorized based on the degree of circularity and complexity. See Figure 3.

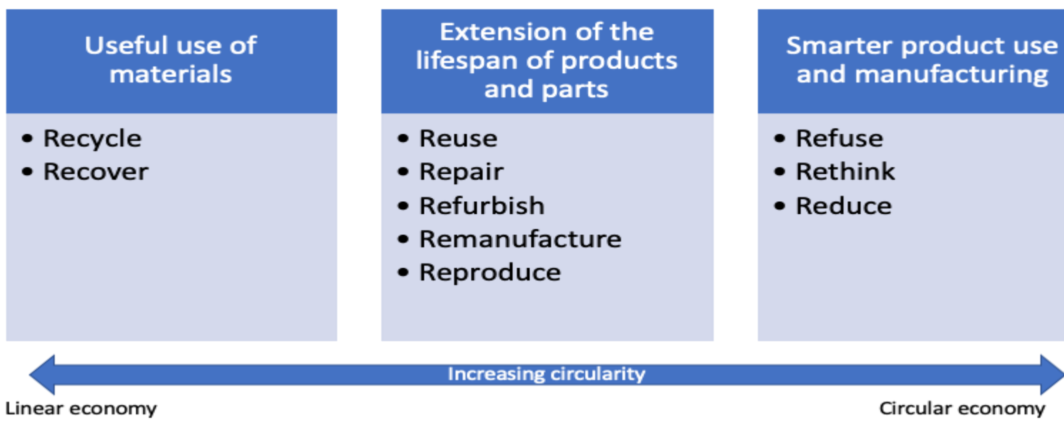

Figure 3: The 9Rs framework for Circular strategies (Potting et al., 2017).

Initially, the useful application of materials strategies is the lowest in circularity and complexity as they require fewer changes to the business's functional strategies and product design than the other categories. The main target of adopting these strategies is to recover materials from products for reuse in manufacturing new products to close the loop of resources. Strategies defined in this category are as follows. First, the recycle strategy entails processing materials from used products to manufacture new products. In contrast, the recovery strategy entails obtaining materials from incineration waste material to generate energy.

Secondly, the extension of products' lifespan category is in the middle of the circularity and complexity spectrum. These strategies aim to extend the lifespan of products after primary use by reusing the product for the same purpose as is or after some changes depending on its condition or by using it for a different purpose. Strategies defined in this category are as follows. First, the reuse strategy entails reselling a product that is still in good condition to another consumer after no changes for being reused. Second, the repair strategy entails the repair and maintenance of defective products so they can be used for their original function. Third, the refurbishment strategy entails restoring an old product and making it up to date. Fourth, the remanufacture strategy is concerned with the use of parts of discarded products in the manufacturing of new products with the same function. Lastly, the repurposing strategy entails using discarded products or their parts to produce a new product with a different function.

Finally, smarter product use and manufacturing strategies are the highest in circularity and complexity. This category involves eco-friendly product designs and manufacturing to create long-lived products. As argued in the literature, those strategies are the most complex as they require significant changes in business models, product design, and supply chain. Strategies enumerated in this notch are as follows. Initially, the refuse strategy is mainly the making products that produce negative environmental externalities redundant either by abandoning their function or offering the same function with a radically different product. Secondly, the rethinking strategy entails making the use of products more intensive by, for example, designing products that can be shared among consumers. Finally, the reduce strategy is concerned with designing and manufacturing products that consume less natural and harmful resources.

Achterbeg et al. (2016a & b) explain the Value Hill model that illustrates the value creation process throughout a product's life cycle through the linear and circular models. This framework is a strategic management tool that helps managers position their business on the circularity spectrum to develop circular strategies. It also allows managers to understand the required collaborations throughout the value chain for successfully implementing circularity.

The Value Hill pyramid has three phases: pre-use, use, and post-use, as illustrated in Figures 4 and 5 for linear and circular models. In a linear economy, value is only added to the product produced in the pre-use phase represented in the uphill slopping part of the pyramid. Then, the product has its maximum value when it reaches the use phase illustrated in the top-hill part of the pyramid. After a relatively short time, the product's value is destroyed and goes downhill. Conversely, the circular model implements value-adding strategies throughout all the pyramid parts to slow down the downhill journey and retain the product's value for the longest time possible (Achterbeg et al., 2016; Gonzalez et al., 2021).

Circular strategies identified in the value hill are divided based on the phase of the product life-cycle phases. Categories of circular strategies identified in the Value Hill model are as follows:

First, uphill strategies aim to achieve product longevity and slow the resources loop by prolonging the use phase and optimizing the product before it reaches the consumer by adopting circular product design strategies. Businesses need to design reusable, re-manufacturable, and recyclable products by creating products that can be easily disassembled and reassembled. Input materials can be sourced from renewable energy and recyclable materials to ensure product longevity and lower carbon footprint. To signal product durability and reliability and to encourage customers to use their products efficiently, companies can impose higher prices on their products. Companies can also offer warranties and additional services around the product that comes for a premium paid upfront (Bakker et al., 2014; Bocken et al., 2016).

Second, top-hill strategies are implemented when the product reaches the final consumer for use, where its value is optimized, and the business has little control over it. At this point, businesses must implement product life extension strategies to prolong this phase and gain more control over their product. For example, Tukker et al. (2004) and Tukker et al. (2015) recommend creating a product-service system where products and services get bundled for businesses to gain more control over their customers' behavior. Such strategies include leasing and renting and providing repair and maintenance services. Companies can also initiate shared platforms to facilitate optimal use of products by offering shared access to the product where several users can use the product together (Stegeman, 2015).

Third, downhill strategies aim to extend the life of products after being used by primary users to slow down the downhill journey of value. Achterbeg et al. (2016) and Gonzalez et al. (2021) suggest four strategies for this phase depending on the use of the product, which are:

- **Reuse:** When a product is in excellent condition and is no longer used by its primary consumer, it can re-enter the market as a second-hand product after no adjustments. This value recovery strategy requires a relatively minor investment as the product is still in good condition. This strategy only requires an investment in reverse logistics to collect and ship used products from their old to new customers. Additionally, this requires setting incentives for customers to trade in used products.
- **Refurbish:** This strategy allows used products to re-enter the market after minor aesthetic adjustments depending on their condition. Like the reuse strategy, this strategy does not require a high investment. However, it requires investment in reverse logistics and setting incentives for the customer to trade in their old products.
- **Remanufacture:** This strategy involves rebuilding a used product to re-enter the market with the characteristics of a new one. Unlike reuse and refurbish, this strategy requires a higher

investment as it might require changing major components of the product so it can have the benefits and characteristics of a new one.

- **Recycle:** Recycling is applicable when a product is longer functional. This strategy entails recovering raw materials and components from old products and using those materials to produce new ones.

Finally, network organization strategies are cross-phase as they aim to facilitate and coordinate the flow of resources and optimize incentives throughout the circular network. One of the most common network organization strategies is tracing facilities, which facilitates the marketing and logistics of second-hand materials and products. Other strategies for value management include better contracting and improved payment schemes. Corporations may also need to invest in information technology solutions for an efficient flow of information throughout the circular network.

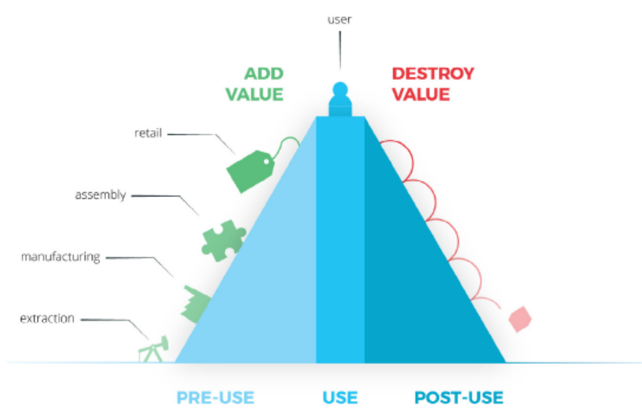

Figure 4: Value Hill in a Linear economy (Achterbeg et al., 2016a).

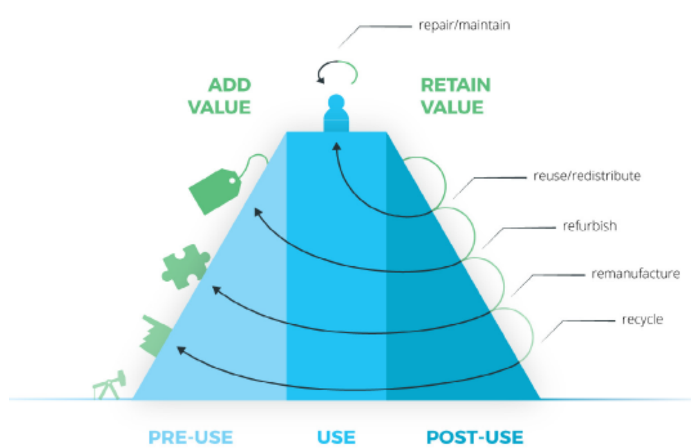

Figure 5: Value Hill in a Circular economy (Achterbeg et al., 2016a).

1.2. Complexity and challenges

Implementing a circular economy model increases the complexity of financial and business decision-making. Ghisellini et al. (2016), Gonzalez et al. (2021), and Uhrenholt et al. (2022) categorize the factors affecting the implementation and performance of the circular projects as follows.

1.2.1. Macro-level challenges

Macro-level challenges arise from external factors on the national level, such as laws and regulations that are uncontrollable by the business organization. Studer et al. (2006), Bechtel et al. (2013), Tura et al. (2019), FinanCE (2016), and Gonzalez and Garcia (2022) suggest that circular challenges on the macro-level are mainly institutional and structural. Tura et al. (2019) state that governmental taxes and subsidies create high uncertainty for businesses wanting to switch to circularity. Policymakers and government officials often misunderstand circularity and have different interpretations of the concept. For example, Sauve et al. (2016) examine 114 definitions and interpretations of circularity. This misunderstanding of the circular economy concept by academics and government officials has increased the complexity of assessing the long-term impact of circularity on the national level. Finally, the current infrastructure needs to support the design of a financially viable system for product take-back for full adoption of circularity.

1.2.2. Meso-level challenges

The business organization has partial control over Meso-level challenges as they are influenced by factors in the external environment. Studer et al. (2006), Bechtel et al. (2013), Tura et al. (2019), Rizos et al. (2016), and Gonzalez and Garcia (2022) group Meso-level challenges into supply-chain, environmental, and technological. Supply chain challenges and risks include collaboration across the supply chain, leading to economies of scale. For example, increased consolidation of shipments of products collected from customers after reaching their end-of-life reduces costs. However, due to macro factors, such collaborations could fail due to the need for circular economy knowledge and governmental regulations. Other supply chain risks include the market risks arising from the volatility of raw materials prices and the secondary raw materials and products market.

1.2.3. Micro-level challenges

Micro-level challenges are internal factors that challenge implementing circularity that are within the control of the business organization. Those factors include business models, corporate culture, risk appetite, strategy, and product design. Bechtel et al. (2013), Tura et al. (2019), Finance working group (2016), Gonzalez and Garcia (2022), and Rizos et al. (2019) claim that there are several challenges on the firm level that hinder the adoption of circular business models. Those challenges include the lack of financial capabilities as such a transition requires a high initial investment that increases corporate risks. Another key barrier is the risk appetite of most managers because as they are highly risk averse when investing with uncertain investments and such transitions given the current global economic and political conditions. In addition, some decision-makers cannot change their mindset to long-term thinking as they are more focused on short term profits and risks (Daddie et al., 2019).

On the other hand, social risks facing the implementation of circularity that the business can control include the need for more societal awareness about the concept. Consumers' responsiveness to such a transition remains uncertain due to the absence of incentives and the inability to predict consumer behavior. Nevertheless, business organizations must dedicate their marketing efforts to influencing and educating consumers about circularity and to normalize returning products. (Tura et al., 2019; Gonzalez and Garcia, 2022).

Dewick et al. (2020) and Uhernholt et al. (2022) claim that some managers believe that selling reused, refurbished, and remanufactured products cannibalizes new product sales, negatively impacting the company's branding. On the contrary, Wang et al. (2020) argue that the risk of increased cannibalization is minimal as reused, refurbished, and remanufactured products target different customer segments than those targeted by the new products sold for primary use.

2. Financial valuation methodologies in the context of circular economy

2.1. Traditional methodologies

Critical financial challenges in valuing circular investment include inadequate information and high uncertainty. The approaches institutions use to assess those projects fail to capture the long-term impacts of those investments (Gonzalez & Garcia, 2022; Tura et al., 2019). As Weskamp et al. (2015) assert, the most widely cited valuation method in corporate valuation and capital budgeting problems is the Net present value (NPV), a static valuation approach widely used in capital budgeting problems due to its simplicity. It is defined as the difference between the present value of future cash inflows and outflows of an investment project discounted at a discount factor known as the Weighted average cost of capital (WACC) that reflects the project's cost of funding.

Schiel et al. (2018), Morel (2020), Ryu et al. (2018), Block (2007), and Rozsa (2016) agree that the critical limitations of the relaying on the NPV method in valuing investments that require strategic flexibility, like circularity are as follows: Firstly, the cash flows of the underlying project are assumed to be fixed and deterministic. In such cases, cash flows are a stochastic random variable due to the high uncertainty. In the same sense, Maron and Merton (1985) acknowledge that traditional capital budgeting approaches assume a project will operate each year within its anticipated lifetime. However, due to the prevailing market conditions, operating in a given year may not be economically viable and efficient due to the inability of the revenues generated to cover variable costs. Secondly, the NPV method does not give the decision-maker the flexibility to make changes to the investment in the case of high uncertainty and changing market conditions, which could strongly contribute to a company's success or failure. Finally, investments are assumed to be irreversible once made. If market conditions are not in the organization's favor, managers may need to abandon or downsize a project.

This valuation approach does not consider changes in the external and internal environment after the investment is made. For example, a company may face financial distress and need to abandon a project. The NPV methodology does not allow the decision-maker to abandon or downscale an investment after making it (Weskamp et al.,2015). In the circular economy context, such approaches tend to fail due to the inherent theoretical limitation of valuing investments where strategic and operational interdependence exists between its stages over time.

2.2. Numerical methodologies: Real options analysis

2.2.1. Definitions and types

Real options analysis (ROA) is a relatively new dynamic valuation framework first introduced by Stewart Myers (1977) after the development the Black-Scholes model for financial options valuation in 1973 for valuing investment opportunities with high uncertainty. This gives the decision-maker the right but not the obligation to make a business decision or an investment in a real asset at a future date, contingent on the price of the underlying asset and market conditions. Myers (1977) treats future investments that can contribute to the company's growth as an option. Real options overcome the drawbacks of the classical investment appraisal methodologies (i.e., NPV) as they give the decision-maker the managerial flexibility to lock in growth options that might enhance the company's value, as Myers (1977) argues. Trigeorgis (1993b) and Weskamp et al. (2015) emphasize that real options analysis results in estimating the value of the project with flexibility, known as the expanded NPV. The expanded NPV is the sum of the passive/ static value of the project without flexibility using the classical NPV and the premium of the real option.

$$NPV_{Expanded} = NPV_{Passive} + Real\ option\ value$$

Real options are similar to financial options as they provide management with the right but not the obligation to invest in a real asset (ie., project, new technologies, land) on or up to a predetermined expiration date. When decision-making is complex, management can postpone strategic decisions (i.e., expansion, abandoning an investment, shifting to a new business model) using real options. On the other hand, financial options give the holder of the option (short position) the right but not the obligation to either buy or sell a financial asset (i.e., stock, bond, FX) that is settled in cash. Similar to financial options, real options are either call or put options. A call option gives the right to buy an asset, while a put option gives the right to sell an asset. Both financial and real options can be American-style or European-style options depending on the time of exercising the contract. American-style options are exercisable at any time until the option contract's expiration date. Conversely, European-style options are only exercisable on the option contract's expiration date (Zeng & Zhang, 2011; Trigeorgis & Reuer, 2017).

Hayes & Garrison (1982) and Mason & Merton (1985) agree that real options are contingent claims on capital budgeting decisions that provide management with a "strategic insurance" against prevailing market conditions. Likewise, Mason and Merton (1985) examine the suitability of contingent claims in valuing corporate securities, such as debt and equity, as they are considered corporate claims on the firm's assets. They emphasize the applicability of contingent claims in valuing managerial flexibility. Unlike traditional methodologies, real options provide strategic and managerial flexibility in cases of high uncertainty, which can enhance the financial value of the company or the project over the long term. High uncertainty usually stems from several factors, such as demand, consumer behavior, climate change, and political and economic factors, among other factors.

Mason & Merton (1985), Trigeorgis (1993a), Trigeorgis & Reuer (2017), Weskamp et al. (2015), Zeng and Zhang (2010), and Brando and Halm (2005), Rozsa (2016) explore and identify several types of real options. The most commonly cited types of real options are as follows:

- **The option to grow:** This option is applicable when an early investment opens up future growth opportunities for the company. In this case, an early investment links a chain of interrelated projects and compound options. This option is widely used in all infrastructure-based strategic industries, R&D investments, pharmaceutical businesses and cases of penetrating new markets.
- **The option to defer:** This gives management the right to postpone investment decisions with high uncertainty and inadequate present information. Accordingly, this allows the investor to benefit from the new information available during the option's life. This option is similar to a call option, giving the investor the right to delay an investment (i.e., acquiring a land or a plant), where the strike price is the required initial investment. Such an option is essential in all natural resources extraction industries, paper products, real estate, and agricultural sectors.
- **The option to abandon:** This allows management to abandon investments amid declining market conditions and financial distress. Accordingly, management can liquidate a project or line of production and realize the resale value of the capital used. This option is a put option, giving management the right to exit an investment with the strike price being the liquidation value of the project. Such an option applies to capital-intensive industries (i.e., airline and railroads businesses), financial services, and cases of new product introductions where market conditions are highly uncertain.
- **The option to switch:** This is applicable if there is a change in either prices or demand, enabling management to change the output mix of a facility (i.e., production flexibility). Alternatively, this option can give management the right to benefit from process flexibility to produce the same outputs using different inputs. In other words, this option gives management the right to switch between different operating strategies depending on the prevailing market conditions.
- **The option to alter an investment:** This permits management to alter the size of an investment depending on the current market conditions. If market conditions are more favorable than forecasted, management can expand the production scale by a certain percentage or maximize the current resource utilization (similar to a call option). This real option is sometimes referred to as the option to grow. Likewise, if market conditions are not in the company's favor, management can reduce the scale of operation by a certain

percentage to cut down losses (similar to a put option). In extreme cases, management may halt or start an investment from scratch. This option is widely used in natural resource industries (i.e., mine operations), fashion apparel, construction businesses, and consumer goods.

- **The option of staged investments (Time to build):** This option is applicable when a project has stages of capital investments, where each phase has an option for the subsequent one. Those options are viewed as sequentially compounded real options. This option is heavily used in R&D investments.

Several studies examine the usefulness of real options analysis in valuing sustainable and climate-related investments. For example, Guthrie et al. (2019), Wreford et al. (2020), and Ginbo (2021) study the use of real options in valuing climate change adaptation and mitigation measures in extreme weather conditions. Abadie et al. (2017), Ryu et al. (2018), and Dittrich et al. (2019) investigate flood risk mitigation measures in different contexts using real options analysis. Likewise, Kim et al. (2018) utilize real options to study the optimal timing of coastal adaptation measures given the rising sea levels. Schiel et al. (2019) analyze emission control measures using real options. In addition, Zhou and Zhou (2016) and Vargas and Chesney (2021) use real options in valuing renewable energy resources, such as solar panels. Finally, Davidson et al. (2011) examine the impact of climate change on water security using real options.

As for circular economy investments, to the best of our knowledge, none of the published papers empirically tests valuing circularity using real options. Nevertheless, Gonzalez et al. (2021) suggest a methodology to value asset circularity using real options. However, this paper did not empirically test the proposed model due to the absence of real data, a frequent limitation and challenge for studies aiming to test valuing circularity and sustainable investments empirically.

2.2.2. Real options valuation methodologies

This section covers the most commonly used methodologies for valuing real options cited in the literature. Since real and financial options are very similar, the methodologies used in pricing financial options can be extended to solving real options problems. Those valuation methods are either analytical approaches (i.e., closed-form solution) for simple plain-vanilla contracts or numerical approaches (i.e., Binomial tree, dynamic programming, and Monte Carlo simulation) for complex contracts. See Figure 6.

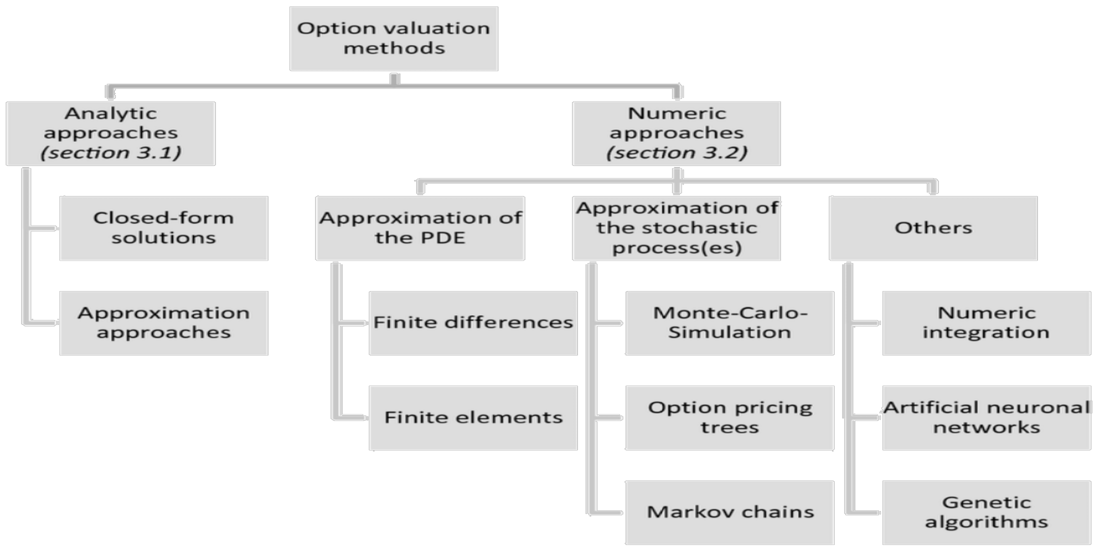

Figure 6: Overview of option valuation methodologies (Baecker et al., 2003)

2.2.2.1.Analytical approaches: The Black-Scholes model

The Black-Scholes model is the most commonly used closed-form solution for pricing financial options contracts proposed by Black, Scholes, and Merton in 1973. This model develops a closed-form solution for pricing plain vanilla European contracts by applying stochastic differential equations (SDE). Assumptions of this model are as follows: First, the underlying asset (i.e., stock) follows a lognormal distribution, where its stochastic process is described by geometric Brownian motion. Second, short-selling is allowed. Third, there are no taxes and transaction costs. Fourth, the underlying asset pays no dividends during the lifetime of the option contract. Finally, there are no arbitrage opportunities; thus, security trading is continuous, and the risk-free rate is constant for all maturities. For example, the price of a plain-vanilla European call option is computed analytically using the following equation.

$$C = S_0 N(d_1) - K e^{-rt} N(d_2),$$

where $N(\blacksquare)$ is the cumulative standard normal distribution density function.

$$d_1 = \frac{\ln\left(\frac{S_0}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

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

Where, C is the price of a plain-vanilla call option, S_0 is the initial stock price, K is the strike price, r is the risk-free rate, σ is the volatility of the stock price and T is the remaining time to maturity. This model is widely used in valuing simple European contracts due to its simplicity and low computational effort relative to other methods. It is also used in research for benchmarking purposes. This methodology's fundamental limitation is that it only applies to European contracts and thus cannot be extended to cases of multidimensionality. Most real options are of American style to allow for more flexibility in decision-making. Therefore, studies investigating using real options in valuing sustainability did not use this methodology (Arnold, 2014; Schiel et al., 2019).

2.2.2.2.Binomial tree

The binomial tree of Cox, Ross, and Rubinstein (1979) is the most cited numerical methodology in valuing sustainable investments using real options. Ryu et al. (2018), Ginbo et al. (2021), Abadie et al. (2017), Guthrie et al. (2019), Schiel et al. (2018), Vargas and Chesney (2021) and Zang and Zhou (2016) apply the binomial tree in their empirical studies. In addition, Gonzalez et al. (2021) propose a framework for valuing asset circularity based on this approach. This methodology values the option contract assuming a discrete-time process of the behavior of the underlying asset and its uncertainty, allowing for only two states of nature for the behavior of the asset (up and down). The up and down scenarios are determined based on the underlying asset's volatility. See Figure 7. The option value can be estimated using two equivalent approaches. The first is the absence of arbitrage approach that constructs a hedge portfolio comprising some shares of the underlying asset and one short-call option. The second approach is risk-neutral, where the option's price is priced under risk-neutral probabilities. Hence, the risk-free rate's expected return on the underlying asset and discount rate. The option's value is calculated recursively by going backward in time, starting at the option's maturity date. This model can be used for pricing both American-style and European-style options. For American-style options, where there are multiple opportunities for exercising the option, the exercise and holding values are compared at each decision node (Brando & Hahn, 2005).

To solve the binomial tree, a risk-neutral portfolio must be set, assuming that there are no arbitrage opportunities in the market earning the risk-free interest rate. First, let f and S denote the value of the option and stock price at inception, respectively, and f_u and f_d be the overall value at the up and down branches, respectively. Under the absence of arbitrage assumption, the following equation must hold true.

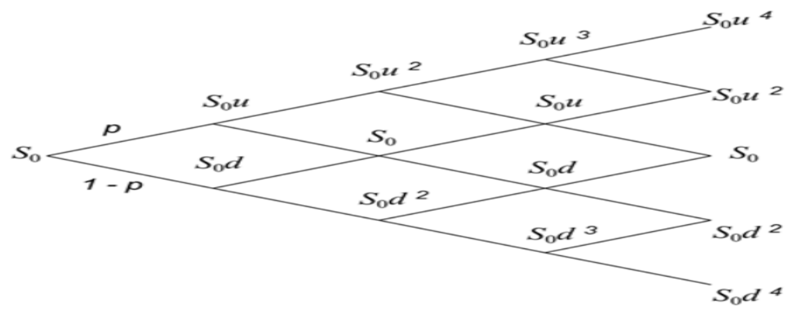

Figure 7: The Binomial Tree

$$Su\Delta - f_u = Sd\Delta - f_d$$

$$\Delta Su - \Delta Sd = f_u - f_d$$

$$\Delta = \frac{f_u - f_d}{Su - Sd}$$

At the maturity of the option T, the option's value at each branch of the tree is known, so the value of Δ can be easily obtained, which represents the optimal hedge ratio. The hedge ratio is the number of shares one must hold while holding a short position in the option market. Since the riskless portfolio is discounted at the risk-free rate, the value of the option can be estimated using the following equation.

$$f = \Delta S - (\,\Delta Su - f_u)e^{-r\Delta t}$$

This valuation approach applies to valuing both American and European contracts. Although this approach can be extended in valuing American options, it numerically collapses when the number of decision nodes increases. A critical shortcoming of this methodology is that it allows for only two states of nature for the underlying asset at each decision node and does not accurately model uncertainty. The algorithm does not capture any other possibilities for the evolution of the underlying asset other than the up and down scenarios, especially in cases of high uncertainty. As a result, other numerical methods are more efficient in valuing option contracts both American-style and European-style in the case of deep uncertainty due to potentially inaccurate results and exponential increase in computational time and effort. Some researchers have recommended using trinomial and multinomial trees to price option contracts to capture more states of nature in cases of high uncertainty. Nevertheless, this could lead to a computational failure of the model (Scheiel et al., 2019).

2.2.2.3. Dynamic programming

Dynamic programming (DP) is a numerical approach for valuing complex options where sequential decision-making is required over time, such as American-style options. DP is used for optimal control, and it states that the solution to a global optimization problem is obtained by breaking down the problem into subproblems. DP starts the resolution at a future date where the value function is known. For example, the value of an American-style option at its maturity date is the exercise value of the contract. The value function is computed as the maximum between exercise and holding values at each decision node using backwardation. Unlike the binomial tree, calculations are done in each node, considering all the possible scenarios that can happen on the following exercise date. Consequently, this methodology achieves more accurate results than the binomial tree with less computational time and effort in the cases of multidimensionality.

This methodology is used in valuing American-style options in jump-diffusion models by Ben-Ameur et al. (2016) and Ben-Ameur et al. (2020), in valuing installment options by Ben-Ameur et al. (2006) and in valuing corporate securities by Ayadi et al. (2016), Ben-Ameur et al. (2016) and Ben-Ameur et al. (2022). In the context of real options, Chorn and Shokhor (2006) and Pringles et al. (2015) use DP to value petroleum development investments and value power transmission investments, respectively.

2.2.2.4. Monte Carlo simulation

Monte Carlo simulation is a numerical methodology that estimates the option value by simulating the stochastic process of the underlying asset under the risk-neutral probability measure. In the context of real options, the most widely used stochastic process is geometric Brownian motion. However, other processes can be used depending on the underlying asset, such as Markov jump and mean-reverting processes. Generally, an underlying asset's trajectories are simulated using the following stochastic differential equation (Baecker et al., 2003; Scheiel et al., 2019).

$$dS(t) = \mu S(t)dt + \sigma S(t)dW \ ,$$

where μ is the average instantaneous rate of return of the underlying asset (i.e. stock), σ is the standard deviation of change in the returns of underlying asset over a short period of time dt and dW is the basic Weiner process, where $dW = W_t - W_0$ follows a standard normal distribution.

The use of Monte Carlo simulation in options pricing was initiated by Boyle (1977) to price European options. This methodology aims to generate samples of paths for the underlying asset at each point in time t over the lifetime of the option contract T with time steps dt. The value of the contract is estimated as the discounted average payoff of the simulated trajectories, as follows:

$$V_0 = e^{-rT} \frac{1}{N} \sum_{j=1}^{N} P_j^T$$

Later, Longstaff and Schwartz (2001) developed a state-of-the-art methodology for pricing American options by combining Monte Carlo simulation with dynamic programming and least squares regression known as the Least-squares Monte Carlo (LSMC). LSMC aims to estimate the value of American-style options using simulation with a low computational effort while maintaining the accuracy of results. A key advantage of Monte Carlo simulation is that it can be used in valuing complex options contracts (Asian options, look-back options, and barrier options), where option value cannot be estimated in closed-form. Some studies use Monte Carlo simulation in valuing sustainable investments using real options, including Pringles et al. (2015), Schiel et al. (2019), and Abadie et al. (2017).

II. Methodology

The methodology adopted in this thesis extends the model developed by Gonzalez et al. (2021) to value circular economy projects using real options based on the stages of the Value Hill model of Achterberg et al. (2016). Our valuation model consists of two components. The first component is related to the design of the circular project explained as per the Value Hill model assuming sequentially compounded real options. The second component aims to approximate the expected value of the real options numerically. To value real options, we implement Longstaff and Schwartz's (2001) recursive dynamic programming algorithm for valuing American-style options. Our model is flexible for adjustment depending on the project and the industry by adding or removing phases. As Achterberg et al. (2016) and Gonzalez et al. (2021) explain in the value hill model, when a product reaches the highest point of the pyramid, it has reached its maximum value in the primary use phase. Moreover, the product goes through different recovery cycles before becoming waste, and each of those cycles represents a different recovery strategy depending on the state of the product. It is possible to identify several real options allowing switching from one stage to another, as shown. Such real options are Sequential compound real options, as each phase has a real option to switch to the subsequent phase. See Figure 8.

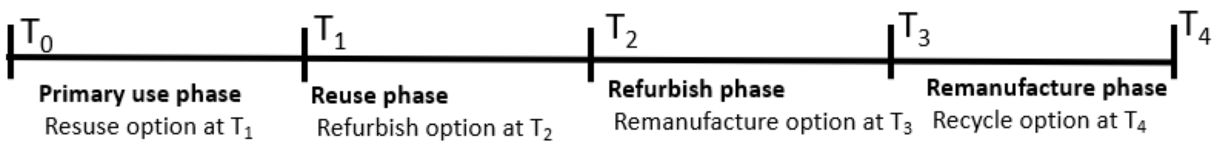

Figure 8: Sequentially compound real options scheme (Gonzalez et al., 2021)

As shown in Figure 8, each phase has an option for the following phase depending on the state of the product. For example, when the primary use phase ends, a real option to reuse the product exists. In the same sense, the reuse phase includes a real option for the refurbishment phase, which includes a real option to remanufacture the product in the next phase. Finally, the remanufacturing phase includes a real option for the final phase, recycling.

Our proposed model follows a backward valuation process, meaning that valuation starts in the remanufacture phase that includes the recycle option until we reach the primary use phase, where the overall value of the sequential compound option is estimated. The overall value is then added to the value of the project using the classical investment appraisal approach (i.e., NPV), resulting in the value of the project with flexibility known as the extended NPV that can be expressed as follows.

$$NPV_{Extended} = NPV + Real\ option\ premium$$

1. The model

We assume that there are $j \in J$ options within an investment. For example, the option $j = 1$ is the option to enter the reuse phase. The investment value in year t_n considering the option j is denoted as $v_{t_n}^j(t_n, X_{t_n}^j)$, where $X_{t_n}^j$ is the terminal value of the investment in phase j without flexibility follows a GBM process with Markov property that assumes that any future change is independent by the previous values. Thus, the terminal value $X_{t_n}^j$ is given by

$$dX_{t_n}^j = rX_{t_n}^j dt + \sigma^j X_{t_n}^j dW_{t_n}^j, \qquad (1)$$

where r is the instantaneous riskless rate of return, σ^j is the standard deviation of phase j of the underlying project, and $W_{t_n}^j$ is the Weiner process that describes the stochastic component. Assume that each option can be executed at $\{t_0, t_1, .., t_N\}$ from the initial date T_{j-1} until the maturity T_j, where T_j is the maturity of each phase j.

The future discounted value of the investment with flexibility can be expressed as follows:

$$v^j(t_n, X_{t_n}^j) = \max_{\tau \in [t_n, t_N]} \{e^{-r(\tau - t_n)} E^Q[v_e^j(\tau, X_\tau^j)]\},$$

where τ is the optimal stopping time and $v_e^j(\tau, X_\tau^j)$ is the payoff value of phase j, and $E^Q[.]$ is the expectation operation under the risk neutral probability measure Q. The process for calculating the optimal stopping time is described by Bellman's principle of optimality, which is expressed as follows:

$$v^j(t_n, X_{t_n}^j) = \max(v_h^j(t_n, X_{t_n}^j), v_e^j(t_n, X_{t_n}^j)),$$

where $v_h^j(t_n, X_{t_n}^j)$ is the continuation value given by

$$v_h^j(t_n, X_{t_n}^j) = e^{-r(t_{n+1} - t_n)} E^Q\left[v^j\left(t_{n+1}, X_{t_{n+1}}^j\right)\right] \quad (2)$$

The payoff v_e^j depends on the investment value without flexibility $X_{t_n}^j$, the investment value with flexibility at phase $j+1$, $v^{j+1}\left(t_n, X_{t_n}^{j+1}\right)$, and the cost of entering phase $j+1$, E^{j+1}:

$$v_e^j((t_n, X_{t_n}^j) = \max(v^{j+1}(t_n, X_{t_n}^{j+1}) - E^{j+1}, 0) \quad (3)$$

The option premium of phase $j+1$, is the difference between the investment value, with and without flexibility at phase j:

$$C^{j+1}(t_n, X_{t_n}^j) = v^j(t_n, X_{t_n}^j) - X_{t_n}^j \quad (4)$$

The real options under valuation are viewed as sequential compound options where each phase encompasses an option concerning the subsequent phase. For instance, we consider four phases as described as follows:

- $j = 0$: Primary use phase, where the reuse option exits at T_1.
- $j = 1$: Reuse phase, where the refurbish option exits at T_2.
- $j = 2$: Refurbish phase, where the remanufacture option exits at T_3.
- $j = 3$: Remanufacture phase, where the recycle option exits at T_4.
- $j = 4$: Recycle option.

Valuation will start in the remanufacture phase at T_3, where the real option of moving to the recycle phase exists between T_3 and T_4. Then we will continue, backward in time, valuing all options in the same manner until we reach the reuse option that exists in the primary use phase at T_0 that embeds the value of all options.

As an example, consider the date T_2 under the refurbish phase, where an option to remanufacture exists from T_2 to T_3. The expected value of the remanufacture option at its inception (C^3) can be estimated as follows:

- Simulate the refurbish value X^3 following Eq. (1).
- Compute the exercise value following Eq. (3).
- Compute the continuation value following Eq. (2).
- Estimate the real option premium following Eq. (4)

This procedure is repeated for all the considered phases recursively to obtain the price of the compound real option which is added to the value of the project without flexibility (the traditional NPV), to obtain the value of the project with flexibility (the expanded NPV).

2. Numerical resolution: Recursive dynamic programming

Most real options are American-style, meaning that the decision-maker has the right to exercise the option at any time before the expiration date. Unlike European options, pricing American options requires finding the optimal stopping time $\boldsymbol{\tau}$ to estimate the expected value of the option. Therefore, we implement the recursive dynamic programming of Longstaff and Schwartz (2001) to value American-style real options by finding the expected value of the option. Moreover, the LSMC is a numerical method that commonly uses American-style options in evaluating investment opportunities that bear a high degree of uncertainty. This methodology proposes a numerical process that combines Monte Carlo simulation, dynamic programming, and ordinary least squares (OLS) regression to estimate the value of the American option and determine the optimal stopping time. This algorithm estimates the optimal stopping time $\boldsymbol{\tau}$ using dynamic programming, while it approximates the expected value of the option contract using Monte Carlo simulation.

This numerical procedure proposes a random visit via Monte Carlo simulation to generate random paths for the underlying asset X. Accordingly, $X_{n,t}$ represents the level of X at the evaluation node (n, t), where n represents a simulated path for $n = 1, \dots, N$ and t represents a potential date for exercising the option for $t = 1, \ldots, T$. This numerical procedure starts the evaluation procedure at the option maturity, where holding the option for another node is no longer viable.

$$v_T(X_T) = v_T^e(X_T).$$

Longstaff and Schwartz (2001) propose a numerical approach for approximating v_t^h, which acts as follows:

Step 1: Calculate the holding value at t_n as the discounted expected overall value at t_{n+1} as follows:

$$\tilde{v}_t^h(X_{t_n}) = e^{-r(t_{n+1}-t_n)} E^Q\left[v_{t+1}\ \left(X_{t_{n+1}}\right)\right],$$

where $\tilde{v}_t^h(X_{t_n})$ is Monte Carlo estimate of $v_t^h\left(X_{t_n}\right)$ for $n = 1, .., N$ based on only 1 path of the underlying asset (of size 1). Thus, it is poor and unreliable due to the fact that simulated paths never interest.

Step 2: To overcome this shortcoming, $\tilde{v}_t^h\left(X_{t_n}\right)$ Monte Carlo estimations are regressed using the ordinary least square (OLS) method on a set of basis functions of state variable (X_T). This is premised on the fact that $v_t^h(X_T)$ is a function of the state variable (X) and thus is conditional expectation of $X_T = X$. The outputs of this step are adjusted approximations of $\hat{v}_t^h(X_t)$ of v_t^h, that is now dependent on all simulated paths. The authors consider quadratic (second-degree) least squares regression by solving the following least square optimization problem:

$$min_{(\alpha,\beta,\gamma)} = \sum_{n=1}^{N} [\tilde{v}_t^h\left(X_{t_n}\right) - \left(\alpha + \beta X_{t_n} + \gamma X_{t_n}^2\right)]$$

The above results in the following conditional expectation function:

$$E[v_t^h|X] = \hat{v}_t^h(X_{t_n}) = \hat{\alpha} + \hat{\beta} X_{t_n} + \hat{\gamma} X_{t_n}^2 \text{ for all values of } n = 1, .., N$$

Step 3: Compute the overall value v_t backward in time as follows:

$$v_t\left(X_{t_n}\right) = \max(\hat{v}_t^h\left(X_{t_n}\right), v_t^e\left(X_{t_n}\right)).$$

Step 4: Repeat steps (1)-(3) backward in time until the inception date to get $v_0\left(X_{t_0}\right)$.

III. Numerical investigation: Monte Carlo simulation study

In implementing our model, we use the parameters presented in Table 1 to explain and test the reliability of our model using hypothetical figures. We use MATLAB program to implement the model. We run the code for 100,000 simulations with 50-time steps to conduct this numerical investigation. Moreover, we assume the 4 phases of the value hill model exist (reuse, refurbish, remanufacture, and recycle) for a hypothetical product to test and explain our model. Volatility, time between phases, and risk-free rate are assumed to be constant across all phases.

Table 1: Numerical Investigation simulation parameters

Initial Primary use value	X^0	\$ 300
Initial Reuse value	X^1	\$ 400
Initial Refurbish Value	X^2	\$ 450
Initial Remanufacture Value	X^3	\$ 500
Recycle value	X^4	\$ 600
Initial investment for reuse phase	E^1	\$ 120
Initial investment for refurbish phase	E^2	\$ 150
Initial investment for remanufacture phase	E^3	\$ 200
Initial investment for recycle phase	E^4	\$ 300
Volatility	σ	25%
Time between phase	T	2 years
Risk-free rate	r	5%

Results of the numerical investigation, as presented in Table 2 suggest that the Reuse option with value $C_{T_0}^1$ has the highest expected value when compared to the other options since it embeds the other options. It also illustrates that as we go backward in time, the expected value of the compounded real option as strategic flexibility increases as the decision-maker has investment opportunities in the future.

Table 2: Numerical investigation results

	American Option value
Reuse option ($C_{T_0}^1$)	\$ 25.81
Refurbish option ($C_{T_1}^2$)	\$ 9.43
Remanufacture option ($C_{T_2}^3$)	\$ 4.69
Recycle option ($C_{T_3}^4$)	\$ 2.32

We conduct a sensitivity analysis to study the impact of changing the volatility of the project and the time between phases on the overall valuation of the project. The expected value of the project is measured by the extended NPV that combines the value of the project using the passive NPV and the expected value of the compounded real option. To do so, we assume the valuation of the above project is $80 using the classical NPV. Then, we run our algorithm while changing the volatility of the project and the time between phases. Table 3 shows the impact of changing the volatility and time between phases on the overall valuation of the project.

Table 3: Sensitivity analysis results

	$\boldsymbol{T = 1\ year}$	$\boldsymbol{T = 2\ years}$	$\boldsymbol{T = 3\ years}$	$\boldsymbol{T = 4\ years}$
$\boldsymbol{\sigma = 10\%}$	$ 81.9	$ 83	$ 83.6	$ 84
$\boldsymbol{\sigma = 20\%}$	$ 90.7	$ 96.5	$ 100.33	$ 103.2
$\boldsymbol{\sigma = 30\%}$	$ 103.6	$ 116.8	$ 126.4	$ 133.7
$\boldsymbol{\sigma = 40\%}$	$ 139.9	$ 143.3	$ 160.6	$ 174.8

Results of our sensitivity analysis show that the overall real options valuation of the project with circularity is highly sensitive to volatility, as when volatility increases, extended NPV increases. For example, when changing volatility σ from 10% to 20% while holding the time between phases T constant for one year, the valuation of the project increased from $81.9m to $90.7m. On the other hand, the valuation of the project also increased when we changed the time between phases T. However, the increase is still smaller relatively to that caused by changing volatility. For instance, changing T from one year to two years, while holding the volatility at 10%, slightly increased the valuation of the project from $81.9m to $83m.

Our sensitivity analysis confirms the literature that when there is high uncertainty and volatility, managerial flexibility enhances the financial valuation of the project. For example, when volatility is 40% and the time between phases is four years, the extended NPV of the hypothetical project recorded the highest value ($ 174.8m). Finally, our analysis shows that investing in circularity when there volatility is high, financial value improves.

IV. Empirical investigation: The business case of Apple's smartphones

1. Apple's sustainability strategy

Apple has a vision of creating products that enrich the lives of their customers while sustaining the ecosystem and natural resources. To achieve this vision, Apple has developed three environmental goals to be achieved by 2030. As stated in their official website and environment progress report for 2023, the three main goals of Apple's sustainability strategy are as follows:

- **Climate change:** First, Apple aims to achieve carbon neutrality for its entire carbon footprint and to create products with a net-zero carbon impact by 2030. Since 2015, the company has reduced emissions throughout its value chain by over 45%. Second, Apple targets using 100% clean electricity throughout its value chain, including manufacturing and product use, by 2030.
- **Resources:** First, Apple aims to use only recycled and renewable materials in its products to preserve the world's precious resources and to enhance its material recovery processes. In 2022, 20% of the material shipped in Apple's products was recycled. Second, The company targets eliminating plastics in their packaging by 2025. Third, Apple aims to reduce the water impacts in the production of its products, the use of its services and the operations of its facilities. Lastly, The corporation aims to eliminate the waste sent to landfills from its corporate facilities and suppliers.
- **Smarter chemistry**: First, Apple strives to avoid exposure to chemicals that could harm both human health and the environment by integrating more innovative chemistry in the design of its products. Second, the company also to foster comprehensive reporting of the chemicals used in their supply chain to make their products.

Apple is working on implementing a circular supply chain to achieve its environment-related vision and resource sustainability. The company's circularity cycle is similar to the Value Hill model explained by Achterbeg et al. (2016). As shown in Figure 9, Apple pursues circularity in its products, starting from product design until materials are recovered after the product has reached its end of life. Apple's circular economy policy is divided into three main categories: sourcing and efficiency, product longevity, and product end-of-life.

The first category of Apple's circularity policies is sourcing and efficiency, similar to the uphill section of the Value Hill model concerned with sourcing materials and adding value to the product.

Furthermore, Apple aims to source raw materials used in producing its products from solely recycled and renewable resources to ensure their durability. In 2022, 20% of Apple's products were made using recycled materials.

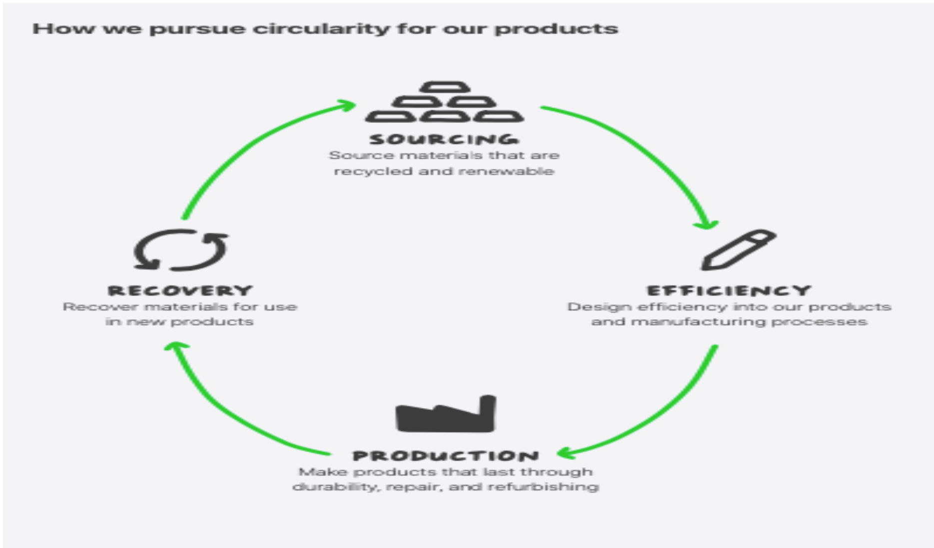

Figure 9: Apple's circularity cycle (Apple sustainability progress report, 2023).

The second category of Apple's circular economy policy is product longevity. The company aims to design products with durable hardware while leveraging software updates for extended functionality. To extend the life of its products, Apple has developed several trade-in programs to encourage its customers to trade in their products after use. Depending on the product's condition, they are either refurbished and sold to new customers, or valuable materials are recovered to produce new products. These programs include the iPhone upgrade program, corporate hardware reuse program, and Apple Care. To ensure product longevity, they also improve access to repair services to make it easier for their customers to repair their Apple products if needed. In 2022, more than 12.1 million devices were sold to new owners for reuse after being refurbished. Moreover, Apple's iPhone has the lowest depreciation rate compared to other top smartphone manufacturers, such as Samsung and LG. As per statistics available in Apple's environment progress report for 2022 and the BankMyCell website (a website that tracks smartphone trade-ins in the US), Apple holds 30% more value than Android devices over a four-year buy-back period. For example, as of January 2023, Apple's 7th generation iPhone, introduced in 2016, still maintained a monetary value for trade-ins in the US. Figure 10 shows the depreciation in Apple's iPhone trade-in value over four years compared to that of Andriod based on the smartphone description reports for 2021-2022 published by the BankMyCell website.

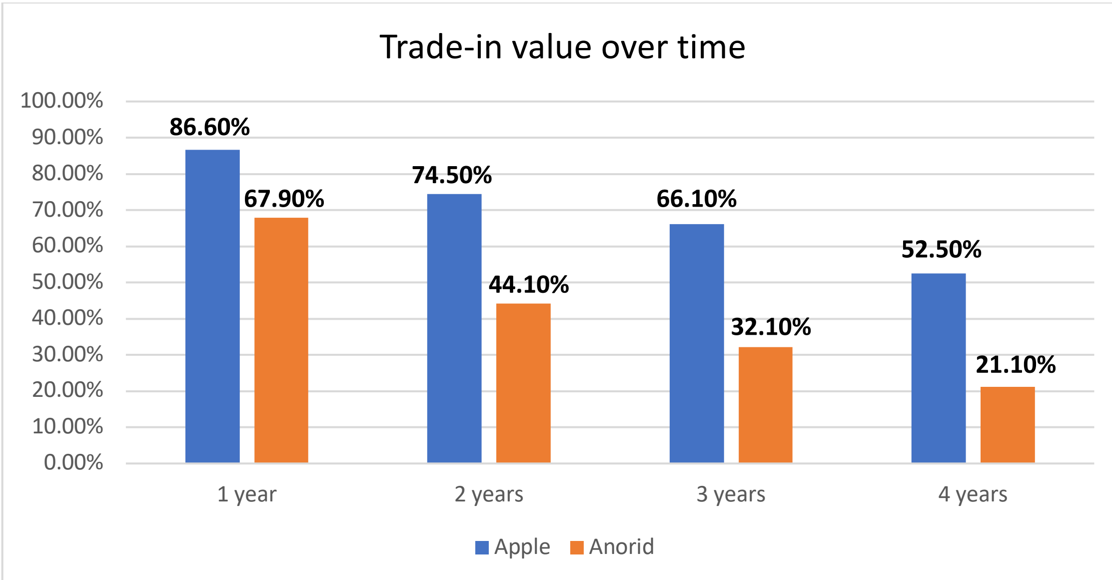

Figure 10: Apple's iPhone trade-in value over time (Apple's sustainability progress report, 2022).

The final part of Apple's circularity strategies concerns the product end of life. To extend the life of its products and slow down their downhill journey, Apple extracts materials from products that reach the end of their life to produce next-generation products. Apple is developing partnerships with academic institutions to improve their material recovery and recycling processes. Moreover, Apple has established a Material recovery lab in Austin, Texas, focusing mainly on the recyclability of their products by designing innovative solutions for material recovery and disassembly. Apple has three material recovery robots: Daisy, Dave, and Taz. Daisy is a disassembly robot capable of skillfully separating 23 iPhone models into discrete components. Simultaneously, Dave specializes in disassembling taptic engines that enable the recovery of rare earth elements. Finally, Taz specializes in assessing the recovered materials to enhance Apple's recovery rate. Apple is currently working on new recovery technologies in their new Santa Clara, California asset recovery center through automation and machine learning to increase the efficiency of the process for time-intensive error-prone processes. This center aims to provide suppliers and the smartphone industry with efficient material recovery solutions.

2. Financial overview

Apple has witnessed fluctuations in its revenues throughout the last five years, mainly due to the impact of the COVID-19 pandemic on the company in 2020. Net sales grew by only 5.51% in 2020. However, sales growth picked up in 2021 with a growth rate of 33.26%. In 2022, Apple witnessed a year-on-year revenue growth of 7.79%, where net sales reached USD 394bn, while net income reached USD 99.8bn for the same year.

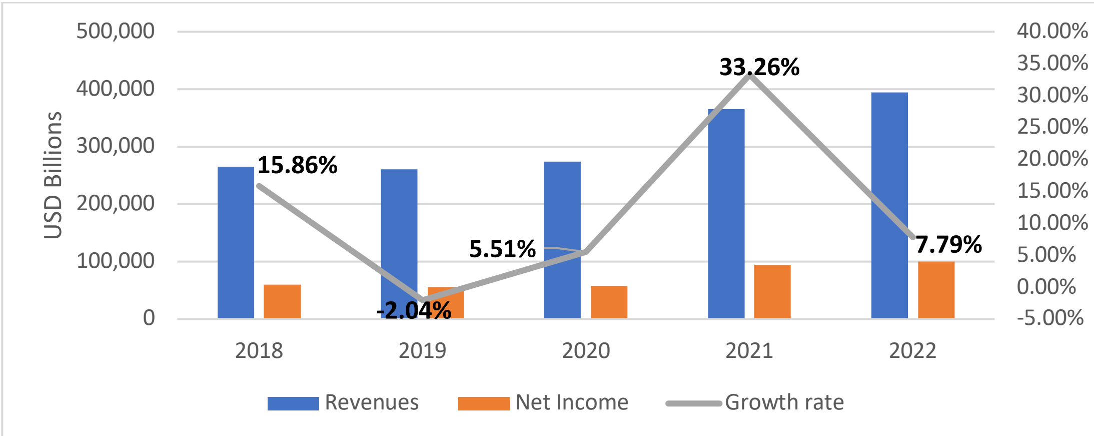

Figure 11: Apple's revenue, Net income and Growth rates from 2018-2022

Apple has a broad portfolio of products, including iPhones, Mac computers, iPads, Apple Home and accessories, besides the services they provide to their customers. In 2022, Apple's iPhone sales made around 52% of the company's overall sales revene (around USD 205.5bn), while the net sales of all the other products were only 48%. See Figure 12. The smartphone product category is the main driver of Apple's revenue growth in recent years.

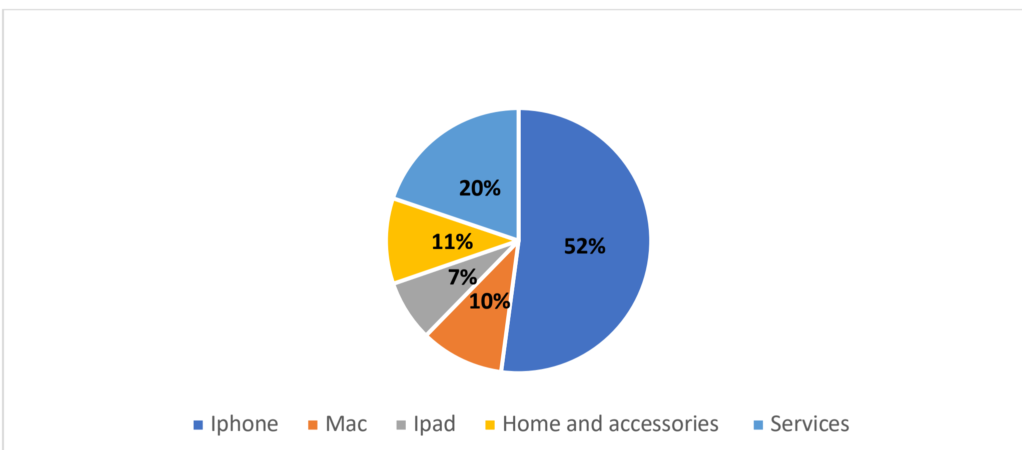

Figure 12: Apple's net sales by product category for year ended 2022

Apple's gross profit margin as a percentage of revenues presented in Figure 13 illustrates the relationship between Apple's revenues and COGS from 2018 until 2022. In 2023, the company's overall gross profit margin for all its offerings (products and services) was 43.30% (around USD 171bn).

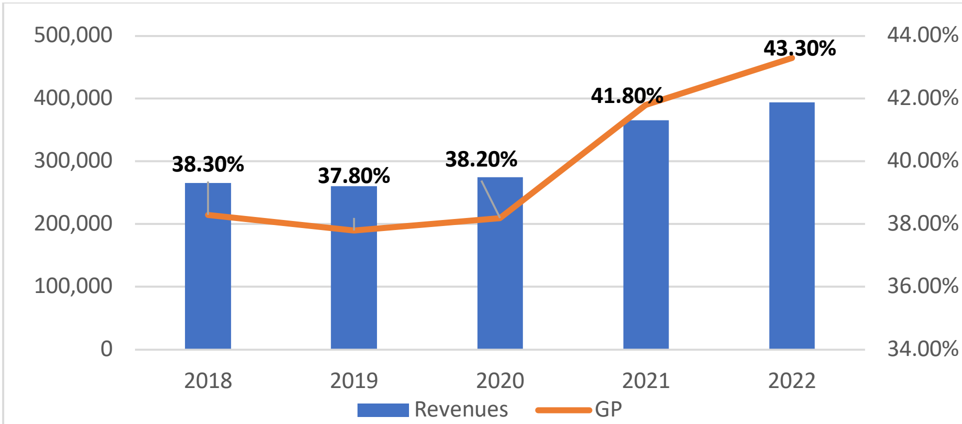

Figure 13: Apple's gross profit margin in relation to Revenue

As per Apple's annual report for 2022, gross profit margin is further classified into products and services gross margins. In 2022, Apple's products and services gross margins were 36.3% (USD 114.73bn) and 71.73% (USD 56.05bn), respectively. It is worth mentioning that the main contributor to the products' gross margin is the iPhone.

Apple's operating expenses were around 13% (USD 51.35bn) of the company's net sales in 2022. Selling, general administrative (SG&A) and Research and Development (R&D) expenses were 6% (USD 25.09bn) and 7% (USD 26.25bn), respectively. On a year-on-year basis, operating expenses increased by 17%, mainly driven by the increase in R&D expenses by 20%. Concurrently, SG&A expenses increased by only 14%. Figure 14 shows the trend of Apple's total operating expenses as a percentage of the company's total net sales over the last five years, from 2018 until 2022.

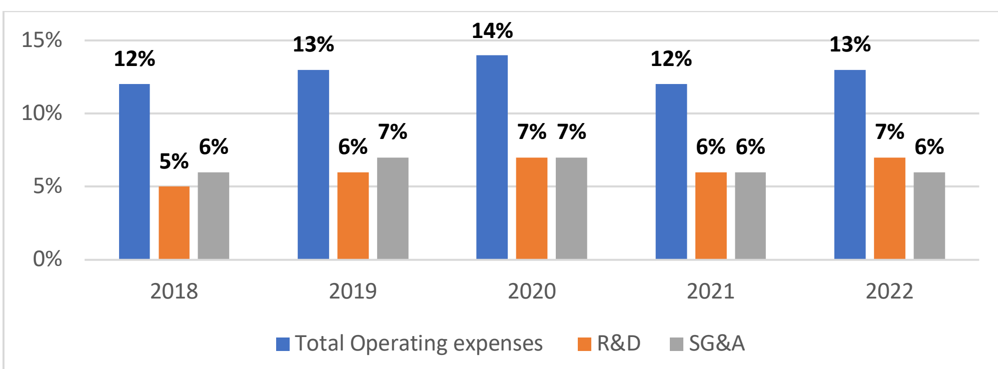

Figure 14: Apple's total operating expenses as % of Net sales

We also estimated Apple's average stock return and standard deviation from 2018 to 2023 to understand the volatility of the company's stock. Apple's five- year average stock price and standard deviation were 2.18% and 8.95%, respectively.

3. Assumptions and proxies

We present the assumptions and proxies for valuing Apple's iPhone business before and after circularity using data presented in Apple's financial statements. Then, we use these assumptions in estimating Apple's iPhone business free cash flow (FCF) without taking the circularity options into account.

- **Revenue:** As stated previously, iPhone net sales make 52% of Apple's total net sales in 2022, equivalent to USD 205.5bn, and it has witnessed a year-on-year growth of 7% in the same year. Accordingly, we will project the iPhone net sales for the five years from 2023 until 2027, assuming an annual growth rate of 7%.
- **Gross Profit:** As mentioned, the gross profit margin of Apple's products was 36.3% in 2022. Accordingly, we assume Apple's iPhone gross profit margin to be 36.3% of the iPhone's total net sales each year, given that it is the primary driver of Apple's sales.
- **Operating (fixed) expenses:** As stated previously, Apple's fixed operating expenses were around 13% of Apple's net sales in 2022. These expenses are mainly R&D and SG&A expenses. Therefore, we project the iPhone's operating expenses, assuming they are 13% of its total net sales for the coming five years.
- **Data from Apple's annual reports:** At the end of 2022, Apple's depreciation and amortization expense was USD 11.10bn, equivalent to 2.81% of the company's net sales. Cash flow generated from operating expenses, such as net account receivables, inventories, Vendor non-trade receivables, other current and non-current assets, accounts payable, deferred revenue, and other current and non-current liabilities, was USD 122.15bn (around 31% of the company's total net sales). Additionally, investments in Property, Plant, and Equipment (PPE) were USD 10.71bn, around 2.71% of their total net sales. Finally, Apple's corporate tax rate is 24%, as indicated on the company's official website.

Based on the above assumptions and proxies, we project Apple's free cash flow for five years from 2023 until 2027 using 2022 as the base year, as shown in Table 4. We then use those proxies in approximating the financial value of Apple's iPhone business using the classical NPV.

Table 4: Apple's Iphone 5 year financial projections

In USD bn	2022	2023	2024	2025	2026	2027
Revenue	205.5	220	235	252	269	288
Gross Profit	75	80	85	91	98	105
Operating expenses	27	29	31	33	35	37
Depreciation	5.77	6.18	6.61	7.07	7.57	8.10
Change in net working capital	63.71	68.71	72.94	78.04	83.50	89.35
Change in PPE investment	5.57	5.96	6.38	6.82	7.30	7.81
Free cash flow	100	107	115	123	131	141

4. Real options implementation and results

We apply the proposed valuation model for circular investments following the work of Gonzalez et al. (2021). As mentioned, Apple adopts two main circular strategies for product life extension: selling refurbished iPhones and recovering and recycling material from old and refurbished iPhones to produce new generation iPhones. Accordingly, we will implement the sequential compound real options valuation model assuming only two hypothetical real options: refurbish and recycle. The refurbishment exists in the primary use phase. In contrast, the recycle option exists in the refurbish phase, meaning that the value of the recycle option is embedded in the refurbish option.

In our implementation, we use the volatility of Apple's five-year stock returns as a proxy for the volatility of the iPhone division sales. We have estimated Apple's volatility to be 8.95% based on Apple's five monthly stock returns over five years from 2018 until 2023. As for the riskless rate of return, we use the US 10-year Treasury bonds yield as a proxy, which is 4.947% as of the end of October 2023, as per Bloomberg terminal. We assume the compound option will exist after two years in 2024 with a maturity of two years. As per Noman and Amin (2017), the lifespan of a smartphone is usually between 18 to 24 months. Therefore, we assume the iPhone's residual value after two years to be for both options 74.5% per Apple's environment progress report and Bank-my-cell website. As illustrated in Figure 14, the trade-in value of Appel's product after two years is 74.5%.

Table 5: Real options parameters

Volatility	$\boldsymbol{\sigma}$	8.95%
Risk-free rate	$\boldsymbol{r}$	4.937%
Time between phase	$\boldsymbol{T}$	2 years
Residual Value		74.5%

For the refurbishment option, we assume that the initial value of the primary use without the refurbishment option is the projected free cash flow for 2024. Given Apple's launches of new iPhone models along with the previously mentioned trade-in programs, we assume a refurbishment rate of 30%. The refurbishment rate assumption is based on the fact that the refurbishment rates for 2010 and 2017 were 20% and 30%, as per Ellen Macarthur Foundation's report in 2013 and a study published by the European Economic and Social Committee in 2019. We also assume that refurbished phones will have a gross profit margin of 1.5 times that of the new iPhones, as per statistics and proxies published by the Ellen Macarthur Foundation in 2013.

Table 6: Refurbish option parameters

Initial Primary use value	$\boldsymbol{X^0}$	\$ 115bn
Refurbish Value	$\boldsymbol{X^1}$	\$ 195bn
Initial investment for refurbish phase	$\boldsymbol{E^1}$	\$ 70bn
Refurbishment rate		30%

As for the recycling option in the refurbishment phase, we assume that this option will not directly impact net sales growth. iPhone sales are expected to grow at the same rate in 2022 as the company will continue introducing new iPhone generations and selling refurbished phones. However, recycling will enhance gross profit margin as it will reduce material costs due to the increased process efficiency through investing in R&D and advanced solutions for material recovery and recycling using machine learning. This option will be available starting in 2026 for two years. Additionally, we assume that by then, Apple's smartphone refurbishment rate will increase to 40% as consumers will be more encouraged to trade in their old iPhones and buy refurbished ones.

Table 7: Recycle option parameters

Initial Refurbish value	$\boldsymbol{X^1}$	$ 131bn
Recycle value	$\boldsymbol{X^2}$	$ 267bn
Initial investment for recycle phase	$\boldsymbol{E^2}$	$ 100bn
Refurbishment rate		40%

The expected value of the compound option and the value of Apple's iPhone business with and without flexibility are presented in the table below. As shown in the Table 8, circularity grew the value of the iPhone business by $46bn. Our results show that investing in circularity enhances the value of the business, especially if there is a high degree of uncertainty, which is aligned with the literature review and the results of our numerical investigation. For high-tech industries like the smartphones industry, where there are frequent launches of new products and generations, investing in circularity and having a trade-in system enhances the value of the business as well as increasing the businesses customer base and loyalty. As previously mentioned, Apple implements various strategies for product longevity, which include encouraging customers to trade in their old iPhones and receive the latest model for a lower price. Apple's circular product design and longevity strategies are reflected in the value of the refurbish option.

Table 8: Value of the Apple's iPhone business

Refurbish option (compound option)	$ 46bn
Classical NPV	$ 442bn
Extended NPV	$ 488bn

Conclusion

Environmental sustainability has been one of the main concerns of governments due to increased competition for the world's most valuable natural resources. The rivalry over natural resources has intensified for several reasons, like the rising population growth, increased urbanization, and consumption. Consequently, the United Nations has established a framework for international commitment to develop policies focused on the long-term impacts of economic activity on sustainability, referred to as the Sustainable Development Goals (SDGs). The circular economy concept has gained significant attention among academics, professionals, and policy-makers as it helps preserve natural resources for future generations and slow down the negative impact of climate change. Moreover, this is an economic system that aims to create additional value from a product after its primary use by creating a closed loop of resources, unlike the linear economy that assumes a linear flow of resources from extraction until divestment.

As highlighted in our literature review, quantifying the economic impacts is one of the main challenges confronting corporations and policy-makers in implementing circularity. Conventional valuation methodologies like the NPV underestimate the value of circular and environmental-related investments as such investments usually bear a high degree of uncertainty that is not captured in the assumptions of those methodologies. To overcome the shortcomings of the traditional valuation methods, Gonzalez et al. (2021) propose a valuation model for valuing circularity using real options analysis. As defined, real options analysis is a numerical approach for valuing investments in a project that bears a high degree of uncertainty. This provides decision-makers the right but not the obligation to invest in a real asset contingent on future information. As stated in our literature review, several studies examine the use of real options in valuing climate and environment-related investments. Nevertheless, there are no published studies that empirically test the implementation of real options analysis in valuing circularity.

In this thesis, we propose a valuation model for circular economy investments using real options analysis following the work of Gonzalez et al. (2021). Our valuation methodology is split into two parts. First, we consider circularity options as sequentially compounded options, where each phase encompasses an option concerning the subsequent phase. Second, we estimate the expected value of those options using the recursive dynamic programming approach of Longstaff and Schwartz (2001) form valuing American-style options, known as the Least-Squares Monte Carlo simulation (LSMC). LSMC is a numerical approach that alternates between dynamic programming, Monte Carlo simulation and least squares regression to estimate the optional exercise time of American-style options. Then, we conduct a numerical investigation using hypothetical figures to validate our model and conduct a sensitivity analysis. Finally, we empirically test on the smartphone business using the business case of Apple. Our valuation model is adaptable to any business case by adding or removing circularity phases.

Our numerical investigation shows that the value of the project using real options increases as uncertainty increases, which is aligned with the literature review. Likewise, the valuation of the project also increased when we changed the time between phases; however, the increase is still minor relative to that caused by changing volatility. Valuing circularity in the smartphone market using Apple as an example revealed that investing in circularity can increase the value of the company's smartphone business. As per Apple's circularity strategy, we have assumed only two options (refurbish and recycle) of the four circularity strategies explained by Gonzalez et al. (2021) and in the Value Hill model of Achterbeg et al. (2016). Our results show that investing in circularity increased the value of Apple's iPhone business by $46bn.

The main challenge we have faced in this research is the availability of actual and reliable data and proxies to quantify the impact of circularity on the financial value of Apple's iPhone business. Thus, most of the parameters used in our valuation exercise are based on Apple's financial statements, circulars and reports published by governmental and private associations. It is worth to mention, the current financial accounting standards do not consider sustainability, climate risk and circularity. Therefore, multinational companies rarely report the impact of the sustainable practices on their financial performance.

Lastly, future research extensions on this topic can focus on empirically testing the implementation of circularity using our model in industries and markets other than the smartphone industry. Other extensions can include extending our proposed model to empirically test the impact of circularity on the company's overall valuation. Nevertheless, empirically testing the model using real data will remain a main challenge to such studies due to the minimal availability of real data and proxies.

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Appendix

MATLAB code:

```
%% Remanufacture phase (recycle option)
%Inputs
file=readtable('inputs.csv');
S0=file.Value(1);   %initial remanufacture value
X4=file.Value(2);  %Recycle value
E4=file.Value(3);   %Initial investmnet for recycle option
sigma=file.Value(4); %Volatility of reamnufacture phase
r=file.Value(5);   %risk free rate
T=file.Value(6);      %Time Horizon of phase (lifetime of recycle option)
n=file.Value(7);       % time steps (exercise dates)
alpha=file.Value(8); %confidence level
[c4, ~,~]=C4(S0,X4,E4,r,T,sigma,n,alpha);
%% Refurbish phase (Remanufacture option)
%Inputs
S0=file.Value(9);    %Initial refurbish value
X3=file.Value(10);   %Remanufacture value
E3=file.Value(11);    %Initial investment for remanufacture option
sigma=file.Value(12); %Volatility of refurbish cash flow
r=file.Value(13);     %risk free rate
T=file.Value(14);     %Time Horizon of phase (lifetime of remanufacture
option)
n=file.Value(15);     %time steps (exercise dates)
alpha=file.Value(16); %confidence level
[c3, ~,~]=C3(S0,X3,E3,c4,r,T,sigma,n,alpha);
%% Reusue phase (Refurbish option)
%Inputs
S0=file.Value(17); %Initial reuse value
X2=file.Value(18); %Refurbish value
E2=file.Value(19);  %Initial investment for refurbish option
sigma=file.Value(20); %Volatility of resue cash flow
r=file.Value(21);     %risk free rate
T=file.Value(22);     %Time Horizon of phase (lifetime of refurbish option)
n=file.Value(23);     %time steps (exercise dates)
alpha=file.Value(24); %confidence level
[c2, ~,~]=C2(S0,X2,E2,c3,r,T,sigma,n,alpha);
%% Primary use phase (Reuse phase)
%Inputs
S0=file.Value(25); %Initial primary use value
X1=file.Value(26); %Reuse value
E1=file.Value(27);  %Initial investent for use option
sigma=file.Value(28); %Volatility of primary use cash flow
r=file.Value(29);     %risk free rate
T=file.Value(30);     %Time Horizon of phase (lifetime of reuse option)
n=file.Value(31);     %time steps (exercise dates)
alpha=file.Value(32); %confidence level
[c1,margin_errorP,CIput]=C1(S0,X1,E1,c2,r,T,sigma,n,alpha);
```

Longstaff and Schwartz valuation function for each option

- **Recycle option**

```
function [c4, margin_errorP,CIput]=C4(S0,X4,E4,r,T,sigma,n,alpha)
% Pricing American options (Longstaff & Schwartz)
K=X4-E4;
%Price of a plain vanilla option [Call, Put]
[~,~]=blsprice(S0,K,r,T,sigma);
%% Simulation of random paths of S and construction of payoff matricies
rng('default')  % For reproducibility
% Step 1: simulating N trajectories over [0,T] of underlying assest St
%Simulate random variables from the standard normal distribution (using
%50,000 observations +50,000 antitheic)
U=rand(N,n);
Ua=[U;1-U];
Za=norminv(Ua);

%initalize S matrix of size N by n+1 to simulate trajectories for S
S=zeros(2*N,n+1);
S(:,1)=S0;

%Simulate random paths for S using GBM
for k=1:n
    S(:,k+1)=S(:,k).*exp((r-0.5*sigma^2)*dt+sigma*sqrt(dt)*Za(:,k));
end

%Initalize polynomial order to 2;
polyOrder=2;

%Initalize discount curve
discountcurve=zeros([n,1]);
rateCurve=zeros([n,1]);

for k=1:n
    rateCurve(k)=r;
    discountcurve(k)=exp(-k*rateCurve(k)*dt);
end
dicountcurve=[1;discountcurve];
rateCurve=[0;rateCurve];

%Payoff matrices for put and call
Payoff_put=max(K-S,0);

%% Longstaff and Schwartz algorithm to price an American Put
%Initalize matricies (Exercise matrix and Cash flows)
E_put=zeros(2*N,n+1); %Excercise matrix for an American put
Cash_flowsPut=zeros(2*N,n+1); %Cash flows matrix
%Set the CFs of the last time step (n+1) to be the the payoffs of the last
%step
Cash_flowsPut(:,n+1)=Payoff_put(:,n+1);
%Find trajectories that are in the money at time expiration date (T)
temp=Payoff_put(:,n+1)>0;
E_put(temp,n+1)=1;
```

```
allIndicesP = 1:2*N;
% Start from the last time step and work recurisevly to first step, i.e go
backwards
% from maturity

for k=n:-1:2
    indeciesP=find(Payoff_put(:,k)>0); %indexies of in the money trajectories
for put
    %Number of in the money
    n_indeciesP=size(indeciesP,1);
    %Fit polynomial between discounted payoffs of t (to t-1) and the Stock
price (s)
    %at t-1 to determine the holding value (polynomial of degree 2)
    %(continuation polymial-conditional expectation)

    put_poly=polyfit(S(indeciesP,k),(exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(indeciesP,k+1)),polyOrder);
    Continuation_polyPut=polyval(put_poly,S(indeciesP,k));

    %Continuation function
    contin_functionPut=zeros(2*N,1);
    contin_functionPut(indeciesP)=Continuation_polyPut;

    %Compare cont. function with PFs from current steps
    Payoffs_usedPut=zeros(n_indeciesP,1);

    for i=1:n_indeciesP
        if Payoff_put(indeciesP(i),k)>contin_functionPut(indeciesP(i))
           %Excercise option early
           Payoffs_usedPut(i)=indeciesP(i);
           %Store results for cash flows and stopping rule
           E_put(indeciesP(i),k)=1;
           Cash_flowsPut(indeciesP(i),k)=Payoff_put(indeciesP(i),k);
           %Set future values to zero as only exercise once
           E_put(indeciesP(i),k+1:n+1)=0;
           Cash_flowsPut(indeciesP(i),k+1:n+1)=0; %By this, the optimal exc
matrix has been constructed
        end
    end
     new_indeciesP=setdiff(allIndicesP,Payoffs_usedPut);
     % Update Stopping rule with the cash flows not previously used and
     % discount to previous step

     Cash_flowsPut(new_indeciesP,k)=exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(new_indeciesP,k+1);
end

%Determining the option value
% Get the discounted cash flows to time zero

Holdingvalue_Put=(E_put.*Payoff_put)*dicountcurve;

% Get American option value
AmericanPut_holdingvalue=mean(Holdingvalue_Put);
c4=max(K-S0,AmericanPut_holdingvalue);
```

```
standevP=std(Holdingvalue_Put);

%Contructiong 95% confidence interval
margin_errorP=norminv(1-alpha/2)*standevP/sqrt(2*N);
CIput=[AmericanPut_holdingvalue-
margin_errorP;AmericanPut_holdingvalue+margin_errorP];
end
```

- **Remanufacture option**

```
function [c3, margin_errorP,CIput]=C3(S0,X3,E3,c4,r,T,sigma,n,alpha)
% Pricing American options (Longstaff & Schwartz)
%inputs
N=50000; %number of simulations
dt=T/n;
K=X3+c4-E3;

%% Simulation of random paths of S and construction of payoff matricies
rng('default')  % For reproducibility
% Step 1: simulating N trajectories over [0,T] of underlying assest St

%Simulate random variables from the standard normal distribution (using
%50,000 observations +50,000 antitheic)
U=rand(N,n);
Ua=[U;1-U];
Za=norminv(Ua);

%initalize S matrix of size N by n+1 to simulate trajectories for S
S=zeros(2*N,n+1);
S(:,1)=S0;

%Simulate random paths for S using GBM
for k=1:n
    S(:,k+1)=S(:,k).*exp((r-0.5*sigma^2)*dt+sigma*sqrt(dt)*Za(:,k));
end
%Initalize polynomial order to 2;
polyOrder=2;

%Initalize discount curve
discountcurve=zeros([n,1]);
rateCurve=zeros([n,1]);

for k=1:n
    rateCurve(k)=r;
    discountcurve(k)=exp(-k*rateCurve(k)*dt);
end
dicountcurve=[1;discountcurve];
rateCurve=[0;rateCurve];

%Payoff matrices for put and call
Payoff_put=max(K-S,0);

%% Longstaff and Schwartz algorithm to price an American Put
%Initalize matricies (Exercise matrix and Cash flows)
E_put=zeros(2*N,n+1); %Excercise matrix for an American put
Cash_flowsPut=zeros(2*N,n+1); %Cash flows matrix
```

```
%Set the CFs of the last time step (n+1) to be the the payoffs of the last
%step
Cash_flowsPut(:,n+1)=Payoff_put(:,n+1);

%Find trajectories that are in the money at time expiration date (T)
temp=Payoff_put(:,n+1)>0;
E_put(temp,n+1)=1;

allIndicesP = 1:2*N;
%
% Start from the last time step and work recurisevly to first step, i.e go
backwards
% from maturity

for k=n:-1:2
    indeciesP=find(Payoff_put(:,k)>0); %indexies of in the money trajectories
for put
    %Number of in the money
    n_indeciesP=size(indeciesP,1);
    %Fit polynomial between discounted payoffs of t (to t-1) and the Stock
price (s)
    %at t-1 to determine the holding value (polynomial of degree 2)
    %(continuation polymial-conditional expectation)

    put_poly=polyfit(S(indeciesP,k),(exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(indeciesP,k+1)),polyOrder);
    Continuation_polyPut=polyval(put_poly,S(indeciesP,k));

    %Continuation function
    contin_functionPut=zeros(2*N,1);
    contin_functionPut(indeciesP)=Continuation_polyPut;

    %Compare cont. function with PFs from current steps
    Payoffs_usedPut=zeros(n_indeciesP,1);

    for i=1:n_indeciesP
        if Payoff_put(indeciesP(i),k)>contin_functionPut(indeciesP(i))
           %Excercise option early
           Payoffs_usedPut(i)=indeciesP(i);
           %Store results for cash flows and stopping rule
           E_put(indeciesP(i),k)=1;
           Cash_flowsPut(indeciesP(i),k)=Payoff_put(indeciesP(i),k);
           %Set future values to zero as only exercise once
           E_put(indeciesP(i),k+1:n+1)=0;
           Cash_flowsPut(indeciesP(i),k+1:n+1)=0; %By this, the optimal exc
matrix has been constructed
        end
    end
     new_indeciesP=setdiff(allIndicesP,Payoffs_usedPut);
     % Update Stopping rule with the cash flows not previously used and
     % discount to previous step

     Cash_flowsPut(new_indeciesP,k)=exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(new_indeciesP,k+1);
```

```
end
%Determining the option value
% Get the discounted cash flows to time zero

Holdingvalue_Put=(E_put.*Payoff_put)*dicountcurve;
% Get American option value
AmericanPut_holdingvalue=mean(Holdingvalue_Put);
c3=max(K-S0,AmericanPut_holdingvalue);
standevP=std(Holdingvalue_Put);

%Contructiong 95% confidence interval
margin_errorP=norminv(1-alpha/2)*standevP/sqrt(2*N);
CIput=[AmericanPut_holdingvalue-
margin_errorP;AmericanPut_holdingvalue+margin_errorP]
End
```

- **Refurbish option**

```
function [c2, margin_errorP,CIput]=C2(S0,X2,E2,c3,r,T,sigma,n,alpha)
% Pricing American options (Longstaff & Schwartz)
%inputs
N=50000; %number of simulations
dt=T/n;
K=X2+c3-E2;

%% Simulation of random paths of S and construction of payoff matricies
rng('default')  % For reproducibility
% Step 1: simulating N trajectories over [0,T] of underlying assest St

%Simulate random variables from the standard normal distribution (using
%50,000 observations +50,000 antitheic)
U=rand(N,n);
Ua=[U;1-U];
Za=norminv(Ua);

%initalize S matrix of size N by n+1 to simulate trajectories for S
S=zeros(2*N,n+1);
S(:,1)=S0;

%Simulate random paths for S using GBM
for k=1:n
    S(:,k+1)=S(:,k).*exp((r-0.5*sigma^2)*dt+sigma*sqrt(dt)*Za(:,k));
end

%Initalize polynomial order to 2;
polyOrder=2;

%Initalize discount curve
discountcurve=zeros([n,1]);
rateCurve=zeros([n,1]);


for k=1:n
    rateCurve(k)=r;
    discountcurve(k)=exp(-k*rateCurve(k)*dt);
end
```

```
dicountcurve=[1;discountcurve];
rateCurve=[0;rateCurve];

%Payoff matrices for put and call
Payoff_put=max(K-S,0);

%% Longstaff and Schwartz algorithm to price an American Put
%Initalize matricies (Exercise matrix and Cash flows)
E_put=zeros(2*N,n+1); %Excercise matrix for an American put
Cash_flowsPut=zeros(2*N,n+1); %Cash flows matrix

%Set the CFs of the last time step (n+1) to be the the payoffs of the last
%step
Cash_flowsPut(:,n+1)=Payoff_put(:,n+1);

%Find trajectories that are in the money at time expiration date (T)
temp=Payoff_put(:,n+1)>0;
E_put(temp,n+1)=1;
allIndicesP = 1:2*N;
%
% Start from the last time step and work recurisevly to first step, i.e go
backwards
% from maturity

for k=n:-1:2
    indeciesP=find(Payoff_put(:,k)>0); %indexies of in the money trajectories
for put
    %Number of in the money
    n_indeciesP=size(indeciesP,1);
    %Fit polynomial between discounted payoffs of t (to t-1) and the Stock
price (s)
    %at t-1 to determine the holding value (polynomial of degree 2)
    %(continuation polymial-conditional expectation)

    put_poly=polyfit(S(indeciesP,k),(exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(indeciesP,k+1)),polyOrder);
    Continuation_polyPut=polyval(put_poly,S(indeciesP,k));

    %Continuation function
    contin_functionPut=zeros(2*N,1);
    contin_functionPut(indeciesP)=Continuation_polyPut;

    %Compare cont. function with PFs from current steps
    Payoffs_usedPut=zeros(n_indeciesP,1);

    for i=1:n_indeciesP
        if Payoff_put(indeciesP(i),k)>contin_functionPut(indeciesP(i))
           %Excercise option early
           Payoffs_usedPut(i)=indeciesP(i);
           %Store results for cash flows and stopping rule
           E_put(indeciesP(i),k)=1;
           Cash_flowsPut(indeciesP(i),k)=Payoff_put(indeciesP(i),k);
           %Set future values to zero as only exercise once
           E_put(indeciesP(i),k+1:n+1)=0;
```

```
           Cash_flowsPut(indeciesP(i),k+1:n+1)=0; %By this, the optimal exc
matrix has been constructed
        end
    end
     new_indeciesP=setdiff(allIndicesP,Payoffs_usedPut);
     % Update Stopping rule with the cash flows not previously used and
     % discount to previous step

     Cash_flowsPut(new_indeciesP,k)=exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(new_indeciesP,k+1);
end

%Determining the option value
% Get the discounted cash flows to time zero

Holdingvalue_Put=(E_put.*Payoff_put)*dicountcurve;

% Get American option value
AmericanPut_holdingvalue=mean(Holdingvalue_Put);
c2=max(K-S0,AmericanPut_holdingvalue);
standevP=std(Holdingvalue_Put);

%Contructiong 95% confidence interval
margin_errorP=norminv(1-alpha/2)*standevP/sqrt(2*N);
CIput=[AmericanPut_holdingvalue-
margin_errorP;AmericanPut_holdingvalue+margin_errorP];
end
```

- **Reuse option**

```
function [c1,margin_errorP,CIput]=C1(S0,X1,E1,c2,r,T,sigma,n,alpha)
% Pricing American options (Longstaff & Schwartz)
%inputs
N=50000; %number of simulations
dt=T/n;
K=X1+c2-E1; %payoff of reuse option

%% Simulation of random paths of S and construction of payoff matricies
rng('default')  % For reproducibility
% Step 1: simulating N trajectories over [0,T] of underlying assest St

%Simulate random variables from the standard normal distribution (using
%50,000 observations +50,000 antitheic)
U=rand(N,n);
Ua=[U;1-U];
Za=norminv(Ua);

%initalize S matrix of size N by n+1 to simulate trajectories for S
S=zeros(2*N,n+1);
S(:,1)=S0;

%Simulate random paths for S using GBM
for k=1:n
    S(:,k+1)=S(:,k).*exp((r-0.5*sigma^2)*dt+sigma*sqrt(dt)*Za(:,k));
end
```

```
%Initalize polynomial order to 2;
polyOrder=2;

%Initalize discount curve
discountcurve=zeros([n,1]);
rateCurve=zeros([n,1]);


for k=1:n
    rateCurve(k)=r;
    discountcurve(k)=exp(-k*rateCurve(k)*dt);
end
dicountcurve=[1;discountcurve];
rateCurve=[0;rateCurve];

%Payoff matrices for put and call
Payoff_put=max(K-S,0);

%% Longstaff and Schwartz algorithm to price an American Put
%Initalize matricies (Exercise matrix and Cash flows)
E_put=zeros(2*N,n+1); %Excercise matrix for an American put
Cash_flowsPut=zeros(2*N,n+1); %Cash flows matrix

%Set the CFs of the last time step (n+1) to be the the payoffs of the last
%step
Cash_flowsPut(:,n+1)=Payoff_put(:,n+1);

%Find trajectories that are in the money at time expiration date (T)
temp=Payoff_put(:,n+1)>0;
E_put(temp,n+1)=1;

allIndicesP = 1:2*N;
%
% Start from the last time step and work recurisevly to first step, i.e go
backwards
% from maturity

for k=n:-1:2
    indeciesP=find(Payoff_put(:,k)>0); %indexies of in the money trajectories
for put
    %Number of in the money
    n_indeciesP=size(indeciesP,1);
    %Fit polynomial between discounted payoffs of t (to t-1) and the Stock
price (s)
    %at t-1 to determine the holding value (polynomial of degree 2)
    %(continuation polymial-conditional expectation)

    put_poly=polyfit(S(indeciesP,k),(exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(indeciesP,k+1)),polyOrder);
    Continuation_polyPut=polyval(put_poly,S(indeciesP,k));

    %Continuation function
    contin_functionPut=zeros(2*N,1);
    contin_functionPut(indeciesP)=Continuation_polyPut;
```

```
    %Compare cont. function with PFs from current steps
    Payoffs_usedPut=zeros(n_indeciesP,1);

    for i=1:n_indeciesP
        if Payoff_put(indeciesP(i),k)>contin_functionPut(indeciesP(i))
           %Excercise option early
           Payoffs_usedPut(i)=indeciesP(i);
           %Store results for cash flows and stopping rule
           E_put(indeciesP(i),k)=1;
           Cash_flowsPut(indeciesP(i),k)=Payoff_put(indeciesP(i),k);
           %Set future values to zero as only exercise once
           E_put(indeciesP(i),k+1:n+1)=0;
           Cash_flowsPut(indeciesP(i),k+1:n+1)=0; %By this, the optimal exc
matrix has been constructed
        end
    end
     new_indeciesP=setdiff(allIndicesP,Payoffs_usedPut);
     % Update Stopping rule with the cash flows not previously used and
     % discount to previous step

     Cash_flowsPut(new_indeciesP,k)=exp(-
rateCurve(k+1)*dt)*Cash_flowsPut(new_indeciesP,k+1);
end

%Determining the option value
% Get the discounted cash flows to time zero
Holdingvalue_Put=(E_put.*Payoff_put)*dicountcurve;

% Get American option value
AmericanPut_holdingvalue=mean(Holdingvalue_Put);
c1=max(K-S0,AmericanPut_holdingvalue);
standevP=std(Holdingvalue_Put);

%Contructiong 95% confidence interval
margin_errorP=norminv(1-alpha/2)*standevP/sqrt(2*N);
CIput=[AmericanPut_holdingvalue-
margin_errorP;AmericanPut_holdingvalue+margin_errorP]
end
```