UNIVERSIDADE FEDERAL DO PARANÁ

GILMARQUES AGAPITO COSTA

ECONOMIC POLICY UNCERTAINTY IN MERGES AND ACQUISITIONS: REAL OPTIONS ANALYSIS

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Dissertação apresentada ao curso de Pós-Graduação em Contabilidade, Setor de Ciências Sociais Aplicadas, Universidade Federal do Paraná, como requisito parcial à obtenção do título de Mestre em Contabilidade.

Orientador: Prof. Dr. Claudio Marcelo Edwards Barros

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Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação CONTABILIDADE da Universidade Federal do Paraná foram convocados para realizar a arguição da Dissertação de Mestrado de **GILMARQUES AGAPITO COSTA** intitulada: **Economic policy uncertainty in mergers and acquisitions: real options analysis**, sob orientação do Prof. Dr. CLAUDIO MARCELO EDWARDS BARROS, que após terem inquirido o aluno e realizada a avaliação do trabalho, são de parecer pela sua APROVAÇÃO no rito de defesa.
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Aos meus pais, sem eles nada seria possível.

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. . . the dynamics of the Exchange will never be an exact science. But it is possible to study mathematically the state of the market at a given instant . . .

Louis Bachelier, 1900

RESUMO

O arcabouço da Teoria das Opções Reais (ROT) em relação ao Índice de Incerteza da Política Econômica (EPU) requer maior reforço empírico, especialmente no contexto de projetos de investimento em fusões e aquisições (F&A). Ainda existem lacunas nesse domínio teórico que precisam ser exploradas. Para contribuir com a discussão, este estudo tem como objetivo investigar o impacto da EPU no processo de avaliação de operações de F&A utilizando o método de Fluxo de Caixa Descontado (FCD) expandido por Opções Reais. Para operacionalizar a avaliação, foi proposto um modelo que consiste em padronizar a variável EPU e reorganizá-la por meio da Análise de Componentes Principais (ACP). Essa abordagem resultou na criação de quatro cenários não discricionários para testar a estimativa. Além disso, quatro cenários discricionários foram gerados por meio de 10.000 simulações de possíveis caminhos para a variável EPU usando o processo Movimento Geométrico Browniano (MGB). No ambiente de teste, os resultados indicaram que a abordagem não discricionária, que se baseou apenas nas características das amostras transformadas por ACP e estimação por FCD expandido por Opções Reais, mostrou-se adequada para estimar valores considerando a volatilidade da EPU. O modelo desenvolvido foi aplicado na aquisição da Latinex pela M. Dias Branco, sendo os valores obtidos muito próximos dos divulgados pela empresa em suas demonstrações financeiras. Além disso, verificou-se que esses valores variam de acordo com o nível de volatilidade da EPU. Os testes de sensibilidade realizados confirmaram a adequação do modelo não discricionário proposto para a incorporação da volatilidade da EPU. Concluiu-se que um aumento no nível de volatilidade da EPU pode levar a maiores valores de projeto, maiores valores de opções e maiores riscos associados. Essas descobertas contribuem para a compreensão dos efeitos da volatilidade da EPU nas avaliações de F&A e enfatizam a importância de considerar a incerteza da política econômica nos processos de tomada de decisão de investimento.

Palavras-Chave: Incerteza da Política Econômica, Opções Reais, Fusões & Aquisições.

ABSTRACT

The Real Options Theory (ROT) framework in relation to the Economic Policy Uncertainty Index (EPU) requires further empirical reinforcement, especially within the context of investment projects in mergers and acquisitions (M&A). There are still gaps in this theoretical domain that need to be explored. To contribute to the discussion, this study aims to investigate the impact of EPU on the valuation process of M&A transactions using the Discounted Cash Flow (DCF) method expanded by Real Options (ROV). To operationalize the evaluation, a model was proposed that involves standardizing the EPU variable and reorganizing it through Principal Components Analysis (PCA). This approach resulted in the creation of four non-discretionary scenarios for testing estimation. Additionally, four discretionary scenarios were generated through 10,000 simulations of possible paths for the EPU variable using the Geometric Brownian Motion (GBM) process. In the test environment, the results indicated that the non-discretionary approach, which solely relied on the characteristics of the PCA-transformed samples and estimation through DCF expanded by ROV, proved suitable for estimating values while considering the EPU volatility. The developed model was applied to the acquisition of Latinex by M. Dias Branco, and the obtained values closely aligned with those disclosed by the company in its financial statements. Furthermore, these values were found to vary based on the level of EPU volatility. The sensitivity tests conducted confirmed the appropriateness of the proposed non-discretionary model for incorporating the EPU volatility. It was concluded that an increase in the EPU volatility level can lead to higher project values, increased option values, and greater associated risks. These findings contribute to the understanding of the effects of EPU volatility on M&A valuations and emphasize the importance of considering economic policy uncertainty in investment decision-making processes.

Keywords: Economic Policy Uncertainty, Real Options, Merges & Acquisitions.

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LIST OF ABBREVIATIONS

BSM	Black-Scholes-Merton Model
CADE	Conselho Administrativo de Defesa Econômica
CPC	Comitê de Pronunciamentos Contábeis
CVaR	Conditional Value-At-Risk
CVM	Comissão de Valores Mobiliários
DCF	Discounted Cash Flow
EBITDA	Earnings Before Interest, Taxes, Depreciation and Amortization
EPU	Economic Policy Uncertainty Index
FV	Fair Value
GBM	Geometric Brownian Motion
GDP	Gross Domestic Product
IFRS	International Financial Reporting Standards
LACFIN	Laboratório de Contabilidade Financeira
MAD	Marketed Asset Disclaimer
M&A	Mergers and Acquisitions
NPV	Net Present Value
PCA	Principal Component Analysis
PPGCONT	Programa de Pós-graduação em Contabilidade
ROV	Real Options Valuation
UFPR	Universidade Federal do Paraná
VaR	Value-At-Risk
WACC	Weighted Average Cost of Capital

CONTENTS

1 INTRODUCTION

The commercial landscape has undergone notable transformations over the course of time, continually aligning with emerging requirements and innovations. This evolution is attributed to legal imperatives as well as the dynamic nature of financial markets. The advent of technological progress has imparted a level of refinement to markets, facilitating heightened integration and expeditious information exchange. Within this context of pricing information, it becomes imperative to discern the determinants that contribute to the formulation of pricing structures. Noteworthy among these considerations are the investments stemming from merger and acquisition (M&A) endeavors, necessitating a comprehensive understanding of all variables that possess the potential to influence such transactions.

In the Latin American context, the phenomenon of M&A gained substantial momentum in the early 1990's (Dakessian & Feldmann, 2013; Flanagan et al., 1997; Metwalli & Tang, 2004). Facilitating M&A transactions demands a conducive environment, albeit instances of exceptional events like the 2008 global financial crisis and the subsequent COVID-19 pandemic introduce pronounced volatility to the business landscape. These events, marked by their uniqueness, necessitate heightened government attention, demanding swift responses capable of mitigating the ensuing economic ramifications while curbing environmental volatility.

Dixit & Pindyck (1994) assert that investment, encompassing M&A ventures, resembles committing immediate resources for future gains, but amidst inherent uncertainties. Consequently, the prudent approach entails assessing probabilities of diverse outcomes, each signifying varying profitability or loss potential for the enterprise. Pindyck (1991) highlights investment irreversibility that renders it susceptible to various risk forms: uncertainties about future product prices and operating costs shaping cash flows, fluctuating interest rates, and the cost-timing uncertainty of the investment itself. In this investigation, the focal point is uncertainty viewed through the lens of economic policy uncertainty, emanating from decisions by economic entities aimed at economic and financial stability. Baker et al. (2016) Economic Policy Uncertainty Index (EPU)[1] endeavors to quantify economic policy uncertainty levels, derived from newspapers and analogous sources, accessible in specific nations, including Brazil.

Numerous scholarly investigations examining the repercussions of economic policy uncertainty have incorporated the Economic Policy Uncertainty (EPU) variable, yielding evidence concerning diverse dimensions: spill-over effects (Biljanovska et al., 2021; Dakhlaoui & Aloui, 2016; Li et al., 2020; Ozili, 2021); anticipated market returns and exchange rates (Beckmann & Czudaj, 2017; Chen et al., 2017; Kang et al., 2014); bank loan loss provisions, lending, and credit expansion (Bordo et al., 2016; Danisman et al., 2021); cash reserves and liquidity (Demir & Ersan, 2017; Duong et al., 2020; Phan et al., 2019); as well as investment levels and cost of capital (Drobetz et al., 2018; Kang et al., 2014; Wang et al., 2014). In each of these outlined

[1] In this study, the acronym EPU was used both to refer to the variable created by Baker et al. (2016) and to address the uncertainty of economic policy in theory.

relationships, a heightened EPU level correlates with detrimental impacts on the business milieu, characterized by varying intensities contingent on the organizational nature, be it public or private, consequently fostering an environment of heightened volatility.

As previously discussed, the EPU factor exerts influence on numerous facets that can exert direct or indirect impacts on decision-making within M&A negotiations. Successfully concluded M&A transactions demand a wealth of accurate information to culminate effectively, given their anticipatory objective of maximizing organizational utility. This necessitates investments in terms of financial resources, time, and comprehensive research to generate reports that offer apt insights into the equitable value of the target company—both prior to, during, and post the acquisition process (Welch et al., 2020).

Additional research has examined the repercussions of EPU on M&A transactions across distinct geographical contexts. Notably, investigations encompassing North America (Bonaime et al., 2018; Cotei et al., 2022; Nguyen & Phan, 2017) and China (Li et al., 2022; Sha et al., 2020) have underscored the sensitivity of M&A endeavors to EPU levels. This sensitivity manifests itself in slight variations that transcend organizational ownership, ultimately influencing cross-border commercial activities and even extending to the domain of startup acquisitions.

In a recent exploration by Batista et al. (2023), the researchers illuminated how EPU exercises a detrimental impact on the proclivity of Brazilian firms to execute M&A transactions. The scholars expound that uncertainty is typified by the incapability to forecast specific occurrences, thereby thwarting investors' ability to react preemptively. Consequently, insights into new information only crystallize post-event. This perspective aligns with Bernanke (1983) assertion concerning an environment marked by pronounced uncertainty. This milieu tends to impede investments irrespective of inherent operational risks, as managers may gravitate towards a posture of caution and delay, opting to await a clearer understanding of unfolding circumstances.

1.1 PROBLEM AND RESEARCH QUESTION

We are presented with the prospect of addressing M&A scenarios within the context of either complete or incomplete markets (Björk, 2020). In financial parlance, a situation is deemed complete when an asset X can be replicated or hedged via a self-funding portfolio denoted as H, the latter term denoting a replicant or hedging portfolio. The market attains completeness when all contingent claims are attainable. However, market incompleteness can manifest through diverse avenues, encompassing scenarios where the number of random sources exceeds the risky underlying assets, constraints on admissible portfolios, the non-tradability of the underlying asset, market illiquidity despite the tradability of the underlying asset, or logistical constraints on portfolio transfer with associated time costs.

Within the realm of both complete and incomplete markets, an avenue of exploration emerges, wherein the direct implications of EPU on cash flow streams during M&A endeavors can be scrutinized. In the context of this investigation, our purview aligns with the incomplete market model, enabling an examination of non-replicable assets devoid of the potential existence of investment portfolios with replicating capabilities. In essence, we factor in the volatility of returns derived from discounted cash flows and the market-provided risk-free rate, while holding all other variables constant. In this instance, the lens excludes the uncertainty encapsulated by EPU and any associated metrics emanating from this parameter. Subsequently, transitioning to a subsequent phase, we delve into an evaluation of the historical trends characterizing the Brazilian EPU, entailing a projection of EPU and encompassing considerations of index volatility and the market-endorsed risk-free rate. This trajectory stems from antecedent research demonstrating the interconnectedness between EPU and variables governing the trading environment.

It's worth noting that numerous empirical inquiries have been conducted to examine the correlation between the level of EPU and investments. Particularly within the realm of M&A operations, a discernible trend is observed where there is a decreased likelihood of deal closures. This trend is even more pronounced in economies characterized by openness, and this pattern holds true for Brazil as well (Batista et al., 2023; Bonaime et al., 2018; Cotei et al., 2022; Li et al., 2022; Nguyen & Phan, 2017; Sha et al., 2020). However, it's imperative to underscore that these studies primarily validate the existence of a linkage between the EPU index and the frequency of M&A operations, or the reduction in the invested amounts within these transactions. What remains unexplored is an in-depth analysis of the implications arising from the integration of the EPU index as a variable within the M&A valuation model, along with its potential influence on investor decision-making.

Within this context, Biljanovska et al. (2021) delineate the presence of three guiding theories for EPU, specifically the Theory of Real Options, Growth Options, and Oil Theory-Hartman-Abel. Here in, our focus is directed towards the utilization of the Theory of Real Options, termed as Real Options Valuation (ROV), owing to its potential to address projects characterized by irreversibility, factors encapsulating environmental uncertainty, and entailing an intrinsic option value. This approach aligns effectively with decision-making processes within M&A contexts.

Concerning the realm of M&A transactions, the application of the Discounted Cash Flow (DCF) method to determine the Fair Value (FV) holds prevalent, a stance also recommended by IFRS 3 and 13. However, there exists a scholarly discourse that deems this approach as potentially inadequate in certain contexts (Bragoli et al., 2020; Heidrich et al., 2021; Ioulianou et al., 2021; Lyandres et al., 2020; Spiegel et al., 2020; Zhang et al., 2021; Zhou et al., 2020; Zormpas, 2021). The DCF model was originally devised for financial assets and primarily relies on market-derived information, thereby excluding the inherent uncertainty stemming from diverse factors that encompass expansion, continuity, and closure dynamics (Brandão, 2002; Marques et al., 2021).

In the context of this study, solely relying on the DCF method proves insufficient for two principal reasons. Firstly, the incorporation of the EPU index through the DCF framework would merely encapsulate a single snapshot of the potential states that the firm's valuation might attain, potentially leading to a distortion of the investor's decision-making process. Secondly, the DCF model fails to comprehensively encompass the multifaceted effects emanating from the EPU variable, as discerned in preceding research endeavors. Notably, these effects extend beyond numerical valuations, encapsulating decision-making dynamics and the potential deferment of investments influenced by EPU considerations.

With recognition that the market initially underestimated the significance of variance in option value attributed to variations in the rate of value change (Black & Scholes, 1973), along with the incorporation of interest rates derived from risk structure (Merton, 1973), the innovative Black-Scholes-Merton Model (BSM) materialized as a novel pricing paradigm. Characteristically, the BSM model is tailored for valuing European options. In our analysis, we adapt the formulation proposed by Cox et al. (1979), which enables the valuation of American options possessing the capacity for exercise at any point. This adaptation closely aligns with M&A operations, offering an avenue to dissect the flexibility inherent in these transactions and the decision-making dynamics they engender.

Consequently, both the EPU variable and the domain of M&A transactions find theoretical grounding within the framework of Real Options Theory. This enables a direct exploration of the influence of EPU on the quantification of M&A endeavors. Recent scholarly contributions investigating the nexus between EPU and M&A activities consistently reveal a negative correlation between heightened EPU levels and M&A outcomes (Batista et al., 2023; Bonaime et al., 2018; Cotei et al., 2022; Li et al., 2022; Nguyen & Phan, 2017; Sha et al., 2020).

Given the myriad uncertainties that encompass an M&A investment undertaking, encompassing factors such as economic policy uncertainty, asset price volatility, exercise of purchase or sale, subjectivity of anticipated cash flows, and more, the present study endeavors to integrate the EPU metric and its inherent volatility into the valuation process of an M&A transaction. This valuation is facilitated by an extension of the DCF Method, utilizing the framework of ROV, thereby facilitating an intricate examination of the ramifications of EPU on the option value within an M&A context. This exploration is carried out through a comparative analysis, contrasting scenarios pre- and post-inclusion of EPU, utilizing a binomial lattice approach anchored in the seminal works of Cox et al. (1979). In this context, wherein the presence of EPU can conceivably influence the valuation of an M&A transaction, thereby granting the investor the latitude to defer the decision regarding deal finalization, an unexplored research avenue emerges. The specific lacuna centers on comprehending the repercussions of EPU on the valuation of cash flow streams inherent in M&A transactions. Hence, our research query is formulated as follows: **What are the impacts observed on cash flows in a M&A operation when considering the EPU variable as part of the model developed through the expansion of the DCF approach by incorporating Real Options?**

1.2 GOALS OF THE RESEARCH EFFORT

Given the quandary posed by the potential of EPU to defer investments and its detrimental impact on M&A transactions, there emerges an implication from prior research that the EPU might instigate an option value within a transaction, thereby prompting the deferral of investments due to heightened uncertainty. As a result, integrating the EPU directly into the DCF method for M&A valuation is regarded as arbitrary, as it fails to account for the essential aspect of flexibility. Hence, in order to address the research question posited in this study, the following overarching objective was established: **Analyze the effects of the EPU variable on the cash flow of a M&A investment using a model developed based on the Expanded DCF by Real Options.**

To help assess the effects of economic policy uncertainty on measuring fair value in M&A, considering incomplete market scenarios, three specific objectives were established:

- Develop a valuation model that includes the EPU variable to measure FV from the combination of DCF and ROV methods. This objective aims to include the uncertainty of economic policy, which are not considered when using only the DCF method, bringing greater precision in the measurement and recognition of FV for the M&A transaction.

- Compare the valuation of business combinations measured by joining DCF and ROV. This objective initially seeks to verify the DCF model expanded by the ROV, then the product of the EPU by the binomial lattice of the expanded DCF, here called the discretionary mode. Afterwards, the analysis of the use of EPU volatility in the DCF model expanded by ROV. Thus, it allows the visualization of the effects before and after the inclusion, and what is the best way to increase the EPU in the calc and evaluation of M&A.

- Apply the model developed in the first objective and tested in the second objective in the case of the M&A of M. Dias Branco and Latinex, which occurred in the Brazilian scenario in 2021, after the adoption of the IFRS. This last objective helps us to demonstrate how the EPU variable affects the evaluation process in an M&A negotiation and corroborates the results found in the test model of the second objective and, finally, gives empirical support to the hypotheses raised in previous studies on o relationship between EPU and M&A processes.

Consequently, in aid of realizing both the overarching and the particular goals stipulated, it becomes imperative to delve into the realm of real options theory and its applicability within the context of M&A processes. This exploration encompasses an assessment of the feasibility of incorporating the EPU variable into the framework of modeling real options. Furthermore, it entails an examination of pertinent inquiries regarding M&A operations. It involves a comprehensive account of the empirical assessments conducted involving the EPU and their implications for the investment landscape, particularly concerning M&A undertakings, while also addressing the ongoing ramifications being deliberated upon.

In culmination, the ultimate endeavor of this study is to formulate a model underpinned by the theoretical underpinnings elucidated. This model aims to adeptly capture the nuanced effects of EPU on the cash flow projections pertaining to M&A operations.

1.3 DELIMITATIONS

The primary objective of this study is to engage in a comprehensive exploration of the effects instigated by the EPU when integrated into a business valuation model. This is achieved through the expansion of the DCF methodology utilizing the ROV framework within a binomial lattice structure. This investigative pursuit is undertaken against the backdrop of the discernible impacts highlighted in preceding studies concerning the EPU on the economic variables that intricately influence the business milieu. The central aspiration of this investigation is to provide a systematic assessment within the context of valuating M&A transactions.

Amidst the array of approaches available for the valuation of corporate entities, our study will employ the ROV methodology to augment the valuation process conducted by the DCF model. The selection of the DCF model as our baseline is underpinned by its extensive utilization and accessibility, coupled with its robust underlying assumptions and well-established theoretical underpinnings. This choice is grounded in accordance with the tenets of the Marketed Asset Disclaimer (MAD), as posited by (Copeland & Antikarov, 2003), which asserts that the most pertinent comparable asset corresponds to the present value of the company's internal cash flows. In embracing this approach, our investigation firmly situates itself within the conceptual framework of incomplete markets.

In the context of ROV, a deliberate choice was made to accommodate the valuation of EPU effects across different temporal junctures. This decision was motivated by the inherent flexibility intrinsic to the M&A transaction, which enables the scrutiny of its repercussions on decision-making dynamics and provides a means to incorporate novel variables. The ROV methodology, in its valuation paradigm, offers a heightened precision concerning asset quantification. Furthermore, it engenders theoretical justification for the utilization of replicating assets in cases devoid of any unobserved data, thereby enriching the framework within incomplete markets. Subsequent to the formulation of the valuation model, its practical application is extended to an M&A scenario. Here, the focal instance involves the acquisition of the non-listed entity Latinex by the corporation M.Dias Branco. This application serves to illuminate the effects engendered by the inclusion of EPU at different stages, culminating in an evaluation of their influence on decision-making processes.

1.4 JUSTIFICATIONS AND CONTRIBUTIONS

Within the scope of this study, an intricate interplay emerges as the EPU significantly impacts an array of macro and microeconomic variables, ultimately influencing private enterprises in multifaceted ways. Against this backdrop, we endeavor to proffer a model designed to appraise the equitable value in M&A negotiations. This model, a product of our research, effectively incorporates the ramifications engendered by variations in the EPU level—be they ascensions or descents—thereby endowing decision-makers with enhanced insights for precise company valuations. The rationale for this study hinges on three distinct pillars. Primarily, a multitude of empirical investigations furnish cogent evidence underscoring the correlation between EPU and the overarching business milieu. Secondly, historical data unfurls a discernible surge in M&A undertakings, driven by the quest for corporate expansion, which correspondingly experiences contractions during periods of upheaval, such as the global financial crisis of 2008 and the ongoing COVID-19 pandemic, engendering an intensified demand for meticulous scrutiny from industry professionals. Lastly, the managerial sphere is predicated on the underpinnings of comprehensive valuation reports for targeted acquisitions, compelling analysts to navigate models that proffer dependable estimations. It is evident that a consensus on the ideal evaluation methodology remains elusive, calling for an adaptable approach that harmonizes with the nuanced requirements of diverse companies.

The EPU factor extends its influence to the realm of equity markets (Chen et al., 2017), where its impact resonates with exchange rate fluctuations (Beckmann & Czudaj, 2017). The ramifications of EPU further extend to fiscal policy effects (Hassett & Metcalf, 2001), encompassing implications on bank losses recognition (Danisman et al., 2021). Furthermore, the impact of EPU precipitates a reduction in bank credit levels, as explored by Bordo et al. (2016). This pervasive phenomenon imparts a higher propensity for cash holdings under heightened EPU conditions, an observation affirmed by studies such as Demir & Ersan (2017); Duong et al. (2020); Phan et al. (2019). Moreover, the broader landscape of EPU's effects extends to investment levels and the cost of capital, as expounded by Drobetz et al. (2018); Kang et al. (2014); Wang et al. (2014). The intricate interplay of EPU's influence on these macro and microeconomic factors exerts a discernible impact on M&A operations. The empirical findings garnered from extant literature emphasize the direct repercussions of EPU on the curtailment of M&A endeavors. This effect on M&A operations significantly permeates the decision-making process, as evidenced by research contributions such as those by Cotei et al. (2022); Li et al. (2022); Nguyen & Phan (2017).

In a recent scholarly investigation, Batista et al. (2023) presented compelling evidence that underscores the adverse impact of the EPU index proposed by Baker et al. (2016) on M&A activities in the Brazilian context. Employing an alternative measure of uncertainty, namely the IIE-Br[2], the study conducted a comparative analysis. Notably, the utilization of the IIE-Br

[2]The IIE-Br (Indicador de Incerteza da Economia Brasileira) is meticulously generated by the Brazilian Institute of Economics (IBRE/FGV). This composite index consists of two distinct components. The first component is predicated on the media coverage, involving the frequency of articles within the six most prominent newspapers of substantial circulation in the country. This influential set of newspapers comprises "Valor Econômico", "Folha de São Paulo", "Correio Brasiliense", "Estadão", "O Globo", and "Zero Hora". The textual analysis involves the identification of terms that signal economic uncertainty, encompassing such descriptors as "ECON" for economics, and "INSTAB", "INCERT", and

failed to yield statistically significant results. This empirical exploration encompassed a dataset comprising companies with a substantial presence of 40% in Brazilian stock exchange trading sessions during the timeframe spanning 2010 to 2019. Consequently, the historical examination of the intricate interplay between EPU, the broader economic milieu, and M&A transactions reveals a recurrent pattern characterized by predominantly unfavorable outcomes. This empirical tendency aligns well with the underlying principles of the Theory of Real Options, which posits the prudence of awaiting the attenuation of uncertainty before committing to significant investment actions. These empirical insights underscore the existence of a research void, necessitating an investigation into the plausible impacts of EPU within the context of valuation processes. Such an endeavor holds the potential to enhance the decision-making process within M&A operations, thereby shedding light on the potential gains or losses associated with such undertakings.

Nations have demonstrated a keen interest in ameliorating both internal and external business bureaucracy, evident through initiatives like the widespread adoption of IFRS by select countries, as well as the implementation of liberalization policies. These efforts have contributed to streamlining business processes, fostering an environment conducive to increased M&A activities (Dakessian & Feldmann, 2013; Metwalli & Tang, 2004). However, it is worth acknowledging that unanticipated crises, beyond managerial control, can exert a contrary influence on M&A transactions on a global scale by amplifying uncertainty. This heightened uncertainty, captured by the EPU index, has been identified in research as a factor capable of inducing a deferral in investments (Bonaime et al., 2018; Cotei et al., 2022; Nguyen & Phan, 2017).

In this regard, industry practitioners should maintain a vigilant awareness of fluctuations between phases of business expansion and contraction. Such attentiveness to the fluctuations in uncertainty aids in conducting more nuanced evaluations to inform prudent decision-making processes. Given this backdrop, this study advances a novel company valuation model. A pivotal aspect of this model is its incorporation of the EPU variable, which takes into account the degree of uncertainty prevailing in the geographic location of the target company. The inclusion of the EPU variable in the model is grounded in the belief that understanding its effects contributes to a more comprehensive evaluation process, thereby bolstering the efficacy of decision-making in the context of M&A transactions.

Amidst the academic and market discourse, a notable divergence exists regarding the most appropriate manner in which to appraise investments in the context of M&A (Ambrose & Steiner, 2022; Becker, 2022; Chen, 2021; Dierkes & Schäfer, 2021; Huang et al., 2022;

"CRISE" to denote uncertainty. The second distinctive component of the IIE-Br metric encompasses an indicator reflecting the dispersion evident within the macroeconomic forecasts of market analysts. These forecasts are centered around pivotal macroeconomic variables, including the basic interest rate (Selic), the Extended Consumer Price Index (IPCA), and the exchange rate (PTAX) (Batista et al., 2023). This comprehensive composition allows the IIE-Br to encapsulate a multifaceted understanding of the prevailing economic uncertainty within the Brazilian context.

Marques et al., 2021; Niu et al., 2021; Schüler, 2021; Zormpas, 2021). This discord underscores a significant research gap that warrants further exploration in the realm of M&A valuation methods. In response, this study capitalizes on the prevailing familiarity and utilization of the DCF method in both the market and academia. By augmenting this method with ROV, a more robust technique capable of accommodating the analysis of non-traded assets within the construct of incomplete markets, an innovative approach emerges. This hybrid approach enables the consideration of the EPU variable, thereby engendering a valuation framework that duly accounts for the well-established impacts of EPU on investment decisions.

The exclusive application of the DCF method has come under scrutiny within scholarly discussions. Several authors contend that this method's design, which assumes constant growth in perpetuity, may not adequately capture the accurate valuation of assets, particularly in instances where flexibility, shifts in valuation, and various forms of uncertainties are integral to an investment undertaking (Becker, 2022; Bodie et al., 2018; Chen, 2021; Huang et al., 2022; Koch-Medina et al., 2021). As a result, the utilization of DCF alone can potentially lead to considerable valuation discrepancies, notably in cross-border M&A transactions (O'Brien, 2022). Such discrepancies may stem from the misjudgment of critical variables or the application of pricing models that do not harmonize with the specific operational characteristics of the company in question.

Hence, the supplementation of the valuation process with the ROV methodology is grounded in its capacity to facilitate valuation even within an environment lacking perfect comprehensive assets and complete markets (Ewald & Taub, 2022). This method is particularly pertinent given the acknowledgement that heightened uncertainty can exert a discernible impact on investment decisions (Ewald & Taub, 2022). Moreover, ROV enables the incorporation of the EPU variable, a facet capable of generating option value within the context of M&A investment transactions (Baker et al., 2016; Gulen & Ion, 2015). As such, the decision to incorporate the local EPU into the company valuation methodology serves to imbue the valuation process with the distinctive economic landscape inherent to the target company's operational environment. This consideration also embraces the potential option value engendered by the EPU within M&A transactions.

This study constitutes a theoretical addition to the burgeoning literature on EPU. Distinguishing itself from earlier research endeavors that primarily concentrated on elucidating the correlation between the EPU variable and its repercussions on diverse investment dimensions (Baker et al., 2016; Gulen & Ion, 2015), such as exchange rates (Beckmann & Czudaj, 2017), stock market performance (Dakhlaoui & Aloui, 2016; Li et al., 2020), and cash reserves (Demir & Ersan, 2017; Duong et al., 2020; Phan et al., 2019), among other aspects. This present inquiry delves into the role of EPU as a pivotal metric for ascertaining the valuation of target enterprises within the context of M&A. The research underscores that EPU, extending beyond its influence on country or company-level variables, assumes a significant role in the evaluation of companies and the discernment of option values that arise from the impact of EPU on the business milieu. Consequently, EPU emerges as a plausible candidate for inclusion within the framework of pricing models that underpin investment undertakings.

Concerning the realm of Real Options Theory, this research significantly contributes to the comprehension of the DCF method's expansion through the application of ROV based on the conceptual framework outlined by Cox et al. (1979), alongside the incorporation of the MAD premise. Additionally, an essential dimension of this study pertains to the exploration of the EPU variable within the context of the real options model. This metric of uncertainty effectively encapsulates the frictions engendered by the decisions made at the national level and the occurrence of momentous events. By delving into the utilization of the option value generated by the volatility inherent in this variable, the investigation enriches existing literature with discussions that revolve around decision-making processes. Furthermore, this study extends the theoretical discourse by elucidating the methodologies employed for integrating the EPU variable within the real options model, as applied within the ambit of M&A processes, thereby enhancing the understanding of the procedures for handling and simulating this variable.

From a pragmatic perspective, this study furnishes substantial practical insights by highlighting the discernible disparities in the attainment of equitable value within M&A undertakings. This is accomplished through the employment of a comprehensive framework that facilitates a comparative evaluation of investment projects gauged by the DCF method vis-à-vis an amalgamation of DCF and ROV. Significantly, this composite approach accommodates the incorporation of the EPU variable as a catalytic element in the generation of option value, particularly relevant in light of the irreversible attributes intrinsic to these investments. This systematic process, therefore, empowers stakeholders with a heightened capacity for informed decision-making through the juxtaposition of the ascertained values. Furthermore, it engenders a critical analysis of potential gains or losses in investment value, thereby facilitating an appraisal of the tangible impacts of the EPU variable on the transaction. Notably, this facet assumes an even greater significance for enterprises that are intricately interwoven with governmental dynamics, as evidenced by extant literature (Chen et al., 2017; Drobetz et al., 2018; Duong et al., 2020; El Ghoul et al., 2021).

Furthermore, this study furnishes a significant contribution by introducing a model that effectively encapsulates the inherent value of EPU within the realm of investments, catering notably to market analysts. This model bears particular relevance for analysts who subsequently utilize the derived value, as disclosed in financial statements, as a corroborative reference for their prognostications founded on cash flow assessments (Claessen, 2021; Nordlund et al., 2022). The innovative valuation model advanced in this research accords due consideration to the EPU variable within the structuring of project cash flows. It vividly presents values both in the presence and absence of strategic flexibility, while also illuminating the distinct option value engendered by the EPU. This facet is instrumental in steering investment decisions within the context of companies undergoing M&A processes, thereby accentuating the significance of this work for both decision-making managers and a diverse spectrum of investors.

In conclusion, this study extends a tangible contribution to both academic discourse and practical application by delineating the development of a robust evaluation model. Furthermore, the provision of the underlying code adds a layer of accessibility, thereby affording the potential for broader experimentation involving EPU across diverse national contexts and within varied M&A scenarios. This proactive approach not only facilitates the exploration of EPU's impact but also accommodates the potential enrichment of the model and its code through unanticipated adaptations. It is important to note that the model's scope is not designed for exhaustive coverage of all potential scenarios but rather seeks to initiate discourse around the EPU variable's pervasive influence within the entire business ecosystem. This engagement actively encourages a dynamic exploration of the model's utility and its applicability to multifaceted contexts.

This dissertation constitutes a significant component of the broader research initiative titled "Accounting Information in Financial Markets", which is housed within the domain of the Laboratorio de Contabilidade Financeira (LACFIN). This research endeavor is closely affiliated with the Financial Accounting and Finance research domain within the Programa de Pós-Graduação em Contabilidade (PPGCONT) at the Universidade Federal do Paraná (UFPR).

1.5 RESEARCH STRUCTURE

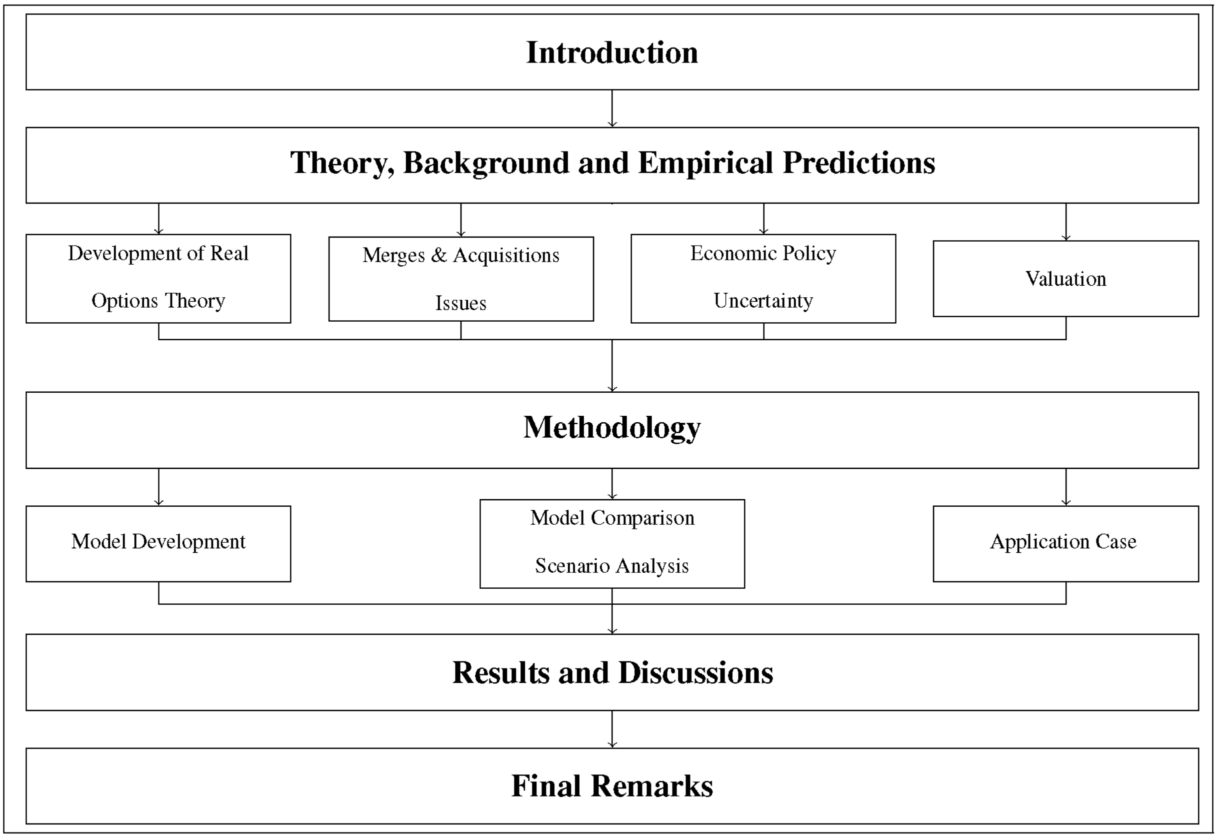
For better organization and a cohesive discussion, this study is structured as shown in Figure 1:

In this way, the work is composed of five chapters: Introduction; Theory, Background and Empirical Predictions; Methodology; Results and discussions; and Conclusion. This introduction is ordered from the contextualization of the theme to the formulation of the research question, general objective and presentation of the specific objectives. In sequence, the delimitation of the study and the justifications used to study the proposed problem and the main contributions are addressed.

The second chapter presents the theoretical framework used to support this research. At first, the Theory of Real Options used to guide the analysis of the study is presented, followed by a brief report on the issues inherent in M&A operations, and some relevant aspects that permeate these transactions. Subsequently, the main theme of the discussion is presented, the uncertainty of economic policy, treated here as EPU. Going through its origins, the problems that can originate them and the effects that it causes in the economic and business environment. We move on to a discussion regarding valuation. Approaching its applications, exploring its construction and importance for the measurement of assets, as well as the relationship of the variables that are used in the procedures. Exploring then, their methodologies and their limitations.

In the third chapter, the methodological choices that best adapt to the intentions of this research are described. Thus, in its composition are found the research design, the collection and treatment of the study variable, the development of the valuation model, the comparative tests and the case in which it will be applied. In the fourth chapter, we discuss the results found after testing and applying the developed model. Finally, we conclude the study, addressing the main topics found and their contributions.

Figure 1
Structure of the Manuscript.



NOTE: The Authors (2023).

2 THEORY, BACKGROUND AND EMPIRICAL PREDICTIONS

2.1 DEVELOPMENT OF REAL OPTIONS THEORY

In accordance with Wu & Buyya (2015) elucidation, a comprehensive understanding of the "Real Options" concept necessitates an exploration of the fundamental notion of an option. Examining it through a financial lens, an option encapsulates the prerogative bestowed upon an individual to either purchase or sell an underlying tangible asset at a predetermined price within a specific timeframe within the financial market, akin to a forthcoming clearinghouse transaction. This entitlement, secured by the individual, is formalized within an option contract, enunciating the stipulated date and price. Within financial parlance, the transaction value is also referred to as the "strike price", and the designated date assumes the appellation of "expiration" or "expiry date". The vested entitlement to purchase is coined as a "call option", whereas the entitlement to vend is designated a "put option". Following this concise delineation of the foundational concepts pertaining to stock options, a historical narrative can be introduced.

In a retrospective exploration of the historical trajectory of financial options trading, Poitras (2009) provides an account that traces back to antiquity. Notably, Aristotle's work *Politics* furnishes evidence of successful speculations conducted by Thales of Miletus through options operations. Thus, it is evident that the practice of options trading dates back to ancient Greek civilization. Poitras further traces the evolution of options trading from the fairs of Champagne during the medieval period to prominent urban centers such as Bruges, Antwerp, and Lyon in 16th century Europe. The account encompasses pivotal events including the Antwerp market's collapse and the consequent shift to Amsterdam, as well as the parallels between Antwerp and London options contracts and the evolution of the English market during the transition from the 16th to the 17th century. The narrative culminates with an examination of the operations of the Chicago Board Options Exchange in the United States during the 1970s, highlighting distinctions between American and European options trading methodologies.

Understanding the historical backdrop of financial options trading contributes to a comprehensive grasp of the evolution of the Real Options Theory. Notably, Bachelier (1900) thesis marks a seminal point as the first academic endeavor to introduce the term "options" and expound upon the various contract types prevalent in the French market. Bachelier's discourse delves into the intricacies of stock price movements and the feasibility of calculating probabilities associated with market fluctuations, which are classified as varying degrees of likelihood. This foundational work holds significant importance in shaping the contours of the contemporary Theory of Geometric Brownian Motion, a crucial tool employed in this study for the projection of pricing, cash flows, and the EPU index. Furthermore, Myers (1977) emerges as a pivotal figure, as he is the first to introduce the term "real options" into the academic lexicon. Myers situates this term within the context of companies' growth prospects, elucidating how debt issuance could potentially diminish the market value of a company equipped with real options. This scenario, in turn, could prompt a sub-optimal investment strategy. This seminal work by Myers has profound implications for understanding how real options interact with financial decisions within corporate frameworks.

An equally significant milestone in the evolution of option pricing theory is attributed to the seminal work of Black & Scholes (1973), which plays a pivotal role in the establishment of the stock option pricing formula. Their groundbreaking contribution rests on the principle that if options were accurately priced within the market, the construction of portfolios featuring long and short positions on options and their underlying stocks would yield no profit.

An important advancement stemming from this foundation was introduced by Merton (1976), wherein he incorporated interest rates derived from the risk structure. This enhancement enabled the model to encompass the pricing of distinct components constituting a company's capital structure. In a parallel vein, Myers (1977) harnessed the theory of options to assess a firm's value, characterizing the company as the summation of two distinct values, namely V and Vg. V represents the tangible value of the assets, while Vg signifies the value of growth or intangible assets. Myers propounds that Vg embodies the option value inherent within a company, a departure from Modigliani & Miller (1958) stance where the value of Vg emerges if investors anticipate a future rate of return on investments that surpasses the company's cost of capital. For the author, Vg embodies the option value inherent within a company, Modigliani & Miller (1958) stance where the value of Vg emerges if investors anticipate a future rate of return on investments that surpasses the company's cost of capital. This distinction underscores the interplay of conceptual frameworks between traditional financial options and real options. These nuances are summarized in Figure 2, elucidating the key disparities between the two domains.

Figure 2

Differences between Real Options and Financial Options.

Class	Financial Options	Real Options
Types of assets	Financial options are based on monetary assets. Financial options are tradable.	Real options are based on real assets. Real options are often non tradable as they are asset specific to the firm or organization
Influence of managerial actions	Holders of financial options have no influence over the value of financial options.	Managerial actions can influence a variety of aspects of the value of real options, such as the NPV* of underlying assets or volatility structure.
Contracts	Financial options are embedded in formal contracts, which explicitly specify options' exercise prices and expiration dates.	Real options are often not included as a clause in formal contracts. Some real options are not even contractual at all.
Realization of potential benefits from the exercise of options	Financial option holders can always realize potential gains when they choose to do so, due to specifications in the formal contracts.	Real option holders sometimes cannot realize potential benefits from exercising real options due to the lack of formal contracts.
Option exercising rules	Financial options have clear cut exercising rules.	Real options sometimes do not have a clear set of exercising rules when these options are created.

NOTE: This figure is adapted from Li (2007). *Net Present Value.

As elucidated by Chevalier-Roignant & Trigeorgis (2011), the framework of real options is grounded in a parallel drawn between financial options and contingent cash flows, albeit with notable distinctions. These distinctions encompass the non-tradability of real options within the capital market, as well as their capacity to be held concurrently by multiple investors, among other distinguishing factors as outlined in Table 2. Despite these disparities, the analogy between real investment ventures and specific financial instruments holds conceptual significance. In scenarios where contracts grant the option to discontinue a project for a residual value under pre-determined circumstances, an equivalence to a put option arises. This put option bestows the right, albeit not the obligation, to vend the underlying asset at an exercise price equivalent to the redemption value. The operationalization of this analogy, posited by Chevalier-Roignant & Trigeorgis (2011), within the realm of real options, is adeptly delineated in Figure 3.

Figure 3
Analogy between Real Options and Financial Options.

	Real Options	**Financial Options**
S	Underlying value of option is the NPV of incoming cash flow of investment project.	Underlying value of the option is the stock price
X	Amount of money to be invested or received in launching (exercising) the action (option).	Exercise (strike) price.
T	Time is based on when the decision must be made.	Time is until the option expires.
σ	The value of option varies with time and usually is very volatile.	The value is normally quite stable.
R	Risk-free discount rate.	Risk-free rate of interest.
D	Payoff will be the cash inflows of the investment project during the lifetime.	Payoff will be the underlying assets or-stock dividends.

NOTE: This figure is adapted from Wu & Buyya (2015) and Chevalier-Roignant & Trigeorgis (2011).

Dixit & Pindyck (1994) introduced the notion that investments in tangible assets are characterized by three pivotal attributes, each of varying degrees of relevance. First and foremost, these investments exhibit partial or complete irreversibility. The second attribute prompts consideration of the forthcoming returns derived from the investment. The third attribute encompasses the ability to either delay the project or adapt the arrangement, reflecting a crucial flexibility. Consequently, the potential to postpone an irreversible investment expenditure can wield a profound influence on the investment decision. The authors contend that the value of the forfeited option constitutes an opportunity cost that necessitates incorporation into the investment outlay. Beyond these three attributes delineated by Dixit & Pindyck (1994), Trigeorgis (1993) and Trigeorgis (1996) have delineated seven distinct categories of real options, expounded upon in Figure 4. These categories encompass the Option to Defer, the Time to Build Option, the Option to Alter Operating Scale, the Option to Abandon, the Option to Switch, the Growth Option, and Multiple Interacting Options.

Following the delineation of distinctions between financial options and real options, the explication of requisite attributes, and the presentation of real option categories, we are poised to characterize M&A operations within the ambit of this study. M&A operations encompass endeavors to procure or amalgamate with other enterprises, all with the overarching aim of attaining strategic and fiscal goals (Hossain, 2021). Notably, M&A agreements often encompass a multitude of constraining clauses, including the stipulation of performance benchmarks intertwined with the designated price and, in certain instances, provisions for the dissolution of the transaction, effectively undoing the deal.

Figure 4

Common Real Options.

Category	Description	Important In
Option to defer or invest*	An American-type call option embedded in projects where management has the right (but no obligation) to delay the project start for a certain time period. The exercise price is the cost needed to initiate the project. The option to defer the investment can be quite valuable, however, since the firm would invest only if prices and project value rise sufficiently, while it has no obligation to invest under unfavorable developments.*	All natural resource extraction industries; real estate development; farming; paper products; M&A's, include earnout settings.*
Time to build option	Staging investment as a series of outlays creates the option to abandon the enterprise in midstream if new information is unfavorable. Each stage can be viewed as an option on the value of subsequent stages, and valued as a compound option.	All R&D intensive industries, especially pharmaceuticals; long-develpment capital-intensive projects.
Option to alter operating scale	If market conditions are more favorable than expected, the firm can expand the scale of production or accelarate resource utilization. Conversely, if conditions are less favorable than expected, it can reduce the scale of operations. In extreme cases, production may temporarily halt and start up again.	Natural resource industries such as mine operations; facilities planning and construction in cyclical industries; fashion apparel; consumer goods; commercial real estate.
Option to abandon	If market conditions decline severely, management can abandon current operations permanently and realize the resale value of capital equipment and other assets in secondhand markets.	Capital intensive industries, such as airlines and railroads; financial services; new product introductions in uncertain markets.
Option to switch	If prices or demand change management can change the output mix of the facility. Alternatively, the same outputs can be produced using different types of inputs.	Consumer eletronics; toys; specialty paper; machine parts, electric power; chemicals; crop switching; sourcing.
Growth option	An early investment is prerequisite or link in a chain of interrelated projects, opening up future growth opportunities. Like interproject compound options.	All infrastructure-based or strategic industries, especially high-tech, R&D, or industries with multiple products generations or applications; multinational operations; strategic acquisitions.
Multiple interacting options	Reak-life projects often involve a "collection" of various options, both upward-potential enhancing calls and downward-protection put options present in combination. Their combined option value may differ from the sum of separate options values, i.e., they interact. They may also interact with financial flexibility options.	Real-life projects in most industries discussed above

NOTE: This figure is adapted from Trigeorgis (1993, 1996). *Changes made by the authors according to Chevalier-Roignant & Trigeorgis (2011), Lukas et al. (2012, 2019) and Battauz et al. (2021).

The M&A operation constitutes a specific genre of investment undertaken by the interested entity. In the purview of Dixit & Pindyck (1994), the determinative choice to invest in a particular asset can engender irrevocable costs. Despite the fact that M&A contractual stipulations confer a degree of adaptability to projects (Monteiro, 2019), the influence of factors such as the EPU index can exert an impact on the oscillation in the value of the option that M&A agreements can potentially engender for the investor. The temporal juncture at which investment is executed holds profound significance within M&A contracts. Upon the activation of the investment option, the acquirer relinquishes the value of said option, precipitating losses if the prospective target company value undergoes depreciation in subsequent periods. In such cases, a resale of the target company would result in a diminution of the invested amount. Conversely, in scenarios where uncertainties pertinent to the project abate, and the investor can ascertain the value of the option, its activation in a subsequent period offers the prospect of realizing accrued gains.

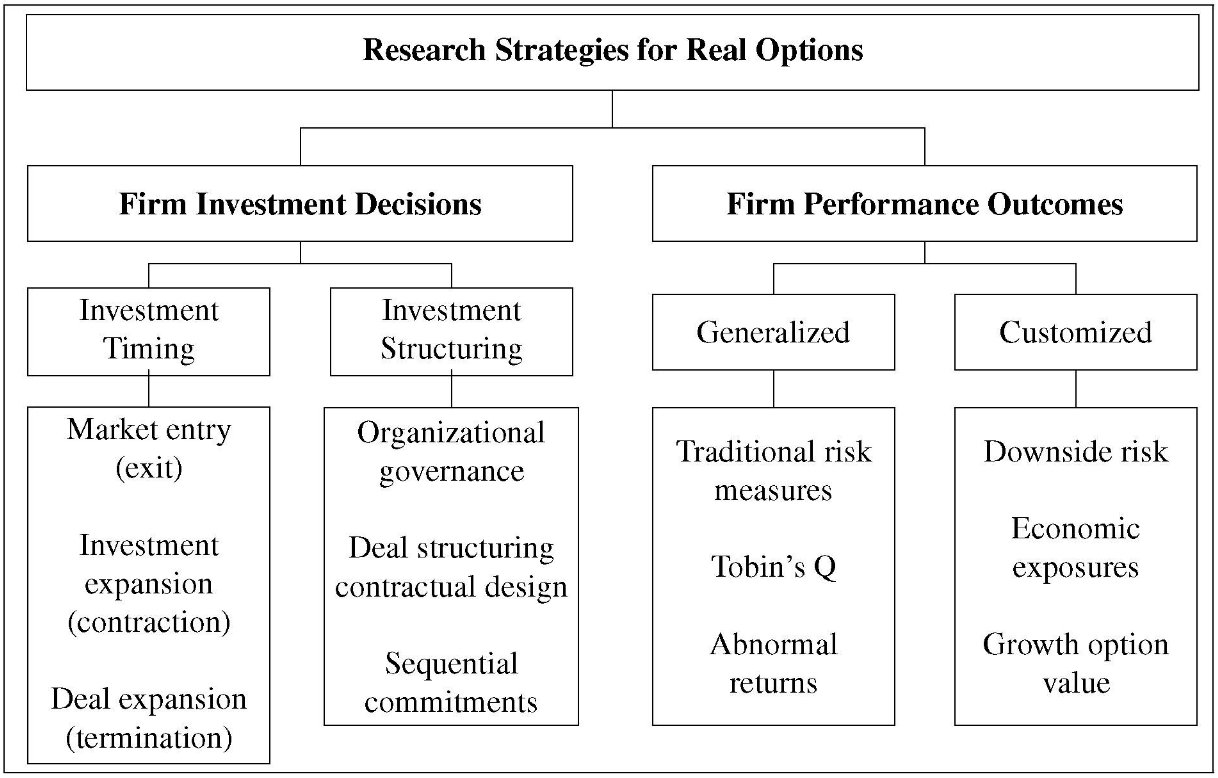
Within the realm of M&A operations, they can be categorized into the domains of "Options to Defer (Invest)" and "Growth Options". In accordance with the perspectives outlined by Dixit & Pindyck (1994) and Trigeorgis (1996), the prospect of investment in M&A ventures parallels the contours of a financial call option. This analogy is apt as the strategic decision to invest engenders the prerogative to either actualize the investment or await an opportune juncture to acquire a distinct entity. In a contrasting vein, Trigeorgis (1996) underscores the notion that the acquisition of alternative entities confers a network of interlinked projects, enriching the investing firm's production chain, logistical operations, or expanding its purview across product or market domains. The objective of acquisitions resides in fostering cash flows through the synergy derived from the amalgamation of the investing entity and the target entity. This collaborative synergy consequently augments value creation through the cultivation of novel opportunities.

This research delves into an assessment of the pre-deal phase of acquisitions, encompassing the incorporation of EPU as a pivotal uncertainty determinant. Drawing on the recent work of Batista et al. (2023), it becomes evident that EPU exerts deleterious ramifications on M&A operations within the specific Brazilian context—a contextual facet scrutinized within the contours of this dissertation. Within the milieu where a company stands poised to acquire a target entity, the spectrum extends from an immediate investment avenue to the potential deferral of investment in anticipation of heightened returns or mitigated risks, thereby mandating a more malleable strategic approach. Zhu & Jin (2011) affirm that when factoring in the investment option variable, the binomial tree option pricing methodology emerges as an apt quantitative tool for dissecting investment prospects.

Employing EPU as a fundamental fount of uncertainty and situating the pre-trade M&A transaction within the framework of an Investment Option, our analysis was executed employing the binomial approach proposed by Cox et al. (1979), often referenced as the CRR model. This approach proffers a more streamlined avenue for assessing options within a discrete temporal context. As noted by Marques et al. (2021) and underscored in the insights of Trigeorgis (1993), the CRR binomial lattice methodology is eminently suited for evaluating intricate projects characterized by the integration of diverse real options, an array of expenditures, dividends, and interplays between these options.

Positioning research within the strategic exploration of investment decisions, the investigation into M&A dynamics through the theoretical prism of real options assumes a pivotal role, as depicted in Figure 5, illustrating the segmentation of the research landscape. As articulated by Reuer & Tong (2007), within this domain, two predominant empirical currents have emerged, with their primary emphasis directed toward the temporal alignment and structural configuration of investments, as well as their resultant outcomes. In order to glean comprehensive insights into the manifold mechanisms of value generation and appropriation intrinsic to real options, a thorough comprehension is imperative.

Figure 5
Empirical Research on Real Options.



NOTE: This figure is adapted from Reuer & Tong (2007).

The inclusion of the EPU variable in the examination of M&A transactions situates this study within the context of investment timing. The discernible influence of EPU levels on the temporal progression of negotiations can potentially instigate delays or even obstruct the fruition of the transaction. The authors further underscore that research focused on real options must exhibit sensitivity toward alternative interpretations of bid-related outcomes, which invariably necessitates consistency verification. Thus, it remains paramount to both integrate recent conceptual advancements and engage with deliberations concerning the descriptive accuracy and prescriptive utility of real options within organizational settings. Furthermore, the incorporation of novel factors exerting influence upon business dynamics merits substantive consideration.

According to Folta & Miller (2002), while deferring commitment may hold advantages in the realm of financial options, real options entail potential opportunity costs associated with waiting. In this context, companies may forfeit potential cash flows or learning opportunities, and additionally face the risk of being preempted by competitors. Kumar (2005), delving into the assessment of value generation in investments and divestments, discerned that divested ventures aimed at realigning the product market portfolio exhibited noteworthy value creation. Bonaime et al. (2018) underscored the pivotal role played by M&A contracts in capital allocation; however, inherent frictions such as transaction costs, information asymmetry, and divergent managerial perspectives can introduce inefficiencies, culminating in sub-optimal capital distribution.

Given these nuances, the application of real options analysis is aptly suited to gauge managerial dexterity and strategic versatility. Notably, the analysis aids in evaluating decisions pertaining to the deferral, abandonment, expansion, or contraction of equity investment projects, all while operating within the parameters of guarantee conditions (Xiong & Zhang, 2016). These considerations, resonating with M&A contracts, shed light on managerial adaptability and the assessment of flexibility, thereby offering a robust framework for comprehending and addressing investment complexities within the M&A arena.

2.2 MERGERS & ACQUISITIONS ISSUES

The process of identifying a viable business opportunity, strategizing its execution, and determining the most opportune timing and equitable valuation for M&A transactions is a complex endeavor. This complexity arises primarily due to the inherent fluidity of the valuation of the target company, particularly when dealing with instances where the target company is publicly listed. Notably, empirical evidence indicates that the acquiring company, on average, captures around two-thirds of the target company's market price increase subsequent to the announcement of the transaction (Schwert, 1996). Consequently, it becomes imperative to account for a multitude of uncertain variables during the valuation process.

These uncertainties encompass a spectrum of factors, encompassing market fluctuations, shifts in the employed discount rate, and variations in other pertinent determinants. These shifts in variables are notably triggered by the acquisition's announcement, leading to consequent alterations in the negotiated value, which in turn hinges on the revised projection of anticipated cash flows. Such revisions reflect the potential sway of new investors who may emerge, further underscoring the intricate nature of this process. As such, navigating the intricate interplay of these elements is essential to arriving at an accurate valuation and informed decision-making in M&A transactions.

Furthermore, the intricacies of M&A negotiations are compounded by their multifaceted origins, spanning both the acquiring and target companies. These origins are often rooted in diverse motivations, ranging from rational decision-making to macroeconomic events, corporate strategies, market influence, and the pursuit of economies of scale (Welch et al., 2020). Consequently, the driving impetus behind a negotiation proposal can significantly shape the financial dynamics of the transaction, exerting a direct influence on the recognition and quantification of M&A endeavors.

The directional source of the negotiation proposition holds the potential to elucidate the extent of capital commitment from the acquiring entity or the concessions offered by the target company. This dynamic interplay between the negotiating parties directly reverberates throughout the M&A assessment and quantification process. Additionally, external factors such as economic policy uncertainty can instigate considerable turbulence during the course of M&A transactions. This uncertainty, stemming from fluctuations in economic policies, holds the capacity to either expedite or defer the progression of the transaction. Consequently, these fluctuations have the potential to permeate the overall organizational structure, inevitably affecting the envisaged value of future cash flows, and thereby warranting meticulous consideration in the valuation procedure.

Lastly, it is noteworthy that investors frequently recalibrate their valuation perspectives subsequent to the culmination of an M&A transaction, assigning augmented significance to the book value metric (Nordlund et al., 2022). In cases where investors discern that the M&A initiative was conceived to harness forthcoming synergies, their focus shifts toward indicators indicative of future expansion, transcending the immediate exit value of the enterprise (Kwon & Wang, 2020). Consequently, the valuation of a company within the context of an M&A negotiation assumes an intricate character, necessitating that the conveyed values align with the multifarious interests of the various stakeholders engaged in the process, spanning the periods preceding, during, and subsequent to the transaction.

Hence, the numerical values relayed through the financial statements, as a product of the valuation procedure, must satisfactorily harmonize the priorities of the vested actors. This entails ensuring alignment with the preferences of acquirers, acquirees, and prospective investors harboring a vested interest in becoming part of the resultant business stemming from the M&A engagement. In this intricate interplay of interests, a meticulously orchestrated valuation process emerges as a pivotal requisite, underpinning the assurance of mutual interest amongst these stakeholders, and thereby cultivating an environment conducive to the realization of a successful M&A enterprise.

In the Brazilian context, publicly listed corporations aspiring to undertake M&A transactions are obligated to adhere to the stipulations delineated by Law 6.404/76 and its subsequent amendments, in conjunction with the regulations enforced by the Brazilian Securities and Exchange Commission (CVM) – an analogue to the US Securities and Exchange Commission. Further to the foundational legal framework, companies are mandated to navigate the requisites established under Law 12.529/11, a statute dedicated to averting and combatting infractions within the ambit of economic order. Furthermore, the pursuing entity is mandated to secure authorization from both the CVM and the Conselho Administrativo de Defesa Economica (CADE) – akin to the role of the Federal Trade Commission (FTC) in the United States – as a prerequisite for actualizing the M&A blueprint.

In terms of transactional accounting, due observance of the stipulations laid out by the Accounting Pronouncements Committee (CPC) is obligatory. Notably, CPC 15 (R1) – Business

Combination – serves as a pertinent reference point in this arena, signifying alignment with the International Financial Reporting Standards (IFRS) 3, within the Brazilian legislative context. As such, the regulatory framework pertains to the harmonization of accounting standards for M&A operations involving Brazilian companies.

Given the intricacies inherent in the valuation procedure within the context of M&A negotiations, compounded by the diverse range of factors that exert influence upon such transactions, including the significant role played by economic policy uncertainty, it becomes imperative to engage in a comprehensive discourse concerning the outcomes of prior research endeavors that have delved into the EPU variable. Furthermore, it is essential to scrutinize its repercussions on the business landscape, with a particular emphasis on investment undertakings within the realm of M&A transactions, as well as its implications for the valuation methodologies employed in these contexts.

2.3 ECONOMIC POLICY UNCERTAINTY

In the discourse presented by Watts & Zimmerman (1986) pertaining to the sources of uncertainty within accounting, it becomes evident that they are essentially enumerating the elements that cast their influence over the broader economic milieu. In a similar vein, the observations of Ng et al. (2020) serve to underscore the fact that economic policy uncertainty can emanate from a spectrum of domains, encompassing fiscal, monetary, and regulatory policy arenas. To elaborate, this uncertainty germinates from inquiries concerning forthcoming alterations in economic policies or the ramifications entailed by the introduction of novel policy measures vis-à-vis the private sector and the broader economy.

Governments, in their capacity, engender implications for economic agents that emanate from their capriciousness and opacity, engendered by the inherent unpredictability characterizing enacted economic policies. Consequently, this scenario ushers in a state of asymmetric information, as expounded by Danisman et al. (2021). The paucity of predictability emerges as a salient predicament, exerting detrimental effects upon the business environment by obstructing informed projections by managers. This, in turn, precipitates delays in decision-making processes, engenders augmented costs, instigates oscillations in discount rates, and impinges upon the overall economic activity in a comprehensive manner.

At its inception, Baker et al. (2013) formulated a monthly index that sought to quantify the magnitude of economic policy uncertainty within the United States. This index was constructed through the amalgamation of three distinct components. The primary and central component was founded on the frequency of occurrences of articles referring to economic policy uncertainty within the most prominent ten newspapers of the United States. To qualify for inclusion in the frequency tabulation, an article was necessitated to encompass a concatenation of three specific terms: economic or economy, uncertain or uncertainty, and a supplementary term affiliated with Congress, deficit, Federal Reserve, legislation, regulation, or White House. The second constituent encapsulated political uncertainty through the incorporation of tax code expiration data. The third element was derived from the divergence of opinions amongst economic analysts concerning forthcoming government procurements at federal, state, and local levels, alongside the trajectory of the consumer price index (CPI).

Subsequent to their initial work, Baker et al. (2016) opted to exclusively utilize the frequency-based component within their index[3], focusing solely on articles that encompassed the trio of aforementioned terms. This decision was motivated by their intent to expand the applicability of the index to other nations, acknowledging that the distinct variables underpinning the remaining components might not be universally accessible. Consequently, this refined model, solely reliant on the frequency of pertinent articles, was employed to gauge the economic policy uncertainty prevalent within Brazil. This amalgamation of data was denominated the Economic Policy Uncertainty Index (EPU), proving notably robust across studies (Al-Thaqeb & Algharabali, 2019; Chen et al., 2020). Moreover, Baker et al. (2016) extended their efforts to craft a daily EPU index, achieved through the utilization of the Newsbank news aggregator. They also formulated an EPU index with eleven distinct categories, each aligned with various policy issues that wield an influence on uncertainty, encompassing domains such as healthcare, safety, and other domestic policies pertinent to the United States.

Regarding Brazil, Baker et al. (2016) utilized text archives from the Folha de São Paulo newspaper, starting from 1991. For each month, they counted the number of articles containing the terms “uncertain” or “uncertainty”, “economic” or “economy”, and one or more of the following policy-relevant terms: regulation, deficit, budget, tax, central bank, *alvorada*, *planalto*, congress, senate, chamber of deputies, legislation, law, tariff. To obtain the EPU rate, they scaled the raw EPU counts by the total number of articles in the same newspaper for that month. The resulting series was then multiplicatively rescaled to have a mean of 100 from January 1991 to December 2011.

The EPU index has also found utility in the assessment of companies and nations by financial data entities, while simultaneously serving as a valuable resource for risk assessment agencies. The pervasive nature of political uncertainty affects a spectrum of stakeholders and sectors within society, exerting potential influence even on financial markets, thereby potentially triggering investment delays or losses (Baker et al., 2016; Gulen & Ion, 2015). This phenomenon can indeed disrupt the projections of market analysts, consequently inducing modifications in the financial reporting landscape. As a result, a comprehensive evaluation of a target company mandates not only meticulous consideration of pertinent legislation but also the intricate web of political uncertainty prevailing in the geographic context of the target company.

As expounded by Ozili (2020) and Ozili (2021), political uncertainty emerges from a plethora of origins and can be discerned through various conduits. From this standpoint, Baker et al. (2016) meticulously delineated political uncertainty into 11 distinct subcategories. To accomplish the stipulated objectives of delving into the realm of political uncertainty within the

[3]The authors report that they continue to post the other two initial components at www.policyuncertainty.com.

extant literature, we categorize these elements as emanating from either external[4] or internal sources vis-à-vis the national level. Conforming to the recent corpus of literature dedicated to the subject, external sources may encompass phenomena such as financial crises, armed conflicts, and assertive economic policies.

Conversely, internal sources may entail inflation, reductions in loans, escalations in unemployment, devaluation of currency, fiscal deficits, changes in government, fiscal policy alterations, and budgetary shortfalls. It is notable that these factors possess the propensity to augment or diminish the level of economic policy uncertainty (Al-Thaqeb & Algharabali, 2019; Baker et al., 2016; Gulen & Ion, 2015; Ozili, 2021). In light of their implications for investment decisions, investors are compelled to diligently monitor these wellsprings of uncertainty. To elucidate, modifications in loan interest rates can be elicited by the accessibility of bank credit. For the context of this study, we center our attention on the aspect of economic policy uncertainty stemming from internal sources, as we intend to scrutinize M&A transactions within the Brazilian milieu.

In the subsequent discussion, we delve into a selection of internal factors that contribute to or are influenced by an increase (decrease) of political uncertainty within a nation. In the investigation conducted by Chen et al. (2017), the focus was on examining the ramifications of Chinese EPU on the Chinese stock market over the period 1996-2013. Notably, China was deemed a transitional market, warranting an assessment of how EPU might exert more pronounced effects on its stock market dynamics. The initial findings of the study underscored that heightened EPU correlates with negative and statistically significant future returns, implying a noteworthy 1.2% contraction in anticipated monthly returns.

As part of a robustness assessment, the researchers incorporated variables such as industrial production growth, shifts in money supply, inflation, valuation index, and stock market volatility. The conclusions drawn from this supplementary analysis reinforce the validity of EPU as an ancillary predictor of projected stock returns. In addition to the integration of macroeconomic indicators and the evaluation of EPU's performance in an out-of-sample context, the results robustly attest to the real-time predictive capacity of EPU concerning the comprehensive Chinese market's return. Moreover, the study's broader tests infer that EPU's negative projections extend to forecasting the forthcoming expansion of aggregate dividends. Remarkably, this predictive attribute emanates from a cash flow conduit; in essence, EPU directly influences the trajectory of anticipated cash flows.

An additional determinant with a direct influence on the stock market is exchange rates, given the widespread practice of trading currencies and associated indices, involving governments and global investors alike. Beckmann & Czudaj (2017) conducted an investigation en-

[4]The studies by Biljanovska et al. (2021), Dakhlaoui & Aloui (2016), Li et al. (2020), and Ozili (2021) deal with the effects caused by countries' policies or economic blocs in other developing countries. For this study, we consider that the local EPU measures all external and internal sources, in view of other results achieved previously.

compassing the years 1986 to 2014, scrutinizing the repercussions of American political uncertainty on exchange rates. This analysis extended to the examination of the impact on exchange rate expectations and the magnitude of forecast errors. The investigation was framed within the context of policy-related announcements and the inherent uncertainty surrounding monetary, economic, and fiscal policies.

The findings of this study revealed that both exchange rate expectations and the errors present in exchange rate forecasts are intrinsically linked to the level of uncertainty regarding the future trajectory of economic policy. Notably, the research discerned a reduction in Japanese yen expectation errors when confronted with an escalation in monetary policy uncertainty. However, this observation stood as an exceptional instance within the broader results. Moreover, the study underscored the phenomenon that exchange rate expectations tend to encapsulate the entirety of accessible information, showcasing market efficiency under specific conditions.

In the realm of fiscal policies, where investment outcomes hinge upon the critical assumption of irreversibility, the study conducted by Hassett & Metcalf (2001) sought to explore the potential influence of alterations in tax credit policies on the aggregate investment landscape within the United States. To achieve this aim, the researchers adopted two distinct models, namely the Geometric Brownian Motion model, simulating the notion that fiscal policies evolve as a stochastic process, and the Poisson jump process model, reflecting sporadic shifts in fiscal policies. The outcomes of the study revealed multifaceted implications based on the adopted model. When tax policy uncertainty was assumed to follow a continuous random walk, engendering a persistent state of flux, heightened uncertainty was found to exert a delaying effect on firm-level investment decisions, ultimately leading to reduced investment levels. In stark contrast, when the tax policy adhered to a discrete and stationary jump process, more aligned with real-world dynamics, increased uncertainty bore the potential to elicit an opposing outcome. Specifically, heightened uncertainty could serve as a catalyst for expediting the timing of investments and bolstering the quantum of capital acquisition, subject to the particular investment conditions prevailing at the time.

Hassett & Metcalf (2001) provide an insightful investigation into the implications of differing models, specifically the Geometric Brownian Motion and the Poisson jump models, on the interplay between fiscal uncertainty and investment dynamics. These models, despite their distinct characteristics, converge on a notable finding: an escalation in uncertainty yields a concomitant escalation in the potential loss of tax revenue for the government. This reciprocal relationship underscores that in scenarios where governmental commitment to a fixed tax policy vis-à-vis investment remains elusive, heightened uncertainty effectively functions as an implicit incentive fostering investment activities. It is important to emphasize that the actual outcome of this implicit incentive, whether it indeed results in an augmentation of investments, remains contingent upon various contextual and situational factors. It is noteworthy that the authors' analytical framework encompasses a foundational premise of a consistent capital price prior to tax considerations, an assumption that holds validity under certain circumstances. Hence, given this contextual foundation, the research underscores that the presence of uncertainty pertaining to tax policies engenders a discernibly adverse impact on investment endeavors.

The investigations conducted by Beckmann & Czudaj (2017), Chen et al. (2017) and Hassett & Metcalf (2001) collectively shed light on the manner in which Economic Policy Uncertainty (EPU) can exert influence over diverse facets such as financial markets, exchange rates, and investment choices grounded in tax credit considerations. These findings collectively reinforce the prevailing understanding of EPU's adverse implications for investment decisions, both within stock markets and among enterprises reliant on government subsidies. This initial phase of analysis unveils how EPU engenders outcomes that reverberate across investments and remain beyond the direct control of managers. Consequently, managerial adaptation becomes a crucial recourse to navigate the circumstances orchestrated by EPU.

The potential curtailment or withdrawal of tax credit policies, as exemplified in the research, holds the potential to exert direct repercussions on production and investment thresholds. Moreover, it complicates the long-term strategizing of managers who have predicated their plans upon such policies. Simultaneously, the dwindling levels of investments within the stock market sphere can ripple out, influencing the quantum of credit accessibility through this pivotal channel of financing. As EPU's ramifications cascade through tax credit policies and market dynamics, ushering in deleterious impacts on economic activity, this can, in turn, impinge on the availability of bank credits within the linked economic ecosystem. Financial institutions, discerning these impacts as indicative of a momentary economic activity slowdown, might exercise caution, which can potentially translate into the curtailment of credit provisions.

In an investigation by Danisman et al. (2021), the interplay between EPU and provisions for loan losses in US banks was scrutinized across the temporal span of 2009 to 2019. The findings of this study underscored that a substantial proportion of the variance in bad debt provisions could be attributed to uncertainty indices grounded in both news-based sources and tax-related deadlines. The research illuminated that, during periods of stability, loan loss provisions were employed by US banks as instruments for capital management and the attenuation of income fluctuations. However, the dynamics shifted during times of heightened uncertainty. In such instances, US banks pivoted their approach, utilizing provisions to smooth income trajectories rather than to manage capital positions. Notably, this practice was found to be more prevalent among privately owned banks, distinguishing them from their publicly listed counterparts.

The EPU index has been observed to exhibit a pro-cyclical tendency (Danisman et al., 2021). This pro-cyclical behavior of the EPU imparts a notable impact on economic shocks, exacerbating their effects and contributing to the sub-optimal allocation of credit resources. This dynamic underscores the significance of careful consideration by policymakers when formulating economic policies. The resultant uncertainties stemming from these policies hold pivotal ramifications for the provisioning of loan loss reserves by banks and the overall credit availability they facilitate. Given that banks serve as vital intermediaries in supplying credit to the domestic economy, the effects of provisions influenced by uncertainty could potentially surpass what is warranted, thereby exerting a detrimental influence on bank credit levels. Such outcomes have the potential to yield severe consequences for economic growth, consequently perpetuating and accentuating the cycle of political uncertainty.

Talavera et al. (2012) conducted an investigation into the intricate interplay between commercial bank lending and macroeconomic uncertainty within the Ukrainian context, spanning the years 2003 to 2008. Their findings illuminate a discernible pattern wherein lending from banks experiences a contraction as the volatility of macroeconomic variables escalates. This responsive behavior of Ukrainian banks aligns harmoniously with the predictive framework of the dynamic model centered on optimizing bank value, particularly within a framework of inelastic credit demand. Consequently, this calculated adjustment in lending activities by banks exerts a palpable influence over the capacity of credit-dependent borrowers to fund their investment ventures through this instrumental channel.

Moreover, Talavera et al. (2012) present compelling evidence substantiating the tangible impacts exerted by monetary policy on the foundational bedrock of banks' balance sheets. This interwoven relationship provides a window into the shifting risk landscape that envelopes the entire financial system. Notably, the observed contraction in loan provision reverberates across the larger spectrum of aggregate investment. This reduction in lending supply, in turn, engenders a corresponding elevation in the cost of financing, thereby amplifying the intensity of macroeconomic fluctuations.

Bordo et al. (2016) embarked on an examination aimed at assessing the potential impact of economic policy uncertainty on credit growth within the realm of individual banks. This study delved into the nuanced dynamics spanning the period from 1961 to 2014, considering the intricate interplay between economic policy uncertainties and the prevailing balance sheet conditions of American banks. Through their meticulous analysis, the researchers discerned a significant linkage between political uncertainty and the deceleration of credit expansion within the United States' banking sector. This alignment was coherent with the anticipated repercussions stemming from the interplay between the supply and demand of loans.

Of particular note, Bordo et al. (2016) observed that the lagged fluctuations inherent to the EPU index wielded a pronounced negative correlation with the growth trajectory of bank loans. This relationship persisted across both the aggregate banking landscape and individual banks. Notably, the study brought into focus a nuanced facet – the adverse influence of EPU on credit growth exhibited heightened prominence within larger banks. Furthermore, while the effect was somewhat mitigated among more well-capitalized banks, it remained significant within institutions boasting greater liquidity. Interestingly, this pattern bore no significant correlation with the diverse spectrum of ownership structures present among the studied banks.

The investigations conducted by Bordo et al. (2016), Danisman et al. (2021) and Talavera et al. (2012) collectively illuminate the multifaceted manner in which the EPU index engenders ramifications within the banking system, delineating two prominent avenues of influence. First and foremost, these studies underscore that heightened levels of uncertainty precipitate a reevaluation of capital allocation strategies, leading to a discernible contraction in the extent of credit extended to the market during periods marked by heightened uncertainty. This phenomenon constitutes a response to the elevated risk environment, as lenders adopt a more cautious approach in their credit disbursement activities. The second channel of impact manifests through amplified provisions for loan losses, an indicator that serves as a forward-looking marker of potential economic difficulties within the nation's economic landscape.

This foresight-driven increase in loan loss provisions serves to curtail access to credit that was previously available, thereby impeding the free flow of credit. Such insights collectively illuminate the notion that fluctuations in political uncertainty can exert a pronounced influence on private investment decisions, often prompting these decisions to be postponed or even retracted. As a result, investors are inclined to revise downwards their expectations pertaining to anticipated returns, thereby engendering the imposition of higher interest rates for financing endeavors. Amidst such circumstances, businesses are necessitated to undertake a recalibration of their financial planning strategies, with a potential emphasis on bolstering cash liquidity as a prudent buffer against prospective adversities.

In a complementary scholarly exploration, Duong et al. (2020) undertook an investigation spanning the time frame of 1985 to 2014 within the United States. This study sought to discern whether companies operating within this milieu exhibited a propensity to augment their cash reserves in tandem with the escalation of political uncertainty within the nation. Evidencing a pertinent linkage, the study illuminates a constructive correlation between the EPU index and heightened cash retention among businesses. Specifically, the research divulges that companies exhibit an inclination to elevate their cash-to-assets ratio by a discernable margin, amounting to up to 3.012%, within the ensuing year subsequent to a doubling of the EPU level.

Moreover, the study delves into the nuanced interplay between financial constraints and corporate interactions with governmental entities. In doing so, the research reveals that companies grappling with financial constraints and harboring deeper entwinements with governmental institutions are more inclined to bolster their cash reserves than their counterparts. This propensity for heightened cash retention among such companies is underscored as an adaptive response to circumvent investment constraints and navigate the mounting cost of financing. This strategic approach serves as a proactive safeguard against potential financial limitations, ultimately manifesting as a prescient maneuver to offset anticipated curtailments in forthcoming cash flows. Overall, the study by Duong et al. (2020) sheds light on how corporate entities strategically navigate the intricate terrain of heightened economic policy uncertainty. By amplifying their cash reserves, companies adopt a proactive stance to offset potential adversities arising from a complex and uncertain economic landscape, thereby substantiating a nuanced linkage between the EPU index and corporate financial decisions.

Phan et al. (2019) as well as Duong et al. (2020), conducted a comprehensive investigation into the potential impact of political uncertainty on the cash reserves maintained by companies operating within the United States. The temporal scope of their study encompassed the period from 1986 to 2015. Their analytical endeavor revealed a noteworthy positive correlation between the EPU index and the magnitude of cash holdings among U.S. corporate entities. Moreover, their findings further unveiled that enterprises with a reliance on government expenditures exhibit a tendency to maintain higher levels of cash reserves in comparison to their counterparts with different dependencies.

Cognizant of the counter-cyclical nature often inherent in political uncertainty, the researchers undertook an additional exploration to assess whether the observed phenomenon of cash retention was intertwined with the cyclicality of business operations. Through a meticulous classification process that stratified companies into either pro-cyclical or counter-cyclical categories, the authors endeavored to ascertain if there existed a discernible relationship between the EPU index and businesses positioned independently of prevailing business cyclicality. The outcomes of their investigation substantiated the existence of a positive correlation between the EPU index and the cash reserves of companies exhibiting business cyclicality independent of the broader economic trends. In essence, this study by Phan et al. (2019) offers a scholarly vantage point into the intricate interplay between political uncertainty, corporate financial strategies, and the nuances of business cycles. Through empirical analysis and cogent interpretation, it contributes to the broader understanding of how the uncertainties stemming from the economic policy landscape can influence the financial comportment of companies, ultimately shaping their cash reserve decisions.

Contrary to previous studies that verified the relationship between EPU and cash liquidity of North American companies, Demir & Ersan (2017) studied whether this relationship also happens for emerging economies, in this case, the authors verified the relationship between EPU and cash liquidity. companies in Brazil, Russia, India and China (BRIC) in the period 2006-2015. The results show that there is a positive relationship between each country's EPU and companies' cash retention. Demir & Ersan (2017) verified another variable not explored by Duong et al. (2020) and Phan et al. (2019), whether EPU Global has a positive relationship with the cash holdings of companies in BRIC countries, since events in these countries generate increments for EPU Global. The results found demonstrate a positive relationship between EPU and cash holdings in BRIC companies. They also point out that greater cash holdings are seen as a preventive measure, but they warn of the cost that companies have when choosing to retain cash longer than necessary in times of uncertainty.

Hence, upon meticulous examination of the findings put forth by Demir & Ersan (2017), Duong et al. (2020) and Phan et al. (2019), a discernible pattern emerges indicating that the sway of political uncertainty reverberates through companies' cash reserves, substantiating this effect across disparate economic contexts. As previously expounded, the influence of EPU on cash retention showcases multifaceted underpinnings, exhibiting a convergence across both major and emerging economies. The outcomes of these studies underscore a confluence of factors that propel companies towards bolstering their cash reserves during periods of political uncertainty. One notable aspect pertains to the conceivable implications for the accessibility of bank credit within the financial system. Elevated EPU levels can trigger an environment where companies are confronted with credit and financial constraints. Consequently, this scenario impels businesses to opt for heightened cash holdings as a prudent recourse to mitigate any potential credit shortfall.

Furthermore, the findings also accentuate how fluctuations in political uncertainty hold pronounced implications for gauging the pulse of economic activity. In particular, the surge or descent of uncertainty serves as a potent gauge of economic vigor. In response, both banks and companies enact strategies aimed at safeguarding against substantial losses, while concurrently enabling the continuity of operations amidst periods characterized by heightened uncertainty. This adaptive approach is encapsulated by the accumulation of cash reserves by companies, coupled with augmented provisions for loan losses by banks. Notably, the concomitant increase in cash retention by companies and the elevation of provisions for loan losses by banks serve as telltale indicators of a dampened climate for private investment within the broader economic landscape. Collectively, these findings corroborate the argument that the intricate interplay between political uncertainty, financial decision-making, and investment patterns materially impacts the overall economic dynamism.

The intricate interplay between cash reserves and the sway of political uncertainty serves as one of the conduits through which corporate investment levels are influenced. In addition to this avenue of investigation, recent research has delved into exploring the potential relationship between fluctuations in EPU and the investment grades of companies. One such study, conducted by Wang et al. (2014), delved into this domain by scrutinizing whether heightened or diminished EPU levels are correlated with the investment behaviors of publicly traded Chinese companies. This empirical inquiry occurred within the context of China's status as a transitional economy, spanning from 2003 to 2012.

The study by Wang et al. (2014) is grounded in the contention that political uncertainty effectively reshapes the economic landscape, thereby exerting an impact on the requisite discount rate utilized to appraise incremental cash flows. The research outcomes gleaned from this investigation reveal that political uncertainty indeed casts a discernible influence on the investment patterns of Chinese corporations at large. This influence is characterized by moderate implications for firms characterized by elevated returns on capital, a pronounced reliance on internal investment channels, and a non-state-owned corporate status. Succinctly put, the empirical findings underscore that EPU tends to wield negative repercussions on the investment endeavors undertaken by Chinese enterprises.

In the realm of investigating the intricate relationship between EPU and corporate investment behavior, Kang et al. (2014) undertook a comprehensive analysis focusing on the distinct impacts of the four constituent components comprising the EPU index. The study encompassed an examination of 2,700 American companies over the span of 1985 to 2010. This analysis was conducted within the conceptual framework established by prior works that delineated the realms of macro and micro uncertainties, as illuminated by Panousi & Papanikolaou (2012) and Temple et al. (2001). Moreover, the discourse put forth by Baum et al. (2010) concerning individual and market uncertainties was also incorporated. The outcomes of this investigation unveiled several nuanced insights. In relation to the component associated with news, the empirical findings indicated a discernible negative impact on long-term investments. Likewise, the component linked to federal spending manifested a detrimental influence on both short and long-term investment endeavors. Furthermore, it was observed that the adverse influence exerted by EPU on investments tends to intensify during periods of economic recession. A pivotal observation is the interaction between EPU, encapsulating macro uncertainty, and stock price volatility, representative of micro uncertainty or self-uncertainty. This interaction demonstrated a magnified negative effect on corporate investments. This implies that EPU, acting as a catalyst, channels its impact on investment reduction through stock prices. This finding alludes to the discernment of investors in foreseeing diminished anticipated cash flows.

Drobetz et al. (2018) conducted a meticulous examination of the interplay between EPU and the intricate nexus existing between corporate investment and the cost of capital. This study encompassed an expansive dataset of companies situated across 21 nations during the interval spanning from 1989 to 2012. Anchored within the tenets of financial theory, which postulates an inverse relationship between investment activities and the cost of capital, the authors embarked on deciphering the impact of EPU on this interrelationship. The outcomes of their inquiry unearthed a noteworthy phenomenon: the presence of EPU engenders a reduction in the sensitivity of investment decisions in response to fluctuations in the cost of capital. This observation not only deviates from the established norms of finance theory but also introduces a new layer of complexity. This distortion of the conventional investment-cost of capital relationship is found to be particularly pronounced among companies reliant on subsidies, government expenditures, and those featuring substantial state involvement.

Intriguingly, the effects of EPU's influence on the investment-cost of capital relationship are accentuated within specific contextual parameters (Drobetz et al., 2018). Companies hailing from nations characterized by greater opacity, lower analyst coverage, absence of credit ratings, and those positioned as smaller entities tend to experience a more profound distortion in this dynamic. This underscores the notion that the reverberations of heightened political uncertainty extend their tendrils deeper into certain sectors of the corporate landscape.

The deleterious implications of EPU on corporate investments have been a recurrent theme in scholarly investigations. Notably, the studies conducted by Drobetz et al. (2018), Kang et al. (2014) and Wang et al. (2014) collectively underscore the pervasive nature of EPU's influence on investment behavior, irrespective of the specific economic context within a country—whether open or undergoing a transitional phase. Evidently, the ramifications triggered by EPU, ranging from shifts in the level of bank credit and interest rates to alterations in expenditures by state-owned enterprises and cash liquidity, engender disarray within the operational plans of various economic stakeholders. While the nature of political uncertainty remains beyond the managerial realm of control, the decisions of corporate leaders hold the potential to either mitigate or exacerbate the effects of EPU on economic activity.

Given this context, prudent management necessitates a keen awareness of the degree of political uncertainty, prompting meticulous consideration in aspects such as capital structure, financing arrangements, production strategies, and more. As a corollary, policymakers and regulatory bodies are called upon to respond promptly and astutely in order to curtail the adverse consequences of political uncertainty. In light of the extensive literature detailing the intricate web of relationships linking political uncertainty with a plethora of factors that both influence and are influenced by it, and acknowledging the potential cascading effects on decisions pertaining to M&A, it is imperative to channel scholarly focus towards comprehending the specific nexus between EPU and M&A. This avenue of exploration aligns seamlessly with the overarching objectives outlined in this study.

The investigation conducted by Bonaime et al. (2018) delves into the intricate interplay between political uncertainty and the realm of M&A, with a focus on North American acquiring firms throughout the period spanning from 1985 to 2014. The study embarked on an examination of the ramifications of EPU on both the value and volume of M&A transactions. Their findings elucidate a significant correlation, demonstrating that an elevation of one standard deviation in EPU is associated with a notable reduction of 6.6% in the added value of transactions, coupled with a decline of 3.9% in the overall volume of M&A activities. Remarkably, the implications extend beyond mere deferment, contributing to tangible business losses. Delving further, Bonaime et al. (2018) scrutinized the effects of EPU on M&A announcements. Their empirical analysis revealed a compelling outcome—namely, an 11.74% decrease in the likelihood of a firm's announcement of an acquisition in the wake of a one-standard-deviation increase in EPU. To comprehend the underlying mechanisms through which EPU exerts its influence on M&A undertakings, the study assessed potential channels encompassing real options, timing risk, empire building, and risk management.

The results of their inquiry delineated that EPU exhibits more pronounced negative effects on acquisitions characterized by greater irreversibility, albeit to a lesser extent for acquisitions of higher costs or those impervious to postponement (Bonaime et al., 2018). Intriguingly, the influence of EPU is most conspicuous within sectors marked by high concentration or limited merger activity, rendering it particularly disadvantageous for M&A endeavors involving companies reliant on government expenditures. The study's conclusion elucidates that EPU's impact on M&A transactions primarily manifests through the real options channel, wherein the allure of deferment gains prominence. While the research attempted to explore cross-border, vertical acquisitions, risk management, and the imperatives of empire building, the conclusive results were less robust in these dimensions. Consequently, the findings substantiate the hypothesis that EPU engenders a reduction in investment propensity. They also highlight the strategic advantage of deferment in the face of heightened political uncertainty, offering insights that are instrumental for investors seeking optimal decisions in a complex and uncertain landscape.

Nguyen & Phan (2017) conducted a meticulous investigation into the impact of EPU on North American acquisitions during the interval spanning from 1986 to 2014, specifically excluding utilities and financial companies, while simultaneously exploring its ramifications for shareholder value. Their empirical findings unequivocally underscore a negative relationship between EPU and acquisitions. Remarkably, an escalation of one standard deviation in EPU corresponds to a significant 5.8 percentage point decrease in the probability of M&A occurrences. Furthermore, the study establishes a positive correlation between EPU and the time taken for the completion of transactions. Notably, the research identifies an inverse association between EPU and purchase premiums, suggesting a heightened acquirer inclination towards conservative approaches with respect to purchase prices. Delving further, Nguyen & Phan (2017) delve into the dynamic between EPU and short-term and long-term acquirer shareholder value. Their robust analysis reveals a positive and resilient relationship between EPU and the short-term accrued returns of acquiring firms. Intriguingly, a one-standard-deviation increase in EPU translates to an average increase of 0.7% or $31.4 million in favor of acquiring shareholders. Moreover, the research yields compelling evidence of the positive impact of EPU on the long-term stock and operating performance of the acquiring entities.

On a different note, Sha et al. (2020) embarked on an inquiry into the effects of EPU on acquisitions within the Chinese context spanning from 2001 to 2018. This study encompassed both state-owned and non-state-owned enterprises, aiming to illuminate the influence on acquiring shareholder value. Counterintuitively, the findings illuminate a disparity compared to their counterparts such as Bonaime et al. (2018) and Nguyen & Phan (2017) concerning U.S. companies. It emerges that non-state-owned companies in China exhibit an increased likelihood of undertaking M&A activities during periods of elevated political uncertainty, in contrast to the postponement tendency observed in U.S. firms. Additionally, the study underscores that Chinese state-owned entities, during periods of heightened uncertainty, are less inclined to solely employ cash transactions. The research also underscores an enhanced wealth accumulation for acquiring shareholders, with this effect being notably more pronounced for state-owned enterprises.

In a study conducted by Cotei et al. (2022), the effects of EPU on M&A involving startups as target companies within the North American market were scrutinized. This analysis encompassed the temporal span of 2004 to 2011. The study's findings furnish compelling evidence that EPU significantly curtails the probability of M&A events transpiring between established corporations and startups. However, the investigation identifies nuanced distinctions within this overarching trend. Specifically, the study establishes that startups characterized by a high degree of innovation quality and robust growth in terms of intellectual property rights exhibit a heightened likelihood of becoming acquisition targets. Additionally, startups featuring outside equity investors, such as angels or venture capitalists, are more prone to being acquired. This is underscored by the fact that these equity investors possess the initial opportunity to liquidate some or all of their equity holdings. Furthermore, startups owned by serial entrepreneurs, with their proven track record in launching and growing businesses, also manifest an elevated propensity to attract M&A interest.

In a study conducted by Li et al. (2022), the impact of EPU on cross-border M&A conducted by Chinese companies across 29 countries during the interval spanning 2008 to 2017 was subjected to scrutiny. The research outcomes unveiled a significant and adverse correlation between EPU and the volume of cross-border transactions. Additionally, the study identified and validated the presence of the real options channel in the context of cross-border transactions—a finding which stands in contrast to the observations made by Sha et al. (2020) concerning domestic M&A activities within China. In terms of the economic ramifications, the authors discerned a U-shaped effect of EPU in the short term, with subsequent negative consequences in the medium and long term for M&A performance. This dynamic, as explained by the authors, is attributed to the gradual emergence of disadvantages within the host country over time. Moreover, operational costs escalate in response to the inherent instability of the external environment, thus contributing to the observed reduction in performance of cross-border M&A endeavors.

Hence, the investigations conducted by Bonaime et al. (2018), Cotei et al. (2022), Li et al. (2022), Nguyen & Phan (2017) and Sha et al. (2020) collectively underscore the negative impact of EPU on open economies. This influence manifests as a reduction in the likelihood of successful completion of M&A transactions, consequently affecting the potential for generating new business opportunities, capitalizing on synergies, and fostering technological advancement.These research findings align with the existing literature, which posits that heightened EPU generates a scenario where the option value of M&A becomes compromised in markets characterized by reduced state control. It is noteworthy that the influence of political uncertainty on investments can take varied forms, necessitating the incorporation of EPU-related impacts for a comprehensive assessment of investment projects. In this regard, the studies under consideration contribute to the endorsement of the real options approach as a viable methodology for the valuation of M&A undertakings, as advocated in this current study. Accordingly, the development of methodologies that encompass the ramifications of EPU holds substantial significance. By integrating such impact factors, a more robust valuation process can be established, thereby furnishing decision-makers with enhanced tools to navigate through periods of heightened uncertainty.

2.4 VALUATION

"Valuation can be considered the heart of finance" (Damodaran, 2007), representing a fundamental aspect of financial analysis. Valuation, in essence, entails the intricate process of determining the intrinsic worth of a company, serving as a gauge for its market value or fair value in the market (Gabrielli & French, 2021). Widely applicable across diverse investment initiatives, the valuation process is also pivotal for endeavors involving research and development, asset acquisitions, or asset disposals, demonstrating its multifaceted utility (Jones, 2018;

Nishihara, 2018). Consequently, the valuation process assumes a paramount role in ascertaining the equitable value of assets or liabilities. It emerges as a crucial instrument for fostering the accuracy of financial statements and augmenting the usefulness of financial information for its intended recipients.

Accounting plays a pivotal role in facilitating the valuation process, aiding analysts in the meticulous preparation of comprehensive reports for diverse investment ventures, encompassing intricate aspects like business combinations. Essentially, the valuation process is intrinsically tied to accounting considerations. The role of a valuation analyst entails the harmonization of values between cash-based accounting and accrual-based accounting, with the ultimate aim of furnishing investors with a clear representation of the present value of anticipated cash flows associated with a specific investment endeavor (Penman, 2015). Undoubtedly, the valuation process maintains a distinct presence within accounting standards, as evidenced by its role in the quantification and recognition of accruals. The judicious incorporation or exclusion of accruals becomes a necessary step in arriving at essential values such as operating cash income, EBITDA, and other key financial metrics. This interplay between valuation and accounting underscores the integral relationship between these disciplines in achieving accurate and insightful financial assessments.

The focal point of investor attention revolves around the meticulous evaluation of investment projects (Brennan, 2003). It is imperative to execute the valuation process with meticulous precision so as to avert potential financial losses in the course of asset acquisition or disposition, thereby effectively addressing the concerns of investors (Myers, 2003). This concerted effort towards accurate valuation serves a dual purpose: enabling investors to optimize the allocation of their resources judiciously and ensuring adherence to stipulated governmental regulations, prevailing accounting standards, and other pertinent regulatory frameworks.

In this vein, the role of a valuator assumes paramount importance, entailing the identification of an apt valuation methodology tailored to the specific asset under scrutiny. Subsequently, the selected mathematical model is meticulously applied to yield a comprehensive assessment (Gabrielli & French, 2021). It is imperative to underscore that the selection of a suitable valuation method should be guided by its congruence with the inherent nature of the business in question, accentuating the importance of alignment between methodological choice and the distinctive characteristics of the enterprise.

While accounting standards do not mandate a particular method, they emphasize the primacy of utilizing available information or drawing upon analogous assets for measurement and recognition purposes (as stipulated in IFRS 3 and 13)[5]. It's noteworthy that the valuation models scrutinized by researchers might diverge from those practically employed by analysts. Furthermore, the utilization of various assumptions for future accounting information across

[5]Regarding the objectives of this research to analyze a Brazilian M&A case, observe CPC's 15(R1) and 46, which correspond respectively to IFRS 3 and 13 and can be found in their most updated version on the website www. cpc.org.br/CPC/Documentos-Emitidos/Pronunciamentos.

these models introduces the potential for substantial discrepancies in value estimations (Huang et al., 2022). Hence, the decision regarding the choice of valuation methodology necessitates contemplation of associated operational costs, familiarity with the technique, and its suitability for the specific asset under scrutiny.

In this investigation, it is not within the scope to comprehensively address all the existing valuation methodologies and their respective adaptations, given the impracticality and infeasibility of delving into every intricate detail. The central focus of this research pertains to the examination of the effects of incorporating the EPU variable into project valuation. The selection of the DCF method is underpinned by its well-established utilization by analysts and its prevalent application in contemporary market practices (Huang et al., 2022; Schüler, 2021). Furthermore, as a complementary approach to the DCF framework, the ROV method has been adopted due to its demonstrated efficacy within the valuation process. This choice is substantiated by the multitude of studies within the field, the adaptability of the method to the unique characteristics of investment projects, its inherent flexibility within M&A procedures, its ability to visualize option pricing, and its applicability across a wide array of asset types (Brandão, 2002; Jiang et al., 2019; Marques et al., 2021; Zhang et al., 2021). Consequently, the choice of DCF and ROV valuation methodologies emerges as a substantive consideration, aligned with the objectives delineated in this research.

Bailey et al. (2003) assert that DCF analysis is a relatively straightforward approach. DCF involves forecasting a sequence of cash inflows and outflows over the expected lifespan of a project and subsequently discounting them at a rate, typically the Weighted Average Cost of Capital (WACC), which accounts for both the time value of money and the risk associated with these cash flows. The time value of money concept implies that money held in the future is worth less than money held today, as present money can be invested and earn interest, while future money cannot. The pivotal element in any DCF calculation is the NPV, which represents the present value of positive cash flows minus the present value of negative cash flows or investments. A positive NPV indicates that the investment creates value, while a negative NPV indicates that the project, as planned, destroys value.

Dehghani & Ataee-pour (2013) contend that several traditional methods, such as DCF, are inadequate in assessing projects with flexibility due to certain limitations. A clear deficiency of the standard DCF approach is its failure to account for uncertainty in cash flows. Haque et al. (2016) emphasize that DCF fails to capture financial options, inadequately incorporates strategies for risk reduction and profit maximization, and overlooks managerial flexibilities in handling uncertainties. To calculate the NPV of an investment project, deterministic cash flows must be discounted at the minimum acceptable rate of return. Although the DCF approach can be modified to incorporate uncertain cash flows, its other shortcomings are deeply ingrained and not easily rectifiable. Indeed, beyond uncertainty, when confronting unforeseeable situations, the DCF method cannot accommodate any managerial flexibility (Dixit & Pindyck, 1994). To address these issues, more precise techniques such as ROV are necessary instead of traditional methods.

Najafi & Talebi (2021) corroborate that most conventional investment appraisal tools rely on the well-established DCF technique. DCF is inherently a deterministic approach in which expected investment costs are discounted back to present value using the NPV calculation. Although capital budgeting analysis with DCF approaches has been employed in many applications, they present challenges and limitations under specific conditions. These techniques either ignore or fail to capture certain realities of the stochastic nature of project cash flows and do not quantify the value of implicit managerial flexibility to adapt and revise subsequent decisions (Haque et al., 2014).

Even when addressing uncertainties through the implementation of sensitivity analyses or stochastic scenarios within DCF techniques, a deeper understanding of the fundamentally probabilistic nature of cash flows remains elusive. Furthermore, the current corporate landscape places significant strategic value on empowering senior decision-makers to facilitate project advancement during the evaluation phase (Najafi & Talebi, 2021). Additionally, based on risk principles, DCF approaches may only consider the negative aspects of contributing risks to the investment, without factoring in potential rewards. This inherent bias could increase the likelihood of rejecting potentially successful projects due to high uncertainty.

Despite DCF techniques, ROV offers a modern theoretical framework in which risks and policies affecting changes in the underlying asset's value can be appropriately assessed. ROV can capture the positive potential of proper management decisions that are presumed to be taken to limit the downside of risks. ROV employs DCF analysis as a building block to incorporate the stochastic nature of NPV and simulation methods into a sophisticated framework that can provide more meaningful insights to decision-makers and analysts (Bailey et al., 2003; Haque et al., 2016; Najafi & Talebi, 2021).

Bailey et al. (2003) underscores that ROV assumes a dynamic environment characterized by constant change, uncertainties, and competitive interactions among businesses. Furthermore, it presumes that management possesses the flexibility to adapt and revise future decisions in response to evolving circumstances, thus treating uncertainty as a manageable component. The future is viewed as a landscape abundant with alternatives and options, both of which have the potential to enhance value. ROV empowers managers to assess tangible real options that can augment their firm's value, equipping them with a tool to identify and respond to opportunities for profit maximization or loss mitigation. Despite managers' limited familiarity with real options, they are acquainted with the notion of intangible project attributes. ROV provides managers with a framework for rendering some of these intangibles tangible and amenable to coherent analysis.

Zhang et al. (2014) asserts that ROV provides a viable and realistic approach for ascertaining the optimal timing of irreversible decisions, incorporating a mean-reverting model for commodity prices. It can also extend the model to underscore the significance of the investment activation timing. The real options method offers a practicable and realistic scheme for assessing the intrinsic value of a project and devising a strategy to govern the timing of activities. Zhang et al. (2014) emphasizes that the real options' value stemming from operational flexibility can be substantial and should not be overlooked when appraising investment properties.

Najafi & Talebi (2021) maintains that Real Options offer modern valuation tools that facilitate the pursuit of optimal decisions. Their study reveals that the option-to-defer value expands as the investment value of flexibility increases, illustrating the potency of ROV in allowing an assessment of the impact of deferring a decision rather than prematurely rejecting an investment project. Haque et al. (2016) corroborates the claim that managerial flexibilities, evaluated through various real options for estimating project values, guide the company in making judicious investment decisions under diverse circumstances. Hence, the principal aim of this study is not to accentuate the disparities between the DCF and ROV methodologies. Rather, it endeavors to expand comprehension by incorporating ROV subsequent to the outcomes derived from DCF analysis, emphasizing the inherent options within the domain of M&A projects, particularly following the inclusion of the EPU variable. In this manner, it furnishes a substantial body of knowledge designed to support the decision-making process of the parties engaged in M&A transactions.

3 METHODOLOGY

3.1 RESEARCH METHODOLOGICAL FRAMEWORK

This study is guided by the classification proposal put forth by Raupp & Beuren (2010), which categorizes research based on objectives, procedures, and approach. With regard to the established objectives, this study is characterized as descriptive since it seeks to describe the characteristics of a specific population or phenomenon and establish relationships between variables. This involves the identification, reporting, and comparison of relevant factors (Raupp & Beuren, 2010). According to Sampieri et al. (2013), descriptive studies are instrumental in providing an accurate depiction of various aspects or dimensions of a phenomenon, event, community, context, or situation. In our research, we explore the methods employed by companies, their deficiencies, and how EPU can influence macro and microeconomic variables, thereby impacting investment decisions.

Regarding the procedures adopted, this study initially falls under the category of bibliographical research, as it utilizes previous studies to map the Theory of Real Options. We also discuss findings from the literature on economic policy uncertainty and valuation methods (Raupp & Beuren, 2010). Additionally, it can be considered a documentary research approach, as it analyzes M&A transactions that have taken place in Brazil, testing the developed model and comparing similarities and differences. In terms of the approach to the research problem, this study is characterized as quantitative since it utilizes mathematical models to evaluate companies and employs statistical methods to compare the values obtained in the estimated EPU scenarios. This is achieved by obtaining cash flows through the DCF method, expanded with ROV. According to Sampieri et al. (2013), quantitative studies seek to explain and predict phenomena, aiming to uncover regularities and causal relationships among elements, ultimately leading to the construction and demonstration of theories.

Within the quantitative approach, this research falls within the realm of financial microeconometrics. As stated by Gruszczyński (2020), financial microeconometrics naturally emerges from the application of statistical and econometric methods to corporate finance and accounting, where data reflects daily processes and encompasses relationships between consumers, investors, companies, society, and government. The author also highlights that corporate finance, along with corporate accounting, is the primary area of finance dedicated to explaining the financial aspects of a company's operations.

Within the scope of financial microeconometrics, Lee & Lin (2010) assert that the mathematical methodology employed in finance has its roots in economic research, focusing on equilibrium analysis, optimization problems, and dynamic analysis, aligning with the observations of Gruszczyński (2020). Mathematical quantitative studies utilize linear and matrix algebra, real analysis, multivariate calculus, constrained and unconstrained optimization, nonlinear programming, and optimal control theory. These methods find application in valuation theories, which are fundamental tools for determining the value of assets. In this research, we employ the DCF and ROV methods, which have been extensively studied in academia.

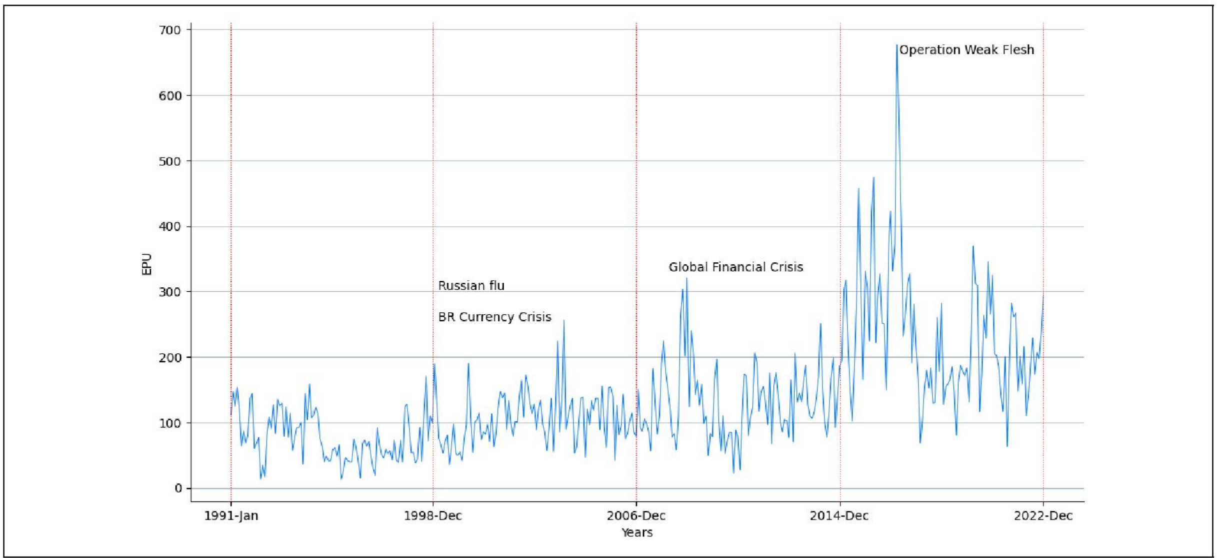
Subsequently, the methodology is presented in three sections aligned with the general and specific objectives of this work: Model Development, Comparison Models, and Application Case. This division arises from the research proposal to suggest the incorporation of EPU as a factor in asset valuation. Accordingly, we propose a model, conduct tests, and subsequently apply it. Throughout the methodological process, the Python programming language is utilized with the assistance of the freely available interpreter provided by Microsoft, VS Code. While other tools for programming in Python, such as Google Colab and Idle, are available, we chose VS Code due to its ease of project management. It should be noted that the replication of this work can be accomplished in any other Python environment with the necessary adjustments for each interpreter. All the developed code is included in Appendix E the end of the manuscript. The initial lines of code (lines 1-30) are used to import the required libraries for the estimations and analyses conducted in this study. The code used for each statistic and graph presented here is referenced accordingly.

3.2 MODEL DEVELOPMENT

The primary focus of this dissertation is to examine the impact of EPU on the pricing of M&A. To achieve this, an analysis of the EPU variable is conducted, followed by its integration into a replicable model. By accomplishing this, the first specific objective of developing an appropriate model is fulfilled, thereby contributing to the attainment of the overall research goal. The EPU index data for Brazil was obtained from http://www.policyuncertainty.com/media/Brazil_Policy_Uncertainty_Data.xlsx. Figure 6 illustrates the behavior of the Brazilian EPU index over the period from 1992 to 2022. To assess stationarity in its statistical properties and differentiate between low and high volatility, the EPU sample was divided into four equal sub-periods, each comprising 96 months.

Certain assumptions were employed to facilitate the development of the methodology. Notably, the EPU values exhibit distinct behaviors across each of the sub-periods, driven by significant historical events in Brazil. The first sub-period encompasses the transition from a high inflation era to the introduction of the new currency (BRL R$) in 1994. This transition marked a period of relative stability until the occurrence of the Russian moratorium and the subsequent Brazilian exchange rate crisis in 1998. The second sub-period corresponds to the period of economic growth in Brazil following 2004. During this phase, the Brazilian EPU remained relatively stable until the onset of the global financial crisis in 2008, which demarcates the beginning of the third sub-period. Lastly, the final sub-period is characterized by heightened volatility in the EPU values. This period coincides with a political crisis within Brazilian society, including the impeachment of President Dilma Rousseff and the outbreak of Operation Weak Flesh in 2017. Notably, the latter event led to the suspension of Brazilian exports to the European Union and fourteen other countries. These assumptions serve as important contextual considerations, shedding light on the distinct dynamics observed in the EPU values throughout the sub-periods.

Figure 6
Brazilian Economic Policy Uncertainty 1992-2022.



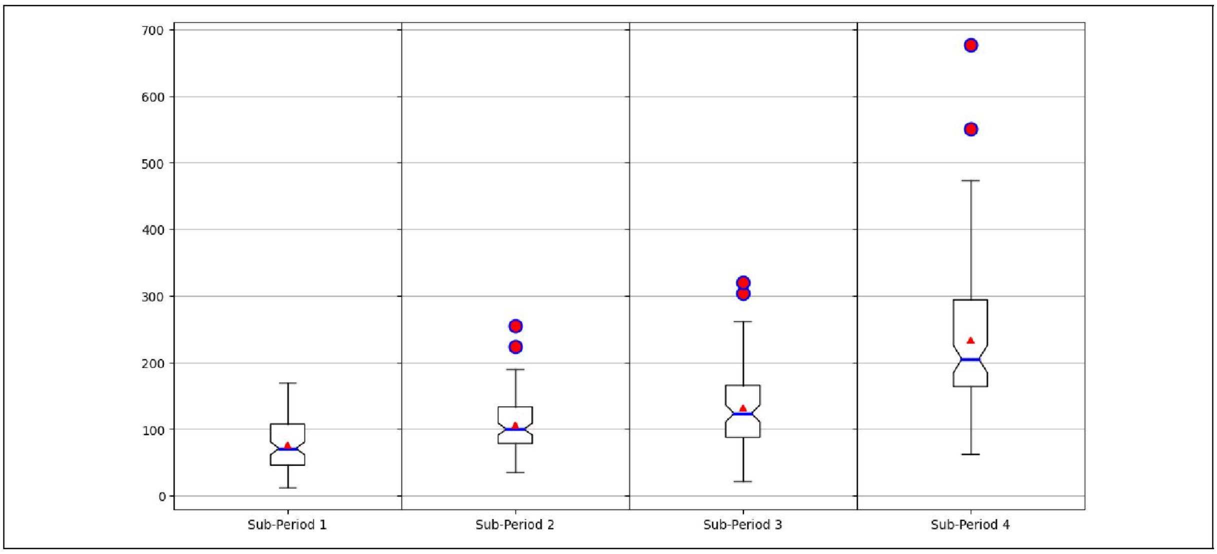
NOTE: The Authors (2023). In this analysis, the EPU index has been divided into four distinct periods, each consisting of 96 months. The red lines in the plot indicate the boundaries between these periods. For more detailed information regarding the data used and the generation of this plot, please refer to Appendix E, specifically lines 32 to 74.

To analyze the EPU sub-periods, descriptive statistics are presented for each period using a boxplot. This boxplot provides an estimation of confidence intervals and facilitates a visual understanding of the data. In Figure 7, the EPU estimates are depicted, with the orange lines representing the medians and the green triangles denoting the means. The lower and upper limits of the box correspond to the 1st and 3rd quartiles, respectively. Additionally, dashes are employed to represent the lower and upper limits, while circles indicate any outliers present within each sub-period.

As evidenced by previous studies discussed in this dissertation, the EPU index is measured on a monthly basis and effectively captures the volatile nature of economic policy uncertainty (Baker et al., 2016). Hence, considering its applicability in the context of M&A measurement, which typically involves investment decisions made within longer five-year forecast cycles, becomes justifiable. Referring to Figure 4, the most recent sub-period (SP4) has been selected due to its higher representativeness of market conditions characterized by pronounced volatility. Moreover, SP4 exhibits a broader confidence interval compared to the other sub-periods, encompassing both high and low levels of EPU. This characteristic is particularly valuable in evaluating investment options within the M&A context.

To incorporate the increased EPU into the valuation of M&A, two methodologies are employed: Principal Components Analysis (PCA) and Geometric Brownian Motion (GBM) simulation. PCA facilitates the integration of the M&A valuation process on a non-discretionary basis, while GBM is implemented for discretionary valuation. These methodologies respectively enable the generation of new samples from the selected dataset and the forecasting of potential paths that the EPU variable may follow.

Figure 7
Descriptive statistics by Box Plot - EPU.



NOTE: The Authors (2023). The means and standard deviations for each sub-period are as follows: SP1 (76.52, 37.015), SP2 (105.26, 39.67), SP3 (131.22, 56.02), and SP4 (233.53, 103.48). For more detailed information regarding the data and plot represented in this image, please refer to the Appendix E, specifically lines 76 to 112.

3.2.1 Principal Components Analysis (PCA)

Principal Components Analysis (PCA) is a multivariate analysis technique employed to summarize a configuration of variables and reduce the dimensionality of a sample while minimizing information loss (Guerra-Urzola et al., 2021). Its application extends across various disciplines, including engineering, biology, and social sciences (Zou et al., 2006). In the context of estimating EPU, prior studies have utilized different methodologies. Gupta & Sun (2020) employed Bayesian VARs to estimate EPU for BRICS countries, while Wang et al. (2015) estimated EPU for the United States through a combination of three forecasts utilizing the prices of 23 commodities. Additionally, Degiannakis & Filis (2019) predicted EPU for the United States and Europe using Heterogeneous Auto-Regressive models.

In this study, PCA analysis was employed to reorganize the data from sub-period 4, which had been standardized. This approach ensures that each new sub-sample retains its initial characteristics while exhibiting the maximum possible variability. PCA has found applications in finance for investigating the interconnections between financial institutions such as hedge funds, banks, broker/dealers, and insurance companies (Billio et al., 2012). It has also been utilized for estimating and forecasting volatility in financial markets (Al-Obaidli et al., 2023; Cheng et al., 2021; Li et al., 2023).

Based on previous studies aforementioned, the PCA decomposes the EPU values into orthogonal factors, let P^i be the EPU of the sample i, $i = 1, 2, ..., N$, and the aggregate EPU represented by the sum $P^S = \sum_i P^i$, and the $E[P^i] = \mu_i$, and $Var[P^i] = \sigma_i^2$. Then we have the following Equation 1:

$$\sigma_S^2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\sigma_i\sigma_j E[Z_i Z_j] \tag{1}$$

where:
$Z_k \equiv (P^k - \mu_k)/\sigma_k,\ k = ij.$

Therefore, Z_k is the standardized EPU of sample k and σ_S^2 is the variance of the system. Then we introduce N zero-mean uncorrelated variables ζ_k, so that it is equal in Equation 2:

$$E[\zeta_k\zeta_l] = \begin{cases} \lambda_k & \text{if } k = l, \\ 0 & \text{if } k \neq l. \end{cases} \tag{2}$$

Therefore, all higher-order co-moments are equal to those of the z's, where λ_k is the kth eigenvalue. We express the z's as a linear combination of the ζ_k's, where it approaches Equation 3:

$$Z_i = \sum_{k=1}^{N} L_{ik}\zeta_k, \tag{3}$$

where:
L_{ik} is a factor loading for ζ_k for a sample i.

Lastly, the PCA analysis is estimated according to Equations 4 and 5:

$$E[Z_i Z_j] = \sum_{k=1}^{N}\sum_{i=1}^{N} L_{ik}L_{jl}E[\zeta_k\zeta_l] = \sum_{k=1}^{N} L_{ik}L_{jk}\lambda_k, \tag{4}$$

$$\sigma_S^2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{N}\sigma_i\sigma_j L_{ik}L_{jk}\lambda_k. \tag{5}$$

As outlined by Billio et al. (2012), PCA yields a variance-covariance decomposition matrix of the logarithms of N samples, which is transformed into an orthogonal matrix of loadings (L) comprising the eigenvectors of the standardized correlation matrix of EPU. Additionally, Zou et al. (2006) note that the initial eigenvalues typically account for the majority of system variation. Consequently, the first sub-sample obtained in this study is expected to exhibit higher volatility compared to the subsequent sub-samples. In this study, we conducted an operation to derive four sub-samples that serve as scenarios for estimating EPU. Notably, each scenario features different levels of volatility as the standardized variables from the selected period were reorganized, maximizing variability within each new sub-sample. Subsequently, we will explore the GBM process, which aims to predict the potential paths of a stochastic variable. The standard deviation and variance of the sub-samples, reorganized through PCA, are employed in this process.

3.2.2 Geometric Brownian Motion (GBM)

According to Dixit & Pindyck (1994), Geometric Brownian Motion (GBM) or Wiener process is a continuous-time stochastic process characterized by three key properties. Firstly, it is considered a Markov process, where in the probability distribution for all future values of the process depends solely on the present value. Secondly, GBM exhibits independent increments, indicating that the probability distribution of changes in the process during any given time interval is independent of changes in other time intervals. Lastly, changes in the process over finite time intervals follow a normal distribution, with the variance increasing linearly with the length of the time interval. In this study, it is assumed that the variables EPU, V_0 (specifically in the sensitivity analysis tests), and PRICE, which are utilized in the estimation of cash flows, follow a random walk pattern. For the sake of simplicity, these variables are collectively denoted as $\tilde{U}$ in Equation 6, representing their GBM movement.

$$dU = \alpha U dt + \sigma U dz \tag{6}$$

where:
α is called the drift parameter;
σ the standard deviation parameter; and
dz is the increment of a Wiener process, that means $dz = \epsilon\sqrt{dt}, \epsilon \sim N(0, 1)$.

The solution to the above equation is integration by Itô's lemma, that is, by applying stochastic differential equations. We demonstrate the necessary calculations below, assuming a risk-neutral world in Equation 7:

$$U_t = U_0 e^{\left(r-\frac{1}{2}\sigma^2\right)t+\sigma W_t} \tag{7}$$

since:
$S(t) = f(X_t, t)$, and $X_t = W_t$;
.
where:
$f(x, t) = U_0 e^{\left(r-\frac{1}{2}\sigma^2\right)t+\sigma x}$

Using Taylor's expansion, we find the Equation 8:

$$dS(t) = U_0\left[\left(r - \frac{1}{2}\sigma^2\right) + \frac{1}{2}\sigma^2\right]e^{\left(r-\frac{1}{2}\sigma^2\right)t+\sigma W_t}dt + U_0\sigma e^{\left(r-\frac{1}{2}\sigma^2\right)t+\sigma W_t}dW_t \tag{8}$$

Simplified in Equation 9:

$$= rU(t)dt + \sigma S(t)dW_t \tag{9}$$

Lastly, considering a risk-neutral world, the considered variable satisfies the Stochastic Differential Equation in 10:

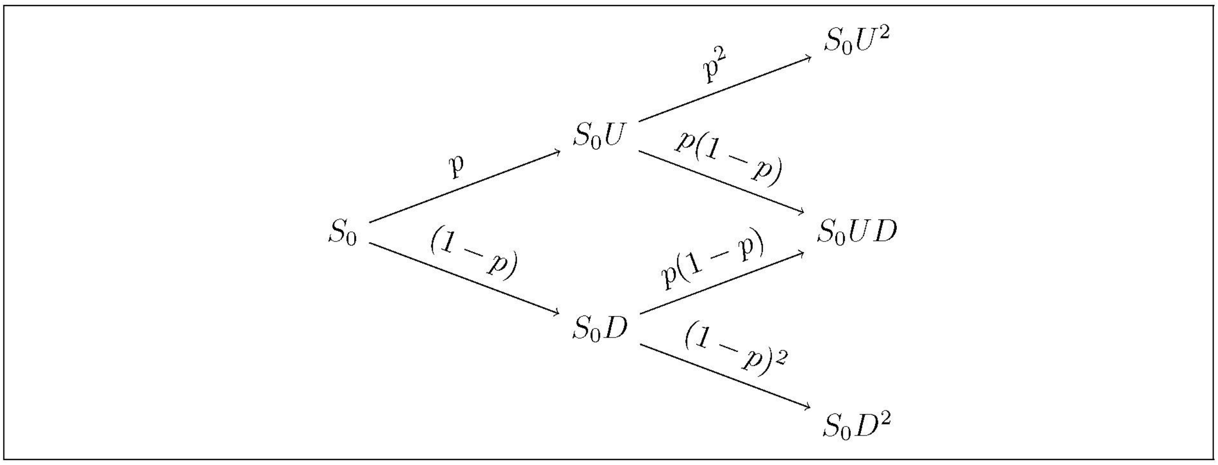
$$\frac{dU_t}{U_t} = rdt + \sigma dW_t \tag{10}$$

By employing the stochastic differential equation mentioned above, we conducted a simulation of EPU using the GBM. For this purpose, we utilized sub-period 4, which had been logarithmically standardized. Subsequently, we divided this sub-period into four distinct sub-samples, using the mean as the initial value for each sub-sample. After undergoing pre-processing and undergoing PCA, we employed the standard deviation (σ) and variance (σ^2) of each scenario in the simulation. To simulate the PRICE within the test model and determine the associated cash flows, we assigned an initial value of BRL 100.00. The parameters (σ) and (σ^2) were set at 6.15% and 15% respectively. With the GBM model defined for projecting both the EPU and PRICE, we are able to explore the results of the simulations. These values can then be integrated into the DCF method expanded by the CRR Binomial Lattice, allowing for a comprehensive analysis of the obtained results.

3.2.3 Cox, Ross & Rubinstein Binomial Lattice (CRR)

The binomial tree serves as a valuable technique for option pricing, providing a graphical representation of the various potential paths that the price of an option may take (Hull, 2016), as depicted in Figure 8. This framework enables a distinct analysis of the expected value at each stage, aiding decision-makers in their choices. Within the binomial tree, we commence from the initial node, representing the value of all anticipated cash flows over the lifespan of a company. Subsequently, we apply the probabilities of upward and downward movements to derive the second node, which signifies the company's value at a subsequent moment while considering market risks and volatility. Finally, by applying the rise and fall probabilities to the previously determined second nodes, we obtain the third set of nodes, thus providing possible values for the company's cash flows, projected one period ahead.

Figure 8
CRR Binomial Lattice.



NOTE: The Authors (2023).

In this study, we will utilize the binomial tree or binomial lattice technique to illustrate the expected values with and without the inclusion of the EPU variable. Specifically, we will apply the binomial tree approach to the methodology developed by Cox et al. (1979), which enables the estimation of the value of an American-style call option, resembling the characteristics of an M&A process. The CRR model offers an advantage over the Black and Scholes options model as it accommodates American-style options, which can be exercised at any point prior to expiration, mirroring the flexibility inherent in M&A deals (Culík, 2016). Within the CRR model, the project value for the final period (n), corresponding to option expiration, is determined through a backward maximization process at each node. Whenever options are exercised, the project values are adjusted to reflect the derived value. Subsequently, the analysis moves to the preceding period ($n-1$), where the same maximization process is applied to each node while considering the continuation value. The continuation value accounts for the present value of expected future nodes, discounted at the risk-free rate and weighted by the respective probabilities (p and $1-p$). Equation 11 provides a more detailed representation of the CRR model.

$$maximum\left[S'_{t-1}; \frac{(S_t'^{+}p + S_t'^{-}(1-p))}{(1+r)}\right] \tag{11}$$

where:

S_t is the asset value at time t, before the exercise of any option;

S'_t after the exercise of an option; and

p and $1-p$ are the risk-neutral probabilities by which the project value at each node is weighted.

In line with the established CRR model, it is necessary to consider certain specifics akin to the Black & Scholes model. Suppose a project with a current value of S_0 and a volatility of σ. At each time step, the project's value S is multiplied by a random variable capable of assuming two values, u or d. In order to ensure that this representation adheres to a lognormal distribution, the values of u, d, and the risk-neutral probability p must align with the equations presented in Equation 12. Here, σ denotes the asset's volatility, while r represents the risk-free discount rate. The multipliers u and d correspond to the upward and downward adjustments applied to the lattice nodes, respectively. Furthermore, p signifies the risk-neutral probability, which serves as the discount factor for the lattice nodes.

$$u = e^{\sigma\sqrt{\Delta t}}; \quad d = \frac{1}{u}; \quad and, \quad p = \frac{(1+r)^{\Delta t} - d}{u-d} \tag{12}$$

Having established the properties of the CRR binomial lattice model, which we utilize to expand the DCF model, we proceed to retrieve the eight EPU scenarios generated—four from the PCA and four from the GBM simulations. Initially, we directly apply the GBM simulations to the DCF expanded via ROV, referred to as the discretionary approach. As an alternative to the previous insertion method, we incorporate the volatilities observed in the PCA-derived samples instead of relying on market volatility. By doing so, we gain insights into the behavior of the DCF model expanded via ROV when the EPU variable is included both in a discretionary and non-discretionary manner. This enables us to analyze the effects of EPU on M&A valuation and discuss the decision-making process within the context of each scenario.

According to Al-Obaidli et al. (2023), the binomial lattice model allows for the identification of robust investments that impact not only the immediate value of projects but also their future value, even when prices may not be favorable. Culík (2016), in a comparison of recombinant and non-recombinant binomial lattices, concluded that under variable volatility, employing the non-recombinant lattice with risk-neutral probabilities is a valuable tool in overcoming options valuation challenges associated with variable parameters. However, for a sufficient number of steps, both approaches yield comparable results. In our binomial lattice modeling approach, we adopt the recombined lattice model, with a total duration equivalent to one year of the project, divided into predefined time intervals of 12 steps. The binomial lattice model effectively depicts the evolution from one time step to the next using "direct induction" paths that follow exponential Brownian motion. In the subsequent section, we discuss the model comparison and introduce the assumption of the Marketed Asset Disclaimer, which facilitates the utilization of DCF and its expansion through ROV.

3.3 MODEL COMPARISON - SCENARIO ANALYSIS

In our previous discussion, we introduced the CRR binomial lattice model, which allows for the application of the EPU index in both discretionary and non-discretionary approaches. This enables a comparative analysis before and after incorporating the EPU. However, to facilitate this comparison, it is necessary to estimate the cash flows and discount them to their present value. To illustrate this process, we consider a basic model where the company's value is determined based on the MAD premise, which will be explained in the subsequent section. Additionally, we assume that prices in the basic model follow a stochastic process using key market indicators such as the Selic rate as the discount rate and an initial volatility of 15% to simulate prices using the GBM model. We analyze the distribution of simulated price trajectories through histograms at three different time points. After determining the prices and obtaining the corresponding cash flows, we calculate the terminal value and capture a new volatility through the returns. Subsequently, we apply the CRR binomial lattice model and compare the results considering the volatility of returns, the four EPU simulations via GBM in a discretionary manner, and the utilization of EPU volatilities obtained from the four scenarios resulting from the PCA in a non-discretionary manner.

3.3.1 Marketed Asset Disclaimer (MAD)

For this study, we employed the replicating portfolio technique as a means to establish parameters such as the initial value, volatility, and rate of return of an asset, utilizing the DCF method and its extension through Real Options (Brandão, 2002). This technique is particularly suitable for assets traded in markets with a constant appreciation. However, our focus was on valuing assets that are not directly traded in markets. In such cases, the use of a comparable asset would not be deemed appropriate, as the returns of a market-traded asset would not align entirely with those of the investment project in all states of nature. Hence, we relied on the Marketed Asset Disclaimer (MAD) premise proposed by Copeland & Antikarov (2003). According to this premise, the NPV of the project itself serves as the best unbiased estimate of the project's market value if it were a traded asset.

Marques et al. (2021) applied the MAD approach to both the DCF and recombining binomial lattice methods in the context of real options, based on the model developed by Cox et al. (1979). The authors argue that since the underlying real asset, such as an investment project, is not traded on the market, it is challenging to determine its true value and risk-return characteristics. Alexander et al. (2021) highlight that many utility models are excessively complex for practical application, being developed for partially complete markets that are challenging to find. They note that the literature commonly adopts the classic risk-neutral valuation technique. The authors further emphasize that the MAD approach has gained wide acceptance in practice due to its minimal data requirements, and they clarify that the MAD approach only derives a Real Option Value (ROV) under a risk-neutral measure. Taking into account the insights provided by Alexander et al. (2021), Brandão (2002) and Marques et al. (2021), our study adopts the MAD approach to determine the initial value of the project, V_0, considering that the estimated value does not encompass flexibility. Accordingly, the NPV can be expressed as shown in Equation 13 below:

$$NPV = -I + \sum_{t=1}^{N} \frac{E(FCF_t)}{(1 + WACC)^t} \tag{13}$$

where:

I is the initial investment cost;
$E(FCF_t)$ represents the expected free cash flows;
$WACC$ is the weighted average cost of capital; and
t are the time periods.

Having defined the use of MAD and that the NPV is the best unbiased estimator of the project value, we can then extend the classical NPV model to meet the objectives of this study in the form of Equation 14, where V_0 will be the value of the project in its initial moment $t = 0$:

$$V_0 = \sum_{t=1}^{n} \frac{F_t}{(1 + \mu)^t} + \frac{CV_n}{(1 + \mu)^n} \tag{14}$$

where:

F_t is cash flow;
CV_n is the continuation value; and

μ is the discount rate.

As shown in Equation 14, which aims to obtain the initial value of the project, we can analyze separately how the structure for cash flow forecast will be given according to Equation 15:

$$F_t = [R_t(1-\gamma) - \lambda_t - \Gamma](1-\pi) + \lambda_t \tag{15}$$

where:
R_t is the total revenue in year t;
γ represents variable costs;
π is the income tax;
λ_t is the depreciation in year t; and
Γ represents fixed costs.

So we can look at the second part of Equation 14, which is related to the CV continuation value, which is detailed as per Equation 16:

$$CV_n = \frac{F_n(1+g)}{(\mu - g)} \tag{16}$$

where:
μ is the risk-adjusted discount rate of the project; and
g is the cash flow perpetuity growth rate.

At this stage, the project's cash flow structure is determined, serving as the initial value for the approach outlined in this study. As discussed in the previous section, the inclusion of the EPU as a factor contributing to the option value has been established. We assume that the EPU variable possesses stochastic process parameters, thus requiring the reorganization of the samples through PCA and subsequent simulation using GBM. Subsequently, we introduce the simulated steps in the EPU via a discretionary process, and the volatility of the PCA samples through a non-discretionary process, utilizing the expansion of the DCF method via ROV within the CRR recombined binomial lattice model.

The CRR model employed in this study enables the exercise of real options through a backward maximization process, where the value V is maximized across the nodes of the binomial lattice. By following this reverse process and reaching the node $V0$, we obtain an enhanced value for the optimal exercise of real options, referred to as the maximized present value $V0^*$. It can be defined as $V0^* = V_0 + ROV$, where ROV represents the Real Options Value. To determine the initial value used in estimating the project, we apply the assumption of the Marketed Asset Disclaimer (MAD), which allows us to obtain an unbiased estimate of the market value of the project if it were a tradable asset.

In order to explain how we derived the company's value in an M&A project using the Discounted Cash Flow (DCF) method expanded by the recombined binomial lattice based on Cox et al. (1979), incorporating the discretionary and non-discretionary inclusion of the EPU variable, we present the necessary parameters for estimating the cash flows of a hypothetical company in Table 1.

Table 1
Parameters used in DCF Model.

DCF Parameters		
Risk-free rate	r	6.15 %
Perpetuity growth rate	g	3 %
Discount rate	μ	15 %
Variable costs	γ	55 %
Depreciation	λ	10 %
Fixed costs	$\mathit{\Gamma}$	BRL 300,000
Investment	I	BRL 1,500,000
Extra investments	EI	BRL 50,000
Income tax	π	34 %
Cost of Investing Now	cin	BRL 50,000

NOTE: The Authors (2023). The presented table includes all the essential parameters required for estimating cash flows and determining the project value. It is worth noting that these parameters can be adjusted as per the specific project to which they are being applied.

The values presented in this section are provided as suggestions and can be adjusted based on the specific research or application objectives. They can also be utilized in other studies or examined in relation to the parameters of M&A contracts in different companies. In the following section, we establish the parameters for analyzing the M&A transaction conducted by M. Dias Branco, and subsequently discuss the methods of analyzing terminal values, comparing the developed model that effectively incorporates the EPU variable in the evaluation process.

3.4 APPLICATION CASE

Finally, we delve into the utilization of the binomial lattice model, incorporating the EPU, which was developed earlier, and compare it with the values related to the Latinex acquisition as described in the financial statements of M. Dias Branco. This case was selected based on the accessibility of variables and methodologies employed to attain the estimated valuations within the context of Brazilian publicly-traded companies. In Appendix A, we provide an adapted version of the statements pertaining to the Latinex acquisition, which were published by M. Dias Branco in the annual financial statements for the years 2021 and 2022. Below, we present some noteworthy aspects of the Latinex acquisition as transcribed from the financial statements:

> The acquisition was carried out for the initial price of BRL 180.000, which may reach a total amount of up to BRL 272,000 if certain performance targets set forth in the acquisition agreement are met, as follows: (i) a fixed installment of up to BRL 147,500, subject to the price adjustment associated with the variation in working capital and the increase in indebtedness between the base balance of the negotiation and the

> closing date; (ii) a variable portion of up to BRL 92,000 linked to the achievement of net revenue growth targets by 2023, and (iii) a portion of BRL 32,500, conditional on obtaining registration with the INPI of certain brands. The amounts payable will be restated by the CDI rate between the acquisition closing date and the effective payment date. [...] (1) installment of BRL 180,000, net of the price adjustment of BRL 6,782; (2) Refers to fair value based on the net revenue target for the year 2023; BRL 27,000, if net revenue reaches a level between BRL 125,000 and BRL 175,000, BRL 59,800, if the net income is between BRL 175,000 and BRL 266,000 or BRL 92,000, if it exceeds the amount of BRL 266,000. The fair value was calculated using Monte Carlo method, considering the maximum payment, brought to present value (M Dias Branco, 2021, pp. 44-45) [6].

Having reproduced the parameters and selected clauses related to the acquisition of Latinex by M. Dias Branco, as stated in the company's financial statements during the negotiation period, it is important to highlight that the valuation of the target company was determined using the Monte Carlo Simulation. This simulation technique, similar to Geometric Brownian Motion, is considered a Markovian process with distinct properties. In their work, Al-Obaidli et al. (2023) emphasize that alternative statistical simulation techniques based on the Monte Carlo approach are often employed for scenario analysis, wherein the analyses are assumed to be independent and identically distributed (i.i.d.).

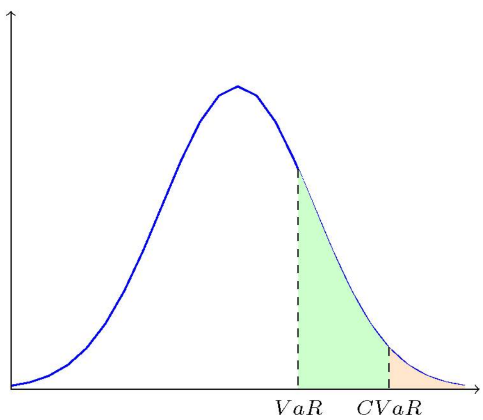
Based on the provided negotiation parameters, two analyses were conducted. Firstly, the present value initially paid, which amounted to BRL 173,218,000.00, was expanded via ROV. The CRR binomial lattice was employed to observe the expected trading values and compare them with the values specified in the contractual clauses. This analysis utilized the Selic rate for the relevant period and the volatility employed by M. Dias Branco. The second analysis focused on applying the model that best incorporates the EPU variable, which was selected following feasibility tests. Within this analysis, the CRR binomial lattice allowed for a comparison with the parameters of the M&A transaction. Subsequently, a sensitivity analysis was performed on two variables, namely Volatility and CVaR (Conditional Value at Risk), in three phases. In the first phase, the sensitivity of the project value to variations in volatility was examined, highlighting the potential option values. In the second phase, the sensitivity of the M&A transaction to CVaR was assessed to determine the magnitude of potential losses in the event of unfavorable outcomes. Finally, a comparative sensitivity analysis was conducted between volatility and CVaR, serving as a robustness test to demonstrate the impact of incorporating the EPU in the valuation method.

[6] The values are in thousands of reais, these can be consulted in the financial statements of M. Dias Branco for the fourth quarter of 2021.

3.4.1 CVaR Analysis

As the aim of the study is to checking the effects of the EPU in an M&A valuation, we consider that the risk analysis is an adequate procedure for this study because the conclusion of the M&A operation precedes a decision making, in this point a risk analysis on the proposed models becomes essential, for this study we used the Conditional Value-At-Risk (CVaR). The CVaR was chosen due to the study conditions that have characteristics described by Rockafellar & Uryasev (2000, 2002): discrete loss distributions, models based on scenarios and finite sampling. Furthermore, CVaR is able to quantify risks beyond Value-At-Risk (VaR), providing optimization shortcuts that, through linear programming techniques, make many large-scale calculations practical that would otherwise be out of reach. Contributions related to CVaR applications have grown rapidly, and CVaR is becoming increasingly popular in various areas of risk management (Fortin et al., 2007; Szolgayová et al., 2011). The Figure 9 demonstrates a basic difference between VaR and CVaR measures.

Figure 9
VaR and CVaR of a Normal Distribution.



NOTE: This illustration was adapted from Szolgayová et al. (2011).

Szolgayová et al. (2011) says that CVaR can be considered an extension of VaR, as it provides a kind of approximation of VaR, and can be interpreted as an upper limit of VaR. CVaR provides more information to the decision maker than VaR, since VaR denotes the maximum losses an investor faces subject to some pre-specified probability, while CVaR also provides information about the size of potential losses in the case of the least likely event (Cui et al., 2023; Malek et al., 2023). VaR is consistent only when based on the standard deviation of normal distributions, e.g. the VaR associated with a combination of two portfolios can be considered greater than the sum of the risks of the individual portfolios (Rockafellar & Uryasev, 2000). Consequently, VaR is difficult to optimize when calculated from scenarios. While the CVaR is a coherent risk measure with the following properties: equivalent transition, positively homogeneous, convex, monotonic with respect to 1st order stochastic and monotonic dominance with respect to 2nd order monotonic dominance. Finally, the CVaR offers a convenient way to evaluate: linear and non-linear derivative options; market, credit and operational risks; circumstances in any corporation that is exposed to financial risk (Rockafellar & Uryasev, 2002).

So far, we have already defined some concepts and clarified some doubts about the choice of CVaR, we are now going to demonstrate the necessary exercise to obtain the CVaR risk measure, based on the papers of Cui et al. (2023), Rockafellar & Uryasev (2000) and Szolgayová et al. (2011), in the most natural and intuitive way possible. First, we need to demonstrate how to obtain the VaR, which is proposed to give the maximum possible loss α with a specified confidence level β, i.e., the probability of the portfolio loss exceeding the threshold α is 1 - β. Let's define $f(x, y)$ as the loss function. The decision vector is $x \in \mathbb{R}^n$ and the uncertain vector is $y \in \mathbb{R}^m$. Denote $p(y)$ as the probability density distribution of y. The probability of the loss function being less than or equal to the limit α can be written in the Equation 17:

$$\Psi(x, \alpha) = \int_{f(x,y) \leq \alpha} p(y)dy \tag{17}$$

where:

given the specified probability β at (0,1), denote $\alpha_\beta(x)$, as the $\beta - VaR$ for the loss random variable

associated with x; and

$\alpha_\beta(x) = \min\{\alpha \in \mathbb{R} : \Psi(x, \alpha) \geq \beta\}$.

Completed the demonstration of how to obtain the VaR, we can work on the following: the CVaR is more consistent due to its subadditivity and convexity, and it is a coherent measure of risk. The CVaR gives the average value of losses greater than the VaR value. According to Equation 18, the CVaR is defined as follows:

$$\Phi(x) = (1 - \beta)^{-1} \int_{f(x,y) \geq \alpha_\beta(x)} f(x, y)p(y)dy \tag{18}$$

Replace $\alpha_\beta(x)$ with an analytical representation, we can have the next Equation 19:

$$F_\beta(x, \alpha) = \alpha + (1 - \beta)^{-1} \int_{f(x,y) \geq \alpha} (f(x, y) - \alpha)p(y)dy \tag{19}$$

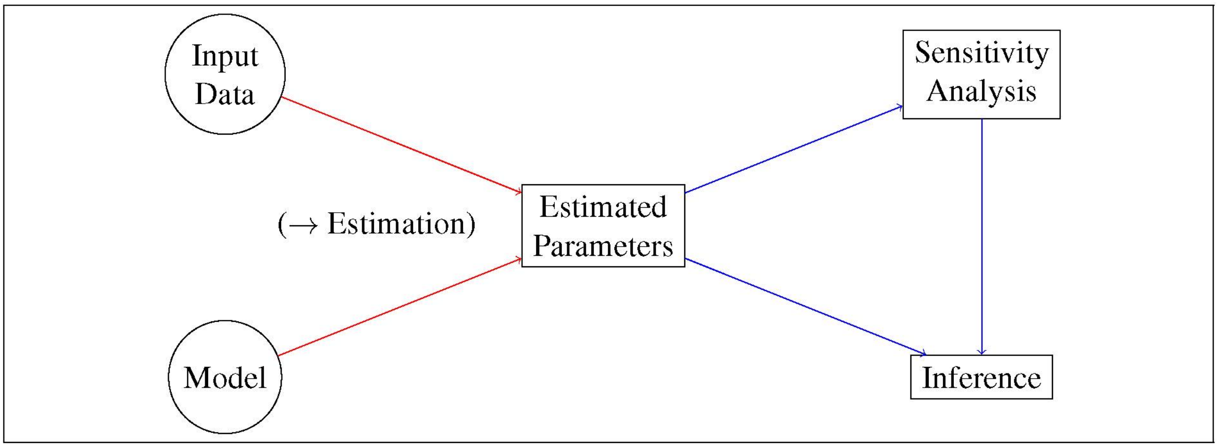
Thus, $F_\beta(x, \alpha)$ is convex with respect to α, and the VaR is the value of α at which $F_\beta(x, \alpha)$ takes the minimum value, the corresponding minimum value is called CVaR (Cui et al., 2023). Having clarified the differences between VaR and CVaR and demonstrated the formulas to obtain each measure, we turn to the application of the CVaR risk measure on real options. Adesi (2016) says that it is very convenient for option prices to reveal VaR and CVaR values, regardless of the distribution that generates them. The VaR in the risk-neutral condition is the difference between the initial value and the strike price of a European put option. With a bit of numerical exercise the author arrive at the CVaR for options and other measures of inherent risk.

Here, we overcome this barrier and put into analysis an American call option that is analogous to the M&A transaction. Fortin et al. (2007) and Szolgayová et al. (2011) used the CVaR for the analysis of an investment option in the electricity sector, we can join the work of Adesi (2016) and extend this analysis of CVaR in options, for the case of M&A, these works give the theoretical and methodological support of this analysis. In this way, we consider the distribution of the terminal values of the stacked binomial lattices, based on the difference between the initial value and the smallest value presented in the binomial lattice.

3.4.2 Sensitivity Analysis - Volatility & CVaR

In order to verify the effects of EPU on M&A valuation, the model used here goes through three stages: an analysis of the variable under investigation (PCA & GBM), an analysis of scenarios with and without the variable (DCF & CRR) and, finally, a sensitivity analysis of volatility and risk (Volatility & CVaR). The scenario analysis performed in the comparison between models section was used to reflect on the ability to incorporate the variable into the model and verify bias. To the best of our knowledge, no other study has attempted to analyze the inclusion of the EPU variable in the real options valuation method. Although sensitivity analysis can be used to test the model during and after its construction, verify the absence of logical errors and ensure that more complex formulas are implemented correctly and that relationships between variables are captured correctly. Once the model is built, sensitivity analysis can be used in the traditional sense, to better understand the range of variation possible around a point forecast (Rees, 2018), the Figure 10 demonstrates the flow of the sensitivity analysis.

Figure 10
Sensitivity Analysis Process.



NOTE: This illustration was adapted from Saltelli et al. (2007).

According to Saltelli et al. (2007) sensitivity analysis is the study of how the uncertainty in the output of a model (numerical or not) can be distributed to different sources of uncertainty in the input of the model. Sensitivity analysis can be related to "uncertainty analysis", which focuses on quantifying the uncertainty in the model output. Ideally, uncertainty and sensitivity analyzes should be performed together, with uncertainty analysis taking precedence in current practice. We explore the uncertainty in the condition of the EPU variable and the sensitivity of the developed model to small variations in the EPU volatility.

In the sensitivity analysis test, we sought to demonstrate what would be the risk considering a change in volatility for the calculation of the CVaR, considering the data obtained from the binomial lattice with the cash flows and the inclusion of the EPU volatility captured by the transformation made in the PCA analysis. Saltelli et al. (2007) say that the sensitivity analysis can be applied to a single or multiple parameters, in our case it is applied to the values of expanded cash flows, the volatility of the EPU and the CVaR. According to the literature cited above, regarding our variable of interest, the EPU index was selected from a specific extract according to the box plot analysis. Subsequently, it was subjected to a standardization via logarithm, and a principal component analysis was performed, and finally, estimates of possible paths via geometric Brownian motion. Only after this protocol of analysis of the EPU variable, we collected its average in the logarithmic base, and the standard deviation and variance through the samples reorganized via PCA, requirements described by Saltelli et al. (2007) for submission to the sensitivity analysis of the parameter of interest.

Pesenti (2022) and Stoyanov et al. (2012) used sensitivity analysis to analyze VaR and CVaR risk measures considering different aspects and applications. Pesenti (2022) points out that sensitivity analysis is essential for model construction, model interpretation and model validation, as it provides information about the relationship between model inputs and outputs. The author adds that the modeler seeks to understand how the model, the distribution of input and output factors, change under stress. Whereas, Stoyanov et al. (2012) say that parameter estimators have a certain amount of variability, which means that changing the input sample will result in different parameter estimates, which will lead to different risk. Knowing the impacts of parameters on risk is important for identifying key aspects of the risk model that may need regular attention, otherwise it can lead to specific recommendations about which areas of the risk estimation process require careful vigilance.

Therefore, we finalize the description of the methodological procedures that we deem necessary for this study. In summary, to analyze the effects of including EPU in an M&A valuation method, we collect the EPU variable of interest, standardize the variable, select the most relevant period, preprocess via PCA, simulate paths through GBM, apply directly in a binomial lattice, alternatively we insert it in a non-discretionary way. Finally we analyze it, we perform a sensitivity analysis of volatility and risk via CVaR, we compare both to infer how much the minimum variation of the EPU increases(decreases) the estimated loss.

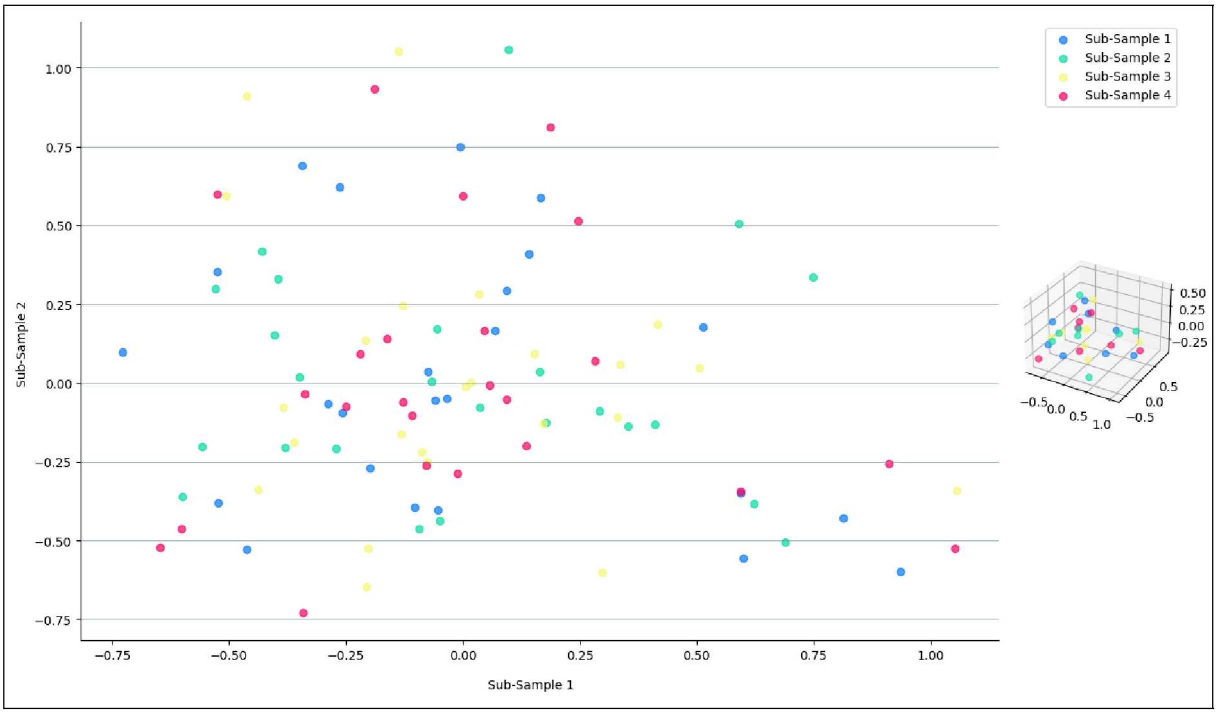
4 RESULTS AND DISCUSSIONS

4.1 EPU - PCA ANALYSIS

In the initial phase of our analysis, we conducted a thorough examination of the historical behavior of the EPU variable within our methodology. To ensure comparability and facilitate further analysis, we applied a logarithmic transformation to standardize the entire series. This standardization step aligns with the approach suggested by Al-Obaidli et al. (2023) and Billio et al. (2012) and helps us gain insights into the trends and volatilities of this stochastic series.

To delve deeper into the characteristics of the EPU variable as a stochastic series, we employed Principal Component Analysis (PCA). By considering the EPU variable as such, PCA proved to be an appropriate method for our analysis. The results of the PCA are presented in Figure 11, which illustrates the extracted principal components and their corresponding contributions. For our analysis, we specifically focused on sub-period 4 of the original data and performed the PCA to reduce and reorganize this sub-period into new samples. Consequently, we obtained four samples, each containing twenty-four elements. These samples exhibit a zero mean and are not correlated with one another. Despite the reduction in dimensionality, the PCA technique accurately estimates the main components without significant loss of their characteristic properties. This makes it an ideal approach for configuring the EPU scenarios that we consider in our analysis.

Figure 11
Principal Component Analysis - EPU.



NOTE: The Authors (2023). For the plot of this image see Appendix E, lines 114 to 149.

According to Al-Obaidli et al. (2023), the analysis using PCA offers a distinct advantage by leveraging correlations to estimate different arrangements or groupings of variables. In the case of our study, we employed PCA to create new groupings of the EPU variable, with the assumption that these relationships will persist in the future. It is worth noting that PCA utilizes correlation modeling, as depicted in Figure 11, to derive the principal components.

In Table 2, Panel B, we present the four sub-samples generated through PCA. These sub-samples were instrumental in capturing the standard deviation and variance of the EPU variable. Moreover, they served as a foundation for simulating the potential paths that the EPU could follow using the GBM technique, which will be discussed further in subsequent sections. It is important to highlight that the principal components obtained through PCA possess desirable properties. They are linear combinations of the original variables, independent from one another, and estimated with the aim of retaining the maximum amount of information in terms of the total variation contained in the data, as emphasized by Billio et al. (2012).

Table 2

EPU Data - Standardized and Transformed via PCA.

Description	Panel A - Standardized				Panel B - PCA Transform			
-	Sample 1	Sample 2	Sample 3	Sample 4	Sample 1	Sample 2	Sample 3	Sample 4
0	-0.4457	-0.1159	-0.1976	0.0127	0.5931	-0.3490	0.0173	0.0001
1	-0.0462	-0.5998	-0.0211	0.0892	-0.5257	0.3522	-0.1366	1.0515
2	0.4054	0.2074	-0.0405	0.2506	0.5989	-0.5567	-0.2019	-0.5253
3	0.3682	0.2993	-0.1124	0.2130	-0.5226	-0.3802	-0.2054	-0.6467
4	0.3687	0.5686	0.2260	-0.5451	-0.3443	0.6891	-0.5062	0.5938
5	-0.5919	-0.1457	0.6104	1.1619	-0.7279	0.0966	1.0566	-0.3419
6	-0.4666	-0.1475	-0.7025	-1.1329	-0.0061	0.7481	0.3365	0.0569
7	-0.4489	-0.0530	-0.1516	-0.3732	0.9345	-0.6002	-0.3603	-0.1883
8	0.4310	0.5385	0.0512	0.0795	0.0929	0.2928	-0.0886	-0.2191
9	0.5881	-0.3843	0.0409	-0.0230	0.8126	-0.4289	0.4169	0.1863
10	-0.6951	0.2610	-0.0685	0.5943	-0.2576	-0.0944	-0.4630	0.9114
11	0.0751	0.2673	0.3375	-0.3119	-0.4618	-0.5289	0.2981	-0.6023
12	0.3131	0.8797	-0.5748	0.2400	-0.2634	0.6222	-0.3847	-0.0788
13	-0.6298	-0.3908	-0.4627	-0.3120	-0.0535	-0.4029	0.1525	0.0931
14	-0.1177	-0.4084	0.1670	0.6779	-0.0353	-0.0490	-0.4375	-0.3373
15	0.7607	-0.1664	0.0109	-0.2425	0.1660	0.5892	0.5063	0.0466
16	-0.2857	0.1667	0.9795	-0.2997	0.1413	0.4103	-0.1309	-0.1630
17	-0.1036	-0.1837	-0.3885	-0.1933	-0.1028	-0.3957	0.3303	-0.1092
18	0.2607	0.3453	-0.4311	0.2806	-0.0597	-0.0550	0.1725	-0.1286
19	0.0066	-0.0058	0.1447	-0.1754	-0.0739	0.0357	-0.0770	-0.2509
20	0.5152	-0.6920	-0.4168	0.0448	-0.2880	-0.0671	0.0056	-0.0116
21	-0.8956	0.3825	0.2649	-0.1843	0.0693	0.1644	0.0351	0.2830
22	-0.1443	-0.4628	-0.2035	-0.2160	0.5131	0.1782	-0.1274	0.2455
23	0.2443	0.7969	0.4646	0.0000	-0.1993	-0.2707	-0.2083	0.1347
Mean	-0.0223	0.0399	-0.0198	-0.0152	0.0000	0.0000	0.0000	0.0000
Std	0.4573	0.4268	0.3900	0.4487	0.4305	0.4185	0.3638	0.4166
Var	0.2004	0.1746	0.1458	0.1929	0.1776	0.1678	0.1268	0.1663

NOTE: The Authors (2023).

The PCA redistributes the variation observed in the original axes in order to obtain a set of uncorrelated orthogonal axes, which can be used to generate indices and group individuals (Guerra-Urzola et al., 2021). From these new sub-samples 1 to 4 of Panel B, we respectively obtain the following standard deviations; 0.4305, 0.4185, 0.3638 and 0.4166, and consequently the following variances; 0.1776, 0.1678, 0.1268 and 0.1663. They were used in the non-discretionary models after obtaining the price estimates found by the expanded DCF method via ROV. Thus, it made it possible to carry out the evaluation of the hypothetical company among the different scenarios proposed in this study.

Al-Obaidli et al. (2023) point out that other statistical simulation techniques based on the Monte Carlo approach for scenario analysis normally perform independent and identically distributed (i.i.d.). These simulations are based on the stochastic process assumption, consequently failing to capture time-based correlations that potentially lead to underestimation of the positive or negative impact of price risk factors on project valuation. Zou et al. (2006) say that the success of the PCA is because the principal components sequentially capture the maximum variability between the columns of X, which guarantee the minimum loss of information, and that because they are not correlated, one can talk about a principal component without referring to the others. Thus, we appropriate Zou et al. (2006)'s statements, and declare that we can do individual analysis for each scenario obtained via PCA, without having other noises arising from the variable of interest. We also point out that the difference between the maximum and minimum values of the standard deviation and continuous variances of the new sub-samples generated by the PCA process are respectively 0.0667 and 0.0508. Later we demonstrate the use of the volatility of each sample reconfigured via PCA in the application of the evaluation process in our test model.

4.2 EPU - GBM SIMULATION

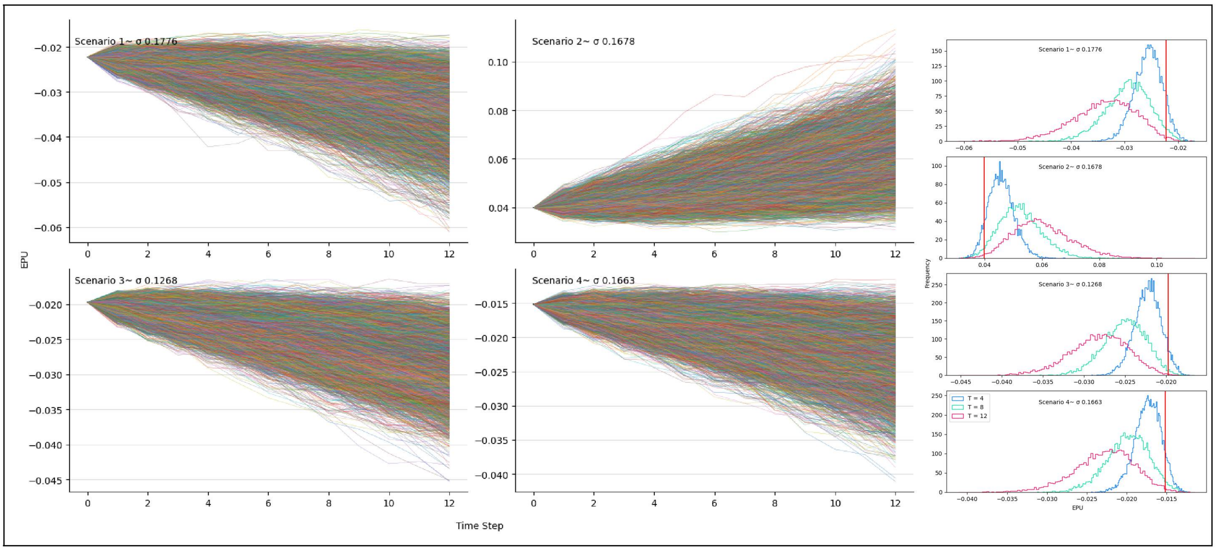
In this section, we focus on evaluating the simulation of the EPU variable via GBM, as well as, Hassett & Metcalf (2001) used the GBM method to estimate the variation of fiscal policies. We performed a simulation for scenarios 1 to 4 considering the following averages -0.0223, 0.0399, -0.0198 and -0.0152 respectively. These values were obtained from standardized EPU sub-samples, contained in Panel A of Table 2 shown in the previous section, because the averages for sub-samples transformed via PCA in Panel B have a value of 0. The EPU simulations shown in Figure 12, demonstrate the possible paths that the EPU could follow if it had a volatility represented by the variance of the sub-samples generated by the PCA.

Hassett & Metcalf (2001) despite using the GBM to estimate the uncertainty of economic policy, they created scenarios for evaluation from the Monte Carlo simulation. In this study, we started from the EPU variation by PCA, and we created four more scenarios simulated by GBM that were applied in our tests in a discretionary way, i.e., in each time step the EPU assumes a different value, and in each node of the DCF expanded by ROV the increment in value will also be different. We used this treatment to reduce the possibility of bias, as sub-period 4 selected from historical EPU data contains very different values, with a standard deviation of 233.53, which is higher than the other sub-periods. If we had just divided the sub-period into four sub-samples without any criteria, the scenarios would have been distorted and would not adequately represent the volatility of Brazilian EPU.

In the simulation by the GBM method for the EPU, in Figure 12, we can initially observe that the graphs demonstrate a sparseness of the values over time in the four scenarios. With greater intensity for scenarios 3 and 4, demonstrating greater variability at the end of the period for these, confirmed by the difference between the initial and final frequencies denoted in the histogram. Scenarios 1, 3 and 4 show a downward trend, to a greater extent for scenario 4, followed by scenarios 1 and 3, justified by the histograms that show a left-skewed distribution. While in scenario 2, a slight upward trend is observed, indicated by the difference in the maximum and minimum frequency peaks, and a right-skewed distribution is depicted. These situations result from the configuration arranged between the mean obtained from the standardized data and the volatility accessed by the PCA analysis.

Figure 12

Geometric Brownian Motion Simulation and Histogram Analysis - EPU



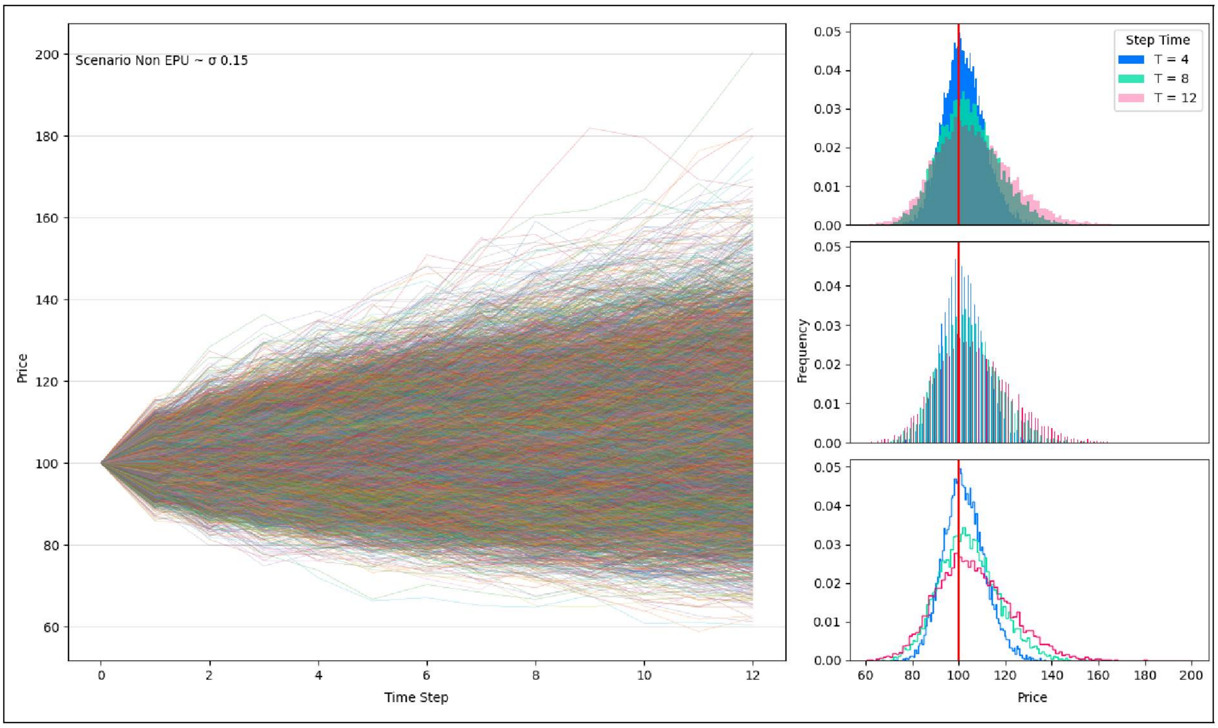
NOTE: The Authors (2023). To generate the graphs and histograms that make up this figure, see Appendix E, lines 155 to 273.

Note that in the third scenario, which has less volatility, this downward trend is less pronounced, i.e., the third scenario is less uncertain in relation to the others. This means that Brazilian companies may find a less uncertain environment in the third scenario, that is, expectations regarding the expected option value would not change significantly taking into account the other scenarios. The gain in the value of the option to wait for the settlement of the operation would be lower in the third scenario compared to the others. We also emphasize that previous studies say that the level of investments is inversely proportional (Drobetz et al., 2018; Kang et al., 2014; Wang et al., 2014). Furthermore, other types of simulation could result in values very close to the initial value, as they are identically distributed and would not reflect these trends over time (Al-Obaidli et al., 2023; Dixit & Pindyck, 1994).

4.3 TESTING MODELS

In this section, we draw an evaluation of the expected prices that the product of a hypothetical company could assume, which will later be used to estimate the discounted cash flows, and to apply the EPU variable, in a discretionary way (i.e., using the simulations of the EPU per GBM found in the previous section) and in a non-discretionary way (i.e., using the volatilities (σ^2) of the transform data scenarios via PCA). The estimation of possible product prices takes place with the following configuration: we use the data stipulated in the methodology section, which has an initial hypothetical product price of BRL 100.00. We also use a Selic rate of 6.15%, combined with a volatility of 15%. These values were determined based on the date on which the acquisition of Latinex by M. Dias Branco took place, an M&A transaction selected for application of the model, which will be explored in the next section. With these data, it was possible to simulate prices for a period of 12 months, as shown in Figure 13.

Figure 13
Geometric Brownian Motion Simulation and Histogram Analysis - PRICES



NOTE: The Authors (2023). The price simulation was based on a hypothetical initial value of BRL 100.00, and we assume that the price follows a GBM-type stochastic process. For the data and graphics in this image, see Appendix E, lines between 314 and 371.

We emphasize that there is only a simulation of prices because the interest of the study is to observe the effects of the EPU variable on expected cash flows. As can be seen in the simulation graph in Figure 13, the possible prices of the product show a slight upward trend over time, and this certainly affects the results of the expected cash flows obtained and explored further on. This slight upward trend in prices is confirmed by histogram analysis, which demonstrates that the data is right-skewed over time. In the first cut, in relation to the 4th period, the data are more distributed around the initial value of BRL 100.00, while in the 12th period, the data increase their distribution frequency on the right side.

After obtaining the prices with the simulation via GBM, we were able to estimate the discounted cash flows observing the MAD premise, which says that the best unbiased value of an asset is its own cash flow brought to present value. The cash flow values were obtained according to Equation 15, the continuation value was obtained following Equation 16, and the present value of the asset follows Equation 14, which is a combination of the two equations mentioned above discounted by the rate. That was the part of using the DCF, which by itself estimates only one step in time of the company's value. Dixit & Pindyck (1994) emphasize the importance of DCF, but if we wanted to know what the company's value would be in another period, we would have to calculate everything again, changing all the variables, which denotes the limitation of the DCF.

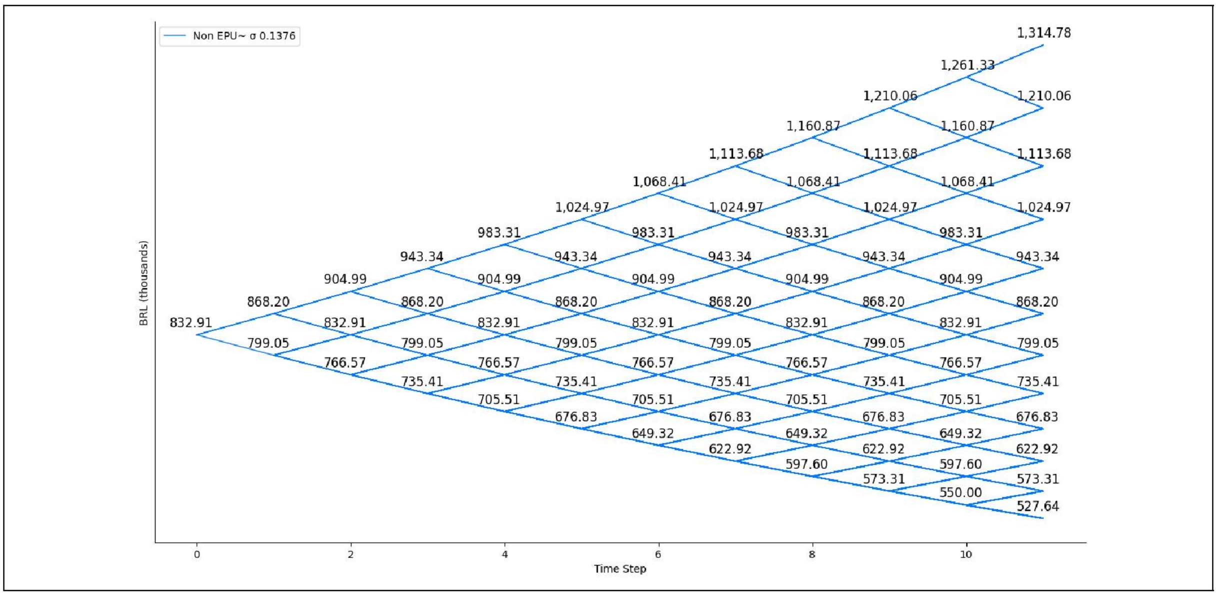
Subsequently, after obtaining the present value at time t_0 via DCF, we expand this assessment of expected cash flows up to time t_{11}. We point out that at this moment it is still operating without the inclusion of the EPU, following the CRR binomial lattice method represented in the methodology by Equation 11. This equation allows the visualization of the option value that the company can reach within the stipulated period, overcoming the limitations of the DCF. It is important for the investor to demonstrate the possibilities that he would find given the variables used, helping in the decision making, between investing now or waiting to invest. We further clarify that to achieve the aforementioned equation it is necessary to find the up and down probabilities, as well as establish the risk-neutral probability established in Equation 12. Figure 14 shows the binomial lattice via CRR, the results presented have the following configuration: Selic rate of 6.15% in September 2021, the volatility of 13.7% that was obtained by the standard deviation of the logarithms of returns, being applied in obtaining the NPV of cash flows and in calculating the options CRR.

The Figure 14 demonstrates that, considering market rates, and that there is no other variation over the estimated time in relation to the discount rate and volatility, the cash flow values projected via CRR assume a slight upward slope. For this study, we consider the M&A contract to be a real option, with options to postpone or invest (Trigeorgis, 1993, 1996; Lukas et al., 2012, 2019; Battauz et al., 2021). The binomial lattice demonstrates the possible values that an investment project can reach, helping the manager to make a decision about when to invest (Folta & Miller, 2002).

We present two aspects here, first, this slight upward slope, which presents higher values in the binomial lattice, represents a better investment opportunity, if the manager decides to wait, he has the possibility of greater returns. Secondly, greater returns imply greater risks to be assumed, for this study we are considering the analysis from the perspective of an M&A project, and greater risks mean sunk costs, and in general M&A operations in their majority are irreversible investments (Dixit & Pindyck, 1994). Considering that we have not yet applied the EPU to the model, and that for this scenario given an initial value of BRL 832,907.76, we then arrive at a maximum value of BRL 1,314,777.63, which would be excellent if at all times of the net there were only the probabilities to go up. Otherwise, the lowest estimated value is BRL 527,644.62, which represents a reduction of approximately 36,7% in relation to the initial estimated value for the hypothetical company's cash flows.

Figure 14

CRR Binomial Lattice - Non EPU.



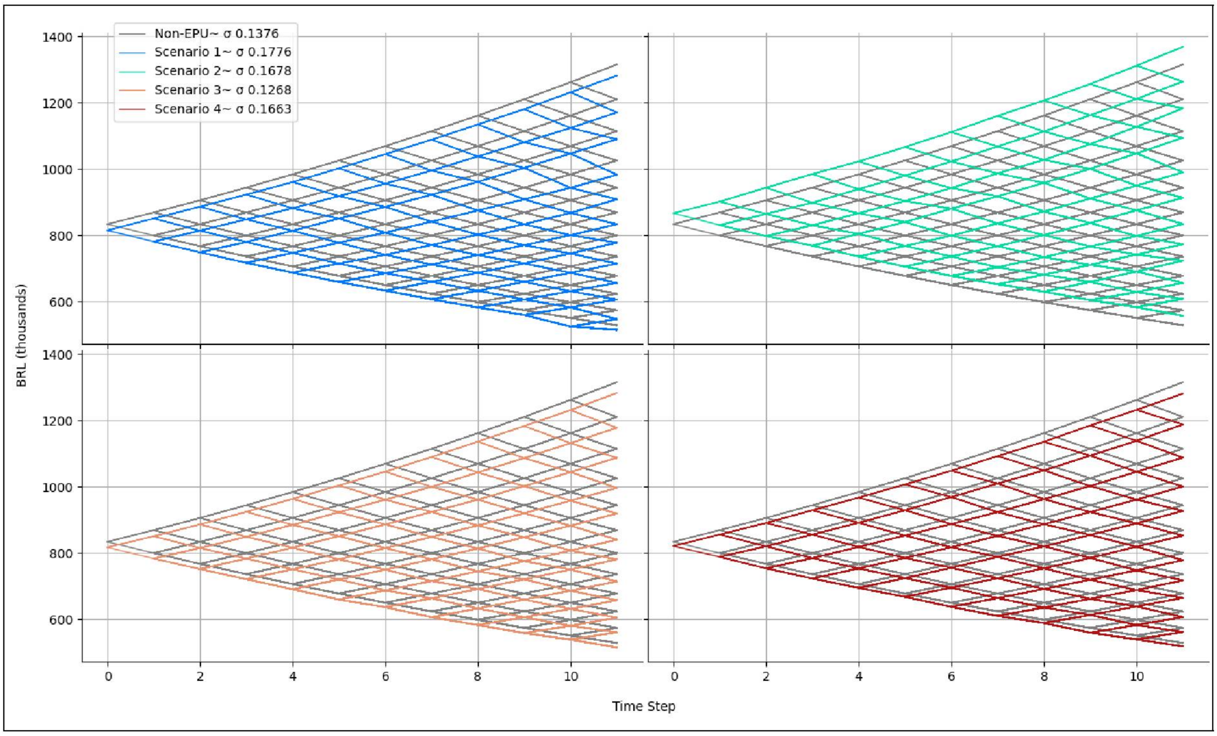
NOTE: The Authors (2023). Here, the price simulation was used to obtain the NPV of cash flows and later the expansion by CRR was carried out. For the formula of the CRR real options equation, see Appendix E, between lines 275 through 311, for the data used and plotting the CRR binomial lattice, see the same appendix from line 373 through line 533.

Considering that we are interested in verifying the effects of including the EPU variable, at this first moment, after obtaining the expansion of discounted cash flows in the previous binomial lattice, we perform our first test regarding the inclusion of EPU in the valuation of a company. Therefore, we carried out a discretionary inclusion, which takes place by the product of the EPU simulation by the binomial lattice of cash flows, whose result is shown in Figure 15. In this study, we used this arbitrary model to produce a comparison with a non-discretionary model, to that we could move forward in the process of including EPU directly in the measurement of a project. This is important because the first thought of an option theory practitioner would be to arbitrarily include the EPU and because each time step would exactly reflect the EPU for that period.

Using the value of BRL 832,907.76, for the four scenarios of Figure 15, considering that the EPU was arbitrarily included, we obtained for the initial values BRL 814,372.85, BRL 866,126.03, BRL 816,454.06 and BRL 820,249.54 respectively for scenarios 1 to 4, according to the index captured by the GBM simulation. While the maximum estimated amounts were BRL 1,280,943.53, BRL 1,368,325.78, BRL 1,282,149.40 and BRL 1,280,186.94, and the minimums are BRL 514,041.27, BRL 556,276.46, BRL 513,916.44 and BRL 51 7,172.62, respectively for scenarios 1 to 4[7].

Figure 15

CRR Binomial Lattice - Non-EPU vs Discretionary EPU.



NOTE: The Authors (2023). In this first model with EPU with four scenarios, it is the product of the simulation of EPU by the binomial lattice without EPU. For the data and plot of this image, see Appendix E, between lines 516 and 645.

As Figure 15 is a direct result of the product between the EPU simulation and the expansion of cash flows via CRR, it presents a slight reduction in the values found in scenarios 1, 3 and 4. Unlike the binomial lattice shown in Figure 14, here the upward trend found in prices decreases, including for the first scenario that has greater volatility in relation to the third, and also the second that has an approximate volatility of the third. As for the second scenario, which presents a volatility between the first and fourth scenarios, the expected values for cash flows increase over time. Such demonstrated scenarios allow us to accurately conclude that it is the combination of arbitrary inclusion and the effects resulting from the averages applied to the simulation that generated indices that do not bring effectiveness in their use, as we can consider them biased.

These results allow us to discuss the discretionary application and use of the GBM method, first because the results presented by Figures 14 and 15, direct us to the indication that the discretionary inclusion of the EPU would not be the most appropriate use. Well, initially it was expected that the binomial lattice of Figure 15 would reveal an increase in the value of the option for scenarios 1, 2 and 4, as in these scenarios there is greater volatility of the EPU and much lower values for the third scenario due to its lower volatility. Previous studies say

[7]The corresponding binomial lattices with all the values that were estimated can be seen in Appendix B

that, in times of high uncertainty, with EPU as a proxy, investments tend to delay or even not materialize, there is evidence that there is greater cash retention by companies (Demir & Ersan, 2017; Drobetz et al., 2018; Duong et al., 2020). Thus, it is expected that cash flows show the same direction with the inclusion of EPU, greater volatility, greater uncertainty regarding cash flows and, consequently, greater option value, returns and risks.

Second, with regard to the simulation by GBM for the production of scenarios, it was expected that the results would present valid values for later application in the binomial lattice. Thus, the estimate of the EPU variable in this study does not produce valid results, contrary to the statements by Al-Obaidli et al. (2023), they say that the GBM process would be a more adequate and robust method to estimate indices, our statement is based on scenarios 1 and 4 of Figure 15 which should present a binomial lattice with cash flow values greater than the basis used to estimate the project. Consequently, we can then discard the model of discretionary inclusion of the EPU in the process of estimating the acquisition value by M&A. Thus, we move forward and also verify the process of including the volatility of the EPU variable in the non-discretionary model.

As mentioned above, the inclusion in an arbitrary way generated some inconsistencies between the values that were expected and the results demonstrated, Brandão (2002) states that this type of inclusion leaves some edges because its purpose is an immediate response, but limited in its real capacities. From now on, we discuss the implementation the EPU volatility in the evaluation of M&A by the Non-Discretionary model. Thus, as in the previous test model, we completed our tests here by performing four simulations as well, considering the volatilities obtained in the samples resulting from the PCA analysis, such values can be consulted in Table 2, already discussed. In order not to be inconsistent in our tests, we took as the initial value of cash flows the same used in the previous test, which is BRL 834,659.19 reais. At the outset, we declare that the inclusion the EPU volatility in this model is non-arbitrary, so the initial value of cash flows did not change with the inclusion the EPU volatility in the four analysis scenarios. Figure 16 demonstrates the results found with the inclusion of the EPU volatility in the non-discretionary model.

We launched some initial data, in order to infer about the results of Figure 16. Considering the initial value for the four scenarios mentioned above, the maximum values captured by the DCF expansion via CRR using the EPU volatility of the PCA scenarios, we obtained the following: BRL 1,500,957.68, BRL 1,453,203.85, BRL 1,268,524.93 and BRL 1,445,979.07, respectively for scenarios 1 to 4 [8]. While, for the minimum values found for scenarios 1 to 4 were BRL 462,195.14, BRL 477,383.36, BRL 546,883.49 and BRL 479,768.59 respectively.

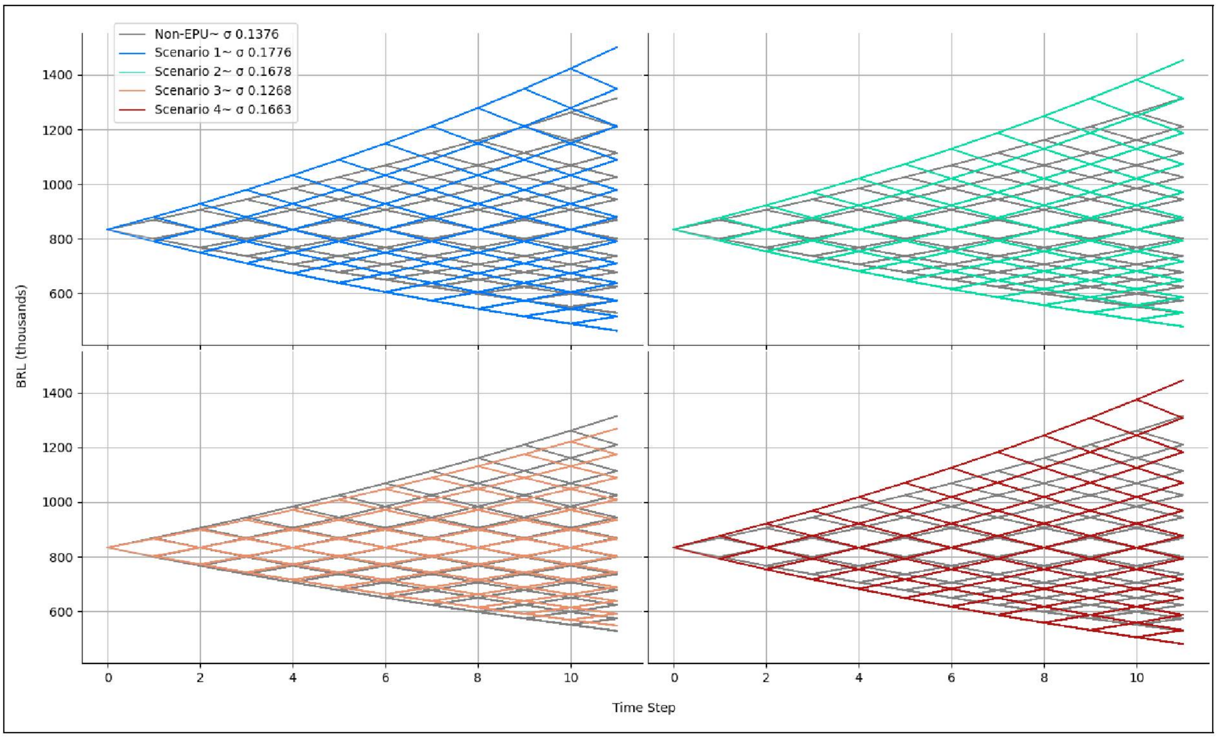
As seen in Figure 16, the binomial lattice generated by the non-discretionary EPU volatility inclusion model, envisages the environment resulting from the combination of expected cash flows based on a simulation of ascending prices, integrated with the volatility of the

[8]The corresponding binomial lattices with all the values that were estimated can be seen in Appendix B

EPU index obtained by PCA. We can say that the maximum values described above, denote that the binomial lattice incorporated the magnitude of the volatilities collected by the redistribution of the sub-samples by the PCA analysis. As well as, in relation to the minimum values found in each scenario, we can verify that for the scenario with the lowest volatility, the value is higher, in relation to scenarios 1, 2 and 4.

Figure 16

CRR Binomial Lattice - Non EPU vs Non Discretionary EPU.



NOTE: The Authors (2023). In this first model with EPU, it is the result of the product of the EPU simulation by the binomial lattice without EPU . For the data and plot of this image, see Appendix E, between lines 647 and 737.

We take as implications that, first in relation to the maximum values, it means that in the environment with greater uncertainty it will demonstrate a greater option value, confirming what the recent literature on economic policy uncertainty (Baker et al., 2013, 2016; Bonaime et al., 2018; Li et al., 2022). Second, regarding the minimum values observed, we can highlight that in the environment with lower volatility the investor takes less risk, since the value of the cash flow estimated for the worst case within the scenario with lower volatility is greater than in relation to the other scenarios.

We can therefore conclude that, in the most volatile environment, based on the EPU volatility, the option value found for the M&A project is higher in relation to the scenario with lower volatility. We must also consider that the environment that offers a higher option value also becomes the riskiest environment, given that the scenario with lower volatility presented a better result in the worst scenario in relation to the scenarios with greater volatility. Regarding the investor, the results mean that in the environment of greater volatility he will be able to obtain greater gains if he waits to invest. While, in a period of lower volatility, if the investor finalizes the investment now, he will not suffer many losses, because the expected cash flows at a time $t + 1$ do not generate significant returns that make it worth the wait to invest. Tracing the results of the test model, we were able to state based on these observations that the non-discretionary inclusion model is able to capture the values with greater significance in relation to the previous test model, the discretionary model. Therefore, after all the operationalization of tests in our hypothetical company, this includes the PCA analysis, GBM simulation, Discretionary and Non-Discretionary models, we highlight that the process of including the EPU volatility in the Latinex case application, took place considering the analysis PCA and the Non-Discretionary model, results and application discussion are in the next section.

4.4 EPU INCLUSION TEST IN LATINEX

Batista et al. (2023) recent study also found significant results on M&A transactions in the Brazilian scenario, as opposed to a locally produced index. Based on these studies, and after running the tests reported in the previous section, we demonstrate the application of the developed model in a real case for evaluation. Figure 17 shows the expected cash flows expanded by real options.

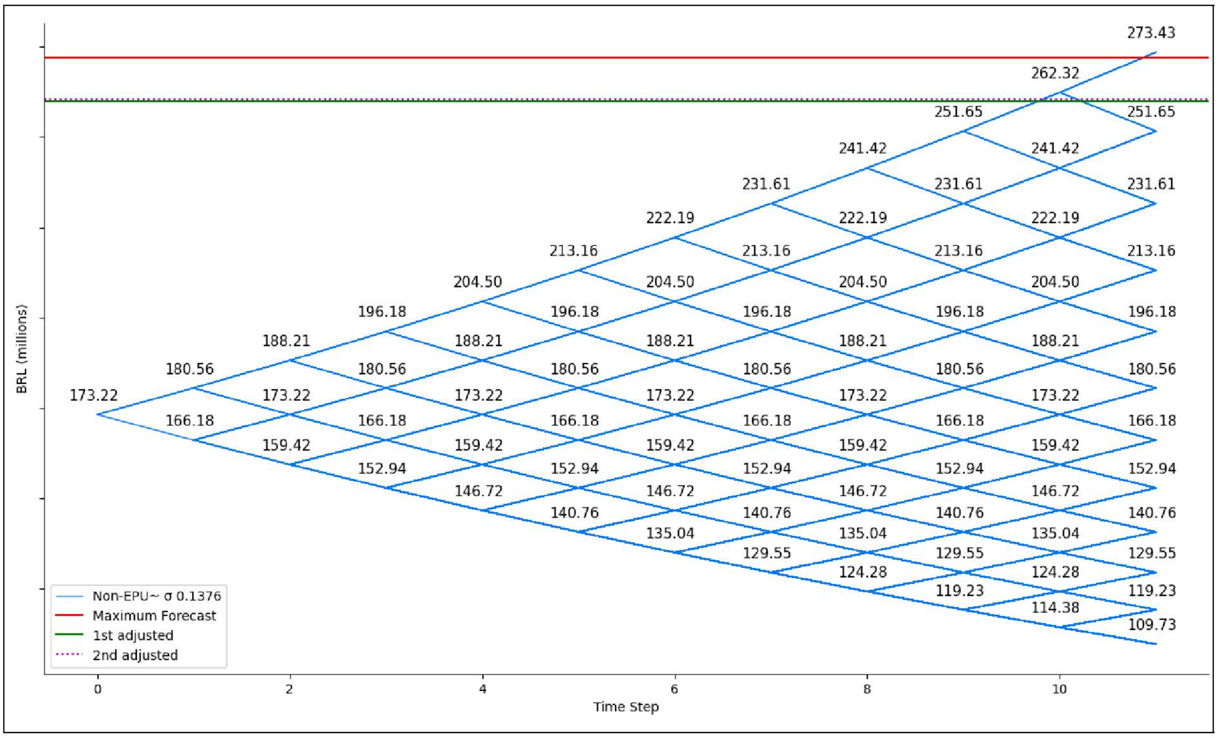
To proceed with our analysis, it was necessary to expand the cash flows estimated by the company via CRR, we emphasize that at this moment we do not include the EPU variable. First, because we needed to observe the option value based only on market data used by the company to estimate the target company. Second, this initial estimation provides us with a point of comparison with the model we propose here. Therefore, as described in the methodology, the estimated initial value for the acquisition of Latinex by M.Dias Branco was BRL 173,218,000.00 reais, with a maximum value of BRL 272,000,000.00. We use a discount rate of 6.40% based on the Selic rate for the period and an estimated volatility of 13.76%. We marked with lines in Figure 17 the maximum value and the adjustments made by the company after the acquisition.

We can see that the expansion of the DCF by real options of backward maximization developed by Cox et al. (1979), results in approximate values of what was estimated by the company's consultancy, which used the Monte Carlo Method to find the estimation disclosed in its financial reports. Our initial estimate reached a maximum value of BRL 273,431,419.53, which represents a variation of 0.53% in relation to that estimated by M.Dias Branco. While, we found a minimum expected value of cash flows of BRL 109,733,093.50. Considering market volatility, the company could bear a loss of approximately BRL 63,484,906.50, if the acquisition operation does not result in success.

Based on these initial results, we can then assume that the DCF expansion method via CRR proves to be adequate to perform M&A valuing in practice, as well as the technique of using binomial trees for estimation, consequently our results so far are according to the real options literature (Cox et al., 1979; Dixit & Pindyck, 1994; Marques et al., 2021; Reuer & Tong, 2007; Trigeorgis, 1996; Zhu & Jin, 2011). In addition, the use of real options allows knowledge of the possible values that a project can reach at different times, and the visualization by binomial trees allows the investor to make a better decision, which allows him to avoid possible losses.

Figure 17

CRR Binomial Lattice - Latinex (M.Dias Branco)



NOTE: The Authors (2023). For the data and plot of this image, see Appendix E, between lines 739 and 795.

Having completed the initial analysis of Latinex's expanded cash flows, we proceed to analyze the application of the developed model that includes the EPU volatility variable in the Non-Discretionary method, selected after the tests carried out in the previous section. In which we used the standardized EPU variable and later redistributed by the PCA analysis, which returned four scenarios for estimating the expected cash flows for real options. These scenarios allowed us a better analysis of the application of the EPU volatility in the M&A valuation. Figure 18 demonstrates the comparison between the cash flows expanded by CRR and the cash flows that integrate the EPU variable as volatility replacing the market data used by the company, in four different scenarios.

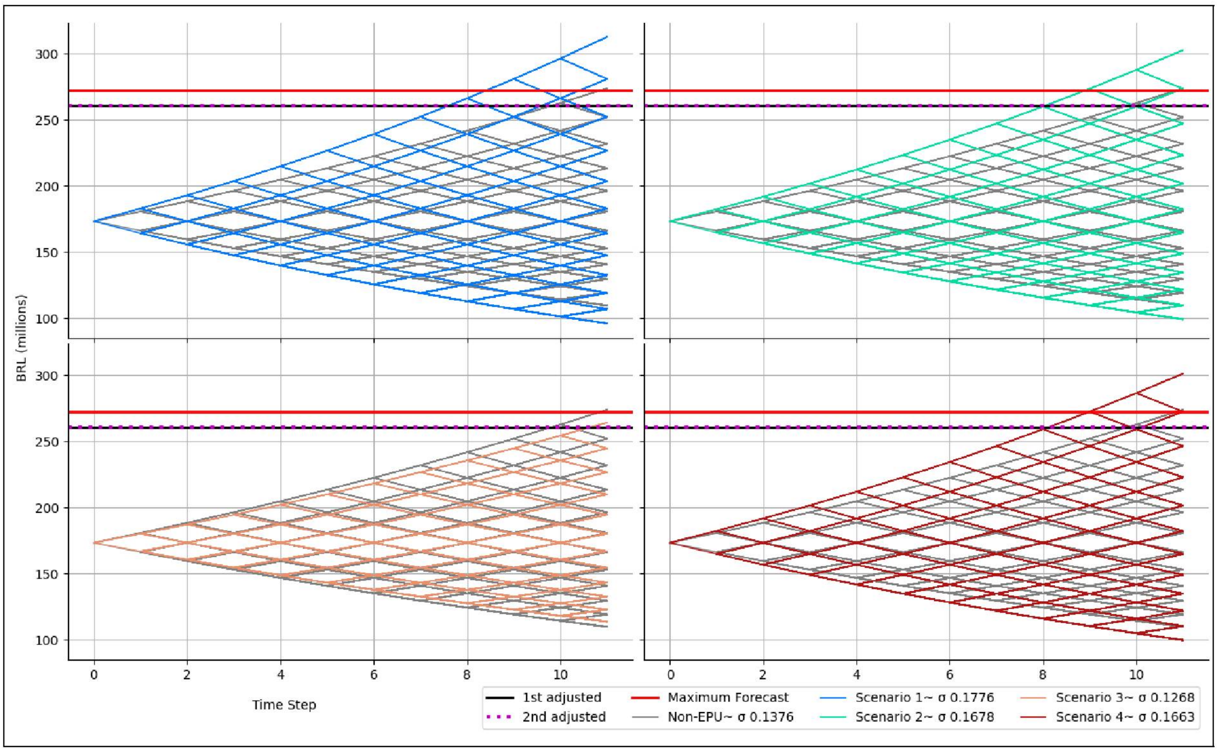
In order to make an inference about the results presented in Figure 18, we emphasize that in the four scenarios that include the EPU volatility, the initial value of the cash flow estimation is the same used for the calculation of the binomial lattice without EPU. Therefore, the maximum values captured by the DCF expansion via CRR, using the volatility generated in the scenarios resulting from the PCA, are presented in the following values: BRL 312,150,875.89, BRL 302,219,617.14, BRL 263,812,347, 29 and BRL 300,717,095.79, respectively for scenarios 1 to 4 [9], being congruent with the magnitude of the volatility of each sce-

[9]The respective binomial lattice with all the values that were estimated can be seen in the Ap-

nario. Meanwhile, the minimum values expected for scenarios 1 to 4 were BRL 96,121,708.58, BRL 99,280,370.38, BRL 113,734,159.27 and BRL 99,776,420.91 respectively.

Figure 18

CRR Binomial Lattice - Latinex EPU



NOTE: The Authors (2023). For the data and plot of this image, see Appendix E, between lines 797 and 896.

The results of Figure 18 proved to be persistent regarding the application of the model developed for the valuation of M&A in real cases. First, we can discuss the estimated values for the cash flows considering EPU volatility instead of market volatility. The values found in scenarios 1, 2 and 4 are greater than the estimated value for the target company without including the EPU volatility, as it is possible to verify that the binomial lattices exceed the maximum estimated value of disbursement by the company denoted by the red line in the scenarios. Only in the third scenario does the option estimate have values lower than the estimate made by the company and our first cash flow estimate, remaining within the limits of the adjustments made by the company after the acquisition of Latinex. If the investor were to consider including the EPU volatility in their analysis, scenarios 1, 2 and 4 suggest to the investor that it might be better to wait before investing now. Because in these scenarios of greater volatility, subject to new information that can bring greater returns than the immediate investment. While for the third scenario, it demonstrates that investing now is better than waiting for new configurations that could change the value of expected cash flows, that is, in a scenario of low EPU volatility, the investor would be more likely to make the investment.

Figure 18 demonstrates that the inclusion of EPU volatility can be substantial in the

pendix D

valuation of companies. This is because, as reported in the recent literature on EPU, the uncertainty associated with this variable is capable of generating option value in M&A projects. By making the investor prefer to wait to invest, which can result in a series of implications, such as cash holding (Demir & Ersan, 2017; Duong et al., 2020; Phan et al., 2019), a decrease in the level of investments in the period (Drobetz et al., 2018; Kang et al., 2014; Wang et al., 2014), among other consequences, this demonstrates that our model converges with previous studies. As demonstrated, the investor will prefer to wait for new information given the level of EPU volatility. Therefore, the model we have developed here allows investors to better evaluate their investment considering the volatility of EPU index. Next, we performed sensitivity and robustness tests to validate the model proposed in this study.

4.5 SENSITIVITY ANALYSIS

In this section we address sensitivity analyses, these tests help us to explain the effects of EPU volatility on the valuation process in an M&A transaction. We also emphasize that all the tests below use the parameters and results obtained in the application of the model in the case of M. Dias Branco. In our first test, we verified how sensitive the value of the target company is in relation to the variation in volatility obtained through the Baker et al. (2016) EPU index. We remind you that the M&A transaction can be considered an American call option (Cox et al., 1979), so this test allows you to verify the gain in relation to the EPU variation.

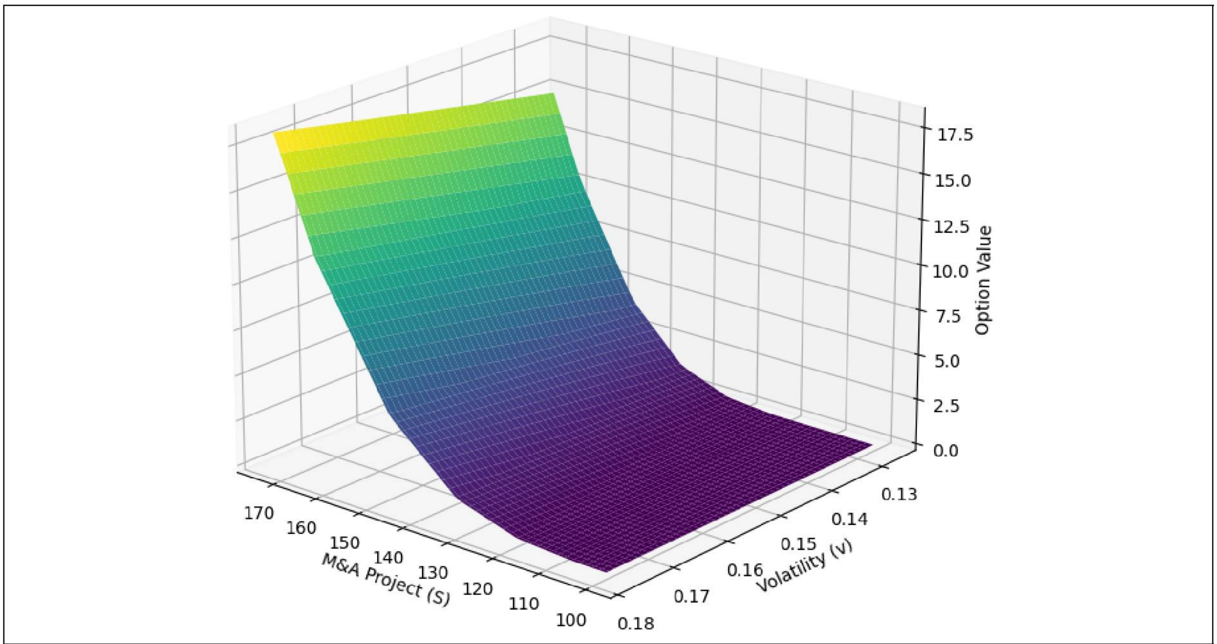
Figure 19 illustrates the results of the initial test, which focuses on the sensitivity analysis of volatility. In this test, we examine the impact of varying the value of S_0 across all the variables encompassed in the vector $\sigma_0 = [\sigma_1, \sigma_2, ..., \sigma_n]$. By systematically testing different values of S_0, we gain valuable insights into how changes in volatility influence the overall outcomes of the analysis. The results obtained from this sensitivity analysis provide a comprehensive understanding of the relationship between volatility and the valuation of the real options, offering valuable information for decision-making processes.

The presented results are based on a simulation that encompasses 100 possible configurations of σ_0 against the value of S_0. S_0, representing BRL 173,218,000.00, is the initial amount paid in the M&A operation and also serves as the strike value. The range of σ_0 values spans from the lowest to the highest volatility observed for the EPU variable, namely 0.1268 and 0.1776, respectively. The remaining parameters remain consistent with the previous analysis. Figure 19 provides valuable insights into the relationship between the EPU volatility and the M&A project. Firstly, it demonstrates that the EPU volatility generates option value throughout the entire period and across all simulated states of the EPU volatility. Secondly, the value of the option gain is influenced by the level of EPU volatilities. Specifically, lower EPU volatility levels result in smaller gains in option value, while higher EPU volatility levels correspond to larger gains. Thirdly, the project value also increases in relation to the EPU volatility level, indicating that changes in EPU volatility directly impact the overall project value. These findings highlight the significance of accurately estimating and predicting volatility, as emphasized by Cheng et al. (2021), in effectively managing risks and allocating assets. The results underscore the importance of considering the volatility of EPU variable in real options analysis, as it introduces additional value and impacts the overall valuation of the M&A project.

Our results are congruent with the findings of Cheng et al. (2021), while they only studied volatility forecasts, here we demonstrate that the volatility obtained from the EPU generates gains in the estimated value, with a difference that the authors reported gains between 6% to 9%, and our results demonstrate initial gains of approximately 4.5%. Our results are also supported by the EPU literature (Baker et al., 2016; Bonaime et al., 2018), which reports that the variation in the EPU volatility level is capable of bringing an option value associated with an investment, making the investor prefer to wait to invest because his returns will be higher, as demonstrated in the figure.

Figure 19

Volatility Sensitivity Analysis

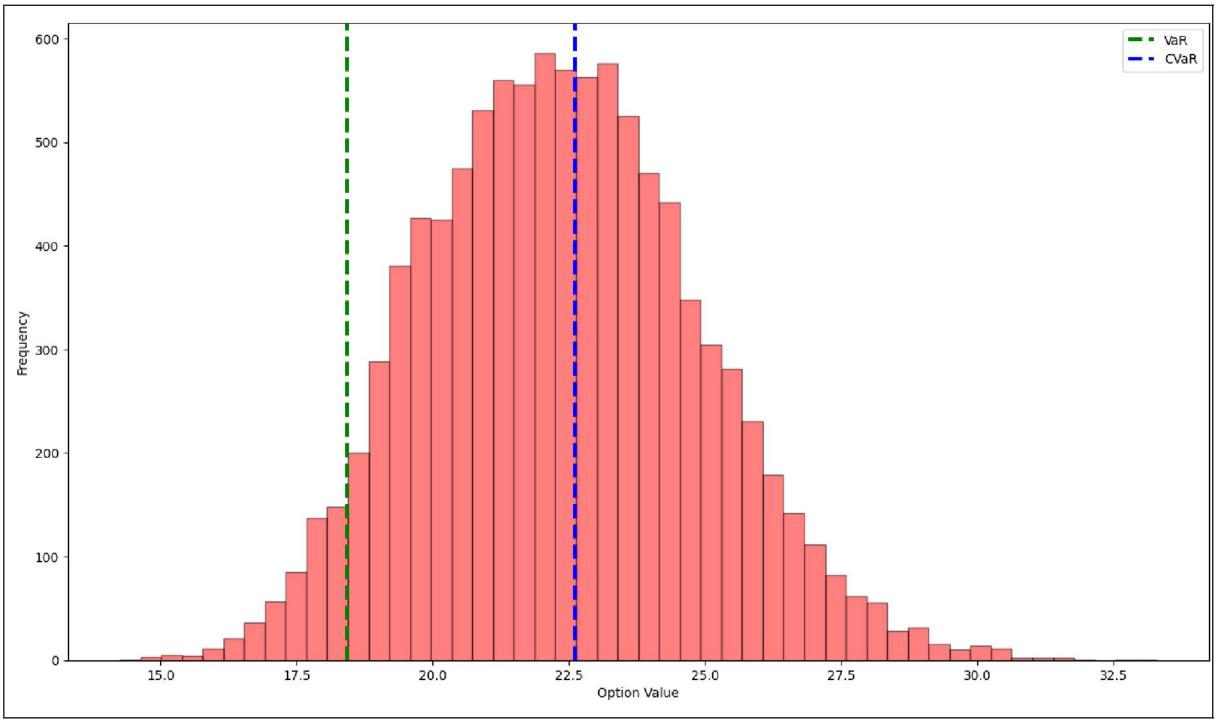


NOTE: The Authors (2023). The estimated values for the project and option value are in millions of BRL. The volatility sensitivity analysis chart is based on the code found in Appendix E, lines 898 to 932.

Subsequently, a risk analysis is conducted using the CVaR model at a 95% confidence level. The purpose of this analysis is to assess the potential magnitude of losses in the event of the least likely scenario for the previously analyzed M&A transaction. The test consists of 10,000 simulations of the initial value, denoted as S_0, which yields an equal number of corresponding option values. The results obtained from this analysis are presented in Figure 20. It is important to note that the same parameter values as the previous analysis were used, specifically S_0 equal to BRL 173,218,000.00 and a volatility σ of 0.1268. The simulations provide valuable insights into the range of potential outcomes and allow for a more comprehensive understanding of the risks associated with the M&A transaction.

We performed the CVaR analysis, for this, it was first necessary to estimate the VaR, our results showed that in a configuration of ten thousand simulations, we found that there is an environment with a 5% chance of estimated loss of approximately 18,200,000.00 on a given time period. Consequently, and our object of interest in this analysis, the estimated CVaR indicates that among the 5% of the worst gains, the average loss of the project would be approximately BRL 20,000,000.00. According to Adesi (2016), the CVaR values based on options can be used as a reference to validate alternative methodologies. In this study, we treat here as methodological support for the results found previously and demonstrated in the binomial lattices that include the volatility obtained from the EPU index. Choosing the risk measure is an important step towards building a realistic picture of risk (Stoyanov et al., 2012). Therefore, considering these implications, we highlight that the CVaR analysis allows investors to have a view on the possible losses, in our case, hypothetically if the EPU volatility value suffers increments, this could result in greater losses recognized by the CVaR analysis.

Figure 20
CVaR Sensitivity Analysis

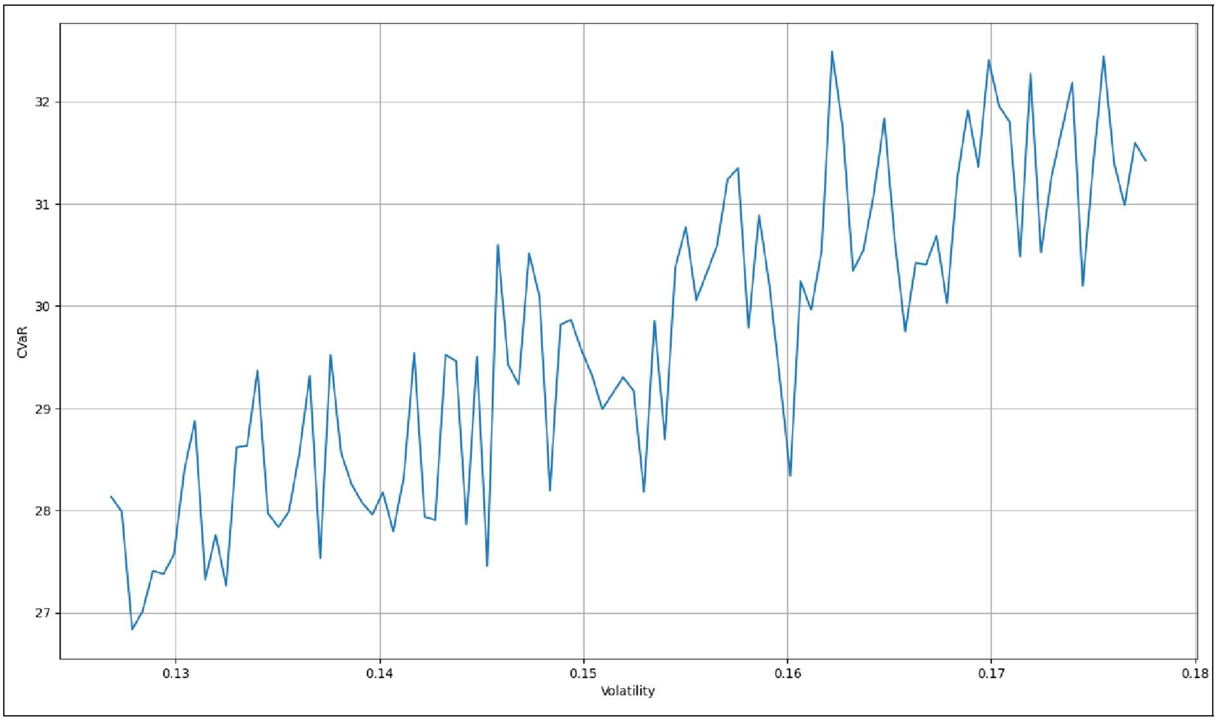


NOTE: The Authors (2023). Confidence level for CVaR analysis of α = 95%. The option value is in millions of BRL. For the data and plot of this image, see Appendix E, between lines 934 and 979.

Lastly, to compare all the results presented since the application of the model in the case of M. Dias Branco and to single out the sensitivity tests of the EPU volatility and the CVaR risk analysis, we applied a last sensitivity test between Volatility and CVaR. The results of this test are shown in Figure 21, considering a confidence level of 95%. This test initially consists of applying to each value of the vector $S_0 = [S_1, S_2, ..., S_n]$ on all the variables contained in the vector $\sigma_0 = [\sigma_1, \sigma_2, ..., \sigma_n]$, so that it was possible to capture the CVaR measure for each state assumed by the volatility. Differently from the first sensitivity analysis, here the values of S_0 were obtained by GBM, as well as the prices to estimate the cash flows of the test model. Formed as follows, one hundred possible values for σ between 0.1268 and 0.1776 were randomized, and prediction simulations of the thousand possible values for S_0 were performed, having as a starting point the amount of BRL 173,218,000.00.

Figure 21

Robustness Test - Sensitivity Analysis between Volatility and CVaR



NOTE: The Authors (2023). Confidence level for CVaR analysis of α = 95%. The option value is in millions of BRL. For the data and plot of this image, see Appendix E, between lines 981 and 1026.

Considering that the other parameters needed for the sensitivity test in Figure 21 remain the same, we discuss the results. The CVaR measure calculates the 5% of the worst possible scenarios that could occur, thus, our results demonstrate that for the configuration of variables used, we would have a loss of approximately BRL 28 million, in a low EPU volatility scenario (0.1268). At another point, losses would reach BRL 32 million when the EPU volatility exceeded 0.16. First, the results show that there is an upward trend in losses as EPU volatility increases. Second, the results also indicate that a positive change of 0.1 p.p. in the volatility of the EPU index could result in approximately BRL 1 million in project losses.

The findings presented in this section align with the existing body of literature on EPU, as highlighted by Baker et al. (2016) and Bonaime et al. (2018). Firstly, it is worth emphasizing that an escalation in EPU volatility levels can generate option value for an investment project, specifically in the case of M&A transactions investigated in this study. This outcome suggests that investors may opt to delay their investments in order to attain higher returns. Secondly, the rise in EPU volatility levels corresponds to an increase in associated risks, leading to a deferral of investment. Consequently, risk-averse investors would demand higher returns, resulting in a greater number of potential restrictive clauses within M&A transactions. This would necessitate the target company to meet a higher number of requirements.

It is important to note that the M&A contract between M. Dias Branco and Latinex, under consideration, proposes revenue targets for the acquiree, with the ultimate aim of influencing the final acquisition disbursement. These findings contribute to the growing body of literature on EPU and its implications for real options, particularly within the context of M&A transactions. They shed light on the rationale behind investor behavior in the face of heightened uncertainty and underscore the significance of incorporating EPU volatility considerations into decision-making processes. Further research in this area is warranted to deepen our understanding and explore the applicability of these findings across a broader range of investment scenarios.

Ultimately, our research findings demonstrate that the model we have developed for assessing the valuation of M&A aligns with the existing literature regarding the impact of EPU. Through conducting sensitivity tests on volatility, CVaR, and a combination of both, we have established the consistency of our model. It is important to emphasize that our model possesses both theoretical and practical validity, despite being limited to a single case study for the sake of feasibility. The theoretical validity of our model is supported by the establishment of scenarios and the subsequent simulations, which have effectively demonstrated its application and robustness. Moreover, the values derived from the model's application underwent rigorous testing protocols, ensuring the proper incorporation of the EPU volatility into the evaluation method. Importantly, the values obtained closely corresponded to the anticipated payment amount by the company if the targeted revenue was achieved, further reinforcing the practical validity of our model.

In conclusion, this study substantiates the credibility and relevance of the developed model within the context of M&A valuation. By aligning with existing research on the effects of EPU volatility, we have provided a valuable contribution to the field. Nonetheless, it is crucial to acknowledge the need for further exploration and validation through additional case studies to enhance the generalizability and robustness of the model.

5 FINAL REMARKS

This study proposes a comprehensive model for integrating the EPU index into the assessment of M&A. Numerous studies have demonstrated the significant impact of EPU on various micro and macroeconomic variables, as well as on the dynamics of M&A operations. To address this, we conducted tests to incorporate EPU using two approaches: PCA and GBM simulations. The results obtained from PCA and GBM were then integrated into the non-discretionary and discretionary models, respectively, through the application of the DCF methodology expanded by ROV. Following an extensive series of tests and simulations, our findings indicate that the inclusion of EPU volatility in the M&A assessment can be successfully achieved by utilizing the PCA treatment within the expanded DCF-ROV framework.

Our study makes contributions to the existing literature in several key aspects. Firstly, we successfully employed the expansion technique of the DCF by the ROV approach, specifically the CRR model, to incorporate EPU into both proposed models. The non-discretionary model yielded more robust results that align with the existing EPU literature. To the best of our knowledge, this is the first study to integrate EPU as a replacement for volatility in the valuation of M&A using real options. The model tests and the application of the case study demonstrated the significance of EPU volatility as a valuable variable for M&A valuation. Furthermore, the sensitivity analysis and robustness tests affirmed that our study's implementation of EPU volatility effectively captures market volatility, as the results align with the relevant literature.

Secondly, our findings reveal that EPU volatility has the ability to generate option value within the valuation process. In addition to capturing market volatility, EPU volatility more efficiently demonstrates the potential gains and losses associated with an investment project. Thus, a higher EPU volatility level leads to increased project option value and, consequently, greater risk. This relationship can be attributed to the instability of economic policies that accompanies elevated levels of EPU volatility. These findings are consistent with the existing literature on uncertainty and EPU.

Thirdly, our investigation found that the GBM method, employed for simulating the standardized EPU index and its application in the discretionary model, was ineffective for our specific purposes. When the initial value is set to zero, the GBM method generates zero values throughout the simulation extension due to its mean reversion property. On the other hand, when a positive or negative value is used, the simulations concentrate around the mean spectrum but exhibit trends based on the sign of the initial value, resulting in an evaluation biased by the value's sign. Given that the discretionary model involves the direct application of EPU in the valuation method, where the EPU at time t_0 is applied to the binomial lattice at t_0 and subsequent periods, this limitation is particularly relevant. Moreover, regarding the EPU variable, the standardization and transformation of the selected period into sub-samples using PCA proved to be effective in our tests, supporting the existing literature on the application of PCA for economic indicator treatment.

This study offers practical contributions through the introduction of a non-discretionary model that applies the EPU volatility to the valuation of M&A. The model showcases that the utilization of EPU volatility exhibits characteristics similar to market volatility, albeit with the advantage of capturing multiple market indices, as supported by existing literature. This enhanced efficiency of EPU volatility as a measure is of significant value to investors. Furthermore, the developed model provides valuable assistance to investors in their decision-making processes, particularly when confronted with scenarios characterized by high levels of EPU volatility. By incorporating the EPU volatility into the valuation framework, investors gain the ability to analyze not only the option value associated with their investment but also the corresponding risk. Armed with this comprehensive understanding, investors can make informed decisions aligned with their investment principles and risk tolerance levels.

Our study introduces a technological contribution by developing an algorithm that graphically reproduces the CRR binomial lattice in the Python programming language. The detailed implementation of this algorithm can be found in Appendix E, specifically between lines 487 and 515, as well as lines 564 and 592. This Python code is of significant value, as it can assist analysts involved in M&A valuation processes and serve as a resource for other researchers seeking to delve into and advance the realms of EPU and Real Options research.

This research acknowledges the potential limitations associated with the treatment of variables, the models utilized, and the selected sample for analysis. It should be noted that this study does not aim to exhaust all possible techniques for handling variables related to economic indicators. Instead, we have chosen to employ PCA and GBM analysis, as these techniques have demonstrated promising outcomes when applied in conjunction with Real Options. With regards to the models employed, we have focused on utilizing the DCF and ROV methods. The DCF approach was selected due to its wide adoption among investors for the valuation process, while ROV allows for the assessment of option value and aligns with previous studies that highlight the potential option value generated by EPU volatility. It is important to acknowledge that this study is limited in its scope by conducting tests on a single company within the consumer and retail sector. Consequently, it was not feasible to evaluate potential differences between companies in different sectors or in terms of financing mechanisms.

In order to facilitate further investigation in this area, we provide several recommendations that can expand the scope of research. Firstly, it is suggested to explore alternative methods for simulating the standardized EPU index within the CRR model, as our findings indicate that the GBM method was not suitable for our specific purposes. Future research endeavors should aim to refine these simulation techniques and delve deeper into examining the impact of EPU on real options analysis in various investment contexts, whether they are of a public or private nature. It would be valuable to explore potential differences in the magnitude of the EPU effect on companies based on their specific types of financing. Additionally, considering our focus on the national industry, there is a possibility for conducting cross-border investment project analyses to gain insights into the implications of EPU on such projects. These recommendations can contribute to a more comprehensive understanding of the relationship between EPU and real options in different investment scenarios.

REFERENCES

Adesi, G. B. (2016). VaR and CVaR implied in option prices. *Journal of Risk and Financial Management*, *9*(1), 2, https://doi.org/10.3390/jrfm9010002.

Al-Obaidli, H., Govindan, R., & Al-Ansari, T. (2023). Multidimensional risk-based real options valuation for low-carbon cogeneration pathways. *Energies*, *16*(3), https://doi.org/10.3390/en16031250.

Al-Thaqeb, S. A. & Algharabali, B. G. (2019). Economic policy uncertainty: A literature review. *The Journal of Economic Asymmetries*, *20*, e00133, https://doi.org/10.1016/j.jeca.2019.e00133.

Alexander, C., Chen, X., & Ward, C. (2021). Risk-adjusted valuation for real option decisions. *Journal of Economic Behavior & Organization*, *191*, 1046–1064, https://doi.org/https://doi.org/10.1016/j.jebo.2021.09.011.

Ambrose, B. W. & Steiner, E. (2022). Economic fundamentals, capital expenditures and asset dispositions. *Journal of Real Estate Finance and Economics*, *64*(3), 361 – 378, https://doi.org/10.1007/s11146-019-09698-9.

Bachelier, L. (1900). *Théorie de la Spéculation*. PhD Thesis, L'Ecole Normale Supérieure http://www.numdam.org/item/10.24033/asens.476.pdf.

Bailey, W., Couet, B., Bhandari, A., Faiz, S., Srinivasan, S., & Weeds, H. (2003). Unlocking the value of real options. *Oilfield Review*, *15*(4), 04–15.

Baker, S. R., Bloom, N., & Davis, S. J. (2013). Measuring economic policy uncertainty. In *Working Paper* (pp.˜47).

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty*. *The Quarterly Journal of Economics*, *131*(4), 1593–1636, https://doi.org/10.1093/qje/qjw024.

Batista, A. T. N., Lamounier, W. M., & do Carmo Mário, P. (2023). Does economic policy uncertainty affect m&a operations? evidence from the brazilian market. *BBR - Brazilian Business Review*, *20*(2), 133 – 156, https://doi.org/10.15728/bbr.2023.20.2.2.

Battauz, A., Gatti, S., Prencipe, A., & Viarengo, L. (2021). Earnouts: The real value of disagreement in mergers and acquisitions. *European Financial Management*, *27*(5), 981 – 1024, https://doi.org/10.1111/eufm.12304.

Baum, C. F., Caglayan, M., & Talavera, O. (2010). On the sensitivity of firms' investment to cash flow and uncertainty. *Oxford Economic Papers*, *62*(2), 286–306, https://doi.org/10.1093/oep/gpp015.

Becker, D. M. (2022). Getting the valuation formulas right when it comes to annuities. *Managerial Finance*, *48*(3), 470 – 499, https://doi.org/10.1108/MF-03-2021-0135.

Beckmann, J. & Czudaj, R. (2017). Exchange rate expectations and economic policy uncertainty. *European Journal of Political Economy*, *47*, 148–162, https://doi.org/10.1016/j.ejpoleco.2016.06.003.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, *98*(1), 85–106, https://doi.org/10.2307/1885568.

Biljanovska, N., Grigoli, F., & Hengge, M. (2021). Fear thy neighbor: Spillovers from economic policy uncertainty. *Review of International Economics*, *29*(2), 409–438, https://doi.org/10.1111/roie.12531.

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559, https://doi.org/10.1016/j.jfineco.2011.12.010.

Björk, T. (2020). *Arbitrage theory in continuous time*. Oxford: Oxford Univ. Press, 4 edition.

Black, F. & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, *81*(3), 637–654, https://doi.org/10.1086/260062.

Bodie, Z., Kane, A., & Marcus, A. J. (2018). *Investments*. McGraw-Hill Education, 11 edition.

Bonaime, A., Gulen, H., & Ion, M. (2018). Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics*, *129*(3), 531–558, https://doi.org/10.1016/j.jfineco.2018.05.007.

Bordo, M. D., Duca, J. V., & Koch, C. (2016). Economic policy uncertainty and the credit channel: Aggregate and bank level u.s. evidence over several decades. *Journal of Financial Stability*, *26*, 90–106, https://doi.org/10.1016/j.jfs.2016.07.002.

Bragoli, u. D., Cortelezzi, F., Giannoccolo, P., & Marseguerra, G. (2020). R&d investment timing, default and capital structure. *Review of Quantitative Finance and Accounting*, *54*(3), 779–801, https://doi.org/10.1007/s11156-019-00807-6.

Brandão, L. E. T. (2002). *Uma aplicação da teoria das opções reais em tempo discreto para avaliação de uma concessão rodoviária no brasil*. PhD Thesis, Pontifícia Universidade Católica do Rio de Janeiro-PUC-RIO https://doi.org/10.17771/PUCRio.acad.5120.

Brennan, M. J. (2003). Corporate investment policy. In Constantinides, George M, and Harris, Milton and Stulz, René M. (Ed.), *Corporate Finance*, volume 1A of *Handbook of the Economics of Finance* chapter 3, (pp. 167–214). Elsevier, 1*st* edition.

Chen, J. (2021). On the theoretical foundation of corporate finance. *Structural Change and Economic Dynamics*, *59*, 256–262, https://doi.org/10.1016/j.strueco.2021.08.012.

Chen, J., Jiang, F., & Tong, G. (2017). Economic policy uncertainty in china and stock market expected returns. *Accounting & Finance*, *57*(5), 1265–1286, https://doi.org/10.1111/acfi.12338.

Chen, X., Le, C. H. A., Shan, Y., & Taylor, S. (2020). Australian policy uncertainty and corporate investment. *Pacific-Basin Finance Journal*, *61*, 101341, https://doi.org/10.1016/j.pacfin.2020.101341.

Cheng, M., Swanson, N. R., & Yang, X. (2021). Forecasting volatility using double shrinkage methods. *Journal of Empirical Finance*, *62*, 46–61, https://doi.org/10.1016/j.jempfin.2021.01.007.

Chevalier-Roignant, B. & Trigeorgis, L. (2011). *Competitive Strategy: Options and Games*. The MIT Press http://www.jstor.org/stable/j.ctt5hhbmq.

Claessen, A. (2021). Relevance of level 3 fair value disclosures and IFRS 13: a case study. *International Journal of Disclosure and Governance*, *18*(4), 378–390, https://doi.org/10.1057/s41310-021-00119-z.

Copeland, T. & Antikarov, V. (2003). *Real Options: A Practioner's Guide*. Cengage Learning, revised edition.

Cotei, C., Farhat, J., & Khurana, I. (2022). The impact of policy uncertainty on the m&a exit of startup firms. *Journal of Economics and Finance*, *46*(1), 99 – 120, https://doi.org/10.1007/s12197-021-09553-9.

Cox, J. C., Ross, S. A., & Rubinstein, M. (1979). Option pricing: A simplified approach. *Journal of Financial Economics*, *7*(3), 229–263, https://doi.org/https://doi.org/10.1016/0304-405X(79)90015-1.

Cui, T., Ding, S., Jin, H., & Zhang, Y. (2023). Portfolio constructions in cryptocurrency market: A cvar-based deep reinforcement learning approach. *Economic Modelling*, *119*, 106078, https://doi.org/10.1016/j.econmod.2022.106078.

Culík, M. (2016). Real options valuation with changing volatility. *Perspectives in Science*, *7*, 10–18, https://doi.org/https://doi.org/10.1016/j.pisc.2015.11.004. 1st Czech-China Scientific Conference 2015.

Dakessian, L. C. & Feldmann, P. R. (2013). Multilatinas and value creation from cross-border acquisitions: an event study approach. *BAR - Brazilian Administration Review*, *10*(4), 462–489, https://doi.org/10.1590/S1807-76922013000400006.

Dakhlaoui, I. & Aloui, C. (2016). The interactive relationship between the us economic policy uncertainty and bric stock markets. *International Economics*, *146*, 141–157, https://doi.org/10.1016/j.inteco.2015.12.002.

Damodaran, A. (2007). Valuation approaches and metrics: A survey of the theory and evidence. *Foundations and Trends® in Finance*, *1*(8), 693–784, https://doi.org/10.1561/0500000013.

Danisman, G. O., Demir, E., & Ozili, P. (2021). Loan loss provisioning of us banks: Economic policy uncertainty and discretionary behavior. *International Review of Economics & Finance*, *71*, 923–935, https://doi.org/10.1016/j.iref.2020.10.016.

Degiannakis, S. & Filis, G. (2019). Forecasting european economic policy uncertainty. *Scottish Journal of Political Economy*, *66*(1), 94–114, https://doi.org/10.1111/sjpe.12174.

Dehghani, H. & Ataee-pour, M. (2013). Determination of the effect of economic uncertainties on mining project evaluation using real option valuation. *International Journal of Mining and Mineral Engineering*, *4*(4), 265, https://doi.org/10.1504/ijmme.2013.056850.

Demir, E. & Ersan, O. (2017). Economic policy uncertainty and cash holdings: Evidence from bric countries. *Emerging Markets Review*, *33*, 189–200, https://doi.org/10.1016/j.ememar.2017.08.001.

Dierkes, S. & Schäfer, U. (2021). Valuation of firms with multiple business units. *Journal of Business Economics*, *91*(4), 401 – 432, https://doi.org/10.1007/s11573-020-01010-z.

Dixit, A. K. & Pindyck, R. S. (1994). *Investment Under Uncertainty*. Princeton University Press.

Drobetz, W., El Ghoul, S., Guedhami, O., & Janzen, M. (2018). Policy uncertainty, investment, and the cost of capital. *Journal of Financial Stability*, *39*, 28–45, https://doi.org/10.1016/j.jfs.2018.08.005.

Duong, H. N., Nguyen, J. H., Nguyen, M., & Rhee, S. G. (2020). Navigating through economic policy uncertainty: The role of corporate cash holdings. *Journal of Corporate Finance*, *62*, 101607, https://doi.org/10.1016/j.jcorpfin.2020.101607.

El Ghoul, S., Guedhami, O., Kim, Y., & Yoon, H. J. (2021). Policy uncertainty and accounting quality. *The Accounting Review*, *96*(4), 233–260, https://doi.org/10.2308/TAR-2018-0057.

Ewald, C. O. & Taub, B. (2022). Real options, risk aversion and markets: A corporate finance perspective. *Journal of Corporate Finance*, *72*, 102164, https://doi.org/10.1016/j.jcorpfin.2022.102164.

Flanagan, D. J., Milman, C. D., & D'Mello, J. P. (1997). A comparison of the characteristics of M&A activity in five latin american countries and the united states 1985-1994. *International Journal of Commerce and Management*, *7*(2), 5 – 20, https://doi.org/10.1108/eb047346.

Folta, T. B. & Miller, K. D. (2002). Real options in equity partnerships. *Strategic Management Journal*, *23*(1), 77 – 88, https://doi.org/10.1002/smj.209.

Fortin, I., Fuss, S., Hlouskova, J., Khabarov, N., Obersteiner, M., & Szolgayova, J. (2007). *An Integrated CVaR and Real Options Approach to Investments in the Energy Sector*. Economics Series 209, Institute for Advanced Studies https://ideas.repec.org/p/ihs/ihsesp/209.html.

Gabrielli, L. & French, N. (2021). Pricing to market: property valuation methods – a practical review. *Journal of Property Investment & Finance*, *39*(5), 464–480, https://doi.org/10.1108/JPIF-09-2020-0101.

Gruszczyński, M. (2020). *Financial Microeconometrics. A Research Methodology in Corporate Finance and Accounting*. Springer Cham.

Guerra-Urzola, R., Deun, K. V., Vera, J. C., & Sijtsma, K. (2021). A guide for sparse PCA: Model comparison and applications. *Psychometrika*, *86*(4), 893–919, https://doi.org/10.1007/s11336-021-09773-2.

Gulen, H. & Ion, M. (2015). Policy uncertainty and corporate investment. *Review of Financial Studies*, (pp. hhv050)., https://doi.org/10.1093/rfs/hhv050.

Gupta, R. & Sun, X. (2020). Forecasting economic policy uncertainty of BRIC countries using bayesian VARs. *Economics Letters*, *186*, 108677, https://doi.org/10.1016/j.econlet.2019.108677.

Haque, M. A., Topal, E., & Lilford, E. (2014). A numerical study for a mining project using real options valuation under commodity price uncertainty. *Resources Policy*, *39*, 115–123, https://doi.org/10.1016/j.resourpol.2013.12.004.

Haque, M. A., Topal, E., & Lilford, E. (2016). Evaluation of a mining project under the joint effect of commodity price and exchange rate uncertainties using real options valuation. *The Engineering Economist*, *62*(3), 231–253, https://doi.org/10.1080/0013791x.2016.1217366.

Hassett, K. A. & Metcalf, G. E. (2001). Investment with uncertain tax policy: Does random tax policy discourage investment. *The Economic Journal*, *109*(457), 372–393, https://doi.org/10.1111/1468-0297.00453.

Heidrich, F., de Morais, D. M. G., & Facó, J. F. B. (2021). A teoria de opções reais na gestão de investimentos na indústria 4.0: Um estudo de caso. *Revista de Gestão, Finanças e Contabilidade*, *10*(2), 60–85, https://doi.org/10.18028/rgfc.v10i2.7304.

Hossain, M. S. (2021). Merger & acquisitions (m&as) as an important strategic vehicle in business: Thematic areas, research avenues & possible suggestions. *Journal of Economics and Business*, *116*, 106004, https://doi.org/10.1016/j.jeconbus.2021.106004.

Huang, S., Tan, H., Wang, X., & Yu, C. (2022). Valuation uncertainty and analysts' use of dcf models. *Review of Accounting Studies*, https://doi.org/10.1007/s11142-021-09658-w.

Hull, J. C. (2016). *Opções, futuros e outros derivativos*. Bookman, 9 edition.

Ioulianou, S. P., Leiblein, M. J., & Trigeorgis, L. (2021). Multinationality, portfolio diversification, and asymmetric MNE performance: The moderating role of real options awareness. *Journal of International Business Studies*, *52*(3), 388–408, https://doi.org/10.1057/s41267-020-00357-3.

Jiang, J., Mu, C., Peng, J., & Yang, J. (2019). Real options maximizing survival probability under incomplete markets. *Quantitative Finance*, *19*(11), 1921–1931, https://doi.org/10.1080/14697688.2019.1617891.

Jones, D. A. (2018). Using real options theory to explain patterns in the valuation of research and development expenditures. *Review of Quantitative Finance and Accounting*, *51*(3), 575 – 593, https://doi.org/10.1007/s11156-017-0681-6.

Kang, W., Lee, K., & Ratti, R. A. (2014). Economic policy uncertainty and firm-level investment. *Journal of Macroeconomics*, *39*, 42–53, https://doi.org/10.1016/j.jmacro.2013.10.006.

Koch-Medina, P., Moreno-Bromberg, S., Ravanelli, C., & Šikić, M. (2021). Revisiting optimal investment strategies of value-maximizing insurance firms. *Insurance: Mathematics and Economics*, *99*, 131–151, https://doi.org/10.1016/j.insmatheco.2021.03.013.

Kumar, M. V. S. (2005). The value from acquiring and divesting a joint venture: A real options approach. *Strategic Management Journal*, *26*(4), 321 – 331, https://doi.org/10.1002/smj.449.

Kwon, S. H. & Wang, G. (2020). The change in the value relevance of accounting information after mergers and acquisitions: evidence from the adoption of SFAS - 141(R). *Accounting & Finance*, *60*(3), 2717–2757, https://doi.org/10.1111/acfi.12411.

Lee, C.-F. & Lin, C. S.-M. (2010). Two alternative binomial option pricing model approaches to derive black-scholes option pricing model. In C.-F. Lee, A. C. Lee, & J. Lee (Eds.), *Handbook of Quantitative Finance and Risk Management* (pp. 409–419). Boston, MA: Springer US.

Li, H., Zhou, D., Hu, J., Li, J., Su, M., & Guo, L. (2023). Forecasting the realized volatility of energy stock market: A multimodel comparison. *The North American Journal of Economics and Finance*, *66*, 101895, https://doi.org/10.1016/j.najef.2023.101895.

Li, J. (2007). Real options theory and international strategy: A critical review. *Advances in Strategic Management*, *24*, 67 – 101, https://doi.org/10.1016/S0742-3322(07)24003-3.

Li, R., Li, S., Yuan, D., & Yu, K. (2020). Does economic policy uncertainty in the u.s. influence stock markets in china and india? time-frequency evidence. *Applied Economics*, *52*(39), 4300–4316, https://doi.org/10.1080/00036846.2020.1734182.

Li, W., Su, Y., & Wang, K. (2022). How does economic policy uncertainty affect cross-border m&a: Evidence from chinese firms. *Emerging Markets Review*, *52*, 100908, https://doi.org/10.1016/j.ememar.2022.100908.

Lukas, E., Pereira, P. J., & Rodrigues, A. (2019). Designing optimal m&a strategies under uncertainty. *Journal of Economic Dynamics and Control*, *104*, 1 – 20, https://doi.org/10.1016/j.jedc.2019.04.006.

Lukas, E., Reuer, J. J., & Welling, A. (2012). Earnouts in mergers and acquisitions: A game-theoretic option pricing approach. *European Journal of Operational Research*, *223*(1), 256 – 263, https://doi.org/10.1016/j.ejor.2012.05.017.

Lyandres, E., Matveyev, E., & Zhdanov, A. (2020). Does the market correctly value investment options?*. *Review of Finance*, *24*(6), 1159–1201, https://doi.org/10.1093/rof/rfaa002.

M Dias Branco (2021). *M. Dias Branco, 2021 Annual Financial Statements*. Technical report, M. Dias Branco. https://api.mziq.com/mzfilemanager/v2/d/fcf0301a-c792-45d6-a615-fc81722c9abe/80b669eb-78d8-5bc0-7d13-a9e374411d21?origin=1.

Malek, J., Nguyen, D. K., Sensoy, A., & Tran, Q. V. (2023). Modeling dynamic var and cvar of cryptocurrency returns with alpha-stable innovations. *Finance Research Letters*, (pp. 103817)., https://doi.org/10.1016/j.frl.2023.103817.

Marques, N. L., Bastian-Pinto, C. d. L., & Brandão, L. E. T. (2021). A tutorial for modeling real options lattices from project cash flows. *Journal of Contemporary Administration*, *25*(1), e200093, https://doi.org/10.1590/1982-7849rac2021200093.

Merton, R. C. (1973). Theory of rational option pricing. *The Bell Journal of Economics and Management Science*, *4*(1), 141–183, https://doi.org/10.2307/3003143.

Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics*, *3*(1), 125–144, https://doi.org/10.1016/0304-405X(76)90022-2.

Metwalli, A. M. & Tang, R. Y. W. (2004). Update: M&A in latin america. *Journal of Corporate Accounting & Finance*, *15*(2), 43–51, https://doi.org/https://doi.org/10.1002/jcaf.10232.

Modigliani, F. & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, *48*(3), 261–297. http://www.jstor.org/stable/1809766.

Monteiro, I. S. (2019). *Valuation of Legal Covenants in M&A Deals: Real Options and Contract Theory*. Phd. thesis, Pontifícia Universidade Católica do Rio de Janeiro - PUC-RIO, Rio de Janeiro https://doi.org/10.17771/PUCRio.acad.46165.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147–175, https://doi.org/https://doi.org/10.1016/0304-405X(77)90015-0.

Myers, S. C. (2003). Financing of corporations. In Constantinides, George M, and Harris, Milton and Stulz, René M. (Ed.), *Corporate Finance*, volume 1A of *Handbook of the Economics of Finance* chapter 4, (pp. 215–253). Elsevier, 1*st* edition.

Najafi, P. & Talebi, S. (2021). Using real options model based on monte-carlo least-squares for economic appraisal of flexibility for electricity generation with VVER-1000 in developing countries. *Sustainable Energy Technologies and Assessments*, *47*, 101508, https://doi.org/10.1016/j.seta.2021.101508.

Ng, J., Saffar, W., & Zhang, J. J. (2020). Policy uncertainty and loan loss provisions in the banking industry. *Review of Accounting Studies*, *25*(2), 726–777, https://doi.org/10.1007/s11142-019-09530-y.

Nguyen, N. H. & Phan, H. V. (2017). Policy uncertainty and mergers and acquisitions. *Journal of Financial and Quantitative Analysis*, *52*(2), 613–644, https://doi.org/10.1017/S0022109017000175.

Nishihara, M. (2018). Valuation of an r&d project with three types of uncertainty. *EURO Journal on Decision Processes*, *6*(1), 93–113, https://doi.org/10.1007/s40070-018-0076-5.

Niu, Y., Yang, J., & Zou, Z. (2021). Investment decisions under incomplete markets in the presence of wealth effects. *Journal of Economics - Zeitschrift fur Nationalokonomie*, *133*(2), 167 – 189, https://doi.org/10.1007/s00712-021-00731-1.

Nordlund, B., Lorentzon, J., & Lind, H. (2022). Practice briefing a note on auditing fair value of investment properties. *Journal of Property Investment & Finance*, *40*(1), 108–115, https://doi.org/10.1108/JPIF-01-2021-0009.

Ozili, P. K. (2020). Financial reporting under economic policy uncertainty. *Journal of Financial Reporting and Accounting*, *19*(2), 325 – 338, https://doi.org/10.1108/JFRA-08-2020-0242.

Ozili, P. K. (2021). Economic policy uncertainty: are there regional and country correlations? *International Review of Applied Economics*, *35*(5), 714–728, https://doi.org/10.1080/02692171.2020.1853075.

O'Brien, T. J. (2022). Cross-border valuation using the international capm and the constant perpetual growth model. *Journal of Economics and Business*, *119*, 106042, https://doi.org/10.1016/j.jeconbus.2021.106042.

Panousi, V. & Papanikolaou, D. (2012). Investment, idiosyncratic risk, and ownership. *The Journal of Finance*, *67*(3), 1113–1148, https://doi.org/10.1111/j.1540-6261.2012.01743.x.

Penman, S. H. (2015). Valuation models: An issue of accounting theory. In S. Jones (Ed.), *The Routledge Companion to Financial Accounting Theory* chapter 11, (pp. 236–253). Routledge, 1*st* edition.

Pesenti, S. M. (2022). Reverse sensitivity analysis for risk modelling. *Risks*, *10*(7), 141, https://doi.org/10.3390/risks10070141.

Phan, H. V., Nguyen, N. H., Nguyen, H. T., & Hegde, S. (2019). Policy uncertainty and firm cash holdings. *Journal of Business Research*, *95*, 71–82, https://doi.org/10.1016/j.jbusres.2018.10.001.

Pindyck, R. S. (1991). Irreversibility, uncertainty, and investment. *Journal of Economic Literature*, *29*(3), 1110–1148 http://www.jstor.org/stable/2727613.

Poitras, G. (2009). The early history of option contracts. In W. Hafner & H. Zimmermann (Eds.), *Vinzenz Bronzin's Option Pricing Models: Exposition and Appraisal* chapter 18, (pp. 487–518). Berlin, Heidelberg: Springer Berlin Heidelberg.

Raupp, F. M. & Beuren, I. M. (2010). Metodologia da pesquisa aplicável às ciências sociais. In I. M. Beuren (Ed.), *Como Elaborar Trabalhos Monográficos em Contabilidade: Teoria e Prática*, volume 1 chapter 3, (pp. 76–97). Atlas.

Rees, M. (2018). *Principles of financial modelling*. Wiley finance series. West Sussex: John Wiley.

Reuer, J. J. & Tong, T. W. (2007). How do real options matter? empirical research on strategic investments and firm performance. *Advances in Strategic Management*, *24*, 145 – 173, https://doi.org/10.1016/S0742-3322(07)24005-7.

Rockafellar, R. & Uryasev, S. (2002). Conditional value-at-risk for general loss distributions. *Journal of Banking and Finance*, *26*(7), 1443 – 1471, https://doi.org/10.1016/S0378-4266(02)00271-6.

Rockafellar, R. T. & Uryasev, S. (2000). Optimization of conditional value-at-risk. *The Journal of Risk*, *2*(3), 21–41, https://doi.org/10.21314/jor.2000.038.

Saltelli, A., et al. (2007). *Global Sensitivity Analysis. The Primer*. Wiley https://doi.org/10.1002/9780470725184.

Sampieri, R. H., Collado, C. F., & Lucio, M. d. P. B. (2013). *Metodologia de pesquisa*. Penso, 5*th* edition.

Schwert, G. (1996). Markup pricing in mergers and acquisitions. *Journal of Financial Economics*, *41*(2), 153–192, https://doi.org/10.1016/0304-405X(95)00865-C.

Schüler, A. (2021). Cross-border dcf valuation: discounting cash flows in foreign currency. *Journal of Business Economics*, *91*(5), 617 – 654, https://doi.org/10.1007/s11573-020-01013-w.

Sha, Y., Kang, C., & Wang, Z. (2020). Economic policy uncertainty and mergers and acquisitions: Evidence from china. *Economic Modelling*, *89*, 590–600, https://doi.org/10.1016/j.econmod.2020.03.029.

Spiegel, A., Severini, S., Britz, W., & Coletta, A. (2020). Step-by-step development of a model simulating returns on farm from investments: The example of hazelnut plantation in italy. *Bio-based and Applied Economics*, (pp. 53–83)., https://doi.org/10.13128/BAE-7961.

Stoyanov, S. V., Rachev, S. T., & Fabozzi, F. J. (2012). Sensitivity of portfolio VaR and CVaR to portfolio return characteristics. *Annals of Operations Research*, *205*(1), 169–187, https://doi.org/10.1007/s10479-012-1142-1.

Szolgayová, J., Fuss, S., Khabarov, N., & Obersteiner, M. (2011). A dynamic cvar-portfolio approach using real options: an application to energy investments. *European Transactions on Electrical Power*, *21*(6), 1825–1841, https://doi.org/10.1002/etep.429.

Talavera, O., Tsapin, A., & Zholud, O. (2012). Macroeconomic uncertainty and bank lending: The case of ukraine. *Economic Systems*, *36*(2), 279–293, https://doi.org/10.1016/j.ecosys.2011.06.005.

Temple, P., Urga, G., & Driver, C. (2001). The influence of uncertainty on investment in the uk: A macro or micro phenomenon? *Scottish Journal of Political Economy*, *48*(4), 361–382, https://doi.org/10.1111/1467-9485.00204.

Trigeorgis, L. (1993). Real options and interactions with financial flexibility. *Financial Management*, *22*(3), 202–224.

Trigeorgis, L. (1996). *Real options: managerial flexibility and strategy in resource allocation*. MIT Press Cambridge, Mass.

Wang, Y., Chen, C. R., & Huang, Y. S. (2014). Economic policy uncertainty and corporate investment: Evidence from china. *Pacific-Basin Finance Journal*, *26*, 227–243, https://doi.org/10.1016/j.pacfin.2013.12.008.

Wang, Y., Zhang, B., Diao, X., & Wu, C. (2015). Commodity price changes and the predictability of economic policy uncertainty. *Economics Letters*, *127*, 39–42, https://doi.org/10.1016/j.econlet.2014.12.030.

Watts, R. L. & Zimmerman, J. L. (1986). *Positive Accounting Theory*. Prentice Hall, Inc.

Welch, X., Pavićević, S., Keil, T., & Laamanen, T. (2020). The pre-deal phase of mergers and acquisitions: A review and research agenda. *Journal of Management*, *46*(6), 843–878, https://doi.org/10.1177/0149206319886908.

Wu, C. & Buyya, R. (2015). Real option theory and monte carlo simulation. In *Cloud Data Centers and Cost Modeling* (pp. 707–772). Elsevier https://doi.org/10.1016/b978-0-12-801413-4.00018-0.

Xiong, W. & Zhang, X. (2016). The real option value of renegotiation in public-private partnerships. *Journal of Construction Engineering and Management*, *142*(8), https://doi.org/10.1061/(ASCE)CO.1943-7862.0001130.

Zhang, K., Nieto, A., & Kleit, A. N. (2014). The real option value of mining operations using mean-reverting commodity prices. *Mineral Economics*, *28*(1-2), 11–22, https://doi.org/10.1007/s13563-014-0048-6.

Zhang, L., Shi, D., Chang, X., & Wen, H. (2021). Timing decisions of housing sales and development based on real option theory. *International Journal of Strategic Property Management*, *25*(2), 90 – 101, https://doi.org/10.3846/ijspm.2020.13973.

Zhou, H.-L., Tang, B.-J., & Cao, H. (2020). Abandonment decision-making of overseas oilfield project coping with low oil price. *Computational Economics*, *55*(4), 1171 – 1184, https://doi.org/10.1007/s10614-018-9837-2.

Zhu, W. & Jin, G. (2011). : (pp. 2468 – 2471).

Zormpas, D. (2021). Jointly held investment options and vertical relationships. *Review of Industrial Organization*, *58*(4), 513 – 530, https://doi.org/10.1007/s11151-020-09784-w.

Zou, H., Hastie, T., & Tibshirani, R. (2006). Sparse principal component analysis. *Journal of Computational and Graphical Statistics*, *15*(2), 265–286, https://doi.org/10.1198/106186006x113430.

APPENDIX A – LATINEX FINANCIAL STATEMENTS

Table 3
Latinex Financial Statements

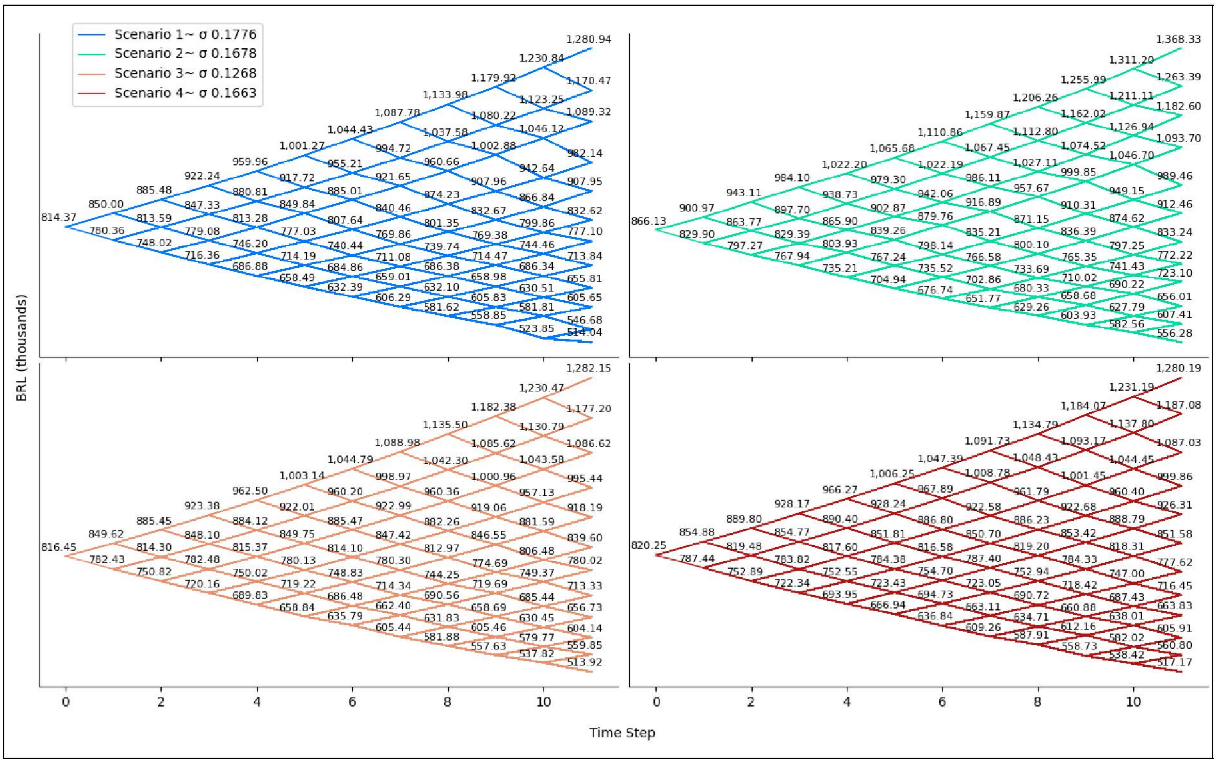
–	December/2021			December/2022		
Description	NAA*	AFV**	NAAFV***	NAA*	AFV**	NAAFV***
Current assets						
Cash and cash equivalents	- 2,657.00		- 2,657.00	- 2,657.00		- 2,657.00
Trade accounts receivable	8,419.00		8,419.00	8,419.00		8,419.00
Advances	1,240.00		1,240.00	1,240.00		1,240.00
Taxes recoverable	749.00		749.00	749.00		749.00
Inventories	10,051.00	1,548.00	11,599.00	10,051.00	1,406.00	11,457.00
Derivative fin. instruments	1,535.00		1,535.00	1,535.00		1,535.00
Prepaid expenses	140.00		140.00	140.00		140.00
Total current assets	19,477.00	1,548.00	21,025.00	19,477.00	1,406.00	20,883.00
Non-current assets						
Long-term receivables	1,882.00	0.00	1,882.00	1,882.00	0.00	1,882.00
Judicial deposits	220.00		220.00	220.00		220.00
Taxes recoverable	256.00		256.00	256.00		256.00
Deferred Taxes	1,393.00		1,393.00	1,393.00		1,393.00
Related parties	13.00		13.00	13.00		13.00
Property, plant and equip.	9,465.00	3,353.00	12,818.00	9,465.00	2,207.00	11,672.00
Intangible assets	43.00	137,537.00	137,580.00	43.00	129,429.00	129,472.00
Brands	43.00	98,869.00	98,912.00	43.00	98,826.00	98,869.00
Customer portfolio		2,753.00	2,753.00		2,928.00	2,928.00
Contract with Poco Loco		34,828.00	34,828.00		26,631.00	26,631.00
Non-competition agreement		1,087.00	1,087.00		1,044.00	1,044.00
Goodwill on inv. acquisition		86,631.00	86,631.00		96,516.00	96,516.00
Total non-current assets	11,390.00	227,521.00	238,911.00	11,390.00	228,152.00	239,542.00
Total assets	**30,867.00**	**229,069.00**	**259,936.00**	**30,867.00**	**229,558.00**	**260,425.00**
Current liabilities						
Trade payables	5,659.00		5,659.00	5,659.00		5,659.00
Advances from customers	112.00		112.00	112.00		112.00
Loans and financing	8,068.00		8,068.00	8,068.00		8,068.00
Labor liabilities	979.00		979.00	979.00		979.00
Tax liabilities	895.00		895.00	895.00		895.00
Other debts	676.00		676.00	676.00		676.00
Total current liabilities	16,389.00	0.00	16,389.00	16,389.00	0.00	16,389.00
Non-current liabilities						
Loans and financing	17,485.00		17,485.00	17,485.00		17,485.00
Tax liabilities	854.00		854.00	854.00		854.00
Advance to partners	1,340.00		1,340.00	1,340.00		1,340.00
Provisions for contingencies	50.00		50.00	50.00		50.00
Total non-current liabilities	19,729.00	0.00	19,729.00	19,729.00	0.00	19,729.00
Shareholders' equity	- 5,251.00	229,069.00	223,818.00	- 5,251.00	229,558.00	224,307.00
Total liabilities and shareholders' equity	**30,867.00**	**229,069.00**	**259,936.00**	**30,867.00**	**229,558.00**	**260,425.00**

NOTE: This table is an adaptation of the financial statements published by M.Dias Branco in 2021 and 2022, and all amounts are expressed in local currency BRL. *NAA (Net assets acquired), **AFV (Adjustments to fair value) and ***NAAFV (Net assets acquired at fair value).

APPENDIX B – CRR TEST MODELS VIA DISCRETIONARY EPU

Figure 22

CRR Binomial Lattice - Discretionary EPU - Four Scenarios.

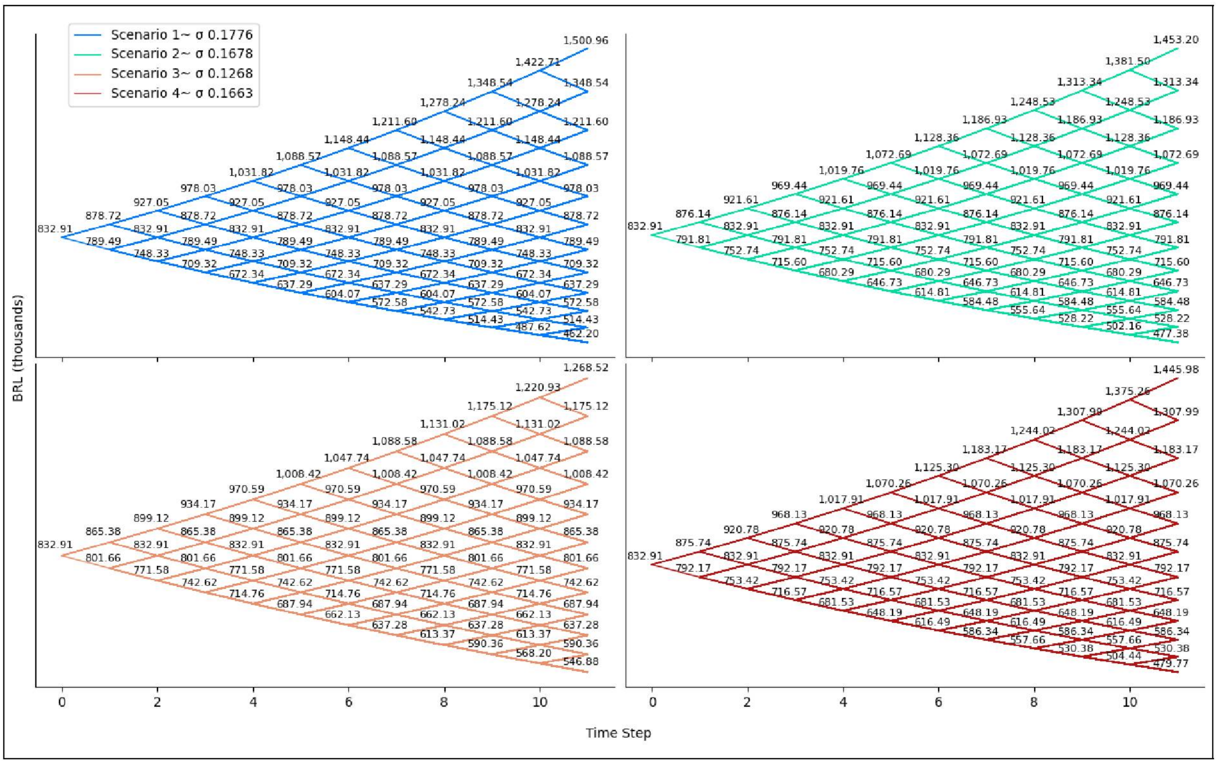


NOTE: The Authors (2023). For the data and plot of this image, see Appendix E, between lines 595 and 618.

APPENDIX C – CRR TEST MODELS VIA NON DISCRETIONARY EPU

Figure 23

CRR Binomial Lattice - Non Discretionary EPU - Four Scenarios.

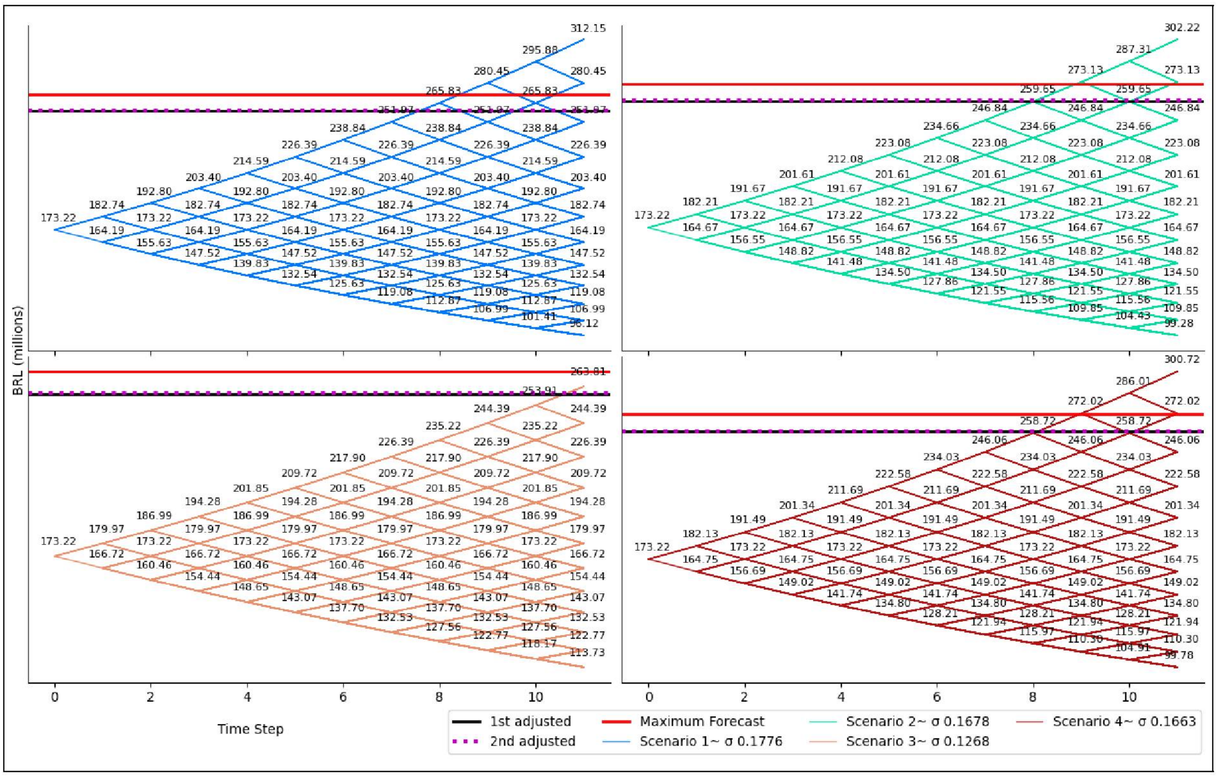


NOTE: The Authors (2023). For the data and plot of this image, see Appendix E, between lines 686 and 710.

APPENDIX D – APLICATION CASE - NON DISCRETIONARY EPU

Figure 24

CRR Binomial Lattice - Non Discretionary EPU (Latinex).



NOTE: The Authors (2023). For the data and plot of this image, see Appendix E, between lines 832 and 863.

APPENDIX E – PYTHON CODE

```python
# Author and contact: Gilmarques A. Costa, gilmarques43@hotmail.com
# Set PC used: Windows 11, Python 3.11.1 and VSCode
# Purpose: This Python code helps researchers and practitioners estimate
# cash flows of a project with the application of real options, considering the
# EPU(Baker et. al. 2016). Run the virtual environment first in the terminal when
# using VS CODE, type the code below.
# python -m venv venv ou .\venv\Scripts\Activate
# Updating all python packages before starting
# in Windows PowerShell
# pip list --outdated
# pip freeze | %{$_.split('==')[0]} | %{pip install --upgrade $_}

# %%
# Importing the libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
import math as m
from numpy_financial import npv
from scipy.stats import norm
from sklearn.decomposition import PCA
import matplotlib.dates as mdates
from mpl_toolkits.mplot3d import Axes3D

# %%
# setting the font size to 12 points for all generated graphics and figures
mpl.rcParams['font.size'] = 12
mpl.style.use('default')

# %%
#################################################################
### The first block corresponds to the first specific objective ###
#################################################################
# Getting the historical EPU data from
# http://www.policyuncertainty.com/media/Brazil_Policy_Uncertainty_Data.xlsx


def get_epu_index():
    url = f"http://www.policyuncertainty.com/media/Brazil_Policy_Uncertainty_Data.xlsx"
    df = pd.read_excel(url)
    df.drop(df.tail(1).index, inplace=True)  # <-- drop last n rows
    df.rename(columns={"Brazil News-Based EPU": "BREPU"}, inplace=True)
    df["month"] = df["month"].astype("int")
    df["Date"] = df["month"].map(str) + "/" + df["year"]
    df["Date"] = pd.to_datetime(df["Date"])
    df = df.drop(columns=["year", "month"])
    df = df[["Date", "BREPU"]]
    return df


EPU_df = get_epu_index()
EPU_dfc = EPU_df.iloc[0:384, :]  # <-- cut to Dec/2022
# <-- Plotting the EPU chart for 4-period analysis 1992-2022
fig, ax = plt.subplots(figsize=(13, 7))
ax.plot("Date", "BREPU", data=EPU_dfc, linewidth=0.7, color="#0078f8")
# plt.title('Economic Policy Uncertainty Index - EPU') <-- if you want to put a title on the chart
ax.spines[['top', 'right']].set_visible(False)
ax.grid(axis='y', color='#758D99', alpha=0.6, zorder=1)
fig.text(0.54, 0.48, 'Global Financial Crisis')
fig.text(0.74, 0.83, 'Operation Weak Flesh')
```

```
fig.text(0.34, 0.45, 'Russian flu')
fig.text(0.34, 0.40, 'BR Currency Crisis')
xlist = [0, 95, 191, 287, 383]
for x in xlist:
    plt.axvline(EPU_dfc.iloc[x, 0], linestyle="dotted",
                color='r', linewidth=0.7)
ax.xaxis.set_major_locator(mdates.MonthLocator(interval=1))
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%b'))
plt.xticks(EPU_dfc.iloc[xlist, 0])
plt.xlabel("Years")
plt.ylabel("EPU")
plt.show()

# %%
# Calc the mean and standard deviation for the four periods of 96 months each
for x in range(0, 384, 96):  # and save to excel the results
    EPU_dfc.iloc[(x):(x+96),
                 1].describe().to_excel(f"./excel/EPU_stat{x}.xlsx")
    print(round(EPU_dfc.iloc[(x):(x+96), 1].describe(), 4))

# %%
# Creating the chart for EPU analysis by Box Plot
xy = [0, 96, 192, 288]
for z, x in enumerate(xy, 1):
    z = str(z)
    locals()['SP'+z] = EPU_dfc.iloc[(x):(x+96),1]
SPs = [SP1, SP2, SP3, SP4]
fig, axs = plt.subplots(1, 4, figsize=(13, 7), sharey=True)
flierprops = dict(marker='o', markeredgewidth=1.5, markerfacecolor='red',
                  markersize=10, markeredgecolor='blue')
meanprops = dict(markeredgewidth=1.5, markerfacecolor='red',
                 markersize=4, markeredgecolor='red')
medianprops = dict(linewidth=2.5, color='blue')
for z, x in enumerate(SPs):
    y = z
    z = str(z+1)
    locals()['bplot'+z] = axs[y].boxplot(x, labels=[f'Sub-Period {z}'],
                                         notch=True,
                                         showmeans=True,
                                         meanprops=meanprops,
                                         medianprops=medianprops,
                                         flierprops=flierprops,
                                         patch_artist=True)
    axs[y].grid(which="major", axis='y', zorder=1)
colors = ['white']
for bplot in (bplot1, bplot2, bplot3, bplot4):
    for patch, color in zip(bplot['boxes'], colors):
        patch.set_facecolor(color)
#fig.suptitle('EPU Boxplot Analysis') <-- if you want to put a title on the chart
plt.subplots_adjust(wspace=0)
plt.show()

# %%
# Performing the PCA analysis test
# Generating the EPU logarithm for standardize the data set
EPU_dfx = EPU_dfc.copy()
EPU_dfx['log'] = np.log(EPU_dfx['BREPU'] /
                        EPU_dfx['BREPU'].shift(periods=-1).ffill())
EPU_df1 = EPU_dfx.tail(96)  # <-- Performs the fourth period cut
# distributing the dataset into four components for PCA
PCA_EPU = EPU_df1.iloc[:, 2].to_numpy()
EPU_ss = np.split(PCA_EPU, 4)
pcs = []  # <-- Perform PCA on each part of the data
for i in range(4):
    pca = PCA(n_components=3)
    pca.fit(EPU_ss[i].reshape(-1, 3))
    pcs.append(pca.transform(EPU_ss[i].reshape(-1, 3)))
# <-- Combine the results of the four PCAs into a single array
```

```python
pcs_combined = np.concatenate(pcs)
# <-- Create a plot of the PCA results
colors = ['#0079FF', '#00DFA2', '#F6FA70', '#FF0060']
zx = [1, 2, 3, 0]
fig = plt.figure(figsize=(16, 9))
gs = plt.GridSpec(nrows=1, ncols=2, width_ratios=[5, 1], wspace=0.01,
    hspace=1)
ax0 = fig.add_subplot(gs[0, 0])
for x, (y, z) in enumerate(zip(colors, zx)):
    ax0.scatter(pcs[x], pcs[z], label=f'Sub-Sample {x+1}', alpha=0.7, color
    =y)
ax0.grid(which="major", axis='y', color='#758D99', alpha=0.6, zorder=1)
ax0.spines[['top', 'right']].set_visible(False)
ax0.legend(bbox_to_anchor=(1.2, 1), loc='upper right')
fig.text(0.08, 0.43, 'Sub-Sample 2', rotation=90)
fig.text(0.41, 0.05, 'Sub-Sample 1')
ax1 = fig.add_subplot(gs[0, 1], projection='3d')
for i in range(0, 4, 1):
    ax1.scatter(pcs[i][:, 0], pcs[i][:, 1], pcs[i]
                [:, 2], color=colors[i], s=25, alpha=0.6)
ax1.set_box_aspect(aspect=None, zoom=0.9)
plt.show()

# %%
# Creating four scenario simulations with each sub-sample from the PCA
    analysis
#################

# %%
# Development of the Geometric Brownian Motion function
# V_0 initial value # mu standard deviation
# sigma -volatility # T time in years
# dt - drift        # nsim number of simulations


def GBM_function(V_0, mu, sigma, T, dt, nsim):
    paths = []
    for i in range(nsim):
        valor = [V_0]
        time = 0
        while (time+dt <= T):
            valor.append(valor[-1]*np.exp((mu - 0.5*(sigma**2))*dt +
                                          sigma*np.random.normal(0, np.sqrt
    (dt))))
            time += dt
        if T - (time) > 0:
            valor.append(valor[-1]*np.exp((mu - 0.5*(sigma**2))*(T-time) +
                                          sigma*np.random.normal(0, np.sqrt
    (T-time))))
        paths.append(valor)
    return paths


# %%
# Creating a DataFrame of standardized EPU
EPU_ssdf = pd.DataFrame(EPU_ss)
EPU_ssdf = EPU_ssdf.T  # <-- We use the mean for GBM sim
print(round(EPU_ssdf, 4))
# Creating a PCA Analysis dataframe
for x in range(0, 4, 1):
    z = str(x)
    locals()['pcsdf'+z] = pd.DataFrame(pcs[x])
    locals()['pcsdf'+z] = locals()['pcsdf'+z].unstack().reset_index(drop=
    True)
pcsdf = pd.concat([pcsdf0, pcsdf1, pcsdf2, pcsdf3], axis=1)
EPU_ssdf.to_excel(f"./excel/EPU_ssdf.xlsx")
pcsdf.to_excel(f"./excel/pcsdf.xlsx")
pcsdf

# %%
```

```
for x in range(0, 4, 1):  # <-- Calc the statistic descriptive
    print(round(pcsdf.iloc[:, x].describe(), 4))

# %%
for x in range(0, 4, 1):  # <-- Calc the variance
    print(round(np.var(pcsdf.iloc[:, x]), 4))

# %%
# Defining the variables to estimate the stochastic process EPU by GBM - For All Scenarios
for x in range(0, 4, 1):
    w = str(x+1)
    locals()['EPU_V0' + w] = np.mean(EPU_ssdf.iloc[:, x])
    locals()['EPU_mu' + w] = np.std(pcsdf.iloc[:, x])
    locals()['EPU_sigma' + w] = np.var(pcsdf.iloc[:, x])
    locals()['EPU_T' + w] = 1
    locals()['EPU_steps' + w] = 12
    locals()['EPU_dt' + w] = locals()['EPU_T' + w]/locals()['EPU_steps' + w]
    locals()['EPU_nsim' + w] = 10000
EPv = [EPU_V01, EPU_V02, EPU_V03, EPU_V04]
EPm = [EPU_mu1, EPU_mu2, EPU_mu3, EPU_mu4]
EPs = [EPU_sigma1, EPU_sigma2, EPU_sigma3, EPU_sigma4]
EPt = [EPU_T1, EPU_T2, EPU_T3, EPU_T4]
EPst = [EPU_steps1, EPU_steps2, EPU_steps3, EPU_steps4]
EPd = [EPU_dt1, EPU_dt2, EPU_dt3, EPU_dt4]
EPsm = [EPU_nsim1, EPU_nsim2, EPU_nsim3, EPU_nsim4]
for a, b, c, d, e, f, g in zip(EPv, EPm, EPs, EPt, EPst, EPd, EPsm):
    print(a, b, c, d, e, f, g)

# %%
# Generating simulations for the four PCA analysis scenarios
for x, (a, b, c, d, f, g) in enumerate(zip(EPv, EPm, EPs, EPt, EPd, EPsm)):
    x = str(x+1)
    locals()['EPU_sim'+x] = GBM_function(a, b, c, d, f, g)
    locals()['EPU_dfsim'+x] = pd.DataFrame(locals()['EPU_sim'+x])
EPms = [EPU_sim1, EPU_sim2, EPU_sim3, EPU_sim4]
EPds = [EPU_dfsim1, EPU_dfsim2, EPU_dfsim3, EPU_dfsim4]

# %%
# Plot the simulations for sub samples
# <-- Plotting the EPU Simulation by the GBM Stochastic Process
fig = plt.figure(figsize=(16, 9))
gs = plt.GridSpec(nrows=2, ncols=2, width_ratios=[
                  1, 1], wspace=0.12, hspace=0.12)
for x, (y, w, data) in enumerate(zip((0, 0, 1, 1), (0, 1, 0, 1), (EPds))):
    x = str(x)
    locals()['ax'+x] = fig.add_subplot(gs[y, w])
    locals()['ax'+x].plot(data.T, linewidth=0.20)
    locals()['ax'+x].grid(which="major", axis='y', alpha=0.4, zorder=1)
    locals()['ax'+x].spines[['top', 'right']].set_visible(False)
for z, (x, y, sig) in enumerate(zip((0.13, 0.55, 0.13, 0.55), (0.84, 0.84, 0.45, 0.45), (EPs)), 1):
    fig.text(x, y, f'Scenario {z}~ \u03C3 {round(sig, 4)}')
fig.text(0.08, 0.48, 'EPU', rotation=90)
fig.text(0.48, 0.05, 'Time Step')
plt.show()

# %%
# Plot the EPU simulation histogram for demonstration
for x, y in enumerate(EPds):
    x = str(x+1)
    locals()['EPU_' + x] = y.to_numpy()
    locals()['EPU_' + x] = locals()['EPU_' + x].transpose()
EP = [EPU_1, EPU_2, EPU_3, EPU_4]
fig, axs = plt.subplots(4, figsize=(8, 14))  # <-- histogram template chart
colors = ['#0079FF', '#00DFA2', '#FF0060']
T = [4, 8, 12]
zw = [0, 1, 2, 3]
for x, y, h in zip(zw, EP, EPv):
```

```
    for w, z in zip(colors, T):
        axs[x].hist(y[z], bins=100, histtype='step',
                    density=True, color=w, label=f'T = {z}')
        axs[x].axvline(h, c='r')
handles, labels = plt.gca().get_legend_handles_labels()
by_label = dict(zip(labels, handles))
plt.legend(by_label.values(), by_label.keys())
for z, (x, y, sig) in enumerate(zip((0.40, 0.40, 0.40, 0.40), (0.86, 0.66, 0.46, 0.26), (EPs)), 1):
    fig.text(x, y, f"Scenario {z}~ \u03C3 {round(sig, 4)}")
fig.text(0.5, 0.08, 'EPU')
fig.text(0.06, 0.46, 'Frequency', rotation=90)
plt.subplots_adjust(hspace=0.15)
plt.show()

# %%
# Creating the Recombine Binomial Lattice function based on Cox, Ross and Rubinstein 1979
# With this formula it will be possible to use the volatility of cash flows and EPU


def RealOpt_function(n, S, K, r, v, T, PC):
    dt = T/n
    u = np.exp(v*np.sqrt(dt))
    d = 1/u
    p = (m.exp(r*dt)-d)/(u-d)
    Pm = np.zeros((n+1, n+1))
    Cm = np.zeros((n+1, n+1))
    tmp = np.zeros((2, n+1))
    for j in range(n+1):
        tmp[0, j] = S*m.pow(d, j)
        tmp[1, j] = S*m.pow(u, j)
    tot = np.unique(tmp)
    c = n
    for i in range(c+1):
        for j in range(c+1):
            Pm[i, j-c-1] = tot[(n-i)+j]
        c = c-1
    for j in range(n+1, 0, -1):
        for i in range(j):
            if (PC == 1):
                if (j == n+1):
                    Cm[i, j-1] = max(K-Pm[i, j-1], 0)
                else:
                    Cm[i, j-1] = m.exp(-.05*dt) * \
                        (p*Cm[i, j] + (1-p)*Cm[i+1, j])
            if (PC == 0):
                if (j == n + 1):
                    Cm[i, j-1] = max(Pm[i, j-1]-K, 0)
                else:
                    Cm[i, j-1] = m.exp(-.05*dt) * \
                        (p*Cm[i, j] + (1-p)*Cm[i+1, j])
    return [Pm, Cm]

# %%
####################################################################
### The second block corresponds to the second specific objective ###
####################################################################


# %%
# Cash flows stream for the hypothetical company XFC
# In this model we will project an initial product price of R$100.00
V_0 = 100                                       # initial value
nsim = 10000                                      # number of simulations
sigma = 0.15                                    # volatility or variance
# risk-free rate in September 2021 6.15%, Selic-Brasil.
mu = 0.0615
T = 1                                           # 1 year for time
```

```
steps = 12                                   # time step
dt = T/steps                                 # drift
print(V_0, mu, sigma, T, dt, nsim)

# %%
# Runs the GBM formula for price simulation
precos_sim = GBM_function(V_0, mu, sigma, T, dt, nsim)
# <-- Transforming an array to dataframe
precos_dfsim = pd.DataFrame(precos_sim)

# %%
# GBM Simulation and Histogram Analysis - PRICES
prices_1 = precos_dfsim.to_numpy()
prices_1 = prices_1.transpose()
fig = plt.figure(figsize=(16, 9))
gs = plt.GridSpec(nrows=3, ncols=2, width_ratios=[
                  2, 1], wspace=0.12, hspace=0.08)
ax0 = fig.add_subplot(gs[:, 0])
ax0.plot(precos_dfsim.T, linewidth=0.15)
ax0.grid(which="major", axis='y', alpha=0.4, zorder=1)
colors = ['#0079FF', '#00DFA2', '#FF0060']
T = [4, 8, 12]
alp = [1, 0.80, 0.30]
ax1 = fig.add_subplot(gs[0, 1])
ax2 = fig.add_subplot(gs[1, 1])
ax3 = fig.add_subplot(gs[2, 1])
for c, a, T in zip(colors, alp, T):
    ax1.hist(prices_1[T], bins=100, alpha=a,
             label=f'T = {T}', density=True, color=c)
    ax1.axvline(100, c='r')
    ax1.set_xticks([])
    ax2.hist((prices_1[4], prices_1[8], prices_1[12]), bins=100, density=
   True,
             color=['#0079FF', '#00DFA2', '#FF0060'])
    ax2.axvline(100, c='r')
    ax2.set_xticks([])
    ax3.hist(prices_1[T], bins=100, histtype='step', density=True, color=c)
    ax3.axvline(100, c='r')
fig.legend(bbox_to_anchor=(0.9, 0.88), loc='upper right', title='Step Time'
   )
fig.text(0.09, 0.45, 'Price', rotation=90)
fig.text(0.620, 0.45, 'Frequency', rotation=90)
fig.text(0.77, 0.06, 'Price')
fig.text(0.34, 0.06, 'Time Step')
fig.text(0.13, 0.83, f'Scenario Non EPU ~ \u03C3 {round(sigma, 4)}')
plt.show()

# %%
# Observations to calc the cash flow considering a production of
# 10,000 units of product, with a simulated price.
# Follow the same parameters for calc the price
# Parameters - Here, you can change the input values to suit your project
r = mu                               # Risk free rate
k = sigma                            # Discount rate
g = 0.03                             # Perpetuity growth rate
prod = 10000                         # Production
VC = 0.55                            # Variable costs
FC = 300000                          # Fixed costs
I = 1500000                          # Investment
EI = 50000                           # Extra investments
IT = 0.34                            # Income tax
# Duplicating the values of r, k and g.
rt = r
kt = k
gt = g
print(rt, kt, gt)

# %%
# Transforming the PRICES dataframe
PRTEST = precos_dfsim.iloc[:, 1:13]
```

```
# <-- Calc of total project revenue given simulated prices
REC = (prod*PRTEST).round(2)
REC.rename(columns={1: 0, 2: 1, 3: 2, 4: 3, 5: 4, 6: 5,
                    7: 6, 8: 7, 9: 8, 10: 9, 11: 10, 12: 11}, inplace=True)
# <-- Preparing the fixed cost matrix to be used
FCOST = np.zeros((nsim, steps))
FCOST[:, :] = FC
FCOST = pd.DataFrame(FCOST)
ROC = REC-(REC*VC)-FCOST  # <-- Creating the Operating Revenue matrix
Imatrix = np.zeros((nsim, steps))  # <-- Creating the Investment matrix
Imatrix[:, :] = I  # <-- Investimento
Imatrix = pd.DataFrame(Imatrix)
EImatrix = np.zeros((nsim, steps))  # <-- Creating the Extra Investment
    matrix
EImatrix[:, :] = EI
EImatrix = pd.DataFrame(EImatrix)
Dep0 = Imatrix/steps  # <-- Creating the investment depreciation matrix
Dep1 = EImatrix/steps
# <-- Calc EBIT - Earnings Before Interest and Taxes
EBIT = round(ROC-Dep0-Dep1, 2)
FCF = round(EBIT-(IT*EBIT)-EImatrix+Dep0+Dep1, 2)  # <-- Calc Free Cash
    Flow
Perpetuidade = round(FCF.iloc[:, 11:12]/(kt-gt)
                     * (1+gt)*(1+kt), 2)  # <-- Calc Perpetuity
FCF_P = round(FCF.join(Perpetuidade, lsuffix="_x"),
              2)  # <-- Merging FCF and Perpetuity
FCF_P.rename(columns={'11_x': 11, '11': 12}, inplace=True)
FCF1 = FCF_P.T  # <-- Found the net present value of the project's cash
    flows
PV = FCF1.to_numpy()
taxa = kt
PV = np.apply_along_axis(lambda x: npv(taxa, x), 0, PV).round(2)
PV = pd.DataFrame(PV)
NPV = PV-Imatrix.iloc[:, 0:1]
FCFPVa = FCF
FCFPVa = FCFPVa.to_numpy()

# %%
# Function to use the rate pass through an array
taxa = sigma


def f(x):
    taxa = sigma
    x = x/(1+taxa)**np.arange(1, 13)
    return x


# %%
# Creating the "Before" Present Value Matrix
PVa = np.array(list(map(lambda x: f(x), FCFPVa)))
PVa = pd.DataFrame(PVa).round(2)
PVA = PVa + FCF
# <-- Creating the "Later" present value array
PVp = np.array(list(map(lambda x: f(x), FCFPVa)))
PVp = pd.DataFrame(PVa).round(2)
PVd = np.mean(PV, axis=0).round(2)  # <-- Defining the dividend matrix
Ret = PVa/PVd  # <-- Creating the returns matrix
Ret = Ret.iloc[:, 0:1]
lRet = np.log(Ret)  # <-- The return log
# <-- The standard deviation of the log of returns
vol = np.std(lRet.iloc[:, 0])
print(vol)  # <-- Check result

# %%
# Defining the values of up, down and risk-neutral probability
T = 1
steps = 11
dt = T/steps
v = vol
```

```
u = np.exp(v*np.sqrt(dt))  # <-- Upside multiplying factor
d = 1/u  # <-- Downside multiplying factor
p = (np.exp(r*dt)-d)/(u-d)  # <-- Probability
divr = FCF/PVA  # <-- Creating the dividend marixs
div = 1-divr
print(u, d, p, vol, PVd.iloc[0,])  # <-- Check variables
# Stipulating parameters for executing Options based on CRR
# Since the objective is to compare the NPV with the Binomial Grid, the Strike price is the initial price.
S_0 = PVd.iloc[0,]                # Initial price
K_0 = PVd.iloc[0,]                # strike price
r_0 = r                           # Standard Deviation
v_0 = v                           # Volatility of returns
T_0 = 1                           # Time 1 year
n_0 = 11                          # Number of intervals + the starting price give 12 points
PC = 0                            # 0 for call, 1 for put
Pm, Cm = RealOpt_function(n_0, S_0, K_0, r_0, v_0, T_0, PC)
print(S_0, K_0, r_0, v_0)  # <-- Check variables
print('Pricing:\n', np.matrix(Pm.astype(int)))  # <-- Check lattice
print('Pricing:\n', np.matrix(Cm.astype(int)))  # <-- Check lattice
Pmdf1 = round(pd.DataFrame(Pm), 2)
Pmdf1.replace(0, np.nan, inplace=True)
Pmdf1.to_excel(f"./excel/Pmdf1.xlsx")

# %%
# Creating the function of the graph for comparison between lattices with
# or without the legend of the values. To run the function you need 4 values
# [database, color, 0=legend and 1=no legend, font size]
# the colors will distinguish the lattices font size can also be chosen


def CRR_graph(data, color, datalabel, fontsize, legend, xytq, xytw):
    rows, cols = data.shape
    for x in range(0, cols-1, 1):
        dx = [x, x+1, x, x+1]*(x+1)
        dy = [data.iloc[x, x], data.iloc[x, x+1], data.iloc[x, x],
              data.iloc[x+1, x+1]]*(x+1)
        ax.plot(dx, dy, color=color, label=legend, linewidth=1)
    for y in range(0, cols-2, 1):
        for x in range(1, cols-1-y, 1):
            dx = [x+y, x+y+1, x+y, x+y+1]*(x+1)
            dy = [data.iloc[x-1, x+y], data.iloc[x-1, x+y+1],
                  data.iloc[x-1, x+y], data.iloc[x, x+y+1]]*(x+1)
            ax.plot(dx, dy, color=color, label=legend, linewidth=0.9)
    for col in range(cols):
        for row in range(rows):
            if datalabel == 0:
                pass
                ax.annotate('{:,.2f}'.format(data.T.iloc[row, col]),
                            xy=(row, data.T.iloc[row, col]),
                            xytext=(row-xytq, ((data.T.iloc[row, col])+xytw)),
                            fontsize=fontsize)


# %%
# Transforming a binomial lattice array into pandas dataframe
Pmdf = round(pd.DataFrame(Pm), 2)
Pmdf.to_excel(f"./excel/Pmdf-InicialCRR.xlsx")
Pmdf.replace(0, np.nan, inplace=True)  # <-- Replacing all zeros with NaN
fig, ax = plt.subplots(figsize=(16, 9))  # <-- Creating the graph
CRR_graph(Pmdf/1000, '#0079FF', 0, 12,
          f'Non EPU~ \u03C3 {round(v_0, 4)}', 0.35, 12.7)
ax.spines[['top', 'right']].set_visible(
    False)  # <-- Remove the top and right sides
ax.set_yticklabels([])  # <-- Remove the tick labels
plt.xlabel("Time Step")
plt.ylabel("BRL (thousands)")
```

```
handles, labels = plt.gca().get_legend_handles_labels()
by_label = dict(zip(labels, handles))
plt.legend(by_label.values(), by_label.keys())
plt.yticks([])
plt.show()

# %%
# Dividend rate calc
div1 = div.iloc[0:12:, 0:12]*0.1
div1.rename(columns={0: 1, 1: 2, 2: 3, 3: 4, 4: 5, 5: 6,
            6: 7, 7: 8, 8: 9, 9: 10, 10: 11, 11: 12}, inplace=True)
# <-- Applying the dividend rate on the binomial lattice without EPU
Dvd = round(div1*Pmdf, 2)
Dvd[0] = round(div1.iloc[0:1, 0] *
               Pmdf.iloc[0:1, 0], 2)
Dvd = Dvd.reindex(columns=[0, 1, 2,
                           3, 4, 5, 6, 7, 8, 9, 10, 11])
Pmdf_div = Pmdf - Dvd  # <-- Creating the lattice after withdrawing dividends

# %%
# For Sub-Samples
# First test between the options without and with the inclusion
# of the EPU in an discretionary way
maskdf = Pmdf  # <-- Turning simulated EPU array into pandas dataframe
maskepu = maskdf.notnull().mul(1)
for x in range(0, 4, 1):
    x = str(x+1)
    locals()['EPU_df' + x] = pd.DataFrame(locals()['EPU_sim' + x])
    locals()['EPU_df' + x] = locals()['EPU_df' + x].iloc[0:12, 0:12]
    locals()['EPU_df' + x] = locals()['EPU_df' + x]+1
    locals()['EPU_df' + x] = maskepu * locals()['EPU_df' + x]
    locals()['EPU_df' + x].replace(0, np.nan, inplace=True)
    locals()['Pmdf_EPU' + x] = round(Pmdf * locals()['EPU_df' + x], 2)
    locals()['Pmdf_EPU' + x].to_excel(f"./excel/Pmdf_EPU{x}.xlsx")
    print(round(locals()['Pmdf_EPU' + x], 2))

# %%
# Function that plots the binomial lattice graph for multiple scenarios in the same figure


def CRR_graph1(data, color, datalabel, fontsize, legend, zeta, xytq, xytw):
    rows, cols = data.shape
    for x in range(0, cols-1, 1):
        dx = [x, x+1, x, x+1]*(x+1)
        dy = [data.iloc[x, x], data.iloc[x, x+1], data.iloc[x, x],
              data.iloc[x+1, x+1]]*(x+1)
        globals()['ax'+zeta].plot(dx, dy, color=color,
                                  label=legend, linewidth=1)
    for y in range(0, cols-2, 1):
        for x in range(1, cols-1-y, 1):
            dx = [x+y, x+y+1, x+y, x+y+1]*(x+1)
            dy = [data.iloc[x-1, x+y], data.iloc[x-1, x+y+1],
                  data.iloc[x-1, x+y], data.iloc[x, x+y+1]]*(x+1)
            globals()['ax'+zeta].plot(dx, dy, color=color,
                                      label=legend, linewidth=0.9)
    for col in range(cols):
        for row in range(rows):
            if datalabel == 0:
                pass
                globals()['ax'+zeta].annotate('{:,.2f}'.format(data.T.iloc[row, col]),
                                              xy=(row, data.T.iloc[row, col]),
                                              xytext=(
                                                  row-xytq, ((data.T.iloc[row, col])+xytw)),
                                              fontsize=fontsize)

```

```
# %%
##############################################################
# Creating graph to binomial lattice with EPU Discretionary
##############################################################
# For Sub-Samples 1, 2, 3 and 4
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=[16, 9],
                                              sharex=True)
EPUdis = [Pmdf_EPU1, Pmdf_EPU2, Pmdf_EPU3, Pmdf_EPU4]
colors = ['#0079FF', '#00DFA2', '#EA906C', '#B31312']
for x, (y, sig, c) in enumerate(zip(EPUdis, EPs, colors), 1):
    x = str(x)
    CRR_graph1(y/1000, c, 0, 8,
               f"Scenario {x}~ \u03C3 {round(sig, 4)}", x, 0.53, 15)
    locals()['ax'+x].spines[['top', 'right']].set_visible(False)
    locals()['ax'+x].set_yticks([])
fig.text(0.11, 0.45, 'BRL (thousands)', rotation=90)
fig.text(0.49, 0.05, 'Time Step')
plt.subplots_adjust(wspace=0.02, hspace=0.02)
labels_handles = {label: handle for ax in fig.axes for handle,
                  label in zip(*ax.get_legend_handles_labels())}
fig.legend(labels_handles.values(), labels_handles.keys(),
           loc="upper center", bbox_to_anchor=(0.21, 0.9),
           bbox_transform=plt.gcf().transFigure)
plt.show()

# %%
##############################################################
# Comparative graph to binomial lattice with EPU Discretionary
##############################################################
# For Sub-Samples in four scenarios
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=[16, 9],
                                              sharex=True, sharey=True)
colors = ['#0079FF', '#00DFA2', '#EA906C', '#B31312']
# Binomial lattice Non-EPU versus EPU Discretionary
for x, (y, sig, c) in enumerate(zip(EPUdis, EPs, colors), 1):
    x = str(x)
    CRR_graph1(Pmdf/1000, "gray", 1, 8,
               f"Non-EPU~ \u03C3 {round(v_0, 4)}", x, 0.3, 10)
    CRR_graph1(y/1000, c, 1, 8,
               f"Scenario {x}~ \u03C3 {round(sig, 4)}", x, 0.3, 10)
    locals()['ax'+x].spines[['top', 'right']].set_visible(False)
    locals()['ax'+x].grid(True)
fig.text(0.08, 0.45, 'BRL (thousands)', rotation=90)
fig.text(0.49, 0.05, 'Time Step')
plt.subplots_adjust(wspace=0.01, hspace=0.02)
labels_handles = {label: handle for ax in fig.axes for handle,
                  label in zip(*ax.get_legend_handles_labels())}
fig.legend(labels_handles.values(), labels_handles.keys(),
           loc="upper center", bbox_to_anchor=(0.21, 0.9),
           bbox_transform=plt.gcf().transFigure,)
plt.show()

# %%
##########################################################################
### Non-discretionary EPU inclusion test2 - Replacing with EPU volatility #
##########################################################################

# %%
# For the Sub-Samples in four Scenarios
for w in range(0, 4, 1):  # <-- Estimate parameters for Options CRR with
    EPU volatility
    w = str(w+1)
    locals()['S_' + w] = PVd.iloc[0,]
    locals()['K_' + w] = PVd.iloc[0,]
    locals()['r_' + w] = r
    locals()['v_' + w] = locals()['EPU_sigma'+w]
    locals()['T_' + w] = 1
    locals()['n_' + w] = 11
    locals()['PC_' + w] = 0
```

```
    print(locals()['S_'+w], locals()['K_'+w],  # <-- Check variables
           locals()['r_'+w], locals()['v_'+w],
           locals()['T_'+w], locals()['n_'+w], locals()['PC_'+w])
NV1 = [S_1, S_2, S_3, S_4]
NV2 = [K_1, K_2, K_3, K_4]
NV3 = [r_1, r_2, r_3, r_4]
NV4 = [v_1, v_2, v_3, v_4]
NV5 = [T_1, T_2, T_3, T_4]
NV6 = [n_1, n_2, n_3, n_4]
NV7 = [PC_1, PC_2, PC_3, PC_4]

# %%
# For the Sub-Samples in four Scenarios
# Options based on CRR with EPU volatility
for w, (a, b, c, d, e, f, g) in enumerate(zip(NV6, NV1, NV2, NV3, NV4, NV5, NV7), 1):
    w = str(w)
    locals()['EPUPm'+w], locals()['EPUCm' +
                                   w] = RealOpt_function(a, b, c, d, e, f, g)
    locals()['EPU_Pmdf'+w] = round(pd.DataFrame(locals()['EPUPm'+w]), 2)
    locals()['EPU_Pmdf'+w].replace(0, np.nan, inplace=True)
    locals()['EPU_Pmdf'+w].to_excel(f"./excel/EPU_Pmdf{w}.xlsx")
    print('Pricing:\n', np.matrix(locals()['EPUPm'+w].astype(int)))

# %%
###########################################################
# Creating graph to binomial lattice with EPU NON-Discretionary
###########################################################
# For Sub-Samples 1, 2, 3 and 4
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=[16, 9],
                                             sharex=True)
EPUndis = [EPU_Pmdf1, EPU_Pmdf2, EPU_Pmdf3, EPU_Pmdf4]
colors = ['#0079FF', '#00DFA2', '#EA906C', '#B31312']
# Graph for binomial lattice with EPU Non-Discretionary = volatility
for x, (y, sig, c) in enumerate(zip(EPUndis, EPs, colors), 1):
    x = str(x)
    CRR_graph1(y/1000, c, 0, 8,
               f"Scenario {x}~ \u03C3 {round(sig, 4)}", x, 0.52, 17)
    locals()['ax'+x].spines[['top', 'right']].set_visible(False)
    locals()['ax'+x].set_yticks([])
fig.text(0.11, 0.45, 'BRL (thousands)', rotation=90)
fig.text(0.49, 0.05, 'Time Step')
plt.subplots_adjust(wspace=0.02, hspace=0.02)
labels_handles = {label: handle for ax in fig.axes for handle,
                  label in zip(*ax.get_legend_handles_labels())}
fig.legend(labels_handles.values(), labels_handles.keys(),
           loc="upper center", bbox_to_anchor=(0.21, 0.9),
           bbox_transform=plt.gcf().transFigure,)
plt.show()

# %%
###########################################################
# Comparative graph to binomial lattice with EPU NON-Discretionary
###########################################################
# For Sub-Samples in four scenarios
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=[16, 9],
                                             sharex=True, sharey=True)
colors = ['#0079FF', '#00DFA2', '#EA906C', '#B31312']
# Binomial lattice without EPU versus non-discretionary EPU.
for x, (y, sig, c) in enumerate(zip(EPUndis, EPs, colors), 1):
    x = str(x)
    CRR_graph1(Pmdf/1000, "gray", 1, 8,
               f"Non-EPU~ \u03C3 {round(v_0, 4)}", x, 0.3, 10)
    CRR_graph1(y/1000, c, 1, 8,
               f"Scenario {x}~ \u03C3 {round(sig, 4)}", x, 0.3, 10)
    locals()['ax'+x].spines[['top', 'right']].set_visible(False)
    locals()['ax'+x].grid(True)
fig.text(0.08, 0.45, 'BRL (thousands)', rotation=90)
fig.text(0.49, 0.05, 'Time Step')
```

```python
plt.subplots_adjust(wspace=0.01, hspace=0.02)
labels_handles = {label: handle for ax in fig.axes for handle,
                  label in zip(*ax.get_legend_handles_labels())}
fig.legend(labels_handles.values(), labels_handles.keys(),
           loc="upper center", bbox_to_anchor=(0.21, 0.9),
           bbox_transform=plt.gcf().transFigure,)
plt.show()

# %%
##################################################################
### The third block corresponds to the third specific objective ###
##################################################################
# Case M. Dias Branco
# Cash flow between
# BRL 180 million, reaching a total amount of up to BRL 272 million
# 259,936 to 260,425 adjusted
# 30,867

# %%
# Defining the parameters according to the M. Dias Branco case
# and the values of up, down and risk-neutral probability
M1 = 173218000.00  # Initial payment
M2 = 272000000.00  # Estimate
M3 = 259936000.00  # Initial adjusted value
M4 = 260425000.00  # Final adjusted value
M5 = 30867000.00  # Book-Value

# %%
# Estimate parameters for executing Options based on CRR with Market Parameters
# and initial values
S_0M = M1  # Initial Price
K_0M = M2  # Strike price
r_0M = 6.15/100  # Standard Deviation - DRIFT Selic 09/2021
v_0M = vol  # Volatility of returns
T_0M = 1  # Time 1 year
n_0M = 11  # Number of intervals + starting price give 12 points
PC_M = 0  # 0 for call, 1 for put
PmM, CmM = RealOpt_function(n_0M, S_0M, K_0M, r_0M, v_0M, T_0M, PC_M)
print(S_0M, K_0M, r_0M, v_0M)
# Checking of the project's generated binomial lattice
# <-- Transforming a binomial lattice array into dataframe
PmdfM = round(pd.DataFrame(PmM), 2)
PmdfM.replace(0, np.nan, inplace=True)  # <-- Replacing all zeros with NaN
PmdfM.to_excel(f"./excel/PmdfM.xlsx")
print('Pricing:\n', np.matrix(PmM.astype(int)))

# %%
# Creating the graph to demonstrate the binomial lattice before EPU - return volatility
fig, ax = plt.subplots(figsize=(16, 9))
CRR_graph(PmdfM/1000000, '#0078f8', 0, 11,
          f'Non-EPU˜ \u03C3 {round(v_0M, 4)}', 0.3, 4)
ax.spines[['top', 'right']].set_visible(False)
ax.set_yticklabels([])   # plt.title("CRR Binomial Lattice - M. Dias Branco")
plt.xlabel("Time Step")
plt.ylabel("BRL (millions)")
plt.axhline(272000000/1000000, label='Maximum Forecast',
            color='r')  # estimated
plt.axhline(259936000/1000000, label='1st adjusted',
            color='g', linestyle='-')  # Initial adjusted value
plt.axhline(260425000/1000000, label='2nd adjusted',
            color='m', linestyle=':')  # final adjusted value
handles, labels = plt.gca().get_legend_handles_labels()
by_label = dict(zip(labels, handles))
plt.legend(by_label.values(), by_label.keys())
plt.show()

# %%
```

```
# Estimate variables for amalysis with M Dias
for w in range(0, 4, 1):  # <-- Estimate parameters for Options CRR with EPU volatility
    w = str(w+1)
    locals()['S_M' + w] = M1
    locals()['K_M' + w] = M2
    locals()['r_M' + w] = 6.15/100
    locals()['v_M' + w] = locals()['EPU_sigma'+w]
    locals()['T_M' + w] = 1
    locals()['n_M' + w] = 11
    locals()['PC_M' + w] = 0
    print(locals()['S_M'+w], locals()['K_M'+w],  # <-- Check variables
          locals()['r_M'+w], locals()['v_M'+w],
          locals()['T_M'+w], locals()['n_M'+w], locals()['PC_M'+w])
MNV1 = [S_M1, S_M2, S_M3, S_M4]
MNV2 = [K_M1, K_M2, K_M3, K_M4]
MNV3 = [r_M1, r_M2, r_M3, r_M4]
MNV4 = [v_M1, v_M2, v_M3, v_M4]
MNV5 = [T_M1, T_M2, T_M3, T_M4]
MNV6 = [n_M1, n_M2, n_M3, n_M4]
MNV7 = [PC_M1, PC_M2, PC_M3, PC_M4]

# %%
# For the Sub-Samples in four Scenarios - M Dias Branco
# Options based on CRR with EPU volatility
for w, (a, b, c, d, e, f, g) in enumerate(zip(MNV6, MNV1, MNV2,
                                              MNV3, MNV4, MNV5, MNV7), 1):
    w = str(w)
    locals()['MEPUPm'+w], locals()['MEPUCm' +
                                   w] = RealOpt_function(a, b, c, d, e, f, g)
    locals()['MEPU_Pmdf'+w] = round(pd.DataFrame(locals()['MEPUPm'+w]), 2)
    locals()['MEPU_Pmdf'+w].replace(0, np.nan, inplace=True)
    locals()['MEPU_Pmdf'+w].to_excel(f"./excel/MEPU_Pmdf{w}.xlsx")
    print('Pricing:\n', np.matrix(locals()['MEPUPm'+w].astype(int)))

# %%
# For Sub-Samples 1, 2, 3 and 4
# Creating the graph to demonstrate the binomial lattice with the inclusion of the EPU
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=[16, 9],
                                             sharex=True)
MEPUndis = [MEPU_Pmdf1, MEPU_Pmdf2, MEPU_Pmdf3,
            MEPU_Pmdf4]  # M. Dias in scenarios
colors = ['#0079FF', '#00DFA2', '#EA906C', '#B31312']
# plt.title("CRR Binomial Lattice + Non-Discretionary EPU - M. Dias Branco")
for x, (y, sig, c) in enumerate(zip(MEPUndis, EPs, colors), 1):
    x = str(x)
    CRR_graph1(y/1000000, c, 0, 8,
               f"Scenario {x}~ \u03C3 {round(sig, 4)}", x, 0.3, 6)
    locals()['ax'+x].spines[['top', 'right']].set_visible(False)
    locals()['ax'+x].axhline(272000000/1000000, label='Maximum Forecast',
                             color='r', linewidth=2)  # estimated
    locals()['ax'+x].axhline(259936000/1000000, label='1st adjusted', color='k',
                             linestyle='-', linewidth=2)  # Initial adjusted value
    locals()['ax'+x].axhline(260425000/1000000, label='2nd adjusted', color='m',
                             linestyle=':', linewidth=3)  # final adjusted value
    locals()['ax'+x].set_yticks([])
fig.text(0.115, 0.45, 'BRL (millions)', rotation=90)
fig.text(0.25, 0.05, 'Time Step')
plt.subplots_adjust(wspace=0.02, hspace=0.02)
labels_handles = {label: handle for ax in fig.axes for handle,
                  label in zip(*ax.get_legend_handles_labels())}
# Reorder the dict for labels_handles
```

```
labels_handles = {key: value for key, value in sorted(labels_handles.items())}
fig.legend(labels_handles.values(), labels_handles.keys(),
           loc="upper center", bbox_to_anchor=(0.65, 0.085),
           bbox_transform=plt.gcf().transFigure, ncols=4)
plt.show()

# %%
# For Sub-Samples in four scenarios
# Comparison chart between the two types of lattice, without EPU, and with non-discretionary EPU.
fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=[16, 9],
                                             sharex=True, sharey=True)
colors = ['#0079FF', '#00DFA2', '#EA906C', '#B31312']
# Binomial lattice without EPU versus non-discretionary EPU.
for x, (y, sig, c) in enumerate(zip(MEPUndis, EPs, colors), 1):
    x = str(x)
    CRR_graph1(PmdfM/1000000, "gray", 1, 8,
               f"Non-EPU~ \u03C3 {round(v_0, 4)}", x, 0.3, 10)
    CRR_graph1(y/1000000, c, 1, 8,
               f"Scenario {x}~ \u03C3 {round(sig, 4)}", x, 0.3, 10)
    locals()['ax'+x].spines[['top', 'right']].set_visible(False)
    locals()['ax'+x].grid(True)
    locals()['ax'+x].axhline(272000000/1000000, label='Maximum Forecast',
                             color='r', linewidth=2)  # estimated
    locals()['ax'+x].axhline(259936000/1000000, label='1st adjusted', color='k',
                             linestyle='-', linewidth=2)  # Initial adjusted value
    locals()['ax'+x].axhline(260425000/1000000, label='2nd adjusted', color='m',
                             linestyle=':', linewidth=3)  # final adjusted value
fig.text(0.09, 0.45, 'BRL (millions)', rotation=90)
fig.text(0.25, 0.05, 'Time Step')
plt.subplots_adjust(wspace=0.02, hspace=0.02)
labels_handles = {label: handle for ax in fig.axes for handle,
                  label in zip(*ax.get_legend_handles_labels())}
# Reorder the dict for labels_handles
labels_handles = {key: value for key, value in sorted(labels_handles.items())}
fig.legend(labels_handles.values(), labels_handles.keys(),
           loc="upper center", bbox_to_anchor=(0.65, 0.085),
           bbox_transform=plt.gcf().transFigure, ncols=4)
plt.show()

# %%
def volatility_analysis():
    # Input parameters
    n = 11  # Number of steps
    S_values = np.linspace((M1/1000000), 100)  # Range of S values
    v_values = np.linspace((np.min(NV4)), (np.max(NV4)),
                           100)  # Range of v values
    K = M1/1000000  # Strike price
    r = np.mean(NV3)  # Risk-free interest rate
    T = 1.0  # Time to maturity
    PC = 0  # 0 for call, 1 for put
    # Create a grid of S and v values
    S_grid, v_grid = np.meshgrid(S_values, v_values)
    # Initialize an empty grid for option values
    option_values = np.zeros_like(S_grid)
    # Calculate option values for each combination of S and v
    for i in range(len(S_values)):
        for j in range(len(v_values)):
            S_val = S_values[i]
            v_val = v_values[j]
            Pm, Cm = RealOpt_function(n, S_val, K, r, v_val, T, PC)
            option_values[j, i] = Cm[0, 0]  # Store the option value
    # Generate a 3D surface plot
    fig = plt.figure(figsize=(16, 9))
```

```
    ax = fig.add_subplot(111, projection='3d')
    ax.plot_surface(S_grid, v_grid, option_values, cmap='viridis')
    ax.set_xlabel('Asset Price (S)')
    ax.set_ylabel('Volatility (v)')
    ax.set_zlabel('Option Value')
    # ax.set_title('Volatility Analysis')
    ax.view_init(elev=20., azim=130, roll=0)
    ax.set_box_aspect(aspect=None, zoom=0.95)
    plt.ticklabel_format(style='plain')
    plt.show()
volatility_analysis()

# %%
def geometric_brownian_motion(S, r, v, T):
    n = len(S)
    dt = T / n
    r_dt = r * dt
    v_sqrt_dt = v * np.sqrt(dt)
    dW = np.random.normal(0, 1, n)
    dW_sqrt_dt = dW * v_sqrt_dt
    return S * np.exp((r - 0.5 * v * v) * dt + v_sqrt_dt * dW_sqrt_dt)


def CVaR_analysis():
    # Input parameters
    n = 11  # Number of steps
    S = (M1/1000000)  # Initial asset price
    K = (M1/1000000)  # Strike price
    r = np.mean(NV3)  # Risk-free interest rate
    v = NV4[2]  # Volatility
    T = 1.0  # Time to maturity
    PC = 0  # 0 for call, 1 for put
    num_simulations = 10000  # Number of simulations
    alpha = 0.95  # Confidence level for CVaR analysis
    # Simulate option values
    option_values = []
    for _ in range(num_simulations):
        S_simulated = geometric_brownian_motion(np.array([S]), r, v, T)
        Pm, Cm = RealOpt_function(n, S_simulated[0], K, r, v, T, PC)
        option_values.append(Cm[0, 0])
    # Sort the option values
    option_values = np.sort(option_values)
    # Calculate VaR and CVaR
    VaR_index = int((1 - alpha) * num_simulations)
    VaR = option_values[VaR_index]
    CVaR = np.mean(option_values[VaR_index:])
    # Plot the histogram with VaR and CVaR lines
    plt.figure(figsize=(16, 9))
    plt.hist(option_values, bins=50, color='r', alpha=0.5, edgecolor='black
    ')
    plt.axvline(x=VaR, color='g', linestyle='--', linewidth=3, label='VaR')
    plt.axvline(x=CVaR, color='b', linestyle='--', linewidth=3, label='CVaR
    ')
    plt.xlabel('Option Value')
    plt.ylabel('Frequency')
    # plt.title('CVaR Analysis')
    plt.legend()
    plt.ticklabel_format(style='plain')
    plt.show()
CVaR_analysis()

# %%
def CVaR_analysis():
    # Input parameters for Real Options CRR
    n = 11  # Number of steps
    S = (M1/1000000)  # Initial asset price
    K = (M1/1000000)  # Strike price
    r = np.mean(NV3)  # Risk-free interest rate
    T = 1.0  # Time to maturity
    PC = 0  # 0 for call, 1 for put
```

```
    # Input parameters for Geometric Brownian Motion
    V_0 = S  # Initial asset price
    mu = r  # Drift (risk-free interest rate)
    dt = T / n  # Time step size
    nsim = 1000  # Number of simulations
    # Volatility values
    volatility_values = np.linspace((np.min(NV4)), (np.max(NV4)), 100)
    # Perform CVaR analysis for each volatility variation
    CVaR_results = []
    for sigma in volatility_values:
        # Simulate option values based on GBM
        option_values = []
        paths = GBM_function(V_0, mu, sigma, T, dt, nsim)
        for path in paths:
            S_simulated = path[-1]
            Pm, Cm = RealOpt_function(n, S_simulated, K, r, sigma, T, PC)
            option_values.append(Cm[0, 0])
        # Sort the option values
        option_values = np.sort(option_values)
        # Define the confidence level for CVaR analysis
        alpha = 0.95
        # Calculate VaR and CVaR
        VaR_index = int((1 - alpha) * nsim)
        VaR = option_values[VaR_index]
        CVaR = np.mean(option_values[VaR_index:])
        # Store CVaR result
        CVaR_results.append(CVaR)
    # Plot the CVaR results
    plt.figure(figsize=(16, 9))
    plt.plot(volatility_values, CVaR_results)
    plt.xlabel('Volatility')
    plt.ylabel('CVaR')
    # plt.title('CVaR Analysis')
    plt.ticklabel_format(style='plain')
    plt.grid(True)
    plt.show()
CVaR_analysis()
```