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The Effects of Monetary Policy on the Banking Industry

An Empirical Analysis on European Data

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CONTENTS

INTRODUCTION

The relationship between monetary policy and bank profitability has long been a topic of discussion in the literature, especially after the 2008 financial crisis. Furthermore, following the restrictive policy implemented by the European Central Bank in response to the inflation crisis of the past two years, the topic has gained more prominence in public debate.

In the literature, opinions regarding the nature of this relationship are conflicting. Borio et al. (2017) found empirical evidence that in G10 countries between 1995 and 2005, the relationship between bank profitability and interest rate levels is positive. Specifically, they noted that the interest margin increases more than proportionally compared to loan loss provisions and non-interest income, leading to the identification of a positive relationship between bank profitability and interest rate levels. Alessandri and Nelson (2015), on the other hand, examined the effect of interest rates on bank profitability in the United Kingdom from 1992 to 2009, finding that large banks are exposed to interest rate fluctuations. In the long run, both the level and the slope of the yield curve contribute positively to profitability. However, in the short term, increases in market rates compress interest margins due to frictions in the credit market. Altavilla et al. (2017) analyzed the impact of various monetary policy actions on bank profitability. The focus is on the Euro Area, which represents an interesting case study due to the heterogeneity among banks and countries within a monetary union that has implemented a wide range of unconventional policies, including negative interest rates and quantitative easing. The authors showed how the main components of bank profitability are asymmetrically affected by accommodative monetary conditions: the negative impact on the net interest margin is largely offset by the positive impact on loan loss provisions and non-interest income. Samuelson (1945), in general and abstract terms, examined the effect of an interest rate increase on university foundations, insurance companies, and banks, concluding that the entire banking system benefits from an interest rate increase.

On the other hand, Flannery (1981) studied the impact of interest rate changes[1] on the costs and revenues of some of the largest U.S. banks from 1959-78 and found that these are significantly influenced by changes in market rates, but that the effects of the changes cancel each other out. The author initially emphasized that the above results apply to large banks, which can access a wide range of financial products, but it was uncertain whether they applied to smaller banks. In a subsequent work, Flannery (1983) analyzed this latter case, not finding any empirical evidence to support the idea that small banks were more exposed to interest rate variability, concluding that they too have access to a sufficient number of financial instruments to hedge against interest rate risk.

It is therefore beyond question that interest rates are one of the main exogenous variables that

[1] Specifically, he studied the impact of changes in Treasury bill rates, which are U.S. federal bonds with maturities of 1 year or less.

banks have to deal with, but the aim of this thesis is to verify, based on some empirical findings, whether interest rates influence (and if so, how) the profitability of credit institutions. In technical terms, the aim is to verify whether banks are exposed to interest rate risk, assuming macroeconomic conditions as given, i.e., the focus will not be on the impact of the banking system on monetary policy, but interest rates will be considered as given and their impact on banks will be analyzed. To this end, the most appropriate statistical tools for the problem in question have been used. Additionally, it is emphasized from the outset that the code, the data used, and all the estimates are available on the author's GitHub page.

Chapter 1 will be devoted to a brief description of monetary policy choices and some theoretical considerations regarding the determination of bank income. Chapter 2 will describe in detail the econometric analysis conducted, starting with the description of the data used, followed by the estimation of linear regression models, and concluding with the analysis of the results and highlighting some critical points of the analysis. The work presented concludes with brief concluding remarks.

CHAPTER 1

ANALYTICAL FRAMEWORK

1.1 Monetary Policy

1.1.1 Interest Rate Decision

The statute of each Central Bank outlines the objectives to be pursued. For example, the statute of the European Central Bank (ECB) highlights that the bank's task is to ensure price stability[1], while that of the U.S. Federal Reserve (FED) states, in addition to maintaining purchasing power, maximum employment as one of the institution's objectives[2], even though in practice, controlling inflation has been the primary motivation for the Federal Reserve's actions (Bagliano & Marotta, 2010).

Monetary authorities have various strategies at their disposal to guide their actions toward achieving price stability. They can opt for an intermediate target or a predefined inflation rate (so-called *inflation targeting*). In the first case, price stability is achieved through controlling a variable other than the inflation rate, which is more easily controllable (typically the exchange rate or the money supply), while in the second case, monetary policy focuses on the inflation rate without explicitly attending to intermediate variables.

Today, most modern Central Banks operate through the *inflation targeting* mechanism, which can be described in the words of former Federal Reserve Chairman Ben Bernanke (Bernanke et al., 2001):

> «*Inflation targeting is a framework for monetary policy characterized by the public announcement of official quantitative targets (or target ranges) for the inflation rate over one or more time horizons, and by explicit acknowledgment that low, stable inflation is monetary policy's primary long- run goal. Among other important features of inflation targeting are vigorous efforts to communicate with the public about the plans and objectives of the monetary authorities, and, in many cases, mechanisms that strengthen the Central Bank's accountability for attaining those objectives.*».

A different case is that of the ECB, which uses a combined strategy that includes both monitoring a monetary aggregate and a series of indicators of inflationary trends.

[1] «Our job is to maintain price stability» ("Monetary policy", n.d.).

[2] «The Federal Reserve Act mandates that the Federal Reserve conduct monetary policy so as to promote effectively the goals of maximum employment, stable prices, and moderate long-term interest rates» ("Monetary Policy Principles and Practice", n.d.).

As highlighted by Blanchard et al. (2020), the debate regarding the optimal inflation rate remains open. Some economists argue that a zero inflation target would be ideal, as it would ensure total price stability, simplifying complex decisions and eliminating the problem of monetary illusion[3]. Conversely, other economists believe that a 4% inflation rate is more appropriate to avoid the risk of a liquidity trap[4], as happened during the financial crisis. Furthermore, the idea that a lower inflation target is preferable is based on the concept that it would avoid hitting the *zero lower bound*[5], which occurred, once again, during the 2008 financial crisis. Currently, most Central Banks seem to prefer low but positive inflation, around 2%.

Typically, the Central Bank modifies the money supply through open market operations, buying and selling securities in the bond market. If it wants to increase the money supply, it buys securities on the market, injecting new money; conversely, if it wants to reduce the monetary base, it sells securities on the market, withdrawing excess liquidity. Obviously, these operations are aimed at achieving the interest rate necessary to meet inflation targets.

Explaining the complex processes that lead to the choice of the rate is not the subject of this thesis, but these can be summarized by the now-famous Taylor Rule (Taylor, 1993):

$$i_t = r_t + \pi_t + \alpha(y_t - y_t^*) + \beta(\pi_t - \pi^*) \tag{1.1}$$

which indicates that the interest rate chosen by the Central Bank i_t is a function of its equilibrium value[6] $\bar{i}$, the *output gap*[7] $(y_t - y_t^*)$, and the *inflation gap*[8] $(\hat{\pi}_t - \pi^*)$.

The parameter α indicates how much the interest rate i_t varies following a unit change in the *output gap*, and similarly, the parameter β represents how averse the Central Bank is to inflation: the higher β, the more significant the institution's response to a deviation from the target inflation rate. The actual value of these parameters has been a subject of debate in the literature since 1993, especially whether they (particularly the one related to the inflation gap) should be greater or less than 1.

It should be noted that Taylor himself does not advocate for this rule to be followed blindly[9], but he believes it represents a useful way of thinking about monetary policy. Indeed, the equation 1.1 presented above is the result of an *ex-post* empirical study on the behavior of the American Federal Reserve in previous years.

1.1.2 Transmission Mechanisms

Central Banks do not have direct contact with the public, but their monetary policy decisions are implemented through the banking system, a set of specific financial intermediaries characterized by having money among their liabilities. Specifically, their balance sheets can be summarized as

[3]Individuals often do not correctly account for inflation, as indicated by Shafir et al. (1997).

[4]A liquidity trap occurs when the interest rate drops below a certain threshold (the so-called zero lower bound), increasing individuals' preference for liquidity and prompting them to hold cash rather than low-yield financial securities, thereby reducing the effectiveness of conventional monetary policy. For a more detailed explanation, see Blanchard et al. (2020).

[5]Interest rate close to zero.

[6]Namely, the nominal interest rate associated with the natural interest rate r_n and the inflation rate $\overline{\pi}$, i.e., $\overline{i_t} = r_t + \pi_t$.

[7]Difference between the observed GDP value and the value obtained if available production factors were used to their full potential (Gaffeo et al., 2015).

[8]Difference between the observed inflation rate and the Central Bank's target rate.

[9]«Operating monetary policy by mechanically following a policy rule like equation [1.1] is not practical». (Taylor, 1993)

follows:

Table 1.1: Balance Sheet of the Central Bank and commercial banks

Central Bank		Commercial Banks	
Assets	**Liabilities**	**Assets**	**Liabilities**
Securities	Currency	Reserves	Deposits
	Reserves	Securities	
		Loans	

Commercial banks account for the deposits of their account holders as liabilities, while their assets include not only securities and loans but also reserves, held partly in cash and partly at the Central Bank. Conversely, the monetary base represents a liability for the Central Bank and is held by commercial banks in the form of reserves, which obviously earn interest. This last point is crucial for the analysis in question, as will be explained later.

The systems through which monetary policy produces real effects are called *transmission mechanisms*. Specifically, modern Central Banks control the interest rate through the «corridor system»: the Central Bank sets a lower limit corresponding to the deposit rate, which is the rate it applies to the banks' deposited funds, and an upper limit equal to the marginal lending rate, which is the maximum rate the Central Bank charges commercial banks that request a loan (overnight rate). Finally, the Central Bank sets the main refinancing rate (MRO), which is the rate it charges on loans to the banking sector (Gaffeo et al., 2015). In the market, interbank rates (Euribor and Libor in this study) develop, which are the rates that various commercial banks charge each other for lending money. It is interesting to note that this rate closely follows the main refinancing rate (Figure 1.1), consistent with no-arbitrage theory. Therefore, it is in the banking liquidity market that monetary policy actions exert their immediate effects, which are then transmitted to the entire interest rate structure, aggregate demand, and price levels.

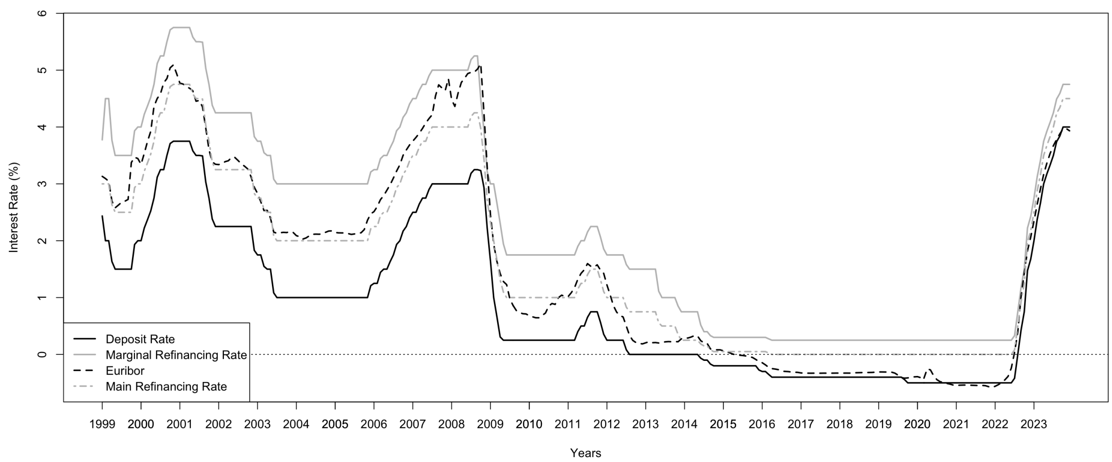

Figure 1.1: Rate Corridor in the Eurozone from 1999 to 2023

Source: personal elaboration on ECB data

1.1.3 Unconventional Monetary Policy

Following the subprime mortgage crisis and the sovereign debt crisis, Central Banks were forced to drastically lower the interest rate, reaching the *zero lower bound* after a few years, thereby losing the ability to use conventional monetary policy. To continue influencing economic activity, so-called unconventional monetary policies were implemented, based on the idea that even if the interest rate is zero, other interest rates remain positive as there is also a risk premium component (Blanchard et al., 2020). The aim was to increase the demand for financial assets, intending to reduce the risk premium and thus lower the interest rates on loans, thereby trying to stimulate economic activity. Of course, the purchase of securities was financed by increasing the money supply. These types of purchase programs are known as *quantitative easing* policies and were primarily implemented by expanding reserves, which, as mentioned earlier, earn interest.

1.2 Hedging Policies

Interest rate exposure, i.e., the impact that a change in interest rates has on revenue and the value of securities, can be reduced or eliminated through appropriate financial techniques. More precisely, the structure of assets and liabilities is said to be locally immunized against the interest rate i if for small movements in the rate around i, the present value of the entire portfolio does not decrease (Scandolo, 2022). This ambitious goal can be achieved in various ways, such as using the Financial Immunization Theorem[10] and using derivatives.

[10] For a more complete treatment, see Scandolo (2022) and Fabrizi (2021). For a practical implementation, see Khang (1983).

CHAPTER 2

EMPIRICAL ANALYSIS

2.1 Data Used

2.1.1 Sample Selection

The analysis was conducted on the 14 largest banks in Europe (including the United Kingdom) based on total assets[1], for which balance sheet data and historical stock price series for the considered period are available.

It is worth noting that the original intention was to include the 20 largest banks, but for UBS, Groupe BPCE, Crédit Mutuel Group, La Banque Postale, Rabobank, DZ Bank, CaixaBank, and Commerzbank[2] the necessary data are not available. Therefore, a smaller sample has been chosen, as listed below.

Table 2.1: Analyzed Sample

Bank	Country
The Hongkong and Shanghai Banking Corporation	United Kingdom
BNP Paribas	France
Crédit Agricole	France
Banco Santander	Spain
Barclays	United Kingdom
Société Générale	France
Deutsche Bank	Germany
Lloyds Banking Group	United Kingdom
Intesa Sanpaolo	Italy
ING Group	Netherlands
UniCredit	Italy

Continued on the next page

[1]As of December 31, 2022, according to "The world's 100 largest banks" (2023).

[2]Respectively, the sixth, seventh, tenth, seventeenth, nineteenth, twentieth, twenty-first, and twenty-second largest banks in Europe by asset size in 2022 ("The world's 100 largest banks", 2023).

Table 2.1: Analyzed Sample (continues)

NatWest Group	United Kingdom
Standard Chartered	United Kingdom
Banco Bilbao Vizcaya Argentaria	Spain

2.1.2 Data Sources

For each bank, balance sheet data were obtained from the commercial platform Orbis, managed by Moody's and Bureau van Dijk. In particular, the available data range from 2005 to 2023, thus constraining the temporal scope of the analysis to this period. Nevertheless, the analyzed time series is sufficient to include both years with high-average interest rates (2006-2008 and 2022-2023, highlighted in gray in Figure 2.1), and years with low interest rates (2009-2021). Interest rate data and the considered macroeconomic variables are sourced from the European Central Bank, the Bank of England, and the Federal Reserve Bank of the United States. Finally, the stock prices of the considered companies were downloaded from the *Yahoo Finance* platform.

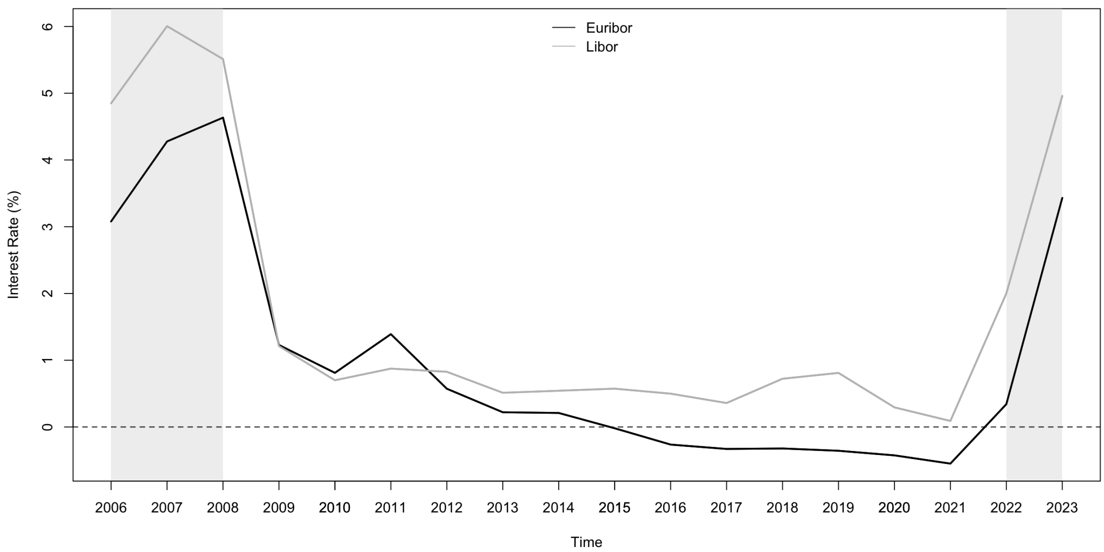

Figure 2.1: Evolution of the Euribor and Libor rates over the period 2005-2023
Source: Author's elaboration based on ECB and FRED data

2.2 Econometric Analysis

As previously described, the objective of this thesis is to estimate the impact of interest rates on the fourteen banks mentioned above. To achieve this, five econometric models were estimated for each institution: four referring to balance sheet data and one referring to stock prices, which are briefly described below.

To assess the profitability of the banks, the ROA (Return on Assets) financial ratio was considered, which provides a measure of the return on invested capital for the year *t-1*. The formula is as follows:

$$ROA_t = \frac{Net\,Income_t}{Invested\,Capital_{t-1}} * 100 \tag{2.1}$$

In order to understand which balance sheet items have influenced the overall profitability of the banks, a model was estimated for each of the two main income components: net interest income and non-interest income. The first component is the difference between interest earned and interest paid, while the second includes all other sources of revenue, such as net commission income, net trading result from derivatives, net result from financial assets valued at *fair value*, and other operating income. Additionally, the last balance sheet data model was estimated with provisions for loan losses as the dependent variable: since this is a cost item (non-monetary), it is reasonable to assume that during a period of rising interest rates, there would be an increase in non-performing loans, forcing financial institutions to allocate a larger portion of their revenues to avoid liquidity crises.

However, it is necessary to normalize these balance sheet items, meaning to evaluate them in relation to the assets of the previous year. This operation results in the loss of one observation (the time series analyzed will therefore cover the period from 2006 to 2023), but it allows for a time-comparable measure across different statistical entities. Therefore, the models were estimated considering the following percentage ratios as dependent variables:

$$NII_t = \frac{Net\,Interest\,Income_t}{Invested\,Capital_{t-1}} * 100 \tag{2.2}$$

$$OI_t = \frac{Non - Interest\,Income_t}{Invested\,Capital_{t-1}} * 100 \tag{2.3}$$

$$PROV_t = \frac{Provisions\,for\,Loan\,Losses_t}{Invested\,Capital_{t-1}} * 100 \tag{2.4}$$

Regarding the impact of interest rates on stock prices, the model was estimated with reference to monthly returns for the reasons described later (Paragraph 2.2.2).

As mentioned in the Introduction, the distinctive feature of both types of models is to take macroeconomic conditions as given: thus, the impact of the dependent variables on interest rates will not be analyzed.

It should be noted from the outset that all models were estimated using both the OLS (*Ordinary Least Squares*) estimator and the SUR (*Seemingly Unrelated Regressions*) estimator, and they were appropriately compared. The reasons for this choice and the preferred estimator will be explained in detail later[3].

2.2.1 Models with Balance Sheet Data

Model Description

The models related to balance sheet data aim to investigate the relationship between bank profits (and their determinants) and interest rates. To achieve this, the following model was estimated

[3]The `Python` programming language was used for processing the datasets to create a single dataset containing all the necessary data for the analysis. The model estimation, including hypothesis tests according to best statistical practices, was performed in `R`. The bibliographic references for the packages and libraries used are provided; the code, data, and estimation results are available on the author's GitHub page.

for each bank and each dependent variable (ROA, NII, OI, PROV):

$$y_t = a_0 + a_1\, i_t + a_2\, dcb_t + crisis + \epsilon_t \tag{2.5}$$

where

- The index $t = 1, ..., 18$ denotes the year, with $t = 1$ corresponding to the year 2006;
- y_t represents the dependent variable under investigation (ROA, NII, OI, PROV);
- i_t denotes the annual interest rate for year t, calculated as the simple average of daily observations. The Euribor rate was considered for European banks and the Libor rate for British banks;
- dcb_t represents the reserves held at the Central Bank in year t, normalized by the total assets of year $t-1$ for the same reasons as mentioned above, as shown in the formula:

$$\frac{Central\ Bank\ Reserves_t}{Total\ Assets_{t-1}} \tag{2.6}$$

- $crisis$ is a *dummy* variable that takes the value of 1 during the crisis years 2008-2012 and 0 otherwise. Its interactions with other regressors were also included in the model estimation;
- ϵ_t denotes the error term.

The choice to include Central Bank reserves as a control variable is due to the desire to account for their influence. Specifically, following the *quantitative easing* policies and monetary expansion programs (PEPP) during the COVID-19 pandemic, the amount of money in the economic system increased significantly. Therefore, it is important to control for the effect of these reserves, held at the Central Bank by commercial banks, on their income due solely to the increase in interest rates. At the same time, Central Bank deposits could be considered a "*bad control*" as interest rates (could) influence bank profitability, but also Central Bank reserves[4], which (could) in turn affect profitability. If this control variable were included, statistical theory suggests that the model estimates would be biased due to *selection bias* (Cinelli et al., 2022), as it would estimate the direct impact of interest rates on the dependent variable without considering the indirect impact through Central Bank reserves. On the other hand, it might be interesting to separate the two effects for a more precise understanding of the phenomenon. For these reasons, both types of models will be presented and the problem discussed subsequently.

Model Estimation

Stationarity Tests When dealing with time series data, the first step is to conduct the classical stationarity tests. More specifically, it is important to ensure that the data-generating processes (DGPs) underlying the time series under analysis are stationary. If this is not the case, any model estimation using Ordinary Least Squares (OLS) could yield spurious results, suggesting a relationship between variables where none actually exists (Granger & Newbold, 1974). To test for (non) stationarity, the classic tests well-established in the literature by Kwiatkowski et al. (1992), Phillips and Perron (1988), and Dickey and Fuller (1979) have been employed. If the processes are

[4]The main cause of changes in Central Bank reserves is indeed monetary policy decisions, where increasing interest rates reduces reserves and vice versa.

stationary, the null hypothesis of the KPSS test [5] should not be rejected, while the null hypotheses of the PP and ADF tests should be rejected. For reasons of space, only the results for the variables of interest in the UniCredit model with ROA as the dependent variable are presented here. It should be noted that this choice is entirely discretionary, as the results, available on the author's GitHub page, and the related considerations are nearly identical for the different response variables and banks [6].

Table 2.2: *p-value* of stationarity tests for the UniCredit model with ROA as the dependent variable

	KPSS	**PP**	**ADF**	**ϕ of AR(1)**
ROA	0.10000	0.09833 .	0.72420	0.02082
Euribor	0.02901 *	0.99000	0.99000	0.75737
dcb	0.09913 .	0.36270	0.53895	0.58821

There appears to be strong empirical evidence supporting the non-stationarity of the Euribor rate, while the nature of the DGP for ROA and reserves appears more ambiguous: according to the KPSS Test, both variables seem to be stationary, whereas both the PP Test and ADF Test indicate non-stationarity. Therefore, the autocorrelation function (ACF) is analyzed to determine how correlated the variables are with their lags. For a non-stationary process, a high correlation is expected for a large number of lags; vice versa, for a stationary process, this is not the case.

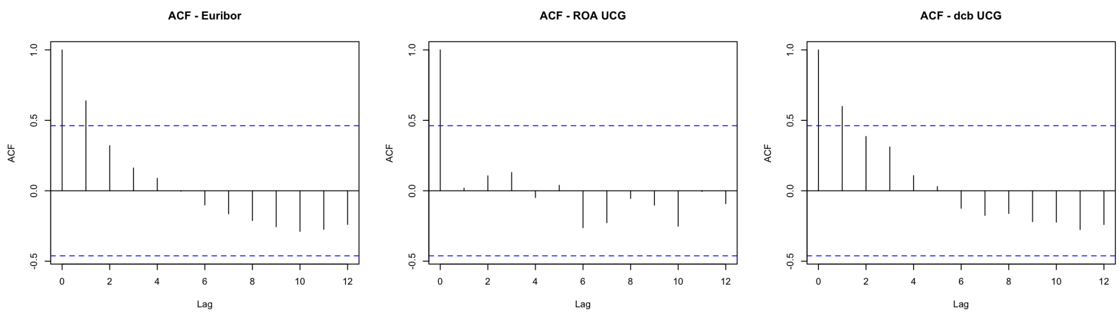

Figure 2.2: ACF for the variables in the model with UniCredit's ROA

It is evident that none of the variables are significantly correlated with their lags, which is a classic characteristic of stationary series. This highlights two main issues with these tests: (i) their power when the autoregressive coefficient ϕ approaches 1 and (ii) when the sample size is small.

Starting with the first case, consider a first-order autoregressive process AR(1), given by:

$$y_t = \phi y_{t-1} + \epsilon_t \tag{2.7}$$

Theoretically, the process is stationary if ϕ is between -1 and 1, but stationarity tests tend to have low power when ϕ is close to 1 (Patterson, 2000). This explains why the Euribor seems non-stationary according to the tests, but its ACF shows otherwise. Indeed, the estimated ϕ coefficient for an AR(1) process based on the Euribor data is about 0.76, close to 1.

[5] It is important to note that the null hypothesis of the KPSS test is stationarity, whereas the null hypotheses of the PP and ADF tests are non-stationarity. Hence the terminology «test for (non) stationarity» used in this thesis.

[6] The test results presented with *p-values* are accompanied by *R-Style* symbols that aid in interpreting significance. A complete legend is available in the Glossary.

Regarding the second issue, all three tests are known to be of low power in small samples, such as those used in this section of the thesis. To illustrate this, a Monte Carlo simulation was conducted in `R`: four stationary AR(1) processes were simulated with coefficients ϕ of 0.2, 0.5, 0.8, and 0.95, respectively, and a (non-stationary) random walk process of the form $y_t = y_{t-1} + \epsilon_t$. All five processes were simulated with a sample size of 18 observations, consistent with the case in this thesis. For each process, the *p-values* of the three tests were computed, and a significance level α of 5% was used to determine the percentage of rejections when the null hypothesis is false. In other words, the power of the (non) stationarity tests with a sample of 18 observations was estimated. The results are as follows [7].

Table 2.3: Power of (non)stationarity tests with a sample of 18 observations

	KPSS	**PP**	**ADF**
$\phi =$ 0.2	–	0.250227 %	0.104403 %
$\phi =$ 0.5	–	0.071852 %	0.080276 %
$\phi =$ 0.8	–	0.021633 %	0.060142 %
$\phi =$ 0.95	–	0.015061 %	0.055225 %
$\phi =$ 1	0.47209 %	–	–

It is evident that the tests are not powerful with such a small sample, whether one has an autoregressive process with a ϕ coefficient approaching 1 or not. Indeed, the best-performing test is KPSS, with a power of 47%, which is far from the 80% threshold commonly accepted in statistical practice.

Therefore, it is concluded that, in this specific case, the best way to determine the nature of the process is through the analysis of the autocorrelation function, which suggests that all three considered variables are stationary. The model can thus be estimated using the OLS estimator.

Tests for OLS Assumptions After estimating the model, it is necessary to verify whether the assumptions underlying the OLS estimator are satisfied to interpret the data. Specifically, one must test for exogeneity, multicollinearity, homoscedasticity, and normality of residuals. Additionally, structural breaks and the correct functional form were tested.

Starting with the last mentioned case, the Ramsey RESET Test was employed. It is worth noting that this test, introduced by Ramsey (1969) and widely used, is not robust if the error term is autocorrelated, as highlighted by Leung and Yu (2001). Indeed, for most models considered, the RESET test does not reject the null hypothesis, indicating that the functional form is correct. However, in some cases, the opposite occurs, but when this happens, the Durbin-Watson Test or the Ljung-Box Test suggest that the error term is autocorrelated. It is concluded that the specified functional form is correct. Additionally, the CUSUM Test was conducted, confirming the absence of structural breaks.

Returning to the assumptions of the OLS model, one of the key assumptions of the Gauss-Markov Theorem[8] is the presence of exogeneity. In other words, it is necessary that the error

[7] The code used for the simulation is provided in Appendix A.1.

[8] Which guarantees that if the conditions of linearity in parameters, absence of multicollinearity, homoscedasticity

term is not correlated with any of the regressors. If this were not the case, it would be impossible to establish a causal relationship between the explanatory and dependent variables. To test this hypothesis, the Hausman (1978) test was not used because it requires an instrumental variable, which unfortunately could not be found[9], but the correlation between the model residuals and its regressors was simply calculated. For this purpose, the following function was written, which returns `TRUE` if the correlation rounded to the second decimal place is zero for all regressors, `FALSE` otherwise:

```
exogeneity = function(res, X){
  cor_boolean = NA
  correlations_saved = NA
  for (i in 1:length(X[1,])){
    x = X[, i]
    cor_tmp = cor(x, res)
    if (round(cor_tmp,2) == 0){
      cor_boolean[i] = TRUE
    } else{
      cor_boolean[i] = FALSE
      correlations_saved = c(correlations_saved, paste0("- x", i, ",res:
          ", round(cor_tmp, 2)))
    }
  }

  correlations_saved = correlations_saved[-1]

  if (any(cor_boolean == FALSE)){
    return(paste(correlations_saved))
  } else{
    return(TRUE)
  }
}
```

For all the estimated models, this fundamental condition was met.

Subsequently, the absence of multicollinearity was verified by calculating the correlation between the two regressors. The lower this correlation is, the better it is for the estimation of the models as a greater amount of the variability of the regressors will be used to explain the phenomenon. In empirical analysis, it is almost impossible for it to be zero, especially in economic disciplines, but statistical practice has established that medium-low values are consistent with the assumptions of the Gauss-Markov Theorem, and this is also the case in this analysis.

Next, the Goldfeld-Quandt and White tests were considered to test the hypothesis of homoscedasticity, and the Jarque-Bera and Shapiro-Wilk tests to verify that the residuals are normally distributed. The first condition is essential to avoid biased standard errors of the coefficient estimates, while the second, if verified, allows for inference even in small samples. If not, statistical theory offers solutions for both cases: in the absence of normality of the residuals, it will be sufficient

of the error term, sample randomization, and exogeneity are met, then the OLS estimator is the best linear unbiased estimator (BLUE). If the normality condition of the errors is also met, then OLS is BUE, i.e., it is the best unbiased estimator.

[9] The main candidate was inflation, but the correlation between it (in Europe) and the Euribor rate is 0.32, thus making it a "weak" instrumental variable.

to increase the sample size and leverage the Central Limit Theorem; in case of heteroscedasticity, other estimators for the standard errors can be used. In addition to the tests reported below, a graphical analysis of the residuals was also conducted to verify if the assumptions hold.

Table 2.4: The *p-value* of the tests for homoscedasticity and normality for the model with ROA and kurtosis and skewness of the errors

	Goldfeld-Quandt	**White**	**Shapiro-Wilk**	**Jarque-Bera**	**Kurtosis**	**Skewness**
hsbc	0.20522	0.47024	0.2263	0.36298	3.01149	-0.82193
bnp	0.90493	0.85305	0.00052 ***	0 ***	8.62193	-2.22653
aca	0.86672	0.06138 .	0.95855	0.85347	2.36413	-0.06745
sanx	0.01389 *	0.33148	8e-05 ***	0 ***	10.24202	-2.53256
bar	0.47431	0.45485	0.57073	0.75199	3.1908	-0.42535
gle	0.62978	0.06374 .	0.68395	0.91178	2.77331	0.22074
dbk	0.03837 *	0.623	0.30841	0.72263	3.42649	-0.41364
lloy	0.45195	0.48714	0.97328	0.94259	2.65251	0.09607
isp	0.93226	0.0473 *	0.11407	0.33294	3.43978	-0.82755
inga	0.61504	0.39029	0.04435 *	0.23729	2.99739	-0.97928
ucg	0.41961	0.25507	0.01604 *	0.1885	2.98707	-1.0547
nwg	0.17256	0.73359	0.95394	0.92485	2.56341	-0.06658
stan	0.01378 *	0.27563	0.37049	0.45271	4.20708	-0.40507
bbva	0.00931 **	0.58789	0.71929	0.87004	2.76818	-0.28173

It is noticeable that for most cases, both hypotheses are verified, but the tests do not always agree on the result. For example, according to the Shapiro-Wilk test, in the UniCredit model, the residuals are not normally distributed, while according to the Jarque-Bera test, they are; or, according to the Goldfeld-Quandt test, the residuals of Intesa Sanpaolo are homoscedastic, while according to the White test, they are not. This discordance is likely due to the small sample size, but to gain a clearer understanding of the nature of the phenomenon, it is useful to graphically analyze the behavior and distributions of the residuals. Thus, their kurtosis and skewness were calculated.

It is easy to notice that the residual distributions for UniCredit and ING Bank have tails very similar to those of a normal distribution[10], but they exhibit slight negative skewness, meaning the left tail is longer than the right tail. The following is the graph.

[10] A value of 3 indicates that the tails of the distribution are the same as those of a normal distribution (mesokurtic). A value lower than 3 means that the tails are lighter than those of a normal distribution (platykurtic), while a value greater than 3 indicates heavier tails (leptokurtic), Gardini et al. (2000).

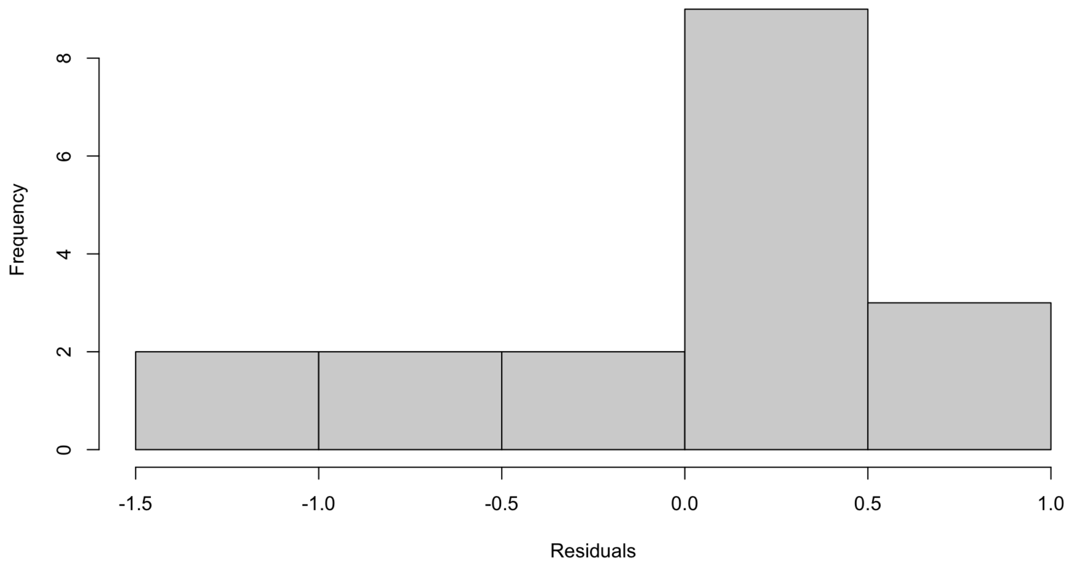

Figure 2.3: Distribution of residuals for the model with ROA for UniCredit

For BNP Paribas and Banco Santander, the tests are quite clear: the residuals are not normally distributed, showing heavy tails and strong left skewness. However, analyzing the QQ plot, which compares the quantiles of the residuals to the theoretical quantiles, reveals that most values align with those of a normal distribution, except for one *outlier*.

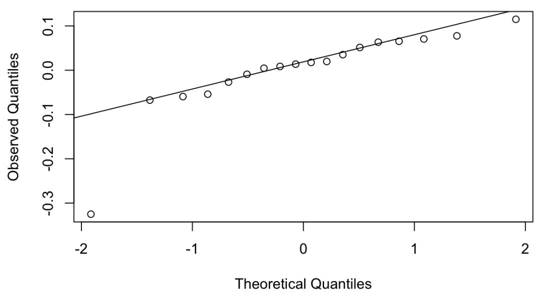

Figure 2.4: QQ Plot of BNP residuals

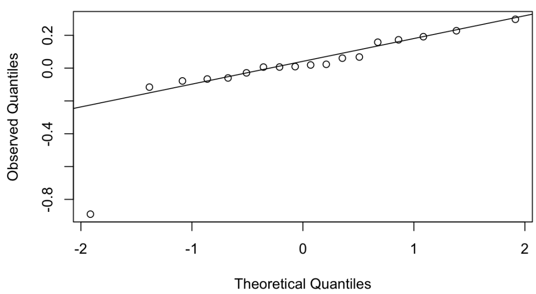

Figure 2.5: QQ Plot of SANX residuals

Moreover, as with the stationarity tests, it has been demonstrated that the power of the Shapiro-Wilk and Jarque-Bera tests in small samples (18 observations)[11] is low, respectively 17% and 8%. Therefore, the residuals of all models are considered to be normally distributed.

To graphically check for homoscedasticity, a classic *plot* of the dependent variable against the predictor might suffice. If the homoscedasticity hypothesis is verified (Figure 2.6), the absolute distance between the observed value and the predicted value should remain constant, while in the opposite case (Figure 2.7), this difference should vary across the sample.

[11] The code is available in Appendix A.2.

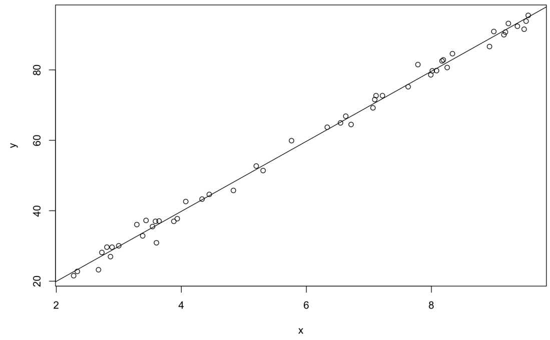

Figure 2.6: Example of homoscedasticity

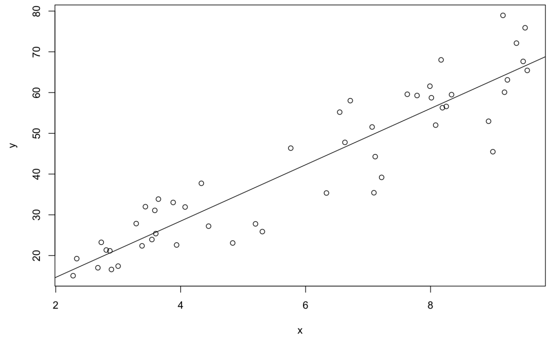

Figure 2.7: Example of heteroscedasticity

Analyzing the scatter-plots, however, does not provide clear evidence for either hypothesis. At this point, another Monte Carlo simulation was conducted to assess the power of the tests in a sample of 18 observations[12], concluding that both the Goldfeld-Quandt and White tests have low power in small samples (9% and 19%, respectively). It seems reasonable to admit the presence of heteroscedasticity, regardless of the test results. In this regard, Long and Ervin (1998) suggest that this decision should not rely on classic tests but should be considered whenever suspected, and in the case of a small sample, the HC3 estimator for standard errors should be used instead of the White estimator. Indeed, the considered sample (2006-2023) includes both crisis periods and normal periods, which suggests that the variance of the response variables may not be constant over time, and may be higher between 2008-2012 compared to other years. This, *ceteris paribus*, leads to a non-constant error variance, i.e., a situation of heteroscedasticity. Additionally, the Monte Carlo simulation showed that in the presence of homoscedasticity, the standard errors estimated with the HC3 estimator are not excessively larger than those estimated with OLS, approximately 5% more, and this also applies to the data for the current analysis. The following graph shows the models with ROA.

[12]The code used for the simulation is also reported in Appendix A.3.

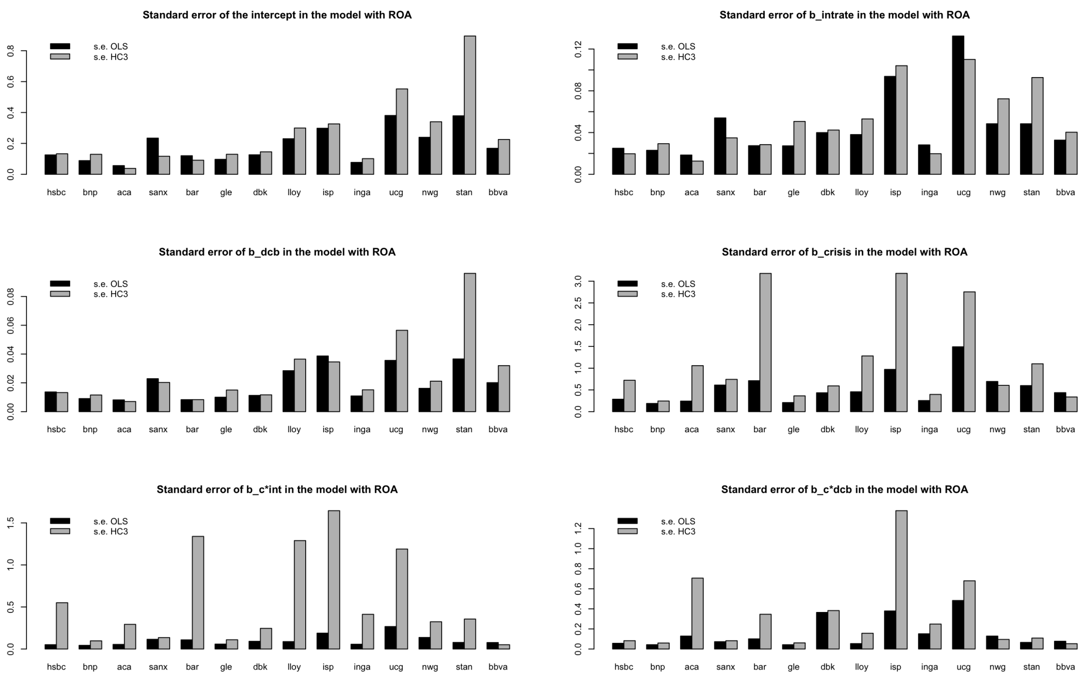

Figure 2.8: Comparison between OLS standard errors and HC3 standard errors for the model with ROA

It is evident that for most cases where the tests confirm the homoscedasticity hypothesis, the standard errors are very similar, except for some singular cases, such as Barclays and UniCredit. This could be due to the low power of the tests, which may not accurately identify the correct nature of the residual variance. Therefore, it is concluded that it is preferable to assume the presence of heteroscedasticity and to estimate the standard deviations using the HC3 estimator.

Correlation Between Error Terms Note that the analysis in question might be an excellent example of *Seemingly Unrelated Regressions*. In other words, there may be common factors affecting all models (i.e., all banks) that could help explain part of the variability in the dependent variables and would not be considered by a simple OLS estimation. In such a case, the relationships should be estimated using the SUR estimator (i.e., *Seemingly Unrelated Regressions*, which is part of the *General Least Squares* class, abbreviated as GLS), introduced by Zellner (1962) and thoroughly explained in Griffiths et al. (1993) and Greene (2017). This is true if and only if the residuals from the 14 banks' models are correlated, which leads to the following null hypothesis:

$$H_0 : \sigma_{\text{bank1, bank2}} = \sigma_{\text{bank1, bank3}} = \cdots = \sigma_{\text{bank13, bank14}} = 0 \tag{2.8}$$

This can be expressed using the Lagrange Multiplier and follows a χ^2 distribution with $\frac{M(M-1)}{2}$ degrees of freedom, where M is the number of estimated equations. In summary:

$$H_0 : T \sum_{i=2}^{14} \sum_{j=1}^{i-1} r_{ij}^2 = 0 \sim \chi^2_{\frac{14*13}{2}} \tag{2.9}$$

Not having found an `R` package that implements this test, the following function was written:

```
surORNOTsur = function(correlations_full, times, number_of_equations){
  vector_of_corrs = NA
  for (i in 1:nrow(correlations_full)){
    for (j in 1:ncol(correlations_full)){
      if (i < j){
        vector_of_corrs = c(vector_of_corrs, correlations_full[i, j])
      }
    }
  }
  vector_of_corrs = vector_of_corrs[-1]
  test_statistic = (sum(vector_of_corrs^2))*times
  df = ((number_of_equations)*(number_of_equations-1))/2
  p_value = 1 - pchisq(test_statistic, df)

  return(list(test_statistic = test_statistic, pvalue = p_value))
}
```

This function takes the correlation matrix as input and returns a list with the test statistic and its *p-value*. The test does not reject the null hypothesis for any of the five dependent variables, so it is concluded that the errors are correlated and it would be preferable to use the SUR estimator.

As with the previous analyses, it is necessary to verify that the assumptions underlying the GLS estimator are met, i.e., that the Aitken Theorem holds (Gardini et al., 2000). Furthermore, for inference in small samples, it is essential that the residuals are normally distributed.

All assumptions have been appropriately verified, and thus, the interpretation of the coefficients can proceed.

Interpretation of Results

Before starting with the interpretation of the results, it is useful to observe the trends and orders of magnitude of the response variables. From Figure 2.9, it is easy to see that the median of the annual observations is around 1% for all cases, and that the 95th percentile has a maximum value of 3% (for NII). This becomes particularly relevant for the interpretation of the estimated coefficients.

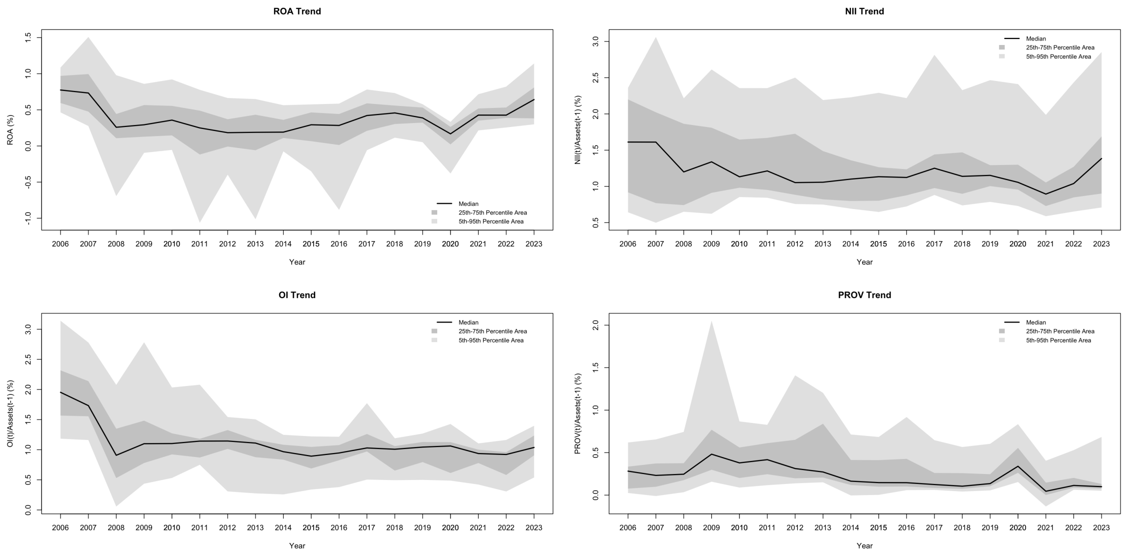

Figure 2.9: Trend of balance sheet components in aggregate for the period 2006-2023

Below are the adjusted R^2 and the *p-values* for the F-test statistic for the models with ROA. Note that `R` does not calculate the F-test for the SUR estimator, so we will rely only on the adjusted R^2.

Table 2.5: Adjusted R^2 and *p-value* of the F-Test for the estimates of the models with ROA

	OLS (with reserves)		**OLS (without reserves)**		**SUR (with reserves)**	**SUR (without reserves)**
	Adjusted R2	F-Test	Adjusted R2	F-Test	Adjusted R2	Adjusted R2
hsbc	0.54023	0.01052 *	0.53628	0.00304 **	0.53108	0.53536
bnp	0.12699	0.26271	0.23533	0.08245 .	0.11813	0.23248
aca	0.70757	0.00085 ***	0.61384	0.00088 ***	0.70267	0.61336
sanx	0.26873	0.11604	0.2107	0.10084	0.25901	0.20899
bar	0.07563	0.33511	0.10352	0.22216	0.04457	0.09771
gle	-0.11547	0.66853	-0.1488	0.84877	-0.135	-0.15162
dbk	0.31445	0.08462 .	0.32333	0.03747 *	0.31164	0.32258
lloy	0.51569	0.01393 *	0.53904	0.00292 **	0.49992	0.53798
isp	0.24692	0.1336	0.21601	0.09662 .	0.23043	0.21131
inga	0.57132	0.00718 **	0.51754	0.00396 **	0.56898	0.51449
ucg	-0.02971	0.51076	0.03157	0.35113	-0.0406	0.00524
nwg	0.71905	0.00067 ***	0.62826	0.00068 ***	0.70565	0.62416

Continued on the next page

Table 2.5: Adjusted R^2 and *p-value* of the F-Test for the estimates of the models with ROA (continues)

stan	0.58938	0.00567 **	0.63004	0.00066 ***	0.58158	0.62712
bbva	0.61901	0.00375 **	0.54173	0.0028 **	0.61406	0.54126

First of all, it is worth noting that there is some consistency between the R^2 values and the F-Test, meaning there are no cases with high R^2 and high *p-value* for the F-Test. Instead, whenever the F-Test does not reject the null hypothesis, the R^2 value is low. This supports the hypothesis of the absence of multicollinearity.

From a quick analysis of these two values, we can state that there are no significant differences in the R^2 of the models estimated with different estimators and controls. In other words, including the *dcb* control and using the SUR estimator do not seem to explain the variability of ROA any better. For a more complete picture, we now analyze the estimates of the individual coefficients, reported below.

Table 2.6: Estimates of the interest rate coefficients for the models with ROA (coefficients in crisis periods are in parentheses, if statistically different from those in normal times)

	OLS (with reserves)	**OLS (without reserves)**	**SUR (with reserves)**	**SUR (without reserves)**
hsbc	0.09026 ***	0.09886 ***	0.08606 ** (-0.04753 *)	0.09563 *** (-0.0684 **)
bnp	0.04298	0.04002 *	0.04137 . (-0.10343 *)	0.04331 * (-0.05835 *)
aca	0.02562 .	0.02613 .	0.02211 (0.11241 *)	0.02812
sanx	0.11141 **	0.12888 *	0.10619 .	0.11964 *
bar	0.06431 *	0.05514 *	0.06031 *	0.04967 .
gle	-0.00122	0.00937	-0.00693	0.00559
dbk	0.12445 *	0.11027 **	0.12076 ** (-0.14045 **)	0.10628 ** (-0.07802 *)
lloy	0.10537 .	0.1076 **	0.08917 *	0.10387 **
isp	0.21875 .	0.20699 *	0.19849 *	0.23401 *
inga	0.06977 **	0.06827 *** (-0.08259 ***)	0.06756 * (-0.10627 **)	0.073 * (-0.09541 **)
ucg	0.2487 *	0.21581 **	0.22694 .	0.23784 **
nwg	0.08934 **	0.08292 **	0.08994 ** (0.03854 *)	0.08147 **
stan	0.12464 **	0.08966 *	0.11016 *	0.08369 *

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Table 2.6: Estimates of the interest rate coefficients for the models with ROA (coefficients in crisis periods are in parentheses, if statistically different from those in normal times) (continues)

bbva	0.12353 *	0.13128 **	0.11641 .	0.12465 **

Table 2.7: Estimates of central bank reserve coefficients for models with ROA (in parentheses the coefficients during crisis periods, if statistically different from those in normal times)

	OLS	**SUR**
hsbc	-0.01102	-0.01392
bnp	0.0022	0.00143
aca	-0.00079	-0.00177 (-0.28568 **)
sanx	-0.0225	-0.01606 (-0.09017 *)
bar	0.0081	0.00793 .
gle	-0.01364	-0.01674 **
dbk	0.00936	0.01081 ** (-0.41554 **)
lloy	-0.00329	-0.00207 (0.05473 *)
isp	0.03107	0.0181
inga	0.00269	0.00436 (0.27729 ***)
ucg	0.03307	0.03707 **
nwg	0.04 .	0.03567 ***
stan	-0.02842	-0.02628 *
bbva	0.01299 (-0.17018 **)	0.01608 . (-0.15941 ***)

The estimates of the coefficients and their levels of significance do not change considerably whether central bank reserves are included or whether the OLS or SUR estimator is used. However, the latter estimates in several cases show a significant impact of central bank deposits, whereas OLS does not[13]. Consistent with theoretical assumptions, it is preferable to make inferences using the SUR estimator and including reserves: this estimator, in the presence of correlated errors, is more efficient, and deposits are included among the regressors as they align with the research question. In this way, the direct effect of the interest rate on the dependent variables and the indirect effect due to higher returns on reserves held at the central bank can be disentangled. The

[13]It should be noted that the theoretical considerations made for the models with ROA as the dependent variable also apply to the other models.

adjusted R^2 values and coefficient estimates for the four models are reported below.

Table 2.8: Adjusted R^2

	ROA	**NII**	**OI**	**PROV**
hsbc	0.53108	0.84485	0.78725	0.78725
bnp	0.11813	0.49127	0.42944	0.42944
aca	0.70267	0.2734	0.45779	0.45779
sanx	0.25901	0.26944	0.50131	0.50131
bar	0.04457	0.47653	0.30444	0.30444
gle	-0.135	0.82488	0.65723	0.65723
dbk	0.31164	0.33044	0.5528	0.5528
lloy	0.49992	0.31125	0.47872	0.47872
isp	0.23043	0.58606	0.15319	0.15319
inga	0.56898	0.43022	0.88466	0.88466
ucg	-0.0406	0.82611	0.61122	0.61122
nwg	0.70565	0.73891	0.64247	0.64247
stan	0.58158	0.31646	0.81359	0.81359
bbva	0.61406	0.40204	0.74708	0.74708

Table 2.9: Estimates of interest rate coefficients (in parentheses the coefficients during crisis periods, if statistically different from those in normal times)

	ROA	**NII**	**OI**	**PROV**
hsbc	0.08606 ** (-0.04753 *)	0.08692 ***	0.12301 ***	0.12301 ***
bnp	0.04137 . (-0.10343 *)	-0.07447 **	0.09852 **	0.09852 ** (-0.02895 *)
aca	0.02211 (0.11241 *)	0.00436	0.06154 **	0.06154 **
sanx	0.10619 .	-0.01771	0.05133 *	0.05133 *
bar	0.06031 *	0.03724 **	0.13073 **	0.13073 **
gle	-0.00693	-0.06691 ***	0.37036 *** (-0.05334 *)	0.37036 ***
dbk	0.12076 ** (-0.14045 **)	-0.00421	0.18183 ** (-0.20584 **)	0.18183 ** (-0.21116 ***)

Continued on the next page

Table 2.9: Estimates of interest rate coefficients (in parentheses the coefficients during crisis periods, if statistically different from those in normal times) (continues)

lloy	0.08917 *	0.11537 *	0.14963	0.14963 (-0.38915 *)
isp	0.19849 *	0.38021 ***	0.15304	0.15304
inga	0.06756 * (-0.10627 **)	-0.06357	0.20531 *** (-0.22499 ***)	0.20531 ***
ucg	0.23225 .	0.1559 *** (0.0327 **)	0.12202 *** (-0.06598 **)	0.12202 *** (-0.08982 ***)
nwg	0.1763 *** (-0.33032 ***)	0.12425 ***	0.12561 *** (-0.13732 **)	0.12561 *** (-0.15392 ***)
stan	0.10367 *	0.15202 *	0.10223 ***	0.10223 ***
bbva	0.15872 *** (0.00956 *)	0.11238 **	0.20285 *** (0.00887 **)	0.20285 *** (0.00843 **)

Table 2.10: Estimates of central bank reserve coefficients (in parentheses the coefficients during crisis periods, if statistically different from those in normal times)

	ROA	**NII**	**OI**	**PROV**
hsbc	-0.01392	-0.06187 *** (-0.02249 *)	-0.05501 ***	-0.05501 ***
bnp	0.00143	-0.0163 ** (0.02191 *)	-0.01014 .	-0.01014 .
aca	-0.00177 (-0.28568 **)	-0.01482 ***	0.0098 * (-0.42497 ***)	0.0098 * (-0.42497 ***)
sanx	-0.01606 (-0.09017 *)	0.03973 ***	-0.02548 ***	-0.02548 ***
bar	0.00793 .	-0.00719 *** (0.09275 ***)	-0.01695 *** (0.08136 *)	-0.01695 *** (0.08136 *)
gle	-0.01674 **	0.01578 *** (-0.0168 *)	-0.08843 *** (-0.36859 ***)	-0.08843 *** (-0.36859 ***)
dbk	0.01081 ** (-0.41554 **)	0.01009 *	-0.00919 *	-0.00919 *
lloy	-0.00207 (0.05473 *)	-0.01898 (0.15574 **)	-0.04519 (0.30071 ***)	-0.04519 (0.3459 ***)
isp	0.0181	-0.00562	0.00136	0.00136
inga	0.00436 (0.27729 ***)	0.03247 ***	-0.00948 . (2.04667 ***)	-0.00948 . (2.04667 ***)

Continued on the next page

Table 2.10: Estimates of central bank reserve coefficients (in parentheses the coefficients during crisis periods, if statistically different from those in normal times) (continues)

ucg	0.03707 **	-0.00268	-0.01193 *** (0.11179 **)	-0.01193 *** (0.11179 **)
nwg	0.03567 ***	0.01347 **	-0.03246 ***	-0.03246 ***
stan	-0.02628 *	-0.00972	-0.01144 *	-0.01144 *
bbva	0.01608 . (-0.15941 ***)	0.08037 ***	-0.05286 ***	-0.05286 ***

Most of the models have a good adjusted R^2 (Table 2.8), indicating that the models explain a significant portion of the variability in the dependent variable. At the same time, the coefficients are often significant at the 5% level, suggesting that interest rates and central bank reserves impact the balance sheets of the banks considered.

In normal periods, the effect of interest rates on ROA is zero for some institutions, but for others, it is positive and of significant impact (Table 2.9), considering a median ROA value around 1% (Figure 2.9). Except for BNP Paribas, Crédit Agricole, Banco Santander, Société Générale, and UniCredit, whose estimates are not statistically different from zero, the two extreme cases are Barclays, where a one-unit increase in the interest rate results in an average ROA increase of 6 basis points, and Intesa Sanpaolo, where the ROA increases by nearly 20 basis points following a one-unit increase in the Euribor rate. During crisis periods, however, the situation changes, and some institutions previously not exposed to interest rate volatility become so (Crédit Agricole), while others show an inverse relationship (HSBC, BNP, Deutsche Bank, ING Bank, and NatWest Group), meaning that as interest rates rise, ROA decreases[14], and others switch from having a positive coefficient to one close to zero. At the same time, central bank reserves (Table 2.10) are significant for some institutions and not significant for others. Excluding Société Générale from the analysis (due to its negative adjusted R^2, indicating poor model fit), only Deutsche Bank, UniCredit, NatWest Group (with a positive sign), and Standard Chartered (with a negative sign) show significant coefficients, but with smaller magnitudes compared to the interest rate. During crisis periods, however, the coefficient is larger and predominantly negative, except for ING Bank and Lloyds Group.

Net interest income is largely explained by the two independent variables, but results are mixed among the different banks. Indeed, some banks (BNP Paribas and Société Générale) show a negative coefficient, others do not have interest income exposed to interest rate variability (Crédit Agricole, Banco Santander, Deutsche Bank, ING Group), while the remaining banks show a positive and considerable impact[15]. Furthermore, all these relationships remain unchanged during the crisis years, except for UniCredit, which sees a significant reduction in its net interest income exposure to interest rate volatility during the 2008-2012 period. Central bank reserves are often significant but with smaller coefficients compared to interest rates and with contrasting signs, both in crisis periods and otherwise. Lastly, Société Générale stands out with a negative Euribor rate coefficient, meaning that net interest income decreases when the rate increases.

Interest rates are also positively related to non-interest income in normal times. Indeed, in

[14] It should be noted that these coefficients were estimated based on only five observations (2008-2012).

[15] The trend and magnitude of the ratio $\frac{NII_t}{Attivo_{t-1}}$ is similar to that of ROA described above (Figure 2.9).

most cases, the coefficient is significant and of non-negligible magnitude. In contrast, central bank reserves often show an inverse relationship with non-interest income.

Finally, provisions for loan losses, consistent with theoretical expectations, have a positive coefficient. As interest rates increase, it is reasonable to assume that default rates and therefore provisions for loan losses also increase. At the same time, central bank reserves show a negative relationship. In this case as well, the results align with theoretical assumptions, as it seems reasonable that provisions decrease if reserves increase. During crisis periods, these two relationships either remain unchanged or reverse, likely due to different risk management policies of the credit institutions.

This section concludes by highlighting that a single conclusion cannot be drawn for all institutions, but in general, it can be stated that the variability of interest rates and central bank reserves explains part of the variability in profitability and balance sheet components of the considered banks.

2.2.2 Model with Stock Prices

Model Description

Successively, an additional econometric model was estimated to investigate the relationship between bank stock prices and interest rates. Monthly data for the period 2006-2023 were used, resulting in a sample size of 216 observations. Work has begun on the following econometric model:

$$price_t = \beta_0 + \beta_1 \, i_t + \beta_2 \, mkt_t + u_t \tag{2.10}$$

where

- $t = 1, ..., 216$ denotes the months, with $t = 1$ corresponding to January 2006;
- $price_t$ represents the average monthly stock price at time t on the stock exchange where the bank is legally based;
- i_t denotes the monthly interest rate, calculated as the simple average of daily observations;
- mkt_t refers to the average monthly value of the stock market index of the country where the bank is legally based;
- u_t is the error term.

The decision was made not to include additional macroeconomic control variables to avoid multicollinearity issues, as these variables are potentially correlated with the market index.

As is well known, stock prices are a classic example of a non-stationary process. Indeed, both the stationarity tests and the autocorrelation function analysis clearly support the non-stationarity of the process. The same result is observed for market indices and monthly interest rates[16].

Testing for the stationarity of the DGP is not merely a statistical formality but necessary for identifying the correct estimator: if the data are stationary, the OLS estimator is correct and consistent; otherwise, it is not. However, there is an exception to this proposition known as

[16] It should be noted that in this case, the interest rates considered are monthly and not annual, as in previous models. There is thus no contradiction with the statement above.

«statistical fun» (Cochrane, 1997)[17]: if the processes are non-stationary but cointegrated, OLS is super-consistent, meaning that as the sample size increases, the OLS estimator converges more rapidly to its true value. To verify this condition, the Engle-Granger Test was used[18], which rejected the hypothesis of cointegration.

At this point, it was decided to estimate, using both OLS and SUR, the model on the logarithms of first differences, which are all stationary processes. After a brief comparison, following the same logic as before, the SUR estimator was chosen. The choice to use the logarithms of first differences rather than the first differences themselves is due to the greater interpretability of the coefficients, as the logarithms of first differences provide a good approximation of percentage changes. The model in this form is:

$$\log(p_{t+1}) - \log(p_t) = \beta_0 + \beta_1(\log(i_{t+1}) - \log(i_t)) + \beta_2(\log(mkt_{t+1}) - \log(mkt_t)) + u_t \qquad (2.11)$$

Model Estimation

Assumption Tests for the SUR Estimator As in the previous case, the assumptions underlying the estimator were verified, concluding that the functional form is correct[19], the assumptions of exogeneity and absence of multicollinearity are met, and there are no structural breaks. It is necessary to carefully comment on the tests assessing the normality of the residuals[20].

Table 2.11: *p-value* of normality tests, kurtosis, and skewness for the residuals of the stock returns model

	Shapiro-Wilk	**Jarque-Bera**	**Kurtosis**	**Skewness**
hsbc	0.41509	0.07752 .	3.56703	0.22774
bnp	0 ***	0 ***	7.17792	-0.84804
aca	0.00241 **	0 ***	4.79163	0.11992
sanx	0.00015 ***	0 ***	4.79127	-0.22168
bar	0 ***	0 ***	10.33193	1.06853
gle	0.23395	0.10753	3.31668	-0.30483
dbk	0.00632 **	0 ***	4.66766	-0.01307
lloy	0 ***	0 ***	8.12399	-0.60783
isp	0.04224 *	0.00167 **	4.15581	0.00488
inga	0 ***	0 ***	8.99587	-0.84149
ucg	0.02465 *	0.06026 .	3.73024	-0.10132
nwg	0 ***	0 ***	14.26407	-1.84404

Continued on the next page

[17]«An example of the statistical fun is that estimates of cointegrating vectors are superconsistent» (Cochrane, 1997).

[18]The Johansen Test was not calculated as we are not interested in studying the direction of the relationship. Recall the initial assumption of taking macroeconomic conditions as given (section 2.2).

[19]The RESET test rejects the null hypothesis in four cases, but two of these indicate that the residuals are autocorrelated, so the RESET test is not robust (Leung & Yu, 2001).

[20]Since the SUR estimator belongs to the class of GLS estimators, it is not necessary to test for the homoscedasticity of errors (Gardini et al., 2000).

Table 2.11: *p-value* of normality tests, kurtosis, and skewness for the residuals of the stock returns model (continues)

stan	0.00051 ***	0 ***	5.13222	0.29899
bbva	0.00093 ***	0 ***	4.39629	0.44883

The null hypothesis of normality is strongly rejected by both tests in all cases. This is also confirmed by the QQ-Plots and the distribution of the residuals. However, since the sample size is sufficiently large, inference can still be made due to the Central Limit Theorem and the consistency of the estimator[21].

Results Interpretation

Following the narrative of the previous section, the values of the adjusted R^2 and the coefficient estimates are reported.

Table 2.12: Adjusted R^2 and coefficients for the stock returns model

	Adjusted R^2	**Interest Rate Percentage Change**	**Market Return**
hsbc	0.26091	0.06529 **	0.69191 ***
bnp	0.57991	-0.00154	1.26531 ***
aca	0.56721	-0.00312	1.43363 ***
sanx	0.75604	-0.00307	1.24538 ***
bar	0.23249	0.01336	1.15276 ***
gle	0.61422	-0.00221	1.5914 ***
dbk	0.43424	0.00103	1.11351 ***
lloy	0.16216	0.08222 *	0.79365 ***
isp	0.73566	-0.00698	1.28597 ***
inga	0.55257	-0.01212 .	1.61812 ***
ucg	0.75522	0.00454	1.58417 ***
nwg	0.26365	0.05478	1.55872 ***
stan	0.2965	0.04721	1.14674 ***
bbva	0.78404	0.00322	1.33646 ***

It is immediately evident that all models are able to explain a substantial portion of the variability in stock returns. The model with the lowest performance is that for Lloyds Banking Group, which still has an adjusted R^2 of 0.16, not low for this type of empirical analysis. At the same time, as one might reasonably expect, stock returns are mostly explained by the market index return. In fact, the interest rate is significant only in the case of HSBC and Lloyds Group. Specifically, for every 100 basis point increase in the monthly interest rate, HSBC's monthly return increases

[21]For an empirical verification, see the simulation in Appendix A.4 conducted on a sample of 216 observations, as in the present analysis.

by an average of 6.5 basis points, while Lloyds' increases by 8 basis points. Whether this impact is significant depends on the level of the return, which is quite volatile (Figure 2.10).

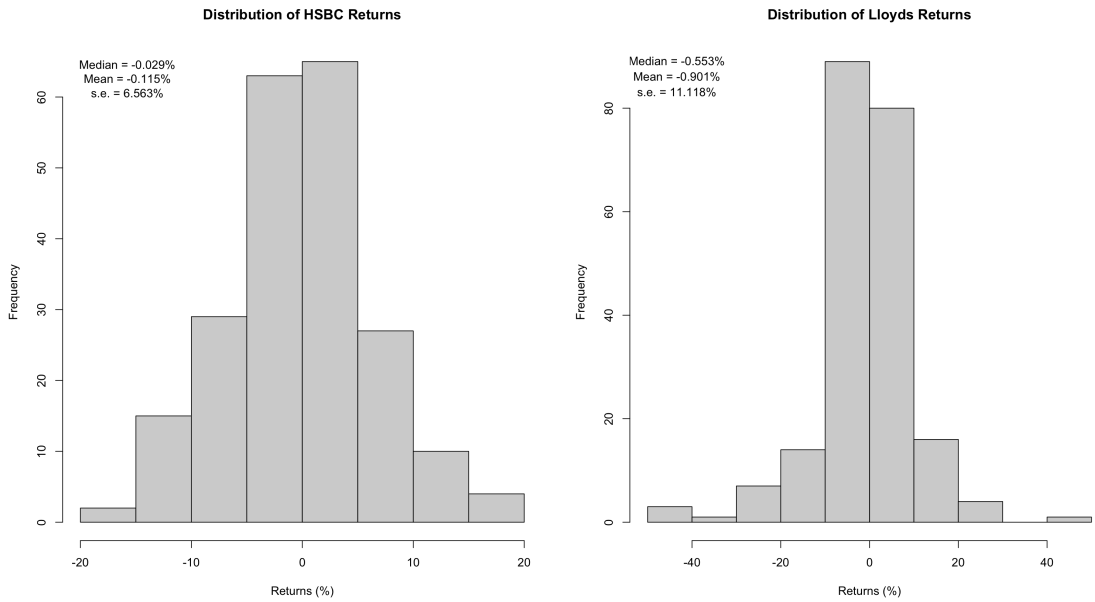

Figure 2.10: Distribution of Returns for HSBC and Lloyds Banking Group

2.3 Weaknesses of the Analysis

The main weakness of the analysis is the small sample size that was necessitated for the balance sheet data models. The period considered is sufficient to include both high and low interest rate periods, but the limited number of observations prevented the inclusion of a greater number of explanatory variables. For example, with a larger sample size, it would have been possible to include the "Non-Performing Loans" (NPL) ratio or the slope of the yield curve as a proxy for expectations.

Additionally, given that financial systems are now globally integrated, it could be interesting to include a weighted average interest rate for each bank's exposure across various countries. Unfortunately, this was not feasible due to the lack of specific data on the international exposure of individual banks, but it could be the subject of future research.

Finally, it is important to note that international accounting standards (IFRS) allow for different methods of accounting for certain phenomena, which can lead to different representations of corporate equity. However, it is reasonable to assume that all the companies considered, being listed on major global markets, adopt principles that maximize their equity to appear stronger to investors. This should minimize differences in equity related to the different application of accounting principles.

CONCLUSIONS

The objective of this thesis was to investigate, based on empirical findings, the impact that interest rates have on the banking sector. In this regard, after briefly explaining the mechanisms underlying monetary policy and hedging strategies (Chapter 1), the empirical examination of the phenomenon was carried out (Chapter 2).

It emerged that both interest rates and central bank reserves help explain the variability of profitability and balance sheet components of the 14 largest banks in Europe. In particular, the relationship between interest rates and balance sheet components is often positive, indicating that an increase in interest rates has a beneficial effect on income components but also leads to an increase in provisions for loan losses. However, given the positive relationship between ROA and interest rates, it can be concluded that the banking sector overall benefits from an increase in interest rates. The differences in the magnitude of the coefficients among banks are attributed to varying risk management policies among the banks themselves.

The variability of balance sheet components is also explained by the variability of central bank reserves, which, however, present a more complex interpretation: they rarely help explain bank profitability, have a negative impact on both non-interest income and provisions for loan losses, but have a positive impact on net interest income for some institutions and a negative impact for others, likely due to different liquidity management choices.

Finally, with the exception of HSBC and Lloyds, there is insufficient empirical evidence to assert that the stock returns of the banks considered are explained by the variability of interest rates.

APPENDIX A

R CODE FOR MONTE CARLO SIMULATIONS

A.1 Stationarity Tests in Small Samples

```
last_time = Sys.time()  # Time at the beginning of the loop
time_elapsed = 0
interval = 15 # Seconds between print statements to track progress in the loop

set.seed(226091)
obs = 18       # Number of observations
reps = 1000000 # Number of simulations

# Matrices to store the p-values of the tests
results_02 = matrix(c(0,0), reps, 3)
results_05 = matrix(c(0,0), reps, 3)
results_08 = matrix(c(0,0), reps, 3)
results_095 = matrix(c(0,0), reps, 3)
results_1 = matrix(c(0,0), reps, 3)
colnames(results_02) = c("kpss - phi=0.2", "pp - phi=0.2", "adf - phi=0.2")
colnames(results_05) = c("kpss - phi=0.5", "pp - phi=0.5", "adf - phi=0.5")
colnames(results_08) = c("kpss - phi=0.8", "pp - phi=0.8", "adf - phi=0.8")
colnames(results_095) = c("kpss - phi=0.95", "pp - phi=0.95", "adf - phi=0.95")
colnames(results_1) = c("kpss - phi=1", "pp - phi=1", "adf - phi=1")
rownames(results_02) = c(1:reps)
rownames(results_05) = c(1:reps)
rownames(results_08) = c(1:reps)
rownames(results_095) = c(1:reps)
rownames(results_1) = c(1:reps)

rejections_02 = matrix(c(0,0), reps, 3)
rejections_05 = matrix(c(0,0), reps, 3)
rejections_08 = matrix(c(0,0), reps, 3)
rejections_095 = matrix(c(0,0), reps, 3)
rejections_1 = matrix(c(0,0), reps, 3)
colnames(rejections_02) = c("kpss - phi=0.2", "pp - phi=0.2", "adf -
```

```
phi=0.2")
colnames(rejections_05) = c("kpss - phi=0.5", "pp - phi=0.5", "adf - phi=0.5")
colnames(rejections_08) = c("kpss - phi=0.8", "pp - phi=0.8", "adf - phi=0.8")
colnames(rejections_095) = c("kpss - phi=0.95", "pp - phi=0.95", "adf - phi=0.95")
colnames(rejections_1) = c("kpss - phi=1", "pp - phi=1", "adf - phi=1")
rownames(rejections_02) = c(1:reps)
rownames(rejections_05) = c(1:reps)
rownames(rejections_08) = c(1:reps)
rownames(rejections_095) = c(1:reps)
rownames(rejections_1) = c(1:reps)

# Significance level
alpha = 0.05

for (i in 1:reps){
  # Simulating stationary processes
  ar_02 = arima.sim(list(order = c(1,0,0), ar = 0.2), n = obs)
  ar_05 = arima.sim(list(order = c(1,0,0), ar = 0.5), n = obs)
  ar_08 = arima.sim(list(order = c(1,0,0), ar = 0.8), n = obs)
  ar_095 = arima.sim(list(order = c(1,0,0), ar = 0.95), n = obs)
  # Simulating a non-stationary process
  rw = 5 + cumsum(rnorm(obs, mean = 0, sd = 1))

  # Testing the processes
  results_02[i, 1] = as.numeric(kpss.test(ar_02)[3])                                  # p-value from KPSS test
  results_02[i, 2] = as.numeric(pp.test(ar_02)[4])                                    # p-value from PP test
  results_02[i, 3] = as.numeric(adf.test(ar_02)[4])                                   # p-value from ADF test

  # Checking p-values
  # If less than 0.05, set 1 in the rejection matrix, otherwise set 0
  for (j in 1:3){
    if(results_02[i, j] < 0.05){
      rejections_02[i, j] = 1
    }
  }

  # Testing the processes
  results_05[i, 1] = as.numeric(kpss.test(ar_05)[3]) # p-value from KPSS test
  results_05[i, 2] = as.numeric(pp.test(ar_05)[4]) # p-value from PP test
  results_05[i, 3] = as.numeric(adf.test(ar_05)[4]) # p-value from ADF test

  # Checking p-values
```

```
# If less than 0.05, set 1 in the rejection matrix, otherwise set 0
for (j in 1:3){
  if(results_05[i, j] < 0.05){
    rejections_05[i, j] = 1
  }
}

# Testing the processes
results_08[i, 1] = as.numeric(kpss.test(ar_08)[3]) # p-value from KPSS test
results_08[i, 2] = as.numeric(pp.test(ar_08)[4]) # p-value from PP test
results_08[i, 3] = as.numeric(adf.test(ar_08)[4]) # p-value from ADF test

# Checking p-values
# If less than 0.05, set 1 in the rejection matrix, otherwise set 0
for (j in 1:3){
  if(results_08[i, j] < 0.05){
    rejections_08[i, j] = 1
  }
}

# Testing the processes
results_095[i, 1] = as.numeric(kpss.test(ar_095)[3]) # p-value from KPSS test
results_095[i, 2] = as.numeric(pp.test(ar_095)[4]) # p-value from PP test
results_095[i, 3] = as.numeric(adf.test(ar_095)[4]) # p-value from ADF test

# Checking p-values
# If less than 0.05, set 1 in the rejection matrix, otherwise set 0
for (j in 1:3){
  if(results_095[i, j] < 0.05){
    rejections_095[i, j] = 1
  }
}

# Testing the processes
results_1[i, 1] = as.numeric(kpss.test(rw)[3]) # p-value from KPSS test
results_1[i, 2] = as.numeric(pp.test(rw)[4]) # p-value from PP test
results_1[i, 3] = as.numeric(adf.test(rw)[4]) # p-value from ADF test

# Checking p-values
# If less than 0.05, set 1 in the rejection matrix, otherwise set 0
for (j in 1:3){
  if(results_1[i, j] < 0.05){
    rejections_1[i, j] = 1
  }
}
```

```
  # Adding instructions to track progress in the loop
  # Time elapsed
  current_time = Sys.time()
  time_elapsed = as.numeric(difftime(current_time, last_time, units =
     "secs"))

  # Print progress every 15 seconds
  if (time_elapsed >= interval) {
    # Print the message and update the last time of printing
    cat("Elapsed time:", round(as.numeric(difftime(current_time,
        last_time, units = "secs")), 1), "seconds. Current simulation
        number:", i, "\n")
    last_time = current_time  # Update the last time of printing
  }
}

# Percentage of rejections
# Summary matrix
powers = matrix(c(0,0), 5, 3)
colnames(powers) = c("kpss", "pp", "adf")
rownames(powers) = c("phi = 0.2", "phi = 0.5", "phi = 0.8", "phi = 0.95",
    "phi = 1")
# AR(1) with phi = 0.2
powers[1,1] = (sum(rejections_02[, 1]))/reps
powers[1,2] = sum(rejections_02[, 2])/reps
powers[1,3] = sum(rejections_02[, 3])/reps
# AR(1) with phi = 0.5
powers[2,1] = (sum(rejections_05[, 1]))/reps
powers[2,2] = sum(rejections_05[, 2])/reps
powers[2,3] = sum(rejections_05[, 3])/reps
# AR(1) with phi = 0.8
powers[3,1] = (sum(rejections_08[, 1]))/reps
powers[3,2] = sum(rejections_08[, 2])/reps
powers[3,3] = sum(rejections_08[, 3])/reps
# AR(1) with phi = 0.95
powers[4,1] = (sum(rejections_095[, 1]))/reps
powers[4,2] = sum(rejections_095[, 2])/reps
powers[4,3] = sum(rejections_095[, 3])/reps
# Random walk
powers[5,1] = (sum(rejections_1[, 1]))/reps
powers[5,2] = sum(rejections_1[, 2])/reps
powers[5,3] = sum(rejections_1[, 3])/reps
# Summary
print(powers)

# Graphical representation
par(mfrow = c(2,2))
# KPSS
plot(ts(powers[, "kpss"], start = 1), type = "l", xaxt = "n", xlab = "",
```

```
    main = "KPSS Test Rejections",
   ylab = "Rejection Percentage")
axis(1, at = c(1:5), labels = c("phi = 0.2", "phi = 0.5", "phi = 0.8",
    "phi = 0.95", "phi = 1"), las = 2)
points(1:5, powers[, "kpss"], pch = 1, col = "black", cex = 1)
# PP
plot(ts(powers[, "pp"], start = 1), type = "l", xaxt = "n", xlab = "",
    main = "PP Test Rejections",
   ylab = "Rejection Percentage")
axis(1, at = c(1:5), labels = c("phi = 0.2", "phi = 0.5", "phi = 0.8",
    "phi = 0.95", "phi = 1"), las = 2)
points(1:5, powers[, "pp"], pch = 1, col = "black", cex = 1)
# ADF
plot(ts(powers[, "adf"], start = 1), type = "l", xaxt = "n", xlab = "",
    main = "ADF Test Rejections",
   ylab = "Rejection Percentage")
axis(1, at = c(1:5), labels = c("phi = 0.2", "phi = 0.5", "phi = 0.8",
    "phi = 0.95", "phi = 1"), las = 2)
points(1:5, powers[, "adf"], pch = 1, col = "black", cex = 1)
par(mfrow = c(1,1))

write.csv(powers, file = "Results/Stationarity_Test_Simulation.csv")
```

A.2 Normality Tests in Small Samples

```
obs = 18
N = 10^6

rejections_normal_jb = 0; rejections_normal_sw = 0
rejections_non_normal_jb = 0; rejections_non_normal_sw = 0

for (i in 1:N){
  normal_process = rnorm(obs)
  non_normal_process = runif(obs)

  # Normality tests for a normal process
  if (as.numeric(shapiro.test(normal_process)[2]) < 0.05){
    rejections_normal_sw = rejections_normal_sw + 1
  }

  if (as.numeric(jarque.bera.test(normal_process)[3]) < 0.05){
    rejections_normal_jb = rejections_normal_jb + 1
  }

  # Normality tests for a non-normal process
  if (as.numeric(shapiro.test(non_normal_process)[2]) < 0.05){
    rejections_non_normal_sw = rejections_non_normal_sw + 1
  }

  if (as.numeric(jarque.bera.test(non_normal_process)[3]) < 0.05){
    rejections_non_normal_jb = rejections_non_normal_jb + 1
  }
}
rejection_summary = cbind(I((rejections_normal_sw/N)*100),
    I((rejections_normal_jb/N)*100),
          I((rejections_non_normal_sw/N)*100),
              I((rejections_non_normal_jb/N)*100))

result = matrix(rejection_summary, nrow = 1, ncol = 4)
colnames(result) = c("SW - Normal", "JB - Normal", "SW - Non-normal",
    "JB - Non-normal")

write.csv(result, "Results/Normality_Test_Simulation.csv")
```

A.3 Homoscedasticity and Heteroscedasticity Tests in Small Samples

```
last_time = Sys.time()  # Time at the beginning of the loop
time_elapsed = 0
interval = 15 # Seconds between print statements to track progress in the
    loop

obs = 18      # Number of observations
rep = 1000000 # Number of simulations

# Matrices to store results
homoskedasticity_result = matrix(NA, rep, 5)
rownames(homoskedasticity_result) = 1:rep
colnames(homoskedasticity_result) = c("Goldfeld-Quandt", "White", "OLS
    s.e.", "White s.e.", "Percentage Difference between s.e.")

heteroskedasticity_result = matrix(NA, rep, 5)
rownames(heteroskedasticity_result) = 1:rep
colnames(heteroskedasticity_result) = c("Goldfeld-Quandt", "White", "OLS
    s.e.", "White s.e.", "Percentage Difference between s.e.")

# Note: By "percentage difference" we refer to (White s.e. - OLS s.e.) /
    (OLS s.e.), which measures
# how much larger or smaller the White standard errors are compared to the
    OLS standard errors.

for (i in 1:rep){
  # Simulation of the two processes
  x = runif(obs, 2, 10)
  y_omo = 10*x + 2*rnorm(obs)
  y_et = 7*x + rnorm(obs)*(x)

  # HOMOSCEDASTICITY
  omo = lm(y_omo ~ x)
  gq_omo = as.numeric(gqtest(omo)[5])
  white_omo = as.numeric(white_test(omo)[2])

  if(gq_omo < 0.05){
      homoskedasticity_result[i, 1] = 1
  } else{
      homoskedasticity_result[i, 1] = 0
  }

  if(white_omo < 0.05){
    homoskedasticity_result[i, 2] = 1
  } else{
```

```
    homoskedasticity_result[i, 2] = 0
  }

  # OLS standard errors
  ols_se_omo = coefficients(summary(omo))[4]
  homoskedasticity_result[i, 3] = ols_se_omo
  # White standard errors
  robust_se_omo = coeftest(omo, vcov = vcovHC(omo, type = "HC3"))[4]
  homoskedasticity_result[i, 4] = robust_se_omo
  # Percentage Difference
  diff_se_omo = ((robust_se_omo - ols_se_omo)/(ols_se_omo))*100
  homoskedasticity_result[i, 5] = diff_se_omo

  # HETEROSCEDASTICITY
  etero = lm(y_et ~ x)
  gq_etero = as.numeric(gqtest(etero)[5])
  white_etero = as.numeric(white_test(etero)[2])

  if(gq_etero < 0.05){
    heteroskedasticity_result[i, 1] = 1
  } else{
    heteroskedasticity_result[i, 1] = 0
  }

  if(white_etero < 0.05){
    heteroskedasticity_result[i, 2] = 1
  } else{
    heteroskedasticity_result[i, 2] = 0
  }

  # OLS standard errors
  ols_se_etero = coefficients(summary(etero))[4]
  heteroskedasticity_result[i, 3] = ols_se_etero
  # White standard errors
  robust_se_etero = coeftest(etero, vcov = vcovHC(etero, type = "HC3"))[4]
  heteroskedasticity_result[i, 4] = robust_se_etero
  # Percentage Difference
  diff_se_etero = ((robust_se_etero - ols_se_etero)/(ols_se_etero))*100
  heteroskedasticity_result[i, 5] = diff_se_etero

  # Adding instructions to track progress as the simulation might take a
      while for large samples
  current_time = Sys.time()  # Current time
  time_elapsed = as.numeric(difftime(current_time, last_time, units =
      "secs"))  # Elapsed time in seconds

  # If more than 15 seconds have passed since the last print, update the
      progress
  if (time_elapsed >= interval) {
```

```
    # Print the progress and update the last print time
    cat("Elapsed time:", round(as.numeric(difftime(current_time,
        last_time, units = "secs")), 1), "seconds. Simulation number:", i,
        "\n")
    last_time = current_time  # Update the last print time
  }
}

# Calculating rejection rates
# Summary matrix
rejections = matrix(c(0,0), 2, 2)
colnames(rejections) = c("Goldfeld-Quandt", "White")
rownames(rejections) = c("Homoscedasticity", "Heteroscedasticity")

rejections[1,1] = sum(homoskedasticity_result[,1])/rep
rejections[1,2] = sum(homoskedasticity_result[,2])/rep

rejections[2,1] = sum(heteroskedasticity_result[,1])/rep
rejections[2,2] = sum(heteroskedasticity_result[,2])/rep

write.csv(rejections,
    "Results/Homoscedasticity-Heteroscedasticity_Simulation_Results.csv")
write.csv(homoskedasticity_result, "Results/Homoscedasticity_Results.csv")
write.csv(heteroskedasticity_result,
    "Results/Heteroscedasticity_Results.csv")
```

A.4 Distribution of SUR Coefficient Estimates in a Medium-to-Large Sample

```
{
  reps = 10^6  # Number of simulations
  obs = 216    # Number of observations per equation
  betas1 = NULL; betas2 = NULL

  last_time = Sys.time()  # Time at the beginning of the loop
  time_elapsed = 0
  interval = 15 # Seconds between print statements to track progress in
      the loop

  # Non-normal and correlated errors (using the SUR model)
  for (i in 1:reps){
    x1 = rnorm(obs)
    x2 = rnorm(obs)
    e1 = runif(obs)
    e2 = e1 + 0.5*runif(obs)
    y1 = 2*x1 + 1.5*e1
    y2 = 2*x2 + 1.5*e2
    data = data.frame(y1, y2, x1, x2)

    eq1 = y1 ~ x1
    eq2 = y2 ~ x2
    eqs = list(eq1 = eq1, eq2 = eq2)

    fit = systemfit(eqs, method = "SUR", data = data)
    betas1[i] = coef(fit)[2]
    betas2[i] = coef(fit)[4]

    # Adding instructions to track progress as the simulation might take a
        while for large samples
    current_time = Sys.time()  # Current time
    time_elapsed = as.numeric(difftime(current_time, last_time, units =
        "secs"))  # Elapsed time in seconds

    # If more than 15 seconds have passed since the last print, update the
        progress
    if (time_elapsed >= interval) {
      # Print the progress and update the last print time
      cat("Elapsed time:", round(as.numeric(difftime(current_time,
          last_time, units = "secs")), 1), "seconds. Simulation number:",
          i, "\n")
      last_time = current_time  # Update the last print time
    }
  }
```

```
  write.csv(betas1, "Results/Simulations/Betas1_n216.csv")
  write.csv(betas2, "Results/Simulations/Betas2_n216.csv")
}

betas1 = (read.csv("Results/Simulations/Betas1_n216.csv"))[, "x"]
betas2 = (read.csv("Results/Simulations/Betas2_n216.csv"))[, "x"]

par(mfrow = c(1,2))
hist(betas1, main = "Betas - eq1")
hist(betas2, main = "Betas - eq2")
par(mfrow = c(1,1))

kurtosis(betas1)
skewness(betas1)
kurtosis(betas2)
skewness(betas2)
```

BIBLIOGRAPHY

Alessandri, P., & Nelson, B. D. (2015). Simple banking: Profitability and the yield curve. *Journal of Money, Credit and Banking*, *47*(1), 143–175.

Altavilla, C., Boucinha, M., & Peydró, J.-L. (2017). *Monetary policy and bank profitability in a low interest rate environment* (tech. rep. No. 2105). European Central Bank.

Bagliano, F. C., & Marotta, G. (2010). *Economia monetaria*. Il Mulino.

Bernanke, B. S., Laubach, T., Mishkin, F. S., & Posen, A. S. (2001). *Inflation targeting: Lessons from the international experience*. Princeton University Press.

Blanchard, O., Amighini, A., & Giavazzi, F. (2020). *Macroeconomia. una prospettiva europea*. Il Mulino.

Borio, C., Gambacorta, L., & Hofmann, B. (2017). The influence of monetary policy on bank profitability. *International Finance*.

Cinelli, C., Forney, A., & Pearl, J. (2022). A crash course in good and bad controls. *Sociological Methods & Research*, 00491241221099552.

Cochrane, J. H. (1997). Time series for macroeconomics and finance [Revised with additional pictures in 2005]. https://static1.squarespace.com/static/5e6033a4ea02d801f37e15bb/t/5eea91f725f16202da96235d/1592431098027/time_series_book.pdf

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427–431.

Fabrizi, P. L. (2021). *Economia del mercato mobiliare*. Egea.

Flannery, M. J. (1981). Market interest rates and commercial bank profitability: An empirical investigation. *The Journal of Finance*.

Flannery, M. J. (1983). Nterest rates and bank profitability: Additional evidence. *Journal of Money, Credit, and Banking*.

Gaffeo, E., Mittone, L., Tamborini, R., et al. (2015). *Introduzione all'economia*. Zanichelli.

Gardini, A., Cavaliere, G., Costa, M., Fanelli, L., & Paruolo, P. (2000). *Econometria. volume primo*. Franco Angeli.

Granger, C. W., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of econometrics*, *2*(2), 111–120.

Greene, W. H. (2017). *Econometric analysis* (8th). Pearson.

Griffiths, W. E., Hill, R. C., & Judge, G. G. (1993). *Learning and practicing econometrics*. Wiley.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 1251–1271.

Henningsen, A., & Hamann, J. D. (2023). Estimating systems of simultaneous equations. https://cran.r-project.org/package=systemfit

Hothorn, T., Zeileis, A., Farebrother, R. W., Cummins, C., Millo, G., & Mitchell, D. (2022). Package 'lmtest': Testing linear regression models. https://cran.r-project.org/package=lmtest

Khang, C. (1983). A dynamic global portfolio immunization strategy in the world of multiple interest rate changes: A dynamic immunization and minimax theorem. *Journal of Financial and Quantitative Analysis*, *18*(3), 355–363.

Komsta, L., & Novomestky, F. (2015). Moments, cumulants, skewness, kurtosis and related tests. https://cran.r-project.org/package=moments

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics*, *54*(1-3), 159–178.

Leung, S. F., & Yu, S. (2001). The sensitivity of the reset tests to disturbance autocorrelation in regression analysis. *Empirical Economics*, *26*, 721–726.

Liu, J. (2020). Durbin-watson test [Ultimo accesso: 23 aprile 2024]. https://pypi.org/project/dwtest/

Long, J. S., & Ervin, L. H. (1998). Correcting for heteroscedasticity with heteroscedasticity consistent standard errors in the linear regression model: Small sample considerations.

McKinney, W. (2010). Data Structures for Statistical Computing in Python. In S. van der Walt & J. Millman (Eds.), *Proceedings of the 9th Python in Science Conference* (pp. 56–61). https://doi.org/10.25080/Majora-92bf1922-00a

Monetary policy [Ultimo accesso: 27 marzo 2024]. (n.d.). European Central Bank. https://www.ecb.europa.eu/ecb/orga/tasks/monpol/html/index.en.html

Monetary policy principles and practice [Ultimo accesso: 27 marzo 2024]. (n.d.). Federal Reserve. https://www.federalreserve.gov/monetarypolicy/monetary-policy-what-are-its-goals-how-does-it-work.htm

Patterson, K. (2000). *An introduction to applied econometrics: A time series approach*. Palgrave.

Perez, J. L. (2022). Package 'whitestrap': White test and bootstrapped white test for heteroskedasticity. https://cran.r-project.org/package=whitestrap

Pfaff, B., Zivot, E., & Stigler, M. (2022). Package 'urca': Unit root and cointegration tests for time series data. https://cran.r-project.org/package=urca

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *biometrika*, *75*(2), 335–346.

Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *31*(2), 350–371.

Samuelson, P. A. (1945). The effect of interest rate increase on the banking system. *The American Economic Review*.

Scandolo, G. (2022). *Matematica finanziaria*. Amon.

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and statistical modeling with python. *9th Python in Science Conference*.

Shafir, E., Diamond, P., & Tversky, A. (1997). Money illusion. *Quarterly Journal of Economics*.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy 39 (1993) 195-214 North-Holland*.

Trapletti, A., Hornik, K., & LeBaron, B. (2023). Package 'tseries': Time series analysis and computational finance. https://cran.r-project.org/package=tseries

The world's 100 largest banks [Ultimo accesso: 09 aprile 2024]. (2023). S&P Global Ratings. https://www.spglobal.com/marketintelligence/en/news-insights/research/the-world-s-100-largest-banks-2023

Zeileis, A., Leisch, F., Hornik, K., Kleiber, C., Hansen, B., Merkle, E. C., & Umlauf, N. (2022). Package 'strucchange': Testing, monitoring, and dating structural changes. https://cran.r-project.org/package=strucchange

Zeileis, A., Lumley, T., Graham, N., & Koell, S. (2023). Robust covariance matrix estimators. https://cran.r-project.org/package=sandwich

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American statistical Association*, *57*(298), 348–368.

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GLOSSARY

***** $1\% <$ p-value $\leq 5\%$.

****** $0{,}1\% <$ p-value $\leq 1\%$.

******* p-value $\leq 0{,}1\%$.

. $5\% <$ p-value $\leq 10\%$.

aca Crédit Agricole.

bar Barclays.

bbva Banco Bilbao Vizcaya Argentaria.

bnp BNP Paribas.

dbk Deutsche Bank.

gle Société Générale.

hsbc The Hongkong and Shanghai Banking Corporation.

inga ING Bank.

isp Intesa Sanpaolo.

lloy Lloyds Bank.

NII $\frac{\text{Reddito netto da interessi}_t}{\text{Attivo}_{t-1}}$.

nwg NatWest Group.

OI $\frac{\text{Reddito non da interessi}_t}{\text{Attivo}_{t-1}}$.

PROV $\frac{\text{Accantonamenti a fondo svalutazione crediti}_t}{\text{Attivo}_{t-1}}$.

ROA Return on Assets $= \frac{\text{Risultato d'esercizio}_t}{\text{Attivo}_{t-1}}$.

sanx Banco Santander.

stan Standard Chartered Bank.

ucg UniCredit.