Enhancing Bank Robustness through Dynamic Control of Leverage (DCL) in Contingent Convertible Bonds (CoCos): A Case Study Analysis

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List of Symbols

Symbol	Description
$PV(.)$	Present Value
$D(.)$	Discount Factor
$\mathbb{E}_t[.]$	Expected Value
$e^{(.)}$	Exponential Function
$N(.)$	Standard Normal Cumulative Distribution Function
$N'(.)$	Probability Density Function of the Normal Distribution
$N_2(.)$	Bivariate Standard Normal Cumulative Distribution Function
$\mathbb{P}(.)$	Probability
$\mathbb{1}(.)$	Indicator function

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Abstract

Contingent Convertible (CoCo) bonds were introduced to strengthen bank stability by automatically converting debt into equity during financial distress. However, the recent collapse of Credit Suisse, where traditional CoCo triggers proved vulnerable to regulatory discretion and market panic, has highlighted critical weaknesses in their design. This study analyses a novel framework—Dynamic Control of Leverage (DCL) CoCo bonds—that addresses these limitations through gradual and predictable conversion triggered by continuous leverage monitoring. Leveraging Refinitiv Eikon data on Credit Suisse's equity, debt, and Additional Tier 1 (AT1) instruments from 2018 to 2023, this study simulates how DCL bonds would have performed during the bank's collapse.

Results suggest that DCL significantly reduces abrupt dilution events and market instability by enabling frequent but incremental interest-to-equity conversions, unlike traditional CoCos, which rely on sudden principal write-downs or full conversions. By providing both theoretical and empirical insights, this research highlights the DCL framework as a more effective and transparent alternative for mitigating systemic risks and regulatory uncertainties inherent in conventional CoCo instruments.

Keywords: Contingent Convertible Bonds, Dynamic Control of Leverage, Banking stability

List of Abbreviations

Abbreviation	Description
AT1	Additional Tier 1
C	Conversion (to equity)
CET1	Core Equity Tier 1
CoCo	Contingent Convertible
DCL	Dynamic Control of Leverage
ERN	Equity Recourse Note
PONV	Point of non viability

Chapter 1

Introduction

The global financial crises of 2008 and the collapse of Credit Suisse in 2023 have underscored critical vulnerabilities in bank capital structures. In response to the 2008 crisis, regulators introduced contingent convertible bonds (CoCos) as a mechanism to bolster bank resilience by automatically converting debt into equity during distress, thereby aiming to avoid taxpayer-funded bailouts [1]. However, traditional CoCo bonds with fixed capital ratio triggers have shown significant limitations. They can fail to trigger conversions in time or create market uncertainty - as seen in Credit Suisse's 2023 failure, where $17 billion in CoCo (AT1) bonds were abruptly written down, highlighting a breakdown in the intended loss-absorbing mechanism. These events point to the need for more effective tools to enhance bank robustness and prevent such destabilizing outcomes [2] [3].

This thesis project analyses the novel Dynamic Control of Leverage (DCL) framework as an alternative approach to conventional CoCos designed to mitigate these shortcomings. DCL-based CoCo instruments monitor a bank's leverage and trigger debt-to-equity conversions dynamically, rather than relying on a single static threshold. By allowing proactive and gradual recapitalization to sensible leverage ratios, the DCL framework is expected to keep a bank's leverage within safe bounds and minimize the likelihood of default. In essence, DCL CoCos aim to provide the flexibility to shore up capital before a crisis point is reached, addressing problems of delay or inflexibility in traditional CoCo triggers [4].

The aims of this research are twofold. First, it seeks to evaluate whether DCL-driven CoCo bonds can more effectively maintain bank stability compared to traditional CoCos. Secondly, it investigates how applying DCL might alter outcomes in real-world scenarios. Specifically, the following research questions will be addressed:

- *How does a DCL-based CoCo structure affect a bank's solvency and risk profile under stress, relative to conventional CoCo bonds?*

- *Would the implementation of DCL in CoCo bonds have changed the outcome of the Credit Suisse 2023 crisis, had it been in place?*
- *What are the key parameters influencing the performance of DCL CoCo bonds, and how can they be optimized?*

To answer these questions, we test the hypothesis that DCL-equipped CoCos significantly reduce the probability of bank default and the need for emergency intervention by enabling timelier, controlled leverage adjustments. A simulation-based case study of Credit Suisse's collapse will serve as a practical testbed for this hypothesis, comparing the bank's capital trajectory and outcomes with and without the DCL mechanism.

This study offers several contributions. First, it advances the financial stability literature by exploring an innovative loss-absorbing instrument that could prevent bank failures more effectively than current tools. Second, it contributes to the CoCo bond literature by rigorously analyzing a dynamic trigger mechanism (DCL) through simulation and case study evidence. Third, it has strong policy implications and practical relevance: the findings can inform regulators and bank risk managers about improving capital regulation. If DCL CoCos prove effective, they could guide reforms in Additional Tier-1 capital requirements, helping policymakers strengthen the resilience of banks and reduce systemic risk.

Overall, by demonstrating the potential benefits of dynamically controlled leverage in CoCo bonds, this research is expected to show that DCL can enhance bank robustness and stability. Under the DCL framework, it is anticipated that a bank like Credit Suisse would experience a more timely, gradual and controlled capitalization process during distress, potentially averting the abrupt collapse witnessed in 2023. Such expected results would underscore DCL's value as a tool for financial stability, bridging a critical gap in current risk management practices.

Chapter 2

Literature Review

2.1 Overview of CoCo Bonds

Contingent Convertible (CoCo) bonds have gained prominence as financial instruments designed to stabilize banks during periods of financial distress. These bonds automatically convert into equity or are written down when a bank's capital falls below a predetermined threshold. CoCo bonds were introduced after the 2008 financial crisis to provide banks with an automatic mechanism for strengthening their capital base during distress [1]. These instruments aim to reduce reliance on government bailouts by ensuring that bondholders absorb losses before a bank's failure. Regulatory frameworks, including Basel III, have played a crucial role in shaping the issuance and structure of CoCo bonds by specifying minimum capital thresholds and loss-absorption mechanisms [5]. However, despite their intended function, CoCo bonds have faced criticism regarding their trigger mechanisms and market perception.

Notably, the design characteristics of CoCos, such as trigger level and loss-absorption method, influence their risk and pricing. For example, CoCos with higher trigger levels or principal write-down (PWD) features tend to offer higher yields at issuance than those with lower triggers or equity conversion features [5]. This reflects the greater risk to investors when conversion is more likely or more severe. Various pricing models have been proposed to value these hybrid instruments. De Spiegeleer and Schoutens, for instance, develop a derivatives-based framework to price CoCo bonds, applying it to early issues by Lloyds (2009) and Credit Suisse (2011). Their analysis quantifies the risks embedded in different CoCo structures and underscores how trigger conditions and conversion terms affect a CoCo's valuation [6].

The purpose of this literature review is to examine the development of CoCo bonds and their limitations, leading to the emergence of the DCL model. We explore how DCL improves upon existing CoCo frameworks by addressing issues related to dilution, regulatory uncertainty, and market volatility. This review is organized into key themes, including traditional CoCo bond structures, their regulatory challenges and criticisms, and the proposed advantages of the DCL approach. While the focus is primarily on the financial engineering literature, broader discussions on capital adequacy and financial stability are referenced where relevant.

2.2 Traditional Trigger Mechanisms

The 2023 Credit Suisse AT1 CoCo bond wipeout exemplified several inherent weaknesses in traditional CoCo designs. In that incident, AT1 bondholders were completely written off while shareholders still retained some value, an inversion of the usual loss hierarchy that shocked many market participants [2]. Note that although controversial, FINMA's decision to wipe out these bonds created a "healthy precedent" by reinforcing investor awareness of the high risks in such instruments. The global reaction – including divergent views from regulators outside Switzerland – underscores how design flaws and misperceptions about CoCos can erode market confidence. This controversy highlights the need to address longstanding criticisms of CoCo bonds in both regulatory and academic discussions.

Beyond these considerations, scholars have identified several structural weaknesses in conventional CoCo bond design. One major concern is that many CoCos carry low capital-ratio triggers (e.g. a Common Equity Tier 1 ratio around 5.125% to qualify as AT1), meaning conversion or write-down occurs only when the bank is already near failure. If the trigger threshold is set too low, the bank could slide into default before the CoCo ever converts, a scenario described as a *debt-induced collapse* where the instrument fails to recapitalize the firm in time [7], [8]. Compounding this issue, most AT1 CoCos include a discretionary point of non-viability (PONV) trigger that allows regulators to force conversion in extremis, adding further uncertainty for investors.

Additionally, the common use of accounting-based triggers (like regulatory CET1 ratios) has been widely criticized for its lack of transparency and responsiveness. The CET1 ratio is updated infrequently and can be influenced by accounting decisions, so relying on it makes the conversion decision backward-looking. This opacity and delay complicate investors' ability to assess conversion risk, potentially leading to mispricing or complacency in good times and then abrupt loss of confidence when conditions deteriorate [2].

To address such problems, researchers have proposed using market-based triggers (e.g. a threshold based on the bank's stock price), since market prices are forward-looking, objective, and continuously observable. A share-price trigger could in theory provide a timelier signal of distress, as it "encompasses all information known about the company" in real time [4]. However, pure market triggers carry their own challenges (such as the risk of self-fulfilling price spirals), so the optimal trigger design for CoCos remains an area of ongoing debate. Overall, the literature suggests that traditional CoCo bonds, as currently designed, may not always perform their intended role of smooth loss absorption and bank stabilization – a concern vividly illustrated by the Credit Suisse case and related studies.

2.2.1 Credit Suisse CoCo Wipeout and Market Reactions

The collapse of Credit Suisse in 2023 and the subsequent write-down of $17 billion worth of Additional Tier 1 (AT1) CoCo bonds by the Swiss Financial Market Supervisory Authority (FINMA) sent shockwaves through financial markets. Unlike traditional cases where equity holders bear losses first, the Credit Suisse case saw bondholders wiped out while shareholders retained some value. This inversion of the creditor hierarchy led to significant backlash and uncertainty surrounding CoCo bonds as a bail-in tool [2].

Regulators such as the European Central Bank (ECB) and the Bank of England responded by reaffirming their commitment to the conventional priority order in financial resolutions. The incident underscored the inherent risks and ambiguities in CoCo bond contracts, particularly those with discretionary triggers allowing regulators to make case-by-case determinations. Market reactions were immediate, with a sharp decline in AT1 bond prices globally and increased scrutiny of regulatory decision-making.

2.3 Introduction to DCL (Dynamic Control of Leverage) CoCo Bonds

In a recently published paper by Segal and Ólafsson, the authors present a novel framework for a contingent convertible bond called *Dynamic Control of Leverage* (DCL) *CoCo bond* [4]. The primary motivation behind this work is to address fundamental weaknesses in traditional CoCo bonds by introducing a mechanism that adapts dynamically to a firm's leverage levels, building on the work of Bulow and Klemperer (2015). The DCL model regulates a company's leverage by converting the traditional coupon payments of the bond to equity while a critical leverage threshold is breached. This process aims to enhance stability, prevent sudden large capital dilution (which has proven to be an issue for traditional CoCo bonds [2], and mitigate market panic compared to conventional CoCo bonds. The methodology integrates the leverage ratio as a transparent control variable, making the conversion process more predictable and reducing reliance on external regulatory intervention.

The contribution of the paper is significant as it presents an innovative alternative to existing CoCo bond structures, which have been criticized for their reliance on regulators. The DCL model provides an automated, self-regulating approach to leverage control, reducing risks associated with conventional CoCo conversions. This research is particularly relevant given recent financial crises (see Credit Suisse, SVN and FRB) and regulatory concerns over capital adequacy in financial institutions.

The authors define a stochastic model, assuming that equity follows geometric Brownian motion (GBM). Then they simulate several theoretical scenarios to demonstrate the model's effectiveness. The study also compares DCL with traditional CoCo bonds and other leverage-based financial instruments, establishing a clear advantage in terms of risk mitigation and predictability.

The technical standards align with established frameworks like the Basel III accords. The conversion mechanism, which limits dilution to interest payments rather than full principal amounts, is a logical improvement. The use of leverage as a trigger metric is a well-reasoned choice, as opposed to conventional models relying on accounting-based, or static triggers that are often subject to delays and discretion.

However, one potential limitation of the model is its reliance on simplified capital structure assumptions. While these assumptions help isolate the effects of DCL, real-world financial structures may introduce complexities not accounted for in the study. Furthermore, while the simulations suggest a reduction in default probability, additional empirical validation using real market data would strengthen the findings. That is particularly regarding potential risks associated with DCL implementation in different market environments.

This thesis aims to address these concerns by expanding the model to incorporate more complex capital structures and external economic factors, Conducting empirical testing with real-world data to validate simulation findings, and addressing potential risks related to investor perception and regulatory acceptance of the DCL model. It also aims to clarify the reduction in likelyhood of market panic and dilution risk, and how predictable their behaviour is affected compared to traditional CoCos.

In summary, the thesis by Segal and Ólafsson represents a valuable advancement in financial instruments for managing leverage and risk. With further empirical validation and refinements, the DCL framework has strong potential for practical application in financial markets in the current regulatory environment.

2.4 Empirical Gaps

Despite the substantial contributions of existing research, several empirical gaps persist in the literature surrounding CoCo bonds and specifically the DCL framework. First, while previous theoretical models and limited simulations exist, comprehensive empirical validations using historical datasets from real-world financial institutions are non-existent. Second, studies examining responses of market participants, including that of investors and regulators, to the introduction and use of DCL CoCos are lacking. Addressing these empirical gaps could significantly enhance understanding of- and aid in the practical implementation of DCL mechanisms.

2.5 Summary of Key Insights

The literature on CoCo bonds has highlighted both their benefits and limitations, particularly their unpredictable conversion mechanisms and regulatory uncertainty. The Credit Suisse CoCo wipeout underscored the risks associated with discretionary regulatory decisions, revealing weaknesses in traditional CoCo frameworks. Given this, alternative approaches like the Dynamic Control of Leverage (DCL) model have gained traction for their structured and self-regulating approach.

The DCL framework offers a promising improvement by dynamically managing leverage through interest payment conversions, mitigating sudden capital dilution and reducing market panic. Its leverage-based trigger mechanism enhances predictability compared to traditional CoCo structures. However, while theoretical models and simulations demonstrate its advantages, further empirical validation using real-world data is necessary to confirm its effectiveness in different market conditions.

Future research should focus on integrating DCL into existing regulatory frameworks and exploring its viability across diverse financial institutions. Additionally, addressing potential challenges such as investor perception and regulatory acceptance will be crucial in assessing its practical implementation. As financial markets evolve, the DCL approach represents a significant step toward enhancing financial stability and risk management in banking institutions.

Chapter 3

Methodology

3.1 Research Design

This study employs a quantitative and empirical research design, combining historical data analysis with simulation modeling to assess the performance of the DCL framework in CoCo bonds. The research replicates and expands upon the theoretical framework established by Segal and Ólafsson [4], applying it specifically to the real-world scenario of Credit Suisse between 2018 and 2023. Historical financial data including share values, total debt, AT1 debt, and outstanding shares were sourced from Refinitiv Eikon and Credit Suisse's publicly available annual reports. A comparative analysis is later applied to contrast outcomes from the simulated DCL bonds against traditional CoCo bonds, analysing the resulting indicators such as the leverage, dilution rates, and the frequency of conversions.

3.2 Data Collection and Sources

In this study, we aimed to examine whether a Dynamic Control of Leverage (DCL) CoCo bond framework would stabilize a bank's capital structure more effectively than a conventional CoCo bond. Specifically, we focused on Credit Suisse's data from 2018 to 2023 to investigate how often leverage ratio thresholds were breached under DCL simulations versus a traditional structure. The research question that will be tackled first is *whether implementing a DCL CoCo bond reduces the severity of threshold breaches compared to a standard CoCo mechanism* We hypothesized that banks using DCL CoCo bonds would experience significantly less severe trigger events, thereby mitigating sudden dilution and market disruptions.

To address the hypothesis, daily and yearly time-series data was collected from Refinitiv Eikon on Credit Suisse, encompassing daily closing stock prices, and yearly shares outstanding and total debt. Data on Additional Tier 1 (AT1) debt was not available on Reuters so it was manually compiled from the bank's yearly 20-F reports. These data points were then used to compute key parameters such as the equity value, total leverage, and the proportion of DCL bonds to total debt (α_k). Simulations at three different trigger-check frequencies (yearly, monthly, and daily) were made to analyse the effect of frequency and lag on the DCL mechanism to convert interest payments into equity. This allowed us to compare both the incidence of trigger events and the resulting leverage ratios over the five-year observation period for Credit Suisse.

3.3 Model Specification: DCL CoCo Bonds

The analysis utilizes comprehensive historical financial data sourced from Refinitiv Eikon and Credit Suisse's financial reports. The focus is placed on examining how varying key parameters—such as leverage thresholds, conversion frequencies, and coupon-to-equity conversion ratios—influence the bank's financial stability, market volatility, and equity dilution under distress conditions. Additionally, a sensitivity analysis is conducted to assess the robustness and reliability of the DCL approach across diverse market stress scenarios.

3.4 Implementation Steps

The implementation process involves several steps: acquiring and preparing financial data, specifying the DCL CoCo bond model parameters, running simulations, and conducting sensitivity analyses. Financial data from 2018–2023, including share prices, shares outstanding, and total debt, were obtained from Refinitiv Eikon and cross-checked against Credit Suisse's 20-F reports. (As noted, AT1 CoCo data were manually compiled from reports due to lack of a direct dataset.) The model parameters defined for the simulations included the bond's nominal amount, one or more leverage trigger thresholds (L_c levels), conversion prices, and conversion frequency. We then simulated the DCL conversion process over the historical period, tracking whenever the simulated leverage exceeded L_c and thus triggered an interest-to-equity conversion.

Finally, we performed sensitivity analyses to explore how varying the key parameters – such as the trigger level (e.g., 88%, 90%, 92%, 94% debt-to-assets), the interest conversion frequency (annual vs. quarterly vs. monthly), and the conversion price – would impact outcomes like the bank's leverage trajectory, the total equity dilution, and the number of conversion events. The results of the DCL simulations are compared against the actual historical outcomes for Credit Suisse's AT1 (which had a static trigger and was ultimately written down) to quantify relative benefits and trade-offs.

3.5 Limitations of the Methodology

Several limitations of this methodology should be noted. First, the model makes simplified assumptions that do not fully capture the complexity of a real bank's capital structure (for example, we assume a single class of CoCo debt and do not model other contingent liabilities or interactions with other capital instruments). This simplification was necessary to isolate the effect of the DCL mechanism, but it means that certain secondary effects are not considered. Second, the analysis relies on historical data and a back-testing approach, which may limit the generalizability of the findings – future crises or market conditions could deviate from historical patterns. Third, the simulations do not explicitly incorporate potential dynamic responses from investors or changes in regulatory behavior. In a real-world setting, the introduction of DCL CoCo bonds could itself influence investor confidence or regulatory actions in ways that are not captured here.

Chapter 4

Empirical Analysis and Results

4.1 Introduction

This chapter presents a detailed empirical analysis of how the Dynamic Control of Leverage framework would have performed for Credit Suisse during its 2018–2023 period, especially in the lead-up to the 2023 collapse. The analysis compares a hypothetical DCL CoCo bond structure to the actual traditional CoCo (AT1) bonds that Credit Suisse had, to evaluate differences in outcomes.

The analysis utilizes historical financial data sourced from Refinitiv Eikon and Credit Suisse's financial reports. The focus is placed on examining how varying key parameters—such as leverage thresholds, conversion frequencies, and coupon-to-equity conversion prices shows how they influence the bank's financial stability, volatility, and equity dilution under distress conditions. Additionally, a sensitivity analysis is conducted to assess the robustness and reliability of the DCL approach across differing market stress scenarios.

Part I

Case Study: Credit Suisse

4.2 Overview of the Credit Suisse Collapse

Credit Suisse's collapse in March 2023 marked a significant event in global financial markets, revealing vulnerabilities within existing regulatory frameworks and highlighting systemic risks associated with traditional contingent convertible (CoCo) bonds. Over several years preceding the collapse, Credit Suisse faced repeated challenges, including substantial financial losses linked to high-profile scandals and investment mishaps, deteriorating investor confidence, and declining stock prices.

The critical moment occurred when Swiss regulators, specifically FINMA, intervened, fully writing down approximately CHF 16 billion of Additional Tier 1 (AT1) CoCo bonds while partially preserving shareholder value. This unconventional regulatory decision led to considerable backlash among bondholders and triggered widespread market panic and uncertainty about the viability and predictability of traditional CoCo instruments. Patrick Bolton et al. (2023) emphasized how this regulatory discretion not only inverted conventional loss hierarchies but also severely undermined investor trust in CoCos, casting doubts on their effectiveness as reliable capital buffers.

Furthermore, traditional CoCo bonds, initially proposed by Flannery (2009) and others, were intended to automatically bolster bank capital during financial stress through predefined conversion triggers based primarily on accounting capital ratios. However, Credit Suisse's experience demonstrated fundamental flaws in this design. The delayed responsiveness of accounting-based triggers and the opaque nature of discretionary regulatory interventions resulted in abrupt, large-scale equity dilution and exacerbated market volatility.

The collapse underscored the urgency to revisit CoCo bond structures, prompting examination into alternative frameworks such as the Dynamic Control of Leverage (DCL). By studying the specific dynamics of the Credit Suisse crisis, this thesis aims to investigate whether the proactive, gradual conversion mechanics of DCL CoCos could have effectively mitigated the severity of the collapse, providing a clearer, more predictable response to financial distress scenarios.

4.3 Application of DCL CoCo Bonds to the Credit Suisse Case

This section presents a detailed empirical analysis investigating the effectiveness of the Dynamic Control of Leverage (DCL) framework for contingent convertible (CoCo) bonds, specifically through the lens of the Credit Suisse collapse. The analysis explores how a DCL-based CoCo structure might have performed differently compared to traditional CoCo bonds during the financial turmoil experienced by Credit Suisse.

4.3.1 Historical data

Figure 4.1 shows data for Credit Suisse gathered from Reuters Refinitiv Eikon API. The timeframe was deliberately chosen to be from 2018 to 2023 to capture the state of the stock during normal times and to contrast with the 2023 crisis. By June 2025, after substantial dilutions and regulatory interventions, the share price had fallen over 95% from 2018 highs, and the stock was finally delisted from the Nasdaq stock exchange.

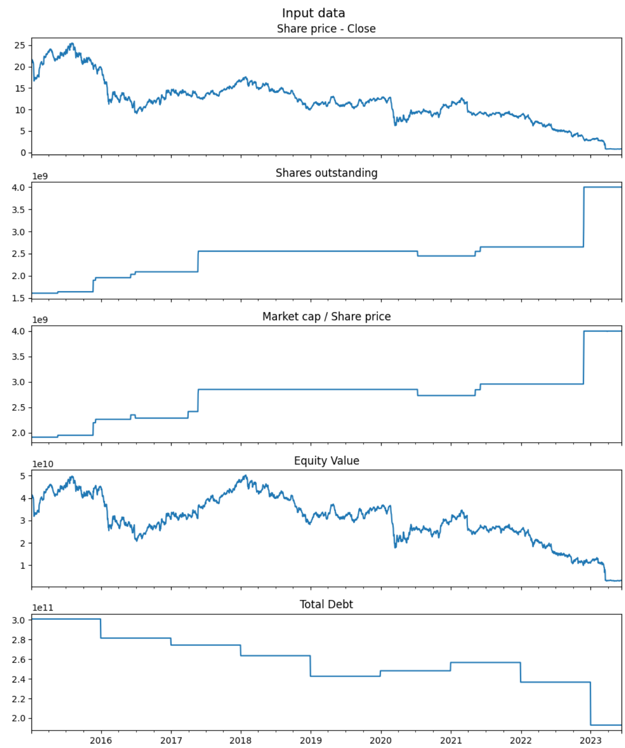

Figure 4.1: Historical data for Credit Suisse

4.3.2 Simulating DCL Contingent Convertible bonds

The DCL framework defines leverage using parameters localized to the DCL CoCo bond, using the proportion of the bond to the total debt of the company to localize the debt-to-asset ratio. The leverage parameter in the DCL bond framework for a company with differing types of debt can be derived as follows:

$$\frac{RQ_k}{RQ_k + \alpha_k \times NS_{k-1} \times S_k} \tag{4.1}$$

Where RQ_k is the residual value of DCL debt at k interval time, α_k is the proportion of the residual value to the total debt of the company, NS_{k-1} is the total number of shares outstanding and S_k is the share price of the company. These values are used as a proxy for the debt-to-asset leverage ratio for the company, used to provide a real-time measure to the bond.

$$RQ_k = Q\left((1+r)^k + \frac{1-(1+r)^k}{1-(1+r)^{-N_n}}\right) \tag{4.2}$$

If the leverage of the company is maintained above the minimum threshold, RQ_k is deterministically drawn down. If the leverage is below the threshold at time k, additional *top-up* DCL bonds are issued with the same maturity to raise the leverage back above the minimum threshold. The other case where RQ_k could deviate is if the regulator determines that the bank has reached a point of non-viability (PONV) and chooses to extraordinarily force a conversion.

If the leverage ratio is above the maximum trigger ratio at interval time k, the interest payment is converted to equity by issuing additional stock using a predetermined conversion share price, S_p. This encourages a gradual dilution of the bondholders, aiming to prevent a sudden collapse by correcting the leverage preemptively over time.

The original thesis introducing the DCL framework simulated a stock using geometric Brownian motion (GBM) with sensible parameters. Many of these parameters can be translated without much change for real-world scenarios. Following are descriptions of the various parameters for the Credit Suisse model.

Banks are generally much more leveraged than non-financial companies. As a result, it is not uncommon to see debt-to-asset ratios for banks in the range of roughly 85% to 95%. source: (https://www.fdic.gov/quarterly-banking-profile). To account for the higher leverage in the banking sector, the minimum leverage threshold was set at 85% and the maximum at 95%. The price of conversion was in every case set at the initial closing price of the shares at issuance.

The initial nominal value of the DCL bond was set to match the size of total AT1 debt at issuance in 2018, to test the case if all traditional CoCo bonds were DCLs instead. This resulted in the initial nominal, Q, to be set at 10.216 billion CHF to match the reported total value of AT1 debt in the 20-f filings. Notably, the total debt of the company does not equal the total amount of DCL bonds, which is why the derivations had to adjust for α_k to be proportional to the total debt of the company.

Similarly, the number of shares outstanding was set at the initial real value in 2018 and allowed to float with the DCL, since it can issue new shares conditional on breach of the lower trigger.

Otherwise, the parameters in the model were set to match those of the simulations from the proposing thesis, which resulted in the inputs shown in table 4.1.

Inputs	**Values**
Nominal debt value, Q	10,216,000,000 CHF
Maturity of loan in years, N	10
frequency of payments per year, n	2
Annual cost of debt, R	5.0%
Initial number of shares NS_0	1,607,168,947
Conversion price, S_p	21,69 CHF
Triggering leverage, L_c	0.90
Lower leverage level, L_{min}	0.85

Table 4.1: Input parameters for modelling a DCL bond on Credit Suisse

Figure 4.2 shows the results of simulating a DCL bond on the input parameters in table 4.1, and it shows how the leverage would change the capital structure of the company over time. Notable for Credit Suisse is the high operating leverage which results in a prevalence and immediacy of additional share issuance (starting in mid-2016) which continued for every subsequent interval date. This is a much earlier intervention than other metrics at the time would permit, since the model set the maximum leverage trigger conservatively at 90% with the aim to adjust for increased stability and preempt or mitigate a potential future crisis.

Comparing the leverage ratios with and without the DCL bond shows that by 2021 the bond had made enough conversions to significantly draw down the leverage ratio, at least to a more sensible level than if the bond had not been in place. This came at the cost of bondholders who only received direct interest on the bonds on the first three payment dates, every later payment being converted into equity. For the shareholders, the resulting dilutions amounted to a total of 5,539,160,028 CHF worth of new shares being issued.

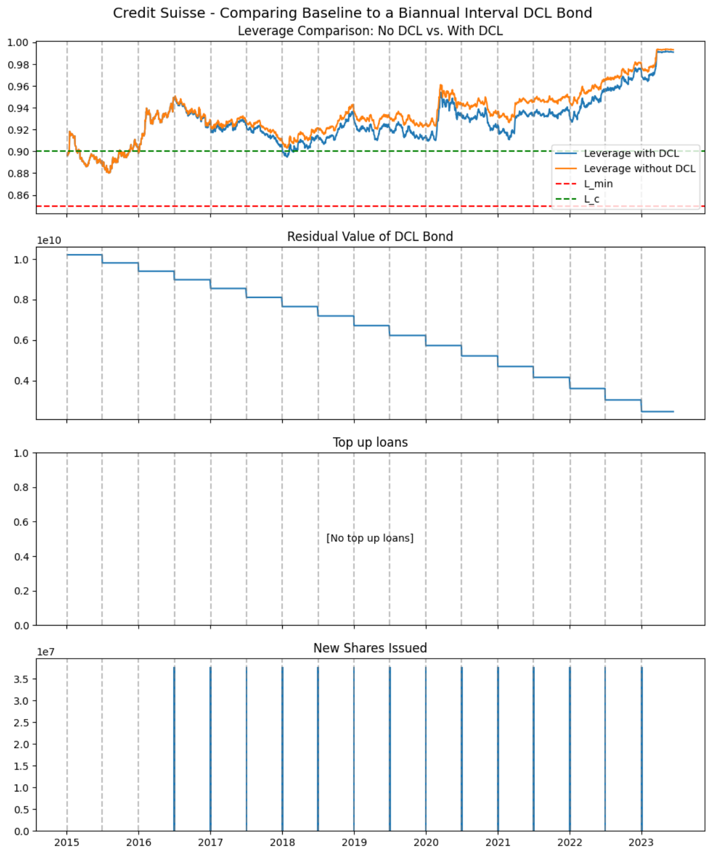

Figure 4.2: Effect of applying a DCL mechanism on AT1 debt for Credit Suisse

4.4 Sensitivity Analysis

Configuring the bond parameters will be vital to balance the interests of bondholders and shareholders, since different parameters can greatly affect the resulting outcomes. The following sensitivity analysis aims to aid management in this decision-making by thoroughly comparing different model parameters and analysing their effect on the bond, and finally deliver some recommendations based on the results.

4.4.1 Frequency of interest payments and leverage adjustments

The DCL contingency mechanism only adjusts at set intervals. Increasing the frequency of checks leads to an increase in the probability of conversion of interest payments and of gradual bondholder dilution. However, it also leads to a more timely and effective adjustment of leverage and decreases the probability of default for the company.

In the Credit Suisse case, the share price and the leverage were highly volatile throughout the period. The leverage frequently crossed the upper threshold, causing the bond to be diluted at interval times. Increasing the frequency of checks also increased the frequency of conversions leading to a larger total adjustment over time, as can be seen in figure 4.3.

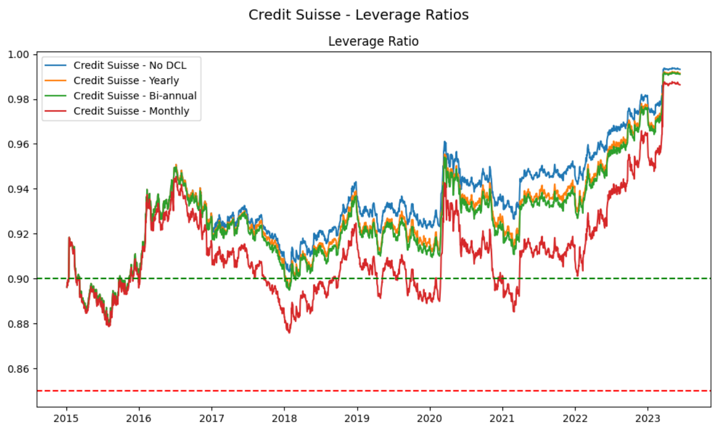

Figure 4.3: Leverage over time for different frequencies of payments (and leverage adjustments)

The effects of the frequency greatly contributes to equity dilution, as can be seen in table 4.2. Note that the initial nominal of the bond was around 16 billion CHF, so in the monthly frequency case the bonds are almost completely converted t equity.

Frequency of payments and adjustments, n	Total dilution [CHF]
Monthly	15,865,642,241
Bi-annual	5,539,160,028
Yearly	4,550,818,975

Table 4.2: Dilution to Credit Suisse stock for different conversion prices.

4.4.2 Converison price and bond conversions

The conversion price plays a crucial role in determining the frequency and extent of bond conversions into equity. If set too low, it can cause excessive dilution for existing shareholders; if set too high, it may not effectively recapitalize the bank during financial distress. Figure 4.4 illustrates how different conversion prices affect the leverage over the observed period.

At higher conversion prices (set above the initial market price), fewer shares are issued per interest payment converted, resulting in less immediate dilution but potentially insufficient leverage adjustments during periods of distress. Conversely, lower conversion prices result in a higher number of shares issued per converted interest payment, facilitating faster leverage corrections at the cost of significant dilution.

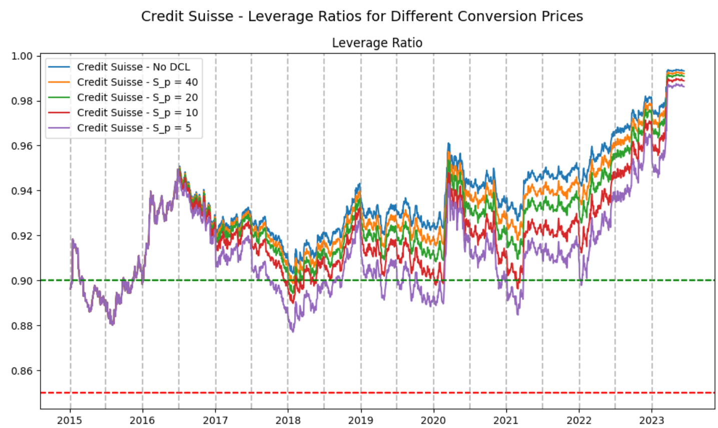

Figure 4.4: Leverage over time for different conversion prices

For Credit Suisse, setting the conversion price near or slightly below the initial share price (around CHF 20) balances recapitalization effectiveness and dilution management. Lowering the conversion price below 10 CHF resulted in excessive shareholder dilution, as can be seen in table 4.3

Conversion price, S_p	**Total dilution [CHF]**
40	3,003,164,177
20	6,006,328,354
10	10,662,511,556
5	15,764,266,353

Table 4.3: Dilution to Credit Suisse stock for different conversion prices.

4.4.3 Leverage triggers

The choice of leverage trigger thresholds significantly impacts the responsiveness and effectiveness of the DCL mechanism. Setting the leverage trigger higher delays conversions, potentially allowing risks to escalate, while a trigger set too low (below 85%) can lead to overly frequent conversions, causing unneccecary risks for bondholders.

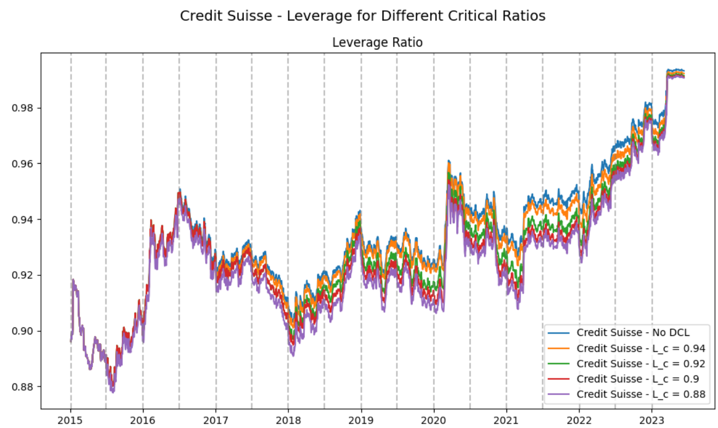

Figure 4.5: Leverage over time for different critical trigger values

Figure 4.5 depicts the impact of varying critical leverage trigger values on Credit Suisse's leverage ratio over time. At a lower trigger, the DCL mechanism responds early to increasing leverage, providing timely but frequent interventions that keep leverage tightly controlled. Conversely, a higher trigger results in fewer adjustments as leverage accumulates closer to critical points.

For Credit Suisse, a sensible leverage trigger around 90% provided a balanced approach, enabling manageable equity dilution while ensuring sufficient leverage corrections to mitigate severe distress scenarios more effectively.

Conversion trigger, L_c	**Total dilution [CHF]**
0.94	1,660,936,706
0.92	3,918,342,039
0.9	5,539,160,028
0.88	7,175,872,082

Table 4.4: Dilution to Credit Suisse stock for different critical triggers.

4.4.4 Conclusions

The sensitivity analysis underscores the importance of carefully calibrating DCL parameters to ensure optimal performance. Setting appropriate conversion prices and leverage triggers can significantly mitigate systemic risks, prevent abrupt dilutions, and enhance stability. Specifically, the analysis recommends a conversion price around the initial market price (approximately CHF 20) to balance dilution and effective recapitalization. Leverage triggers set around 90% to ensure timely yet controlled adjustments to leverage, mitigating both frequent minor and rare significant market disruptions.

Implementing these recommendations would have likely provided Credit Suisse with a more gradual and predictable recapitalization path, potentially preventing the market panic and bondholder wipeout which occurred during the 2023 collapse.

4.5 Comparison to Traditional CoCo Bonds

Compared to traditional CoCo bonds, DCL CoCos offer distinct advantages by addressing critical shortcomings highlighted during the Credit Suisse collapse. Traditional CoCo bonds typically rely on fixed capital ratio triggers or regulatory discretion, which can lead to delayed conversions or abrupt, substantial write-downs. In contrast, the dynamic leverage monitoring and incremental equity conversions inherent in DCL bonds provide a more controlled, predictable approach to recapitalization.

The analysis clearly demonstrates that, under the traditional CoCo bond structure, leverage adjustments were significantly delayed, only occurring once severe distress thresholds were breached. This delay likely amplified market panic and caused excessive investor losses, as seen in the 2023 crisis. Conversely, the DCL framework proactively adjusted leverage through frequent, smaller conversions of interest payments into equity, significantly reducing abrupt equity dilution and investor uncertainty.

Therefore, adopting a DCL structure could have considerably mitigated the magnitude of Credit Suisse's crisis; at least it could have substantially alleviated the catastrophic outcomes experienced under traditional CoCo bond mechanisms.

Chapter 5

Discussion

The analysis presented in this study underscores several critical implications regarding the efficacy of the Dynamic Control of Leverage (DCL) framework compared to traditional Contingent Convertible (CoCo) bonds. Primarily, this research contributes significantly to the existing body of literature by empirically validating the theoretical advantages of DCL mechanisms through real-world simulation, particularly in the context of the Credit Suisse collapse.

One of the most salient insights from this study is that the DCL approach substantially enhances bank stability by providing proactive, incremental equity adjustments rather than relying on abrupt, large-scale interventions. The findings demonstrate that, had Credit Suisse implemented DCL-based CoCo bonds, the effect of dramatic market disruptions and the following bondholder wipeout could have been mitigated. These results also address some of the criticisms highlighted in the literature concerning traditional CoCo mechanisms—namely, their reliance on static triggers and the opacity associated with regulatory discretion [2].

The sensitivity analysis revealed that selecting appropriate parameters, particularly conversion prices and leverage thresholds, is crucial to balancing recapitalization efficiency and market impact. The preferred parameters identified through simulation suggest a conversion price close to or just under the initial market price and a leverage trigger around 90%, providing an effective compromise between immediate leverage correction and gradual shareholder dilution. These results should aid issuers and regulators in understanding the effectiveness of choosing appropriate parameters.

Moreover, this research illustrates the limitations of traditional CoCo bonds, especially during periods of market stress. Traditional mechanisms often trigger conversions only after severe financial distress (or leave the decision to regulators at PONV), which tends to exacerbate market instability and investor panic, demonstrated by the abrupt AT1 bond wipeout for Credit Suisse. In contrast, the

DCL framework, with its gradual and rules-based conversions, significantly reduces the likelihood of sudden large-scale losses and systemic disruptions. Essentially, no single drastic event occurs under DCL; instead, the pain is distributed in smaller doses, which may be more manageable for markets and stakeholders (hence, "no pain, no gain" – small pains to avoid a big one, echoing Flannery's original concept of reverse convertible debentures [9].

However, several limitations warrant consideration when interpreting the results. First, the study relies on historical simulation data, inherently carrying assumptions that may oversimplify real-world complexities. Second, investor perception and regulatory acceptance of DCL instruments were not directly modeled, potentially impacting market dynamics differently than predicted, since persistent conversions could adversely affect shareholder perceptions of the health of the company. Future research could address these gaps by conducting more extensive empirical studies across diverse banking environments and assessing investor behavior through surveys or experimental market studies.

Despite these caveats, the evidence presented is robust in showing the theoretical and simulated benefits of DCL over traditional CoCo structures. Importantly, the analysis is grounded in a real-world case study, giving the results practical relevance. The proactive leverage control of DCL appears to address the core weakness identified in traditional CoCos: the delay in response. Our results align with the views of Calomiris and Herring that well-designed CoCos (with high triggers and strong incentives) can motivate banks to strengthen capital well before insolvency [7]. In the DCL model, conversions happen early and often enough to keep the bank out of the danger zone, embodying that principle.

From a regulatory and policy perspective, these findings are significant. They suggest that incorporating a DCL-like mechanism could enhance the resilience of banks and reduce systemic risk. A DCL framework could be seen as an automated stabilizer for bank capital. By embedding market-based, continuous triggers, it removes some discretion from regulators (which, as seen, can be a double-edged sword) and provides more transparency to investors about how a bank will recapitalize under stress. This could, in theory, reduce moral hazard and increase market discipline, as bank management knows that any excessive leverage will promptly dilute shareholders, aligning incentives more with prudent risk management [9].

Naturally, implementing such a framework would require careful design of the trigger and conversion terms (as we have analyzed) and clear communication to the market. There may also be legal and operational hurdles to issuing DCL CoCos, and it would be important to ensure that these instruments qualify as regulatory capital (just as AT1 CoCos do under Basel III).

In summary, the DCL approach addresses many of the shortcomings observed in the Credit Suisse episode and in traditional CoCo literature. It provides a continuous, market-aligned mechanism for recapitalization that could prevent the kind of sudden collapse witnessed in 2023. The potential downsides (dilution and possibly investor wariness of frequent conversions) seem manageable with proper calibration and are arguably a necessary trade-off for greater stability.

Chapter 6

Conclusion

The research conducted in this thesis offers comprehensive insights into the effectiveness of Dynamic Control of Leverage (DCL) contingent convertible bonds in enhancing bank stability, particularly through the case study of Credit Suisse's 2023 collapse. The empirical analysis demonstrates clear advantages of DCL bonds in comparison to traditional CoCo structures, notably in terms of mitigating abrupt equity dilution, reducing systemic risk, and preventing market instability.

A key finding is that proactive, incremental equity adjustments through DCL significantly outperform traditional mechanisms that rely heavily on static, inflexible triggers. The sensitivity analyses underscore the critical importance of setting appropriate leverage thresholds and conversion prices to balance effective bank recapitalization with market stability and investor confidence.

This thesis contributes substantially to the existing literature by providing empirical validation of the theoretical advantages of the DCL framework, especially valuable in the wake of recent financial crises. It also holds significant implications for regulatory policy, suggesting a practical alternative that enhances transparency and predictability in capital adequacy regulations.

Future research directions include further empirical investigations across different financial institutions and market conditions, as well as studies on investor perception and regulatory adoption challenges for DCL instruments. For example, it would be worthwhile to test DCL CoCos in a broader set of scenarios or with multiple banks to see if the benefits hold generally. Additionally, exploring how markets would price DCL CoCos (compared to traditional CoCos) could provide insight into the feasibility of issuing such instruments.

Overall, given the increased focus on regulatory effectiveness and financial stability post-Credit Suisse, the DCL framework represents a promising and actionable path forward for policymakers, regulators, and banking institutions alike. By embracing dynamic leverage control in bank capital structures, we may significantly improve the resilience of the banking sector and reduce systemic financial risk.

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Appendix A

Code

```
# %% [markdown]
# ## DCL CoCo Bonds
#
# The following code imports data exported from Reuters, then uses it to model DCL CoCo bonds.

# %%
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import configparser as cp
import warnings

# Ignore Eikon python library deprecation warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

# %%
# ================================================================
#                     Load data from Reuters
# ================================================================

def load_reuters_data(ticker_ric, data_folder = "data") -> pd.DataFrame:
    """
    Load timeseries data from Reuters
    """

    close_df                = pd.read_excel(f'{data_folder}/{ticker_ric}/Close.xlsx', index_col = 0, parse_dates = True)
    shares_outstanding_df = pd.read_excel(f'{data_folder}/{ticker_ric}/TR.IssueSharesOutstanding.xlsx', index_col = 0, parse_dates = True)
    market_cap_df           = pd.read_excel(f'{data_folder}/{ticker_ric}/TR.CompanyMarketCapitalization.xlsx', index_col = 0, parse_dates =
```

```
    True)
    total_assets_df        = pd.read_excel(f'{data_folder}/{ticker_ric}/TR.TotalAssets.xlsx', index_col = 0, parse_dates = True)
    total_debt_df          = pd.read_excel(f'{data_folder}/{ticker_ric}/TR.TotalDebtOutstanding.xlsx', index_col = 0, parse_dates = True)
    # at1_debt_df            = pd.read_excel(f'{data_folder}/cs_at1_debt.xlsx', index_col = 0, parse_dates = True)

    # Drop duplicates
    # TODO: see if we can not do this in the first place
    close_df               = close_df[~close_df.index.duplicated(keep='first')]
    shares_outstanding_df = shares_outstanding_df[~shares_outstanding_df.index.duplicated(keep='first')]
    market_cap_df          = market_cap_df[~market_cap_df.index.duplicated(keep='first')]
    total_assets_df        = total_assets_df[~total_assets_df.index.duplicated(keep='first')]
    total_debt_df          = total_debt_df[~total_debt_df.index.duplicated(keep='first')]
    # at1_debt_df            = at1_debt_df[~at1_debt_df.index.duplicated(keep='first')]

    # Fill days inbetween with the last available value
    start_date = close_df.index.min()
    end_date = close_df.index.max()
    full_range = pd.date_range(
        start=start_date - pd.DateOffset(years=1),
        end=end_date,
    )
    close_df = close_df.reindex(full_range).ffill()
    shares_outstanding_df = shares_outstanding_df.reindex(full_range).ffill()
    market_cap_df = market_cap_df.reindex(full_range).ffill()
    total_assets_df = total_assets_df.reindex(full_range).ffill()
    total_debt_df = total_debt_df.reindex(full_range).ffill()
    # at1_debt_df = at1_debt_df.reindex(full_range).ffill()

    # Remove non-business days
    full_range = pd.date_range(
        start=start_date,
        end=end_date,
        freq='B'
    )
    close_df = close_df.reindex(full_range)
    shares_outstanding_df = shares_outstanding_df.reindex(full_range)
    market_cap_df = market_cap_df.reindex(full_range)
    total_assets_df = total_assets_df.reindex(full_range)
    total_debt_df = total_debt_df.reindex(full_range)
    # at1_debt_df = at1_debt_df.reindex(full_range)

```

```python
    input_data = close_df.merge(shares_outstanding_df, left_index=True, right_index=True, how='left')
    input_data = input_data.merge(market_cap_df, left_index=True, right_index=True, how='left')
    input_data = input_data.merge(total_assets_df, left_index=True, right_index=True, how='left')
    input_data = input_data.merge(total_debt_df, left_index=True, right_index=True, how='left')
    # input_data = input_data.merge(at1_debt_df, left_index=True, right_index=True, how='left')

    return input_data


class DCL_Bond:
    def __init__(self, name, ticker_ric, Q_init, L_min, L_c, S_p, r, T_years = 10, freq = 1):
        self.name = name

        # Load ticker data exported from Reuters Eikon
        self.ticker_ric = ticker_ric
        self.reuters_data = load_reuters_data(ticker_ric)

        # Initialize the results dataframe
        self.dcl_data = self.reuters_data.copy()
        self.dcl_data["Market cap / Share price"] = self.dcl_data["Company Market Capitalization"] / self.dcl_data["Close"]

        self.Q_init = Q_init # Initial nominal value of the DCL bond
        self.L_min = L_min   # Min leverage ratio trigger
        self.L_c = L_c       # Max leverage ratio trigger

        # Set conversion price
        if S_p == "initial share price": # Sets the first close price in the time series as S_p
            self.S_p = self.dcl_data['Close'][0]
        elif type(S_p) == int or type(S_p) == float: # We don't accept np.float as input
            self.S_p = S_p
        else:
            raise ValueError

        self.r = r
        self.T_years = T_years
        self.freq = freq

        self.results = self.simulate_DCL()

    def calculate_residual_value_of_dcl(self, Q, r, T_years, k_years):
        """
        Calculate the residual value of DCL bond at time k.
        """
```

```

        return Q * ((1 + r)**k_years + (1 - (1 + r)**k_years)/(1 - (1 + r)**(-T_years)))

    def calculate_alpha(self, RQ_k, book_value_of_total_debt):
        """
        Calculate the ratio of CoCos to total debt.
        """

        return RQ_k / book_value_of_total_debt

    def calculate_leverage_ratio(self, RQ_k, NS_k_1, S_k, alpha_k):
        """
        Calculate the leverage ratio.
        """

        return RQ_k / (RQ_k + alpha_k * NS_k_1 * S_k)

    def compute_period_index(self, dates):
        """
        Given a DatetimeIndex, returns two arrays:
        - period_array: which 'period' you are in
        - k_array: how many 'periods' have passed since the start

        """
        if self.freq == 365: # Daily
            # Number of days since the start date
            base = dates[0]
            day_counts = (dates - base).days
            return day_counts, day_counts  # (period, k) are effectively the same

        elif self.freq == 12: # Monthly
            # A convenient measure: year*12 + month
            base_year  = dates[0].year
            base_month = dates[0].month

            period_array = (dates.year - base_year) * 12 + (dates.month - base_month)
            return period_array, period_array

        elif self.freq == 2: # Bi-annual
            # Count how many 6-month periods have passed since the start
            base_year = dates[0].year
            base_month = dates[0].month
            base_half_year = (base_month - 1) // 6  # 0 for Jan-Jun, 1 for Jul-Dec

            period_array = (dates.year - base_year) * 2 + ((dates.month - 1) // 6) - base_half_year
            return period_array, period_array
```

```python

        elif self.freq == 1: # yearly
            base_year = dates[0].year
            year_offset = (dates.year - base_year)
            return year_offset, year_offset

        elif self.freq == 0: # No DCL (no rebalancing)
            return np.zeros(len(dates)), np.zeros(len(dates))

        else:
            raise ValueError(f"Invalid frequency '{self.freq}'.")


    def simulate_DCL(self):
        """
        Simulate the DCL model.
        """

        period_array, k_array = self.compute_period_index(dates = self.dcl_data.index)
        # print(period_array)
        # print(k_array)
        self.dcl_data['period'] = period_array
        # self.dcl_data['k'] = self.dcl_data.index.year - self.dcl_data.index.year[0]
        self.dcl_data['k']      = k_array

        # Conversion constant for period number to year
        if self.freq == 0:
            period_to_years = 99999
        else:
            period_to_years = 1 / self.freq

        self.dcl_data['Book value of debt'] = self.dcl_data['Total Debt']
        # self.dcl_data['Shares outstanding'] = self.dcl_data['Common Shares - Outstanding - Total']
        self.dcl_data['Shares outstanding'] = self.dcl_data['Issue Default Shares Outstanding'][0]
        self.dcl_data['Q']                  = self.Q_init
        self.dcl_data['Top up loan']        = 0.0
        self.dcl_data['New shares issued']  = 0.0
        self.dcl_data['RQ_k']               = np.nan
        self.dcl_data['alpha_k']              = np.nan
        # self.dcl_data['Leverage ratio']     = np.nan
        self.dcl_data['Payment size'] = 0

        all_dates = self.dcl_data.index
        for idx, day in enumerate(all_dates):
            # Compute the fraction of a year that has elapsed for this k
            k_in_years = self.dcl_data.loc[day, 'k'] * period_to_years
```

```

        if idx != 0:
            # By default, carry forward the nominal Q from prior day
            previous_day = self.dcl_data.index[idx - 1]
            self.dcl_data.loc[day, 'Q'] = self.dcl_data.loc[previous_day, 'Q']

        self.dcl_data.loc[day, 'RQ_k'] = self.calculate_residual_value_of_dcl( # Compute the residual value of DCL
            self.dcl_data.loc[day, 'Q'],
            self.r,
            self.T_years,
            k_in_years,
        )
        self.dcl_data.loc[day, 'alpha_k'] = self.calculate_alpha( # Compute alpha_k (the proportion of DCL to total debt)
            self.dcl_data.loc[day, 'RQ_k'],
            self.dcl_data.loc[day, 'Book value of debt']
        )
        self.dcl_data.loc[day, 'Leverage ratio'] = self.calculate_leverage_ratio( # Compute the leverage ratio
            self.dcl_data.loc[day, 'RQ_k'],
            self.dcl_data.loc[day, 'Shares outstanding'],
            self.dcl_data.loc[day, 'Close'],
            self.dcl_data.loc[day, 'alpha_k'],
        )

        # On the very first day, we just fill RQ_k but do no payments / rebalancing
        if idx == 0:
            continue


        # TODO: Check for correctness (T_years * freq ?)
        if self.freq != 0:
            self.dcl_data.loc[day, 'Payment size'] = self.r * self.dcl_data.loc[day, 'Q'] / (1 - (1 + self.r)**(-self.T_years * self.freq))
        # We only rebalance once per "period" change under freq.
        # For example, if freq='monthly', this triggers once a new month starts.
        if self.dcl_data.loc[day, 'period'] != self.dcl_data.loc[previous_day, 'period']:
            L_k = self.dcl_data.loc[day, 'Leverage ratio']

            if L_k < self.L_min: # In this case, issue new debt to raise the leverage ratio
                # print(f"{day} - Leverage ratio is below minimum: L_k = {L_k}")
```

```
                    self.dcl_data.loc[day, 'Top up loan'] = -self.dcl_data.loc[day, 'RQ_k'] + self.L_min * self.dcl_data.loc[day, 'Shares outstanding'] * self.dcl_data.loc[day, 'Close'] / (1 - self.L_min)
                    # print(f"{day} - Top up loan: {self.dcl_data.loc[day, 'Top up loan']:,.2f}")
                    self.dcl_data.loc[day, 'Q'] += self.dcl_data.loc[day, 'Top up loan'] # Nominal of the DCL
                    self.dcl_data.loc[day, 'Book value of debt'] += self.dcl_data.loc[day, 'Top up loan'] # Total debt of the company

                    # Recompute the residual value of DCL
                    self.dcl_data.loc[day, 'RQ_k'] = self.calculate_residual_value_of_dcl(
                        self.dcl_data.loc[day, 'Q'],
                        self.r,
                        self.T_years,
                        k_in_years,
                    )

                elif L_k > self.L_c: # In this case, convert DCL interest payments to new shares instead
                    # print(f"{day} - Leverage ratio is above critical: L_k = {L_k}")

                    # New shares issued for converting the interest payment to shares
                    shares_issued = self.dcl_data.loc[day, 'Payment size'] / self.S_p

                    # New shares issued to make the leverage ratio be exactly at L_c
                    shares_issued_to_L_c = self.dcl_data.loc[day, 'RQ_k'] * (1 - self.L_c) / (self.L_c * self.dcl_data.loc[day, 'alpha_k'] * self.dcl_data.loc[day, 'Close']) - self.dcl_data.loc[day, 'Shares outstanding']

                    # We don't convert beyond the leverage ratio
                    if shares_issued > shares_issued_to_L_c:
                        shares_issued = shares_issued_to_L_c

                    # print(f"{day} - New shares issued: {self.dcl_data.loc[day, 'New shares issued']}")
                    if shares_issued > 0:
                        self.dcl_data.loc[day:, 'Shares outstanding'] = self.dcl_data.loc[day:, 'Shares outstanding'] + shares_issued

                    self.dcl_data.loc[day, 'New shares issued'] = shares_issued # Document additional shares issued

                if k_in_years >= self.T_years:
```

```
                    print(f"Final k in years for freq {self.freq}: ", k_in_years)
                    break




        self.dcl_data.to_excel(f'data/{self.ticker_ric}/Results - frequency {self.freq}.xlsx')
        return self.dcl_data

    def plot_input_data(self):
        """
        Plot the stock data.
        """

        fig, ax = plt.subplots(5, 1, sharex=True, figsize=(10, 12))
        fig.suptitle("Input data", fontsize=14)
        self.dcl_data["Close"].plot(ax=ax[0])
        ax[0].set_title("Share price - Close")
        self.dcl_data["Issue Default Shares Outstanding"].plot(ax=ax[1])
        ax[1].set_title("Shares outstanding")
        ax[2].set_title("Market cap / Share price")
        self.dcl_data["Market cap / Share price"].plot(ax=ax[2])
        self.dcl_data["Company Market Capitalization"].plot(ax=ax[3])
        ax[3].set_title("Equity Value")
        self.dcl_data["Total Debt"].plot(ax=ax[4])
        ax[4].set_title("Total Debt")
        plt.tight_layout()
        plt.savefig(f"images/input_data.png")
        plt.show()



# =========================================================================
#                               Simulations
# =========================================================================

# -------------------------- Credit Suisse -------------------------------

cs_r = 0.05
cs_Q_init = 10_216_000_000 # Initial nominal value of DCL bonds -> Set as initial AT1 debt value
# cs_L_min = 0
cs_L_min = 0.85
# cs_L_c   = 1
```

```
cs_L_c   = 0.9

cs_dcl_daily = DCL_Bond(
    name       = "Credit Suisse - Daily",
    ticker_ric = "CSGN.S^F23",          # Reuters Intrument Code (RIC) for the ticker
    Q_init     = cs_Q_init,             # Initial value of DCL bonds
    L_min      = cs_L_min,              # Minimum leverage ratio
    L_c        = cs_L_c,                # Critical leverage ratio
    S_p        = "initial share price", # Conversion price
    r          = cs_r,                  # Risk free rate TODO: change to timeseries?
    T_years    = 10,                    # Number of years to maturity for DCL bonds
    freq       = 365,                   # Frequency of interest payments and leverage considerations
)

cs_dcl_monthly = DCL_Bond(
    name       = "Credit Suisse - Monthly",
    ticker_ric = "CSGN.S^F23",          # Reuters Intrument Code (RIC) for the ticker
    Q_init     = cs_Q_init,             # Initial value of DCL bonds
    L_min      = cs_L_min,              # Minimum leverage ratio
    L_c        = cs_L_c,                # Critical leverage ratio
    S_p        = "initial share price", # Conversion price
    r          = cs_r,                  # Risk free rate TODO: change to timeseries?
    T_years    = 10,                    # Number of years to maturity for DCL bonds
    freq       = 12,             # Frequency of interest payments and leverage considerations
)

cs_dcl_biannual = DCL_Bond(
    name       = "Credit Suisse - Bi-annual",
    ticker_ric = "CSGN.S^F23",          # Reuters Intrument Code (RIC) for the ticker
    Q_init     = cs_Q_init,             # Initial value of DCL bonds
    L_min      = cs_L_min,              # Minimum leverage ratio
    L_c        = cs_L_c,                # Critical leverage ratio
    S_p        = "initial share price", # Conversion price
    r          = cs_r,                  # Risk free rate TODO: change to timeseries?
    T_years    = 10,                    # Number of years to maturity for DCL bonds
    freq       = 2,            # Frequency of interest payments and leverage considerations
) # TODO: bi-annual

cs_dcl_yearly = DCL_Bond(
    name       = "Credit Suisse - Yearly",
```

```
    ticker_ric = "CSGN.S^F23",           # Reuters Intrument Code (RIC) for the ticker
    Q_init     = cs_Q_init,              # Initial value of DCL bonds
    L_min      = cs_L_min,               # Minimum leverage ratio
    L_c        = cs_L_c,                 # Critical leverage ratio
    S_p        = "initial share price",  # Conversion price
    r          = cs_r,                   # Risk free rate TODO: change to timeseries?
    T_years    = 10,                     # Number of years to maturity for DCL bonds
    freq       = 1,               # Frequency of interest payments and leverage considerations
)

# No DCL bond, freq = 0
cs_no_dcl = DCL_Bond(
    name       = "Credit Suisse - No DCL",
    ticker_ric = "CSGN.S^F23",           # Reuters Intrument Code (RIC) for the ticker
    Q_init     = 1,                      # Initial value of DCL bonds
    L_min      = cs_L_min,               # Minimum leverage ratio
    L_c        = cs_L_c,                 # Critical leverage ratio
    S_p        = "initial share price",  # Conversion price
    r          = cs_r,                   # Risk free rate TODO: change to timeseries?
    T_years    = 10,                     # Number of years to maturity for DCL bonds
    freq       = 0,          # Frequency of interest payments and leverage considerations
)

# cs_dcl_yearly.reuters_input_data
cs_dcl_yearly.results



# %%
# ================================================================
#                         Plot the input data
# ================================================================

cs_dcl_yearly.plot_input_data()



# %% [markdown]
# $RQ_k = Q * ((1 + r)^k + (1 - (1 + r)^k)/(1 - (1 + r)^{-N_m}))$ (only applies if the triggers are not breached)
#
# $L_k = \text{Total debt} / (\text{Total equity} + \text{Total debt}) = RQ_k / (RQ_k + NS_{k-1} * S_k)$
#
```

```python
# $\alpha = RQ_k / (RQ_k + \text{Book value of non CoCo debt})$

# %%
# ================================================================
#                          Plot the results
# ================================================================

def plot_results(no_dcl_bond: DCL_Bond, dcl_bond: DCL_Bond, title: str) -> None:
    """
    Plot the results.
    """

    fig, ax = plt.subplots(3, 1, sharex=True, figsize=(10,12))
    fig.suptitle(title, fontsize=14)
    i = 0

    # ------------------------------------------------------------------
    # 1) Stock price
    # ------------------------------------------------------------------
    # ax[0].plot(df.index, df['Close'], label='Close')
    # ax[0].set_title('Stock Price')
    # ax[0].legend(loc='best')
    # i += 1

    # TODO: Add shares outstanding plot
    # ax[1].plot(df.index, df['Shares outstanding'], label='Shares outstanding')
    # ax[1].set_title('Shares outstanding')

    # ------------------------------------------------------------------
    # 2) Leverage ratio
    # ------------------------------------------------------------------
    ax[i].plot(dcl_bond.results.index, dcl_bond.results['Leverage ratio'], label='Leverage Ratio')
    if dcl_bond.L_min != 0:
        ax[i].axhline(y=dcl_bond.L_min, linestyle='--', label='L_min', color='red')
    if dcl_bond.L_c != 1:
        ax[i].axhline(y=dcl_bond.L_c,   linestyle='--', label='L_c', color='green')
    ax[i].set_title('Leverage Ratio')
    ax[i].legend(loc='best')
    i += 1

    # ------------------------------------------------------------------
    # 3) Residual value of DCL bond
```

```python
    # -----------------------------------------------------------------
    ax[i].plot(dcl_bond.results.index, dcl_bond.results['RQ_k'], label='RQ_k')
    ax[i].set_title('Residual Value of DCL Bond')
    # ax[1].legend(loc='best')
    i += 1

    # TODO: Add alpha plot
    # TODO: Add new debt issued plot

    # -----------------------------------------------------------------
    # 4) New Debt Issued
    # -----------------------------------------------------------------
    # if dcl_bond.results['Top up loan'].sum() > 0:
    #     ax[i].bar(dcl_bond.results.index, dcl_bond.results['Top up loan'], label='Top up loan', width=8)
    #     ax[i].set_title('Top up loan')
    #     # ax[i].legend(loc='best')
    # else:
    #     ax[i].text(0.5, 0.5, 'No top up loans', ha='center', va='center', transform=ax[i].transAxes)
    # i += 1

    # -----------------------------------------------------------------
    # 5) New Shares Issued
    # -----------------------------------------------------------------
    if dcl_bond.results['New shares issued'].sum() > 0:
        ax[i].bar(dcl_bond.results.index, dcl_bond.results['New shares issued'], label='New Shares Issued', width=8)
        ax[i].set_title('New Shares Issued')
    else:
        ax[i].text(0.5, 0.5, 'No new shares issued', ha='center', va='center', transform=ax[i].transAxes)
    i += 1

    # -----------------------------------------------------------------
    # Add vertical lines at the start of each period k
    # -----------------------------------------------------------------
    if dcl_bond.freq <= 52: # Clearer to not have vertical lines for daily intervals
        for k_val in dcl_bond.results['k'].unique():
            # For that k_val, find the first time index (i.e., the earliest date)
            # in the DataFrame where k == k_val
```

```python
            first_date_k = dcl_bond.results[dcl_bond.results['k'] == k_val].index[0]

            # You can choose on which subplot(s) you want the lines.
            # If you want the line in all subplots, iterate over `ax`.
            # If you want it only in the last subplot, do just ax[2].axvline(...).
            for axis in ax:
                axis.axvline(first_date_k, color='gray', linestyle='--', alpha=0.5)

    plt.tight_layout()
    plt.savefig(f"images/{title}.png")
    plt.show()

plot_results(cs_no_dcl, cs_dcl_yearly, title="Credit Suisse - Yearly Interval DCL Bond")
plot_results(cs_no_dcl, cs_dcl_biannual, title="Credit Suisse - Biannual Interval DCL Bond")
plot_results(cs_no_dcl, cs_dcl_monthly, title="Credit Suisse - Monthly Interval DCL Bond")
plot_results(cs_no_dcl, cs_dcl_daily, title="Credit Suisse - Daily Interval DCL Bond")


# %%
# Plot compare leverage with no DCL

def plot_compare_with_no_DCL(no_dcl_bond: DCL_Bond, dcl_bond: DCL_Bond, title: str) -> None:
    """
    Plot the results.
    """

    fig, ax = plt.subplots(4, 1, sharex=True, figsize=(10,12))
    fig.suptitle(title, fontsize=14)
    i = 0

    # -----------------------------------------------------------------
    # 1) Stock price
    # -----------------------------------------------------------------
    # ax[0].plot(df.index, df['Close'], label='Close')
    # ax[0].set_title('Stock Price')
    # ax[0].legend(loc='best')
    # i += 1

    # TODO: Add shares outstanding plot
    # ax[1].plot(df.index, df['Shares outstanding'], label='Shares outstanding')
    # ax[1].set_title('Shares outstanding')
```

```python

    # -------------------------------------------------------------------
    # 2) Leverage ratio
    # -------------------------------------------------------------------

    ax[i].plot(dcl_bond.results.index, dcl_bond.results['Leverage ratio'], label='Leverage with DCL')
    ax[i].plot(no_dcl_bond.results.index, no_dcl_bond.results['Leverage ratio'], label='Leverage without DCL')
    if dcl_bond.L_min != 0:
        ax[i].axhline(y=dcl_bond.L_min, linestyle='--', label='L_min', color='red')
    if dcl_bond.L_c != 1:
        ax[i].axhline(y=dcl_bond.L_c,   linestyle='--', label='L_c', color='green')
    # ax[i].set_ylim(dcl_bond.L_min - 0.01, 1)
    # ax[i].set_ylim(0.875, 1)
    ax[i].set_title('Leverage Comparison: No DCL vs. With DCL')
    ax[i].legend(loc='best')
    i += 1

    # -------------------------------------------------------------------
    # 3) Residual value of DCL bond
    # -------------------------------------------------------------------
    ax[i].plot(dcl_bond.results.index, dcl_bond.results['RQ_k'], label='RQ_k')
    ax[i].set_title('Residual Value of DCL Bond')
    # ax[1].legend(loc='best')
    i += 1

    # TODO: Add alpha plot
    # TODO: Add new debt issued plot

    # -------------------------------------------------------------------
    # 4) New Debt Issued
    # -------------------------------------------------------------------
    if dcl_bond.results['Top up loan'].sum() > 0:
        ax[i].bar(dcl_bond.results.index, dcl_bond.results['Top up loan'], label='Top up loan', width=10)
    else:
        ax[i].text(0.5, 0.5, '[No top up loans]', ha='center', va='center', transform=ax[i].transAxes)
    ax[i].set_title('Top up loans')
    i += 1

```

```
    # -----------------------------------------------------------------
    # 5) New Shares Issued
    # -----------------------------------------------------------------
    if dcl_bond.results['New shares issued'].sum() > 0:
        ax[i].bar(dcl_bond.results.index, dcl_bond.results['New shares issued'], label='New Shares Issued', width=10)
    else:
        ax[i].text(0.5, 0.5, 'No new shares issued', ha='center', va='center', transform=ax[i].transAxes)
    ax[i].set_title('New Shares Issued')
    i += 1

    # -----------------------------------------------------------------
    # Add vertical lines at the start of each period k
    # -----------------------------------------------------------------
    if dcl_bond.freq <= 52: # Clearer to not have vertical lines for daily intervals
        for k_val in dcl_bond.results['k'].unique():
            # For that k_val, find the first time index (i.e., the earliest date)
            # in the DataFrame where k == k_val
            first_date_k = dcl_bond.results[dcl_bond.results['k'] == k_val].index[0]

            # You can choose on which subplot(s) you want the lines.
            # If you want the line in all subplots, iterate over `ax`.
            # If you want it only in the last subplot, do just ax[2].axvline(...).
            for axis in ax:
                axis.axvline(first_date_k, color='gray', linestyle='--', alpha=0.5)

    plt.tight_layout()
    plt.savefig(f"images/{title}.png")
    plt.show()

plot_compare_with_no_DCL(cs_no_dcl, cs_dcl_biannual, "Credit Suisse - Comparing Baseline to a Biannual Interval DCL Bond")



# %%
# -------------------------  Deutsche Bank ------------------------------

db_r = 0.05
db_Q_init = 10_216_000_000 # TODO: find deutsche bank value Initial value of DCL bonds -> Set to initial AT1 debt value
```

```
db_L_min = 0.85
db_L_c   = 0.9

db_dcl_biannual = DCL_Bond(
    name       = "Deutsche Bank - DCL",
    ticker_ric = "DBKGn.DE",           # Reuters Intrument Code (RIC) for the ticker
    Q_init     = db_Q_init,            # Initial value of DCL bonds
    L_min      = db_L_min,             # Minimum leverage ratio
    L_c        = db_L_c,               # Critical leverage ratio
    S_p        = "initial share price", # Conversion price
    r          = db_r,                 # Risk free rate TODO: change to timeseries?
    T_years    = 10,                   # Number of years to maturity for DCL bonds
    freq       = 2,             # Frequency of interest payments and leverage considerations
)

db_no_dcl = DCL_Bond(
    name       = "Deutsche Bank - No DCL",
    ticker_ric = "DBKGn.DE",           # Reuters Intrument Code (RIC) for the ticker
    Q_init     = 1,                    # Initial value of DCL bonds
    L_min      = db_L_min,             # Minimum leverage ratio
    L_c        = db_L_c,               # Critical leverage ratio
    S_p        = "initial share price", # Conversion price
    r          = db_r,                 # Risk free rate TODO: change to timeseries?
    T_years    = 10,                   # Number of years to maturity for DCL bonds
    freq       = 0,         # Frequency of interest payments and leverage considerations
)


plot_results(db_no_dcl, db_dcl_biannual, title="Deutsche Bank - Biannual Interval DCL Bond")



# %%
# Calculate the book value leverage ratio and compare with DCL values
```

```python




# %%
# Compare levarage ratios

def plot_leverage_ratios(dcl_bonds: list[DCL_Bond], title: str,
    interv_lines = False, L_c_lines = True) -> None:
    """
    Plot the leverage ratios.
    """

    fig, ax = plt.subplots(1, 1, sharex=True, figsize=(10,6))
    fig.suptitle(title, fontsize=14)

    for dcl_bond in dcl_bonds:
        ax.plot(dcl_bond.results.index, dcl_bond.results['Leverage
    ratio'], label=f"{dcl_bond.name}")
    if L_c_lines:
        ax.axhline(y=dcl_bond.L_min, linestyle='--', color='red')
        ax.axhline(y=dcl_bond.L_c,   linestyle='--',   color='green')
    if interv_lines:
        for k_val in dcl_bond.results['k'].unique():
            first_date_k = dcl_bond.results[dcl_bond.results['k'] ==
    k_val].index[0]
            ax.axvline(first_date_k, color='gray', linestyle='--',
    alpha=0.5)
    ax.set_title('Leverage Ratio')
    ax.legend(loc='best')
    plt.tight_layout()
    plt.savefig(f"images/{title}.png")
    plt.show()


# Compare different frequencies
plot_leverage_ratios([
    cs_no_dcl,
    cs_dcl_yearly,
    cs_dcl_biannual,
    cs_dcl_monthly,
    # cs_dcl_daily
    ],
    title="Credit Suisse - Leverage Ratios"
)



# %%

# Compare different conversion prices, S_p

```

```
cs_dcl_conversion_prices = [
    DCL_Bond(
        name        = f"Credit Suisse - S_p = {db_S_p}",
        ticker_ric = "CSGN.S^F23",          # Reuters Intrument Code (RIC) for the ticker
        Q_init      = cs_Q_init,            # Initial value of DCL bonds
        L_min       = cs_L_min,             # Minimum leverage ratio
        L_c         = cs_L_c,               # Critical leverage ratio
        S_p         = db_S_p,                   # Conversion price
        r           = cs_r,                 # Risk free rate TODO: change to timeseries?
        T_years     = 10,                   # Number of years to maturity for DCL bonds
        freq        = 2,             # Frequency of interest payments and leverage considerations
    ) for db_S_p in [40, 20, 10, 5]
]
cs_dcl_conversion_prices.insert(0, cs_no_dcl)


# %%
# Plot the leverages different conversion prices
plot_leverage_ratios(cs_dcl_conversion_prices, title="Credit Suisse - Leverage Ratios for Different Conversion Prices", interv_lines = True)


# %%
# Compare different L_c values

cs_dcl_leverage_ratios = [
    DCL_Bond(
        name        = f"Credit Suisse - L_c = {db_L_c}",
        ticker_ric = "CSGN.S^F23",          # Reuters Intrument Code (RIC) for the ticker
        Q_init      = cs_Q_init,            # Initial value of DCL bonds
        L_min       = cs_L_min,             # Minimum leverage ratio
        L_c         = db_L_c,               # Critical leverage ratio
        S_p         = "initial share price", # Conversion price
        r           = cs_r,                 # Risk free rate TODO: change to timeseries?
        T_years     = 10,                   # Number of years to maturity for DCL bonds
        freq        = 2,             # Frequency of interest payments and leverage considerations
    ) for db_L_c in [0.94, 0.92, 0.9, 0.88]
]
cs_dcl_leverage_ratios.insert(0, cs_no_dcl)
```

```
# %%

# Plot the leverages different L_c values
plot_leverage_ratios(cs_dcl_leverage_ratios, title="Credit Suisse - Leverage for Different Critical Ratios", interv_lines = True, L_c_lines = False)



# %%
# Calculate total value of dilutions for new shares issued

def calculate_total_dilution(dcl_bond: DCL_Bond):
    dilutions = dcl_bond.results['New shares issued'] * dcl_bond.results['Close']
    total = dilutions.sum()
    print(f"    {dcl_bond.name}: {total:>15,.0f} CHF")

print("Total dilution from share issuances of DCL bonds - Credit Suisse: ")
calculate_total_dilution(cs_dcl_daily)
calculate_total_dilution(cs_dcl_monthly)
calculate_total_dilution(cs_dcl_biannual)
calculate_total_dilution(cs_dcl_yearly)
print("Total dilution from share issuances of DCL bonds - Deutsche Bank:")
calculate_total_dilution(db_dcl_biannual)

print("Dilutions for different S_p values")
for dcl_bond in cs_dcl_conversion_prices:
    calculate_total_dilution(dcl_bond)

print("Diltuions for different L_c values")
for dcl_bond in cs_dcl_leverage_ratios:
    calculate_total_dilution(dcl_bond)
```

Listing A.1: Jupyter Notebook Code