



Evaluation des options sur devises en présence des coûts d'information statiques et dynamiques : modèles théoriques et validation empirique

Wael Dammak

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***Assessment of European Currency Options in the
Presence of Static and Dynamic Information Costs:
Theoretical Models and Empirical Validation***

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DAMMAK WÆL 🐉

To the soul of my father...

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To my family...

To my friends...

To all those I love...

To all those who love me...

And above all, to all those who deserve it... 2

Preface

This thesis is conducted within the framework of a co-supervision program between the University of Sfax and the University of Lyon 1. It was partially financed through a scholarship awarded by the Ministry of Higher Education and Scientific Research of Tunisia under a work-study program. The remaining funding was obtained through part-time teaching positions at the University of Lyon 3, the Centrale Lyon School, and the Institute of Industrial Pharmacy at Lyon University-Lyon1. During the last two years of this journey, I held two temporary teaching and research contracts at the University of Lyon 2.

To approach the thesis topic from various angles and to align with the evolving themes in academic and professional research, this work is structured as an essay-based thesis. Each chapter represents an individual essay, all of which are currently being submitted for review to academic journals with a rigorous peer-review process. The structure of these chapters does not correspond to the production order of the essays, but rather to a coherent succession of ideas highlighted in the general introduction.

This thesis comprises four essays, each providing a deeper insight into the researched topic. Before the thesis defense, some of these essays have already undergone the publication process. Specifically, the second essay was published in "*The Journal of Economic Asymmetries*," and the third in the "*Global Finance Journal*." The remaining essays have been submitted to academic journals and are currently under review by a scientific committee.

For both administrative and policy reasons, this thesis started on December 14, 2017.

This thesis represents the culmination of extensive research and analysis spanning several years in the field of finance, with a specific focus on currency option valuation. The study delves into the influence of information costs on the valuation of currency options, examining both static and dynamic information within this context. The inspiration for this thesis arose from my keen interest in applying option pricing theory to the foreign exchange market. During my research, it became apparent that the existing literature did not adequately address the impact of information costs on option valuation. To conduct this analysis, I leveraged a variety of data sources, including financial databases, academic research, and industry professionals' reports. Consequently, this thesis embodies years of research, analysis, and reflection in the realm of finance, particularly in the area of currency option pricing.

Résumé

Évaluation des options sur devises en présence des coûts d'information statiques et dynamiques : Modèles théoriques et validation empirique

La littérature montre l'importance cruciale de l'information dans l'évaluation des actifs financiers, en soulignant deux catégories d'anomalies : statiques (ou classiques) et dynamiques. Les anomalies classiques enveloppent des modèles qui défient les suppositions relatives à l'évolution des prix des actifs, tandis que les anomalies dynamiques sont axées sur des suppositions orientées marché. Ces dernières proviennent souvent de recherches qui réfutent l'hypothèse de l'efficacité en admettant les imperfections du marché, tout en préservant la notion de rationalité des acteurs. Ceci couvre une variété de facteurs comme les coûts de transaction et d'information statiques, le sentiment du marché, les coûts d'information dynamiques, l'asymétrie d'information, les restrictions de vente à découvert, les primes de liquidité, et certains délais....

Le modèle fondamental pour évaluer les options sur devises, proposé par Garman et Kohlhagen (1983), repose sur l'hypothèse de l'efficacité des marchés financiers. Cette hypothèse est bâtie sur deux piliers : premièrement, elle présume que les acteurs économiques sont parfaitement rationnels ; et deuxièmement, elle suppose une absence d'imperfections du marché. Ces hypothèses entraînent une réaction immédiate des prix des actifs face à une nouvelle information, reflétant ainsi toutes les données disponibles.

L'objectif principal de cette thèse est d'évaluer si l'intégration des coûts d'information statiques et dynamiques dans le modèle fondamental de Garman et Kohlhagen (1983), améliore l'efficacité des modèles d'évaluation des options sur devises étrangères. Autrement dit, la recherche explore si la tarification des options sur devises étrangères, façonnée par cette intégration, offre une approximation plus proche du prix du marché d'une option européenne sur devises étrangères que celle obtenue en utilisant le modèle de base de Garman et Kohlhagen (1983). Cette thèse se déploie au travers de quatre chapitres interconnectés. À travers ces chapitres exhaustifs, ce travail de recherche entrelace minutieusement des narrations détaillées, soulignant astucieusement les interactions subtiles et les impacts des coûts d'information

statiques et dynamiques au sein du modèle de tarification des options sur devises, en particulier dans le modèle de Garman et Kohlhagen (1983).

Le premier chapitre introduit le concept de coûts d'information statiques dans le modèle de tarification des options sur devises de Garman et Kohlhagen (1983) dans le cadre de l'information incomplète de Merton (1987). En employant l'algorithme de l'Évolution Différentielle (ED) et en examinant un vaste ensemble de données, les résultats mettent en lumière la nature impérative de prendre en compte les coûts d'information statiques, alignant de manière cohésive les résultats de l'algorithme avec les observations du marché et soulignant le dialogue essentiel entre les coûts d'information et la tarification des actifs.

Le deuxième chapitre s'immerge dans les répercussions de la pandémie de COVID-19 sur le comportement des investisseurs au sein du marché des options de change, introduisant les "imperfections du marché" comme une nouvelle variable pour encapsuler les écarts entre les prix des options du marché théorique et observé. L'utilisation du modèle de changement de régime de Markov révèle des modèles de divergence et de convergence dans le comportement des investisseurs, offrant une vue globale sur la dynamique et les ramifications de tels comportements pendant les périodes de crise, avec la pandémie agissant comme un exemple illustratif puissant.

Le troisième chapitre navigue à travers le domaine complexe des coûts dynamiques et leur impact profond sur la tarification des options de change européennes. L'intégration d'une fonction d'intensité pour mesurer les coûts d'information dynamiques non seulement améliore la compétence du modèle à gérer la volatilité implicite, mais met également en lumière l'impératif d'incorporer ces coûts d'information dynamiques pour assurer la précision et la fiabilité des modèles de tarification des options de change en terme de maturité et de moneyness.

Enfin, le quatrième chapitre revisite les coûts d'information dynamiques dans le contexte du modèle de Garman et Kohlhagen et s'immerge dans des approches méthodologiques innovantes. En utilisant l'algorithme DE et en mettant en œuvre une technique d'apprentissage automatique, à savoir la régression de forêt aléatoire, pour prédire les taux d'intérêt intérieurs et étrangers effectifs, le chapitre illustre la robustesse et la précision améliorée du nouveau modèle lorsque les coûts d'information dynamiques sont incorporés. Cette dernière étape de la recherche souligne le rôle pivot de l'intégration des techniques d'apprentissage automatique, contribuant ainsi de manière substantielle au domaine de la tarification des options.

En résumé, cette thèse explore en profondeur le monde complexe de la tarification des prix des options sur devises. Elle introduit de nouvelles idées et mélange des méthodes classiques avec des approches plus modernes, donnant ainsi un outil plus complet et détaillé pour comprendre et se déplacer dans les marchés financiers. En reliant des théories avec des données de marché concrètes et en mélangeant différentes sortes de coûts d'information avec le comportement des investisseurs, cette recherche met non seulement en avant, mais aussi renforce les discussions sur comment fixer justement les prix des actifs et gérer les risques efficacement dans le domaine complexe de la finance.

Mots clés : Modèle de Garman et Kohlhagen ; Options de change ; Coûts d'information Statiques/ Dynamiques ; Imperfections ; Fundamentalistes-Chartistes ; Covid-19 ; Sensibilité ; Simulation ; Evolution Différentielle ; Apprentissage Automatique

Abstract

Assessment of European Currency Options in the Presence of Static and Dynamic Information Costs: Theoretical Models and Empirical Validation

Prevalent literature substantiates the pivotal role of information in financial asset evaluation, highlighting two distinct anomaly types: static (or classical) and dynamic. While classical anomalies encapsulate models challenging asset price evolution assumptions, dynamic anomalies focus on market-centric assumptions. The latter often stem from research opposing the efficiency hypothesis by acknowledging market imperfections while maintaining the rationality of participants. This spans various factors such as static transaction and information costs, market sentiment, dynamic information costs, asymmetrical information, short selling restrictions, liquidity premiums, and certain delays...

The fundamental model for evaluating currency options, proposed by Garman and Kohlhagen (1983), is grounded in the financial market efficiency hypothesis. This hypothesis rests on two pillars: firstly, it presumes that economic actors are perfectly rational; and secondly, it assumes an absence of market imperfections. These assumptions lead to an immediate response of asset prices to new information, reflecting all available data.

The primary goal of this thesis is to evaluate the potential benefits of integrating both static and dynamic information costs into the foundational Garman and Kohlhagen (1983) model for foreign currency option evaluation. In simpler terms, the research seeks to determine if this integration allows for more accurate pricing of European foreign currency options, bringing the results closer to actual market prices than when using the original Garman and Kohlhagen (1983) model. This exploration is spread across four cohesive chapters. Throughout these chapters, the research delves deep, highlighting the nuanced interactions between static and dynamic information costs within the currency option pricing model, especially in the context of the Garman and Kohlhagen (1983) framework.

Chapter One introduces the concept of static information costs into the Garman and Kohlhagen (1983) currency option pricing model within Merton's (1987) incomplete information framework. Through the employment of the Differential Evolution (DE) algorithm

and scrutiny of a vast dataset, the results spotlight the imperative nature of considering static information costs, aligning algorithm results cohesively with market observations and underscoring the essential dialogue between information costs and asset pricing.

The second chapter delves into the repercussions of the COVID-19 pandemic on investor behavior within the currency option market, introducing "market imperfections" as a novel variable to encapsulate discrepancies between theoretical and observed market option prices. The utilization of the Markov switching model unveils patterns of divergence and convergence in investor behavior, offering a comprehensive view into the dynamics and ramifications of such behaviors during crisis periods, with the pandemic serving as a potent illustrative example.

Chapter third Chapter navigates through the intricate domain of dynamic costs and their profound impact on the pricing of European currency options. The integration of an intensity function to gauge dynamic information costs not only enhances the model's proficiency in handling implied volatility but also illuminates the imperative of incorporating dynamic information costs to assure the accuracy and reliability of currency option pricing models.

Lastly, Chapter Four revisits dynamic information costs within the context of the Garman and Kohlhagen model and delves into innovative methodological approaches. Utilizing the DE algorithm and implementing a machine learning technique, namely the random forest regression, to predict effective domestic and foreign interest rates, the chapter illustrates the robustness and enhanced accuracy of the new model when dynamic information costs are incorporated. This final leg of research underscores the pivotal role of integrating machine learning techniques, thereby contributing substantively to the field of option pricing.

In synthesis, this thesis traverses the multifaceted landscapes of currency option pricing, introducing novel variables, and blending traditional models with contemporary methodologies, thereby providing a richer, more nuanced framework for understanding and navigating the financial markets. By bridging theoretical models with practical market data and interlacing static and dynamic information costs with investor behavior, this research not only underscores but also elevates the dialogue around accurate asset pricing and effective risk management in the nuanced domain of financial economics.

Keywords: Garman and Kohlhagen's model; Currency options; Static/Dynamic information costs; Imperfections; Market sentiment; Fundamentalists-Chartists; Covid-19; Sensitivity; Simulation; Differential Evolution; Machine Learning

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LIST OF ABBREVIATIONS AND ACRONYMS

AE	Absolute Error
ADF	Augmented Dickey-Fuller
ATM	at-the-money
B-S	Black–Scholes
CAPM	Capital Asset Pricing Model
CAPMI	Capital Market Equilibrium with incomplete information
COVID	Corona virus decease
DE	Differential Evolution
ECDC	European Centre for Disease Prevention and Control
EMH	Efficient Market Hypothesis
EURIBOR	Europe Inter Bank Offered Rates
Forex	Foreign Exchange Market
G-K	Garman-Kohlhagen
GKDIC	Garman-Kohlhagen with dynamic information costs
GKS	Garman-Kohlhagen with sentiment
GKSIC	Garman-Kohlhagen with static information costs
IBOR	Inter Bank Offered Rates
ISD	Implied Standard Deviation
ITM	In-The-Money
IV	Implied Volatility
LIBOR	London Inter Bank Offered Rates
MI	Market Imperfections
ML	Machine Learning
MowIBOR	Moscow Inter Bank Offered Rates

MS	Markov switching
MS (2) – AR	Autoregressive two-regime Markov switching model
MSD	Mean Squared Deviation
MSE	Mean Square Error
OTC	Over The Counter
OTM	Out-of-The-Money
PDE	Partial Differential Equation
QIBOR	Qatar Inter Bank Offered Rates
RF	Random Forest
TIBOR	Tokyo Inter Bank Offered Rates
USD	United States Dollar
VB	Visual Basic
WHO	World Health Organization

General Introduction

General Introduction

1. Background and Motivation for Study

Economic and financial models always aim to provide a simplified framework that captures the main analytical or numerical ideas in a manageable way. However, it is important to acknowledge that certain details are overlooked at this stage, as their impact is considered negligible and confined to "second-order effects." While these ideas generally do not significantly alter the overall message, the traditional approach of finance simplifies the behavior of all participants in the financial market by favoring a perfectly rational economic agent. This approach assumes that the calculation of the fundamental value of financial assets incorporates all relevant information and that all other agents are also perfectly rational. Such assumptions form the basis of the market efficiency hypothesis. Nonetheless, dealing with additional characteristics, like information costs in the evaluation of financial assets, proves to be technically challenging. Subsequent studies on these imperfections reveal that their effects are often more significant than initially anticipated. At times, this realization leads to radical changes in well-established results, paving the way for new developments and improvements in underlying theories.

In recent decades, there has been substantial growth in hedge instruments, particularly derivatives, within global financial markets. These instruments serve a pivotal role in mitigating unfavorable or uncertain fluctuations and changes in underlying asset prices. They are traded either through over-the-counter (OTC) platforms or organized markets with a clearinghouse that ensures transaction counterparties and maintains market liquidity. The options market, in particular, has experienced significant development due to the inherent flexibility of these contingent assets. Options, as conditional assets, provide holders with the right, though not the obligation, to buy or sell the underlying asset at a predetermined price before the expiration date. In addition to enabling coverage, speculation, and arbitrage strategies, options offer adaptability to changing circumstances and unfavorable shifts, while also providing the opportunity to capitalize on favorable market fluctuations. However, ongoing research endeavors are currently dedicated to proposing various models for option evaluation.

Louis Bachelier (1900) is the pioneering figure who introduced a model that laid the foundation for the first option evaluation formula. However, a major breakthrough came in

1973 when Fischer Black, Myron Scholes, and Robert Merton derived a formula to evaluate European call options on non-dividend paying stocks. This groundbreaking discovery paved the way for the evaluation of various types of options, including those on stocks, indices, and currencies. Building upon the work of Black, Scholes, and Merton, subsequent studies have focused on the evaluation of call or put options on currencies. Notably, the work of Garman and Kohlhagen (1983) explores the evaluation of options on currencies from a similar perspective. These developments in option evaluation have significantly advanced the field, allowing for a more comprehensive understanding and assessment of different financial instruments. The contributions of these researchers have shaped the way options are evaluated and have opened new avenues for financial analysis and decision-making. The work conducted by Garman and Kohlhagen (1983) is widely regarded as the starting point for numerous theoretical research articles focused on the evaluation of currency options. In their model, they assume a constant interest rate for both the domestic and foreign currencies. Similar to the Black, Scholes, and Merton model, they consider the exchange rate as the underlying asset. The model offers a theoretical and empirical framework for evaluating European-style currency options. However, it is important to acknowledge that like all economic and financial models, the Garman and Kohlhagen model relies on certain assumptions that may not align perfectly with the actual conditions of option trading. As a result, the application of this model has revealed the presence of evaluation biases associated with these underlying assumptions. This model is based on certain assumptions. One of these assumptions is that the foreign exchange market is perfectly efficient, disregarding information costs and market sentiment. Incorporating these additional features into the evaluation of financial assets proves to be technically challenging. Despite these limitations, the Garman and Kohlhagen model has provided valuable insights into the evaluation of currency options and has served as a foundational framework for further research in this area. As the field continues to evolve, ongoing efforts are being made to refine and enhance these models by incorporating additional factors and addressing the shortcomings of existing assumptions.

In the context of my thesis, I intend to incorporate these factors into the evaluation of currency options. The complexity arises from the difficulty of quantifying and incorporating information costs and market sentiment into the model. These factors introduce subjective elements that are not easily captured within the framework of the model. As a result, the Garman and Kohlhagen model focuses primarily on the more tractable aspects of option evaluation,

such as interest rates and exchange rates. However, the role of information costs in the evaluation of financial assets is crucial, and its impact on asset prices varies depending on the timing of acquisition. Further research has revealed that these imperfections have a more significant effect than initially anticipated, sometimes leading to radical changes in well-established results and driving advancements and improvements in underlying theories. In the literature, two types of anomalies have been identified: static or classic anomalies and dynamic anomalies. Classic anomalies encompass models that challenge assumptions regarding the evolution of underlying asset prices, while dynamic anomalies focus on assumptions related to the market. Nevertheless, the applicability of the Garman and Kohlhagen (1983) model is limited, prompting academic researchers to delve into the challenges of options evaluation. Developing a new theoretical model that provides a more reliable evaluation has become an important endeavor for them. Conversely, practitioners are in search of a simpler and more accurate model that can effectively replace the Garman and Kohlhagen model in practical applications. For a considerable period, options have been viewed as assets requiring advanced mathematical calculations for evaluation, often disregarding other economic and behavioral concepts. Furthermore, the pricing of options fails to capture desires, information costs, or trader predictions. Consequently, the influx of mathematicians and physicists into the field of financial mathematics has resulted in the generation of increasingly complex option evaluation models that deviate from reality.

The Garman and Kohlhagen (1983) base model relies on the market efficiency hypothesis, which is a fundamental concept in modern finance. This hypothesis is built upon two assumptions. Firstly, it assumes the absence of market imperfections. Secondly, it assumes that economic agents behave perfectly rationally. According to this view, asset prices promptly adjust to the arrival of new information, reflecting the totality of available information (Fama, 1991). There are two key characteristics of efficient markets. Firstly, they rapidly eliminate any arbitrage opportunities through pure and perfect competition, making it virtually impossible to outperform the market. Secondly, asset prices in financial markets are considered to be equal to their fundamental values, implying that prices are fair. However, when it comes to evaluating currency option prices, errors can arise due to various constraints within the financial market. Market imperfections can be attributed to multiple factors, including static information costs (Merton, 1987; Bellalah & Jacquillat, 1995; Kim & Konishi, 2001; Pour, 2017; Kim, 2022), dynamic information costs (Ben Hamad & Eleuch, 2008a and 2008b; Li & Xiong, 2016; Zghal

et al., 2020; Dammak et al., 2023), transaction and information costs (Jensen, 1978; Grossman & Stiglitz, 1980; Longjin et al., 2016; Blankespoor et al., 2020; Baek, 2022), information asymmetry (Allen and Gorton, 1993; Zghal et al., 2020), and short selling restrictions (Duffie et al., 2002; Harrison, Scheinkman, & Xiong, 2006; Feng & Fhan, 2016; Bohl et al., 2016; He et al., 2022; Duong et al., 2023), among others. These imperfections lead to the unprofitability of arbitrage operations. Another approach from behavioral finance questions the efficiency of financial markets due to unrealistic rationality of participants. Moreover, there are behavioral finance studies that show the impact of psychology on decisions made by investors, which can influence the market and make it inefficient. Many studies have shown that evaluation errors occur when rational investors face irrational investors such as noisy traders (De Long et al., 1990) or investors suffering from overconfidence (Abreu and Brunnermeier, 2003).

Therefore, it becomes apparent that the market efficiency assumptions underlying the Garman and Kohlhagen model may not hold in practice, as there are various factors that introduce imperfections and constraints within financial markets. Recognizing and accounting for these imperfections is crucial in developing more accurate models for evaluating currency option prices. By doing so, we can improve our understanding of market dynamics and enhance decision-making in the field of financial markets.

"Information is power. However, like any power, there are those who want to keep it for themselves."

Aaron Swartz

This quote is directly relevant, highlighting the importance of information availability in improving the evaluation of financial asset models, especially options. In the field of finance, information is a valuable resource that enables individuals and organizations to make informed decisions and gain a competitive advantage. Recognizing that some individuals or entities seek to monopolize information, we acknowledge the importance of promoting openness and accessibility of information. In the context of options evaluation, having access to comprehensive and reliable information is essential for developing accurate and robust models.

Through our research, we aim to emphasize the significance of information availability and its positive impact on the evaluation of currency options models. By advocating for transparency and open access to relevant data and information, we can enhance the precision and reliability of these models. The ability to access and analyze a wide range of information

allows for a deeper understanding of market dynamics, influencing the development and refinement of financial asset models. It enables researchers and practitioners to incorporate relevant factors such as information costs, market sentiment, and other essential elements into their models, leading to more precise evaluations and improving decision-making processes in financial markets. In summary, the options market, with its flexible nature, has seen significant advancements, allowing market participants to navigate changing conditions and capitalize on favorable opportunities. Nonetheless, ongoing research focuses on refining option evaluation models to further enhance understanding and decision-making in this dynamic financial landscape.

2. Objectives

“Even modest recognition of institutional structures and information costs can go a long way toward explaining financial behavior...”

Merton

In this quote, Merton's insight on the significance of recognizing institutional structures and information costs offers a foundational perspective. He asserts that even a slight acknowledgment of these factors can unravel and elucidate much about financial behavior. If Merton's views hold true, even marginal incorporations related to information costs might greatly improve the accuracy of financial asset evaluation models.

Therefore, the main objective of this thesis is to determine if the introduction of either static or dynamic information costs into the Garman and Kohlhagen (1983) base model improves the performance of foreign currency option evaluation models. In other words, does the price of foreign currency options generated by this introduction provide a better approximation of the market price of a European foreign currency option compared to that obtained using the Garman and Kohlhagen (1983) base model.

This research undertakes a multifaceted investigation into currency option pricing model of Garman and Kohlhagen (1983) and investor behavior, with the following interrelated sub-objectives and research questions guiding the study. First, it seeks to calibrate static information cost parameters using the Differential Evolution (DE) algorithm within the Merton's capital market equilibrium model with incomplete information, addressing the question of whether static information costs can be effectively determined. Second, this study

investigates how investor behavior impacts the precision of currency option pricing. Furthermore, in the context of the COVID-19 pandemic, the research examines changes in investor behavior, distinguishing specifically between fundamentalists and chartists within the currency options market. Third, it assesses the incorporation of dynamic information costs through an intensity function, evaluating whether this integration improves pricing accuracy and implied volatility management. Finally, the research investigates the calibration of dynamic information cost parameters through the DE algorithm, combined with machine learning techniques, aiming to enhance the precision and stability of currency option pricing models. These objectives collectively form the framework for a comprehensive exploration of the intricate dynamics within the currency options market.

More specifically, the main objective of this thesis is to answer the following questions:

- Does the inclusion of either static or dynamic information costs in the Garman and Kohlhagen (1983) model enhance the performance of currency option evaluation models? In simpler terms, do these additions result in currency option prices that more accurately reflect the market price of a European currency option compared to the original Garman and Kohlhagen (1983) model?
- Does the introduction of dynamic information costs in the Garman and Kohlhagen (1983) model reduce the estimation errors caused by the model, i.e., reduce the biases of under- and over-evaluation and thus approach the prices observed in the market?
- Does the integration of dynamic information costs via an intensity function lead to improvements in pricing accuracy and the effective management of implied volatility?
- Are the new parameters estimated using the DE algorithm of the option assessment perfectly observed or measured?
- How does introducing these imperfections affect the economic agent's behavior?
- Does the discrepancy in evaluation errors within the Garman and Kohlhagen (1983) model influence the behavior of economic agents during distinct periods, particularly prior to and amid crises?
- Can the utilization of the DE algorithm in conjunction with machine learning techniques enhance the precision and stability of currency option pricing models through the calibration of dynamic information cost parameters?

- Finally, among all the models studied in this thesis, which is the most performant between parametric and non-parametric models?

3. Methodology

In this research, a comprehensive methodology was employed to advance the understanding of currency option pricing models and their accuracy. To address the critical issue of static information costs, the Differential Evolution (DE) algorithm, renowned for its proficiency in numerical optimization, was utilized to calibrate static information cost parameters. This calibration was conducted within the context of Merton's capital market equilibrium model with incomplete information. The assessment of option pricing values involved the utilization of metaheuristic algorithms, as exemplified by Kumar et al., (2009). In this study, we have opted for the Differential Evolution (DE) algorithm, a metaheuristic employed in prior research by Jebaraj et al., (2017), Pant et al., (2020), and Hu et al., (2021) across diverse optimization and engineering applications. Notably, the DE algorithm is recognized for its ease of implementation and robust capabilities in terms of exploration and exploitation strategies. While numerous studies and practical evaluations of derivative instruments have enriched quantitative techniques, including works by Brennan and Schwartz (1978), Jiang and Li (2005), Cerny (2004), and Hull (2014), these methods often fall short in delivering solutions closely aligned with market values. To enhance both accuracy and efficiency in option pricing, we propose this technique that frames option pricing as an optimization problem. This approach finds precedence in studies conducted by Deb et al. (2002), Deb (2011), Singh et al. (2018), and Febrianti et al. (2023). Daily data from a diverse range of currency call option pairs spanning a specific timeframe were harnessed to ensure robust results.

To explore investor behavior dynamics during the COVID-19 pandemic, we applied a Markov switching model, which unveiled unique market patterns. In this empirical analysis, we recognized the Markov Switching model as a highly effective tool for detecting these behavioral shifts. Markov Switching models are conventionally employed to account for structural breaks that can significantly alter the trajectory of variables. They operate on the principle that the likelihood of transitioning to a particular regime is dependent on past observations of the variables of interest (Engel and Hamilton, 1990). Furthermore, owing to the dynamic nature of transition probabilities in Markov models, they enable the calculation of probabilities

associated with future regime realizations and the prediction of future values of the endogenous variable, regardless of the prediction horizon's duration. This approach initially took shape with the pioneering work of Goldfeld and Quandt (1973) and has since been expanded upon and refined by Hamilton (1989, 1990, and 1994). We applied this model to study the change in beliefs between the fundamentalists and the chartists in the currency market. We used variable named market imperfections, which represents the valuation errors of the theoretical model of Garman and Kohlhagen (1983) and helps to detect the change in the investors' behaviour between the chartists and the fundamentalists following the Covid-19 health crisis.

Additionally, dynamic information costs were tackled by introducing an intensity function inspired by the Beer-Lambert law into interest rates, leading to a marked reduction in pricing errors and improved implied volatility management. Through our empirical approach, we apply an inductive technique to verify the presence and impact of dynamic information costs in financial markets. By analyzing real-world data and market dynamics, we seek to provide empirical evidence supporting dynamic information costs and their influence on currency option pricing. This approach bridges the gap between theoretical insights and empirical observations, enhancing our understanding of financial market dynamics. Our approach was structured as follows: Firstly, we calculate the price of the currency call option using both models. Secondly, we evaluate the models' performance through the analysis of valuation gaps, considering errors reported by maturity and skewness, as well as overall errors, and comparing theoretical prices with market prices. Finally, we delve into the effects of introducing dynamic imperfections on the behavior of market participants in the financial sector, focusing on errors categorized by maturity, skewness, and overall errors. We also explored the incorporation of investor behavior, as a refinement to conventional models. To determine the Garman-Kohlhagen implied volatility, we employed the Newton algorithm, programmed in Visual Basic (VBA). This approach calculates the implied volatility using the Garman-Kohlhagen formula based on the option's market value.

Moreover, machine learning techniques, such as random forest regression, were applied to predict effective interest rates, enhancing the overall robustness and accuracy of the model. The Random Forest Regression is a method in machine learning that enhances prediction accuracy by combining multiple decision trees. In this technique, each tree in the ensemble depends on the values of a randomly sampled vector from the training set, which is independent and has a similar distribution with all the trees in the forest (Breiman, 2001). This algorithm

has been applied in various fields, including machine learning, pattern recognition, bioinformatics, and big data modeling. Several financial literature studies have used the RF algorithm in the forecasting of stock price and in developing investment strategies (Theofilatos et al., 2012; Qin et al., 2013; Basak et al., 2019), forecasting Bitcoin price (Basher & Sadorsky, 2022), risk management (Chang et al., 2018; Arora & Kaur, 2020) and option pricing (Ivaşcu, 2021; Li & Yan, 2023).

In sum, these methodological approaches collectively contribute to a more comprehensive and insightful understanding of currency option pricing, emphasizing the importance of considering both static and dynamic factors, as well as investor behavior, in achieving more accurate and reliable pricing outcomes.

4. Contribution

This thesis offers multiple contributions to current literature in unique ways. First, we notably incorporate a range of market imperfections into the financial markets, especially within the currency option pricing model. This includes the integration of static information costs following Merton's framework, and dynamic information costs using an intensity function drawn from the Beer-Lambert law. Both of these haven't been jointly used in previous empirical studies. Second, we adopt diverse methodologies and present new frameworks that haven't been applied to this specific topic before.

Certainly, we utilized artificial intelligence, specifically Differential Evolution (DE) and Machine Learning (ML), in our methodologies. Moreover, the impact of various crises—such as the health crisis posed by COVID-19 and geopolitical crises exemplified by the Ukrainian conflict—is underscored in its influence on the dynamics of currency option markets throughout these studies. Furthermore, each econometric exercise is followed by an extensive economic discussion to elucidate the findings and implications therein.

To sum up, this dissertation holds dual significance from both theoretical and empirical perspectives.

At the theoretical level, first, this research stands at the forefront of academic inquiry by seamlessly intertwining various market imperfections - including static information costs, and dynamic information costs - into the currency option pricing models, thereby furnishing a revitalized perspective to decode the underlying behaviors and patterns in pricing. Additionally,

our work ventures into uncharted territories by developing and introducing new models, which have not been illuminated in previously published works. These models, transcending conventional paradigms, proffer groundbreaking approaches and methodologies for comprehending the intricate dynamics of financial markets. Furthermore, we have meticulously determined the 'Greek letters' for the new variables integrated into these innovative models, providing a robust analytical framework for assessing the sensitivity and exposure related to each incorporated market imperfection. Therefore, not only does our research enrich the academic dialogue by providing a novel and holistic lens to view and explore market imperfections and their impacts on pricing, but it also lays down a potential practical pathway for financial practitioners, offering them new tools and strategies to navigate through the convoluted corridors of the financial markets, especially amidst the varied challenges rendered by market imperfections.

Additionally, the innovative aspect of our study lies in its multifaceted exploration of investor behavior within the currency market, particularly focusing on the divergence and convergence between exchange rates and currency options. We break new ground by introducing a unique 'market imperfections' proxy variable, ingeniously designed to encapsulate shifts in investor behavior by measuring the discrepancy between observed option prices in the market and theoretical prices deduced from the Garman and Kohlhagen model (1983). This meticulous examination and introduction of the 'market imperfections' proxy not only pave the way for a nuanced understanding of the influences that market imperfections can have on investor behavior but also illuminate the pivotal role these imperfections play, especially amid times brimming with instability and uncertainty, exemplified by periods like the COVID-19 pandemic. Thus, our study provides a fresh, theoretical scaffold upon which future research and practical financial strategies can be constructed, thereby enhancing both academic and pragmatic discourses in finance.

On the empirical level, this dissertation pioneers the use of innovative methodologies, specifically Differential Evolution and Machine Learning models, within groundbreaking frameworks. This approach enhances our understanding of currency options pricing in the face of varied market conditions and imperfections. Beyond just applying these methodologies, the research merges strong theoretical bases with hands-on empirical analysis, shedding light on the intricate dynamics of currency option pricing amidst market anomalies. Our journey into these untapped areas is marked by rigorous empirical methods. We dissect and interpret data

through the prism of our novel models, offering a deeper insight into the intricacies of financial markets. By venturing through the complex landscape of market imperfections and investor behavior, this research elevates existing literature and paves the way for future studies in the realm of financial markets. The empirical results not only affirm the theoretical constructs but also serve as a guiding light for future research and practical applications, enriching the multifaceted world of global financial markets.

From a policy perspective, these results carry significant implications. They highlight the criticality of these imperfections during the pricing and trading of currency options. By recognizing the impact of information costs, market participants can more adeptly navigate the complex arena of the currency options market and make more informed decisions. These findings bolster the importance of incorporating dynamic information costs into option pricing models and shed light on the complexities introduced by information asymmetry. Furthermore, by identifying and accommodating these elements, market participants can enrich their understanding of option pricing and augment their risk management practices within the currency options market

5. Research design and structure

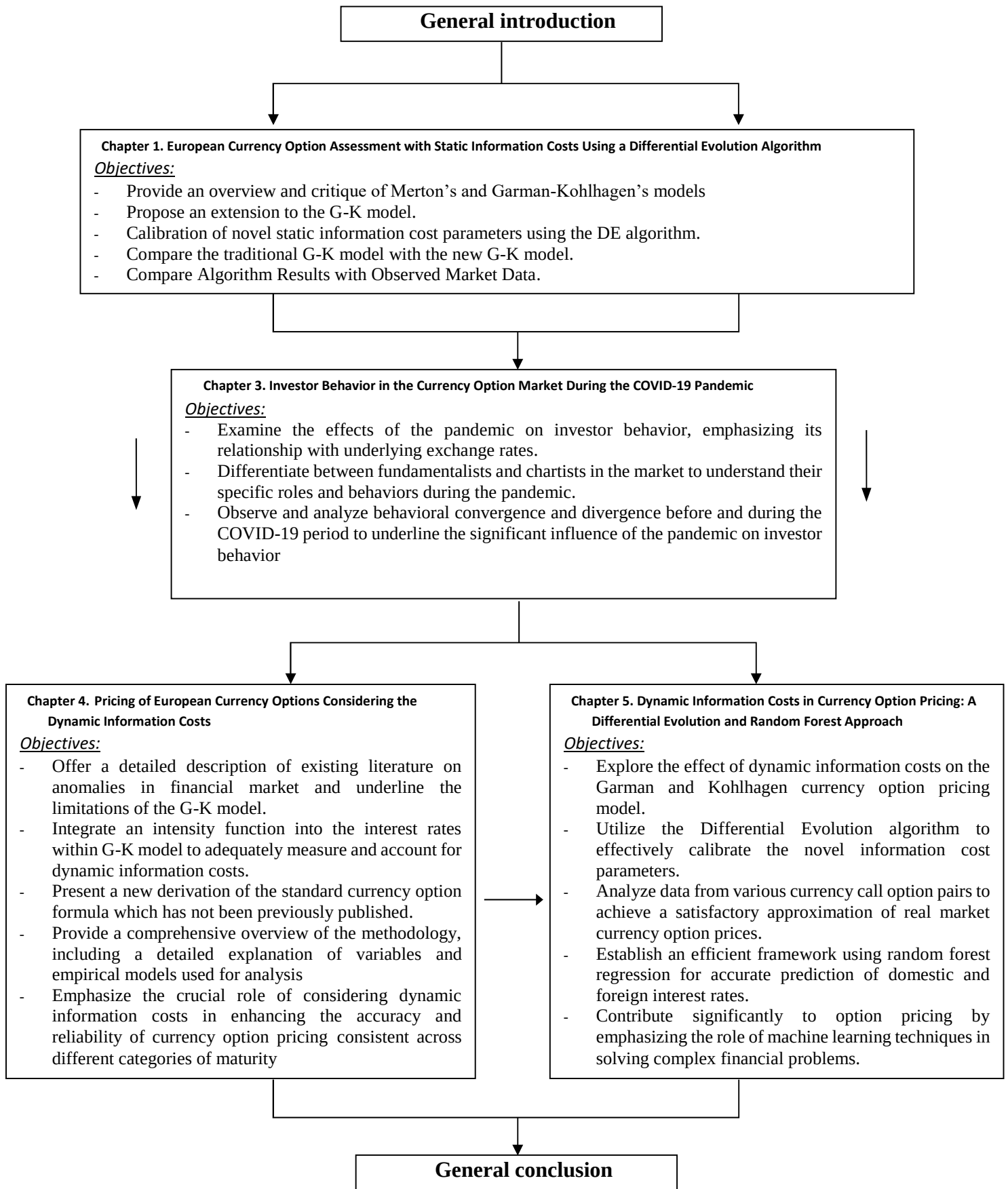


Figure 1. Thesis Structure

The structure of the remainder of this thesis is organized as follows:

Chapter 1 studies the impact of static information costs on the evaluation of European currency options using a differential evolution algorithm. This chapter lays the foundation by introducing the Garman and Kohlhagen (1983) model as well as its limitations, various anomalies present in the financial market, and the key principles and methods used, such as the differential evolution algorithm, which will be utilized in the following chapters. It is essential to understand how static information costs affect the evaluation of currency options before examining more complex factors.

After understanding the influence of static information costs, it becomes essential to explore other factors that influence the pricing of currency options, such as investor behavior. In Chapter 2, we highlight how the backdrop of the COVID-19 pandemic offers a unique opportunity to study the shifts in investor behavior between exchange rates and currency options. This deepens the analysis initiated in the previous chapter regarding the impact of information costs on the currency options market. The insights from this chapter led to the publication of an article in the academic journal “*The Journal of Economic Asymmetries*”.

Investor behavior can be dominated by both rational and irrational actions. The optimism of irrational investors, exercising dominance in the market, creates difficulties for rational investors trying to restore market balance. This situation underscores the asymmetric effect of sentiment and the dynamism observed in financial markets, thus showing that information costs are not static but genuinely dynamic. Indeed, irrational investors, guided by their optimism, can often disproportionately influence market prices. This influence can sometimes overwhelm the attempts of rational investors to keep asset prices aligned with their fundamental values, thereby exacerbating market volatility and making market balancing even more challenging. This dynamic highlights the critical importance of considering not only static information costs but also their dynamic nature, which evolves in response to market fluctuations and changes in investor behavior. It is therefore essential for market actors and regulators to consider these dynamic elements to implement effective risk management and asset evaluation strategies.

After exploring the effects of static information costs and investor behavior, it is logical to question the impact of dynamic information costs. Examining the pricing of European currency options by considering these costs, a more sophisticated element, is the subject of Chapter 3. The study conducted in this chapter was the subject of an article published in the journal “*Global Finance Journal*”

Finally, in Chapter 4, we apply advanced methods to evaluate dynamic information costs in option pricing. This last chapter builds on the methods and analyses of previous chapters to deeply examine dynamic information costs using machine learning techniques.

Each chapter in the following sections begins with a comprehensive review of the literature, followed by an exposition of the data characteristics and the methodology employed. Furthermore, each chapter concludes with an extensive economic discourse aimed at emphasizing the implications of our findings.

6. Results

As mentioned before, we begin this dissertation by investigating the impact of static information costs on the evaluation of European currency options using a differential evolution algorithm. While considering these new parameters of static information in the Garman and Kohlhagen model (1983), it is found that it has a significant impact on the valuation of currency options. Thus, we assume that incorporating these imperfections into the model can lead to more accurate and reliable evaluations of currency options. The findings of this study show that these costs, which differ from transaction costs, are necessary to account for the considerable expenses incurred by institutional and individual investors in analyzing, evaluating, and processing fundamental information for asset price determination. Consequently, these information costs refer to the expenses incurred by investors to obtain and process information about domestic and foreign markets, which can impact investment decisions and financial asset prices. Consequently, investors must carefully monitor information cost trends to adapt to changes in the economic climate.

In the second chapter, we explore investor behavior during the COVID-19 pandemic by analyzing the divergence and convergence between exchange rates and currency options. We found that the health crisis instigated a role reversal between fundamentalist and chartist investors across different currency pairs. Our analysis reveals that investor strategies

demonstrated significant variations, rather than being uniform, and were notably responsive to distinct market conditions during different timeframes. Prior to the pandemic, fundamentalist investors largely influenced market trends. However, with the emergence of COVID-19, chartists gained more influence, significantly impacting market dynamics. These shifts underscore the diversity in market strategies, indicating that investors adapt to a multitude of influencing factors, including information costs and the distinctive characteristics of various investment periods. Furthermore, our findings suggest that market imperfections played a substantial role in shaping investor behavior, particularly during times of crisis. The COVID-19 pandemic triggered a sudden and palpable transformation in strategies across all studied currency pairs. This observation highlights the diverse reactions that crises can provoke, encompassing mimetic behavior, risk aversion, and loss aversion, often driven by information deficits and pervasive uncertainty.

Having delved into the influences of static information costs, and investor behavior, the inquiry naturally progresses to the implications of dynamic information costs. These results are considered in the third chapter. The research findings have proven that the revised model incorporating dynamic information costs surpasses the classical model in pricing accuracy. This superior accuracy, highlighted in longer-term and out-of-the-money options, is a testament to the profound impact of dynamic information costs. By calibrating the new parameters of information costs, we have successfully minimized the discrepancies between our model's predictions and the actual market values of currency options, augmenting the precision of our estimations. The maturity and moneyness-based analysis conducted post-simulation reveals a significant error reduction for our model that integrates dynamic information costs. This enhancement reinforces the model's validity and practicability for accurately valuing currency options. Furthermore, the analysis further showed that the extended model persistently displays a higher average implied volatility than the classical model. This finding supports the hypothesis that integrating information costs into option pricing correlates with a surge in implied volatility. These results are congruent with existing literature, emphasizing the role of informed investors and the destabilizing effect of information asymmetry in the options market.

In the fourth and final chapter, which builds upon the third study, the DE parameters for dynamic information costs are utilized to construct a robust machine learning model, the Random Forest Regression, that accurately predicts the values of effective domestic and foreign interest rates. By integrating these imperfections into the valuation of currency options, our

study demonstrates that the novel model, which incorporates dynamic information costs, achieves improved accuracy and stability in pricing outcomes. This enhancement enables us to provide more precise forecasts for currency option prices, thereby contributing to a deeper understanding of financial markets. This approach provides a comprehensive understanding of the dynamics of information costs in the currency options market. The experimental results indicate that the Random Forest model fits the data well and provides valuable insights for investors. Overall, this research establishes a framework for pricing various options with different characteristics, enhancing the understanding and application of option pricing models.

Chapter 1. European Currency Option Assessment with Static Information Costs Using a Differential Evolution Algorithm

Chapter 1. European Currency Option Assessment with Static Information Costs Using a Differential Evolution Algorithm

Abstract

This research addresses the impact of static information costs in the currency option pricing model proposed by Garman and Kohlhagen (1983) within the framework of Merton's (1987) capital market equilibrium model with incomplete information. Previous academic literature has extensively criticized the theory of rational asset pricing, emphasizing the significance of considering information costs for accurate asset evaluation and effective risk management. In this study, we propose a new partial differential equation for currency options and focus on the calibration of novel static information cost parameters. To accomplish this, we employ the Differential Evolution algorithm, an evolutionary metaheuristics algorithm known for its effectiveness in solving numerical optimization problems. By utilizing this algorithm, we aim to solve objective optimization problems associated with the calibration process. By analyzing daily data from various currency call option pairs spanning from January 1, 2018, to November 24, 2022, our findings demonstrate a satisfactory level of agreement between the algorithm's results and the observed market data in terms of currency option prices. These results highlight the significance of considering static information costs and offer insights into the correlation between information costs and asset pricing within the currency option market.

Keywords: Currency Options; Garman and Kohlhagen's model; Static Information Costs; Derivatives; Differential Evolution Algorithm.

JEL classification: C63, G13, G14, G15, G17

1.1. Introduction

Over the years, the concept of information cost has been refined and applied to a broad spectrum of decision problems, including those related to price competition, investment decisions, and product differentiation.

In fact, static information costs refer to the costs associated with acquiring and processing information that remains constant over time. These costs are important because they impact decision-making processes and can affect the accuracy and efficiency of outcomes. For example, in markets where there is a high static information cost, it may be more difficult for buyers to find the information they need to make informed decisions, leading to inefficiencies and potentially suboptimal outcomes. Additionally, high static information costs can also limit competition, as firms with greater resources for acquiring and processing information may have an advantage over those with limited resources. As a result, it is important to minimize static information costs in order to promote more efficient and effective decision-making processes.

Static information cost has been extensively studied in the fields of economics and game theory as a way to understand the complexity of decision problems and to analyze the optimal strategies for decision-makers. Empirical studies have shown that the level of static information cost can affect the behavior of firms and consumers, and can play a key role in determining market outcomes. For example, in markets with high static information cost, firms may have greater incentives to engage in price differentiation or to invest in advertising and other forms of information provision. Theoretical work on static information cost has also shed light on the relationship between information and incentives. For example, the presence of strategic uncertainty can lead to higher levels of static information cost, which can affect the incentives of decision-makers and influence the outcomes of the decision-making process. Overall, the literature on static information cost has contributed to our understanding of the role of information in decision-making and the way it affects market outcomes. The concept continues to be an active area of research, with ongoing studies exploring new applications and refining existing models.

The Garman and Kohlhagen (G-K) (1983) model is a widely used framework for pricing currency options. To incorporate the impact of static information costs into this model, researchers would need to modify the underlying assumptions and calculations used in the model to account for the costs of acquiring and processing information. One way to do this

would be to include a term in the model that reflects the static information cost of obtaining exchange rate data. For example, the cost of acquiring exchange rate data could be represented as a percentage of the option's notional value, and this cost could be subtracted from the option's expected return in order to account for the impact of information costs on pricing. Additionally, the model could be modified to take into account the impact of information costs on volatility, which is a key factor in the pricing of currency options. For example, if the static information cost of obtaining volatility data is high, it may be more difficult for market participants to accurately estimate the volatility of exchange rates, leading to mispricing and inefficiencies in the market.

Incorporating static information costs into the G-K (1983) model necessitates a thorough evaluation of the costs and benefits associated with acquiring and processing information. It also requires a deep understanding of the factors influencing the pricing of currency options. Our study extends into exploring the consequences of introducing static information costs into the valuation of currency options using the G-K model within the framework of Merton's (1987) Capital Market Equilibrium Model with Incomplete Information (CAPMI). Furthermore, the expected information cost linked to a currency option varies based on specific circumstances and an investor's situation. Thus, a prudent approach involves a careful assessment of these associated information costs before committing to any investment. The Merton model can effectively accommodate information costs when pricing options by integrating these costs into the option's expected return.

In the context of currency options, static information costs hold significant relevance as they impact the pricing and valuation of these financial instruments. Various factors such as exchange rates, interest rates, and volatility can influence currency option pricing and can be influenced themselves by static information costs. When it comes to option pricing models like the Black-Scholes model, they serve as tools for calculating the anticipated option payoff. Simultaneously, estimating the expected information cost hinges on evaluating the information required for making a decision about the option and the accompanying costs. After establishing the expected return on the option, a comparison with the expected return on a risk-free investment, such as a government bond, provides insight into whether the option merits investment.

To empirically analyze pairs of Currency call options spanning from January 1, 2018, to November 24, 2022, we employed the Differential Evolution algorithm to estimate parameters associated with static information costs in both the domestic and foreign markets within our model. This methodology will enable us to gain a more comprehensive understanding of the dynamics of the currency options market. By accounting for the effect of static information costs on currency option valuation, we can offer more precise forecasts for currency call prices, ultimately contributing to a better understanding of financial markets. The results showed that the pricing outcomes of the new model, which considers static information costs, are more accurate and stable. Ultimately, the practical implication is that both investors and policymakers should prioritize a comprehensive understanding of static information costs and their multifaceted impact on financial markets. This awareness can lead to more informed investment decisions, improved market regulation, and a more accurate representation of asset values, benefiting both individual investors and the broader economy.

Therefore, the paper follows this structured outline: In Section Two, we offer a comprehensive literature review on information costs, delve into Merton's Model of Capital Market Equilibrium with incomplete information (CAPMI), and pinpoint the limitations of the G-K model. Additionally, we introduce the Differential Evolution Algorithm as a tool for modeling option pricing within an optimization framework. Section Three outlines our contributions, presenting an extended G-K model that accommodates static information costs. We also provide a novel derivation of the standard currency option formula, a unique aspect of our work. Furthermore, we explore the sensitivity of currency option prices to their determinants, particularly in the context of static information costs, and detail our research methodology, including the utilization of the Differential Evolution algorithm for parameter estimation. In Section Four, we offer insights into our empirical analysis, which involves a comparison between the traditional G-K model and the enhanced G-K model considering static information costs. Section Five synthesizes our key findings and delves into their implications for the field. Finally, in the concluding Section Six, we summarize our research and highlight potential future research directions in this domain.

1.2. Literature review

1.2.1. Information Costs

Static information costs pertain to the expenses linked to obtaining and analyzing information essential for making decisions within a financial market. This concept has received extensive scrutiny in the literature, with an emphasis on comprehending how these costs influence market dynamics, including pricing efficiency, competition, and market dominance. In recent times, researchers have extended their investigation of static information costs to various financial markets, encompassing the stock market, currency option market, and credit market.

Fama (1970) made a noteworthy discovery, revealing that efficient markets tend to exhibit reduced information costs. Moreover, the pace at which information gets integrated into prices plays a pivotal role in determining market efficiency. Building upon this, Fama and French (1989) established a connection between higher information costs in the foreign exchange (forex) market and the subsequent consequences of reduced trading volume and less precise option pricing. In a related vein, Wu et al. (1996) expanded upon Merton's (1987) asset-pricing model by considering scenarios in which investors hold differing beliefs and short selling is constrained. Their study uncovered that the presence of diverse beliefs contributes to greater inefficiency in the mean-variance of the market portfolio and an escalation in the shadow cost of information. They also demonstrated that this shadow cost of information becomes more pronounced, and equilibrium security returns rise when expectations among investors diverge. Additionally, their research highlighted an inverse relationship between the impact of differing beliefs on both information costs and the required rates of return and the relative size of the investor base for a specific security.

Bellalah et al. (2019) delve into the realm of optimal portfolio selection in the context of labor income risk, retirement horizon, and the associated shadow costs tied to incomplete information and short selling. Their findings reveal that employed investors, when factoring in idiosyncratic labor income risk, incomplete information, and short selling constraints, tend to allocate a larger portion of their portfolios to stocks compared to retired investors. This research builds upon existing literature by incorporating the supplementary considerations of information costs and restrictions on short selling.

The theory of financial markets places substantial emphasis on the presence of information costs, encompassing various expenses. These costs include expenditures related to short selling constraints, as examined by Scheinkman and Xiong (2003), Sobaci et al. (2014), and Kim et al. (2016). Additionally, the costs associated with research and information acquisition, as explored by Grossman and Stiglitz (1980), Easley and O'Hara (1987), Bellalah (1999), Argenziano et al. (2016), Weller (2018), MacLennan and Wood (2021), the cost of information transmission as discussed by Bhuyan et al. (2016), Ahmed and Huo (2019) and Dammak et al. (2023) and the expenses tied to adverse selection or asymmetric information, as scrutinized by Ahmad et al. (2021) and Ranaldo and Somogyi (2021), all play pivotal roles within financial asset pricing models and in the determination of international portfolio selections.

These studies are interrelated in their exploration of the consequences of static information costs on financial markets. They collectively underscore the significance of taking into account the expenses and advantages associated with obtaining and analyzing information when devising mechanisms. Furthermore, they emphasize how these costs can exert influence on market efficiency, market concentration, and competition dynamics. Consistently, these studies affirm that the reduction of information costs has the potential to enhance market efficiency and effectiveness. These insights offer a comprehensive perspective on the ramifications of static information costs and can offer valuable guidance for policymaking endeavors aimed at fostering greater efficiency within financial markets.

Numerous studies have delved into the influence of static information costs on option pricing. For instance, Bellalah and Jacquillat (1995) introduced a model that integrated information costs into the Black-Scholes option pricing model. They discovered that information costs have the potential to reduce option prices and alter the pattern of the implied volatility smile. These investigations underscore the importance of factoring in information costs when pricing options. They also caution against the omission of such costs, as doing so can result in pricing discrepancies.

In his paper, Bellalah (2016) investigates how the shadow costs associated with incomplete information and short sales impact the valuation of real options and capital budgeting models. He aligns these shadow costs with Merton's (1987) concept of sunk costs within the framework of capital market equilibrium marked by incomplete information. The

outcomes of his study hold substantial implications for pricing derivative assets and various forms of real options. This framework proves valuable for making investment decisions and evaluating the inherent flexibility in real projects. Furthermore, it enables the reframing of investment decisions in uncertain scenarios, with applications even in cases involving incomplete information and investment constraints. In his 2018 work, Bellalah presents a straightforward framework for the assessment of exotic derivatives, considering shadow costs arising from incomplete information and short sales. The methodology applied accommodates these shadow costs in both the options themselves and their underlying securities. The authors provide formulas that utilize either the conventional Black and Scholes method or the martingale method. Given the importance of shadow costs in the context of illiquidity, these formulas prove particularly beneficial for valuing over-the-counter (OTC) derivatives.

Hence, in a study by Zghal et al. (2020) focusing on S&P 500 options, it was observed that incorporating imperfections like market sentiment and information asymmetry into the Black-Scholes model yielded more precise outcomes compared to the traditional model. Similarly, Dammak et al. (2023) conducted research concerning EUR/USD currency call options, utilizing the G-K model while accounting for dynamic information costs. Their examination of daily data spanning from September 21, 2012, to September 23, 2022, resulted in more accurate and reliable findings for the analysis of currency options. Collectively, these studies underscore the significance of factoring in information costs in the analysis of financial markets. They also suggest that future research endeavors should continue to explore the influence of these costs on option pricing and various other outcomes within financial markets

1.2.2. Merton's Model of Capital Market Equilibrium with incomplete information, CAPMI

The Merton Model of Capital Market Equilibrium with Incomplete Information (CAPMI), developed by Robert Merton in the 1970s, builds upon the foundation of the Capital Asset Pricing Model (CAPM), originally formulated by William Sharpe in the 1960s. However, unlike the CAPM, which assumes that investors possess complete information regarding future stock returns, Merton's model acknowledges the reality that investors do not have perfect information. Consequently, CAPMI incorporates a risk premium associated with investments. It's crucial to highlight that both the Merton Model (1970) and the Black-Scholes model (1973) rest on a set of assumptions. These assumptions encompass the absence of transaction costs,

market frictions, and the assumption of constant volatility. These conditions may not necessarily hold true in the real world, making it imperative to exercise caution when applying these models to real-world scenarios. Moreover, the expected information cost of an option is contingent on the specific circumstances of the option and the individual investor. Therefore, it is of utmost importance to meticulously assess the information costs associated with a particular option before making any investment decisions.

The Merton (1987) model revolutionized financial theory by introducing the concept of incomplete information, specifically by injecting uncertainty into the dynamics of underlying assets in the capital market. Merton's key premise was that investors possess only partial information concerning the future cash flows and risks associated with the assets they invest in. Consequently, they make investment decisions based on this limited information. Merton formulated a dynamic optimization problem within this framework. In this model, investors base their decisions on their subjective beliefs about the distribution of future cash flows and associated risks. He then proceeded to derive equilibrium prices and investment strategies, all while accounting for the influence of incomplete information and the impact of investors' beliefs and expectations. The fundamental behavioral assumption underlying this model is that an investor contemplates adding security S to their portfolio only when they possess certain information about this particular security. This model can be expressed in the following manner:

$$\bar{R}_S - r = \beta_S [\bar{R}_m - r] + \lambda_S - \beta_S \lambda_m \quad (1.1)$$

where, $\bar{R}_S$ is the equilibrium expected return on security S , $\bar{R}_m$ is the equilibrium expected return on the market portfolio, r is equal to $1 +$ the riskless rate of interest, $\beta_S = \frac{cov(\bar{R}_S/\bar{R}_m)}{var(\bar{R}_m)}$ is the beta of security S , λ_S is the equilibrium aggregate “shadow cost” for the security S and λ_m is the weighted average shadow cost of incomplete information over all securities.

Merton's model illustrates that market prices are reflective of the collective beliefs held by investors regarding underlying assets, and these prices adapt as fresh information emerges. This model offers a structured framework for examining the consequences of information asymmetry and uncertainty in financial markets, offering insights into the impact of incomplete information on market prices and investment choices. It plays a pivotal role in elucidating the dynamics of capital markets, providing valuable understanding into how investors maneuver

through uncertainty and formulate investment decisions rooted in their subjective assessments of asset cash flows and associated risks.

1.2.3. Garman and Kohlhagen (1983) model

Based on the assumptions that include the neutral delta hedging technique, the G-K (1983) model suggested that the sale of a call option for a foreign currency can be perfectly hedged by the purchase of a quantity of foreign government bonds with r_f as the interest rate. On the other hand, according to the G-K model and under a number of assumptions based on the market efficiency, the value of a European currency call according to this model can be calculated through the partial differential equation on condition that there is no arbitrage opportunity:

$$\frac{1}{2} \cdot \sigma^2 \cdot S^2 \frac{\delta^2 V}{\delta S^2} + (r_d - r_f) S \frac{\delta V}{\delta S} - r_d V + \frac{\delta V}{\delta t} = 0 \quad (1.2)$$

where, V represents the price of the currency option which is considered as a function of two variables: the exchange rate ' S ' and the time ' t ', $\delta^2 V / \delta S^2$ is the second derivative of V relative to S , $\delta V / \delta S$ is the first derivative of V relative to S , $\delta V / \delta t$ is the first derivative of V relative to t , σ is the exchange rate volatility, r_d is the domestic risk-free interest rate and r_f is the foreign risk-free interest rate.

In fact, equation (1) can be rewritten:

$$\frac{1}{2} \cdot \sigma^2 \cdot S^2 \frac{\delta^2 V}{\delta S^2} + \frac{\delta V}{\delta t} = r_d V - (r_d - r_f) S \frac{\delta V}{\delta S} \quad (1.3)$$

Looking at equation (2), we noticed that the left-hand side represents the change in the value of the currency option V due to the effect of time while the right-hand side represents the risk-free return of a long currency option position and a short position consisting of $\frac{\delta V}{\delta S}$ the exchange rate.

With the boundary condition that the European currency call option must be verified at maturity (T). In fact, it is a condition to get the value of the call at maturity, which is equal to:

$$C_T = \max[S_T - X; 0] \quad (1.4)$$

Moreover, the value of a put is equal to:

$$P_T = \max[X - S_T; 0] \quad (1.5)$$

where,

S_T represents the value of the exchange rate at maturity and X is the exercise price.

Then, the analytical solution that coincides with that of the B-S model through the partial derivatives of the equation of the call price can be written as follow:

$$C_t = S_t e^{-r_f \tau} N(d_1) - X e^{-r_d \tau} N(d_2) \quad (1.6)$$

where, C_t is the value of a European currency call paying an interest rate r_f , S_t is the price of the underlying asset, X is the strike price of the call, r_f is the interest rate of the foreign currency, r_d is the interest rate of the domestic currency, τ is the period of time calculated in year or fraction of year and $N(.)$ is the cumulative distribution function of a normal distribution: $N(0,1)$.

Finally, d_1 and d_2 can be calculated as follow:

$$d_1 = \frac{\ln\left(\frac{S}{X}\right) + (r_d - r_f)\tau + \frac{1}{2}\sigma^2\tau}{\sigma\sqrt{\tau}} \quad (1.7)$$

and,

$$d_2 = d_1 - \sigma\sqrt{\tau} \quad (1.8)$$

where σ represents the volatility of the underlying asset.

Moreover, using the parity relationship, we noticed that the price of a European currency put is:

$$P_t = S_t e^{-r_f \tau} N(-d_1) + X e^{-r_d \tau} N(-d_2) \quad (1.9)$$

1.2.4. Differential Evolution (DE) algorithm applications

The assessment of option pricing values involves the application of metaheuristic algorithms, as exemplified by Kumar et al. (2009). For our study, we have chosen the Differential Evolution (DE) algorithm as one of the metaheuristic tools. Notably, previous research, such as the work of Jebaraj et al. (2017), Pant et al. (2020), and Hu et al. (2021), has also effectively utilized the DE algorithm across various optimization and engineering applications. This algorithm, inspired by Darwin's theory of evolution, has gained widespread popularity and undergone extensive scrutiny since its inception by Storn in 1997.

DE is well-regarded as one of the foremost optimization algorithms for tackling intricate problems. It falls within the realm of Evolutionary Algorithms (EA) and is a population-based method used to address a diverse range of optimization challenges. Unlike other EAs that create offspring by perturbing solutions with scaled difference vectors, DE generates new offspring through solution recombination under specific conditions. Given that our option pricing model in this study encompasses multiple parameters, conventional parameter estimation techniques like least squares and maximum likelihood methods are unsuitable. Instead, we employ the DE algorithm for parameter estimation. This algorithm proves robust and efficient in seeking minimum solutions for complex option pricing problems. Furthermore, it is straightforward to implement and possesses strong capabilities for both exploration and exploitation strategies.

Numerous studies and practical evaluations of derivative instruments have contributed to enhancing various quantitative techniques, as demonstrated by works from Brennan and Schwartz (1978), Jiang and Li (2005), Cerny (2004), and Hull (2014). However, these methods often fall short in providing accurate solutions closely aligned with market values. To enhance the precision and efficiency of option pricing, we propose an approach that frames option pricing as an optimization problem. This approach has previously been employed in research conducted by Deb et al. (2002), Deb (2011), Singh et al. (2018), and Febrianti et al. (2023). In our study, we embrace this approach and leverage the DE algorithm to explore and identify potential solutions.

1.3. A valuation formula for currency option considering static information costs and Methodology

1.3.1. The actual discount rate in the presence of static information costs

We have developed a pricing model for currency options that incorporates static information costs. To do so, we made use of the same assumptions as the G-K model, with the exception of market efficiency. By departing from the market efficiency hypothesis, we were able to derive a formula for evaluating currency options that takes into account the impact of static information costs.

“When investors move from a risk-neutral world to a risk-averse world, two things happen: the expected growth rate in the stock price changes and the discount rate that must be used for any pay-off from the derivative changes.” (John Hull, 2008).

Thus, when considering static information costs, the expected growth rate of the underlying rate and the discount rate are assumed to include the risk-free rate as well as the costs incurred due to these imperfections. In a market where there are both informed and uninformed but rational investors, the effect of static information can be likened to the application of an extra discount rate. This is supported by several studies, including those conducted by Merton (1987), Bellalah and Jacquillat (1995), Ben Hamad and Eleuch (2008a, 2008b), Zghal et al. (2020), and Dammak et al. (2023). Then, we have:

$$r_1 = r + \text{the costs associated with static information costs} \quad (1.10)$$

where, r_1 Means the effective risk-free interest rate and r Refers to the real risk-free interest rate.

To incorporate the impact of static information, the costs associated with these imperfections are defined as follows:

$$r_1 = r + \lambda \quad (1.11)$$

where, λ represents the amplitude of static information costs, which ranges from 0 to 1. If the information is not significant and the market is efficient (i.e., there is no private information), λ takes a value of 0. On the other hand, if the information is relevant, λ tends to approach 1.

In our cases, we consider two amplitudes of static information costs: λ_d for the domestic market and λ_f for the foreign market.

Therefore, r_{1d} presents the effective domestic interest rate in the presence of static information costs associated with the domestic market, with:

$$r_{1d} = r_d + \lambda_d \quad (1.12)$$

where, r_d is the domestic risk-free rate and λ_d presents the static information costs related to the domestic market.

And, r_{1f} presents the effective foreign interest rate in the presence of static information costs associated with the foreign market, with:

$$r_{1f} = r_f + \lambda_f \quad (1.13)$$

where, r_f is the foreign risk-free rate and λ_f presents the static information costs related to the foreign market.

1.3.2. Derivation of the currency option pricing model in the presence of static information costs

A short position composed of selling an $\frac{1}{\frac{\partial C(S,T)}{\partial S}}$ option against a long position on the shares can be created according to the G-K model.

By adopting a similar methodology to G-K (1983) model and incorporating static information costs, it is evident that a small change in the share price (δS) results in a corresponding change in the option value $\frac{\partial C(S,T)}{\partial S} \delta S$. Therefore, the change in the long position on the currency is approximately compensated by the $\frac{1}{\frac{\partial C(S,T)}{\partial S}}$ options variation.

Next, consider what occurs at any time for a portfolio that consists of a currency and $\frac{1}{\frac{\partial C(S,T)}{\partial S}}$ options.

At the initial time, the position value is:

$$V = S - \frac{1}{\frac{\partial C(S,T)}{\partial S}} C(S,T) \quad (1.14)$$

During an infinitesimal interval δS , the change of this position is given by:

$$\delta V - r_f S - \frac{1}{\frac{\partial C(S,T)}{\partial S}} r_f C(S,T) \quad (1.15)$$

where:

$$r_f C(S,T) = C(S + r_f S, T + r_f T) - C(S,T) \quad (1.16)$$

Geometric Brownian motion governs the currency price: i.e. the differential representation of the spot price movements is:

$$ds = \mu S dt + \sigma S dZ \quad (1.17)$$

Where, μ is the drift of the spot currency price, σ is the volatility of the spot currency price and dZ represents the standard wiener process.

Using the differential stochastic calculation and Itô's lemma, we get:

$$\Delta C = \frac{\partial C}{\partial t} \Delta S + \frac{\partial C}{\partial t} dt + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} dt \quad (1.18)$$

In order to ensure a risk-free covered position, the return must be equal to $(r_{1d} - r_{1f})$, where r_{1d} represents the effective domestic risk-free interest rate and r_{1f} represents the effective foreign risk-free interest rate. To derive the partial derivative equation, it is necessary to satisfy the condition of absence of arbitrage opportunity resulting from continuous changes in portfolio composition, thereby maintaining a risk-free portfolio.

We get the following equation:

$$\frac{1}{2} \sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + (r_{1d} - r_{1f}) S \frac{\partial C}{\partial S} + \frac{\partial C}{\partial t} - r_{1d} C = 0 \quad (1.19)$$

So, equation (8) can be written as follows:

$$\begin{aligned} \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + ((r_d + \lambda_d) - (r_f + \lambda_f)) S \frac{\partial C}{\partial S} + \frac{\partial C}{\partial t} - (r_d + \lambda_d) C &= 0 \\ \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + ((r_d - r_f) + (\lambda_d - \lambda_f)) S \frac{\partial C}{\partial S} + \frac{\partial C}{\partial t} - (r_d + \lambda_d) C &= 0 \\ \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + (r_d - r_f) S \frac{\partial C}{\partial S} + (\lambda_d - \lambda_f) S \frac{\partial C}{\partial S} + \frac{\partial C}{\partial t} - (r_d + \lambda_d) C &= 0 \end{aligned} \quad (1.20)$$

The equation (11) will be considered the new partial derivative equation in the G-K model in the presence of static information costs.

Under this condition:

$$C(S, t^*) = \max[0; S_{t^*} - X] \quad (1.21)$$

Where, t^* designates the maturity.

The search for the solution requires a change of variables that leads to the heat equation. Let's start by writing the currency option price in this following form:

$$C(S, t) = f(t) y(u_1, u_2) \quad (1.22)$$

Where $f(t)$ and $y(u_1, u_2)$ are unknown functions that need to be found.

Let's then calculate the derivatives of the currency option price with respect to time and with respect to the underlying asset price:

$$\frac{\partial C}{\partial t} = \frac{\partial f}{\partial t} y + f \frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial t} + f \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial t} \quad (1.23)$$

$$\frac{\partial C}{\partial S} = f \left(\frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial S} + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) \quad (1.24)$$

$$\frac{\partial^2 C}{\partial S^2} = f \left(\frac{\partial^2 y}{\partial u_1^2} \left(\frac{\partial u_1}{\partial S} \right)^2 + \frac{\partial y}{\partial u_1} \frac{\partial^2 u_1}{\partial S^2} \right) + f \left(\frac{\partial^2 y}{\partial u_2^2} \left(\frac{\partial u_2}{\partial S} \right)^2 + \frac{\partial y}{\partial u_2} \frac{\partial^2 u_2}{\partial S^2} \right) + 2f \left(\frac{\partial^2 y}{\partial u_1 \partial u_2} \frac{\partial u_2}{\partial S} \frac{\partial u_1}{\partial S} \right) \quad (1.25)$$

Let's then substitute these derivatives into the equation (11):

$$\begin{aligned} & \frac{1}{2} \sigma^2 S^2 f \left(\frac{\partial^2 y}{\partial u_1^2} \left(\frac{\partial u_1}{\partial S} \right)^2 + \frac{\partial y}{\partial u_1} \frac{\partial^2 u_1}{\partial S^2} \right) + \frac{1}{2} \sigma^2 S^2 f \left(\frac{\partial^2 y}{\partial u_2^2} \left(\frac{\partial u_2}{\partial S} \right)^2 + \frac{\partial y}{\partial u_2} \frac{\partial^2 u_2}{\partial S^2} \right) \\ & + \sigma^2 S^2 f \left(\frac{\partial^2 y}{\partial u_1 \partial u_2} \frac{\partial u_2}{\partial S} \frac{\partial u_1}{\partial S} \right) + (r_d - r_f) S f \left(\frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial S} + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) \\ & + (\lambda_d - \lambda_f) S f \left(\frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial S} + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) + \frac{\partial f}{\partial t} y + f \frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial t} + f \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial t} \\ & - (r_d + \lambda_d) f y = 0 \end{aligned} \quad (1.26)$$

It is possible to solve the equation by using the heat transfer equation for the function y :

$$\frac{\partial y}{\partial u_2} = \frac{\partial^2 y}{\partial u_1^2} \quad (1.27)$$

$$\text{Let's now search for } f(t), u_1(S, t), u_2(S, t), \text{ so that: } -(r_d + \lambda_d) f y + \frac{\partial f}{\partial t} y = 0 \quad (1.28)$$

$$\Rightarrow (r_d + \lambda_d) f = \frac{\partial f}{\partial t}$$

$$\Rightarrow f(t) = e^{(r_d + \lambda_d)(t - t^*)} \quad (1.29)$$

Let's designate by:

$$a^2 = \frac{1}{2} \sigma^2 S^2 \left(\frac{\partial u_1}{\partial S} \right)^2 \quad (1.30)$$

Simplifying by $f(t)$ and rewriting the equation to identify the different terms.

The term:

$$\begin{aligned} \frac{1}{2}\sigma^2 S^2 \left(\frac{\partial^2 y}{\partial u_1^2} \left(\frac{\partial u_1}{\partial S} \right)^2 \right) + \frac{1}{2}\sigma^2 S^2 \left(\frac{\partial y}{\partial u_2} \frac{\partial^2 u_2}{\partial S^2} \right) + (r_d - r_f) S \left(\frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) + \\ (\lambda_d - \lambda_f) S \left(\frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial t} \end{aligned} \quad (1.31)$$

cancels out when:

$$-a^2 = \frac{1}{2}\sigma^2 S^2 \left(\frac{\partial^2 u_2}{\partial S^2} \right) + (r_d - r_f) S \left(\frac{\partial u_2}{\partial S} \right) + (\lambda_d - \lambda_f) S \left(\frac{\partial u_2}{\partial S} \right) + \frac{\partial f}{\partial t} y + \frac{\partial u_2}{\partial t} \quad (1.32)$$

Assuming that:

$$\frac{\partial u_2}{\partial S} = \frac{\partial^2 u_2}{\partial S^2} = 0 \quad (1.33)$$

We find that: $\frac{\partial u_2}{\partial t} = -a^2$, then,

$$u_2 = -a^2(t - t^*) \quad (1.34)$$

Under these conditions, the partial derivative equation of G-K in the presence of static information costs is written as follows:

$$\begin{aligned} \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 u_1}{\partial S^2} + (r_d - r_f) S \frac{\partial u_1}{\partial S} + (\lambda_d - \lambda_f) S \frac{\partial u_1}{\partial S} + \frac{\partial u_1}{\partial t} = 0 \\ \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 u_1}{\partial S^2} + \left((r_d - r_f) + (\lambda_d - \lambda_f) \right) S \frac{\partial u_1}{\partial S} + \frac{\partial u_1}{\partial t} = 0 \end{aligned} \quad (1.35)$$

Using the expression for a^2 , it follows that:

$$\frac{\partial u_1}{\partial S} = \sqrt{2} \frac{a}{\sigma} \frac{1}{S} \quad (1.36)$$

Where, $u_1 = \sqrt{2} \frac{a}{\sigma} \ln\left(\frac{S}{X}\right) + b(t)$

By replacing u_1 by (21), it follows that:

$$\frac{1}{2}\sigma^2 S^2 \left(-\frac{1}{S^2} \sqrt{2} \frac{a}{\sigma} + \frac{\partial b}{\partial t} \right) + \left((r_d - r_f) + (\lambda_d - \lambda_f) \right) S \sqrt{2} \frac{a}{\sigma} \frac{1}{S} = 0 \quad (1.37)$$

Or:

$$-\frac{1}{2}\sigma \sqrt{2} + \frac{\partial b}{\partial t} + \left((r_d - r_f) + (\lambda_d - \lambda_f) \right) \frac{a}{\sigma} \sqrt{2} = 0 \quad (1.38)$$

then,

$$\frac{\partial b}{\partial t} = \frac{\sigma\sqrt{2}}{\sigma} \left(\frac{\sigma^2}{2} - ((r_d - r_f) + (\lambda_d - \lambda_f)) \right) \quad (1.39)$$

$$\Rightarrow b(t) = \frac{\sigma\sqrt{2}}{\sigma} \left(\frac{\sigma^2}{2} - ((r_d - r_f) + (\lambda_d - \lambda_f)) \right) (t - t^*) \quad (1.40)$$

$$\Rightarrow u_1 = \frac{\sigma\sqrt{2}}{\sigma} \left[\ln \frac{S}{X} + \left(\frac{\sigma^2}{2} - ((r_d - r_f) + (\lambda_d - \lambda_f)) \right) (t - t^*) \right] \quad (1.41)$$

Using the fact that: $C(S, t^*) = f(t)y(u_1, u_2)$ and $\frac{\partial y}{\partial u_2} = \frac{\partial^2 y}{\partial u_1^2}$,

The result at maturity is written as:

$$C(S, t^*) = [y(u_1(S, t^*), u_2(S, t^*))] = y \left[\frac{a\sqrt{2}}{\sigma} \ln \frac{S}{X}, 0 \right] \quad (1.42)$$

The solution to the heat equation is in the following form:

$$y(u_1, u_2) = \frac{1}{\sqrt{2\pi u_2}} \int_{-\infty}^{+\infty} u_0(\epsilon) e^{\frac{-\epsilon^2}{2u_2}} dq \quad (1.43)$$

The value of the option at maturity is written as:

$$C(S, t^*) = y(k, 0) = \begin{cases} X \left[e^{\frac{-\epsilon^2}{a\sqrt{2}}} - 1 \right], & \text{if } k \geq 0 \\ 0, & \text{if not} \end{cases} \quad (1.44)$$

Where, $k = \frac{a\sqrt{2}}{\sigma} \ln \left(\frac{S}{X} \right)$

Using this condition and the solution (29), we obtain:

$$y(u_1, u_2) = \frac{1}{\sqrt{2\pi u_2}} \int_{-\infty}^{u_1} X \left[e^{(u-\epsilon) \left(\frac{1}{2\sigma^2} \right) \left(((r_d - r_f) + (\lambda_d - \lambda_f)) - \frac{1}{2\sigma^2} \right)} - 1 \right] e^{\frac{\epsilon^2}{2S}} dq \quad (1.45)$$

By using a change of variables, the equation (31) becomes:

$$y(u_1, u_2) = \frac{1}{\sqrt{2\pi u_2}} \int_{\frac{-u_1}{\sqrt{2S}}}^{+\infty} X \left[e^{(u_1 - q\sqrt{2S}) \left(\frac{\sigma}{a\sqrt{2}} \right)} - 1 \right] e^{\frac{q^2}{2}} dq \quad (1.46)$$

By using (20) and (27), we have:

$$\begin{aligned}\frac{-u_1}{\sqrt{2} u_2} &= \frac{a}{\sigma} \sqrt{2} \left[\ln \left(\frac{S}{X} \right) + \left(\frac{\sigma^2}{2} - ((r_d - r_f) + (\lambda_d - \lambda_f)) \right) (t - t^*) \right] \left(\frac{1}{\sqrt{2} a \sqrt{t - t^*}} \right) \\ \frac{-u_1}{\sqrt{2} u_2} &= \frac{-\frac{1}{\sigma} \left[\ln \left(\frac{S}{X} \right) + \left(\frac{\sigma^2}{2} ((r_d - r_f) + (\lambda_d - \lambda_f)) \right) (t - t^*) \right]}{\sqrt{t^* - t}} \\ \frac{-u_1}{\sqrt{2} u_2} &= \frac{-\frac{1}{\sigma} \left[\ln \left(\frac{S}{X} \right) + \left(\frac{\sigma^2}{2} ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*) \right]}{\sqrt{t^* - t}}\end{aligned}\quad (1.47)$$

$$\begin{aligned}\text{and, } \frac{\sigma}{a\sqrt{2}} \left[\frac{a\sqrt{2}}{\sigma} \left(\ln \left(\frac{S}{X} \right) + \left(\frac{\sigma^2}{2} - ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*) \right) + q\sqrt{2} a \sqrt{t^* - t} \right] \\ = \left(\ln \left(\frac{S}{X} \right) + \left(\frac{\sigma^2}{2} - ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*) \right) + q\sigma\sqrt{t^* - t}\end{aligned}\quad (1.48)$$

We designate by d the following term (34). By replacing these values in the heat equation, we obtain

$$y(u, t) = \frac{k}{\sqrt{2\pi}} \left[\int_d^\infty e^{\ln \left(\frac{S}{X} \right) + \left(\frac{\sigma^2}{2} - ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*) + q\sigma((r_d + \lambda_d) - (r_f + \lambda_f))} - 1 \right] e^{\frac{-q^2}{2}} dq \quad (1.49)$$

In other words, the heat equation can be written as:

$$\begin{aligned}y(u, t) &= e^{((r_d + \lambda_d) - (r_f + \lambda_f))(t - t^*)} \left[\frac{X}{\sqrt{2\pi}} \int_d^\infty (e^{q\sigma\sqrt{t^* - t}}) e^{\frac{-q^2}{2}} dq \frac{S}{X} e^{\left(\left(\frac{\sigma^2}{2} - ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*) \right)} \right] \\ &\quad - \int_d^\infty e^{\frac{-q^2}{2}} dq\end{aligned}\quad (1.50)$$

By making the change of variable $p = -q$, then the equation becomes:

$y(u, t)$

$$= e^{((r_d + \lambda_d) - (r_f + \lambda_f))(t - t^*)} \left(\frac{X}{\sqrt{2\pi}} \right) \left(\frac{S}{X} e^{\left(\left(\frac{\sigma^2}{2} - ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*) \right)} \right) \int_d^\infty (e^{-p\sigma\sqrt{t^* - t}}) e^{\left(\frac{-p^2}{2} \right)} dq$$

$$- X e^{((r_d + \lambda_d) - (r_f + \lambda_f))(t - t^*)} N(d'_2) \quad (1.51)$$

If we use the fact that:

$$\frac{1}{2} (q - \sigma((r_d + \lambda_d) - (r_f + \lambda_f))\sqrt{t^* - t})^2 = \frac{1}{2} q^2 + 2q\sigma\sqrt{t^* - t} + \frac{1}{2} \sigma^2 \sqrt{t^* - t}$$

$$= -\frac{1}{2} (q + \sigma\sqrt{t^* - t})^2 - \frac{1}{2} q^2 + q\sigma\sqrt{t^* - t} + \frac{1}{2} \sigma^2 \sqrt{t^* - t} \quad (1.52)$$

And by setting, $p = q + \sigma\sqrt{t^* - t}$, the integral becomes:

$$\int_{-\infty}^{-d + \sigma\sqrt{t^* - t}} e^{\left(\left[-\frac{q^2}{2} \right] (-q\sigma\sqrt{t^* - t}) \right)} dq$$

$$= \int_{-\infty}^{-d} e^{\left(\left[-\frac{q^2}{2} \right] (-q\sigma\sqrt{t^* - t}) \right)} dq = e^{\frac{\sigma^2}{2}(t^* - t)} \int_{-\infty}^{-d} e^{\left(-\frac{1}{2}(q + \sigma\sqrt{t^* - t})^2 \right)} dq \quad (1.53)$$

Finally, we have:

$$y(u, t) = e^{((r_d + \lambda_d) - (r_f + \lambda_f))(t - t^*)} e^{\left(\left(\frac{\sigma^2}{2} - ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*) \right)} e^{\frac{\sigma^2}{2}(t^* - t)} SN(d'_1)$$

$$- X e^{((r_d + \lambda_d) - (r_f + \lambda_f))(t - t^*)} N(d'_2) \quad (1.54)$$

In other words, the calla of currency option considering static information costs is presented as follow:

$$C(S, t) = S e^{-(r_f + \lambda_f)(t - t^*)} N(d'_1) - X e^{-(r_d + \lambda_d)(t - t^*)} N(d'_2) \quad (1.55)$$

with:

$$d'_1 = \frac{\ln\left(\frac{S}{X}\right) + \left(\frac{\sigma^2}{2} + ((r_d + \lambda_d) - (r_f + \lambda_f)) \right) (t - t^*)}{\sigma\sqrt{t^* - t}} \quad (1.56)$$

and

$$d'_2 = \frac{\ln\left(\frac{S}{X}\right) + \left(\left((r_d + \lambda_d) - (r_f + \lambda_f)\right) - \frac{\sigma^2}{2}\right)(t - t^*)}{\sigma\sqrt{t^* - t}} = d'_1 - \sigma\sqrt{t^* - t} \quad (1.57)$$

1.3.3. The new parity relationship and the price of a currency put considering the static information cost

The parity relationship in the presence of static information cost is:

$$C_t - P_t = Se^{-r_{1f}T} + Xe^{-r_{1d}T} \quad (1.58)$$

Here, we have the variables C representing the price of a call option, P representing the price of a put option, T denoting the time to maturity, r_{1f} representing the effective foreign (riskless) interest rate with foreign information cost, which can be calculated as $r_{1f} = r_f + \lambda_f$. Similarly, we have r_{1d} representing the effective domestic (riskless) interest rate with domestic information cost, which can be calculated as $r_{1d} = r_d + \lambda_d$.

From this relationship, we can deduct the value of European currency put in the presence of static information costs as

$$C_t - P_t = Se^{-r_{1f}T} + Xe^{-r_{1d}T} \quad (1.59)$$

$$C_t = S_t e^{-r_{1f}T} N(d'_1) - Xe^{-r_{1d}T} N(d'_2) \quad (1.60)$$

So, we can write:

$$S_t e^{-r_{1f}T} N(d'_1) - X_t e^{-r_{1d}T} N(d'_2) - P_t = S_t e^{-r_{1f}T} - X_t e^{-r_{1d}T} \quad (1.61)$$

$$\Rightarrow P_t = -S_t e^{-r_{1f}T} [1 - N(d'_1)] + X_t e^{-r_{1d}T} [1 - N(d'_2)] \quad (1.62)$$

We know that: $N(d) + N(-d) = 1$.

Furthermore, the price of the European currency put considering the static information costs is:

$$P_t = S_t e^{-r_{1f}T} N(-d'_1) + X_t e^{-r_{1d}T} N(-d'_2) \quad (1.63)$$

1.3.4. The sensitivity of the currency option price considering the static information costs to its determinants

Understanding the impact of changes in various determinants on the currency option price, considering static information costs, is crucial, particularly when devising hedging strategies for option portfolios. Traders operating in the options market navigate a world of uncertainty as option prices fluctuate with variations in their determinants. Greeks, including

Delta, Theta, Gamma, Vega, Omega and Rho, serve as indicators that quantify the sensitivity of an option's premium to specific determinants such as the underlying price, time, volatility, risk-free rate, and static information costs. These metrics assist traders in assessing and managing the risks associated with their option positions.

1.3.4.1. The Delta

The delta of a European currency call option, taking into account static information costs, quantifies the sensitivity of the option's premium to a small variation in the underlying currency's price. Mathematically, it corresponds to the slope of the curve connecting the option price and the underlying price. More precisely, the delta represents the partial derivative of the currency option's value with respect to the underlying's value. In the context of considering static information costs, the delta can be expressed as follows:

$$\Delta_c = \frac{\partial C}{\partial S} \quad (1.64)$$

$$\Delta_c = \frac{\partial C}{\partial S} = e^{-r_{1f}T} N(d'_1) = e^{-r_{1f}T} \int_{-\infty}^{d'_1} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \quad (1.65)$$

Based on the Black-Scholes model, the delta of a European call option on a non-dividend paying stock, considering static information costs, is given by:

$$\Delta_c = N(d'_1) \quad (1.66)$$

Furthermore, the delta of a European put option on a non-dividend paying stock, taking into account static information costs, is given by:

$$\Delta_p = N(d'_1) - 1 \quad (1.67)$$

The delta of a currency call option with static information costs is consistently positive and ranges between 0 and 1. This indicates a direct relationship between the currency's exchange rate and the option's premium value. Consequently, as the currency rate increases, it is expected that the premium price will also rise. This aligns with the notion that a higher currency rate would naturally entail a greater cost for the privilege of purchasing it at a fixed price. Within this context, when there is an increase (decrease) in foreign information costs, the delta increases (decreases).

The formula for calculating the delta of a currency put option, taking into account static information costs, is as follows:

$$\Delta_P = \frac{\partial P}{\partial S} \quad (1.68)$$

$$\Delta_P = \frac{\partial P}{\partial S} = -e^{-r_{1f}T} N(-d'_{11}) = -e^{-r_{1f}T} \int_{-\infty}^{-d'_{11}} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \quad (1.69)$$

The delta of a put option with static information costs is consistently negative and ranges between -1 and 0. This indicates an inverse relationship between the exchange rate of the underlying currency and the premium value. Hence, when the exchange rate of the currency increases, the premium value of the put option decreases. In this scenario, when there is an increase in foreign information costs, the delta tends to decrease. Conversely, when there is a decrease in foreign information costs, the delta tends to increase.

The delta serves as a measure of the probability that an option will be in-the-money and therefore exercisable at expiration. For an in-the-money option, the delta is nearly 1 (for a call option) or -1 (for a put option). As a result, any change in the underlying's price is reflected in the option premium. Conversely, for an out-of-the-money option, the delta approaches 0 as the likelihood of exercise is very low. Moreover, the delta also represents the hedge ratio, indicating the number of shares to be bought or sold to establish a perfect hedge. In the case of a short position in a call option, hedging with a delta hedge involves taking a long position of Δ_C units of the underlying asset. Conversely, in the case of a long position in a call option, hedging with a delta hedge involves taking a short position of Δ_C units of the underlying asset. For put options, a long position is covered by taking a long position of Δ_P units of the underlying asset, while a short position is covered by taking a short position of Δ_P units of the underlying asset (considering Δ_P as negative).

1.3.4.2. The Gamma

The gamma quantifies how sensitive the delta of an option is to changes in the underlying price. Mathematically, the gamma corresponds to the partial derivative of the delta with respect to the underlying price. In simpler terms, it can be understood as the second derivative of the option price with respect to the underlying price.

The mathematical representation of the gamma is given by: $\Gamma_C = \frac{\partial \Delta_C}{\partial S} = \frac{\partial^2 C}{\partial S^2}$ and $\Gamma_P = \frac{\partial \Delta_P}{\partial S} = \frac{\partial^2 P}{\partial S^2}$

According to the model, the gamma for a European call and put option with static information costs on a foreign currency is as follows:

$$\Gamma_c = \Gamma_p = \frac{e^{-r_{1f}T}}{S\sigma\sqrt{T}} \cdot \frac{e^{-\frac{d_1'^2}{2}}}{\sqrt{2\pi}} \quad (1.70)$$

When the gamma is low, the delta of an option exhibits relatively low sensitivity to changes in the underlying currency price. Consequently, frequent adjustments to maintain a delta-neutral portfolio may not be necessary. This results in a flat curve depicting the changes in the overall position value. Conversely, when the gamma has a high absolute value, the delta becomes highly responsive to variations in the underlying asset price. In such instances, the curve representing the portfolio value exhibits convexity if the gamma is positive and concavity if the gamma is negative. Thus, the gamma is sensitive to changes in effective foreign interest rate. Within this context, when there is an increase (decrease) in foreign information costs, the gamma increases (decreases).

1.3.4.3. The Theta

It represents the rate at which the value of the currency option with static information costs changes in relation to its life. Mathematically, this is determined using the following equation:

$$\theta_c = \frac{\partial C}{\partial T} \text{ for a currency call option.}$$

$$\text{et } \theta_p = \frac{\partial CP}{\partial T} \text{ for a currency put option.}$$

In the model that takes into account static information costs, the theta of a European call option on a foreign currency is equal to:

$$\Theta_c = \frac{\partial C}{\partial T} = -r_{1f} \cdot S e^{-r_{1f}T} N(d'_1) + r_{1d} \cdot X e^{-r_{1d}T} N(d'_2) + \frac{\sigma}{2\sqrt{T}} S \cdot e^{-r_{1f}T} \frac{e^{-\frac{d_1'^2}{2}}}{\sqrt{2\pi}} \quad (1.71)$$

Furthermore, for a currency put option considering static information costs, the theta is equal to:

$$\Theta_c = \frac{\partial C}{\partial T} = -r_{1f} \cdot S e^{-r_{1f}T} N(-d'_1) + r_{1d} \cdot X e^{-r_{1d}T} N(-d'_2) + \frac{\sigma}{2\sqrt{T}} S \cdot e^{-r_{1f}T} \frac{e^{-\frac{d_1'^2}{2}}}{\sqrt{2\pi}} \quad (1.72)$$

The theta of a call option (put option) can be divided into three components. The first component is negative (positive), while the second component is positive (negative). The second component reflects that as the option's lifetime increases, the disbursement (inflow) of the exercise price is delayed, thereby increasing (reducing) the value of the currency call option (put option). The third component is the most significant, with a positive value that is identical for both call and put options. This component represents the time value of the option and increases with maturity and information costs related to the foreign market. It implies that a holder or buyer of short-term options, which are the most liquid in the market, would experience losses (gains) as the maturity approaches, assuming all other factors remain constant. Generally, the theta of an option is negative as it loses its time value as the maturity date approaches. A parity option typically has a higher theta than an in-the-money or out-of-the-money option since it carries the highest time value.

1.3.4.4. The Vega

In practical trading, the volatility of assets tends to fluctuate, and traders must consider this source of risk when formulating their strategies. The vega serves as a measure of the sensitivity of the option value, considering static information, to changes in volatility. Mathematically, it represents the rate at which the option value changes in response to alterations in the underlying asset's volatility. This can be expressed as:

For a call option : $\vartheta_C = \frac{\partial C}{\partial \sigma}$, and for a Put option : $\vartheta_P = \frac{\partial P}{\partial \sigma}$

In the G-K model with static information costs, the Vega of both currencies call and put options is equal and positive. The formula for calculating the Vega is as follows:

$$Vega_c = Vega_p = \frac{\partial C}{\partial \sigma} = \frac{\partial P}{\partial \sigma} = Se^{-r_{1f}T} \cdot \frac{e^{-\frac{d_1'}{2}}}{\sqrt{2\pi}} \cdot \sqrt{T} > 0 \quad (1.73)$$

The Vega is at its highest level when the currency option is at parity, meaning when the strike price is equal to the current price of the underlying currency. As the options move deeper into either in-the-money or out-of-the-money territory, the Vega approaches zero. A high Vega indicates that the value of the currency option, considering static information costs, is highly sensitive to even small changes in volatility. Conversely, a low Vega suggests that the value of

the currency option, taking into account static information costs, is relatively less influenced by changes in volatility.

1.3.4.5. The Omega: sensitivity of the currency option price to changes in domestic and foreign static information costs

Mathematically, it is represented as the partial derivative of the currency option price with respect to the domestic static information costs (λ_d) and the foreign static information costs (λ_f).

Either : $\Omega_C = \frac{\partial C}{\partial \lambda}$ for a currency call option and $\Omega_P = \frac{\partial P}{\partial \lambda}$ for a currency put option.

The calculation of options on foreign currencies requires determining two Omega values for each option, whether it is a call or a put option. The first value, represented by p^{λ_d} , measures the risk associated with the domestic information costs, while the second value, represented by p^{λ_f} , measures the risk associated with the foreign information costs. The calculation of the derivatives of the currency call option and currency put option in relation to λ_d and λ_f results in the following values:

$$p_c^{\lambda_d} = \frac{\partial C}{\partial \lambda_d} = X e^{-\lambda_d T} N(d'_2) T > 0 \quad (1.74)$$

$$p_p^{\lambda_d} = \frac{\partial P}{\partial \lambda_d} = X e^{-\lambda_d T} N(-d_2) T > 0 \quad (1.75)$$

$$p_c^{\lambda_f} = \frac{\partial C}{\partial \lambda_f} = S e^{-\lambda_f T} N(d'_1) T > 0 \quad (1.76)$$

$$p_p^{\lambda_f} = \frac{\partial P}{\partial \lambda_f} = S e^{-\lambda_f T} N(-d'_1) T > 0 \quad (1.77)$$

The value of a call option increases (or decreases) with rising (or falling) domestic static information costs, primarily because it impacts the present value of the exercise price to be paid (or received). Conversely, the value of a put option behaves oppositely—it rises (or falls) with declining (or increasing) domestic static information costs. In contrast, the influence of foreign static information costs on option values follows a different pattern. Due to the concept of interest rate parity, an increase in foreign static information costs corresponds to an elevated likelihood of the underlying currency depreciating. Consequently, for a fixed exercise price, the value of the right to buy (or sell) a depreciating currency must decrease (or increase).

To assess the overall risk of an option portfolio concerning both domestic and foreign information costs, a global Omega measure can be calculated using the following formula:

$$\Omega_G = \frac{\partial V}{\partial \lambda} = \sum_i n_i \rho_i = \sum_i n_i \frac{\partial V_i}{\partial \lambda} \quad (1.78)$$

1.3.4.6. The Rhô: sensitivity of the currency option price to a variation of static information costs

The rho measures the sensitivity of the currency option price to changes in the domestic and foreign interest rates considering the static information costs. Mathematically, it is represented as the partial derivative of the currency option price with respect to the effective domestic interest rate (r_{1d}) and the effective foreign interest rate (r_{1f}).

Either : $\rho_C = \frac{\partial C}{\partial r}$ for a currency call option and $\rho_P = \frac{\partial P}{\partial r}$ for a currency put option.

The calculation of options on foreign currencies requires determining two rho values for each option, whether it is a call or a put option. The first value, represented by p^{d_1} , measures the risk associated with the effective domestic interest rate, while the second value, represented by p^{f_1} , measures the risk associated with the effective foreign interest rate. The calculation of the derivatives of the currency call option and currency put option in relation to r_{1d} and r_{1f} results in the following values:

$$p_c^{d_1} = \frac{\partial C}{\partial r_{1d}} = X e^{-r_{1d}T} N(d'_2) T > 0 \quad (1.79)$$

$$p_p^{d_1} = \frac{\partial P}{\partial r_{1d}} = X e^{-r_{1d}T} N(-d_2) T > 0 \quad (1.80)$$

$$p_c^{f_1} = \frac{\partial C}{\partial r_{1f}} = S e^{-r_{1f}T} N(d'_1) T > 0 \quad (1.81)$$

$$p_p^{f_1} = \frac{\partial P}{\partial r_{1f}} = S e^{-r_{1f}T} N(-d'_1) T > 0 \quad (1.82)$$

The value of a call option (put option) increases (decreases) with the domestic interest rate due to the decrease (increase) in the present value of the exercise price to be paid (received). Conversely, the value of the call option (put option) decreases (increases) with the foreign interest rate. In fact, due to the interest rate parity, the probability of a depreciation of the

underlying currency increases when the effective foreign interest rate increases. As a result, for a fixed exercise price, the value of the right to buy (sell) a depreciating currency must decrease (increase).

It is also possible to calculate a global rho measuring the risk of an option portfolio with respect to the domestic interest rate or the foreign interest rate. It can be given by the following formula

$$P_G = \frac{\partial V}{\partial r} = \sum_i n_i \rho_i = \sum_i n_i \frac{\partial V_i}{\partial r} \quad (1.83)$$

1.3.5. Methodology: A Differential Evolution algorithm

The basis of the differential evolution algorithm lies in evolutionary computation, where it simulates the survival of the fittest among a population of individuals. Each individual is denoted as a point in the solution space of an optimization problem (Storn 1997, Zaheer et al. 2017). The DE algorithm, being a swarm intelligence-based optimization approach, exploits the synergy between cooperation and competition among individuals to iteratively evolve and converge towards the optimal solution. Its purpose is to address multi-objective optimization problems and to discover the most favorable solution across multiple dimensions. The initialization of the population involves generating NP random variables with D dimensions (where NP represents the number of variables to generate and D signifies the dimensionality of each variable). The fitness function value is then calculated for each vector. If the conditions for obtaining the optimal parameter value are met, the algorithm terminates. Otherwise, the algorithm proceeds with mutation, crossover, and selection operations on the newly generated vector, followed by recalculating the fitness function value. These steps are repeated until the fitness function value fulfills the conditions, ultimately yielding the optimal parameter value.

In fact, individuals in the algorithm are represented by data structures known as chromosomes, specifically vectors referred to as Gen-chromosomes. Each chromosome comprises undetermined parameters p_k that correspond to the static domestic and foreign information cost parameters, denoted as $S: Gen = \{P\} = \{p_1, p_2, \dots, p_k\}, k \geq 0$. In the context of this paper, these parameters play a crucial role in currency option pricing assessment, denoted as $S (Gen)$. Consequently, a population is essentially a collection of chromosomes represented by Gen, and it establishes a corresponding set of static information costs denoted as $S (Gen)$.

The main idea of the algorithm revolves around evolutionary transformations applied to sets of chromosomes, which represent the parameters of the static information cost. This transformation is driven by natural selection, where only the fittest individuals survive. In our specific case, these individuals represent the parameters of the static domestic and foreign information costs that yield the best possible value for the objective (fitness) function.

The algorithm begins with the generation of an initial population, where all individuals are randomly created. The best individuals are then selected and preserved. To create the next generation, new solutions are formed through genetic operations, including selection, mutation, and crossover. This entire process is depicted in Figure 1 and can be summarized as follows:

- **STEP1: Population initialization**

In the D-dimensional space, a population of NP real-valued parameter vectors is generated randomly for each generation. The initial population is uniformly distributed, ensuring a general representation across the space. The value of the j^{th} dimension of the j^{th} vector is denoted as:

$$x_{i,j}^G (i = 1, 2, \dots, NP; j = 1, 2, \dots, D) \quad (1.84)$$

- **STEP2: Mutation operation**

The mutation vector is generated using the following formula:

$$H_i^{G+1} = X_1^G + F(X_2^G - X_3^G) \quad (1.85)$$

Here, H_i^{G+1} represents the i^{th} vector in the next generation. The scaling factor, denoted by F and ranging from 0 to 2, acts as a mutation operator. It controls the extent to which the deviation vector is amplified, thus influencing the algorithm's ability to find optimal solutions. A smaller F value indicates better local search capability, allowing the algorithm to explore nearby solutions effectively. Conversely, a larger F value allows the fitness function to escape local minimum points, but it can slow down the convergence speed. X_1^G , X_2^G , X_3^G represent three individuals in the population that have the best fitness function values.

- **STEP 3: Crossover operation**

To enhance the diversity of vectors within the population, an additional crossover operation is implemented:

$$V_{i,j}^{G+1} \begin{cases} H_{i,j}^{G+1}, \text{rand}(0,1) \leq CR \text{ or } j = \text{rand}(1,D) \\ X_{i,j}^{G+1}, \text{else} \end{cases} \quad (1.86)$$

when, $V_{i,j}^{G+1}$ represents the value of the j^{th} dimension in the i^{th} vector. The function $\text{rand}(0,1)$ generates random numbers within the range of $[0, 1]$. The crossover operator CR, which ranges from 0 to 1, is used. A higher value of CR leads to a faster convergence speed of the algorithm. This paper adopts a crossover operator that involves randomly selecting values within a specified range, and it is implemented as follows:

$$CR = 0.5[1 + \text{rand}(0,1)] \quad (1.87)$$

By maintaining a mean value of the crossover operator around 0.75, this approach effectively preserves the diversity within the population.

- **STEP 4: Selection operation**

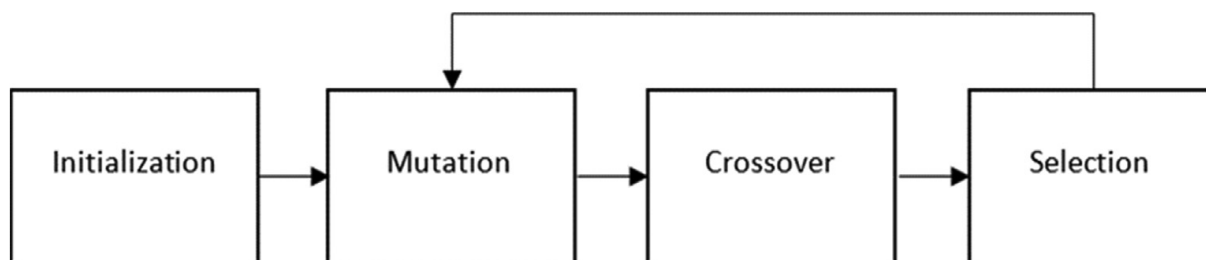
To determine whether a vector in the population qualifies for inclusion in the next generation, a comparison is made between the test vector and the current target vector. The fitness function value, $F(K)$, is then calculated for each vector. Subsequently, a selection operation is carried out based on these fitness function values.

$$X_i^{G+1} = \begin{cases} V_i^{G+1}, \text{if } F(V_i^{G+1}) < F(X_i^G) \\ X_i^G, \text{otherwise} \end{cases} \quad (1.88)$$

The chosen fitness function in this paper is:

$$F(K) = \frac{1}{n} \sum_{i=1}^n (C_i^y - C_i^M)^2 \quad (1.89)$$

with 'n' representing the sample size, C_i^y denoting the predicted currency call option price for the i-th data point, and C_i^M indicating the corresponding market currency call option price, the fitness value $F(K)$ of the K^{th} is calculated for each individual. The vector with the lowest fitness function value is selected to appear in the next generation.

Figure 1. 1. Flowchart of differential evolution algorithm

1.4. Applications

1.4.1. Data sources and variable measures

The initial step in our methodology is to collect data. Our dataset consists of daily observations of four pairs of currency call options collected from the Thomson Reuters over the period running from January 1, 2018, to November 24, 2022. The options under consideration in this study are of the European type. Daily data is employed to examine the impact of static information costs on currency option prices. A substantial sample of 1279 daily observations is utilized for each currency pair, covering multiple variables including the underlying price (S), exercise price (X), time remaining until maturity (T), risk-free domestic interest rate (r_d), risk-free foreign interest rate (r_f), volatility (σ) and market price (CM). A detailed presentation of these variables is provided in Table 1.

Table 1. 1. Variable description

Variables	Description
The price of the underlying asset S	The currency pairs included in our dataset are EUR-USD, EUR-JPY, EUR-RUB, and USD-RUB, representing the exchange rates. The closing price of the exchange rate is used because it reflects the day's market activity and serves as a reliable indicator for the currency option's valuation.
The strike price of the currency option X	The currency option strike price and its data type indicate the price at which the option is set, particularly focusing on the at-the-money level.
The time to maturity T	The remaining days until maturity is a known contractual characteristic. We calculate T as the number of days remaining divided by 360,

	representing the fraction of the year remaining until maturity.
the domestic interest rate r_d	The domestic interest rate with a constant time to maturity of 90 days is given by: LIBOR for the EUR/USD pair, TIBOR for the EUR/JPY pair and MowIBOR for the EUR/RUB and USD/RUB pairs.
The foreign interest rate r_f	The foreign interest rate by with a constant time to maturity of 90 days is given by EURIBOR for the EUR/USD, EUR/QAT, EUR/JPY and EUR/RUB pairs, and by LIBOR for the USD/RUB pair.
The volatility of the underlying asset σ	A constant maturity 3-month implied volatility related to the underlying is used. It represents the implied volatility at the at-the-money (ATM) level, with a fixed time to maturity of 90 days.
The market price CM	The observed price of a European currency call option on the market is used. It represents the market prices of the currency option series at the at-the-money (ATM) level.

1.4.2. Derivatives Pricing

This study examines the impact of information costs on the evaluation of currency call options within the G-K (1983) model framework. The introduction of static information costs introduces a level of irrationality into the model, which can influence option prices. To address this, we delve into how investor strategies are influenced by the availability of information in both domestic and foreign markets. To evaluate the performance of the G-K model in pricing currency options with static information costs, we conducted an empirical analysis. This analysis involved calculating the price of a currency call option using both the conventional G-K model and the modified version that accounts for static information costs.

In particular, our research aims to answer the following key question: Can the modified G-K model effectively reduce the evaluation errors that may arise from the standard G-K model (1983)?

Our approach will involve the following sequential steps:

- i. **Parameter Simulation:** As an initial step in implementing the new currency option pricing model, we will employ a metaheuristic approach known as Differential

Evolution to simulate the values of λ_d and λ_f . These parameters represent the static information costs associated with the domestic and foreign markets, respectively. The primary goal here is to minimize the disparity between the currency call option price projected by the new model and the market-observed price.

- ii. **Parameter Estimation:** Following the simulation of the new parameters, we will utilize them to estimate the price of the currency call option. This estimation will be performed within the G-K model, accounting for the static information costs. The computation of the currency call price necessitates input factors including the underlying price, exercise price, domestic and foreign risk-free interest rates, time to maturity (expressed as a fraction of a year), and volatility.
- iii. **Model Comparison:** To assess and compare the performance of the two models, we will utilize the mean square error (MSE) criteria. In our pursuit to gauge the effectiveness of this approach relative to the standard G-K model, we conducted a valuation error analysis using the MSE criteria across all the pairs studied in this research. Additionally, we compared the results by calculating the MSE variation and the relative change in MSE between the two models. It's noteworthy that negative MSE variation and relative change in MSE values indicate the superiority of the G-K model that accounts for static information costs over the standard G-K model. This is due to its ability to provide estimated currency option prices that closely align with market prices. To facilitate this comparison, we will define the following variables, which will require calculation:
 - C_{GK} : the price of a European currency call option calculated using the G-K model (1983) formula.
 - C_{GKSIC} : the price of a European currency call option calculated using the model in the presence of the static information costs.
 - C_M : the observed price of a European currency call option on the market.

Hence, in order to calculate the price of a currency call option using both the standard G-K model formula and the G-K model with static information costs, we have developed a Visual Basic (VBA) procedure named "Currency Call_GK" and "Currency Call_GKSIC." These procedures have been created to streamline the calculation process.

1.5. Empirical Results and Discussion

1.5.1. Calculation of Optimized Parameters and Model Analysis

In this section, we embark on a series of steps to analyze the impact of incorporating static information costs into the G-K (1983) model for currency option valuation. Our initial step involves simulating the values of λ_d and λ_f using the DE algorithm. The objective here is to minimize the disparity between the currency call option price estimated by the new model and the price observed in the market. Following this, we calculate the currency call option prices, both with and without considering static information costs. A comparative analysis of these results allows us to gauge the influence of these imperfections on the model's outcomes. Table 2 presents the static information costs for both the domestic and foreign markets concerning the currency call option pairs under study. Specifically, the data reveals that for the EUR/USD pair, the domestic static information cost is 0, while for the EUR/JPY pair, it stands at 0.76695. Similarly, for the EUR/RUB pair, the domestic static information cost is 0.72858, and for the USD/RUB pair, it reaches 0.92322. Conversely, the foreign static information costs are 0.090994 for the EUR/USD pair, 0.76606 for the EUR/JPY pair, 0.78469 for the EUR/RUB pair, and 1 for the USD/RUB pair. These findings hold notable practical significance, as they can be utilized by market participants to determine currency option prices across various strike prices. Furthermore, they offer a means to mitigate errors in the evaluation process that may arise from employing the standard G-K model (1983). It's noteworthy that our study's results align with earlier research conducted by Bellalah and Jacquillat (1995), Ben Hamad and Eleuch (2008), Zghal et al. (2020), and Dammak et al. (2023).

Table 1. 2. Domestic and Foreign Static Information Costs for Studied Currency Call Option Pairs in %

Pairs	λ_d	λ_f
EUR/USD	0	0,090994
EUR/JPY	0,76695	0,76606
EUR/RUB	0,72858	0,78469
USD/RUB	0,92322	1

Figure 2 shows the C_{GK} , C_{GKSIC} , and C_M of the selected currency call option pairs in the study. Based on the graphs displaying estimated currency call prices calculated from the G-K model, both with static information costs (CGKSIC) and without (CGK), it's evident that the values of currency call options across all studied pairs closely align with observed market prices when static information costs are incorporated. This is in stark contrast to the standard G-K model (1983), where there is a noticeable divergence from observed prices. This observation underscores the notion that factoring in static information costs can significantly enhance the accuracy of currency option valuation. By accounting for the impact of static information, which has the potential to introduce irrationality into the pricing model, we achieve a more precise valuation of currency options. The incorporation of these imperfections into the model allows us to better capture the intricacies of investor strategies, which are influenced by information availability in both domestic and foreign markets. Through simulating static information costs via the DE algorithm, the resulting currency call prices closely align with observed market prices, leading to enhanced accuracy in option valuation.

The identification of negative MSE variation and relative change in MSE values strongly supports the assertion that the G-K model, when integrated with static information costs, outperforms the standard G-K model. This superiority is particularly evident in its ability to provide currency option price estimates that closely match market prices. For a comprehensive breakdown of these findings, please consult Table 3.

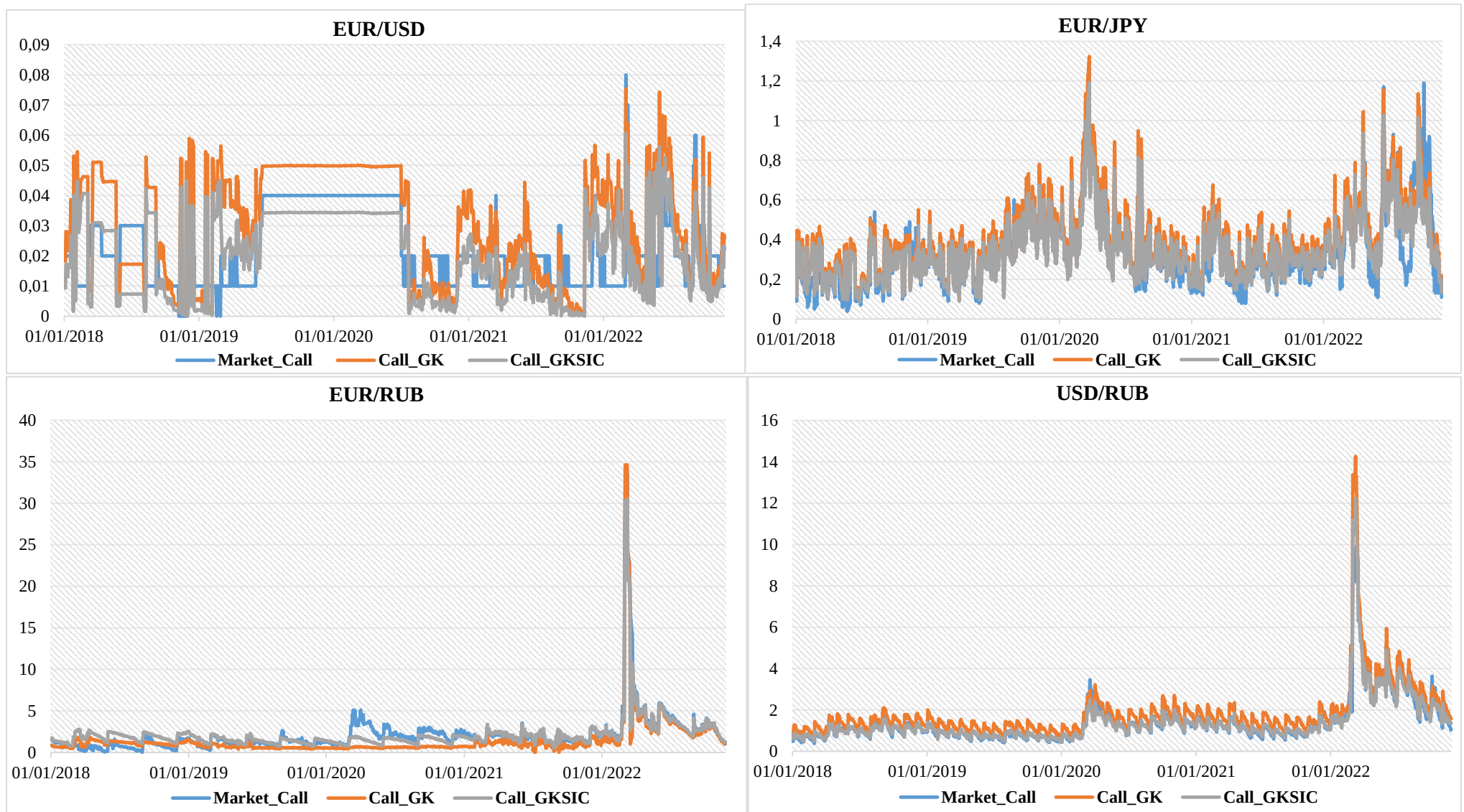
Table 1. 3. the MSE and its relative change

Pairs	MSE Call_GK	MSE Call_GKSIC	MSE Variation	Relative change in MSE in % ¹
EUR/USD	0,00029086	0,00016831	-0,00012256	-42,1359%
EUR/JPY	0,00717496	0,00553311	-0,00164185	-22,883101%
EUR/RUB	1,82885803	1,11927428	-0,70958375	-38,79928%
USD/RUB	0,30154363	0,07456212	-0,2269815	-75,273188%

¹ The relative change in the MSE in percentage is calculated as follows: $\frac{(MSE(C_{GKSIC}) - MSE(C_{GK}))}{MSE(C_{GK})} * 100$

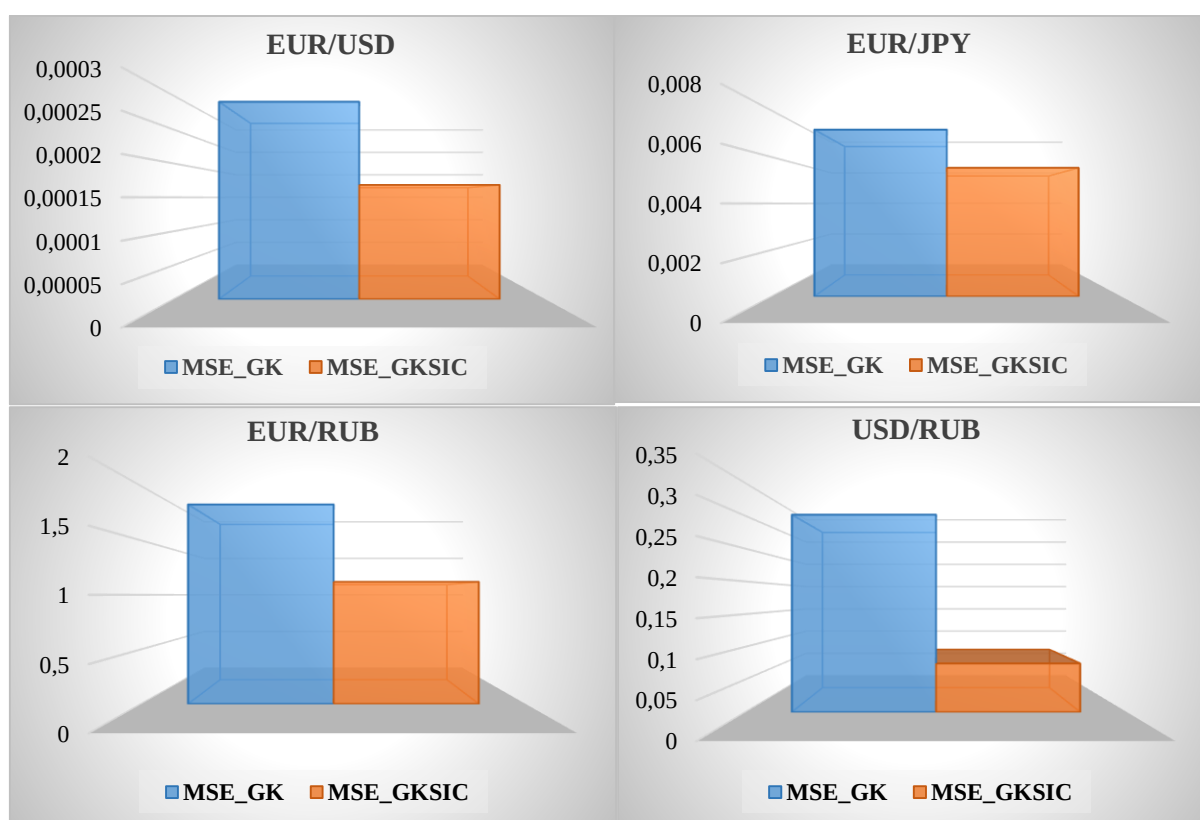
Table 3 provides a performance comparison between the G-K model, which integrates static information costs, and the standard G-K model. The results reveal a relative change in the Mean Squared Error (MSE) ranging from 23% to 75% for all the examined currency call option pairs. For instance, in the case of the EUR/RUB pair, the MSE decreased from 0.00029086 to 0.00016831, representing an approximate 42% relative change. These findings offer clear evidence that the G-K model excels when static information costs are considered, outperforming the basic G-K model (1983). Notably, the USD/RUB pair exhibited a MSE variation exceeding 75%, primarily due to its high sensitivity to market conditions, including information availability. The incorporation of static information costs into the G-K model magnifies this sensitivity, resulting in more significant fluctuations in currency call option prices. These results underline that the presence of static information costs has a more pronounced impact on the valuation of currency call options for the USD/RUB pair compared to other pairs examined in the study. Consequently, for a comprehensive assessment of the model's accuracy incorporating static information costs versus the basic G-K model, we present a comparison of their Mean Squared Error (MSE) values for the currency option pairs analyzed in this research.

Figure 1. 2. Values of the currency call option according to the GK model, GK_SIC model and the call market price for the studied pairs of the call currency options



The outcomes are visually represented in Figure 3, which effectively illustrates the enhanced performance of the G-K model when static information costs are factored in while estimating currency call options within the period spanning from January 1, 2018, to November 24, 2022. This observation solidifies the notion that static information costs exert a substantial influence on currency option valuation, and their neglect can introduce inaccuracies into the pricing model. Static information costs encapsulate the expenses borne by investors in their pursuit of gathering and processing information regarding domestic and foreign markets. Their inclusion in the pricing model contributes to a more realistic portrayal of market dynamics. The integration of static information costs into the G-K model yields notably more precise estimations of currency call options for the four pairs under examination in this research, as compared to the basic G-K model. In summary, the G-K model with static information costs emerges as a more reliable reflection of the market price for a European currency option.

Figure 1. 3. The Mean Squared Deviation (MSD) of the standard G-K model and the model taking into account the static information costs for the pairs of currency call options studied in the sample



1.5.2. Discussion and Practical Implications

In the real world, static information cost, which encompasses the expenses incurred by investors when they seek to gather and analyze information about domestic and foreign markets,

exerts a tangible impact on investment decisions and financial asset prices. Consequently, static information cost assumes a pivotal role in comprehending market trends and making informed investment choices. It's worth noting that static information cost can exhibit high volatility and rapid fluctuations in response to economic events. Therefore, investors must remain vigilant, attuned to the ever-changing landscape of static information costs, and adapt their strategies to evolving economic conditions.

In the presence of information asymmetry within the market and the presence of irrational investors, the influence of informed investors possessing positive or negative private information about underlying assets can significantly sway prices. Irrational investors, often referred to as "noise traders" in studies such as De Long et al. (1990a) and Ramiah et al. (2015), or overconfident investors in works like Daniel et al. (2002) and Abreu and Brunnermeier (2003), can cause prices to deviate from their equilibrium values, leading to increased valuation errors in environments marked by limited information. These studies have consistently revealed that valuation errors are prone to arise when rational investors interact with their irrational counterparts. Asset prices respond promptly to the arrival of new information, aligning with the principle underscored by Fama (1991) that prices reflect all available information. This underscores the paramount importance of considering investor irrationality in asset valuation and recognizing the profound impact of information availability on market prices.

However, it's essential to recognize that the foundational assumptions of the G-K (1983) model, which presume market informational efficiency and investor characteristics like risk neutrality, expected rate of return equality, and a discount rate equal to the risk-free rate, have faced challenges from research in economics and neuroeconomics. This body of research has revealed that the discount rate can be influenced by subjective factors such as beliefs, psychology, emotions, and the costs associated with acquiring information. To address these anomalies, we have introduced an effective discount rate that accommodates both factors—specifically, the real risk-free rate adjusted for the costs linked to these anomalies.

Our study has demonstrated that the incorporation of static information costs exerts a substantial impact on the valuation of currency options when utilizing the G-K (1983) model. By integrating these costs into the model, we observe a more precise valuation of currency options, one that more accurately aligns with market expectations regarding future exchange rate movements. This influence on the value of currency options becomes particularly significant, contingent on the nature of private information (whether it's positive or negative

regarding the future evolution of the underlying asset). In cases where private information is positive, we observe an increase in the price of a call option and a decrease in the price of a put option.

Ultimately, the effect of integrating static information into the valuation of currency options is subject to various intricate factors and may vary based on the specific currency and prevailing market conditions. Nevertheless, by accounting for these imperfections, the assessment of currency options attains greater precision, aligning more closely with market expectations concerning future exchange rate fluctuations.

The most crucial practical implication for both investors and policymakers is the recognition of the profound influence of static information costs on investment decisions and asset prices. Investors should be acutely aware of these costs and their potential volatility, as they can significantly affect financial outcomes. Acknowledging the impact of informed investors and the irrational behavior of market participants is also essential, as it underscores the importance of a nuanced approach to asset valuation. For policymakers, understanding the dynamic nature of static information costs and their role in market inefficiencies is vital. It highlights the need for regulatory frameworks that promote transparency, reduce information asymmetry, and enhance market efficiency. Policymakers should also consider the implications of information-related costs on discount rates and the accuracy of asset valuation when formulating economic policies.

1.6. Conclusion and Perspectives

In conclusion, our study underscores the significant impact of static information costs on currency option valuation within the G-K model (1983). The incorporation of these costs enhances the accuracy and reliability of our evaluations. Our approach amalgamates the G-K model with Merton's framework, accounting for static information costs. These costs, distinct from transaction costs, account for the substantial expenses borne by both institutional and individual investors when analyzing fundamental information to determine asset prices. Incomplete and limited information often characterizes the available data, omitting crucial details like expected return and its variability.

Our model extends the G-K model for European currency options by introducing two additional parameters calibrated to market prices. These parameters effectively address biases present in the G-K model and reduce discrepancies between model prices and market values.

Utilizing a Differential Evolution optimization method, we estimate these new parameters, resulting in a notable reduction in mean squared error and an improved accuracy in currency option valuation.

The model's optimization approach for parameter estimation offers a promising avenue to enhance currency option pricing by accounting for static information costs associated with domestic and foreign markets. These information costs represent expenses incurred by investors in acquiring and processing market information, ultimately influencing investment decisions and asset prices. Thus, vigilant monitoring of information cost trends is essential to adapt to dynamic economic conditions.

In the continuum of our research, it is imperative to acknowledge that future research prospects offer fertile ground for enhancing the accuracy of currency option valuation models. Our current findings rely on simplifying assumptions that, while necessary to establish a working framework, can be further refined. An intriguing research avenue would involve exploring the possibility of modeling volatility and interest rates more realistically, taking into account their temporal variations. Additionally, quantifying information costs more precisely remains a significant challenge, and novel methods could be developed for this purpose. Furthermore, it would be relevant to extend our model to account for market irrationality by incorporating elements of behavioral finance to better grasp market reactions to information and economic events. Another fruitful research path would be to investigate information costs in a dynamic context, analyzing how they evolve in response to specific economic and financial events. Finally, a more in-depth analysis of the microstructure of the foreign exchange market and its impact on information costs, liquidity, and bid-ask spreads could provide additional insights into understanding the complexity of currency option pricing. Overall, these future research prospects aim to enhance the accuracy of currency option valuation models and strengthen our understanding of international financial markets for the benefit of investors and policymakers.

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Chapter 2. Investor Behavior in the Currency Option Market During the COVID-19 Pandemic

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Abstract

This study investigates the COVID-19 pandemic's impact on investor behavior in the currency options market, emphasizing its relationship with underlying exchange rates. Using a sample of daily data from select futures continuous calls from September 22, 2016, to December 31, 2021, we introduce a novel variable, "market imperfections," to quantify the gap between observed and theoretical currency option prices based on the Garman and Kohlhagen model. Through the application of a Markov switching model, we identify pandemic-related changes in investor behavior, characterized by patterns of divergence and convergence. Our research distinguishes between two key behavioral types in the market: fundamentalists and chartists. This study enriches the literature by clarifying how crises, specifically the COVID-19 period, influence investor dynamics and affect market responses. Overall, we provide critical insights into the factors shaping behavior during challenging periods.

JEL classification: F37, G01, G15, G41

Keywords: Behavioural Finance; Market Imperfections; Garman and Kohlhagen's Model; Two-State Markov Switching Model; Fundamentalists and Chartists; COVID-19

2.1. Introduction

On March 11, 2020, the World Health Organization declared COVID-19 a global pandemic, setting off an unprecedented disruption to economies worldwide, including those of the USA, Europe, Russia, Japan, and Qatar. This event triggered extensive research into the pandemic's wide-ranging effects on financial markets. Zhang et al. (2020) were among the pioneers in highlighting the substantial shockwaves that COVID-19 sent through global financial markets, resulting in significant increases in market volatility worldwide. Building on these findings, Gao et al. (2021) identified the pandemic as the primary driving force behind the pronounced fluctuations in the U.S. stock market. Interestingly, in contrast to China, the U.S. market displayed reduced sensitivity to the pandemic due to a continued increase in daily cases.

Baker et al. (2020) attributed the notable reaction of the U.S. stock market to government restrictions and voluntary social distancing, underscoring the pandemic's unique impact when compared to previous global health crises. This unprecedented global crisis, as comprehensively described by Boubaker et al. (2023), resulted in simultaneous shocks with the potential to alter risk assessments and future outlooks in global finance. In alignment with this, Bossman et al. (2022) emphasized the significant influence of increasing COVID-19 cases on Real Estate Investment Trust (REIT) returns, further illustrating the far-reaching financial impact of the pandemic.

Akhtaruzzaman et al. (2021) pinpointed China and Japan as major sources of financial spillover during the turbulent phase of the pandemic. Adding to these findings, Hoshikawa & Yoshimi (2021) underscored additional challenges arising as new waves of infections contributed to heightened volatility in stock price indices and the depreciation of the South Korean won. Vuong et al. (2022) provided crucial insights into the increased transmission of volatility from China's equity market to the U.S. equity market in March 2020. Broadening the global financial perspective, Akhtaruzzaman, Abdel-Qader et al. (2021) and Zorgati & Garfatta (2021) further expanded our understanding by revealing heightened spillover effects from Chinese and U.S. financial institutions and a notable spatial contagion effect connecting China with several other countries.

Zehri (2021) offered a more expansive view of the global scene by observing heightened spillover effects from the US to East Asian stock markets during the pandemic era. This observation is complemented by further insight from Sharif et al. (2020) and Liu et al. (2020),

who emphasized the economic ramifications of COVID-19, highlighting its significant and negative influence on worldwide stock markets. The economic impact of the pandemic was further elucidated by Mishra et al. (2020) and Narayan (2020), who reported widespread negative stock returns during the COVID-19 period and a notable change in the Yen's ability to negative shocks, respectively.

When examining the financial dynamics in the early stages of the COVID-19 pandemic, research by Al-Nassar, Boubaker et al. (2023) and Akhtaruzzaman, Boubaker et al. (2023) sheds light on the roles of gold and the Oil Volatility Index (OVX) as significant hedges, potentially serving as somewhat subdued safe havens for investors. Simultaneously, Akhtaruzzaman, Boubaker et al. (2022) emphasize the heightened interconnections within cryptocurrency systemic networks, contributing to an expansion of systemic contagion channels. This insight is complemented by a focused analysis of gold's position. As per Akhtaruzzaman, Boubaker et al. (2021), gold showcased its ability as a secure asset for stock markets in the initial phase of the pandemic. These diverse roles and impacts underscore the multifaceted financial repercussions of the COVID-19 pandemic across various asset types, as demonstrated by these comprehensive studies.

Consequently, Investors experienced substantial losses within a short timeframe as a result of the COVID-19 pandemic. To address both the health and economic consequences, governments worldwide implemented a range of strategies, including lockdowns and restrictions, which had a profound impact on economic activities and financial landscapes on a global scale. Zhou et al. (2021) underscored that the repercussions of the pandemic surpassed even those of the 2009 global recession.

This global health crisis brought about significant changes in currency demand and supply, directly affecting exchange rates. The substantial shifts in the foreign exchange market, a critical component of the global financial system, garnered considerable attention from researchers and policymakers alike. Their primary objective is to comprehend and navigate the pandemic's far-reaching impact on economic growth and exchange rate stability across nations. The universal reach of COVID-19 has undeniably left a lasting impact on the economic structures of countries, underscoring the importance of a robust understanding and effective management of exchange rate dynamics during these challenging times

To comprehend the impact of pandemics such as COVID-19 on decision-making within foreign exchange markets, this study leverages the heterogeneous market participants'

hypothesis introduced by Muller (1993). This concept gains further support from the work of Bossman et al. (2022), which underscores the influence of prevailing market conditions on decision-making during the COVID-19 era. It accentuates the pivotal roles played by both types of agents in shaping dynamics within the foreign exchange market. This theory challenges the traditional assumption of uniformity among investors.

Within this framework, two primary categories of market participants emerge: fundamentalists and chartists. Fundamentalists formulate their strategies based on market fundamentals such as dividends and macroeconomic indicators, whereas chartists rely solely on past price movements for their speculative activities. Reflecting this dichotomy, studies by De Grauwe and Dewachter (1993), Vigfusson (1997), and Youssefmir et al. (1998) illustrate the dynamic interplay between chartists and fundamentalists in the foreign exchange market. Chartists have the potential to induce deviations in the exchange rate from its equilibrium value, while fundamentalists aim to align the exchange rate with fundamental economic factors. It is crucial to acknowledge the adaptability of market participants in transitioning between chartist and fundamentalist roles over time

Furthermore, this study delves into the concept of market efficiency, as initially proposed by Fama (1965), which suggests that all available information is efficiently incorporated into asset prices. Despite its theoretical significance, this notion has faced scrutiny from a growing body of research that has unveiled market anomalies and inconsistencies in financial markets. This critique against the efficiency of financial markets and the rationality of economic agents has given rise to the field of behavioral finance, which combines elements of social psychology and economic decision-making (Kahneman & Tversky, 1979; Barberis et al., 1998).

In tandem with these developments, numerous factors contribute to the evident imperfections in the market, leading to inaccuracies in evaluations. These factors encompass constraints on short selling (Feng & Fhan, 2016; Bohl et al., 2016; He et al., 2022; Duong et al., 2023), transaction and information costs (Jensen, 1978; Grossman & Stiglitz, 1980; Longjin et al., 2016; Blankespoor et al., 2020; Baek, 2022; Dammak et al., 2023), as well as issues related to asymmetric and incomplete information (Pour, 2017; Kim, 2022; Bellalah & Jacquillat, 1995). Additionally, factors like liquidity premium (Bellalah, 2006) and market sentiment (Yang et al., 2016; Zghal et al., 2020; Ryu et al., 2023) have been identified as

potential sources of market imperfections, which are further exacerbated during global crises (Arfaoui et al., 2022).

By examining the behavior and decision-making of market participants within this framework and taking into account the comprehensive array of market imperfections, this research aims to provide a comprehensive understanding of foreign exchange market dynamics during the COVID-19 pandemic.

Our perspective begins with the Garman and Kohlhagen model (1983), applied to European currency option pricing. This model is based on the assumption of market efficiency, presuming perfect rationality among economic agents and the absence of financial market imperfections. However, the theoretical currency option price derived from this model incurs a valuation error, failing to consider existing market flaws. Operating under these assumptions, individuals optimize their decisions based on available market information (Dammak et al., 2023). Despite this, the substantial growth of the options market since the 1970s, driven by factors like excessive volatility and financial crises, has prompted researchers to explore more adaptable methods beyond conventional techniques. This shift aims to ensure effective hedging for economic agents against unforeseen market movements.

The primary objective of this research is to investigate how the COVID-19 pandemic has influenced investor behavior in the currency option market and its connection with underlying exchange rates. To achieve this, we conduct an analysis using a dataset of daily data from currency call options on pairs like EUR/USD, EUR/RUB, EUR/QAT, and EUR/JPY. This dataset spans from September 22, 2016, to December 31, 2021.

Our study contributes significantly to the existing body of research. It is the first of its kind to delve into the divergence and convergence of investor behavior specifically in the currency market, focusing on both exchange rates and currency options. We introduce a novel "market imperfections" proxy variable to capture shifts in investor behavior. This proxy measures the difference between observed option prices in the market and theoretical prices based on the Garman and Kohlhagen model (1983). By thoroughly examining this variable, our study offers a comprehensive exploration of how these market imperfections might impact investor behavior, especially during periods of significant instability and uncertainty, such as the COVID-19 pandemic. To estimate market imperfections and exchange rates, we employ the two-state Markov switching model. This approach enables us to assess the diversity in investor behavior within the currency market before and during the COVID-19 pandemic.

Our research highlights the substantial impact of the COVID-19 pandemic on investor behavior, particularly emphasizing the differences between fundamentalists and chartists. We observe both behavioral convergence and divergence for the variables we studied, both before and during the COVID-19 period. This underscores the significant influence of the pandemic on investor behavior in both foreign exchange and currency options markets. Our examination of these dynamics contributes to a deeper understanding of how investors make decisions in the foreign exchange market. This insight is valuable not only for market participants but also for policymakers and regulators. It can help in effectively managing and mitigating the effects of market imperfections on financial markets

The rest of the paper is organized as follows. Section 2 provides an extensive review of the existing literature. Section 3 outlines the data used and the econometric framework employed in the analysis. Section 4 presents the empirical results and provides a discussion of their implications. Finally, Section 5 concludes the paper by summarizing the main findings, discussing the limitations of the study, and suggesting directions for future research.

2.2. Literature Review

Our literature review is divided into two subsections. Firstly, we provide an overview of the literature concerning the impact of crises on the foreign market. Secondly, we discuss the literature on behavioral finance and the heterogeneity between fundamentalists and chartists.

2.2.1. The Foreign Exchange Market (Forex) and Covid-19

The relationship between the COVID-19 pandemic and its impact on underlying exchange rates plays a pivotal role in comprehending changes in the behavior of economic agents within the foreign exchange market (Forex). Existing literature offers numerous hypotheses aimed at explaining the behavior of exchange rates.

For instance, Muth (1961) introduced the concept of rational expectations, suggesting that asset values fluctuate in response to agents' expectations of the future. MacDonald and Taylor (1992) underscored the influence of current expectations on future movements in exchange rates. Additionally, Frenkel (1981) drew attention to the transformative effect of unprecedented events and crises on the behavior of economic agents as well as exchange rates. In light of its unexpected and unparalleled nature, the COVID-19 pandemic was anticipated to exert a substantial impact on global exchange rates and the behavior of investors in the Forex

market. This recognition underscores the significance of studying the relationship between the pandemic and exchange rate dynamics.

The efficiency of foreign exchange markets and the behavior of exchange rates have been extensively studied. Fama (1970) posits that an efficient foreign exchange market accurately reflects all available information. Echoing this view, Firoj and Khanom (2018) argue that the level of information is crucial in determining market efficiency and in shaping exchange rate behaviors. The impact of the COVID-19 pandemic serves as a critical test case for these theories. Government interventions like worldwide lockdowns have significantly impacted the expectations of economic agents, consequently influencing their behavior in financial markets. Aslam et al. (2020) found that despite monetary policy adjustments made to mitigate the pandemic's impact, market fluctuations didn't align with these interventions, leading to decreased market efficiency during the outbreak. In light of Narayan's observations (2020), the Covid-19 pandemic had a significant global impact, disrupting the economy and leading to substantial changes in the supply and demand for currencies, as well as exchange rates.

The impact of the COVID-19 pandemic on exchange rate volatility has also been a prominent focus of researchers. Konstantakis et al. (2021) employed a two-regime Markov switching model to elucidate alterations in the determinants and an escalation in the volatility of the EUR/USD exchange rate during the pandemic. In addition, Corbet et al. (2021) provided further evidence, illustrating that the pandemic had a noteworthy and statistically significant effect in elevating exchange rate volatility. Taking a broader perspective, Sethi et al. (2021) conducted a comprehensive study encompassing 37 countries. They utilized metrics such as the global pandemic uncertainty index (WPUI), daily confirmed cases, and deaths. Their fixed-effects regression model revealed a positive impact of the pandemic on exchange rates and highlighted currency depreciation in emerging economies while noting currency appreciation in advanced economies. These findings collectively contribute to our understanding of how the pandemic has influenced exchange rate dynamics across the globe.

Other research extends beyond exchange rates to explore the pandemic's impact on various financial variables. Benzid and Chebbi (2020) focused on the volatility of U.S. exchange rates using Covid-19 intensity measures and found a positive and significant impact on multiple USD exchange rates. Ozturk and Cavdar (2021) expanded the scope to include variables like gold, oil prices, and Bitcoin. Using the ARMA-EGARCH model, they found statistically significant effects on the conditional variability of these financial variables. In a

similar vein, Akhtaruzzaman et al. (2021) delved into the occurrence of financial contagion during the pandemic. They observed highly volatile trading days across international stock and foreign exchange markets. Their research yields valuable insights that can aid investors, policymakers, and regulators in gaining a better understanding of the transmission of financial contagion across markets during global disruptions, such as the COVID-19 crisis.

All these studies provide an explanation for the fluctuations in exchange rates caused by the shocks of the COVID-19 pandemic. It is therefore evident that this pandemic has had a major impact on both the currency market and investor behavior.

2.2.2. Behavioural Finance and Heterogeneity Between Fundamentalists and Chartists

Because of the anomalies observed in the market, which contradict the efficiency theory, there are many opportunities for researchers in this field to find new solutions for regulation. At that time the notion of behavioral finance was emerging. In fact, in the late 1980s, several studies tried to develop new models or approaches to describe the dynamics of financial markets in a better way than the assumption of the market efficiency and the homogeneity anticipation of the agents. This led to the emergence of the agents' heterogeneity models that take into account the differences among the agents, in terms of beliefs and preferences. For their part, De Long et al. (1990) demonstrated the presence of diverse investor types in their model in which rational investors look for opportunities.

The existing body of literature highlights the presence of diverse agent types in the financial market, emphasizing the significance of models that incorporate agent heterogeneity as an alternative to the rational expectation approach. This diversity among investors allows for the categorization of various economic agents and an exploration of their respective strategies. Chiarella (2001) contributes significantly to this field by centering on asset price and wealth dynamics, shedding light on the interplay of different agents, notably fundamentalists and chartists, within a discrete-time stationary model. De Grauwe and Grimaldi (2005) echo this perspective, underscoring the utilization of simple forecasting rules by heterogeneous agents and the subsequent transition to more profitable rules based on their evaluations.

LeBaron (2006) further delves into this theme, examining the importance of investor heterogeneity in various financial contexts. Chiarella et al. (2009) build on this foundation by exploring diverse risk preferences and expectations among agents, moving beyond the confines

of a homogeneous rational expectation framework. They emphasize the pivotal role of information and beliefs in shaping agents' expectations. Nappo et al. (2023) bridge theory and practice by establishing a link between traders' heterogeneous expectations and the emergence of the implied volatility skew. Additionally, Owusu Junior et al. (2021) explore the complex transmission of information during the COVID-19 pandemic and its implications for investor behavior and global equity markets. These collective contributions enrich our understanding of agent diversity and its profound impact on financial markets

The literature on trading behaviors often categorizes traders into two main groups: fundamentalists and chartists. Fundamentalists base their decisions on underlying economic factors, whereas chartists prioritize patterns in historical price movements. This conceptual framework was initially proposed by Frankel and Froot (1990) and has since been enriched by subsequent studies. Brock and Hommes (1998, 2001) introduced a dynamic element to this framework, suggesting that agents can transition between being fundamentalists and chartists based on their performance. This dynamic aspect adds complexity and non-linearity, challenging traditional models that assume fixed and homogenous agents. Shiller (2015) further nuanced this concept by presenting a model that incorporates both rational and irrational agents, acknowledging the presence of rational investors in historical periods.

Empirical support for these ideas was provided by Westerhoff and Reitz (2003) and Boswijk et al. (2007), who demonstrated disruptions in the fundamentalist regime and confirmed the heterogeneity between the two groups. Hommes (2017) centered their analysis on these primary types of agents, offering insights into their distinct market beliefs and behaviors. Li & Miu (2022) expanded on this exploration by identifying new factors that influence the ratio of fundamentalists to chartists in the market. Collectively, these diverse studies contribute to a comprehensive understanding of the nature and role of behavioral agents in financial markets. They underscore the importance of recognizing these varied perspectives and approaches in market analysis and prediction

In a similar vein to these studies, the influence of heterogeneous beliefs on option pricing has been explored. Guo (1998) was among the pioneers to integrate this heterogeneity into option pricing, identifying two groups based on their outlook: bulls and bears. Shefrin (2001) further delineated how such diversity could prompt deviations from the Black-Scholes model. His study elucidated that the equilibrium price of an option is a weighted average of

diverse opinions, which assists in explaining phenomena like the "smile" observed in implied volatilities.

Several studies have expanded our understanding of market dynamics by examining how traders with diverse perspectives are attracted to various types of options. Research by Benninga and Mayshar (2000) and Buraschi and Jiltsov (2006) has shown how traders' differing views lead them to gravitate towards specific options. The concept of heterogeneous beliefs extends to foreign currency option markets and their underlying markets as well. Rzepkowski (2001) and Ziegler (2002) provided empirical evidence supporting the idea that traders hold varying levels of confidence and distinct outlooks regarding future exchange rates and dividends, respectively.

Frijns et al. (2010) took this a step further by developing a model for the option market that accounted for the presence of different types of agents and their shifting behaviors. Kawakubo et al. (2014) explored how these diverse expectations played out between the option market and its underlying asset market, shedding light on the impact of factors like volatility mean reversion and the presence of chartists on option pricing. Lastly, Boutouria et al. (2020) refined the classic Black and Scholes (1973) model by incorporating sentiment, reaffirming the persistent market heterogeneity between fundamentalists and chartists. These studies collectively contribute to a deeper understanding of how market participants with varying beliefs and behaviors interact within financial markets.

2.3. Data and Methodology

2.3.1. Sample and Data Description

The aim of our study is to analyze changes in investor behavior within the currency options market. To achieve this, we utilize a comprehensive database comprising continuous currency option series for the EUR/USD, EUR/RUB, EUR/QAT, and EUR/JPY pairs provided by Thomson Reuters. Unlike individual series, the continuous series do not expire until the corresponding option class expires. Our sample encompasses 1378 daily observations of continuous call options on the aforementioned currency pairs traded on the Russian Trading System. The data spans from September 22, 2016, to December 31, 2021. It is important to note that these foreign currency options follow the European type. We have gathered a range of data for our analysis, the underlying price (S), the option strike price (X), the current date, the number of days remaining to maturity (T), the price of the currency call option (Price), the

implied volatility at 3 months, the transaction volume, the foreign interest rate (EURIBOR) for each currency pair in our sample, and domestic interest rates (LIBOR, MowIBOR, TIBOR and QIBOR for EUR/USD, EUR/RUB, EUR/JPY, and EUR/QAT pairs respectively).

The use of currency options relies on the premise that individual behavior changes during periods of crisis, and investor behavior may vary depending on the study period (pre-crisis or post-crisis). To examine investor behavior before and during the COVID-19 health crisis, we divided the sample into two sub-periods based on criteria established by the World Health Organization (WHO), Zhang et al. (2020), and GAO et al. (2021):

- Pre-Covid-19: our sample is composed of 904 daily observations of futures continuous call on the studied pairs from 22 September 2016 to 10 Mars 2020.
- During Covid-19, our sample is composed of 474 daily observations of futures continuous call on the studied pairs from 11 Mars 2020 to 31 December 2021.

2.3.2. Methodological Issues

Firstly, we calculated a proxy variable named market imperfections², which represents the difference between the theoretical price of the currency option according to the GK (1983) model³ and the price observed on the market. This variable helps to evaluate the importance of the investors' behaviour in the currency option market and deduce the behavioural typology that characterizes the strategies of the fundamentalists and the chartists. Subsequently, we used the Markov switching model to analyse the heterogeneity between the fundamentalists and the chartists in the currency options market before and during the Covid-19. However, the traditional assumption made by Garman and Kohlhagen (1983)⁴ suggests that the market is efficient, investors are rational, and market imperfections are not considered in their model. In reality, markets are often inefficient, and investors can display irrational behaviour, leading to

² The introduction of market imperfections in the currency option valuation formula, led to theoretical prices closer to the market price.

³ The equation of call price can be written as follow: $C_t = S_t e^{-r_f \tau} N(d_1) - X e^{-r_d \tau} N(d_2)$, where: $d_1 = \frac{\ln(S/X) + (r_d - r_f)\tau + \frac{1}{2}\sigma^2\tau}{\sigma\sqrt{\tau}}$

and $d_2 = d_1 - \sigma\sqrt{\tau}$. To facilitate the calculation of the currency call option price according to this formula, we have developed a procedure on Visual Basic (VBA), named Currency Call_GK.

⁴Garman-Kohlhagen model (1983) is a pricing model used to determine the fair price for a currency call option or a currency put option based on the following variables: type of option, strike price, underlying exchange rate price, volatility, time, strike price, domestic risk-free rate and foreign risk-free rate. This model was employed to the case of European currency call option.

valuation errors. To account for this, we propose using this proxy variable to validate the presence of heterogeneous investor behaviour during the study period.

4.3.2.1. Specification and Diagnostic Test: Unit Root Test

For this purpose, the Augmented Dickey-Fuller (1979) test was employed, consisting of three equations to test for unit roots.

- No constant, no trend: $\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^n \alpha_i \Delta y_{t-i} + \varepsilon_t$ (2.1)

- Constant, no trend: $\Delta y_t = C + \gamma y_{t-1} + \sum_{i=1}^n \alpha_i \Delta y_{t-i} + \varepsilon_t$ (2.2)

- Constant and Trend: $\Delta y_t = C + \gamma y_{t-1} + \delta_t \sum_{i=1}^n \alpha_i \Delta y_{t-i} + \varepsilon_t$ (2.3)

4.3.2.2. Econometric Methodology: Two State Markov Switching Model

The primary aim of this paper is to investigate the diversity in behavior exhibited by economic agents within the currency market. We hypothesize that this behavior may undergo changes during times of crisis. In our empirical analysis, we have identified the Markov Switching model as a highly suitable tool for detecting these shifts in behavior.

Markov Switching models are conventionally employed to account for structural breaks that can significantly alter the trajectory of variables. They operate on the principle that the likelihood of transitioning to a particular regime is dependent on past observations of the variables of interest (Engel and Hamilton, 1990). Furthermore, owing to the dynamic nature of transition probabilities in Markov models, they enable the calculation of probabilities associated with future regime realizations and the prediction of future values of the endogenous variable, regardless of the prediction horizon's duration. This approach initially took shape with the pioneering work of Goldfeld and Quandt (1973) and has since been expanded upon and refined by Hamilton (1989, 1990, and 1994).

We applied this model⁵ to study the change in beliefs between the fundamentalists and the chartists in the currency market. We used variable named market imperfections, which represents the valuation errors of the theoretical model of Garman and Kohlhagen (1983) and helps to detect the change in the investors' behaviour between the chartists and the fundamentalists following the Covid-19 health crisis. Therefore, we have taken into account an

⁵ We consider in this paper the two states, Markov switching models, as we have divided investors in two types: fundamentals and chartists. These models allow greater flexibility to accommodate for different behaviors in the time series data.

autoregressive two-regime Markov switching model of order p , denoted $MS(2) - AR(p)$, which is presented as follows:

$$X_t - \mu(S_t) = \varphi_1[X_{t-1} - \mu(S_{t-1})] + \varphi_2[X_{t-2} - \mu(S_{t-2})] + \dots + \varphi_p[X_{t-p} - \mu(S_{t-p})] + \varepsilon_t \quad (2.4)$$

Where: $\varphi_1, \varphi_2 \dots \varphi_p$ represent the coefficients of the process $AR(p)$, $\varepsilon_t \sim iid(0, \sigma_\varepsilon^2)$ and $\mu(S_t)$ are constants which depend on the states / regimes (S_t) and represent:

- μ_1 : if the process is in state / regime 1 ($S_t = 1$) for fundamentalist
- μ_2 : if the process is in state / regime 2 ($S_t = 2$) for chartist

The transition from one state to another is governed by the first-order Markov chain of state S with transition probabilities that can be expressed as:

$$p_{ij} = p(S_t = j | S_{t-1} = i), i, j = 1, 2 \quad (2.5)$$

where p_{ij} presents the probability of going from state i at time $t - 1$ to state j at time t , using the fact that:

$$p_{1i} + p_{2i} = 1 \quad (2.6)$$

In this study, two states are assumed and the underlying $MSIAH(2) - AR(p)$ model is given by:

$$X_t = \begin{cases} c_1 + \sum_{i=1}^p \varphi_{1,i} X_{t-i} + \varepsilon_{1,t} & \text{with } S_t = 1 \\ c_2 + \sum_{i=1}^p \varphi_{2,i} X_{t-i} + \varepsilon_{2,t} & \text{with } S_t = 2 \end{cases} \quad (2.7)$$

The $MSIAH - AR$ can be used to obtain the value of the observed regime, S_t , through the observed behavior of X_t .

4.3.2.3. Test for Linearity in MS Models: The Hansen Test

Hansen (1992, 1996) presents a theoretical framework for hypothesis testing that enables the evaluation of linearity in the presence of nuisance parameters and scores that are zero under the null hypothesis, as observed in MS models. In this framework, the likelihood function is viewed as a function of unknown parameters, and the empirical process theory is utilized to establish bounds on the asymptotic distribution of a standardized LR statistic. Our

objective is to test the adequacy of a linear model compared to a specified non-linear model and the null hypothesis can be presented as:

$$H_0 : \text{linear model} \text{ vs } H_1 : \text{nonlinear model} \quad (2.8)$$

2.4. Empirical Results

2.4.1. Data Analysis

Table 1 provides a summary of key statistics for various variables, including daily exchange rates, call options calculated using Garman and Kohlhagen's model (1983), observed market call options, and the daily proxy for the market imperfections (MI) variable. These variables pertain to futures continuous calls on the EUR/USD, EUR/RUB, EUR/QAT, and EUR/JPY pairs, spanning from September 22, 2016, to December 31, 2021. The study period is further divided into two distinct sub-periods: the pre-Covid-19 period, comprising 904 observations, and the Covid-19 period, consisting of 473 observations. The table reveals that most variables exhibit significant variation between their minimum and maximum values. Additionally, all skewness coefficients differ from zero, indicating that these variables possess asymmetric distributions. Furthermore, kurtosis coefficients vary, with some indicating thick-tailed distributions (playkurtotic) and others suggesting leptokurtosis, characterized by fatter tails. It is evident from these observations that the variables do not follow a Gaussian distribution, thus corroborating the results of the Jarque Bera test.

To assess the stationarity of the variables, the Augmented Dickey Fuller (ADF) test was employed. The results demonstrate that the application of the first difference procedure to non-stationary variables achieved stability.

From figure 1, we observe a significant change in the quotations of the different exchange rate pairs studied from the end of 2019. This change is due to the spread of the Covid-19 pandemic in the world, which became more serious on March 10, 2020 when the World Health Organization (WHO) declared the covid-19 as a global pandemic.

From figure 2, we observed a significant change in the studied proxy variable from the end of 2019, especially for the EUR/USD and the EUR/RUB pairs when the Covid-19 appeared at the end of 2019.

Variable	Mean	Max	Min	Std.Dev	Skewness	Kurtosis	J-B	Prob	ADF
Pair 1 : EUR /USD Futures Continuous Call									
Panel 1 : EUR/USD Pre-Covid-19									
MI	-0.003	0.026	-0.028	0.009	-0.396	2.879	24.165	0.000	-3.619**
S	1.136	1.251	1.039	0.047	0.309	2.623	19.751	0.000	-1.535
Call-GK	0.020	0.041	0.001	0.008	0.026	2.908	0.417	0.812	-
Call-Mkt	0.023	0.040	0.000	0.012	0.253	1.821	61.954	0.000	-
Panel2 : EUR/USD During Covid-19									
MI	-0.002	0.012	-0.030	0.010	-1.424	4.370	196.872	0.000	-2.680**
S	1.168	1.233	1.069	0.040	-0.709	2.607	42.693	0.000	-1.383
Call-GK	0.017	0.040	0.004	0.006	1.000	4.322	113.309	0.000	-
Call-Mkt	0.019	0.040	0.010	0.011	0.921	2.516	71.429	0.000	-
Pair 2 : EUR / QAT Futures Continuous Call									
Panel 3 : EUR/QAT Pre-Covid-19									
MI	0.147	1.221	-4.811	1.095	-3.259	13.586	5821.108	0.000	-5.005**
S	156.467	172.800	145.000	6.794	0.649	2.255	84.428	0.000	-0.281
Call-GK	1.134	2.183	0.539	0.239	0.560	3.540	58.175	0.000	-
Call-Mkt	0.988	5.650	0.020	1.110	2.997	12.170	4520.533	0.000	-
Panel 4 : EUR/QAT During Covid-19									
MI	0.037	1.210	-6.782	1.478	-3.959	17.781	5541.490	0.000	-3.441**
S	165.519	171.800	158.000	3.254	-0.632	2.248	42.637	0.000	-2.628
Call-GK	1.098	2.332	0.546	0.281	1.123	4.969	175.766	0.000	-
Call-Mkt	1.061	7.830	0.020	1.516	3.834	16.997	5020.286	0.000	-
Pair 3 : EUR / RUB Futures Continuous Call									
Panel 5 : EUR/RUB Pre-Covid-19									
MI	1.062	3.726	-1.471	0.714	0.722	3.443	85.939	0.000	-3.965**
S	72.434	85.500	60.500	5.390	0.013	2.478	10.304	0.006	-0.999
Call-GK	2.276	4.106	0.698	0.785	0.129	2.078	34.509	0.000	-
Call-Mkt	1.214	4.611	0.015	0.522	0.352	4.673	124.109	0.000	-
Panel 6 : EUR/RUB During Covid-19									
MI	0.498	2.518	-2.292	0.870	-0.628	3.194	31.852	0.000	-3.848**
S	87.341	94.250	78.000	4.022	-0.629	2.379	38.743	0.000	-2.067
Call-GK	2.559	5.009	0.781	0.853	0.165	2.452	8.077	0.018	-
Call-Mkt	2.061	5.091	0.253	0.791	1.016	4.769	143.099	0.000	-
Pair 4 : EUR / JPY Futures Continuous Call									
Panel 7 : EUR/JPY Pre-Covid-19									
MI	0.048	0.409	-0.386	0.167	-0.132	1.935	45.328	0.000	14.686**
S	151.573	155.500	149.500	1.424	0.835	2.708	108.147	0.000	-1.009
Call-GK	0.340	0.941	0.116	0.122	0.633	4.032	100.522	0.000	-
Call-Mkt	0.292	0.930	0.040	0.141	0.712	3.492	85.615	0.000	-
Panel 8 : EUR/JPY During Covid-19									
MI	0.056	0.384	-0.605	0.157	-0.408	2.926	13.219	0.001	15.049**
S	151.874	155.000	150.500	0.485	0.715	7.901	513.736	0.000	-5.811**
Call-GK	0.380	1.361	0.108	0.163	1.831	8.622	887.220	0.000	-
Call-Mkt	0.324	1.290	0.080	0.182	2.123	8.732	1003.030	0.000	-

Table 2. 1. Descriptive statistics and non-stationarity tests of the sample

Notes: The table reports descriptive statistics for the daily exchange rate ‘S’, the daily market imperfections proxy variable ‘MI’, the theoretical currency call price according to the Garman and Kohlhagen model (1983) ‘Call-GK’ and the currency call price observed on the market of the EUR/USD, EUR/RUB, EUR/QAT and EUR/JPY pairs from 22 September 2016 to 31 December 2021. Max., Min. and Std. Dev. denote respectively the maximum, the minimum and the standard deviation. J-B is Jacque Berra test. Prob is the Probability. Then, the Augmented-Dickey Fuller is a unit root test that inform about the stationarity of the time-series with a null hypothesis of the presence of a unit root in the process. *, ** and *** refer to the statistical significance at respectively 10%, 5% and 1% levels.

Figure 2. 1. Daily exchange rates for the four pairs of currencies over the entire study period, from 22 September, 2016 to 31 December, 2021

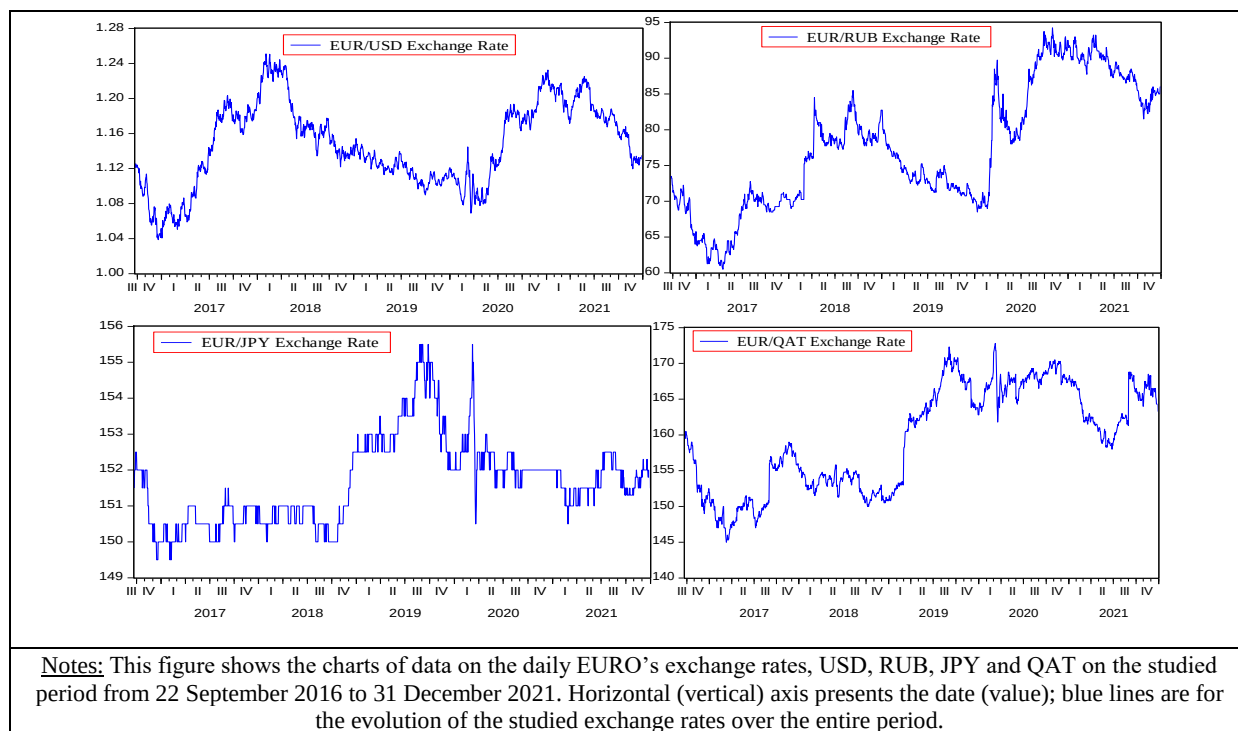
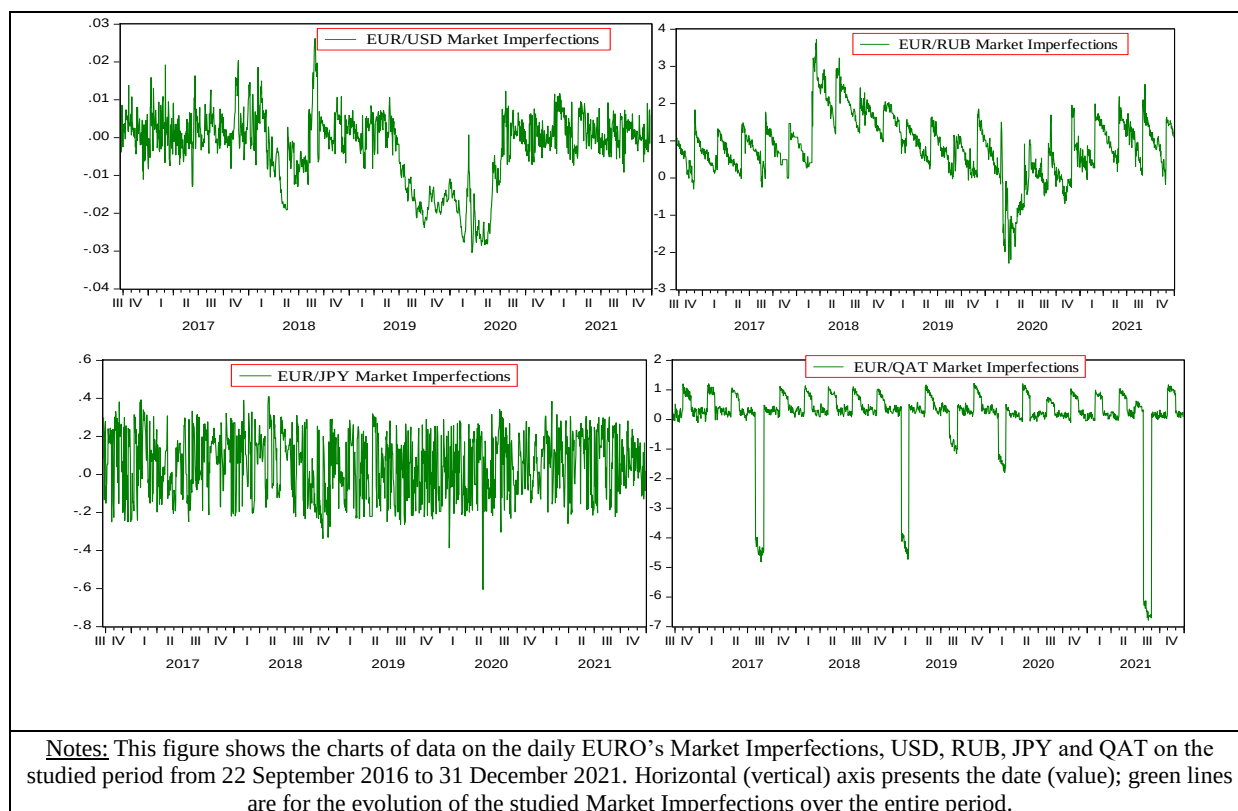


Figure 2. 2. Daily market imperfections for the four pairs of currencies over the entire study period from 22 September 2016 to 31 December 2021.



2.4.2. Empirical Findings

For the exchange rate, we use the Markov switching model in which we specify a $MSIH(2) - AR(0)^6$ process for both periods where we have assumed common variance for each regime and no autoregressive lags in order to avoid the replication and degradation of the stylised facts of the cycles.

Table 2. 2. Markov switching estimation results of the Exchange rate

	μ_1	μ_2	σ_1	σ_2	ρ_{11}	ρ_{22}	ρ_{12}	ρ_{21}	Duration State1	Duration State2	Linearity test
Pair 1 : EUR /USD Exchange rate											
EUR/USD Pre-Covid-19	1.1071**	1.187**	0.0268	0.028	0.9982	0.9969	0.0018	0.0031	568.01	327.2	971.0484**
EUR/USD During Covid-19	1.1218**	1.1929**	0.02666	0.0173	0.9939	0.9967	0.0061	0.0033	163.24	307.22	626.5562**
Pair 2 : EUR / QAT Exchange rate											
EUR/QAT Pre-Covid-19	152.02**	164.52**	2.6527	4.0244	0.9966	0.9938	0.0034	0.0062	290.4	160.66	1393.4353**
EUR/QAT During Covid-19	161.24**	167.46**	1.5963	1.4603	0.9862	0.9908	0.0138	0.0092	72.55	108.58	683.9123**
Pair 3 : EUR / RUB Exchange rate											
EUR/RUB Pre-Covid-19	69.537**	78.969**	3.5147	2.2291	0.9968	0.9964	0.0032	0.0036	313.36	275.08	993.2831**
EUR/RUB During Covid-19	84.051**	90.566**	3.0273	1.4026	0.9955	0.9955	0.0045	0.0045	220.85	224.43	615.3981**
Pair 4 : EUR / JPY Exchange rate											
EUR/JPY Pre-Covid-19	150.54**	153.08**	0.4004	0.9669	0.9981	0.9973	0.0019	0.0027	534.2	367.23	1620.6010**
EUR/JPY During Covid-19	151.39**	152.14**	0.2742	0.3564	0.9625	0.9778	0.0375	0.0222	26.66	44.95	292.9489**
Notes: The table displays the estimation of the Markov switching models for the exchange rate during the two study periods. μ_1 , μ_2 , σ_1 , σ_2 , ρ_{11} , ρ_{22} , ρ_{12} and ρ_{21} are respectively the estimated coefficients of the intercepts of state 1 and 2, the standard errors of state 1 and 2, the probabilities of staying in the same regime and the probabilities of switching from one regime to another. ** indicates that the null hypothesis is not accepted at 5% significance level.											

In Table 2, we conduct a test to assess the null hypothesis regarding the uniformity of investors' beliefs regarding the exchange rate for the four currency pairs studied, both before and during the Covid-19 pandemic.

Upon examination, it becomes evident that the null hypothesis proposed by the linear model is rejected. This rejection signifies the presence of non-linearity in the data, a characteristic attributed to inherent asymmetries within the time series. These asymmetries further emphasize the distinction between fundamentalists and chartists in the foreign exchange

⁶ The two - state Markov switching intercept heteroscedasticity model.

market. It suggests that each group adopts a specific strategy tailored to these underlying asymmetries.

Additionally, we identify significant disparities between the chartist and fundamentalist regimes. The results align with the findings of Menkhoff et al. (2009) and are supported by the positive and statistically significant coefficients of the intercepts, probabilities, and standard errors. These outcomes corroborate the existence of differential behaviors between chartists and fundamentalists within the foreign exchange market, consistent with the study by Chen et al. (2020).

Before the covid-19, we obtained the following results. For the EUR/USD pair, the first regime (fundamentalist) exhibited higher volatility compared to the second regime (chartist), with the first regime having a longer duration than the second regime. Concerning the EUR/QAT pair, the second regime displayed greater volatility than the first regime, while the first regime had a longer duration in comparison to the second regime. In the case of the EUR/RUB pair, the first regime demonstrated higher volatility than the second regime, and the duration in the first regime exceeded that in the second regime. Finally, for the EUR/JPY pair, the second regime exhibited higher volatility than the first regime, with the first regime having a longer duration than the second regime.

Conversely, during the Covid-19 pandemic, our observations reveal the following dynamics. For the EUR/USD pair, the first regime (fundamentalist) continues to exhibit higher volatility than the second regime (chartist), while the duration in the second regime surpasses that in the first regime. Regarding the EUR/QAT pair, the first regime maintains higher volatility than the second regime, but the duration in the first regime shortens in comparison to that of the second regime. In the case of the EUR/RUB pair, the first regime remains more volatile than the second regime, while the duration in the second regime extends beyond that in the first regime. Lastly, for the EUR/JPY pair, the second regime consistently exhibits higher volatility than the first regime, and the duration in the second regime becomes longer than that in the first regime.

In summary, our comprehensive analysis of the four studied currency pairs revealed the presence of two distinct regimes in each period examined. Notably, our estimations indicated that during the pre-Covid-19 period, fundamentalists exhibited greater persistence in their behavior compared to chartists. However, this pattern underwent a significant reversal during the Covid-19 period, with investors adopting chartist strategies characterized by higher

persistence than fundamentalists. This outcome serves as compelling evidence of the profound influence of the pandemic on investor behavior within the foreign exchange market.

Furthermore, our research unveiled a striking heterogeneity in the behaviors of chartists and fundamentalists. Remarkably, during the health crisis, investors experienced a sudden and substantial shift in their strategies, a phenomenon observed across different exchange rate pairs. This phenomenon highlights the adaptability of market participants in response to information shortages and heightened uncertainty.

Therefore, our findings firmly reject the null hypothesis that posits uniformity in beliefs within the foreign exchange market. Instead, our results align with the existing financial literature, underlining the significance of the heterogeneous market hypothesis, as evidenced by studies such as those conducted by Li and Miu (2022), Owusu Junior et al. (2021), Hommes (2017), Dick & Menkhoff (2013), and De Jong et al. (2010). Moreover, our research aligns with empirical studies emphasizing the diverse and heterogeneous impacts of COVID-19 on financial markets, as exemplified by Bossman et al. (2022) and Hashmi et al. (2021).

In our analysis of market imperfections, we employed the Markov-switching model, specifically specifying an $MSIH(2) - AR(0)$ process for both periods. We assumed a common variance for each regime, except for the EUR/USD pair during the Covid-19 period and the EUR/QAT pair during the pre-Covid-19 period. In these exceptional cases, we utilized the Markov-switching model with an $MSI(2) - AR(0)$ specification, also assuming a common variance for the two regimes. Therefore, for both estimation models, no autoregressive lags are included to prevent the replication and degradation of the stylized facts of the cycles (Ferrara, 2003).

Our modeling approach deliberately excluded autoregressive lags to prevent the replication and degradation of the stylized facts of market cycles. The results of our estimation of the Markov-switching models for market imperfections during the two study periods are presented in Table 3.

In line with our research objectives, we initially tested the null hypothesis, examining the homogeneity of investors' beliefs regarding the proxy variable (market imperfections) for the four currency pairs across the two sub-periods. Notably, our findings revealed a rejection of the null hypothesis, decisively confirming the presence of heterogeneity in the beliefs of fundamentalists and chartists within the currency options market. These results align with our

expectations and are further substantiated by the significant coefficients of the intercepts, probabilities, and standard errors, which collectively support the existence of this heterogeneity.

These results provide valuable insights into the distinct beliefs and strategies employed by fundamentalists and chartists in the currency options market, underlining the complexity and diversity of investor behavior in this context.

During the Covid-19 pandemic, our analysis revealed significant findings regarding the behavior of the different regimes for the four currency pairs. For the EUR/USD pair, we observed that regime 1 (fundamentalists) exhibited higher volatility compared to regime 2 (chartists). However, regime 2 displayed greater persistence than regime 1. In the case of the EUR/QAT pair, both regime 1 and regime 2 demonstrated similar levels of volatility. However, regime 2 exhibited higher persistence compared to regime 1. For the EUR/RUB pair, regime 1 displayed greater volatility than regime 2. Conversely, regime 2 exhibited higher persistence than regime 1. Regarding the EUR/JPY pair, we found that regime 2 was characterized by higher volatility than regime 1. However, regime 2 also displayed greater persistence compared to regime 1, with shorter durations for both regimes.

These observations shed light on the nuanced dynamics of investor behavior in response to the Covid-19 pandemic within the context of these currency pairs. The variations in volatility and persistence between fundamentalists and chartists highlight the complex interplay of factors influencing their strategies and decisions during this unprecedented global crisis.

In contrast, our analysis during the Covid-19 pandemic yielded different results for the behavior of the different regimes in the four currency pairs. For the EUR/USD pair, we found that both regime 1 and regime 2 exhibited similar levels of volatility. However, the persistence of investors' behavior was predominantly observed in regime 1. In the case of the EUR/QAT pair, a notable shift occurred during the pandemic. Regime 2 became more volatile than regime 1, and the persistence of investors' behavior switched from regime 2 to regime 1. For the EUR/RUB pair, there was a reversal in both volatility and persistence. Regime 2 displayed higher volatility, while investors' persistence was primarily observed in regime 1 during the Covid-19 period. Regarding the EUR/JPY pair, regime 2 continued to exhibit higher volatility than regime 1. However, investors' persistence shifted to regime 1, with relatively short durations for both regimes.

These findings underscore the dynamic nature of investor behavior, particularly during the Covid-19 crisis, highlighting significant shifts in volatility and persistence patterns among fundamentalists and chartists in these currency pairs. The pandemic-induced uncertainties appear to have influenced investors' strategies and decisions in unique ways, reflecting the evolving nature of financial markets during such challenging times.

Based on the findings obtained from our analysis, our research confirms the presence of two distinct regimes in each of the study periods, indicating that investors' behavior in the currency option market exhibits a dynamic and changing nature over time. Interestingly, when examining the proxy variable known as "market imperfection," our results show a reversal in estimates compared to those for the exchange rate. Specifically, during the pre-Covid-19 period, investors' persistence was higher among chartists than fundamentalists, but this pattern reversed during the Covid-19 period. This abrupt shift in strategy across the four currency pairs underscores the significant impact of the health crisis on investor behaviors in the currency option market. These findings strongly support the notion that market imperfections, such as information costs and market sentiment, play a substantial role in shaping investor strategies. The Covid-19 pandemic acted as a catalyst for changing investor behavior, highlighting the phenomenon of strategy adaptation within the currency options market.

Based on the observed heterogeneity in behavior, we reject the null hypothesis that posits uniform investor behavior in the currency option market. Our results align with the existing financial literature, which emphasizes the diverse and heterogeneous nature of options markets, as evidenced by studies like Nappo et al. (2023), Li et al. (2023), Boutouria et al. (2020), and Frijns et al. (2010). These findings contribute to a deeper understanding of the intricacies of options markets and highlight the need to consider the evolving strategies of market participants when analyzing currency options.

Table 2. 3. The Markov-switching estimation results of the market imperfections

	μ_1	μ_2	σ_1	σ_2	ρ_{11}	ρ_{22}	ρ_{12}	ρ_{21}	Duration State1	Duration State2	Linearity test
Pair 1 : EUR /USD Futures Continuous Call											
EUR/USD Pre-Covid-19	-0.0165**	0.0016**	00.0859	0.0455	0.9831	0.9955	0.0169	0.0045	59.12	220.76	939.5392**
EUR/USD During Covid-19	0.0011**	-0.0219**	0.0308	0.0308	0.9955	0.9823	0.0045	0.0177	223.001	56.5	666.6526**
Pair 2 : EUR / QAT Futures Continuous Call											
EUR/QAT Pre-Covid-19	-4.3183**	0.3697**	0.0467	0.0467	0.9525	0.9977	0.0475	0.0023	21.04	440.02	1969.4314**
EUR/QAT During Covid-19	0.3544**	-6.4793**	0.0335	0.1517	0.9979	0.9527	0.0021	0.0473	470.18	21.14	1400.5342**
Pair 3 : EUR / RUB Futures Continuous Call											
EUR/RUB Pre-Covid-19	1.7904**	0.6177**	0.0399	0.0344	0.9744	0.9856	0.0256	0.0144	39.1	69.48	860.8896 **
EUR/RUB During Covid-19	0.9708**	0.4468**	0.0447	0.0584	0.9907	0.9833	0.0093	0.0167	108.03	59.85	398.0205 **
Pair 4 : EUR / JPY Futures Continuous Call											
EUR/JPY Pre-Covid-19	-0.1117**	0.1716**	0.0583	0.0505	0.7177	0.7807	0.2823	0.2191	3.54	4.57	302.3390**
EUR/JPY During Covid-19	0.1232**	-0.1092**	0.247	0.1191	0.8699	0.6796	0.1301	0.3204	7.69	3.12	137.6731 **
Notes: The table displays the estimation of the Markov switching models for the market imperfections during the two study periods. μ_1 , μ_2 , σ_1 , σ_2 , ρ_{11} , ρ_{22} , ρ_{12} and ρ_{21} are respectively the estimated coefficients of the intercepts of state 1 and 2, the standard errors of state 1 and 2, the probabilities of staying in the same regime and the probabilities of switching from one regime to another. ** indicates that the null hypothesis is not accepted at 5% significance level.											

2.4.3. Discussion

The Covid-19 pandemic has profoundly influenced the dynamics of global financial markets, with particular emphasis on the foreign exchange markets. The outbreak has triggered a twofold response: firstly, a decline in economic activities due to government-imposed lockdowns; and secondly, a significant impact on financial indicators such as exchange rates. This has necessitated a reconsideration of long-term investment strategies, particularly for hedging against potential losses. Amidst this backdrop, our study delves into shifts in investor behavior, highlighting divergences and convergences across both exchange rates and currency options. We found that the health crisis has instigated a role reversal between fundamentalist and chartist investors in different currency pairs. Simultaneously, there were corresponding changes in the behavior relating to our proxy variable, Market Imperfections (MI). These observations underscore the complex, fluid nature of investor behavior in today's uncertain

economic climate, compelling a nuanced understanding of both converging and diverging tendencies among market participants.

The profound impact of the pandemic extended its reach to Europe, where a surge in COVID-19 cases prompted the implementation of stringent measures. These measures, aimed at curbing the spread of the virus, disrupted supply chains and economic activities on a significant scale. As a consequence, the region experienced a staggering 40% decline in real GDP during the second quarter of 2020. Notably, countries like France and Italy grappled with a host of vulnerabilities, including mounting levels of debt, a rising inflationary trend, and declining stock market indices. In the midst of this economic turbulence, the U.S. dollar emerged as a prominent safe haven currency, garnering considerable attention and demand. This shift had a profound impact on the EUR/USD currency pair, reshaping the dynamics of exchange rates in the European and American context.

Commodity-producing nations, such as Russia, faced significant challenges during the pandemic, primarily stemming from a dramatic drop in oil prices. The Russian economy, which was already grappling with pre-existing difficulties, found itself in a recessionary phase. However, it demonstrated a degree of resilience amidst these adverse circumstances. This resilience can be attributed to Russia's strategic emphasis on vital industries that remained relatively unaffected by the pandemic's disruptions.

In contrast, Qatar exhibited remarkable resilience throughout this period of turbulence. Despite facing challenges such as a regional embargo and plummeting oil prices, the nation's substantial natural gas reserves and robust export infrastructure played a pivotal role in preserving its economic stability. Furthermore, Qatar's future growth outlook remains promising, buoyed by several factors, including its role as the host of the 2022 World Football Cup and the continuous progress of key infrastructure projects.

In Japan, the world's third-largest economy, the pandemic's influence was indeed palpable, although it was relatively milder when compared to the challenges faced by some other advanced nations. The economic downturn resulted from Japan's heavy dependence on exports, which experienced a significant slump. However, the anticipated impact on inflation was deemed to be less severe than what was witnessed following the 2011 Tohoku Earthquake. This suggests that both demand and supply were impacted by the pandemic. Notably, sectors such as tourism and leisure bore the brunt of the crisis. Nevertheless, Japan has recently taken

steps to reopen its borders to foreign tourists, hinting at the possibility of an eventual recovery in these areas.

In summary the pandemic has highlighted the limited persistence in trading strategies, notably between fundamentalists and chartists, in the forex markets. This suggests that traders continually adapt their approaches in response to changing economic conditions, emphasizing the need for flexible, adaptive strategies in turbulent times.

2.4.4. Practical Implications

This study carries several policy implications that warrant careful consideration. First and foremost, policymakers must take a proactive stance in anticipating potential future uncertainties and devising preemptive measures to shield financial markets and exchange rates from impending crises. This proactive approach could encompass the implementation of economic support initiatives, interventions to stabilize markets, and the adoption of accommodating monetary policies. Enhancing preparedness is paramount for both governments and financial institutions, achieved through improved risk assessment, reinforcement of institutional resilience, and the formulation of robust crisis management protocols.

Secondly, there is an urgent need for comprehensive investigations into the factors influencing exchange rates and the aftermath of crises like the COVID-19 pandemic on financial landscapes. Gaining a thorough understanding of investor behavior, particularly during tumultuous periods, holds significant importance. Economic actors and policymakers should devote attention to the divergent behaviors of investors in both the currency market and currency options. Emphasis should also be placed on portfolio diversification and hedging strategies to mitigate financial losses during crisis episodes.

Lastly, fostering international coordination and collaboration is indispensable to mitigate the adverse effects of crises and stimulate economic recovery. Nations should consider sharing crucial information, extending mutual support through synchronized policies, and aligning financial market regulations. Such unified global efforts are vital for addressing shared challenges and ensuring both economic and financial stability.

These key points underscore the critical necessity of prudent risk management, stringent regulatory frameworks, and judicious economic policies to cushion the detrimental impacts of crises on financial markets and exchange rates. In summary, proactive strategies are imperative

to instill resilience and maintain stability in an inherently uncertain and volatile economic landscape.

2.5. Conclusion

Several months after the COVID-19 pandemic began, its negative consequences reached far beyond global health, causing significant disruptions in international financial markets, including foreign exchange and currency options. Recognizing the lasting impact of the pandemic, we conducted an investigation to understand its influence on investor behavior. Our study relied on an extensive dataset covering foreign exchange markets across Europe, the United States, Japan, Russia, and Qatar.

Our research makes a significant contribution to the existing body of knowledge by examining the shifts in investor behavior within the context of the pandemic, with a particular focus on the foreign exchange and currency options markets. We introduced an innovative metric, labeled "Market Imperfections," to gauge the disparities between theoretical and actual call option prices, drawing from the Garman and Kohlhagen (1983) model.

To validate our discoveries, we employed a two-state Markov switching model, which provided nuanced insights into the contrasting behaviors exhibited by fundamentalist and chartist investors. Our dataset, spanning from September 22, 2016, to December 31, 2020, encompasses four currency option pairs: EUR/USD, EUR/JPY, EUR/QAT, and EUR/RUB. Our analysis reveals that investor strategies exhibited significant variations rather than being uniform. These variations were notably responsive to distinct market conditions during different timeframes. Prior to the onset of the pandemic, fundamentalist investors largely influenced market trends. However, with the emergence of COVID-19, chartists gained more influence, significantly impacting market dynamics. These shifts underscore the diversity in market strategies, indicating that investors adapt to a multitude of influencing factors, including information costs and the distinctive characteristics of various investment periods.

Furthermore, our findings suggest that market imperfections played a substantial role in shaping investor behavior, particularly during times of crisis. The COVID-19 pandemic triggered a sudden and tangible transformation in strategies across all studied currency pairs. This observation highlights the diverse reactions that crises can provoke, encompassing mimetic behavior, risk aversion, and loss aversion, often driven by information deficits and pervasive uncertainty.

Contrary to the assumption of universally shared investor beliefs, our study reveals evidence of both convergence and divergence in investor behavior during specific sub-periods preceding and during the pandemic. This supports our assertion that the COVID-19 crisis has significantly reshaped investor behavior, prompting adjustments in their risk profiles and hedging strategies.

Nonetheless, it's important to acknowledge the constraints of our study. One major limitation relates to the availability of extensive, long-term data covering currency options across various markets. These data gaps present an opportunity for future research to explore. To address this limitation, future studies might consider widening the scope of investigation by incorporating a broader historical timeframe and incorporating additional market factors. Expanding the research in this manner would serve a dual purpose: enhancing the reliability of our findings and facilitating comparative examinations of investor conduct during various critical events, including but not limited to the global financial crisis, Brexit, and geopolitical conflicts like the Russia-Ukraine situation.

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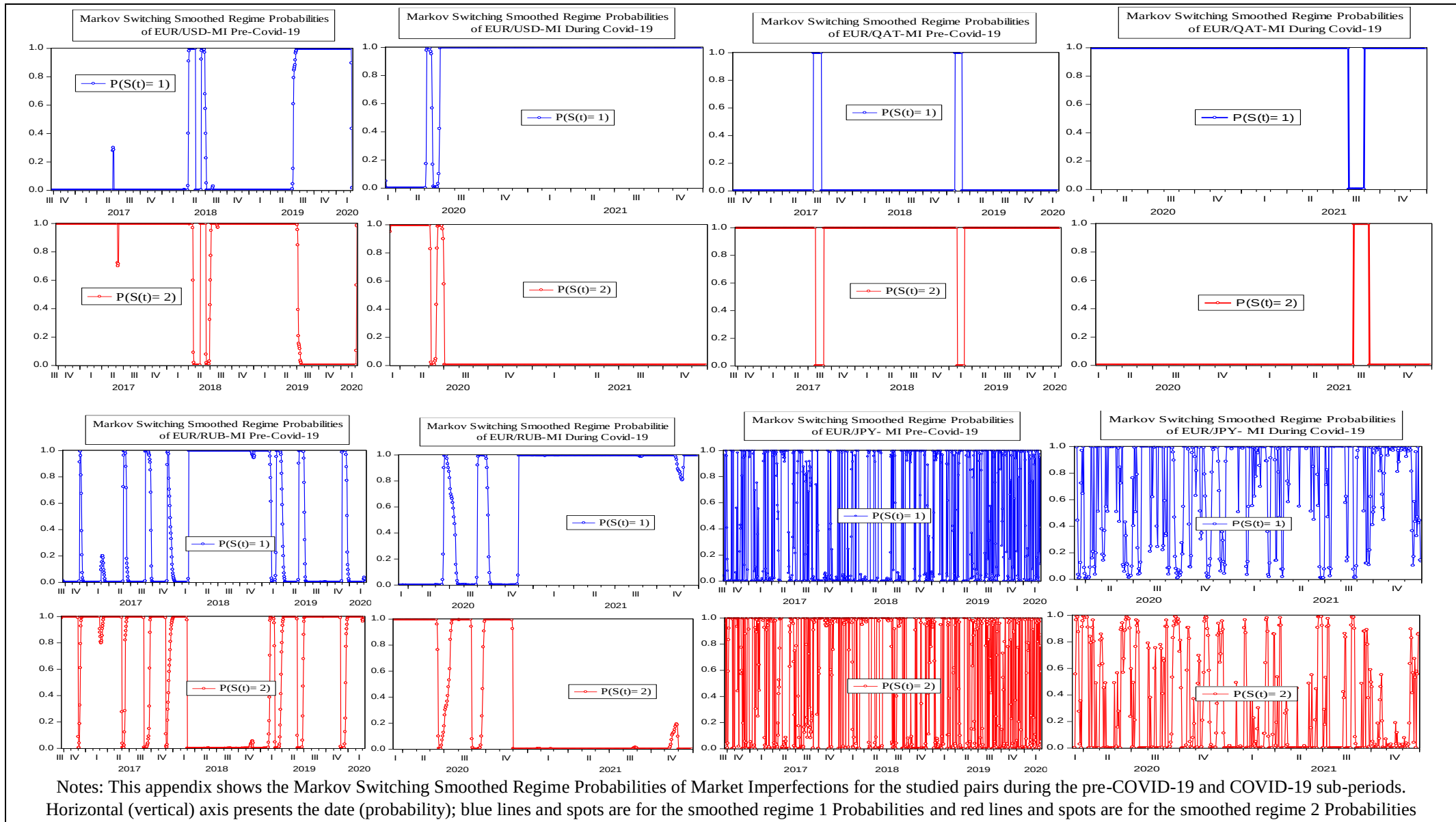
Appendices

Appendix 2.A. Regime classification for the four pairs of Exchange rate

Pair	Pre-Covid-19		During Covid-19	
	State 1	State 2	State 1	State 2
EUR/USD	1:1 - 212:1 [0.9945] 543:1 - 904:1 [0.9971]	213:1 - 542:1 [0.9961]	1:1 - 97:1 [0.9948] 407:1 - 473:1 [0.9886]	98:1 - 406:1 [0.9966]
EUR/QAT	26:1 - 289:1 [0.9950] 319:1 - 636:1 [0.9954]	1:1 - 25:1 [0.9793] 290:1 - 318:1 [0.9213] 637:1 - 904:1 [0.9980]	4:1 - 7:1 [0.9341] 248:1 - 385:1 [0.9930] 468:1 - 473:1 [0.9036]	1:1 - 3:1 [0.9998] 8:1 - 247:1 [0.9966] 386:1 - 467:1 [0.9933]
EUR/RUB	1:1 - 376:1 [0.9989] 648:1 - 897:1 [0.9956]	377:1 - 647:1 [0.9969] 898:1 - 904:1 [0.8506]	1:1 - 117:1 [0.9953] 357:1 - 473:1 [0.9919]	118:1 - 356:1 [0.9930]
EUR/JPY	38:1 - 572:1 [0.9998]	1:1 - 37:1 [0.9846] 573:1 - 904:1 [0.9974]	6:1 - 9:1 [0.9601] 62:1 - 64:1 [0.5527] 121:1 - 130:1 [0.9460] 235:1 - 327:1 [0.9960] 332:1 - 341:1 [0.9138] 399:1 - 447:1 [0.8922] 472:1 - 473:1 [0.6271]	1:1 - 5:1 [0.9999] 10:1 - 61:1 [0.9697] 65:1 - 120:1 [0.9946] 131:1 - 234:1 [0.9976] 328:1 - 331:1 [0.8613] 342:1 - 398:1 [0.9869] 448:1 - 471:1 [0.9474]

Notes: This appendix displays the regime classification for the four studied pairs of Exchange rate into the two sub-periods (pre and during Covid-19)

Appendix 2.B. Markov Switching Smoothed Regime Probabilities of Market Imperfections for the studied pairs



Chapter 3. Pricing of European Currency Options Considering the Dynamic Information Costs

Chapter 3. Pricing of European Currency Options Considering the Dynamic Information Costs

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Abstract

Dynamic costs arising from the variable impact of information on asset pricing present a challenge for accurate European currency option pricing. The Garman and Kohlhagen model, though influential in the literature, does not adequately account for these costs. This study extends the model by integrating an intensity function into the interest rates to measure dynamic information costs. Inspired by the Beer–Lambert law, the function is applied to a decade-long dataset of daily futures continuous calls on the EUR/USD pair from September 21, 2012, to September 23, 2022. The augmented model reduces pricing errors and manages implied volatility better than the 1983 model, consistent across different categories of maturity and moneyness. Our findings emphasize the need to consider dynamic information costs in asset pricing, demonstrating that their inclusion can significantly enhance the accuracy and reliability of currency option pricing.

JEL classification: C61, F47, G13, G14

Keywords: Currency options; Garman and Kohlhagen’s model; Dynamic information costs; Derivatives; Market imperfections; Beer–Lambert law

3.1. Introduction

Using options for hedging or speculative purposes has gained popularity in recent decades. Consequently, businesses have adopted options to mitigate interest rate risk and minimize price fluctuations in real commodities and securities. Furthermore, options are employed in foreign exchange as a derivative instrument based on a fixed amount of foreign currency. Firms with substantial international operations and exposure to currency exchange rates often utilize foreign exchange options, commonly called “forex” options. Forex options have gained popularity as both speculative tools and components of investment portfolios; however, the widely acclaimed Black–Scholes model (1973), which won the Nobel Prize, is unsuitable for pricing forex options. The Black–Scholes model is primarily designed for non-dividend paying stocks following geometric Brownian motion, and it considers only the domestic risk-free interest rate in its calculations. Currency exchange pricing requires a more comprehensive approach incorporating both domestic and foreign risk-free rates. To address this, Garman and Kohlhagen proposed a forex option pricing model in 1983, which accounts for interest rate parity and the equalization of forward premiums with interest rate differentials. This model is grounded on several key hypotheses. First, it assumes that exchange rate changes evolve gradually and do not exhibit abrupt jumps (H1). Second, the model assumes continuous exchange in the market (H2). Additionally, it assumes constant interest rates in both the domestic and international markets (H3). Moreover, the model assumes an ideal foreign exchange market where transaction and information costs are absent (H4). Lastly, it posits that option prices are determined by a single stochastic variable, denoted as S . Consequently, the exchange rate price follows a geometric Brownian motion or the Gauss–Wiener process (H5).

The pioneering Garman and Kohlhagen model (G–K model) and its subsequent extensions exhibit several limitations closely tied to the validity of its underlying assumptions. These assumptions include the hypothesis of constant interest rates, constant volatility, absence of transaction and information costs, and the assumption of market sentiment. In contrast, the growth of the options market can be attributed to various factors, primarily driven by episodes of excessive volatility and financial crises during the era of internationalization. These circumstances created a demand for more flexible risk coverage beyond traditional techniques; thus, significant theoretical research on currency option pricing can be traced back to the pioneering work of Garman and Kohlhagen (1983). Subsequently, the research conducted by Black, Scholes, and Merton served as a source of inspiration for both this study and the work

of Grabbe (1983). Over time, these models underwent further development and improvement, with various researchers making notable advancements (Melino & Turnbull, 1990; Hilliard et al., 1991; Heston, 1993; Blenman & Ayadi, 1997; Sarwar & Krehbiel, 2000; Carr & Wu, 2007, Hoque et al., 2008; Xiao et al., 2010; Van Haastrecht & Pelsser, 2011; Swishchuk et al., 2014; Liu et al., 2015; Shokrollahi et al., 2016; Lv et al., 2016; Liu et al., 2016; Wang & Ning, 2017; Liu et al., 2022). Each model has contributed to the refinement of currency option evaluation.

Still, empirical studies based on surveys of the G–K model have revealed the presence of biases in the derived theoretical prices. The hypotheses of Garman and Kohlhagen’s model (1983) do not hold in the financial market, prompting the need to develop more suitable and realistic new valuation models. Nonetheless, pricing financial instruments, including options, relies on an accurate assessment of various factors, with information being critical. In the context of European currency options, the influence of pricing information is particularly significant; however, the impact of information on option pricing is not static but varies over time, leading to dynamic information costs. These dynamic costs reflect the changing nature of information availability, market conditions, and investor behavior. Existing literature has recognized the importance of information in asset pricing, but limited research has explicitly focused on its time-dependent nature and the associated dynamic information costs in the context of option pricing; therefore, there is a need to examine how these dynamic costs affect the performance of currency option pricing models. This situation raises the following questions for which we endeavor to provide a preliminary response:

- i. Would Garman–Kohlhagen’s modified model, considering the dynamic information costs, reduce the evaluation mistakes caused by the standard G–K model?
- ii. How does introducing these imperfections affect the economic agent’s behavior?
- iii. Are the parameters of the option assessment perfectly observed or measured?

This study addresses this research gap by proposing extending the Garman and Kohlhagen (G–K) model for pricing European currency options. The extension incorporates an intensity function based on interest rates to measure dynamic information costs. This approach draws inspiration from the Beer–Lambert law, an empirical relationship between light absorption and the properties of the medium it passes through. By analogy to the Beer–Lambert law, we introduce the dynamic information costs into the interest rates in the G–K model.

This paper employs a specific methodology to address the questions above. Our analysis focuses on the pricing of options, considering their dependence on maturity and moneyness. To evaluate the performance of the pricing models, we utilize the average mean squared errors (MSE) in option prices and implied volatility. We conduct a comprehensive empirical analysis by categorizing the data based on maturity and moneyness. Our empirical methodology utilizes daily data from future continuous calls on the EUR/USD pair from September 21, 2012, to September 23, 2022. We compare the pricing errors and implied volatility obtained from the proposed model, which incorporates dynamic information costs, with those derived from the original G–K model. This approach allows us to assess the effectiveness and accuracy of the extended model in currency option pricing. By employing the average MSE in option prices and implied volatility across different maturity and moneyness categories, we gain valuable insights into the performance of the pricing models under various conditions. This method comprehensively assesses the models' ability to accurately estimate option prices and implied volatility in different market scenarios. The significance of this research lies in its contribution to a more comprehensive understanding of the relationship between information costs and currency option pricing. By considering the time-dependent nature of information and incorporating dynamic costs, we aim to enhance the accuracy and reliability of currency option pricing models. This enhanced model approach has practical implications for investors and market participants, enabling more informed decision-making in currency options trading.

The structure of this paper is as follows. Section 2 provides a descriptive overview of existing literature on real anomalies in currency options pricing, highlighting the limitations of the G–K model. Section 3 introduces an extended version of the G–K model that incorporates dynamic information costs, and it presents a novel derivation of the standard currency option formula, which has not been published. Section 4 of this study presents a comprehensive overview of the adopted methodology, providing a detailed explanation of the data utilized, the variables considered, and the empirical models employed for the analysis. In Section 5, the empirical results are presented and discussed. Finally, the paper concludes in Section 6, where the main findings are summarized, the study's limitations are discussed, and suggestions are provided for future research directions.

3.2. Literature review

Numerous theoretical and empirical research has demonstrated the significance of imperfections in option valuation. The literature in this field distinguishes between classic

anomalies and real anomalies. Classic anomalies are models that scrutinize factors associated with the underlying asset's price movement. Conversely, real anomalies encompass models that focus on assumptions related to the market.

3.2.1. Classic Anomalies: Models for Assessment Under Stochastic Volatility and Interest

As employed by Black and Scholes (1973) for asset pricing, the geometric Brownian motion has faced criticism for multiple reasons. One significant criticism stems from the assumption that the instantaneous profitability of the underlying asset follows a Gaussian distribution with a constant variance. In light of this limitation, researchers have sought to generalize the geometric Brownian motion by incorporating stochastic volatility. Black (1976) argues that if volatility changes over time, an assessment formula based on constant volatility is inaccurate. Moreover, the Black–Scholes model is unsuitable for valuing all options simultaneously in a given market due to the observed skew effect commonly encountered in practice. Various researchers have thoroughly investigated the issue of stochastic volatility (Aït-Sahalia & Kimmel, 2007; Heston, 1993; He & Lin, 2021; He & Lin, 2023; Hull & White, 1987; Hurn et al., 2015; Johnson & Shanno, 1987; Kirkby & Nguyen, 2020; Lyu et al., 2022; Schobel & Zhu, 1999; Wiggins, 1987; Wang et al., 2017). Empirical research commonly addresses the stochastic volatility problem through the solutions proposed by Hull and White (1987) and Heston (1993). Hull and White (1987) propose the assumption of constant volatility for the underlying asset price and suggest using a geometric Brownian motion with uncorrelated increments for the variance process. In contrast, Heston (1993) presents an alternative approach by advocating for the direct modeling of volatility instead of the variance. In this framework, the variance is governed by a process that exhibits mean-reversion, often called the “squared root” process.

Furthermore, some consider the presence of a stochastic interest rate in option assessment models. This area of research focuses on extending the Black and Scholes (B&S) model by questioning the assumption of a constant interest rate. Assuming that the interest rate is deterministic can be overly restrictive since anticipated interest rate fluctuations constitute a significant source of market uncertainty for bondholders. Merton (1973) relaxed the restrictive assumption of interest rate stability by generalizing the B&S formula for risk-free interest rates that vary according to a Gaussian Wiener process. Following the works of Merton (1973) and Vasicek (1977), subsequent models have been developed (Amin & Jarrow, 1991, 1992;

Brennan & Schwartz, 1980; Grabbe, 1983; He & Zhu, 2018; Ho & Lee, 1986; Jaimungal & Wang, 2006; Liang & Xu, 2020; Liu et al., 2016; Lyu et al., 2022; Pearson & Sun, 1994; Van Haastrecht & Pelsser, 2011; Zhang & Wang, 2013).

3.2.2. Real Anomalies

The assumption of market efficiency plays a significant role in the framework proposed by Black and Scholes (1973) and is also an essential assumption in Garman and Kohlhagen's model (1983). This assumption implies that the absence of imperfections in financial markets is assumed and that economic agents are perfectly rational.

The market microstructure theory reveals the presence of information costs, which play a crucial role in forming international portfolios. Consequently, these costs should be considered in pricing financial asset models. Thus, the underlying asset's price reflects the availability or arrival of new information, as Fama (1991) highlighted. Indeed, several factors contribute to the imperfections observed in the market, including information asymmetry (Allen & Gorton, 1993; Benkraiem et al., 2022; De Long et al., 1990; Kadan et al., 2018; Leland & Pyle, 1977; Pan & Misra, 2022; Pour, 2017; Zghal et al., 2020), transaction and information costs (Ardalan, 1999; Govindaraj et al., 2020; Grossman & Stiglitz, 1980; Gu et al., 2012; Hansen Henten & Maria Windekilde, 2016; Jensen, 1978; Li & Fang, 2022), and restrictions on short selling (Bohl et al., 2016; Duffie et al., 2002; Duong et al., 2023; Feng & Chan, 2016; He, 2022; Scheinkman & Xiong, 2003). Incorporating these imperfections is crucial as it prevents arbitrage operations from eliminating evaluation errors. Additionally, behavioral finance plays a role in investors' decision-making, contributing to market inefficiency and challenging the assumptions of investor rationality. Research has shown that evaluation errors can arise when rational investors interact with irrational ones, such as the presence of noise traders (Gao & Ladley, 2022; Ramiah et al., 2015; Ryu & Yang, 2020) and over-confident investors (Abreu & Brunnermeier, 2003; Du & Budescu, 2018).

The extant literature also shows that several studies on option pricing models have overlooked the impact of information costs, highlighting the need to examine various types of information costs and investor motivations. These costs can be categorized into search and information acquisition costs, where Grossman and Stiglitz (1980) highlight the equilibrium price implications of acquiring costly information. Easley and O'Hara (1987) emphasize the additional costs of learning and experience in assessing information quality. Bellalah and Jacquillat (1995) introduce a new cost of information, considering its indispensable role in

collection and analysis. Gu et al. (2012) and Hansen Henten and Maria Windekilde (2016) demonstrate that information costs can lead to evaluation errors. As studied by Marin and Rahi (2000), information transmission costs correlate with the number of informed investors, while Duffie and Rahi (1995) highlight the importance of private information transmission in asset allocation decisions. Gul et al. (2010) and Pour (2017) find a positive correlation between transaction volume and information. Furthermore, adverse selection or asymmetric information costs, explored by Grossman (1976), Harrison and Kreps (1978), and Hellwig (1980), assume heterogeneous information among investors, with some possessing specific knowledge about future asset performance. Kovalenkov and Vives (2014) extend this to endogenous information acquisition, while Easley et al. (1998), Cremers et al. (2015), and Goncalves et al. (2020) show that informed investors in the options market can cause deviations in the call-put relationship. Gapeev and Li (2022) highlight the incorporation of asymmetric information into option pricing models and introduce dynamic exercise strategies based on stochastic boundaries. Market sentiment, as examined by Mahani and Potesman (2008) and Bauer et al. (2009), influences option pricing without a specific theoretical model. Moreover, empirical findings reveal systematic effects of sentiment metrics from underlying and options markets on option pricing (Boutouria et al., 2021; Daniel et al., 2002; Maghyereh et al., 2022; Nagarajan & Malipeddi, 2009; Yang et al., 2016; Zghal et al., 2020).

Therefore, the extension of option pricing models is motivated by the lack of transparency and liquidity observed in certain markets, resulting in the search for costly information. This extension introduces the dynamic nature of information costs, highlighting that the cost depends on the speed of information acquisition. Consequently, investors who receive information earlier can reduce their risk exposure; however, conventional option pricing methods neglect the impact of information costs. Building upon this notion, previous studies by Bellalah (2006), Minehan and Simons (1995), Bellalah and Jacquillat (1995), and Merton (1987) incorporated the costs associated with statistical information. Additionally, Ben Hamad and Eleuch (2008a, 2008b) addressed the dynamic imperfections related to information costs. These studies provide valuable insights into the biases present in option pricing models.

3.3. The Garman and Kohlhagen model considering the dynamic information costs

Developing a new model in the presence of dynamic information costs highlights the significance of introducing the theoretical model of Garman and Kohlhagen (1983). This model

suggests that the sale of a call option for a foreign currency can be effectively hedged by purchasing a specific quantity of foreign government bonds, considering the interest rate on these bonds (r_f). The effectiveness of this hedging strategy is based on the assumptions mentioned earlier. Consequently, under these assumptions, the price of a European currency call can be determined using the following formula:

$$C_t = S_t e^{-r_f \tau} N(d_1) - X e^{-r_d \tau} N(d_2). \quad (3.1)$$

Then, the price of a European currency *put* is given by this formula:

$$P_t = S_t e^{-r_f \tau} N(-d_1) + X e^{-r_d \tau} N(-d_2). \quad (3.2)$$

In this context, the variables used in the currency option pricing framework are defined as follows. C_t Is the value of a European currency call paying an interest rate r_f , P_t is the value of a European currency put, and S_t is the price of the underlying asset. X is the strike price of the call, r_f is the interest rate of the foreign currency, and r_d is the interest rate of the domestic currency. Finally, τ is the time calculated in years or a fraction of a year, and $N(\cdot)$ is the cumulative distribution function of a normal distribution: $N(0,1)$; d_1 and d_2 are calculated as follows:

$$d_1 = \frac{\ln\left(\frac{S}{X}\right) + (r_d - r_f)\tau + \frac{1}{2}\sigma^2\tau}{\sigma\sqrt{\tau}} \quad (3.3)$$

and,

$$d_2 = d_1 - \sigma\sqrt{\tau}. \quad (3.4)$$

3.3.1. Study of the New Function of Dynamic Information Costs by the Analogy of Beer–Lambert Law

The extension of the classical model in this study builds upon most of its assumptions; however, it introduces a new hypothesis that considers the presence of dynamic information costs. Accordingly, we propose to expand Garman and Kohlhagen's model by incorporating these dynamic imperfections, utilizing the risk-neutral framework established by Black and Scholes (1973). Therefore, we propose a function inspired by the Beer–Lambert law, also known as the Beer–Lambert–Bouguer law. This empirical relationship describes light absorption as it passes through different media. The law was initially discovered by Pierre Bouguer in 1729 and published in his book “An Optical Essay on the Gradation of Light” (Claude Jombert, Paris, 1729). Later, in 1760, Johann Heinrich Lambert reformulated the law,

further developed by August Beer in 1852. This reformulation establishes that the intensity of light propagating through an optical medium is given by the following:

$$I_t(l) = I_0 e^{-\alpha l}. \quad (3.5)$$

Therefore, the absorbed light through the medium can be expressed by the following:

$$I_{ab} = I_0 - I_t = I_0(1 - e^{-\alpha l}). \quad (3.6)$$

where α is the light absorption coefficient, and l is the optical length in the medium.

Drawing on the principles of this law, we propose introducing a function in our extended model that captures the dynamic characteristics of information costs. This function is referred to as the temporal advantage function of information, denoted as $w(l)$, and can be defined as follows:

$$\begin{aligned} W:]-\infty, +\infty[&\rightarrow]-\infty, +\infty[\\ l &\rightarrow 1 - e^{-\alpha l}. \end{aligned} \quad (3.7)$$

where “ l ” represents the temporal advantage, defined as the difference between the time of information acquisition and the maturity of a currency option. The quality of the acquired information influences the value of this temporal advantage. To quantify its impact on the currency option value, we introduce a coefficient “ α ” that ranges between zero and one. Specifically, when the information is deemed less significant, the coefficient approaches zero, while it tends toward one for highly relevant information.

The derivative of $w(l)$ concerning l is given by the following formula:

$$w'(l) = \alpha e^{-\alpha l} > 0. \quad (3.8)$$

Then, $w(l)$ is strictly increasing on $\mathbb{R}$,

and,

$$\begin{cases} \lim_{l \rightarrow -\infty} w(l) = -\infty \\ \lim_{l \rightarrow +\infty} w(l) = 1 \end{cases}. \quad (3.9)$$

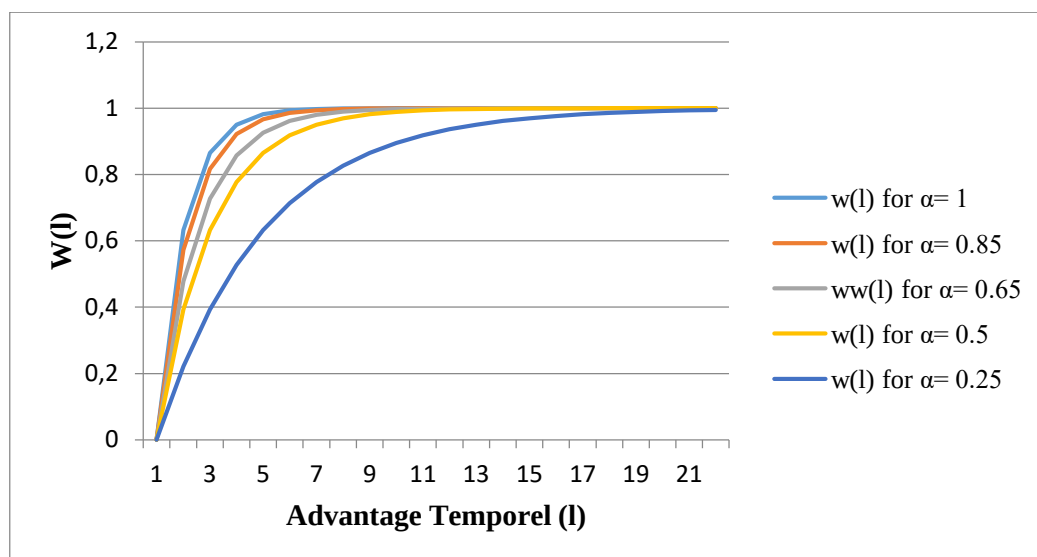
The temporal advantage function $w(l)$ is enhanced by increasing the temporal advantage l or reducing the coefficient α .

Table 1 includes values for the temporal advantage “ l ” going from 0 to 21 and for different coefficients of the temporal advantage “ α ” ($\alpha = 1$; $\alpha = 0.85$; $\alpha = 0.65$, $\alpha = 0.5$ and $\alpha = 0.25$).

Table 3. 1. The evolution of the values acquired by the time advantage function

l	w(l) for $\alpha = 1$	w(l) for $\alpha = 0.85$	w(l) for $\alpha = 0.65$	w(l) for $\alpha = 0.5$	w(l) for $\alpha = 0.25$
0	0	0	0	0	0
1	0.632120559	0.572585068	0.477954223	0.39346934	0.221199217
2	0.864664717	0.817316476	0.727468207	0.632120559	0.39346934
3	0.950212932	0.921918334	0.857725928	0.77686984	0.527633447
4	0.981684361	0.96662673	0.925726422	0.864664717	0.632120559
5	0.993262053	0.985735766	0.961225792	0.917915001	0.713495203
6	0.997521248	0.993903253	0.979758089	0.950212932	0.77686984
7	0.999088118	0.997394159	0.989432796	0.969802617	0.826226057
8	0.999664537	0.998886225	0.994483436	0.981684361	0.864664717
9	0.99987659	0.999523956	0.997120101	0.988891003	0.894600775
10	0.9999546	0.999796532	0.998496561	0.993262053	0.917915001
11	0.999983298	0.999913035	0.999215136	0.995913229	0.936072139
12	0.999993856	0.99996283	0.999590265	0.997521248	0.950212932
13	0.99999774	0.999984113	0.9997861	0.998496561	0.961225792
14	0.999999168	0.99999321	0.999888334	0.999088118	0.969802617
15	0.999999694	0.999997098	0.999941705	0.999446916	0.976482254
16	0.999999887	0.99999876	0.999969568	0.999664537	0.981684361
17	0.999999959	0.99999947	0.999984113	0.999796532	0.985735766
18	0.999999985	0.999999773	0.999991706	0.99987659	0.988891003
19	0.999999994	0.999999903	0.99999567	0.999925148	0.991348305
20	0.999999998	0.999999959	0.99999774	0.9999546	0.993262053
21	0.999999999	0.999999982	0.99999882	0.999972464	0.994752482

Note: The table below illustrates the values obtained by the time advantage function for the temporal advantage “ l ” ranging from 0 to 21, with varying coefficients of the temporal advantage “ α .”

Figure 3. 1. The evolution of the temporal advantage function $w(l)$ 

Note: This figure shows the evolution of the temporal advantage function $w(l)$. The horizontal (vertical) axis presents the advantage temporel (l) and the temporal advantage function $w(l)$

Figure.1 shows the evolution of the temporal advantage function, indicating that the temporal advantage function increases as “ l ” increases and tends to 1, whatever the value of the temporal advantage coefficient “ α ” is. Nevertheless, the speed of evolution of $w(l)$ varies depending on the value of “ α ”; In fact, $w(l)$ tends more quickly toward 1 when α increases. We also see that the value of $w(l)$ for a temporal advantage l increases when α tends toward 1. For example, for the same temporal advantage of 5, the value of the temporal advantage function is 0.993262053 for $\alpha = 1$, 0.629633437 for $\alpha = 0.5$, and 0.467212935 for $\alpha = 0.25$. The effect of obtaining information five days before the maturity date varies depending on the degree of relevance of this information as measured by α . This means that the obtained information’s relevance modifies the temporal advantage’s impact on the option value.

3.3.2. The Actual Discount Rate in the Presence of Dynamic Information Costs

Consequently, it is necessary to include dynamic information costs in the Garman and Kohlhagen formula by incorporating them alongside the risk-free domestic and foreign interest rates. The effect of information costs on currency option prices can be likened to applying an additional discount rate. *“When investors move from a risk-neutral world to a risk-averse world, two things happen: the expected growth rate in the stock price changes and the discount rate that must be used for any pay-off from the derivative changes.” (John Hull 2008).*

In this context, Thaler (1981), Merton (1987), Bellalah and Jacquillat (1995), Ben Hamad and Eleuch (2008), and Zghal et al. (2020) assert that the discount rate and expected growth rate of the underlying asset are presumed to be equal to the risk-free rates plus the costs associated with these anomalies. By deviating from the market efficiency hypothesis, including dynamic information costs in the model is akin to applying an additional discount rate that accounts for the dynamic information costs. It can be written as follows:

$$r_1 = r + \text{dynamic Information Costs.} \quad (3.10)$$

$$r_1 = r + \lambda w(l). \quad (3.11)$$

where, r_f is the effective interest rate, r represents the nominal interest rate, l is the temporal advantage, $w(l) = 1 - e^{-\alpha l}$ represents the temporal advantage function, and λ designates the information costs. Furthermore, several information-related costs arise: search, acquisition, transmission, and adverse selection. These costs are represented in the new model by “ λ .” If λ is equal to zero, then there are no information costs; therefore, we are in an efficient market in which we find the initial model of Garman and Kohlhagen (1983).

In our case, we define two functions of dynamic information costs, denoted as $w(l)$ and $w(l_1)$, which are related to the domestic and foreign markets, respectively. These functions capture the varying nature of information costs over time, considering each market's specific dynamics and characteristics. By incorporating these functions into our model, we aim to reflect the impact of dynamic information costs on currency option pricing.

In this scenario, the effective domestic interest rate r_{1d} is presented as follow:

$$r_{1d} = r_d + \lambda w(l). \quad (3.12)$$

where, r_d is the real risk-free domestic interest rate, and λ is the information costs amplitude associated with domestic information. The function $w(l)$ corresponds to the advantage function related to domestic information and is equal to $1 - e^{-\alpha l}$. Here, α is the advantage coefficient related to domestic information, and l is the temporal advantage associated with domestic information.

Therefore, the effective foreign interest rate r_{1f} is presented as follows:

$$r_{1f} = r_f + \lambda_1 w(l_1). \quad (3.13)$$

where, r_f is the real risk-free foreign interest rate and λ_1 is the information cost amplitude associated with foreign information. The function $w(l_1)$ corresponds to the advantage function related to foreign information and is equal to $1 - e^{-\alpha_1 l_1}$. Here, α_1 is the advantage coefficient

related to foreign information and l_f is the temporal advantage associated with foreign information.

3.3.3. Derivation of the Model in the Presence of Dynamic Information Costs

The extension of the new model relies on most of the assumptions of the classical model. We introduce a new assumption based on dynamic information costs in the currency options pricing.

According to the Black–Scholes’s model⁷, it is possible to create a short position composed of the sale of $\frac{1}{\frac{\partial C(S,T)}{\partial S}}$ for an option against a long position on the shares.

Following the same approach of Black and Scholes (1973) and replacing $Se^{-\delta\tau}$ of the model of Black, Scholes, and Merton by $Se^{-\tau r_f}$ of the model of Garman, we can deduce that if the price of the active support changes by a small amount ΔS , the option will change by $\frac{\partial C(S,T)}{\partial S} \Delta S$. This cover can be maintained without interruption so that the return of the short position becomes completely independent of the change of the value of the active support, i.e., the return to the covered position becomes sure.

As a result, the change in the long position of the currency is approximately offset by the change in $\frac{1}{\frac{\partial C(S,T)}{\partial S}}$ options.

The value of PF is composed of the purchase of a currency and the sale of $\frac{1}{\frac{\partial C(S,T)}{\partial S}}$ options, is as follows::

⁷ The derivation of Black–Scholes is founded on arbitration, which constitutes a covered position formed by a long one (or purchase) on the actions and a short position (or sale) on the options, and vice versa. Then, the composition of the PF of arbitration depends on the type of the option:

- Case of option of purchase “call”: the position detained on the action must be the inverse to that of the call [purchase (sale) of the call + sale (purchase) of the action].
- Case of sale “option”: the same position detained on the action and the option of sale [purchase (sale) of the call+ purchase (sale) of the action].

$$V = S - \frac{1}{\frac{\partial C(S, T)}{\partial S}} C(S, T). \quad (3.14)$$

During one-time intervals, the change of this position is given by the following:

$$\Delta V - r_f S - \frac{1}{\frac{\partial C(S, T)}{\partial S}} r_f C(S, T) \quad (3.15)$$

where:

$$r_f C(S, T) = C(S + r_f S, T + r_f T) - C(S, T) \quad (3.16)$$

Geometric Brownian motion governs the currency spot price, i.e., the differential representation of the spot price movements is as follows:

$$ds = \mu S dt + \sigma S dZ \quad (3.17)$$

where dS is the evolution of the spot currency price. The μ between t and dt is the mathematical expectation of equity return, and dZ is the Gauss–Wiener standard process, $N(0, dt)$, $V(dz) = \emptyset dt$. Finally, σ is the standard deviation of instantaneous equity return, which is supposed to be a known constant.

Using the differential stochastic calculation and Itô's lemma, we get:

$$\Delta C = \frac{\partial C}{\partial t} \Delta S + \frac{\partial C}{\partial t} dt + \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} dt. \quad (3.18)$$

The return to the covered position is sure and must be equal to $(r_{1d} - r_{1f})$, where r_{1d} is the effective risk-free domestic interest rate and r_{1f} is the effective risk-free foreign interest rate.

A specific condition is required to deduce the partial derivative equation: the lack of arbitrage opportunity from the continuous change in portfolio composition (it remains risk-free).

We get:

$$\left(-\frac{\partial C}{\partial t} - \frac{1}{2} \sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} \right) dt = (r_{1d} - r_{1f}) \left(-C + \frac{\partial C}{\partial S} S \right) dt \quad (3.19)$$

$$\frac{1}{2}\sigma^2S^2\frac{\partial^2C}{\partial S^2} + (r_{1d} - r_{1f})S\frac{\partial C}{\partial S} + \frac{\partial C}{\partial t} - (r_{1d} - r_{1f})C = 0, \quad (3.20)$$

which is the partial differential equation in the presence of dynamic information costs.

The problem is solving this partial differential equation (PDE) (see Appendix 1: the resolution of the PDE); thus, to determine the value of the currency call option, we can proceed as follows. First, we assume that the underlying asset's return equals the effective risk-free rate, accounting for dynamic information costs. Next, we calculate the expected pay-off of the derivative asset at the option's maturity. This expectation is then discounted using the effective risk-free domestic interest rate (r_{1d}) and the effective, risk-free foreign interest rate (r_{1f}), considering the dynamic information costs. As a result, the modified pricing formula for European currency call options in the presence of dynamic information costs can be expressed as follows:

$$C(S, t) = Se^{-r_{1f}T}N(d'_1) - Xe^{-r_{1d}T}N(d'_2) \quad (3.21)$$

with,

$$d'_1 = \frac{\ln\left(\frac{S}{X}\right) + \left(\frac{\sigma^2}{2} + (r_{1d} - r_{1f})\right)T}{\sigma\sqrt{T}} \quad (3.22)$$

and,

$$d'_2 = d'_1 - \sigma\sqrt{T}. \quad (3.23)$$

Then, the parity relationship in the presence of dynamic information is as follows:

$$C_t - P_t = Se^{-r_{1f}T} + Xe^{-r_{1d}T} \quad (3.24)$$

where C is the price of the call, P is the price of the put, and S is the price of the underlying asset. X is the strike price, T is the time to maturity, r_{1f} is the effective foreign (riskless) interest rate, and r_{1d} is the effective domestic (riskless) interest rate.

Therefore, we can write:

$$S_te^{-r_{1f}T}N(d'_1) - X_te^{-r_{1d}T}N(d'_2) - P_t = Se^{-r_{1f}T} - X_te^{-r_{1d}T} \quad (3.25)$$

As a result, we can deduct the value of the European currency put in the presence of dynamic information costs as follows:

$$P_t = -S_t e^{-r_1 f^T} [1 - N(d'_1)] + X e^{-r_1 d^T} [1 - N(d'_2)] \quad (3.26)$$

We know that $N(d) + N(-d) = 1$.

The price of the European currency put is then:

$$P_t = S_t e^{-r_1 f^T} N(-d'_1) + S e^{-r_1 d^T} N(-d'_2) \quad (3.27)$$

3.4. Methodological issues

This section empirically tests the modified Garman and Kohlhagen model in dynamic imperfections. Our objective is to assess the accuracy of the modified model in approximating currency option prices compared to the theoretical Garman–Kohlhagen model (1983); therefore, we formulated a set of research questions that guide our empirical analysis, aiming to evaluate different aspects of the modified model's performance and its ability to capture market dynamics. Through our empirical approach, we apply an inductive technique to verify the presence and impact of dynamic information costs in financial markets. By analyzing real-world data and market dynamics, we seek to provide empirical evidence supporting dynamic information costs and their influence on currency option pricing. This approach bridges the gap between theoretical insights and empirical observations, enhancing our understanding of financial market dynamics.

Our approach will be structured as follows:

- We calculate the price of the currency call option using both models.
- We evaluate the models' performance through analysis of the valuation gaps.
- We examine the impact of introducing dynamic imperfections on market participants' behavior in the financial market.

3.4.1. Data Sources and Variables

Our sample comprises 2.612 observations of currency call options on the EUR/USD pair traded on the Russian Trading System. Specifically, we focus on the prices of European-type foreign currency options obtained from the DATASTREAM database. The study period spans September 9, 2012, to September 9, 2022, and the options included in our analysis are at the money and out-of-the-money options. We utilize daily data to conduct our empirical analysis and examine the performance of the modified model in capturing the dynamics of these currency options.

We use currency option evaluation formulas with and without information costs and their corresponding variables to implement our analysis. The variables include the underlying price (S), exercise price (X), time remaining until maturity (T), risk-free domestic interest rate (r_d), risk-free foreign interest rate (r_f), and volatility (σ). These variables are identified and specified as follows:

- The underlying price (EUR/USD exchange rate), represented by a continuous series with the data type (OU), reflects the closing price of the underlying asset in the options market, providing daily activity information.
- The option strike price, represented by the data type (OS), indicates the option's strike price at the money.
- The implied volatility with a constant maturity of 3 months, represented by the data type (O3), displays the ATM implied volatility with a fixed time to maturity of 90 days.
- The market price, represented by the data type (OM), shows the price of the option series at the money.
- The number of days remaining to maturity is a known contract characteristic, denoted as T , calculated as the number of days until maturity divided by 360.
- The domestic interest rate is derived from the "LIBOR," with a constant time to maturity of 90 days.
- The foreign interest rate is derived from the "EURIBOR," with a constant time to maturity of 90 days.

Hull (2008) posits that these rates serve as accurate estimators of the risk-free rate.

3.4.2. Study of the Model Performance

This study primarily aims to assess the performance of the extended model in capturing market prices compared to the standard Garman–Kohlhagen model (1983). Our methodology encompasses multiple steps: first, we simulate the dynamic information cost parameters; next, we calculate option prices using the modified Garman–Kohlhagen and standard G-K model. We then analyze the model's performance by examining evaluation errors, including errors reported by maturity, skewness, and overall errors, and comparing theoretical prices with market prices. To compare the models, we define the following variables that need to be

calculated. C_{GK} is the price of a European currency call option calculated using the G–K model (1983) formula. Furthermore, C_{GKDIC} is the price of a European currency call option calculated using the model in the presence of the dynamic information costs, and C_M is the observed price of a European currency call option on the market.

To simplify the calculation of the currency call option using the formula derived from the theoretical model of Garman–Kohlhagen, we have created a Visual Basic (VBA) procedure called *Call_GK* (refer to Appendix 2). This procedure allows us to use the function in Excel just like any other calculation function. Additionally, considering the dynamic information costs, we need to simulate the values of λ , λ_1 , $w(l)$ and $w(l_1)$ to calculate the value of the currency call option using the new model. We have utilized a simulation method in Excel using VBA. Initially, we assign initial values to λ , λ_1 , α , α_1 , l , and l_1 , and then calculate the effective interest rates “ r_{1d} ” and “ r_{1f} .” Next, we iteratively adjust these parameters to minimize the average difference. This statistical procedure aims to reduce the difference toward zero by modifying the values of the information cost parameters. To achieve this, we utilize the “goal seek” feature available in the tools menu of Excel. This method helps us estimate the implicit values of λ , λ_1 , α , α_1 , l , and l_1 that minimize the average difference. Lastly, to simplify the calculation of the currency call option using the formula derived from the new model, we have developed a Visual Basic procedure named *Call_GKIC* (refer to Appendix 3).

Then, to compare the models, we consider the following variables. GK represents the price of a European currency call option calculated using the Garman–Kohlhagen (G–K) theoretical model formula. GKIC represents the price of a European currency call option calculated using the modified model with information costs, and VM represents the observed market prices of the currency options. Subsequently, we define the following variables:

- $EGK = GK - VM$, which represents the deviation of the price obtained by the Garman–Kohlhagen (G–K) model (1983) compared to the market prices of the currency options.
- $EGKIC = GKIC - VM$, which represents the deviation of the price obtained by the model considering dynamic information costs compared to the market prices of the currency options.

Then, if we observe a positive (negative) difference, it indicates that the option is overvalued (undervalued), suggesting that the theoretical model of G–K (1983) either

overestimates or underestimates the market price. These differences are computed for each call on every sample day, allowing us to determine the average error for each call. Moreover, since option prices are influenced by factors such as maturity and moneyness, we calculate the average squared deviation by considering maturity and skewness, in addition to overall errors, across the entire sample of currency calls. This approach enables us to derive the average squared error evaluation $EGKM$ and $EGKICM$, respectively:

$$EGKM = (EGK^2) \quad (3.28)$$

$$EGKICM = (EGKIC^2). \quad (3.29)$$

To demonstrate that our new model provides a more accurate approximation of currency option values compared to the basic G–K model, we aim to test the null hypothesis as follows:

$$H_0: EGKICM - EGKM < 0.$$

We must establish our expectations regarding this type of test, considering how the question is posed moving forward:

In the case of rejecting the null hypothesis (H_0), several reasons can be considered:

- The model incorporating dynamic information costs is either equivalent or less effective than the Garman–Kohlhagen (1983) model.
- The estimation of the variables $EGKM$ and $EGKICM$ in the presence of dynamic information costs and Garman–Kohlhagen’s model may have resulted in distortions.
- The data quality may have affected the results, including issues such as the synchronization of the call option value with the underlying asset, exchange rate, and simultaneous measurement of the interest rate.

If the null hypothesis (H_0) is not rejected, both models are adequately estimated, which suggests that the new model provides a better average approximation of currency options’ market value than the Garman–Kohlhagen (1983) model.

To further explore the comparison between the model considering dynamic information costs and the G–K model, we utilize the relative deviation of the average errors ($RDAE$), which is calculated as follows:

$$RDAE = \frac{EGKICM - EGKM}{EGKICM} \quad (3.30)$$

where *EGKM* represents the average errors of Garman and Kohlhagen's model (1983). Additionally, *EGKICM* represents the average errors of our modified model considering dynamic information costs, and *RDAE* denotes the relative deviation of the average errors of the model considering dynamic information costs compared to the Garman–Kohlhagen's theoretical model (1983).

3.4.3. Analysis of Implied Volatility and Its Implications for Economic Agent Behavior in Financial Markets

Implied volatility refers to the volatility implied by an option's market price. It plays a crucial role as it reflects the market's collective perception of the expected future volatility of the underlying asset (Poterba & Sammers, 1986). The supply and demand dynamics in the currency options market influence this measure of volatility; thus, by introducing dynamic information costs into the assessment of currency options, we can examine how it affects the behavior of economic agents. This comparative study analyzes the impact of these dynamic information costs on implied volatility and compares it with the implied volatility derived from both the modified and basic models.

We follow a systematic procedure to calculate implied volatility. First, we input the relevant parameters into the currency option assessment model, including the underlying price, domestic and foreign interest rates, dynamic information costs, strike price, and time to maturity. The goal is to align the calculated value with the observed market value, with the only unknown parameter being the volatility. We employ the Newton algorithm to estimate this implied volatility, which can be implemented through a VBA script named IVGKICM (refer to Appendix 4). By iteratively adjusting the volatility parameter, we can find the value that brings the calculated model price in line with the market price. This process is repeated daily in our sample, enabling us to derive implied volatility for the entire dataset.

To further analyze the impacts of introducing these imperfections on the behavior of economic agents in financial markets, we examine the relative deviation of the average implied volatility, referred to as “DAIVM,” in the model incorporating dynamic information costs compared to the theoretical Garman–Kohlhagen (1983) model. This relative deviation allows us to assess the extent to which dynamic information costs affect the implied volatility and, consequently, the behavior of economic agents in the currency options market. It is defined as follows:

$$DAIVM = \frac{IVGKICM - IVGKM}{VIVGKICM} \quad (3.31)$$

where IVGKM represents the average implied volatility extracted from the Garman–Kohlhagen (1983) model, while IVGKICM represents the average implied volatility extracted from the model considering dynamic information costs. Comparing these two averages allows us to analyze the impact of introducing dynamic information costs on the implied volatility.

3.5. Empirical Results and Discussion

3.5.1. Evaluating Performance of the Extended Model and Analyzing Valuation Discrepancies

We first assign initial values to the parameters λ , λ_1 , α , α_1 , l , and l_1 . Then, we employ a simulation method in Excel to optimize the average difference between EGKICM and EGKM. We utilize the “goal seek” feature located in the tools menu. This approach allowed us to refine the estimations of the new parameters. After performing the simulation, we obtained the following values: $\lambda = 0.8$, $\lambda_1 = 0.01$, $\alpha = 0.8$, $\alpha_1 = 0.7$, $l = 1$, and $l_1 = 4$. Using these adjusted parameter values, we calculate the prices of currency options using both the modified and basic models. The resulting MSE are then computed for each combination of maturity and moneyness, and these MSE values are presented in Table 2.

Table 3. 2. Mean squared errors by maturity and moneyness

Moneyiness	Total Observations/ Category			At the Money			Out of the Money		
Maturity (in days)	N° of obs	EGKICM - EGKM	RDAE in %	N° of obs	EGKICM-EGKM	RDAE in %	N° of obs	EGKICM - EGKM	RDAE in %
1–14	12	6.031E-06	18.189%	3	6.037E-06	19.338%	9	6.029E-06	17.835%
15–30	356	−0.0036	−41.105%	161	−0.005	−39.393%	195	−0.002	−44.594%
31–60	747	−0.013	−44.492%	419	−0.015	−45.484%	328	−0.009	−42.514%
61–90	1021	−0.045	−47.05%	437	−0.033	−46.846%	584	−0.055	−47.151%
91–112	475	−0.078	−46.384%	263	−0.091	−45.548%	212	−0.061	−48.018%
Total	2612	−0.036	−45.816%	1283	−0.036	−45.816%	1329	−0.036	−47.035%

Note: The table below illustrates the Mean Squared Errors by maturity and moneyness. N° of obs is the number of studied observations. EGKICM – EGKM represents the difference between the average errors of our modified model considering dynamic information costs and the average errors of Garman and Kohlhagen’s model (1983). RDAE denotes the relative deviation of the average errors of both models.

An in-depth review of Table 2 reveals how our new model, incorporating dynamic information costs, performs relative to the traditional Garman–Kohlhagen model. The primary goal was to prove that our model yields a more accurate valuation of currency options. To support this, we examined the average errors (EGKICM – EGKM) and the relative deviation of average errors (RDAE) over various maturity and moneyness categories.

The EGKICM – EGKM values indicate negative differences in all categories, signifying that our advanced GK model produces fewer average errors than the original model, indicating a better approximation of the real currency option values. Figure 2 graphically demonstrates this finding. Evaluating the RDAE, we found negative figures throughout all categories, corroborating that our novel model provides enhanced accuracy regarding percentage error than the original. These negative figures suggest that our model incorporating dynamic information costs tends to undervalue option values, implying a closer approximation to the true currency option values. This outcome is beneficial for market participants and investors, as the increased precision of our model aids better risk evaluation and decision-making for currency options trading strategies.

Moving on to a more detailed analysis, we observe that the RDAE values generally increase as the options' term lengthens, suggesting that the models' estimates and market prices deviate more for longer-term options. This result indicates the more significant impact of dynamic information costs on long-term options.

Examining the maturity categories, for 1–14 days, with a small sample size of 12, we have an RDAE of 18.189% for “at the money” and 17.835% for “out of the money” options, showing our model undervalues option prices. For the 15–30 days' maturity category, we find negative RDAE values across all moneyness categories, ranging from –39.393% to –44.594%, indicating a consistent underestimation of option values. This pattern continues for the 31–60 days, 61–90 days, and 91–112 days' maturity categories, with negative RDAE values of up to –48.018%, signifying a continued underestimation of option values.

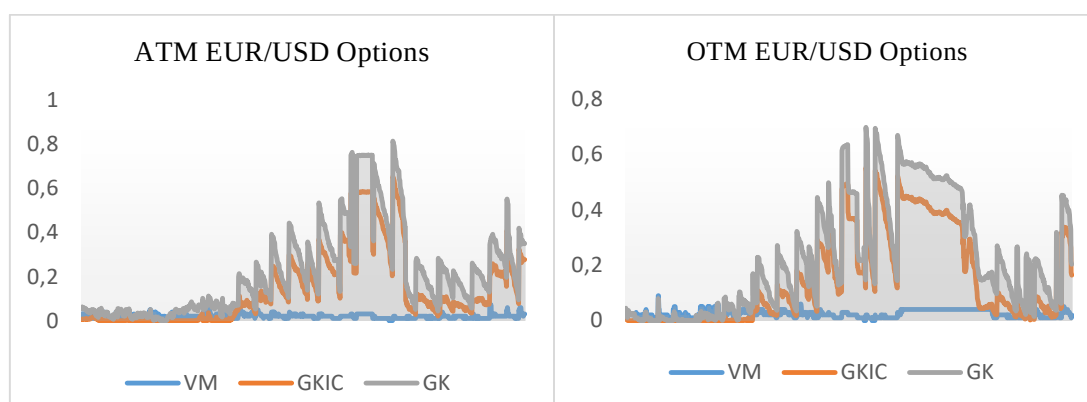
In terms of moneyness, the RDAE values vary. For instance, “at the money” options show relatively low RDAE values, suggesting close approximations to market prices; however, “out of the money” options reveal higher RDAE values, indicating greater disparities between the models' estimates.

Looking at “at the money” options, we see negative RDAE values across all maturities, increasing from -41.105% for 15–30 days’ maturity to -47.05% for 61–90 days’ maturity, indicating price underestimations. Similarly, for “out of the money” options, negative RDAE values continue across all maturities, with values ranging from -39.393% to -48.018% . This finding means our model consistently undervalues these options compared to market observations. Overall, the variability in RDAE values is influenced by the moneyness category, with “at the money” options showing closer alignment with market prices than “out of the money” options.

Our data indicates that our extended model, which incorporates dynamic information costs, outperforms the basic model across all option categories and maturities. The consistent underestimation of prices, as evidenced by the negative RDAE values, underscores the model’s capacity to effectively integrate dynamic information costs in pricing currency options. As such, it offers a more precise approximation of the real-world values of currency options compared to the basic model. These findings underscore the benefits for investors and market participants, as the extended model can provide a more accurate valuation of currency options. The results reiterate the importance for market participants to acknowledge the influence of information costs when pricing options across diverse currency pairs. This analysis is in harmony with existing financial literature that posits the role of informed investors in the options market can cause a deviation from the call-put parity relationship driven by privately held information (Anand et al., 2023; Alexander et al., 2023; Cremers & Weinbaum, 2010; Easley et al., 1998; Gapeev & Li, 2022; Goncalves-Pinto et al., 2020; Wu et al., 2022; Zhou, 2022). The amplified precision offered by our extended model can facilitate superior risk assessments and inform decision-making in currency options trading strategies.

These results bear considerable implications for professionals operating in the currency options market, offering a model that enables more accurate trading and risk management decisions. The data suggests that incorporating dynamic information costs can substantially impact longer-term and out-of-the-money options, which could reflect the higher levels of uncertainty and potential for larger price swings inherent in these categories. Thus, from a practical standpoint, market professionals need to consider the maturity and moneyness of options when making trading evaluations. Utilizing our extended model could aid in garnering more accurate estimations of market prices by integrating dynamic information costs into the calculation.

Figure 3. 2. Comparison of currency call option prices: Base model vs. extended model by moneyness



Note: This figure displays charts comparing call options calculated using the Garman–Kohlhagen model (GK in gray), the extended model (GKIC in orange), and the observed market call prices (VM in blue) categorized by moneyness.

3.5.2. Analyzing Implied Volatility

Table 3 presents the IVGKICM – IVGKM values for the “at the money” and “out of the money” categories across various maturities. These values are uniformly positive across all maturities, illustrating that the average implied volatility values are consistently higher in the revised model compared to the traditional model, a conclusion that is further corroborated by Figure 3. This discovery lends empirical credence to our initial supposition that integrating information costs in the valuation process of European currency call options results in escalated implied volatility. The integration of dynamic information costs signifies that the market anticipates a more pronounced future volatility of the underlying price compared to a market scenario devoid of these costs. This finding is consistent with Stein’s (1987) model, which asserts that the participation of informed agents can cause a surge in volatility due to their potential destabilizing impact. Similarly, Easley and O’Hara (1987) observed that the involvement of uninformed investors can engender surplus volatility. In situations of information asymmetry, economic agents tend to foresee a higher volatility in markets where information costs are present compared to those with perfectly symmetric information. Consequently, the pricing of currency options in the presence of information costs intimates the existence of informational asymmetry, culminating in elevated implied volatility values.

Table 3. 3. Deviation of the average of implied volatility by maturity and moneyness

Moneyness	Total Observations/Category			At the Money			Out of the Money		
Maturity (in days)	N° of obs	IVGKICM - IVGKM	DAIVM in %	N° of obs	IVGKICM - IVGKM	DAIVM in %	N° of obs	IVGKICM - IVGKM	DAIVM in %
1–14	12	0.006	8.295%	3	0.014	12.038%	9	0.004	5.962%
15–30	356	0.109	52.378%	161	0.143	58.289%	195	0.081	45.606%
31–60	747	0.146	61.987%	419	0.170	65.058%	328	0.115	56.921%
61–90	1021	0.197	66.982%	437	0.170	69.092%	584	0.218	65.805%
91–112	475	0.191	64.891%	263	0.180	61.646%	212	0.205	68.848%
Total	2612	0.169	63.643%	1283	0.169	64.881%	1329	0.168	62.483%

Notes: The table below illustrates the deviation of the average of implied volatility by maturity and moneyness. N° of obs is the number of studied observations. IVGKICM – IVGKM represents the difference between the average implied volatility extracted from the model considering dynamic information costs and the average implied volatility extracted from the Garman–Kohlhagen (1983) model. DAIVM denotes the relative deviation of the average implied volatility.

Our assessment of implied volatility values by maturity highlights distinct patterns that elucidate the effect of the modified Garman and Kohlhagen’s model compared to the traditional one. A closer look at the different maturity categories yields the following insights. In the 1–14 days’ maturity category, the “at the money” and “out of the money” observations all yield positive IVGKICM – IVGKM values, indicating an increase in implied volatility in the modified model. The DAIVM percentages span from 5.962% to 19.338%, signifying a notable surge in implied volatility relative to the traditional model. We observe the same trend in the 15–30 days’ maturity category, with both “at the money” and “out of the money” options displaying positive IVGKICM – IVGKM values, thus pointing to heightened implied volatility in the modified model. The accompanying DAIVM percentages fall between 45.606% and 58.289%, representing a substantial jump in implied volatility relative to the traditional model. A similar pattern persists in the 31–60 days’ maturity category, with both “at the money” and “out of the money” options registering positive IVGKICM – IVGKM values, suggesting increased implied volatility in the modified model. The DAIVM percentages, ranging from 56.921% to 65.058%, underscore a marked increase in implied volatility relative to the traditional model. The 61–90 days and 91–112 days’ maturity categories also consistently yield positive IVGKICM – IVGKM values for both “At the Money” and “Out of the Money” options, insinuating a higher implied volatility in the modified model. The DAIVM percentages vary from 61.646% to 69.092% for the 91–112 days’ category and from 65.805% to 69.092% for

the 61–90 days’ category. These percentages demonstrate a sizable increase in implied volatility relative to the traditional model for these extended maturities.

Our examination across different maturity categories reveals a consistent trend of the modified Garman and Kohlhagen’s model exhibiting higher implied volatility than the traditional model. This finding bolsters the theory that integrating information costs in the valuation of currency options leads to a rise in the anticipated volatility of the underlying price. Our results align with the understanding that the involvement of informed investors and the existence of information asymmetry can drive volatility levels higher in financial markets (Attanasio, 1990; Dávila, & Parlato, 2023; Vlastakis & Markellos, 2012) and specifically in the currency options market (Baek, 2022; Jin et al., 2012; Zhou, 2022). These detailed insights underscore the importance of accounting for the impact of information costs on implied volatility when pricing and trading currency options across different maturities. Market participants should recognize the escalated volatility linked to information asymmetry and fine-tune their risk management strategies accordingly.

When analyzing the implied volatility values by moneyness, we encounter unique patterns illuminating the impact of the dynamic information costs-infused Garman and Kohlhagen model concerning the traditional model.

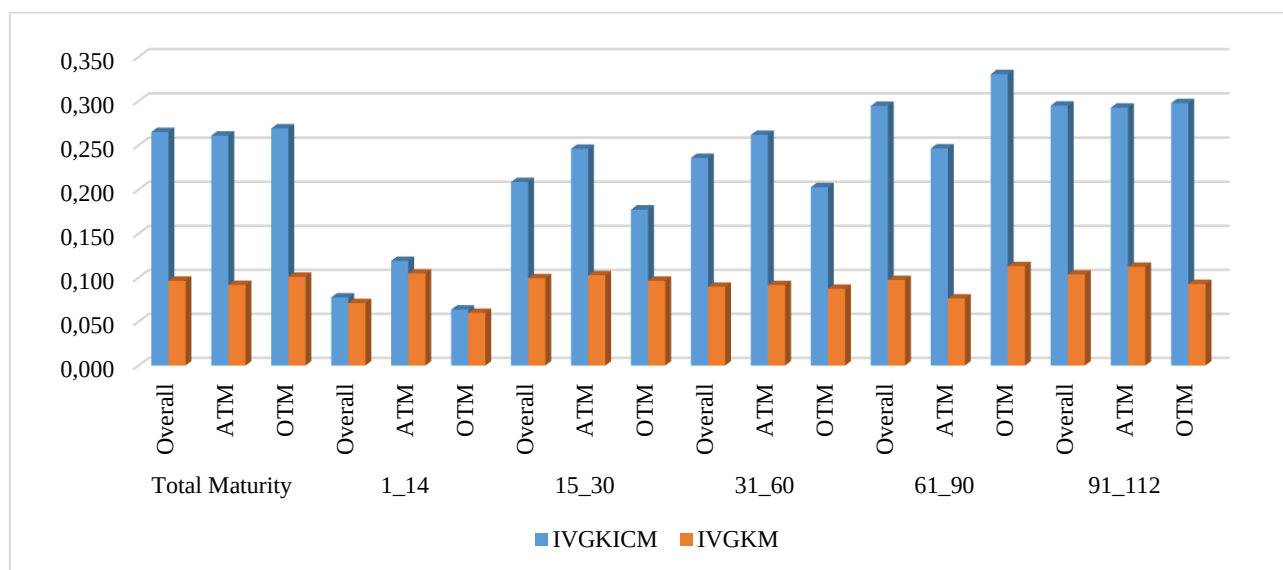
In the realm of “at the money” options, we consistently register positive IVGKICM – IVGKM values across all maturity categories, signifying a higher level of implied volatility in the modified model. Within the 1–14 days’ maturity segment, DAIVM percentages fluctuate between 5.962% and 8.295%. Progressing toward the 15–30 days, 31–60 days, 61–90 days, and 91–112 days’ maturity segments, DAIVM percentages span from 45.606% to 66.982%. This notable uptick in implied volatility underscores the considerable impact of integrating information costs into the valuation model for “at the money” options. Mirroring this pattern, “out of the money” options also demonstrate consistently positive IVGKICM – IVGKM values across all maturity categories, indicative of heightened implied volatility in the modified model. Within the 1–14 days’ maturity bracket, DAIVM percentages vary from 12.038% to 19.338%. Shifting toward the 15–30 days, 31–60 days, 61–90 days, and 91–112 days’ maturity brackets, DAIVM percentages extend from 58.289% to 69.092%. These figures underline the pronounced increase in implied volatility when contrasted with the traditional model for “out of the money” options. In summary, the moneyness-centered examination reveals that both “at the money” and “out of the money” options display higher implied volatility within the

modified Garman and Kohlhagen model than the classical one. This insinuates that incorporating information costs escalates the perceived volatility for both types of options. These meticulous findings accentuate the significance of considering the influence of information costs on implied volatility when valuing and trading currency options across varying levels of moneyness. It is crucial for market participants to acknowledge the inflated volatility associated with the inclusion of information costs and to subsequently calibrate their risk management strategies. The elevated implied volatility within the modified model implies a heightened perception of risk that should be considered when valuing and transacting options across diverse moneyness. When pricing and trading options across a range of moneyness categories, we notice a larger increase in implied volatility for “at the money” options versus “out of the money” options when dynamic information costs are factored in. This phenomenon can be attributed to several contributing elements. First, “at the money” options possess strike prices closely aligned with the underlying asset’s current price. Consequently, even minor shifts in the asset’s price can significantly influence the option’s value. In the presence of dynamic information costs, an augmented sense of volatility within the marketplace can instigate larger fluctuations in the option’s value, yielding a higher implied volatility for “at the money” options. Second, dynamic information costs infer the presence of informed traders who hold private, market-influencing information. Due to their superior comprehension of market trends and anticipated price shifts, these traders can inject additional volatility into the market. As a result, the implied volatility of “at the money” options may be more profoundly impacted than “out of the money” options. Additionally, “at the money” options are generally seen as more susceptible to market conditions changes and tend to carry a higher risk level than “out of the money” options. When dynamic information costs are woven into the pricing model, the market’s perception of risk may be elevated, leading to higher implied volatility for “at the money” options. Lastly, “at the money” options draw higher trading volumes and more market engagement than “out of the money” options. In situations where dynamic information costs are present, increased trading activity and the involvement of informed traders can culminate in higher implied volatility for “at the money” options.

The subsequent examination of implied volatility values indicates that the modified Garman and Kohlhagen’s model, which accounts for information costs, consistently generates higher average implied volatility than its classical counterpart. This revelation underscores the criticality of acknowledging information costs in pricing currency options and amplifies the ramifications of information asymmetry within the market.

From a policy standpoint, these outcomes hold substantial implications. They underscore the urgency of factoring in information costs and their impact on implied volatility during the pricing and trading of currency options. Market players must understand the escalated volatility resulting from information asymmetry and calibrate their risk management strategies accordingly. By acknowledging the influence of information costs on implied volatility, market participants can better navigate the complex landscape of the currency options market and make more informed decisions. These findings fortify the significance of integrating dynamic information costs into option pricing models and illuminate the intricacies that information asymmetry introduces. Moreover, by identifying and accounting for these elements, market participants can deepen their comprehension of implied volatility and enhance their risk management practices within the currency options market.

Figure 3. 3. Comparison of implied volatility: Base model vs. extended model by maturity and moneyness



Notes: The histograms presented in this figure depict the volatility for two different models; the Garman–Kohlhagen model with dynamic information costs (IVGKICM) is displayed in blue, and the new model with dynamic information costs (IVGKM) is displayed in orange. The data is presented based on moneyness (ATM = at the money, and OTM = out of the money) and maturity (1–14 days, 15–30 days, 31–60 days, 61–90 days, and 91–112 days).

3.6. Conclusion and Perspectives

This study thoroughly examined the pricing of European currency options, uniquely incorporating dynamic information costs into the traditional Garman and Kohlhagen model. This research utilized an intensity function inspired by the Beer–Lambert law, which was

integrated into domestic and foreign interest rates to effectively capture the variable nature of information costs. We analyzed daily data from EUR/USD futures continuous calls from September 21, 2012, to September 23, 2022. This analysis provided a wide-lens perspective on the fluctuations in currency option pricing over a considerable period. This empirical examination, focused on understanding the currency options market in greater depth, adds a valuable dimension to the prevailing discourse on option pricing. The research findings have proven that the revised model incorporating dynamic information costs surpasses the classical model in pricing accuracy. This superior accuracy, highlighted in longer-term and out-of-the-money options, is a testament to the profound impact of dynamic information costs. By calibrating the new parameters of information costs, we have successfully minimized the discrepancies between our model's predictions and the actual market values of currency options, augmenting the precision of our estimations. The maturity and moneyness-based analysis conducted post-simulation reveals a significant error reduction for our model that integrates dynamic information costs. This enhancement reinforces the model's validity and practicability for accurately valuing currency options. Furthermore, the analysis further showed that the extended model persistently displays a higher average implied volatility than the classical model. This finding supports the hypothesis that integrating information costs into option pricing correlates with a surge in implied volatility. These results are congruent with existing literature, emphasizing the role of informed investors and the destabilizing effect of information asymmetry in the options market.

From a practical standpoint, these findings are pivotal for the currency options market. They improve the accuracy of option pricing and refine risk assessment. Market participants must take note of the elevated volatility due to information asymmetry and adjust their risk management strategies.

Although this research underscores the necessity of considering dynamic information costs in currency option pricing and offers valuable insights for stakeholders, it has some limitations. The study does not compare the extended model with other potential extensions like stochastic volatility models or those incorporating stochastic interest rates. Moreover, it relies on daily data, which might not fully capture intraday market dynamics and potential changes in implied volatility. Future research should overcome these limitations by delving into comparisons with other model extensions and utilizing more granular, high-frequency data to deepen the understanding of the effects of dynamic information costs on option pricing. While this study primarily evaluates the extended Garman and Kohlhagen model vis-à-vis the baseline

model, the inclusion of other model extensions and intraday data in future research could further illuminate the dynamics of option pricing in the presence of dynamic information costs.

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Appendices

Appendix 3.A. The resolution of the PDE

The value of the purchase option must fill the condition to the boundary mark, expressing the value of the call at the date of maturity:

$$C(S, t^*) = \text{Max}[0; S(t^*) - X] \quad (3A. 1)$$

The search for the solution requires a change of the variables that lead to the equation of heat. We start by writing the price of the option in the following form:

$$C(S, t) = f(t)y(u_1, u_2) \quad (3A. 2)$$

where, $f(t)$ and $y(u_1, u_2)$ are unknown functions.

Therefore, we calculate the derivative of the option price regarding time and compared it to the price of the underlying asset:

$$\frac{\partial C}{\partial t} = \frac{\partial f}{\partial t} y + f \frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial t} + f \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial t} \quad (3A.3)$$

$$\frac{\partial C}{\partial S} = f \left(\frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial S} + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) \quad (3A.4)$$

$$\frac{\partial^2 C}{\partial S^2} = f \left(\frac{\partial^2 y}{\partial u_1^2} \left(\frac{\partial u_1}{\partial S} \right)^2 + \frac{\partial y}{\partial u_1} \frac{\partial^2 u_1}{\partial S^2} \right) + f \left(\frac{\partial^2 y}{\partial u_2^2} \left(\frac{\partial u_2}{\partial S} \right)^2 + \frac{\partial y}{\partial u_2} \frac{\partial^2 u_2}{\partial S^2} \right) + 2f \left(\frac{\partial^2 y}{\partial u_1 \partial u_2} \frac{\partial u_2}{\partial S} \frac{\partial u_1}{\partial S} \right) \quad (3A.5)$$

Then, we replace these derivatives in equation (20). We get:

$$\begin{aligned} & \frac{1}{2} \sigma^2 S^2 f \left(\frac{\partial^2 y}{\partial u_1^2} \left(\frac{\partial u_1}{\partial S} \right)^2 + \frac{\partial y}{\partial u_1} \frac{\partial^2 u_1}{\partial S^2} \right) + \frac{1}{2} \sigma^2 S^2 f \left(\frac{\partial^2 y}{\partial u_2^2} \left(\frac{\partial u_2}{\partial S} \right)^2 + \frac{\partial y}{\partial u_2} \frac{\partial^2 u_2}{\partial S^2} \right) \\ & + \sigma^2 S^2 f \left(\frac{\partial^2 y}{\partial u_1 \partial u_2} \frac{\partial u_2}{\partial S} \frac{\partial u_1}{\partial S} \right) + (r_{1d} - r_{1f}) S f \left(\frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial S} + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) + \frac{\partial f}{\partial t} y \\ & + f \frac{\partial y}{\partial u_1} \frac{\partial u_1}{\partial t} + f \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial t} - (r_{1d} - r_{1f}) f y = 0 \end{aligned} \quad (3A.6)$$

Now, we can solve equation (26) by using the « Head Transfer » equation for the function y:

$$\frac{\partial y}{\partial u_2} = \frac{\partial^2 y}{\partial u_1^2} \quad (3A.7)$$

Let us search $f(t), u_1(S, t), u_2(S, t)$; thus:

$$-(r_{1d}) f y + \frac{\partial f}{\partial t} y = 0 \rightarrow (r_{1d}) f = \frac{\partial f}{\partial t} \rightarrow f(t) = e^{r_{1d} t}. \quad (3A.8)$$

We designate by the following: $a^2 = \frac{1}{2} \sigma^2 S^2 \left(\frac{\partial u_1}{\partial S} \right)^2$, simplify by $f(t)$, and rewrite the equation to identify the different terms.

$$\text{So, } \frac{1}{2} \sigma^2 S^2 \left(\frac{\partial^2 y}{\partial u_1^2} \left(\frac{\partial u_1}{\partial S} \right)^2 \right) + \frac{1}{2} \sigma^2 S^2 \left(\frac{\partial y}{\partial u_2} \frac{\partial^2 u_2}{\partial S^2} \right) + (r_{1d} - r_{1f}) S \left(\frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial S} \right) + \frac{\partial y}{\partial u_2} \frac{\partial u_2}{\partial t} \text{ is canceled}$$

$$\text{when: } -a^2 = \frac{1}{2} \sigma^2 S^2 \left(\frac{\partial^2 u_2}{\partial S^2} \right) + (r_{1d} - r_{1f}) S \left(\frac{\partial u_2}{\partial S} \right) + \frac{\partial f}{\partial t} y + \frac{\partial u_2}{\partial t}$$

Assuming that

$$\frac{\partial u_2}{\partial S} = \frac{\partial^2 u_2}{\partial S^2} = 0 \quad (3A.9)$$

We find that $\frac{\partial u_2}{\partial t} = -a^2$, then,

$$u_2 = -a^2 T \quad (3A.10)$$

In these conditions, the EDP is written as follows:

$$\frac{1}{2} \sigma^2 S^2 \frac{\partial^2 u_1}{\partial S^2} + (r_{1d} - r_{1f}) S \frac{\partial u_1}{\partial S} + \frac{\partial u_1}{\partial t} = 0 \quad (3A.11)$$

Using the expression of a^2 , we get:

$$\frac{\partial u_1}{\partial S} = \sqrt{2} \frac{a}{\sigma} \frac{1}{S} \quad (3A.12)$$

Then,

$$u_1 = \sqrt{2} \frac{a}{\sigma} \ln \left(\frac{S}{X} \right) + b(t) \quad (3A.13)$$

Replacing (33) in (31), we get:

$$\frac{1}{2} \sigma^2 S^2 \left(-\frac{1}{S^2} \sqrt{2} \frac{a}{\sigma} + \frac{\partial b}{\partial t} \right) + (r_{1d} - r_{1f}) S \sqrt{2} \frac{a}{\sigma} \frac{1}{S} = 0 \quad (3A.14)$$

But,

$$-\frac{1}{2} \sigma \sqrt{2} + \frac{\partial b}{\partial t} + (r_{1d} - r_{1f}) \frac{a}{\sigma} \sqrt{2} = 0 \quad (3A.15)$$

Then,

$$\frac{\partial b}{\partial t} = \frac{\sigma \sqrt{2}}{\sigma} \left(\frac{\sigma^2}{2} - (r_{1d} - r_{1f}) \right) \quad (3A.16)$$

$$\Rightarrow b(t) = \frac{\sigma \sqrt{2}}{\sigma} \left(\frac{\sigma^2}{2} - ((r_{1d} - r_{1f})) \right) T \quad (3A.17)$$

$$\Rightarrow u_1 = \frac{\sigma \sqrt{2}}{\sigma} \left[\ln \frac{S}{X} + \left(\frac{\sigma^2}{2} - (r_{1d} - r_{1f}) \right) T \right]. \quad (3A.18)$$

Because $C(S, t^*) = f(t)y(u_1, u_2)$ and $\frac{\partial y}{\partial u_2} = \frac{\partial^2 y}{\partial u_1^2}$, the result at maturity is written as follows:

$$C(S, t^*) = [y(u_1(S, t^*), u_2(S, t^*))] = y \left[\frac{a \sqrt{2}}{\sigma} \ln \frac{S}{X}, 0 \right]. \quad (3A.19)$$

The solution of the Head Transfer equation is of the following form:

$$y(u_1, u_2) = \frac{1}{\sqrt{2\pi}u_2} \int_{-\infty}^{+\infty} u_0(\epsilon) e^{\frac{-\epsilon^2}{2u_2}} d\epsilon \quad (3A.20)$$

The value of the call at the date of maturity can be expressed as follows:

$$C(S, t^*) = y(k, 0) = \begin{cases} X \left[e^{\frac{-\epsilon^2}{2u_2}} - 1 \right], & \text{if } k \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (3A.21)$$

where, $k = \frac{a\sqrt{2}}{\sigma} \ln\left(\frac{S}{X}\right)$

Appendix 3.B. Visual Basic program for computing European currency call option by using the standard G–K model

```
Function Call_GK(S, K, r_d, r_f, sigma, T)
d1 = ((Application.Ln(S / (K))) / ((sigma) * Sqr(T)) + (r_d - r_f) * T / ((sigma) * Sqr(T)) + (0.5 * sigma) * Sqr(T))
d2 = d1 - sigma * Sqr(T)
nd1 = Application.NormSDist(d1)
nd2 = Application.NormSDist(d2)
Call_GK = (S * Exp(-r_f * T) * nd1) - (K * Exp(-r_d * T) * nd2)
End Function
```

Appendix 3.C. Visual Basic program for computing European currency call option by using the new G–K model

```
Function Call_GKIC(S, K, r_1d, r_1f, sigma, T)
d1 = ((Application.Ln(S / (K))) / ((sigma) * Sqr(T)) + (r_1d - r_1f) * T / ((sigma) * Sqr(T)) + (0.5 * sigma) * Sqr(T))
d2 = d1 - sigma * Sqr(T)
nd1 = Application.NormSDist(d1)
nd2 = Application.NormSDist(d2)
Call_GKIC = (S * Exp(-r_1f * T) * nd1) - (K * Exp(-r_1d * T) * nd2)
End Function
```

Appendix 3.D. Visual Basic program for computing implied volatility

```

Function IVGKICM (Market_Call As Double, K As Double, S As Double, r1d As Double, r1f As Double, T As Double)
sigma = 0.2
dv = 0.0001 + 1
While Abs(dv) > 0.0001
d1 = ((Application.Ln(S / (K))) / ((sigma) * Sqr(T)) + (r1d - r1f) * T / ((sigma) * Sqr(T)) + (0.5 * sigma) * Sqr(T))
d2 = d1 - sigma * Sqr(T)
nd1 = Application.NormSDist(d1)
nd2 = Application.NormSDist(d2)
erreurprice = (S * Exp(-r1f * T) * nd1) - (K * Exp(-r1d * T) * nd2) - Market_Call
Vega = S * Sqr(T / 3.1415926 / 2) * Exp(-0.5 * d1 ^ 2)
dv = erreurprice / Vega
sigma = sigma - dv
Wend
IVGKICM = sigma
End Function

```

**Chapter 4. Enhancing Currency
Option Pricing Models: Incorporating
Dynamic Information Costs and
Machine Learning Techniques**

Chapter 4. Enhancing Currency Option Pricing Models: Incorporating Dynamic Information Costs and Machine Learning Techniques

Abstract

The concept of information cost has evolved over time and has been applied to various decision problems, including currency option pricing. This research delves into the impact of dynamic information costs on the currency option pricing model, innovatively developed by Dammak et al. (2023). We utilize the Differential Evolution algorithm to calibrate the novel information cost parameters, using data from various currency call options pairs from January 1, 2018, to November 24, 2022. A satisfactory approximation of real market currency option prices is achieved through this methodology. Additionally, we harness the power of machine learning, specifically the random forest regression technique, to predict the values of effective domestic and foreign interest rates within a changing information cost landscape. By partitioning our dataset into training and test sets, our study demonstrates that the new model, incorporating dynamic information costs, generates more accurate and stable pricing outcomes. This research marks a substantive contribution to the evolving field of option pricing, emphasizing the potential of machine learning techniques in solving complex financial problems.

Keywords: Dynamic Information Costs; Currency Options; Garman and Kohlhagen's model; Machine Learning; Random Forest Regression; Differential Evolution

JEL classification: C45, C63, G14, G15, G17

4.1. Introduction

Financial derivative problems consistently manifest as complex, dynamic, and uncertain, inherently complicating their resolution. Nevertheless, the derivative market provides a distinctive avenue to evaluate the potential benefits of option pricing. A detailed analysis of factors, including price, maturity time, rate of return, and neutral interest rate risk, permits investors to anticipate the value of real market data prior to making a decision to buy or sell an option value contract. This pivotal information is integral for making informed decisions and maximizing profits amidst the capricious and competitive milieu of financial markets. By leveraging mathematical models and advanced analytical tools, investors can unravel a more comprehensive understanding of the intricate relationships amidst various financial variables, subsequently making informed decisions that augment their returns while concurrently minimizing their risks.

As financial markets inexorably advance in complexity and dynamism, the demand for sophisticated analytical tools and adept financial knowledge is projected to perpetually escalate, thereby positioning financial derivatives as a stimulating and formidable area of study. Notably, options, being instruments derived from other financial instruments, inherently encapsulate additional complexity and risk. Regardless, their pivotal role in shaping the financial system and fueling economic growth is indisputable. Option pricing emerges as a focal point of interest within finance and mathematics, magnetizing attention from academics, financial corporations, and investors.

The Garman and Kohlhagen (1983) model (G-K model) pioneered providing an analytical solution for currency option pricing using the traditional arbitrage argument and has been widely utilized. It has often been fine-tuned through numerical methods like Monte Carlo simulations. Nevertheless, with the advent of breakthroughs in computing power and machine learning techniques, promising alternatives have emerged for navigating complex problems. The G-K model, while seminal, has encountered obstacles particularly in accounting for both domestic and foreign interest rates, electing to treat the foreign interest rate as the dividend rate on the underlying exchange rate. Notably used for pricing European currency options, the model is not without its limitations. It operates under the presumption of market efficiency, which inherently implies that economic agents behave rationally and that financial markets are devoid of imperfections. Furthermore, it assumes the existence of only one risky asset and one

risk-free asset, a scenario that isn't wholly reflective of real-world contexts. Consequently, the market efficiency assumption is challenging to validate empirically.

Elaborating on its foundation, the G-K model's assumption of market efficiency rests principally on two pillars: rational economic agents and an absence of imperfections within financial markets. Under this framework, as posited by Fama (1991), asset prices are presumed to instantaneously adapt to new information and accurately encapsulate all available data. A market adhering to these characteristics would inherently exhibit two pivotal features. Firstly, the competitive nature of the market nullifies opportunities for profitable arbitrage, rendering market outperformance an impossibility. Secondly, prices are deemed fair, implying that the market price of each asset equates to its fundamental value, defined as the present value of its anticipated future cash flows.

However, Biases in evaluation can emerge due to various market constraints, as financial market theory acknowledges the existence of imperfections within the market, attributable to several types of information costs. These include costs tied to short selling constructions (Scheinkman and Xiong, 2003; Kim et al., 2016; Bohl et al., 2016), and those arising from research and information acquisition (Grossman and Stiglitz, 1980; Easley and O'Hara, 1987; Bellalah, 1999; Argenziano et al., 2016; Weller, 2018; Maclellan and Wood, 2021). These market imperfections can inadvertently lead to pricing evaluation errors, which become particularly crucial when pricing financial asset models and selecting an international portfolio. Additional facets of market imperfections comprise transmission costs (Bhuyan et al., 2016; Ahmed and Huo, 2019), as well as costs related to adverse selection or asymmetric information (Ahmad et al., 2021; Ranaldo and Somogyi, 2021). However, it's paramount to recognize that the impact of these imperfections on option pricing is time-varying. This implies that their dynamic costs and resultant implications oscillate over time, as explicated by Dammak et al. (2023).

In this study, we focus on the dynamic information costs, which vary over time, in the currency options market as proposed by Dammak et al. (2023). The currency options market is characterized by high volatility, with information that can change rapidly and unpredictably. Consequently, information costs can fluctuate, depending on market circumstances, and exert a significant impact on option valuation. Our objective is to comprehend how information costs evolve over time and how they influence the valuation of currency options. This innovative

approach aims to enhance our understanding of the dynamics within the currency options market and propose more apt solutions for financial risk management.

This research combines machine learning, statistics, and mathematical finance to forecast option prices using contemporary financial technology. We begin in our experimental section by simulating new parameters of information costs via the Differential Evolution (DE) algorithm. This approach was chosen for its robustness in identifying minimum solutions for option value problems and for its straightforward implementation and efficacy in exploration and exploitation strategies. Though popular, this method sometimes struggles to provide accurate solutions that mirror real-world market values.

Therefore, the DE parameters optimized for information costs are employed to construct a potent machine learning model that predicts the values of effective domestic and foreign interest rates with precision. This model, attuned to the dynamic nature of information costs, is applied to various currency call options, such as EUR-RUB, EUR-QAT, USD-RUB, RUR-JPY, and EUR-USD, from January 1, 2018, to November 24, 2022. Over recent years, the utility of machine learning (ML) in addressing real-world problems has seen a remarkable rise, spawning a plethora of techniques and applications.

Focusing on financial industry applications, ML has brought forth flexible and robust predictive capabilities, outperforming classical mathematical and econometric models, and has offered pivotal advantages to financial decision-makers and market participants, especially in the realms of financial modeling and data forecasting. Specifically, our study utilizes the Random Forest Regression ML technique, amalgamating multiple decision trees to bolster prediction accuracy, to anticipate the values of effective domestic and foreign interest rates while accounting for the dynamic information costs. Furthermore, we introduce three binary variables – Before Covid-19, During Covid-19, and Russia-Ukraine Conflict – to demarcate the observation period. This inclusion aids in evaluating and interpreting outcomes for any region or period under scrutiny. To attain a comprehensive understanding of the dynamics of information costs within the currency options market, we conducted experiments with five distinct Random Forest Regression models, utilizing five disparate datasets for both the training and test data.

Our findings, incorporating these imperfections into currency option valuation, unveiled that the novel model's pricing outcomes, which embed dynamic information costs, demonstrated heightened accuracy and stability. Consequently, we are enabled to furnish more

precise forecasts for currency option prices, thus enriching the comprehension of financial markets. By employing the DE algorithm and incorporating the random forest method, we forge a coherent and efficient framework for currency option pricing, ultimately aiding investors, financial institutions, and policymakers in making informed decisions regarding currency options, risk mitigation, and investment strategy optimization.

The subsequent sections of this study are structured as follows: Section 2 offers a thorough review of pertinent literature. In Section 3, we highlight the contributions of the research. Section 4 introduces the extended Garman-Kohlhagen model, which integrates dynamic information costs as proposed by Dammak et al. (2023). Section 5 discusses the sensitivity of the currency option price to the new variables of dynamic information costs, a topic not previously published. Section 6 explains the data utilized in this study and the predictive models. Section 7 presents our analysis's key findings, and finally, Section 8 provides a conclusion to the research, encapsulating the key findings, addressing the limitations of the study, and proposing directions for forthcoming research.

4.2. Literature review

4.2.1. Information Costs

While standard financial theory's Efficient Market Hypothesis (EMH) posits that financial markets are 'informationally efficient,' with rational arbitrage neutralizing irrational impacts on asset prices, aligning them more closely with fundamentals, various anomalies—viewed as EMH paradoxes—have surfaced since the 1970s, presenting a contrasting reality. Indeed, investors in tangible financial markets might find their actions swayed by these imperfections. Notably, the nexus between informed trading and option prices has garnered extensive research attention. A number of studies have scrutinized the implied volatility (IV) spread between call and put options—having identical exercise prices and maturity—as a surrogate for informed investor activities, with researchers like Cremers and Weinbaum (2010) and Yigit (2014) employing this approach. Contrary to the foundational Black-Scholes (1973) model, which presumes a zero IV spread, these investigations reveal that this presupposition does not hold in actual market conditions.

Findings indicate that when investors are privy to positive (negative) information regarding an event, the demand for call (put) options surges relative to put (call) options, causing a departure from the zero IV spread. Several research initiatives, including those by

Xing et al. (2010), Cremers and Weinbaum (2010), Jin et al. (2012), An et al. (2014), and Govindaraj et al. (2015), advocate that the engagement of informed investors in the options market can provoke a shift in the call-put parity relation towards private information, as outlined by Easley et al. (1998). Additionally, a considerable body of literature exists, elucidating the influence of information costs on option pricing, including works by Bellalah and Jacquillat (1995), Bellalah (2006), Ben Hamad and Eleuch (2008), Bellalah (2018), Zghal et al. (2020), Ryu and Yu (2021), Lee et al. (2021), Luo et al. (2022), Lockwood et al. (2022), Song et al. (2023), and Dammak et al. (2023).

Traditional options pricing models, such as those proposed by Black and Scholes (1973), Garman and Kohlhagen (1983), Bick (1987), Ricardo (2002), and Guo and Yuan (2014), typically assume that investors are rational and risk-neutral, positing that the expected growth rate of the underlying asset and the discount rate should both equate to the risk-free rate. However, a myriad of studies presents a contrast, indicating that when information costs are considered, the expected growth rate of the underlying asset and the discount rate incorporate not only the risk-free rate but also costs emerging from related imperfections. In a market populated by both informed and uninformed—yet rational—investors, the impact of information can be likened to the application of an additional discount rate. This viewpoint has been corroborated by various research efforts, including works by Merton (1987), Bellalah and Jacquillat (1995), Ben Hamad and Eleuch (2008), Zghal et al. (2020), and Dammak et al. (2023).

4.2.2. Materials and Methods

Financial derivatives present inherent complexity, dynamicity, and uncertainty. A focal point in the derivative market is the determination of option pricing values. Investors can forecast the value of real market data prior to engaging in buying or selling option value contracts by considering various factors, such as price, maturity time, rate of return, and risk-neutral interest rate. Metaheuristic algorithms, such as the Differential Evolution (DE) algorithm showcased by Kumar et al. (2014), have been utilized to determine option pricing values. While this issue has been scrutinized in previous studies (Deb et al., 2002; Deb, 2011; Ardia et al., 2011; Singh et al., 2018; Hu et al., 2022; Febrianti et al., 2023), they also illustrate that employing the DE algorithm can significantly amplify the robustness and efficiency of the option pricing process amidst complex scenarios.

Much of the existing research in currency option pricing has primarily concentrated on formulating equations and enhancing numerical methods to minimize errors, while a subset explores machine learning (ML) applications using historical data. The integration of ML into option pricing models has been pivotal in fortifying and refining pricing techniques for financial derivatives. For instance, Fang and George (2017) advocated for ML's use alongside Levy approximation to sharpen the accuracy of Asian option valuation techniques. Similarly, Chowdhury et al. (2020) reconfigured the Monte Carlo method, adjusting parameters like strike price, time, and volatility, and employed decision trees, neural networks, and ensemble learning to predict call and put option values, providing insights into the correlation between stock price and volatility. In another approach, Klibanov et al. (2021) leveraged the method of quasi-reversibility and ML to foresee option prices in corporations using the Black-Scholes model.

In the broader literature, models such as classification and regression tree models, alongside various ML techniques, have been developed to create prediction rules for classifying and regressing outcome variables. Breiman (2001) unveiled the random forests (RF) algorithm, an ensemble strategy that serves as a form of nearest neighbor predictor, initiating with a prevalent ML method known as "decision trees." This algorithm has found applications across diverse fields like machine learning, bioinformatics, and big data modeling, with numerous financial studies employing the RF algorithm for stock price forecasting and strategizing investments (Theofilatos et al., 2012; Qin et al., 2013; Basak et al., 2019), Bitcoin price prediction (Basher and Sadorsky, 2022), and risk management (Chang et al., 2018; Arora and Kaur, 2020).

In a related exploration, Ivaşcu (2021) scrutinized the efficacy of popular ML algorithms in option pricing, evaluating the potency of Support Vector Regressions and Genetic Algorithms, and introducing three additional Decision Tree methods: Random Forest, XGBoost, and LightGBM, focusing on European call options with WTI crude oil futures as the underlying asset. Independent of contract moneyless and maturity, ML algorithms noticeably surpass traditional methods by a significant measure. Lastly, Li and Yan (2023) compared various ML methods for option pricing, concluding that random forest and artificial neural network methods notably yield superior fitting and performance with minimized prediction errors.

4.3. Research Objectives and Contributions

The objective of the present paper is to shed light on the intricate realm of currency option pricing, specifically within the framework of dynamic information costs. As currency markets continuously evolve, understanding the nuanced impact of dynamic information costs becomes increasingly crucial. Our key contributions include:

- i. Analyzing the impact of dynamic information costs on currency option pricing to unravel their multifaceted role in shaping market dynamics.
- ii. Comparing the traditional currency option pricing model with a modified version incorporating dynamic information costs, allowing us to discern the value of incorporating real-time data into pricing strategies.
- iii. Exploring the integration of machine learning techniques for predicting interest rates while considering dynamic information costs, bridging the gap between traditional financial models and cutting-edge technology.
- iv. Evaluating the stability and precision of the enhanced pricing model, providing insights into its robustness under varying market conditions.
- v. Highlighting practical implications for financial risk management, offering actionable strategies for investors, financial institutions, and policymakers in navigating the complexities of currency options within a dynamic information cost landscape.

These contributions collectively illuminate the intricate interplay between dynamic information costs and currency option pricing while offering tangible insights for financial decision-makers and market participants.

4.4. The Garman–Kohlhagen Model Considering Dynamic Information Costs

According to Dammak et al. (2023), the value of a European currency call can be determined through the partial differential equation, ensuring no arbitrage opportunity and amidst dynamic information costs. The equation is presented as follows:

$$\frac{1}{2}\sigma^2 S^2 \frac{\partial^2 C}{\partial S^2} + (r_{1d} - r_{1f})S \frac{\partial C}{\partial S} + \frac{\partial C}{\partial t} - r_{1d}C = 0 \quad (4.1)$$

where, the effective domestic interest rate r_{1d} is presented as follow:

$$r_{1d} = r_d + \lambda_d w(l_d) \quad (4.2)$$

where, r_d represents the actual risk-free domestic interest rate, while λ_d denotes the amplitude

of information costs related to domestic information. The function $w(l_d)$ is the advantage function associated with domestic information, defined as $1 - e^{-\alpha_d l_d}$. Here, α_d is the coefficient pertaining to the advantage related to domestic information, and l_d signifies the temporal advantage associated with domestic information.

Therefore, the effective foreign interest rate r_{1f} is presented as follow

$$r_{1f} = r_f + \lambda_f w(l_f) \quad (4.3)$$

where, r_f is the actual risk-free foreign interest rate, and λ_f is the amplitude of information costs connected with foreign information. The function $w(l_f)$ represents the advantage function tied to foreign information and is defined as $1 - e^{-\alpha_f l_f}$. In this equation, α_f is the coefficient related to the advantage associated with foreign information, and l_f indicates the temporal advantage connected with foreign information.

To calculate the currency call option, a specific process has employed. Initially, it is assumed that the underlying return is analogous to the effective risk-free rate, taking into account the dynamic information costs. Following this, the expected payoff of the derivative asset at maturity is computed. In the concluding step, this expected value is discounted at both the effective risk-free domestic and foreign interest rates (r_{1d} and r_{1f} respectively), factoring in dynamic information costs. By following this procedure, a redefined formula for European currency call option pricing emerges. This updated formula, an adaptation of the Garman and Kohlhagen model, has been revised to consider the role of dynamic information costs and can be represented as follows:

$$C_t = S_t e^{-r_{1f}T} N(d'_1) - X e^{-r_{1d}T} N(d'_2) \quad (4.4)$$

where,

$$d'_1 = \frac{\ln \frac{S}{X} + \left((r_{1d} - r_{1f}) + \frac{1}{2} \sigma^2 \right) T}{\sigma \sqrt{T}} \quad (4.5)$$

and,

$$d'_2 = d'_1 - \sigma \sqrt{T} \quad (4.6)$$

where, S is the underlying spot price; X is the strike price; σ represents the underlying volatility; T corresponds to time to maturity; $N(x)$ is the distribution function of the normal centered reduced law $N(0,1)$; r_{1d} is the effective domestic interest rate and r_{1f} is the effective foreign interest rate.

Then, using the new parity relationship:

$$C_t - P_t = S e^{-r_{1f}T} + X e^{-r_{1d}T} \quad (4.7)$$

We find the new formula of the European currency put option pricing of Garman and Kohlhagen modified in the presence of dynamic information costs.

$$P_t = S_t e^{-r_1 f T} N(-d'_1) + X e^{-r_1 d T} N(-d'_2) \quad (4.8)$$

Dammak et al. (2023) propose that the function for the propagation of light intensity, introduced by Beer-Lambert (1729), is analogous to the spread of information in financial markets. This is referred to as the temporal advantage function of information, $w(l)$. This function consistently rises over $\mathbb{R}$, implying that as the temporal advantage l escalates, $w(l)$ similarly advances. However, the growth rate of $w(l)$ is reliant on the coefficient of information advantage, α . Consequently, an enhancement in the information advantage culminates in a more accelerated growth of $w(l)$, underlining the significant influence of private information.

The temporal advantage function, $w(l)$, increases as ' l ' rises, approaching 1 regardless of the ' α ' value. However, the speed at which $w(l)$ progresses varies with ' α '; $w(l)$ tends more swiftly to 1 as ' α ' grows. If ' l ' equals zero, information asymmetry vanishes irrespective of ' α ' value, causing the disappearance of the $w(l)$ function, signaling an efficient market scenario. In such a condition, the absence of private information ensures all available information is seamlessly integrated into the price, eliminating the scope for information advantage. This situation aligns with the assumptions of Garman and Kohlhagen, leading to the application of the same formula as proposed by Garman and Kohlhagen (1983).

Hence, the advantage coefficient α , varying between 0 and 1, denotes the significance of information. It is 0 when the information holds no importance and approaches 1 as the information becomes increasingly relevant. The ' l ' parameter symbolizes the temporal advantage based on its value, reaching its peak at T , equivalent to the remaining time until maturity. This means that as the option matures, information is fully garnered, resetting the parameter to 0. The information costs amplitude λ , also fluctuating between 0 and 1, is 0 when no private information is held by the investor, and approaches 1 as information is obtained.

4.5. The sensitivity of the option price to the new variables

4.5.1. Sensitivity of the option price to ' l_d ': the temporal advantage related to domestic information

This concerns the study of the sensitivity of the option price to the variation in the temporal advantage related to domestic information.

For a call, we have:

$$\frac{\partial C}{\partial l_d} = \frac{\partial C}{\partial r_{1d}} \frac{\partial r_{1d}}{\partial l_d} \quad (4.9)$$

$$= \frac{\partial \left(S e^{-r_{1d}T} N(d'_{1}) - X e^{-r_{1d}T} N(d'_{2}) \right)}{\partial r_{1d}} \frac{\partial (r_d + \lambda_d (1 - e^{-\alpha_d l_d}))}{\partial l_d} \quad (4.10)$$

$$= T X e^{r_{1d}T} N(d'_{2}) \alpha_d \lambda_d e^{-\alpha_d l_d} > 0 \quad (4.11)$$

Thus, an increase in the domestic temporal advantage parameter ' l_d ' results in an increase in the currency call price, as denoted by the partial derivative of the call option price with respect to ' l_d ' being positive. This suggests that if an investor has private information about the domestic underlying rate, the price of the currency call option will be positively affected.

For a put, we have:

$$\frac{\partial p}{\partial l_d} = \frac{\partial p}{\partial r_{1d}} \frac{\partial r_{1d}}{\partial l_d} \quad (4.12)$$

$$= \frac{\partial \left(S e^{-r_{1d}T} N(-d'_{1}) + X e^{-r_{1d}T} N(-d'_{2}) \right)}{\partial r_{1d}} \frac{\partial (r_d + \lambda_d (1 - e^{-\alpha_d l_d}))}{\partial l_d} \quad (4.13)$$

$$= -T X e^{r_{1d}T} N(-d'_{2}) \alpha_d \lambda_d e^{-\alpha_d l_d} < 0 \quad (4.14)$$

Unlike the currency call option, $\frac{\partial p}{\partial l_d} < 0$ i.e., the increase in ' l_d ' implies a decrease in the currency put price. Indeed, if an investor possesses optimistic private information regarding the domestic underlying rate, it will result in a decrease in the currency put price.

4.5.2. Sensitivity of the option price to ' l_f ': the temporal advantage related to foreign information

This concerns the study of the sensitivity of the option price to the variation in the temporal advantage related to foreign information.

For a call, we have:

$$\frac{\partial C}{\partial l_f} = \frac{\partial C}{\partial r_{1f}} \frac{\partial r_{1f}}{\partial l_f} \quad (4.15)$$

$$= \frac{\partial \left(S e^{-r_{1f}T} N(d'_{1f}) - X e^{-r_{1d}T} N(d'_{2f}) \right)}{\partial r_{1f}} \frac{\partial (r_{1f} + \lambda_f (1 - e^{-\alpha_f l_f}))}{\partial l_f} \quad (4.16)$$

$$= -T S e^{r_{1f}T} N(d'_{1f}) \alpha_f \lambda_f e^{-\alpha_f l_f} < 0 \quad (4.17)$$

Thus, an increase in the foreign temporal advantage parameter ' l_f ' results in a decrease in the currency call price, as denoted by the partial derivative of the currency call option price with respect to ' l_f ' being negative. This suggests that if an investor has private information about the foreign underlying rate, the price of the currency call option will be negatively affected.

For a put, we have:

$$\frac{\partial P}{\partial l_f} = \frac{\partial P}{\partial r_{1f}} \frac{\partial r_{1f}}{\partial l_f} \quad (4.18)$$

$$= \frac{\partial \left(S e^{-r_{1f}T} N(-d'_{1f}) + X e^{-r_{1d}T} N(-d'_{2f}) \right)}{\partial r_{1f}} \frac{\partial (r_{1f} + \lambda_f (1 - e^{-\alpha_f l_f}))}{\partial l_f} \quad (4.19)$$

$$= -T S e^{r_{1f}T} N(-d'_{1f}) \alpha_f \lambda_f e^{-\alpha_f l_f} < 0 \quad (4.20)$$

Thus, an increase in the foreign temporal advantage parameter ' l_f ' results in a decrease in the currency put price, as denoted by the partial derivative of the currency put option price with respect to ' l_f ' being negative. This suggests that if an investor has private information about the foreign underlying rate, the price of the currency put option will be negatively affected.

4.5.3. Sensitivity of the option price to ' α_d ': the advantage coefficient related to domestic information

For a call, we have:

$$\frac{\partial C}{\partial \alpha_d} = \frac{\partial C}{\partial r_{1d}} \frac{\partial r_{1d}}{\partial \alpha_d} \quad (4.21)$$

$$= \frac{\partial \left(S e^{-r_{1f}T} N(d'_{1f}) - X e^{-r_{1d}T} N(d'_{2f}) \right)}{\partial r_{1d}} \frac{\partial (r_d + \lambda_d (1 - e^{-\alpha_d l_d}))}{\partial \alpha_d} \quad (4.22)$$

$$= T X e^{r_{1d}T} N(d'_{2f}) l_d \lambda_d e^{-\alpha_d l_d} \quad (4.23)$$

The sign of $\frac{\partial C}{\partial \alpha_d}$ depends on the sign of ' l_d '.

If $l_d > 0$, there is a time advantage.; then, the increase in the advantage coefficient related to domestic information ' α_d ' leads to an increase in the call price. Indeed, if the advantage coefficient related to domestic information is increasing (α_d increases), in the same sense as the temporal advantage related to domestic information ($l_d > 0$), then the transactions of the informed (those who own the private information go in the same direction, which pushes the price of the call to increase faster.

In contrast, if $l_d < 0$, i.e., there is a temporal disadvantage, then the increase in the advantage coefficient related to domestic information ' α_d ' does not increase the price of the call. Therefore, if the coefficient of advantage related to domestic information (α_d) increases in the opposite direction to the temporal advantage related to domestic information ($l_d < 0$), the value of the call option decreases.

For a put, we have:

$$\frac{\partial p}{\partial \alpha_d} = \frac{\partial P}{\partial r_{1d}} \frac{\partial r_{1d}}{\partial \alpha_d} \quad (4.24)$$

$$= \frac{\partial \left(S e^{-r_{1f}T} N(-d'_{1}) + X e^{-r_{1d}T} N(-d'_{2}) \right)}{\partial r_{1d}} \frac{\partial (r_{1d} + \lambda_d (1 - e^{-\alpha_d l_d}))}{\partial \alpha_d} \quad (4.25)$$

$$= -T X e^{r_{1d}T} N(-d'_{2}) l_d \lambda_d e^{-\alpha_d l_d} \quad (4.26)$$

As in the case of the call, the sign of $\frac{\partial P}{\partial \alpha_d}$ depends on that of ' l_d '. If $l_d > 0$, then $\frac{\partial P}{\partial \alpha_d} < 0$ i.e., if α_d increases, then it reduces the currency put price. On the other hand, if $l_d < 0$ then $\frac{\partial P}{\partial \alpha_d} > 0$ which means that an increase in the coefficient of advantage related to domestic information ' α_d ' leads to an increase in the price of the currency put. Indeed, if the coefficient of advantage related to domestic information (α_d increases) in the opposite direction of the temporal advantage related to domestic information ($l_d < 0$), which increases the gain in the put price. Hence, an increase in α_d leads to an increase in the value of the currency put.

4.5.4. Sensitivity of the option price to ' α_f ': the advantage coefficient related to foreign information

For a call, we have:

$$\frac{\partial C}{\partial \alpha_f} = \frac{\partial C}{\partial r_{1f}} \frac{\partial r_{1f}}{\partial \alpha_f} \quad (4.27)$$

$$= \frac{\partial \left(S e^{-r_1 f T} N(d'_{11}) - X e^{-r_1 d T} N(d'_{22}) \right)}{\partial r_{1f}} \frac{\partial \left(r_f + \lambda_f (1 - e^{-\alpha_f l_f}) \right)}{\partial \alpha_f} \quad (4.28)$$

$$= -S X e^{r_1 f T} N(d'_{11}) l_f \lambda_f e^{-\alpha_f l_f} \quad (4.29)$$

The sign of $\frac{\partial C}{\partial \alpha_f}$ depends on that of ' l_f '. If $l_f > 0$, then $\frac{\partial C}{\partial \alpha_f} < 0$ i.e., if α_f increases, then it reduces the currency call price. On the other hand, if $l_f < 0$ then $\frac{\partial C}{\partial \alpha_f} > 0$ which means that an increase in the coefficient of advantage related to foreign information ' α_f ' leads to an increase in the price of the currency call. Indeed, if the coefficient of advantage related to foreign information (α_f increases) in the opposite direction of the temporal advantage related to foreign information ($l_f < 0$), which increases the gain in the call price. Hence, an increase in α_f leads to an increase in the value of the currency call.

For a put, we have:

$$\frac{\partial P}{\partial \alpha_f} = \frac{\partial P}{\partial r_{1f}} \frac{\partial r_{1f}}{\partial \alpha_f} \quad (4.30)$$

$$= \frac{\partial \left(S e^{-r_1 f T} N(-d'_{11}) + X e^{-r_1 d T} N(-d'_{22}) \right)}{\partial r_{1f}} \frac{\partial \left(r_f + \lambda_f (1 - e^{-\alpha_f l_f}) \right)}{\partial \alpha_f} \quad (4.31)$$

$$= -S X e^{r_1 f T} N(-d'_{11}) l_f \lambda_f e^{-\alpha_f l_f} \quad (4.32)$$

As in the case of the currency call, the sign of $\frac{\partial P}{\partial \alpha_f}$ depends on that of ' l_f '. If $l_f > 0$, then $\frac{\partial P}{\partial \alpha_f} < 0$ i.e., if the increase in α_f increases, then it reduces the currency put price. On the other hand, if $l_f < 0$ then $\frac{\partial P}{\partial \alpha_f} > 0$ which means that an increase in the coefficient of advantage related to foreign information ' α_f ' leads to an increase in the price of the currency put. Indeed, if the coefficient of advantage related to foreign information (α_f increases) in the opposite direction of the temporal advantage related to foreign information ($l_f < 0$), which increases the gain in the put price. Hence, an increase in α_f leads to an increase in the value of the currency put.

4.5.5. Sensitivity of the currency option price to ' λ_d ': the information costs related to domestic information amplitude

For a call, we have:

$$\frac{\partial C}{\partial \lambda_d} = \frac{\partial C}{\partial r_{1d}} \frac{\partial r_{1d}}{\partial \lambda_d} \quad (4.33)$$

$$= \frac{\partial \left(S e^{-r_1 f T} N(d'_1) - X e^{-r_1 d T} N(d'_2) \right)}{\partial r_{1d}} \frac{\partial (r_d + \lambda_d (1 - e^{-\alpha_d l_d}))}{\partial \lambda_d} \quad (4.34)$$

$$= T X e^{r_1 d T} N(d'_2) (1 - e^{-\alpha_d l_d}) \quad (4.35)$$

The sign of $\frac{\partial C}{\partial \lambda_d}$ depends on the sign of ' l_d '. If $l_d > 0$, in other words, if the temporal advantage coefficient is positive, $\frac{\partial C}{\partial \lambda_d} > 0$ then the increase in ' λ_d ', the amplitude of information costs related to domestic market, leads to an increase in the price of the currency call. Indeed, if the amplitude of domestic information costs increases, the gain relative to the positive private information increases, which generates an increase in the currency call value. However, if $l_d < 0$, i.e., if the temporal advantage coefficient is negative, the sensitivity of the currency call price is $\frac{\partial C}{\partial \lambda_d} < 0$, then the increase in ' λ_d ' does not increase the currency call price, but there is a decrease in its value. Indeed, the loss relative to the domestic temporal disadvantage, ($l_d < 0$), multiplies if the amplitude of information costs related to domestic market increases, which results in a decrease in the currency call value.

For a put, we have:

$$\frac{\partial p}{\partial \lambda_d} = \frac{\partial P}{\partial r_{1d}} \frac{\partial r_{1d}}{\partial \lambda_d} \quad (4.36)$$

$$= \frac{\partial \left(S e^{-r_1 f T} N(-d'_1) + X e^{-r_1 d T} N(-d'_2) \right)}{\partial r_1} \frac{\partial (r_d + \lambda_d (1 - e^{-\alpha_d l_d}))}{\partial \lambda_d} \quad (4.37)$$

$$= -T X e^{r_1 d T} N(-d'_2) (1 - e^{-\alpha_d l_d}) \quad (4.38)$$

Similarly, the sign of $\frac{\partial P}{\partial \lambda_d}$ depends on the sign of ' l_d '. If $l_d > 0$, i.e., if the domestic advantage temporal coefficient is positive, $\frac{\partial P}{\partial \lambda_d} < 0$, then the increase in ' λ_d ', the amplitude of information costs related to domestic market, results in a decrease in the currency put price. Therefore, if the amplitude of the domestic information costs increases, the loss relative to the positive private information related to the domestic market increases, which leads to a decrease in the currency put value.

However, if $l_d < 0$, i.e., if the domestic temporal advantage coefficient is negative, the price sensitivity of the currency put is $\frac{\partial P}{\partial \lambda_d} > 0$, then the increase in ' λ_d ' increases the currency put price. Indeed, the gain relative to the negative domestic advantage temporal coefficient ($l_d < 0$)

0) multiplies if the amplitude of information costs related to domestic market increases, which gives rise to an increase in the value of the currency put option.

4.5.6. Sensitivity of the currency option price to ' λ_f ': the information costs related to foreign information amplitude

For a call, we have:

$$\frac{\partial C}{\partial \lambda_f} = \frac{\partial C}{\partial r_{1f}} \frac{\partial r_{1f}}{\partial \lambda_f} \quad (4.39)$$

$$= \frac{\partial \left(S e^{-r_{1f}T} N(d'_{1f}) - X e^{-r_{1d}T} N(d'_{2f}) \right)}{\partial r_{1f}} \frac{\partial (r_f + \lambda_f (1 - e^{-\alpha_f l_f}))}{\partial \lambda_f} \quad (4.40)$$

$$= -S X e^{r_{1f}T} N(d'_{1f}) (1 - e^{-\alpha_f l_f}) \quad (4.41)$$

The sign of $\frac{\partial C}{\partial \lambda_f}$ depends on the sign of ' l_f '. If $l_f > 0$, i.e., if the foreign advantage temporal coefficient is positive, $\frac{\partial C}{\partial \lambda_f} < 0$, then the increase in ' λ_f ', the amplitude of information costs related to foreign market, results in a decrease in the currency call price. Therefore, if the amplitude of the foreign information costs increases, the loss relative to the positive private information related to the foreign market increases, which leads to a decrease in the currency call value.

However, if $l_f < 0$, i.e., if the foreign temporal advantage coefficient is negative, the price sensitivity of the currency call is $\frac{\partial C}{\partial \lambda_f} > 0$, then the increase in ' λ_f ' increases the currency call price. Indeed, the gain relative to the negative foreign advantage temporal coefficient ($l_f < 0$) multiplies if the amplitude of information costs related to foreign market increases, which gives rise to an increase in the value of the currency call option.

For a put, we have:

$$\frac{\partial P}{\partial \lambda_f} = \frac{\partial P}{\partial r_{1f}} \frac{\partial r_{1f}}{\partial \lambda_f} \quad (4.42)$$

$$= \frac{\partial \left(S e^{-r_{1f}T} N(-d'_{1f}) + X e^{-r_{1d}T} N(-d'_{2f}) \right)}{\partial r_{1f}} \frac{\partial (r_f + \lambda_f (1 - e^{-\alpha_f l_f}))}{\partial \lambda_f} \quad (4.43)$$

$$= -S X e^{r_{1f}T} N(-d'_{1f}) (1 - e^{-\alpha_f l_f}) \quad (4.44)$$

The sign of $\frac{\partial P}{\partial \lambda_f}$ depends on the sign of ' l_f '. If $l_f > 0$, i.e., if the foreign advantage temporal coefficient is positive, $\frac{\partial P}{\partial \lambda_f} < 0$, then the increase in ' λ_f ', the amplitude of information costs related to foreign market, results in a decrease in the currency put price. Therefore, if the amplitude of the foreign information costs increases, the loss relative to the positive private information related to the foreign market increases, which leads to a decrease in the currency put value. However, if ' $l_f < 0$ ', i.e., if the foreign temporal advantage coefficient is negative, the price sensitivity of the currency put is $\frac{\partial P}{\partial \lambda_f} > 0$, then the increase in ' λ_f ' increases the currency put price. Indeed, the gain relative to the negative foreign advantage temporal coefficient ($l_f < 0$) multiplies if the amplitude of information costs related to foreign market increases, which gives rise to an increase in the value of the currency put option.

4.5.7. The sensitivity of the option price to changes in the domestic and foreign interest rates considering dynamic costs: The Rhô

Mathematically, this sensibility is represented as the partial derivative of the currency option price with respect to the domestic interest rate considering information costs (r_{1d}) and the foreign interest rate considering the information costs (r_{1f}).

The calculation of options on foreign currencies requires determining two ρ values for each option, whether it is a call or a put option. The first value, represented by $p_{c/p}^{d1}$, measures the risk associated with the domestic interest rate considering the information costs, while the second value, represented by $p_{c/p}^{f1}$, measures the risk associated with the foreign interest rate considering the information costs. The calculation of the derivatives of the currency call and put options in relation to r_{1d} and r_{1f} results in the following values:

$$p_c^{d1} = \frac{\partial C}{\partial r_{1d}} = X e^{-r_{1d} \cdot T} N(d'_2) T > 0 \quad (4.45)$$

$$p_p^{d1} = \frac{\partial P}{\partial r_{1d}} = X e^{-r_{1d} \cdot T} N(-d'_2) T > 0 \quad (4.46)$$

$$p_c^{f1} = \frac{\partial C}{\partial r_{1f}} = S e^{-r_{1f} \cdot T} N(d'_1) T > 0 \quad (4.47)$$

$$p_p^{f1} = \frac{\partial P}{\partial r_{1f}} = S e^{-r_{1f} \cdot T} N(-d'_1) T > 0 \quad (4.48)$$

The value of a currency call option (put option) increases (decreases) with the domestic interest rate considering the information costs due to the decrease (increase) in the present value of the exercise price to be paid (received). Conversely, the value of the currency call option (put option) decreases (increases) with the foreign interest rate considering the information costs. In fact, due to the interest rate parity, the probability of a depreciation of the underlying currency increases when the effective foreign interest rate r_{1f} increases. As a result, for a fixed exercise price, the value of the right to buy (sell) a depreciating currency must decrease (increase). It is also possible to calculate a global ρ measuring the risk of an option portfolio with respect to the effective domestic and foreign interest rate. It can be given by the following formula:

$$P_G = \frac{\partial V}{\partial r_1} = \sum_i n_i \rho_i = \sum_i n_i \frac{\partial V_i}{\partial r_1} \quad (4.49)$$

4.6. Methodological issues

4.6.1. Data Description

In this study, a dataset comprising five pairs of currency call options (EUR/USD, EUR/QAT, EUR/JPY, EUR/RUB, and USD/RUB) is utilized. The options chosen are of the European type, and the dataset comprises 1279 daily observations recorded at market close for each pair. The time span covered in the dataset ranges from January 1, 2018, to November 24, 2022. The observation data are the exchange rate value, the strike price, the time to maturity, the volatility of the underlying asset and the option market value.

An interest rate with a constant time to maturity of 90 days is also used as a risk-free rate estimator. Hull (2008) assumes that such a rate is a correct estimator of the risk-free rate. To obtain this, three-month daily Inter Bank Offered Rates (IBOR) data are utilized in this research. The specific IBOR rates used are as follows: EURIBOR for Europe, LIBOR for the USA, QIBOR for Qatar, TIBOR for Japan, and MowIBOR for Russia.

To ensure the validity of the analysis, two filters were applied to this sample. First, options that do not satisfy the arbitrage condition, as outlined by Merton (1973), are excluded from the sample. This condition states that for call options, C must be greater than or equal to $S - Xe^{rT}$. By removing these options from the sample, the implied volatilities are calculated only for those that adhere to the arbitrage condition, providing more accurate and reliable results for further analysis. Furthermore, in accordance with the methodology proposed by Bakshi and Kapadia (2003), certain data filtering criteria are applied. This includes the

exclusion of days with missing observations and the removal of implied volatilities that are below 1% or above 100%. These extreme volatilities are often associated with synchronization bias and are therefore eliminated from the analysis to ensure the reliability and integrity of the data.

4.6.2. Study of the model performance

Numerous research studies have aimed to enhance the accuracy of option pricing models by challenging the underlying assumptions of existing models. In line with these studies, we propose enhancing the Garman-Kohlhagen model by considering dynamic information costs, as proposed by Dammak et al. (2023).

Our methodology encompasses several steps: simulating dynamic information cost parameters using the Differential Evolution metaheuristic approach; calculating the option price using both the modified and standard Garman-Kohlhagen models; analyzing the model's performance by assessing evaluation errors and correlation coefficients between theoretical and market prices; and developing a high-performing machine learning model to predict effective domestic and foreign interest rates that account for dynamic information costs.

The primary objective of this study is to assess the performance of a model that considers dynamic information costs in approximating market prices, in comparison to the standard Garman-Kohlhagen model. The refined model seeks to diminish estimation errors from the theoretical model, thus minimizing biases in undervaluation and overestimation, and enhancing market price approximation.

To address our research question and achieve our objective, this empirical study is organized as follows: An initial step in utilizing the new currency option pricing model involves simulating the parameters of the temporal advantage function related to both domestic and foreign markets, using the Differential Evolution algorithm. After estimating the implied parameters, we will utilize them to calculate the price of the currency call option, employing the G-K model that accounts for dynamic information costs. Subsequently, we will compare the performance of the two models using the Mean Square Error (MSE) criteria and the correlation coefficient between theoretical and market prices. To compare the models, we define the following variables which need to be calculated: C_{GK} : the price of a European currency call option calculated using the G-K model (1983) formula, C_{GKDIC} : the price of a

European currency call option calculated using the model in the presence of the dynamic information costs and C_M : the observed price of a European currency call option on the market.

Then, we define:

$$\begin{cases} E_{CGK} = C_{GK} - C_M \\ E_{CGKDIC} = C_{GKDIC} - C_M \end{cases} \quad (4.50)$$

where, E_{CGK} represents the difference between the currency call price calculated by the theoretical model of Garman and Kohlhagen (1983) and the currency call market price and E_{CGKDIC} represents the difference between the currency call price calculated by the model in the presence of dynamic information costs and the currency call market price.

If the difference is positive (negative), then the currency option is overvalued (undervalued). In other words, the theoretical models use overestimated (underestimated) market prices. These differences are calculated for each option and each day of the sample to calculate the mean square error MSE for the two models for each currency option of the sample as follow:

$$\begin{cases} MSE\ CALL_{GK} = \frac{1}{n} \sum (C_{GK} - C_M) \\ MSE\ CALL_{GKDIC} = \frac{1}{n} \sum (C_{GKDIC} - C_M) \end{cases} \quad (4.51)$$

where, $MSE\ CALL_{GK}$ represents the mean square error for the Garman and Kohlhagen (1983) and $MSE\ CALL_{GKDIC}$ represents the mean square error for the model in the presence of dynamic information costs.

Another measure of the model efficiency is the correlation of the prices calculated by the two models with those of the market. We then define the following:

- $\rho\ CALL_{GK} / C_M$: the correlation coefficient of the currency call options calculated by the models of Garman and Kohlhagen with those of the market
- $\rho\ CALL_{GKDIC} / C_M$: the correlation coefficient of the currency call options calculated by the models in the presence of dynamic information costs with those of the market

Then, we calculate the $\rho Variation$ as below:

$$\rho\ Variation = \rho\ CALL_{GKDIC} / C_M - \rho\ CALL_{GK} / C_M \quad (4.52)$$

Furthermore, to argue that the model in the presence of dynamic information costs constitutes, on average, a better approximation of the market values of currency options

compared with those obtained using the Garman -Kohlhagen model (1983) amounts to testing the following null hypothesis:

$$H_0: MSE\ CALL_{GKDIC} - MSE\ CALL_{GK} < 0, and \rho\ CALL_{GKDIC} / C_M - \rho\ CALL_{GK} / C_M > 0$$

Finally, we employ the Random Forest Regression machine learning technique, which integrates multiple decision trees to enhance predictive accuracy, aiming to forecast the values of effective domestic and foreign interest rates while considering dynamic information costs. Additionally, we incorporate three binary variables – 'Before Covid-19', 'During Covid-19', and 'Russia-Ukraine Conflict' – to segment the observation period, assisting in the assessment and interpretation of results across various regions or periods. For a thorough exploration of the dynamics of information costs in the currency options market, experiments were conducted using five unique Random Forest Regression models, each utilizing distinct datasets for both training and testing phases.

4.6.3. Materials and Methods

4.6.3.1. Differential Evolution algorithm

Differential Evolution (DE) is a well-known evolutionary algorithm inspired by Darwin's theory of evolution and extensively studied for solving optimization problems in various fields of engineering and optimization applications. It is considered a global optimization method and was initially introduced by Storn and Price in 1997. DE encompasses different schemes, such as $DE/a/b/c$, where "a" represents the mutation vector, "b" denotes the total number of distinct pair vectors in the mutation, and "c" signifies the type of crossover. Further details on these schemes can be found in the work of Febrianti et al. (2021).

The DE algorithm consists of several steps, namely mutation, crossover, and selection. In the classic $DE/rand/1/bin$ mutation strategy, the formula for a generation "G" of populations can be expressed as follows:

$$V_{i,G+1} = x_{r_1,G} + \lambda(x_{r_2,G} - x_{r_3,G}) \quad (4.53)$$

In the mutation algorithm, three distinct vectors are involved. The base vector, denoted as $x_{r_1,G}$, serves as the reference, while the vectors $x_{r_2,G}$ and $x_{r_3,G}$ are utilized to compute the difference. These vectors are randomly selected from the population, denoted as "rand". The scale factor λ , which ranges between 0 and 1, is responsible for controlling the magnitude of

mutation. The term "bin" signifies the binomial crossover, and the number "1" denotes the total number of pairs of different vectors utilized in the crossover operation.

When the base vector ($x_{r_1,G}$) is updated to the best vector ($x_{best,G}$), the algorithm yields improved results in the pursuit of optimal solutions. In our mutation algorithm, a constant scale factor of $\lambda = 0.5$ is chosen, and the mutation strategy is as follows:

DE/best/1/bin:

$$V_{i,G+1} = x_{best,G} + \lambda(x_{r_1,G} - x_{r_2,G}) \quad (4.54)$$

DE/current-to-best/1/bin:

$$V_{i,G+1} = x_{i,G} + \lambda(x_{best,G} - x_{i,G}) + \lambda(x_{r_1,G} - x_{r_2,G}) \quad (4.55)$$

A vector's target, denoted as ($x_{i,G}$), can potentially be influenced by a mutant vector, ($v_{i,G+1}$), resulting in the creation of a trial vector, ($u_{i,G+1}$). The acceptance of this trial vector as the new target is determined by a binomial uniform formula with the probability of crossover, Cr . The value of Cr is selected from the range between 0 and 1.

$$u_{i,G+1} = \begin{cases} v_{i,G+1}^j; & rand < Cr \text{ or } j_{rand} = j \\ x_{i,G}^j; & other \end{cases} \quad (4.56)$$

Subsequently, the fitness function value of the trial vector is compared to that of the target vector. If the fitness function value of the trial vector is lower than that of the target vector, the trial vector is incorporated as a new generation in the population. Conversely, if the fitness function value is higher, the trial vector is not included. In this research, the iteration process is terminated once the maximum iteration limit is reached. These criteria ensure that the results obtained are optimized for the selected data. Specifically, in this study, the Absolute Error (AE) is utilized to measure the discrepancy between the numerical solution x_{app} and the corresponding market price x .

$$AE = |x_{app} - x| \quad (4.57)$$

This error metric quantifies the differences between the currency call prices predicted by the Garman-Kohlhagen with dynamic information costs model and the actual currency call market prices.

4.6.3.2. Random Forest Regression

The Random Forest Regression is a method in machine learning that enhances prediction accuracy by combining multiple decision trees. In this technique, each tree in the ensemble depends on the values of a randomly sampled vector from the training set, which is independent and has a similar distribution with all the trees in the forest (Breiman, 2001). To improve its predictive ability and accuracy, the random forest regression uses averaging. We define $f(X; \beta_n)$ as a set of tree predictors, where $n = 1, 2, \dots, N$ represents the number of trees. In this context, X is the input vector observed from the random vector X , and β_n represents independent and identically distributed random vectors.

The random forest prediction is given by

$$\bar{f}(X) = \frac{1}{N} f(X; \beta_n) \quad (4.58)$$

where $\bar{f}(X)$ is the unweighted average over the tree collection $f(X)$. As the number of trees in the ensemble increases, the tree structure converges, leading to a limiting value of the generalization error. This convergence property ensures that the random forest model does not over fit the data, and it has improved prediction accuracy (Breiman, 2001; Segal, 2004).

Thus, we have that as $n \rightarrow \infty$, the law of large numbers ensures that

$$E_{X,Y} [Y - \bar{f}(X)]^2 \rightarrow E_{X,Y} [Y - E_{\beta} [\bar{f}(X; \beta)]]^2 \quad (4.59)$$

Here, the response variable Y is the outcome of the training data, which is assumed to be independently drawn from the joint distribution of (X, Y) . Subsequently, we employ train-test splitting techniques to divide the complete dataset into distinct training and testing sets. Ultimately, we initialize the regression model, train the model by fitting it to the training data, and subsequently utilize it to predict the target values.

In order to assess the performance of these machine learning methods, it is necessary to analyze the discrepancies between the predicted outcomes and the actual values within both the training and test sets. The magnitude of prediction errors serves as an indicator of model performance, with smaller errors suggesting better performance. One commonly used statistical measure for evaluating models is the R-squared, also known as the coefficient of determination. It quantifies the proportion of variance in the dependent variable that can be explained by the independent variables in a regression model. Ranging from 0 to 1, higher values indicate a better fit of the model to the data. The specific threshold for an acceptable R-squared value may

vary depending on the field and complexity of the problem. However, a general guideline suggests that an R-squared value of 0.7 or higher is considered good, while a value of 0.5 or lower is regarded as poor. The formula for calculating R-squared is as follows:

$$R - squared = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (4.60)$$

where, y_i represents the actual value, $\hat{y}_i$ represents the predicted value, and $\bar{y}$ represents the mean value of the variable within the models.

The Random Forest Regression has several advantages, including robustness, accuracy, adaptability, interpretability, and generalization. It is more robust and reliable than other machine learning algorithms when it comes to handling outliers and missing values. It is also highly accurate, especially for datasets with many features. Additionally, it can be used for both regression and classification problems, and for datasets of different sizes. Moreover, it can provide feature importance measures, which help to understand the relative importance of different variables in predicting outcomes. Finally, it is less likely to over fit training data and can effectively generalize to unknown test datasets.

4.7. Empirical results and discussion

4.7.1. Validation of the model considering dynamic information costs

In this section, start by employing the DE algorithm to simulate the parameters of the temporal advantage function associated with the domestic and foreign markets. This simulation aims to minimize the disparity between the estimated currency call option price using the new model and the price observed in the market. The resulting parameter values of the advantage function, including the amplitude of information costs (λ_d, λ_f) , advantage coefficients (α_d, α_f) , and temporal advantages (l_d, l_f) for domestic and foreign information costs, are presented in Table 1.

Table 4. 1. Parameters of the advantage function related to domestic and foreign information costs for Studied Currency Call Option Pairs

Pairs	advantage function related to domestic information			advantage function related to foreign information		
	λ_d	α_d	l_d	λ_f	α_f	l_f
EUR/USD	0	0	8,34092	0,08910008	0,9973	31,529
EUR/QAT	1	0,409484	13,9023	1	1	38
EUR/JPY	1	0,255755	37,5252	1	0,540735	15,5454
EUR/RUB	0,72966	0,328883	47,4453	0,785761	0,707197	46,9293
USD/RUB	0,923224	0,777331	32,5822	1	0,87552	32,2961

Next, we calculate the currency call option prices considering both the dynamic information costs and without considering them⁸. To evaluate the effectiveness of incorporating dynamic information costs into the standard GK model, a comprehensive analysis of valuation errors was conducted. The mean square error (MSE) and correlation coefficient were calculated for all the pairs studied in this research. Specifically, the deviations $MSE CALL_{GKDIC}$ and $MSE CALL_{GK}$, along with the correlation coefficients $\rho CALL_{GKDIC}/C_M$ and $\rho CALL_{GK}/C_M$, were determined for the entire sample. These results are presented in Tables 2 and 3 for further analysis and interpretation.

Table 4. 2. Correlation coefficient of the theoretical prices calculated from the two models studied and the market prices

Pairs	$\rho CALL_{GK}/C_M$	$\rho CALL_{GKDIC}/C_M$	ρ Variation	ρ Variation in % ⁹
EUR/QAT	0,39730133	0,40058651	0,00328517	0,826872%
EUR/JPY	0,92841866	0,9290443	0,00062564	0,067387%
EUR/RUB	0,90354774	0,9183055	0,01475775	1,633312%
USD/RUB	0,96616312	0,97215014	0,00598702	0,61967%

⁸ The Garman-Kohlhagen model (1983) serves as a pricing model devised to ascertain the fair price of a currency call option or a currency put option, utilizing several variables: option type, strike price, underlying exchange rate price, volatility, time, and both domestic and foreign risk-free rates. This model was applied to European currency call options. The equation of call price following to this model can be written as follow: $C_t = S_t e^{-r_f \tau} N(d_1) - X e^{-r_d \tau} N(d_2)$, where: $d_1 = \frac{\ln(S/X) + (r_d - r_f)\tau + \frac{1}{2}\sigma^2\tau}{\sigma\sqrt{\tau}}$ and $d_2 = d_1 - \sigma\sqrt{\tau}$

⁹ The relative change in the ρ in percentage is calculated as follows: $\frac{(\rho_{GKDIC/M} - \rho_{GK/M})}{\rho_{GK/M}} * 100$

Table 4. 3. MSE of the two models, the variation of MSE and the relative variation of MSE

Pairs	MSE CALL _{GK}	MSE CALL _{GKDIC}	MSE Variation	Relative change in MSE in % ¹⁰
EUR/USD	0,00029086	0,00016831	-0,00012256	-42,1359%
EUR/JPY	0,00717496	0,00553311	-0,00164185	-22,883101%
EUR/RUB	0.01828858	0,01119274	-0,07095838	-38,79928%
USD/RUB	0,30154363	0,07456212	-0,2269815	-75,273188%

Upon examining Table 3, we noted a substantial correlation between the prices generated from both theoretical models and their respective market values, except for the EUR/QAT pair, which exhibited a comparatively lower correlation relative to the other pairs. Nonetheless, incorporating dynamic information costs into the currency option valuation model amplified the correlation. The correlation coefficient ascended across all analyzed pairs.

Findings depicted in Table 2 reveal notable fluctuations in the Mean Squared Error (MSE) across all analyzed currency call option pairs, with variations ranging from 23% to 75%. For instance, the EUR/RUB pair underwent an MSE reduction from 0.00029086 to 0.00016831, translating to a relative change of roughly 42%. This underscores the enhanced performance of the modified Garman-Kohlhagen model introduced by Dammak et al. (2023) in contrast to the foundational G-K model (1983), particularly when dynamic information costs are considered. A standout observation is the notably high MSE variation of over 75% for the USD/RUB pair, which can be attributed to its acute sensitivity to market conditions and information availability. Incorporating dynamic information costs into the Garman-Kohlhagen model accentuates this sensitivity, precipitating more pronounced fluctuations in currency call option prices. Thus, dynamic information costs appear to exert a more substantial impact on the valuation of currency call options for the USD/RUB pair compared to other pairs examined in this study. Figures 1 and 2 visually encapsulate the optimized performance of the G-K model, evidencing its enhanced efficacy in estimating currency call options when dynamic information costs are integrated.

¹⁰ The relative change in the MSE in percentage is calculated as follows: $\frac{(MSE(C_{GKSDIC}) - MSE(C_{GK}))}{MSE(C_{GK})} * 100$

Figure 4. 1. Mean square error of the Garman and Kohlhagen model and the model in the presence of Dynamic information costs

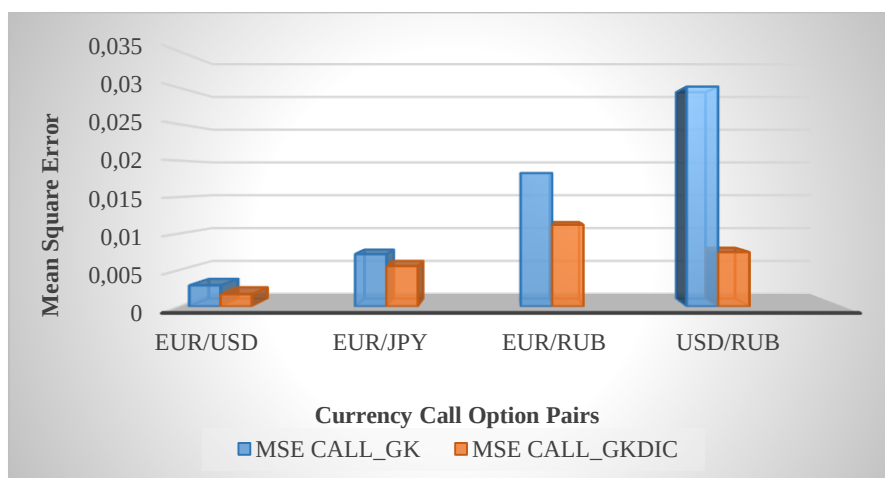
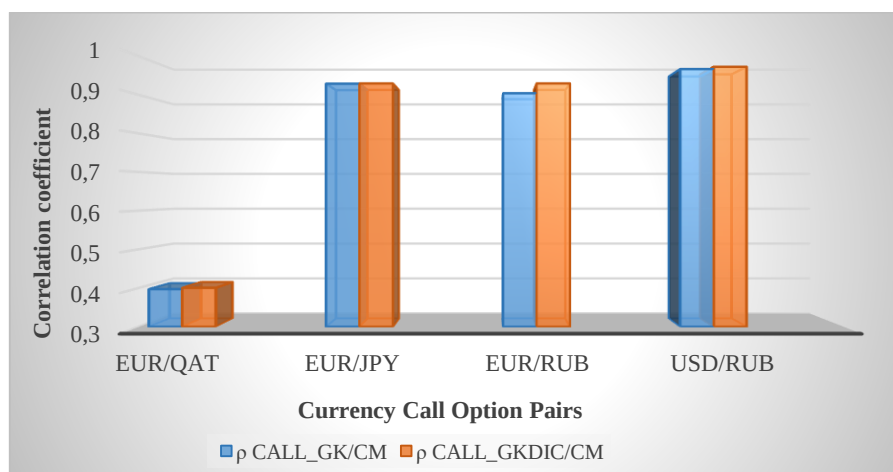


Figure 4. 2. Correlation coefficient of theoretical prices calculated from the two models studied and the market prices



Hence, it is clear that the model with dynamic information costs performs better for the currency call options. For the whole sample, we find: $MSE CALL_{GKDIC} - MSE CALL_{GK} < 0$, and $\rho CALL_{GKDIC} / C_M - \rho CALL_{GK} / C_M > 0$. Thus, the hypothesis H_0 is confirmed. This finding highlights the substantial impact of dynamic information costs on the valuation of currency options, drawing attention to the potential inaccuracies that may emerge when these costs are overlooked. Dynamic information costs, which represent the expenses borne by investors to acquire and process information about domestic and foreign markets, enhance the model's capability to precisely estimate currency call options when they are incorporated. By integrating dynamic information costs into the Garman-Kohlhagen model, this research attains more accurate estimations for the four pairs studied, surpassing the basic G-K model in terms of accuracy. This superior performance of the Garman-Kohlhagen model, when incorporating

dynamic information costs, compared to the basic G-K model aligns with theoretical expectations. This underscores the concept that the integration of relevant and current information into pricing models yields more accurate estimates and enriches understanding of market dynamics. The findings of this research align with existing theories in financial markets (e.g., De Fontnouvelle, 2000; Ahearne et al., 2004; Huber et al., 2008; Greenwood, 2010; Bonaparte & Kumar, 2013; Guo & Mota, 2021; Kim, 2022; Baek, 2022; Arora and Chauhan, 2023) and, more specifically, in the field of option pricing (e.g., Merton, 1987; Bellalah and Jacquillat, 1995; Bellalah, 2006; Jin et al., 2012; Zghal et al., 2020; Gapeev & Li, 2022; Augustin et al., 2023; Dammak et al., 2023).

Moving on to a more detailed analysis of the various parameters of the dynamic information cost function presented in Table, we observe that:

The advantage coefficient, denoted by α , spans from 0 to 1, reflecting the importance of information. A value of 0 for α indicates insubstantial information, while a value approaching 1 signifies its relevance. The results reveal that the impact of domestic information is notably significant for the EUR/QAT, EUR/JPY, and USD/RUB currency pairs. In contrast, it is less significant for the EUR/RUB pair and is not statistically significant for the EUR/USD pair. Conversely, foreign information shows significance across all the currency option pairs examined.

The amplitude of information cost, denoted by λ , ranges between 0 and 1. A value of 0 implies the absence of private information for the investor, while a value nearing 1 suggests its availability. Findings indicate that, in the case of the USD/RUB currency pair, the investor has access to more private information compared to other pairs. Conversely, no domestic private information is available for the EUR/USD pair. Nonetheless, for all investigated currency option pairs, private information related to the foreign market is available.

The parameter l symbolizes the temporal advantage, varying in its value. When it attains its maximum value of T (the time remaining until maturity), the information is fully acquired, thus assigning the parameter a value of 0. An examination of the time to maturity for the analyzed currency call option pairs, as depicted in Table 4, reveals that investors secure the information before the full maturity time in both the domestic and foreign markets for all pairs. This observation underscores the existence of a temporal advantage in both domestic and foreign markets, highlighting the criticality of timely decision-making predicated on accessible information.

Table 4. 4. Mean of time to maturity for Studied Currency Call Option Pairs

Pairs	Time to maturity
EUR/USD	70
EUR/QAT	38
EUR/JPY	45
EUR/RUB	63
USD/RUB	33

These findings suggest that investors must consider the presence or absence of private information when pricing options across various currency pairs. Our results reinforce existing financial literature, positing that informed investors' participation in the options market leads to a deviation from the call-put parity relation influenced by private information (Easley et al., 1998; Xing et al., 2010; Cremers & Weinbaum, 2010; An et al., 2014; Andreou et al., 2018; Goncalves-Pinto et al., 2020; Wu et al., 2022; Zhou, 2022; Cao et al., 2023; Anand et al., 2023; Alexander et al., 2023). In practice, these results imply that market participants should consider the significance of domestic and foreign market factors, assess the availability of private information, and make timely decisions based on acquired information when pricing currency options. Understanding the interplay of these factors can help investors optimize their option pricing strategies and improve their decision-making processes in the currency options market. This study augments existing literature by supplying empirical evidence that underscores the significance of dynamic information costs in currency option pricing. The enhanced precision in estimations provided through this research delivers valuable insights for investors and financial institutions, aiding in informed investment decisions, risk management, and the optimization of trading strategies. By incorporating dynamic information costs, market participants gain a clearer understanding of how the availability and costs of information impact currency option prices, thereby facilitating improved investment performance and the maximization of returns.

4.7.2. Predicting domestic and foreign interest rates using the Random Forest Regression

The primary focus of this section is to develop highly effective machine learning models capable of accurately predicting the values of effective domestic and foreign interest rates (

r_{1d} and r_{1f}), while taking into account the dynamic information costs for five currency option pairs (EUR-RUB, EUR-QAT, USD-RUB, RUR-JPY, and EUR-USD). In our case study, we initially considered five explanatory variables, including exchange rate value, strike price, time to maturity, volatility of the underlying asset, and option market value. Additionally, we incorporated three binary variables: "Before Covid-19," "During Covid-19," and "Russia-Ukraine Conflict," which indicate the observation period. This approach allows us to evaluate and interpret the outcomes for specific currency pairs or time periods of interest. We employed five Random Forest Regression models on the respective datasets for training and testing. The results of R-squared for this machine learning method are presented in Table 5.

Table 4. 5. R-squared of Random Forest Regression models in train and test sets

Pairs	effective domestic interest rate r_{1d}		effective foreign interest rate r_{1f}	
	Train	Test	Train	Test
EUR - RUB	-	-	0.991	0.940
EUR - QAT	0.991	0.958	0.984	0.938
USD - RUB	-	-	0.996	0.965
EUR - JPY	0.973	0.791	0.970	0.663
EUR - USD	0.986	0.974	0.985	0.950

The results presented in Table 5 demonstrate the effectiveness of the Random Forest method, as evidenced by the R-squared values exceeding 0.9. This high level of R-squared, observed in both the training and test sets for the EUR-RUB, EUR-QAT, USD-RUB, and EUR-USD cases, indicates excellent model performance. The Random Forest method exhibits superior fitting capabilities with lower prediction errors, highlighting its suitability for the given dataset. Our findings align with the existing literature, confirming the effectiveness of the Random Forest method in option pricing (Ivaşcu, 2021; Li and Yan, 2023), in forecasting Bitcoin price (Basher and Sadorsky, 2022) and in the forecasting of stock price and in developing investment strategies (Theofilatos et al., 2012; Qin et al., 2013; Basak et al., 2019). It is worth noting that with the integration of dynamic information costs into the domestic risk-free interest rate for the EUR-RUB and USD-RUB currency pairs, the effective interest rate has remained nearly constant throughout the study period. Due to this stability, we deemed it unnecessary to develop a specific prediction model for these two cases. In the case of RUR-JPY, the Random Forest model demonstrates excellent performance in the training data, as

indicated by the high R-squared values for both the domestic and foreign effective interest rates. However, the model's performance is slightly lower in the test data, with R-squared values of 0.79 for the domestic effective interest rate and 0.66 for the foreign effective interest rate. Although these values are lower compared to the other cases, they are still considered acceptable, indicating reasonable predictive capabilities of the model. Overall, we can conclude that the models are generally performing well for all cases and excellent for the majority of cases. To confirm the results, additional metrics, MSE (Mean Square Error) and MAE (Mean Absolute Error), were calculated. It is noteworthy that all values are close to zero, which reaffirms the findings obtained by the R-squared. Detailed results for these metrics are presented in Tables 6 and 7.

Table 4. 6. Results of MSE

	r_{1d}		r_{1f}	
	Train	Test	Train	Test
EUR – RUB	-	-	1.654 e-07	8.678 e-07
EUR – QAT	6.567 e-07	2.669 e-06	2.970 e-07	9.041 e-07
USD – RUB	-	-	2.043 e-07	1.706 e-06
EUR – JPY	4.345 e-10	3.467 e-09	5.499 e-07	4.913 e-06
EUR – USD	3.214 e-09	5.892 e-09	2.778 e-07	7.249 e-07

Table 4. 7. Results of MAE

	r_{1d}		r_{1f}	
	Train	Test	Train	Test
EUR - RUB	-	-	9.853 e-05	2.641 e-04
EUR - QAT	3.322 e-04	7.279 e-04	1.517 e-04	3.156 e-04
USD - RUB	-	-	2.140 e-04	6.010 e-04
EUR – JPY	7.557 e-06	2.357 e-05	2.448 e-04	6.777 e-04
EUR - USD	3.020 e-05	4.948 e-05	1.663 e-04	2.541 e-04

Finally, the models developed in this study have undergone rigorous validation and demonstrate accurate predictions of domestic and foreign effective interest rates for each of the five currency pairs studied. By incorporating specific binary variables such as Before Covid-19, During Covid-19, and Russia-Ukraine Conflict, we have obtained even more precise forecasts and conducted comprehensive testing across different periods. This approach has allowed us to compare forecast results in normal contexts, during the Covid-19 pandemic, and during the Russia-Ukraine conflict, to evaluate the impact of each period on the predictions. These models provide powerful tools for finance professionals and investors, enabling them to make informed investment decisions, optimize their strategies, and manage risks more effectively. From a policy perspective, the results of this study offer valuable insights for

policymakers. By gaining a better understanding of interest rate dynamics, the factors that influence them, and incorporating dynamic information costs, policymakers can formulate more effective and tailored economic policies for different currency pairs. They can also take measures to mitigate risks associated with events such as the Covid-19 pandemic or geopolitical conflicts. In summary, this study confirms the effectiveness of the developed prediction models, particularly when utilizing specific binary variables and incorporating dynamic information costs. These models provide practical benefits for finance professionals and investors, while also offering valuable information for policymakers in shaping appropriate economic policies.

4.8. Conclusion and Perspectives

Information exerts a pivotal role in asset pricing, notably with its impact on option pricing being time-variant, indicating that dynamic information costs fluctuate over time. Contrary to the foundational assumptions of the Garman-Kohlhagen base model (1983)—which presumes investor neutrality, market efficiency, and equivalence between rates of return and discount rates—our research incorporates the sway of subjective, psychological, and informational factors on the discount rate, as suggested by Dammak et al. (2023). These anomalies, coupled with information costs, can affect the expected rate of return. To accommodate these anomalies, our approach involves testing the impact of dynamic information costs into the new model, culminating in an effective discount rate that mirrors the real risk-free rate, adjusted for these variables.

In analyzing specific currency call options—namely EUR-RUB, EUR-QAT, USD-RUB, RUR-JPY, and EUR-USD—from January 1, 2018, to November 24, 2022, this study sets out to juxtapose the Garman and Kohlhagen currency option pricing model with an augmented model that weaves in dynamic information costs. A fusion of machine learning, statistics, and mathematical finance techniques forms the methodological core of our approach. The Differential Evolution (DE) algorithm, renowned for its robustness in pinpointing solutions for option value problems and efficacy in exploration and exploitation strategies, is employed to simulate the parameters of domestic and foreign information costs. Our aim is to narrow the gap between the option price estimated via the new model and the price observed in the market. And, for that, as we integrate these imperfections, estimated by the DE algorithm, into the currency option valuation, the model, characterized by the incorporation of dynamic information costs, demonstrates an enhancement in the accuracy and stability of pricing outcomes and bolsters its evaluative performance.

We then harness the optimized DE parameters for information costs to deploy a potent machine learning method—Random Forest Regression—to forecast the currency option prices, all while accounting for the dynamic nature of information costs. By partitioning our dataset into a training set and a test set, our study demonstrates that the novel model, enriched with dynamic information costs, consistently yields more accurate and stable pricing outcomes than traditional methods. Notably, in a market defined by information asymmetry and the activity of irrational investors, prices can be swayed by informed actors.

This research contributes to advancing our understanding of option pricing models and their practical implications in the field of finance. By adopting this innovative approach, we gain valuable insights into the dynamics of the currency options market and propose more effective solutions for financial risk management. This refined predictive capability, in turn, facilitates more accurate currency option price forecasts, enriching our comprehension of financial markets and serving investors, financial institutions, and policymakers by aiding more astute decision-making related to currency options and investment strategies.

While our research provides valuable insights, it encounters several significant limitations worth noting. Firstly, the lack of data primarily constrained our empirical study on currency options, limiting the evaluation to errors and correlation coefficients as performance indicators. Furthermore, applying our study to intra-day data, which might potentially yield different or even enhanced results, was not feasible due to the aforementioned data constraints. Nonetheless, our work opens up several promising avenues for future research. We advocate for a further exploration of the models' performance, particularly by examining the volatility smile and scrutinizing the relationship between volatility and the S/X ratio. Furthermore, to bolster the applicability of our findings, we suggest extending the research to encapsulate intraday data and diverse underlying assets, including options on stocks and futures, as well as American and exotic options. Such an expansion would illuminate the models' functionality and relevance across various market contexts, thereby enhancing their practical utility in financial analyses. Furthermore, in continuously evolving financial landscape, the role of machine learning in option pricing continues to grow. It is crucial to further explore the capabilities of this technology and its potential to enhance the accuracy of pricing models. Interdisciplinary collaboration between mathematics, finance, statistics, and machine learning is essential for developing more robust option pricing models.

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General Conclusion

General Conclusion

The fundamental model for evaluating currency options, proposed by Garman and Kohlhagen (1983), is grounded in the financial market efficiency hypothesis. This hypothesis rests on two pillars: firstly, it presumes that economic actors are perfectly rational; and secondly, it assumes an absence of market imperfections. These assumptions lead to an immediate response of asset prices to new information, reflecting all available data.

The existing literature proves that information plays a crucial role in the process of evaluating financial assets. The literature distinguishes two types of anomalies: static (or classical) anomalies and dynamic anomalies. Classical anomalies encompass models that challenge assumptions related to the evolution of the asset price. Conversely, dynamic anomalies group models that center on assumptions related to the market.

This may arise from research that challenges the efficiency hypothesis by considering market imperfections while assuming the rationality of participants. This involves factors such as static transaction and information costs, dynamic information costs, information asymmetries, restrictions on short selling, liquidity premium, delays, and so forth.

In this thesis, our objective is to introduce the study of static and dynamic information costs in the evaluation of currency options. Specifically, we examined the evaluation performance by comparing several currency option evaluation models, including the theoretical model of Garman and Kohlhagen (1983), the model with static information costs and the model with dynamic information costs. This performance comparison among these different currency option evaluation models is analyzed using mean squared error. We aimed to provide decision-making tools for investors to accurately apprehend the evaluation of currency options in the presence of these imperfections. In order to conduct a comparison between the different models, we utilized daily data of five pairs of European call options on currencies, which are traded on the Russian currency exchange market, spanning a study period from November 21, 2012, to November 24, 2022.

The primary objective of this thesis is to more accurately mirror the realities of financial markets by rejecting the market efficiency hypothesis and testing the impact of incorporating static and dynamic information costs on the performance of models for evaluating European currency options. Within the scope of this thesis, the goal is to identify the optimal model for assessing European currency options utilizing two methods. First, beginning with the Garman

& Kohlhausen model, we endeavored to modify the assumptions to bring them closer to actuality through the use of parametric models. Secondly, in order to attain a model that is both accurate and rapid, we explored a non-parametric model capable of capturing the nuances of the currency options market, employing techniques such as evolutionary algorithms, physical simulations, fuzzy sets, neural networks, etc. These models do not necessitate assumptions regarding asset price dynamics, distinguishing them from parametric models. Through our investigations, we strive to highlight the importance of the availability of information and its beneficial impact on the evaluation of currency options models. By championing transparency and unrestricted access to pertinent data and information, we can amplify the accuracy and dependability of these models.

An alternative avenue for research may emerge from the field of behavioral finance, shedding light on how psychology influences investor decisions. Behavioral finance has become a crucial component in the study of financial markets, providing insights into the behavior of option investors and aiding in the adoption of appropriate strategies. Thus, the ability to gauge investor sentiment is essential for accurately assessing options, emphasizing the importance of the sentiment variable. This variable remains one of the most effective means of interpreting the theoretical price of an option in comparison to its market price. If the objective of utilizing options is to protect against market fluctuations and stand out by capitalizing on underlying asset volatility, it becomes imperative to reevaluate investors' strategies and behaviors. When formulating their strategies, investors take into account market disruptions to identify periods of high and low volatility and assess their investment capabilities. In this context, the diversity in investor behavior not only reflects overall investor sentiment but also highlights variations in strategies. Our study aligns with previous research in behavioral finance and option evaluation, aiming to illustrate the diversity in economic agents' behavior in the options market during different periods, including both normal market conditions and times of crisis.

Consequently, the study we propose is conducted through four complementary research projects, each based on different sub-objectives.

In Chapter One, we explore the impact of static information costs in the currency option pricing model proposed by Garman and Kohlhausen (1983), situated within the framework of Merton's (1987) capital market equilibrium model with incomplete information. The theory of rational asset pricing has faced extensive criticism in existing academic literature, which

emphasizes the crucial importance of accounting for information costs for accurate asset valuation and effective risk management. In this study, we introduce a new partial differential equation for currency options and focus our attention on the calibration of new static information cost parameters. To achieve this, we employ the Differential Evolution (DE) algorithm, a metaheuristic evolutionary algorithm renowned for its efficacy in solving numerical optimization problems. This algorithm is utilized with the objective of solving optimization problems associated with the calibration process. Analyzing daily data of various currency call option pairs from January 1, 2018, to November 24, 2022, our findings exhibit a commendable level of concurrence between the results of the algorithm and the observed market data in terms of currency option prices. Consequently, these results underscore the importance of accounting for static information costs and provide insights into the relationship between information costs and asset pricing within the currency option market.

In the second chapter, we explore the impact of the COVID-19 pandemic on investor behavior within the currency option market and its association with underlying exchange rates. Utilizing a sample of daily data from futures continuous calls on EUR/USD, EUR/RUB, EUR/QAT, and EUR/JPY pairs, which spans from September 22, 2016, to December 31, 2021, we introduce a novel variable, "market imperfections." This variable captures the discrepancy between observed market option prices and theoretical prices derived from the Garman and Kohlhagen model (1983). By employing the Markov switching model, our analysis unveils the pandemic's influence on investor behavior, evident in divergence and convergence patterns, thereby illuminating the heterogeneity between fundamentalists and chartists within the currency market. This study augments existing literature by scrutinizing the dynamics and implications of investor behavior during crisis periods and illuminating the divergence and convergence of investor behavior in the currency market between the exchange rate and the currency options. By elucidating a clear mechanism, this research illuminates the underlying factors and repercussions of these behavioral shifts, utilizing the COVID-19 crisis as an exemplary instance.

In the third chapter, we begin by addressing dynamic costs, which arise from the variable impact of information on asset pricing and present a challenge for accurately pricing European currency options. The Garman and Kohlhagen model, while pivotal in the literature, does not adequately accommodate these costs. This study enhances the model by integrating an intensity function into the interest rates to measure dynamic information costs. Inspired by the Beer–Lambert law, the function is applied to a decade-long dataset of daily futures continuous calls

on the EUR/USD pair, spanning from September 21, 2012, to September 23, 2022. The refined model mitigates pricing errors and manages implied volatility more adeptly than the 1983 model, exhibiting consistency across different maturities and moneyness categories. Our findings underscore the importance of considering dynamic information costs in asset pricing and demonstrate that their inclusion can significantly enhance the accuracy and reliability of currency option pricing models.

In the final chapter, chapter four, we also investigate the impact of dynamic information costs on the currency option pricing model proposed by Garman and Kohlhagen. The concept of information cost has evolved over time and has been applied to various decision-making problems, including investment decisions. To tackle this, we utilize the Differential Evolution algorithm to calibrate the novel information cost parameters. By using data from various currency call options pairs, which spans from January 1, 2018, to November 24, 2022, we achieve a satisfactory approximation of real market currency option prices. Additionally, we employ a machine learning technique—specifically, the random forest regression—to accurately predict the values of effective domestic and foreign interest rates. In this instance, our dataset is divided into a training set and a test set for the random forest analysis, illustrating that the new model, which incorporates dynamic information costs, yields more accurate and stable pricing outcomes. The significance of our findings lies in the notable improvement in approximating real market currency options prices and the robustness of this new model. By employing the DE algorithm and integrating the random forest method, we establish a logical and efficient framework for currency option pricing. This research contributes to the evolving field of option pricing, underscoring the potential of machine learning techniques in solving complex financial problems.

In summary, this research does not merely demystify the complexities related to the pricing of currency options and investor behavior. More than a mere exploration, it establishes itself as a noteworthy landmark in both academic and practical realms, introducing innovative, empirically validated methods to the fore. This study does not only shed new light on current market mechanisms but also provides insights that will undoubtedly shape and steer future strategies in risk management and asset pricing within international financial settings. By melding advanced algorithms with a deep understanding of investor behavior and the influence of information costs, both static and dynamic, this work bridges financial theory and market practice, suggesting pathways toward more accurate pricing and shrewder risk management in the volatile currency markets. Essentially, it does not simply reflect the current state of

knowledge but pushes the boundaries of our understanding of the currency option market, thereby creating a valuable legacy for future research and applications in the field.

1. Contributions

This research has yielded several significant contributions and findings that enhance the field of finance, particularly in the context of currency option pricing across varied market conditions. Firstly, it delves into a multi-dimensional analysis of various market imperfections, such as static information costs within the Merton model and dynamic information costs within the intensity function. These imperfections are integrated simultaneously into the currency option pricing model, marking a novel approach in empirical investigations. Furthermore, the adoption of innovative methodologies and frameworks, including Artificial Intelligence, Differential Evolution (DE), and Machine Learning (ML), has opened up uncharted territory in the exploration of this subject matter. These approaches have paved the way for groundbreaking insights and advancements in the field.

Moreover, the significance of various crises, notably the health crisis triggered by COVID-19 and geopolitical crises like the Ukrainian conflict, is illuminated, revealing their considerable influence on the dynamics of currency option markets. Our thesis goes beyond a mechanical application of methodologies, intertwining robust theoretical foundations with practical empirical analysis, hence shedding light on the nuanced undercurrents of currency option pricing amidst multifaceted market anomalies and imperfections.

In our exploratory journey, several salient findings have been deduced. The research identified significant impacts of static information costs on the valuation of currency options, revealing their necessity to account for the substantial expenses incurred by both institutional and individual investors in information analysis and processing.

As we probed into the influence of investor behavior, especially during the turbulent period of the COVID-19 pandemic, we observed a notable role reversal between fundamentalist and chartist investors, which varied across different currency pairs and timeframes. The crisis instigated a significant impact on investor strategies and market dynamics, highlighting the considerable role of market imperfections in shaping investor behavior during times of crisis and uncertainty.

Pivoting to dynamic information costs, our investigations unveiled that integrating them into our pricing model dramatically enhanced pricing accuracy, notably for longer-term and

out-of-the-money options. Calibration of new parameters minimized discrepancies between predictive and actual market values, enhancing estimation precision, and correlating a surge in implied volatility with the incorporation of information costs into option pricing.

In a subsequent effort, we harnessed the DE parameters for dynamic information costs to construct a robust machine learning model, namely, the Random Forest Regression, which adeptly predicts the values of effective domestic and foreign interest rates, thereby achieving improved accuracy and stability in pricing outcomes. This enhanced precision allows for more accurate currency option price forecasts, contributing to a richer understanding and application of option pricing models.

From a policy viewpoint, these findings carry substantial implications, highlighting the urgency of considering these imperfections during the pricing and trading of currency options. The results not only validate the theoretical frameworks but also act as a beacon, guiding and informing subsequent research and practical applications in the intricate, ever-evolving tapestry of global financial markets. Moreover, by identifying and accommodating the static and dynamic information costs, market sentiment, and related imperfections, market participants can deepen their understanding of option pricing, thereby enhancing their risk management practices within the currency options market.

In summary, this thesis stands both as a significant theoretical contribution and a practical guide in the complex domain of financial markets, providing a multifaceted examination and understanding of investor behavior, pricing, and the intricate dynamics introduced by various market imperfections. This research not only elevates existing literature to new heights but also forges robust pathways for future explorations and applications within the complex realm of financial market studies, providing academia and practitioners with new tools, strategies, and insights to navigate the multifaceted world of financial markets.

2. Limits and future work avenues

While this research underscores the importance of considering both static information costs and dynamic information costs in the pricing of currency options, offering valuable insights for stakeholders, it is essential to acknowledge its limitations. The most significant limitation pertains to data availability and the application of our study to intra-day data. The study relies on daily data, which might not fully encapsulate the intra-day market dynamics and potential shifts in implied volatility that could alter and enhance the obtained results.

Furthermore, the study does not compare the extended model with other potential extensions, such as stochastic volatility models or those incorporating stochastic interest rates. Additionally, the foreign exchange options markets are currently undergoing significant expansion and are becoming an indispensable instrument for hedging, speculation, and arbitrage strategies. In this context, it becomes imperative to scrutinize the performance of the models highlighted in these various strategies, not only to comprehend but also to optimize risk management mechanisms and decision-making processes within these flourishing financial markets.

Despite the limitations encountered, our research opens avenues for prospective work in several directions. Firstly, it advocates for extending the study by comparing our proposed model with other model extensions and employing high-frequency data, which could provide deeper insights into the impact of dynamic information costs on option pricing across various underlying assets like stock options, futures, and American and exotic options. Secondly, further analysis on model performance could involve examining the volatility smile and exploring the relationship between volatility and the S/K ratio. Thirdly, while this study primarily assesses the extended Garman and Kohlhagen model against the baseline model, future research could embrace the inclusion of other model extensions, such as those featuring stochastic volatility models or stochastic interest rates, and explore the implications of using intra-day data. Fourthly, the data gaps acknowledged in our research pave the way for future studies to delve deeper by incorporating a wider historical timeframe and additional market factors, thereby not only strengthening the reliability of our findings but also facilitating comparative examinations of investor behavior across various pivotal events such as the global financial crisis, Brexit, and geopolitical confrontations like the Russia-Ukraine conflict. Fifthly, there is scope to analyze the model's performance in financial risk hedging, speculation, and arbitrage strategies. Finally, deploying genetic programming with varying configurations may serve as beneficial extensions to the basic algorithm. Employing alternative selection methods, such as tournament selection, and applying dynamic, non-static crossover and mutation operators could potentially enhance the learning performance of the genetic program and provide nuanced insights into financial modelling.

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