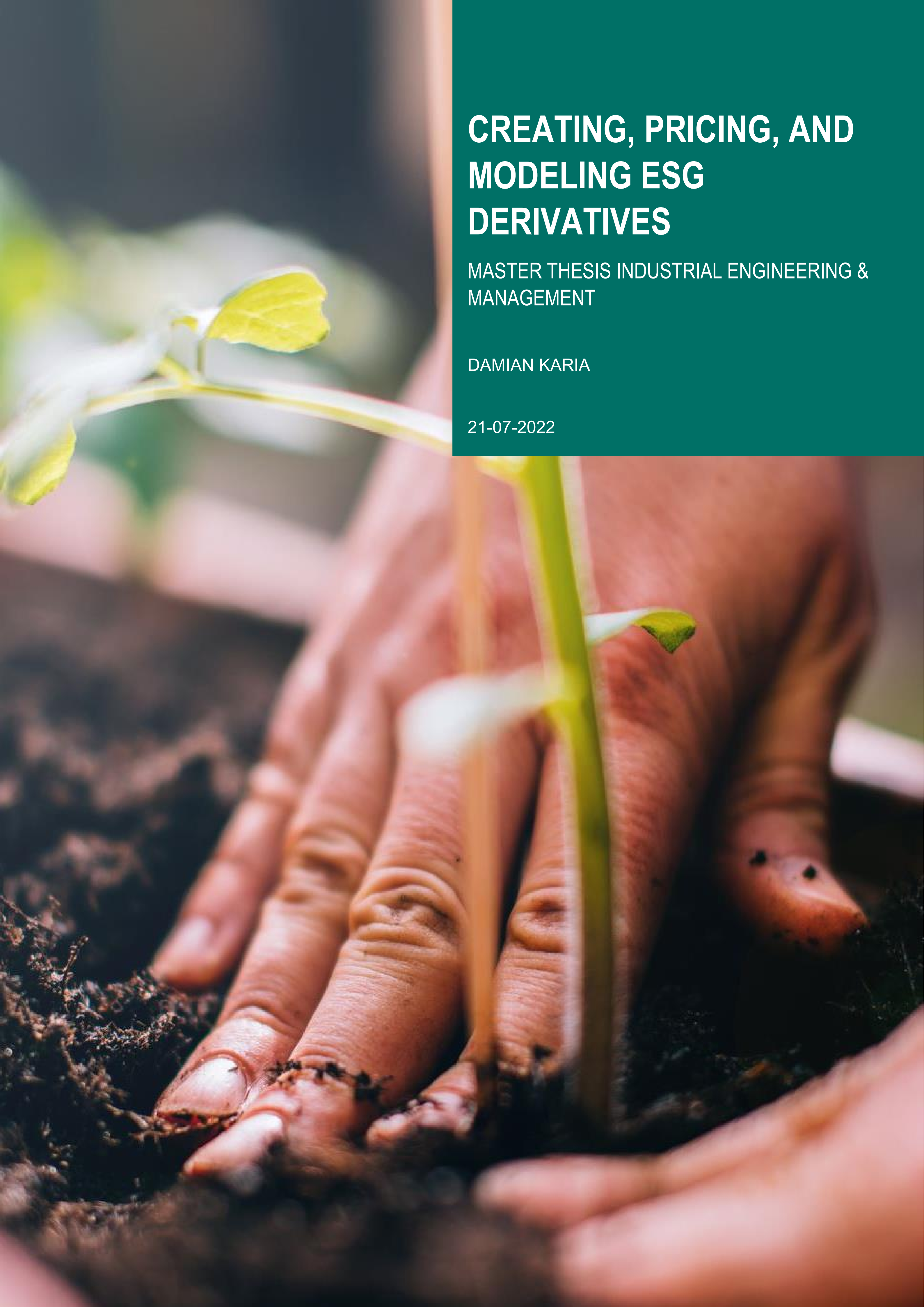

CREATING, PRICING, AND MODELING ESG DERIVATIVES

MASTER THESIS INDUSTRIAL ENGINEERING & MANAGEMENT

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Creating, Pricing, and Modeling ESG Derivatives

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EXECUTIVE SUMMARY

Regulations and pressure from society have led to new climate policies for businesses. Last years, this pressure expanded its range to social and governance aspects within companies. ESG (Environment, Social, and Governance) is therefore a trending topic for businesses but especially for banks, as they play a significant role because they are at the center of the economy. Banks have constructed financial ESG-linked products that stimulate companies to improve ESG-related KPIs within their organization. However, the range of financial ESG-linked products that are currently offered by banks is still limited, therefore, we researched how we can create new ESG-related products, how we can price them, and how we can model them. This research is commissioned by ABN AMRO but the research is general and not focused on the Dutch bank. The answers to the research questions were found by a combination of literature research, conversations with different departments of ABN AMRO, and modeling.

Before the creation of new ESG-linked products, we researched the reasons were to creating and offering ESG-linked products. We found that there are four main reasons: customer demand, regulations, profit potential, and competition. Customer demand for sustainability-linked products increased rapidly in 2021, which shows the opportunities for banks and the interest in ESG products. It also shows that competition is already offering ESG-linked products and that this competition is profiting from this flourishing market. Several regulations like the Sustainable Finance Disclosure (SFDR), the Corporate Sustainability Reporting Directive (CSRD), and more are forcing banks to report on ESG aspects not only from the bank itself but also from their portfolio. The regulations are a trigger for banks to think about their ESG strategies and policies. Next to those reasons, we have profit potential. Banks that are offering ESG-related products focus mostly on green businesses, but there is a market of transition businesses that is relatively untapped. Within this transition business market, banks should focus on the companies that face the biggest pressure to adapt and at the same time, are the most competent to transform.

ESG-linked products always have a KPI component. There are different guidelines for setting up KPIs for ESG-linked products, however, there are no general restrictions that hold for every company. Therefore, we wanted to create a KPI framework that can be used by every business. We think that focusing on material ESG KPIs would contribute to a higher financial performance of the organization. We found that SASB's Materiality Map which tries to generalize material ESG issues is a good starting framework. We expanded the Materiality Map with a "Corporate Governance" column and their corresponding material issues, as we found that SASB's Materiality Map did not incorporate the "G" of ESG accurately. With SASB's Materiality Finder, we can find the material ESG issues in a certain sector for every company. The bank needs to inspect the "Corporate Governance" material issues at the company themselves. Together with the counterparty, they decide on which material ESG issues are the most important. Once this is set, the bank can look up the material ESG issues in World Economic Forum's 2020 whitepaper about ESG metrics. Here, the material ESG issues can be coupled with the material ESG KPIs. Again, the bank and the counterparty decide together which KPIs are chosen to be tracked in the financial product. The tracking can be done either by the bank themselves by analyzing the ESG KPIs out of the company's annual report or by an independent third party. The latter reduces the chances of issues like corruption and bribery.

After analyzing the current ESG-linked products being offered, we found that these products are all constructed in the same way. There is a base financial product, e.g. an interest rate swap or bond with on top of it a bonus/malus KPI structure, which is offered to the counterparty. If the counterparty achieves a predetermined KPI goal, it will get a discount of a particular amount of basis points on its base product till maturity otherwise. If the counterparty does not reach this goal, the counterparty pays either a certain amount of basis points penalty till maturity or nothing happens. Most of the times, the KPIs are based on an educated guess and therefore KPI targets are often reached. This way of offering ESG-linked products is not viable for the bank in the long run. We tried to model the KPI structure as an option, using the binomial tree model and the binary model as the foundation. We created two KPI option models, which allow banks to price KPI options on top of the base financial product they offer. Our KPI option models are based on the company's historical volatility of a KPI, or that of a company of a similar size and sector. This way of pricing the KPI gives banks a viable model.

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1. INTRODUCTION

1.1 ABN AMRO

ABN AMRO is a Dutch bank whose head office is located in Amsterdam. The history of ABN AMRO reaches back to 1720. The bank originated from multiple mergers throughout history. The most important ones happened in 1991 and 2010. In 1991 ABN merged with AMRO (a merger between the Amsterdamsche Bank and Rotterdamsche Bank) which created the largest bank in the Netherlands at that moment in time. In 2010 ABN AMRO Bank merged with Fortis Bank Nederland and became ABN AMRO Bank N.V. In 2021, the bank had nearly 20.000 employees, which serves more than 5+ million clients around the world with products and services like loans, mortgages, payments, financial advice and asset management (ABN AMRO Bank N.V., 2022). The bank serves over 365.000 commercial clients of which most are small and medium-sized enterprises (SMEs). ABN AMRO amounted 50.6 billion euros to their corporate and institutional clients in loans and advances.

1.2 RESEARCH MOTIVATION

ABN AMRO offers an extensive bundle of financial products for their corporate and institutional clients. The products and services offered to their clients worldwide, produce a turnover of more than €250 million (ABN AMRO, 2020a). However, after ABN AMRO's strategy review in 2020, they decided to focus more on Northwest Europe and limit their Corporate and Institutional Banking (CIB) to their core sectors. To increase their market share, in Northwest Europe, they set new targets and ambitions up till 2024. The strategic pillars are customer experience, sustainability, and future-proof banking. In this research, we will especially focus on the second pillar, sustainability. When banks are talking about sustainability, they do not solely focus on the environmental part anymore. Nowadays, sustainability is also connected to social and governance aspects. Are companies sustainably managing their social capital? Is the management capable to mitigate possibilities for corruption in a sustainable manner? These questions are tied to the term ESG, which stands for environment, social, and governance. The demand from corporate and institutional clients for ESG-linked products is rapidly increasing. ABN AMRO offers already a variety of ESG-linked products reaching from sustainability-linked loans (SLLs) to sustainability-linked swaps. In 2020 ABN AMRO was an underwriter of a sustainability-linked loan to Royal Avebe, a Dutch starch manufacturer. The parties involved agreed on certain KPIs that would stimulate sustainability factors within Avebe's company. If Avebe reached the sustainability targets, they get a discount on their interest rate (ABN AMRO, 2020b).
Because of the rising volume of such investment, banks are in a position where they need to decide whether they want to be a leader in the sector, follow the competitors, or just want to comply with regulations. ABN AMRO stated in their strategy that "*Sustainability is a differentiator. We want to be a first choice partner on it for our clients and lead by example*" (ABN AMRO, 2021a). In their 2021 annual report, they listed that for the short to medium term (0-5 years) they want to increase insight into the needs of their clients to be able to help them in their sustainability shift and to discover new financing opportunities to enable this transition (ABN AMRO Bank N.V., 2022). Therefore, ABN AMRO is seeking possibilities to expand the package of financial products that are ESG related.

1.3 PROBLEM STATEMENT

ABN AMRO wants to be the first choice partner on sustainability-linked products. Currently, the bank is already offering ESG products for retail investors. However, these only contain ETFs, bonds, and investment funds. ABN AMRO also wants to offer products that can meet the specific wishes of a company or investor. We already know that ABN AMRO offers different ESG-linked products, which can be structured with company-specific KPIs. Nevertheless, the bank wants to research whether there are more options to expand the current financial product offering that is ESG related and not limited to environmental issues. At the moment, knowledge of ESG products, especially on ESG-linked derivatives and ESG data are scarce, these are an obstacle to creating ESG products. In Figure 1 we depicted the problem in a simplified problem cluster.

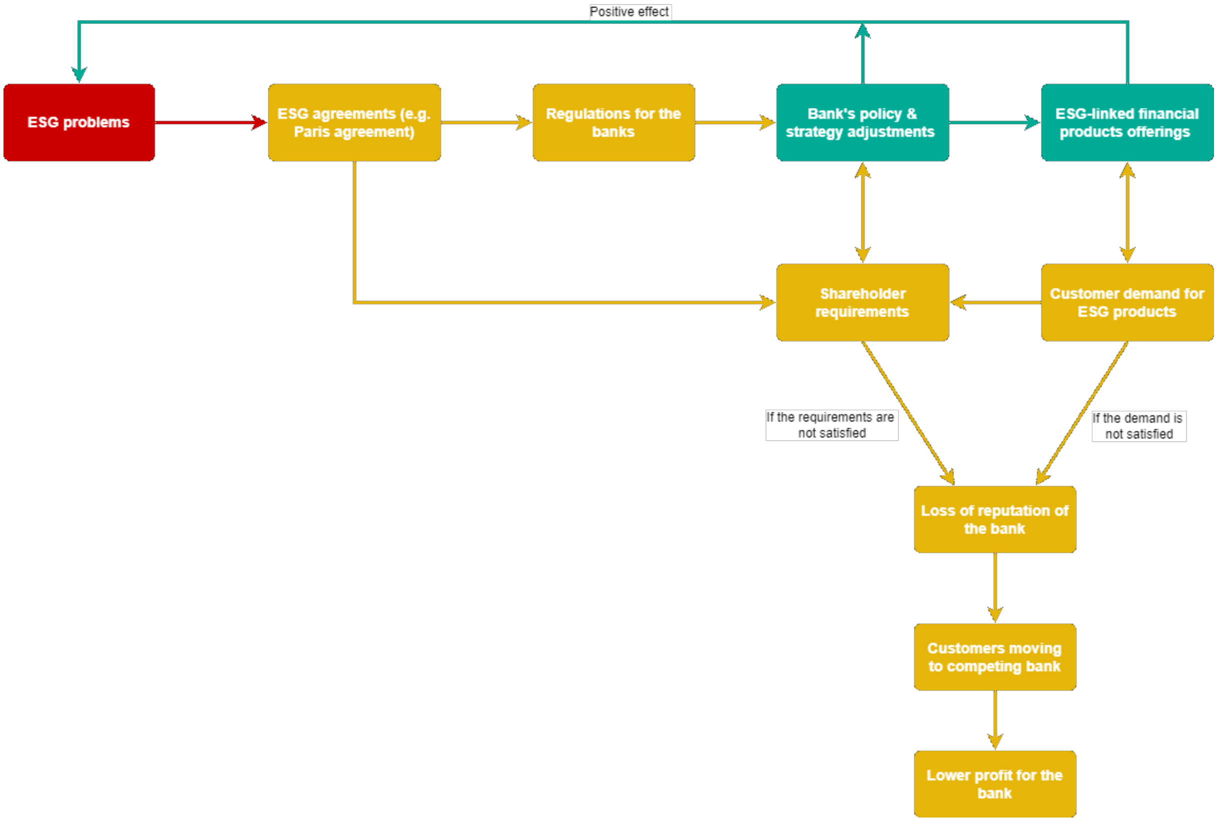


Figure 1: Simplified problem cluster for banks

1.4 RESEARCH GOAL & SCOPE

The goal of this research is to gain knowledge on ESG products that are currently available in the market, construct an ESG KPI framework, create and price an ESG-linked derivative using the framework, and develop a tool that allows the bank to design a tailor-made derivative which is linked to ESG. The aim is that this tool can be used to create products that are tailored and made for specific corporate and institutional clients. We will create this tool using Python. We limit the scope of this research to corporate and institutional clients and focus on one specific ESG-linked derivative because of the time constraint of 20 weeks. However, this tool might lay the foundation for the creation of other derivatives. We chose to focus on ESG-linked derivatives because other ESG-linked products like sustainability-linked bonds and sustainability-linked loans are already getting familiar in the financial market.

1.5 RESEARCH QUESTIONS

The core problem is that there is a knowledge gap between what is wanted and the current situation of the bank (Heerkens & van Winden, 2012). The ideal situation is that ABN AMRO knows how to create, price, and model ESG-linked products. The main research question is therefore stated as follows:

How could ABN AMRO create, price, and model financial products that promote ESG among its corporate and institutional clients, and third parties?

To answer this research question, we need to answer some other questions first. We, therefore, created a list of sub-research questions that need to be answered first, to answer the main one. To discover why ABN AMRO wants to create, price, and model ESG-related products, we need to find out the goal of offering ESG-linked products. We set up the following questions:

1. *What is the goal of creating ESG-related products?*
    a. *What are the reasons to offer ESG products?*
        i. *How do clients promote/stimulate ESG among third parties?*
    b. *What are relevant products to offer?*

Once we have identified the reasons behind offering ESG-connected products, we need to know how to build these products. What do we need to create the products? How do we value them? How do we take into account certain risks? These are the questions that are going to be answered with the help of the following sub-questions:

2. *How do we construct ESG-linked products?*
    a. *Which ESG KPIs are important? How do we classify them?*
        i. *How do we measure those KPIs?*
        ii. *How do we stimulate the clients to reach the KPI goals?*

    b. *How do we price these products?*
        i. *What does our ESG-linked need to look like?*
        ii. *How sensitive are certain values in the pricing model?*

    c. *What are the risks and how do we incorporate these into the price?*
        i. *Which risks are related to offering our ESG-linked product?*
        ii. *How can we mitigate ESG risks in general?*

By gathering the knowledge that is found in the answers to the questions that are mentioned above, we will ultimately have congregated enough information to start building a model for our ESG-linked product. Afterward, we will start modeling the product using Python to price it. This will also help us visualize and test our model and would act as a foundation for other future ESG-linked derivative pricing models.

1.6 APPROACH

For every question, we will perform literature research. However, for questions 2.a. and 2.c. we will also have conversations with the appropriate departments within ABN AMRO to see which KPIs are currently used and if there are already frameworks in use for sustainability-linked products. Furthermore, we will discuss which risks are taken into account at this moment and if these are incorporated into the price of sustainable financial products.
We will first explain ESG and thereafter perform literature research for every question, then we will create a KPI framework and construct a pricing model for our ESG-linked product and ultimately we will program this in Python.

2. ENVIRONMENT, SOCIAL & GOVERNANCE

2.1 ESG

Environment, social, and governance, better known as ESG, is becoming increasingly important. In 2015 two major agreements were adopted. The first one was the “2030 Agenda for Sustainable Development” which was adopted by all United Nations member states (UN, 2015). This agenda contained the 17 sustainable development goals (SDGs) which reach from reduced inequality to climate action. The second agreement was the Paris Agreement. The goal of the Paris Agreement was to limit global average temperature warming to a maximum of 2 °C above pre-industrial levels and to pursue efforts to limit the increase to 1.5 °C (UNFCCC, 2015). These agreements, together with the European Green Deal, form the basis for the European ESG targets. Lannoo & Thomadakis (2020) call the European Green Deal the cornerstone of the EU’s response to the Covid-19 pandemic because of the large amounts required for a sustainable and green recovery. Their research showed that ESG products were resilient during the market decline caused by the pandemic and will play a vital role in fastening the transition to a sustainable economy. We believe that also the war between Russia and Ukraine will accelerate the transition to a sustainable economy as fewer Western countries want to be dependent on Russian gas and oil. Accordingly to the agreements, companies in all sectors have adjusted their goals and missions to contribute to these common goals. Banks are at the centre of the economic transformation. Also, ABN AMRO implemented ESG goals in its three strategic pillars. ABN AMRO does not only try to include ESG in their own company but also tries to stimulate other companies. A few examples are:

- To make at least €46 billion in ESG impact investments by 2024
- To make at least 25% of the corporate loans sustainable by 2024
- To be in the top 5% of the most sustainable banks worldwide (ABN AMRO, 2021b)

ABN AMRO partnered up with Sustainalytics. Sustainalytics investigates and assesses ESG risk scores of companies. This score is an aggregated score of the amount a company is exposed to different material ESG issues and how well the management of a company is handling relevant ESG issues (Sustainalytics, 2022). These scores can be used by investors to see how well a company is scoring on ESG factors.

In the next part, we will explain each letter of ESG and show some examples of focus areas of each aspect.

2.1.1 Environment

Environment is the most known factor in ESG. When people are talking about ESG, most of the time the emphasis lies on sustainability. When looking at a company’s environmental part, it may include the company’s energy use, waste, greenhouse gas (GHG) emissions, or circularity. Banks stimulate the “E” in various ways. The first way is by making their products and services more sustainable, e.g. offering financial products that have a positive impact on the environment. Sustainability-linked loans (SLLs) and sustainable/green bonds have rapidly grown over the years. In 2021 sustainable bonds reached one trillion dollars, which is 20 times as much as in 2015 (Toole, 2022). Investors seem to become more interested in the environmental impact they could have (EY, 2021a). The second way is by investing in companies that have a positive effect on the environment or in enterprises that want to transition to a more sustainable way of operating. In this way, the bank does not only have a direct impact with its products and services but also with its investment portfolio.

2.1.2 Social

Social is the part where we are talking about how companies treat stakeholders, e.g. how are the relationships with employees/suppliers/customers/shareholders managed? What are the gender and diversity ratios within the firm? These are questions that are asked when the social aspect of a business is measured. When is looked at investment decisions of fund managers and institutional investors, according to (EY, 2021a) the social aspects, Human rights practices, Diversity, Equity, and Inclusion (DEI), are the least chosen top characteristics of these investors (see Figure 2).

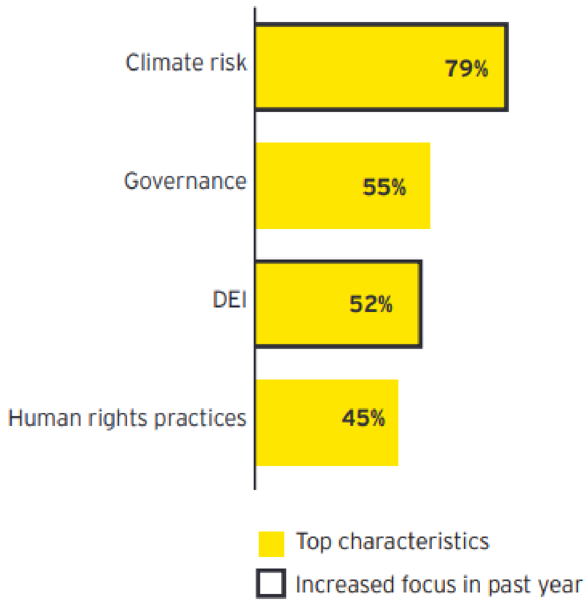


Figure 2: Investment focus of fund and institutional investors. Source: EY, 2021.

2.1.3 Governance

The latest aspect of ESG is governance. This deals with the company's leadership. Here, the composition of the board, executive pay, audit teams, and shareholder rights are examined. Robust governance has always been at the center of attention for investors. Investors believe that strong shareholder rights lead to higher returns due to the increased influence of the shareholders at firms (EY, 2021a).

3. LITERATURE REVIEW

3.1 THE GOAL OF OFFERING ESG PRODUCTS

3.1.1 Reasons to offer ESG products

When we are talking about reasons for banks to offer ESG products, we can divide the reasons into four categories, namely: customer demand, regulations, profit potential, and competition. In this section, we will describe the reasons to offer ESG products as a bank for each category.

Customer demand

When we are looking at SMEs, nearly 70% of the companies that were surveyed by Zeb expect their bank to offer ESG financing products (Rupp et al., 2021). This means that there is a great market to offer ESG financing products. We see that ESG financing products like sustainability-linked loans surged last years. These loans saw a 300% rise in 2021 to $717 billion (Toole, 2022).
To find out which specific wishes there are from corporate and institutional clients, the bank needs to address these clients to find out what ESG financing products the clients are looking for. Obviously, this can differ drastically per bank, as each bank focuses on various clients that work in different sectors. We do not know whether ESG-linked derivatives will see the same increase in demand as ESG financing products but we know from a study by Lannoo & Thomadakis (2020) that derivatives can play a significant role in the context of the European Green Deal and the transition towards a low-carbon economy. Therefore, banks should be prepared for a market that could rapidly expand.
Investors are also asking for ESG investing products to gain exposure to ESG. Therefore, banks need to think about how they would facilitate this. ABN AMRO is already offering ESG funds which are a combination of portfolios of ESG equities or ESG bonds. Most of these portfolios exclude companies that are involved in the tobacco, alcohol, or weapon industry. Furthermore, these portfolios are selecting companies that score high on different ESG KPIs such as low CO2 emission or a high percentage of women in the top management.

Regulations

It can be difficult for banks to formulate a comprehensive ESG strategy because banks have to deal with a flood of information and speculations about regulatory changes (KPMG, 2021). Once banks pass this hurdle and defined a comprehensive ESG strategy, the next obstacle is already waiting. Banks are at the risk of facing reputational loss when the bank does not live up to their ESG missions and statements. There is a growing number of ESG activist which publicly accuse banks of greenwashing, *"making people believe that their company is doing more to protect the environment than it really is"* (Cambridge Dictionary, 2019), when they do not follow their own ESG statements. An example of this is the "Banking on Climate Chaos" report of Rainforest Action Network and others. This report shows that the 60 biggest banks in the world have financed $3.8 trillion to fossil fuel companies in the five years since the Paris Agreement (Rainforest Action Network et al., 2021). This financing contradicts most banks' own ESG missions and statements and therefore led to a reputational loss for most of these banks. Regulators are trying to get a hold of this by forming a regulatory ESG framework.
The first action of the European Commission is the Sustainable Finance Disclosure Regulation (SFDR). The SFDR is part of the Action Plan for Financing Sustainable Growth of the European Commission (AFM, 2021). The SFDR is based on the UN's SDGs and aims to create transparency for sustainable financial products to investors. The SFDR imposes mandatory obligations to all financial market participants., which comprise banks, investment funds, pension funds, and equity funds. The disclosures should make the sustainable profile of financial products more comparable and easier to understand.
The second measure taken by the European Commission is the Non-Financial Reporting Directive which aims to enable investors, communities, and stakeholders to evaluate a large company's non-financial performance on environmental protection, social responsibility, human rights, anti-corruption, and diversity (European Commission, 2022). The Commission now calls the plan the Corporate Sustainability Reporting Directive (CSRD).
The third action taken by the European Commission is the Taxonomy Regulation. This is a classification system with criteria that determine which economic activities are environmentally sustainable and which economic activities may harm the environment (S&P Global, 2021).
The fourth is MiFID II. The goal of MiFID II is to make the European financial markets more efficient and transparent while increasing investor protection. The directive will require banks to consider sustainability risk in investment decisions. Furthermore, it expects banks to scrutinize sustainability factors throughout the organization, reaching from governance to product development (Patrick Schmucki, 2022).
The fifth action taken is Capital Requirements Regulation (CRR II). CRR II necessitates large banks with public listed issuances to disclose ESG risk in their Pillar 3 disclosures (Patrick Schmucki, 2022).
The last measure is a global one. At the 2021 United Nations Climate Change Conference (COP26) in Glasgow, the International Financial Reporting Standards (IFRS) Foundation announced that the International Standards Board (ISSB) will be working under the authority of the IFRS (EY, 2021c). They will develop the "IFRS Sustainability Disclosure Standards"

which will make the disclosures more comparable and consistent throughout different industries and jurisdictions, as currently there are around 600 different ESG reporting standards around the world.
These regulations stimulate banks to increase ESG product development and create a foundation for ESG financing and investing. However, due to the large stream of information and speculations about future regulatory changes, it keeps challenging for most institutions to develop a thorough ESG strategy (KPMG, 2021).

Not only the regulatory frameworks are founded but also courts are taking action against individual companies who do not act well enough on their responsibility to people and the climate. A revolutionary example is the case of Shell in 2021. A Dutch Court ordered Shell to reduce its CO2 emission to net 45% by 2030 compared to its 2019 levels (de Rechtspraak, 2021). This is the first time that an individual company is obliged to change its current climate policy by a court (Merle et al., 2021). The Shell case might be the first of many court cases against companies with high greenhouse gas emissions. This case might be another incentive for banks to contribute as much as possible in the ESG area and to keep involved in conversations with ESG activists.

Profit potential

A bank's loan portfolio can be categorized into three segments. First, the "dark green" businesses. These are the businesses that are inherently contributing to ESG aspects, e.g. solar farms, wind farms, etc. Zeb found that the primary focus of banks is on these businesses, which leads to high competition and lower profit margins (Rupp et al., 2021). They suggest focusing more on the "transition" businesses, the companies that are not ESG-compliant yet but can achieve it in the future. According to Zeb's assessment, the average loan portfolio consists of 90% of "transition" businesses. This market is relatively untapped and therefore has significant profit potential. The last segment is the "brown" businesses, the companies that are having a negative ESG impact and are not able to transform. The latter is obviously not a market that banks should look into when they are looking for ESG-linked financing. Figure 3 shows the average loan portfolio structure of a bank and the implications and forecasts for banks in the different segments. Furthermore, companies that score well on ESG metrics are to a greater extent identified as conceivably offering higher returns and showing fewer risks than companies with low ESG scores (ISDA, 2021a).

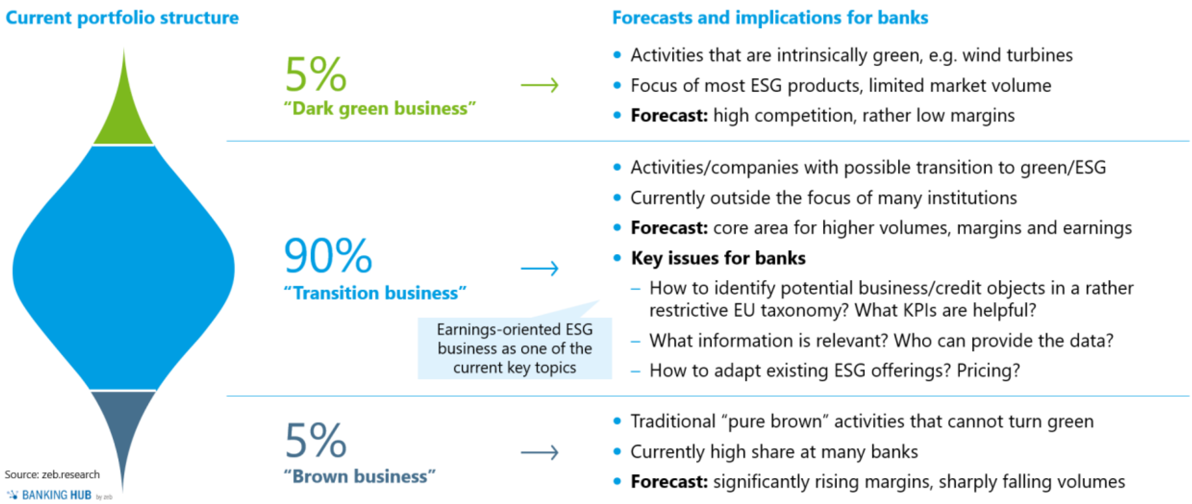


Figure 3: Profit potential within loan portfolios. Source: BankingHUB by zeb

To develop a solid ESG strategy, banks should look at their current focus on sectors/segments and find out where the main financing needs are for "transition" companies (Dell'Aversana & Paltenghi, 2021). Furthermore, banks should be open to innovating their current ESG product offerings to cover the needs of their potential clients. Banks could think about offering loan/bond + derivative packages to become the one-shop hop. Banks might decide to expand/limit their scope after their findings. To prioritize the sectors/segments within the addressable market, banks should outline the niches within the sectors. Zeb uses two variables to prioritize the focus on specific niches (Dell'Aversana & Paltenghi, 2021). They put the "pressure to adapt", which can be from the regulatory side but also from customers and competitors, on the x-axis and put "adaptability", the capability to implement ESG requirements, on the y-axis. Figure 4 shows the four quadrants that arise from filling in the niches. The size of the blue dots represents the size of the niche market. The niches in the "transformation prospects" quadrant should be the initial focus of the bank, as these niches face the biggest pressure to adapt and have the highest adaptability scores.

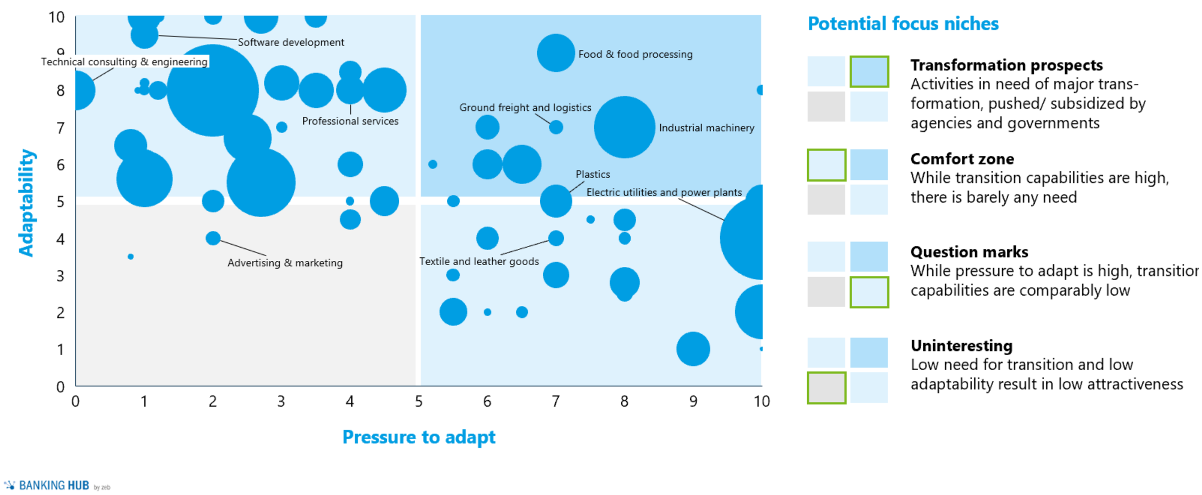


Figure 4: Prioritization of the addressable market. Source: BankingHUB by zeb

Competition
Not only did the volume of issued sustainability-linked loans surge, but also the volume of ESG bonds which comprise green bonds, social bonds, and sustainability bonds grew significantly. In 2021, ESG bonds reached $1 trillion, which was mostly because of the green bond issuance (Toole, 2022). The increase represents a 20-fold rise compared to 2015 and accounts for 10% of the global debt market. This indicates that there are already players on the market that can profit from this flourishing market. The analysis of the cash flow channel by Mendiratta et al. (2021) showed that bond issuers with a high ESG score showed statistically stronger financials than issuers with a low ESG score. Eventually, this leads to a better credit score. When competing banks are already offering ESG products and your bank is not, it will lead to a competitive disadvantage. On the other hand, banks that are pioneers in the ESG field and offer ESG-linked products, have a competitive advantage and might profit from higher volumes, margins, and earnings. The results of Deloitte's research (2019) suggest that commercial banks who score high on material ESG issues have better future performance than banks that score low on these issues. To be a pioneer in the field, banks should reach further than the upcoming regulations and consider ESG as a unique selling point through all of the bank's facets (Rupp et al., 2021). Discovering and offering new ESG-linked products is a solid first step in being a pioneer in the ESG field.

3.1.2 How do clients stimulate ESG among third parties?

Banks can have a significant impact by financing "transition" businesses with ESG-linked products. However, it would be even better to have an impact on the whole supply chain of the financed business. This goal can be reached by implementing supply chain wide KPIs. For example, if a bank finances a retail shop that sells cotton clothing. The supply chain begins with the fields where cotton grows. These fields rely on good weather. Depending on the location of these fields, there might be a high climate risk. If bad weather strikes the cotton fields, it will drive up the price of cotton. This increase is felt through the whole supply chain. When the cotton arrives at the clothing manufacturer, there are other ESG risks. Clothing manufacturing is often linked to child labor and a bad labor environment. This does not have to be the case. Banks or an external party needs to perform a comprehensive supply chain scan to figure out where the ESG risks are and how the whole supply chain can be improved on ESG aspects. Banks can construct ESG-linked products which impact the whole supply chain with KPIs like "percentage of recycled product used", "percentage of greenhouse gas (GHG) reduction through the supply chain", and "Total overtime divided by total FTEs". Banks can choose to reject financial products from retail clothing stores when child labor, unsafe working conditions, or other human rights problems are discovered in their supply chain. In this way, the risk of supply chain disruption is mitigated and working conditions might improve.
Blockchain can also help to tackle these problems. Blockchain can help to improve transparency through the entire supply chain and can expose corruption, human rights abuses, or modern-day slavery (Accenture, 2020). Walmart is using a blockchain platform to reduce the time to track their mangoes across the US from a week to two seconds. It enables Walmart to find out where a foodborne disease might have begun within seconds, which facilitates quick communication with their customers about an issue with the product.

3.2 WHAT ARE RELEVANT PRODUCTS TO OFFER?

The first question we need to address is: how do we define relevant products? We could argue that every product that is linked to ESG is relevant as it has a positive effect on ESG aspects, however, this would create a limitless amount of ESG products. We would define relevant products as demand fulfilling with a positive impact. We know already that last year the demand for sustainable bonds (green bonds, social bonds, and sustainability-linked bonds), sustainability-linked loans, and sustainable equity increased significantly. We want to tap into the part of the market which is still in the beginning phase, therefore we decided to research ESG derivatives. ESG derivatives help to increase capital towards sustainable investments, hedge against ESG risks, facilitate transparency, price discovery, market efficiency, and contribute to long-termism (ISDA, 2021a).

In 2021, the International Swaps and Derivatives Association (ISDA) published a list of ESG-related derivatives products and transactions. The list contains sustainability-linked derivatives, ESG-linked credit default swaps (CDS) indices, exchange-traded derivatives on listed ESG-linked equity indices, emission trading derivatives, renewable energy/fuels derivatives; and catastrophe and weather derivatives (ISDA, 2021a). Depending on the focus of a bank, some derivatives are more traded than others and some derivatives are not even traded at all. For this thesis, we decide to start with one kind of derivative as a basis and work onwards from that basis. Therefore, we decide to go with a more general derivative. We take the sustainability-linked interest rate swap as our basis for this research, as this could be adjusted to other kinds of derivatives like FX derivatives, and CDSs.
The interest rate swap (IRS) is mostly used to hedge against the interest rate risk. The most common IRS is a derivative between two parties where the floating interest rate is “swapped” for a fixed interest rate. Counterparty A pays counterparty B a fixed interest rate based on an agreed-upon notional principal amount. In return, counterparty B pays counterparty A the floating interest, which is based on a floating interest rate index like the LIBOR or EURIBOR. If the average floating interest rate is below the fixed rate, during the length of the contract, counterparty B makes a profit. Counterparty A makes a profit when the floating interest rate is on average above the fixed interest rate during the length of the contract. In a sustainability-linked IRS, depending on the wishes of both parties, they can agree to only give a penalty on the fixed interest rate when sustainability-linked KPIs are not met, only give a bonus when KPIs are accomplished, or both. Both parties can agree on a bonus and/or penalty. For example, counterparty A pays counterparty B a fixed interest rate of 4% on the notional principal amount of 100 million euros and set the bonus and penalty both on 10 basis points (0.1%). Counterparty A pays 4 million euros every year of the contract. When company A reduces its CO_2 emissions by 10% before the end of the IRS contract, counterparty A only needs to pay 3.9 million euros every year of the contract. On the other hand, if counterparty A does not reduce its CO_2 emissions by 40%, then it needs to pay 4.1 million per year. Another option is to pay the bonuses and/or penalties to a predetermined charity or ESG-related project. To engage shareholders with the ESG business decisions, banks and companies can decide to let shareholders vote on which project the money should go to.

We found that the published list of ISDA contained a lot of ESG products that were focused on sustainability only, which is also something we found through a wide span of literature. In a solid amount of literature, ESG is almost seen as a synonym for sustainability. When we will create the ESG-linked derivative, we will make sure that all three aspects of ESG can be covered in the product. Furthermore, we will also look into the possibilities of a bonus/penalty system on the floating interest rate side.

3.3 HOW TO CONSTRUCT ESG-LINKED DERIVATIVES?

In the previous section, we decided to take the sustainability-linked IRS as our basic derivative. This product is commonly offered by a bank to a company that wants to hedge interest rate risk. Generally, the company is the counterparty that pays the fixed rate, and therefore the bank pays the floating rate. To construct an ESG-linked IRS we need the regular pricing model of an IRS plus a discount/penalty model. To create the bonus/malus system on top of the IRS, we need to define KPIs that can be used. Banks have already set up different sustainability-linked KPIs. In the ISDA list, we have seen multiple examples. KPIs in this list are linked to ESG ratings, sustainability certificates, increasing renewable energy power generation, UNSDGs, and sales of projects that aim to reduce GHG emissions, safe and healthy working environment, reducing energy consumption (ISDA, 2021a). Most of these KPIs are linked only to the environmental impact, we will also explore KPIs for the social and governance part of ESG. The ISDA guidelines are a good start in steering ESG-linked products in the right way. However, ESG-linked products are still tailor-made regarding the wishes and the scope of the client. In this section, we will create a basic framework of ESG KPIs, research how those KPIs can be measured, and look into the possibilities of how clients can be stimulated to reach the KPI goals.

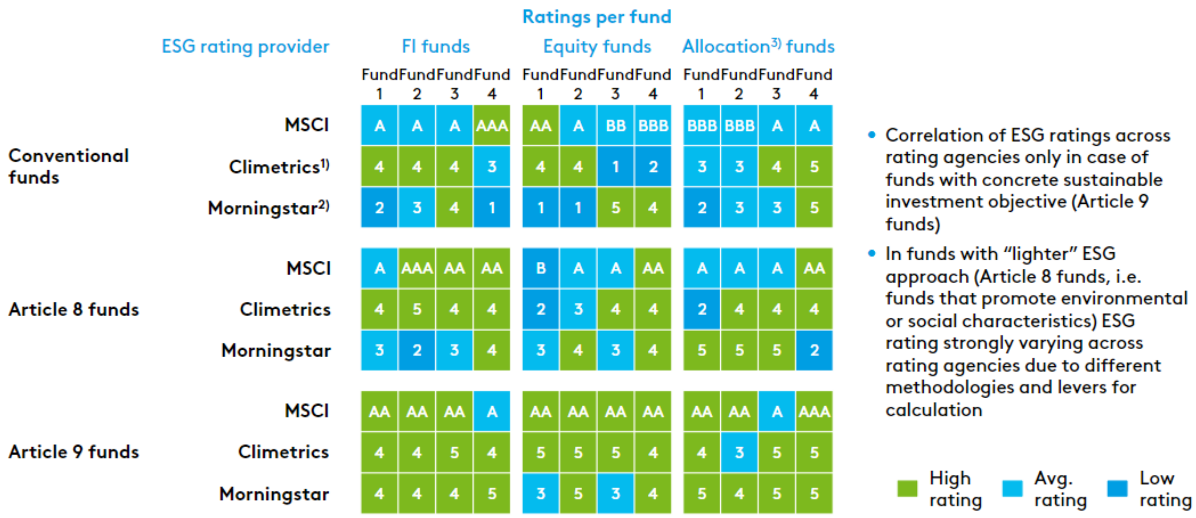
3.3.1 Classification of ESG KPIs

Before we can set up a basic framework of ESG KPIs, we first define guidelines for these KPIs. In 2021, ISDA published a document that proposed KPI guidelines for sustainability-linked derivatives. The guidelines proposed have five principles (ISDA, 2021b). The first principle is “specific”. The specific principle states that KPIs and their calculation methodology should be clearly defined. Furthermore, it is important to include fallbacks into the documentation to cover situations where KPIs cannot be calculated. Drafting KPIs as precisely as possible decreases the chance of being ambiguous. The second principle is “measurable”. This principle describes that KPIs should be quantifiable, objective, and possible to reach. The third

principle is “verifiable”. The verifiable principle explains that KPIs should be verifiable by either one of the counterparties or a third party. Choosing an independent third party decreases the risk of disputes and potential reputational damage. The fourth principle is “transparent”. This principle clarifies that counterparties should think about which information should be disclosed, to whom, and at which frequency. The last principle is “suitable”. In this section is pointed out that KPIs should be relevant to the counterparties of their ESG strategy to avoid greenwashing accusations. The KPIs should be material, strategically significant, and ambitious enough. Making information publicly available improves verifiability and transparency but also reduces the chance of greenwashing allegations.
Furthermore, the document also provides a classification of KPIs. This classification has four main categories:

- Reducing negative impacts on the environment,
- Encouraging positive impact on the environment
- Linking counterparty performance to requirements under international agreements (e.g. Paris Agreement)
- Tracking ESG scores by independent third parties

When we analyze the ESG-linked derivatives that are already issued in the market, we see that a solid amount of KPIs is linked to ESG scores. We found rating providers are mostly involved when ESG-linked derivatives are linked to ESG scores. Sustainalytics is one of the rating agencies that is involved in multiple ESG-linked derivative contracts that are based on their ESG score. Other rating agencies are MSCI, S&P, and Refinitiv. Zeb Research and Morningstar analysed 36 funds and their ratings by different rating agencies (see Figure 5) (Zeb & Morningstar, 2021).



1) Climate score, a climate-focused rating, was introduced to the market in 2017 by ISS ESG and CDP 2) Morningstar rating is based on the rating of Sustainalytics (a Morningstar company), Climetrics rating is the fund rating of CDP and ISS ESG 3) Multi-asset class strategy

Figure 5: ESG ratings of funds by different rating providers. Source: ESG rating agencies, Zeb research.

They analysed 12 conventional funds, 12 funds that promote ESG (Article 8 funds), and 12 funds with a concrete sustainable investment objective (Article 9 funds). We see that the ratings for a fund can differ significantly between the rating agencies, especially at the conventional and Article 8 funds. We assume that we will see the same pattern for other companies because rating agencies use different methodologies and focus on different points. Standardization of methodological frameworks for rating providers would provide an ESG score that could better be compared between different companies and industries. Before this happens, we do not recommend banks to use ESG scores as a KPI for ESG-linked derivatives.
For this research, we will still include “tracking ESG scores” in our classification but we would recommend waiting for using this as a KPI till there are more transparent and standardized methodological frameworks for ESG rating providers.

The first three mentioned classification categories by ISDA (2021) can easily be translated to all ESG aspects. If we generalize the first three categories, we get the following result:

- Reducing negative impacts on the ESG aspects
- Encouraging positive impact on the ESG aspects
- Linking counterparty performance to requirements under international agreements (e.g. UNSDGs)
- Tracking ESG scores by independent third parties

The three generalized categories can focus on individual parts of ESG, two parts, or all of them. Based on the business of the counterparty, it can be decided together with the bank on which part(s) of ESG the derivative will focus.

3.3.2 Which ESG KPIs are important in general?

Once the focus and scopes are determined by the counterparties, they need to decide which ESG KPIs are relevant for the ESG-linked derivative. The German Association of Investment Professionals (DVFA) was the first to publish a list of KPIs for ESG and gained the status of an official EFFAS (European Federation of Financial Analysts Societies) standard (DVFA & EFFAS, 2009). Their paper defined nine topical ESG areas and their corresponding KPIs (see Figure 6) which apply to all sectors and industries.

ESG	KPI
ESG 1 Energy efficiency	ESG 1-1 Energy consumption, total
	ESG 1-2 Energy consumption, specific (intensity); Options: per unit of revenue, per employee, per unit of production volume (tons of steel, for example)
ESG 2 GHG emissions	ESG 2-1 GHG emissions, total
	ESG 2-2 GHG emissions, specific; Options: per unit of revenue, per employee, per unit of production volume (tons of steel, for example)
ESG 3 Staff turnover	ESG 3-1 Percentage of employees leaving p.a./total employees (FTE?)
ESG 4 Training & qualification	ESG 4-1 Percentage of trained employees p.a./total employees (FTE?)
	ESG 4-2 Average expenses on training per employee p.a
ESG 5 Maturity of workforce	ESG 5-1 Age structure/distribution (number of employees per age group, 10 year intervals)
	ESG 5-2 Percentage of workforce to retire in next 5 years
ESG 6 Absenteeism rate	ESG 6-1 Number of mandays lost per employee p.a.
ESG 7 Litigation risks	ESG 7-1 Expenses and fines on filings, law suits related to anti-competitive behavior, anti-trust and monopoly practices
	ESG 7-2 Reserves on preventive measurements against anti-competitive behaviour, anti-tust and monopoly practices
	ESG 7-3 (other) litigation payments, total
	ESG 7-4 (other) litigation payments, reserves
ESG 8 Corruption	ESG 8-1 Percentage of revenues in regions with TI corruption index below 6.0
ESG 9 Revenues from new products	ESG 9-1 Percentage of revenues from products at end of life-cycle
	ESG 9-2 Percentage of new products or modified products introduced less than 12 months ago

Figure 6: Overview of the topical ESG areas and their KPIs. Source: DVFA (2009).

A year later, DVFA & EFFAS also published a list of KPIs which are sector-specific (DVFA & EFFAS, 2010). They provided a comprehensive list of sectors with their corresponding KPIs. These KPIs are a solid basis for ESG KPIs per sector but are lacking an amount of KPIs which are trending nowadays (e.g. human rights, diversity, and inclusion). The challenge here is to determine which KPIs are most relevant for a company/sector because it is not possible to tackle all ESG problems. PwC (2021) argues that materiality is the key to success in this case. Materiality is the relevance of a factor that could have an impact on a company's financial performance (Robeco, 2020), immaterial factors are the ones that do (almost) have no impact on a company's financial performance. Understanding the ESG risks of a company and its sector is essential for getting insight into which issues are important for the business and its stakeholders. Industry and geography are the two leading criteria for understanding the ESG risks and could generate a long list of potential material issues. (PwC, 2021). The list can be reduced to the most material issues of the business. From practical experience with their current ESG-linked products, ABN AMRO finds three KPIs as the golden standard, where there is a maximum of five (Tieleman, 2022). These numbers seem reasonable as three KPIs are not difficult to track, and five KPIs seem to be possible but not desired.

A study by Khan, Serafim, and Yoon in 2016 found that firms with high ratings on material sustainability issues significantly outperform firms with a low score, in terms of investment returns, on these issues (Khan et al., 2016). Another important finding is that firms with a good rating on immaterial sustainability issues do not outperform firms with bad ratings and that investments in high material and low immaterial gave the highest annualized alpha (the return compared to the benchmark), (see Figure 7).

FOUR FACTOR ALPHAS² (1991-2013)	ANNUALIZED ALPHA	DIFFERENCE IN ALPHAS
1. **High Material, Low Immaterial**	6.01%	
2. **Low Material, Low Immaterial**	-2.9%	8.90%***
3. **Low Material, High Immaterial**	0.60%	5.41%***
4. **High Material, High Immaterial**	1.96%	4.05%***

*Figure 7: Annualized alphas on the four investment categories. Source: Khan, Serafeim, and Yoon (2016) and Russell Investments. Alphas refer to portfolio returns regressed on four-factor models including Mkt-Rf, SMB, HML, and UMD. *** Refers to significance at the 1% level.*

These results were later verified in another study by Steinbarth & Bennett in 2018. They used the materiality map of the Sustainability Accounting Standards Board (SASB) to determine which of the 145 ESG issues from Sustainalytics were material. With their findings, they created a "material ESG score" which they benchmarked against the immaterial ESG issues and the traditional ESG score (Steinbarth & Bennett, 2018). They found that low performance on material issues is especially costly, even if the firm scores high on other ESG issues.

We learn from these studies that investing in immaterial ESG issues does not contribute to the performance of an investment. However, investing in material ESG issues does. We therefore decide to make a difference between material ESG issues and immaterial ESG issues. We would like to argue that when selecting KPIs for a derivative, the bank should focus on material ESG KPIs (which obviously differ per industry and sector). We think that the focus on material ESG KPIs would contribute to a higher potential financial performance of a company when it is compared to randomly selecting industry-specific material or immaterial ESG KPIs. Selecting material ESG KPIs will eventually lead to lower credit risk (Deloitte, 2019). A growing body of research also suggests that companies with high ESG ratings exhibit lower credit risk (Mendiratta et al., 2021). Furthermore, we believe that the chance of being accused of greenwashing also decreases because the bank focuses only on ESG issues that can financially impact a business. It is the responsibility of the business itself to address immaterial issues when needed.

We will use SASB's 26 general material ESG issues that apply to every industry as our general ESG KPI framework. However, we will expand this framework as Steinbarth & Bennett (2018) found that SASB's framework did not accurately incorporate the "G" of ESG. They added a "Corporate Governance" column to the framework which was based on the corporate governance assessment of Sustainalytics (see Table 1). We divided the framework into the three parts of ESG. The environment part is green, the social part is yellow and the governance part is blue. Obviously, these are general issues, and specific KPIs can be made up from these general issues. We recommend banks to use SASB's "Materiality Finder" to find out which of these issues are material for a specific industry or company, but they must also assess the relevant issues of the company on corporate governance, as these are not included in SASB's framework. SASB's Materiality Finder contains all publicly-listed companies. Material ESG issues for private companies can be found by identifying their industry on SASB's online tool.

Environment	Social Capital	Human Capital	Business Model & Innovation	Leadership & Governance	Corporate Governance
GHG Emissions	Human Rights & Community Relations	Labor Practices	Product Design & Lifecycle Management	Business Ethics	Board & Management Quality
Air Quality	Customer Privacy	Employee Health & Safety	Business Model Resilience	Competitive Behavior	Board Structure
Energy Management	Data Security	Employee Engagement, Diversity & Inclusion	Supply Chain Management	Management of the Legal & Regulatory Environment	Shareholder Rights
Water & Wastewater Management	Access & Affordability		Materials Sourcing & Efficiency	Critical Incident Risk Management	Remuneration
Waste & Hazardous Materials Management	Product Quality & Safety		Physical Impacts of Climate Change	Systemic Risk Management	Audit and Financial Reporting
Ecological Impacts	Customer Welfare				Stakeholder Governance
	Selling Practices & Product Labeling				

Table 1: Extended version of SASB's general material ESG issues

Once the general material ESG issues for a company are determined, the bank can dive together with the counterparty into possible KPIs within the company-specific material ESG factors. As mentioned before, these KPIs must be strategically significant and ambitious enough (relative to the scope of the company) to prevent greenwashing allegations.

World Economic Forum’s International Business Council (IBC) worked together with Deloitte, EY, KPMG, and PwC to identify a set of universal, material ESG metrics (World Economic Forum, 2020). The survey of their study showed that 88% of the respondents found that a universal set of ESG metrics and disclosures would be helpful for their business. An even higher percentage, 91%, saw the importance of such metrics for financial markets and the economy. Eventually, they identified 21 core metrics and 34 expanded indicators to help companies consistently measure and report progress towards ESG goals. One of the criteria for these metrics was: “Materiality to long-term value creation”. We believe that their metrics can be used by banks to establish company-specific material ESG KPIs. We recommend using SASB’s Materiality Finder to pinpoint the relevant ESG issues and to use the core metrics and expanded indicators of the World Economic Forum’s research consequently to choose material ESG KPIs.

Suppose that a private company, Company ABC wants to enter an ESG-linked interest rate swap with the bank for 5 years. Company ABC is active in air cargo transportation. At SABS’s Materiality Finder we can categorize the business in the industry “Air Freight & Logistics”. We find that there are six relevant general material ESG factors for Company ABC (see Figure 8). The bank and Company ABC can look into these issues and check how Company ABC is currently performing on these six factors. The counterparties could agree to specify KPIs on the environment, social, and governance aspects, which are especially related to the company’s business strategy, missions, and values but should also be connected to the bank’s own strategy. Company ABC and the bank could decide to specify KPIs for “GHG Emissions”, “Employee Health & Safety” and “Critical Incident Risk Management” because these are the most relevant issues for the business.

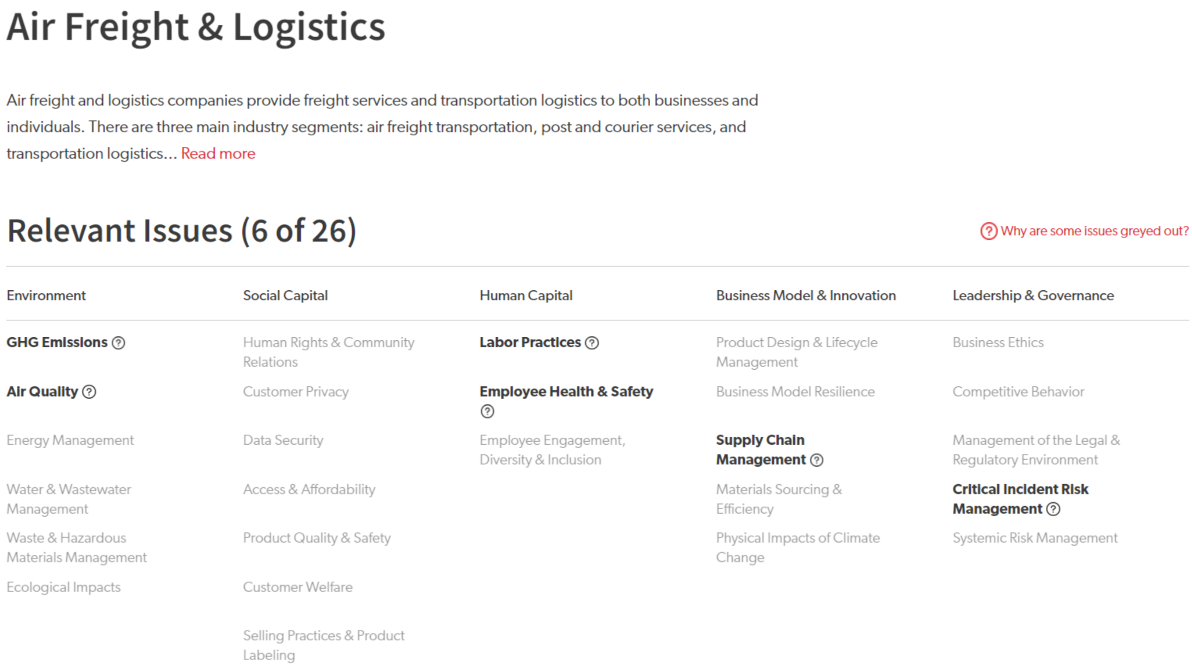


Figure 8: Air Freight & Logistics industry on SASB's Materiality Finder

When we look up these issues in World Economic Forum's paper we find the following metrics and disclosure recommendations:

GHG emissions
Greenhouse gases are the main reason for the rising temperatures worldwide. The paper recommends companies to report all relevant greenhouse gases in metric tonnes of the carbon dioxide equivalent (tCO2). Counterparties can look at the current GHG emissions and set ambitious goals each year to reduce the total emissions, e.g. reducing total GHG emissions by 50%. We can cut this end goal into smaller and more manageable targets, for example by agreeing on a 10% reduction of total greenhouse gasses per year during the length of the derivative contract.

Health & Safety (%)
Mitigating health and safety risks in the working environment can contribute to higher employee morale and productivity. The paper advises reporting on the following matters:

- The number and rate of fatalities as a result of work-related injury;
- The number and rate of high-consequence work-related injuries (excluding fatalities);
- The number and rate of recordable work-related injuries
- The main types of work-related injury;
- The number of hours worked

Furthermore, the advocate for an explanation of how the organization facilitates workers' access to non-occupational medical and healthcare services, and the scope of access provided for employees and workers.
The counterparties can agree to attach KPIs to the matters that score the lowest, In Company ABC, employees work on average 30 hours per month of overtime. The banks and the company could agree to reduce the over hours worked per full-time employee by 10% each year during the length of the contract.

Integrating risk and opportunity into the business process:
Companies should be aware of their risks, not only from the sector risks but also the risks that are tied to the company-specific. It is therefore important that these risks are identified as soon as possible to measure how these risks change over time and how to react to these risks and potential changes. The paper mentions incorporating material economic, environmental, and social issues, and data stewardship in their risk assessment. When such assessments and corresponding policies are not in place or not complete, counterparties can agree to have such assessments and or policies finished before the end of the interest rate swap. It is hard to make this quantifiable or to break it down into smaller pieces. Therefore, counterparties can choose to define beforehand which parts a risk assessment and its corresponding policies must consist of before the end of the contract. Making the goal quantifiable can be troublesome but it should be clear, verifiable, suitable, and transparent (ISDA, 2021b). In this case, the goal can be verified by a third independent party at the end of the interest rate swap.

As can be seen from the example above, most KPI end goals can be cut down to yearly KPI goals to build a feedback loop for both counterparties. However, making governance goals quantifiable can be a challenge. We encourage counterparties to make the goals quantifiable where possible. Otherwise, goals should still be drafted according to the rest of ISDA's KPI guidelines. The reason that ISDA did not provide specific KPIs but only guidelines are because goals can be really specific and differ through industries and sectors. Another reason is that trends can change quickly and specific KPIs could get outdated quickly. The counterparties could agree on a bonus per KPI that is reached and a penalty for when a KPI is not achieved. The bonuses and/or penalties do not have to be equally weighted.

3.3.3 How do we measure those KPIs?

There are two options for measuring KPIs. Either it is measured by one of the counterparties by publishing the specific KPIs in public reports or it is done by an independent third party. Both are reasonable options to choose from and both options have their advantages and disadvantages. When the KPIs are measured by one of the counterparties, the KPI calculation methodology must be well documented. This can be done by a specific equation or formula so that in case of a disagreement between the two counterparties, the KPI can still be measured by an independent third party. Another way to track and measure a KPI is to couple one to an operation that has been documented and published throughout the (last) years already. This can be an operation mentioned in an annual, quarterly, or ESG report. When the measurement is done by one of the counterparties, it saves costs for both parties. However, in practice, banks prefer the measurement being executed by an independent third party like a classification/audit bureau or technical expert. The con is that it brings extra costs to the transaction. On the other side, it decreases the chance of disputes and therefore also mitigates the risk of reputational damage significantly.

3.3.4 How do we stimulate the clients to achieve the KPI goals?

Banks can play an important role in stimulating clients to reach KPI goals that are coupled with an ESG-linked loan or derivative. The penalty and bonus system is one of the potential motivations for clients. When the counterparties are constructing an ESG-linked product, they should aim for certain ambitions as targets. When the targets are set, it can be a stimulus to break down the targets into smaller ones. Instead of agreeing on reducing CO2 emission by 40% in 5 years, the counterparties can set smaller goals for each year, e.g. reduction of CO2 by 8% each year and couple smaller bonuses and penalties to them. Through this way of working, the client is stimulated to take direct action. However, banks do not want bonuses to be the main reason to apply for an ESG-linked product. Therefore, the bonuses are relatively small (a few basis points) and only represent a "symbolic" value.
Another motivation for the client to achieve the KPI goals is the reputational image of the company. Most of the ESG-linked loans and derivatives are published by both counterparties in an article. By doing this, the counterparties are publicly committed to the settled goals. Therefore, the client might face a loss of image and reliability when it does not meet the set KPI goals.
The last stimulant for clients can be by benchmarking KPIs against the market in which they are operating. By generating ambitious KPIs to improve the market's standards, clients can be pioneers in their industry. This position might create a competitive advantage and it would therefore be an encouragement to achieve the defined KPI goals.

3.4 HOW DO WE PRICE THE ESG-LINKED DERIVATIVE?

3.4.1 What does our ESG-linked derivative look like?

In order to price the ESG-linked derivative, we need to think about how we can value an interest rate swap through the length of the contract where there is a possibility on predetermined timepoints that a bonus or a penalty needs to be distracted/added from the floating or fixed rate, depending on whether a KPI target is reached or not. Banks are currently using a method with a step-up and step-down structure to add the bonus or penalty to the leg of the counterparty (or where the penalty is paid to a charity). The bonus/penalty for next year is based on how many KPI targets are reached in the current year. Let's assume that a company buys an interest rate swap with an ESG component and pays the fixed leg. If we look at the table below, this means that when the counterparty reaches two KPI targets this year (2022), it will get a discount of 1 bp on its fixed leg in 2023. We see that the figures with minus signs are penalties and with plus signs are bonuses and therefore decrease the fixed rate leg.

AMOUNT OF KPI TARGETS REACHED	PENALTY/BONUS (BPS)
0	-3
1	-1
2	+1
3	+3

Table 2: Example of the bonus/penalty structure of banks

If we take a look at the process, we see that nothing changes for the calculation of the IRS. There is only a kind of ESG structure on top of the IRS. We can therefore also alter this process to an interest rate swap plus a European option. The price of the product is the value of an interest rate swap plus the present value of the expected payoff of the option, which means that both products can be added up to get the total price. We see that by looking at the ESG derivative in this way, enables more financial products besides the IRS to be the base product. There may be multiple KPIs, we will take this into account by calculating the prices of multiple options. By looking at the valuation of the derivative as an IRS plus an option, it is not possible to take a potential penalty into account. However, this penalty is substituted by the payment of the option. This means that the costs of the option will be paid at the start of the option the counterparty that wants to achieve certain ESG KPI targets. In the next section, we will shortly outline the pricing of the KPI option and the potential option pricing model candidates that can act as a KPI option model.

Option on KPI

To model the price of an option on a KPI, we had to discover which already existing option pricing models would be able to fit. For every KPI goal that is achieved, we want to offer a discount of x basis points times the principal amount. However, if a KPI goal is not reached, we want to penalize the counterparty. When a counterparty enters a KPI option contract, it has to pay the price of the option This price can be seen as the penalty the counterparty has to pay for not reaching the KPI goal. We looked at the potential option pricing models and concluded that there are only a few candidates that can in theory incorporate our requirements. The candidates are; the binomial tree and the binary option because we can adjust the maximum payoff in both models.

Binomial tree

Binomial trees are used to price European options or American options. It visualizes the possible prices of an asset and the corresponding payoffs. Binomial trees are valued using the risk-neutral valuation, meaning that we assume that the world is risk-neutral (Hull, 2015). This suggests that the expected return from a traded asset is the risk-free interest rate. Payoffs from the option are priced by calculating their expected values and discounting them at a risk-free rate.

The advantage of using a binomial tree to value the options is that you can determine with which steps the asset price increases and decrease. As we cannot use the binomial tree in its original form, we can alternate the model to fit our situation. The payoff of a plain vanilla call option is normally the maximum of the asset price at maturity minus the strike price or zero (max(S-K,0)). The payoff can therefore not be zero at a plain vanilla call option. However, we want to limit the payoff to the number of basis points that are agreed between the bank and the counterparty. The next issue is that we have no asset like a stock value as an underlying asset. We will explain the requirements and the characteristics of the model in Chapter 4.

Binary option

When we look at the cash-or-nothing call options, it means that the payoff of those binary options will pay off nothing if the asset price ends up below the strike price at maturity (Hull, 2015). However, if the asset price ends up above the strike price, it will pay off a predetermined amount Q at the time of maturity. The price is just like with the binomial option, the expected payoff is discounted at the risk-free rate. In Chapter 4 we explain how we altered the original model to comply with our requirements for a binary KPI option model.

3.5 WHAT ARE THE POSSIBLE RISKS AND HOW DO WE INCORPORATE THESE INTO THE PRICE?

3.5.1 Which risks are related to offering our ESG-linked product?

The bank has four kinds of risks for which capital is required: market risk, credit risk, operational risk, and liquidity risk (Hull, 2018). Market risk is the risk that emerges from trading activities. It is the risk of losing value on the bank's trading book. Credit risk is the risk that a counterparty cannot pay back its loan or derivative transaction due to a default. The third risk is the operational risk and is seen as the bank's biggest risk. Operational risk is often divided into internal and external risk. Internal risk is the risk a bank has control over, such as the people it hires, the IT systems in place, and the controls. External risks are the external activities that have an impact on the bank's operations, like natural disasters, changing regulatory frameworks, or security breaches. The last risk is the liquidity risk. Liquidity risk is the ability of a company to make cash payments as they become due. If a bank for example mostly has illiquid assets, like long-term fixed mortgages, the bank can run into trouble when it has to pay short-term liabilities like interest on saving accounts. These are the standard risks for a bank. We already know that not offering ESG-linked products can cause a competitor disadvantage. Banks that do not adapt now to the upcoming ESG regulations will barely have enough time to implement them and will have even more problems keeping up with the changing market demand (KPMG, 2021). However, this is a risk of not following the ESG trend but which risks are related to our ESG-linked product?

A thorough assessment of the main risks and vulnerabilities faced by the significant institutions under the European Central Bank's (ECB's) direct supervision, conducted by ECB Banking Supervision and national competent authorities, concluded that risks originating from climate change and environmental degradation will be the main challenge for banks and supervisors in the coming years (European Central Bank, 2021). This underlines the importance and the gratitude of the tasks that the banks are awaiting. The ECB defines two main risks that are linked to climate-related risks and environmental risks, namely physical risk and transition risk (European Central Bank, 2020). Physical risks are the negative impacts of a changing climate on the bank's assets, financial and earnings situation, or reputation. Physical risks are categorized as "acute" or "chronic. Examples of acute physical risks are storms, floods, or wildfires and examples of chronic physical risks are rising temperatures, increasing sea levels, and loss of biodiversity. These risks can lead to damaged properties, reduced productivity, and indirectly even to supply chain disruptions. Transition risks are the (in)direct negative consequences on a bank's financial situation towards a more ESG-friendly economy. Transition risks can come from (sudden) changing regulations, market changes, or technological developments. The physical and transition risks will have an impact on the four risks we mentioned at the start of this paragraph. Figure 9 (ING Group, 2021) gives a clear overview of how the physical and transition risks are related to credit risk, market risk, operational risk, and liquidity risk. For example, when a flood hits a certain part of the Netherlands because of the rising sea levels, it will most likely lead to damage to certain properties. This will consequently affect the collateral of banks and their mortgages. Property damage will decrease the value of the collateral and would therefore lead to a higher loss given default (LGD), the loss when a counterparty cannot pay back its loan. This would increase the credit risk of a bank. One of our KPI option models could also easily be applied to mortgages. The bank and the client could have agreed that the client would have energy label A after 5 years to receive the discount of, for example, 0.5 basis points on the mortgage interest rate. Making such deals is positive for the client (who saves energy costs), the bank (because the probability of the client defaulting on the loan decreases and it increases the value of the property) and for the environment as less grey energy is used. However, when a flood hits this particular home, what is the effect on the product and the bank? The client still has to pay the mortgage and the price of the KPI option is already paid. There are 4 scenarios before the flood:

1. The client did not (yet) increase his/her home in a way that it has energy label A now. The period of 5 years is not over yet. The house is now hit by a flood and loses 40% of its value because of the water damage.
2. The client made sufficient changes to his/her home to increase the house's energy label to A. The period of 5 years is not over yet. The house is now hit by a flood and loses 40% of its value because of the water damage.
3. The client did not (yet) increase his/her home in a way that it has energy label A now. At the end of the 5 years, the house's energy label was not A. The house is now hit by a flood and loses 40% of its value because of the water damage.
4. The client made sufficient changes to his/her home to increase the house's energy label to A. At the end of the 5 years, the house's energy label was A. The house is now hit by a flood and loses 40% of its value because of the water damage.

In scenario 1, the bank does not have to pay a discount on the mortgage of the client and it received the price of the option before the contract started. The bank does therefore not have more risk than normal. However, the client does not have a fair chance of getting energy label A within the 5 years. The bank could consider building a clausula into the contract where it would pay the full costs of the option or a percentage back to the client.
Scenario 2 would result most likely in the same outcome as scenario 1, as the client is most likely not able to bring back the energy label till A within the 5 years. Also in this scenario, the client did not get a fair chance of achieving energy label A. It would be fair to compensate the client in a way for this.
Scenario 3 is a different situation. Here the 5-year term is already over and the client did not meet the KPI goal. Therefore, it still has to pay the full mortgage interest rate. This situation compensates a little for the depreciation of the collateral.
Scenario 4 is the worst outcome for the bank. It would have to pay a discount of 0.5 basis points on the mortgage interest rate to the client and the value of the home has decreased.
When we analyze the scenarios above, we can see that the implementation of one of our KPI option models does only in scenario 4 leads to an extra risk for the bank because a discount has to be paid on the mortgage interest rate. However, this would have been the outcome no matter if the house flooded or not. Therefore, we want to incorporate the probability of a KPI being reached in our KPI option models. This probability can be set so that the bank breaks even, or it can choose the probabilities in a way that it makes a profit on average. However, finding the right probabilities might be complicated at this point in time, and historical data on these matters is scarce. We expect that the availability of such data will grow significantly in the coming years as an increasing amount of banks are going to offer financial ESG products. Therefore, it might be smart for banks to test the KPI option model for different KPIs on select groups of both corporate and retail clients. These groups can be used to test probabilities on the KPI option model before such a model is widely implemented.
From this situation, we can conclude that our KPI option models do not create extra risks, except for the underwriting risk (inaccurate assessments of certain parameters) that is created by taking probabilities that are too low.

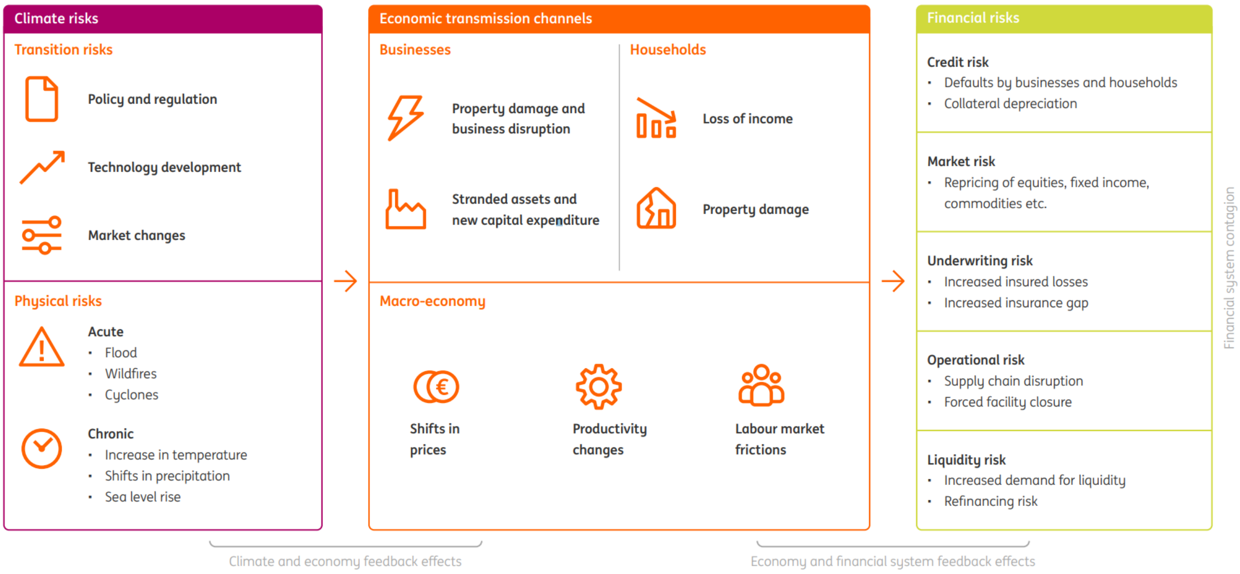


Figure 9: Climate risks to financial risks. Source: ING Group 2021 Climate Report (Adapted from NGFS Climate Scenarios for central banks and supervisors, June 2020)

In the situation described above, only the "E" of ESG was covered. However, also social risks and governance risks can also impact our KPI option models. Social risks include noncompliance with labor standards, inadequate payment of labor, lack of assurance of industrial safety standards, health protection for employees, and lack of assurance of product safety (KPMG, 2021). A social risk that can arise from offering the KPI option models is indirectly excluding certain people from our product. This can happen when KPIs are chosen that can only reasonably be achieved by a select group of people. Therefore, it is important to look at the different groups of people in our society and think about how every group can be stimulated with our KPI option model to contribute to an ESG-friendly environment. This might be an interesting topic for further research.
The last risk is the governance risk. Governance risks can exist of compliance with tax law, corruption or attempted bribery, inappropriate senior management compensation, and lack of proper assurance of data protection. Offering our KPI option model can cause corruption and bribery attempts. A company that has a contract for a KPI option to reduce work incidents, might bribe employees in exchange for not reporting work incidents. The company can also try to bribe people from the bank to change certain KPI values or parameters which calculate the option's price. When such events happen and are discovered, it will lead to a reputational loss for both the company and the bank.

3.5.2 How can we mitigate those risks?

It is not possible to completely eliminate the ESG risks that are related to our ESG-linked product. However, we can take some measures to mitigate those risks. The possible measures that we will describe in this section will not specifically tackle the ESG risks are related to our KPI option model but are more general measures, which help the bank to be prepared for ESG risks and their possible consequences of them.

The first step a bank can take is identifying, measuring, and evaluating its current ESG exposure. This step includes the consideration of ESG risks while evaluating capital adequacy and while regulatory and economic capital are calculated (KPMG, 2021). The bank has to analyze its current portfolio and see whether it has too much exposure to particular ESG risks. It can divide the risks of retail and corporate clients into short-term risks (<3 years), medium-term risks (3-7 years), and long-term risks (>7 years). Figure 10 is an example of how NIBC Bank (2022) modeled its climate-related risk which was related to its current portfolio. To indicate the size of the exposure, the circles can be made bigger or smaller. The bank can decide to reduce the investments that are overexposed to certain ESG risks.

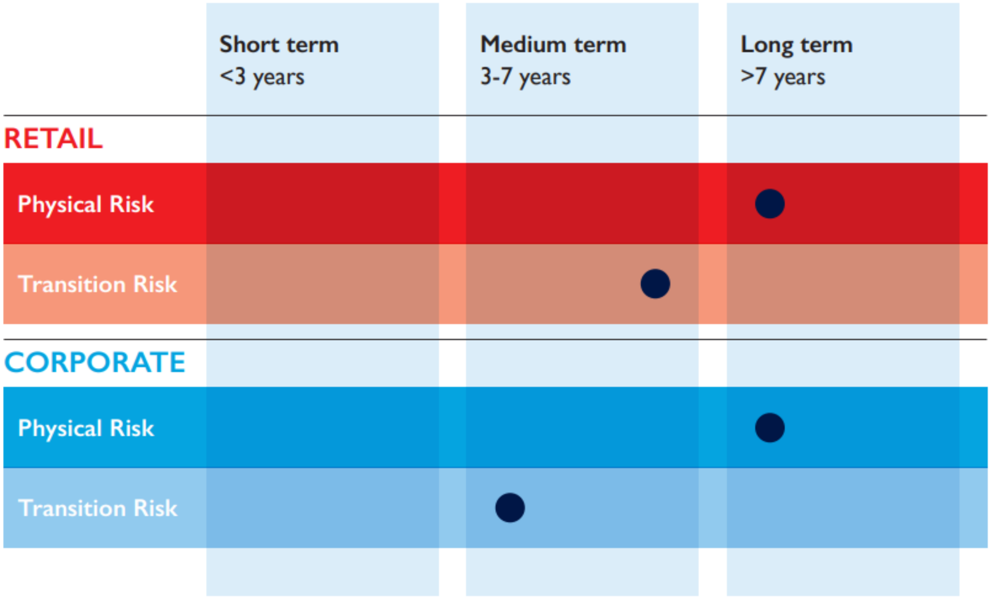


Figure 10: An example of how NIBC modeled the climate-related risk of its portfolio. Source: Annual Report NIBC Bank N.V. 2021.

The second step is to prepare for the climate-risk stress tests. The ECB's climate stress test examined the resilience of banks to a range of climate scenarios, which were plausible representations of future climatic conditions (ECB, 2021). The stress test makes it possible to see the impact on the costs and the probability of defaults of companies. In January 2022, the ECB started its first climate risk stress test which will run through the first half of 2022 (KPMG, 2022). Preliminary results of the test show that the costs for companies that arise from extreme climate events will rise considerably when no further climate policies are implemented. The preliminary results of the ECB show again that taking action early is the wise choice because the short-term costs of adapting green policies are extensively lower than the potentially much higher costs that arise from medium to long-term climate disasters. From the 2021 EY Global Climate Risk Disclosure Barometer we can see that organizations are improving the quality and coverage of climate risk disclosure reporting (EY, 2021b). The coverage of reporting on climate-related financial disclosures was on average 70% but the average quality of the maximum quality score was only 42%. This demonstrates that there is still a notable gap in the integration of climate risk and associated impacts into the overall risk management process.

The third step is to add an ESG risk inspection method to the KYC (know your customer) processes. As mentioned earlier, using the information of ESG data providers is not always comparable or complete. Therefore, ESG risk inspection should assess which ESG factors can significantly impact the credit worthiness of the corporate customer and debilitate loan repayments (Deloitte, 2019). Integrating ESG risk inspection into the KYC processes would not only provide optimal data collection for a new corporate customer but it would also remove the need to design and implement new channels and systems for client outreach (PwC, 2021). This integration would avoid reporting fatigue on the client's side. However, reassessment of ESG risks should become the norm after certain periods of time because the ESG risks of a corporate customer can change over the years.

The European Banking Authority (EBA) also provides guidelines on the incorporation of ESG risks in for example a loan origination, which can be seen in Figure 11 (European Banking Authority, 2021). We see in the first box that the EBA also advises including ESG factors/risks in their credit risk procedures. In the "Loan origination" box, we see a piece of advice that we did not see before, namely collecting information on the borrower's ESG risk mitigation strategies. This might also help our KPI option model to create a better idea of the probability that a client will reach a certain KPI. Furthermore, these strategies can be analyzed to see whether they actually reduce the ESG risks and therefore decrease the probability of default. The third box is important for our KPI option model and cannot be skipped. The borrower should be able and willing to monitor and report certain ESG KPIs. These must otherwise be assessed by a third independent party. The last box, "Monitoring", is important to see if the loan is used for ESG practices and whether it had an effect on certain ESG KPIs. The latter is also important for the possible granting of a discount on the loan.

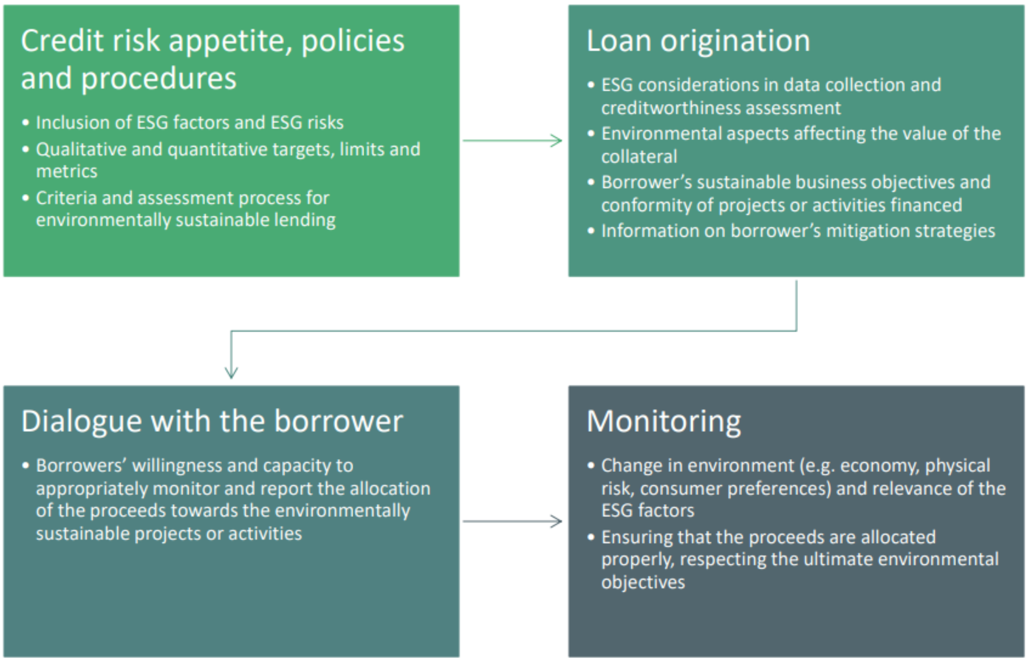


Figure 11: EBA's advice on incorporating ESG risks at loan origination. Source: REPORT ON MANAGEMENT AND SUPERVISION OF ESG RISKS FOR CREDIT INSTITUTIONS AND INVESTMENT FIRMS.

When the steps described above are followed, it would mitigate the consequences of ESG risks for a bank. Furthermore, it would probably lead to the reevaluation of the bank's financial products. For example, it might be the case in the future that an extra safety margin needs to be paid for ESG risks on mortgages. If you live in an area where there is a higher chance of a flood, the bank needs to think about how it can absorb this risk. The question can be asked if covering the costs of certain climate risks is the responsibility of the bank at all. The risk can be compensated by increasing the mortgage interest rate in ESG risky areas. The latter can have a decreasing effect on house prices in environment risky areas. Another solution is that this kind of environmental risk will be covered by insurers and/or governments.

4. MODELS

In this chapter, we will describe in which way the original binomial tree model and the binary options model are modified to comply with our requirements. We will build our models in Jupyter Notebook (Python) because in that way we can directly test our models using different parameters. First, we list the requirements for the models:

- The model should be able to calculate the potential discount
    - The model should take basis points as a parameter
    - The model should take the principal amount as a parameter
- The payoff of the model should not exceed the number of basis points that are given as parameter
- The payoff should be zero if the KPI target is not reached
- The model should be able to calculate the price of the option
    - This should be done by taking the KPI goal into account or by taking the historical volatility of the KPI

4.1 BINOMIAL KPI TREE

In a regular binomial tree option model, we have the asset as the underlying asset. In our case, for pricing a European option, we obviously have no asset but we can use the value of a KPI as the underlying asset. We call the parameter of the KPI value at the start of the contract KPI_0. We use the following formulas from Cox, Ross & Rubinstein (CRR) to calculate the KPI target and the probability of an up move (p):

$$u = e^{\sigma\sqrt{\Delta t}} \qquad \textbf{(1)}$$

$$d = e^{-\sigma\sqrt{\Delta t}} = \frac{1}{u} \quad \textbf{(2)}$$

$$p = \frac{e^{r\Delta t} - d}{u - d} \quad \textbf{(3)}$$

It is hard to determine the probability of a company reaching a KPI goal. We therefore want to estimate this probability as accurately as possible. The probability obviously differs per KPI per company. To estimate probabilities, we need historical volatilities of ESG KPIs. Such volatilities can be extracted from a company's annual report or paid databases like the Bloomberg Terminal, NASDAQ's database, or the ESG database of Refinitiv. To get accurate historical volatilities of a certain company that does not have annual reports or ESG data in a database, it can be helpful to classify companies based on industry, location, and size and take averages of this pool of similar companies. In the Bloomberg Terminal (see Figure 12) (Bloomberg, 2020), KPIs can be benchmarked against their competition in the industry and the historical performance of ESG metrics can be checked. Based on this data, it can be estimated what an "average volatility" of a KPI can be. Then a bit more ambitious target can be determined and probabilities of a company reaching a KPI target can be estimated. The only restriction in this case is that the metric should also be available in the chosen ESG database.

Metrics	Current	History	Change	Low	Range	High	Median	Difference	History
1) Environmental									
11) GHG/Revenue	174.7		18.6 W	167.5		491.5	346.9	-172.1 B	
12) GHG/MBOE	38.8		-9.2 B	19.6		216.6	73.2	-34.3 B	
13) Carbon Reserves	8141.7		1012.3 W	87.6		4611.3	1648.2	6493.5 W	
14) Oil in Total Prod %	56.8		-4.4 B	36.5		88.4	48.6	8.2 W	
15) Energy/MBOE	156		-37 B	92.1		834.4	224.6	-68.6 B	
2) Social									
21) Women Empls Mgmt Ratio	0.69		0.11 B	0.3		0.77	0.62	0.06 B	
22) Women Employees %	35		4 B	23.6		42	31	4 B	
23) Employee Turnover %	12		0	2.6		23	11.7	0.3 W	
24) Employees Unionized %	--		--	71.5		88.6	85	--	
25) Lost Time Incident Rate	0.05		-0.04 B	0.06		0.45	0.17	-0.12 B	
3) Governance									
31) Independent Directors %	86.7		8.1 B	26.3		81.8	60.3	26.4 B	
32) Percent of Board Member...	44.4		31.1 B	21.4		60	34.8	9.6 B	
33) Director Avg Age	63		1 W	52		64	58	5 W	
34) Director Meeting Attd %	94.4		-1.4 W	82		100	95	-0.6 W	
35) Board Size	9		-6 B	9		19	13	-4 B	

Figure 12: Bloomberg Terminal ESG data. Source: Bloomberg 2020.

The KPI target, which is called KPI_goal in our code, is calculated by multiplying KPI_0 by u (u is calculated with the given historical volatility, i.e. the sigma). If the KPI goal is reached after a predetermined contract length (T), the counterparty receives a predetermined amount of basis points as discount on their leg payments. We have to calculate the expected payoff to calculate the price of our binomial KPI option. To do that, we will use backward induction. We first calculate the KPI values at the end of the binomial tree and we calculate their corresponding payoff. The payoff at the end of a regular binomial call option tree is the maximum of zero and the strike price minus the asset price at maturity ($K-S_T$). This gives max(0, $K-S_T$). However, a requirement in our model is that the discount to a counterparty never exceeds the predetermined amount of basis points. Furthermore, the payoff should be zero if the KPI goal is not reached. Therefore, we limit the payoff to the principal amount (P) times the predetermined amount of basis points (bps), which is therefore the potential discount. This will give us: max(0, P*bps). For a call option, the payoff is P*bps when the KPI value at maturity exceeds the KPI_goal, otherwise, the payoff is zero. We multiply the payoff by (maturity of the underlying – T)*(observations). So, we multiply the payoff by the number of periods that a discount can still be given (the remaining periods of the underlying contract). Call options can be used if a bank wants to stimulate the counterparty to increase a certain KPI value, for example, the number of sustainable machines with respect to the total machines. However, in some situations, the bank wants to stimulate a company to bring a KPI value down. This can be the case with CO_2 emissions. For a put option, the payoff is P*bps when the KPI value at maturity is below the KPI_goal. When the payoffs at the end of the tree are calculated, we can work backward. To work backward, we first have to calculate the continuous discount factor. The discount factor is given by:

$$discount = e^{-r\Delta t} \quad (4)$$

Let's assume that we have a two-step binomial KPI tree. If we take one step (Δt) back in the tree we can calculate the payoff by:

$$f_u = discount * (p * f_{uu} + (1-p) * f_{ud}) \quad (5)$$

$$f_d = discount * (p * f_{ud} + (1-p) * f_{dd}) \quad (6)$$

$$f = discount * (p * f_u + (1-p) * f_d) \quad (7)$$

In the latter formulas f_{uu} is the expected payoff at the most upper node after two time steps, f_{ud} is the expected payoff at the node in the middle and f_{dd} is the expected payoff at the lowest node. Those three expected payoffs are at maturity in this case, from there we can work backward to calculate f_u and f_d. Once these are known, we can determine f, the expected payoff of the binomial, which is the same as the price of the option.

Our function has the following parameters: KPI_0 (the KPI value at the start of the contract), KPI_goal (the strike price), KPI_u (the value of the KPI at the upper node after one timestep), r (the risk-free rate), T (time to maturity of the option in years), N (number of observations of the option), observations (the number of payment moments of the underlying contract per year), maturity_underlying (the time to maturity of the underlying contract in years), bps (basis points), P (the principal amount of the underlying contract). In the original binomial option tree, the parameters are S_0, K, sigma, r, T, and N. Here it can easily be seen that we added four parameters, namely observations, maturity_underlying, bps, and P and that we replaced KPI_0 for S_0 and KPI_goal for K, and KPI_u for sigma. At first sight, it might seem redundant to also have KPI_u when we have a KPI_goal which must be reached in order to receive a discount. However, KPI_u is the value of the KPI of the first upper node after one timestep, which depends on the historical volatility. The counterparties can agree to set the KPI_goal price lower than KPI_u.

4.2 BINARY KPI OPTIONS

We can use different methods to find the call price of an all-or-nothing European call option. The first method is using Monte Carlo simulations to simulate possible price/KPI paths using the Geometric Brownian Motion. The second option is using the Black-Scholes formula. We will use the latter as this is computationally more efficient and also more accurate.
We can use this binary option with a quantifiable KPI as the "asset price" (S_0). When a KPI goal is reached at the time of maturity (T), it will pay off Q, which will be equal to a predetermined amount of basis points (bps) times the principal amount (P). The probability of this happening is N(d2), where N(x) is the cumulative probability distribution for a variable with a standard normal distribution. If a KPI goal is not achieved, then there is no payout. The only money exchanged in this case is the price of the binary option at the start of the contract. According to (Hull, 2015), the pricing formulas of the binary options are:

$$Price\ binary\ call\ = Qe^{-rT}N(d_2) \quad (8)$$

$$Price\ binary\ put = Qe^{-rT}N(-d_2) \quad (9)$$

Where,

$$Q = \ bps * P \quad (10)$$

$$N(y) = \ \int_{-\infty}^{y} \frac{1}{\sqrt{2\pi}}\ e^{-\frac{x^2}{2}} dx = Cumalitive\ Standard\ Normal \quad (11)$$

$$d_2 = \frac{\ln\left(\frac{S_0}{K}\right) + \left(r - \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \quad (12)$$

We replace S_0 with KPI_0 (the value of the chosen KPI at the start of the contract) and K with KPI_goal (the target of the KPI at maturity). Furthermore, we add some parameters: observations (the number of payment moments of the underlying contract per year), maturity_underlying (the time to maturity of the underlying contract in years). The risk-free rate (r) can be set equal to the overnight interest rate ESTR of the corresponding maturity. The only factor that is still unknown is the volatility (σ). The volatility can be estimated using the data of an ESG database or a company's annual report. The price of the binary option will be paid at the start of the option's contract.

5. ANALYSES & RESULTS

5.1 BINOMIAL KPI TREE

We created a few Python scripts to calculate the price of a European binomial KPI option. To run the code, we first need to fill in the parameters of the functions that we programmed in Python. The first function that we created, calculates a KPI target based on the historical volatility of a KPI. The input parameters are KPI_0, sigma, T, and N. The function uses Equation 1 to calculate the KPI target.

```
In [3]: sigma_to_goal(100, 0.2, 1, 1)

        The KPI goal is:  122.14027581601698
```

Figure 13: Historical volatility to KPI goal calculator function

The output of this function can be used as input for the function that calculates the price of the KPI option. The input parameters are described in Chapter 4.1. Once these input parameters are filled in and the code is executed, it will generate the following output:

- The potential discount
- The value of u (calculated with Equation 1)
- The volatility of the KPI
- The probability of an up move of the KPI value
- The discount factor
- The KPI values at each node at maturity
- The payoff at each node
- The KPI option price

A more detailed overview of the code and the results can be found in the Appendix. We wrote two different functions for the binomial KPI options, namely a call and a put variant. We will describe the outputs of these functions in the section below.

5.1.1 Binomial KPI Call

As mentioned above, we wrote two different functions to calculate the KPI option price, a call and a put function. However, to see the complete price path of the KPI options in a plot, we wrote separate scripts for the call and the put function to see how the option price develops as the KPI value increases. The result can be seen in Figure 14.

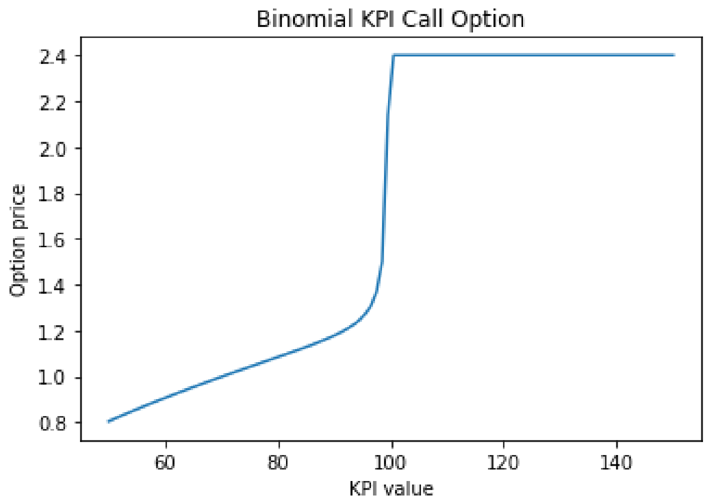


Figure 14: The binomial KPI call option price path, with KPI goal & KPI_u = 100, r = 0.004, T = 1, N = 1, observations = 12, maturity_underlying = 5, bps = 5 and P = 100

We see that the plot differs from the regular plain vanilla call option price plot. The first point is that the left side of the function increases already from the start as it usually is flat at the start. Another difference is the rapid increase in price around the strike price. The last difference is that the option price is flat once it hits the KPI goal. The option price is equal to the principal amount times the predetermined amount of basis points, which makes sense because the discount can never be more than this amount. This flat option price is programmed in on purpose because we want to stimulate banks and their counterparties to choose KPI goals that are a little ambitious with respect to the current KPI value. We therefore maximize the option price as the KPI goal is smaller or equal to the starting KPI value.

After analyzing the model, we found that the model has an inverse relationship with volatility because of the following. At a regular plain vanilla call option where the volatility would rise and the other parameters stay constant, the price of this option will increase, as the chance that the option will end up in the money also increases. However, in our model, the payoff is limited to the number of basis points that are predetermined. Therefore, when the volatility increases, there is a higher chance of ending up in the money but the payoff would stay constant at a maximum of the number of basis points times the principal amount. In other words, the expected payoff usually increases as volatility increases, but in our model, the maximum payoff is never more than the predetermined amount of basis points, which let the price of the option decrease as the volatility increases.

5.1.2 Binomial KPI Put

When we run the script which generates KPI put option prices corresponding to their KPI values and then plot the results, we get the plot in Figure 15.

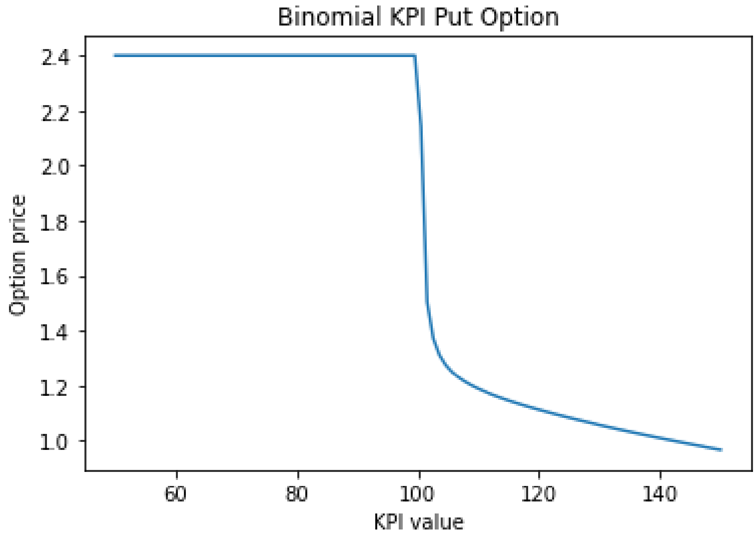


Figure 15: The binomial KPI put option price path, with KPI goal & KPI_u = 100, r = 0.004, T = 1, N = 1, observations = 12, maturity_underlying = 5, bps = 5 and P = 100

We see that this plot is the opposite of the KPI call option price plot. This makes sense as this is the KPI put option. The option is in the money when it is lower or equal to the KPI goal. This plot has the same deviations as the KPI call option: the option price maximizes from the moment it is at the money, just before the KPI goal, the option price increases exponentially and the option price is not flat when it is deeply out of the money.

5.2 BINARY KPI OPTIONS

For the binary KPI options, we wrote two different scripts, one for the call option and one for the put option. Before the function is executed, the right parameters need to be filled in. Once this is done, it will generate the following outputs:

- The potential discount at maturity
- The price of the binary option

5.2.1 Binary KPI Call

For calculating the binary KPI call option price we followed Equation 8, where Q is the principal amount times the predetermined amount of basis points. To get an insight into the option price path, we used scripts that are looking like the ones that we used for the binomial KPI tree. This generated Figure 16.

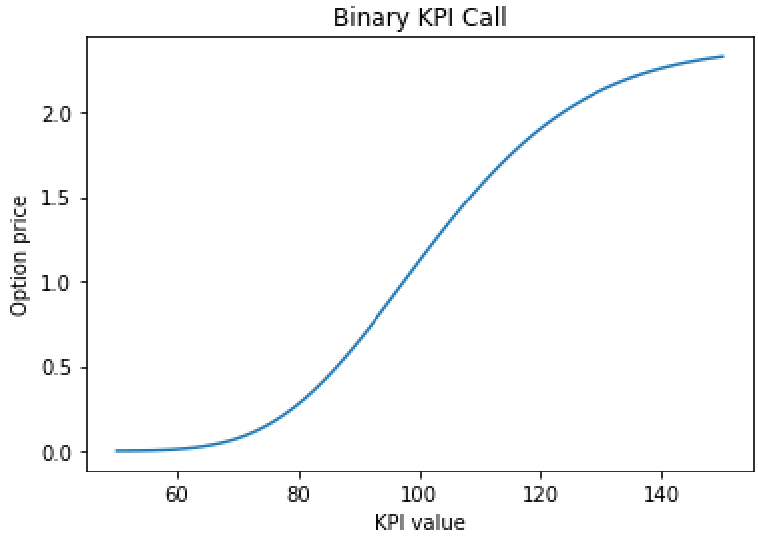


Figure 16: The binary KPI call option price path, with KPI goal = 100, r = 0.004, T = 1, N = 1, observations = 12, maturity_underlying = 5, bps = 5 and P = 100

We can see from this plot that the price starts increasing more and more once the KPI values move to around the at the money levels. Once the KPI value is getting more and more in the money, the increase in the option price flattens around the level of the principal amount times the predetermined amount of basis points.

5.2.2 Binary KPI Put

For calculating the binary KPI put option price we followed Equation 9, where just like with the call option, Q is the principal amount times the number of basis points. Once we calculated the option price path, it resulted in Figure 17.

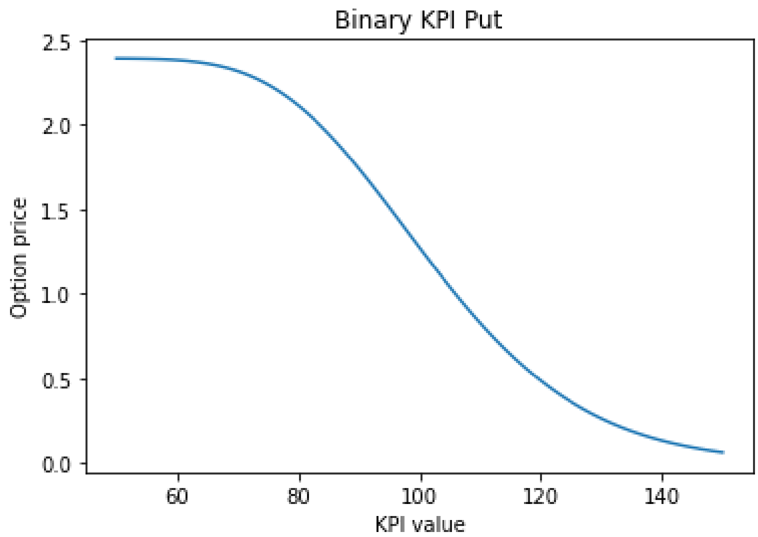


Figure 67: The binary KPI put option price path, with KPI goal = 100, r = 0.004, T = 1, N = 1, observations = 12, maturity_underlying = 5, bps = 5 and P = 100

The plot is the opposite of the binary KPI call option plot. We see that the option price decreases more as the KPI value moves to around the at the money level for the put option. Once it gets to the deep out of the money levels, the price decrease flattens.

5.3 ESG GREEKS

In this section, we look at the ESG Greeks. We look at how sensitive the option price is when underlying parameters change. When we calculated the Greeks using the static formulas that are used for plain vanilla options, we doubted if the results would give correct Greeks for the binomial KPI options. After we generated the results, our hypotheses were confirmed. The Greeks from the results did not make sense for the binomial KPI option model. Therefore, we looked at the dynamic formulas to calculate the ESG Greeks, which gave different results. These Greeks seem to be more logical, therefore we will analyze these in the section below. For the binary KPI options, we only used the static formulas as these seem to be correct. We first defined functions for every Greek per model and then we wrote complementary scripts to see how the Greeks develop through different parameters. In this section, we will analyze the Greeks for both models by focusing on one Greek at a time. However, we will only analyze the Greeks of the call options as it is redundant to analyze the Greeks of the put options as well. For comparing, we used the same parameters for both models: KPI_0 = 90, KPI_goal = 100, KPI_u = 100 (only for the binomial KPI model as it is no parameter in the binary KPI model), r = 0.004, T = 1, N = 1, observations = 12, maturity_underlying = 5, bps = 5, P = 100. However, for calculating theta, we used different KPI_0 values for creating an in-the-money (ITM), an out-the-money (OTM), and an at-the-money (ATM) option.

5.3.1 Delta

We start the analyses with one of the most popular Greeks, the delta. Delta is the price of the option with respect to the underlying asset. The delta is often used for hedging purposes.

Binomial KPI

The delta of a plain vanilla call option can be calculated using the following formulas (Hull, 2015).

$$\Delta_{call} = \Phi(d_1) \tag{13}$$

$$\Delta_{put} = -\Phi(-d_1) \tag{14}$$

Where Φ is the cumulative distribution function (CDF) of a standard normal distribution. We tried to calculate the delta using the formulas above, but it gave not a logical result, so we concluded that this is not a suitable solution to calculate the delta for our binomial KPI model. Therefore, we had to use a different method to calculate the delta. We used Equation 15 to calculate the delta. In Equation 15, the V is the option price and S is the price of the underlying asset, which we replaced for the KPI value.

$$\Delta = \frac{\delta V}{\delta S} \tag{15}$$

We programmed a script that used Equation 15 as the basis of the code and plotted Figure 18.

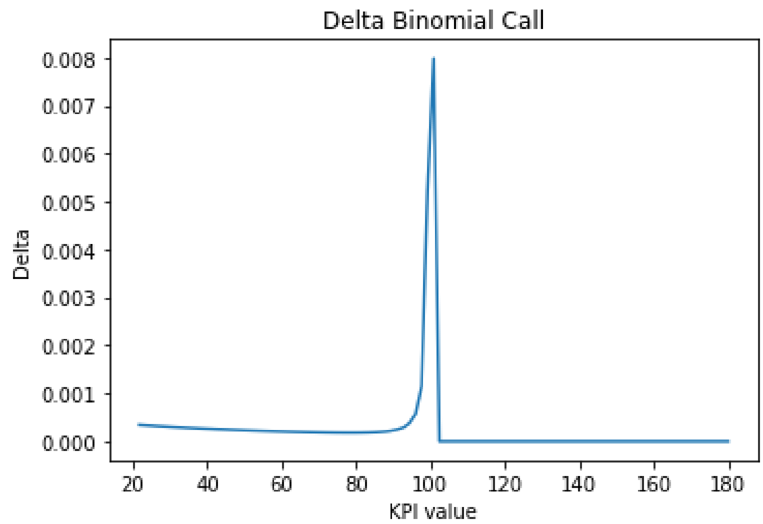


Figure 78: The delta of a binomial KPI call option, with KPI goal = 100, bps = 5, and P = 100

We see that the delta of the call option starts a little higher than zero and has the most activity around the strike price (and KPI goal). Once the option is in the money, its delta goes to zero and stays at this level as the KPI value increases. If we think about why this is happening, we look again at Equation 15. The steps of the KPI value stay the same, so what we see in the plot are only the changes in the option price with respect to the KPI value changes. If the steps of the option price changes increase, the delta becomes bigger. Obviously, when the option price changes decrease, the delta decreases. We see that the delta slightly decreases from deep out of the money till a little bit before it becomes at the money, which means that the option price steps slightly decrease. The delta quickly rises just before the strike price, which means that the option price steps become bigger. Once the KPI value reaches the strike price, the delta drops to zero. When we look at the plot of the KPI call option price path in Figure 14, the movement of the delta makes sense. We see in this figure that the price of the option indeed rapidly increases before the strike price and that the price stays constant after the strike price is hit. If the option price stays constant, the delta indeed drops to zero and stays on this level. Usually, we can talk about how the delta movements affect hedging procedures. However, it is not possible to take a position in our underlying asset, the KPI. Therefore we will not further discuss hedging implications.

Binary KPI

The delta of a cash or nothing call option can be calculated with Equation 16 (Quantpie, 2018). When we expect the formula, we see no Q, which was the only thing we adjusted to fit our model. Therefore, Equation 16 is suitable for calculating the delta of our binary KPI option pricing model. In this formula, we see a new function, $n(d_2)$, which is nothing else than the probability density function (PDF) of d_2. As can be seen in Equation 17, the PDF of the standard normal distribution can be derived by taking the derivative of the CDF of the standard normal distribution.

$$\Delta = \frac{e^{-r*dt}}{S\sigma\sqrt{T}} n(d_2) \quad \textbf{(16)}$$

Where,

$$n(y) = \frac{dN(y)}{dy} = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} = Standard\ Normal\ Density \quad \textbf{(17)}$$

We programmed Equation 16 to calculate the delta. After that, we wrote another script to see how the delta develops through different starting KPI values. The result is given in Figure 19.

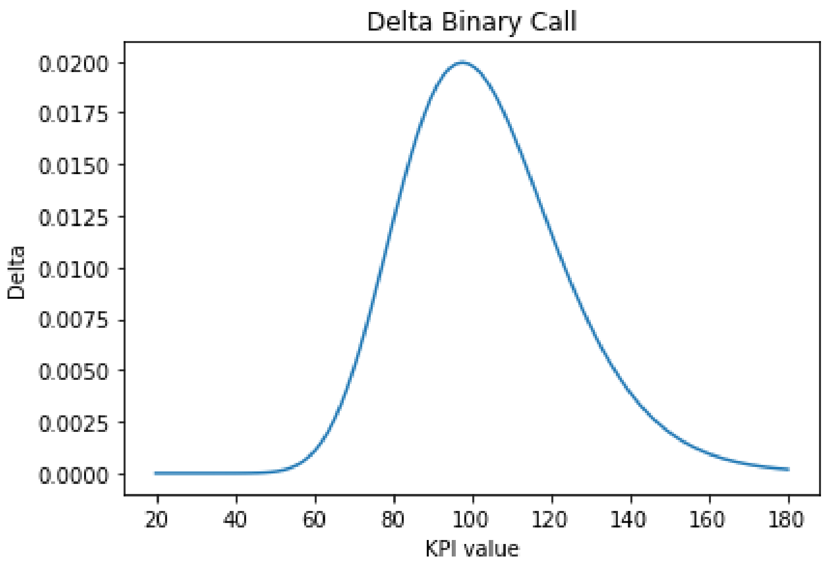


Figure 198: The delta of a binary KPI call option, with KPI goal = 100, bps = 5, and P = 100

Figure 19 shows that the delta of a binary option starts at the left side around zero and starts to gradually increase once the KPI value is around 50% of the KPI goal. At 70% the increase starts to reach its maximum, which continues till 80% of the KPI goal. The parabola reaches its top just at the left side of the KPI goal. This shows that the delta of this binary option is positively skewed. The tail on the right side is also somewhat fatter than the left side. When we compare this curve with the curve of the delta of the binomial KPI call option, we see that the delta of the binary option has a wider parabola whereas the curve of the binomial option increases sharply around the at the money levels. This means that the changes between the option price steps of the binary KPI option increase faster than the option price steps from the binomial KPI option. Another thing that stands out is that the delta at the top is at least twice as high for the binary option in comparison with the binomial option.

5.3.2 Gamma

Gamma is the rate of change of the option's delta with respect to the price of the underlying's asset price (in our case the KPI value). Gamma has the highest value around the at the money levels, so gamma is relatively small when it is deeply out of the money or deeply in the money.

Binomial KPI

The gamma of a binomial option can be calculated using Equation 18 (Hull, 2015).

$$\Gamma = \frac{\delta \Delta}{\delta S} = \frac{\delta^2 V}{\delta S^2} \quad \textbf{(18)}$$

For the calculation of gamma, we needed to calculate the delta of the binomial KPI option first. In Figure 20 we see the gamma of the binomial KPI call option with respect to the KPI value.

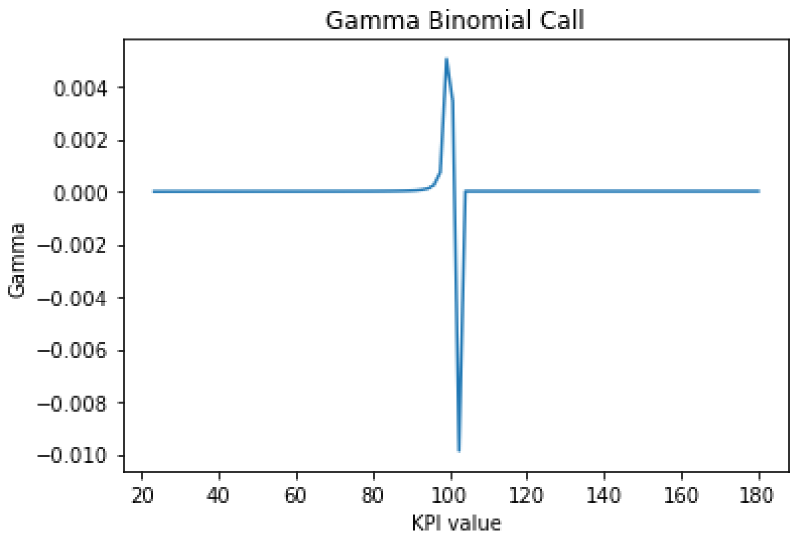


Figure 20: The gamma of a binomial KPI call option, with KPI goal = 100, bps = 5, and P = 100

What is striking about Figure 20 is that the gamma movement is only just before the KPI goal, at the KPI goal, and shortly after it. What is hard to see is that the left side (before the spikes) lies around the plus side of zero and the right side (after the spikes) lies just below zero and has therefore a negative gamma. When we compare this with the delta plot (Figure 18), it makes sense that the gamma plot looks this. The delta plot starts a little above zero and strongly increases before the KPI goal and declines sharply to zero once the KPI goal is reached. When the differences between the delta points increase, gamma increases. When the differences between the delta points decrease, we see gamma also decreasing. After the delta reaches its top, gamma becomes instantly negative (which is the spike to the bottom), as the difference between the delta points becomes negative. Gamma quickly moves back to the (negative) levels around zero as delta stays constant around this level.

Binary KPI

For the calculations of gamma of the binary call option, we used Equation 19 (Quantpie, 2018). This formula introduces d_1, which has a few parameters that are replaced with parameters from our model. Namely, $S_0 = KPI\_0$ and $K = KPI\_goal$.

$$\Gamma = \frac{e^{-r*dt}}{S^2\sigma^2 T} n(d_2) d_1 \quad \textbf{(19)}$$

Where,

$$d_1 = \frac{\ln\left(\frac{S_0}{K}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \quad \textbf{(20)}$$

Once these formulas were coded and the path of gamma was programmed, we got Figure 21, as a result.

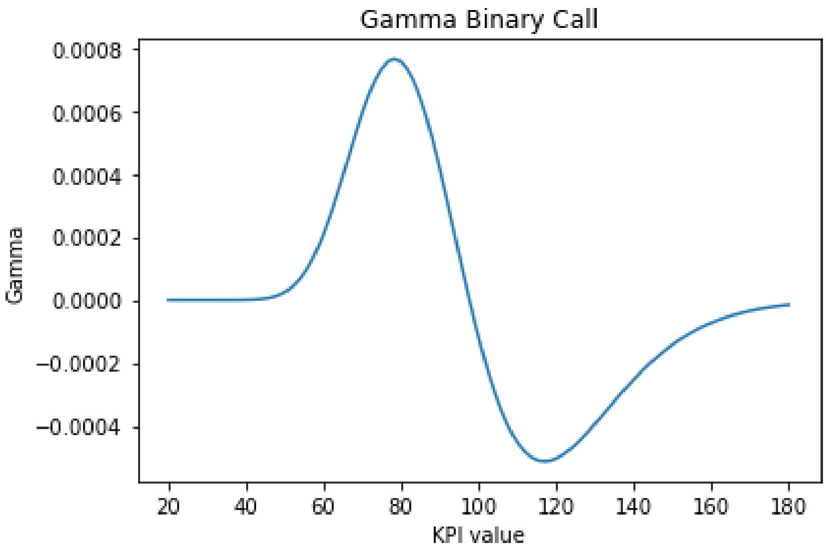


Figure 21: The gamma of a binary KPI call option, with KPI goal = 100, bps = 5, and P = 100

In this graph we see movements happening already far before the KPI goal. We know that the gamma ratio is the change in delta with respect to the underlying's asset price, which is the KPI value in our case. When we look at the delta of the binary call option (Figure 19), we can explain what is happening in this plot. The delta starts moving upwards after the KPI value passes 40. We see that the delta accelerates (the changes between the delta points become bigger) and maximizes around a KPI value of 80, this gives the upper peak in the gamma graph. Then the acceleration of the delta slows down and the delta reaches its top just before the KPI value is 100. From the top, the delta starts accelerating downwards and reaches its maximum decline speed between a KPI value of 110-120, which gives a bottom at the gamma chart. Then the delta starts decreasing more slowly and therefore the gamma increases again.

When we look at the differences between the gamma of the binomial and the binary option, the first thing we noticed were the different values of gamma. The maximum movements (top and bottom of the plot) of gamma for the binary option were at least 10 times lower than the movements of the binomial option. As we saw with the delta of both models, the parabolas of the binary option are wider and the movements there do not only happen close to the KPI goal.

5.3.3 Vega

Vega measures the sensitivity of the option price if the implied volatility of the underlying asset changes.

Binomial KPI

The vega of a binomial option can be calculated with Equation 21 (Hull, 2015).

$$\upsilon = \frac{\delta V}{\delta \sigma} \tag{21}$$

In our model, we do not have sigma as a parameter. The parameter that sets the implied volatility is KPI_u. KPI_u is the value of the first upper node after one timestep. When we have the value of KPI_u, we can calculate the implied volatility using Equation 1. We wrote another script to calculate the implied volatility for different KPI_u values and plotted this against the option price. The result can be seen in Figure 22.

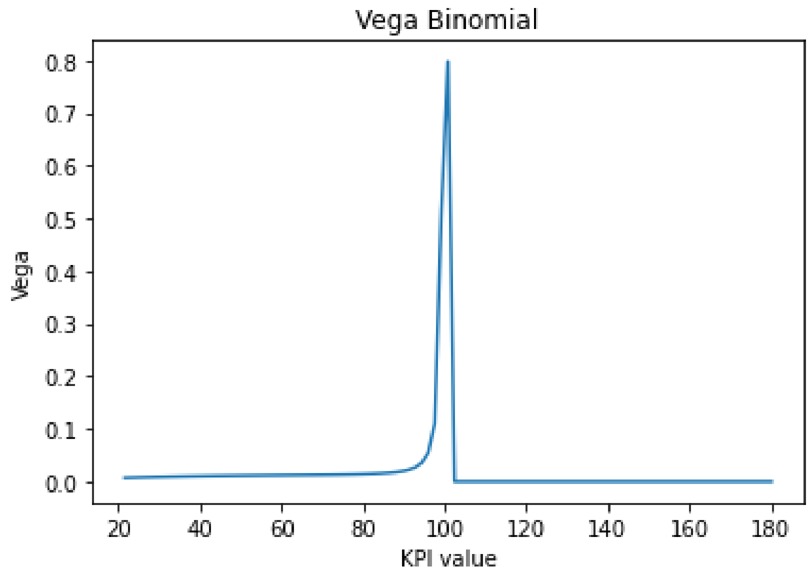


Figure 22: The vega of a binomial KPI option, with KPI goal = 100, bps = 5, and P = 100

The first thing that strikes us is that the graph looks exactly like the delta chart. However, the values of the vega are 1000 times higher than the delta. Vega changes if there are large moves in the underlying asset, we see this happening around the KPI goal. Furthermore, the vega declines as maturity comes closer. We can see this if we plot different times to maturity.

Binary KPI

The vega of a binary call option can be calculated with Equation 22 (Quantpie, 2018). Usually, the vega is the same for both the call and the put option, but this is not the case for the vega of binary options.

$$\upsilon = -\frac{e^{-r*dt}}{\sigma} d_1\, n(d_2) \tag{22}$$

After programming this formula and defining a list of implied volatilities, we were able to calculate the vega for different implied volatilities. The result is visible in Figure 23.

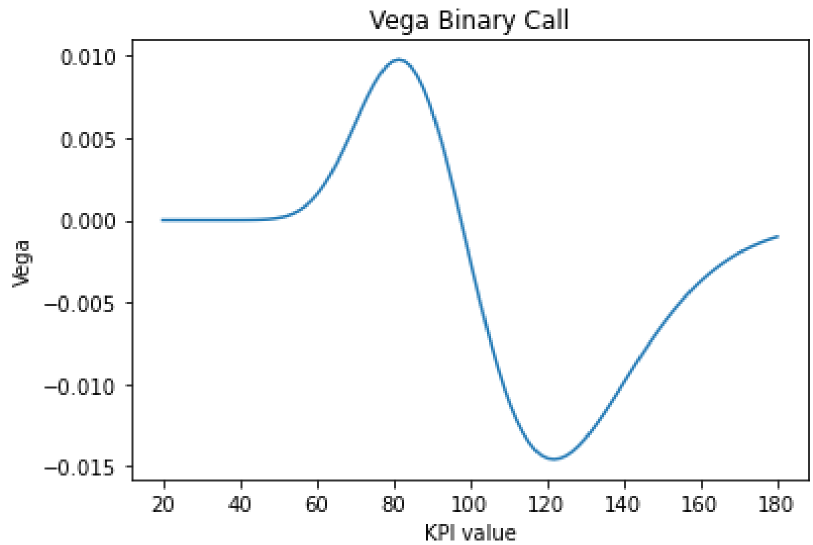


Figure 23: The vega of a binary KPI call option, with KPI goal = 100, bps = 5, and P = 100

The first thing we see is that the binary vega takes both positive and negative values, as the conventional vega is always positive. Around the at the money levels, vega is close to zero, while at the conventional vega, this is the highest point of vega. This can also be seen in the vega of the binomial KPI option. We can also see that this figure follows the same pattern as the gamma plot of the binary call. However, the graph seemed to have slightly moved to the right and the values of vega are different from the gamma values. We see that the values of vega are more than 10 times higher. Another difference is that the positive parabola is smaller than the negative parabola, which is the other way around in the gamma graph. We know that vega shows the sensitivity of the option price as the implied volatility of the underlying asset changes.

At the lower KPI values, an increase in the implied volatility does not make the difference to end up in the money. However, as the KPI value increases, the impact of an increasing implied volatility becomes bigger. Therefore, vega rises. When the binary call option is in the money, there is no upside anymore if the implied volatility increases. On the contrary, if the implied volatility increases, there is a higher chance now to get out the money again. Therefore, vega moves down. As the KPI value increases, the chance of getting out the money again decreases, and therefore the vega moves back to the zero levels.

5.3.4 Theta

Theta measures the sensitivity of the value of the derivative to the passage of time, which is also called time decay. At plain vanilla options, we can see that if every other parameter stays constant, the option will lose value.

Binomial KPI

To calculate the theta of the binomial KPI, we used the formula given by Equation 23 (Hull, 2015).

$$\Theta = -\frac{\delta V}{\delta T} \tag{23}$$

We chose to plot an ITM, OTM, and an ATM binomial call option because this would show the differences in theta between those options. Plotting these options gave us the following output:

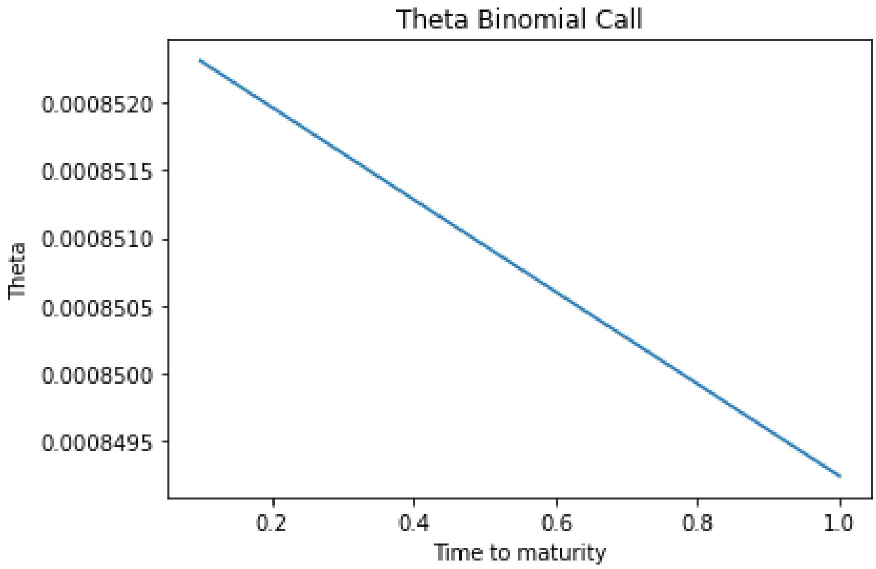


Figure 24: The theta of an OTM binomial KPI call option, with KPI_0 = 90, KPI goal = 100, bps = 5 and P = 100

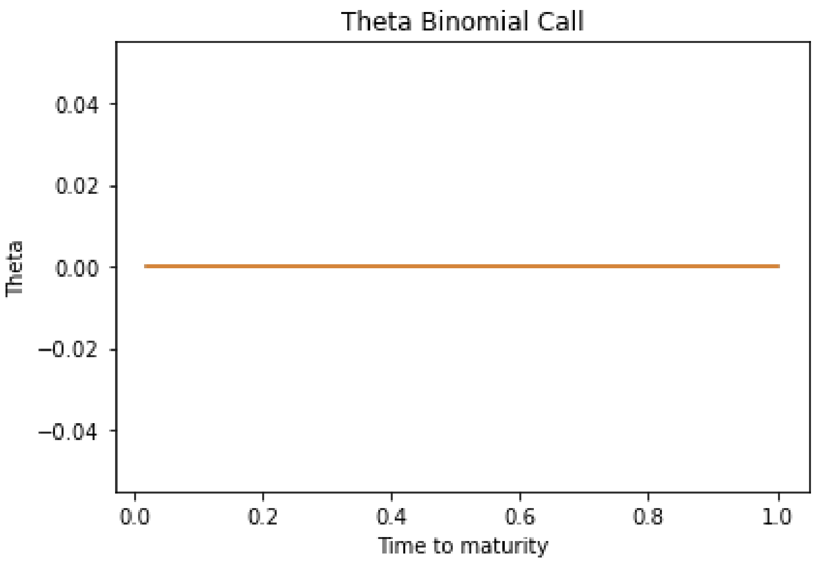


Figure 25: The theta of an ATM and ITM binomial KPI call option, with KPI_0 = 100 & 110, KPI goal = 100, bps = 5 and P = 100

We plotted the ITM in a different graph than the OTM and the ATM plots, because otherwise the movement of the ITM theta was not visible. There are a few remarkable things about the plots in Figure 24 & Figure 25. The first remarkable thing is that both the ITM and ATM plots are all exactly on the same line, namely on the x-axis. We expected the plots to differ because an ATM option has a lower chance to end up in the money at maturity than an ITM option. The second remarkable thing is that the OTM plot is linear. We expected the ITM theta to grow exponentially as maturity comes close and the OTM theta to decrease exponentially as maturity approaches. However, the OTM theta does the opposite and the ITM theta is zero at all times.

Binary KPI
The theta of a binary call option can be calculated using Equation 24 (Quantpie, 2018).

$$\Theta = e^{-r*dt}\left(n(d_2)\frac{1}{2T}\frac{1}{\sigma\sqrt{T}}\left(\ln\left(\frac{S_0}{K}\right) - \left(r - \frac{\sigma^2}{2}\right)T\right) + N(d_2)\right) \quad \textbf{(24)}$$

After implementing the formula, we created three different theta plots. One for an in-the-money binary option, one for an out-the-money binary option, and one binary option which was at the money. The result can be found in Figure 26.

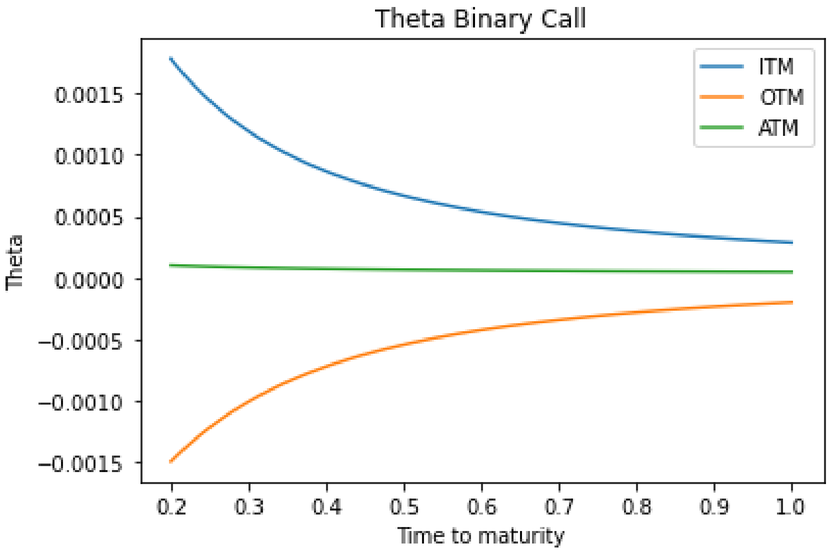


Figure 26: The time decay (theta decay) of an OTM, ATM and ITM binary KPI call option, with KPI_0 = 90, 100, 110, KPI goal = 100, bps = 5 and P = 100

Theta expresses how much the option's value will decline or rise to maturity. We can see in the graph that this differs per plot. The theta of the ITM binary call increases the closer it comes to maturity as the chance that it will end up above the KPI goal grows. For the theta of the OTM binary call, it is the other way around. The chance that it will end up above the KPI goal decreases as maturity approaches, therefore theta decreases as it comes closer to maturity. For the ATM binary call it can still go two sides as maturity nears, consequently, theta stays constant around zero.

5.3.5 Rho

Rho measures the sensitivity of the interest rate change on the option's price. It is the derivative of the option value with respect to the risk-free rate.

Binomial KPI
To calculate the rho of the binomial KPI call option, we used Equation 25 (Hull, 2015).

$$\rho = \frac{\delta V}{\delta r} \quad \textbf{(25)}$$

We plotted the rho of a binomial KPI call in Figure 27.

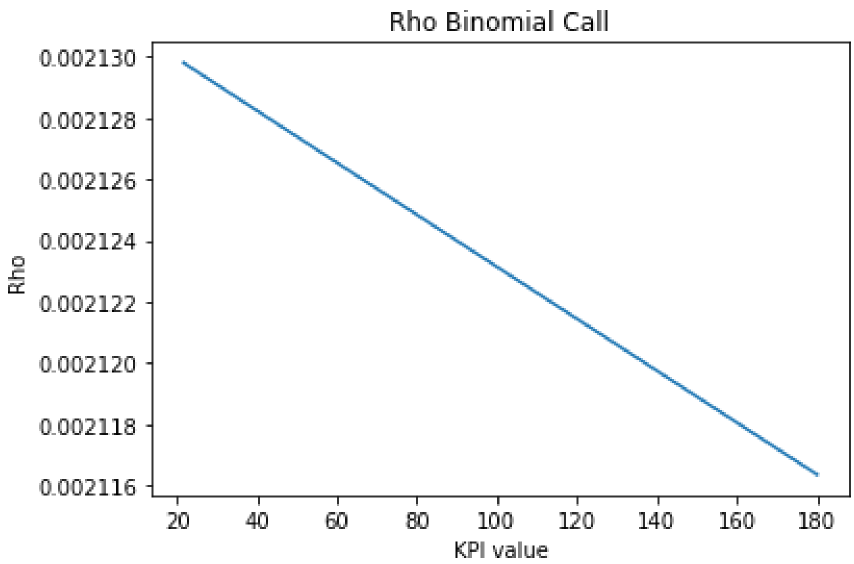


Figure 27: The rho of a binomial KPI call option, with KPI goal = 100, bps = 5, and P = 100

We can interpret the rho value as follows: if the interest rate increases by 1% (e.g. from 1% to 2%) and rho is 0.00212, then the price of the call option rises by 0.00212 (e.g. from 0.002 to 0.00412). One noticeable thing is that the rho decreases for the call option. Usually, rho increases for call options. However, the effect of rho on the binomial KPI call option is relatively low compared to other parameters.

Binary KPI

The rho of a binary call option can be calculated using Equation 26 (Quantpie, 2018).

$$\rho = e^{-r*dt}\left(\frac{\sqrt{T}}{\sigma}\, n(d_2) - T\, N(d_2)\right) \tag{26}$$

We implemented Equation 26 in our script and it generated the following graph:

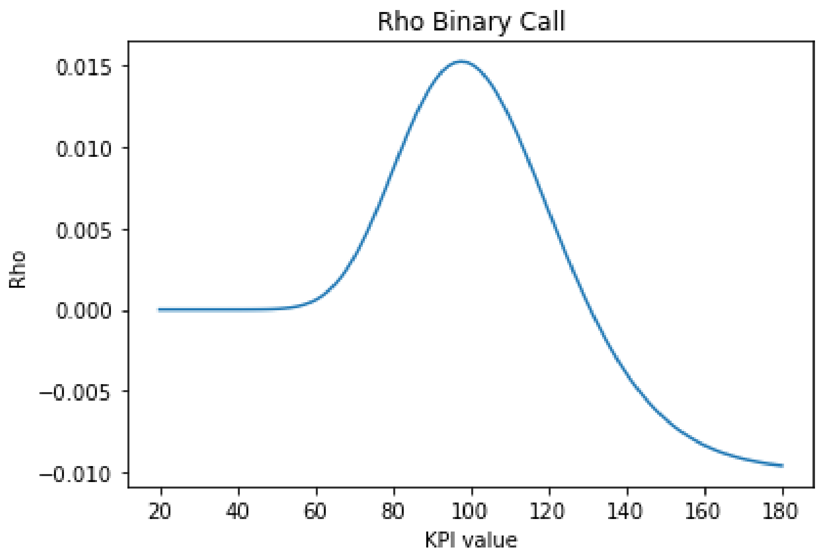


Figure 28: The rho of a binary KPI call option, with KPI goal = 100, bps = 5, and P = 100

The rho of a binary option moves differently than regular plain vanilla call options because at binary options, once the strike price is reached, the payoff does not increase if the asset price keeps rising. Therefore, we see in Figure 28, that once the KPI goal is passed, the value of rho decreases and at a certain point even becomes negative, which means that the call option price decreases as the interest rate goes up.

5.4 WHAT DOES THE TOTAL FINANCIAL PRODUCT LOOK LIKE?

Our ESG-linked financial product consists of two components, the base product, and the KPI option. The base product can be any financial product with an interest rate or spread that the bank offers, e.g. bonds, loans, mortgages, interest rate swaps, credit rate swaps, etc. On top of the base product, we can use either the binomial KPI option or the binary KPI option. After analyzing the price paths and the Greeks of the models, we see that the binomial KPI option model has sharp movements around the KPI goal value. This is because we programmed our model in a way that the price of the option is directly equal to the potential payoff once the KPI value reaches the KPI goal value. We decided to program it this way to stimulate banks to set ambitious KPI targets. In the case of a binomial call option, the price of the option is maximum when the starting KPI value is at or above the KPI goal.

To sketch an image of what the complete product looks like, we will describe an interest rate swap + binary KPI option. Suppose Company XYZ wants to protect itself against the interest rate risk and therefore goes to the bank to get into an interest rate swap with a principal amount of 3 million euros for a duration of 5 years. The banks offer the company to pay the variable rate and would in return receive a fixed rate of 5% from the company every month. On top of that, the bank gives the company the option to enter an ESG-focused binary KPI option which would give the company x basis points discount on the fixed rate if a certain ESG-related KPI target is reached. Company XYZ is an IT business that uses a lot of energy to run its servers and cooling systems. They have already quite some solar panels on their roof to use a little bit of sustainable energy for their energy usage. The sustainable energy/total energy ratio is 25%. Furthermore, the company has 20 employees of which 90% are men. Company XYZ wants to improve on its environmental and social responsibility, so the company tells the bank that it wants to enter two binary KPI options. The bank sees that the social situation of the company is more important to improve than the environmental one as the company already uses quite some solar energy. Therefore, the bank and Company XYZ come to an agreement that the business would receive a discount of 2 basis points if it decreases the men employees/total employees ratio to 70% percent in 3 years. The company will receive a 1 basis point discount on the monthly paid fixed rate if the company increases its sustainable energy/total energy ratio to 35% in 2 years.

We can now get into the calculations of the price of the binary KPI options. To calculate prices that are fair for both parties, we want to find the historical volatilities for the "E" binary KPI option and the "S" binary KPI option to calculate the probabilities that those KPIs will be achieved. From Company XYZ's annual reports, we can calculate that the historical volatility of sustainable energy/total energy is 31.4%. Unluckily, the men employees/total employees ratio is not a ratio which is stated in the business's annual report. Company XYZ is also not a publicly traded company, so those ratios can also not be found in ESG databases. Therefore, we search for publicly traded companies of around the same size out of the same sector. We found a publicly traded company of around the same size as Company XYZ which's men employee/total employee ratio historical volatility was 24.9%. Now that all the parameters are known, we can calculate the prices of the binary KPI options. In Figures 29 & 30 we can see the results of our binary KPI call and put option. With the call option, we calculated the price for the "E" binary KPI option, and for the "S" we used the put option.

```
In [4]: binary_call(0.25,0.35,0.004,0.314,3,12,5,2,3000000)

        The potential total payoff =  14400.0 euro
        The price of the binary option is:  2739.6472990665116 euro
```

Figure 29: Binary call environmental KPI example

```
In [11]: binary_put(0.9,0.7,0.004,0.249,2,12,5,1,3000000)

         The potential total payoff =  10800.0 euro
         The price of the binary put option is:  3081.6291756955584 euro
```

Figure 30: Binary put social KPI example

As can be seen in the figures above, the binary option price for the environmental KPI is €2739.65 and has a potential payoff of in total €14,400.-. The latter amount is calculated by computing how many periods the amount of bps times the principal amount is paid out. This is done by subtracting the T (the time to maturity of the option) from the time to maturity of the underlying contract and multiplying this amount by the number of times the fixed leg is paid per year (12, because there are monthly payments in this case) by Company XYZ. So, in our example, it is (5-3)*12 = 24. This amount is multiplied by bps*principal amount, which gives 24*(0.0002*3,000,000) = €14,400.-. In other words, if Company XYZ increased its sustainable energy/total energy ratio to at least 35% at the end of the 3 years, it will receive €600.- discount every month till the end of the IRS contract (starting logically after the KPI option period, 3 years). The calculations of the binary put option follow the same principles. Instead of the binary KPI options, we could also have used the binomial KPI options. The calculations differentiate a little bit and also provide a different price path. Depending on the ambitions of a company and the risk preferences of the bank, the right KPI option model can be chosen.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 CONCLUSIONS

ESG is a trending topic for companies and especially for financial institutions. Banks are at the center of the transition of the business landscape towards a more ESG-embraced field. The main research question therefore was:

How could ABN AMRO create, price, and model financial products that promote ESG among its corporate and institutional clients, and third parties?

Reasons to offer ESG products

We created a theoretical framework and built our own ESG-linked derivatives to get an answer to this research question. We started by investigating the goal of offering ESG-related financial products. We concluded that there are four main reasons for creating such products. The four main reasons were: customer demand, regulations, profit potential, and competition. We will summarize the reasons per point.

- **Customer's demand**
  More than 2/3 of the surveyed SMEs were expecting their banks to offer ESG-financing products. The sustainability-linked loan market increased more than 300% in 2021 and therefore underlines the opportunities that arise from anticipating the customer's demand. Also, ESG investment products are getting more interest, because they offer easy exposure to highly rated ESG companies. Banks are already offering the latter.

- **Regulations**
  To protect banks against greenwashing, regulators are trying to form a comprehensive ESG regulatory framework. Six measures will contribute to this framework. The first is the Sustainable Finance Disclosure (SFDR) from the European Commission. This disclosure imposes mandatory disclosures to all financial market participants and aims to make the sustainable profile of a financial product more comparable and easier to understand (AFM, 2021).
  The second point is the Corporate Sustainability Reporting Directive (CSRD) the European Commission which intends to make ESG aspects evaluable for investors (European Commission, 2022).
  The third measure is the Taxonomy Regulation. This classification system's purpose is to set up criteria that determine whether an economic activity is good for the environment or not (S&P Global, 2021).
  The fourth is MiFID II, this directive aims to make European financial markets more efficient and transparent while investor's protection increases (Patrick Schmucki, 2022).
  The fifth one is the Capital Requirements Regulation (CRR II), which requires large banks to disclose ESG risks (Patrick Schmucki, 2022).
  The last measure is a worldwide action. The International Standards Board (ISSB) will create the Sustainability Disclosure Standards. These standards should also contribute to making disclosures more comparable and consistent throughout different industries and jurisdictions (EY, 2021c).
  The regulations that are developed will trigger banks to take action. A regulatory ground is being formed and will stimulate banks to create or expand their current ESG-linked financial product offerings. Despite this regulatory ESG foundation, due to the large stream of speculations on future regulatory changes, it keeps a challenge for banks to develop a solid ESG strategy (KPMG, 2021).

- **Profit potential**
  The loan portfolio of banks can be divided into three different business segments: dark green, transition, and brown. The dark green businesses are the once that are intrinsically having a positive impact on ESG aspects, like wind and solar farms. The part that consists of 90% of the bank's loan portfolio is the transition businesses. These are the once that are not yet ESG compliant but may be able to reach this state in the future. Zeb's research forecasts that the highest volumes, margins, and earnings are in this group (Rupp et al., 2021). This market is relatively untapped and has significant profit potential. To target this group, banks should research where the main financing needs are for businesses that lie in the bank's current focus sectors or segments (Dell'Aversana & Paltenghi, 2021). Furthermore, the initial focus should be on the companies that face the biggest pressure to adapt from regulators, competition, or customers and are the most capable to implement ESG requirements (Dell'Aversana & Paltenghi, 2021). The brown businesses on the other side, the businesses that can never become ESG compliant, are obviously not a market where banks should look for ESG-linked financing.

- **Competition**
  The volume of ESG-linked products is increasing significantly every year. This means that there are companies that are already benefiting from this flourishing market. For the bond market, bond issuers with a higher ESG score

had statistically stronger financials than their competitors with an average or low ESG score, which eventually led to a higher credit score (Mendiratta et al., 2021).

Banks who are pioneers in the field of ESG will create a competitive advantage and will profit from higher volumes, margins, and earnings. Commercial banks that score high on material ESG issues will perform better in the future than banks with low material ESG scores (Deloitte, 2019).

Customer demand, regulations, profit potential, and competition all play a part in the reasons to offer ESG-linked financial products. When banks are considering offering such products, they will have to focus on every single of the points that are mentioned above.

Stimulating ESG among third parties

The next thing we researched was how clients could stimulate ESG among third parties. The conclusion of this question was to implement supply chain wide ESG-related KPIs when a company comes to the bank for financing products. KPIs that are meaningful throughout the whole supply chain can improve multiple ESG aspects while decreasing the credit risks of the party that requests financing. Supply chain wide KPIs can be the percentage of recycled products used, the percentage of GHG reduction throughout the whole supply chain, or the total overtime/total FTEs. A problem that banks are likely to face is conducting a supply chain wide ESG risk scan. Some companies especially in certain jurisdictions won't have to disclose ESG risks. In this situation, blockchain can help to create transparency.

ESG-derivatives

Now that we know that there are multiple reasons to offer ESG products and how ESG could also be stimulated among third parties, we wanted to know which products were relevant to offer. We found that ISDA (2021a) provided a long list of ESG-related derivatives. We initially decided to focus on ESG-linked interest rate swaps because otherwise, the focus on all the different derivatives would have been very broad. However, later on, when we found out that we could use KPI option models to add to a base product, we stopped focusing on interest rate swaps alone and looked at where these KPI option models could further be used.

Constructing ESG-linked derivatives

At the next sub-research question we looked at how ESG-related derivatives could be set up. For the bonus/malus system on top of a derivative, we need to choose an ESG KPI. To find out which ESG KPIs are relevant, we did some literature research and found that we could better focus on material ESG issues as investments in companies who score high on material issues, outperform those who score low on material issues (Khan et al., 2016). Selecting material ESG KPIs will also lead to lower credit risk (Deloitte, 2019). We use SASB's Materiality Finder to find which material ESG issues are relevant to a company in a specific sector. We extended SABS's material ESG framework and incorporated the "Corporate Governance" column because the "G" of ESG was not accurately covered in the original framework (Steinbarth & Bennett, 2018). With SASB's Materiality Finder, we can search for corresponding ESG metrics in World Economic Forum's 2020 whitepaper, which can be used as KPIs for our option model. We found that the KPIs can be measured by analyzing annual public reports or by an independent third party. Next to that, the clients can be stimulated to achieve the KPI goals by financial motivation, reputational motivation, or competition.

Pricing ESG-linked derivatives

In this section, we questioned ourselves what the ESG-linked derivative should look like and how it could be priced. Current ESG derivatives are based on a step-down and/or step-up structure which adds a penalty or a discount to the counterparty's payments, depending on whether a KPI target was achieved or not. At the moment, banks are setting KPI targets that are feasible to achieve, which results in many companies reaching the KPIs and that the bank has to pay them a discount of a certain amount of basis points. These targets are currently not based on historical numbers from the company or similar companies because of data scarcity. When we analyzed the structure, we found that the base financial product in ESG derivatives did not change and that we could also view ESG derivatives as a base product plus an option depending on a KPI on top of it. We determined to research how we could create and price a KPI option. Therefore, we decided to look at which existing option pricing models were suitable to fit the requirements of a KPI option model, offering a discount of x basis points when a KPI target is achieved. We concluded that we could alternate a binomial tree model and a binary option model to price a KPI option.

Risks and their mitigation

We analyzed multiple scenarios to see whether offering a KPI option model would create extra risks for a bank. We saw that our model would create no direct environmental-related risks. However, we want to incorporate the probability that a company will reach a certain KPI in our model. The scarce data at the starting phase might lead to inaccurate estimations of probabilities and can lead to underwriting risks. We want to mitigate this risk by testing our KPI option model on small groups of corporate and retail clients while testing a variety of KPIs. Next to the environmental risks, also social and governance risks can arise. A social risk that our model can bring is the indirect exclusion of certain clients. KPIs should be formulated in a way that each client of the target client group should be reasonably able to achieve an ESG KPI goal. A governance risk that can occur is attempted bribery or corruption. Working together with an independent third party that measures KPIs can reduce this risk.

Furthermore, we looked at how general ESG risks can be assuaged. The findings consist of three steps. The first step is to identify, measure and evaluate the bank's current ESG exposure. This can help to pinpoint which assets in the portfolio create too much exposure to ESG risks. The second step is to prepare for a climate stress test, this can help to create more resilience for plausible future climatic conditions. The last step is to add ESG risk inspection to the KYC methods. This can help collect more comparable ESG data of clients, more accurate credit worthiness assessments, and would avoid reporting fatigue on the client's side (PwC, 2021) because it does not have to enter two different procedures.

KPI option models

After we programmed the binary and binomial models, we adjusted them in a way so that they would meet the requirements of the KPI option model. We analyzed not only the price paths of both models but also the Greeks, to see how sensitive the option prices are with respect to certain changing parameters. There are two important differences between the models. The first one is that the option price of the binomial model starts at a significantly higher point. This might be positive if the bank wants to take less risk on such options, however, it might also be that the counterparty would not want to enter such an option when they know that it is more expensive than the binary variant. The other important difference is that the option price of the binomial option model hits the maximum price once the KPI starting value reaches the KPI goal. This was a decision made before programming the model because it would stimulate banks to choose ambitious KPI targets for the counterparty. The binary options on the other hand show a more gradual price movement, even after the KPI starting values cross the KPI target values. From the Greeks, we can also see that changing parameters has the most effect on the binomial model close to the KPI goal. At other levels, however, these changing parameters have a relatively low impact on the option's price. For the binary model, we see that the effects are more spread around the KPI goal. Hedging these options seem no possibility as no positions can be taken in the underlying asset, the KPI.

Now that we found the answers to our sub-research questions and we created the model, we are able to answer the main research question. For the creation of financial ESG products, one needs to think about the reasons to offer such products. These reasons can be categorized into four categories: customer demand, regulations, profit potential, and competition. To build a financial ESG product, it is optimal to use a KPI framework that can internationally be used across different sectors and segments. With SASB's Materiality Finder we check which general material ESG issues are relevant for a company in that specific industry. We look at the strategy and ESG ambitions of the company and select the most important issues for the company out of the expanded SASB framework. After this step, we look up the chosen ESG issues in the World Economic Forum's 2020 paper and find the corresponding ESG metrics. In collaboration with the company, the bank sets up material ESG KPIs. We think that focusing on material ESG KPIs would contribute to a higher financial performance of businesses. Preferably, banks also take into account ESG KPIs that can be used supply chain wide but this may be a step too far yet. We found that current ESG derivatives are just a base financial product (e.g. bond, IRS, or with a bonus/malus system on top of it. We transformed the bonus/malus system into a KPI option, which gives x basis points discount on the underlying base product till maturity of this base product if a KPI target is achieved. If the KPI goal is not reached, the counterparty did already pay for the KPI option at the start of the contract, and therefore only paid a "penalty". We set up a list of requirements for our KPI option model. Then we analyzed different existing models and concluded that a binomial tree model and a binary model were good candidates for our KPI option model. We adjusted a binomial tree model and a binary model as KPI option models. This made it possible for us to price every quantifiable KPI. The binary KPI model seems to be the more "fair" model for both parties because its option price starts at zero and has gradual price movements, also for starting KPI values that are bigger than the KPI goal (for call options).

6.2 RECOMMENDATIONS

From the conclusions we made, we can derive a list of recommendations for ABN AMRO, but also for banks in general.

1. Analyze the needs for ESG-linked derivatives from transition businesses within the bank's own customers list. This will give insights into what most customers want and helps to understand where the demand is for ESG-linked derivatives. This might also help to better focus on targeting new customers that are transition businesses.

2. Explore which transition businesses outside the bank's customer list could potentially be new customers. Growing the number of customers within the focus sector and segments of the bank increases the insight into ESG product needs, but also delivers data on KPIs, which is essential for banks to accurately estimate volatilities and calculate the probabilities that a company will achieve a KPI goal. This would contribute to more "fair" pricing of the KPI option models. We recommend that the bank should initially focus on the companies that face the biggest pressure to adapt from regulators, competition, or customers and are the most capable to implement ESG requirements.

3. Create an ESG hub that enables the innovation of financial ESG products. This ESG hub should in the end facilitate the bank to be a one-hop stop for all ESG-linked financial products a customer may need. Creating new ESG products might also create a competitor advantage. Besides that, the ESG hub should also stay on top of the newest regulatory developments, so that they could immediately get an idea of how new regulations would affect the current processes.

4. Try to get or maintain a high ESG score from ESG rating providers. It is shown that this will lead to stronger financials and eventually to a better credit risk score for a bank (Mendiratta et al., 2021). ESG rating providers do not only look at the products a bank offers but also at its investments, its clients, the board, the work environment, etc. Therefore, ESG strategies and policies should be implemented throughout the whole organization to show that it intrinsically emphasizes ESG.

5. We recommend using the binary KPI model over the binomial KPI model because of the “fair” pricing issue. Using one of our KPI option models decreases the underwriting risks compared to original ESG derivatives because our models are based on historical data. The KPI option models also have a different cash flow structure. At the original ESG derivatives, both penalties and bonuses were paid out from the end of a predetermined period till the maturity of the base product. With the KPI option models, bonuses still work the same but the “penalty” is the price of the option, which is paid at once at the start of the option’s contract. So, in cases of defaults, the bank still receives the “penalty” with the KPI option models.

6. Use SASB’s Materiality Finder to pinpoint the material ESG issues of the counterparty. Thereafter, discuss with the client which of these material ESG issues deserve the most attention. When the priorities are given to certain material ESG issues, corresponding material ESG KPIs can be found in World Economic Forum’s 2020 whitepaper. Again, together with the client, material ESG metrics can be chosen for the KPI options. We recommend to not use ESG scores as KPIs as rating agencies are not transparent about their methodologies yet. When ESG rating providers will have standardized/universal methodological frameworks, banks can use ESG scores as KPIs.

7. Both of our KPI option models use historical volatility as a parameter. We recommend fetching these values from annual reports or ESG databases. If a company is underperforming on a KPI with respect to its competitors, we recommend taking the average historical volatility of the sector where the company operates. If a company performs better than the average of a sector, we recommend using the company’s own historical volatility of the KPI.

8. For big potential payoffs, so a high principal amount and/or high amount of basis points, we recommend involving an independent third party in the KPI measuring process. The involvement of a third independent party also decreases the risk of bribery and corruption.

9. We recommend identifying, measuring, and evaluating the bank’s current exposure to ESG risks. This will help to understand to which risks the bank may be overexposed and allows reconsidering certain positions.

10. Banks should prepare for climate stress tests, or better said, improve their resilience to different climate scenarios. Herefore, it is also important to know the current exposure to ESG risks. If the bank's current exposure is known, various climate scenarios can be simulated to see how it will impact the ESG risks and what the effect on the bank’s portfolio will be. It may be the case in the future that extra capital is required for an increase in the ESG risks of a bank’s portfolio.

11. The last recommendation is to implement ESG risk inspections to the bank’s current KYC procedures. Banks should also retrieve information on the borrower’s ESG risk mitigation strategies. This will help to obtain more comparable ESG data and will lead to a more accurate assessment of the company’s credit worthiness. Furthermore, it will also help to avoid reporting fatigue of the client (PwC, 2021).

7. DISCUSSION

7.1 GENERALIZATION

This research, with its recommendations and the models it provides, is not only applicable to ABN AMRO but could be used by every bank around the world. This research forms a theoretical foundation for banks to implement new financial ESG-linked products. SASB's Materiality Finder and World Economic Forum's whitepaper are publicly accessible and the code of our KPI models can be shared on request. The KPI options can not only be used on top of interest rate swaps, but also on FX swaps, credit default swaps, loans, bonds, mortgages, etc. This means that our research is not limited to a bank's corporate and institutional clients but that it can also be used for retail clients. Next to that, certain products, like mortgages are also offered by insurers and pension funds. Therefore, these parties may also have an interest in the KPI option models.

Furthermore, transition businesses can use this research as well to focus on the relevant material ESG issues from the sector where they operate. They can also check which material ESG metrics are important for the corresponding ESG issues. They can consider using these KPIs in their annual report to improve their ESG strategies and policies.

7.2 SCIENTIFIC RELEVANCE

This research is the first to combine SASBs Materiality Finder with World Economic Forum's ESG metrics. This gives banks a good insight into which material ESG KPIs can be used for each sector. It creates the foundation for our KPI option models.

Furthermore, we are the first in the literature that created KPI options. The KPI options we created enable pricing for different potential payoffs, i.e. different values for the basis points and principal amount. KPI options might enable a new stream of other financial products. Our KPI options are an update of the ESG derivatives that are currently used because ours are based on historical data and verified existing financial models. We are willing to share our codes to let other researchers improve our KPI option models.

Our research also has some limitations. The first one is that our binomial KPI model is not proven to be fairly priced. Especially when it is compared to the binary KPI model, the price movements look heavier. We programmed the binomial KPI model on purpose to give back the maximum price if the starting KPI value (KPI zero) is equal to or higher than the KPI goal, to stimulate ambitious KPI targets. However, we also see that the starting values of the binomial KPI option are higher than that of the binary KPI option. Therefore, further research for especially the binomial KPI model is recommended.

ESG is a trending topic in the financial sector. More and more research around this topic is being conducted, this might lead to new insights around ESG KPI standards and frameworks. This might outdate the research we have done on this matter. However, we do think that the KPI option models will stay relevant for a longer period, as those are a new concept in literature.

7.3 FURTHER RESEARCH

We recommend to further researching the validity of our KPI option models and exploring whether other models might serve as a foundation of KPI option models. We would recommend starting dummy testing our KPI models with real-world data. We would recommend taking a look into Monte Carlo simulations, as it depends on the path that is followed by the underlying (the KPI) as well as it depends only on the final KPI value. In our case, we use a KPI option for every single KPI. However, Monte Carlo simulations might allow the payoff to be dependent on multiple KPIs and their paths (Hull, 2015).

A social risk that can arise from offering the KPI option models is indirectly excluding certain people from our product. This can happen when KPIs are chosen that can only reasonably be achieved by a select group of clients. Therefore, it is important to look at the different groups of clients and think about how every kind of client can be stimulated with our KPI option model to contribute to an ESG-friendly environment. This might be further researched.

Another interesting further research can be the exploration of a negative payoff for counterparties. We have not tested the willingness of clients to buy certain KPI options but it might be that paying in advance is a small boundary for some parties. A negative payoff can decrease the price of the option and can maybe even make it free at the start. We recommend further looking into the literature for shifting the binomial tree.

We already mentioned it in our research but the most effect of improving ESG KPIs can be reached by implementing them throughout the whole supply chain. Further research is suggested into how this can be made possible.

Empirical research on SASB's Materiality Finder and WEF's material ESG metrics might lead to improvements. Such research can test what kind of impact material ESG KPIs make and if the material ESG issues related to certain sectors are accurate enough.

The last recommendation for further research is on the possibilities of KPI options in the retail side of banks. We already mentioned how KPI options might be combined with mortgages but there are most probably more possibilities.

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9. APPENDIX

9.1 JUPYTER NOTEBOOK SCRIPTS

9.1.1 Binomial KPI options

Binomial KPI Tree

In our code we will use the Cox-Ross-Rubenstein (CRR) formulas to calculate the price of our option on a KPI.

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

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

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

In [1]:
```
#First we import the libraries we need for the calculations
import numpy as np
import math
import matplotlib.pyplot as plt
```

The Binomial KPI Call Model

In [2]:
```
def sigma_to_goal(KPI_0, sigma, T, N):
    dt = T/N
    u = np.exp(sigma*np.sqrt(dt))
    KPI_u = KPI_0*u
    print("The KPI upper node value after 1 dt is: ", KPI_u)
```

In [3]:
```
sigma_to_goal(100, 0.2, 1, 1)
```

```
The KPI upper node value after 1 dt is:  122.14027581601698
```

In [4]:
```
def KPI_call(KPI_0, KPI_goal, KPI_u, r, T, N, observations, maturity_underlying, bps, P):
    '''
    Rules:
    - KPI_0 < KPI_goal, otherwise the price is just the amount of bps
    - The discount can never be more than the amount of bps
    - The risk-free rate is a constant. It can be equal to the ESTR of the right tenor
    '''
    K = KPI_goal
    bps_percentage = bps/10000
    potential_discount = bps_percentage*P*(maturity_underlying-T)*observations
    print("The potential discount is: ", potential_discount, "euro")

    if KPI_0 < K: #The start value of the KPI should be smaller than the strike value
        #We first precompute the constants for the KPI tree
        dt = T/N
        u = 1+(KPI_u-KPI_0)/(KPI_0) #In this way the KPI_u is the first uppervalue of the tree
        print("u: ", u)
        d = 1/u
        sigma = (np.log(u))/(np.sqrt(dt))
        print("The volatility of the KPI is: ", sigma)
        p = min((np.exp(r*dt)-d)/(u-d),1)
        print("The probability of an KPI value upmove is: ", p)
        discount = np.exp(-r*dt)
        print("The discount factor is: ", discount)

        #We calculate the KPI values at maturity
        KPI = np.zeros(N+1)
        KPI[0] = KPI_0*d**N #We start at the bottom of the tree at the right side (because we start at maturity)
        print("The KPI value at y: 0 , = ", KPI[0])

        #From there on we go upwards in the tree
        for y in range(1, N+1):
            KPI[y] = np.round(KPI[y-1]*u/d,2) #From one KPI value to the one above, you multiply by u/d
            print("The KPI value at y:", y, ", = ", KPI[y])

        #We now calculate the payoff at maturity
        C = np.zeros(N+1)
        for y in range(0, N+1):
            if KPI[y] >= K:
                C[y] = bps_percentage*P
            else:
                C[y] = 0
            print("The payoff at y:",y,", = ", C[y])

        #Now we step backwards through the tree. We do not have to calculate the KPI values inbetween 0 and maturity.
        for x in np.arange(N,0,-1): #numpy.arange([start, ]stop, [step, ]), We start at N and stop at 0 with steps of 1 to the le
            for y in range(0,x):
                C[y] = discount*(p*C[y+1]+(1-p)*C[y])
                print("The payoff at x:",x-1,",y:",y,", = ", C[y])

        #Now that the payoffs at each node are calculated,
        #We print the one at the starting node and multiply it by the remaining periods of the underlying contract
        return C[0]*(maturity_underlying-T)*observations

    else: #if the strike value is below the initial KPI value at the start,
        #the price of the option is the basispoint percentage times the principal amount
        return bps_percentage*P*(maturity_underlying-T)*observations
```

In [5]:
```
KPI_call(100, 120, 122.14027581601698, 0.004, 1, 1, 12, 5, 5, 100)
```

```
The potential discount is:  2.4000000000000004 euro
u:  1.2214027581601699
The volatility of the KPI is:  0.2
The probability of an KPI value upmove is:  0.46011953962765245
The discount factor is:  0.9960079893439915
The KPI value at y: 0 , =  81.87307530779819
The KPI value at y: 1 , =  122.14
The payoff at y: 0 , =  0.0
The payoff at y: 1 , =  0.05
The payoff at x: 0 ,y: 0 , =  0.02291413687612106
```

Out[5]: 1.0998785700538107

We calculate the option prices for different KPI_0 values and plot the result

In [24]:
```
#We need to define a range of values to try for the KPI_0 parameter
KPI_T = np.linspace(50,150,100) #between 50 and 150, create 1000 points

#We create empty listst to later fill with values
KPI_zero = []
option_prices = []

#Here we fill for each list with their corresponding values
for i in range(len(KPI_T)):
    KPI_zero.append(KPI_T[i])
    option_prices.append(KPI_call(KPI_T[i], 100, 100, 0.004, 1, 1, 12, 5, 5, 100))
```

```
The potential discount is:  2.4000000000000004 euro
u:  2.0
The volatility of the KPI is:  0.6931471805599453
The probability of an KPI value upmove is:  0.3360053404515613
The discount factor is:  0.9960079893439915
The KPI value at y: 0 , =  25.0
The KPI value at y: 1 , =  100.0
The payoff at y: 0 , =  0.0
The payoff at y: 1 , =  0.05
The payoff at x: 0 ,y: 0 , =  0.016733200177600147
The potential discount is:  2.4000000000000004 euro
u:  1.9603960396039604
The volatility of the KPI is:  0.6731465138532757
The probability of an KPI value upmove is:  0.34055622513276157
The discount factor is:  0.9960079893439915
The KPI value at y: 0 , =  26.020304050607077
The KPI value at y: 1 , =  100.0
The payoff at y: 0 , =  0.0
The payoff at y: 1 , =  0.05
```

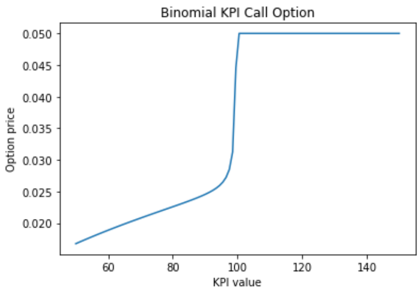
In [7]:
```python
print(KPI_zero)
```

```
[50.0, 51.01010101010101, 52.02020202020202, 53.03030303030303, 54.04040404040404, 55.05050505050505, 56.06060606060606, 57.070
70707070707, 58.08080808080808, 59.09090909090909, 60.101010101010104, 61.111111111111114, 62.121212121212125, 63.1313131313131
35, 64.14141414141415, 65.15151515151516, 66.16161616161617, 67.17171717171718, 68.18181818181819, 69.1919191919192, 70.2020202
0202021, 71.21212121212122, 72.22222222222223, 73.23232323232324, 74.24242424242425, 75.25252525252526, 76.26262626262627, 77.2
7272727272728, 78.28282828282829, 79.2929292929293, 80.30303030303031, 81.31313131313132, 82.32323232323233, 83.33333333333334,
84.34343434343435, 85.35353535353536, 86.36363636363637, 87.37373737373738, 88.38383838383884, 89.3939393939394, 90.40404040404040
42, 91.41414141414143, 92.42424242424244, 93.43434343434345, 94.44444444444446, 95.45454545454547, 96.46464646464648, 97.474747
47474749, 98.48484848484848, 99.4949494949495, 100.5050505050505, 101.51515151515152, 102.52525252525253, 103.53535353535354, 1
04.54545454545455, 105.55555555555556, 106.56565656565657, 107.57575757575758, 108.58585858585859, 109.5959595959596, 110.60606
060606061, 111.61616161616162, 112.62626262626263, 113.63636363636364, 114.64646464646465, 115.65656565656566, 116.666666666666
67, 117.67676767676768, 118.68686868686869, 119.6969696969697, 120.70707070707071, 121.71717171717172, 122.72727272727273, 123.
73737373737374, 124.74747474747475, 125.75757575757576, 126.76767676767678, 127.77777777777779, 128.7878787878788, 129.79797979
79798, 130.80808080808083, 131.8181818181818, 132.82828282828285, 133.83838383838383, 134.84848484848487, 135.85858585858585, 1
36.86868686868869, 137.87878787878788, 138.88888888888889, 139.8989898989899, 140.90909090909093, 141.91919191919192, 142.9292929
2929296, 143.93939393939394, 144.94949494949498, 145.95959595959596, 146.96969696969697, 147.97979797979798, 148.989898989899,
150.0]
```

In [8]:
```python
print(option_prices)
```

```
[0.016733200177600147, 0.01695983605265308, 0.017183688129130258, 0.017404826142663858, 0.01762331927580732, 0.0178392363184936
46, 0.01805264584178232, 0.018263616387491154, 0.018472216676788396, 0.018678515841407218, 0.01888258368186667, 0.0190844909579
74643, 0.01928430971799534, 0.01948211367424432, 0.019677978634606207, 0.019871983001654568, 0.02006420835382608, 0.02025474012
6642197, 0.02044366841652547, 0.020631088935656045, 0.020817104154012833, 0.02100182467487478, 0.021185370903504988, 0.02136787
5086755545, 0.02154948382570529, 0.021730361196771297, 0.02191069266282891, 0.022090690020406794, 0.022270597720569888, 0.02245
0701032840803, 0.02263133671405068, 0.022812907130220574, 0.02299589921297781, 0.02318091030181916, 0.02336868398225994, 0.0235
60160745777797, 0.02375655115724354, 0.02395944413435947, 0.024170971711972626, 0.024394067948203764, 0.0246328913404242, 0.024
89354540665449, 0.025185375720551812, 0.025523464196644852, 0.025933844399409257, 0.026465670580581153, 0.027224247901980348,
0.02848333516433921, 0.031246658405204703, 0.044547587537853095, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.
05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.0
5, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05]
```

In [9]:
```python
plt.plot(KPI_zero, option_prices)
plt.title("Binomial KPI Call Option")
plt.xlabel("KPI value")
plt.ylabel("Option price")

plt.show()
```



The Binomial KPI Put Model

In [10]:
```
def KPI_put(KPI_0, KPI_goal, KPI_u, r, T, N, observations, maturity_underlying, bps, P):
    '''
    Rules:
    - KPI_0 > K, otherwise the price is just the amount of bps
    - The discount can never be more than the amount of bps
    - The risk-free rate is a constant. It can be equal to the ESTR of the right tenor
    '''
    K = KPI_goal
    bps_percentage = bps/10000
    potential_discount = bps_percentage*P*(maturity_underlying-T)*observations
    print("The potential discount is: ", potential_discount, "euro")

    if KPI_0 > K: #The start value of the KPI should be bigger than the strike value
        #We first precompute the constants for the KPI tree
        dt = T/N
        d = 1+(KPI_u-KPI_0)/(KPI_0) #In this way the KPI_u is the first uppervalue of the tree
        print("d: ", d)
        u = 1/d
        sigma = (-np.log(d))/(np.sqrt(dt))
        print("The volatility of the KPI is: ", sigma)
        p = min((np.exp(r*dt)-d)/(u-d),1)
        q = 1-p
        print("The probability of an KPI value downmove is: ", p)

        discount = np.exp(-r*dt)
        print("The discount factor is: ", discount)

        #We calculate the KPI values at maturity
        KPI = np.zeros(N+1)
        KPI[0] = np.round(KPI_0*d**N,2) #We start at the bottom of the tree at the right side (because we start at maturity)
        print("The KPI value at y: 0 , = ", KPI[0])

        #From there on we go upwards in the tree
        for y in range(1, N+1):
            KPI[y] = np.round(KPI[y-1]*u/d,2) #From one KPI value to the one above, you multiply by u/d
            print("The KPI value at y:", y, ", = ", KPI[y])

        #We now calculate the payoff at maturity
        C = np.zeros(N+1)
        for y in range(0, N+1):
            if KPI[y] <= K:
                C[y] = bps_percentage*P
            else:
                C[y] = 0
            print("The payoff at y:",y,", = ", C[y])

        #Now we step backwards through the tree. We do not have to calculate the KPI values inbetween 0 and maturity.
        for x in np.arange(N,0,-1): #numpy.arange([start, ]stop, [step, ]), We start at N and stop at 0 with steps of 1 to the le
            for y in range(0,x):
                C[y] = discount*(q*C[y+1]+(1-q)*C[y])
                print("The payoff at x:",x-1,",y:",y,", = ", C[y])

        #Now that the payoffs at each node are calculated,
        #We print the one at the starting node and multiply it by the remaining periods of the underlying contract
        return C[0]*(maturity_underlying-T)*observations

    else: #if the strike value is above the initial KPI value at the start,
        #the price of the option is the basispoint percentage times the principal amount
        return bps_percentage*P*(maturity_underlying-T)*observations
```

In [11]:
```
KPI_put(100, 80, 80, 0.004, 1, 1, 12, 5, 5, 100)
```

```
The potential discount is:  2.4000000000000004 euro
d:  0.8
The volatility of the KPI is:  0.2231435513142097
The probability of an KPI value downmove is:  0.4533511348385375
The discount factor is:  0.9960079893439915
The KPI value at y: 0 , =  80.0
The KPI value at y: 1 , =  125.0
The payoff at y: 0 , =  0.05
The payoff at y: 1 , =  0.0
The payoff at x: 0 ,y: 0 , =  0.022577067613867425
```

Out[11]:
```
1.0836992454656365
```

We calculate the option prices for different KPI_0 values and plot the result

In [12]:
```
#We need to define a range of values to try for the KPI_0 parameter
KPI_T = np.linspace(50,150,100) #between 50 and 150, create 1000 points

#We create empty lists to later fill with values
KPI_zero = []
option_prices = []

#Here we fill for each list with their corresponding values
for i in range(len(KPI_T)):
    KPI_zero.append(KPI_T[i])
    option_prices.append(KPI_put(KPI_T[i], 100, 100, 0.004, 1, 1, 12, 5, 5, 100))
```

```
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
The potential discount is:  2.4000000000000004 euro
```

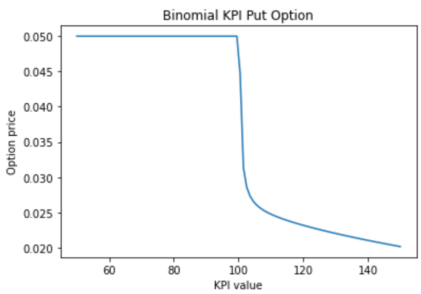
In [13]:
```
print(KPI_zero)
```

```
[50.0, 51.01010101010101, 52.02020202020202, 53.03030303030303, 54.04040404040404, 55.05050505050505, 56.06060606060606, 57.070
70707070707, 58.08080808080808, 59.09090909090909, 60.101010101010104, 61.111111111111114, 62.12121212121212125, 63.1313131313131
35, 64.14141414141415, 65.15151515151516, 66.16161616161617, 67.17171717171718, 68.18181818181819, 69.1919191919192, 70.2020202
0202021, 71.21212121212122, 72.2222222222223, 73.23232323232324, 74.24242424242425, 75.25252525252526, 76.26262626262627, 77.2
7272727272728, 78.28282828282829, 79.2929292929293, 80.30303030303031, 81.31313131313132, 82.32323232323233, 83.33333333333334,
84.34343434343435, 85.35353535353536, 86.36363636363637, 87.37373737373738, 88.38383838383838384, 89.3939393939394, 90.404040404040
42, 91.41414141414143, 92.42424242424244, 93.43434343434345, 94.44444444444446, 95.45454545454547, 96.46464646464648, 97.474747
47474749, 98.48484848484848, 99.4949494949495, 100.5050505050505, 101.51515151515152, 102.52525252525253, 103.53535353535354, 1
04.54545454545455, 105.55555555555556, 106.56565656565657, 107.57575757575758, 108.58585858585859, 109.5959595959596, 110.60606
060606061, 111.61616161616162, 112.62626262626263, 113.63636363636364, 114.64646464646465, 115.65656565656566, 116.666666666666
67, 117.67676767676768, 118.68686868686869, 119.6969696969697, 120.70707070707071, 121.71717171717172, 122.72727272727273, 123.
73737373737374, 124.74747474747475, 125.75757575757576, 126.76767676767678, 127.77777777777779, 128.7878787878788, 129.79797979
79798, 130.80808080808083, 131.8181818181818, 132.82828282828285, 133.83838383838383, 134.84848484848487, 135.85858585858585, 1
36.8686868686869, 137.87878787878788, 138.8888888888889, 139.8989898989899, 140.90909090909093, 141.91919191919192, 142.9292929
2929296, 143.93939393939394, 144.94949494949498, 145.95959595959596, 146.96969696969697, 147.97979797979798, 148.989898989899,
150.0]
```

In [14]:
```
print(option_prices)
```

```
[0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05,
0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05,
0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.05, 0.04464770601488195, 0.03134932271337347, 0.0285910919141 6853, 0.02733964526334
913, 0.0265912590638 9795, 0.026072177638576728, 0.02567709973441943, 0.025356875796903183, 0.025085477750734653, 0.024847829966
760687, 0.024634593957737573, 0.02443967409856884, 0.024258920597425935, 0.02408940892110217, 0.023929017386442847, 0.023776168
262288132, 0.02362966301390888, 0.02348857403300682, 0.02335217148042619, 0.02321987263707091, 0.023091206077351562, 0.02296578
583927044, 0.022843292481124117, 0.022723458973531917, 0.022606060045306495, 0.022490904035088303, 0.022377826586876835, 0.0222
66685720133364, 0.022157357936869522, 0.022049735119683667, 0.02194372203924052, 0.021839234335785458, 0.021736196872614987, 0.
021634542383801556, 0.021534210356487705, 0.021435146101 51425, 0.02133729997628028, 0.021240626731434058, 0.021145084958 89482,
0.021050636623262044, 0.020957246662212593, 0.020864882644 26159, 0.020773514474450482, 0.02068311414026102, 0.020593655491437 68
5, 0.02050511404851204, 0.020417466835717133, 0.020330692234707005, 0.02024476985608641, 0.020159680426240348]
```

In [15]:
```
plt.plot(KPI_zero, option_prices)
plt.title("Binomial KPI Put Option")
plt.xlabel("KPI value")
plt.ylabel("Option price")

plt.show()
```



9.1.2 Binary KPI Options

All-or-Nothing Call Option

In [1]:
```
#First we import the libraries we need for the calculations
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
```

We can use different methods to find the call price of an all-or-nothing European call option. The first method is using Monte Carlo simulations to simulate possible price/KPI paths using the Geometric Brownian Motion. The second option is using the Black-Scholes formula. We will use the latter as this is computationally more efficient and also more accurate.
The formula used to price an all-or-nothing European call option is:

$Qe^{-rT}N(d_2)$

where $d_2 = \frac{\ln(\frac{S_0}{K})+(r-\sigma^2/2)T}{\sigma\sqrt{T}}$

and $Q = \text{basis points} * \text{principal amount}$

In [2]:
```
#Here we create a function for the binary call option:
#Instead of using S0, we use KPI_0, because we have no asset price at T=0
#Instead of using K, we use KPI_goal, because we have no asset strike price at maturity
#Sigma is the only parameter that should be estimated or extracted from an ESG database.
def binary_call(KPI_0, KPI_goal, r, sigma, T, observations, maturity_underlying, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate of the corresponding tenor
    T = time to maturity in years
    observations = observations per year
    maturity_underlying = the time to maturity of the underlying contract, e.g. a loan or IRS
    """
    #Then we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    bps_percentage = bps/10000
    Q = bps_percentage*P*(maturity_underlying-T)*observations
    print("The potential total payoff = ", Q ,"euro")
    N = norm.cdf
    n = norm.pdf
    price = Q*np.exp(-r*T)*N(d2,0,1)

    print("The price of the binary option is: ", price, "euro")
    return price
```

In [3]:
```
#Here the outcome of the binary call option for the following input values:
"""
Suppose we have a situation where the bank and a counterparty agree on a KPI where the counterparty has to increase its
renewable energy consumption with respect to their total energy consumption by 20%.
Their current renewable energy consumption levels w.r.t. the total energy consumption is: 31%
KPI_0 cannot be equal to zero. In this case its value can be set to 100.
Input for binary_call_option:
KPI_0 = 31
KPI_goal = 37.2
r = 0.02
sigma = 0.2
T = 1
observations = 12
maturity_underlying = 5
bps = 5
P = 2000000
"""
binary_call(31,37.2,0.02,0.2,1,12,5,5,2000000)
```

```
The potential total payoff =  48000.0 euro
The price of the binary option is:  8515.38320782542 euro
```

Out[3]: 8515.38320782542

We calculate the option prices for different KPI_0 values and plot the result

In [5]:
```
#We need to define a range of values to try for the KPI_0 parameter
KPI_T = np.linspace(50,150,100) #between 50 and 150, create 1000 points

#We create empty listst to later fill with values
KPI_zero = []
option_prices = []

#Here we fill for each list with their corresponding values
for i in range(len(KPI_T)):
    KPI_zero.append(KPI_T[i])
    option_prices.append(binary_call(KPI_T[i], 100, 0.004, 0.2, 1, 12, 5, 5, 100))
```

```
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.00046794651606241433 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.0006806881957262206 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.0009739529302512205 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.001371912804739718 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.001903932751400287 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.0026051313676469408 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.0035168777831724746 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.004687195983552377 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary option is:  0.006171048663456309 euro
The potential total payoff =  2.4000000000000004 euro
```

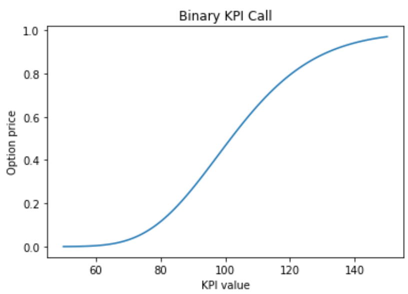
In [6]:
```
print(KPI_zero)
```

```
[50.0, 51.01010101010101, 52.02020202020202, 53.03030303030303, 54.04040404040404, 55.05050505050505, 56.06060606060606, 57.070
70707070707, 58.08080808080808, 59.09090909090909, 60.101010101010104, 61.111111111111114, 62.121212121212125, 63.1313131313131
35, 64.14141414141415, 65.15151515151516, 66.16161616161617, 67.17171717171718, 68.18181818181819, 69.1919191919192, 70.2020202
0202021, 71.2121212121212122, 72.22222222222223, 73.23232323232324, 74.24242424242425, 75.25252525252526, 76.26262626262627, 77.2
7272727272728, 78.28282828282829, 79.29292929292929, 80.30303030303031, 81.31313131313132, 82.32323232323233, 83.33333333333334,
84.34343434343435, 85.35353535353536, 86.36363636363637, 87.37373737373738, 88.38383838383838, 89.3939393939394, 90.404040404040
42, 91.41414141414143, 92.42424242424244, 93.43434343434345, 94.44444444444446, 95.45454545454547, 96.46464646464648, 97.474747
47474749, 98.48484848484848, 99.4949494949495, 100.5050505050505, 101.51515151515152, 102.52525252525253, 103.53535353535354, 1
04.54545454545455, 105.55555555555556, 106.56565656565657, 107.57575757575758, 108.58585858585859, 109.5959595959596, 110.60606
060606061, 111.61616161616162, 112.62626262626263, 113.63636363636364, 114.64646464646465, 115.65656565656566, 116.666666666666
67, 117.67676767676768, 118.68686868686869, 119.6969696969697, 120.70707070707071, 121.71717171717172, 122.72727272727273, 123.
73737373737374, 124.74747474747475, 125.75757575757576, 126.76767676767678, 127.77777777777779, 128.7878787878788, 129.79797979
79798, 130.80808080808083, 131.8181818181818, 132.82828282828285, 133.83838383838383, 134.84848484848487, 135.85858585858585, 1
36.8686868686869, 137.87878787878788, 138.8888888888889, 139.8989898989899, 140.90909090909093, 141.91919191919192, 142.9292929
2929296, 143.93939393939394, 144.94949494949498, 145.95959595959596, 146.96969696969697, 147.97979797979798, 148.989898989899,
150.0]
```

In [6]:
```
print(option_prices)
```

```
[0.00019497771502600595, 0.0002836200815525919, 0.0004058137209380085, 0.0005716303353082158, 0.0007933053130834528, 0.00108547
14031862253, 0.0014653657429885309, 0.0019529983264801566, 0.0025712702764401282, 0.0033460311769023684, 0.004306062097 0932,
0.005483005862914051, 0.006911153446950205, 0.008627228447771616, 0.010670026727299038, 0.013080001604455785, 0.015898772769462
936, 0.01916857266400986, 0.02293164228150346, 0.027229590208749276, 0.032102730073801516, 0.03758941234370504, 0.0437253666185
9078, 0.05054307021036003, 0.058071157914463906, 0.06633388654163323, 0.07535066604790218, 0.08513566707141496, 0.0956975124443
707, 0.10703905788997257, 0.11915726472602314, 0.13204316506077354, 0.14568191775513606, 0.16005295139942793, 0.175130188760744
63, 0.19088234563420928, 0.20727329580009388, 0.22426249285938427, 0.2418054390919057, 0.25985419114307196, 0.2783578922790879
7, 0.2972633211309911, 0.3165154472456053, 0.33605798434352663, 0.355833932916374, 0.3757861046431726, 0.3958576220352618, 0.41
599238769879243, 0.4361355186044855, 0.4562337417498414, 0.4762357485667633, 0.49609250634868746, 0.5157575258304322, 0.5351870
848394273, 0.5543404086403855, 0.5731798082116524, 0.5916707782179934, 0.6097820568815193, 0.6274856503019387, 0.64475682404322
42, 0.6615740649913423, 0.6779190166031294, 0.6937763907167165, 0.7091338590864826, 0.7239819277479834, 0.738313797218182, 0.75
21252114010423, 0.765414297905 1454, 0.7781814022950606, 0.7904289185978487, 0.802161118175768, 0.8133839788609382, 0.8241050160
316156, 0.834333117096569, 0.8440783806468711, 0.8533519613357485, 0.8621659213589673, 0.8705330892320657, 0.8784669263976799,
0.8859814020468738, 0.893090876403207, 0.8998099925972187, 0.9061535771519698, 0.9121365490067874, 0.9177738369259226, 0.923080
3050707016, 0.928070686457207, 0.9327595239756745, 0.9371611186117916, 0.9412894844829858, 0.9451583102837525, 0.94878092672213
84, 0.9521702795238691, 0.9553389075804273, 0.958298925821905, 0.961062012403907, 0.9636393998095546, 0.9660418694820553, 0.968
2797496198531, 0.9703629157845326]
```

In [7]:
```
plt.plot(KPI_zero,option_prices)
plt.title("Binary KPI Call")
plt.xlabel("KPI value")
plt.ylabel("Option price")

plt.show()
```



All-or-Nothing Put Option

Some KPIs do need to decrease in order to improve a situation, e.g. GHG emissions, gap between men's and women's salary, work incidents, etc.
With the current binary call option, we cannot price KPIs that should decrease. We therefore also define a binary put option.
The price of a all-or-nothing European binary put option can be calculated with the following formula:

$$Qe^{-rT}N(-d_2)$$

In [9]:
```
#Here we create a function for the binary put option:
def binary_put(KPI_0, KPI_goal, r, sigma, T, observations, maturity_underlying, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate of the corresponding tenor
    T = time to maturity in years
    observations = observations per year
    maturity_underlying = the time to maturity of the underlying contract, e.g. a loan or IRS
    """

    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    bps_percentage = bps/10000
    Q = bps_percentage*P*(maturity_underlying-T)*observations
    print("The potential total payoff = ", Q ,"euro")
    N = norm.cdf
    price = Q*np.exp(-r*T)*N(-d2,0,1)
    print("The price of the binary put option is: ", price, "euro")

    return price
```

In [10]:
```
#Here the outcome of the binary put option for the following input values:
"""
Suppose we have a situation where the bank and a counterparty agree on a KPI where the counterparty has to increase its
current CO2 emission levels by 20%.
Their current CO2 emission levels in tonnes: 4.4
KPI_0 cannot be equal to zero. In this case its value can be set to 100.
Input for binary_put_option:
KPI_0 = 4.4
KPI_goal = 3.52
r = 0.002
sigma = 0.2
T = 1
observations = 12
maturity_underlying = 5
bps = 5
P = 10000000
"""
binary_put(4.4,3.52,0.002,0.2,1,12,5,5,10000000)
```

```
The potential total payoff =  240000.0 euro
The price of the binary put option is:  36529.82429452871 euro
```

Out[10]:
```
36529.82429452871
```

We calculate the option prices for different KPI_0 values and plot the result

In [12]:
```python
#We need to define a range of values to try for the KPI_0 parameter
KPI_T = np.linspace(50,150,100) #between 50 and 150, create 1000 points

#We create empty listst to later fill with values
KPI_zero = []
option_prices = []

#Here we fill for each list with their corresponding values
for i in range(len(KPI_T)):
    KPI_zero.append(KPI_T[i])
    option_prices.append(binary_put(KPI_T[i], 100, 0.004, 0.2, 1, 12, 5, 5, 100))
```

```
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3899512279095174 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3897384862298536 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3894452214953286 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3890472616208402 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3885152416741797 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.387814043057933 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3869022966424076 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3857319784420272 euro
The potential total payoff =  2.4000000000000004 euro
The price of the binary put option is:  2.3842481257621237 euro
The potential total payoff =  2.4000000000000004 euro
```

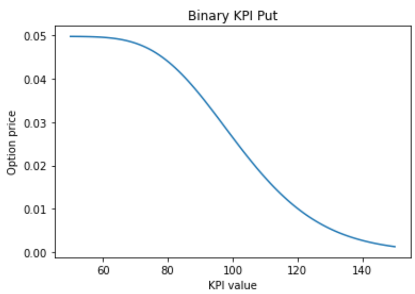
In [13]:
```python
print(KPI_zero)
```

```
[50.0, 51.01010101010101, 52.02020202020202, 53.03030303030303, 54.04040404040404, 55.05050505050505, 56.06060606060606, 57.070
70707070707, 58.08080808080808, 59.09090909090909, 60.101010101010104, 61.11111111111114, 62.12121212121225, 63.1313131313131
35, 64.14141414141415, 65.15151515151516, 66.16161616161617, 67.17171717171718, 68.18181818181819, 69.1919191919192, 70.2020202
0202021, 71.2121212121212122, 72.22222222222223, 73.23232323232324, 74.24242424242425, 75.25252525252526, 76.26262626262627, 77.2
727272727272728, 78.28282828282829, 79.2929292929293, 80.30303030303031, 81.31313131313132, 82.32323232323233, 83.33333333333334,
84.34343434343435, 85.35353535353536, 86.36363636363637, 87.37373737373738, 88.38383838383838384, 89.393939393939394, 90.404040404040
42, 91.4141414141414143, 92.42424242424244, 93.43434343434345, 94.44444444444446, 95.45454545454547, 96.46464646464648, 97.474747
47474749, 98.48484848484848, 99.4949494949495, 100.5050505050505, 101.51515151515152, 102.52525252525253, 103.53535353535354, 1
04.54545454545455, 105.55555555555556, 106.56565656565657, 107.57575757575758, 108.58585858585859, 109.5959595959596, 110.60606
060606061, 111.61616161616162, 112.62626262626263, 113.63636363636364, 114.64646464646465, 115.65656565656566, 116.666666666666
67, 117.67676767676768, 118.68686868686869, 119.6969696969697, 120.70707070707071, 121.71717171717172, 122.72727272727273, 123.
73737373737374, 124.74747474747475, 125.75757575757576, 126.76767676767678, 127.77777777777779, 128.7878787878788, 129.79797979
79798, 130.80808080808083, 131.8181818181818, 132.82828282828285, 133.83838383838383, 134.84848484848487, 135.85858585858585, 1
36.8686868686869, 137.87878787878788, 138.8888888888889, 139.8989898989899, 140.90909090909093, 141.91919191919192, 142.9292929
2929296, 143.93939393939394, 144.94949494949498, 145.95959595959596, 146.96969696969697, 147.97979797979798, 148.989898989899,
150.0]
```

In [12]:
```python
print(option_prices)
```

```
[0.04979065058144828, 0.04978621846312195, 0.04978010878115268, 0.04977181795043417, 0.04976073420154540б, 0.049746125897040264, 0.04972713118005015б, 0.04970274955087557, 0.04967183595337757б, 0.04963309790835446, 0.04958509615671411б, 0.04952624917405
388, 0.04945484179485207, 0.049369038044811, 0.04926689813083463, 0.04914639938697679, 0.04900546082872643 5, 0.0488419708339990
9, 0.0486538173531244 1, 0.04843891995676211, 0.04819526296350950 4, 0.04792092885001432 4, 0.04761413113627004, 0.04727324595668 1
58, 0.04689684157147638, 0.04648370514011792, 0.04603286616480447, 0.04554361611362883, 0.04501552384498104 5, 0.04444844657270 0
95, 0.04384253623089842, 0.0431982412141609, 0.04251630357944278, 0.04179775189722818, 0.04104389002916234 6, 0.04025628218548 91
15, 0.03943673467719488 5, 0.03858727482423036, 0.03771012751260429 5, 0.03680768991004598, 0.03588250485324518, 0.0349372334106 5
0026, 0.03397462710491931, 0.03299750025002324 4, 0.03200870282138088, 0.03101109423504094 8, 0.03000751836543649, 0.029000780082
259956, 0.02799362353697530 3, 0.02698871237970751, 0.02598861203886141, 0.02499577414976520 2, 0.02401252317567796 6, 0.023041045
225228207, 0.0220833790351803, 0.02114140905661695 4, 0.02021686055629990 5, 0.01931129662312360 7, 0.01842611695210264, 0.0175625
5826503837, 0.01672169621763246, 0.01590444863704310 4, 0.01511157993136375 5, 0.01434370651287544 3, 0.01360130307980040 6, 0.0128
84709606290472, 0.01219413889714746 2, 0.01152968457194230 8, 0.01089132935244654 2, 0.01027895353730713 8, 0.00969234355841118 1,
0.0091312005241526 7, 0.00859514866561879 7, 0.00808374361237112 9, 0.00759648043485602 1, 0.00713280140041214 4, 0.006692103399251 2
14, 0.00627374500559628 6, 0.00587705314731558 3, 0.00550132936485588 7, 0.00514585564703922 5, 0.00480989983733864 1, 0.00449272060
9601082, 0.00419357201686020 6, 0.00391170762090344 1, 0.00364638421366449 3, 0.00339686514433922 6, 0.00316242326841584 4, 0.002942
3435366099904, 0.00273592524305028 67, 0.00254248395301194 7, 0.00236135313109264 85, 0.00219188549100611 8, 0.00203345408817820 8,
0.00188545317610432 37, 0.00174729884700422 9, 0.00161842947672184 28, 0.00149830599309681 4, 0.00138641198620692 05, 0.001282253677
972947]
```

In [13]:
```python
plt.plot(KPI_zero,option_prices)
plt.title("Binary KPI Put")
plt.xlabel("KPI value")
plt.ylabel("Option price")

plt.show()
```



9.1.3 ESG Greeks

We commented out the call plots in the code, as those are already shown in Chapter 5.3.

In each section we first define the pricing model and then we calculate the corresponding ESG Greeks. We start with the binomial KPI option pricing model and end with the binary option pricing model.

In [1]:
```
#First we import the libraries we need for the calculations
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm
```

The Binomial KPI Option Pricing Model

In [2]:
```
def KPI_call(KPI_0, KPI_goal, KPI_u, r, T, N, bps, P):
    '''
    Rules:
    - KPI_0 < KPI_goal, otherwise the price is just the amount of bps
    - The discount can never be more than the amount of bps
    - The risk-free rate is a constant. It can be equal to the ESTR of the right tenor
    '''
    K = KPI_goal
    bps_percentage = bps/10000
    potential_discount = bps_percentage*P
    #print("The potential discount is: ", potential_discount, "euro")

    if KPI_0 < K: #The start value of the KPI should be smaller than the strike value
        #We first precompute the constants for the KPI tree
        dt = T/N
        u = 1+(KPI_u-KPI_0)/(KPI_0) #In this way the KPI_u is the first uppervalue of the tree
        #print("u: ", u)
        d = 1/u
        sigma = (np.log(u))/(np.sqrt(dt))
       #print("The volatility of the KPI is: ", sigma)
        p = min((np.exp(r*dt)-d)/(u-d),1)
        #print("The probability of an KPI value upmove is: ", p)
        discount = np.exp(-r*dt)
        #print("The discount factor is: ", discount)

        #We calculate the KPI values at maturity
        KPI = np.zeros(N+1)
        KPI[0] = KPI_0*d**N #We start at the bottom of the tree at the right side (because we start at maturity)
        #print("The KPI value at y: 0 , = ", KPI[0])

        #From there on we go upwards in the tree
        for y in range(1, N+1):
            KPI[y] = np.round(KPI[y-1]*u/d,2) #From one KPI value to the one above, you multiply by u/d
            #print("The KPI value at y:", y, ", = ", KPI[y])

        #We now calculate the payoff at maturity
        C = np.zeros(N+1)
        for y in range(0, N+1):
            if KPI[y] >= K:
                C[y] = bps_percentage*P
            else:
                C[y] = 0
            #print("The payoff at y:",y,", = ", C[y])

        #Now we step backwards through the tree. We do not have to calculate the KPI values inbetween 0 and maturity.
        for x in np.arange(N,0,-1): #numpy.arange([start, ]stop, [step, ]), We start at N and stop at 0 with steps of 1 to the le
            for y in range(0,x):
                C[y] = discount*(p*C[y+1]+(1-p)*C[y])
                #print("The payoff at x:",x-1,",y:",y,", = ", C[y])

        #Now that the payoffs at each node are calculated, we print the one at the starting node
        return C[0]

    else: #if the strike value is below the initial KPI value at the start,
        #the price of the option is the basispoint percentage times the principal amount
        return bps_percentage*P
```

In [3]:
```
def sigmas(KPI_0, KPI_goal, KPI_u, r, T, N, bps, P):
    '''
    Rules:
    - KPI_0 < K, otherwise the price is just the amount of bps
    - The discount can never be more than the amount of bps
    - The risk-free rate is a constant. It can be equal to the ESTR of the right tenor
    '''
    bps_percentage = bps/10000
    potential_discount = bps_percentage*P
    #print("The potential discount is: ", potential_discount, "euro")

    #We first precompute the constants for the KPI tree
    dt = T/N
    u = 1+(KPI_u-KPI_0)/(KPI_0) #In this way the KPI_goal is the first uppervalue of the tree
    #print("u: ", u)
    d = 1/u
    sigma = (np.log(u))/(np.sqrt(dt))

    #Now that the payoffs at each node are calculated, we print the one at the starting node
    return sigma
```

In [4]:

```python
def KPI_put(KPI_0, KPI_goal, KPI_u, r, T, N, bps, P):
    '''
    Rules:
    - KPI_0 > K, otherwise the price is just the amount of bps
    - The discount can never be more than the amount of bps
    - The risk-free rate is a constant. It can be equal to the ESTR of the right tenor
    '''
    K = KPI_goal
    bps_percentage = bps/10000
    potential_discount = bps_percentage*P
    #print("The potential discount is: ", potential_discount, "euro")

    if KPI_0 > K: #The start value of the KPI should be bigger than the strike value
        #We first precompute the constants for the KPI tree
        dt = T/N
        d = 1+(KPI_u-KPI_0)/(KPI_0) #In this way the KPI_u is the first uppervalue of the tree
        #print("d: ", d)
        u = 1/d
        sigma = (-np.log(d))/(np.sqrt(dt))
        #print("The volatility of the KPI is: ", sigma)
        p = min((np.exp(r*dt)-d)/(u-d),1)
        q = 1-p
        #print("The probability of an KPI value downmove is: ", p)

        discount = np.exp(-r*dt)
        #print("The discount factor is: ", discount)

        #We calculate the KPI values at maturity
        KPI = np.zeros(N+1)
        KPI[0] = np.round(KPI_0*d**N,2) #We start at the bottom of the tree at the right side (because we start at maturity)
        #print("The KPI value at y: 0 , = ", KPI[0])

        #From there on we go upwards in the tree
        for y in range(1, N+1):
            KPI[y] = np.round(KPI[y-1]*u/d,2) #From one KPI value to the one above, you multiply by u/d
            #print("The KPI value at y:", y, ", = ", KPI[y])

        #We now calculate the payoff at maturity
        C = np.zeros(N+1)
        for y in range(0, N+1):
            if KPI[y] <= K:
                C[y] = bps_percentage*P
            else:
                C[y] = 0
            #print("The payoff at y:",y,", = ", C[y])

        #Now we step backwards through the tree. We do not have to calculate the KPI values inbetween 0 and maturity.
        for x in np.arange(N,0,-1): #numpy.arange([start, ]stop, [step, ]), We start at N and stop at 0 with steps of 1 to the le
            for y in range(0,x):
                C[y] = discount*(q*C[y+1]+(1-q)*C[y])
                #print("The payoff at x:",x-1,",y:",y,", = ", C[y])

        #Now that the payoffs at each node are calculated, we print the one at the starting node
        return C[0]

    else: #if the strike value is above the initial KPI value at the start,
        #the price of the option is the basispoint percentage times the principal amount
        return bps_percentage*P
```

Delta

Delta measures the rate of change of the theoretical KPI option value with respect to the underlying. It's formula is given by:

$\Delta = \frac{\delta V}{\delta S}$

Where, V = the value of the KPI option
S = the value of the KPI itself

Gamma

Gamma measures the rate of change in delta with respect to changes in the KPI value (or bps value???). It's formula is given by:

$\Gamma = \frac{\delta \Delta}{\delta S} = \frac{\delta^2 V}{\delta S^2}$

Vega

Vega measures the sensitivity to volatility. Vega is the derivative of the option value with respect to the volatility of the underlying KPI. It's formula is given by:

$\nu = \frac{\delta V}{\delta \sigma}$

Theta

Theta measures the sensitivity of the value of the derivative to the passage of time, which is also called the time decay. The formula of Theta is given by:

$\Theta = -\frac{\delta V}{\delta \tau}$

Rho

Rho measures the sensitivity to the interest rate change. It is the derivative of the option value with respect to the risk free interest rate. It's formula is given by:

$\rho = \frac{\delta V}{\delta r}$

Summary binomial ESG Greeks

In [5]:
```
#We define some starting values for the parameters first
KPI_0 = 90
KPI_goal = 100
KPI_u = 100
r = 0.004
T = 1
N = 1
bps = 5
P = 100

x = 100
y = 0.8

#Then we need to define some ranges of values to try for the different parameters
KPI_T = np.linspace(KPI_goal-y*KPI_goal,KPI_goal+y*KPI_goal,x) #between (1-y)KPI_goal till (1+y)KPI_goal, create x points
Goal_KPI = np.linspace(KPI_u-y*KPI_u,KPI_u+y*KPI_u,x) #between (1-y)KPI_goal till (1+y)KPI_goal, create x points
TTM = np.linspace(T-0.99*T,T,x) #between (T-y)*T and T, create x points
rfr = np.linspace(r-y*r,r+y*r,x) #between (1-y)r till (1+y), create x points

#We create empty listst to later fill with values
spots = []
call_prices = []
put_prices = []
gammas = []
sigma_list = []
vega_prices = []
TTM_list = []
OTM_theta_prices_c = []
ITM_theta_prices_p = []
rfr_list = []
rfr_prices_c = []
rfr_prices_p = []

#Here we fill for each ESG greek the list with corresponding values
for i in range(len(KPI_T)):
    spots.append(KPI_T[i])
    call_prices.append(KPI_call(KPI_T[i], KPI_goal, KPI_u, r, T, N, bps, P))
    put_prices.append(KPI_put(KPI_T[i], KPI_goal, KPI_u, r, T, N, bps, P))

for j in range(len(TTM)):
    TTM_list.append(TTM[j])
    OTM_theta_prices_c.append(KPI_call(KPI_0, KPI_goal, KPI_u, r, TTM[j], N, bps, P))
    ITM_theta_prices_p.append(KPI_put(KPI_0, KPI_goal, KPI_u, r, TTM[j], N, bps, P))

for k in range(len(Goal_KPI)):
    sigma_list.append(sigmas(KPI_0, KPI_goal, Goal_KPI[k], r, T, N, bps, P))
    vega_prices.append(KPI_call(KPI_0, KPI_goal, Goal_KPI[k], r, T, N, bps, P))

for l in range(len(rfr)):
    rfr_list.append(rfr[l])
    rfr_prices_c.append(KPI_call(KPI_0, KPI_goal, KPI_u, rfr[l], T, N, bps, P))
    rfr_prices_p.append(KPI_put(KPI_0, KPI_goal, KPI_u, rfr[l], T, N, bps, P))
```

In [6]:
```
#We define some starting values for the parameters first
KPI_0 = 110
KPI_goal = 100
KPI_u = 100
r = 0.004
T = 1
N = 1
bps = 5
P = 100

x = 100
y = 0.8

#We create empty listst to later fill with values
ITM_theta_prices_c = []
OTM_theta_prices_p = []

#Here we fill for the thetas the list with corresponding values
for j in range(len(TTM)):
#    TTM_list.append(TTM[j])
    ITM_theta_prices_c.append(KPI_call(KPI_0, KPI_goal, KPI_u, r, TTM[j], N, bps, P))
    OTM_theta_prices_p.append(KPI_put(KPI_0, KPI_goal, KPI_u, r, TTM[j], N, bps, P))
```

In [7]:
```
#We define some starting values for the parameters first
KPI_0 = 100
KPI_goal = 100
KPI_u = 100
r = 0.004
T = 1
N = 1
bps = 5
P = 100

x = 100
y = 0.8

#We create empty listst to later fill with values
ATM_theta_prices_c = []
ATM_theta_prices_p = []

#Here we fill for the ATM thetas the list with corresponding values
for j in range(len(TTM)):
    ATM_theta_prices_c.append(KPI_call(KPI_0, KPI_goal, KPI_u, r, TTM[j], N, bps, P))
    ATM_theta_prices_p.append(KPI_put(KPI_0, KPI_goal, KPI_u, r, TTM[j], N, bps, P))
```

In [8]:
```
deltas_c = np.zeros(len(KPI_T))
deltas_p = np.zeros(len(KPI_T))

for n in range(1, len(KPI_T)):
    deltas_c[n] = (call_prices[n]-call_prices[n-1])/(spots[n]-spots[n-1])
    deltas_p[n] = (put_prices[n]-put_prices[n-1])/(spots[n]-spots[n-1])
```

In [9]:
```
gammas_c = np.zeros(len(KPI_T))
gammas_p = np.zeros(len(KPI_T))

for n in range(1, len(KPI_T)):
    gammas_c[n] = (deltas_c[n]-deltas_c[n-1])/(0.5*(spots[n]-spots[n-1]))
    gammas_p[n] = (deltas_p[n]-deltas_p[n-1])/(0.5*(spots[n]-spots[n-1]))
```

In [10]:
```
vegas = np.zeros(len(Goal_KPI))

for n in range(1, len(Goal_KPI)):
    vegas[n] = (call_prices[n]-call_prices[n-1])/(sigma_list[n]-sigma_list[n-1])
```

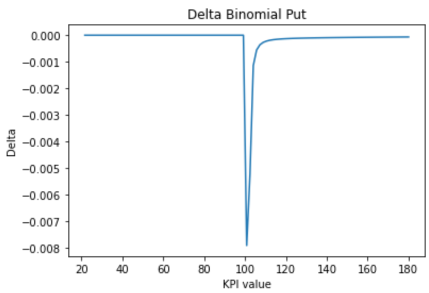
In [11]:
```
OTM_thetas_c = np.zeros(len(TTM))
ITM_thetas_p = np.zeros(len(TTM))

ITM_thetas_c = np.zeros(len(TTM))
OTM_thetas_p = np.zeros(len(TTM))

ATM_thetas_c = np.zeros(len(TTM))
ATM_thetas_p = np.zeros(len(TTM))

for n in range(1, len(TTM)):
    OTM_thetas_c[n] = (OTM_theta_prices_c[n]-OTM_theta_prices_c[n-1])/(TTM_list[n]-TTM_list[n-1])
    ITM_thetas_p[n] = (ITM_theta_prices_p[n]-ITM_theta_prices_p[n-1])/(TTM_list[n]-TTM_list[n-1])

    ITM_thetas_c[n] = (ITM_theta_prices_c[n]-ITM_theta_prices_c[n-1])/(TTM_list[n]-TTM_list[n-1])
    OTM_thetas_p[n] = (OTM_theta_prices_p[n]-OTM_theta_prices_p[n-1])/(TTM_list[n]-TTM_list[n-1])

    ATM_thetas_c[n] = (ATM_theta_prices_c[n]-ATM_theta_prices_c[n-1])/(TTM_list[n]-TTM_list[n-1])
    ATM_thetas_p[n] = (ATM_theta_prices_p[n]-ATM_theta_prices_p[n-1])/(TTM_list[n]-TTM_list[n-1])
```

In [12]:
```
rhos_c = np.zeros(len(rfr))
rhos_p = np.zeros(len(rfr))

for n in range(1, len(rfr)):
    rhos_c[n] = ((rfr_prices_c[n]-rfr_prices_c[n-1])/(rfr_list[n]-rfr_list[n-1]))/100
    rhos_p[n] = ((rfr_prices_p[n]-rfr_prices_p[n-1])/(rfr_list[n]-rfr_list[n-1]))/100
```

The plots

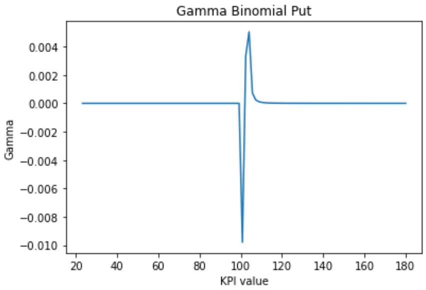
In [13]:
```
# plt.plot(spots[1:], deltas_c[1:])
# plt.title("Delta Binomial Call")
# plt.xlabel("KPI value")
# plt.ylabel("Delta")

# plt.show()
```

In [14]:
```
plt.plot(spots[1:], deltas_p[1:])
plt.title("Delta Binomial Put")
plt.xlabel("KPI value")
plt.ylabel("Delta")

plt.show()
```



In [15]:
```
# plt.plot(spots[2:], gammas_c[2:])
# plt.title("Gamma Binomial Call")
# plt.xlabel("KPI value")
# plt.ylabel("Gamma")

# plt.show()
```

In [16]:
```
plt.plot(spots[2:], gammas_p[2:])
plt.title("Gamma Binomial Put")
plt.xlabel("KPI value")
plt.ylabel("Gamma")

plt.show()
```

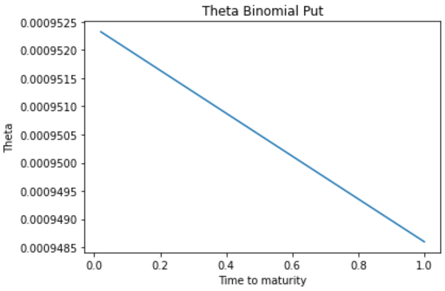


In [17]:
```
# plt.plot(spots[1:], vegas[1:])
# plt.title("Vega Binomial")
# plt.xlabel("KPI value")
# plt.ylabel("Vega")

# plt.show()
```

In [18]:
```
# #plt.plot(TTM[1:], ITM_thetas_c[1:])
# plt.plot(TTM[1:], OTM_thetas_c[1:])
# #plt.plot(TTM[1:], ATM_thetas_c[1:])
# plt.title("Theta Binomial Call")
# plt.xlabel("Time to maturity")
# plt.ylabel("Theta")

# plt.show()
```

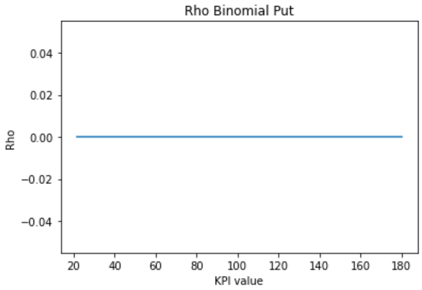
In [19]:
```
# plt.plot(TTM[1:], ITM_thetas_c[1:])
# plt.plot(TTM[1:], ATM_thetas_c[1:])
# plt.title("Theta Binomial Call")
# plt.xlabel("Time to maturity")
# plt.ylabel("Theta")

# plt.show()
```

In [20]:
```
#plt.plot(TTM[1:], ITM_thetas_p[1:])
plt.plot(TTM[1:], OTM_thetas_p[1:])
#plt.plot(TTM[1:], ATM_thetas_p[1:])
plt.title("Theta Binomial Put")
plt.xlabel("Time to maturity")
plt.ylabel("Theta")

plt.show()
```



In [21]:
```
# plt.plot(spots[1:], rhos_c[1:])
# plt.title("Rho Binomial Call")
# plt.xlabel("KPI value")
# plt.ylabel("Rho")

# plt.show()
```

In [22]:
```
plt.plot(spots[1:], rhos_p[1:])
plt.title("Rho Binomial Put")
plt.xlabel("KPI value")
plt.ylabel("Rho")

plt.show()
```



The Binary KPI Option Pricing Model

In [23]:
```
#Here we create a function for the binary call option:
#Instead of using S0, we use KPI_0, because we have no asset price at T=0
#Instead of using K, we use KPI_goal, because we have no asset strike price at maturity
#Sigma is the only parameter that should be estimated or extracted from an ESG database.
def binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    bps_percentage = bps/10000
    Q = bps_percentage*P
    #print("The potential payoff (Q) at maturity = ", Q ,"euro")
    N = norm.cdf
    n = norm.pdf
    price = Q*np.exp(-r*T)*N(d2,0,1)

    return price
```

In [24]:
```
binary_call(31,37.2,0.02,0.2,1,5,2000000)
```

Out[24]: 177.40381682969624

In [25]:
```
#Here we create a function for the binary put option:
def binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """

    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    bps_percentage = bps/10000
    Q = bps_percentage*P
    #print("The potential payoff (Q) at maturity = ", Q ,"euro")
    N = norm.cdf
    price = Q*np.exp(-r*T)*N(-d2,0,1)

    return price
```

In [26]:
```
binary_put(100,90,0.02,0.2,1,5,2000000)
```

Out[26]: 293.24147538131024

Binary Delta

Delta measures the rate of change of the theoretical KPI binary option value with respect to the underlying. It's formula is given by:

$$\Delta = \frac{\phi e^{-rdt}}{S\sigma\sqrt{T}} n(d_2)$$

Where
ϕ = 1 for a call and -1 for a put
S = the value of the KPI itself

In [27]:
```
#Here we create a function for delta of the binary call option:
def delta_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    delta = ((np.exp(-r*T))/(KPI_0*sigma*np.sqrt(T)))*n(d2,0,1)

    return delta
```

In [28]:
```
delta_binary_call(31,37.2,0.02,0.2,1,5,2000000)
```

Out[28]: 0.041627169948189595

In [29]:
```
#Here we create a function for delta of the binary put option:
def delta_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    delta = ((-np.exp(-r*T))/(KPI_0*sigma*np.sqrt(T)))*n(d2,0,1)

    return delta
```

In [30]:
```
delta_binary_put(31,37.2,0.02,0.2,1,5,2000000)
```

Out[30]: -0.041627169948189595

Binary Gamma

Gamma measures the rate of change in delta with respect to changes in the KPI value. It's formula is given by:

$$\Gamma = -\frac{\phi e^{-rdt}}{S^2\sigma^2\sqrt{T}} n(d_2)d_1$$

In [31]:
```
#Here we create a function for gamma of the binary call option:
def gamma_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    gamma = -((np.exp(-r*T))/(KPI_0**2*sigma**2*np.sqrt(T)))*n(d2,0,1)*d1

    return gamma
```

In [32]:
```
gamma_binary_call(31,37.2,0.02,0.2,1,5,2000000)
```

Out[32]:
```
0.004777777122542635
```

In [33]:
```
#Here we create a function for gamma of the binary put option:
def gamma_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    gamma = -((-np.exp(-r*T))/(KPI_0**2*sigma**2*np.sqrt(T)))*n(d2,0,1)*d1

    return gamma
```

In [34]:
```
gamma_binary_put(31,37.2,0.02,0.2,1,5,2000000)
```

Out[34]:
```
-0.004777777122542635
```

Binary Vega

Vega measures the sensitivity to volatility. Vega is the derivative of the option value with respect to the volatility of the underlying KPI. It's formula is given by:

$$v = -\frac{\phi e^{-rdt}}{\sigma} n(d_2) d_1$$

In [35]:
```
#Here we create a function for vega of the binary call option:
def vega_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    vega = -((np.exp(-r*T))/(sigma))*n(d2,0,1)*d1

    return vega/100
```

In [36]:
```
vega_binary_call(31, 37.2, 0.02, 0.2, 1, 5, 2000000)
```

Out[36]:
```
0.009182887629526947
```

In [37]:
```
#Here we create a function for vega of the binary put option:
def vega_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    vega = -((-np.exp(-r*T))/(sigma))*n(d2,0,1)*d1

    return vega/100
```

In [38]:
```
vega_binary_put(31, 37.2, 0.02, 0.2, 1, 5, 2000000)
```

Out[38]:
```
-0.009182887629526947
```

Binary Theta

Theta measures the sensitivity of the value of the derivative to the passage of time, which is also called the time decay. The formula of Theta is given by:

$$\Theta = e^{-rdt}(\phi n(d_2)\frac{1}{2T}\frac{1}{\sigma\sqrt{T}}(\ln\frac{S}{K} - (r - \frac{\sigma^2}{2})T) + rN(\phi d_2))$$

In [39]:
```
#Here we create a function for theta of the binary call option:
def theta_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    theta = np.exp(-r*T)*(n(d2,0,1)*(1/(2*T))*(1/(sigma*np.sqrt(T)))*(np.log(KPI_0/KPI_goal)-(r-(sigma**2)/2)*T)+r*N(d2,0,1))

    return theta/365
```

In [40]:
```
theta_binary_call(90, 100, 0.004, 0.2, 1, 100, 100)
```

Out[40]:
```
-0.00019933777541059183
```

In [41]:
```
#Here we create a function for theta of the binary put option:
def theta_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    theta = np.exp(-r*T)*(-n(d2,0,1)*(1/(2*T))*(1/(sigma*np.sqrt(T)))*(np.log(KPI_0/KPI_goal)-(r-(sigma**2)/2)*T)+r*N(-d2,0,1))

    return theta/365
```

In [42]:
```
theta_binary_put(31, 37.2, 0.02, 0.2, 1, 5, 2000000)
```

Out[42]:
```
0.00036628388710325535
```

Binary Rho

Rho measures the sensitivity to the interest rate change. It is the derivative of the option value with respect to the risk free interest rate. It's formula is given by:

$$\rho = e^{-rdt}(\frac{\phi\sqrt{T}}{\sigma}n(d_2) - TN(\phi d_2))$$

In [43]:
```
#Here we create a function for rho of the binary call option:
def rho_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    rho = np.exp(-r*T)*((np.sqrt(T)/sigma)*n(d2,0,1)-T*N(d2,0,1))

    return rho/100
```

In [44]:
```
rho_binary_call(31, 37.2, 0.02, 0.2, 1, 5, 2000000)
```

Out[44]:
```
0.01113038451564181
```

In [45]:
```
#Here we create a function for rho of the binary put option:
def rho_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P):
    """
    Input:
    bps = amount of basispoints bonus if a KPI goal is reached at maturity
    P = principal amount
    Q = payoff at maturity if the KPI is equal or above the KPI goal
    r = risk-free interest rate
    T = time to maturity in years
    """
    #First we calculate d1 and d2:
    d1 = (np.log(KPI_0/KPI_goal) + (r + sigma**2/2)*T)/(sigma*np.sqrt(T))
    d2 = d1 - sigma*np.sqrt(T)

    N = norm.cdf
    n = norm.pdf
    rho = np.exp(-r*T)*((-np.sqrt(T)/sigma)*n(d2,0,1)-T*N(-d2,0,1))

    return rho/100
```

In [46]:
```
rho_binary_put(31, 37.2, 0.02, 0.2, 1, 5, 2000000)
```

Out[46]:
```
-0.020932371248709364
```

Summary binary ESG Greeks

In [47]:
```
#For a binary option we use the following data as an example:
KPI_0 = 100
KPI_goal = 110
r = 0.004
sigma = 0.2
T = 1
bps = 5
P = 100

print("Delta of the call option: ", delta_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Delta of the put option: ", delta_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Gamma of the call option: ", gamma_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Gamma of the put option: ", gamma_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Vega of the call option: ", vega_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Vega of the put option: ", vega_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Theta of the call option: ", theta_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Theta of the put option: ", theta_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Rho of the call option: ", rho_binary_call(KPI_0, KPI_goal, r, sigma, T, bps, P))
print("Rho of the put option: ", rho_binary_put(KPI_0, KPI_goal, r, sigma, T, bps, P))
```

```
Delta of the call option:  0.017016951948029647
Delta of the put option:  -0.017016951948029647
Gamma of the call option:  0.0003033704757838877
Gamma of the put option:  -0.0003033704757838877
Vega of the call option:  0.006067409515677754
Vega of the put option:  -0.006067409515677754
Theta of the call option:  -0.0001817255363258 95
Theta of the put option:  0.00019264069237350 04
Rho of the call option:  0.014139314005435302
Rho of the put option:  -0.024099393898875218
```

Defining the range of parameters

In [48]:
```python
#We define some starting values for the parameters first
KPI_0 = 90
KPI_goal = 100
r = 0.004
sigma = 0.2
T = 1
bps = 5
P = 100

x = 100
y = 0.8

#Then we need to define some ranges of values to try for the different parameters
KPI_T = np.linspace(KPI_goal-y*KPI_goal,KPI_goal+y*KPI_goal,x) #between (1-y)KPI_0 till (1+y)KPI_0, create x points
TTM = np.linspace(T-y*T,T,x) #between (T-y)*T and T, create x points

#We create empty listst to later fill with values
spots = []
option_prices_c = []
option_prices_p = []
deltas_c = []
deltas_p =[]
gammas_c = []
gammas_p = []
vegas_c = []
vegas_p = []
OTM_thetas_c = []
ITM_thetas_p = []
rhos_c = []
rhos_p = []

#Here we fill for each ESG greek the list with corresponding values
for i in range(len(KPI_T)):
    spots.append(KPI_T[i])
    option_prices_c.append(binary_call(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    option_prices_p.append(binary_put(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    deltas_c.append(delta_binary_call(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    deltas_p.append(delta_binary_put(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    gammas_c.append(gamma_binary_call(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    gammas_p.append(gamma_binary_put(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    vegas_c.append(vega_binary_call(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    vegas_p.append(vega_binary_put(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    rhos_c.append(rho_binary_call(KPI_T[i], KPI_goal, r, sigma, T, bps, P))
    rhos_p.append(rho_binary_put(KPI_T[i], KPI_goal, r, sigma, T, bps, P))

for j in range(len(TTM)):
    OTM_thetas_c.append(theta_binary_call(KPI_0, KPI_goal, r, sigma, TTM[j], bps, P))
    ITM_thetas_p.append(theta_binary_put(KPI_0, KPI_goal, r, sigma, TTM[j], bps, P))
```

In [49]:
```python
#We define some starting values for the parameters first
KPI_0 = 110
KPI_goal = 100
r = 0.004
sigma = 0.2
T = 1
bps = 5
P = 100

x = 100
y = 0.8

#Then we need to define some ranges of values to try for the different parameters
TTM = np.linspace(T-y*T,T,x) #between (T-y)*T and T, create x points

#We create empty listst to later fill with values
ITM_thetas_c = []
OTM_thetas_p = []

#Here we fill the theta lists with corresponding values
for j in range(len(TTM)):
    ITM_thetas_c.append(theta_binary_call(KPI_0, KPI_goal, r, sigma, TTM[j], bps, P))
    OTM_thetas_p.append(theta_binary_put(KPI_0, KPI_goal, r, sigma, TTM[j], bps, P))
```

In [50]:
```python
#We define some starting values for the parameters first
KPI_0 = 100
KPI_goal = 100
r = 0.004
sigma = 0.2
T = 1
bps = 5
P = 100

x = 100
y = 0.8

#Then we need to define some ranges of values to try for the different parameters
TTM = np.linspace(T-y*T,T,x) #between (T-y)*T and T, create x points

#We create empty listst to later fill with values
ATM_thetas_c = []
ATM_thetas_p = []

#Here we fill the ATM theta lists with corresponding values
for j in range(len(TTM)):
    ATM_thetas_c.append(theta_binary_call(KPI_0, KPI_goal, r, sigma, TTM[j], bps, P))
    ATM_thetas_p.append(theta_binary_put(KPI_0, KPI_goal, r, sigma, TTM[j], bps, P))
```

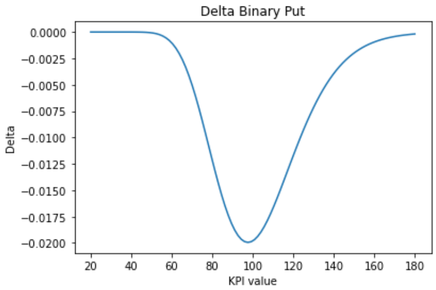
The plots

In [51]:
```
# plt.plot(spots, option_prices_c)
# plt.title("Binary KPI Call")
# plt.xlabel("KPI value")
# plt.ylabel("Price")

# plt.show()
```

In [52]:
```
# plt.plot(spots, option_prices_p)
# plt.title("Binary KPI Put")
# plt.xlabel("KPI value")
# plt.ylabel("Price")

# plt.show()
```

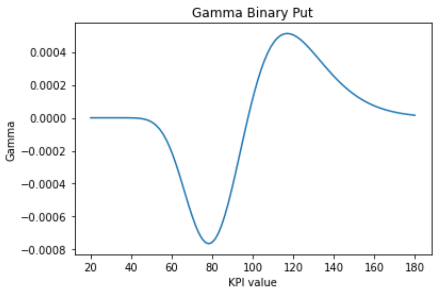
In [53]:
```
# plt.plot(spots, deltas_c)
# plt.title("Delta Binary Call")
# plt.xlabel("KPI value")
# plt.ylabel("Delta")

# plt.show()
```

In [54]:
```
plt.plot(spots, deltas_p)
plt.title("Delta Binary Put")
plt.xlabel("KPI value")
plt.ylabel("Delta")

plt.show()
```



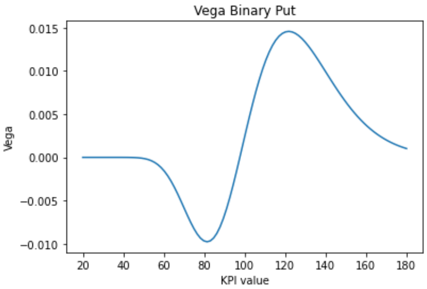
In [55]:
```
# plt.plot(spots, gammas_c)
# plt.title("Gamma Binary Call")
# plt.xlabel("KPI value")
# plt.ylabel("Gamma")

# plt.show()
```

In [56]:
```
plt.plot(spots, gammas_p)
plt.title("Gamma Binary Put")
plt.xlabel("KPI value")
plt.ylabel("Gamma")

plt.show()
```



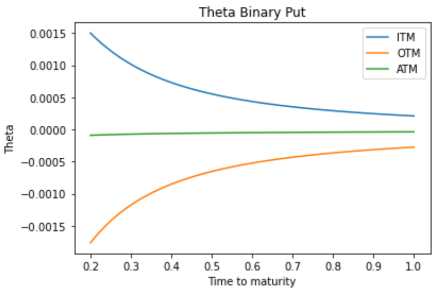
In [57]:
```
# plt.plot(spots, vegas_c)
# plt.title("Vega Binary Call")
# plt.xlabel("KPI value")
# plt.ylabel("Vega")

# plt.show()
```

In [58]:
```
plt.plot(spots, vegas_p)
plt.title("Vega Binary Put")
plt.xlabel("KPI value")
plt.ylabel("Vega")

plt.show()
```



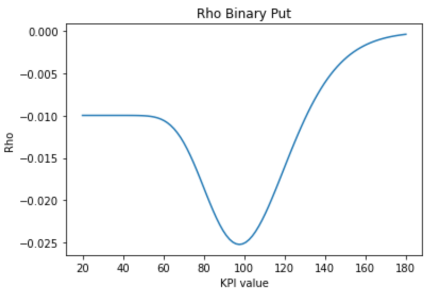
In [59]:
```
# plt.plot(TTM, ITM_thetas_c) #Blue line
# plt.plot(TTM, OTM_thetas_c) #Orange line
# plt.plot(TTM, ATM_thetas_c) #Green line
# plt.title("Theta Binary Call")
# plt.xlabel("Time to maturity")
# plt.ylabel("Theta")
# plt.legend(['ITM', 'OTM', 'ATM'])

# plt.show()
```

In [60]:
```
plt.plot(TTM, ITM_thetas_p) #Blue line
plt.plot(TTM, OTM_thetas_p) #Orange line
plt.plot(TTM, ATM_thetas_p) #Green line
plt.title("Theta Binary Put")
plt.xlabel("Time to maturity")
plt.ylabel("Theta")
plt.legend(['ITM', 'OTM', 'ATM'])

plt.show()
```



In [61]:
```
# plt.plot(spots, rhos_c)
# plt.title("Rho Binary Call")
# plt.xlabel("KPI value")
# plt.ylabel("Rho")

# plt.show()
```

In [62]:
```
plt.plot(spots, rhos_p)
plt.title("Rho Binary Put")
plt.xlabel("KPI value")
plt.ylabel("Rho")

plt.show()
```



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