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Three Essays on Financial Markets

A PhD Thesis
Submitted in Fulfillment of the Requirements
for the Degree of
Doctor of Philosophy in Finance

by
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Abstract

Three Essays on Financial Markets

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2025

The objective of this thesis is to investigate three distinct aspects of financial markets: (1) Credit Default Swaps and Bank Distress, (2) Deviations from Covered Interest Rate Parity for Sovereign Bonds and (3) Deviations from Covered Interest Rate Parity and Carry Trade.

It starts with the cross-country study which indicates how credit default swaps (CDS) predict bank distress for European banks. As bankruptcies in Europe are relatively rare, the paper introduces a new dataset that divides these banks into two categories (healthy and distressed banks) to examine the relationship between credit default swaps (CDS) and bank failure, together with bank information, market discipline and macroeconomic indicators. Specifically, we define a future downgrade in financial condition as bank distress and we use four sets of variables: accounting indicators, market discipline, macroeconomic information and CDS to predict a future downgrade in bank's financial condition. First, we conduct some logistic regressions to investigate the explanatory power of credit default swap spreads on bank distress for European banks from 2005 to 2018. We conclude that after other variables are controlled for, CDS have strong and significant predictive power on future bank downgrade. In order to provide stronger evidence for such predictive power, we do some robustness tests: (1) short-term CDS on bank distress, (2) the impact of CDS on bank distress during crisis and out of crisis, (3) the explanatory power for small and large banks respectively. The result is that only out of financial crisis, CDS cannot explain much on bank distress. Therefore, we use data from 2005 to 2013 to examine a model for predicting bank failure in European banks using simulation after crisis. The key findings of this analysis are that CDS, together with bank-level and country-level indicators, improves the estimation model performance and generates more accurate out-of-sample predictions of bank distress.

For the second study, we examine deviations from covered interest parity (CIP) for sovereign bond market and three types of frictions that may cause CIP violation for bond pairs. In frictionless market, the no-arbitrage condition holds fairly well. However, arbitrage opportunities will exist after financial crisis due to

debt overhang. Therefore, from 2017 to 2019, we still find small CIP violations for sovereign bond markets due to bank regulation after financial crisis. The CIP violations are proxied by $Basis_{bond}$. However, during Covid-19 crisis, we find the significant emergence of CIP violations for sovereign bond markets in three emerging markets (China, South Korea and Mexico). Besides, three different categories of frictions can help to explain large violations of sovereign bonds market especially during Covid-19 crisis. We choose bond pairs denominated in dollar and euro of China, South Korea and Mexico to study the impact of these frictions on bond price violations. We conclude that funding costs and macroeconomic conditions do influence CIP arbitrage opportunities for bond markets. In addition, we do some robustness tests to explore other possible determinants of the observed large basis for sovereign bonds during the COVID-19 shock: (1) the relationship of cash flow risk associated with bond characteristic and violation of defaultable sovereign bonds prices, (2) whether stock risk can explain CIP deviations for sovereign bonds, (3) the role of foreign exchange correlation risk and (4) the interaction of liquidity and economic conditions on CIP basis for bond pairs. The conclusion of robustness checks is that cash flow risk cannot explain bond price anomalies which means that we choose good bond pairs. Besides, stock risk, FX correlation risk and interply of liquidity and economic conditions cannot explain large CIP basis for sovereign bonds. Therefore, CIP arbitrage for bond markets can be only interpreted by increased secured funding cost and economic conditions.

For the third paper, we explore the relationship between deviations from the covered interest rate parity (CIP) and carry trade. Deviations from the covered interest rate parity (CIP) condition shows arbitrage opportunities in one of the largest asset markets. CIP violations could be explained by the constrained intermediaries after financial crisis. Large CIP deviations indicate that financial intermediaries are quite constrained, thus arbitragers could gain profits. During post-crisis period, large persistent deviations for major currencies are explained by debt overhang. The first section of this paper investigates the significant explanatory power of debt overhang on violations from covered interest parity after financial crisis. Then, the effect of quarter-end debt overhang on CIP deviations is examined. We conclude that tightened balance sheet constraints at week-ends translate into larger impact of debt overhang on CIP deviations in the post financial crisis period. Besides, we do an event study to examine this relationship especially during Covid-19 crisis. The finding is that as compared to the normal time, debt overhang during the Covid-19 crisis has a higher explanatory power. The second section of this paper is to adopt forward CIP trading strategy to compute excess return as a new indicator of CIP. After examining the impact of debt overhang on CIP deviations, we use cross-currency basis proxied by CIP violations to do carry trade by adopting forward CIP trading strategy that help identify the price of currency risk to do carry trade. We conclude that positive excess return of forward CIP trading strategy is associated with large deviations. In addition, we do some additional robustness tests: (1) we use return of forward CIP trading strategy as an alternative factor of CIP deviations, (2) we adopt a new indicator as a proxy of debt overhang and (3) We also consider the predictive power of 1-week debt overhang on 1-week CIP violations. The key findings of robustness tests are that there is there is a significant relationship between CIP deviations and debt overhang with the relationship being stronger for shorter maturities.

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Author's Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Printed Name: Yan Kong

Signature:

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Chapter 1

Introduction

In this dissertation, three studies have been undertaken to explore various facets of pricing and risks within financial markets.

1.1 Background and Motivation

1.1.1 Background and Motivation of First Paper

The initial study investigates the effectiveness of Credit Default Swaps (CDS) spreads in predicting bank distress. Credit Default Swaps are financial instruments that enable investors to hedge or speculate on the credit risk associated with entities like corporations or financial institutions. In the case of banks, CDS spreads indicate the cost of insuring against the default of the bank's debt. The movements in CDS spreads are closely observed by various stakeholders, including market participants, regulators, and policymakers, as they provide timely insights into market perceptions of credit risk.

The relationship between CDS spreads and bank distress is a critical area of study within the broader field of financial risk management and market stability (Stulz, 2010; Giglio, 2016; Augustin et al., 2016). Understanding this relationship is essential. First, CDS spreads often serve as leading indicators of financial distress. Rapid increases in CDS spreads for a bank can signal deteriorating creditworthiness and potential financial troubles. Studying this relationship provides insights into how well market participants anticipate and react to emerging risks. The relationship between CDS spreads and bank distress is part of a complex system of market dynamics. Changes in CDS spreads can, in turn, impact a bank's funding costs and access to capital. Understanding these feedback loops is crucial for comprehending how financial distress can propagate through the broader financial system. The pricing of CDS contracts is intricately linked to the perceived risk of default. Understanding how CDS spreads are influenced by factors related to a bank's financial condition contributes to the broader understanding of risk pricing in financial markets. It also informs risk management strategies for investors and financial institutions.

Besides, changes in CDS spreads are influenced by market sentiment and perception of a bank's financial health (Zhang et al., 2010). Analysing the relationship between CDS spreads and bank distress helps in understanding how market participants interpret and respond to information regarding a bank's solvency and creditworthiness. Regulatory bodies and policymakers closely monitor indicators of financial distress, including CDS spreads, to assess the health of the financial system. Research in this area contributes to the development of effective regulatory policies and intervention strategies aimed at maintaining financial stability. Policymakers use insights from this research to formulate policies that enhance the resilience of the financial system. Understanding the dynamics of CDS spreads during periods of stress contributes to the development of effective crisis preparedness and response strategies.

In summary, the study of the relationship between CDS spreads and bank distress is a critical area that combines insights from finance, risk management, and financial stability. It offers valuable perspectives on market behaviour, risk perception, and the resilience of financial institutions in the face of economic challenges.

1.1.2 Background and Motivation of Second Paper

The second research paper explores the presence of deviations from covered interest parity (CIP) in the sovereign bond market, particularly during the Covid-19 crisis, and examines factors that may contribute to bond price anomalies. Covered Interest Rate Parity (CIP) is a foundational concept in international finance that outlines the interplay between interest rates, exchange rates, and cross-currency borrowing costs. In an efficient market, CIP posits that the interest rate differential between two currencies should align with the forward premium or discount of the exchange rate between those currencies. Deviations from CIP occur when this equilibrium is disrupted, creating opportunities for arbitrage.

Studying deviations from Covered Interest Parity (CIP) in sovereign bond markets holds significant importance in comprehending the intricacies of global financial markets. Sovereign bonds, issued by governments, constitute pivotal elements of international capital markets. Several key aspects underscore the background and motivation for investigating deviations from CIP in sovereign bond markets. Firstly, sovereign bond markets play a pivotal role in directing global capital flows. Deviations from CIP can serve as indicators of shifts in monetary policy, alterations in risk perceptions, or changes in economic conditions. A nuanced understanding of these deviations is critical for policymakers and central banks as they shape monetary and fiscal policies, impacting capital movements on a global scale. Secondly, sovereigns frequently engage in cross-border borrowing and lending activities. Deviations from CIP influence the costs associated with these transactions. Research in this domain aids sovereign entities in optimizing their funding strategies and managing risks tied to cross-currency transactions. Moreover, CIP violations suggest market inefficiencies. Investigating the factors contributing to these deviations provides insights into the efficiency of sovereign bond markets and identifies potential arbitrage opportunities. Traders and investors actively seek to capitalize on these inefficiencies to generate profits. Deviations from CIP can exert profound effects on currency and interest rate markets. These deviations may influence capital flows, exchange rates, and interest rate differentials, thereby impacting the broader macroeconomic landscape. Analysing these deviations contribute to a comprehensive understanding of the interdependencies within financial markets. Additionally, investors and institutions must comprehend and manage the risks associated with CIP deviations. Research in this realm aids in the development of effective hedging strategies and risk management approaches for sovereign bond portfolios

In conclusion, the examination of deviations from Covered Interest Rate Parity in sovereign bond markets provides valuable insights into the operations of global financial markets, practices in risk management, and the repercussions of market inefficiencies on economic stability.

1.1.3 Background and Motivation of Third Paper

The third study aims to explore the correlation between debt overhang and carry trade. Our focus extends to the interplay of debt overhang and deviations from covered interest rate parity (CIP). Debt overhang refers to a scenario where a company or a sovereign entity carries an excessively high level of existing debt, potentially hindering its capacity to undertake new investments or participate in productive endeavors. In the realm of sovereign debt, debt overhang's repercussions extend to economic growth, fiscal policy, and the overall stability of a nation's financial system. Concurrently, deviations from CIP signify market inefficiencies and offer insights into diverse factors influencing global capital flows.

First, debt overhang can affect a country's creditworthiness and increase its perceived risk of default (Botta, 2020; Argimón and Roibás, 2023). The relationship between debt overhang and deviations from CIP is motivated by the desire to understand how elevated levels of debt influence sovereign borrowing costs in international markets. High levels of debt may lead to higher interest rate differentials, impacting exchange rates and contributing to CIP deviations (Kalemli-Özcan et al., 2022; Picarelli et al., 2016). The relationship between debt overhang and deviations from CIP can shed light on market expectations. If investors anticipate that a heavily indebted country may struggle to meet its debt obligations, this expectation may be reflected in forward rates and contribute to deviations from CIP. Besides, the presence of debt overhang can influence market sentiment and risk perception. Investors may demand higher yields for sovereign bonds of countries with significant debt burdens. Studying the relationship between debt overhang and CIP deviations provides insights into how market participants perceive and react to the risk associated with heavily indebted countries. In addition, debt overhang in one country can have spillover effects on global capital flows and economic stability. The relationship with CIP deviations is motivated by a broader interest in understanding how the debt dynamics of one country can impact the stability of international financial markets. This is particularly relevant in a globalized economy where capital flows across borders. Furthermore, the level of debt a country carries is often reflective of its economic health. High levels of debt may signal economic challenges and potential vulnerabilities. Studying the relationship with CIP deviations provides a lens through which to assess the broader economic implications of debt overhang. governments and policymakers seek to manage their debt effectively to maintain fiscal sustainability. Research on the relationship between debt overhang and deviations from CIP informs debt management strategies. Understanding how debt levels impact currency and interest rate dynamics guide policymakers in making informed decisions regarding fiscal and monetary policies.

On the one hand, we link deviations from covered interest rate parity with carry trade by adopting forward CIP trading strategies and then study debt overhang and carry trade (Menkhoff et al., 2012; van Wijnbergen and Jakucionyte, 2017). Carry trade strategies involve borrowing in a low-interest-rate currency and investing in a higher-yielding asset. Debt overhang introduces an additional layer of risk, as heavily indebted countries may face challenges in meeting their debt obligations. Research in this area seeks to explore how the risk associated with debt overhang interacts with the risk and return profile of carry trade strategies. The presence of debt overhang can influence market sentiment and risk perception. Investors engaging in carry trade strategies need to assess not only interest rate differentials but also factors influencing currency risk. Studying the relationship between debt overhang and carry trade provides insights into how market participants perceive and incorporate debt-related risks into their trading decisions (Pavlova and de Boyrie, 2015; Caballero and Doyle, 2012). Besides, debt overhang in a country may lead to capital outflows as investors seek safer assets. Carry trade strategies, which involve borrowing in one currency to invest in another, contribute to global capital flows. Research in this area is motivated by the broader interest in understanding how the debt dynamics of a country impact global capital movements and economic stability (Brunnermeier et al., 2008).

In summary, the motivation to study the relationship between debt overhang and carry trade stems from the need to understand how the financial health of a sovereign entity, as indicated by its debt burden, influences international capital markets. This research contributes to the broader understanding of the factors that drive deviations from CIP and their implications for economic and financial stability. The motivation to study the relationship between debt overhang and carry trade arises from the complex interplay between debt dynamics, currency markets, and global capital flows. This research contributes to a deeper understanding of the factors influencing currency trading strategies and their implications for financial markets and economic stability.

1.2 Key Findings

In the first study, we investigate if bank CDS spreads can be used to predict bank distress both during crisis and out of crisis, particularly for banks in Europe. And then, establish a more accurate predictive model of bank distress and to give policy suggestions for supervisors. Further research on factors to predict financial distress under crisis should be focused. In this paper, we build a model based on downgrades from three major rating agencies (Fitch, Moody's and Standard &. Poor's) and divided banks into two conditions (e.g. financially sound and failure). We then present the first analysis of the capacity of single-name 5 year senior CDS spreads[1] on different types of banks to influence bank's financial condition. Apart from accounting, macroeconomic and market information, we explore the marginal contribution of CDS spreads changes to predict bank financial distress during 2005-2018, a period of banking crises when some banks may experience severe financial distress. We conclude that after controlling for accounting, market and macroeconomic variables, CDS have strong and significant predictive power on future bank downgrade for whole sample. To provide stronger evidence for such predictive power, we run additional robustness tests: (1) CDS spreads with different maturities on bank distress, (2) the impact of CDS on bank distress during crisis and out of crisis, (3) the explanatory power for small and large banks respectively. The result is that CDS cannot have strong explanatory power on bank distress. Therefore, we use data from 2005 to 2013 to examine a model for predicting bank failure in European banks using simulation after crisis. The key findings of this analysis are that CDS, together with bank-level and country-level indicators, improves the estimation model performance and generates more accurate out-of-sample predictions of bank distress. Finally, we investigate the impact of size effect and opacity effect on such predictive power of bank CDS spreads on bank financial condition. The result shows that CDS spreads have less predictive ability on bank financial condition for large banks than that for small banks and the higher degree of opacity tends to weaken the relationship between CDS spreads and the probability of bank future downgrade.

[1] Single-name or firm-level CDS contracts are a derivative where the underlying instrument is a bond of a particular company.

In the second study, we explore if deviations from covered interest parity (CIP) for sovereign bond market exist, especially during Covid-19 crisis and three types of frictions that may cause CIP violation for bond. The results show that deviations from covered interest parity ($Basis_{bond}$) are slightly different from zero before covid-19 crisis and are dramatically outside of zero during covid-19 crisis. Besides, we report a number of empirical results. First, liquidity risks play a limited role in explaining $Basis_{bond}$. However, secured funding costs are statistically and economically significant. This empirical finding supports an explanation based on funding frictions in wholesale credit markets during Covid-19 crisis. In mid-March 2020, short-term dollar funding markets faced severe disruptions as investors withdrew from unsecured markets and switched to secured markets and government MMFs (Eren et al., 2020). Besides, some macroeconomic factors are significant in explaining $Basis_{bond}$. This finding is consistent with hypothesis that marginal arbitrageurs face sources of risk that go beyond those affecting local markets. Gromb and Vayanos (2010) study a model in which global arbitrageurs, who are present across different markets, are affected by common wealth shocks. When arbitrageurs find it difficult to absorb these shocks by accessing debt markets, the resulting friction becomes a source of contagion across seemingly unrelated assets.

In addition, we do some robustness tests: (1) We do duration and convexity gap to investigate the relationship of cash flow risk associated with bond characteristic and violation of defaultable sovereign bonds prices, (2) whether stock risk can explain CIP deviations for sovereign bonds, (3) the role of foreign exchange correlation risk using Quanto CDS and (4) the interaction of liquidity and economic conditions on CIP basis for bond. We find cash-flow mismatch and FX correlation risk cannot explain much on the dynamics of $Basis_{bond}$. After considering stock risk and interaction, we can conlude that local stock risk and interplay of liquidity and economic conditions cannot explain the violation of CIP for bond markets. Besides, we adopt an alternative variable of $Basis_{bond}$ called excess return. We also find that secured funding frictions and macroeconomic conditions play important roles on excess return which is consistent with our result.

In the third study, we first examine the relationship between debt overhang and deviations from covered interest rate parity for nine liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). We consider each cross-currency basis vis-à-vis the U.S. dollar (USD) and the sample period is from 2013 to 2022. We compute 3-month and 1-week cross-currency basis based on different kinds of interest rate: Libor, OIS, repo and IOER. The key finding of this research question is that debt overhang is an important driver of violations of covered interest rate parity, particularly for 1-week cross-currency basis. Debt overhang has larger explanatory power on deviations from CIP with shorter maturities. Then, we find the quarter-end effect on CIP basis which is consistent with the finding of Du et al. (2018) and explore the impact of quarter end effect on the explanatory power of debt overhang on CIP violations.

We then consider the relationship between CIP deviations and carry trade [2]. Firstly, we investigate the link between cross-currency basis and nominal interest rates to provide the theory for carry trade. The result is that cross-currency basis is negatively correlated to interest rate which may give arbitragers opportunities gain benefits from carry trade. In addition, we adopt forward CIP trading strategy (Du et al., 2023) to do bilateral carry trade in foreign exchange market. CIP deviations are associated with the return of forward trading strategy. To be concrete, an arbitrageur goes long in one low-interest-rate currency and short in one high-interest-rate currency with currency risk hedged from $t + 1$ to $t + 4$ using forward contract. After one month, an arbitrageur will take long position in the same high-interest-rate currency and take short position in the same low-interest-rate currency. Therefore, cash flows can be ignored under forward CIP trading strategy. The excess return of this strategy is just associated with the spread between one-month forward three-month CIP deviations today and actual three-month CIP deviations after one month. The excess return of forward trading strategy are greater than zero if the difference of future CIP deviations and the market-implied forward CIP deviations today is negative. If the constraints of intermediaries are indeed a priced factor, we expect positive excess return from forward CIP trading strategy to compensate investors for bearing the risk exposure of intermediary. After computing excess return, we then investigate the link between debt overhang and profits of forward CIP trading strategy.

To be concrete, we choose 6 liquid currencies (AUD, CAD, DKK, EUR, JPY, NZD) and create cross-currency basis vis-à-vis USD and non-USD currencies, then estimate the excess returns of forward CIP trading strategies from 2013 to 2022. First, we focus on the excess return in individual currencies against USD among cross-currency pairs. We also compute additional excess returns between non-USD currency pairs as robustness test. We find the significant positive excess return for forward CIP trading strategies for currency pairs vis-à-vis USD and non-USD currencies after Global Financial Crisis. Therefore, the investors are supposed to gain profits from this bilateral carry trade-forward CIP trading strategies. What's more, we also test the robustness test for the excess return of the forward CIP trading strategies for portfolios. We divide 6 currency pairs to two groups to create the new portfolio: high-interest-rate currencies (AUD, CAD and GBP) and short in low-interest-rate currencies (DKK, EUR and JPY), then compute excess return of this portfolio. We conclude that average excess return are large and positive. The results show that the investor will gain profit from this portfolio for bilateral carry trade based on differences in norminal interest rates for any two currencies.

[2]The traditional unhedged carry trade is going long in low-interest-rate currencies and short in high-interest-rate currencies. The hedged carry trade has opposite direction to traditional unhedged carry trade, arbitrageurs take long position in high-interest-rate currencies and go short in low-interest-rate currencies.

1.3 Contribution and Implications

This paper contributes to the literature in several ways. In the first study, we first add to the existing literature on CDS and bank financial distress in the aftermath of the crisis. Connecting with previous research on the relationship between bank CDS and bank distress, we provide evidence that bank CDS also affects bank financial distress after the crisis, but the effect is not obvious and CDS can predict bank distress only at a 10% significance level. However, we can use data during financial crisis for simulation to predict bank distress during post-crisis period. Then, we also examine whether the impact of CDS on bank distress varies depending on the size and opacity of the bank. The use of bank Credit Default Swaps (CDS) to predict bank distress after a crisis offers several notable contributions to the understanding of financial markets, risk management, and regulatory practices. Here are key contributions associated with employing bank CDS as a predictive tool for bank distress post-crisis: (1) Investors can benefit from using CDS-based predictions to make more informed decisions. Anticipating distress allows investors to adjust their portfolios, reallocate assets, and implement hedging strategies, enhancing their ability to navigate post-crisis market conditions. (2) Regulatory authorities can use CDS-based predictions to enhance supervisory frameworks and stress testing methodologies. By incorporating market-based indicators like CDS spreads, regulators can assess the resilience of banks post-crisis and tailor regulatory interventions to address specific vulnerabilities identified in the CDS market. Secondly, based on the significance of studying the relationship between bank CDS spreads and bank distress, we design a predictive model using bank CDS spreads, together with bank information, market discipline and macroeconomic indicators to predict bank distress after crisis.

The second study contributes to the existing literature in several ways. First, we examine deviations from covered interest parity (CIP) for sovereign bond market during the Covid-19 crisis. The Covid-19 crisis led to unprecedented financial market stress. As uncertainty and volatility surged, examining deviations from CIP provides insights into how disruptions in global financial markets impacted the pricing and dynamics of sovereign bonds. Besides, during times of crisis, there is often a ”flight to safety” phenomenon where investors seek refuge in assets perceived as less risky. Sovereign bonds, particularly those issued by stable countries, are considered safe-haven assets (Cerutti et al., 2021). Studying CIP deviations can reveal how this flight to safety influenced interest rate differentials and exchange rates. Many central banks implemented unconventional monetary policies and interventions during the Covid-19 crisis. These actions could have implications for interest rates and currency values, potentially leading to deviations from CIP. Understanding the impact of central bank interventions is crucial for gauging the effectiveness of policy measures (Edmans et al., 2012). Secondly, we find that there is small violation for price discrepancies for sovereign bond markets from 2017 to 2019. Sovereign bond price anomalies still exist before Covid-19 crisis, but not much. The reason is that limited arbitrage opportunities persist after financial crisis due to bank regulation (Pinnington and Shamloo, 2016; Avdjiev et al., 2019; Duffie, 2017).

The third study contributes to the existing literature in several ways. First, we investigate the relationship between debt overhang and deviations from covered interest parity (CIP). The study contributes to discussions about market efficiency and the presence of anomalies. Persistent deviations from CIP associated with debt overhang may indicate market frictions, information asymmetry, or behavioural factors that influence currency markets beyond what traditional models predict. Besides, examining the relationship contributes to the understanding of the dynamics of sovereign credit markets. Debt overhang may influence credit spreads, and studying its impact on deviations from CIP helps to unravel the intricate connections between sovereign debt markets and currency markets (Duffie, 2017). Secondly, we adopt forward CIP trading strategies to link CIP and carry trade, thus study the impact of debt overhang and carry trade. The study provides insights into how debt overhang influences capital flows and investment decisions, especially in the context of carry trades. Investors may adjust their carry trade strategies based on expectations of currency movements linked to sovereign debt conditions, impacting global capital allocation and cross-border investment flows.

1.4 Structure of the Thesis

The rest of the thesis constructs as follows. Chapter 2 explores if bank CDS spreads can predict bank distress. Chapter 3 investigates if deviations from covered interest rate parity for sovereign bond markets exist and different types of frictions can influence such bond price anomalies. Chapter 4 studies the impact of debt overhang on deviations from covered interest rate parity and carry trade. Chapter 5 concludes.

Chapter 2

Credit Default Swaps and Bank Distress

2.1 Introdution

During the period from 2007 to 2012, there were two crises happening around the world, including the subprime mortgage crisis in the United States causing global economic shutdown in 2008, the European sovereign debt crisis in 2012. Financial crises have disastrous effects on the financial system and have produced significant changes on financial regulation and individual banks.

The banking is a group of financial institutions that collect funds from society and distribute those funds for credit and provide other banking services. Banks also have a natural advantage in providing liquidity to businesses through credit lines and other commitments established during normal times (Acharya and Mora, 2015). Berger and Bouwman (2009) also show that the main central roles of banks is to create liquidity and to transform risk and take these measures by financing themselves with more liquid, low risk deposits and investing in higher-risk illiquid assets (Boot and Thakor, 2011; Bhattacharya and Thakor, 1993; Diamond and Dybvig, 1983). According to these basic functions, banks tent to face insolvency and liquidity risk which means banks are vulnerable to risks, both external and internal, including systemic risk. Therefore, as an important part of the financial system, the banking sector should receive attention and the measures of bank supervision must be strengthened and the stability of banks should be enhanced.

For example, at its core, banking involves institutions accepting short-term liquid deposits and transforming them into long-term liquid loans. During this intermediation process, banks privately monitor and collect information about the quality of their loan portfolio. Since bank loans are informationally opaque, external stakeholders cannot possess all relevant information to assess the true value of bank assets (Morgan, 2002). As a result, managers may pursue policies that increase bank risk, without this being reflected on backward-looking balance sheets (Mehran et al., 2011; Becht et al., 2011).Further, banks are unique because they benefit from explicit deposit insurance guarantees and more implicit guarantee in the form of emergency liquidity and the possibility of capital assistance (i.e. bailouts) in times of distress(Bhattacharya and Thakor, 1993). Government guarantees act as a put option on a bank's assets and the value of this put is increasing in bank risk. Banks seek to maximize the value of the put by pursuing policies that increase overall risk. Consistent with this view, the extant literature has provided evidence of increased risk-taking in the presence of government guarantees (Hovakimian and Kane, 2000; Dam and Koetter, 2012). Finally, banks are highly leveraged financial institutions where leverage exists as a factor of production. Leverage results in exacerbating risk-taking concerns because the option value of government guarantees to shareholders is increasing with firm leverage, which leads to magnified benefits of increasing bank risk for highly leveraged banks (John et al., 2010; Bebchuk and Spamann, 2009).

Banking crises often uncover weaknesses in the design and implementation of bank regulation and supervision. The 2007–2009 global financial crisis (GFC) was no different, and it revealed structural weaknesses in capital regulations that were in place before the crisis (Global Financial Development Report 2019/2020 and references therein). Capital buffers proved to be too thin to cover unexpected losses. The crisis also highlighted the importance of bank heterogeneity in addressing the relationship between bank risk and capital holdings. Large financial institutions, for instance, lacked high-quality capital to absorb losses, necessitating bailouts using public funds (Laeven et al., 2016). Bank distress still exist out of crisis. Studying bank distress, particularly outside of a crisis period, can be motivated by several factors: (1) Preventive Measures: Understanding the signs and factors leading to bank distress during non-crisis periods helps in implementing preventive measures. Identifying vulnerabilities in the banking system in advance allows for timely interventions to avoid a full-blown crisis. (2) Early Warning Systems: Developing robust early warning systems for identifying signs of bank distress before it escalates into a crisis is a key motivation. Early detection allows regulators and policymakers to take corrective actions and implement policies to safeguard the financial system. (3) Risk Management: Banks and financial institutions can benefit from a deeper understanding of the factors leading to distress. This knowledge aids in improving risk management practices, enabling banks to identify and manage risks more effectively. In summary, studying bank distress outside of crises is motivated by a proactive approach to maintaining financial stability, improving risk management, and fostering a more resilient and transparent banking sector.

Credit Default Swaps (CDS) have witnessed active trading since the 2000s and currently stand as the predominant hedging instrument in credit derivatives, holding approximately two-thirds of the market share. Functioning as financial derivatives, CDS provide investors with a means to safeguard against default or credit risk associated with underlying assets like bonds or loans. These instruments have gained widespread adoption in the financial industry, playing a crucial role in risk management strategies. As a novel financial derivative aimed at mitigating risk and reducing bank exposure, CDS offer the potential to separate a bank's credit risk from other risk categories, providing an effective risk transfer mechanism. The commitment benefits of CDS are notable, acting as a commitment device for borrowers to fulfil cash payments, thereby adding value and offering important ex-ante commitment benefits. Specifically, they stimulate investment and enhance the efficiency of existing projects by minimizing the likelihood of strategic defaults (Bolton and Oehmke, 2011). Consequently, CDS function as a risk transfer mechanism, allowing banks to either offload or hedge their credit risk exposures. Understanding the utilization of CDS by banks in risk management is crucial for grasping the dynamics of risk transfer within the financial system. Bank CDS spreads, observed both during and after the crisis period, reflect the risk encapsulated by balance sheet ratios, particularly in the crisis period. However, in the pre-crisis period, bank CDS spreads remained relatively flat, and the explanatory power of balance sheet variables was lower during that time frame. The explanatory power of bank CDS spreads on balance sheet data increased as CDS spreads grew, particularly during the crisis. Consequently, researchers suggest that credit default swaps could serve as a valuable tool for regulators to predict potential bank distress (Avino et al., 2019).

Studying the relationship between bank Credit Default Swaps (CDS) and bank distress, particularly in the aftermath of a financial crisis (Augustin et al., 2016), makes significant contributions to the understanding of financial markets, risk management, and regulatory policy. Firstly, analysis of the relationship between bank CDS and distress provides a potential early warning system for financial stress. CDS spreads can act as leading indicators, reflecting market participants' perceptions of a bank's creditworthiness. Understanding the dynamics post-crisis enhances the ability to identify signs of distress before it manifests in other market indicators. Then, the relationship between bank CDS and distress contributes to discussions about market efficiency and the rapid transmission of information in financial markets. Studying how CDS spreads respond to post-crisis conditions helps assess the speed and accuracy with which market participants incorporate new information into pricing. Besides, analyzing the relationship aids in quantifying and pricing risks associated with bank distress. Researchers and practitioners can develop models that better capture the linkages between CDS spreads and the likelihood of distress, contributing to more accurate risk assessments for investors, financial institutions, and regulators. In addition, understanding how CDS spreads evolve in the aftermath of a crisis contributes to improved credit risk assessment. It helps investors and risk managers gauge the resilience of banks and financial institutions as they recover from crises, providing insights into the effectiveness of post-crisis strategies.

Jones and Hensher (2004) indicate that early-warning model models are used for many aims including: monitoring the solvency of financial organisations by supervisors, assessing loan security by auditors, pricing bonds, credit derivatives and other products exposed to credit risk. According to bank's crisis management process, regulators are required to distinguish banks into different types (healthy banks and banks with distress) and intervene them if necessary. The main goal of bank management is to preserve bank financial stability and reduce the reliance on public funds. For instance, the Single Supervisory Mechanism (SSM) has been found in 2014 which consists of European Central Bank (ECB) and the national supervisory authorities of the participating countries to supervise banks and improve banking system. The crisis management of ECB includes recovery plan to prepare for crisis situations in advance. The supervisors also identify the deterioration of banks and use intervention powers at early stage. However, the framework of management has some disadvantages (e.g. inefficient implementation). Specifically, early intervention is underdeveloped and cannot define the accurate criteria of bank distress. Recovery plan and early intervention could ensure that bank financial distress is handled by banks themselves or by regulators which requires a suitable framework (Union and of Auditors, 2012). Thus, effective crisis management of banks depends on their supervisory capacity to distinguish and react to deteriorating developments at early time. Early warnings of a banking distress are important signals to minimize negative impacts.

Over the past few years, various early warning monitoring systems and factors have been introduced and employed to predict financial distress. During early 1990s, models of financial distress rely primarily on public information contained in financial statements, accounting-based variables and macroeconomic variables (Tinoco et al., 2018). Bank supervisors utilize early warning signals to predict which banks are likely to become distressed. However, previous research has found that market discipline signals do not significantly improve out-of-sample forecasts relative to accounting-based signals. Moreover, we will consider more types of indicators which could predict bank distress. To be concrete, market forces act as a signal to promote safe and sound banking systems to improve the accuracy of bank financial conditions. Previous studies have explored the role of market indicators to distinguish between healthy and distressed banks, especially bond markets. To be concrete, bank's funding cost can be increased by market prices of its debt and thus causes market discipline, complementing traditional supervisory measures to ensure healthy and sound banks. The market may have special powers to avoid the risks of large, complex and internationalised banking systems. What's more, regulators introduce market data to complement accounting and macroeconomic information for predicting bank fragility (Evanoff and Wall, 2002).

The To-Big-To-Fail (TBTF) problem occurs when bank creditors will anticipate a public bailout of a large failing bank if financial stability is at stake. The anticipation decreases the motivations to implement adequate market discipline on banking and promote managers to take riskier strategies which may increase the overall risk in the financial system. The reason for a public bailout is that the bankruptcy of large banks is able to deal with further financial distress by direct credit losses, contagion effects through markets or a general loss of confidence by investors[1]. Besides, according to previous papers, we find that CDS spreads can reflect the risk of banks and one percentage increase in the mean size of a bank to a country's GDP reduces the CDS spread by about two basis points. Therefore, examining the relationship between TBTF effects and CDS predictive power is necessary.

The contribution of the paper is two-fold. One is to assess if bank CDS spreads can be used to predict bank distress both during crisis and out of crisis, particularly for banks in Europe. And second, to establish a more accurate a predictive model of bank distress and to give policy suggestions for supervisors. Further research on factors to predict financial distress under crisis should be focused. In this paper, we build a model based on downgrades from three major rating agencies (Fitch, Moody's and Standard &. Poor's) and divided banks into two conditions (e.g. financially sound and failure). We then present the first analysis of the capacity of single-name 5 year senior CDS spreads[2] on different types of banks to influence bank's financial condition. Apart from accounting, macroeconomic and market information, we explore the marginal contribution of CDS spreads changes to predict bank financial distress during 2005-2018, a period of banking crises which some banks may experience severe financial distress. We conclude that after controlling accounting, market and macroeconomic variables, CDS have strong and significant predictive power on future bank downgrade for whole sample. To provide stronger evidence for such predictive power, we run additional robustness tests: (1) CDS spreads with different maturities on bank distress, (2) the impact of CDS on bank distress during crisis and out of crisis, (3) the explanatory power for small and large banks respectively. The result is that CDS cannot have strong explanatory power on bank distress. Therefore, we use data from 2005 to 2013 to examine a model for predicting bank failure in European banks using simulation after crisis. The key findings of this analysis are that CDS together with bank-level and country-level indicators improve the estimation model performance and generates more accurate out-of-sample predictions of bank distress. Finally, we investigate the impact of size effect and opacity effect on such predictive power of bank CDS spreads on bank financial condition. The result shows that CDS spreads have less predictive ability on bank financial condition for large banks than that for small banks and the higher degree of opacity tends to weaken the relationship between CDS spreads and the probability of bank future downgrade.

The paper is laid out as follows. Section 2.2 discusses the relevant literature review to our study. Section 2.3 defines our sample, dependent and independent variables, and data description. Section 2.4 introduces the Logit regression method and the establishment of a predictive model. Section 2.5 presents empirical

[1]Large scale financial crisis can cause substantial cost of the real economy and thus make a public bailout inevitable. Honohan and Klingebiel (2003) estimate that the cost of a sample of 40 banking crisis in different countries was 12.8 percent of GDP on average.

[2]Single-name or firm-level CDS contracts are a derivative where the underlying instrument is a bond of a particular company.

results and robustness tests. Section 2.6 concludes.

2.2 Literature Review

In this section, the paper is structured into two main segments of literature. Initially, we conduct a comprehensive literature review, delving into various categories of indicators that have been proposed to elucidate factors contributing to bank distress. Additionally, we delve into the exploration of a predictive model designed to anticipate instances of bank distress, with implications for financial regulation.

Previous papers examine determinants of regulations that were implemented in the aftermath of the crisis (Demirguc-Kunt et al., 2013; Anginer et al., 2020; Conlon et al., 2020). Many factors have effects on the cause of banking distress, which can be categorized into four groups: accounting information, macroeconomic environment, market indicators and credit default swaps. The individual bank failures rely heavily on the Uniform Financial Rating System, called CAMELS ratings system which refers to Capital adequacy, Asset quality, Management quality, Earnings, Liquidity. The rating system is an internal management tool to evaluate the soundness of financial institutions and to identify those institutions requiring special supervisory concern.

Some studies indicate that bank's balance-sheet measured by CAMEL are significant to predict bank distress in accounting-based models (Thomson, 1992; Cole and Gunther, 1998). Several studies investigate bank distress during crisis by using proxies for CAMELS variables. To be concrete, accounting information is measured by CAMELS ratio including seven variables: capital adequacy ratio, the tier 1 regulatory capital ratio, the loan-loss-provisions-to-assets ratio, the cost-income ratio, the return on average equity, the liquidity ratio and the log of total assets (size). The first component of CAMEL ratings system is capital adequacy. Capital generally plays an important role in maintaining the stability or solvency for large companies, such as banks. To assess capital adequacy, most of study use Tier 1 regulatory capital ratio (TIRC) and Capital adequacy ratio (CAR) which evaluate the risk of bank assets(Rahman et al., 2014). Trussel and Johnson (2012) present a conclusion that financial indicators on balance sheet are associated with U.S bank financial distress and an increase in Tier 1 ratio and return on assets could reduce the likelihood of failure. Banking sectors which have worse capitalization and liquidity conditions are still under heavy stress as liquidity insurers (Acharya and Steffen, 2020) and liquidity negatively affects the assessment of bank distress. Sabela et al. (2018) emphasize the importance of liquidity, profitability and turnover of assets in predicting financial distress. Khan et al. (2017) investigates the link between funding liquidity and bank risk taking using U.S. bank data from 1986 to 2014. The conclusion of this paper is that banks are less likely to be distressed with lower funding liquidity during global financial crisis. Moreover, Low banking scale indicates a decline in trade activities for banking sector. Bank capital, charter value, off-balance sheet activities, dividend payout ratio and size can determine bank equity risk and credit risk (Haq and Heaney, 2012). Size should be introduced in prediction models in variation. Because the purpose of this paper is to predict a change in bank financial condition, it is more appropriate to introduce not the values taken by the ratios, but their time changes. In this study, we treat all 32 European banks equally, regardless of their initial financial strength which shows that the ratings downgrade of a sound, safe bank can only be captured by changes in the values of ratios as reflected by the level of financial ratios.

Management quality (e.g. cost-income ratio) has positive relationship with banking distress. Almilia and Herdiningtyas (2005) examine the ability of bank's management by using an efficiency ratio and find that a lower cost-income ratio could decrease the possibility of banking distress. However, Peltonen et al. (2015), Molina (2002) and Sahut and Mili (2011) indicate management quality has negatively affected on banking distress. Other results discovered by Boyacioglu et al. (2009), Cihak and Poghosyan (2009), Betz et al. (2014) as well as Messai and Gallali (2015) present management quality has no effect on banking distress. Therefore, further research of management quality on bank financial condition should be focused. In addition, the negative correlation between earning quality (e.g. the return on average equity) and banking distress has been discovered, which means the higher return will reduce the possibility of bank distress. This negative relationship owes to earning quality reflecting the efficiency and operational activities (Dzingirai and Katuka, 2014).

Bank income structure and loan growth also play important roles in financial distress of bank. DeYoung and Torna (2013) explore whether income from non-traditional banking trade cause the failure of U.S. banks during financial crisis. They conclude that pure fee-based non- traditional activities (e.g. insurance sales) can reduce the probability of bank failure and asset-based non-traditional activities (e.g. investment banking, asset securitization) can increase the likelihood of bank failure. Besides, the considerable underperformance of many banks has been related to less capital, more non-performing loans and loan loss provisions, weaker liquidity, smaller interest margins and more loan concentration (Alnassar and Chin, 2015). Lepetit et al. (2008) focus on the relationship between bank risk and product diversification in European banks and reveal that banks with more non-interest income activities present a higher level of risk than banks with traditional intermediation activities and income structure of banks is more robust for small banks. Foos et al. (2010) test three hypothesis: past abnormal loan growth is positively and significantly correlated to subsequent loan losses with a lag of 2 to 4 years. Besides, abnormal loan growth reduces interest income of banks. Abnormal loan growth has a negative and highly significant impact on bank solvency and profitability. Therefore, loan growth has a significant impact on bank risks. The papers on bankruptcy of U.S.

banks since 2009 has been investigated by Serrano-Cinca et al. (2014) which concludes that failed banks had higher loan growth, higher risk ratios and lower margins than banks without distress. For failed banks, the percentage of real estate loans is highly linked with bank risk. Bank size effect also has influences on bank financial condition. For example, Boyd and Runkle (1993) investigate the relationship between bank failure and bank size. However, the author cannot find strong evidence that financial leverage has a positive relationship with bank size. Hakenes and Schnabel (2011) investigate the relationship between bank risk-taking and bank size. Under Basel II Capital Accord,large banks have a competitive advantage and small banks are more likely to take higher risks, thus causing higher risk-taking.

However, only accounting variables applied in predicting model cannot explain distress accurately. Several studies study the accounting-based models with macroeconomics indicators and asset prices. To be concrete, macroeconomic and market indicators have useful predictive information but not reflected in the CAMELS indicators (Flannery, 1998; González-Hermosillo, 1999; Jagtiani and Lemieux, 2001; Bharath and Shumway, 2008; Arena, 2008). Cleary and Hebb (2016) investigate the analysis of distinguishing between US banks that failed and those that didn't shows that two most important variables are related to bank capital and loan quality. Therefore, a new factor, macroeconomic information, is added to predict bank distress. The author combine banking system with asset prices in a dynamic macroeconomic model to investigate the characteristic of financial instability (Von Peter, 2009). Macroeconomic factors for predicting banking distress include GDP growth, inflation and unemployment rate. GDP growth has negative correlation with the assessment of banking financial distress, which indicates higher economic growth worsen bank distress (Oehmke and Zawadowski, 2017; Caggiano et al., 2014). What's more, macroeconomic situation measured by inflation has positive effect on the evaluation of bank distress. Baselga-Pascual et al. (2015) investigate high inflation rates harm general economic environment, thus increasing unanticipated Non-Performing Loan. Moreover, lower unemployment rates can increase the probability of banking distress, which means higher unemployment rates will lead the bank to bear higher risks (Agarwal and Taffler, 2008). Markoulis et al. (2023) conclude that a combination of the traditional CAMEL variables, plus size and revenue diversification,along with macroeconomic, banking sector, and stock market variables, explains the probability of bank distress quite well.

Apart from above indicators, a few papers have explored whether the market prices of bank securities signal the risks of banks. Studies in U.S. have found that bank's subordinated debt spreads in secondary market could reflect bank's risks by indicators on balance sheet and macroeconomics (Flannery and Sorescu, 1996; Flannery, 1998; Allen and Jagtiani, 2000) and same conclusion by Morgan and Stiroh (2001). Sironi (2003) indicates that cross- sectional differences tend to be reflected by bank's debenture spreads. Recommendation enlarges the role of market forces to predict bank distress and market-based Information added to pricing distress has been embraced by academics and practitioners. This result can be supported by some previous studies. The emphasis on market power is at the core of the new regulatory framework developed by Basel Committee on Banking and Supervision, the Basel II Accord. Distinguin et al. (2006) aim to assess whether stock market prices improve the credibility of future bank financial distress and to ensure the effectiveness of market discipline in banking system. (Lu and Whidbee, 2013) estimate a series of Logit regressions to identify the causes of failure and assess the role of bank-level characteristics while controlling for the economic and regulatory environment. The empirical results indicate that the failure of established institutions depended on whether the bank received bailout funds, had relatively low capital ratios, had relatively low liquidity, relied more heavily on brokered deposits, held a relatively large portfolio of real estate loans, had a relatively large proportion of nonperforming loans, and had less income diversity. However, Miller et al. (2015) explore that supervisors use market signals as additional factors to predict bank distress and the research has shown that adding market data to prediction models only marginally improves forecasting accuracy. Miller et al. (2015) investigate that expected default frequency or subordinated note and debenture yield spreads cannot explain bank holding company distress, thus should not be systematic inputs into bank supervision early warning systems.

Using credit derivatives as hedging instruments may increase costs of financial distress and destabilize banking sector. Instefjord (2005) is the first person to identify potential destabilizing factors in bank and to investigate regulatory responses to reduce destabilization of bank sector. The author finds that credit derivatives trading does harm to bank stability even though banks use credit derivatives solely to hedge credit exposures. A financial innovation in the credit derivatives market may increase bank risk, particularly those that operate in highly elastic credit market segments. Credit derivatives trading is, therefore, a potential threat to bank stability even if banks use these instruments solely to hedge or securitize their credit exposures. Zhang et al. (2009) attempt to identify the equity volatility and jump risks to explain CDS. Subrahmanyam et al. (2014) use credit default swap trading data to demonstrate that the credit risk of reference firms, reflected in rating downgrades and bankruptcies, increases significantly upon CDS trading. Ballester et al. (2016) show the securitization and credit derivatives on the risk of European banks is negatively associated with financial stability, so the higher capital requirements of new Basel III banking regulations is essential. During the 2007–2008 financial crisis, corporate bond mutual funds increased their credit protection sales in the credit default swap (CDS) market, however, CDS opportunistic trading of the fund exposes holders to counterparty risks (Avino et al., 2019).

CDS has various advantages in providing market discipline for banks. First, Oehmke and Zawadowski (2017) suggests that although bond and CDS reflected hedging motives, speculative trading which is likely to be more sensitive to the liquidity of the CDS market, is concentrated in the CDS market. The paper also shows that bond fragmentation is linked to both higher trading costs and lower turnover in the underlying reference bonds. Second, CDS market has great price discovery than bond market for a sample of high-grade credits (Blanco et al., 2005). Compared with the bond market, the CDS market reacts faster to the stock market (Norden and Weber, 2004). Finally, CDS market has faster information processing ability relative to the equity market (Acharya and Johnson, 2007). Evidence shows that CDS markets reveal information for entities that experience (or are likely to experience) adverse credit events in advance of the equity market. In addition, CDS return has inclined significantly since financial crisis. Previous studies put forward aggregate CDS spreads and CDS indices to examine bank fragility (Ballester et al., 2016; Knaup and Wagner, 2012; Caggiano et al., 2014). Building on the extant literature considering banks and CDS contracts, the present study assesses the cross-sectional ability of single-name bank CDS contracts to perform a disciplining role on banks.

Furthermore, there have been several papers using different methods to predict bank distress. Concretely, Lane et al. (1986) present different analysis (survival analysis vs discriminant analysis) to predict bank failure models by using Cox proportional hazards model. Kumar and Ravi (2007) compare statistical techniques (e.g. logistic regression and factor analysis) and intelligent techniques (e.g. neural networks, nearest neighbour classifiers, operations research methods, and decision tree induction methods). In addition, U.S. bank failures are able to be well predicted by a simple and parsimonious probit model. Apart from binary choice models, Jordan et al. (2010) assess U.S bank distress by using proxies for CAMELS and multiple discriminant analysis. However, the literature prefers a logit model (Betz et al., 2014). Fuertes and Kalotychou (2006) present that accounting information and country- specific effects causes better in-sample fitness, but reduce the assessment performance on out-sample data.

Some prior polytomous response financial distress/bankruptcy prediction models include only accounting measures and market-based information as independent variables. However, we have strong evidence to show that such models would benefit from utilizing the macroeconomic variables. Tinoco et al. (2018) add new factor into model and the result shows that combining accounting, market and macroeconomic variables improves the accuracy of models to predict bank financial distress. Wulandari et al. (2017) examine the impact of macroeconomic factors (i.e. economic growth, inflation, interest rate, exchange rate) and internal banking factors consist of CAMELS ratio (capital ratio, asset quality ratio, management quality ratio, earnings, liquidity, and SMR) toward market risk for predicting banking distress using the banking stability index.

2.3 Data

In this section, we present the data sources and their descriptions. We commence by providing an overview of factors associated with bank distress, encompassing accounting variables, market indicators, macroeconomic variables, and other relevant factors.

2.3.1 Sample

The sample includes different kinds of indicators that are regularly listed on bank distress, credit default swaps spreads, accounting, stock market and macroeconomic information. The dependent variable is bank distress and the potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR). In order to examine the predictive power of CDS spread to distinguish between healthy and distressed banks, we choose senior five year CDS spreads from Bloomberg and Markit. The initial dataset contains 45 European banks with senior CDS spreads data. We restrict our focus to banks with senior CDS spreads data from 2005 to 2018, leaving 32 European banks [3]. Excluding banks without senior five year CDS spreads results in a final sample. CDS spreads are downloaded from Bloomberg and Markit. All other variables are obtained from Bankscope, Bloomberg and three major rating agencies (Fitch, Moody's and Standard & Poor's). Table 2.1 shows the banks by country and specialization. We obtain accounting indicators from Bankscope and market information from Bloomberg following Distinguin et al. (2006). For dependent variables, we get 5-year CDS spread from Markit and Bloomberg. Besides, the macroeconomic indicators are selected from OECD database. We select the 2005–2018 period for two reasons: Firstly, we are interested in assessing the explanatory power of CDS before and around periods of crisis (in particular, the financial crisis of 2007–2009 and the subsequent European sovereign debt crisis beginning from 2010); Secondly, the CDS market is well developed and mature during this cohort. These choices help to ensure that my empirical study is focused on a liquid, actively traded security during a period of significant instability for the banking industry.

[3] In some cases, particularly when dealing with regression analysis, the presence of heteroskedasticity (i.e., non-constant variance in the error terms) can lead to biased and inefficient estimates of standard errors. This issue can significantly impact the validity of hypothesis testing, as traditional standard errors may no longer be accurate. To address this, heteroskedasticity-consistent standard errors (commonly referred to as robust standard errors) can be used to correct for such variability. These robust standard errors adjust for heteroskedasticity, ensuring that hypothesis tests are more reliable, even when the underlying assumptions of homoskedasticity (constant error variance) are violated. This correction is especially useful in models with small sample sizes, where the effects of heteroskedasticity can be more pronounced.) can be applied to account for variability in regression estimates, making hypothesis tests more reliable with small samples.

Table 2.1: Banks by Country and Specialization

Country	Number	Specialization	Number
United Kingdom	5	Commercial Bank	11
Germany	2	Cooperative Bank	1
France	3	Retail Bank	4
Italy	4	Investment Bank	4
Spain	4	Saving Bank	1
Switzerland	2	Bank Holding and Holding Company	9
The Netherlands	1	Private Bank	2
Austria	2		
Finland	1		
Denmark	1		
Norway	1		
Belgium	1		
Sweden	4		
Portugal	2		

Notes: The table reports the number of banks for different countries and Specialization. We choose diversified 32 European banks as sample from 2005 to 2018. All European banks are divided into different categories: commercial bank, cooperative bank, retail bank, investment bank, saving bank, bank holding and holding company and private bank.

2.3.2 Measurement of Bank Financial Distress and CDS

Using credit rating downgrades is a common and effective method to measure bank distress. Credit rating agencies assess the creditworthiness of banks and assign ratings based on various factors, including financial health, risk management practices, and market conditions. When a bank experiences deteriorating financial conditions or faces heightened risks, credit rating agencies may downgrade its credit rating. The degree of downgrade can be indicative of the severity of the distress. Agencies such as Moody's, Standard & Poor's (S&P), and Fitch are prominent credit rating agencies. They assign credit ratings to banks based on their credit analysis. Credit ratings are alphanumeric symbols that represent the creditworthiness of a bank. Higher ratings indicate lower credit risk, while lower ratings suggest higher risk. A downgrade occurs when a credit rating agency lowers a bank's credit rating. Downgrades typically happen in response to financial challenges, increased default risk, or concerns about the bank's ability to meet its financial obligations. The severity of a downgrade is crucial in measuring distress. A minor downgrade may signal moderate challenges, while a significant downgrade indicates more severe financial stress.

Assessing the ability of market indicators to predict bank financial distress requires choosing events that capture the changing financial condition of each bank. Due to insufficient actual bankruptcies in the European banking industry, checking downgrading by the three major rating agencies (Fitch, Moody's and Standard & Poor's) can be used to identify changes in a bank's financial condition (Avino et al., 2019). In conclusion, we apply only the first downgrade date to build the binary variable Y if the bank is subsequently downgraded by the rest of different rating agencies. Ratings are from at least one of three major rating agencies (Fitch, Standard & Poor's and Moody's).

The dependent variable Y is equal to: (1) 1, if the bank is downgraded by rating agencies with no upgrading happening during the entire year. (2) 0, if bank rating remains stable during the entire year. (3) NA (not available), for other cases.

This approach implies that our study will capture a deterioration in a bank's financial health by pinpointing a downgrading from any initial level and down to any level below. Identifying both narrow and broad changes is essential for the robustness of results and provides a more general framework for predictive model estimations. Also, accounting for downgrades by using more than just one rating agency ensures that in our specification, the event date is the earliest possible for announcements by one of the three major agencies covering financial institutions in Europe. Table 2.2 shows a summary of distress indicator measured by downgrade rating from Standard & Poor's, Fitch and Moody's. A large percentage of bank distress happen during 2008-2013 with the period of global financial crisis and European sovereign debt crisis. 87 out of 447 observations are downgraded by different rating agencies from 2005 to 2018.

Table 2.2: Distribution of Downgrades

Downgrade	2005	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
448(87)	1	9	13	11	19	11	4	7	4	2	5	2

Notes: The table reports the number of bank downgrades from 2005 to 2018. Most of bank downgrades occurred during global financial crisis and sovereign debt crisis. We choose diversified 32 European banks as sample for different countries and Specialization.

Using accounting variables to predict bank distress is grounded in the idea that financial statements and accounting metrics provide essential information about a bank's financial health and risk profile. Accounting variables offer a quantitative and structured way to assess a bank's performance, solvency, and overall stability. Accounting ratios introduced in prediction models in variation. The explanatory variables considered were primarily balance sheet variables relating to the quality of bank assets, capital, earning potential and liquidity, as these are regarded as the key indicators capable of providing concise information about the health of an organization. We select some accounting variables that can predict bank financial distress. Accounting indicators employed to control bank risk are obtained from Bankscope database. We apply these variables divided into 5 categories to the model, CAMELS: Capital, Asset Quality, Management Quality, Earnings, Liquidity and Size (Avino et al., 2019). We apply several accounting ratios for each category.

Capital

The first ratio for capital is Tier 1 regulatory capital ratio (T1RC) which measures the capital adequacy of a bank. TIER 1 capital ratio measures the ability of the bank to absorb losses. The Tier 1 Regulatory Capital Ratio is a key indicator of a bank's capital adequacy and solvency. A higher ratio indicates that a significant portion of the bank's capital consists of high-quality Tier 1 capital, which serves as a financial cushion to absorb losses. Conversely, a lower ratio may suggest a vulnerability to financial distress. The higher the ratio, the higher the risk buffer and the lower should be the bank distress. Hence, a negative sign is expected.

Besides, the other ratio for capital is Capital adequacy ratio (CAR) which is expressed as a percentage of a bank's risk-weighted credit exposures. The Capital Adequacy Ratio (CAR) is a key regulatory requirement designed to ensure that banks maintain a minimum level of capital to cover their risk-weighted assets. The higher the ratio, the higher the risk buffer and the lower should be the bank distress. Therefore, a higher Capital Adequacy Ratio indicates that a bank has a larger capital buffer relative to its risk exposure.

Asset Quality

The ratio for asset quality is loan loss provisions to total assets (LLPTA). The ratio measures the amount of loan loss provisions as a percentage of total assets. Loan loss provisions are the amount needed to make reserves adequate to absorb estimated credit losses. The higher the ratio, the lower the quality of the asset portfolio. Hence, an increase in LLPTA should lead to an increase the probability of bank failure.

Management Quality

The cost-to-income ratio (CI) is one of the efficiency ratios used in financial management through the relationship between the cost and income of an entity. The cost-to-income ratio reflects how efficiently a bank is managing its resources to generate income. A lower ratio indicates higher efficiency, meaning the bank is able to generate more income relative to its operating costs. Efficient operations contribute to profitability, which is essential for a bank's stability.

Earnings

Return on average equity (ROAE) is a good proxy for earnings. The Return on Average Equity (ROAE) is a key financial metric that measures a bank's profitability by assessing its ability to generate earnings from shareholders' equity. Consistent and healthy ROAE is often associated with financial stability. Banks with sustained profitability are better positioned to absorb losses, build capital, and withstand economic downturns. Conversely, a declining or negative ROAE may signal financial distress or operational challenges.

Liquidity and Size

This gross loans-to-customer and short-term funding ratio (LADEPST) is a measure of liquidity. The relationship linking this index to bank financial condition is uncertain. The relationship can be interpreted positively when banks with fewer deposits, and hence lower liquidity, are not perceived positively by the market. An increase in this liquidity ratio should therefore correspond to growth in bank failure (Kotomin et al., 2008). On the other hand, the relationship can be interpreted negatively when a high level of loans, for the same level of deposits, is perceived by the market as a positive signal, since sample banks are commercial banks and loans represent their core business. Growth in LADEPST should therefore correspond to a decrease in bank distress.

We use natural logarithm of total assets (SIZE) as a proxy of bank size. The relationship between bank size and bank distress is a complex and multifaceted topic studied in the field of banking and finance. Large banks often have diversified portfolios and business lines, which can provide some level of risk mitigation. However, large banks are sometimes considered "too big to fail." This concept suggests that the failure of a large bank could have severe systemic consequences for the entire financial system, leading to government interventions to prevent such failures. This perception might provide implicit government support to large banks.

2.3.3 Market Indicators

Using market indicators to predict bank distress is based on the idea that financial markets reflect the collective wisdom and expectations of investors, and changes in market indicators may signal underlying issues with a bank's financial health. Berger and Bouwman (2013) investigate how capital have influences bank performance during banking crisis. The results show market capital helps small banks increase their likelihood of bank distress (during banking crises, and normal times) and market forces improve the performance of medium-sized and large banks primarily during banking crisis. We assume that the equity market conveys useful information for predicting financial condition. If the market is efficient, prices and returns should consist of the risk exposure of banks and thus their default risk. We introduce two market variables into early-warning model: STOCK, DD. These two variables are introduced to capture the stock return and the default risk of banks.

The use of bank stock returns in predicting bank distress is grounded in the idea that stock prices reflect market participants' collective assessment of a bank's financial health, future prospects, and risk profile. Bank stock returns provide market-based information, capturing the sentiment and expectations of investors and stakeholders. Stock prices are influenced by a variety of factors, including financial performance, management decisions, and macroeconomic conditions. Stock returns reflect investor confidence and perceptions of a bank's ability to generate future profits. Sustained declines in stock prices may indicate eroding confidence and heightened concerns about the bank's financial stability. Stock prices are forward-looking indicators. Investors anticipate future events and risks, and their reactions are reflected in stock returns. As such, changes in stock prices can signal expectations of future financial distress or improvement. Stock returns integrate a broad range of information, including financial statements, market conditions, regulatory developments, and news. This holistic view enhances the predictive power of stock returns in assessing a bank's overall risk. Therefore, stock prices capture the collective perception of investors regarding a bank's financial condition. Sudden changes in these indicators may indicate a shift in market sentiment and concerns about the bank's stability. STOCK means the annual return of stock in this paper.

Distance to Default (DD) is a financial metric that estimates how far a firm's value is from the point of default. It is commonly used in predicting bank distress and assessing credit risk. Distance to Default is a measure of credit risk, indicating the proximity of a firm (or a bank) to defaulting on its financial obligations. As a bank approaches default, the Distance to Default decreases, reflecting a higher level of credit risk. A decreasing Distance to Default can serve as an early warning indicator of financial distress. Monitoring changes in DD allows for timely identification of deteriorating financial conditions, giving stakeholders the opportunity to take preventive or corrective actions. DD (distance to default) is defined as the number of standard deviations between market value of bank assets and the default point (the point is that market value of bank assets equal to book value of total liabilities) which measures default risk of a bank. We employ Black and Scholes (1973) and Merton's DD as market variable to predict bank distress.V_A means bank's asset value and δ_A is the bank's asset value volatility.

$$V_E = V_A N(d1) - De^{-rT} N(d2) \tag{2.1}$$

$$\delta_E = \frac{C}{V_E} N(d1)\delta_A \tag{2.2}$$

$$d1 = \frac{ln(\frac{V_A}{D}) + (r + \frac{\delta_A^2}{2})T}{\delta_A \sqrt{T}} \tag{2.3}$$

$$d2 = d1 - \delta_A \sqrt{T} \tag{2.4}$$

That is, the distance to default (DD)

$$DD = \frac{E(V_A) - D}{E(V_A)\delta_A} = \frac{ln(\frac{V_A}{D}) + (r - \frac{\delta_A^2}{2})T}{\delta_A \sqrt{T}} \tag{2.5}$$

We obtain daily market values of bank's equity (V_A) from Bloomberg and compute the volatility of bank's equity (δ_E) on the subsequent 12 months. The maturity of the debt (T) equals to 1 year. We use 10-year government treasury bill as risk-free rates and obtain data on debt liabilities and market value of equity from Bankscope.

2.3.4 Macroeconomic Variables

The use of macroeconomic variables to predict bank distress is based on the recognition that the overall economic environment can significantly impact the financial health and stability of banks. This paper also aimed to analyse the macroeconomic environment influencing bank distress for European banks during 2005 to 2018. The data is collected from OECD database. According to Markoulis et al. (2023), three macroeconomic indicators are introduced in the models: Inflation (INF), Economic Growth (EG) and Unemployment Rate (UNR), both measured on an annual basis.

The use of inflation as a predictor of bank distress is rooted in its impact on various economic and financial factors that can influence the stability and performance of banks. The reasons why inflation is considered relevant in predicting bank distress are as follows: First, inflation is closely linked to changes in interest rates. Central banks may adjust interest rates in response to inflationary pressures. Changes in interest rates impact banks' net interest margins, a critical component of their profitability. Higher inflation may lead to higher interest rates, affecting the cost of funds for banks. Secondly, inflation can influence the quality of banks' loan portfolios. High inflation may erode the purchasing power of borrowers, making it challenging for them to service their debts. This can result in an increase in non-performing loans, negatively impacting asset quality. Besides, inflation can lead to wealth redistribution effects. Banks may experience changes in the financial health of their clients, impacting their ability to meet financial obligations. These effects can cascade through the banking system. In addition, inflationary pressures can lead to higher borrowing costs for banks. If interest rates rise to combat inflation, banks may face increased costs of funds, impacting their overall profitability.

The use of economic growth as a predictor of bank distress is grounded in the understanding that the overall health and performance of banks are closely tied to the broader economic conditions in which they operate. First, economic growth has a direct impact on the credit quality of borrowers. During periods of economic expansion, businesses are more likely to generate profits and individuals are more likely to have stable incomes, reducing the likelihood of loan defaults. Conversely, economic contractions can lead to increased default risk, affecting the asset quality of banks. Then, economic growth influences the performance of banks' loan portfolios. Strong economic growth typically corresponds to increased demand for loans as businesses expand and consumers make major purchases. Economic downturns, on the other hand, can lead to a decline in loan demand and an increase in delinquencies. Besides, the level of economic growth often influences central bank policies, including decisions on interest rates. Changes in interest rates can impact banks' net interest margins, a critical component of their profitability. Economic growth can signal potential changes in interest rate environments.

Using the unemployment rate as a predictor of bank distress is grounded in the recognition that employment trends have significant implications for the overall health of the economy and, consequently, the stability of the banking sector. First, the unemployment rate is directly linked to individuals' ability to repay loans. Secondly, as unemployment rises, borrowers may face difficulties in meeting their financial obligations, leading to an increase in loan defaults. This, in turn, can negatively impact the asset quality of banks. Besides, unemployment is a key driver of mortgage delinquencies. Individuals who lose their jobs may struggle to make mortgage payments, leading to an increase in delinquencies and potential foreclosures. This dynamic can adversely affect banks with exposure to mortgage-backed assets and contribute to distress in the housing market.

It is expected that a high inflation should increase the likelihood of distress/failure and a high level of economic growth (measured by GDP growth) will affect positively firms' possibilities of falling into the financial distress/failure category (Tinoco et al., 2018). In addition, unemployment rate also has a negative effect on bank financial distress.

2.3.5 Bank CDS Spreads

Credit Default Swap (CDS) spreads for banks represent the cost of insurance against the default of a bank's debt. Investors and financial institutions use CDS contracts to hedge against or speculate on the credit risk of a particular entity, in this case, a bank. Here are some key points related to bank CDS spreads: A higher CDS spread for a bank generally implies a higher perceived risk of default. Conversely, a lower CDS spread suggests lower perceived credit risk. The level of CDS spreads is influenced by market perceptions, economic conditions, regulatory environment, and the financial health of the bank. The financial stability of a bank is a crucial factor for bank CDS spreads. Weak financial indicators or concerns about a bank's solvency can lead to higher CDS spreads.

This paper uses as core independent variable five-year senior CDS spreads in the European banking sector. CDS spreads were chosen since they are widely considered an excellent indicator of markets' perception of a bank's default risk. Bloomberg and Markit are the source of data on bank CDS spreads. The rate is expressed in basis points (bp). This study uses five-year quotes in so far as this is the benchmark maturity in the CDS market. We also investigate the relationship between shorter bank CDS spreads and bank financial condition. Senior CDS spreads were used since senior offers better data coverage than subordinated. Yearly CDS spreads were used, a choice strictly related to the type of dependent variables considered (bank distress).

Table 2.3 describes a set of variables influencing banking distress by different categories.

Table 2.4 presents the summary statistics relating to the 32 balance sheet variables of the whole banks and distressed banks for all independent variables (2005-2018). The average of change of CDS spreads is higher for distressed banks than the whole sample. Similar conclusions are observed for the most of other accounting, market variables: the values of most of balance sheet and market variables for whole banks are larger than those for distressed banks. To be concrete, the variables relating to the bank balance sheet (TIRC, CAR, SIZE, LADF, LLPTA and CI) remained substantially unchanged for whole banks and distressed banks. However, the difference of average value of ROAE between whole banks and distressed banks is relatively large, 7.04 percent and 1.14 percent respectively. However, the sample banks, despite being adversely affected by the crisis, are affected by macroeconomic conditions. the difference of two macroeconomic variables (inflation and unemployment rate) between whole banks and distressed banks shows that bad economic conditions are positively related to bank failure. Table 2.4 also enables us to explore further on the robustness of the relationship between credit default swap spreads and the probability of financial downgrade with different size of banks.

Table 2.3: Data Description

Variables	Mnemonics	Definitions
Dependent Variables		
Bank distress	BIS	
Z-score	Z	$Z = \frac{r-b}{\delta}$ where r is average return of stock b, δ is the standard deviation of the return
Financial Accounting Variables		
Capital Adequacy		
Tier 1 regulatory capital ratio	T1RC	Tier 1 capital / risk weighted assets and off balance sheet risks
Capital adequacy ratio	CAR	(Tier 1+Tier 2 capital) / risk weighted assets and off balance sheet risks
Asset Quality		
Loan-loss-provisions-to-assets ratio	LLPTA	Loan loss provisions / Total assets
Management Quality		
Cost-income ratio	CI	Cost / Income
Earnings Quality		
Return on average equity	ROAE	Net Income / Average Equity
Liquidity		
Liquidity ratio	LADEPST	Gross loans / Customer and short term funding
Size of Institution		
Bank size	SIZE	Natural logarithm of total assets
Financial Market Variables		
CDS spread		
	CDS	5-year log senior CDS spread
	CDS1Y	1-year log senior CDS spread
	CDS2Y	2-year log senior CDS spread
	CDS3Y	3-year log senior CDS spread
Equity market		
Yearly log stock return	STOCK	
Distance to Default	DD	
Macroeconomics Variables		
Inflation	INF	
Economic growth	EG	Measured by GDP growth
Unemployment rate	UNR	

Notes: The table summarizes dependent variables and independent variables. The dependent variables is bank distress proxied by binary and continuous indicators. The binary indicator is bank downgrades by three rating agencies (Standard & Poors, Fitch and Moody's) and the continuous indicator is Z-score. Our sample is from 2005 to 2018. The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR).

Table 2.4: Summary Statistics

	Healthy Banks					Banks with Distress						
	Obs	Mean	Std	Min	Max	Obs	Mean	Std	Min	Max	diff_{mean}	p-value
TIRC	353	12.69	4.38	5.50	28.70	83	11.77	3.06	5.13	21.60	-0.92^{*}	0.07
CAR	354	15.63	4.41	8.50	31.80	83	14.52	3.12	9.30	21.80	-1.11^{**}	0.03
SIZE	359	5.64	0.47	4.47	6.40	83	5.64	0.52	4.61	6.40	0.00	0.99
LADF	351	137.63	64.30	40.25	710.63	81	147.13	57.49	66.34	356.77	9.51	0.22
LLPTA	359	0.31	0.43	-0.16	4.13	83	0.49	0.32	-0.13	1.50	0.18^{***}	0.00
CI	357	37.25	14.85	9.38	81.73	83	38.36	12.80	13.35	77.65	1.11	0.53
ROAE	354	8.11	12.17	-90.61	36.15	83	1.14	11.66	-43.50	22.39	-6.97^{***}	0.00
CDS	343	1.79	0.45	0.58	2.83	86	2.23	0.34	1.18	3.23	0.46^{***}	0.00
STOCK	359	2.57	34.20	-87.76	147.06	50	-6.10	49.99	-86.71	168.73	-8.66^{*}	0.06
DD	347	3.64	2.19	-3.19	10.83	87	1.53	2.33	-8.97	6.26	-2.22^{***}	0.00
EG	359	1.54	1.98	-8.07	5.95	83	0.06	2.32	-5.28	5.95	-1.49^{***}	0.00
INF	359	1.50	1.13	-1.14	4.08	83	1.94	1.17	-0.49	4.49	0.44^{***}	0.00
UNR	359	8.30	4.49	2.49	26.09	83	9.52	5.31	3.10	24.79	1.22^{**}	0.03

Notes: The table summary statistics of each independent variable for 32 European banks from 2005 to 2018. The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR). Obs is the number of observations. Mean is the average of each variable. Std is the standard deviation. Min and Max are the minimum and maximum vaule of each variable. In addition, we test the significance of mean difference between healthy banks and distressed banks.

2.4 Methodology

2.4.1 Evaluation of Model Signals

According to different bank financial status, the statistical analysis requires a binomial logistic model in order to describe healthy and unhealthy banks.The dependent variable in logistic regression is binary, meaning it takes on two possible outcomes (usually coded as 0 and 1). To study the explanatory power of 5-year CDS spreads for banking financial distress, we estimate the probabilities of distress over the next period using Logit model following Jones and Hensher (2004). We test a two-state financial distress/failure model based on a logistic regression model, where the conditions are divided into 2 groups.

The probability of the outcome is measured by the odds of occurrence of an event.

$$P_{i,t}(Y_{i,t+1} = 1) = \frac{1}{1 + e^{-\alpha - \beta X_{i,t}}} \tag{2.6}$$

Where $P_{i,t}$ is the probability that the bank will be downgraded in the next 12 month. $Y_{i,t+1}$ is a dummy variable that equals to 1 if the bank experience bank distress, 0 otherwise at time t. $X_{i,t}$ is the vector of independent variables (predictor indicators) at time t. A higher value of $\alpha + \beta X_{i,t}$ means a higher probability of distress.

$$ln(\frac{p}{1-p}) = \alpha + \beta X_{i,t} \tag{2.7}$$

The Equation 2.7 is binomial Logit model which is used for binary classification problems. The coefficients of binomial Logit model indicate the marginal effect of a change in every explanatory variable on the probability of bank distress. The logistic regression model transforms the odds of the event happening into a logarithmic scale. The odds $\frac{p}{1-p}$, where p is the probability of the event) are transformed using the natural logarithm. The coefficients is not constant because the marginal effect rely on the value of $X_{i,t}$. The coefficients β represent the change in the log-odds of the event for a one-unit change in the corresponding predictor variable, assuming all other variables are held constant.

Consist with most research combining accounting, macroeconomic and market variables to explain bank distress, the problem is that we are unable to get data at same frequencies. Therefore, we use accounting-based and macroeconomic information on yearly basis and market-based information related to CDS and equity on the final trading day of each year[4] (Arena, 2008; Distinguin et al., 2013)

2.4.2 Estimation and Prediction

The previous literature presents a variety of conventional statistical methods to predicting distress condition. The problem with most models (e.g. discrete-choice models) is that some assumptions on data properties are unable to meet. For example, hazard model focuses on estimating the timing of distress and could not have assumptions about distributional features (Whalen et al., 1991). Instead, this paper aims at predicting severe bank condition and whether CDS is a leading indicator leading to bank distress event. Besides, the advantage of Logit model outweighs Probit model because its more fat-tailed error distribution is more suitable to frequency of bank distress event (Van den Berg et al., 2008).

A confusion matrix, Receiver Operating Characteristic (ROC) curve, and Area Under the Curve (AUC) are concepts commonly used in binary classification problems to assess the performance of a predictive model. Table 2.5 describes a confusion matrix which is used to evaluate the performance of a classification algorithm. It summarizes the predictions of a model on a set of data by comparing the predicted labels to the actual labels. The matrix consists of four components: (1) True Positive (TP): Instances where the model correctly predicts the positive class. (2) True Negative (TN): Instances where the model correctly predicts the negative class. (3) False Positive (FP): Instances where the model incorrectly predicts the positive class (Type I error). (4) False Negative (FN): Instances where the model incorrectly predicts the negative class (Type II error).

Figure 2.1 plots ROC and AUC. Receiver operating characteristics (ROC) curves and the area under the ROC curve (AUC) are vital measures for comparing effect of early warning models. It plots the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity) as the threshold for classifying positive instances is varied. The curve helps visualize the trade-off between sensitivity and specificity. The ROC curve describes the balance between benefits and costs at time t. The better model has more benefits (TPR on the vertical axis) at the same cost (FPR horizontal axis).

AUC is the area under the ROC curve. It provides a single scalar value to summarize the overall performance of a classification model. A model with a higher AUC generally indicates better discrimination ability. A perfect model has an AUC of 1, while a random or poor model has an AUC close to 0.5 (the diagonal line in the ROC space). The interpretation is that the AUC represents the probability that the model will rank a randomly chosen positive instance higher than a randomly chosen negative instance. AUC ranges between

[4]The majority of banks in our sample do not report intermediate results, therefore, in this study, we use annual accounting data to forecast bank distress over the following year.

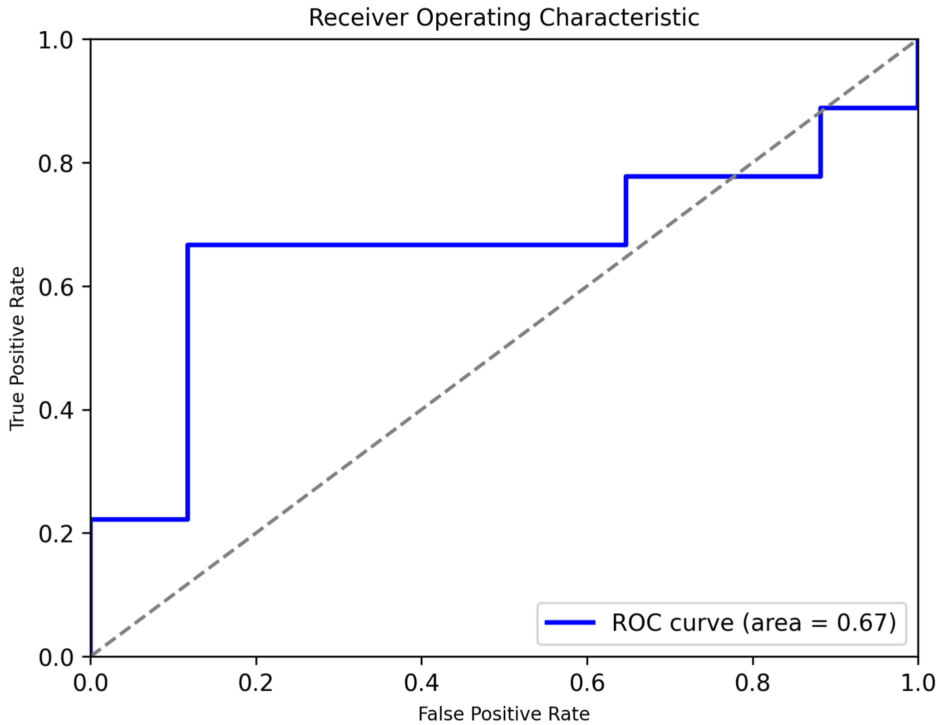
0 and 1, and the higher the AUC, the better the model's ability to distinguish between positive and negative instances.

Table 2.5: Confusion Matrix

		Model Prediction	
		No Default (0)	Default (1)
Actual Status	No Default (0)	TN	FP
	Default (1)	FN	TP

Notes: The table presents four different combinations of predicted and actual values. Confusion Matrix is a performance measurement for classification. The four conditions are true positive (TP), true negative (TF), false negative (FN) and false positive (FP). According to these four classifications, we compute 2.8 and 2.9 and thus use warning model to predict future bank distress by using ROC curve.

Figure 2.1: ROC Curve



Notes: The figure plots ROC curve ny Logit regression from 2008 to 2013 using 26 banks randomly selected. The vertical axis (TPR) computes the probabilities of default if actual status is default, while FPR means the likelihood of no default if actual status is no default. AUC describes area under the ROC Curve. Therefore, AUC measures the entire two-dimensional area underneath the entire ROC curve from (0,0) to (1,1). AUC ranges in value from 0 to 1. A model whose predictions are completely wrong has an AUC of 0.0; one whose predictions are totally correct has an AUC of 1.0.

$$TPR = \frac{TP}{TP + FN} \tag{2.8}$$

$$FPR = \frac{FP}{TN + FP} \tag{2.9}$$

2.5 Empirical Analysis

In this section, we first examine the predictive power of CDS in Logit model and we run logistic regressions which explanatory variable of each category are introduced respectively. We then do some robustness to explain the impact of CDS spread on bank distress: (1) the predictive power of CDS spread with different maturities on bank financial condition, (2) the explanatory power of CDS spread after crisis and (3) alternative indicator of bank distress proxied by Z-score and (4) the relationship between CDS and bank failure for small and large banks separately. Secondly, we investigate the impact of the too-big-to-fail effect (bank size) and the opacity effect (balance sheet structure) on the predictive power of CDS spread. Finally, we adopt an predictive model to predict future bank downgrades and examine whether CDS spreads in Logit models could predict the out-of-sample bank condition effectively.

2.5.1 CDS Spreads and Bank Distress

We first analyse whether 5 year CDS spreads are significant indicator of early-warning models, rather than the model only using accounting and market indicators, to predict bank distress. The results in Table 2.6 (Column (1)) shows a highly significant positive coefficient of 3.21[5] on bank financial condition, which implies CDS significantly explains bank condition.

According to Appendix 2.1, Table 2.13 presents the regression results examining the causal relationship between 5-year CDS spreads and bank distress. The coefficient for CDS_{t-1} is both positive and statistically significant across all specifications, indicating that the lagged CDS value has a strong positive influence on the dependent variable. Additionally, the coefficient for BIS_{t-1} suggests that financially distressed banks contribute to wider CDS spreads compared to healthy banks. Consequently, CDS spreads are shown to increase significantly in response to downgrades.

Having examined that CDS spreads have obvious effects on bank distress, we next control for various variables influencing bank risk. To this end, accounting variables and market information are incorporated in the model as shown in Table 2.6 (Columns (2) and (3)). Most of accounting ratios are significant and negative. The DD (distance to default) and STOCK are significant before adding macroeconomic variables. Coefficient of CDS spreads stay positive and significant (at 1% level) in all models. Besides, controlling

[5] In addition to 5-year log CDS spreads, we also consider log CDS spreads for 1, 2 and 3 years before the forecasting interval. Table 2.9 shows a highly significant positive coefficient across all horizons when using the z-score to represent bank distress. For these univariate regressions the highest value of the McFadden R-squared is obtained for the 5-year log CDS spreads. The estimated coefficient is negative and statistically significant.

Table 2.6: Logit Regressions of Downgrade Indicator on CDS Spreads with Control Variables

	(1)	(2)	(3)	(4)
CDS	3.21***	3.76***	3.75***	4.00***
	(7.29)	(6.47)	(5.02)	(4.40)
TIRC		-0.17*	-0.20*	-0.16
		(-1.66)	(-1.83)	(-1.46)
CAR		0.06	0.10	0.06
		(0.70)	(1.01)	(0.61)
SIZE		0.96***	0.97***	0.86**
		(1.28)	(2.61)	(2.19)
LADF		0.01**	0.01**	0.01**
		(2.41)	(2.24)	(1.86)
LLPTA		-0.79*	-1.05**	-1.05*
		(-1.71)	(-2.05)	(-1.95)
CI		-0.02	-0.02*	-0.03**
		(-1.23)	(-1.71)	(-2.06)
ROAE		-0.01	-0.01	-0.01
		(-0.78)	(-0.63)	(-0.59)
STOCK			0.10**	0.01*
			(2.55)	(1.76)
DD			0.20*	-0.11
			(-1.74)	(-0.83)
EG				-0.18**
				(-2.19)
INF				0.11
				(0.77)
UNR				-0.05
				(-1.23)
Pseudo R^2	0.194	0.228	0.249	0.265
Nobs	425	408	401	401

Notes: This table summarizes results of binary Logit regressions of the failure indicator on log CDS of 5 year from 2005 to 2018. The distress indicator is 1 (0) if the bank with distress (without distress) during the subsequent 12 months. The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR). Pseudo R^2 is the value of the McFadden R-squared. Nobs is the number of observations. We report the t-statistics in parentheses and adjust standard errors by using Huber-White method. We report 4 different specifications of the Logit regressions. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

accounting and macroeconomic indicators, the coefficient of both CDS spreads and other market variables are highly significant on bank condition changes which implies market forces are able to largely explain bank financial condition. Adding accounting information, market force and macroeconomic variables, CDS spreads have stronger predictive power of bank distress (coefficient of 3.21 and 4.00 at 1% significance before and after adding other control variables). However, according to Column (3) and Column (4) models, CDS have stronger explanatory power than market indicators. The same conclusion also can be found in previous research, these findings indicate that CDS spreads have strong ability to identify between safe and distressed banks, even relative to equity market indicators.

In order to get marginal contributions of CDS spreads, this impact on bank distress likelihood from a one-standard-deviation is examined by using Equation 2.7, assuming an initial mean value of the explanatory variables. For example, in terms of the fourth model (Column (4)), a one-standard-deviation increase in the CDS spreads could increase the probability of bank distress by 81.45% of its initial.

We do some robustness tests to explore the impact of CDS spread on bank distress. First, Table 2.7 describes the explanatory power of CDS spread with different maturities on bank failure. The results are consistent with the previous result. We observe that CDS spread with different maturities has strong and significant impact on bank distress and CDS spread with longer maturities has larger explanatory power. To be concrete, the coefficient of 1-year CDS spread on bank distress is 1.99, while the coefficient of 5-year CDS spread is 3.21.

Besides, we conduct additional regression to investigate the relationship between CDS spread and bank distress during post-crisis period. Table 2.8 reports the results of the first four panel regressions from 2014 to 2018. The whole sample consists of 159 observations for 32 European banks. The Column (4) in Table 8 indicates that the bank CDS spreads for 32 European banks explain nearly 26 per cent of bank distress (R-squared value). The coefficient of 5-year CDS spread is large but not much significant on bank distress. The result indicates that there is not enough explanatory power of CDS spread on bank condition out of crisis. Therefore, we will put forward a warning model to predict bank distress after financial crisis.

We also run baseline regression by using alternative indicator (Z-score) proxied by bank distress. Z-score for banks, is a financial metric designed to evaluate the financial health and risk of bankruptcy of a bank. A higher Z-score generally indicates a lower probability of financial distress, while a lower Z-score suggests an increased risk of financial distress. Therefore, there is a negative relationship between Z-score and bank distress, because profits will be not too much due to bank distress. Z-score which reflects excess return of bank stock is negatively correlated to CDS spread [6]. Table 2.9 shows that the coefficients of CDS are large, negative and significant in all specifications. The results show that an increase in one percent CDS is associated with smaller value of Z-score and less bank distress. To be concrete, the coefficient estimate on CDS in Column (1) implies that 1 percent increase of CDS is related to a 3.68 percent decrease of bank Z-score - that is, low CDS spreads causes a widening Z-score and less probability of bank failure. After controlling other variables in Column (4), an one percentage increase in CDS is associated with a 1.52 percent decrease in Z-score. The conclusion is consistent with the results in Table 2.6: CDS spreads can be an important and significant indicator as bank distress.

[6] A Z-score is the log of the number of standard deviations required for earnings losses to exceed the bank holding company's capital and current earnings (Laeven and Levine, 2009).

Table 2.7: Regression of CDS Spread on Bank Distress With Different Maturities

Variables	(1)	(2)	(3)	(4)
CDS1Y	1.11**			
	(2.51)			
CDS2Y		1.25**		
		(2.28)		
CDS3Y			1.35**	
			(2.28)	
CDS5Y				4.00***
				(4.40)
TIRC	0.01	0.01	0.01	-0.16
	(0.09)	(0.09)	(0.07)	(-1.46)
CAR	-0.03	-0.03	-0.03	0.06
	(-0.19)	(-0.18)	(-0.17)	(0.61)
SIZE	0.42	0.37	0.37	0.86**
	(0.85)	(0.74)	(0.75)	(2.19)
LADF	0.01*	0.01*	0.01*	0.01**
	(1.92)	(1.89)	(1.90)	(1.86)
LLPTA	-1.09	-1.06	-1.04	-1.05*
	(-1.55)	(-1.55)	(-1.56)	(-1.95)
CI	-0.06***	-0.06***	-0.06***	-0.03**
	(-3.31)	(-3.31)	(-3.27)	(-2.06)
ROAE	-0.04	-0.03	-0.03	-0.01
	(-1.59)	(-1.57)	(-1.54)	(-0.59)
STOCK	0.01	0.01	0.01	0.01*
	(1.56)	(1.47)	(1.45)	(1.76)
DD	-0.49***	-0.49***	-0.49***	-0.11
	(-4.08)	(-4.07)	(-4.06)	(-0.83)
EG	-0.08	-0.07	-0.07	-0.18**
	(-0.77)	(-0.75)	(-0.73)	(-2.19)
INF	0.43**	0.43**	0.43**	0.11
	(2.33)	(2.27)	(2.29)	(0.77)
UNR	0.05	0.04	0.04	-0.05
	(1.28)	(1.24)	(1.20)	(-1.23)
Pseudo R^2	0.236	0.234	0.235	0.265
Nobs	286	285	287	401

Notes: This table summarizes results of binary Logit regressions of the failure indicator on log CDS of 1, 2, 3, 5 year from 2005 to 2018. The distress indicator is 1 (0) if the bank with distress (without distress) during the subsequent 12 months. The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR). Pseudo R^2 is the value of the McFadden R-squared. Nobs is the number of observations. We report the t-statistics in parentheses and adjust standard errors by using Huber-White method. We report 6 different specifications of the Logit regressions. T statistics are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Besides, we also run additional regression for trends in impact of credit default swap spreads differentiating between large versus small banks. This differentiation is key during crisis and post-crisis period to deal with problems with too-big-to-fail banks. Large banks refer to banks that total assets are greater than "300 billion" or the bank is ranked first or second in its country. According to Table 2.10, the coefficient of

Table 2.8: Regression of CDS Spread on Bank Distress, 2014-2018

	(1)	(2)	(3)	(4)
CDS	2.42***	3.18**	5.06**	3.89*
	(2.87)	(2.33)	(2.30)	(1.70)
TIRC		-0.01	0.05	0.15
		(-0.05)	(0.32)	(0.89)
CAR		0.12	0.10	-0.07
		(0.84)	(0.75)	(-0.44)
SIZE		-0.58	0.05	-0.39
		(-0.80)	(0.06)	(-0.41)
LADF		-0.01	-0.01	-0.01
		(0.42)	(-1.22)	(-1.03)
LLPTA		-0.20	-0.22	0.41
		(-0.21)	(-0.22)	(0.34)
CI		0.02	0.01	0.01
		(0.54)	(0.45)	(0.39)
ROAE		-0.01	-0.02	-0.01
		(-0.22)	(-0.57)	(-0.23)
STOCK			0.03**	0.03**
			(2.25)	(0.09)
DD			-0.09	-0.18
			(-0.33)	(-0.60)
EG				-1.00**
				(-1.94)
INF				0.30
				(0.70)
UNR				-0.22
				(-1.46)
Pseudo R^2	0.076	0.119	0.169	0.259
Nobs	159	159	159	159

Notes: This table summarizes results of binary Logit regressions of the failure indicator on log CDS of 5 year after crisis, from 2014 to 2018. The distress indicator is 1 (0) if the bank with distress (without distress) during the subsequent 12 months. Pseudo R^2 is the value of the McFadden R-squared. Nobs is the number of observations. We report the t-statistics in parentheses and adjust standard errors by using Huber-White method. We report 4 different specifications of the Logit regressions. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

CDS is large and significant for all models. Therefore, we find strong evidence that CDS has significant explanatory power on bank distress for both large and small banks. However, the coefficient of CDS spreads in small banks is larger than that in large banks[7].

[7] According to Column (4) and (8), the coefficient of CDS is 3.74 for large banks, while the coefficient of CDS is 5.78 for small banks.

Table 2.9: Regression of CDS Spread on Alternative Indicator of Bank Distress

	(1)	(2)	(3)	(4)
CDS	-3.68***	-4.04***	-1.49***	-1.52***
	(-9.67)	(-8.03)	(-4.34)	(-4.21)
TIRC		0.12	-0.11*	-0.11*
		(0.97)	(-1.72)	(-1.65)
CAR		-0.01	-0.01	-0.01
		(-0.72)	(1.07)	(0.09)
SIZE		-1.08**	-0.15	-0.10
		(-2.42)	(-0.64)	(-0.42)
LADF		0.00	0.00	0.00
		(-1.36)	(-0.66)	(-0.49)
LLPTA		-0.19	-0.76**	-0.72**
		(0.31)	(-2.50)	(-2.30)
CI		-0.01	0.00	-0.01
		(-0.52)	(0.03)	(-0.85)
ROAE		-0.01	-0.04***	-0.05***
		(-0.39)	(-3.69)	(-4.05)
STOCK			0.09***	0.09***
			(34.73)	(32.68)
DD			-0.01	-0.07
			(-0.11)	(-0.99)
EG				0.15***
				(2.85)
INF				0.11
				(1.16)
UNR				0.03
				(1.26)
Pseudo R^2	0.181	0.183	0.808	0.813
Nobs	425	394	389	389

Notes: This table summarizes results of regressions of the failure indicator on log CDS of 5 year from 2005 to 2018. The distress indicator is continuous (Z-score). The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR). Pseudo R^2 is the value of the McFadden R-squared. Nobs is the number of observations. We report the t-statistics in parentheses and adjust standard errors by using Huber-White method. We report 4 different specifications of regressions. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.5.2 Size Effect and Opacity Effect

The contribution of CDS to early prediction of bank distress is a challenge to modern banking theory, because the theory requires that only banks are able to obtain private information on borrowers and the outsiders do not acquire. This theory, known as bank-centric view of information asymmetry, indicates that banks have informational advantages over other market participants due to their close relationship with borrowers. Thus, any external signal that effectively predicts bank distress, such as that from CDS

Table 2.10: Regressions of Downgrade Indicator on CDS Spreads for Small and Large Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CDS	3.59**	3.87***	3.58***	3.74***	2.96***	3.86***	4.54***	5.78***
	(5.28)	(4.35)	(3.35)	(2.79)	(2.03)	(4.59)	(3.42)	(3.39)
TIRC		-0.01	0.01	0.07		-0.49***	-0.65***	-0.81***
		(-0.08)	(0.10)	(0.53)		(-2.66)	(-3.05)	(-3.29)
CAR		0.03	0.05	0.05		0.32*	0.36*	0.47*
		(0.21)	(0.37)	(0.33)		(1.73)	(1.90)	(2.21)
SIZE		1.42	1.15*	1.38*		0.62	1.32	1.67
		(1.32)	(1.56)	(1.22)		(0.60)	(1.15)	(1.38)
LADF		0.00	0.00	-0.00		0.01*	0.01**	0.01*
		(0.59)	(0.18)	(-0.56)		(1.71)	(2.01)	(1.71)
LLPTA		0.03	-0.03	0.22		-1.32*	-1.59*	-1.87**
		(0.04)	(-0.04)	(0.20)		(-1.73)	(-1.88)	(-2.16)
CI		-0.00*	-0.01	-0.02		-0.02	-0.04	-0.01
		(-0.07)	(-0.57)	(-0.81)		(-0.89)	(-1.52)	(-0.25)
ROAE		-0.02	-0.01	-0.01		-0.01	-0.00	0.01
		(-1.03)	(-0.63)	(-0.33)		(-0.51)	(-0.05)	(0.23)
STOCK			0.01	-0.00			0.02***	0.02***
			(0.94)	(-0.06)			(2.86)	(2.80)
DD			-0.27*	-0.16			-0.17	-0.18
			(-1.86)	(-0.89)			(-0.77)	(-0.77)
EG				-0.39***				0.12
				(-3.05)				(0.88)
INF				0.42*				-0.58**
				(1.77)				(-2.02)
UNR				-0.07				-0.01
				(-1.02)				(-0.16)
Pseudo R^2	0.171	0.209	0.230	0.302	0.145	0.158	0.353	0.381
Nobs	255	228	228	228	170	166	161	161

Notes: This table summarizes results of binary Logit regressions of the failure indicator on log CDS of 5 year from 2005 to 2018 for small and large banks respectively. The distress indicator is 1 (0) if the bank with distress (without distress) during the subsequent 12 months. The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR). Large banks refer to banks that total assets are greater than "300 billion" or the bank is ranked first or second in its country. We report t-statistics in parentheses and adjust standard errors by using Huber-White method. We report 8 different Logit regressions: (1)-(4) for large banks and (5)-(8) for small banks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

spreads, suggests that information about borrower riskiness is leaking into the market, challenging the underlying assumption that only banks possess and act on such private insights. Modern banking theory is also negatively affected by liquidity services of banks and supports public safety networks, particularly for large banking organisations.

The relationship between the interaction of Credit Default Swaps (CDS) and bank size on bank distress is a complex area of study that involves analysing how the joint effects of these variables influence the likelihood of a bank facing financial distress. The interaction effect between CDS and bank size helps determine whether the relationship between CDS and bank distress varies based on different levels of bank size. A positive interaction term suggests that the impact of CDS on distress is magnified for larger banks, while a negative interaction term suggests the opposite. Bank size acts as a moderating factor in this context. It moderates the relationship between CDS and distress, indicating whether the influence of CDS on distress is stronger or weaker for banks of different sizes. Understanding the interaction helps assess whether the presence of CDS amplifies or mitigates the impact of size on bank distress. For instance, if the interaction is positive, it implies that CDS exacerbates the distress for larger banks. The interaction between CDS and size may reflect market perceptions and investor behavior. If larger banks are more sensitive to changes in CDS prices, it may indicate that investors view these banks as more interconnected or susceptible to market sentiment.

The relationship between bank opacity and bank distress is a critical aspect of financial stability and risk management. Opacity in the context of banking refers to the lack of transparency or clarity in a bank's operations, financial condition, or risk exposures. When banks are opaque, it becomes challenging for stakeholders, including investors, regulators, and the public, to fully understand the risks the bank is facing, potentially leading to distress or financial instability. For example, bank opacity contributes to information asymmetry between the bank and external stakeholders. If investors and regulators do not have a clear understanding of a bank's financial health and risk profile, they may not be able to make informed decisions. Regulators are concerned about bank opacity because it can impede their ability to supervise and regulate the financial system effectively. Regulators need accurate and timely information to identify emerging risks and take preemptive measures to prevent distress. Therefore, regulators have responded to concerns about bank opacity by implementing measures to enhance transparency and disclosure requirements. These measures aim to improve the quality and accessibility of information about a bank's financial condition and risk exposures. Bank opacity also have significant effects on bank distress. The banking institutions usually acquire private information by the structure of banking financial statements. In theory, the source of opacity is the intermediation function of banks and loans- to-total-assets as a proxy of asymmetric information[8]. Deposit-to-total-assets ratio also can be used as another proxy because liquidity ratio makes a difference for market signals to transmit accurate information. Some papers also use the percentage of market funding on the liability of balance sheet as a determining variable (Goyeau et al., 2001; Crouzille et al., 2004).

We test for the size effect and opacity effects by estimating following model:

$$Prob(Y_i = 1) = \phi(\alpha + \alpha' D_i + \beta CDS * D_i + \sum_{k=1}^{K} \eta_k C_{ki} + \sum_{l=1}^{L} \lambda_l M_{li} + \sum_{q=1}^{Q} \theta_q E_{qi} \tag{2.10}$$

[8] This ratio is unavailable and we adopt a new ratio (deposit-to-total-assets ratio) as opacity.

Where D_i is a dummy variable, either the size effect ($DBIG_i$) or the opacity effect ($DOPAC_i$).

Size Effect

Table 2.11 displays the findings related to the size effect. DBIG is a binary variable, taking the value of 1 if a bank's total assets exceed 308.42 billion (a notable threshold within our sample size) or if the bank ranks as the first or second largest in its country; otherwise, it takes the value of 0.

The results indicate that the size of a bank can have a relative impact on the predictive capacity of CDS spreads concerning bank distress. Specifically, for larger banks, CDS spreads exhibit a diminished ability to predict the financial condition of the bank. The coefficients for DBIG and DBIG*CDS are both negative and statistically significant. To confirm the robustness of these findings, we conducted stepwise analyses separately for small and large banks, yielding consistent results. These additional results are presented in Table 2.10, emphasizing that CDS exert a more pronounced influence in explaining bank financial distress for smaller banks. This evidence suggests that an increase in asset size may weaken the effectiveness of CDS spreads in conveying valuable information about the future financial health of a bank.

Opacity Effect

In order to explore the relationship between bank opacity and the predictive power of CDS spreads, we introduce several definitions of binary variable DOPAC. Concretely, we consider the ratio of net loans to total assets, the ratio of deposits to total assets, the ratio of subordinated debt to total assets, and the ratio of market-funded liability to total assets (Distinguin et al., 2006). We adopt the ratio of d eposits to total assets in discriminating the predictive power of CDS spreads due to data limitations. Therefore, in Table 2.11, we report the results when DOPAC equals one if the ratio of deposits to total assets is lower than its median, 36.85 percent. The results in Table 2.11 show that the opacity is more likely to alter the predictive power of CDS spreads. The coefficient of CDS and the coefficient of the interacting indicator CDS* DOPAC are significant on bank distress. The significance reaches the one unit increase in CDS* DOPAC in Table 2.11 decreases $e^{0.086}$ probability of occurrence of bank distress. Therefore, the higher degree of opacity tends to weaken the relationship between CDS spreads and the probability of bank future downgrade.

In Column (3) of Table 2.11, we incorporate both the size effect and opacity effect into the regression model. The results indicate that these factors enhance the predictive power of CDS spreads for bank distress. Specifically, the interaction terms CDSDOPAC and CDSDBIG are significant, suggesting that both opacity and size effects contribute to the model's explanatory strength. However, the standalone coefficients for

DOPAC and DBIG are not significant.

Table 2.11: Regression of CDS Spread on Bank Distress With Bank Size and Opacity

	(1)	(2)	(3)
CDS	3.773***	3.176***	3.938***
	(0.881)	(0.948)	(0.908)
DOPAC		0.122	-4.127
		(2.217)	(3.756)
DOPAC*CDS		0.086***	0.771*
		(0.010)	(0.428)
DBIG	-6.147*		-6.137
	(3.717)		(7.609)
DBIG*CDS	-1.143***		-1.090***
	(0.127)		(0.276)
TIRC	-0.152	-0.121	-0.142
	(0.145)	(0.151)	(0.112)
CAR	0.074	0.049	0.049
	(0.130)	(0.133)	(0.109)
LADF	0.007*	0.003	0.006
	(0.004)	(0.004)	(0.004)
LLPTA	-0.911*	-1.040**	-1.102*
	(0.509)	(0.529)	(0.577)
CI	-0.028**	-0.034***	-0.029**
	(0.013)	(0.013)	(0.015)
ROAE	-0.008	-0.014	-0.008
	(0.014)	(0.015)	(0.016)
STOCK	0.007	0.005	0.007*
	(0.004)	(0.004)	(0.004)
DD	-0.110	-0.178	-0.157
	(0.118)	(0.127)	(0.136)
EG	-0.200**	-0.198**	-0.180**
	(0.091)	(0.092)	(0.085)
INF	0.152	0.221	0.117
	(0.148)	(0.143)	(0.151)
UNR	-0.057	-0.044	-0.056
	(0.037)	(0.036)	(0.040)
Pseudo R^2	0.266	0.253	0.315
Nobs	398	398	401

Notes: This table reports Logit estimation results when we regress the dependent variable on a constant, the accounting indicators and the market indicators selected by stepwise processes. The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR). We take opacity effect into account with a dummy variable (DOPAC and DBIG) associated with CDS spreads. DOPAC is equal to one if the value of the ratio deposits / total assets is lower than its median (36.85%) and. DBIG is equal to one if bank's total assets are greater than "308.42 billion" or if the bank is ranked first or second in its country, and zero otherwise. We use robust standard error.

2.5.3 Testing for Predictive Ability of Models Out of Crisis

In this section, we provide tests of out-of-sample predictive ability of several Logit models of future bank distress. For distress signals to add value as early warning signals, they must integrate new information promptly and accurately. In total, we test four different kinds of distress signals: accounting, market information, credit default swaps, and macroeconomic conditions. We conclude that the majority of bank distress happening during the period 2008-2013, therefore leading us to concentrate on this period and estimate model parameters with 2008-2013 observations. The estimated results are used to calculate the ex-ante bank distress probabilities during banking crisis for forthcoming year without crisis. Previous studies have examined the out-of-sample performance of early-warning prediction models (Bauer and Agarwal, 2014; Betz et al., 2014; Agarwal and Taffler, 2008). Similarly, we introduce a Receiver Operating Characteristics (ROC) curve to assess out-of-sample performance[9]. To determine the ability of CDS spreads to identify between healthy and distressed banks out-of-sample, we adopt simulation approach. For each Logit model, we run 1000 simulations of the ROC curve area. For each simulation, model parameters are estimated during the 2008–2013 period using 26 banks randomly selected.

Table 2.12: ROC Curve Areas for Different Distress Models

Variables	AUC	SE	Z	AR	t-test
CDS	0.59	0.37	4.86	0.17	-
STOCK	0.50	0.35	-0.05	-0.00	3.78
Accounting	0.73	0.21	24.01	0.47	-4.38
DD	0.79	0.20	31.64	0.58	-7.78
CDS+STOCK	0.62	0.35	7.00	0.23	-0.87
CDS+DD	0.72	0.25	18.96	0.43	-4.58
CDS+Accounting	0.74	0.19	27.90	0.49	-5.57
STOCK+Accounting	0.75	0.20	26.34	0.50	-5.73
DD+Accounting	0.80	0.18	37.58	0.61	-7.47
CDS+STOCK+Accounting	0.73	0.20	24.57	0.46	-4.75
CDS+Accounting+DD	0.79	0.18	36.49	0.59	-8.82
CDS+Accounting+DD+STOCK+Macroeconomic	0.73	0.22	22.65	0.46	-5.89

Notes: This table reports the results of out of sample analysis. We use 1000 simulations for the area under the Receiver Operating Characteristics curve obtained using several logit models that calculate ex-ante bank default probabilities for year 2014. The potential determinants for bank distress are, namely, financial accounting variables (capital TIRC and CAR, asset quality LLPTA, management quality CI, earnings quality ROAE, liquidity LADEPST and size SIZE), CDS spread, market information (STOCK and DD) and macroeconomic condition (INF, EG and UNR).

Results are shown in Table 2.12. We introduce four models, each model considering the single indicator influencing bank risk (based on CDS, STOCK, DD and Accounting). To be concrete, The Accounting

[9]The receiver operating characteristic measures the trade-off between correctly predicted failure and incorrectly predicted non-failures. An area under the ROC curve of 1 would indicate complete forecasting accuracy. The area less than 0.50 suggests that random selection would better predict distress out-of-sample than the prediction model.

model only apply accounting variables (e.g. T1RC, CAR, LLPTA, CI, ROAE, LADF, SIZE) as covariates to predict bank distress. Then, we incorporate two univariate variables and run five bivariate models. We run two trivariate models by combining three sets of risk predictors and four-variable model. The area under the ROC curve (AUC) is computed using the trapezoidal rule and its simulated mean value reported in Column 1 of Table 2.12 for each model. Column 2 shows the simulated mean AUC standard error based on the unbiased estimator, Column 3 the test statistic for the null hypothesis that the AUC is equal to 0.5 and Column 4 the simulated mean accuracy ratio $AR = \frac{2}{AUC-0.5}$ based on Engelmann et al. (2003). Column 5 reports the t-statistic of a two-sample one-tailed t-test for the null of equality between the simulated mean AUC of a univariate logit based on CDS and that obtained from any of the remaining eleven logit models.

When considered alone, CDS has an AUC of 0.59, significantly different from the accuracy obtained from random sampling. Combining CDS with stock returns results in a decrease in AUC, in keeping with the finding that information from the stock market information adds little additional information relative to CDS. Combining CDS with DD, we get an AUC of 0.72, greater than that from CDS alone and the same results are discovered in other models. After Controlling accounting variables, market information and macroeconomic conditions, we obtain an AUC of 0.73, surpassing the AUC achieved solely with CDS, and consistent results are observed across other models. This predictive analysis further confirms that CDS together with all other control variables can be employed to generate useful predictive signals of bank distress either during crisis or normal time.

2.6 Conclusion

In this paper, the primary objective is to examine the extent to which bank Credit Default Swaps (CDS) contracts contribute to the explanation of bank distress, incorporating accounting information, market discipline, and macroeconomic conditions. Specifically, we investigate whether an increase in CDS spreads correlates with a higher probability of distress. Subsequently, we introduce control variables, such as accounting and market measures, along with macroeconomic variables, to further explore the predictive power of CDS spreads. Additionally, we assess the predictive capability of CDS spreads while considering bank size and the opacity effect. The main finding of this study reveals a significant association between CDS spreads and future bank distress, particularly evident for smaller banks. This result remains robust even after accounting for equity market information, as well as accounting and macroeconomic variables. Consequently, monitoring fluctuations in CDS spreads could assist supervisors in anticipating distress for individual banks and indirectly contribute to enhancing market discipline.

Several robustness tests are conducted in order to provide stronger evidence for this predictive power: (1) the analysis was conducted on CDS spreads with different maturities (1-year, 2-year, 3-year and 5-year senior CDS spreads), and also on the post-crisis period. Logit panel regression yielded the following results. Firstly, consistently with what was emphasised during the crisis, it is thus correct to consider bank CDS spreads a proxy for bank riskiness, given that bank CDS spreads explain a large part of bank failure. Besides, bank CDS spreads, both in the post-crisis period, but especially in the crisis period, reflect the bank distress condition. However, after financial crisis, bank CDS only generate weak explanatory power on bank financial condition. The lower explanatory power of the bank CDS spreads in the post-crisis period is mainly because bank distress reduce at that time. As bank failure grow, so does the explanatory power of bank CDS spread, together with other control variables. This result enables us to establish a simulation model to predict bank distress after controlling other indicators, in order to examine the accuracy for current Logit model (see in Section 2.4.3). Based on data from 2008 to 2013, we examine a simulation model for predicting bank failures in European banks. According to this study, CDS together with bank-level and country-level indicators improve the estimation model's performance and generate more accurate out-of-sample predictions of bank distress. (2) to determine whether the relationship between bank CDS spreads and bank distress changed between small and large banks, two further panel regressions were performed: We run baseline regression for small and large banks, respectively. The conclusion is that he coefficient of CDS spreads in small banks is larger than that in large banks, which is consistent with the phenomenon 'too-big-to-fail'.

Credit Default Swaps are financial derivatives that allow investors to protect themselves against the default or credit risk of an underlying asset, such as bonds or loans. These instruments gained widespread use in the financial industry, becoming integral to risk management strategies. CDS function as a risk transfer mechanism, enabling banks to offload or hedge credit risk exposures. Understanding how banks utilize CDS in risk management is crucial for comprehending the dynamics of risk transfer within the financial system. The existence and functioning of the CDS market create a parallel market for credit risk. Banks, as key participants in this market, use CDS for various purposes, including hedging, speculation, and managing their overall risk exposure.

The use of Credit Default Swaps (CDS) in studying bank distress has several political significance and implications. Firstly, the pricing and trading of CDS on banks can serve as an early warning system for potential financial distress. Political authorities and policymakers closely monitor these indicators to gauge the stability of the financial system. Secondly, the use of CDS data puts a spotlight on the regulatory oversight of banks. Political bodies may use information from CDS markets to assess whether banks are meeting regulatory requirements and may intervene if distress signals are evident. Thirdly, in the event of a banking crisis or distress, political leaders may rely on CDS data to assess the severity and potential economic impact. This information can inform crisis management strategies and policy responses. Then, this paper can make contributions to policy reforms. Political authorities may use insights from CDS markets to formulate financial and economic policies. Understanding the credit risk perceptions reflected in CDS prices can guide policymakers in developing strategies to address potential distress scenarios. Political pressure, especially in the aftermath of a financial crisis, may lead to calls for regulatory reforms. Knowledge gained from studying CDS markets can influence the design and implementation of new regulations aimed at preventing future bank distress. Finally, with the development of globalization, bank distress is not limited to national borders, and political entities may engage in international coordination to address global financial challenges. CDS data can be part of the information shared between countries to foster cooperation in crisis response. Political leaders may use information from CDS markets to communicate with the public about the stability of the banking sector. Maintaining public confidence in the financial system is crucial, and political figures may reference CDS data in their communication.

In summary, the political significance of using CDS to study bank distress lies in its role as an information source for policymakers, regulators, and political leaders. The insights gained from CDS markets can inform policy decisions, crisis response strategies, and regulatory reforms, contributing to the overall stability and resilience of the financial system.

Appendix 2.1: Cause and Effect

The relationship between CDS and bank distress is close and mutually influential. In this paper, we examine that CDS spreads can predict bank distress in the future. Changes in a bank's CDS spreads can serve as an early warning signal of bank distress. If a bank's CDS spreads continue to widen, it may indicate that the bank's financial condition is deteriorating.

However, bank distress usually leads to an increase in its CDS spread, which in turn may exacerbate market concerns about the bank, further push up financing costs, and increase the probability of bank distress. In Appendix 2.1, we examine if bank distress does affect the bank CDS spreads using GMM model. Dynamic panel data models are often used to analyze panel data including lagged dependent variables. The model is:

$$CDS_{it} = \alpha CDS_{i(t-1)} + \beta BIS_{i(t-1)} + u_i \tag{2.11}$$

Where BIS is a dummy variable that equals to 1 if the bank experience bank distress, 0 otherwise at time $t-1$. CDS is the vector of dependent variables (5 year CDS spread) at time t and $t-1$.

Table 2.13: Dynamic Panel-Data Estimation: System GMM

Variables	Coefficient	z-Statistic	P-value
CDS_{t-1}	0.64***	19.75	0.00
BIS_{t-1}	0.09***	2.66	0.01
Arellano-Bond Test			
$AR(1)$		z=-4.85	p=0.00
$AR(2)$		z=-4.99	p=0.00
Difference-in-Hansen Tests of Exogeneity of Instrument Subsets			
GMM for levels			
Hansen Test Excluding Group		χ^2 (23)=31.44	p=0.112
Difference (Null H = exogenous)		χ^2 (2)=0.17	p=0.920
IV: BIS for levels			
Hansen Test Excluding Group		χ^2 (24)=31.50	p=0.140
Difference (Null H = exogenous)		χ^2 (1)=0.10	p=0.747

Notes: This table reports the results of out of Dynamic Panel-Data Estimation GMM. Dependent variable is 5-year CDS spread and BIS is bank distress.

Table 2.13 indicates our regression results for 5 year CDS and bank distress. The coefficient of CDS_{t-1} is positive and significant in all specifications. The results show that the lagged value of CDS has a significantly positive impact on the dependent variable. In addition, the coefficient estimate on BIS_{t-1} implies that compared with healthy banks, banks with financial distress cause larger CDS spreads. Therefore, CDS spreads will also increase in response to downgrades.

We also conduct the Arellano-Bond autocorrelation test. The AR(1) test in first differences checks for the presence of first-order autocorrelation in the differenced error terms. With a z-value of -4.85 and a p-value of 0.00, the results indicate significant first-order autocorrelation in the differenced errors, which is expected since differencing the data typically introduces such autocorrelation. Additionally, the AR(2) test in first differences examines second-order autocorrelation in the differenced error terms. The z-value of -4.99 and a p-value of 0.00 suggest significant second-order autocorrelation. This is a concern because, ideally, second-order differenced errors should not show significant autocorrelation. The presence of such autocorrelation may point to potential issues with the model, such as incorrect specification or the need to reconsider the selection of instruments.

To address this, we perform the Difference-in-Hansen test to assess the exogeneity of instrument subsets. High p-values (e.g., 0.112, 0.920, 0.140, 0.747) indicate that these subsets of instruments do not significantly violate the exogeneity assumption, confirming their validity as instruments. Consequently, the instruments used in the estimation process are indeed exogenous, and the model is not significantly impacted by autocorrelation issues that could compromise the results. This suggests that the findings are robust and reliable.

Chapter 3

Deviations from Covered Interest Rate Parity for Sovereign Bonds

3.1 Introdution

The CIP condition, known as no-arbitrage condition, stipulates that the interest rates in cash market must be equal to the interest rates in the foreign exchange (FX) markets due to arbitrage activities. According to CIP condition, it is impossible to earn a profit by borrowing in one currency and lending in another currency while fully covering the foreign exchange (FX) risk. The deviation from CIP means that investors are required to pay a premium to borrow U.S. dollars or other currencies on hedged basis through cross-currency swap markets. One such measure is known as the as the cross-currency basis, which is the difference between the dollar interest rate in cash market and in FX swap market when exchange foreign currency into dollars. The cross-currency basis is usually negative which means borrowing dollars through FX swap market is more expensive than borrowing dollars in the cash market, which reflects a scarcity of dollar funding.

In tranquil times, the basis is close to zero because it is impossible for arbitrageurs to exploit the basis in FX swap markets to pocket the difference. However, since Global Financial Crisis (GFC), CIP has failed to hold on and CIP deviations occur. The phenomenon can also be found in Covid-19 distress. Based on CIP deviations, we construct CIP deviations for bonds (Garleanu and Pedersen, 2011). This paper examines the nature of frictions that affect bond markets during the period of market distress. We investigate these economic questions by studying price convergence in sovereign bonds. Some nations issue debt dominated in more than one foreign currency. For example, China issues a considerable number of bonds denominated in USD and euro with close maturity. In absence of frictions, the yield spreads across two foreign currencies must satisfy a simple condition: for example, the yield of a USD- denominated Chinese bond should equal the yield of synthetic dollar bond using the euro-denominated bond with same maturity from same issurers when the investor swaps all cash flows in the USD/EUR foreign exchange (FX) forward market. Therefore, for bond pairs, we can construct a proxy of the yield difference between cash and synthetic bond ($Basis_{bond}$) during Covid-19 distress.

Studying deviations from Covered Interest Rate Parity (CIP) in sovereign bond markets is motivated by several factors, each providing valuable insights into market dynamics, risks, and potential arbitrage opportunities. Here are some key motivations: (1) Risk Management: Understanding deviations from CIP is essential for risk management. Sovereign bond investors face various risks, including interest rate risk, credit risk, and exchange rate risk. Deviations from CIP can signal potential risks associated with currency movements and interest rate differentials. (2) Arbitrage Opportunities: Deviations from CIP may present arbitrage opportunities for market participants. Investors and financial institutions can exploit these opportunities to generate profits by taking advantage of interest rate differentials and exchange rate movements. (3) Market Inefficiencies: Persistent deviations from CIP may indicate market inefficiencies or frictions. Analyzing the nature and causes of these deviations can help identify areas where the market may not be functioning optimally, leading to potential improvements in market structure and efficiency. (4) Policy Implications: Deviations from CIP can have policy implications, especially in the context of monetary and fiscal policies. Central banks and policymakers may need to assess whether observed deviations are temporary or indicative of broader economic or financial imbalances.

During Covid-19 crisis, the law of one price (LOP) was impaired in the sovereign bond markets by different types of frictions (e.g., liquidity frictions). We find relatively small violations before Covid-19 crisis. Generally, net absolute deviations in China, South Korea and Mexico are less than 50 basis points (bps). However, we find large pricing anomalies in these sovereign bond markets in three countries during Covid-19 crisis. For example, in May 2021, deviations between 2022 Chinese USD bond and its synthetic bond reached almost -200 basis points (bps) after hedging the exchange risk. This result reveals different types of limitations that prevent price convergence. Three different frictions have been introduced in this paper (Gromb and Vayanos, 2010; Buraschi et al., 2015): (1) market liquidity, (2) funding liquidity and costs affecting the debt capacity of arbitrageurs (leverage constraints), (3) macroeconomics shocks.

According to Buraschi et al. (2015), we choose the three large sovereign bond markets (by notional amount outstanding) with issuing denominated in both dollars and euros: China, South Korea and Mexico[1]. There

[1]The specific bond pairs (with total issue size of each bond reported in parenthesis) are as follows. For China, EUR-bond 08.06.2022, 0.75% (Euro 550000m) and USD-bond 14.03.2022, 2.625% (USD 1150000m). For South Korea, EUR-bond 30.05.2022, 0.5% (Euro 750000m) and USD-bond 11.04.2022, 5% (USD 1000000m). For Mexico, EUR-bond 15.01.2025, 1.375% (Euro 1200000m) and USD-bond 30.01.2025, 3.6% (USD 3000000m).

are three common important features for these countries: (1) the Eurobond markets are large[2] and liquid and transaction costs are relatively small before crisis, (2) Several pairs of tradable assets are available across different continents and (3) Prior to the crisis, their bond prices were in accordance with the law of one price[3]. We calculate $Basis_{bond}$ in the following steps: firstly, the bonds are issued by the same issuers and have nearly identical maturities denominated in different currencies. We swap the cash flows of euros into dollars to hedge the foreign exchange risk and to construct $Basis_{bond}$, which measures the violation of Law of One Price. Then, we examine how the dynamics of $Basis_{bond}$ evolve during covid-19 crisis. Finally, we investigate the extent to which three main frictions have affected the $Basis_{bond}$ of different sovereign bond markets.

We use a simple arbitrage relationship (Covered Interest Parity) that relates two bonds issued by the same issuer in two different currencies (euros and dollars). We build a panel dataset for the $Basis_{bond}$ of bond pairs to study the dynamics of the $Basis_{bond}$ during the Crisis and differences across different markets. After calculating $Basis_{bond}$, we find that $Basis_{bond}$ is not largely different from zero before crisis. However, during Covid-19 crisis, $Basis_{bond}$ is large, persistent and volatile. According to this, bond markets issued by the same sovereign were segmented for long period of time. Therefore, we investigate the role of different types of frictions in models. To study these frictions, we use unique dataset which provides detailed information on sovereign bonds. The dataset also provides information on liquidity, funding and macroeconomic frictions which may cause CIP arbitrage for sovereign bonds. We use this information to help distinguish between alternative models of limits to arbitrage and, in particular, to explore the impact of different frictions.

We report a number of empirical results. First, liquidity risks plays a limited role in explaining $Basis_{bond}$. However, secured funding costs are statistically and economically significant. This empirical finding supports an explanation based on funding frictions in wholesale credit markets during Covid-19 crisis. In mid-March 2020, short-term dollar funding markets faced severe disruptions as investors withdrew from unsecured markets and switched to secured markets and government MMFs (Eren et al., 2020). Besides, some macroeconomic factors are significant in explaining $Basis_{bond}$. This finding is consistent with hypothesis that marginal arbitrageurs face sources of risk that go beyond those affecting local markets. Gromb and Vayanos (2010) study a model in which global arbitrageurs, who are present across different markets, are affected by common wealth shocks. When arbitrageurs find it difficult to absorb these shocks by accessing debt markets, the resulting friction becomes a source of contagion across seemingly unrelated assets.

[2]The market share of bond markets is 26.5% (China), 1.61% (South Korea), 0.67% (Mexico). We excluded European countries and the United States because the issuance of euro-denominated bonds in European countries and the issuance of dollar-denominated bonds in the United States will have lower financing costs.

[3]Some studies find that the violations of CIP condition have persisted after crisis (Borio et al., 2016, 2018; Pinnington and Shamloo, 2016).Therefore, there may be relatively small violations for $Basis_{bond}$ from 2017 to 2019.

Additionally, we conduct robustness tests to enhance the reliability of our findings: (1) Duration and Convexity Gap Analysis: We investigate the relationship between cash flow risk associated with bond characteristics and the violation of defaultable sovereign bond prices through duration and convexity gap analysis. (2) Stock Risk Impact: We explore whether stock risk can account for deviations in Covered Interest Rate Parity (CIP) for sovereign bonds. (3) Foreign Exchange Correlation Risk: We assess the role of foreign exchange correlation risk using Quanto Credit Default Swaps (CDS) in understanding CIP deviations. (4) Liquidity and Economic Conditions Interaction: We examine the interaction of liquidity and economic conditions on CIP basis for bonds. Our results indicate that cash-flow mismatch and FX correlation risk have limited explanatory power for the dynamics of $Basis_{bond}$. After considering stock risk and the interaction of liquidity and economic conditions, we conclude that local stock risk and the interplay of liquidity and economic conditions cannot sufficiently explain the violation of CIP for bond markets. Additionally, we introduce an alternative variable, excess return, and find that secured funding frictions and macroeconomic conditions play crucial roles in determining excess return, aligning with our primary results.

The structure of the paper is organized as follows. In Section 3.2, we delve into the pertinent literature review relevant to the paper. Section 3.3 articulates the theory underlying Covered Interest Rate Parity (CIP) violations within sovereign bond markets. Our sample, data description, and methodology for examining the persistence of CIP violations in sovereign bond markets are expounded in Section 3.4. Empirical results are presented in Section 3.5, and Section 3.6 comprises various robustness tests. Finally, Section 3.7 concludes the paper.

3.2 Literature Review

Sovereign bond markets play a pivotal role in global finance, serving as a crucial avenue for governments to raise capital. The efficient functioning of these markets is essential for economic stability. However, anomalies in sovereign bond prices can have far-reaching implications, impacting government financing costs, investor confidence, and overall financial stability. This literature review aims to explore existing research on sovereign bond price anomalies, with a focus on key themes and findings.

Market efficiency and asset pricing are profoundly affected by violations of the arbitrage-based pricing relationship. Particularly, price violations can lead to market disintegration and asset price distortions. Various sources of asset mispricing have been suggested in the literature. Limits-to-arbitrage are commonly cited as causes of price violations (Mitchell and Pulvino, 2012; Pontiff, 2006; Brav et al., 2010). Arbitrage may not be feasible when transaction costs and the risk of a firm's security are excessively high. Funding constraints or limited arbitrage capital provision can prevent arbitrage activity (Mitchell and Pulvino, 2012; Brunnermeier and Pedersen, 2009) and cause serious mispricing in similar securities. In this section, we present relevant literature on deviations from covered interest rate parity in sovereign bond markets and different types of frictions which may cause CIP deviations in sovereign bond markets.

Many studies have focused on covered interest parity (CIP) deviations before crisis, during the crisis, and post crisis. Before crisis, cross-currency basis measuring CIP deviations is close to zero, because arbitragers exploit the FX swap market basis and supply dollars to pocket the difference (Avdjiev et al., 2020). During crisis episodes, Mancini-Griffoli and Ranaldo (2011) suggests that the lack of dollar funding liquidity prevents traders from arbitraging excess profits, thus fails to balance the CIP condition, McGuire and von Peter (2012) and Coffey et al. (2009) argue that widening of CIP deviations during global financial crisis are driven by counterparty risk and dollar funding constraints. During sovereign debt crisis, CIP deviations influenced by tools of central banks widened significantly as a result of dollar funding shortage (Bottazzi et al., 2012; Ivashina et al., 2015).

Based on previous studies, we can assume that there may be also deviations for bond markets. To explore the CIP deviations for sovereign bond, our paper sheds light on some literature on different frictions and constraints of CIP deviations condition in bond markets. Deviations from CIP for bonds are associated with liquidity risk, funding costs and macroeconomic shocks during Covid-19 crisis. The Covid-19 crisis has adversely affected EM, suffering from collapsing exports and tightening international credit conditions (Djankov and Panizza, 2020). According to Hevia and Neumeyer, 2020a, EM are harder hit by the pandemic as many policy measures to fight it are less effective, mainly due to difficulties to issue debt for smoothing Covid-19 shocks. Barnett Howell and Mobarak, 2020, find that benefit from social distancing and travel restrictions are less valuable in poorer countries due to a relatively younger population of EM economies. Goldberg and Reed, 2020, document that developing economies have seen massive capital outflows and declines of commodity prices.

CIP deviations for bond are linked with FX market liquidity. Previous papers assess how market liquidity, or the lack thereof, interacts with funding constraints in sovereign bond markets and its implications for deviations from CIP for sovereign bond markets. Financial markets worldwide have been severely affected by the global pandemic of Covid-19 (Goodell, 2020), while emerging markets (EM) have faced a mass exit by foreign investors seeking safe assets (e.g., Das et al., 2020) that highlighted their excessive dependence on external financing. As Covid-19 has been negatively affecting emerging economies' growth prospects (Djankov and Panizza, 2020) foreign investors have rushed from high uncertainty of the EM to the safety of the developed ones, triggering an enormous flight-to-quality episode (e.g., Gubareva and Borges, 2016).

Nonetheless, the impact of Covid-19 pandemic on financial markets is mostly addressed in relation to the stock markets in the developed economies (Alfaro et al., 2020; He et al., 2020; Rameli and Wagner, 2020). However, the coverage of Covid-19 impacts on debt markets is rather scant (Acharya and Steffen, 2020; Haddad et al., 2020; and Kargar et al., 2020). These studies are limited to the developed economies, not addressing EM debt. Pinnington and Shamloo (2016) focus on FX market rather than broader funding market. Due to reduced dealer capacity as result of the SNB decision, a reduction in forward contracts resulted in wide bid-ask spreads in the forward market, allowing deviations from CIP to persist. Viswanath-Natraj (2020) argues that due to unconventional monetary policies in the Eurozone, Japan, and Switzerland, demand for dollar funding in the FX swap market will remain structurally imbalanced which means CIP deviations will continue to persist. Cenedese et al. (2021) investigate actual trading activity by different market participants and how this relates to CIP deviations and balance sheets costs. They find that wider CIP deviations in the next quarter is related to lower leverage ratio buffer of major bank dealers for short time and the wider basis is associated with regulatory capital ratios for long duration, consistent with longer-term contracts having a higher risk-weight in the risk-weighted assets (RWA)-type balance sheet constraint, similar results in Du et al. (2018). Keller (2021) study that bank lending can affect CIP deviations. The banks attempt to arbitrage covered interest rate parity (CIP) deviations. In the presence of borrowing frictions, banks raise deposit rates to arbitrage or shift a portion of lending resources to fund arbitrage activities. Arbitrage-related bank lending decreases. Avdjiev et al. (2019) focus on the triangular relationship among the US dollar, CIP deviations, and cross-border bank lending denominated in dollars: the magnitude of CIP deviations can be interpreted by the cost of bank balance sheet capacity and bank leverage measured by dollar credit.

Besides, CIP deviations for bond markets maybe relate to funding costs. Some studies examine how funding constraints faced by sovereigns impact their bond issuance and whether these constraints contribute to deviations from CIP for sovereign bond markets. Liao (2020) concentrates on aggregate corporate debt issuance flow and links strategic funding cost arbitrage across different currencies with long-term CIP deviations. Duffie (2017) investigates that capital regulations and new failure-resolution rules after crisis increase the funding costs by bank shareholders, and the cost to buy-side firms for access to space on the balance sheets of large banks. Kisin and Manela (2016) study that banks' capital and liquidity requirements have substantially tightened, resulting in higher capital costs after crisis. The impact of demand effects on deviations from arbitrage pricing in a range of markets is discovered Acharya et al. (2013).

In addition, the violation of LOP for bond markets is also associated with economic reasons. There is some literature that investigates the impact of macroeconomic conditions, such as economic growth, inflation, and unemployment, on sovereign bond pricing and whether these factors contribute to deviations from CIP for sovereign bond markets. Du et al. (2018) show that CIP deviations cannot be explained by credit risk and transaction costs and the basis is correlated with interest rates and monetary policy shocks. Balima et al. (2015) find that inflation targeting (IT) adoption reduces sovereign debt risk in 38 emerging countries. It provides valuable insights for enhancing emerging market economies' access to international financial markets for financing long-term investment projects and supporting potential economic growth through IT implementation. However, Shleifer and Vishny (1997) discuss the link between susceptibility in the capital structure of arbitrageurs (availability of risk capital) and the transmission of initial price shocks to persistent deviations from the LOP. Amador et al. (2020) explore that an exchange rate policy in conflict with covered interest rate parity may create problems for a monetary authority because of a binding zero lower bound constraint.

The fourth stream of the literature deals with default risk. Some papers investigate the decomposition of yield spreads of defaultable bonds (Csávás, 2016; Du and Schreger, 2021; Choi et al., 2017; Coudert and Mignon, 2013). These studies show that yield spread levels and dynamics are difficult to reconcile with traditional structural credit risk models with additive preferences when calibrated to historical default and recovery rates. Based on Zinna (2013), a term structure model is used in this study to examine the risk premium embedded in sovereign default swaps. Unexpected changes in default intensity reward remunerative investors. Acharya et al. (2014) model a loop between sovereign and bank credit risk. Government bailouts resulting from distressed financial sectors increase sovereign credit risk. In turn, increased sovereign credit risk erodes the value of government guarantees and bonds, weakening the financial sector. The result shows that bailouts triggered the rise of sovereign credit risk in 2008 by using credit default swap (CDS) rates on European sovereigns and banks. Despite controlling for aggregate and bank-level determinants of credit spreads, post-bailout changes in sovereign CDS explain changes in bank CDS. According to Gennaioli et al. (2018), 20,000 banks in 191 countries are examined as well as 20 sovereign default episodes over the period 1997–2012. Two robust facts emerge from these analyses. In normal times, banks hold many government bonds (on average 9% of assets), especially those making fewer loans and operating in less-developed countries. Secondly, during default years, banks with average government bond exposure grow their loans more slowly than banks without government bonds (7 points lower). Based on the same reference entity, Palladini and Portes (2011) examine the price discovery relationship between sovereign CDS premia and bond yield spreads. The conclusion is that during and before the crisis, the euro area CDS market seems to adjust prices faster than the corresponding bond market. Badaoui et al. (2013) decompose sovereign Credit Default Swap (CDS) spreads into default, liquidity, systematic liquidity by using a factor model. The result shows that there is a strong correlation between sovereign CDS spreads and liquidity frictions and therefore sovereign bond spreads may offer a better reflection of sovereign default risk.

3.3 Covered Interest Rate Parity

In this section, we describe how we measure CIP deviations for sovereign. Covered interest rate parity (CIP) is an economic concept that relates interest rates, exchange rates, and the cost of hedging in the foreign exchange market. It represents an equilibrium condition in which the interest rate differential between two countries is equal to the forward premium or discount of the exchange rate.

The covered interest rate parity condition is derived from the principle that, in an efficient and well-functioning financial market, there should be no opportunity for risk-free arbitrage profits. The condition is particularly relevant for participants engaged in international financial transactions, such as investors, banks, and corporations. Deviations from covered interest rate parity (CIP) condition can occur due to various factors, leading to potential arbitrage opportunities or market inefficiencies. Covered interest rate parity is an equilibrium condition that, in theory, should hold in efficient financial markets. When deviations occur, they may signal market imperfections, transaction costs, or other frictions.

3.3.1 Libor-Based CIP deviations

We follow Fleckenstein et al. (2010) and Buraschi et al. (2015) to retrive the CIP for bonds but before that lets try how that relates FX covered interest rate parity (CIP) condition. Suppose that an investor borrows 1 U.S. dollar today and deposit 1 dollar for n years, earning payoff $e^{ny^{USD}_{t,t+n}}$. Besides, the investor could also exchange 1 U.S. dollars for S_t foreign currency i and enter into a n-year forward contract today, then deposit the foreign currency and earn payoff $e^{ny^{i}_{t,t+n}}$. Based on a frictionless market, the two strategies should have the same payoff.

$$e^{ny^{USD}_{t,t+n}} = \frac{e^{ny^{i}_{t,t+n}} S_t}{F_{t,t+n}}, \tag{3.1}$$

If CIP condition doesn't hold, we add a variable - CIP deviations- which we call the cross-currency basis.

$$e^{ny^{USD}_{t,t+n}} = \frac{e^{ny^{i}_{t,t+n}+nx^{i}_{t,t+n}} S_t}{F_{t,t+n}}, \tag{3.2}$$

The deviation of CIP, $x^i_{t,t+n}$, can be defined as the n-year cross-currency basis of currency i vis-à-vis dollar at time t.The continuously compounded cross-currency basis is

$$x^i_{t,t+n} = y^{USD}_{t,t+n} - (y^i_{t,t+n} - \rho^i_{t,t+n}) \tag{3.3}$$

Where $\rho^i_{t,t+n} = \frac{1}{n}[log(F^i_{t,t+n}) - log(S^i_{t,t+n})]$, $y^{USD}_{n,t}$ is continuously compounded n-year risk-free interest rate for U.S. dollars at time t, $y^i_{n,t}$ is continuously compounded n-year risk-free interest rate for currency i at time t. The cross-currency basis can be described by equation: the difference between dollar interest rate in cash market, $y^{USD}_{n,t}$, and the dollar interest rate in FX swap market, $y^i_{t,t+n} - \rho^i_{t,t+n}$.

3.3.2 CIP deviations for Sovereign Bond Market

We now describe how CIP discussed above links with sovereign bond market, including zero-coupon bond and defaultable bond. For more details and conditions need to be satisfied for CIP for defautable sovreign bonds, please refer to Buraschi et al (2014).

CIP Deviations Involving Risk-free Bond Yield

Covered Interest Rate Parity (CIP) can be extended to the risk-free sovereign bond markets Popper (1993). In a frictionless market, two bonds should have the same yield.

$$(1 + Y^a_{t,T})^{T-t} = (1 + Y^b_{t,T})^{T-t} \frac{S^i_{t,T}}{F^i_{t,T}}, \tag{3.4}$$

where $Y^a_{t,T}$ and $Y^b_{t,T}$ are risk-free yield for USD-denominated bond and EUR-denominated bond, respectively. $S^i_{t,T}$ and $F^i_{t,T}$ are spot and forward exchange rate for euro/dollar at time t, respectively.

CIP Deviations Based on Defaultable Bond

For defaultable sovereign bonds, let P^i_c be the market price of a coupon bond denominated in the currency of country i = a, b and the bond's cash flow payment equals to C^i and face value equals to FV^i. $Basis_{bond}$ $(Y^{a^*} - Y^a)$ is the difference between the yield to maturity of the USD-denominated coupon bond Y^{a^*} and the yield to maturity of the synthetic USD bond Y^{a^*}. For example, the investor shorts 1 dollar of the USD-denominated bond, swaps the revenue for $S^i_{t_1}$ euros in the spot FX market and buys $S^i_{t_0}$ euros of the euro-denominated bond and then pays coupons (coupon rate, times the face value). The calculated face value of the euro-denominated bond is S^i_T euros. Finally, all cash flows will be converted into USD cash flows and face value of USD-denominated bond will be converted into USD face value. The yield to maturity of the synthetic bond Y^{a^*} is

$$P(t,T)^a = \sum_{n=1}^{T} \frac{\frac{C^b}{F(t,n)}}{(1+Y^{a^*})^{n-t}} + \frac{\frac{FV^b}{F(t,T)}}{(1+Y^{a^*})^{T-t}}, \tag{3.5}$$

$Basis_{bond}$ is $Y^{a^*} - Y^a$. If $Basis_{bond} > 0$, then the expected return of the synthetic bond is higher than that of the cash bond. Therefore, arbitrageurs could short cash bond and long synthetic bond. If three conditions are not satisfied, basis may not equal zero, which could be explained by incomplete markets or arbitrage opportunities[4]. We use traded forward contracts $F^i_{t,T}$ to construct the synthetic bond. This approach minimizes the mismatch in coupon rates and payment dates between bond and swaps.

Calculating the Basis for Sovereign Bond Markets

To calculate $Basis_{bond}$ in Eurobond markets, we adopt the procedure from Fleckenstein et al. (2010). Firstly, we select bond pairs from the same issuer with almost matching maturities. Then, at each time t, we enter into forward contracts to convert euro coupon flows into USD and euro face value into USD at maturity date. This approach creates a synthetic USD bond and we can calculate the yield to maturity Y^{a^*} [5]. In a frictionless bond market, the yield to maturity of original USD-dominated bond Y^a equals the yield to maturity of the synthetic USD bond Y^{a^*}. The violation $Basis_{bond}$ is $Y^{a^*} - Y^a$.

For example, taking USD- and euro-denominated foreign bonds of South Korea. The maturity date of USD bond is May 30, 2022. On November 4, 2020, the yield to maturity of the Korean USD bond is 0.56% and that of euro bond is -0.293%. With almost 1.5 years until maturity date, the investor sells 100 dollars USD bond, swap the proceeds for 85.28 euros in the spot foreign exchange market and buy 85.28 euros of the euro bond which pays two coupons (coupon rate is 0.5%). The calculated face value of the euro-denominated bond is 85.28 euros, so each coupon payments are 0.42 euros. Using forward rate F_t for each coupon date (May 31, 2021 and May 30, 2022), all euro cash flows and face value are converted into USD dollars. This creates a synthetic USD bond consisting of only USD coupon flows: \$0.49 on May 31, 2021 and \$0.50 on May 30, 2022. Finally, the face value is \$99.9. The yield to maturity of the synthetic bond Y^{a^*} (calculated based on these USD flows) is -0.369%. Therefore, $Basis_{bond} = Y^{a^*} - Y^a$= -36.9 bps- 56 bps = -92.9 bps. Specifically, the synthetic USD bond that is constructed from the EUR-denominated bond generates a substantially lower yield than does its original USD bond. As the bonds used in this study do not have matching maturities, in Appendix 3.1 we shall consider cash flow risks. To minimize the impact

[4] If markets are complete and the synthetic bond has the same future cash flows in all states.

[5] we use day-count convention of USD-denominated bonds (30/360) and EUR-denominated bonds (ACT/ACT) and adjust for the accrued interests.

of cash flow risk, we only include pairs of bonds with a maturity mismatch of less than 60 days (e.g. 2022 Korean bonds with a maturity mismatch of 49 days).

Buraschi et al. (2015) choose bond pairs with a maturity mismatch of less than 70 days and Fleckenstein et al. (2010) only include pairs of TIPS and Treasury bonds if the maturity mismatch is less than or equal to 31 days. A stricter threshold, such as 31 days, would further minimize cash flow differences. However, it can significantly reduce the number of bond pairs available for analysis, potentially leading to biased results due to limited data. However, a looser threshold, such as 70 days, increases the sample size but also increases the potential impact of cash flow mismatches on the results. In this paper, to reduce the impact of cash flow risk, we adopt euro- and USD-denominated bonds with a maturity mismatch of 60 days. The 60-day threshold is a middle ground. It is conservative enough to control for significant cash flow risks while still allowing for a robust sample size of bond pairs for analysis. However, we want to select bond pairs with identical maturities, rather than merely similar ones. Therefore, the specific mismatch in days between bond pairs is not the focus and the key point is whether differences in cash flow structure can significantly impact the basis. We test robustness of cash flow risk. As Table 3.6 shows, cash flow risk cannot explain price anomalies of bond pairs.

3.4 Data

We obtain daily yields from Bloomberg on euro- and USD-denominated bonds for maturities up to thirty years for the three large market sovereign issuers: China, South Korea and Mexico. Each bond has fixed coupon rate and is not callable, puttable, or sinkable. We choose 1 euro- and USD-denominated outstanding bonds pairs in China, South Korea and Mexico, respectively. The sample is from June 2017 to December 2021. Besides, we also collect EUR/USD spot and forward exchange rates using matching maturities from Bloomberg.

Buraschi et al. (2015) choose 2 euro- and USD-denominated outstanding bond pairs for Brazil, Mexico, and Turkey according to three criteria: (1) These countries have large and liquid USD bond and Eurobond markets with small transaction costs. (2) The bond must reach maturity and cannot be callable, puttable, or sinkable. (3) Bond pairs have same or close maturties issued by same company. In this paper, we select three countries: China, Korea, and Mexico. For each country, there is only one bond pair that meets the criteria, with a maturity mismatch of less than 60 days.

3.4.1 The Basis

Our sample period is divided into two main subsamples: pre-crisis period (June 30, 2017-December 24th, 2019) and Covid-19 crisis period (December 25th, 2019-December 31th, 2021). Table 3.1 reports descriptive statistics of $Basis_{bond}$ (in basis points) for China, South Korea and Mexico from 2017 to 2021. From Table 1, we observe that in the Pre-crisis period, the mean of $Basis_{bond}$ is -13.57 bps, -27.10 bps and -21.49 bps for China 2022, South Korea 2022 and Mexico 2025, respectively. The story changes dramatically during the COVID-19 shock period when deviations in $Basis_{bond}$ becomes markedly large, highly volatile, and strongly persistent. persistence in the basis would suggest that the sign of the basis during this period is driven by more than temporary shocks. Mexico is one of the countries investigated in Buraschi et al. (2015) and they show that the Mexican was positive (136bp) during the credit crisis (September 2008 to March 2009). That is, Mexico euro borrowing costs were higher than the relative US$ one. We show a completely different picture for Mexico during the COVID-19 crisis. In fact, in line with China and South Korea we document that US$ costs for all the three countries have been significantly higher than euro one.

Table 3.1: Descriptive Statistics

	Pre-Crisis			Covid-19 Crisis		
	Mean	Standard Deviation	N	Mean	Standard Deviation	N
China	-13.57	34.01	648	-201.81	157.51	528
South Korea	-27.10	20.91	648	-147.13	115.53	528
Mexico	-21.49	32.00	648	-92.63	35.37	528

Notes: This table reports the summary statistics of the $Basis_{bond}$ (in basis points) for China, South Korea and Mexico from 2017 to 2021. $Basis_{bond}$ should be zero in frictionless market. The specific bond pairs (with total issue size of each bond reported in parenthesis) are as follows. For China, EUR-bond 08.06.2022, 0.75% (Euro 550000m) and USD-bond 14.03.2022, 2.625% (USD 1150000m). For South Korea, EUR-bond 30.05.2022, 0.5% (Euro 750000m) and USD-bond 11.04.2022, 5% (USD 1000000m). For Mexico, EUR-bond 15.01.2025, 1.375% (Euro 1200000m) and USD-bond 30.01.2025, 3.6% (USD 3000000m).

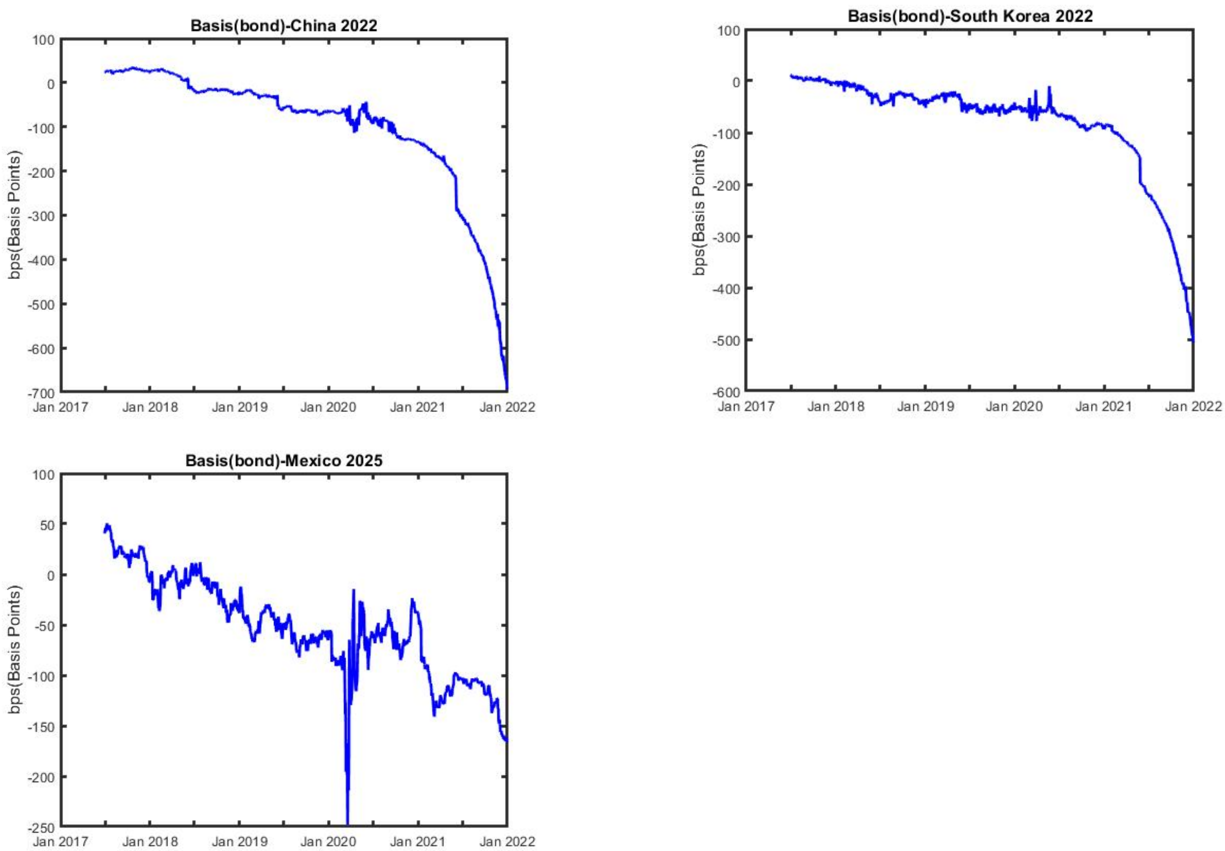
Figure 3.1 shows that for the three countries[6]. In the next sections we the nature of these large and persistent deviations for the basis.

3.4.2 Three Frictions of $Basis_{bond}$

In credit markets, misalignment is not only marked by extreme price discrepancies but also by their unusual persistence. The sources of pricing discrepancies can be revealed by investigating the causes of persisting discrepancies. Pricing discrepancies can persist when investment capital is slow to move to trading opportunities (Duffie, 2010). In addition to funding constraints, illiquidity and market uncertainty can increase the

[6] A negative cross-currency basis for EUR/USD implies higher borrowing costs for dollars in cash market.

Figure 3.1: Time-Series of $Basis_{bond}$



Notes: The graph shows the dynamics of $Basis_{bond}$ for China 2022, South Korea 2022 and Mexico 2025. $Basis_{bond}$ is negative when the USD-denominated bond is trading "cheap". The specific bond pairs (with total issue size of each bond reported in parenthesis) are as follows. For China, EUR-bond 08.06.2022, 0.75% (Euro 550000m) and USD-bond 14.03.2022, 2.625% (USD 1150000m). For South Korea, EUR-bond 30.05.2022, 0.5% (Euro 750000m) and USD-bond 11.04.2022, 5% (USD 1000000m). For Mexico, EUR-bond 15.01.2025, 1.375% (Euro 1200000m) and USD-bond 30.01.2025, 3.6% (USD 3000000m).

cost of arbitrage and prolong price violations (Pontiff, 2006). This section proposes a persistence measure based on the long memory model and explores the relationship between persistence in pricing discrepancies and proxy variables for slow-moving capital and arbitrage impediments.

Several frictions can influence sovereign bond price violations, causing deviations from what economic models might predict. These frictions introduce complexities and imperfections into the sovereign bond market. For example, (1) Sovereign bond markets may experience liquidity constraints, especially in emerging markets or during times of financial stress. Limited liquidity can lead to larger price swings and deviations from fundamental values. During financial crises or economic downturns, market illiquidity can become pronounced. Investors may face difficulty selling bonds at desired prices, leading to deviations from fundamental values. (2) Sovereign bonds are subject to credit risk, representing the risk that the issuing government may default on its debt obligations. Changes in perceived credit risk can lead to variations in bond prices, especially if investors reassess the creditworthiness of a sovereign. Changes in interest rates can impact the prices of sovereign bonds. If interest rates rise, existing bonds with lower yields become less attractive, leading to price decreases. This interest rate risk can cause deviations, especially if rate movements are unexpected. (3) Changes in the global economic environment, such as shifts in trade dynamics or global economic slowdowns, can impact sovereign bond prices. Economic interconnectedness means that events in one part of the world can influence bond markets globally.

Understanding these frictions is crucial for investors, policymakers, and analysts when interpreting sovereign bond price movements. While economic models provide a theoretical framework, the real-world complexities introduced by these frictions contribute to the variability and dynamics observed in sovereign bond markets. In the previous sections, we discussed a number of papers investigating deviations from the LOP in different markets. Generally, that literature discusses frictions related to: (1) market liquidity,(2) funding liquidity and leverage constraints, (3) macroeconomic conditions. Equation 3.6 below summarises this and details about each determinant are explained in Table 3.2. i refers to three countries: China, South Korea and Mexico and t represents time.

Table 3.2: Data Description

Variables	Mnemonics	Definition
Dependent variables	$Basis_{bond}$	Deviations from CIP for sovereign bonds
Liquidity frictions	Liq-FX	Latent FX liquidity based on Mancini-Griffoli and Ranaldo (2011)
	Liq-OIS	Borrowing liquidity based on Mancini-Griffoli and Ranaldo (2011)
	TED	3M Treasury bill minus 3M U.S. LIBOR
Funding costs	Unsecured	U.S. LIBOR minus U.S. OIS (Bloomberg)
	Secure	U.S. MBS minus U.S. Treasury (Bloomberg)
Macro factors	VIX	VIX option volatility index (Bloomberg)
	TP	10Y U.S. Treasury minus 3M LIBOR (Bloomberg)
	LN-Macro	Macroactivity risk factor based on OECD
	CDX	Market CDX index

Notes: The table shows the potential determinants of $Basis_{bond}$. Our sample is from 2017.6.30 to 2021.12.31. Each proxy is assigned to the related category with the corresponding explanations. Determinants are, namely, Liquidity Frictions [Liq-FX, Liq-OIS, TED]; Funding Costs [Unsecured, Secured]; Macroeconomic factors [VIX, CDX, TP, LN-Macro]. $Basis_{bond}$, liquidity frictions and funding costs are daily data. The macroeconomic indicators are monthly and quarterly data and we need to convert low frequency data (monthly and quarterly) to high frequency data (daily) by using cubic spline interpolation.

$$\begin{aligned} Basis(bond)_{i,t} = \alpha + \beta_1[LiquidityFrictions]_{i,t} + \beta_2[FundingCosts]_{i,t} \\ +\beta_3[MacroFactors]_{i,t} + \epsilon_{i,t} \end{aligned} \tag{3.6}$$

Liquidity

Liquidity is a critical factor in the bond market, and it can significantly influence sovereign bond prices. In a liquid market, it is generally easier for buyers and sellers to transact at prevailing market prices. If a market lacks liquidity, it may be prone to inefficiencies, such as wider bid-ask spreads and increased price volatility. Besides, liquidity is crucial for accurate price discovery. In a liquid market, the prices of bonds are more likely to reflect all available information. However, in illiquid markets, prices may not fully incorporate new information, leading to potential mispricing and price violations. Then, liquidity directly impacts transaction costs. In an illiquid market, it may be more costly to buy or sell bonds due to wider bid-ask spreads. High transaction costs can affect the overall return on investment and influence investor behavior. Finally, liquidity risk can contribute to credit spreads. Illiquid bonds often have higher credit spreads to compensate investors for the added risk associated with potentially higher transaction costs and difficulty in selling the bonds. Overall, liquidity factors play a pivotal role in influencing sovereign bond prices. Investors, policymakers, and market participants closely monitor liquidity conditions to assess market efficiency, manage risks, and identify potential violations or mispricing in the sovereign bond market. The interaction between liquidity and other market factors can have a profound impact on bond prices and overall market stability.

A possible explanation for the large $Basis_{bond}$ could be associated with market liquidity (Duffie, 2017; Brunnermeier and Pedersen, 2009; Garleanu and Pedersen, 2011; Hong et al., 2021). Trading requires capital and if the market is illiquid, a bond's transaction will have a large impact on its price. Therefore, the bond must be discounted in order to sell quickly.

We consider three liquidity proxies. The first proxy is related to the potential liquidity risk in foreign exchange markets.That is we aim to capture liquidity conditions due to CIP deviations. We follow Mancini-Griffoli and Ranaldo (2011), and compute the first principal component (see Apprendix A.1) of bid-ask spreads across different currency pairs contributing to CIP deviations. This generates a latent liquidity variable. We use spot and forward bid-ask spreads of USD/EUR for different maturities (3 months, 6 months, 1 year to 10 years) and define the variable Liq-FX. Mancini-Griffoli and Ranaldo (2011) also use an alternative proxy: bid-ask spreads of OIS for different maturities (3 months, 6 months, 1 year to 10 years) and define it Liq-OIS. The final proxy for liquidity risk used in this study is the TED spread (Coffey et al., 2009) which is calculated as the difference between the interest rate banks can lend to each other over a three-month time frame and the interest rate at which the government is able to borrow money for a three-month period. The TED spread is an indicator of liquidity risks in the interbank market.

Funding and Leverage Constraints

Funding costs are a critical consideration in the context of sovereign bonds and can influence their prices in various ways. The reasons are as follows: First of all, sovereign bonds are a key instrument for governments to raise funds. The cost of issuing and servicing these bonds directly affects a government's budget and fiscal policy. Higher funding costs may lead to increased debt service payments, potentially impacting the government's ability to finance its activities. Secondly, higher funding costs can be associated with credit risk. Credit rating agencies consider a government's ability to meet its debt obligations, and if funding costs rise significantly, it may lead to credit rating downgrades. Changes in credit ratings can affect investor demand for sovereign bonds and influence prices. Thirdly, funding costs are influenced by prevailing interest rates. In a rising interest rate environment, governments may face higher costs when issuing new bonds or rolling over existing debt. This can put upward pressure on yields and impact bond prices. Finally, funding costs are sensitive to market sentiment and risk appetite. If investors are risk-averse, they may demand higher yields to compensate for perceived risks associated with a particular sovereign. Changes in market sentiment can impact funding costs and, consequently, sovereign bond prices.

Therefore, funding costs are a critical factor that can influence sovereign bond prices, reflecting the economic and fiscal health of a country. Investors and market participants closely monitor these costs as part of their assessment of sovereign credit risk and as a factor in determining the fair value of sovereign bonds. Any significant changes in funding costs can have implications for bond prices and the overall stability of the sovereign bond market.

The capital needed for trades is scarce during negative shocks and arbitrageurs have limited access to external capital. This may amplify the initial negative shock, leading to large deviation from the LOP. Two types of funding are usually used by traders to exploit arbitrage opportunities: secured funding and unsecured funding. We use the average agency MBS-GC (general collatered) repo spread. This is the repo rate using MBS as collateral minus the repo rate using Treasury securities as collateral. Agency MBSs become illiquid during a crisis and this will increase the spread between MBS and GC repo loans signalling higher funding risks (Coffey et al., 2009; Gabaix et al., 2007). We proxy unsecured funding frictions by the spread between three-month LIBOR and the U.S. OIS rates (Duffie, 2017). An increased spread implies that financial institutions are less willing to lend to each other.

Macroeconomic Conditions

Macroeconomic factors play a crucial role in influencing sovereign bond prices. Investors consider a range of macroeconomic indicators and conditions when assessing the risk and potential return associated with investing in sovereign bonds. For example, (1) Economic Growth: The overall economic growth of a country is a fundamental factor influencing sovereign bond prices. Higher economic growth is generally associated with increased government revenue and a lower risk of default, which can positively impact investor confidence and sovereign bond prices. (2) Inflation Rates: Inflation rates are closely monitored because they affect the real return on fixed-income securities, including sovereign bonds. Central banks often adjust interest rates to control inflation, and changes in inflation expectations can influence bond yields and prices. (3) Interest Rates: Central bank interest rate policies have a direct impact on sovereign bond prices. Changes in interest rates influence the yield on bonds, and investors adjust their expectations based on the prevailing interest rate environment. (4) Unemployment Rates: High levels of unemployment can signal economic distress and impact a government's ability to meet its debt obligations. Conversely, low unemployment rates can indicate a healthier economy, positively affecting investor sentiment and bond prices. (5) Budget Deficits and Surpluses: Government fiscal policies, including budget deficits or surpluses, influence sovereign bond prices. Persistent deficits may raise concerns about a country's ability to manage its debt, potentially leading to higher yields and lower bond prices. (6) Current Account Balances: The current account balance reflects a country's trade and investment position. A large current account deficit may raise concerns about external financing needs, affecting investor perception and sovereign bond prices.

Overall, macroeconomic factors provide essential context for assessing the overall health and stability of a country's economy, which, in turn, influences investor confidence in sovereign bonds. Investors use these factors to gauge the risk-return profile of sovereign bonds and make informed decisions about their bond portfolios. Any deviations or violations in sovereign bond prices may be attributed, in part, to changes in macroeconomic conditions that impact investor perceptions and market dynamics.

The role of market liquidity and funding costs may be driven by countries' macroeconomic conditions and this could be different across different subperiods. For these reasons, in addition to the two channels already discussed, we also consider and control for the effect of such factors using VIX option volatility index, CDX, TP and other macroeconomic variables which may reflect economic environment. We obtain data for macroeconomic factors (LN-Macro) from OECD database, FRED and Wind. Since these variables are monthly or quarterly frequency, we use cubic spline interpolation to get daily data. The LN-Macro is computed as the first principal component of 11 economic series. It excludes price-based information (e.g. S & P dividend yield, Federal Funds (FF) rate). Details about macroeconomic variables are given in Table

3.3.

Table 3.3: Summary of Factors for LN-Macro

Variables	Definition
Inflation	The change in the prices of a basket of goods and services that are typically purchased by specific groups of households.
Unemployment rate	The unemployed are people of working age who are without work, are available for work, and have taken specific steps to find work.
Producer price indices	The rate of change in prices of products sold as they leave the producer.
Composite leading indicator	Designed to provide early signals of turning points in business cycles showing fluctuation of the economic activity around its long term potential level.
Business confidence index	Provide information on future developments, based upon opinion surveys on developments in production, orders and stocks of finished goods in the industry sector.
Consumer confidence index	Provide an indication of future developments of households' consumption and saving, based upon answers regarding their expected financial situation, their sentiment about the general economic situation, unemployment and capability of savings.
U.S. Imports of Goods	U.S. imports of goods by Customs Basis from China, Mexico and South Korea.
FDI flows	Record the value of cross-border transactions related to direct investment during a period of time, usually a quarter or a year.
Exports: Value Goods	Exports: Value Goods for the China, Mexico and South Korea.
Total Reserves	Total Reserves except Gold for China, Mexico and South Korea.
Gross domestic product	The standard measure of the value added created through the production of goods and services in a country during a certain period.

Notes: The table summarizes the potential factors which may reflect economic conditions (Ludvigson and Ng, 2009). The original data source is OECD database, FRED and Wind. The indicators above are monthly and quarterly data and we need to convert low frequency data (monthly and quarterly) to high frequency data (daily) by using cubic spline interpolation.

3.5 Empirical Analysis

Table 3.4 (Columns (1)-(3)) summarizes the regression results for each friction and considering the sample before and during the COVID-19 shock. We first consider the impact of each single friction on the basis (Columns (1)-(3)), while in Column (4) we consider the impact of all of them on the basis. We focus on the results reported in Column (4). Clearly over the full sample, liquidity and funding costs are very significant. The largest impact on the basis seem to be associated with an increase in secured funding costs. Countries' macro-economic conditions have also a negative impact on the basis. In sum, the three frictions

(Liquidity frictions: *Liq-FX*, *Liq-OIS*, TED; Funding costs: Unsecured, Secured; Macroeconomic factors: VIX, CDX, TP, LN-Macro) are all statistically significant. However, if we only consider liquidity frictions, the explanatory power of these factors is quite limited, therefore this would suggest that funding costs play an important role in explaining $Basis_{bond}$ as well as macroeconomic economic factors given the relatively large R^2 (83%).

These results show a strong evidence that a deteriorated macro environment in deterring arbitrageurs from exploiting mispricing. Furthermore, the VIX is also positive and statistically significant suggesting a higher degree of concern among market participants for how deteriorating market conditions affect the $Basis_{bond}$.

In Table 3.5, we split results into Pre-crisis (Column (1)) and Covid-19 crisis (Column (2)). During the pre-crisis period, when the size of $Basis_{bond}$ was relatively small, most of the variables are statistically insignificant with R^2 (66%), although secured funding costs risk and macro economic risk remain important. However, during COVID-19 period, funding, liquidity and macro economic frictions were in place and they have a significant impact on the net absolute $Basis_{bond}$. CDX are negative but statistically insignificant. This result suggests that the three channels of frictions (liquidity, funding cost and macroeconomic conditions) have an important role in explaining the size of the net absolute $Basis_{bond}$ during the Covid-19 shock[7].

3.6 The Basis at Microscope

Robustness tests are essential to assess the reliability and stability of empirical results, especially in studies examining deviations from Covered Interest Rate Parity (CIP) in sovereign bond markets. Here are several robustness tests that researchers commonly employ to validate and strengthen their findings: (1) duration and convexity, (2) stock risk, (3) FX correlation risk, (4) liquidity and macroeconomic conditions and (5) an alternative indicator for violation.

In the next sections we shall investigate other possible determinant of the observed large basis during the COVID-19 shock.

[7]The purpose of conducting separate regressions for the Covid-crisis and non-crisis periods is to demonstrate that more variables contribute to the price anomalies of bond pairs during the Covid-crisis period. Therefore, it is not necessary to test whether the differences between these coefficients are statistically significant.

Table 3.4: Regressions on Liquidity Frictions, and Funding Costs and Macroeconomic Factors

	(1)	(2)	(3)	(4)
Liquidity Frictions				
Liq-FX	-0.001*			0.000
	(0.066)			(0.952)
Liq-OIS	-0.029			0.002**
	(0.105)			(0.035)
TED	0.372*			0.007
	(0.066)			(0.853)
Funding Costs				
Unsecured		0.017		-0.066
		(0.768)		(0.153)
Secured		0.091*		0.110***
		(0.074)		(0.000)
Macro Factors				
TP			0.054***	0.017**
			(0.000)	(0.019)
VIX			0.011***	0.008***
			(0.000)	(0.004)
LN-Macro			-0.029***	-0.029***
			(0.000)	(0.000)
CDX			-0.056	-0.014
			(0.354)	(0.415)
Country FE	√	√	√	√
Time FE	√	√	√	√
R^2	66%	66%	83%	83%
Obs	3526	3526	3526	3526

Notes: The table shows the 4 fixed effects regressions on $Basis_{bond}$ of China 2022, South Korea 2022 and Mexico 2045. P-value is reported in parentheses. *, ** and *** pertain to 10%, 5% and 1%. Explanatory variables are, namely, Liquidity Frictions [Liq-FX, Liq-OIS, TED]; Funding Costs [Unsecured, Secured]; Macroeconomic factors [VIX, CDX, TP, LN-Macro]; The dependent variable is net absolute value $Basis_{bond}$. $Basis_{bond}$, liquidity frictions and funding costs are daily data. The macroeconomic indicators are monthly and quarterly data and we need to convert low frequency data (monthly and quarterly) to high frequency data (daily) by using cubic spline interpolation.

3.6.1 Duration and Convexity

Duration and convexity are important concepts in fixed-income securities, including sovereign bonds. They play a crucial role in understanding how bond prices may change in response to interest rate movements. First, duration is a measure of the sensitivity of a bond's price to changes in interest rates. It represents the weighted average time it takes for the bond's cash flows (coupon payments and principal repayment) to be received. If interest rates rise, bond prices typically fall, and if rates fall, bond prices rise. Duration helps

Table 3.5: Regressions on Liquidity Frictions, and Funding Costs and Macroeconomic Factors During Pre-crisis and Crisis Period

	(1)	(2)	(3)
Liquidity Frictions			
Liq-FX	-0.000	0.000	-0.000
	(0.630)	(0.443)	(0.970)
Liq-OIS	-0.003	0.002***	0.002***
	(0.261)	(0.000)	(0.000)
TED	-0.074	0.026	0.016
	(0.152)	(0.668)	(0.733)
Funding Costs			
Unsecured	-0.035	-0.063	0.042
	(0.374)	(0.298)	(0.293)
Secured	0.163***	0.241*	0.248*
	(0.000)	(0.064)	(0.085)
Macro Factors			
TP	-0.006	0.021**	-0.009
	(0.484)	(0.040)	(0.161)
VIX	0.003	0.008**	0.006**
	(0.733)	(0.020)	(0.043)
LN-Macro	-0.031***	-0.027***	-0.022***
	(0.000)	(0.005)	(0.008)
CDX	-0.019	-0.017	0.017
	(0.618)	(0.180)	(0.234)
Post-Crisis			0.063*
			(0.007)
Country FE	√	√	√
Time FE	√	√	√
R^2	66%	42%	43%
Obs	1942	1584	3525

Notes: The table indicates the 3 fixed effects regressions on $Basis_{bond}$ of China 2022, South Korea 2022 and Mexico 2025. Columns (1) and (2) show the fixed effects regression pre-crisis and crisis period. Columns (3) shows add dummy variable (Post-Crisis) that equals 1 after December 25th, 2019. P-value is reported in parentheses. *, ** and *** pertain to 10%, 5% and 1%. Explanatory variables are, namely, Liquidity Frictions [Liq-FX, Liq-OIS, TED]; Funding Costs [Unsecured, Secured]; Macroeconomic factors [VIX, CDX, TP, LN-Macro]; The dependent variable is net absolute value $Basis_{bond}$. $Basis_{bond}$, liquidity frictions and funding costs are daily data. The macroeconomic indicators are monthly and quarterly data and we need to convert low frequency data (monthly and quarterly) to high frequency data (daily) by using cubic spline interpolation.

investors estimate how much a bond's price will change in response to interest rate movements. Besides, convexity is a measure of the curvature in the relationship between bond prices and interest rates. It provides additional information beyond duration by accounting for the nonlinear relationship between bond prices and interest rates. Convexity helps investors refine their estimates of bond price changes, especially in the presence of larger interest rate movements. Duration and convexity can be used to identify potential price violations or mispricing in the bond market. If the actual bond price diverges significantly from what would be expected based on changes in interest rates and the bond's duration and convexity, it may present an opportunity for investors to exploit these discrepancies through trading strategies.

We start with cash flow risk associated with bond characteristic which could explain violation of the LOP for defaultable sovereign bonds. In fact, the LOP would imply that cash flows from cash and syntetic markets were identical. But in Section 3.3.2, we noted that cash flows are different when all euro cash flows are converted into USD dollars [8]. Therefore, large and significant basis could be driven by these different cash flows associated with bond characteristics.

In fact, based on the coupon rates, forward rates and maturity date, the duration and convexity of the USD- and EUR-denominated bonds may be different and this would expose traders to a potential cash flow risk. To estimate the economic impact of this cost and see if it can helps us to rationalise what we have seen in Table 3.1, we calculate duration and convexity of convergence trade in the construction of $Basis_{bond}$. The Table 3.6 shows the results. Columns 1,2 and Columns 3,4 show the duration and convexity of the cash USD bond and synthetic USD bond respectively. Column 5 reports the net duration of the long-short strategy: the investor longs the bond trading cheap and shorts the bond trading higher. The net duration is defined as:

$$Duration = d_A - d_L * (\frac{L}{A}), \tag{3.7}$$

L,A represents quantity invested in the Euro- and USD-denominated bonds. A positive net duration implies a decrease in the value of the convergence trade when the interest rate increases.

In all the cases, the net duration is negative. Column 6 reports the change in interest rate levels (in terms of bps) Δi. The last Column reports change in $Basis_{bond}$ with a parallel shift in both yield curves of 1 and 2.32 standard deviation. From Table 3.6, the net duration of China and Mexico are relatively large, that is. there is significant cash flow risk for China and Mexican bond. However, convexity of each bond is also large, which may imply that the interest rate risk measured by modified duration is not accurate [9]. We use the definition of duration to examine the impact of interest rate on basis. We note that, even if we increase $2.32\sigma_Y$ interest rate [10], we find that the $Basis_{bond}$ will slightly decrease by 0.51 bps, 0.17 bps, 4.90 bps in three countries respectively. Clearly, these changes are too small to explain such a large and negative basis.

[8] For example, taking USD- and euro-denominated foreign bonds of South Korea. after all euro cash flows and face value are converted into USD dollars, the cash flows of synthetic bond for each coupon day are \$0.49, \$100.4 (\$0.56, \$100.56 for original USD bond).

[9] Duration assumes a linear relationship between price and yield changes, which is only accurate for small changes. As interest rates change significantly, this relationship becomes curved rather than straight. Convexity helps account for this curvature. Therefore, large convexity accounts for the limitations of duration.

[10] We use σ_Y and $2.32\sigma_Y$ rather than 1% increase in interest rate to get more accurate prediction.

Table 3.6: Duration and Convexity

	Original USD Bond		Synethic USD Bond		Net Duration	Interest Rate	Basis Changes
	Duration	Convexity	Duration	Convexity		Δi	$\Delta Basis$
China	3.05	13.45	3.13	14.04	-3.26	σ_Y=34bps	-0.18
						$2.32\sigma_Y$	-0.51
South Korea	2.95	12.79	3.12	13.97	-0.81	σ_Y=37bps	-0.03
						$2.32\sigma_Y$	-0.17
Mexico	5.33	34.42	5.62	37.37	-7.69	σ_Y=66bps	-1.94
						$2.32\sigma_Y$	-4.90

Notes: This table reports the duration and convexity of the cash and synthetic dollar bonds. Net duration means the dollar-weighted net duration for the long-short strategy as implemented by a trader who goes long the cheap bond, which is the cash dollar bond for China, South Korea and Mexico and short the rich bond. The net duration is small for China and South Korea, which means cash flow structure cannot explain price discrepancies of bond pairs. However, Mexico has relatively large net duration and large convexity that measures accuracy of duration. Therefore, in order to measure the impact of net duration of $basis_{bond}$, we use the definition of net duration to compute the bond's sensitivity to interest rate changes.

In sum, we conclude that cash flow risk cannot help us to rationalise the results in Table 3.1.

3.6.2 Stock Risk

The relationship between stock risk and sovereign bond prices is complex and can be influenced by various factors. First, investors often assess risk across different asset classes, including stocks and sovereign bonds. If there is increased perceived risk in the stock market, investors may become more risk-averse and seek safer assets, such as sovereign bonds. This increased demand for bonds can drive up their prices. Second, during periods of economic uncertainty or market turbulence, investors may engage in a "flight to safety," moving their investments from riskier assets like stocks to safer assets like sovereign bonds. This increased demand for bonds can lead to higher prices. Third, stock risk and sovereign bond prices can be influenced by changes in interest rates. Generally, when interest rates rise, bond prices fall, and vice versa. If stocks are perceived as risky, and investors move towards bonds, it could impact interest rates and subsequently bond prices. Fourth, sovereign bonds are often denominated in a specific currency. Currency movements can impact the attractiveness of bonds to investors. If a country's currency is strengthening, it can make its bonds more attractive to international investors, affecting bond prices.

Could stock market risk help us to explain the results in Table 3.1 ? According to Schneider (2011), a company's environmental performance will be reflected in its bond pricing. The environmental performance measure came from the Investor Responsibility Research Centre, which only covered the S&P 500. Therefore, we use $EM - MSCI$ to address this question. We introduce two new indicators associated with

$Basis_{bond}$: $S\&P$ 500 dividend/price ratio and $EM - MSCI$ (Buraschi et al., 2015). From Table 3.7, the regression shows that these and are insignificant and have no impact on the $Basis_{bond}$.

Table 3.7: Regressions on Local Stock Risk

	(1)	(2)
Liquidity Frictions		
Liq-FX	-0.000	0.000
	(0.550)	(0.637)
Liq-OIS	0.002**	0.002*
	(0.024)	(0.061)
TED	0.025	0.017
	(0.360)	(0.589)
Funding Costs		
Unsecured	-0.025	-0.065
	(0.501)	(0.154)
Secured	1.521***	1.163***
	(0.001)	(0.000)
Macro Factors		
TP	0.013**	0.015**
	(0.037)	(0.020)
VIX	0.008**	0.009***
	(0.011)	(0.000)
LN-Macro	-0.029***	-0.029***
	(0.000)	(0.000)
CDX	-0.023	-0.027
	(0.158)	(0.121)
SP	0.027	
	(0.258)	
MSCI		-0.026
		(0.258)
Country FE	√	√
Time FE	√	√
R^2	83%	83%
Obs	3527	3527

Notes: The table indicates the 2 fixed effects regressions on $Basis_{bond}$ of China 2022, South Korea 2022 and Mexico 2025. P-value is reported in parentheses. *, ** and *** pertain to 10%, 5% and 1%. Explanatory variables are, namely, Liquidity Frictions [Liq-FX, Liq-OIS, TED]; Funding Costs [Unsecured, Secured]; Macroeconomic factors [VIX, CDX, TP, LN-Macro]; Local Stock risk [SP,MSCI].The dependent variable is net absolute value $Basis_{bond}$. $Basis_{bond}$, liquidity frictions, funding costs and local Stock risk are daily data. The macroeconomic indicators are monthly and quarterly data and we need to convert low frequency data (monthly and quarterly) to high frequency data (daily) by using cubic spline interpolation.

3.6.3 FX Correlation Risk

Using Quanto Credit Default Swap (CDS) spreads denominated in USD and EUR can be a relevant factor in assessing deviations from Covered Interest Rate Parity (CIP) in sovereign bond markets. Quanto CDS spreads, which are designed to eliminate the impact of exchange rate movements on the cost of credit protection, can provide insights into market perceptions of credit risk and potential deviations from CIP. Here's how Quanto CDS spreads in USD and EUR may influence deviations from CIP in sovereign bond markets: (1) Quanto CDS spreads reflect the cost of credit protection against the default of a sovereign entity, denominated in a specified currency (e.g., USD or EUR). These spreads are influenced by market assessments of credit risk. Higher Quanto CDS spreads suggest a higher perceived risk of default, potentially impacting deviations from CIP. (2) Quanto CDS spreads are designed to mitigate the impact of currency risk on credit default swaps. By providing protection in a specified currency (e.g., USD), they decouple credit risk from exchange rate movements. This can be particularly relevant when assessing deviations from CIP, as it allows for a more focused analysis of credit risk without being confounded by currency movements. (3) Quanto CDS spreads are influenced by interest rate differentials between currencies. If the interest rate differentials between USD and EUR impact the cost of credit protection, it may contribute to deviations from CIP. Traders and investors may adjust their expectations based on interest rate differentials, impacting sovereign bond prices and yields. (4) Quanto CDS markets and sovereign bond markets are interconnected. Changes in liquidity and trading dynamics in the Quanto CDS market can spill over into sovereign bond markets. If liquidity conditions or trading activity in Quanto CDS spreads change, it may impact deviations from CIP in sovereign bond markets. (5) Deviations from CIP can create arbitrage opportunities. Traders may assess Quanto CDS spreads as part of their risk premia calculations, adjusting their strategies based on perceived deviations from CIP and potential arbitrage opportunities.

In summary, the use of Quanto CDS spreads in USD and EUR can be a valuable factor in understanding deviations from CIP in sovereign bond markets. It provides insights into credit risk perceptions and interest rate differentials, which are crucial components in the analysis of sovereign bond pricing and deviations from CIP.

In case of default at time $t > T$, the bond terminal payoff at time T is the face value of bond. If $t < T$, the bond payoff at time T is a fraction δ (recovery rate) of face value. Therefore, the payoff of the defaultable bond can be defined as $P(T,T)^a = (1USD) \times I^a_{t>T}$, $P^b(T,T) = (1EUR) \times I^b_{t<T}$, where $I^a_{t>T}$ equal to 1 if default occurs at time $t > T$ or δ otherwise. In case of default at time $t > T$, traders would normally hedge the residual risk with a Quanto CDS spread (Longstaff et al., 2005) which is the difference between the CDS quotes in USD and EUR on the same underlying asset. To estimate the economic value of default risk, we obtain data on Quanto CDS spreads during our sample period and see if this risk can help explaining the results in Table 3.1.

Figure 3.2: Quanto CDS Spreads

Notes: A Quanto CDS lets investors transfer credit risk between parties while also managing foreign exchange (FX) rate risk. The graph shows the USD CDS and EUR CDS with different maturities. The right panel just displays USD CDS for three countries, because there is no difference between USD CDS and EUR CDS. We just plot one of them. During the COVID-19 crisis period, all CDS spread increase dramatically indicating higher default risk for counterparties. The result shows that the CDS basis is zero and therefore does not add much to the large $Basis_{bond}$ in the sovereign bond market.

Figure 3.2 shows that, during the COVID-19 crisis period, all CDS spread[11] (with different maturities) increase dramatically indicating higher default risk for counterparties. However, as it is clear from Figure

[11]The right panel just displays USD CDS for three countries, because there is no difference between USD CDS and EUR CDS. We just plot one of them.

3.2, the CDS basis is zero and therefore does not add much to the large $Basis_{bond}$ in the sovereign bond market. In sum, FX correlation risk is not a significant factor for CIP basis for sovereign bonds.

3.6.4 Liquidity and Macroeconomic Conditions

Interacting liquidity frictions with macroeconomic conditions can indeed be a significant factor influencing deviations from Covered Interest Rate Parity (CIP) in sovereign bond markets. Liquidity frictions and macroeconomic conditions play crucial roles in shaping market dynamics, and their interaction can have implications for the pricing of sovereign bonds and deviations from CIP. First, liquidity frictions can affect the ease with which market participants can buy or sell sovereign bonds. In periods of low liquidity, the bid-ask spreads may widen, leading to less efficient pricing. Interacting liquidity frictions with macroeconomic conditions, such as economic uncertainty or financial market stress, may exacerbate liquidity challenges, impacting bond prices and contributing to deviations from CIP. Secondly, in times of economic uncertainty or financial stress, there is often a flight to quality, where investors seek safer assets, including sovereign bonds. Liquidity frictions during such periods can amplify the impact on bond prices. The interaction between liquidity frictions and macroeconomic conditions may lead to increased demand for sovereign bonds, affecting yields and deviations from CIP. Thirdly, liquidity frictions can contribute to increased risk aversion among investors. Interacting liquidity frictions with macroeconomic conditions, such as changes in inflation expectations or economic growth prospects, may influence risk premia demanded by investors. Changes in risk premia can impact sovereign bond prices and deviations from CIP. Finally, government economic policies, especially during periods of economic stress, can influence both liquidity conditions and macroeconomic factors. For example, fiscal stimulus measures or changes in monetary policy may impact liquidity in sovereign bond markets. The interaction with macroeconomic conditions can affect deviations from CIP.

In summary, understanding the interaction between liquidity frictions and macroeconomic conditions is crucial for comprehending deviations from CIP in sovereign bond markets. The interplay of these factors can influence investor behavior, market dynamics, and the pricing of sovereign bonds, ultimately affecting deviations from Covered Interest Rate Parity. Empirical analysis and modeling techniques are often employed to quantify and explore these interactions in the context of sovereign bond markets.

We now consider whether the interplay of liquidity and economic conditions help to explain the observed large negative basis. In fact, the effect of liquidity frictions may be affected by the economic condition. To examine this relationship, we interact liquidity frictions with LN-Macro, LN-Macro is a proxy of the sate of the economy:

$$
\begin{aligned}
Basis_{bond} &= \alpha + \beta_1[LiquidityFrictions]_{i,t} + \beta_2[FundingCosts]_{i,t} \\
&+\beta_3[MacroFactors]_{i,t} + \beta_4[LiquidityFrictions * LN - Macro]_{i,t} + \epsilon_{i,t}
\end{aligned}
\tag{3.8}
$$

Table 3.8 shows the results. The results (Columns (1)-(4)) show that, the three interactions cannot explain much to $Basis_{bond}$. In sum, the interplay of liquidity and macro economic frictions does not add much to the results in Table 3.4.

3.6.5 An Alternative Indicator for CIP Violation

To explore CIP arbitrage in sovereign bond market, we adopt an alternative variable-constructed new $Basis_{bond}$ to describe deviations from CIP for sovereign bond. According to Buraschi et al. (2015), the bond yield maturity can be divided into two components (Equation 3.9 and 3.10) which is related to violations of the CIP condition and credit spreads.

$$
(1 + R^a(t,T) + S^a(t,T))^{T-t} = (1 + R^b(t,T) + S^b(t,T))^{T-t}\frac{S_t^i}{F_{t,T}^i} \tag{3.9}
$$

$$
Y^a(t,T) = R^a(t,T) + S^a(t,T), Y^b(t,T) = R^b(t,T) + S^b(t,T) \tag{3.10}
$$

Where $R(t,T)$ is risk-free rate, $S(t,T)$ is credit spread for bond.

To calculate $R(t,T)$ and $S(t,T)$, We choose most of USD-denominated or most of euro-denominated sovereign bonds in two countries (South Korea and Mexico)[12] to compute zero-coupon bond Y_{NS} with same maturities as actual bond pairs using a Nelson-Siegel methodology. Then, we calculate risk-free rate with matching maturities by spline interpolation and compute difference between actual bond yield to maturity and Y_{NS} proxied by credit spread for each bond with matching maturities. Finally, we get new interpolated yield to maturity of USD-denominated or most of euro-denominated sovereign bonds,Y_{New}^a and Y_{New}^b. Therefore, we follow the process of Section 1.2.3 to compute the alternative indicator $Basis_{bond}$.

Figure 3.3 shows that the new $basis_{bond}$ is close to the original basis for South Korea and Mexico. The sign of new $basis_{bond}$ is also generally negative for these two countries, especially during Covid-19 crisis. The result reveals that these two countries usually pay a higher yield in cash bond denominated in U.S, dollars

[12]We can find only three Chinese euro-denominated sovereign bonds to get zero-coupon bond, which causes large estimation errors. Therefore, we just choose sovereign bonds of South Korea and Mexico.

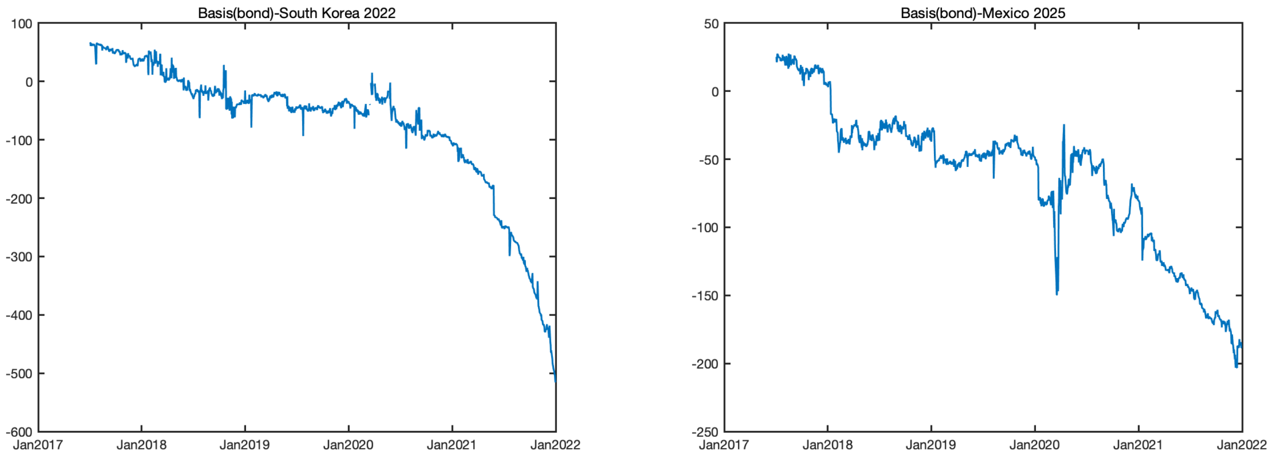
Table 3.8: Regressions on Interacting Liquidity Frictions with LN-Macro

	(1)	(2)	(3)	(4)
Liquidity Frictions				
Liq-FX	0.000	0.000	0.000	0.000
	(0.775)	(0.952)	(0.950)	(0.695)
Liq-OIS	0.002**	0.002**	0.002**	0.002**
	(0.035)	(0.033)	(0.036)	(0.035)
TED	0.007	0.007	0.003	0.003
	(0.860)	(0.853)	(0.926)	(0.931‘)
Interations				
LN-Macro*Liq-FX	0.000			0.000
	(0.707)			(0.695)
LN-Macro*Liq-OIS		0.000		0.000
		(0.568)		(0.547)
LN-Macro*TED			0.002	0.002
			(0.205)	(0.213)
Funding Costs				
Unsecured	-0.066	-0.066	-0.066	-0.066
	(0.159)	(0.152)	(0.158)	(0.167)
Secured	1.101***	1.099***	1.105***	1.107***
	(0.000)	(0.000)	(0.000)	(0.000)
Macro Factors				
TP	0.018**	0.018**	0.018**	0.018**
	(0.021)	(0.019)	(0.020)	(0.022)
VIX	0.008***	0.008***	0.008***	0.008***
	(0.004)	(0.004)	(0.004)	(0.004)
LN-Macro	-0.029***	-0.029***	-0.029***	-0.029***
	(0.000)	(0.000)	(0.000)	(0.000)
CDX	-0.014	-0.014	-0.014	-0.014
	(0.421)	(0.416)	(0.413)	(0.423)
Country FE	√	√	√	√
Time FE	√	√	√	√
R^2	83%	83%	83%	83%
Obs	3527	3527	3527	3527

Notes: The table indicates the 4 fixed effects regressions on $Basis_{bond}$ of China 2022, South Korea 2022 and Mexico 2025. P-value is reported in parentheses. *, ** and *** pertain to 10%, 5% and 1%. Explanatory variables are, namely, Liquidity Frictions [Liq-FX, Liq-OIS, TED]; Funding Costs [Unsecured, Secured]; Macroeconomic factors [VIX, CDX, TP, LN-Macro].The dependent variable is net absolute value $Basis_{bond}$. $Basis_{bond}$, liquidity frictions and funding costs are daily data. The macroeconomic indicators are monthly and quarterly data and we need to convert low frequency data (monthly and quarterly) to high frequency data (daily) by using cubic spline interpolation.

than synthetic bond in foreign exchange market which may be associated with CIP deviations. Therefore, when we reconstruct the bond yield using new method, price anomalies of bonds still exist.

Figure 3.3: Time-Series of $Basis_{bond}$ Using Nelson-Siegel Method



Notes: The graph shows the dynamics of $Basis_{bond}$ for South Korea 2022 and Mexico 2025. $Basis_{bond}$ is negative when the USD-denominated bond is trading "cheap". According to Buraschi et al. (2015), the bond yield maturity can be divided into two components zero-coupon bond and credit spreads for bond. We recalculate $Basis_{bond}$ by using Nelson-Siegel methodology to compute zero-coupon bond and credit spread for each bond. we can construct a new interpolated yield using zero-coupon yield and credit spreads for bond pairs.

3.7 Conclusion

How can two similar bonds issued by the same company have large pricing discrepancies? This is an extremely important issue that bears on asset pricing and the arbitrage activities. Our paper addresses this issue using the data of three sovereign bond markets (China, South Korea and Mexico), which issue large number of shares denominated in both dollars and euros. We examine the persistence of pricing anomalies and investigate the potential factors behind it. In this paper, we calculate $Basis_{bond}$ using bond pairs denominated in dollars and euros of three countries (China, South Korea and Mexico). From our study, $Basis_{bond}$ is small before crisis and become significantly large and persistent during the Covid-19 crisis. This phenomenon shows that CIP arbitrage opportunities occurred during crisis and arbitrageurs faced some market frictions, such as liquidity frictions, funding cost and macroeconomic frictions. The sign of $Basis_{bond}$ in three countries is all negative which means three countries usually pay a higher yield in synthetic bond in foreign exchange market than cash bond denominated in U.S, dollars.

To substantiate our hypothesis, we conduct extensive tests to examine the role of different types of factors (market liquidity, funding liquidity and leverage constraints and macroeconomic conditions) to arbitrage in sovereign bond mispricing. We find that sovereign bond pricing violations are quite common and closely related to variables of secured funding cost and economic conditions. However, liquidity frictions have limited impact on $Basis_{bond}$. A company with high leverage, risk, and low liquidity is more likely to experience a financial crisis disintegration in credit markets. Additionally, firms with greater barriers to arbitrage tend to have more persistent pricing discrepancies. Limited arbitrage in sovereign bond markets is important not only in the Covid-19 crisis period, but also in normal times. The reason is that funding-related variables and macroeconomic condition follow a persistence pattern similar to bond pricing discrepancies before and during Covid-19 crisis. Pricing discrepancies are more persistent among firms that are more sensitive to a shortage of arbitrage capital. In this paper, there is evidence that persistent arbitrage capital shortages contribute to bond pricing discrepancies. Finally, we find that the $Basis_{bond}$ persists during pre-crisis period. This phenomenon is attributable to dealers' debt overhang to market making, which reduces their ability and willingness to provide liquidity to sovereign bond markets, and hence, adversely affects market quality and dealers' intermediary.

The motivation to investigate the violation of sovereign bond prices stems from the potential insights it can provide into market inefficiencies, risk factors, and the functioning of financial markets. Here are key motivations for studying the violation of sovereign bond prices: (1) Market Efficiency Concerns: Sovereign bond markets are expected to be efficient, where prices reflect all available information. Detecting violations of sovereign bond prices may suggest inefficiencies in the market, providing opportunities for investors or indicating a need for market reforms. (2) Risk Assessment: Sovereign bonds are considered relatively low-risk investments, particularly those issued by economically stable countries. Price violations may signal changes in perceived risk, providing valuable information for investors assessing the risk-return profile of sovereign debt. (3) Impact on Portfolio Management: Investors often include sovereign bonds in their portfolios for diversification and risk mitigation. Understanding the factors contributing to price violations helps portfolio managers make informed decisions about asset allocation and risk management. (4) Global Economic Conditions: Violations in sovereign bond prices may be linked to broader economic conditions, geopolitical events, or shifts in monetary policy. Investigating these violations can offer insights into the interconnectedness of financial markets and the global economic landscape. (5) Market Liquidity Dynamics: Liquidity in sovereign bond markets is crucial for their smooth functioning. Price violations may be associated with liquidity challenges, and studying these violations can contribute to a better understanding of liquidity dynamics in sovereign debt markets.

The political significance of studying sovereign bond price anomalies is multifaceted, involving implications for government policies, investor confidence, international relations, and financial stability. Here are some key political considerations: (1) Government Financing and Fiscal Policy: Sovereign bond prices impact the cost of borrowing for governments. Political leaders may be concerned about anomalies in bond prices as they influence the affordability of financing public expenditures and implementing fiscal policies. (2) Crisis Preparedness and Risk Management: Anomalies in sovereign bond prices can serve as an early warning system for potential economic crises. Political leaders may use such anomalies to assess risks and implement preventive measures to avoid financial instability. (3) Financial Stability Oversight: Anomalies in sovereign bond prices may contribute to systemic risks. Political bodies responsible for financial stability may use insights from bond markets to assess the overall health of the financial system and take preventive measures. (4) Debt Sustainability and Credit Ratings: Bond price anomalies can affect a country's creditworthiness. Political leaders may be concerned about the impact on credit ratings, as downgrades can lead to higher borrowing costs and reduced access to international capital markets. (5) International Financial Cooperation: Bond price anomalies can introduce political risks, especially during election cycles. Political leaders may need to navigate economic challenges to maintain stability and secure electoral support. In summary, studying sovereign bond price anomalies is politically significant as it involves navigating the intersection of economic policies, international relations, public perception, and financial stability. Political leaders must be attuned to signals from bond markets to make informed decisions that safeguard economic health and maintain public trust.

In summary, studying sovereign bond price anomalies is politically significant as it involves navigating the intersection of economic policies, international relations, public perception, and financial stability. Political leaders must be attuned to signals from bond markets to make informed decisions that safeguard economic health and maintain public trust.

Appendix 3.1: Principal Component Analysis

When using statistical analysis methods to study multivariate subjects, too many variables will increase the complexity of the subject. Generally, we expect more information with fewer variables. In many cases, there is a certain correlation between variables, which can be interpreted that the information of the two variables reflecting the issue overlaps to a certain extent. Principal component analysis (PCA) is to eliminate redundant variables (closely related variables) and construct few uncorrelated new variables which keep the original information as much as possible.

After an orthogonal linear transformation, PCA transforms the data to a new coordinate system such that the greatest variance by some scalar projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on.

Proof:

$$Y = A(X - \bar{X}), \bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i$$

$$Y = \begin{bmatrix} a_1(X-\bar{X}) \\ a_2(X-\bar{X}) \\ a_3(X-\bar{X}) \\ \ldots\ldots \end{bmatrix} = \begin{bmatrix} y_i1 \\ y_i2 \\ y_i3 \\ \ldots\ldots \end{bmatrix}$$

Variance:

$$\begin{aligned}\sum_{i=1}^{N}(y_{i1}-\bar{y})^2 = \sum_{i=1}^{N} y_{i1}^2 = \sum_{i=1}^{N} a_1(X-\bar{X})^2 = \sum_{i=1}^{N}[a_1(X-\bar{X})][a_1(X-\bar{X})]^T \\ = a_1\sum_{i=1}^{N}[(X-\bar{X})][(X-\bar{X})]a_1^T = a_1\sum a_1^T\end{aligned}$$

Where $\sum$ is defined as covariance matrix.

$\sum_{i=1}^{N}(y_{i1}-\bar{y})^2 = \sum_{i=1}^{N} y_{i1}^2$, because $\bar{y}$ equals 0.

Proof:$\bar{y} = 0$

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i = \frac{1}{N}\sum_{i=1}^{N} a_1(X - \bar{X})$$
$$= \frac{a_1}{N}\sum_{i=1}^{N} a_1(X - \bar{X})$$
$$= \frac{a_1}{N}(\sum_{i=1}^{N} X - N\bar{X}) = 0$$

.

Maxinum variance: $a_1 \sum a_1^T$

Subject to the contraint: $a_1 \sum a_1^T = \|a_1\|^2 = 1$

Langrage multiplier equation:

$$L = \max a_1 \sum a_1^T - \lambda_1(a_1 \sum a_1^T - 1) = \frac{\partial L}{\partial a_1} = (\sum a_1^T - \lambda_1 a_1^T) = 0$$

$$\sum a_1^T = \lambda_1 a_1^T$$

Therefore, λ_1 is eigenvalue of Σ, a_1^T is eigenvector of Σ.

$$a_1 \sum a_1^T = a_1(\lambda_1 a_1^T) = \lambda_1(a_1 a_1^T) = \lambda_1$$

In this case, in order to compute maxinum variance, we need to get maximum value of λ_1. We can use similar method to calculate λ_1, λ_2,....λ_n,choose the result that $\lambda > 1$ (λ is eigenvalue of covariance matrix) and adopt first few principal components F1, F2......

$$F = \lambda_1 F_1 + \lambda_2 F_2 + \lambda_3 F_3$$

In this paper, we use PCA to compute Liq-FX, Liq-OIS and Ln-Macro. For Liq-FX, X_1, X_2...... represent spot exchange rate and 3M, 6M, 1Y-10Y EUR/USD forward exchange rate bid-ask spread. For Liq-OIS, X_1, X_2...... mean 3M, 6M, 1Y-10Y USD bid-ask spread. For Ln-Macro, X_1, X_2...... show 11 economic factors (see in Table 3.3).

Appendix 3.2: $Basis_{bond}$ Calculation

For example, taking USD- and euro-denominated foreign bonds of China. The maturity date of USD bond is March 14, 2022. On November 4, 2021, the yield to maturity of the Chinese USD bond is 0.683% and that of euro bond is -0.079%.

With almost 0.5 years until maturity date, the investor sells 100 dollars USD bond, swap the proceeds for 86.55 euros in the spot foreign exchange market (1 euro = 1.1554 dollar)

$$\frac{100}{1.1554} = 86.55\,\text{euros} \tag{3.11}$$

Using euros of the euro bond which pays one coupon (coupon rate is 0.75%). The calculated face value of the euro-denominated bond is 85.28 euros, so each coupon payments are 0.42 euros. T is actual days (from November 4, 2021 to euro bond maturity date June 8, 2022) / 360. Day count for euro bond is ACT / 360.

$$86.55 = \frac{FV \times 0.0075 + FV}{(1 - 0.00079)^T} \tag{3.12}$$

Therefore, FV = 87.2552 euros and Coupon =87.2552 $\times 0.0075 = 0.6544 euros$

Using forward rate F_t for each coupon date (June 8, 2022), all euro cash flows and face value are converted into USD dollars. This creates a synthetic USD bond consisting of only USD coupon flows: \$0.49 on June 8, 2022 (1 euro = 1.161201 dollar) and the face value is \$101.3208.

$$0.6544 \times 1.161201 = 0.7599\,\text{dollars} \tag{3.13}$$

$$87.2552 \times 1.161201 = 101.3208\,\text{dollars} \tag{3.14}$$

The yield to maturity of the synthetic bond Y^{a^*} (calculated based on these USD flows) is -4.15%.

$$100 = \frac{0.7599 + 101.3208}{(1 + Y^{a^*})^T} \tag{3.15}$$

Therefore,

$$Basis_{bond} = Y^{a^*} - Y^a = -414.74\,\text{bps} - 68.3\,\text{bps} = -483.04\,\text{bps} \tag{3.16}$$

Chapter 4

Deviations from Covered Interest Rate Parity, Debt Overhang and Carry Trade

4.1 Introduction

Many countries have a high demand for U.S. dollars and are sensitive to the cost of U.S. dollar funding. Many participants lack access to borrow money directly from dollar-rich lenders, such as U.S. money market funds (MMFs) and central bank reserve managers. As a result, financial intermediaries, such as banks, plays a significant role to supply dollars in order to satisfy the strong demand for dollars. Since Global Financial Crisis (GFC), balance sheet constraints for financial intermediaries due to bank regulation. Therefore, deviation from the covered interest rate parity (CIP) exists.

The CIP condition, known as no-arbitrage condition, stipulates that the interest rates in cash market must be equal to the interest rates in the foreign exchange (FX) markets due to arbitrage activities. According to CIP condition, it is impossible to earn a profit by borrowing in one currency and lending in another currency while fully covering the foreign exchange (FX) risk. In tranquil times, the basis is close to zero because it is possible for arbitrageurs to exploit the basis in FX swap markets to pocket the difference. Since Global Financial Crisis (GFC), CIP has failed to hold on and CIP deviations occurred. The dollar funding costs on foreign exchange markets have increased significantly. The indicator which can measure violations of CIP condition is called cross-currency basis. To understand the violations, it starts to consider the demand and supply of dollars. On the demand side, the investors swap their domestic currency into U.S. dollars to finance the purchase of dollar-denominated assets. On the supply side, a bank or other financial intermediary sources dollars from global capital markets to provide dollars.

However, some studies find that the violations of CIP condition have persisted after crisis, especially since mid-2014. One of the most notable financial market anomalies in the post-global financial crisis (GFC) period has been the violation of the no-arbitrage condition known as covered interest parity (CIP), or, equivalently the persistence of the cross-currency basis, in a period characterized by low volatility and absence of a major credit strains. A distinguishing feature of the post-GFC CIP violations is the persistence of longer-term deviations in the pricing of currency swaps and longer-term forwards. The recent and growing literature on CIP deviations has not converged on the first-order drivers of the persistent level of CIP deviations and pays little attention to longer-term deviations. This paper provides an explanation for the sign and persistence of long-term CIP deviations. In contrast to the textbook notion of CIP, we first show that quantities of FX hedging demand affect prices of FX derivatives leading to CIP violations. We construct measures of the relevant FX hedging imbalances and find that their direction and size explain the sign and magnitude of currency basis against the USD. This finding calls the long-standing interpretation of CIP as a no-arbitrage condition into question.

Debt overhang and deviations from Covered Interest Rate Parity (CIP) can have interconnected impacts on financial markets and the broader economy. Here are some ways in which these two phenomena may influence each other and contribute to various market dynamics. First, debt overhang, which implies excessive levels of debt that may be challenging to service, can lead to widening credit spreads. As investors become more concerned about the creditworthiness of a borrower (e.g., a sovereign), they demand a higher risk premium. This can result in higher yields on bonds issued by countries with debt overhang, contributing to deviations from CIP as interest rate differentials are affected. Besides, debt overhang often increases risk aversion among investors. This can trigger a flight to safety, where investors move their capital to safer assets. In the context of CIP, this flight to safety can impact exchange rates and interest rate differentials, leading to deviations from the parity condition. In addition, debt overhang can impact interest rate differentials between countries. If a country is perceived to have a high level of debt that poses a risk of default, investors may demand higher interest rates. This can affect the interest rate differentials used in CIP calculations, contributing to deviations. Then, concerns about debt overhang influence market expectations. Expectations about future economic and fiscal conditions can impact forward rates, which are a component of CIP calculations. Changes in expectations may contribute to deviations from the parity condition. Furthermore, central banks may respond to debt overhang by adjusting monetary policy. Changes in interest rates or the implementation of unconventional monetary policies can impact exchange rates and interest rate differentials, influencing CIP. Finally, debt overhang can affect market liquidity, especially if concerns about default lead to reduced investor confidence. Market segmentation may occur, with investors becoming more selective about the assets they hold. This can contribute to deviations from CIP as different segments of the market may experience varying dynamics.

The relationship between debt overhang and forward Covered Interest Rate Parity (CIP) trading strategy involves considering how concerns about excessive debt levels in a country might impact currency markets and the effectiveness of trading strategies based on CIP. Firstly, debt overhang can lead to changes in interest rate differentials between countries. If a country is perceived to have a high level of debt and faces challenges in servicing that debt, investors may demand higher interest rates. This can impact the interest rate differentials used in CIP calculations, influencing the potential profitability of forward rate-based trading strategies. Secondly, concerns about debt overhang can influence market sentiment and expectations about future economic and fiscal conditions. This, in turn, can impact forward rates used in CIP calculations. Traders implementing forward CIP strategies need to consider how market sentiment and expectations, driven by debt-related concerns, may affect the accuracy of forward rate predictions. In the end, central banks often respond to debt overhang through monetary policy measures. Changes in interest rates or unconventional monetary policies can influence forward rates and interest rate differentials, impacting the success of forward CIP trading strategies. Traders need to monitor central bank actions and their potential effects on currency markets.

The violations of CIP condition would cause the likelihood of unlimited excess profits. An important premise of this paper is that big banks are less willing to use their balance sheet for intermediation due to increased funding costs and tighter regulations (Erik et al., 2020). According to some previous studies, deviations from covered interest rate parity can be explained by constrained intermediaries during post-crisis period (Du et al., 2018; Avdjiev et al., 2019). The key message of our paper is that debt overhang plays the role of deviations from covered interest rate parity. One assumption is that debt overhang costs on trading market could be reduced since financial crisis by increasing bank capitalization. To be concrete, banks almost never rely entirely on equity to finance asset purchases. Shareholders, to some extent, also maintain their values by repo or debt financing. One assumption is that the debt overhang on trading markets has declined significantly since financial crisis by increasing bank capital that reduces bank insolvency risk. If a bank's debt is safe, bank creditors have less opportunities to gain profit from improving credit quality related to finance new asset purchase. Therefore, debt overhang should be lower after financial crisis. Actually, debt overhang is more severe now than before financial crisis as bank credit spreads are higher (Duffie, 2017). We define debt overhang proxied by bank credit spreads.

It starts with the relationship between debt overhang and deviations from covered interest rate parity. We use nine liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). We consider each cross-currency basis vis-à-vis the U.S. dollar (USD) and the sample period is from 2013 to 2022. We compute 1-month and 1-week cross-currency basis based on different kinds of interest rate: Libor, OIS, repo and IOER. The key finding of this research question is that debt overhang is an important driver of violations of covered interest rate parity, particularly for 1-week cross-currency basis. Debt overhang has larger explanatory power on deviations from CIP. Then, we investigate the link between cross-currency basis and norminal interest rates to provide the theory for carry trade. The result is that cross-currency basis is negatively correlated to interest rate which may give arbitragers opportunities to gain benefits from carry trade.

We then consider the relationship between CIP deviations and carry trade [1]. We adopt forward CIP trading strategy (Du et al., 2023) to do bilateral carry trade in foreign exchange market. CIP deviations is associated with the return of forward trading strategy. To be concrete, an arbitrageur goes long in one low-interest-rate currency and short in one high-interest-rate currency with currency risk hedged from $t+1$ to $t+4$ using forward contract. After one month, an arbitrageur will take long position in the same high-interest-rate currency and take short position in the same low-interest-rate currency. Therefore, cash flows can be ignored under forward CIP trading strategy. The excess return of this strategy is just associated with the spread between one-month forward three-month CIP deviations today and actual three-month CIP deviations after one month. The excess return of forward trading strategy is greater than zero if the difference of future CIP deviations and the market-implied forward CIP deviations today is negative. If the constraints of intermediaries are indeed a priced factor, we expect positive excess return from forward CIP trading strategy to compensate investors for bearing the risk exposure of intermediary. After we compute excess return, we then investigate the link between debt overhang and profits of forward CIP trading strategy.

We choose 6 liquid currencies (AUD, CAD, DKK, EUR, JPY, NZD) and create cross-currency basis vis-à-vis USD and non-USD currencies, then estimate the excess returns of forward CIP trading strategies from 2013 to 2022. First, we focus on the excess return in individual currencies against USD among cross-currency pairs. We also compute additional excess returns between non-USD currency pairs as robustness test. We find the significant positive excess return for forward CIP trading strategies for currency pairs vis-à-vis USD and non-USD currencies after Global Financial Crisis. Therefore, the investors are supposed to gain profits from this bilateral carry trade-forward CIP trading strategies. Secondly, we also investigate the excess return of the forward CIP trading strategies for portfolios. We divide 6 currency pairs to two groups to create the new portfolio: high-interest-rate currencies (AUD, CAD and GBP) and short in low-interest-rate currencies (DKK, EUR and JPY), then compute excess return of this portfolio. We conclude that average excess return are large and positive. The results shows that the investor will gain profit from this portfolio for bilateral carry trade.

[1]The traditional unhedged carry trade is going long in low-interest-rate currencies and short in high-interest-rate currencies. The hedged carry trade have opposite direction to traditional unhedged carry trade, arbitrageurs take long position in high-interest-rate currencies and go short in low-interest-rate currencies.

In this study, our primary contribution is the exploration of debt overhang as a significant indicator of risk-taking capacity in capital markets during the post-crisis period. We establish that CIP arbitrage is primarily driven by constraints on bank balance sheets (Wallen, 2020), which expand due to arbitrage costs. The growth of these balance sheet constraints results from the expenses associated with equity financing, with debt overhang emerging as a notable cost. Therefore, a thorough examination of the influence of debt overhang on CIP deviations is imperative. Additionally, we uncover a correlation between the profits of a forward CIP trading strategy and CIP deviations. We further investigate how debt overhang impacts the excess return on carry trade, considering it as the cost to bank balance sheet space, represented by the annualized return above the risk-free rate that banks must utilize.

The structure of this paper unfolds as follows. Section 4.2 delves into pertinent literature concerning debt overhang, deviations from covered interest rate parity, and carry trade. In Section 4.3, we expound on the theory and definition of cross-currency, debt overhang, and other factors that could impact deviations from covered interest rate parity. Empirical analysis is explicated in Section 4.4. Section 4.5 outlines various robustness tests, and Section 4.6 concludes by summarizing key findings.

4.2 Literature Review

Numerous research endeavours have concentrated on scrutinizing deviations from covered interest parity (CIP) across various temporal phases, encompassing the pre-crisis, crisis, and post-crisis periods. This section is bifurcated into two facets of the literature. Initially, we delve into pertinent studies elucidating the influence of debt overhang on observed deviations from covered interest rate parity. Additionally, we provide an overview of literature exploring the interplay between intermediaries and carry trade.

4.2.1 CIP Deviations and Factors

A large literature studies the CIP condition, notably Lotz (1889) and much more clearly in Hawtrey (1924). Before crisis, cross-currency basis measuring CIP deviations is close to zero, because arbitragers exploit the FX swap market basis and supply dollars to pocket the difference (Avdjiev et al., 2020). Akram et al. (2008) found that deviations disappear almost instantly, with the exception of temporary episodes when arbitrage was inhibited by bank counterparty risk. Sharp and persistent CIP deviations during the crisis are observed.

During the global financial crisis, CIP deviations were wide, driven again by bank counterparty risk as well as wholesale US dollar funding strains (Coffey et al., 2009; Baba et al., 2009; Baba and Packer, 2009). To be concrete, Coffey et al. (2009) argue that widening of CIP deviations during global financial crisis are driven by counterparty risk and dollar funding constraints. Besides, during the sovereign debt crisis, some authors find the widening of CIP deviations due to further dollar funding shortages (Bottazzi et al., 2012; Ivashina et al., 2015). The former posit that CIP deviations arise due to USD collateral shortage; the latter that CIP deviations can arise when banks shift some of their funding away from wholesale dollar funding markets due to default risk premium. These studies all focus on CIP deviations associated with short tenors (typically 1-month) because these have largely characterized dislocations during crises. Mancini-Griffoli and Ranaldo (2011) suggests that the lack of dollar funding liquidity prevents traders from arbitraging excess profits, thus fails to balance the CIP condition. However, excess return from CIP arbitrage is profitable and persistent (McGuire and von Peter, 2012). During sovereign debt crisis, CIP deviations influenced by tools of central banks widened significantly as a result of dollar funding shortage (Bottazzi et al., 2012; Ivashina et al., 2015). The former shows that USD collateral shortage causes CIP deviations and the latter that if banks transfer part of their funds from wholesale dollar funding markets because of default risk premia, CIP deviations can arise. Avdjiev et al. (2020) found indicators of dollar funding costs measured by FX swap basis in FX market have risen sharply during the Covid-19 crisis, reflecting the currency hedging needs of investors and scarce balance sheet.

However, some papers have examined that CIP deviations still exist after crisis and arbitrage has not reduced the basis to zero. The basis has widened since 2014 despite recovery in bank credit quality and wholesale dollar funding markets. CIP violations have persisted even after crisis dissipated (Borio et al., 2018). Borio et al. (2016) discover that the cross-currency basis measuring CIP deviations has widened since 2014, despite recovery in bank credit quality and dollar funding. The conclusion is that persistent violation of CIP after financial crisis is caused by FX hedging demand and limits to arbitrage arising from lower balance sheet capacity, thus reflected by tighter management of risks and balance sheet constraints. The volatility and magnitude of short-term CIP deviations have increased largely due to reduced liquidity in foreign exchange markets the first half of 2015 (Pinnington and Shamloo, 2016). Against this backdrop, academics, central bankers, and market participants alike have been baffled by the above-mentioned pre-crisis evidence.

To advance our understanding of the CIP puzzle, our paper sheds light on some literature on combining re-emergence of CIP deviations with other factors and constraints during and out of crisis. To be concrete, Du et al. (2018) show that CIP deviations cannot be explained by credit risk and transaction costs and the basis is correlated with interest rates and monetary policy shocks. Avdjiev et al. (2019) focus on the triangular relationship among the US dollar, CIP deviations, and cross-border bank lending denominated in dollars: the magnitude of CIP deviations can be interpreted by dollar index, the cost of bank balance sheet capacity and bank leverage measured by dollar credit. Amador et al. (2020) explore that an exchange rate policy in conflict with covered interest rate parity may create problems for a monetary authority because of a binding zero lower bound constraint. Liao (2020) concentrates on aggregate corporate debt issuance flow and links strategic funding cost arbitrage across different currencies with long-term CIP deviations. Cenedese et al. (2021) investigate actual trading activity by different market participants and how this relates to CIP deviations and balance sheets costs. They find that wider CIP deviations in the next quarter is related to lower leverage ratio buffer of major bank dealers for short time and the wider basis is associated with regulatory capital ratios for long duration, consistent with longer-term contracts having a higher risk-weight in the risk-weighted assets (RWA)-type balance sheet constraint, similar results in Du et al. (2018). Keller (2021) study that bank lending can affect CIP deviations. The banks attempt to arbitrage covered interest rate parity (CIP) deviations. In the presence of borrowing frictions, banks raise deposit rates to arbitrage or shift a portion of lending resources to fund arbitrage activities. Arbitrage-related bank lending decreases.

Our paper relates to the literature that studies regulations in financial markets and banks in a broader context. Duffie (2017) investigates that capital regulations and new failure-resolution rules after crisis increase the funding costs by bank shareholders, and the cost to buy-side firms for access to space on the balance sheets of large banks. Encouraging market infrastructure and trading methods can reduce the amount of space on bank balance sheets when conducting an amount of trade. Kisin and Manela (2016) study that banks' capital and liquidity requirements have substantially tightened, resulting in higher capital costs after crisis. Abbassi et al. (2023) argue that before supervisory audits, banks adjust their assets holdings of riskier securities and loans, but undo those changes afterward. Similarly, some papers show that end-of-period effects are associated with increased bank capital regulations in several financial markets (e.g., Anderson and Huther (2016) for the Federal Reserve System's reverse repo facility, Munyan [2015] in the Repurpose Agreement [repo] market). The impact of demand effects on deviations from arbitrage pricing in a range of markets is discovered (Acharya et al., 2013). Puriya and Bräuning (2021) suggest that CIP deviations are driven by demand effects related to bank's management of FX exposure. Avdjiev et al. (2020) review recent policy actions in the context of the longer-term trends in the demand for dollars from institutional investors and particularly focus on central bank swap lines from central banks to alleviate stress. Puriya and Bräuning (2021) suggest that CIP deviations are driven by demand effects related to bank's management of FX exposure. Avdjiev et al. (2020) review recent policy actions in the context of the longer-term trends in the demand for dollars from institutional investors and particularly focus on central bank swap lines from central banks to alleviate stress.

Apart from regulation, a strand of papers closely related this paper combines limits to arbitrage with activities in FX swap markets. An important stream of the LOP literature examines the role of funding markets.

Gromb and Vayanos (2002) study a model in which arbitrageurs must collateralize their positions in each asset in order to implement an arbitrage. Arbitrageurs can enforce the LOP if their wealth is large relative to both the demand shock and the margin requirements; in that case, demand shocks cannot affect relative price changes. Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2010) extend this analysis to multiple assets and show that leverage constraints can generate "contagion" of shocks to seemingly unrelated assets through changes in the arbitrageur's balance sheet. This argument is related to our analysis: the simultaneous operation of trading desks on multiple sovereign bond markets could explain how wealth shocks can propagate frictions internationally across these assets. Cenedese et al. (2021) also conduct that the leverage ratio requirement of dealer banks causes deviations from covered interest parity. The large cross-currency basis during crisis is related to dollar funding shortage in the limits to arbitrage. Central banks are supposed to establish Fed swap lines to reduce dollar shortage, thus largely alleviate the cross-currency basis (McGuire and von Peter, 2012; Baba and Packer, 2009; Goldberg et al., 2010). Borio et al. (2018) explore that the failure of CIP for some liquid currency crosses in tranquil times runs contrary to the majority of the pre-crisis literature and our measures of FX hedging demand are key drivers of the persistent level of CIP deviations. Global interest rate differentials replace bank's creditworthiness as main factors in determining CIP deviations and real money investors increase the supply of dollars in FX swap market (Iida et al., 2018). Borio et al. (2016) combine demand for FX hedges with new strains on arbitrage activity. They use the volume of hedging demand and balance sheet costs to explain CIP violations across currencies. Mancini-Griffoli and Ranaldo (2011) attribute CIP violations to insufficient funding liquidity, because deleverage imperatives, prudential hoarding and limited capital to pledge decrease liquidity. Pinnington and Shamloo (2016) focus on FX market rather than broader funding market. Due to reduced dealer capacity as result of the SNB decision, a reduction in forward contracts resulted in wide bid-ask spreads in the forward market, allowing deviations from CIP to persist. Viswanath-Natraj (2020) argues that due to unconventional monetary policies in the Eurozone, Japan, and Switzerland, demand for dollar funding in the FX swap market will remain structurally imbalanced which means CIP deviations will continue to persist.

4.2.2 Debt Overhang and CIP Deviations

We now turn to a brief overview of the related literature of debt overhang. Myers (1977) puts forward debt overhang theory: an increase in leverage increases the likelihood that a firm's debt obligations exceed the value of its assets and lead to inappropriate investment strategies. In this theory, leverage changes have a negative impact on stock prices but a stronger effect for firms to experience debt overhang. This theory is consistent with the results in Cai and Zhang (2011). Wilson (2012) explore that debt overhang causes inefficiency, because shareholders resist recapitalization although this would increase the value of the firm to shareholders and debt holders. The economy would be better served by banks funded with much more equity without being exposed to excessive risks and costs. For banks, a significant increase in equity would greatly enhance the health and stability of the financial system and remove significant distortions. Occhino (2017) studies the risk of a debt-overhang banking crisis accompanied by a significant drop in the value of banks' assets and a contraction of bank lending and economic activity. Barbiero et al. (2020) investigate that firms with high debt financing invest more if facing good global growth chances. High levels of corporate debt have a negative average impact on investment and are detrimental to investment in low-growth-opportunity sectors. Therefore, the authors illustrate the importance of regulatory tools and prudential supervision in curbing the credit boom that make firms over-leveraged.

Leverage that relies on capital structure is limitless in theory but an arbitrage position (involves borrowing and lending) is provided by intermediaries, typically banks. The ability of traders to exploit arbitrage opportunities depends on the leverage by banks. Therefore, banks have restrictions on using leverage as a source of CIP deviation. Two main factors that determines bank leverage constraints are the broad strength of the dollar and debt overhang (Avdjiev et al., 2019). First, deviations from CIP move in lock-step with US dollar appreciation. In the banking sector, the dollar exchange rate becomes an indicator of risk capacity. The tendency of dollar should be affected by the interaction of demand for dollar credit of borrowers with the dollar credit by lenders, which reflects an appreciating US dollar can dampen dealer banks' intermediation capacity (Avdjiev et al., 2019, 2020). For this reason, the dollar exchange rate and dollar funding costs tend to move in lock-step, which cause CIP deviations. Dollar strength is one factor determining bank leverage constraints, thus causing debt overhang. Specifically, a stronger dollar is associated with lower bank leverage measured by dollar credit (Avdjiev et al., 2019), which may cause debt overhang. For global banks providing different portfolios of dollar credits to borrowers, the dollar depreciation reduces the perceived riskiness of the borrowers and thus reduces the tail risk of the credit portfolio. Reducing tail risk implies increased lending capacity at any given economic level which means higher bank leverage.

In addition, banks with debt overhang have more close relationship with CIP deviations. A higher leverage ratio may adversely affect future investment and expected future cash flow when a bank is more prone to debt overhang. These results also show that higher leverage increase the probability of debt overhang (Cai and Zhang, 2011). Therefore, dollar strength is negatively associated with banks with debt overhang. Since crisis, regulatory reforms have significantly raised the costs of banks' market making and arbitrage activities. Bank regulations are likely to affect other non-regulated firms, increasing the cost of leverage for the financial market (Duffie, 2017). As explained earlier in this chapter, debt overhang implies that trades with a positive mark-to-market dealer profit can imply a negative return on bank's equity. In order to overcome debt-overhang costs to shareholders, the excess return on balance sheet-expanding is proportional to the bank's unsecured credit spreads (Andersen et al., 2019). As regulators mandate a substantial increase in bank capitalization, the impact of debt overhang on the trading markets will be much reduced since the Great Financial Crisis. Once a bank's debt has become safer, bank creditors have less opportunity to profit from an improvement in the credit quality of their claims related to the financing of new assets. Thus, debt overhang should be lower. However, due to higher bank credit spreads, bank debt overhang is actually more severe now than before the Great Financial Crisis (GFC). Higher credit spread also coincide with larger CIP violations in the direction of more expense to swap other currencies to US dollar in the cash market (Liao, 2020). Therefore, banks with more severe debt overhang plays an important role in larger CIP violations.

4.3 Data and Methodology

In this segment, we provide an overview of the Covered Interest Rate Parity (CIP) condition and delineate deviations from it, quantified through the cross-currency basis. Subsequently, we furnish details on the sources of data and the methodology employed for calculating these bases.

4.3.1 Libor-Based CIP Deviations

We follow 1 and 2 to retrieve the CIP for bonds but before that lets try how that relates FX covered interest rate parity (CIP) condition. Suppose that an investor borrows 1 U.S. dollar today and deposit 1 dollar for n years, earning payoff $e^{ny^{USD}_{t,t+n}}$. Besides, the investor could also exchange 1 U.S. dollars for S_t foreign currency i and enter into a n-year forward contract today, then deposit the foreign currency and earn payoff $e^{ny^{i}_{t,t+n}}$. Based on a frictionless market, the two strategies should have the same payoff.

$$e^{ny^{USD}_{t,t+n}} = \frac{e^{ny^{i}_{t,t+n}} S_t}{F_{t,t+n}}, \tag{4.1}$$

If CIP condition does not hold, we add a variable - CIP deviations- which we call the cross-currency basis.

$$e^{ny^{USD}_{t,t+n}} = \frac{e^{ny^{i}_{t,t+n}+nx^{i}_{t,t+n}} S_t}{F_{t,t+n}}, \tag{4.2}$$

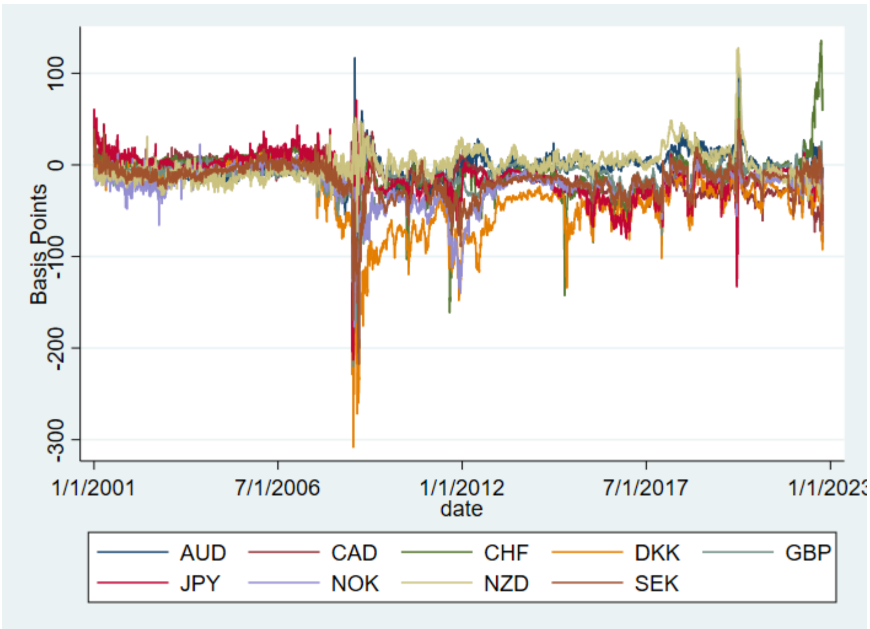
The deviation of CIP, $x^i_{t,t+n}$, can be defined as the n-year cross-currency basis of currency i vis-à-vis dollar at time t.The continuously compounded cross-currency basis is

$$x^i_{t,t+n} = y^{USD}_{t,t+n} - (y^i_{t,t+n} - \rho^i_{t,t+n}) \tag{4.3}$$

Where $\rho^i_{t,t+n} = \frac{1}{n}[log(F^i_{t,t+n}) - log(S^i_{t,t+n})]$, $y^{USD}_{n,t}$ is continuously compounded n-year risk-free interest rate for U.S. dollars at time t, $y^i_{n,t}$ is continuously compounded n-year risk-free interest rate for currency i at time t. The cross-currency basis can be described by equation: the difference between dollar interest rate in cash market, $y^{USD}_{n,t}$, and the dollar interest rate in FX swap market, $y^i_{t,t+n} - \rho^i_{t,t+n}$.

Our primary dataset encompasses the time frame spanning from 2013 to 2022. Throughout this period, our analysis delves into the cross-currency basis concerning the U.S. dollar across nine highly liquid currencies. These currencies are the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), and the Swedish krona (SEK).

Figure 4.1: Three-Month Libor-Based Deviations from Covered Interest Rate Parity

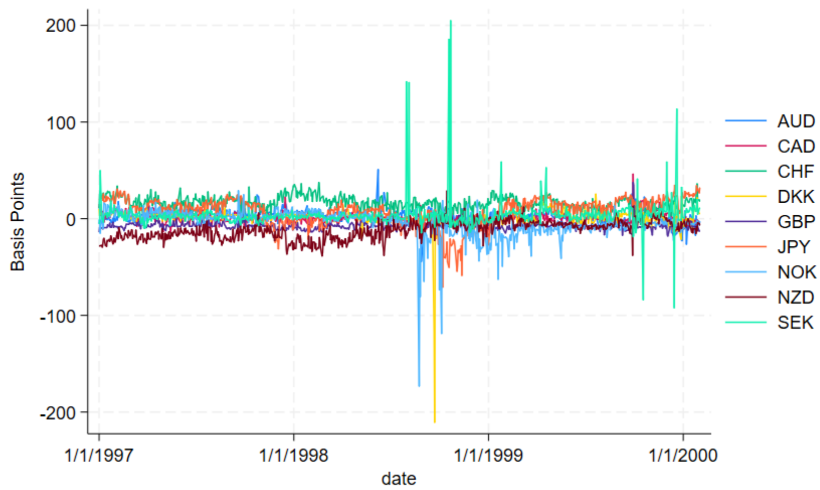


Notes: The graph shows three-month Libor cross-currency basis, measured in bps for G9 currencies. the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Cross-currency basis is $y^{USD}_{t,t+n} - (y^i_{t,t+n} - \rho^i_{t,t+n})$, n is 0.25 years. $y^i_{t,t+n}$ and $y^{USD}_{t,t+n}$ denote foreign and U.S. three-month continous Libor rates. $\rho^i_{t,t+n} = \frac{1}{n}[log(F^i_{t,t+n}) - log(S^i_{t,t+n})]$ denote forward premium.

The cross-currency basis can be described by equation: the difference between dollar interest rate in cash market, $y^{USD}_{n,t}$, and the dollar interest rate in FX swap market, $y^i_{t,t+n} - \rho^i_{t,t+n}$. To calculate the cross-currency basis, we use benchmark interbank rates in the respective currency, measured by Libor rates and interest rate swap rates indexed to the Libor. We obtain daily spot exchange rates, forward points and mid rates for Libor from Bloomberg. Figure 4.1 shows three-month Libor basis for G10 currencies between January 2001 and October 2022.

From Figure 4.1 and 4.2 [2], three-month Libor CIP basis was almost zero for 10 currencies before 2007 and during 1997 financial crisis, deviations from CIP exists. During financial and sovereign debt crisis, there were significant deviations from CIP. Especially for Danish krone (DKK), the basis reached -250bps. However, the deviations from CIP did not disappear after crisis: since 2013, the three-month Libor CIP basis was persistently different from zero. During Covid-19 crisis, large cross-sectional dispersion of basis appears for all currencies. Most of currencies exhibit almost 100bps or -100bps.

Figure 4.2: Three-Month Libor-Based Cross-Currency Basis During 1997 Financial Crisis



Notes: The graph shows three-month Libor cross-currency basis, measured in bps for G9 currencies from 1997 to 2000: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Cross-currency basis is $y^{USD}_{t,t+n} - (y^i_{t,t+n} - \rho^i_{t,t+n})$, n is 0.25 years. $y^i_{t,t+n}$ and $y^{USD}_{t,t+n}$ denote foreign and U.S. three-month continous Libor rates. $\rho^i_{t,t+n} = \frac{1}{n}[log(F^i_{t,t+n}) - log(S^i_{t,t+n})]$ denote forward premium.

4.3.2 Debt Overhang

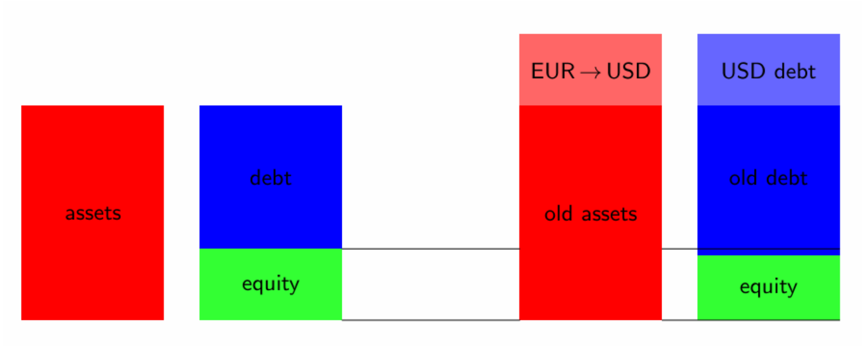
Due to debt overhang, post-crisis financial reform has adversely affected some key financial markets' liquidity. Since the Great Financial Crisis, one might predict that significant increases in bank capitalization have been mandated by regulators, thus reducing the impact of debt overhang on trading markets. The increasing capital results in a decrease in bank insolvency risk. Once a bank's debts have become safer,

[2] Figure 4.1 and 4.2 highlight that the cross-currency basis is significantly larger during crisis periods compared to non-crisis periods, indicating a notable deviation from covered interest rate parity during crises. Therefore, in the next section of this paper, we explore the factors that could lead to deviations from covered interest rate parity. There is no need to conduct a formal test to compare the differences in the cross-currency basis between crisis and non-crisis periods.

bank creditors will have less opportunity to benefit from further improvements in the credit quality of their claims associated with financing new asset purchases. As a result, debt overhang should now be lower. However, bank debt overhang is actually worse today than it was before the Great Financial Crisis (GFC) because bank credit spreads are higher, not lower, than before. Therefore, debt overhang is proxied by credit spreads.

A credit spread which reflects overall economic conditions is the difference in yield between a U.S. Treasury bond and another debt security of the same maturity and different credit quality. Credit spreads will decline during economic expansion and will rise during economic contraction. This is because during economic contraction, investors lack confidence and are more willing to invest in high credit quality bonds to avoid risks, and banks must provide higher interest rates to attract investors to buy corporate bonds, which will result in higher credit spreads.

Figure 4.3: Debt Overhang Cost for Funding Synthetic Dollar Deposits



Notes: This figure illustrates how Covered Interest Parity (CIP) arbitrage can be costly for dealer shareholders due to debt overhang issues when funding synthetic dollar deposits (Duffie, 2017).

In Figure 4.3, the left column represents a basic balance sheet with assets in red funded by debt and equity. This shows a simple structure without additional synthetic or foreign exchange positions. The right columns show CIP arbitrage involving EUR to USD synthetic funding (for example). Specifically, 'EUR - USD' indicates assets through CIP arbitrage, which introduces foreign exchange risk. 'USD debt' is an addition and has been taken on to fund the synthetic dollar position. This Funding Value Adjustment (FVA) arises from the additional debt used to finance the synthetic USD position, increasing the debt burden on the balance sheet, known as debt overhang. Thus, we utilize the bank credit spread for USD funding to represent debt overhang.

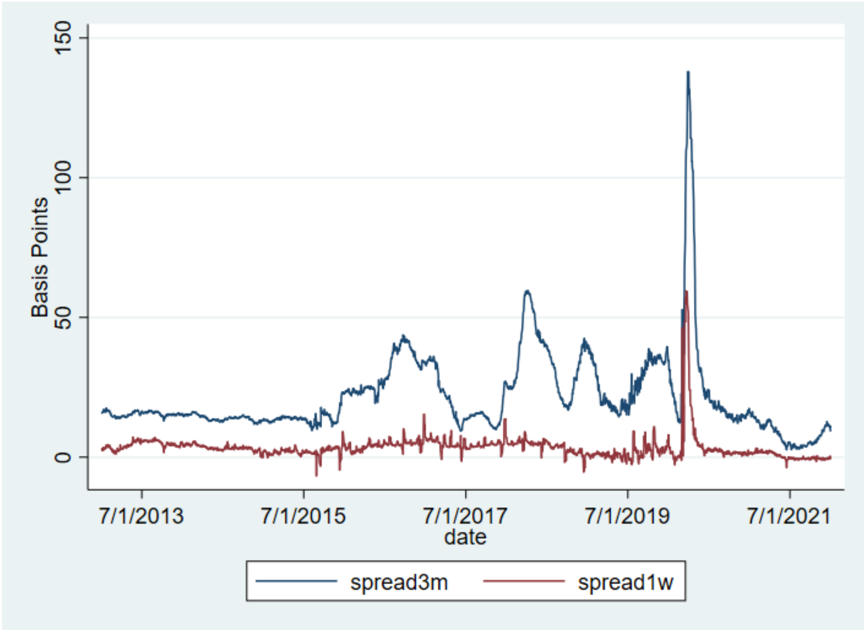
Andersen et al. (2019) demonstrate that the excess rate of return on a balance-sheet-expanding trade, which is necessary to offset the debt-overhang costs to shareholders, is directly proportional to the bank's unsecured credit spreads. Given this, one might have expected that the impact of debt overhang on trading markets would have significantly diminished since the Great Financial Crisis due to the substantial increases in bank capitalization mandated by regulators. These increases in capital have greatly reduced the risk of bank insolvency. As a bank's debt becomes more secure, the potential for creditors to benefit from further improvements in the credit quality of their claims associated with financing new asset purchases should decrease. Consequently, debt overhang would be expected to be lower. However, contrary to this expectation, bank debt overhang is actually more pronounced now than it was before the Great Financial Crisis, because bank credit spreads are higher, not lower, than their pre-crisis levels.

When applying credit spread as a proxy for debt overhang in the context of Covered Interest Rate Parity (CIP), several considerations come into play: (1) As credit spreads widen, interest rate differentials between the higher-yielding and lower-yielding bonds increase. This can impact the interest rate differentials used in CIP calculations. The spread may reflect concerns about the ability of the country with higher credit risk to meet its debt obligations, influencing investor behaviour and market dynamics. (2) In the context of CIP, a widening credit spread can contribute to deviations from the parity condition. If the credit spread reflects concerns about sovereign risk and the potential for default, it can influence both interest rates and exchange rates. The deviation from CIP may occur as the relationship between interest rate differentials and forward premiums or discounts is affected by changes in perceived credit risk. (3) An increasing credit spread may trigger a flight to safety, where investors move towards assets perceived as less risky. In the context of sovereign bonds, this could involve a shift towards bonds from countries with lower credit risk. Flight to safety dynamics can impact exchange rates and interest rate differentials, influencing deviations from CIP. (4) Widening credit spreads may prompt central banks and policymakers to respond with monetary or fiscal measures to address concerns about debt sustainability. These responses can, in turn, influence interest rates and exchange rates, impacting the relationship between the variables used in CIP calculations. (5) Changes in credit spread can influence market expectations about future economic and financial conditions. These expectations can impact forward rates used in CIP calculations, contributing to deviations from the parity condition.

It's important to note that while credit spread can serve as a useful indicator of debt-related concerns,so We use dollar Libor-OIS with different maturities (short-term) to measure large U.S. bank credit spreads. Other factors also contribute to deviations from CIP. These factors include liquidity constraints, market segmentation, political risk, and global economic conditions. The use of credit spread as a proxy for debt overhang in the context of CIP analysis should be complemented by a broader assessment of relevant market and economic factors.

As depicted in Figure 4.4, wholesale bank credit spreads exhibit a significant elevation above their pre-crisis levels, despite improvements in capital levels. This heightened major-bank credit spread profile is

Figure 4.4: Three-Month and One-Week Credit Spread



Notes: This figure shows three-month and one-month credit spread from 2013 to 2021. The credit spread is defined by the different between Libor interest rate and OIS interest rate for dollars (Duffie, 2017).

evident across all maturities. This study employs the five-year Credit Default Swap (CDS) spread data from the top-largest U.S. banks. Figure 4.2 illustrates the substantial post-crisis surge in short-term unsecured credit spreads, represented by 3-month and 1-week credit spreads for dollars. This outcome aligns with the findings of Duffie (2017), prompting us to consider credit spreads as a crucial factor driving deviations from covered interest rate parity.

4.3.3 Other Factors for Deviations from Covered Interest Rate Parity

Deviations from Covered Interest Rate Parity (CIP) can occur due to a variety of factors, reflecting the complexities and frictions present in financial markets. Deviations from Covered Interest Rate Parity are influenced by a combination of market frictions, risk factors, and unexpected events that can impact the relationship between interest rates and exchange rates in the short term. Market participants and policymakers closely monitor these factors to assess the potential for deviations and their implications for investment strategies and economic conditions.

For example, here are some key factors: (1) Market Expectations: Investor expectations and sentiment play a crucial role. If market participants anticipate changes in economic conditions, interest rates, or geopolitical events, it can lead to deviations from CIP. (2) Risk Premiums: Investors may demand a risk premium to compensate for uncertainties, including credit risk, liquidity risk, or political risk. Higher perceived risk can lead to deviations from CIP. (3) Transaction Costs: Transaction costs, such as bid-ask spreads and fees, can impact the effectiveness of arbitrage and contribute to deviations from CIP. (4) Liquidity Constraints: Market participants may face liquidity constraints, limiting their ability to engage in arbitrage transactions and narrowing the scope for interest rate differentials to equate with forward and spot exchange rates. (5) Regulatory Restrictions: Regulatory constraints on capital movements, currency controls, or other regulatory measures can limit the effectiveness of arbitrage and contribute to deviations from CIP. (6) Market Interventions: Central banks or other market participants may intervene in the foreign exchange market to stabilize or influence their currency's value, impacting the relationship between interest rates and exchange rates. (7) Market Frictions: Various market frictions, such as imperfect information, asymmetric information, or delayed adjustment to new information, can contribute to deviations from CIP. (8) Forward Rate Bias: Empirical evidence suggests the existence of a forward rate bias, where forward rates might not fully reflect future spot rates. This bias can contribute to deviations from CIP. (8) Inflation Differentials: Differences in inflation rates between two countries can impact real interest rates and contribute to deviations from CIP. (9) Credit Ratings and Default Risk: Variations in credit ratings and default risk for different countries can influence interest rate differentials and contribute to deviations from CIP. (10) Global Economic Conditions: Broader economic conditions, such as global economic growth, monetary policy stances of major central banks, and trade dynamics, can influence interest rates and contribute to deviations from CIP.

Hence, discrepancies from Covered Interest Rate Parity (CIP) can be influenced by a myriad of factors, signifying market inefficiencies and potential arbitrage opportunities. In this context, we not only explore the impact of debt overhang but also introduce various control variables that might contribute to substantial deviations in CIP basis. The definitions for each variable are outlined in Table 4.1.

4.4 Empirical Analysis: Debt Overhang and CIP Deviations

The relationship between debt overhang and deviations from Covered Interest Rate Parity (CIP) involves considerations related to financial stability, risk perception, and market dynamics. Debt overhang, which occurs when a government or entity has excessive debt that may be challenging to service, can influence investor perceptions of risk. If there are concerns about the ability of a country to manage its debt, investors may demand higher yields on its sovereign bonds, contributing to deviations from CIP.

In this section, we first investigate the strong relationship between the debt overhang and CIP deviations. Next, we explore that the debt overhang acts as a risk factor to price different levels of CIP deciations for

Table 4.1: Data Description

Variables	Definition
Libor-CIP	Libor-based deviations from covered interest rate parity
OIS-CIP	OIS-based deviations from covered interest rate parity
Repo-CIP	Repo-based deviations from covered interest rate parity
IOER-Libor	Basis by borrow U.S. at IOER and invest foreign currencies at Libor rate
IOER-OIS	Basis by borrow U.S. at IOER and invest foreign currencies at OIS rate
IOER-Repo	Basis by borrow U.S. at IOER and invest foreign currencies at Libor rate
Libor-OIS	Debt overhang measured by U.S. banks credit spread
Dollar Index	US trade-weighted broad dollar index from FRB
Spot	Exchange rate between dollar and foreign currencies
VIX	A measure of the stock market's expectation
Vol	Implied volatility on 3-month at-the-money currency options
RR	25-delta FX option risk reversal
Spread	Spread of the 10-year foreign Treasury yield over the 10-year U.S.
Slope	Difference between the foreign and the U.S. Treasury term spreads (10-year/2-year)

Notes: The table shows the dependent variable basis and potential determinants. Our sample is from 2013.1.1 to 2022.10.07. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Each proxy is assigned to the related category with the corresponding explanations. The dependent variables are CIP deviations based on different interest rates. Libor-CIP indicates the Libor cross-currency basis. OIS-CIP indicates the OIS cross-currency basis. IOER-Libor refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at Libor rate. Repo basis refers to repo cross-currency basis. IOER-OIS refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at OIS rate. IOER-Repo basis indicates the basis by borrowing in U.S. dollars at the excess reserves and invest foreign currency at the repo rate. The core independent variable is debt overhang and other indicators are regarded as control variables. I report 6 different specifications of the fixed effect regressions. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

all currencies.

4.4.1 Debt Overhang and the Libor Cross-currency Basis

We explore the relationship between the debt overhang and the cross-currency basis in the panel data using fixed effects model[3]. We regress changes in the cross-currency basis on changes in debt overhang and on changes in the dollar index. We consider daily changes in case of the three-month basis and control for

[3]Before we choose model, we do Hausman test between fixed effects model and random effects model. p-value=0.00, therefore, we use fixed effects model to do the regression.

other potential determinants. The regression [4] is

$$\Delta x_{i,t} = \alpha + \beta\Delta Debt_{i,t} + \gamma\Delta Dollar_{i,t} + \lambda Control_{i,t} + \epsilon_{i,t} \tag{4.4}$$

Where $\Delta x_{i,t}$ is the change in cross-currency basis of foreign currency i vs US dollar from 2013 to 2022. The indicator $\Delta Debt$ describes the changes in U.S. banks credit spread and $\Delta Dollar$ indicates the changes in the U.S. trade-weighted broad dollar index. The positive coefficients of these two variables denote increase in debt overhang and dollar appreciation. Control denotes all control variables, including spot exchange rate ($\Delta Spot$), VIX index (ΔVIX and $lnVIX$), implied volatility on 3-month at-the-money currency options (ΔVol), 25-delta FX option risk reversal (ΔRR), spread of the 10-year foreign treasury yield over the 10-year U.S. ($\Delta Spread$) and the difference between the foreign and the U.S. treasury term spreads (10-year over 2-year) ($\Delta Slope$)(Avdjiev et al., 2019).

Table 4.2 indicates our regression results for three-month cross-currency basis. We do regressions using daily changes in the three-month cross-currency basis on daily changes in the debt overhang and other control variables. $\Delta 3M$ is defined as 3-month debt overhang. The coefficient of $\Delta 3M$ is positive and significant in all specifications. The results show that an increase in debt overhang is associated with larger absolute value of cross-currency basis and greater CIP deviations. To be concrete, the coefficient estimate on $\Delta Debt$ in Column 1 implies that 1 percent increase of debt overhang is related to a 0.639 basis point increase of cross-currency basis-that is, large debt overhang causes a widening CIP deviations. After controlling other variables in Column (6), an one basis increase in debt overhang is associated with a 0.624 basis point decrease in cross-currency basis. However, in all other specifications (except Column (2) [5]), the coefficient of debt overhang is larger than that of other control variables. This results indicates the role of debt overhang as a significant driver of cross-currency basis.

According to control variables, we note that the broad dollar index is negatively with highly significance in all regressions. The coefficient of $\Delta Dollar$ in Column (6) shows that a one percent appreciation of the US dollar is related to a 0.403 basis point decrease in the Libor CIP basis. The level in VIX index enters significantly in our regression. Changes in the implied volatility of 3-month at-the-money currency options are significant and negatively correlated with changes in the Libor cross-currency basis. This result is consistent with our theory: higher currency volatility makes the VaR constraint more binding and reduces the risk-bearing ability of the financial intermediary. Besides, the (foreign currency over US Treasury) yield differential has a significantly positive impact on CIP deviations, because the nominal interest rate

[4] We test stationarity for each currency in Appendix 4.1.

[5] In Column (2), the coefficient of debt overhang is 0.639 which is only slightly lower than the absolute value of the coefficient of dollar index.

Table 4.2: Regressions of the Cross-Currency Basis on Debt Overhang and Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta D3M$	0.639***	0.639***	0.636***	0.636***	0.641***	0.624***
	(0.030)	(0.031)	(0.030)	(0.030)	(0.030)	(0.033)
$\Delta Dollar$		-0.760***	-0.617**	-0.577**	-0.423**	-0.403**
		(0.167)	(0.232)	(0.217)	(0.156)	(0.141)
$\Delta Spot$			-0.146	-0.146	-0.176	-0.137
			(0.115)	(0.113)	(0.157)	(0.148)
$lnVIX$				0.260**	0.255**	0.245**
				(0.083)	(0.084)	(0.081)
ΔVIX				-0.010***	-0.003	-0.003
				(0.002)	(0.002)	(0.002)
ΔVol					-0.074***	-0.074***
					(0.016)	(0.016)
ΔRR					0.719	0.683
					(1.078)	(1.061)
$\Delta Spread$						0.028
						(0.016)
$\Delta Slope$						-0.064**
						(0.025)
Currency FE	√	√	√	√	√	√
R^2	0.104	0.108	0.108	0.109	0.111	0.112
N	18351	17001	17001	17001	17001	17001

Notes: The table indicates regressions of changes in the 3-month Libor cross-currency basis and changes in debt overhang, dollar index together with other controls. Our main sample concentrates on the period from 2013.1.1 to 2022.10.07. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Currency fixed effects are included in all regressions. The dependent variables are CIP deviations based on 3-month Libor interest rates. The core independent variable is debt overhang and other indicators are regarded as control variables. I report 6 different specifications of the fixed effect regressions. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

differential in one of drivers of the basis (Du, Tepper and Verdelhan). The difference in the slope of the government bond yield curves between foreign countries and the US has a negative sign. However, spot rate, changes in VIX index and changes in FX option risk reversal have no significant influence on basis.

4.4.2 Quarter-End Effects on CIP Deviations

As of 2015, the leverage ratio had become a key regulatory metric for assessing a bank's capital adequacy. The leverage ratio is a non-risk-based measure that compares a bank's Tier 1 capital to its average total consolidated assets. It is designed to complement the risk-based capital ratios and act as a backstop to prevent excessive leverage within the banking sector.

According to the findings of Du et al. (2018), we find quarter-end effects of CIP basis. There are more quarter-end anomalies since January 2015, due to the change in the method used to calculate leverage ratios and the public disclosure of those ratios for European banks. To be concrete, as of 2015, the leverage ratio had become a key regulatory metric for assessing a bank's capital adequacy. The leverage ratio is a non-risk-based measure that compares a bank's Tier 1 capital to its average total consolidated assets. It is designed to complement the risk-based capital ratios and act as a backstop to prevent excessive leverage within the banking sector. Key points related to the leverage ratio calculation method and public disclosure for European banks in 2015 include (1) leverage ratio calculation method. The leverage ratio is calculated as the ratio of a bank's Tier 1 capital to its average total consolidated assets over a specified period. Tier 1 capital includes common equity Tier 1 (CET1) capital, which consists of common equity instruments and certain other instruments that represent the highest quality of capital. (2) regulatory minimum requirements. The CRR sets out the regulatory minimum requirements for the leverage ratio. European banks are required to maintain a leverage ratio above a certain threshold to ensure an adequate level of capital relative to their total assets. (3) monitoring and supervision. Regulatory authorities, including the European Banking Authority (EBA) and national competent authorities, are responsible for monitoring and supervising banks to ensure compliance with leverage ratio requirements.

Based on new bank regulation, We test whether quarter-end effects of CIP deviations can significantly impact the explanatory power of debt overhang on CIP deviations. Our simple fixed effect model for the one-week contract and one-month contract takes the form:

$$x_{1w,it} = \alpha_i + \beta_1 QendW_t + \beta_2 QendW_t * \Delta D1W + \beta_3 \Delta D1W + Controls + \epsilon_t \tag{4.5}$$

$$x_{1m,it} = \alpha_i + \beta_1 QendM_t + \beta_2 QendM_t * \Delta D1M + \beta_3 \Delta D1M + Controls + \epsilon_t \tag{4.6}$$

Where $x_{1w,it}$ and $x_{1m,it}$ are one-week and one-month cross-currency basis based on different interest rates for currency i at time t. α_i is a currency fixed effect. $\Delta D1M$ and $\Delta D1W$ mean debt overhang for one month and one week. The variable $QendW_t$ and $QendM_t$ is an indicator variable that equals one if the settlement date for the contract traded at time t is within the last week or last month of the current quarter and the maturity date is in the following quarter.

Table 4.3 indicates the regression results for 1-month and 1-week CIP basis. Columns (1) to (2) pertain to the one-month and 1-week CIP deviations based on Libor rates. In Column (1), the slope coefficients β_1

Table 4.3: Regressions of the Cross-Currency Basis with Quarter-End Effects

	1M Libor	1W Libor
$QendW_t$		1.276***
		(0.359)
$QendW_t * \Delta D1M$		-17.682***
		(4.349)
$QendM_t$	0.547**	
	(0.175)	
$QendM_t * \Delta D1W$	-0.066	
	(0.048)	
$\Delta D1M$	0.616 ***	
	(0.034)	
$\Delta D1W$		0.693***
		(0.079)
Controls	√	√
Currency FE	√	√
R^2	0.023	0.122
N	17001	15111

Notes: The table indicates regressions of changes in the 1-month and 1-week cross-currency basis together with other controls. Our main sample concentrates on the period from 2013.1.1 to 2022.10.07. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Currency fixed effects are included in all regressions. The variable $QendW_t$ and $QendM_t$ is an indicator variable that equals one if the settlement date for the contract traded at time t is within the last week or last month of the current quarter and the maturity date is in the following quarter. Control Variables include dollar index, spot rate, CBOE Volatility Index (VIX), implied volatility on 3-month at-the-money currency options (Vol), 25-delta FX option risk reversal (RR), Spread of the 10-year foreign Treasury yield over the 10-year U.S (Spread) and Difference between the foreign and the U.S. Treasury term spreads (10-year/2-year) (Slope). Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

and β_3 are positive and statistically significant. The results shows that tightened balance sheet constraints at quarter-ends, caused by banking regulation, translate into wider CIP deviations during the postcrisis period. The quarter-end CIP deviation relative to the mean deviation in the rest of the quarter is on average 0.5 to 0.6 bps higher for the one-month contracts. However, the intersection of $QendM_t * \Delta D1M$ is insignificant which means that the month-end deviation cannot have profound impact on the explanatory power of debt overhang on CIP deviations. The rationale for this observation could be attributed to the stability of debt overhang throughout the month, with minimal fluctuations specifically at month-end. In such a scenario, the explanatory power of debt overhang may not be significantly affected by variations in Covered Interest Rate Parity (CIP) deviations during that particular period. Consequently, our continued focus remains on the week-end effect.

Column (2) pertains to the one-week CIP deviations. Again, we find that β_1 and β_3 are consistently significantly positive. For CIP deviations based on Libor rates, the week-end deviation relative to the rest of the quarter is on average 1 to 2 bps higher than month-week deviation. The result shows that debt overhang and quarter-end effects translate into wider CIP deviations for 1-week maturity. Furthermore, we note that the coefficients on $QendM_t * \Delta D1W$ is significantly negative, suggesting that the week-end deviation decreases the impact on the explanatory power of debt overhang on CIP deviations. The explanation for this phenomenon could be that financial markets tend to consider various factors during the week-end, including economic indicators, corporate earnings releases, and overall market trends. If other noteworthy events attract the market's focus, the influence of debt overhang on Covered Interest Rate Parity (CIP) violations may diminish during the week-end.

4.4.3 CIP Arbitrage Based on Different Borrowing Rates

Covered Interest Rate Parity (CIP) is a financial principle that suggests that the interest rate differential between two currencies should be equal to the forward premium or discount of the foreign exchange rate. Violations of CIP can present arbitrage opportunities for investors to take advantage of discrepancies in interest rates and currency values. The cross-currency basis refers to the difference between the foreign interest rate and the equivalent synthetic foreign rate derived from the domestic interest rate and the exchange rate. It is often quoted in basis points (bps). It is crucial to use rates that most accurately capture the marginal funding costs of critical arbitrageurs in interbank offered rates (IBOR) that is traditionally used for CIP calculations. Then, we turn to other interest rates, including interest rates on Overnight-Index-Swaps (OIS) contracts and General Collateral (GC) repo rates. A general collateral (GC) repo is a repurchase agreement in which the cash lender is willing to accept a variety of Treasury and agency securities as collateral. OIS swaps are generally very liquid and traded at a large range of maturities (unlike General Collateral (GC) repo rates). OIS rate is close to risk-free and do not include terms funding liquidity premia. The same applies to General Collateral (GC) repo rates. Besides, we use excess reserves (IOER) as benchmark rate. According to monetary policies by major central banks, depositary institutions have large amounts of excess reserves on major central banks. Excess reserves (IOER) are paid at a rate set by the central bank.

We construct cross-currency basis based on different borrowing rates: OIS-, IOER-Libor, Repo-, IOER-OIS and IOER-repo based cross-currency basis. To be concrete, x_t^{OIS} indicates the OIS cross-currency basis by borrowing at the U.S. dollar interest rate on OIS rate and invest the foreign currency at OIS rate. IOER-Libor refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at Libor rate. x_t^{Repo} refers to repo cross-currency basis. IOER-OIS refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at OIS rate. IOER-Repo basis indicates the basis by borrowing in U.S. dollars at the excess reserves and invest foreign currency at the repo rate.

Table 4.4: Three-Month Libor-, OIS-, Repo- and IOER-Based Basis

		x_t^{Libor}	x_t^{OIS}	IOER-Libor	x_t^{Repo}	IOER-OIS	IOER-Repo
AUD	Mean	5.180	3.624	-13.58		5.793	
	SD	(13.16)	(15.47)	(19.47)		(22.95)	
CAD	Mean	-28.29	-15.61	-47.05		-13.44	
	SD	(11.03)	(11.33)	(28.53)		(22.78)	
CHF	Mean	-9.524		-28.28	-26.87		11.144
	SD	(25.28)		(25.07)	(21.56)		(6.593)
DKK	Mean	-36.27	-33.23	-55.03	-28.94	-31.06	14.091
	SD	(17.08)	(17.19)	(24.67)	(25.03)	(24.99)	(6.205)
EUR	Mean	-12.09	-24.36	-30.85		-22.19	
	SD	(14.8)	(27.76)	(24.86)		(26.72)	
GBP	Mean	-7.765	-24.36	-26.52		-16.09	
	SD	(10.43)	(27.76)	(26.05)		(23.56)	
JPY	Mean	-21.62	-40.49	-40.37	-31.25	-38.32	8.454
	SD	(17.83)	(23.97)	(29.11)	(18.16)	(29.73)	(6.774)
NZD	Mean	5.344	0.484	-13.41		2.653	
	SD	(18.01)	(12.22)	(23.34)		(25.81)	
SEK	Mean	-15.31	-26.48	-34.07		-24.31	
	SD	(11.92)	(18.12)	(21.57)		(26.05)	

Notes: We investigate the 3-month cross-currency basis based pn Libor rates against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Columns (1) to (6) report the means and standard deviations for the three-month Libor and GC repo basis and IOER basis for different currencies during the 01/01/2013 to 07/10/2022 period. Column (1), denoted as x_t^{Libor}, indicates the Libor cross-currency basis. Column (2), denoted as x_t^{OIS}, indicates the OIS cross-currency basis. Column (3), IOER-Libor, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at Libor rate. Column (4), x_t^{Repo}, refers to repo cross-currency basis. Column (5), IOER-OIS, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at OIS rate. Column(6), IOER-Repo basis, indicates the basis by borrowing in U.S. dollars at the excess reserves and invest foreign currency at the repo rate. Standard errors are reported in parentheses.

Table 4.4 indicates descriptive statistics for the three-month cross-currency basis based on different borrowing rates for our sample of 9 currencies vis-à-vis the US dollar. The cross-currency basis based on different interest rate is defined as the difference between the US borrowing rate and the implied dollar interest rate by swapping foreign currency into dollars. The mean three-month Libor, OIS and IOER-Libor CIP basis is only positive for the Australian dollar and the New Zealand dollar, but negative for all other currencies, ranging from -7.8 to -36.3 basis points. The mean IOER-Libor basis is generally negative for other currencies. The negative basis indicates that the dollar interest rate in the cash market is lower than the implied dollar interest rate in the forrign exchange market. Therefore, the banks could make arbitrage benefits by borrowing dollars in the cash market and lending dollars in the swap market.

Table 4.5: Regressions of the Cross-Currency Basis on Debt Overhang and Control Variables

	x_t^{Libor}	x_t^{OIS}	IOER-Libor	IOER-OIS	x_t^{Repo}	IOER-Repo
$\Delta D3M$	0.624^{***}	0.285^{***}	0.172^{***}	0.256^{***}	0.252^{***}	0.149^{*}
	(0.033)	(0.040)	(0.035)	(0.044)	(0.047)	(0.044)
Controls	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Curr FE	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
R^2	0.112	0.031	0.018	0.023	0.027	0.027
Obs	17001	15112	17001	15112	5667	5667

Notes: The table indicates regressions of changes in the 3-month cross-currency basis and changes in debt overhang, dollar index together with other controls. Our main sample concentrates on the period from 2013.1.1 to 2022.10.07. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Currency fixed effects are included in all regressions. Control Variables include dollar index, spot rate, CBOE Volatility Index (VIX), implied volatility on 3-month at-the-money currency options (Vol), 25-delta FX option risk reversal (RR), Spread of the 10-year foreign Treasury yield over the 10-year U.S (Spread) and Difference between the foreign and the U.S. Treasury term spreads (10-year/2-year) (Slope). Column (1), denoted as x_t^{Libor}, indicates the Libor cross-currency basis. Column (2), denoted as x_t^{OIS}, indicates the OIS cross-currency basis. Column (3), IOER-Libor, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at Libor rate. Column (4), IOER-OIS, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at OIS rate. Column (5), x_t^{Repo}, refers to repo cross-currency basis. Column(6), IOER-Repo basis, indicates the basis by borrowing in U.S. dollars at the excess reserves and invest foreign currency at the repo rate. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.5 indicates the highly positive correlation between changes in the cross-currency basis (based on different benchmark rates) and 3 month debt overhang. The impact of the debt overhang is not restricted to Libor CIP basis. We obtain similar results for OIS-, repo-, IOER-based CIP. The coefficient on $\Delta D3M$ is significantly positive in all regressions, which is close to 1. After considering all controls, we find that a one percentage increase on 3 month debt overhang corresponds to about 1 basis point increase in the 3 month OIS-, repo-, IOER-based CIP. The explanatory power of debt overhang on cross-currency basis is not only significant statistically but also economically meaningful.

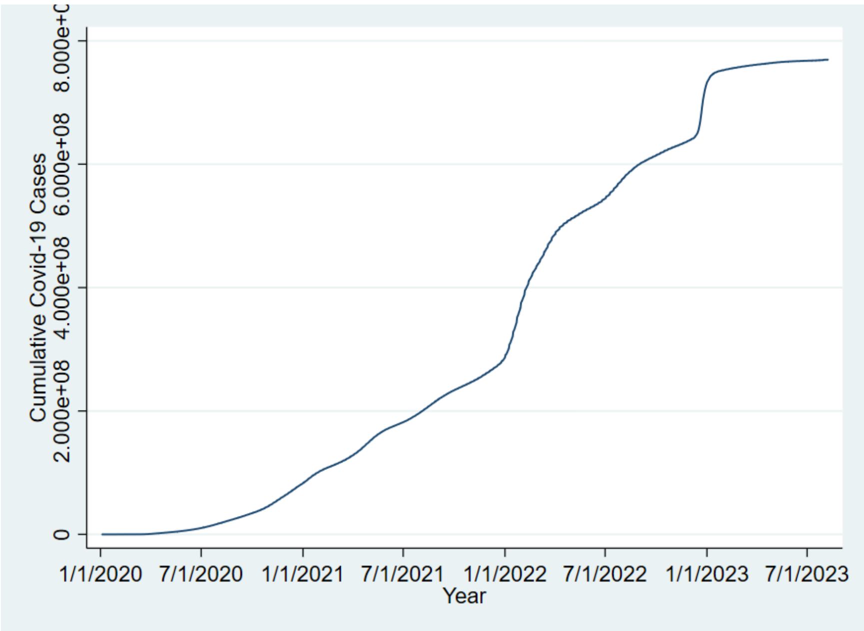
4.4.4 Robustness Test Following 2020 Covid-19 Crisis

Conducting a robustness test following the 2020 COVID-19 crisis involves analyzing the impact of the pandemic on financial markets, individual securities, and economic variables. Robustness tests typically focus on identifying abnormal returns or changes in financial metrics surrounding a specific event.

In the context of the relationship between debt overhang and deviations from Covered Interest Rate Parity (CIP), a robustness test could be employed to assess how specific events related to debt overhang influence currency markets and the observed deviations from CIP. The COVID-19 crisis, which emerged in 2019 and led to a global pandemic, had profound and multifaceted effects on financial markets, economies, and government policies. Examining the relationship between debt overhang and deviations from Covered Interest Rate Parity (CIP) during the COVID-19 crisis involves understanding the impact of the crisis on sovereign debt dynamics and currency markets.

The sample covers the period from 2013 to 2022, including Covid-19 crisis. We assume that Covid-19 pandemic case may increase the impact of debt overhang on CIP deviations. Therefore, we compare the relationship between three-month cross-currency basis and debt overhang beta between full sample and the subsample during Covid-19 crisis. Figure 4.5 describes the cumulative Covid-19 cases worldwide from WHO database from 2020 to 2023. The largest growth rate of cases can be found from January 2022 to March 2022, which means Covid-19 crisis may have the greatest impact on society. Therefore, we choose Covid-19 crisis as an important signal from 14 January 2022 to 1 March 2023.

Figure 4.5: Cumulative Covid-19 Cases Worldwide



Notes: This figure reports cumulative Covid-19 cases worldwide from 2020 to 2023. The growth rate is highest on first two months of 2022.

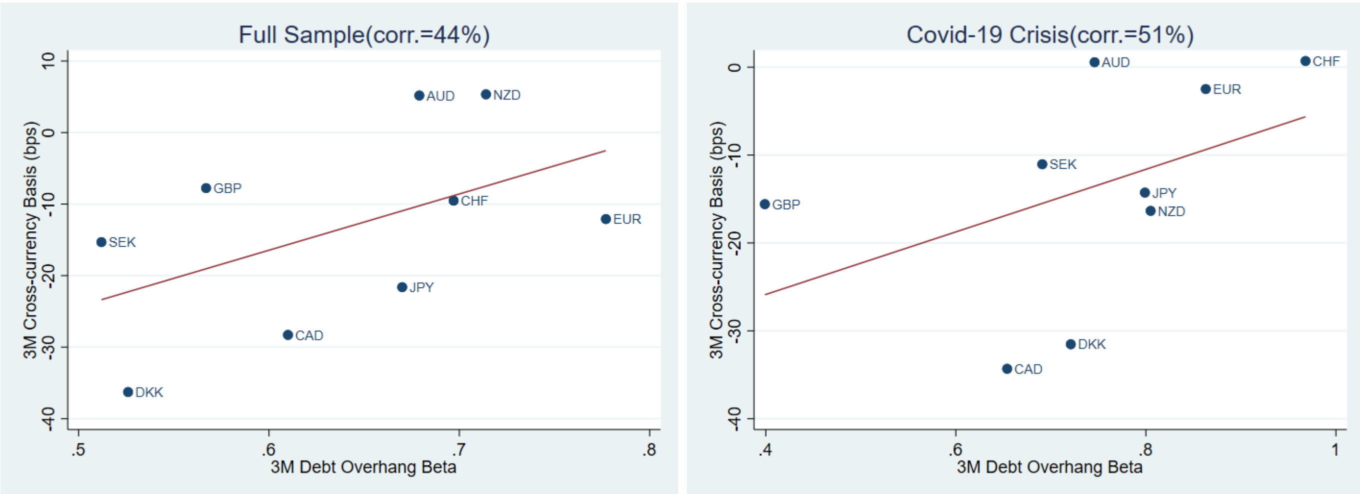
In this paper, we conclude that debt overhang differential can explain the magnitude of the cross-currency basis. We first examine currency-specific factors on the influence of debt overhang.

$$\Delta x_{i,t} = \alpha + \beta \Delta Debt_{i,t} + \epsilon_{i,t} \tag{4.7}$$

Where $\Delta x_{i,t}$ is the change in 3-month cross-currency Libor basis of each currency i. We do daily regressions to estimate debt overhang beta. The debt overhang beta represents the impact of debt overhang on CIP violations. The higher debt overhang beta lead to the larger the influence of debt overhang on CIP violations.

Table 4.6 presents debt overhang beta for whole sample and Covid-19 crisis period. The debt overhang beta is significant for all currencies and all samples. However, the debt overhang beta during Covid-19 crisis is higher than that in full sample, which means Covid-19 crisis can strengthen the explanatory power of debt overhang on CIP deviations. Figure 4.6 plots the relationship between mean 3-month cross-currency basis and debt overhang beta. We can see a significantly positive relationship between average basis and debt overhang beta and the correlation equals to 44% and 51% for full sample and Covid-19 crisis respectively. The correlation coefficient is higher with the basis during Covid-19 crisis. Therefore, these findings suggest that debt overhang is a risk factor in CIP arbitrage returns. The explanatory power of debt overhang during Covid-19 crisis is higher than that in full sample. The results are consistent with Table 4.6.

Figure 4.6: Cross-Currency Basis vs. Debt Overhang Beta



Notes: This figure reports the cross-currency relationship between 3-month cross-currency basis based on Libor rates on the y-axis and debt overhang beta on the x-axis. The left panel shows the whole sample from 2013 to 2022. The right panel focuses on Covid-19 crisis period.

Table 4.6: Debt Overhang Beta by Country

	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NZD	SEK
					Full Sample				
$\Delta D3M$	0.679***	0.610***	0.697***	0.526***	0.777***	0.567***	0.670***	0.714***	0.512***
	(0.047)	(0.058)	(0.109)	(0.073)	(0.102)	(0.081)	(0.158)	(0.057)	(0.092)
					Covid-19 Crisis Period				
$\Delta D3M$	0.746***	0.654***	0.968***	0.721***	0.863***	0.399***	0.799***	0.805***	0.691***
	(0.058)	(0.093)	(0.059)	(0.053)	(0.054)	(0.063)	(0.083)	(0.050)	(0.064)

Notes: This table shows the coefficients of debt overhang on changes in 3-month Libor-based cross-currency basis for G9 currencies at daily frequency respectively. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Robust standard errors are in parentheses. The first panel reports the regression from 2013 to 2022. The second regression shows results during Covid-19 crisis. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Besides, the debt overhang beta also can be defined as the ratio of the change in the three-month cross-currency basis (in basis points) over changes in the debt overhang (in basis points). As shown in Table 4.7, the 3-month debt overhang rises 6.497 basis points between 14 January 2022 and 1 March 2023. The cross-currency basis widened for all 9 currencies during the same time. The smallest movement is for the Australian dollar from 1.068 basis points to -6.580 basis points. The reason is that AUD basis is relatively small itself. Consistent with the previous finding, the debt overhang beta during Covid-19 crisis in Table 4.6 is also larger than that in full sample.

Table 4.7: Robustness Test

Currency	14/01/2022	01/03/2022	Change (abs.)	Debt Overhang Beta
Debt Overhang	6.489	12.986	6.497	
AUD	1.068	-6.580	7.647	1.177
CAD	-22.5548	-51.463	28.909	4.450
CHF	3.020	-16.384	19.404	2.987
DKK	-27.387	-49.421	22.035	3.391
EUR	2.506	-22.350	24.857	3.826
GBP	-10.680	-31.651	20.971	3.228
JPY	-9.423	-27.527	18.104	2.786
NZD	-11.382	-21.530	10.148	1.562
SEK	-8.885	-24.838	15.953	2.455

Notes: The Table reports changes in debt overhang and 3-month cross-currency basis since the large growth rate in Covid-19 cases.We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). The debt overhang beta is computed as the ratio of changes in the three-month cross-currency basis over changes in the debt overhang between 5 January and 4 February 2022.

4.5 Empirical Analysis: Debt Overhang and Carry Trade

In this section, we link the carry trade to debt overhang. The relationship between debt overhang and the carry trade involves considerations related to interest rate differentials, risk appetite, and investor behavior. Debt overhang may be associated with countries facing economic challenges, leading to lower interest rates as policymakers implement accommodative monetary policies. Carry trade strategies involve borrowing in low-interest rate currencies and investing in higher-yielding ones. Countries with debt overhang may be perceived as riskier, affecting investor risk appetite. Carry trade strategies involve taking advantage of interest rate differentials, but the risk of adverse currency movements can be significant, especially in risk-off environments. We introduce a "forward CIP trading strategy" to identify the currency risk for carry trade. By this strategy, we need to describe two different basis: spot CIP basis and forward CIP basis, then go long in high-interest-rate currencies (AUD, CAD and GBP) and take short position in low-interest-rate currencies (DKK, EUR and JPY) respectively.

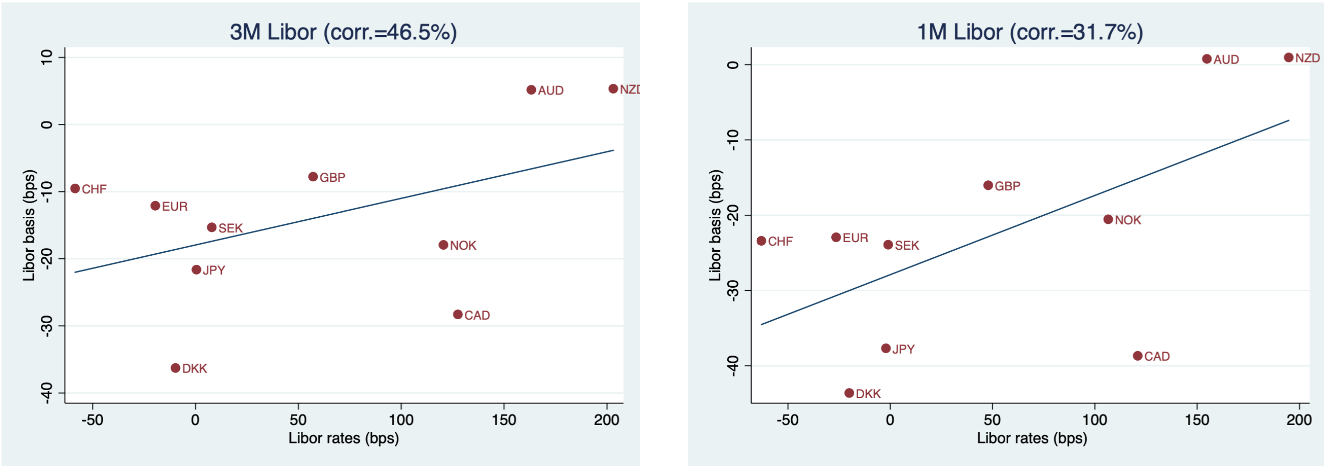
Our main sample focuses on the post-GFC period, which features a non-risk weighted leverage ratio constraint under the Basel III regulatory environment. This stands in sharp contrast to the pre-GFC and GFC samples, during which bank capital constraints were largely based on risk and riskless short-term CIP arbitrages faced no capital charge. An important lesson from the GFC turmoil was that the ex ante risk weights could inaccurately reflect risk, and in 2010 the non-risk-weighted leverage ratio requirement was drafted as an important pillar of Basel III. Since then, the Basel III regulations have been finalized and gradually implemented. Even before the final rules took effect, early compliance of Basel III was common among large banking organizations, as it takes time to reorganize complex business activities. Regulators and bank shareholders may also have taken Basel III regulatory metrics into account even before the regulations were formally implemented. CIP deviations also widened significantly during post-crisis period and we get positive excess return of forward CIP trading strategy.

4.5.1 Cross-Currency Basis and Nominal Interest Rates

The cross-currency basis refers to the difference in the interest rates between two currencies after accounting for the currency basis swap. It is a measure of the cost or benefit associated with swapping one currency for another while simultaneously engaging in a currency swap to convert the principal and interest payments back into the original currency. The cross-currency basis is influenced by various factors, including nominal interest rates in both currencies. The cross-currency basis is closely related to the interest rate differentials between two currencies. Nominal interest rates represent the cost of borrowing or the return on investment in a particular currency. Differences in nominal interest rates between two currencies contribute to the cross-currency basis.

According to Du et al. (2018), large cross-currency basis represents arbitrage opportunities. To be concrete, arbitrageurs have large supply for investments in high-interest rate currencies, such as the Australian and New Zealand dollars, and large demand of savings in low-interest-rate currencies, such as the Japanese yen and Swiss franc. For example, arbitrageurs may sell high-interest-rate currencies and buy low-interest-rate currencies for carry trade. Meanwhile, financial intermediaries provide currency hedging and are not willing to undertake currency risk. Therefore, financial intermediaries take long position in low-interest-rate currencies and short in high-interest-rate currencies to hedge the currency exposure in cash market. The profit is defined as the absolute value of cross-currency basis, compensating the financial intermediaries for the cost of capital during trade.

Figure 4.7: Cross-Sectional Variations in Cross-Currency Basis, 2013-2022



Notes: This figure shows the cross-currency relationship between various cross-currency bases on the y-axis and nominal interest rates on the x-axis. The left panel shows the relationship for three-month Libor and the right panel shows the relationship for one-month Libor.

We first investigate a cross-sectional relationship between nominal interest rates and cross-currency basis with different maturities. Figure 4.7 plots the mean cross-currency basis as a function of average nominal interest rates between 2013 and 2022. The Libor cross-currency basis is positively correlated with Libor with 10 currencies at one and three month. Besides, The correlation is particularly strong at three month (long maturities), about 50% for G10 currencies. Based on Figure 4.7, we find that low interest-rate currencies tend to have larger absolute value of cross-currency basis and high interest-rate currencies tend to have smaller basis.

4.5.2 Spot CIP Basis

The Spot Covered Interest Rate Parity (CIP) Basis, also known as the Spot CIP Basis, is a measure that reflects the deviation between the spot exchange rate and the rate implied by interest rate differentials according to the Covered Interest Rate Parity principle. Covered Interest Rate Parity suggests that the spot exchange rate should reflect the interest rate differentials between two currencies. We define β-month spot cross-currency basis of foreign currency c vis-à-vis the USD, $x_{t,0,\beta}^{c,USD}$, following Du et al. (2018). The CIP condition is a no-arbitrage condition if $x_{t,0,\beta}^{c,USD}$ equals zero. We choose OIS rates as our proxy for benchmark interest rate. If the Spot CIP Basis is positive, it suggests that the actual spot exchange rate is higher than the rate implied by interest rate differentials. Otherwise, this condition is known as a negative basis. A Spot CIP Basis of zero implies that the actual spot exchange rate aligns exactly with the rate implied by interest rate differentials, consistent with the Covered Interest Rate Parity condition.

The Spot Covered Interest Rate Parity (CIP) Basis for two non-USD currencies can be calculated similarly to the formula mentioned earlier, with the primary difference being that you are considering two non-U.S. currencies. We extend this CIP basis to spot cross-currency basis between two non-USD currencies c_1 and c_2. The equations is

$$x_{t,0,\beta}^{c_1,c_2} = x_{t,0,\beta}^{c_1,USD} - x_{t,0,\beta}^{c_2,USD} \tag{4.8}$$

$x_{t,0,\beta}^{c_1,c_2}$ is the difference in two foreign currencies, c_1 and c_2, spot cross-currency basis vis-à-vis the USD. We use this definition to construct the cross-currency basis between c_1 and c_2.

4.5.3 Forward CIP Basis

The Forward Covered Interest Rate Parity (CIP) Basis is a measure that reflects the deviation between the forward exchange rate implied by interest rate differentials and the actual forward exchange rate in the market. In theory, according to Covered Interest Rate Parity, interest rate differentials between two currencies should be offset by the forward premium or discount on the exchange rate. However, deviations from this relationship can occur, leading to a Forward CIP Basis. In order to hedge currency risk, we start to create currency portfolio and using 'forward CIP trading strategies'. Forward CIP trade is conducted by using FX forwards and forward-starting interest rate swaps, and then unwound at the forward starting date. For example, a trader enters into a forward-starting CIP trade and take long position in Swiss franc (low-interest-rate currencies) and short Australian dollars (high-interest-rate currencies) for three months from t+1 to t+4 and hedge the currency risk. This trade is associated with a one-month forward three-month CIP trade. To be concrete, one month later, a trader will go long Australian dollars and short Swiss franc for three months and then unwind the forward CIP trade. All cash flows will be eliminated by this strategy. The profits of forward CIP trading strategies are related to the difference between the market-implied one-month forward three-month CIP deviation observed at present and the actual three-month CIP deviation realized one month later.

According to Du et al. (2023), at time t, we can define the α-month forward β-month cross-currency basis based on two spot cross-currency basis [6] under the assumption of no-arbitrage between foreign currencies and U.S. dollars:

$$x_{t,\alpha,\beta}^{c,USD} = \frac{\alpha + \beta}{\beta} x_{t,0,\alpha+\beta}^{c,USD} - \frac{\alpha}{\beta} x_{t,0,\alpha}^{c} \tag{4.9}$$

Based on Equation (8), we define the forward cross-currency basis between two non-USD foreign currencies

[6] We calculate spot cross-currency basis following Du et al. (2018)

c_1 and c_2 as

$$x^{c_1,c_2}_{t,\alpha,\beta} = x^{c_1,USD}_{t,\alpha,\beta} - x^{c_2,USD}_{t,\alpha,\beta} \tag{4.10}$$

We then investigate the term structure of CIP violations- the cross-currency forward basis. We create forward CIP basis of many different time α and tenors β. In this paper, we adopt different OIS tenors- 1M, 2M, 3M, 4M, 6M, 9M, and 12M. In Figure 4.6, we present the forward curves of AUD, CAD, DKK and NZD (example) vs the USD for many horizons and tenors. The tenor β of these forward CIP trades differs from one month and increasing to three months.

We show forward CIP basis curves using averages for four currencies, AUD, CAD, DKK and NZD (example). These four currencies have large positive or negative spot cross-currency basis after financial crisis. Based on four currencies, we divide the whole sample into three sub-samples according to 25th percentile, 50th percentile and 75th percentile. We then calculate average of spot and forward cross-currency basis within three sub-samples. In Figure 4.8, we conclude that forward cross-currency basis tends to be positive than spot cross-currency basis for AUD, CAD and NZD. However, the forward cross-currency basis is smaller for DKK. The fact is analogous to the trend of upward sloping term-structure of interest rates.

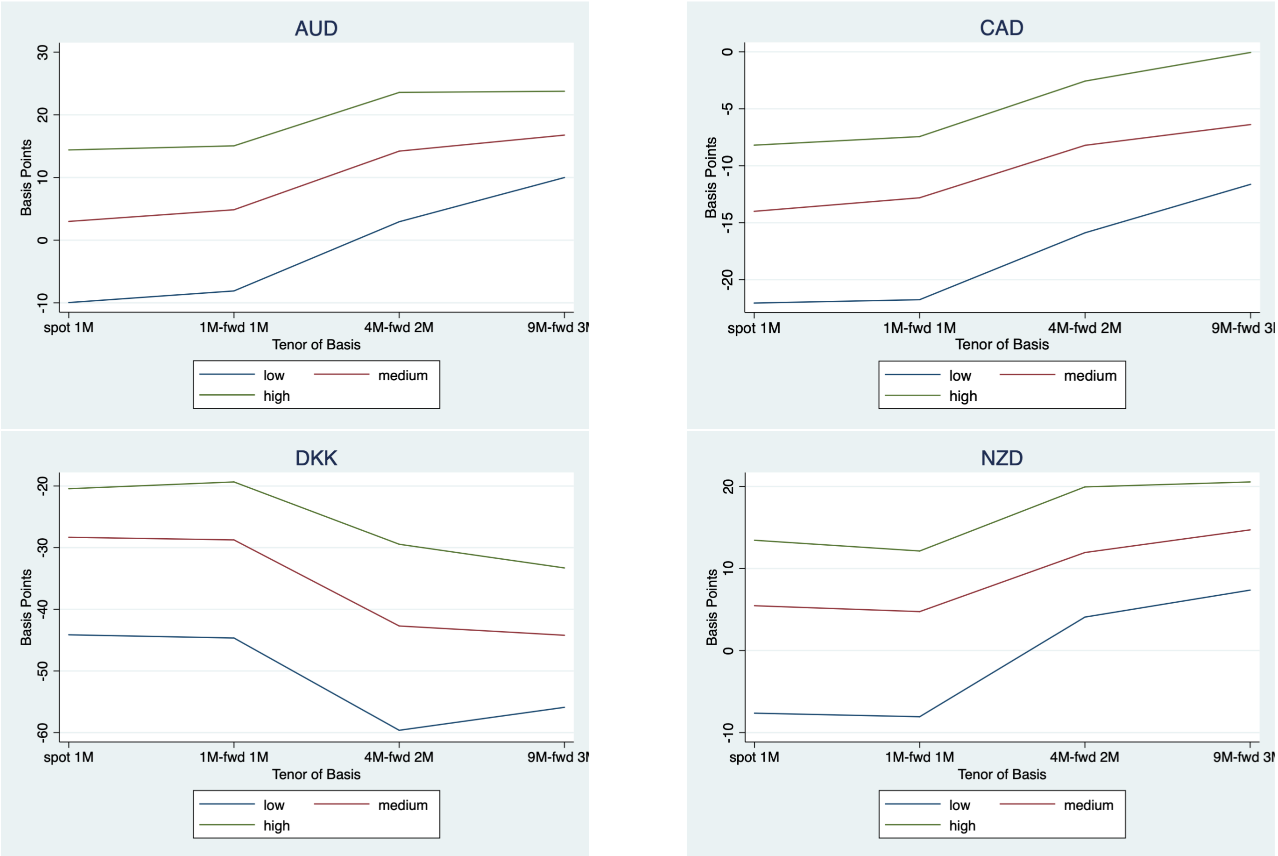
4.5.4 Portfolio Forward CIP Trading Strategies

Implementing portfolio forward Covered Interest Rate Parity (CIP) trading strategies involves capitalizing on interest rate differentials between two currencies by using forward contracts. CIP suggests that the interest rate differential should be equal to the forward premium or discount in the foreign exchange market. Deviations from CIP may present opportunities for profitable trades. Forward CIP deviations are associated with the return of forward CIP trading strategy. To be concrete, large positive CIP deviations shows constrained financial intermediaries and forward CIP trading strategy is not much profitable due to these constraints. Therefore, in general, we can expect positive excess returns from forward CIP trading to compensate investors for bearing the risk exposure of intermediary. The return of forward CIP trading strategy will be positive (negative) if the future CIP deviation is smaller (bigger) than the market-implied forward CIP deviation today.

The excess return from this trading strategy is a difference between α-fwd β forward cross-currency basis and actual spot cross-currency basis after α months. According to Du et al. (2023), the excess return is

$$\pi^{c_1,c_2}_{t+\alpha,\alpha,\beta} = \frac{\beta}{\alpha}(x^{c_1,c_2}_{t,\alpha,\beta} - x^{c_1,c_2}_{t+\alpha,0,\beta}) \tag{4.11}$$

Figure 4.8: Spot and Forward CIP Basis, 2013-2022



Notes: This figure illustrates the time series average spot and forward cross-currency bases in AUD, CAD, DKK and NZD, vis-à-vis the USD. For each currency, the sample from January 2013 to October 2022 is split into three subsamples based on 25th percentile, 50th percentile and 75th percentile. Within each sub-sample, the time series average of the relevant spot/forward OIS cross-currency basis is shown.

The focus of the forward CIP trading strategy is to investigate whether forward cross-currency basis will be higher or lower than actual spot cross-currency basis after α months. If the difference is greater than zero, we will gain from forward CIP trading strategy. Meanwhile, financial intermediaries will predict that whether constraints will be tighter or looser in the future according to this strategy. Initially, we investigate the individual excess returns of forward Covered Interest Rate Parity (CIP) trading. Our analysis focuses on the excess returns observed in specific individual currencies against the USD within cross-currency pairs. As depicted in Table 4.8, the sign of a currency's forward CIP trading profits varies and is influenced by country characteristics. Specifically, AUD, CAD, GBP, and NZD exhibit positive excess returns from forward CIP arbitrage profits, while EUR, DKK, and JPY display negative excess returns. This divergence can be attributed to the nature of the forward CIP trading strategy, which involves taking long positions in high-interest-rate currencies and short positions in low-interest-rate currencies. Referring to the data in Column (4) of Table 4.8, we observe that the OIS rates for AUD, CAD, and NZD are higher than the USD OIS rate, contributing to positive excess returns. In contrast, the OIS rates for EUR, DKK, and JPY are lower than the USD OIS rate, resulting in negative excess returns for these currency pairs.

Furthermore, Column (5) illustrates that AUD, CAD, and NZD exhibit an upward-sloping CIP term structure on average, while DKK, EUR, and JPY display a downward-sloping CIP term structure on average. This observation aligns with the term structure depicted in Figure 4.8.

Table 4.8: Summary Statistics of Returns on OIS 1M-fwd 3M Forward CIP Trading Strategy

	Mean	Sharpe Ratio	Avg. Basis	Avg. Diff.	Avg. Slope
AUD-USD	13.683	0.940	2.865	0.662	4.578
CAD-USD	7.678	0.680	-15.873	0.163	2.436
DKK-USD	-9.556	-0.531	-33.368	-1.112	-3.568
EUR-USD	-7.967	-0.263	-24.909	-1.057	-1.443
JPY-USD	-6.584	-0.286	-40.972	-0.791	-2.484
NZD-USD	12.068	1.081	-0.652	1.094	3.803

Notes: This table shows the annualized profits and Sharpe ratios of the OIS 1M-forward 3M forward CIP trading strategy. "Mean" is the annualized profit from the forward CIP trading strategy; "Avg. Basis" is the average 1M-forward 3M OIS cross-currency basis; "Avg. Diff." is the average spread between the 3M foreign OIS rate and the US OIS rate. Our sample are from 2013 to 2022; "Avg. Slope" is is the average spread between the 1M-forward 3M and spot 3M OIS cross-currency basis.

We do an additional regression to study the impact of debt overhang on excess return of forward CIP trading. Table 4.9 summarizes that the coefficient on $\Delta D3M$ is significantly positive in all regressions. After all other variables are controlled for, we find that a one percentage increase on 3 month debt overhang corresponds to above 1 basis point increase in the excess return by using forward CIP strategy. The predictive power of debt overhang on forward CIP strategy profits is not only significant statistically but also economically meaningful.

4.6 Robustness

4.6.1 Return of Forward CIP Trading Strategy and CIP Deviations

To validate the robustness of our findings, we conduct additional tests examining excess returns between non-USD currency pairs and the Covered Interest Rate Parity (CIP) basis. In this analysis, we adopt a long position in high-interest-rate currencies (specifically AUD, CAD, and GBP) and a short position in low-interest-rate currencies (specifically DKK, EUR, and JPY). The former group is referred to as "investing currencies," while the latter is designated as "funding currencies" in the context of unhedged foreign exchange carry trade.

During the post-crisis period, we observe that "investing currencies" tend to depreciate, while "funding currencies" appreciate. Consequently, CIP deviations make "funding currencies" more attractive for con-

Table 4.9: Regressions of the Forward CIP Strategy Profits on Debt Overhang and Control Variables

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta D3M$	1.019**	0.991**	0.983**	0.955**	1.083***	1.091***
	(0.348)	(0.341)	(0.346)	(0.346)	(0.246)	(0.233)
$\Delta Dollar$		1.655	2.433	1.533	0.186	0.559
		(0.861)	(1.220)	(1.457)	(2.459)	(2.371)
$\Delta Spot$			-0.639	-0.681	1.056	0.590
			(0.883)	(1.095)	(2.101)	(2.139)
$lnVIX$				-5.464*	-4.056	-4.290
				(2.491)	(3.735)	(4.389)
ΔVIX				0.136**	0.109	0.102
				(0.047)	(0.055)	(0.057)
ΔVol					0.392	0.450
					(0.340)	(0.331)
ΔRR					-20.75**	-20.40**
					(6.163)	(5.907)
$\Delta Spread$						-0.116
						(0.090)
$\Delta Slope$						-0.347***
						(0.069)
Currency FE	√	√	√	√	√	√
R^2	0.115	0.121	0.122	0.131	0.176	0.187
N	690	666	666	666	666	666

Notes: The table indicates regressions of monthly changes in the 3-month Libor cross-currency basis and changes in debt overhang, dollar index together with other controls. Our main sample concentrates on the period from 2013 to 2022. We investigate the cross-currency basis against dollar for six more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD). Currency fixed effects are included in all regressions. The dependent variables are excess return by adopting forward CIP strategy based on 3-month OIS interest rates. The core independent variable is debt overhang and other indicators are regarded as control variables. I report 6 different specifications of the fixed effect regressions. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

structing a synthetic dollar, leading to more negative cross-currency basis (indicative of higher synthetic dollar interest rates). As presented in Table 4.10, the excess return of the forward CIP trading strategy is consistently positive for various currency pairs.

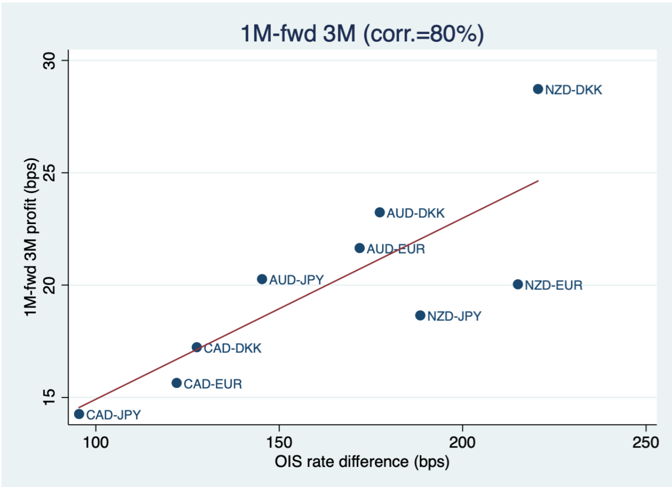
Our results align with the theory suggesting that the interaction between customer demand for carry trade and intermediary constraints influences the basis. This theory posits a positive relationship between spot basis, interest rate differentials, and the excess return of the forward CIP trading strategy. This positive relationship is further supported by the findings in Figure 4.9, which illustrates the correlation between profit and interest rates. Therefore, the excess return of the forward trading strategy serves as an alternative factor to the CIP basis.

Table 4.10: Forward CIP Trading Profits for Currency Pairs with Large CIP Deviations

	Mean	Sharpe Ratio	Avg. Basis	Avg. Diff.
AUD-DKK	23.239	1.021	44.507	1.774
AUD-EUR	21.650	0.614	33.489	1.719
AUD-JPY	20.267	0.740	51.008	1.453
CAD-DKK	17.235	1.118	23.660	1.275
CAD-EUR	15.645	0.533	12.642	1.220
CAD-JPY	14.262	0.745	30.161	0.954
NZD-DKK	28.727	1.864	23.660	2.206
NZD-EUR	20.035	0.554	29.286	2.151
NZD-JPY	18.652	0.697	46.805	1.885

Notes: This table shows the annualized profits and Sharpe ratios of the OIS 1M-forward 3M forward CIP trading strategy. "Mean" is the annualized profit from the forward CIP trading strategy; "Average Basis" is the average 1M-forward 3M OIS cross-currency basis; "Avg. Diff." is the average spread between the 3M currency 1 OIS rate and the currency 2 OIS rate. Our sample are from 2013 to 2022.

Figure 4.9: 1M-fwd 3M Forward CIP Strategy Profit in Cross-currency Basis, 2013-2022



Notes: This figure shows the cross-currency relationship between excess return of forward CIP strategy on the y-axis and OIS interest rates difference on the x-axis from 2013 to 2022. There are nine currency pairs. For example, AUD-JPY means that the investor takes long position in Japanese yen (low-interest-rate currency) and shorts Australian dollar (high-interest-rate currency).

Next, we also investigate portfolio forward CIP trading excess return. We create a new portfolio to examine forward CIP trading excess return. We divide 6 currency pairs to two groups to create the new portfolio: high-interest-rate currencies (AUD, CAD and GBP) and short in low-interest-rate currencies (DKK, EUR and JPY). All single currency pairs are vs USD and equally weighted. To be concrete, we take long position in the forward CIP trading strategy for the AUD, CAD, and GBP vs the USD, and short in the forward CIP trading strategy for the EUR, DKK, and JPY vs the USD. Based on Equation (11), we define c_1, c_2 as weighted high-interest-rate currencies and weighted low-interest-rate currencies.

Table 4.11 indicates that the mean excess return and basis are notably positive. Additionally, this portfolio exhibits a significant Sharpe ratio exceeding 2. These findings suggest that investors can expect to profit from this portfolio when engaging in unhedged carry trade using the forward Covered Interest Rate Parity (CIP) trading strategy. This conclusion aligns with the results presented in Table 4.10.

Table 4.11: Forward CIP Trading Excess Return for Portfolio

	Mean	Sharpe Ratio	Avg. Basis	Avg. Diff.
Forward	6.393	2.133	34.762	1.719

This table shows the annualized excess return and Sharpe ratios of the OIS 1M-forward 3M forward CIP trading strategy and spot CIP trading strategy. ”Mean” is the annualized profit from the forward CIP trading strategy and spot strategy; “Average Basis” is the average spot 1M-forward 3M OIS cross-currency basis; “Avg. Diff.” is the average spread between the 3M group 1 (AUD, CAD and NZD) OIS rate and the group 2 (DKK, EUR and JPY) OIS rate. Our sample are from 2013 to 2022.

4.6.2 An Alternative Factor of Debt Overhang

When employing regression analysis to investigate the association between debt overhang and various variables, the inclusion of alternative factors or control variables is a standard practice. This approach is commonly adopted to strengthen the reliability and precision of the analysis. Incorporating alternative factors allows for the consideration of additional influences that could impact the dependent variable, thereby contributing to a more comprehensive and nuanced comprehension of the relationship.

According to Fleckenstein and Longstaff (2020), debt overhang can be described as $e^{-r_U T}(r_U - r)$, where T indicates time to maturity. We use financial commercial paper with different maturities to measure unsecured financing rate r_U and the risk-free rate is U.S. Treasury bill r.

Table 4.12 displays the outcomes of the regression analyses examining the relationship between daily changes in the 3-month cross-currency basis, alterations in debt overhang, and various control variables across different borrowing rates. Specifically, the coefficient of $\Delta D3M$ exhibits a consistently significant positive association in all regressions. This implies that a one basis point increase in 3-month debt overhang results in an approximately 0.1 basis point rise in the cross-currency basis post-financial crisis. Moreover, the dollar index, a crucial factor, also demonstrates significant explanatory power in the cross-currency basis. A one percentage point appreciation in the dollar index correlates with roughly a 0.5 basis point reduction in the 3-month cross-currency basis, indicating a 0.5 widening of CIP deviations. However, certain control variables, such as spot exchange rate, $lnVIX$, and risk reversal, do not exhibit significant effects in most regressions.

The dramatically positive relationship between changes in the 3-month cross-currency basis and debt over-

Table 4.12: Regressions of the Cross-Currency Basis on An Alternative Factor of Debt Overhang

	x_t^{Libor}	x_t^{OIS}	IOER-Libor	IOER-OIS	x_t^{Repo}	IOER-Repo
$\Delta D3M$	0.056**	0.038*	0.093***	0.091***	0.099**	0.145***
	(1.755)	(1.946)	(1.760)	(1.891)	(0.013)	(0.008)
$\Delta Dollar$	-0.541***	-0.597***	-0.474**	-0.478**	-1.220**	-1.203**
	(0.139)	(0.158)	(0.170)	(0.169)	(0.129)	(0.190)
$\Delta Spot$	-0.167	0.096	-0.106	-0.033	-0.016	0.334
	(0.160)	(0.141)	(0.164)	(0.171)	(0.422)	(0.568)
$lnVIX$	0.602***	-0.033	-0.136	0.042	-0.271	-0.209
	(0.111)	(0.115)	(0.110)	(0.125)	(0.178)	(0.118)
ΔVIX	0.002	-0.014**	0.017***	0.016**	0.009	0.017
	(0.004)	(0.005)	(0.004)	(0.006)	(0.015)	(0.011)
ΔVol	-0.076***	-0.091***	-0.017	0.010	-0.154*	-0.083
	(0.018)	(0.025)	(0.021)	(0.034)	(0.050)	(0.029)
ΔRR	0.443	0.149	-0.377	-1.169	0.599	-1.030
	(1.171)	(0.988)	(1.408)	(1.396)	(3.167)	(4.315)
$\Delta Spread$	0.087***	-0.038**	0.015	0.009	0.115	0.055
	(0.011)	(0.012)	(0.017)	(0.012)	(0.044)	(0.052)
$\Delta Slope$	-0.134***	0.012	-0.101***	-0.097***	-0.176**	-0.164*
	(0.020)	(0.016)	(0.026)	(0.025)	(0.023)	(0.049)
Currency FE	√	√	√	√	√	√
R^2	0.031	0.016	0.025	0.026	0.037	0.046
N	15048	13376	15048	13376	5016	5016

Notes: The table indicates regressions of changes in the 3-month cross-currency basis and changes in debt overhang proxied by discounted commercial paper spread, dollar index together with other controls. Our main sample concentrates on the period from 2013.1.1 to 2022.10.07. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Currency fixed effects are included in all regressions. Control Variables include dollar index, spot rate, CBOE Volatility Index (VIX), implied volatility on 3-month at-the-money currency options (Vol), 25-delta FX option risk reversal (RR), Spread of the 10-year foreign Treasury yield over the 10-year U.S (Spread) and Difference between the foreign and the U.S. Treasury term spreads (10-year/2-year) (Slope). Column (1), denoted as x_t^{Libor}, indicates the Libor cross-currency basis. Column (2), denoted as x_t^{OIS}, indicates the OIS cross-currency basis. Column (3), IOER-Libor, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at Libor rate. Column (4), IOER-OIS, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at OIS rate. Column (5), x_t^{Repo}, refers to repo cross-currency basis. Column (6), IOER-Repo basis, indicates the basis by borrowing in U.S. dollars at the excess reserves and invest foreign currency at the repo rate. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

hang $e^{-r_U T}(r_U - r)$ can be found in Table 4.12. We get same results for the shorter-term cross-currency basis at the daily frequency. Table 4.13 shows regressions results for changes in 1-month cross-currency basis with different borrowing rates at daily frequency. Specifically, the coefficient estimate of 1-month debt overhang is significantly positive and higher than that of $\Delta D3M$ for all borrowing rates. After controlling other variables, one basis point in 1-month debt overhang increase cause a around 0.2-0.3 basis point rise in CIP deviations with different borrowing rates. Similar to regressions in Table 4.12, most of control vari-

Table 4.13: Regressions of the Cross-Currency Basis on An Alternative Factor of Debt Overhang

	x_t^{Libor}	x_t^{OIS}	IOER-Libor	IOER-OIS	IOER-Repo
$\Delta D1M$	0.188***	0.132**	0.213***	0.208***	0.326**
	(0.043)	(0.047)	(0.044)	(0.047)	(0.035)
$\Delta Dollar$	-1.260**	-0.941	-1.419**	-1.164*	-3.508**
	(0.492)	(0.541)	(0.504)	(0.492)	(0.791)
$\Delta Spot$	0.076	-0.019	0.066	-0.057	0.199
	(0.215)	(0.265)	(0.238)	(0.228)	(0.822)
$lnVIX$	1.452***	1.279**	1.786***	1.939***	2.758
	(0.419)	(0.443)	(0.413)	(0.436)	(1.037)
ΔVIX	-0.016	-0.025*	-0.004	0.002	-0.026
	(0.010)	(0.011)	(0.010)	(0.012)	(0.018)
ΔVol	-0.167***	-0.172**	-0.095*	-0.074	-0.120
	(0.042)	(0.055)	(0.046)	(0.065)	(0.059)
ΔRR	4.767*	4.325	3.997	3.076	7.050
	(2.136)	(2.493)	(2.692)	(3.123)	(6.194)
$\Delta Spread$	0.203***	0.087*	0.099**	0.061	0.154
	(0.038)	(0.042)	(0.037)	(0.044)	(0.080)
$\Delta Slope$	-0.266***	-0.137**	-0.205***	-0.152**	-0.271**
	(0.034)	(0.042)	(0.043)	(0.056)	(0.046)
Currency FE	√	√	√	√	√
R^2	0.045	0.027	0.039	0.038	0.060
N	9792	8704	9792	8704	3264

Notes: The table indicates regressions of changes in the 1-month cross-currency basis and changes in debt overhang proxied by discounted commercial paper spread, dollar index together with other controls. Our main sample concentrates on the period from 2013.1.1 to 2022.10.07. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Currency fixed effects are included in all regressions. Control Variables include dollar index, spot rate, CBOE Volatility Index (VIX), implied volatility on 3-month at-the-money currency options (Vol), 25-delta FX option risk reversal (RR), Spread of the 10-year foreign Treasury yield over the 10-year U.S (Spread) and Difference between the foreign and the U.S. Treasury term spreads (10-year/2-year) (Slope). Column (1), denoted as x_t^{Libor}, indicates the Libor cross-currency basis. Column (2), denoted as x_t^{OIS}, indicates the OIS cross-currency basis. Column (3), IOER-Libor, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at Libor rate. Column (4), IOER-OIS, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at OIS rate. Column (5), IOER-Repo basis, indicates the basis by borrowing in U.S. dollars at the excess reserves and invest foreign currency at the repo rate. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

ables remain significant in 1-month CIP basis for most of regressions, including $lnVIX$, implied volatility on 3-month at-the-money currency options ΔVol, $\Delta Spread$ and $\Delta Slope$. In conclusion, we find that debt overhang have significant explanatory power in 1-month and 3-month cross-currency basis with different borrowing rates, if we use an alternative factor $e^{-r_U T}(r_U - r)$ to define debt overhang.

4.6.3 Debt Overhang and Cross-currency Basis for Shorter-Maturity

The relationship between debt overhang and cross-currency basis, particularly for shorter-maturity debt instruments, can be complex and influenced by various factors. Debt overhang refers to a situation where a company or a country carries a high level of debt that might hinder its ability to invest, grow, or meet its debt obligations. Cross-currency basis refers to the difference in interest rates between two currencies when adjusting for the exchange rate. Shorter-maturity debt instruments typically have lower yields than longer-term bonds. If a country or entity is experiencing debt overhang, it might face higher perceived credit risk. This could lead to an increase in short-term funding costs, affecting the cross-currency basis as investors demand a premium for holding debt from that entity.

We conducted additional tests to explore the explanatory power of debt overhang on deviations from covered interest rate parity (CIP). The results of additional regressions, presented in Table 4.14, reveal a positive correlation between debt overhang and 1-week cross-currency basis across different interest rates. All estimates are both statistically significant and substantial, even after controlling for other variables. Notably, the coefficients in the 1-week regressions are larger compared to those in the 3-month regressions. For instance, in Column (2) of both Table 4.5 and Table 4.14, the estimated coefficient for 3-month debt overhang on OIS-based CIP is 0.285, while the coefficient for 1-week debt overhang on OIS-based CIP is 1.014.

4.7 Conclusion

We present conclusive evidence supporting the assertion that deviations from Covered Interest Rate Parity (CIP) can be attributed to the presence of debt overhang. Such deviations in the CIP condition unveil opportunities for arbitrage in one of the largest asset markets. The explanation for CIP violations lies in the constraints faced by intermediaries post-financial crisis. Notably, substantial CIP deviations indicate the constraints on financial intermediaries, creating profit opportunities for arbitragers. In the post-crisis period, the persistence of large deviations for major currencies finds explanation in the phenomenon of debt overhang. Our study pioneers an investigation into the explanatory power of debt overhang in the context of violations of covered interest parity. Additionally, we explore the predictive capacity of 1-week debt overhang on CIP violations, revealing a robust relationship across different maturity periods. Furthermore, CIP deviations exhibit a significant and negative correlation with nominal interest rates, presenting lucrative opportunities for arbitragers engaged in carry trade. Following the examination of the impact of debt overhang on CIP deviations, we utilize cross-currency basis, proxied by CIP violations, to execute carry

Table 4.14: Regressions of the Cross-Currency Basis on Debt Overhang and Control Variables

	x_t^{Libor}	x_t^{OIS}	IOER-Libor	IOER-OIS	IOER-Repo
$\Delta D1W$	1.293**	1.014**	0.932***	0.620**	0.923***
	(0.589)	(0.300)	(0.178)	(0.197)	(0.035)
Controls	√	√	√	√	√
Curr FE	√	√	√	√	√
R^2	0.011	0.010	0.009	0.006	0.007
Obs	16312	15112	15112	15112	5667

Notes: The table indicates regressions of changes in the 1-week cross-currency basis and changes in debt overhang, dollar index together with other controls. Our main sample concentrates on the period from 2013.1.1 to 2022.10.07. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Currency fixed effects are included in all regressions. Control Variables include dollar index, spot rate, CBOE Volatility Index (VIX), implied volatility on 3-month at-the-money currency options (Vol), 25-delta FX option risk reversal (RR), Spread of the 10-year foreign Treasury yield over the 10-year U.S (Spread) and Difference between the foreign and the U.S. Treasury term spreads (10-year/2-year) (Slope). Column (1), denoted as x_t^{Libor}, indicates the Libor cross-currency basis. Column (2), denoted as x_t^{OIS}, indicates the OIS cross-currency basis. Column (3), IOER-Libor, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at Libor rate. Column (4), IOER-OIS, refers to the basis by borrowing at the U.S. dollar interest rate on excess reserves (IOER) and invest the foreign currency at OIS rate. Column (5), IOER-Repo basis, indicates the basis by borrowing in U.S. dollars at the excess reserves and invest foreign currency at the repo rate. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

trade through a forward CIP trading strategy. This strategy aids in identifying the price of currency risk for carry trade, leading to the conclusion that a positive excess return in forward CIP trading is associated with substantial deviations.

The examination of the correlation between debt overhang and deviations from covered interest rate parity holds substantial political significance, influencing economic stability, policy formulation, and international relations. Several key points underscore the political implications: (1) Economic Stability: Debt overhang and deviations from covered interest rate parity can act as contributors to economic instability. Political leaders are compelled to address these issues to preserve financial stability and avert economic crises, which can adversely impact a government's popularity and legitimacy. (2) International Reputation: The manner in which a government addresses issues related to debt overhang and interest rate deviations directly affects its international reputation. Close scrutiny by creditors, investors, and international financial institutions underscores the importance of political leaders navigating global perceptions to attract foreign investment and secure favorable terms for international borrowing. (3) Negotiations and International Relations: Managing challenges associated with debt often entails negotiations with international creditors and financial institutions. Political leaders engage in diplomatic efforts to secure advantageous debt restructuring terms, navigate economic cooperation agreements, and sustain positive international relations despite economic challenges. (4) Impact on Sovereignty: The handling of debt and interest rate issues may involve external actors influencing a country's economic policies. Striking a delicate balance between seeking international assistance and safeguarding national sovereignty becomes a critical task for political leaders, especially considering the potential impact of conditions attached to financial aid on domestic policy autonomy. (5) Social and Political Stability: Economic challenges stemming from debt and interest rates have the potential to contribute to social unrest and political instability. Effectively managing these challenges becomes imperative for political leaders to prevent social upheaval, recognizing that economic grievances can translate into broader dissatisfaction with the government. (6) Global Financial Governance: Addressing the intricate relationship between debt overhang and interest rate parity often necessitates active participation in global financial governance. Political leaders engage in international forums and negotiations to shape policies, influence the actions of international financial institutions, and contribute to the development of frameworks for global economic governance.

In conclusion, delving into the connection between debt overhang and deviations from covered interest rate parity holds paramount political importance, impacting both economic and political stability. The implications extend to the formulation of sound policies, the preservation of international reputation, and the dynamics of global financial governance. Navigating these challenges becomes an essential task for political leaders, ensuring sustainable economic growth and upholding credibility on both domestic and international fronts.

Appendix 4.1: Stationarity and Cross-Sectional Dependence

First, Several statistical tests are available to check the stationarity of a time series. In this paper, we adopt Augmented Dickey-Fuller (ADF) to test unit root for each currency. According to Table 4.14 and 4.16, p-value is less than the chosen significance level (e.g., 0.01), we reject the null hypothesis. This suggests the series is stationary. Therefore, we calculate first difference for each variable before regression.

Table 4.15: Stationarity Test for the First Difference of Each Variable

	$\Delta Debt3M$	$\Delta Dollar$	$\Delta Spot$	$\Delta lnVIX$
ADF	-11.500***	-45.829***	-47.745***	-19.926***
	(0.000)	(0.000)	(0.000)	(0.000)
	ΔVol	ΔRR	$\Delta Spread$	$\Delta Slope$
ADF	-12.945***	-10.795 ***	-27.294***	-27.061***
	(0.000)	(0.000)	(0.000	(0.000)

Notes: This table shows the stationarity of first difference of each variable. Independent variable is 3-month debt overhang. Control Variables include dollar index, spot rate, CBOE Volatility Index (VIX), implied volatility on 3-month at-the-money currency options (Vol), 25-delta FX option risk reversal (RR), Spread of the 10-year foreign Treasury yield over the 10-year U.S (Spread) and Difference between the foreign and the U.S. Treasury term spreads (10-year/2-year) (Slope). P-value is in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4.16: Stationarity Test for the First Difference of $Basis_{bond}$ (All Currency)

	AUD	CAD	CHF	DKK	EUR
ADF	-10.893***	-12.638***	-12.196***	-15.285***	-11.569***
	(0.000)	(0.000)	(0.000)	(0.000)	
	GBP	JPY	NZD	SEK	
ADF	-12.812***	-12.970***	-9.300***	-11.697***	
	(0.000)	(0.000)	(0.000)	(0.000)	

Notes: This table shows the the stationarity of first difference of dependent variable (cross-currency basis) for 9 currencies. We investigate the cross-currency basis against dollar for 9 more liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), the Swedish krona (SEK). Robust standard errors are in parentheses. P-value is in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Second, Breusch-Pagan Lagrange Multiplier (LM) test is adopted to test is cross-sectional dependence across the currencies in the dataset. Null Hypothesis (H_0) is no cross-sectional dependence (i.e., error terms across units are independent). Alternative Hypothesis (H_1) is cross-sectional dependence (i.e., error terms across units are correlated). According to Equation 4.4, p-value of LM test is 1 and we cannot reject null hypothesis, suggesting that cross-sectional dependence is not detected.

Chapter 5

Conclusion

This thesis comprises three studies that scrutinize the repercussions and effects of pricing and risks within the context of financial regulatory reform and development spanning recent decades. The outcomes underscore the critical significance of well-crafted regulatory frameworks and offer insights with direct implications for future policy reforms. This chapter encapsulates the key findings, contributions, and implications of the studies, subsequently addressing limitations and providing recommendations for prospective research endeavors.

5.1 Key Findings, Contributions and Implications

In the first study, our study examines whether bank CDS spreads, together with accounting information, market discipline and macroeconomic conditions, can explain bank distress in European banks, particularly. And then, we provide supervisors with policy suggestions for dealing with bank distress by developing a more accurate predictive model. Further exploration into the factors influencing financial distress during crises is warranted. This study introduces a model utilizing downgrades from major rating agencies (Fitch, Moody's, Standard & Poor's) to categorize banks as financially sound or facing failure. The primary focus is on analyzing the predictive capacity of single-name 5-year senior Credit Default Swap (CDS) spreads, where the underlying instrument is a bond of a specific company. Examining the period from 2005 to 2018, encompassing a banking crisis, the study evaluates the marginal contribution of CDS spread changes in predicting bank financial distress. For the entire sample, CDS exhibits robust and statistically significant predictive power even after accounting for accounting, market, and macroeconomic variables. To strengthen this evidence, additional robustness tests are conducted, including analyzing CDS spreads with different maturities, assessing the impact of CDS on bank distress during and outside of crises, and exploring the explanatory power for small and large banks. Surprisingly, the results indicate that CDS lacks strong explanatory power for predicting bank distress. Subsequently, a predictive model for bank failures in European banks post-crisis is examined using data from 2005 to 2013. The analysis demonstrates that integrating CDS with bank-level and country-level indicators enhances the model's performance, leading to more accurate out-of-sample predictions of bank distress. In the final phase, the study investigates the impact of size and opacity on the predictive power of bank CDS spreads for bank financial conditions. The findings suggest that CDS spreads are less predictive for large banks than for small banks. Additionally, a higher degree of opacity weakens the relationship between CDS spreads and future downgrades.

This paper makes substantial contributions to the existing literature in several dimensions. In the initial study, we extend the body of knowledge on Credit Default Swaps (CDS) and their relationship with bank financial distress in the aftermath of a crisis. Building on prior research that explores the link between bank CDS and bank distress, our study furnishes evidence that, even post-crisis, bank CDS has an impact on bank financial distress, albeit not prominently evident. The utilization of bank Credit Default Swaps (CDS) as a predictive tool for anticipating bank distress following a crisis holds significance for financial markets, risk management practices, and regulatory considerations. The key contributions associated with employing bank CDS in predicting post-crisis bank distress include: (1) Enhanced Decision-Making for Investors: Investors can derive benefits from leveraging CDS-based predictions to make more informed decisions. The ability to anticipate distress empowers investors to adapt their portfolios, reallocate assets, and implement hedging strategies, thereby improving their capacity to navigate the conditions prevailing in the aftermath of a crisis. (2) Improved Regulatory Frameworks: Regulatory authorities can enhance supervisory frameworks and stress testing methodologies by incorporating CDS-based predictions. By considering market-based indicators such as CDS spreads, regulators gain insights into the post-crisis resilience of banks. This information enables them to tailor regulatory interventions to address specific vulnerabilities identified in the CDS market. In addition, recognizing the importance of studying the relationship between bank CDS spreads and distress, we develop a predictive model. This model integrates bank CDS spreads with bank-specific information, market discipline measures, and macroeconomic indicators to effectively predict instances of bank distress post-crisis.

In our second investigation, we examine the presence of deviations from covered interest parity (CIP) within sovereign bond markets, with a particular focus on the Covid-19 crisis and three potential frictions that could lead to violations of CIP conditions. The findings reveal that deviations from covered interest parity ($Basis_{bond}$) are marginally different from zero before the onset of the Covid-19 crisis but significantly deviate from zero during the crisis. Additionally, several empirical outcomes are reported. Firstly, liquidity risks are found to play a limited role in explaining $Basis_{bond}$. Conversely, secured funding costs emerge as both statistically and economically significant. This outcome supports the notion that funding frictions in wholesale credit markets during the Covid-19 crisis contributed to deviations from covered interest parity. In March 2020, disruptions in short-term dollar funding markets were observed as investors shifted from unsecured markets to secured markets and government money market funds (Eren et al., 2020). Moreover, certain macroeconomic factors are identified as significant contributors to explaining $Basis_{bond}$. This discovery aligns with the hypothesis that marginal arbitrageurs face risks extending beyond those impacting local markets. Gromb and Vayanos (2010) present a model in which global arbitrageurs, present in various markets, are influenced by common wealth shocks. When these arbitrageurs encounter difficulty in absorbing shocks through debt market access, the resulting friction becomes a source of contagion across seemingly unrelated assets.

Furthermore, we conduct several robustness tests to enhance the robustness of our findings: (1) We employ duration and convexity gap analysis to explore the association between cash flow risk related to bond characteristics and the violation of defaultable sovereign bond prices. (2) We investigate whether stock risk can elucidate deviations from Covered Interest Parity (CIP) for sovereign bonds. (3) We examine the impact of foreign exchange correlation risk using Quanto Credit Default Swaps (CDS). (4) We assess the interaction between liquidity and economic conditions on the CIP basis for bonds. Our results indicate that cash-flow mismatch and FX correlation risk contribute minimally to the dynamics of $Basis_{bond}$. Despite the consideration of stock risk and interaction effects, we find that local stock risk and the interplay of liquidity and economic conditions do not offer a significant explanation for the violation of CIP in bond markets. Additionally, we introduce an alternative variable, termed excess return, for $Basis_{bond}$ and observe that secured funding frictions and macroeconomic conditions play crucial roles in explaining excess return, aligning with our primary findings.

The second study makes several noteworthy contributions to the existing literature. Firstly, our examination of deviations from covered interest parity (CIP) in the sovereign bond market during the Covid-19 crisis addresses a critical gap. The unprecedented financial market stress triggered by the crisis prompted heightened uncertainty and volatility. Analyzing deviations from CIP offers valuable insights into how disruptions in the global financial markets influenced the pricing and dynamics of sovereign bonds. Furthermore, during periods of crisis, the phenomenon of a ”flight to safety” often occurs, with investors seeking refuge in assets perceived as less risky. Sovereign bonds, particularly those issued by stable countries, are considered safe-haven assets (Cerutti et al., 2021). Investigating CIP deviations sheds light on how this flight to safety impacted interest rate differentials and exchange rates. Given the implementation of unconventional monetary policies and interventions by many central banks during the Covid-19 crisis, the potential implications for interest rates and currency values may result in deviations from CIP. Understanding the impact of central bank interventions is pivotal for assessing the efficacy of policy measures. Secondly, our findings indicate that sovereign bond price anomalies still exist, albeit to a lesser extent, before the Covid-19 crisis. This persistence is attributed to limited arbitrage opportunities that endured post-financial crisis due to regulatory constraints on banks (Pinnington and Shamloo, 2016).

In our third paper, we initially explore the correlation between debt overhang and deviations from covered interest rate parity across nine highly liquid currencies: the euro (EUR), the Danish krone (DKK), the Japanese yen (JPY), the British pound (GBP), the Swiss franc (CHF), the Australian dollar (AUD), the New Zealand dollar (NZD), the Canadian dollar (CAD), and the Swedish krona (SEK). The focus is on each cross-currency basis in relation to the U.S. dollar (USD), spanning the period from 2013 to 2022. Various interest rates, including Libor, OIS, repo, and IOER, are considered in computing 3-month and 1-week cross-currency bases. A pivotal outcome of this inquiry is the identification of debt overhang as a significant catalyst for deviations from covered interest rate parity, especially in the context of the 1-week cross-currency basis. Debt overhang emerges as a powerful explanatory factor for deviations from CIP, with notable influence. Next, we investigate the impact of quarter-end debt overhang on deviations from Covered Interest Parity (CIP). Our findings suggest that heightened balance sheet constraints towards the end of quarters result in a more pronounced influence of debt overhang on CIP deviations, particularly in the post-financial crisis period. Subsequently, we delve into the relationship between cross-currency basis and nominal interest rates, offering theoretical insights into the carry trade phenomenon. The findings reveal a negative correlation between cross-currency basis and interest rates, potentially providing arbitragers with opportunities to benefit from carry trade strategies.

We subsequently examine the correlation between deviations from Covered Interest Parity (CIP) and carry trade strategies. Specifically, we implement a forward CIP trading strategy, as outlined by Du et al. (2023), engaging in bilateral carry trades within the foreign exchange market. The relationship between CIP deviations and the returns of the forward trading strategy is explored. In this context, an arbitrageur takes a long position in a low-interest-rate currency and a short position in a high-interest-rate currency, with currency risk hedged from $t + 1$ to $t + 4$ using forward contracts. After one month, the arbitrageur reverses the positions, going long in the same high-interest-rate currency and short in the same low-interest-rate currency. Cash flows are negligible under the forward CIP trading strategy. The excess return of this strategy is contingent upon the spread between one-month forward three-month CIP deviations today and actual three-month CIP deviations after one month. Positive excess returns from the forward trading strategy are expected if the disparity between future CIP deviations and the market-implied forward CIP deviations today is negative. Assuming the constraints of intermediaries represent a priced factor, we anticipate positive excess returns from the forward CIP trading strategy, serving as compensation for investors bearing the risk exposure of intermediaries. Following the computation of excess returns, we further explore the relationship between debt overhang and profits derived from the forward CIP trading strategy.

We select six highly liquid currencies (AUD, CAD, DKK, EUR, JPY, NZD) and establish cross-currency bases against both USD and non-USD currencies. Subsequently, we estimate the excess returns of forward Covered Interest Parity (CIP) trading strategies spanning the period from 2013 to 2022. Initially, our focus is on the excess returns in individual currencies against USD within cross-currency pairs. To bolster the robustness of our findings, we also calculate additional excess returns between non-USD currency pairs. Post the Global Financial Crisis, we observe significant positive excess returns for forward CIP trading strategies for both currency pairs against USD and non-USD currencies. This implies that investors stand to achieve profits from engaging in bilateral carry trade-forward CIP trading strategies. Additionally, we extend our analysis to investigate the excess returns of forward CIP trading strategies for portfolios. By categorizing the six currency pairs into two groups—high-interest-rate currencies (AUD, CAD, and GBP) and low-interest-rate currencies (DKK, EUR, and JPY)—we create a new portfolio and compute the excess returns. Our conclusion is that the average excess returns are substantial and positive. This suggests that investors can expect to derive profits from this portfolio-based bilateral carry trade strategy.

The third study makes valuable contributions to the existing literature in several dimensions. Initially, our investigation delves into the connection between debt overhang and deviations from covered interest parity (CIP). The study not only provides insights into market efficiency but also sheds light on the potential presence of anomalies. Persistent deviations from CIP associated with debt overhang may indicate the influence of market frictions and information asymmetry in currency markets, surpassing predictions made by traditional models. This exploration extends our understanding of sovereign credit market dynamics, unraveling the intricate relationship between sovereign debt markets and currency markets, as noted by Duffie (2017). Secondly, we employ forward CIP trading strategies to establish a link between CIP and carry trade, thereby examining the impact of debt overhang on carry trade dynamics. This facet of the study specifically investigates how debt overhang influences carry trades and capital flows. Currency movements tied to sovereign debt conditions may affect capital allocation and cross-border investment flows, thereby influencing the effectiveness of carry trade strategies.

5.2 Limitation and Future Research

While using bank Credit Default Swap (CDS) spreads to predict bank distress can provide valuable insights, there are several limitations and challenges associated with this approach. First of all, CDS spreads are influenced by both market sentiment and fundamental factors. High CDS spreads may reflect concerns about a bank's financial health, but they can also be driven by broader market sentiment, liquidity conditions, or speculative trading. Distinguishing between sentiment-driven and fundamentals-driven movements is challenging. Secondly, the use of CDS spreads assumes that the market for CDS contracts is efficient and that there is no significant counterparty risk. However, during times of financial stress, concerns about counterparty risk can affect CDS spreads and may not accurately reflect the bank's standalone credit risk. Thirdly, basis risk arises from the imperfect correlation between CDS spreads and the actual default risk of the bank. Changes in market conditions, regulatory developments, or other factors can introduce basis risk, limiting the reliability of CDS spreads as a precise predictor of bank distress. Furthermore, rating agencies play a crucial role in assessing a bank's creditworthiness. Changes in credit ratings, which are influenced by various factors, may not align perfectly with CDS spread movements. Additionally, rating agencies may have their own methodologies and criteria for evaluating credit risk. Finally, CDS spreads are influenced by investor behavior, market psychology, and herding effects. These behavioral factors can introduce noise into the signal provided by CDS spreads, making it challenging to discern the true credit risk of a bank.

In summary, while bank CDS spreads can be a useful tool for assessing credit risk and predicting potential distress, it is essential to recognize and account for these limitations when interpreting CDS spread movements and drawing conclusions about a bank's financial health. Combining CDS spread analysis with other indicators and a comprehensive risk assessment framework is often advisable for a more robust evaluation.

In the second paper, studying deviations from Covered Interest Parity (CIP) in sovereign bond markets comes with certain limitations and challenges. Here are some key limitations associated with analyzing CIP deviations in the context of sovereign bonds: First, CIP models often assume risk neutrality, which may not accurately reflect real-world conditions. In sovereign bond markets, risk aversion, credit risk, and other factors can significantly impact pricing and lead to deviations from the theoretical parity. Second, market frictions, such as transaction costs and liquidity constraints, are often neglected in CIP models. In reality, trading sovereign bonds may involve substantial transaction costs, particularly in less liquid markets, which can influence the effectiveness of arbitrage strategies and contribute to CIP deviations. Third, market participants may not always behave in a rational and risk-neutral manner. Behavioral biases, sentiment, and herding behavior can contribute to market dynamics that deviate from the predictions of CIP models. Fourth, unforeseen macroeconomic shocks can disrupt the relationship between interest rates and exchange rates, leading to deviations from CIP. External shocks, such as natural disasters or global economic crises, can impact market dynamics unpredictably.

Therefore, understanding and accounting for these limitations is crucial when interpreting the results of studies on deviations from Covered Interest Parity in sovereign bond markets. Researchers and practitioners should be cautious about generalizing findings and consider the complexities inherent in the bond and currency markets.

In the third study, while the relationship between debt overhang and deviations from Covered Interest Parity (CIP) can provide valuable insights into financial markets, risk management, and sovereign debt dynamics, there are several limitations and challenges associated with studying this relationship. Some of the key limitations include: (1) complexity of factors, (2) endogeneity issues (3) behavioral factors, (4) policy interventions and (5) modelling assumptions. To be concrete, financial markets are influenced by a multitude of factors, and isolating the specific impact of debt overhang on deviations from CIP can be challenging. Other economic, geopolitical, and market-specific factors may confound the relationship. Then, the relationship may be subject to endogeneity issues, where the causality between debt overhang and deviations from CIP is not straightforward. Both variables may interact with each other in a complex manner, making it difficult to establish a clear cause-and-effect relationship. Besides, investor behavior and sentiment can significantly impact currency markets. The relationship between debt overhang and deviations from CIP may be influenced by market participants' perceptions, expectations, and behavioral biases, which are difficult to quantify. In addition, central bank interventions and policy decisions can influence both debt markets and currency markets. The impact of debt overhang on deviations from CIP may be masked or amplified by policy measures aimed at stabilizing financial markets or managing currency values. Finally, studies examining the relationship often rely on economic models and assumptions. The accuracy of results may be sensitive to the chosen model specifications and assumptions, and different models may yield divergent findings.

In summary, although the association between debt overhang and deviations from Covered Interest Parity (CIP) offers promising insights, it is crucial for researchers and practitioners to be cognizant of certain limitations. A thorough evaluation of the study's methodology, robustness checks, and recognition of the intricate interactions among various factors will contribute to a more nuanced comprehension of the dynamics governing the relationship between sovereign debt and currency markets.

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