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VOLATILITY AND TAIL RISK IN THE 2023 BANKING CRISIS: A PORTFOLIO ANALYSIS OF THE U.S. BANKING SECTOR

Omar Barroso Khodr[1] and Mathias Schneid Tessmann[2]
[1]*Brazilian Institute of Education, Development and Research – IDP.*
[2]*Brazilian Institute of Education, Development and Research – IDP., E-mail: mathias.tessmann@idp.edu.br*

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Abstract: This paper conducted to analyze the current banking crisis that began in 2023. The study focuses on the overall portfolio performance and risk in the U.S. banking sector, using a five-asset portfolio consisting of JP Morgan, Bank of America, Morgan Stanley, Wells Fargo, and The Charles Schwab Corporation. The portfolio outperformed the benchmark in dollar terms, but exhibited outliers and significant tail risk. Various risk measurement methods were employed, including the Sharpe Ratio, Monte Carlo simulation, and Generalized Autoregressive Conditional Heteroskedasticity (GARCH). The work found high levels of volatility clustering, skewness, and kurtosis in the portfolio returns, indicating a risky financial scenario. The distribution of returns was tested for normality and found to deviate from a normal distribution. The work aimed to present an accurate snapshot of the current situation and did not manipulate the data to simulate future trading days, as it could introduce biases.

Keywords: Banking Crisis; Portfolio-Analysis; Monte-Carlo; GARCH.

1. INTRODUCTION

The purpose of this paper on examining the recent banking crisis that unfolded at the beginning of 2023. Our objective was not to delve into the qualitative causes or to provide an in-depth analysis of the crisis's origins and future implications. Instead, we conducted an empirical study to assess the overall performance and risk of a specific portfolio. For our analysis, we selected the U.S. banking sector spanning from 2013 to April 25th 2023, using a five-asset portfolio benchmarked against the New York Stock Exchange. The chosen assets for this analysis were JP Morgan, Bank of America, Morgan Stanley, Wells Fargo, and The Charles Schwab Corporation. We based our selection on the uniqueness of their trading days over approximately a ten-year period and their relevant market capitalization.

In terms of dollar performance (assuming an initial investment of US$1), the portfolio outperformed the benchmark. However, our tests revealed the presence of outliers in the data, indicating a significant level of tail risk within the portfolio. Furthermore, we observed high levels of variance in the portfolio returns, reinforcing its classification as "risky" and aligning with the current financial landscape.

To assess the normality of the distribution, we conducted the Jarque Bera test and the Shapiro test, both of which rejected the assumption of normality (Royston, 1982). Moving on to measure risk, we employed three different methods, all of which indicated evidence of volatility risk. First, we used the classic Sharpe Ratio (1994), a straightforward approach. Second, we implemented a Monte Carlo simulation based on the Multivariate Normal distribution proposed by Richardson-Smith (1993). This simulation was performed 1000 times over the next 100 days for the testing portfolio. In order to analyze the time series characterized by volatility, we employed the AR-GARCH and ARMA-GARCH models, based on Engle (1982) and Engle-Mezrich (1996), respectively. Additionally, we conducted a simple Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model to explain volatility clustering, skewness, and kurtosis of the returns.

Lastly, we made a deliberate choice not to train and improve the model for simulating a normal distribution for future trading days. Our aim was to present an authentic snapshot of the current scenario. We believe that manipulating the data to create a bias towards hypothetical future events may lead to misleading results.

Several papers evaluated banking crises and brought important contributions to their understanding. We can highlight the works White (1984), Campello et al. (2010), Dell'Ariccia et al. (2008), Berger and Bounman (2013), Floyd et al. (2015), Kahle and Stulz (2013), Chronopoulos et al. (2015), Pol (2012), Li et al. (2016), Giovanis (2012), Edison (2003) and it is with this scientific literature that our work seeks to contribute by bringing evidence from the perspective of the returns of the roles of these banks during a period of crisis.

In addition to this introduction, the paper has three more sections. Section two exposes the methodology employed, section three presents the results and, finally, section four concludes.

2. METHODOLOGY

In this work, we focused on the U.S. banking sector, specifically analyzing the period from the first trading day of January 2013 until the last day of the 1st quarter of 2023 (March 31st, 2013). To assess the performance, we utilized a five-asset portfolio that served as a benchmark, which was based on the New York Stock Exchange (NYSE). The selected assets for our analysis included JP Morgan (JPM), Bank of America (BAC), Morgan Stanley (MS), Wells Fargo (WFC), and The Charles Schwab Corporation (SCHW). Our asset selection criteria considered the individual trading days of each asset spanning approximately ten years and the market cap relevance of each company.

Table 1: Market cap of the chosen companies (as of March 31st, 2023)

Companies	*Market Cap (US$B)*
JP Morgan	367.65
Bank of America	221.55
Morgan Stanley	141.19
Wells Fargo	136.84
Charles Schwab	97.40

Sources: Yahoo Finance and S&P Global. Table made by the authors.

In the initial stage, we computed the daily returns of the portfolio, consisting of the five selected assets. Subsequently, we allocated weights (w_i) to each stock based on a symmetrical distribution, where each stock represented 1/5 or 0.2 of the portfolio ($w_i = 1/5$ for $i = 1, 2, 3, 4, 5$). By analyzing the portfolio returns, we assessed the overall performance and conducted an examination of its descriptive statistics. Additionally, we employed various tests to gauge the levels of risk and volatility associated with the portfolio.

2.1. Testing for Normality

Our initial test to assess the normality of the dataset was the Jarque-Bera test (JBT), a Lagrange multiplier test widely employed for this purpose. The JBT is particularly suitable for large datasets, typically with n > 2000, making it an appropriate choice for our dataset containing 2,579 entries. By conducting the JBT, we aimed to confirm whether the dataset follows a normal distribution. Additionally, this test evaluated the skewness and kurtosis of the data, providing insights into the degree to which it aligns with a normal distribution, as proposed by Bera and Jarque (1987).

(1) JBT is defined as:

$$JB = \frac{n}{6}\left(s^2 + \frac{1}{4}(k-3)^2\right)$$

To ensure the reliability of our analysis, we utilized the Shapiro-Wilk test to examine the normality of the data distribution. The null hypothesis of this test posits that the population adheres to a normal distribution. By comparing the p-value to the predetermined alpha level of 0.05, we could determine whether to reject the null hypothesis. A p-value below 0.05 would lead us to reject the null hypothesis, indicating that the data deviates from a normal distribution. In such circumstances, we would possess substantial evidence supporting the violation of the normality assumption, as outlined by Royston (1982).

(2) Shapiro-Wilk test is defined as:

$$W = \frac{(\Sigma_{i=1}^{n} \alpha_i x(i))^2}{\Sigma_{i=1}^{n} (xi - \overline{x})^2}$$

Where, $x(i)$ = is the ith order statistic (the smallest number in the sample); and, x(bar) = is the sample mean.

2.2. Monte Carlo (MC)

Initially, we assumed that the daily returns follow a Multivariate Normal (MVN) distribution with a mean vector (μ) and covariance (Σ) as can be seen in (3). To justify this assumption, we adopted an alternative procedure proposed by Richardson-Smith (1993). The author put forth this method for testing the MVN distribution of a multivariate time series. In this context, the MVN distribution is characterized by a limited number of parameters, namely means, variances, and correlations between the multivariate normal series $R1_t$ ... Rn_t. For t ∈ {1, ..., T} where T is the final time horizon. By considering these parameters, the MVN distribution effectively expresses the moments of the series.

(3) MVN is defined as:

$$R_t \sim MVN\ (\mu, \Sigma)$$

Next, we used the Cholesky decomposition to find the Lower Triangular Matrix. Where A is real matrix (thus, being symmetric positive-definite) that represents Σ. Where L is a real lower triangular matrix with positive diagonal entries. Such that may be written.

$$A = LL' \rightarrow LL' = \Sigma$$

Therefore, we can generate the returns as, $R_t = \mu + Z_t$, where $Z \sim N\ (0, 1)$. Next, the returns are simulated over a 100-day period, where the 100-day return can be formulated as (4).

(4) 100 day returns MC simulation is defined as:

$$R_{100} = \prod_{t=1}^{100} (1 + R_t)$$

Lastly, the portfolio returns for each MC trial m becomes the inner product between the 100-day returns and the vector of portfolio weights (5).

(5) Portfolio returns for each MC trial is defined as:

$$P_m = w \cdot R_{100} P_m = w \, . \, R_{100}$$

2.3. Modeling for Volatility

The Autoregressive Conditional Heteroskedasticity (ARCH) model is widely used in econometric analysis of time-series data. ARCH, as an acronym, represents its key characteristics: Autoregressive, indicating the presence of volatility lags; Conditional, as it captures the dependence of new values on past observations; and Heteroskedasticity, signifying time-varying volatility. This model is particularly effective when the error variance is believed to exhibit serial autocorrelation, meaning that it systematically varies over time. The ARCH model is appropriate when the error variance in a time series follows an autoregressive (AR) model, as proposed by Engle (1982). In certain cases, the error variance may be assumed to follow an autoregressive moving average (ARMA) model, resulting in a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. The GARCH model incorporates lagged values of both the error variance and the squared error term, providing a more flexible and accurate representation of the time series, as outlined by Bollerslev (1986).

This modeling framework is particularly valuable for analyzing financial time series characterized by intermittent periods of significant price movements interspersed with calmer phases. The inclusion of lags in the model requires careful consideration, as it necessitates the examination of historical data. Consequently, the volatility under analysis is deterministic in nature rather than purely stochastic. The AR-ARCH was modelled starting with z(t) that represents standard normal variables, initial volatility series, white noise process, and the stochastic piece. Next, $\sigma(t)^2$ signifies a squared time-dependent standard deviation that characterizes the typical size of the terms (3).

(3) AR-ARCH modelling is defined as:

$$\sigma(t)^2 = z(t)^2$$

In this context, the model is then conditioned to variate with the square of variances (4), for each date $t = 1, ..., n$.

(4) The conditioned model is defined as:

$$\varepsilon(t) = (\sigma^2)^{\frac{1}{2}} z(t)$$

As proposed by Engle (1982), we use a method to test whether the residuals et exhibit time-varying heteroskedasticity using the Lagrange multiplier test. We estimated the best fitting autoregressive model as it can be seen in (5). Next, with this method we used the conditional error as we calculated the autoregression with lag of 1 and centered around the mean μ (6).

(5) Best fitting Autoregressive model is defined as:

$$AR(q)y_t = \alpha_0 + \alpha_1 y_{t-1} + ... + \alpha_q y_{t-q} + \varepsilon_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i y_{t-i} + \varepsilon_t$$

(6) Autoregression with lag of 1 is defined as:

$$y_t = \mu + \varphi(y(t-1) - \mu) + \varepsilon_t$$

Second, we modelled for volatility with the ARMA-GARCH (Engle-Mezrich, 1996). We used the first lags of residuals squared and variance (ω as the average variance of σ^2_p) for the portfolio returns. In variance targeting, as described by the authors, the intercept in the equation is replaced with a value derived from the persistence and the unconditional variance. The persistence is calculated as 1 minus the sample counterpart of the squared residuals during estimation. If external regressors are present in the variance equation, the sample average of these regressors is multiplied by their coefficient and subtracted from the variance target. Further, for higher orders, we have a fixed lag-1 autoregressive structure.

(7) The ARMA-GARCH is defined as:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_{t-1} \sigma_{t-1}^2$$

Next (8), we specify the mean of portfolio returns with a long-run average of μ.

$$r_t = \mu + \tau_1 y_t + \tau_2 \varepsilon_{t-1}$$

Lastly, we specified the distribution of the ARMA-GARCH for normally distributed innovations of the error term. Moreover, we compared the ARMA-GARCH distribution with the standard deviation of the student's t-distribution using the Akaike Information Criterion. To finish, we observed the conditional quantiles from the model (VaR limits) set at 99%.

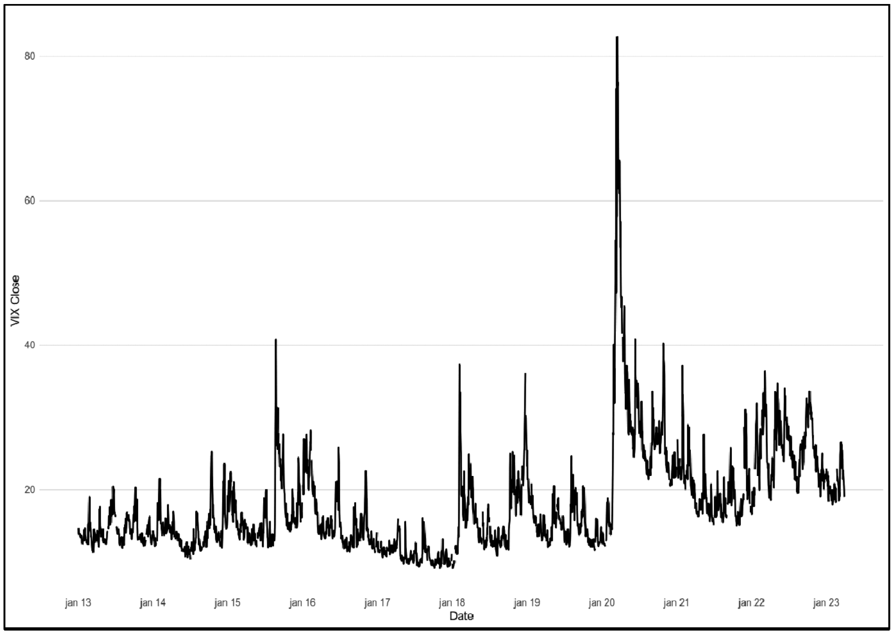
3.4. Data

3.4.1. VIX Overview

Before we begin our portfolio analysis, we examined the CBOE VIX (Chicago Board of Exchange - Volatility Index). While the VIX does not provide predictive insights on how volatility may affect the market in the future, it can serve as a useful index to understand the overall market sentiment.

The VIX closing volume exhibited a significant peak in the early months of 2020 during the COVID-19 pandemic. However, the trend has since gradually declined throughout 2020, 2021, and the beginning of 2023. The peak in 2020 reflected a period of market anxiety, with the volatility volume only returning to pre-pandemic levels between April and November 2021, accompanied by notable fluctuations. These

Figure 1 - CBOE VIX (Close) from January 1st, 2013 until March 30, 2023



Source: Yahoo Finance. Figure made by the authors with Rstudio.

observations are further illustrated in Table 2, specifically the VIX Close section, which highlights the highest peak at 82.69 recorded during the onset of the Covid-19 pandemic (March 16, 2020), and the lowest value at 9.14 (March 1st, 2018).

Table 2: VIX Statistics

Statistics	*VIX Open*	*VIX High*	*VIX Low*	*VIX Close*	*VIX Adjusted*
Min	9.01	9.31	8.56	9.14	9.14
1st Quartile	13.16	13.74	12.65	13.09	13.09
Median	15.90	16.68	15.10	15.78	15.78
Mean	18.07	19.12	17.10	17.93	17.93
3rd Quartile	21.50	22.66	20.14	21.14	21.14
Max	82.69	85.47	70.37	82.69	82.69

Source: Table made by the authors

Further on, in table 2, the average volume over the past 10 years has not exceeded 20, indicating that markets have generally not been as euphoric as one might expect (at least in the pre-pandemic years). Nonetheless, as shown in Figure 1, there was a period of heightened anxiety in comparison to the years 2013 to 2019.

3.4.2. Portfolio Diagnostics

Upon analyzing the correlation among the selected stocks, we discovered a high degree of correlation, indicating a significant level of market exposure. As a result, we must acknowledge that our portfolio carries a high level of risk (table 3).

Table 3: Stocks Correlation

	JPM Close	*BAC Close*	*MS Close*	*WFC Close*	*SCHW Close*
JPM Close	1	0.89	0.82	0.81	0.70
BAC Close	0.89	1	0.82	0.82	0.73
MS Close	0.82	0.82	1	0.74	0.72
WFC Close	0.81	0.81	0.74	1	0.66
SCHW Close	0.70	0.73	0.72	0.66	1

Source: Table made by the authors.

Additionally, the portfolio possesses an average return at zero, however, with a maximum return of 18%. In other words, this confirms that the portfolio possesses a high-risk, high-return characteristic (*see, board 1*).

Board 1: Portfolio Descriptive Statistics

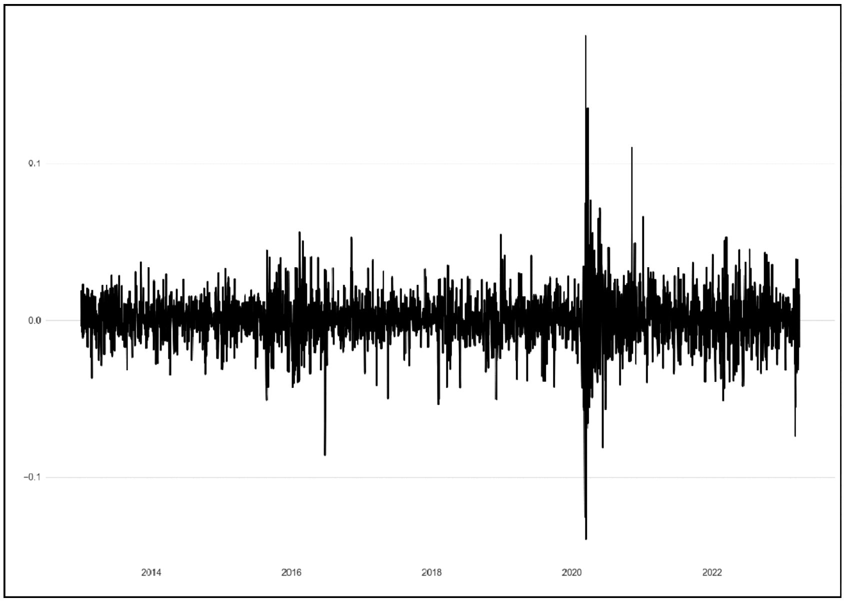
Min	-0.1387
1st Quartile	-0.007
Median	0.000
Mean	0.000
3rd Quartile	0.009
Max	0.1815
Cumulative Return	0.0183

Source: Board made by the author.

From a visual inspection of the data (Figure 2), we can observe that the returns remain stationary over the 10-year period. However, there was a significant increase in the variation of returns during the first few months of 2020, indicating a period of high volatility.

Prior to conducting a more thorough evaluation of the portfolio's performance, we will briefly examine the dollar growth equivalent of investing 1 US$ in the portfolio at the outset of the experiment. As shown in Figure 3, the investment of 1 US$ yielded a final amount of 2.83 US$ at the conclusion of the experiment. Although the portfolio exhibits volatility, we can reasonably assume that it has the potential for profitability.

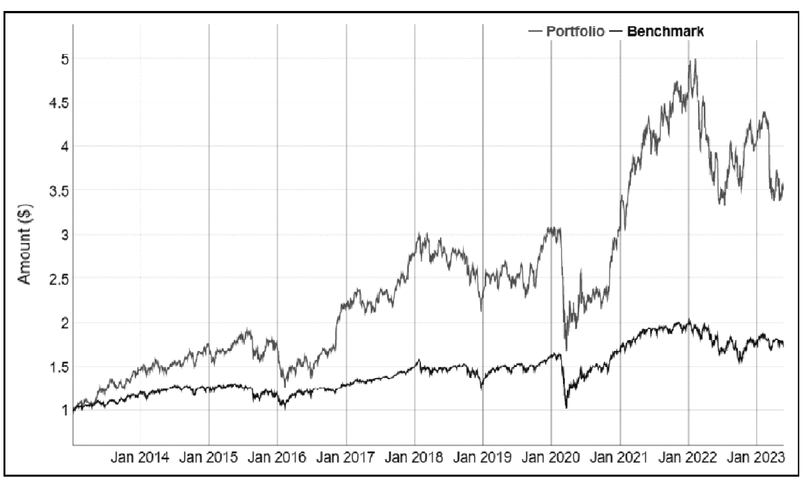
Figure 2: Portfolio time series returns



Source: Figure made by the authors with Rstudio.

Nonetheless, it is crucial to evaluate its performance against a benchmark. In this case, we have chosen the New York Stock Exchange (NYSE), where the selected stocks are traded. We can use a straightforward heuristic to compare the portfolio's performance with that of the benchmark. From Figure 3 (below), we can see that during the entire

Figure 3: Dollar Growth vs Benchmark



Source: Figure made by the authors with Rstudio.

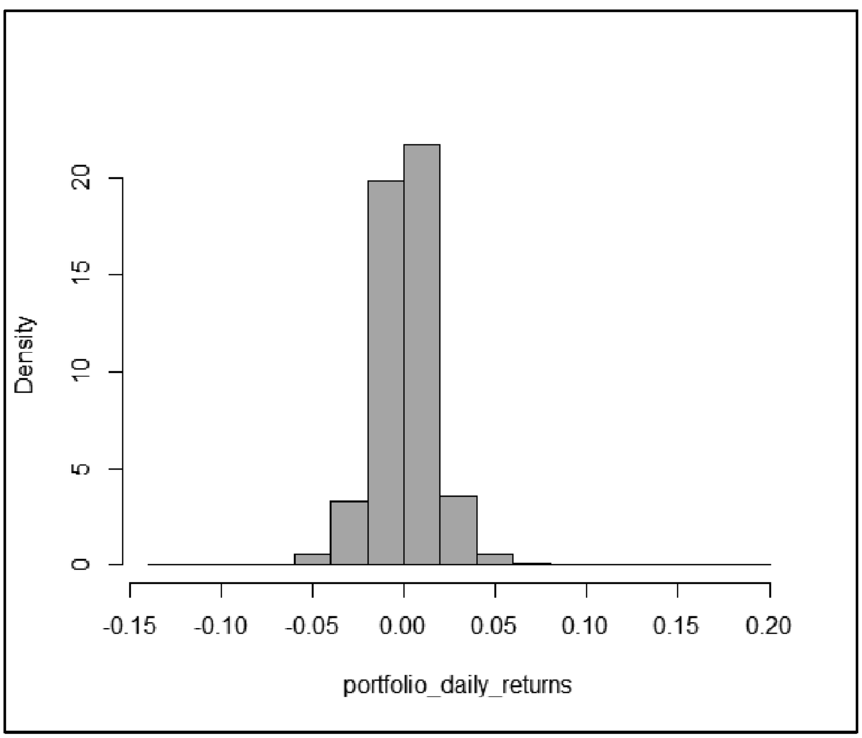
period of analysis, the portfolio performs better than the benchmark. Therefore, we can assume that the portfolio is not unreliable.

3. RESULTS

3.1. Skewness and Kurtosis

As we delve deeper into analyzing the portfolio's returns, the findings reveal increasing complexity. Utilizing the skewness function, we observed a moderate skewness of 0.20 in the data, indicating a slight departure from a perfectly symmetrical distribution. However, the examination of kurtosis unveiled a value of 14.38, signaling a leptokurtic distribution. This characteristic is visually evident in Figure 4, where the histogram demonstrates a pronounced peak with heavy tails extending beyond the typical bell curve. Notably, the kurtosis value exceeding 3 suggests the presence of numerous outliers within the data distribution. Although the histogram may initially resemble a uniform distribution, closer scrutiny unveils subtle tails on both ends, reinforcing the existence of outliers.

Figure 4: Histogram for Daily Returns



Source: Figure made by the authors using Rstudio.

3.2. Stationary and JBT results

The augmented Dickey-Fuller test provides a means to evaluate the null hypothesis (H_0) that a time series lacks stationarity, meaning it possesses a time-dependent structure and variable variance over time. In contrast, the alternative hypothesis (H_a) suggests stationarity. Our test yielded a test statistic of -13.81 and a corresponding p-value of 0.01. With the p-value being less than the predetermined significance level of 0.05, we reject the null hypothesis and conclude that the time series is indeed stationary. This implies that the series lacks a discernible trend, maintains a consistent variance over time, and exhibits constant autocorrelation. Moreover, we proceeded with the Jarque-Bera test, which confirmed the earlier observation of a leptokurtic distribution (p-value: < 2.2e-16).

3.3. Sharpe Ratio

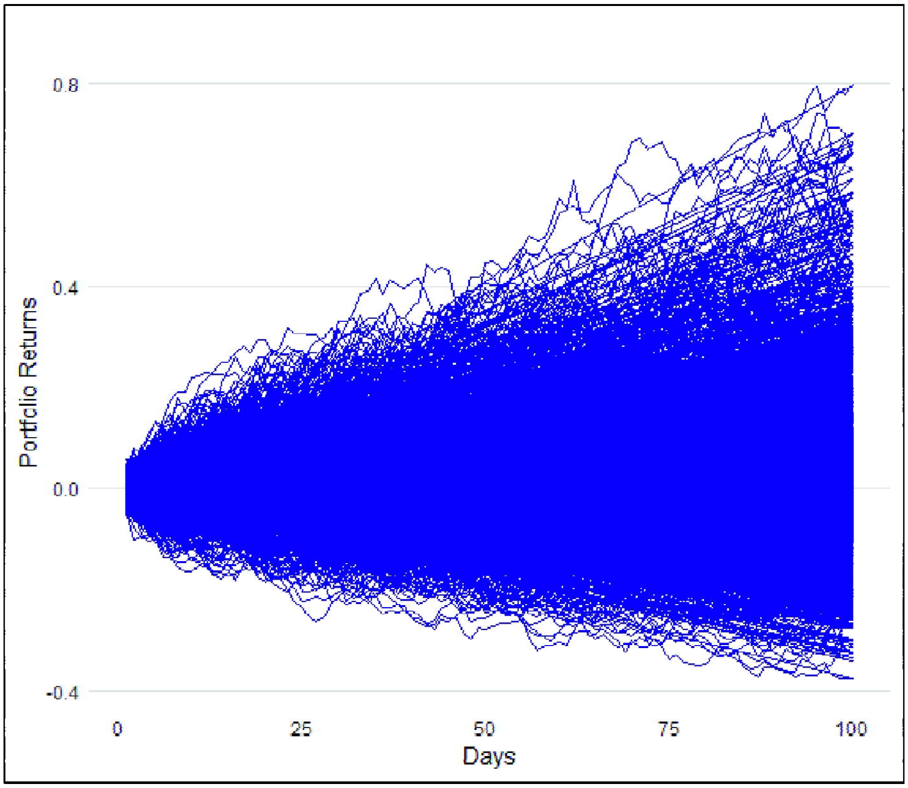
According to Israelsen (2009), the Sharpe Ratio can exhibit negative values during periods characterized by economic downturns and uncertainty. This pattern aligns with the results of our tests, which yielded a Sharpe Ratio of -0.69. In this scenario, our portfolio performed below the risk-free rate of 1.25%, representing the average yield of the 10-year T-bill since 2018. Nevertheless, it is important to note that our findings are not definitive. McLeod and Vuuren (2004) propose that portfolios with negative Sharpe Ratios should be compared to similar funds for a more comprehensive analysis. Since our experiment does not encompass robustness testing and solely compares a single portfolio over time, we can only infer that the portfolio carries risk based on the Sharpe Ratio.

3.4. Monte Carlo's

We conducted a thorough analysis of the daily returns, employing a combination of Monte Carlo simulations (MCs) and descriptive statistics. Specifically, we ran 1000 MCs, gathering data from 100 training days to gain a deeper understanding of the risk and return characteristics of our investment strategy. The MCs revealed a classic trade-off between high risk and high return associated with our investment approach. The data also indicated that the standard deviation levels were significantly higher than the average returns, with an average portfolio return of 0.06, a standard deviation of 0.18, and a median of 0.05. Notably, the descriptive statistics of the MCs showcased the potential outperformance of the MC portfolio compared to the original portfolio, at least within the 100 trained days.

Furthermore, we calculated the confidence interval with an alpha level of 0.05, determining a margin of error of approximately 0.012. This implies that the true mean is likely to fall between 0.048 and 0.072 in 95% of cases. It is worth noting that the average returns gradually improved with an increase in the number of training days, as depicted in Figure 5, resembling the shape of a crocodile's mouth.

Figure 5: Monte Carlo Portfolio Daily Returns



Source: Figure made by the authors using Rstudio.

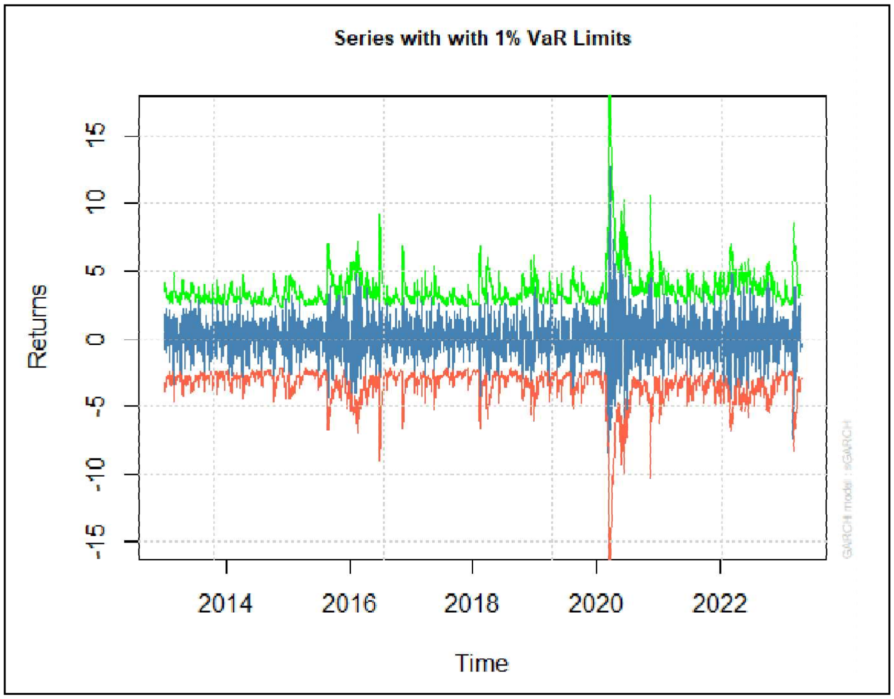
3.5. Volatility analysis

3.5.1. First look

First, we will add to the returns graph (figure 2) a series with 1% VaR limits. This test shows us, the potential growth (green) or decline (red) relative to the portfolio volatility. We can see from Figure 6, that the pattern does not really change much as we are convinced that the past 3 years were marked by significant economic downturns.

We generated several plots to evaluate serial correlation, normality, and residual status, as illustrated in Figure 7. The first plot, located in the top left corner, presents the ACF of Absolute Observations, revealing a positive serial correlation. This indicates a tendency for returns to exhibit persistent changes in a single direction over future

Figure 6: Series with 1% VaR Limits



Source: Figure made by the authors using Rstudio.

time periods. Moving to the second plot, the QQ plot highlights the leptokurtosis of the standardized residuals, confirming the presence of outliers in the tails, consistent with our previous analyses.

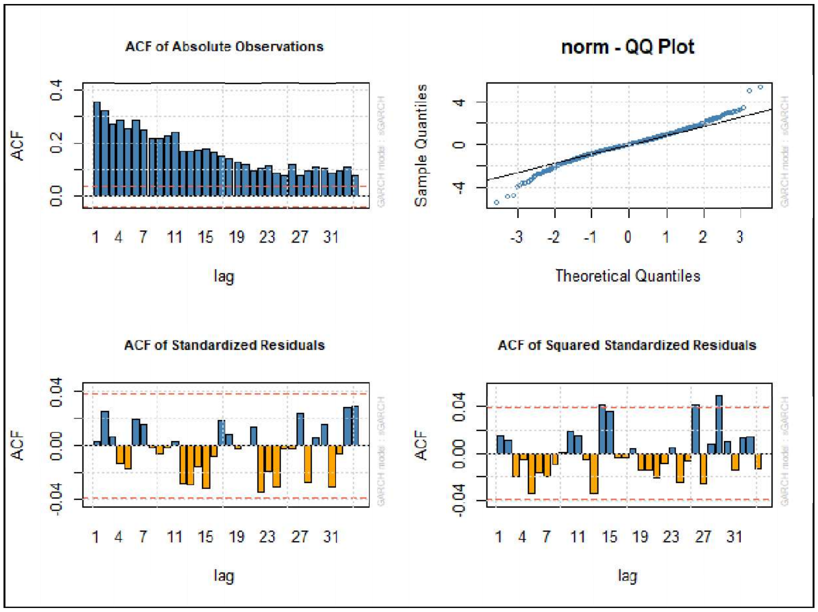
Examining the ACF of standardized residuals provides valuable insights into the autoregressive (AR) dynamics, as it effectively captures the conditional mean. Lastly, the ACF of squared standardized residuals unveils the presence of generalized autoregressive conditional heteroskedasticity (GARCH) dynamics, explaining the conditional standard deviation.

As we redo the GARCH estimation with the student's t-distribution for the error innovations (Figure 8), we see similar patterns from Figure 7. However, we can see a smaller, but still relevant presence of outliers in the QQ plot.

3.5.2. AR-Garch Analysis

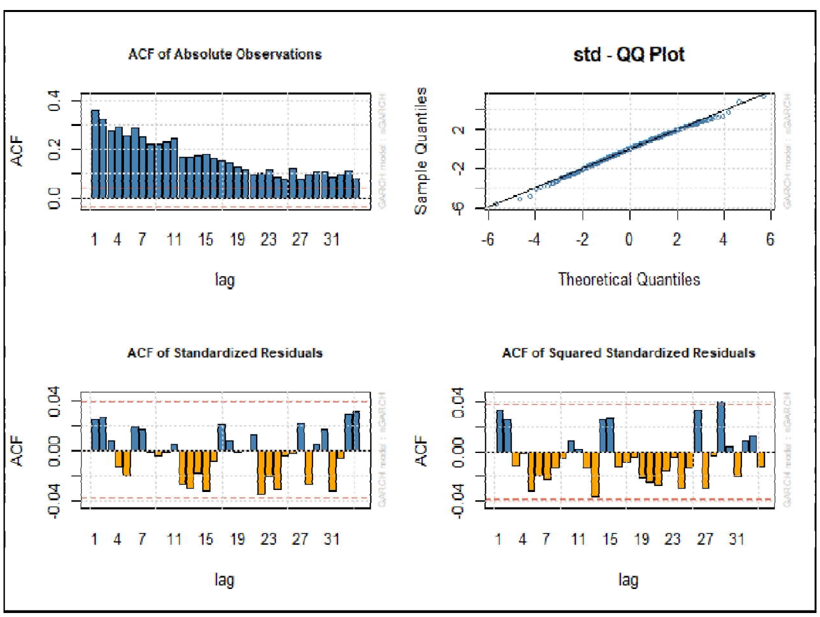
Subsequently, using Rstudio we applied the AR-GARCH model with t-distribution specifications to our portfolio, allowing us to uncover crucial insights concealed within the portfolio returns (*see, Engle and Mezrich (1996) and R Documentation: ugarch function*). In

Figure 7: Panel of Plots I



Source: Figure made by the authors using Rstudio.

Figure 8: Panel of Plots II



Source: Figure made by the authors using Rstudio.

Table 5, we present key findings that shed light on various aspects of the model. The 'mu' parameter represents the long-run average return of the portfolio, providing an indication of its overall performance. The 'Ar1' coefficient signifies the impact of the previous day's lagged return on today's return, helping to identify potential momentum effects. 'Omega' denotes the long-run variance of returns, providing insights into the portfolio's inherent volatility characteristics. 'Alpha1' captures the influence of lagged squared variance on today's returns, indicating the persistence of volatility clustering. 'Beta1' reflects the impact of lagged squared residuals on today's portfolio returns, allowing us to assess the presence of residual volatility effects. Lastly, the 'Shape' parameter corresponds to the degrees of freedom in the student's t-distribution, with a higher value indicating a thicker tail.

Board 2: AR-GARCH diagnosis

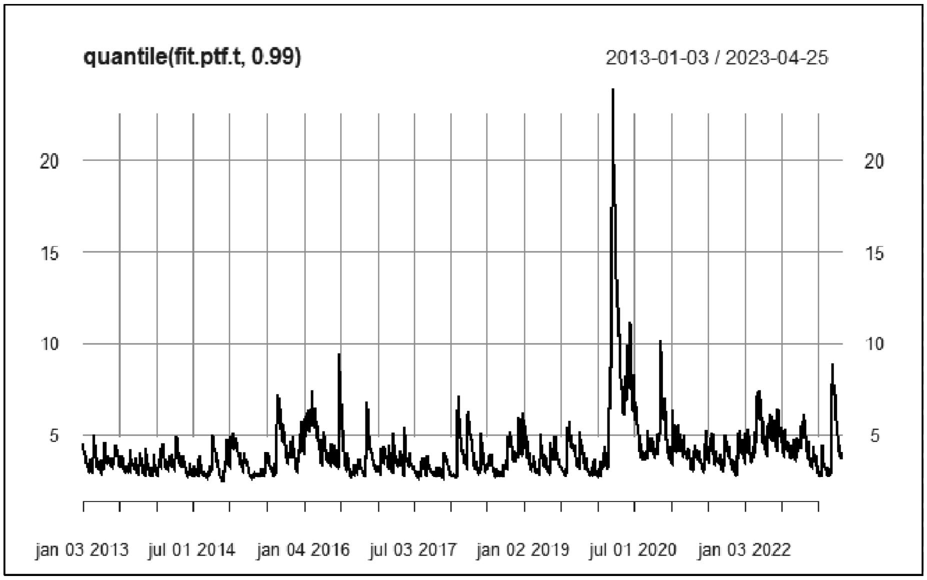
Mu	0.099
Ar1	-0.024
Omega	0.11
Alpha1	0.12
Beta1	0.84
Shape	6.25

Source: Board made by the authors.

Initially, the parameter 'mu' reveals a noteworthy trend, indicating that the portfolio's returns demonstrate significant improvement over the long term, approaching nearly 10%. However, the negative impact of lagged returns, as indicated by 'Ar1', suggests a potential adverse effect on current daily returns. Furthermore, 'Omega' highlights that the variance remains high within our model, despite the observed long-term improvement in returns. This observation is further supported by the presence of 'Alpha1', underscoring the persistence of volatility. Additionally, the significant influence of residuals on today's returns, denoted by 'Beta1', underscores the importance of considering residual effects when assessing portfolio performance. Lastly, the parameter 'Shape' confirms the presence of thick tails in the distribution, indicating that extreme events are more likely to occur in the portfolio's returns.

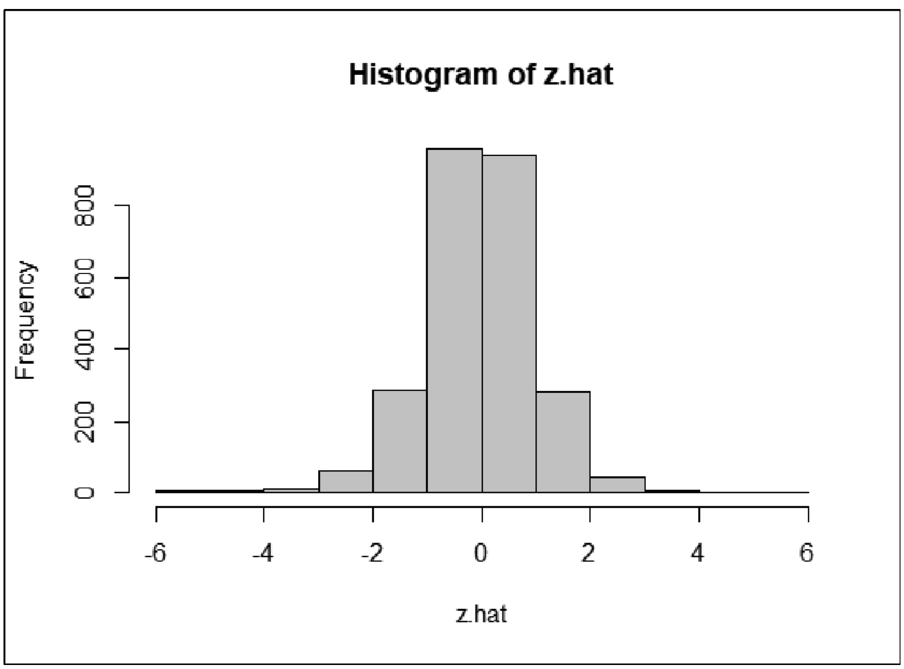
Next, with the considerations presented earlier, we can visualize the volatility range of our model. In this case, we can see a significant peak during the first months of the Covid-19 pandemic, as the pattern is repeated with similar experiments we did before.

Figure 9: Volatility Range



Source: Figure made by the authors using Rstudio.

Figure 10: Histogram of Residuals



Source: Figure made by the authors using Rstudio.

3.5.3. Residual Analysis

The residuals in an AR-GARCH model (or its variations) are important because they provide information about the volatility of the data that cannot be explained by the model's past information. As we can see in Figure 10, the residuals (z hat) are slightly left skewed (skewness: - 0.23 and Kurtosis: ~2).

Nonetheless, the visual representation of the residuals is not enough to test for normality. Like in previous exercises, for the residuals we employ the Shapiro and Jarque Bera tests once more. The results yield a similar result to other analyses, in which the standard tests indicate rejection of the null hypothesis that the series is normally distributed (p-value Shapiro and JBT: < 2.2e-16).

4. CONCLUSION

The portfolio analysis reveals distinct patterns of underperformance and exposure, highlighting a risk-reward trade-off characterized by skewness and kurtosis levels. Outliers in the returns contribute to this dynamic, further reinforcing the negative Sharpe ratio, which confirms the underperformance relative to the risk-free ratio. While a robust comparison was not conducted, it is reasonable to infer that the portfolio may not be the optimal choice for investors seeking conservative returns.

Future studies could enhance the analysis by examining the robustness of portfolios through comparisons across different markets and varying levels of risk. This can be achieved by employing the Capital Asset Pricing Model (CAPM) and Fama-French factor models to assess portfolio performance. Additionally, conducting Monte Carlo simulations (MCs) under different historical contexts and using alternative measures of volatility would provide valuable insights. These investigations would contribute to a more comprehensive understanding of portfolio dynamics and risk management strategies.

However, a deeper analysis incorporating Monte Carlo simulations and AR-GARCH models uncovers a long-term improvement trend in the portfolio, despite its inherent volatility risks. This reinforces the earlier risk-reward dilemma, as the presence of thick tails indicates a probability of extreme outliers. Additionally, considering the high correlation among the stocks in the portfolio, qualitative factors are likely to exert a significant influence on its long-term performance. One notable observation is the gradual dollar growth of the portfolio, as depicted in Figure 3, suggesting a relatively favorable performance compared to its benchmark.

Overall, the portfolio analysis implies that the banking sector offers potential gains amidst uncertainty and turmoil. As a suggestion for future research, we can list the use of a database composed of financial institutions and banks that have the largest market share in the OECD.

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