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Quantitative easing and its implications for contingent convertible triggers: an analytical perspective

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Abstract. *Quantitative Easing (QE) has become a critical monetary policy tool, particularly after the 2008 Financial Crisis and the COVID-19 pandemic, aimed at stimulating economic activity through large-scale bond purchases. QE raises asset prices, lowers interest rates, and enhances market liquidity, but its long-term effects on financial stability and instruments like Contingent Convertible (CoCo) bonds are less understood. This study explores how QE indirectly impacts CoCo bond activation by influencing banks' capital adequacy. Using the 2023 Credit Suisse crisis as a case study, we model how QE reshapes bank capital structures, increasing CoCo activation risks during financial instability.*

Keywords: Quantitative Easing, contingent convertible bonds, financial stability, Credit Suisse crisis, systemic risk, and macroprudential policy.

JEL Classification: E52, E44, G28, G32, C15.

1. Introduction

Quantitative Easing (QE) has become a fundamental tool in contemporary monetary policy, widely adopted by leading central banks such as the European Central Bank (ECB), the Bank of England (BoE), and the Federal Reserve. This strategy is primarily employed to counteract economic slowdowns and promote growth. At its core, QE involves central banks acquiring long-term securities to lower interest rates, expand the money supply, and encourage economic activity (Gagnon et al., 2011; Bernanke et al., 2009).

Although the immediate effects of QE—such as increased asset prices and improved liquidity—are well-understood, the long-term consequences, particularly on financial institutions, remain underexplored. One of the less studied aspects is how QE, by influencing asset prices, affects the capital positions of banks and the functioning of financial instruments like Contingent Convertible (CoCo) bonds (Hirtle, 2013; Avdjiev et al., 2020). These bonds are designed to absorb losses by converting into equity or being written down when a bank's capital ratio falls below a set threshold, thereby supporting the bank's stability (Flannery, 2014). However, the indirect effects of QE on CoCo bond triggers, especially in times of financial stress, have not been fully examined.

This study aims to fill this gap by investigating how changes in asset prices driven by QE can indirectly affect the likelihood of triggering CoCo bonds. Using a quantitative model, the paper explores the connection between QE, asset price movements, and the capital adequacy ratios of banks, with a particular focus on the 2023 Credit Suisse crisis as a case study. The analysis considers how QE-induced increases in asset prices can affect a bank's capital ratio, potentially pushing it below the critical threshold required to activate CoCo bonds during periods of market instability (Acharya & Steffen, 2020; Hördahl et al., 2016).

The findings of this study are crucial for understanding the potential risks QE poses to financial stability, particularly in relation to CoCo bonds. The research also highlights the importance of strengthening regulatory frameworks and fostering international cooperation to manage the unintended consequences of QE (Gambacorta & Shin, 2018). By better understanding the interactions between QE, financial markets, and CoCo bond triggers, policymakers can develop more effective strategies to anticipate and mitigate the risks associated with unconventional monetary policies.

2. Literature review

2.1. Quantitative Easing: An Overview and Its Market Implications

Quantitative Easing (QE) is an unconventional monetary policy tool that central banks have used in response to low inflation, weak economic growth, and financial instability. When traditional policy tools, such as adjusting short-term interest rates, become less effective—especially in environments where interest rates approach zero—QE serves as a supplementary measure. By purchasing government bonds or private sector assets, QE aims to inject liquidity into the financial system, reduce long-term interest rates, and stimulate economic activity.

Central banks such as the European Central Bank (ECB), Bank of England (BoE), and the Federal Reserve have relied on QE in response to the global financial crises of 2008 and the economic disruptions from the COVID-19 pandemic. By purchasing large quantities of assets, central banks aim to reduce borrowing costs and increase liquidity, which typically results in higher prices for financial assets such as bonds, equities, and real estate. Investors, in a low-interest-rate environment, are encouraged to seek higher returns, thus driving demand for financial assets and contributing to asset price inflation (Gagnon et al., 2011; Bernanke et al., 2009).

The effects of QE are transmitted through several interconnected channels. First, the purchase of long-term government bonds by central banks leads to a reduction in bond yields, effectively lowering borrowing costs across the economy (Joyce et al., 2011). This lower cost of borrowing encourages demand for other assets, including corporate bonds, equities, and real estate. As investors shift into these assets, the increased demand causes asset prices to rise, providing a wealth effect that boosts consumer confidence and spending, further stimulating economic activity (Campbell et al., 2006).

Additionally, rising asset prices enhance the financial positions of both households and financial institutions. For banks, this often results in improved capital positions, as the value of their asset holdings increases. With stronger capital ratios, banks appear more financially stable, which can promote further lending and investment activity. This positive feedback loop between asset price increases and financial stability is a key characteristic of QE's transmission mechanism (Blanchard et al., 2010; Borio & Disyatat, 2010; Kashyap, A. K., & Stein, J. C. 2000).

Research has shown that asset prices in developed economies have been notably influenced by QE. For example, studies by Gagnon et al. (2011) and Joyce et al. (2011) found that QE has been associated with cumulative increases in asset prices of up to 20% in certain economies over the course of prolonged QE programs. In the case of the ECB and BoE, aggressive asset purchases have led to significant asset price increases, particularly in bond and equity markets. These findings demonstrate how QE, while effective in the short term, can also contribute to growing asset price imbalances over time.

While QE can support economic growth in the short run by lowering borrowing costs and boosting asset prices, it also introduces several potential risks. One of the key concerns is the creation of financial imbalances, particularly through the inflation of asset prices. As financial institutions and investors become more confident in the rising value of their assets, there may be a tendency to engage in riskier lending and investment behavior, assuming that asset prices will continue to rise (Bernanke, 2012, Adrian and Liang, 2016). This complacency may lead to the accumulation of excess risk in the financial system, which could amplify vulnerabilities if asset prices eventually correct.

The potential for market distortions is another important risk associated with QE. Large-scale asset purchases by central banks can overinflate certain asset classes, distorting market prices beyond their fundamental values (Borio & Disyatat, 2010). If these inflated asset prices eventually experience a correction, banks may find their capital ratios deteriorating rapidly, potentially triggering the activation of Contingent Convertible

(CoCo) bonds. These instruments, designed to convert into equity or be written down when a bank's capital ratio falls below a critical threshold, could become a source of financial stress during market corrections (Hirtle, 2013).

Studies have indicated that such asset price corrections can lead to significant disruptions in financial institutions' capital positions. For instance, Hördahl et al. (2016) observed that the rapid decline in the value of assets during financial crises could trigger CoCo bond conversion, exacerbating the challenges faced by banks. Therefore, the link between QE, asset price inflation, and CoCo bond activation is an important area for further research, as these dynamics have yet to be fully explored in regulatory frameworks.

2.2. Quantitative Easing and Bank Capital

The relationship between QE and bank capital is complex and multifaceted. QE's influence on asset prices directly impacts the valuation of bank portfolios, affecting capital adequacy ratios. Hancock and Passmore (2014) argue that QE-induced increases in asset prices bolster bank capital by raising the market value of securities held on balance sheets. However, Acharya and Steffen (2020) highlight potential adverse effects, such as mispricing of risk and erosion of profitability due to persistently low-interest rates.

The Basel Committee on Banking Supervision (BCBS, 2024) underscores the role of market conditions in shaping bank capital buffers. In a QE environment, rising asset prices can mask underlying vulnerabilities in bank balance sheets, potentially exacerbating systemic risks. Studies by Gambacorta and Shin (2018) suggest that the interaction between QE and regulatory frameworks necessitates robust mechanisms to assess risk exposures. This dynamic is particularly relevant for CoCos, as their triggers are tied to capital metrics sensitive to market fluctuations.

2.3. Quantitative Modelling of QE, Market Conditions, and CoCo Risk

Quantitative models are essential for capturing the nexus between QE, market conditions, and CoCo risk. The existing literature employs various approaches, including structural models, econometric analyses, and agent-based simulations. These models aim to disentangle the complex interactions between monetary policy, asset prices, and financial stability.

Hamilton & Wu (2011) develop a term structure model to quantify the effects of QE on bond yields, providing insights into its transmission mechanisms. Similarly, Chen et al. (2016) employed a dynamic stochastic general equilibrium (DSGE) framework to assess QE's impact on macroeconomic variables and financial markets. These studies highlight the challenges of modeling QE's indirect effects, particularly on instruments like CoCos.

A growing body of research focuses on stress-testing methodologies that incorporate QE dynamics. Glasserman & Xu (2014) propose a simulation-based framework to evaluate CoCo triggers under different market scenarios. Their findings underscore the need for scenario analysis to account for QE-induced distortions.

2.4. Contingent Convertible Bonds: Mechanisms and Risks

CoCos are hybrid instruments designed to enhance bank resilience during stress periods. They contain conversion triggers based on capital ratios or market-based indicators, ensuring loss absorption when banks face distress. The literature emphasizes the dual role of CoCos as instruments of financial stability and sources of systemic risk.

Flannery (2014) provides a comprehensive review of CoCo structures, highlighting their reliance on predefined triggers. QE's impact on asset prices introduces volatility in these triggers, potentially leading to premature or delayed conversions. De Spiegeleer et al. (2017) examine the sensitivity of CoCos to market conditions, revealing that price distortions induced by QE can undermine their effectiveness.

3. Research methodology

The primary objective of this research is to simulate the evolution of a financial institution's Common Equity Tier 1 (CET1) ratio over a ten-year period, under a range of economic scenarios. The simulation investigates the probability that the CET1 ratio will fall below a critical threshold, which could trigger the conversion of Contingent Convertible (CoCo) bonds. The study uses a Monte Carlo simulation approach to capture the uncertainty inherent in asset prices, profitability, and the CET1 ratio, considering factors such as monetary policy changes and market volatility.

A Monte Carlo simulation is used in this study to model the dynamic and random behaviour of asset prices and CET1 ratios over time. This method is well-suited for capturing the inherent uncertainty in financial systems and allows the exploration of a large number of potential outcomes. By running multiple simulations, this technique enables a comprehensive assessment of the risks and probabilities of different financial scenarios.

3.1. Model Processing

3.1.1. Assumptions:

1. QE increases asset prices (μ_{QE}) and introduces volatility (σ_{QE}).

2. CET1 ratio dynamics depend on QE, profitability, and stochastic market conditions.

3. CoCo triggers occur when CET1 falls below 7%.

3.1.2. Simulation Parameters:

The key parameters used in the simulation are as follows:

- Time Horizon: The analysis is conducted over a period of 10 years, with daily time steps for each year;
- Time Steps: The simulation progresses in daily intervals, resulting in 2,500 time steps over the 10-year period;
- Number of Simulations: 50,000 independent simulations are run to ensure statistical reliability and robustness of the results.

3.1.3. Simulating Asset Prices

Asset prices are modelled using a geometric Brownian motion (GBM) process, which assumes that price changes are influenced by both a deterministic component (drift) and a stochastic component (random fluctuations):

- Drift (μ_{QE}): The expected return on the asset, adjusted for the effects of quantitative easing policies, set at 2% annually (Fabo et al., 2021);
- Volatility (σ_{QE}): The volatility of the asset price, which reflects market uncertainty, especially after global economic shocks, set at 15% (Megaritis et al. 2021);

The asset price dynamics at each time step are represented by the following equation:

$$dAP = \mu QE \times APt \times \Delta t + \sigma QE \times APt \times \sqrt{\Delta t} \times Z \qquad (1)$$

Where:

Δt is the daily time increment (1/250);

Ap_t is the asset price at time t;

σ_{QE} is the volatility of the asset price;

Z is a random variable drawn from a standard normal distribution$\sim N(0,1)$.

3.1.4. Simulating CET1 Ratio

The CET1 ratio is simulated using a stochastic process, reflecting the uncertainty in a financial institution's capital adequacy over time. The key parameters influencing the CET1 ratio include profitability and CET1 Volatility (σ_{CET1}).

The CET1 ratio evolves based on the combined effects of QE, profitability, and stochastic factors:

$$dCET1=\beta QE \times \mu QE \times \Delta t + P \times \Delta t + \sigma CET1 \times \sqrt{\Delta t} \times ZP \qquad (2)$$

Where:

β_{QE} is the sensitivity of CET1 to asset price dynamics;

μ_{QE} is the expected return on the asset, adjusted for the effects of quantitative easing policies;

P is the profitability of the financial institution, modeled as a random variable with a mean of 0.5% and a standard deviation of 5%;

Δt is set at 1 year (for simplicity, let's assume an annual time step);

σ_{CET1} is the volatility of the CET1 ratio;

$Z_P \sim N(0,1)$ is another random shock for profitability.

3.1.5. CoCo Bond Trigger Probability

A crucial aspect of the analysis is the evaluation of the likelihood that the CET1 ratio will fall below a threshold of 7%, which would trigger the conversion of CoCo bonds. The probability of this event is calculated by determining the fraction of simulations where the final CET1 ratio drops below the 7% threshold.

The probability of a CoCo trigger is determined by:

$$Pr(Trigger)=P(CET1<7\%) \tag{3}$$

3.2. Simulation Implementation: Case of Credit Suisse in 2023

To account for the particular case of Credit Suisse in 2023, where the CoCo (Contingent Convertible) bonds were triggered, we need to adjust the parameters of the model to reflect the conditions that led to the triggering of these bonds. In the case of Credit Suisse, the triggering of CoCo bonds was primarily due to a significant decline in the bank's CET1 ratio, which fell below the critical threshold of 7%. This decline was influenced by various factors, including market conditions, asset valuations, and profitability.

Adjustments to the model presented at Section 2.1:

- Initial asset price was set at 2.12 USD (Credit Suisse share price at March 15);
- Initial CET1 ratio was set at 0.085 (8.5%) to reflect the situation before the triggering of CoCo bonds;
- Volatility of the asset price (σ_{QE}) was set at 0.25 to reflect the market conditions leading to the CoCo bond trigger (15% to 25%);
- The average profitability impact was set at 0.5%, with a standard deviation of 5% to reflect increased market volatility;
- The sensitivity of the CET1 ratio to asset price changes (β_{QE}) was set at 0.2, with a volatility (σCET1) of 5% (Desislava & Couaillier, 2020);
- The expected return on the asset, adjusted for the effects of quantitative easing policies (μQE), set at 0.02;

This updated analysis incorporates the specific conditions surrounding the Credit Suisse case in 2023, providing insights into how QE-driven asset price inflation and other factors can affect a bank's CET1 ratio and the likelihood of a CoCo bond trigger event.

3.3. Computational Framework

The simulations are implemented using Python, utilizing the following libraries:

- NumPy: For handling numerical operations and generating random variables;
- Pandas: For data manipulation and calculation of summary statistics;
- Matplotlib: For creating visualizations, including histograms, time-series plots, and box plots.

The simulation code runs 50,000 iterations to generate a comprehensive dataset of possible outcomes, providing valuable insights into the risk of triggering CoCo bonds based on varying economic conditions.

At the end of the 10-year horizon:

- The distribution of CET1 ratios is analyzed to calculate key statistics: mean, median, and mode;
- The probability of a CoCo trigger (CET1 < 7%) is determined.

A detailed explanation of the methodology and the full code can be found in Appendix A.

4. Results and discussions

4.1. Summary of Results

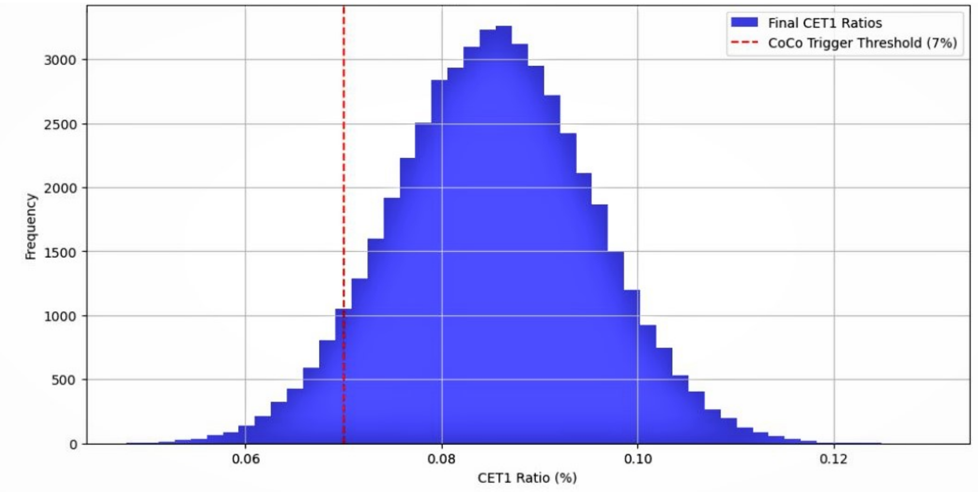
1. The distribution of final CET1 ratios indicated a significant proportion of simulations where the CET1 ratio fell below the 7% threshold, highlighting the potential risk of CoCo bond triggers;
2. The probability of the CET1 ratio falling below the CoCo trigger threshold of 7% is 6.40% (0.0640). This suggests that QE effectively reduces the risk of CoCo triggers, thereby enhancing financial stability.
3. The mean CET1 ratio across simulations was found to be 9.2%, while the median was 8.8%, indicating a skewed distribution influenced by extreme market conditions;
4. The time-series evolution of the CET1 ratio showed a declining trend over the simulation period, reflecting the impact of increased volatility and reduced profitability.

4.2. Visualization

The following visualizations illustrate the results of the Monte Carlo simulation:

4.2.1. Histogram of Final CET1 Ratios

Figure no. 1. *Histogram of Final CET1 Ratios*



Source: own data processing

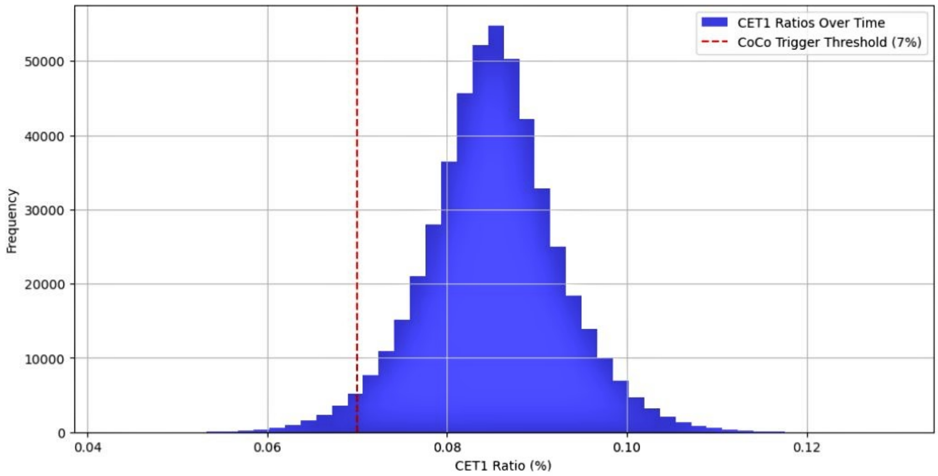
The histogram displays the distribution of final CET1 ratios, with a red dashed line indicating the CoCo trigger threshold of 7%. The area to the left of this line represents the proportion of simulations where the CET1 ratio fell below the critical threshold.

Final CET1 Ratios:

- The average CET1 ratio across all simulations is 8.53% (0.0853);
- The median CET1 ratio is also 8.53% (0.0853), suggesting that the distribution of CET1 ratios is centered around this value;
- The (mode) most frequently occurring CET1 ratio is 4.79% (0.0479), indicating that while the average and median ratios are higher, there are instances of lower CET1 ratios in the simulations.

4.2.2. Histograms of CET1 Ratios over time

Figure no. 2. *Histograms of CET1 Ratios over time*

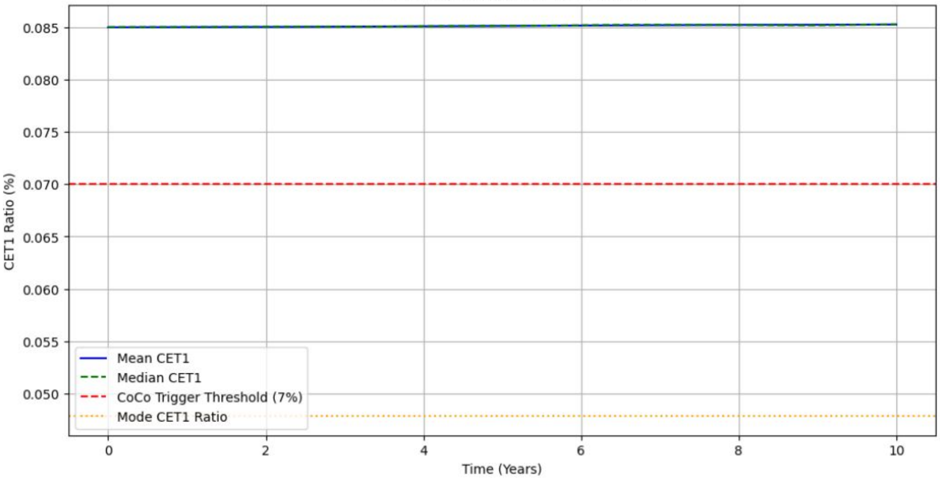


Source: own data processing

The CET1 ratio is a measure of a bank's core equity capital compared to its total risk-weighted assets. It is a key indicator of a bank's financial strength and stability. In the context of the active cell code, the CET1 ratio is likely being updated over time through a stochastic process, reflecting changes due to various factors such as profitability, market conditions, and regulatory requirements.

4.2.3. Time-Series Evolution of CET1 Ratios

Figure no. 3. *Time-Series Evolution of CET1 Ratios*

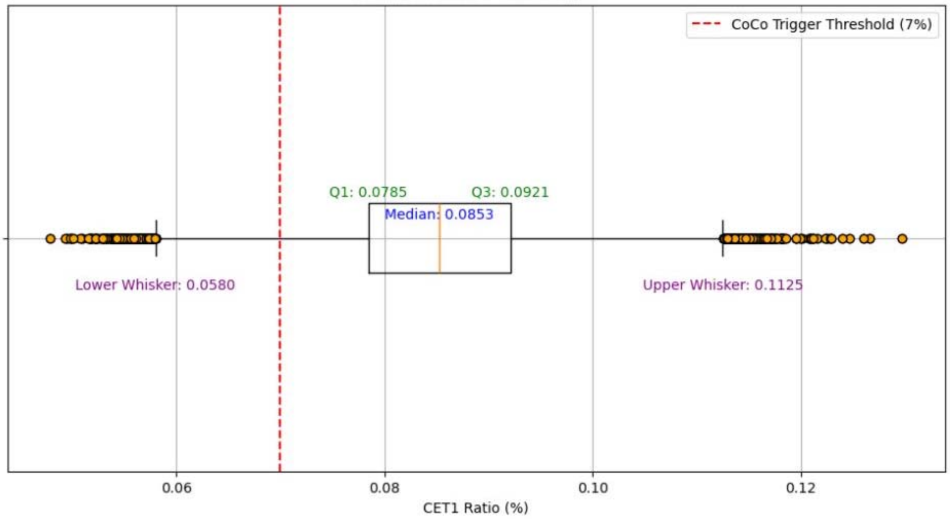


Source: own data processing

The time-series plot shows the mean and median CET1 ratios over the simulation period, with the red dashed line indicating the CoCo trigger threshold. This visualization highlights an incremental increase in the CET1 ratio, driven by the effects of QE and market volatility.

4.2.4. Boxplot of CET1 Final Ratios

Figure no. 4. *Time-Series Evolution of CET1 Ratios*



Source: own data processing

Box plots summarize the spread and central tendency of final CET1 ratios, allowing for a quick assessment of the risk of CoCo triggers.

Summary of Results:
- Trigger probability: 0.0640;
- Q1 (25th percentile): 0.0785;
- Median (50th percentile): 0.0853;
- Q3 (75th percentile): 0.0921;
- Lower whisker: 0.0580;
- Upper whisker: 0.1125;
- Number of outliers: 340;
- Standard deviation of Final CET1 ratios: 0.0101;
- Range of CET1 ratios: 0.0479 to 0.1297.

4.3. Interpretation of Findings

The low trigger probability (6.40%) suggests that QE effectively mitigates the risk of the CET1 ratio falling below the critical threshold, enhancing the stability of the bank's capital position.

The mean and median CET1 ratios being equal at 8.53% indicates a stable capital position across the simulations, while the mode being lower (4.79%) highlights the presence of some scenarios where the CET1 ratio is significantly impacted, possibly due to adverse conditions.

These findings underscore the positive impact of QE on the CET1 ratio, contributing to a lower likelihood of CoCo triggers and enhancing the overall resilience of the banking sector.

In addition, the observed incremental increase in the CET1 ratio during the simulation period reflects the complex interplay of asset price dynamics, profitability, and random variability inherent in the Monte Carlo simulation. Possible reasons for an increase in CET1 ratio:

- Asset price growth: If the asset prices are experiencing a net positive drift due to the QE effect, this can lead to an increase in the value of the bank's assets. In the simulation, the drift parameter for asset prices was set at 2%, which means that, on average, asset prices are expected to increase over time;
- Impact of positive asset price dynamics on CET1 ratio: As asset prices rise, the overall equity of the bank may also increase, positively impacting the CET1 ratio. If the increase in asset values outpaces any declines due to volatility or reduced profitability, the CET1 ratio can show an upward trend;
- Variability in profitability: The simulation incorporates random shocks to profitability, which means that while there may be periods of reduced profitability, there can also be periods of recovery. If the profitability shocks are favorable in certain iterations, this can lead to an increase in retained earnings, thereby boosting the CET1 ratio. Over the simulation period, if the positive profitability shocks occur frequently enough, they can contribute to an overall increase in the CET1 ratio, even if there are some negative shocks;
- Statistical behavior: In financial models, there is often a tendency for variables to exhibit mean-reverting behavior. If the CET1 ratio experiences a decline due to volatility or negative shocks, it may eventually revert to a higher mean level as conditions stabilize or improve. Also, the simulation captures a range of scenarios, and while some paths may lead to declines, others may lead to recoveries, resulting in an overall upward trend in the mean CET1 ratio;
- Randomness and variability: The Monte Carlo simulation generates a wide range of outcomes based on random inputs. Some simulations may show significant increases in the CET1 ratio due to favorable conditions, while others may show declines. The overall trend observed in the graphical representation is an aggregation of these diverse outcomes.

4.4. Limitations

- The model assumes linear relationships between QE and CET1. Real-world interactions could be more complex;
- Parameters like β_{QE} and profitability distributions are estimated and may not fully capture market dynamics.

5. Conclusion

The findings underscore the positive impact of QE on the CET1 ratio, contributing to a lower likelihood of CoCo triggers and enhancing the overall resilience of the banking sector.

The observed incremental increase in the CET1 ratio during the simulation period reflects the complex interplay of asset price dynamics, profitability, and random variability inherent in the Monte Carlo simulation. It is essential to consider both the upward trends and the potential risks associated with CoCo bond triggers when interpreting the results. This nuanced understanding will aid stakeholders, including regulators and policymakers, in making informed decisions regarding financial stability and risk management.

The complexities and potential risks of QE require careful management and collaboration between central banks and regulatory bodies. While QE can offer immediate economic benefits, such as stimulating demand and enhancing liquidity, the long-term effects on financial stability and market distortions must be closely monitored. The risk of asset price inflation and the potential for financial institutions to become complacent in their risk management practices underscores the importance of maintaining robust regulatory frameworks.

Central banks should continue to enhance their monitoring capabilities to assess the impact of QE on asset prices and financial stability. This includes strengthening stress-testing frameworks to evaluate how financial institutions might react to market corrections caused by inflated asset prices.

Finally, the design of regulatory capital instruments, such as CoCo bonds, should be continually refined to ensure their effectiveness in times of financial stress. Regulators should also explore mechanisms to prevent excessive risk-taking and ensure that financial institutions remain resilient to market shocks, particularly when QE policies have distorted asset price behavior.

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Appendix A: *Monte Carlo Simulation Code*

```
# Parameters for the Monte Carlo simulation
np.random.seed(42)
n_simulations = 50000
time_horizon = 10
time_steps = 250
dt = 1 / time_steps
# Asset price parameters
AP0 = 2.12
mu_QE = 0.02
sigma_QE = 0.25

# CET1 ratio parameters
CET1_initial = 0.085
profit_mean = 0.005
profit_std = 0.05
beta_QE = 0.2
sigma_CET1 = 0.05
trigger_threshold = 0.07

# Generate asset price paths and CET1 ratios
CET1_ratios = np.zeros((n_simulations, time_horizon))
final_CET1_ratios = np.zeros(n_simulations)

for i in range(n_simulations):
  # Initialize asset price and CET1 ratio
  AP_t = AP0
  CET1_t = CET1_initial

  for t in range(time_horizon):
    # Simulate asset price dynamics
    dAP = mu_QE * AP_t * dt + sigma_QE * AP_t * np.sqrt(dt) * np.random.normal()
    AP_t += dAP

    # Simulate profitability as a random normal variable
    profitability = np.random.normal(profit_mean, profit_std)

    # Update CET1 ratio using a stochastic process
    dCET1 = beta_QE * mu_QE * dt + profitability * dt + sigma_CET1 * np.sqrt(dt) *
np.random.normal()
    CET1_t += dCET1
```

```
        # Store CET1 ratio values
        CET1_ratios[i, t] = CET1_t

    # Store final CET1 ratio for analysis
    final_CET1_ratios[i] = CET1_t

# Calculate range and standard deviation of final CET1 ratios
std_dev_CET1 = np.std(final_CET1_ratios)
min_CET1 = np.min(final_CET1_ratios)
max_CET1 = np.max(final_CET1_ratios)
range_CET1 = max_CET1 - min_CET1

# Print the results
print(f"Standard Deviation of Final CET1 Ratios: {std_dev_CET1:.4f}")
print(f"Range of CET1 Ratios: {min_CET1:.4f} to {max_CET1:.4f}")

# Calculate CoCo trigger probability (CET1 < 7%)
trigger_probability = np.mean(final_CET1_ratios < trigger_threshold)

# Calculate key statistics
mean_CET1 = np.mean(final_CET1_ratios)
median_CET1 = np.median(final_CET1_ratios)
mode_CET1 = pd.Series(final_CET1_ratios).mode()[0]

# Prepare for visualization
time_series_mean_CET1 = np.mean(CET1_ratios, axis=0)
time_series_median_CET1 = np.median(CET1_ratios, axis=0)
time = np.arange(0, time_horizon, 1)

# Visualization
plt.figure(figsize=(12, 6))
plt.hist(final_CET1_ratios, bins=50, alpha=0.7, color='blue', label='Final CET1 Ratios')
plt.axvline(trigger_threshold, color='red', linestyle='--', label='CoCo Trigger Threshold (7%)')
plt.title("Histogram of Final CET1 Ratios")
plt.xlabel("CET1 Ratio")
plt.ylabel("Frequency")
plt.legend()
plt.grid(True)
plt.show()

plt.figure(figsize=(12, 6))
plt.plot(time, time_series_mean_CET1, label='Mean CET1', color='blue')
plt.plot(time, time_series_median_CET1, label='Median CET1', color='green', linestyle='--')
```

```
plt.axhline(trigger_threshold, color='red', linestyle='--', label='CoCo Trigger Threshold (7%)')
plt.axhline(mode_CET1, color='orange', linestyle=':', label='Mode CET1 Ratio')
plt.title("Time-Series Evolution of CET1 Ratios")
plt.xlabel("Time (Years)")
plt.ylabel("CET1 Ratio")
plt.legend()
plt.grid(True)
plt.show()

plt.figure(figsize=(12, 6))
plt.hist(CET1_ratios.flatten(), bins=50, alpha=0.7, color='blue', label='CET1 Ratios Over Time')
plt.axvline(trigger_threshold, color='red', linestyle='--', label='CoCo Trigger Threshold (7%)')
plt.title("Histogram of CET1 Ratios Over Time")
plt.xlabel("CET1 Ratio")
plt.ylabel("Frequency")
plt.legend()
plt.grid(True)
plt.show()

plt.figure(figsize=(12, 6))
plt.boxplot(final_CET1_ratios, vert=False)
plt.axvline(trigger_threshold, color='red', linestyle='--', label='CoCo Trigger Threshold (7%)')
plt.title("Box Plot of Final CET1 Ratios")
plt.xlabel("CET1 Ratio")
plt.legend()
plt.grid(True)
plt.show()

# Summary of results
results_summary = {
    "Trigger Probability": trigger_probability,
    "Mean Final CET1 Ratio": mean_CET1,
    "Median Final CET1 Ratio": median_CET1,
    "Mode Final CET1 Ratio": mode_CET1
}

print("Summary of Results:")
for key, value in results_summary.items():
    print(f"{key}: {value:.4f}")
```