Charles University

Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Impact of the low yield environment on banks and insurers: Evidence from equity prices

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Signature

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Abstract

Using static and dynamic panel data analysis, we examine how interest rates influenced equity prices of European banks and insurance companies between 2006 and 2015. Identification and quantification of effects of the low yield environment, which is a consequence of decreasing interest rates, are crucial for regulators and policy makers. Our static and dynamic models show that decreasing short-term interest rates had a negative impact both on banks and insurers. In this thesis, dynamic models are estimated by means of the Blundell-Bond system GMM estimator and we consider their results superior to the results of static models because all underlying assumptions of the dynamic models are met here. Results obtained by employing the Blundell-Bond system GMM estimator suggest that life insurers were effected more than banks, while banks were effected more than non-life insurers. In case of a 1 percentage point decrease in short-term interest rates, equity prices of life insurers are estimated to decrease on average by 18 %, equity prices of banks by 8 %, and equity prices of non-life insurers by 3 %.

JEL Classification	C33, C36, C61, E44, G21, G22
Keywords	interest rates, equity prices, static panel analysis, dynamic panel analysis, system GMM estimator

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Abstrakt

Pomocí statické a dynamické analýzy panelových dat zkoumáme, jak úrokové míry ovlivňovaly ceny akcií evropských bank a pojišťoven mezi lety 2006 a 2015. Identifikace a kvantifikování dopadu prostředí nízkých výnosů, které je způsobené snížením úrokových měr, jsou zásadní především pro regulátory a centrální banky. Naše statické a dynamické modely ukazují, že klesající krátkodobá úroková míra měla negativní vliv na banky i pojišťovny. Dynamické modely jsou v této práci odhadovány prostřednictvím Blundellova-Bondova systémového GMM estimátoru a jejich výsledky považujeme za nadřazené výsledkům statických modelů, protože všechny předpoklady dynamických modelů jsou zde splněny. Podle výsledků získaných pomocí Blundellova-Bondova systémového GMM estimátoru byly životní pojišťovny ovlivňovány více než banky, které zase byly ovlivňovány více než neživotní pojišťovny. V případě poklesu krátkodobých úrokových měr o 1 procentní bod poklesnou dle našeho odhadu ceny akcií životních pojišťoven v průměru o 18 %, ceny akcií bank o 8 % a ceny akcií neživotních pojišťoven o 3 %.

Klasifikace JEL	C33, C36, C61, E44, G21, G22
Klíčová slova	úrokové míry, ceny akcií, statická analýza panelových dat, dynamická analýza panelových dat, systémový GMM estimátor

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Acronyms

ECB European Central Bank

QE Quantitative easing

ESRB European Systemic Risk Board

OLS Ordinary Least Squares

GMM Generalized Method of Moments

j Number of instruments

ar2p p-value of the Arellano-Bond test for zero autocorrelation in first-differenced errors

hansenp p-value of the Hansen test of overidentifying restrictions

Master's Thesis Proposal

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Proposed topic	Impact of the low yield environment on banks and insurers: Evidence from equity prices

Motivation As a consequence of the economic and financial crisis that started in 2007 and 2008, the European Central Bank (ECB) has been gradually decreasing the policy rates. The aim of decreasing the policy rates was to prevent deflation and to reach the inflation target. The ECB has additionally been using quantitative easing (QE). Recently, for example, non-financial corporate bonds have been added to the list of assets eligible for QE. Decreasing the policy rates as well as QE should stimulate economic activity in the euro area economies. Nevertheless, both decreasing the policy rates and QE have an important side effect that interest rates go down.

Reducing interest rates shifts the yield curves down, which may have an adverse impact on banks and insurers. The reason is that their investment income drops with a negative change in the yield. In addition to problems on the asset side, some of the items on the liabilities side may inflate, at least in case of life insurers, e.g. because the discount rates applied to future payments are lower. This results in vulnerabilities in the banking and insurance sectors—profits and equity values of banks and insurance companies are lowered. On that account, low yields have been included in the European Systemic Risk Board (ESRB) overview of systemic risks.

Regarding banks, empirical evidence that interest rates and banks profitability are positively correlated is provided by Molyneux and Thornton (1992) and Bourke (1989), who consider interest rates a proxy for scarcity of resources, or more recently by Macit (2012) who deals with Turkish participation banks. Dorofti and Jakubik (2015) or Shiu (2004) provide evidence that low interest rates reduce insurers' profitability. The topic of the impact of protracted low interest rates on insurance companies is elaborated in detail by Antolin et al. (2011).

The aims of the diploma thesis will be the following:

- To examine whether negative changes in interest rates indeed have a negative impact on banks and insurers. If we found out that reducing interest rates does have a negative impact on banks and insurers, we could also conclude that the low yield environment is not preferable for these financial institutions. This is because low yield environment is created by a sequence of negative changes in interest rates and it is a period without positive changes in interest rates. Hence, changes in interest rates are an important transmission channel for the low yield environment.

- To quantify the effects on various segments of the banking and insurance industries.

In the diploma thesis, we will focus on Europe, although the issue of the low yield environment may be considered global.

The reason for taking the equity price as the dependent variable in the thesis instead of balance-sheet indicators (e.g. profitability) is the forward-looking nature of equity prices. Equity prices reflect the overall situation of the financial institution, do not suffer from the short-term bias as much as balance-sheet indicators, and are more in line with the theoretical firm value maximization objective. So, if the low yield environment brought about an expected decrease in future profits, share prices would consequently reflect such expectations. Nevertheless, we need to make an assumption that markets have been determining equity prices correctly.

Hypotheses

Hypothesis #1: Negative changes in interest rates indeed have a negative impact on banks as well as insurers.

Hypothesis #2: The effect of negative changes in interest rates is more profound in case of banks or, on the contrary, in case of insurers.

Hypothesis #3: The effect of negative changes in interest rates differs significantly for various segments of the banking industry (retail vs. commercial vs. investment banks) and the insurance industry (life vs. non-life insurers).

Methodology

- Econometric panel data approach
- From static panel data models to dynamic ones: using e.g. the GMM estimation technique described by Blundell and Bond (2000)
- The Blundell and Bond technique is commonly used to explain the drivers of banks and insurers performance, for example by Ameur and Mhiri (2013) or Dorofti and Jakubik (2015)

- Dependent variable: equity price
- Considered independent variables: macroeconomic variables (interest rate, exchange rate, inflation rate, GDP growth, ...), institution-specific variables (liquidity risk indicators, ratio of non-performing loans to total loans in case of banks, real assets, equity to assets ratio, ...), other variables (dummy variable indicating the segment in which the institution operates, ...)
- Historical data on equity prices and detailed data on institution-specific variables can be extracted e.g. from Thomson Reuters Eikon, Bloomberg Terminal or Morningstar, while data on macroeconomic variables can be downloaded from Eurostat or OECD.

Expected Contribution

- In contrast to previous works on this topic, we will deal with banks and insurers at the same time. We will apply the same methodology to both banks and insurers, which will enable us to make direct comparisons. Moreover, the data will be collected individually for important banks and insurers. This means that institution-specific variables such as liquidity risk indicators will come into consideration, which cannot be captured in studies employing aggregated data. Last but not least, such an individual approach will allow us to conduct the analysis from the point of view of equity prices which is not common and will shed brighter light on how low interest rates influence banks and insurers.
- Determination and quantification of effects of lowered interest rates is crucial for regulators and policy makers. The analysis may also be useful for banks and insurers themselves.

Outline

1. Introduction & Literature Review
2. Data & Methodology
3. Empirical Results & Robustness Checks
4. Conclusion

Core bibliography

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Author

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Chapter 1

Introduction

As a consequence of the financial crisis that started in 2007 and the subsequent economic crisis, the European Central Bank (ECB) gradually decreased policy rates. The aim of decreasing the policy rates was to prevent deflation and to reach the inflation target. The ECB additionally used quantitative easing (QE). In 2016, for example, non-financial corporate bonds were added to the list of assets eligible for QE. Decreasing the policy rates as well as QE were supposed to stimulate economic activity in the euro area economies.

Nevertheless, both decreasing the policy rates and QE have an important side effect that interest rates diminish. Diminishing interest rates shift the yield curves down and possibly create low yield environment. Low yield environment may have an adverse impact on banks and insurers. The reason is that the investment income of banks and insurers drops with a negative change in the yield because future returns on the assets under management will be lower. There is yet another effect of decreasing rates on the asset side—the value of assets increases because discount rates applied to future payments are lower. But since the value of liabilities increases for the same reason, the overall effect of decreasing interest rates on banks and insurers should be negative. In addition, life insurance companies typically operate with a negative duration gap, so the effect of interest rate on this kind of insurance companies is expected to be higher than on non-life insurance companies or banks. All in all, decreasing interest rates result in vulnerabilities in the banking and insurance sectors—profits and equity values of banks and insurance companies are lowered. On that account, low yields have been included in the European Systemic Risk Board (ESRB) overview of systemic risks.

The aims of the diploma thesis are twofold. The first aim is to examine whether negative changes in interest rates are reflected in banks and insurers equity prices. Equity prices should in turn reflect future profitability. If we found out that reducing interest rates does have a negative impact on banks and insurers, we could also conclude that the low yield environment is not preferable for these financial institutions. The second aim is to quantify the effects of decreasing interest rates on various segments of the banking and insurance industries. In this thesis we will focus on European banks and insurance companies.

The reason for taking the equity price as the dependent variable in the thesis instead of balance-sheet indicators (e.g. profitability) is the forward-looking nature of equity prices. Equity prices reflect the overall situation of the financial institution, do not suffer from the short-term bias as much as balance-sheet indicators, and are more in line with the theoretical firm value maximization objective. So, if the low yield environment brought about an expected decrease in future profits, share prices would consequently reflect such expectations. Nevertheless, we need to make an assumption that markets have been determining equity prices correctly.

In our thesis, we will examine the following hypotheses:

- Hypothesis #1: Negative changes in interest rates indeed have a negative impact on banks as well as insurers.
- Hypothesis #2: The effect of negative changes in interest rates is more profound in case of banks or, on the contrary, in case of insurers.
- Hypothesis #3: The effect of negative changes in interest rates differs significantly for various segments of the banking industry (global vs. regional banks) and the insurance industry (life vs. non-life insurers).

In contrast to previous works on this topic, we will deal with banks and insurers at the same time. We will apply the same methodology to both banks and insurers, which will enable us to make direct comparisons. Moreover, the data will be collected individually for important banks and insurers. It means that institution-specific variables can come into consideration, which cannot be captured in studies employing aggregated data. Last but not least, such an individual approach will allow us to conduct the analysis from the point of view of equity prices which is not common and will shed brighter light on how low interest rates influence banks and insurers. Identification and quantification of effects of lowered interest rates are crucial for regulators and policy makers. The analysis may also be useful for banks and insurers themselves.

Regarding the results, both banks and insurers are negatively influenced by negative changes in short-term interest rates, while they are not influenced significantly by long-term interest rates. Changes in short-term interest rates influence life insurers more than banks, and banks more than non-life insurers. The impact of short-term interest rates does not differ significantly for global and regional banks—regional banks are effected only slightly more. In contrast, changes in short-term interest rates influence life insurance companies much more than non-life insurance companies. Expected GDP growth has positive impacts on both banks and insurers, inflation has negative impacts.

As for the structure of the thesis, we will first review relevant literature and outline the methodology used in the thesis. This will be done in Chapter 2. Then in Chapter 3 we will present static panel data models where banks and insurers will be examined together. In Chapter 4 we will conduct static panel data analysis for banks and insurers separately. In Chapter 5 we will move to dynamic panel data models. Although Chapters 3 and 4 contain important pieces of information, we actually reach the most reliable and interesting results in Chapter 5. Chapter 6 concludes the thesis.

Chapter 2

Literature Review & Methodology

The purpose of the chapter is to review relevant literature and to discuss the methodology that we will be using throughout the thesis. In addition to describing our econometric approach, we will also have remarks on how we have collected the data.

2.1 Relationship of Bank Profitability and Interest Rates

In this subsection, we will shortly review the literature about the relationship of bank profitability and interest rates. In our thesis, we do not deal with profitability but with equity prices. It is much more common in the literature to examine the impact of interest rates on profitability than on equity prices. Still, profitability and equity prices are closely connected so it makes sense to review the literature about profitability. At the end of this subsection, we also draw attention to two papers in which the relationship of equity prices and interest rates was examined.

Borio *et al.* (2017) find a positive relationship between the level of short-term interest rates and bank profitability. Hence they conclude that the positive impact of high interest rates on bank income dominates the negative impact on loan loss provisions and on non-interest income. The negative impact on loan loss provisions is caused by the fact that the amount of bad loans and customer defaults tends to rise with rising interest rates, especially in case of already existing variable-rate loans. The negative impact on non-interest income is explained thoroughly by Borio *et al.* (2015)—one of the reasons may be that at lower rates savers require more professional services to manage their portfolios.

Bourke (1989) takes a sample of 90 best-performing banks for each year between 1972 and 1981 from selected countries in Europe, North America and Australia with the purpose of finding the determinants of bank profitability. Bourke focuses mainly on the relationship between bank profitability and concentration and finds that these variables are positively related. That is, banks that do not have many competitors to compete with, generally perform better than banks with many competitors. Nevertheless, he also finds a positive relationship between profitability and nominal interest rates.

Several years later Molyneux and Thornton (1992) replicated the methodology of Bourke, using samples of around 1,000 banks for the years between 1986 and 1989. They also find a positive relationship between profitability and nominal interest rates. Selected capital ratios also showed to be positively related to profitability in both Bourke's and Molyneux and Thornton's studies. Liquidity ratios are, according to Molyneux and Thornton, inversely related to profitability.

Macit (2012) finds that real interest rate has a positive impact on Turkish participation banks. Participation banks are banks whose lending and deposit collection activities follow Islamic rules. Their savers are not promised fixed interest payments but they rather share the profits or losses resulting from trading activities of their bank. Macit also finds that exchange rate has a positive relationship with profitability.

Moss & Moss (2010) conclude that bank stock prices are sensitive to changes in short-term interest rates. In order to draw the conclusion, they use an index of bank common stock prices, i.e. they do not take into account bank-specific factors. They examine both short-term and long-term interest rates. Short-term interest rates, the S&P500 stock index and the Commodity Research Bureau index of commodity prices are found significant. Most importantly, short-term interest rates are positively related to the bank stock prices.

In contrast, Akella & Chen (1990) find a positive relationship between bank stock prices and long-term government security returns, while they do not find significant relationship between stock prices and short-term government security returns.

2.2 Relationship of Insurer Profitability and Interest Rates

This subsection presents literature about the relationship of insurers profitability and interest rates.

Dorofti & Jakubik (2015) study European Union panel data. They find that nominal and real interest rates are positively related to insurance company profitability. Dorofti & Jakubik argue that insurers suffer from the low yield environment because they typically invest in high-quality bonds. Dorofti & Jakubik also believe that interest rates influence profitability with a lag because the majority of insurers' income stems from previous years investments. Interest rates play a role also on the liabilities side of insurers' balance sheet because future payments are discounted at lower interest rates. Generally, the problem is that there is often a duration mismatch between assets and liabilities because liabilities are often long-term while investments are short-term. Economic growth and equity market performance are also positively related to profitability, while inflation is found to be negatively related.

Shiu (2004) seeks for the determinants of non-life insurance company performance in the United Kingdom. He uses three different measures for performance: investment yield, percentage change in shareholders' funds and return on shareholders' funds. Shiu finds that insurance company performance is positively related to interest rate level, and furthermore to liquidity. It is negatively related to unexpected inflation.

Antolin *et al.* (2011) investigate the impact of low interest rates on insurance companies and pension funds. They argue that a period of protracted interest rates should be expected to have a negative impact on insurance companies, especially life insurance companies. The reason is that their business is based on promises that extend over long periods.

2.3 Description of the Econometric Approach

The data we have collected has two dimensions. One of the dimensions is the entity dimension, where each entity is represented by a bank or by an insurance company. The other dimension is the time dimension, as we have collected data for each year between 2006 and 2015. As soon as some data has both the entity dimension and the time dimension, it is called the panel data. Hence we will take an econometric panel data approach.

The dependent variable in all models will be the log return of equity price for selected banks and insurers. The log return is calculated as follows:

$$log\ return = \log(p_t/p_{t-1})$$

where log is the natural logarithm, p_t is the equity price in the year t and p_{t-1} is the equity price in the year $t-1$. We will work with stock returns rather than the stock prices because each company may have a different number of shares and therefore the prices of the shares are not comparable between companies. Another reason is that stationarity of stock returns is much more likely than stationarity of equity prices themselves. Furthermore, taking the log return instead of the raw return has several advantages. A problem with the raw return is for example that it cannot be lower than -100 %, while it can be higher than +100 %. If it happened that in year 1 a company's equity price would decrease to 20 % of its year 0 value, the raw return would be $(0.2-1)/1 = -80\%$. If in year 2 the equity price went back to the year 0 value, the raw return would be $(1-0.2)/0.2 = +400\%$. This is not a good property because the year 2 increase in equity price would have a much larger impact on the regression results than the year 1 decrease in equity price. Moreover it could lead to violation of some normality assumptions because the right tail of the distribution would be longer than the left tail. Actually, these big changes in equity prices really happened during the 2006-2015 period, partly because of the financial crisis. In contrast, the value of the log return in year 1 would be $\log(0.2/1) \doteq -1.6$, while in year 2 it would be $\log(1/0.2) \doteq +1.6$, which illustrates the suitability of the log return.

The most closely observed explanatory variables will be (1) the yield to maturity (YTM) of long-term government bonds, also referred to as the long-term interest rate throughout the thesis, and (2) the yield to maturity of short-term government bonds, also referred to as the short-term interest rate. It implies that we have to assign a country to each bank and insurer based on their headquarters because yields to maturity of government bonds are different for each country.

As Allen *et al.* (2000) argue, long-term interest rates reflect market expectations of interest rates in the future. If the value of assets or liabilities of banks and insurers depends on future interest rates, then long-term interest rates may have an impact on share prices of banks and insurers.

The yield to maturity of short-term government bonds (i.e. short-term interest rate) contains a different piece of information that could explain changes in shares prices. Short-term interest rates may serve as a proxy for changes in the cost of funds (Allen *et al.* 2000). Financial institutions that heavily rely on deposits to finance their assets may be therefore influenced a lot by changes in the short-term interest rates, which would be also reflected in their share prices.

Other considered explanatory variables will include real GDP growth, expected GDP growth, inflation rate, debt-to-GDP ratio, financial leverage, free cash flow / net income ratio or asset turnover. We will also include dummy variables indicating whether a financial institution is a life insurance company, non-life insurance company, global bank or regional bank. Furthermore, we will work with dummy variables indicating whether a given financial institution's headquarters are in the euro area, or outside the euro area, and whether the headquarters are in a country that suffered from the debt crisis or not.

Including the real GDP growth and inflation rate into the analysis might be important also if the hypothesis of secular stagnation was true. Summers (2016) explains that, according to the hypothesis of secular stagnation, developed economies suffer from imbalances due to an increasing propensity to save and a decreasing propensity to invest. Excessive savings drag demand down, and lead to low economic growth and low inflation. The imbalance between savings and investments also pulls down real interest rates and equity prices could go down as well.

We will start our analysis with static panel data models, including random effects models, fixed effects models and also pooled ordinary least squares (OLS) models. Then we will move to dynamic panel data models. The nature of dynamic panel data models lies in the fact that lags of the dependent variable are included in the regression equation as independent variables. Ameur & Mhiri (2013) and Dorofti & Jakubik (2015) also wanted to explain the drivers of banks and insurers performance and in both cases they used a GMM estimation technique described by Blundell and Bond (1998, 2000). This Blundell and Bond's estimator is also known as the system GMM estimator. The system GMM estimator is appropriate in case of panel data covering a large sample of companies observed for a small number of time periods, which is also our case. The system GMM estimator is based on the assumption of weak correlations between the current and lagged levels of all variables and uses lagged first-differences as instruments (Dorofti & Jakubik 2015).

According to Roodman (2009), system and difference GMM estimators are popular because they handle endogeneity of regressors and fixed effects, and help to avoid dynamic panel bias. They can also be used with unbalanced panels. The advantage of the system GMM estimator over the difference GMM estimator is that it reduces finite-sample biases that arise because of weak instruments (Dorofti & Jakubik 2015). That is why we will give preference to the system GMM estimator. More information on static and dynamic panel data models will be given in chapters 3 and 5, respectively.

It is important to realize that on the right-hand side we will have some country-level variables (YTM of long-term government bonds, short-term interest rate, real GDP growth, expected GDP growth, inflation rate, debt-to-GDP ratio), while on the left hand side we will have a variable that is specific for each bank and insurer. It means that we will have to cluster standard errors on the country level. Each country in the data set represents one cluster. A very useful guide on choosing the best approach to estimating standard errors in finance panel data sets is offered by Petersen (2009). In this case, we will be simply using the *cluster* option offered by the Stata software.

2.4 Data Collection: Remarks

First of all, we have to decide which banks and insurers will be in our sample. It is necessary to keep in mind that we must not take an *ex post* sample of companies that were the most successful in the end of the examined period but rather an *ex ante* sample of companies that were the most successful in the beginning of the examined period. Here we are applying a similar reasoning to the reasoning of De Long (1988) who argued that Baumol (1986) had found convergence among industrial nations just because he had used an *ex post* sample of successful countries. Similarly, if we chose a sample consisting only of well-performing companies, we could get wrong results because share prices of most of these companies would rise while yields have been generally decreasing recently. The results could be pre-determined by this pattern.

So we construct our sample based on an older edition of the Forbes's list of world's largest companies, Global 2000. More specifically, we utilize the edition of Global 2000 from the beginning of the year 2007 because it is based on data from the year 2006 and we want to collect data for the period between 2006 and 2015. Although the issue of the low yield environment may be considered global, we will focus on Europe. Hence we will only collect data for European financial institutions from the Global 2000 list.

In order to gather the company data, we used Morningstar, Google Finance, and Yahoo Finance. In all of these sources we could readily access data for last 10 years with an annual frequency. Regarding the data for macroeconomic variables, we downloaded them from the OECD website and from the European Commission's European Economic Forecasts. The data for stock indices was downloaded from Google Finance, Yahoo Finance, Financial Times or Investing.com.

We have to face the issue that our variables have different frequencies. Equity price usually has a daily frequency, while other variables are available only at a quarterly or yearly frequency. According to Wohlrabe (2008), in most empirical applications the higher frequency data is aggregated to the lower frequency by averaging, summing up, or by taking a representative corresponding value. More advanced techniques dealing with mixed-frequency data have been developed, such as VARMA and MIDAS but these are designated for forecasting. In the case of equity prices we will use averaging rather than taking a representative value e.g. from the end of the year because the series is much more stable after taking the averages and is not influenced by short-term changes in investors' mood.

After considering pros and cons, we have decided to work with annual data. The main reason for this is that historically not all institutions published all the necessary data more often than once in a year. Therefore we could examine data only for a shorter historical period than 10 years and could not reflect the period before the financial crisis at all. Moreover, we will still have a sufficient number of observations because there are many financial institutions in our sample. The number of observations is sufficient for both the fixed effects model and random effects model and also for the Blundell and Bond technique, which is actually even intended for short panels with many entities and few time periods.

2.5 Data Collection: Procedure

As we want to work with data for last ten years and we want to use an *ex ante* sample, we choose our companies based on the edition of The Forbes Global 2000 issued on March 29, 2007. The Forbes Global 2000 is a list of 2000 world's biggest and most powerful companies. The list is based on data from 2006 and beginning of 2007 because the market value, one of the criteria to determine the company's size, is as of February 28, 2007. The list is based on a composite ranking for sales, profits, assets, and market value. The list also assigns an industry and the country of headquarters to each company, which is very useful for our analysis. We will consider only companies from the banking and insurance industries and examine how these companies performed in the period between 2006 and 2015.

In order to download the macroeconomic variables, we mostly use the OECD database. Although we focus on Europe and not all European countries are members of OECD, we can still get there all the data needed. It is because of two reasons:

- European countries that are not included in the database do not have any banks and insurance companies on the Forbes Global 2000 list.
- Some countries are included in the OECD database even though they are not OECD members.

We still bumped into one marginal problem—the OECD database did not contain all data for Hungarian short-term interest rates. But since we will have an unbalanced data set anyway due to the institution-specific variables, it does not make any large difference.

In order to download expected GDP growth data, we use the European Commission's European Economic Forecasts from autumns 2006-2015 to get forecasts for the years 2007-2016. In other words, we always take the autumn forecast for the next year. We assign the forecast to the year when the forecast was made rather than to the year for which the forecast was made. The reason is that the stock prices might already reflect the forecast for the next year—if the future GDP growth is projected to be good, the stock prices will most likely go up.

Regarding the long-term and short-term interest rates, we downloaded them from the OECD database. The long-term interest rates refer to government bonds maturing in 10 years. For each year, they are calculated as daily averages. The long-term interest rates are actually yields on these government bonds. They are implied by prices at which these government bonds are traded on financial markets. The short-term interest rates on the OECD website are based primarily on three-month money market rates. They are the rates for which financial institutions lend to each other or for which short-term government papers are issued or traded in the market. Short-term interest rates are also calculated as daily averages. A specific fact about the short-term rates in this format is that they are the same for the euro area countries, so we will also try to include a dummy variable indicating whether a given financial institution is in the euro area to control for possible positive or negative effects of the euro area membership on stock prices. In this thesis, we work with nominal long-term and short-term interest rates.

We download the real gross domestic product (GDP) growth rates from the OECD database as well. Real GDP is GDP calculated as if the prices were fixed. The prices are expressed in terms of a base period. In this case, the previous year is always taken as the base period.

Another variable we got from the OECD database is the inflation rate. The inflation rate is measured by the consumer price index and therefore expresses the change in the prices of a basket of goods and services of constant quantity and characteristics that are purchased by a typical household. This measure of the inflation rate is constructed as a weighted average of a large number of elementary indices, where each of these indices composes of a specific set of goods and services.

Yet another variable from the OECD database is the general government debt-to-GDP ratio. It is measured as a country's total gross government debt divided by the country's GDP. OECD calculates debt as the sum of the following: currency and deposits; securities other than shares, except financial derivatives; loans; insurance technical reserves; and other accounts payable. In our analysis, we will use the year-on-year change of the debt-to-GDP ratio as an independent variable rather than the debt-to-GDP ratio itself because of stationarity issues.

From Morningstar we extract data for these variables: financial leverage, free cash flow / net income ratio and asset turnover. A positive fact about this is that all of these variables could be downloaded and are meaningful for both banks and insurers which makes possible an analysis where both insurers and banks are treated in the same way.

We download closing equity prices for each trading day between 2005 and 2015 from Google Finance. Then we calculate averages for each year. The reason for why we download equity prices also for 2005 when we want to conduct our analysis for a period starting in 2006 is that we will need to calculate the log returns which are calculated relatively to the previous year. We also take into account stock splits. E.g. in case of a stock split of the type 4:1, we multiply the stock prices for the periods before the stock split by 4 if it was not already done by Google Finance. If we could not find historical prices for a financial institution on Google Finance, we used the adjusted close prices at Yahoo Finance. If we could not find them on Yahoo Finance, we took the stock prices from Morningstar.

With stock prices it is slightly more difficult. If a financial institution is listed at more stock exchanges, the developments at each stock exchange may be slightly different. In such a case, we take into account stock prices from that exchange where the financial institution was listed first. Most often it was done at a stock exchange in the country from which the financial institution comes.

Another problem to deal with is the problem of missing values. There is a lot of banks and insurance companies for which there is at least one empty entry. As far as this problem concerned stock prices, we did our best to find another source to extract them. In case of macroeconomic variables, there is no problem with missing values, with the small exception of short-term interest rates in case of Hungary. However, there are a lot of missing values as far as the institution-specific variables are concerned. Here we have decided to rely solely on one source, Morningstar, because of possible differences in measurement between different sources. Usually we could collect almost all of the necessary data for the institutions in our sample but for some years the value of a variable for a given institution was missing. Dropping the problematic observation creates an unbalanced panel data set which has to be treated slightly differently to a balanced panel data set, but most importantly, still can be treated. Dropping an observation for only the problematic years is better than deleting all the observations relating to a company for which at least one year is problematic. The reason is that we will retain more observations in our sample. It should make our analysis more precise.

We divided the financial institutions in our sample into 4 categories—life insurance companies, non-life insurance companies, global banks and regional banks. Then we created 3 dummy variables using dummy coding. The first one, called *life*, equals 1 if the financial institution is classified as a life insurance company and 0 otherwise. The second one, called *nonlife*, equals 1 if the financial institution is classified as a non-life insurance company and 0 otherwise. The third one, called *global*, equals 1 if the financial institution is classified as a global bank and 0 otherwise. Similarly for regional banks, where the dummy variable is called *regional*. We cannot just create one dummy variable that would be equal 0, 1, 2, and 3 for life insurers, non-life insurers, global banks and regional banks, respectively, because the interpretation of the results would be made impossible. It is because these four categories actually cannot be ordered in a reasonable way. We have no way to decide whether non-life insurance group should have number 1 or 3 but the decision would influence the results.

Regarding insurance companies, we divided them into life and non-life insurance companies based on Financial Times. As for banks, we divided them into global and regional (where the region is Europe) based on Morningstar.

Besides, we transformed some independent variables to prevent possible stationarity issues. We first-differenced the data for long-term and short-term interest rates. The reason why we do not take log returns as with equity prices is that interest rates may also be negative and natural logarithm of a negative number cannot be calculated. As we already mentioned, we will also consider the year-on-year change in the debt-to-GDP ratio instead of the debt-to-GDP ratio itself. We also tried to first-difference the institution-specific variables but the transformation stole one year of our observations and did not bring about any interesting contributions to the results so we decided to conduct our analysis without the transformation.

Table 2.1 represents an overview of variables that will be used throughout the thesis.

In order to conclude this chapter, we present summary statistics corresponding to variables that will play an important role in this thesis. See Table 2.2. The last column of the table, denoted as N, gives the number of observations.

Table 2.1: Overview of variables

Type	**Name**	**Description**
Dependent	*log_return*	Log return of equity prices
Macroeconomic	*shortterm_rate*	Differenced nominal short-term interest rate
Macroeconomic	*longterm_rate*	Differenced nominal long-term interest rate
Macroeconomic	*gdp*	Real GDP growth
Macroeconomic	*expected_gdp*	Expected real GDP growth
Macroeconomic	*inflation*	Inflation rate
Macroeconomic	*debt_to_gdp*	Year-on-year change in debt-to-GDP ratio
Macroeconomic	*debt_crisis*	Dummy variable for whether a given country experienced a debt crisis
Macroeconomic	*eurozone*	Dummy variable for whether a given country belongs to the euro zone
Institutional	*turnover*	Asset turnover
Institutional	*leverage*	Financial leverage
Institutional	*fcfni*	Free cash flow / net income ratio
Institutional	*regional*	Dummy variable for whether a given institution is a regional bank
Institutional	*global*	Dummy variable for whether a given institution is a global bank
Institutional	*life*	Dummy variable for whether a given institution is a life insurer
Institutional	*nonlife*	Dummy variable for whether a given institution is a nonlife insurer
Institutional	*insurer*	Dummy variable for whether a given institution is an insurer
Interaction	*shortterm_rate_insurer*	Product of *shortterm_rate* and *insurer*
Interaction	*shortterm_rate_nonlife*	Product of *shortterm_rate* and *nonlife*
Interaction	*shortterm_rate_glob*	Product of *shortterm_rate* and *global*
Lag dependent	*L.log_return*	First lag of *log_return*
Lag dependent	*L2.log_return*	Second lag of *log_return*

Table 2.2: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
log_return	-0.043	0.35	-1.828	1.508	761
shortterm_diff	-0.265	1.192	-4.291	1.858	761
longterm_diff	-0.209	1.367	-12.44	6.75	761
growth	0.844	2.891	-9.130	26.28	761
expected_growth	1.28	1.209	-4.2	5.600	761
inflation	1.518	1.391	-4.48	4.92	761
debt_change	3.496	10.001	-30.172	73.104	761
debt_crisis	0.143	0.351	0	1	761
eurozone	0.594	0.491	0	1	761
turnover	8.67	10.749	1	81	761
regional	0.581	0.494	0	1	761
global	0.104	0.305	0	1	761
life	0.087	0.282	0	1	761
nonlife	0.229	0.42	0	1	761
insurer	0.315	0.465	0	1	761

Chapter 3

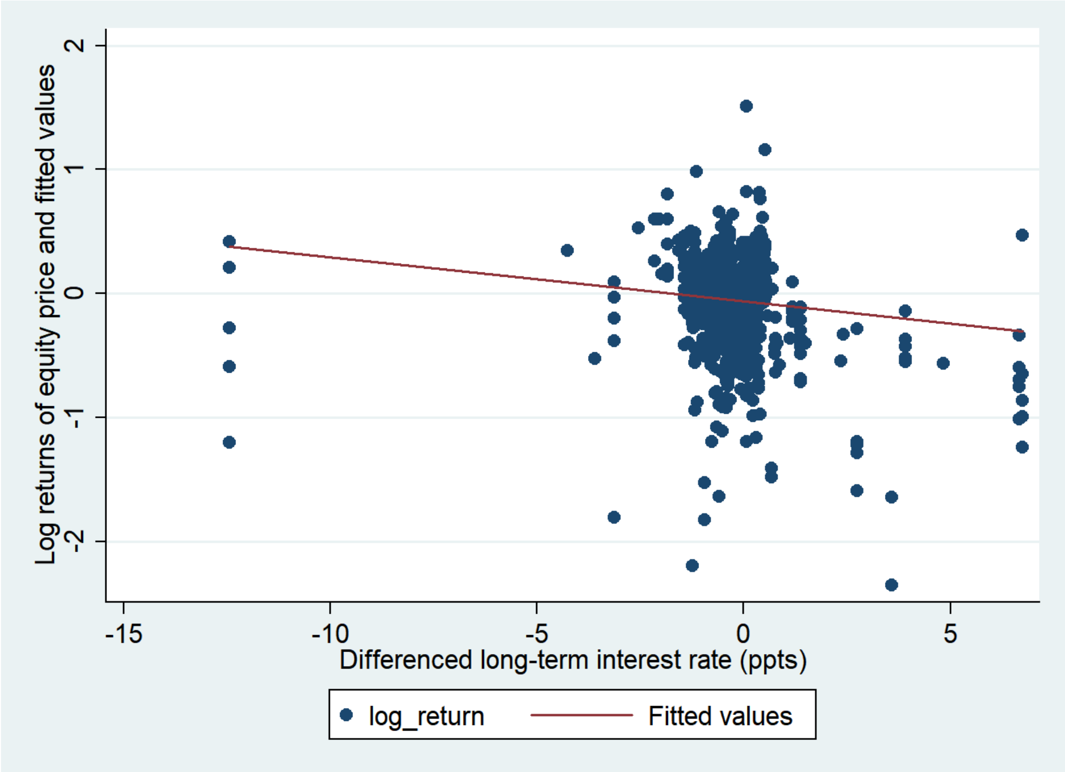
Static Models: Banks and Insurers Together

3.1 Scatter Plots

The relationship between log returns of equity prices and interest rates is what we are mainly interested in. Hence, let us first have a look at a scatter plot for log returns of equity prices and differenced long-term interest rates. By differenced interest rates we mean that we subtracted previous year interest rates from current year interest rates. In the scatter plot, denoted as Figure 3.1, all observations from our data set are simply put together, for all the years and all the financial institutions.

It seems that there is no clear-cut relationship between the stock returns and long-term interest rates, which are derived from government bond yields. The line of best fit shows a slightly negative relationship. This could be possibly explained by the fact that during the crisis yields on government bonds went steeply up in some countries with debt problems, while equity prices went generally down. After the crisis, when the stock prices were recovering, the yields were going down because economic situation in Europe started to improve and central banks were additionally trying to push the interest rates down to further support the economy. However, it does not mean at all that there is a causal relationship between the yields on government bonds and equity prices of financial institutions. Actually, there are reasons to believe that lower interest rates are actually harmful for financial institutions, e.g. because there are no really profitable investment opportunities. We first need to control for the effect of other relevant variables before we can draw any conclusions. That

Figure 3.1: All institutions: log returns and long-term interest rates



is why we will include variables such as GDP growth, expected GDP growth, inflation or debt-to-GDP ratio into the models.

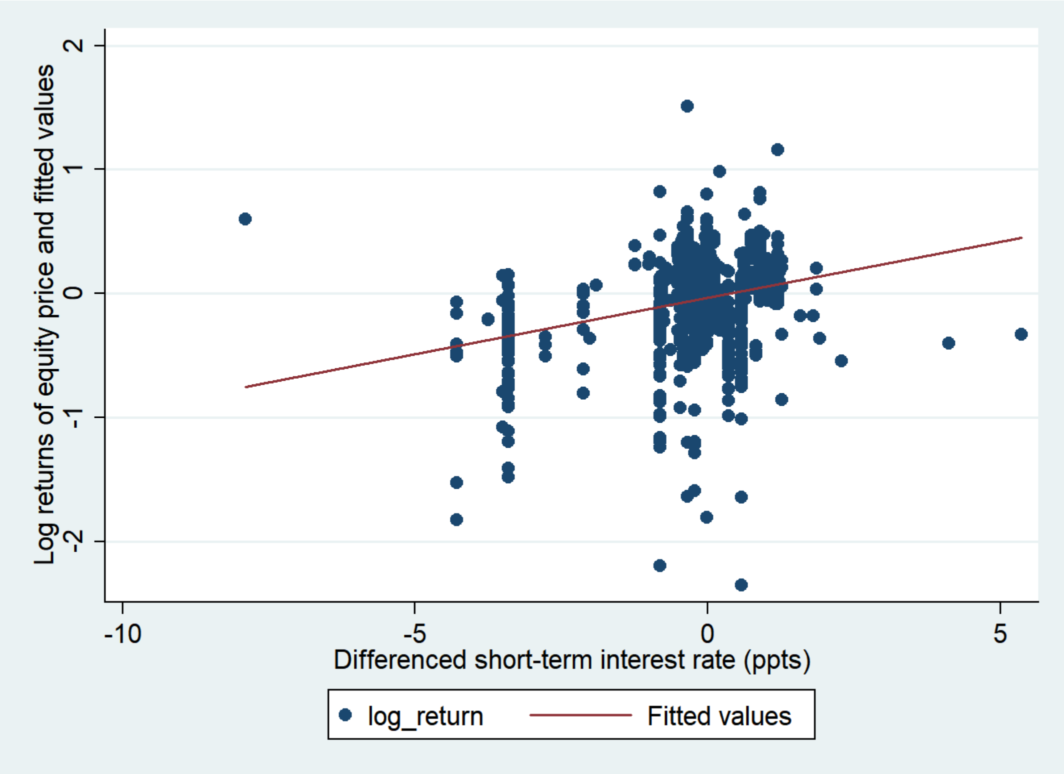
In the figure it can be immediately noticed that there are some points corresponding to a negative change in the yield by more than 12 ppts (percentage points). This really happened, in 2013 the yields on Greek government bonds decreased from 22.50 % to 10.05 %.

Let us draw the same scatter plot as before, but this time for short-term interest rates. See Figure 3.2.

Here the story is quite different to the previous story with long-term yields. In this case, the relationship is rather positive. It would be more in accordance with our expectations and also with empirical results e.g. by Moss & Moss (2010) or Shiu (2004). Nevertheless, the argument that there may be no causal relationship and that we therefore have to include also other relevant variables into the model holds also here.

In the figure it can be also seen that for some values of the differenced short-term interest rate there are many different points corresponding to log returns. It is because the short-term interest rates as measured by the OECD are generally the same for all countries in the euro area.

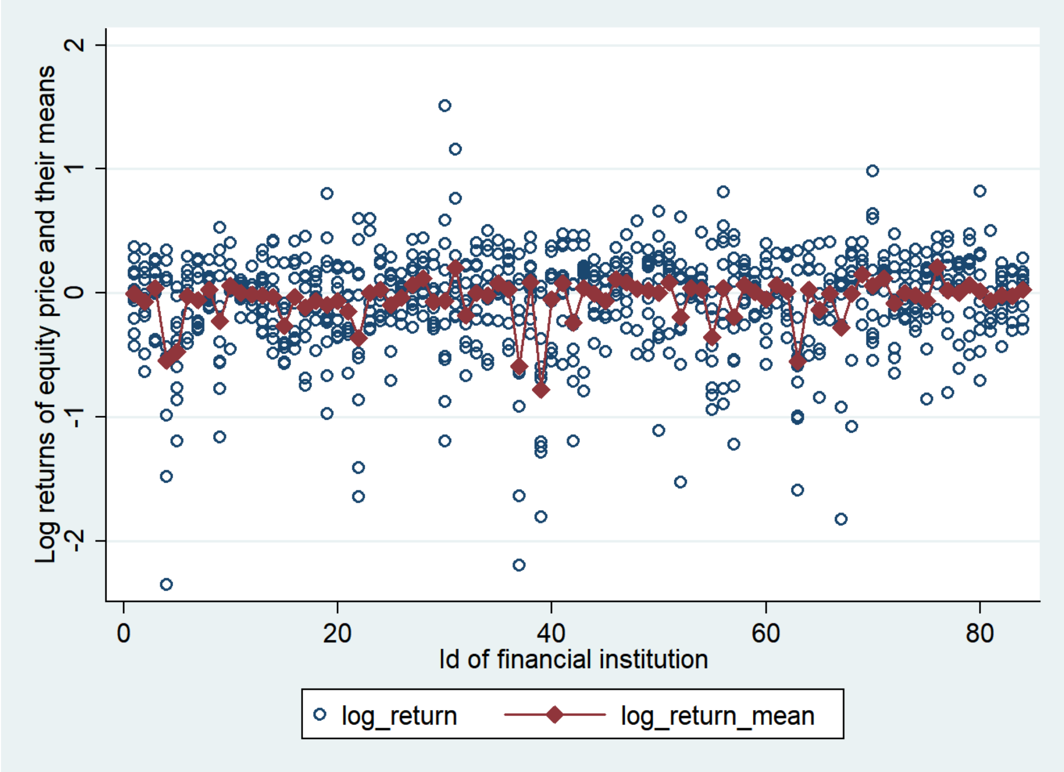
Figure 3.2: All institutions: log returns and short-term interest rates



As we have already mentioned, we include also those financial institutions in the sample for which we do not have data for all of the ten years. Our condition to include a financial institution into our sample is that we must have a complete observation for at least one year, i.e. for at least one year we must have data for all the variables that turn out to be relevant in the model. It will create an unbalanced data set, which requires some special treatment. Nevertheless, it has the advantage that we will make use of more available information as we will have more observations. It should make our results more precise. In total we have 84 financial institutions in our sample. Taking into account the time dimension, we have 761 observations in our data set but this number can be decreased later on when we decide to use some variables that are not available for all the combinations of financial institutions and years, or when we decide to treat banks and insurance companies separately.

We can also examine how the log returns developed over the period between 2006 and 2015 for each individual financial institution, using Figure A.1 in the Appendix. Interestingly, there is not a single financial institution whose equity prices would grow every year in the examined period. Almost all of the institutions saw a decrease in their stock prices during the financial crisis in

Figure 3.3: Heterogeneity across institutions



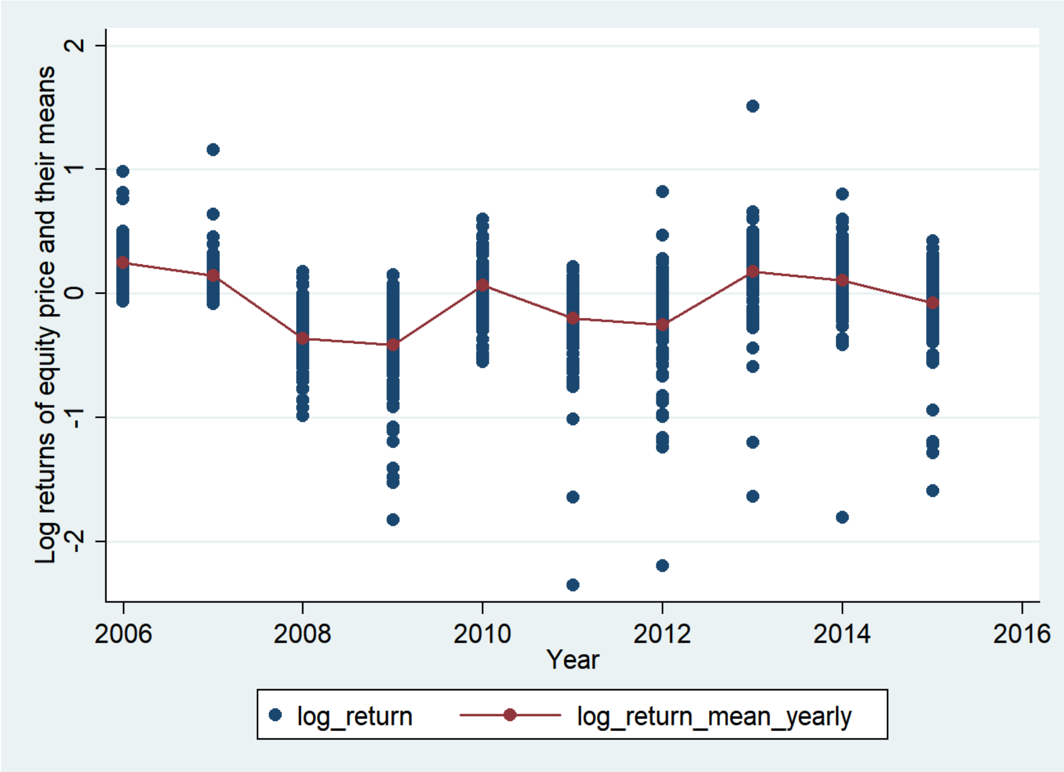
2008 and 2009. Another point is that equity prices of Swiss financial institutions, such as Luzerner Kantonalbank, BEKB-BCBE (Berner Kantonalbank) or BLKB Group (Basellandschaftliche Kantonalbank), were very stable, while equity prices of Irish and Greek financial institutions were really volatile because institutions in these countries had serious bankruptcy problems and in some cases had to be rescued by national governments. Generally, the log returns move around zero which means that they should be a stationary variable.

In the Figure 3.3 we can see the heterogeneity across institutions.

We can see that there were two financial institutions which had a higher average log return than the others. These are the Svenska Handelsbanken and Corporation Mapfre. On the other hand, there were quite many financial institutions which performed really poorly. It illustrates the fact that in the examined period it was much more common for financial institutions to face a really poor financial situation and insecurity than to enjoy growth. Nevertheless, the picture also shows that the stock prices of a vast majority of the institutions behaved somewhat normally, with average log return over the 10 years around 0.

Figure 3.4 shows heterogeneity across years.

Figure 3.4: All institutions: heterogeneity across years



The figure illustrates nicely the development of equity prices of banks and insurers over the years. In 2006 and 2007, the average log return is higher than zero which means that the equity prices grew on average. Then the financial crisis came and the equity prices plunged. In 2010 it started to seem that the banking and insurance industry could recover but there were other decreases in the equity prices in 2011 and 2012. Only in 2013 the situation in the industry improved again.

Let us have a look at how unbalanced the panel actually is when we drop observations that have a missing value for a relevant variable and also outlier observations with log return higher than +2 or lower than -2. We will find out what the underlying patterns in missing information are.

```
     Freq.  Percent    Cum. |  Pattern
 ---------------------------+------------
        53    63.86   63.86 |  1111111111
         8     9.64   73.49 |  .111111111
         7     8.43   81.93 |  ..11111111
         3     3.61   85.54 |  11.1111111
         1     1.20   86.75 |  ......1111
```

```
        1       1.20    87.95 |   .....1...1
        1       1.20    89.16 |   ..11111...
        1       1.20    90.36 |   ..111111..
        1       1.20    91.57 |   11...11111
        7       8.43   100.00 |  (other)
 ---------------------------+------------
       83     100.00          |   XXXXXXXXXX
```

It turns out that there are many patterns for which observations are missing. Most frequently, observations for the years 2006 or 2007 are missing and all of the other observations are not missing, but it is not a rule. It is a good sign that there is no strict rule in which observations are missing because then the problem could be systematic and distort the results. Here it seems that observations are often missing for some random reasons because we have 15 different patterns of which observations are missing.

3.2 Pooled OLS Regression

Everything is ready so we can start a basic empirical analysis. At the beginning we will analyze banks and insurance companies together, using only dummy variables to distinguish at least partially between their overall effects on the dependent variable of log returns. The most basic approach is the pooled OLS regression. In this case, we disregard the time dimension of the data. We pool everything together and proceed as if we had cross-sectional data. First, we run a pooled OLS regression with clustered standard errors which includes all variables in our data set except financial leverage and the free cash flow net income ratio. These two variables turned out to be insignificant in this setting and caused a large decline in the number of observations so we do not include them for now. On the other hand, we include dummy variables specific for each year into the model. The reason is that we want to control for the vast variability across the years caused by the financial and economic crisis and many other events that we cannot actually account for in another acceptable way. The results are in Table 3.1. Description of the variables can be found in Table 2.1 at the end of Chapter 2.

The dummy variables for years are highly significant in many cases. It is not surprising at all because the behaviour of stock prices during the crisis was different to the behaviour before and after the crisis. Actually, all the significant

Table 3.1: OLS for all institutions: all variables

	(1)	
	log_return	
shortterm_rate	0.0446	(0.119)
longterm_rate	-0.0220	(0.307)
gdp	0.00810	(0.437)
expected_gdp	0.0275	(0.091)
inflation	-0.00294	(0.794)
debt_to_gdp	-0.00303	(0.307)
debt_crisis	-0.0850	(0.339)
eurozone	-0.0219	(0.446)
turnover	0.00364*	(0.011)
regional	-0.0310	(0.556)
life	-0.00334	(0.967)
nonlife	-0.0295	(0.657)
2006.year	0	(.)
2007.year	-0.117***	(0.000)
2008.year	-0.458***	(0.000)
2009.year	-0.334**	(0.009)
2010.year	-0.0745	(0.215)
2011.year	-0.291***	(0.000)
2012.year	-0.282**	(0.001)
2013.year	0.0708	(0.332)
2014.year	-0.0106	(0.857)
2015.year	-0.212***	(0.000)
_cons	0.131	(0.078)
N	761	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

year dummy variables have a negative beta coefficient which indicates that the developments of stock prices were less favourable than in the baseline year 2006. The beta coefficients are lowest for years 2008 and 2009 which were the years of the financial crisis.

It turns out that the only variable that is not a dummy variable for a year and is significant at the 5% significance level is the asset turnover. The sign before the corresponding beta coefficient is positive which makes sense because the asset turnover is an indicator for efficiency and it holds that the higher the asset turnover, the higher the efficiency. More efficient companies should, in turn, experience more favourable developments regarding their equity prices. Nevertheless, later on we will find that asset turnover is actually not statistically significant in the most appropriate models we will deal with.

The other explanatory variables are not significant at the 5% significance level at this moment but majority of them influence the dependent variable of log returns in the expected direction. Indeed, GDP growth and expected GDP growth are in a positive relationship with the dependent variable, while the year-on-year change in the debt-to-GDP ratio or the dummy variable for countries that experienced the debt crisis are in a reverse relationship with the dependent variable. Furthermore, the differenced short-term interest rate is in a positive relationship with the dependent variable and not far from being statistically significant.

The reason why almost none of the explanatory variables are statistically significant may be that there are variables in the model that have almost no explanatory power but are somehow correlated with other explanatory variables and make effects of these explanatory variables unclear. That is why we will look for a set of independent variables that are jointly insignificant and can therefore be excluded from the regression equation so that the effects of remaining variables become clearer and so that we have more degrees of freedom.

It turns out that when we run an F test whether *regional, life, nonlife, eurozone, inflation, longterm_rate, debt_to_gdp* and *debt_crisis* are jointly significant, the p-value is higher than 0.05 which means they are jointly insignificant. The result of the F test is here.

```
( 1)  regional = 0
( 2)  life = 0
( 3)  nonlife = 0
```

```
( 4)  eurozone = 0
( 5)  inflation = 0
( 6)  longterm_rate = 0
( 7)  debt_to_gdp = 0
( 8)  debt_crisis = 0

      F(  8,    17) =    1.49
           Prob > F =    0.2331
```

Hence we can safely exclude these variables from the regression equation, and re-run the model including only the remaining set of independent variables. The results are in Table 3.2.

Table 3.2: OLS for all institutions: significant variables

	(1) log_return	
shortterm_rate	0.0584*	(0.032)
gdp	0.0118	(0.322)
expected_gdp	0.0514**	(0.009)
turnover	0.00379**	(0.001)
2006.year	0	(.)
2007.year	-0.126***	(0.000)
2008.year	-0.430***	(0.000)
2009.year	-0.237*	(0.037)
2010.year	-0.0468	(0.356)
2011.year	-0.268***	(0.000)
2012.year	-0.230***	(0.001)
2013.year	0.133*	(0.019)
2014.year	0.0209	(0.660)
2015.year	-0.157**	(0.003)
_cons	0.000891	(0.985)
N	761	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Now the results look much cleaner. The directions of the effects did not change but we have identified new variables that are statistically significant in explaining the variation in the log return. Asset turnover is even more significant than before, already at the 1% significance level, and still in a positive relationship. The expected GDP growth is also significant at the 1% significance level and also in the positive direction.

But considering the purpose of the thesis, the most important fact is that the differenced short-term interest rate is significant at the 5% significance level and also in the positive direction. Nevertheless, our analysis is still only at the beginning and it will actually turn out later that the pooled OLS regression is definitely not the best approach in this case.

There is also one variable, the GDP growth, that is not individually significant at the 5% significance level. But when we tried to include the GDP growth variable, *gdp*, into the previous F test, the *p*-value was really low, even so low that Stata reports just 0.000.

```
( 1)  regional = 0
( 2)  life = 0
( 3)  nonlife = 0
( 4)  eurozone = 0
( 5)  inflation = 0
( 6)  longterm_rate = 0
( 7)  debt_to_gdp = 0
( 8)  debt_crisis = 0
( 9)  gdp = 0

      F(  9,    17) =   11.75
           Prob > F =    0.0000
```

Hence it is better to keep the variable in the regression equation despite individual statistical insignificance. The reason why the variable is individually insignificant will probably be a high correlation with other variables, especially with the expected GDP growth.

Now, let us move forward to models that are usually more appropriate for panel data analysis. As Cameron and Trivedi (2005) pinpoint, the pooled OLS estimator is inconsistent if the fixed effects model is appropriate. In addition to the fixed effects model, we will also have a look at the random effects model, which might be more appropriate than the fixed effects model because error terms in the fixed effects model could be correlated, which would be a violation of an underlying assumption. When working with the fixed effects and random effects models, we will loosely follow the procedure outlined by Torres-Reyna (2007). In his paper, Torres-Reyna gives some suggestions how to proceed in conducting basic panel data analysis in Stata.

3.3 Fixed Effects Model

Let us first concentrate on the fixed effects model. The equation for the fixed effects model can be written as follows:

$$Y_{it} = \beta_1 X_{it}^1 + \ldots + \beta_k X_{it}^k + \alpha_i + u_{it},$$

where

- Y_{it} is the dependent variable,
- $X_{it}^1, \ldots, X_{it}^k$ are the independent variables,
- $\beta_1, \ldots, \beta_k$ are the beta coefficients,
- α_i is the intercept for each entity (financial institution in our case),
- u_{it} is the error term.

The fixed-effects model is used when we are interested only in effects of variables that vary over time (Torres-Reyna 2007). According to Williams (2016), the fixed-effects model is used when we want to control for the effects of time-invariant variables with time-invariant effects. These effects are controlled for whether the variable is explicitly measured or not. Stock and Watson (2007) claim that the rationale behind the fixed-effects model is that "if the unobserved variable does not change over time, then any changes in the dependent variable must be due to influences other than these fixed characteristics".

According to Torres-Reyna (2007), when using the fixed effects model, we assume that something within the entities, i.e. financial institutions in our case, may impact the independent variables and we should control for this. We further assume that those time-invariant characteristics are unique to the particular financial institution and are not correlated with the characteristics of other financial institutions. These characteristics are captured in the error terms and if the error terms are correlated we should consider using the random effects model. In order to make the decision, we will conduct the Hausman test later on.

Now let us run the fixed effects regression using the least squares dummy variable approach. The least squares dummy variable approach means that we assign a dummy variable to each financial institution. The dummy variable then absorbs the effects specific for each financial institution and we therefore control for the unobserved heterogeneity (Torres-Reyna 2007). That is why it is not possible to use any other dummy variables that do not change over time, such as whether a given financial institution is a non-life insurance company. This additional variable would cause collinearity in the model. In Table 3.3 we provide results of the fixed effects regression with clustered standard errors.

Table 3.3: Fixed effects for all institutions: all variables

	(1)	
	log_return	
shortterm_rate	0.0346	(0.244)
longterm_rate	-0.0237	(0.223)
gdp	0.0101	(0.057)
expected_gdp	0.0232	(0.187)
inflation	0.0230	(0.154)
debt_to_gdp	-0.00235	(0.346)
turnover	0.00170	(0.501)
2006.year	0	(.)
2007.year	-0.118***	(0.000)
2008.year	-0.511***	(0.000)
2009.year	-0.345**	(0.004)
2010.year	-0.0948	(0.087)
2011.year	-0.332***	(0.000)
2012.year	-0.316***	(0.000)
2013.year	0.0645	(0.377)
2014.year	-0.00853	(0.894)
2015.year	-0.195***	(0.001)
_cons	0.0714	(0.293)
N	761	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

None of the independent variables are significant but for the year-specific dummy variables and but for the institution-specific dummy variables that are not reported because of the high number of them. With the help of another F test, we can exclude a large set of variables that are jointly insignificant from the model. We can exclude the variables that appear in the F test because the p-value is higher than 0.05. Now we will re-run the regression with the remaining variables only, see Table 3.4.

Actually only the GDP growth and expected GDP growth variable are left in the model. Both of them are significant and both of them with a positive beta coefficient, which is to be expected, because high GDP growth and expected

Table 3.4: Fixed effects for all institutions: significant variables

	(1) log_return	
gdp	0.0145*	(0.013)
expected_gdp	0.0359*	(0.031)
2006.year	0	(.)
2007.year	-0.107***	(0.000)
2008.year	-0.479***	(0.000)
2009.year	-0.479***	(0.000)
2010.year	-0.127*	(0.012)
2011.year	-0.322***	(0.000)
2012.year	-0.339***	(0.000)
2013.year	0.0466	(0.342)
2014.year	-0.0515	(0.258)
2015.year	-0.250***	(0.000)
_cons	0.115***	(0.001)
N	761	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

GDP growth make investors more optimistic. Nevertheless, the model is not very informative because these results could be guessed by anyone without running any regressions.

3.4 Random Effects Model

Now let us proceed to the random effects model. Unlike the fixed effects model, the variation across entities is assumed to be random and uncorrelated with the independent variables included in the model (Torres-Reyna 2007). Another important aspect is that although the fixed effects model gives us consistent results, the random effects model gives us more efficient results if the Hausman test justifies us to use the random effects model (Stock and Watson 2007). There is also an important disadvantage of the random effects model. If we were not able to specify individual characteristics of the financial institutions by including appropriate explanatory variables, then we would get omitted variable bias in our random effects model. Therefore the random effects model is appropriate only when it is possible to identify relevant explanatory variables and collect data for these variables.

The random effects model can be described by the following equation:

$$Y_{it} = \beta_1 X_{it}^1 + \ldots + \beta_k X_{it}^k + \alpha + u_{it} + \epsilon_{it},$$

where

- Y_{it} is the dependent variable,
- $X_{it}^1, \ldots, X_{it}^k$ are the independent variables,
- $\beta_1, \ldots, \beta_k$ are the beta coefficients,
- α is the intercept,
- u_{it} is the between-entity error term,
- ϵ_{it} is the within-entity error term.

In Table 3.5 see the results of the random-effects regression, again with the clustered standard errors.

Again, most of the variables are insignificant, only the asset turnover is significant at the 5% significance level. We will see more after excluding a set of jointly insignificant variables using the following F test.

```
 ( 1)  regional = 0
 ( 2)  life = 0
 ( 3)  nonlife = 0
 ( 4)  eurozone = 0
 ( 5)  inflation = 0
 ( 6)  debt_to_gdp = 0
 ( 7)  longterm_rate = 0
 ( 8)  debt_crisis = 0

           chi2(  8) =   13.70
         Prob > chi2 =    0.0899
```

Although the p-value is just slightly higher than 0.05, the F test can be trusted because any of the excluded variables would be insignificant in the following model if we decided to include them despite of the results of the F test. Table 3.6 contains results where the insignificant variables have already been excluded.

Table 3.5: Random effects for all institutions: all variables

	(1)	
	log_return	
shortterm_rate	0.0416	(0.129)
longterm_rate	-0.0224	(0.272)
gdp	0.00895	(0.324)
expected_gdp	0.0254	(0.110)
inflation	0.00208	(0.857)
debt_to_gdp	-0.00288	(0.296)
debt_crisis	-0.0909	(0.306)
eurozone	-0.0258	(0.363)
turnover	0.00341**	(0.006)
regional	-0.0294	(0.584)
life	-0.000439	(0.996)
nonlife	-0.0211	(0.758)
2006.year	0	(.)
2007.year	-0.117***	(0.000)
2008.year	-0.470***	(0.000)
2009.year	-0.340**	(0.002)
2010.year	-0.0806	(0.156)
2011.year	-0.301***	(0.000)
2012.year	-0.291***	(0.000)
2013.year	0.0679	(0.338)
2014.year	-0.0125	(0.832)
2015.year	-0.211***	(0.000)
_cons	0.129	(0.075)
N	761	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Random effects for all institutions: significant variables

	(1)	
	log_return	
shortterm_rate	0.0519*	(0.029)
gdp	0.0127	(0.170)
expected_gdp	0.0473**	(0.003)
turnover	0.00377***	(0.000)
2006.year	0	(.)
2007.year	-0.125***	(0.000)
2008.year	-0.438***	(0.000)
2009.year	-0.265**	(0.008)
2010.year	-0.0578	(0.238)
2011.year	-0.279***	(0.000)
2012.year	-0.246***	(0.000)
2013.year	0.120*	(0.018)
2014.year	0.00906	(0.842)
2015.year	-0.170***	(0.000)
_cons	0.0131	(0.771)
N	761	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

And the results are very similar to the results of the pooled OLS regression, with the same set of significant variables and with the same directions of the effects of the variables. It happens also here that the GDP growth variable is not significant in the regression but should not actually be excluded because the previous F test would not allow this. The other variables in the model, i.e. the differenced short-term interest rate, asset turnover and expected GDP growth, are significant and in a positive relationship with the dependent variable of stock returns.

3.5 Tests and Diagnostics

In Table 3.7 we compare all pooled OLS, fixed effects and random effects estimates.

The table confirms that the pooled OLS and random effects estimates are very similar. The fixed effects estimates differ a bit and moreover the differenced short-term interest rate and asset turnover are not significant, which is

Table 3.7: Static analysis results for all institutions

	(1) log_return	(2) log_return	(3) log_return
shortterm_rate	0.0584*		0.0519*
	(0.032)		(0.029)
gdp	0.0118	0.0145*	0.0127
	(0.322)	(0.013)	(0.170)
expected_gdp	0.0514**	0.0359*	0.0473**
	(0.009)	(0.031)	(0.003)
turnover	0.00379**		0.00377***
	(0.001)		(0.000)
2006.year	0	0	0
	(.)	(.)	(.)
2007.year	-0.126***	-0.107***	-0.125***
	(0.000)	(0.000)	(0.000)
2008.year	-0.430***	-0.479***	-0.438***
	(0.000)	(0.000)	(0.000)
2009.year	-0.237*	-0.479***	-0.265**
	(0.037)	(0.000)	(0.008)
2010.year	-0.0468	-0.127*	-0.0578
	(0.356)	(0.012)	(0.238)
2011.year	-0.268***	-0.322***	-0.279***
	(0.000)	(0.000)	(0.000)
2012.year	-0.230***	-0.339***	-0.246***
	(0.001)	(0.000)	(0.000)
2013.year	0.133*	0.0466	0.120*
	(0.019)	(0.342)	(0.018)
2014.year	0.0209	-0.0515	0.00906
	(0.660)	(0.258)	(0.842)
2015.year	-0.157**	-0.250***	-0.170***
	(0.003)	(0.000)	(0.000)
_cons	0.000891	0.115***	0.0131
	(0.985)	(0.001)	(0.771)
N	761	761	761

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

why these variables were excluded from the model and there are no estimates corresponding to these variables in the Table 3.7.

So, how to decide which one of these models is the most appropriate one? First of all, we should have the same set of variables in all of the models so for now we will include also the differenced short-term interest rate and asset turnover into the fixed effects model. The dummy variables for each year are clearly jointly significant in all the models so we will also keep them. Their joint significance can formally be tested using the *testparm* command in Stata, but because almost all of the time effects are significant even individually, we do not report the results of these tests. We will start with making the decision whether the pooled OLS or the fixed effects model is better. It can be done by testing whether the fixed effects are jointly significant, using the *testparm* command. The results of the test are below.

```
F( 12,    17) = 28526.90
     Prob > F =    0.0000
```

The p-value is really low so the fixed effects model is more appropriate than the pooled OLS model.

Now we have to decide whether the fixed effects model or the random effects is more appropriate. In order to make the decision, we will use the Hausman test. The null hypothesis of such a test is that the difference in beta coefficients is not systematic and that the random effects model is therefore better, while the alternative hypothesis is that the fixed effects model is better. It tests whether the unique errors (u_i) are correlated with the independent variables, where the null hypothesis is that they are not (Torres-Reyna 2007). The results of the Hausman test are as follows.

```
                ---- Coefficients ----
              |  fixed      random    Difference      S.E.
--------------+-------------------------------------------------
  expected_gdp|   .03728   .0472549     -.009975     .0040473
shortterm_rate| .0449446   .0519457    -.0070011     .0014156
           gdp| .0127193   .0126881     .0000311     .0021614
      turnover| .1567799    .377163    -.2203831     .2303425
   2007bn.year|-.1265719    -.12473    -.0018419            .
     2008.year|-.4592136  -.4376182    -.0215954     .0072479
     2009.year|-.3104064  -.2649886    -.0454177     .0066938
```

```
    2010.year|-.0773325  -.0577509    -.0195816           .
    2011.year|-.3081245  -.2785826     -.029542     .0047242
    2012.year|-.2834046  -.2461503    -.0372543      .006842
    2013.year| .0916544    .120442    -.0287876           .
    2014.year|-.0173697   .0090565    -.0264262           .
    2015.year|-.1997598  -.1702333    -.0295265           .
------------------------------------------------------------------------------

    Test:  Ho:  difference in coefficients not systematic

                  chi2(13) =      2.28
                Prob>chi2 =      0.9995
```

Since the p-value is much higher than 0.05, we cannot reject the null hypothesis. We can therefore consider the random effects model as a better model, and therefore the best model out of the static models.

However, we have not checked yet whether the assumptions underlying the regression we conducted are met. First, let us run the Breusch and Pagan Lagrange multiplier test for random effects. The null hypothesis here is that there are no random effects in the model.

```
Breusch and Pagan Lagrangian multiplier test for random effects

log_return[institution,t] =
                       = Xb + u[institution] + e[institution,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
               log_re~rn |   .1221852         .34955
                       e |   .0591605       .2432293
                       u |    .004065       .0637573

        Test:   Var(u) = 0
                             chibar2(01) =    21.53
                          Prob > chibar2 =   0.0000
```

We convincingly reject the null hypothesis which confirms us that the random effects model is more appropriate than the pooled OLS model.

In order to test for stationarity, we use the Fisher-type tests because these work well with unbalanced panels. The null hypothesis of these tests is that all the panels contain a unit root. We make use of the *drift* and *demean* options. The *drift* option is useful when the means of given variables are non-zero. The *demean* option is used to reduce the influence of cross-sectional dependence (Levin *et al.* 2002). We strongly reject the null hypothesis in case of all variables, including the dependent variable of log return. The null hypothesis is rejected whether we use one lag or two lags, and also when we omit the *demean* option. On the other hand, the strength of this test is rather limited because it can be expected that at least one of the panels will not contain a unit root considering we have many panels in our data set. Nevertheless, we also transformed the variables in a way that should make it likely that the series are stationary.

Another test we can perform is the Wooldridge test for autocorrelation in panel data. The null hypothesis is that there is no first-order autocorrelation. Autocorrelation would make standard errors of the beta coefficients lower than they actually are, which would make the corresponding standard errors more significant. Since the Wooldridge test for autocorrelation in panel data does not work with factor variables, we generate the time dummy variables for each year manually.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       81) =     25.437
           Prob > F =      0.0000
```

Unfortunately, the test reveals that there is a problem with first-order autocorrelation, as the p-value is very low. On the other hand, according to Torres-Reyna (2007), autocorrelation can only be an issue in longer panels, with 20 or 30 periods. Anyways, we will see later that the problem can be solved by using a dynamic panel data model instead of the static panel data model.

We would also like to test for cross-sectional dependence but because our panel is highly unbalanced, we cannot use neither the CD Pesaran's test, nor the Friedman's test, nor the Frees' test. Nevertheless, cross-sectional dependence is generally more of an issue in long panels with 20-30 periods as well (Torres-Reyna 2007). As for heteroskedasticity, we should have no problem because we use the clustered standard errors which are also heteroskedasticity-robust.

3.6 Interpretation of the Most Appropriate Model

All in all, the random effects model we have been testing now can be considered the most acceptable out of the static panel data models we presented here for explaining the effects that govern the behaviour of stock prices of financial institutions. Let us show the regression results once more in Table 3.8, which is identical with Table 3.6 so that we can discuss them little bit more.

Table 3.8: Random effects for all institutions: significant variables

	(1) log_return	
shortterm_rate	0.0519*	(0.029)
gdp	0.0127	(0.170)
expected_gdp	0.0473**	(0.003)
turnover	0.00377***	(0.000)
2006.year	0	(.)
2007.year	-0.125***	(0.000)
2008.year	-0.438***	(0.000)
2009.year	-0.265**	(0.008)
2010.year	-0.0578	(0.238)
2011.year	-0.279***	(0.000)
2012.year	-0.246***	(0.000)
2013.year	0.120*	(0.018)
2014.year	0.00906	(0.842)
2015.year	-0.170***	(0.000)
_cons	0.0131	(0.771)
N	761	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We concluded that the effects of the differenced short-term interest rate, expected GDP growth and asset turnover are statistically significant but let us have a look at their economic effect as well. It follows that the impact of expected GDP growth is much larger than the impact of GDP growth. Indeed, if the expected GDP growth increases by 1 percentage point, then the ratio p_t/p_{t-1} increases *ceteris paribus* by 4.7 % on average. If the GDP growth increases by 1 percentage point, then p_t/p_{t-1} increases only by 1.3 %. The reason why the interpretation is like this lies in the fact that our regression is of the log-level type because on the left-hand size we have $\log{(p_t/p_{t-1})}$. At the same time, we use the approximation that $\%\Delta y = 100 * \beta_i * \Delta x_i$. This is a good approximation when $\beta_i * \Delta x_i$ is not far from zero, ideally between -0.1

and +0.1, which is true in our case. If we put the interpretation in simpler words, we can just say that a 1 percentage point increase in expected GDP growth leads to an average increase by 4.7 % in equity prices. Similarly, a 1 percentage point increase in GDP growth leads to an average increase by 1.3 % in equity prices.

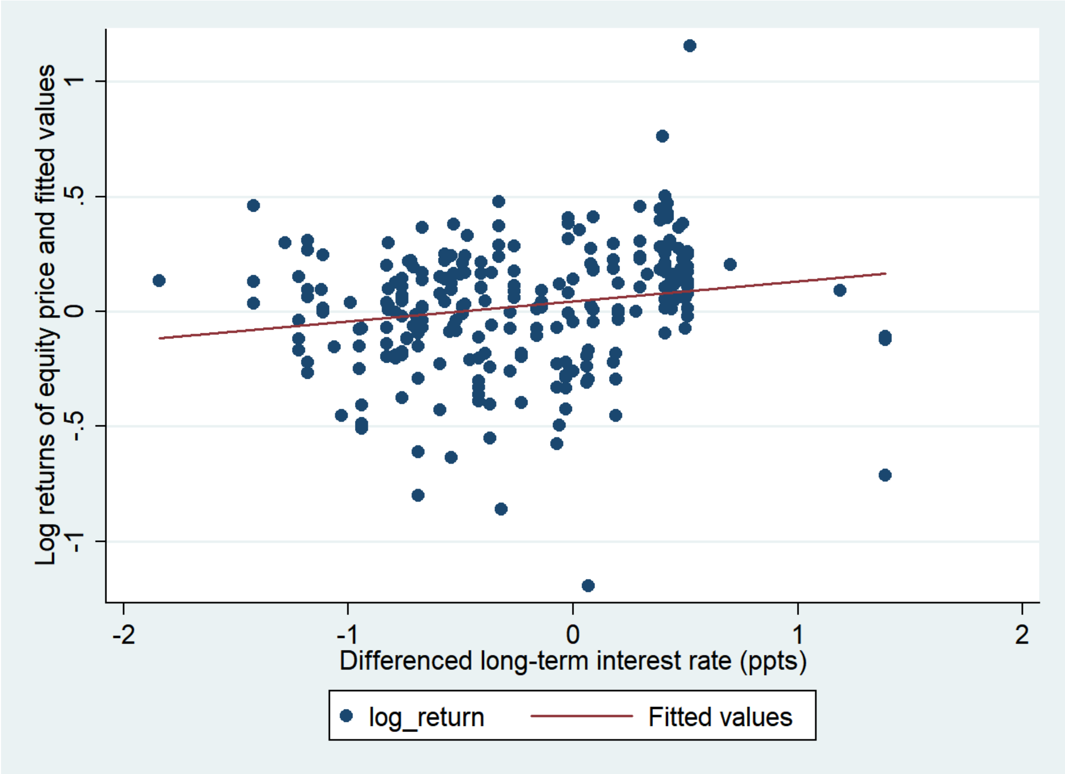
The effect of the short-term interest rate is quite large. An increase in the short-term interest rate by 1 percentage point brings about an increase in p_t/p_{t-1}, *ceteris paribus*, by 5.2 % on average. Alternatively we can say that a decrease in the short-term interest rate by 1 percentage point brings about a decrease in p_t/p_{t-1}, *ceteris paribus*, by 5.2 % on average. We prefer this interpretation because we are concerned by the low yield environment and therefore rather by decreases of interest rates than increases. The effect of asset turnover is relatively small but it may be because the average asset turnover is higher than average GDP growth or average short-term interest rate. An increase by 1 percentage point means an increase in p_t/p_{t-1} *ceteris paribus* by 0.4 % on average. The effect of the time dummy variables is really high in some cases. For example the beta coefficient for the year 2008 is approximately -0.44. It means that p_t/p_{t-1} in 2008 was *ceteris paribus* by 44 % lower on average than in 2006, which is the baseline year.

Chapter 4

Static Models: Banks and Insurers Separately

Although we chose the random effects model rather than the fixed effects model, the dummy variables for whether a given financial institutions is a global bank, regional bank, life insurance company or non-life insurance company turned out to be jointly insignificant. However, one of the purposes of the thesis is to make comparisons between life insurance companies, non-life insurance companies, global banks and regional banks. At the same time, we cannot say that there is no difference just because the dummy variables are insignificant. The reason is that some variables, even the short-term interest rate, may be significant just because they are significant for regional banks, which is the group containing most financial institutions. A solution to the problem might be to treat banks and insurance companies separately. We can find the best model for both insurance companies and banks separately and if it turns out that the random effects model is better than fixed effects model, we will be even able to include dummy variables characterizing whether a given insurer is a life insurer or a non-life insurer, and whether a given bank is considered global or regional. When analyzing banks and insurance companies separately, we will not consider the dummy variable for debt crisis anymore because the samples do not contain many institutions from countries that suffered from the debt crisis.

Figure 4.1: Insurers: log returns and long-term interest rates



4.1 Insurers

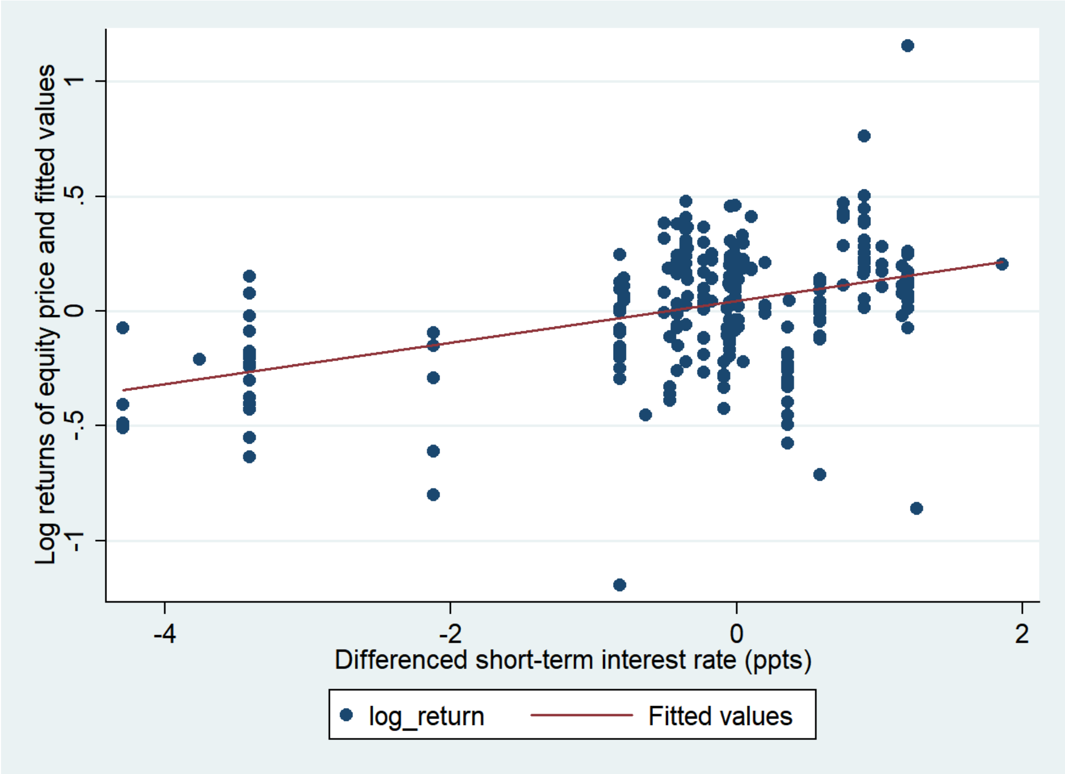
Let us start with the analysis of insurance companies. We will be following the same procedure as before. We will also be examining the same set of variables as before when we were analyzing financial institutions as a whole, with a little exception that asset turnover and any other institution-specific variables will not be included because they turned out to be statistically insignificant even after applying various transformations. Excluding them brings the advantage that we can keep more observations in the models.

In Figure 4.1, we present a scatter plot with the differenced long-term interest rates on the horizontal axis, and the log return on the vertical axis.

We can see that this figure differs a lot from the figure for all financial institutions where the line of the best fit was downward sloping in case of long-term interest rates. We will see whether the relationship is positive and significant for insurance companies also in the panel data analysis framework which will include control variables.

Another scatter plot displays the relationship between the differenced short-term interest rates and log returns. See Figure 4.2.

Figure 4.2: Insurers: log returns and short-term interest rates



The line of the best fit is upward sloping also in case of short-term interest rates. This was true also when we analyzed all financial institutions in the sample.

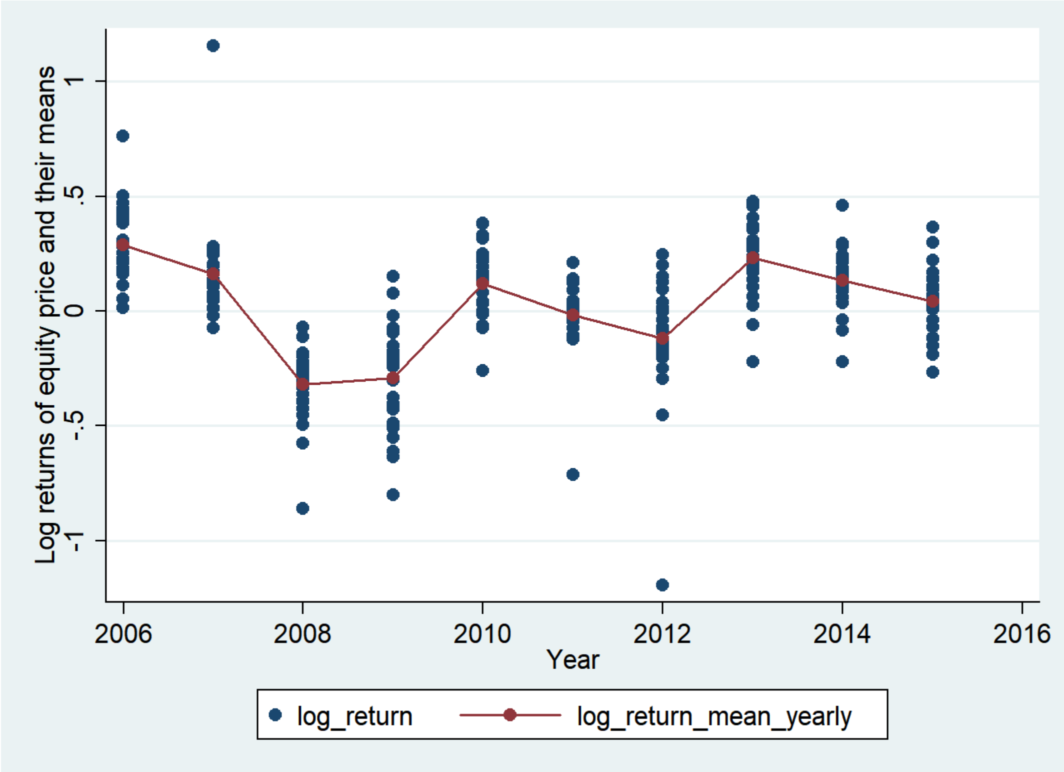
Figure 4.3 shows how the log return developed over the examined years.

The figure is unbelievably similar to the figure for all financial institutions, although there are more banks in the sample than insurance companies. Indeed, the brown line connecting the average log returns for each year has almost identical shape. There are only slight differences. First, in case of insurance companies, year 2008 was worse than 2009, which is *vice versa* in case of banks. These two years were however by far the worst ones for both banks and insurance companies. Another difference is that insurance companies performed better than banks in 2010, 2011 and 2015.

We can also have a look at how much unbalanced the panel data is.

```
     Freq.  Percent    Cum. |  Pattern
 ---------------------------+------------
        25    100.00  100.00 |  1111111111
 ---------------------------+------------
        25    100.00         |  XXXXXXXXXX
```

Figure 4.3: Insurers: heterogeneity across years



It turns out that the the panel is actually balanced. That means that we could conduct the CD Pesaran's test for cross-sectional dependence. Unfortunately, later we will find out that the tests and diagnostics do not even have to be conducted because the static panel data models do not yield very informative results.

Now we can proceed to the regression analysis. As before, we will start with the simple pooled OLS model, whose results are in Table 4.1.

Table 2.1 at the end of Chapter 2 describes the variables that appear in the regression. In addition to the variables in Table 2.1, the regression also includes time dummies. All the variables are insignificant but for the time dummies. Maybe surprisingly, both the differenced long-term interest rate and differenced short-term interest rate are in a reverse relationship with the dependent variable, although the scatter plots above showed that when we do not control for other variables, the relationships are rather positive. It can be caused by the fact that the number of explanatory variables is relatively high compared to the number of observations. We can exclude a set of variables that are jointly insignificant from the model, using an F test. But when we re-run the model with the remaining set of variables, all of them turn to be

Table 4.1: OLS for insurers: all variables

	(1)	
	log_return	
shortterm_rate	-0.0209	(0.676)
longterm_rate	-0.0652	(0.169)
gdp	0.0207	(0.262)
expected_gdp	0.0380	(0.218)
inflation	-0.0103	(0.596)
debt_to_gdp	0.00194	(0.410)
eurozone	0.0332	(0.368)
life	-0.00675	(0.848)
2006.year	0	(.)
2007.year	-0.114*	(0.044)
2008.year	-0.537***	(0.000)
2009.year	-0.568*	(0.018)
2010.year	-0.232**	(0.005)
2011.year	-0.265***	(0.001)
2012.year	-0.413***	(0.001)
2013.year	-0.0421	(0.485)
2014.year	-0.195**	(0.002)
2015.year	-0.318**	(0.002)
_cons	0.190	(0.099)
N	250	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

individually insignificant. See Table 4.2.

Table 4.2: OLS for insurers: significant variables

	(1) log_return	
longterm_rate	-0.0739	(0.148)
gdp	0.0126	(0.471)
expected_gdp	0.0324	(0.251)
2006.year	0	(.)
2007.year	-0.119**	(0.010)
2008.year	-0.550***	(0.000)
2009.year	-0.516***	(0.000)
2010.year	-0.205**	(0.005)
2011.year	-0.269***	(0.000)
2012.year	-0.407***	(0.000)
2013.year	-0.0372	(0.204)
2014.year	-0.175***	(0.000)
2015.year	-0.296***	(0.000)
_cons	0.207*	(0.013)
N	250	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Moreover, based on the following F test, all of them are insignificant even jointly.

```
 ( 1)  gdp = 0
 ( 2)  expected_gdp = 0
 ( 3)  longterm_rate = 0

       F(  3,     9) =    0.96
            Prob > F =    0.4530
```

Again, it may be because there are not so many observations, only 249, and at the same we use the time dummy variables which consume some degrees of freedom. But if we did not use the time dummy variables, we would explain just a little part of the variation in the dependent variable and the results could be really inaccurate.

The situation is quite similar when we use the fixed effects model. First we run the regression using all of the variables. The results when we include all of the variables are in Table 4.3.

Table 4.3: Fixed effects for insurers: all variables

	(1)	
	log_return	
shortterm_rate	-0.00591	(0.891)
longterm_rate	-0.0787	(0.082)
gdp	0.00335	(0.770)
expected_gdp	0.0457	(0.099)
inflation	0.0182	(0.536)
debt_to_gdp	-0.000396	(0.859)
2006.year	0	(.)
2007.year	-0.116*	(0.028)
2008.year	-0.572***	(0.000)
2009.year	-0.562*	(0.011)
2010.year	-0.212**	(0.007)
2011.year	-0.277***	(0.000)
2012.year	-0.424**	(0.001)
2013.year	-0.0498	(0.414)
2014.year	-0.168*	(0.011)
2015.year	-0.283*	(0.010)
_cons	0.179	(0.140)
N	250	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We can exclude a part of them using an F test. Then we re-run the regression—results are in Table 4.4.

Table 4.4: Fixed effects for insurers: significant variables

	(1) log_return	
longterm_rate	-0.0720	(0.105)
expected_gdp	0.0446	(0.106)
2006.year	0	(.)
2007.year	-0.120**	(0.009)
2008.year	-0.557***	(0.000)
2009.year	-0.584***	(0.000)
2010.year	-0.209**	(0.008)
2011.year	-0.270***	(0.001)
2012.year	-0.425**	(0.001)
2013.year	-0.0596	(0.205)
2014.year	-0.187***	(0.000)
2015.year	-0.310***	(0.001)
_cons	0.219**	(0.003)
N	250	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Both remaining variables are insignificant and they can be excluded using an F test. So essentially nothing is left in the model and we did not manage to obtain any interesting results even in the fixed effects model framework.

The results of the random effects model where all variables are included are in Table 4.5.

Again almost all of the variables can be excluded based on an F test and the only variable left is the differenced long-term interest rate, which is insignificant. So even the random effects model cannot tell us anything interesting about the relationship of stock prices and interest rates. That is why we will have to think of something else. A solution to this is a dynamic panel data model, in which the time dummy variables are not so necessary. The reason is that lagged dependent variables are included in the model as additional independent variables and explain another portion of the variation in the dependent variable. Another reason is that there are a lot of instrumental variables in the type of the dynamic model that we will use. These instrumental variables should make the precision of results even higher.

Hence, here in the case of insurance companies we will not even try to find

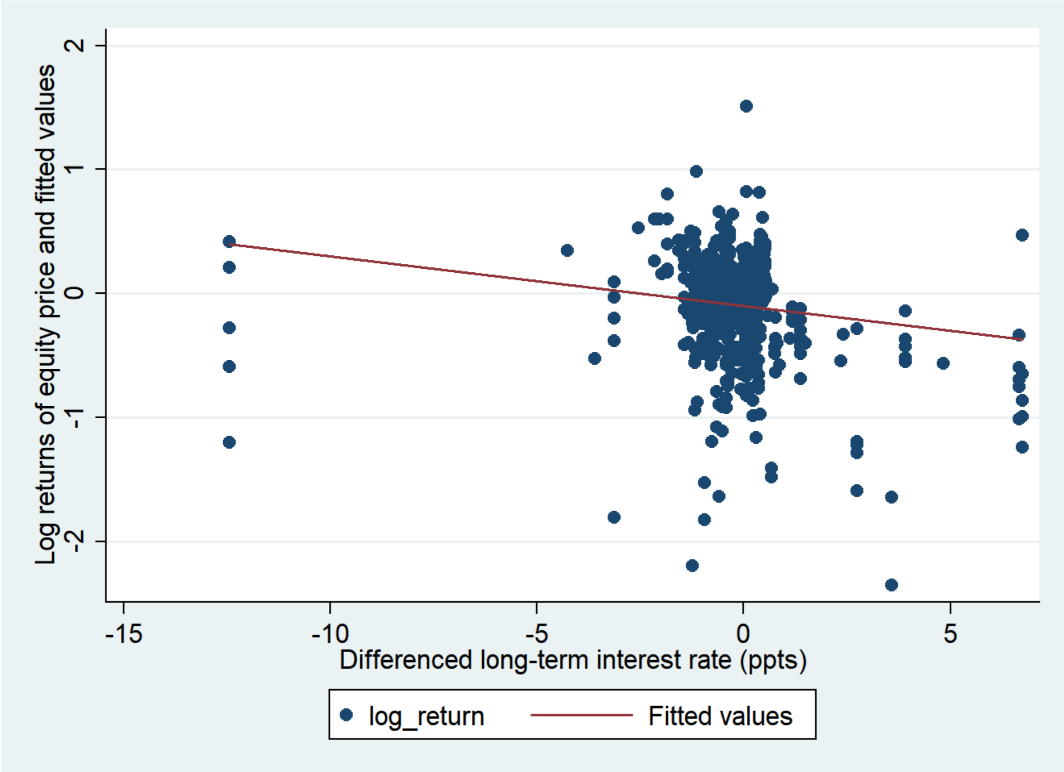
Table 4.5: Random effects for insurers: all variables

	(1)	
	log_return	
shortterm_rate	-0.0180	(0.691)
longterm_rate	-0.0697	(0.102)
gdp	0.0147	(0.312)
expected_gdp	0.0387	(0.147)
inflation	-0.00246	(0.909)
debt_to_gdp	0.000766	(0.708)
eurozone	0.0277	(0.449)
life	-0.00848	(0.807)
2006.year	0	(.)
2007.year	-0.113*	(0.015)
2008.year	-0.547***	(0.000)
2009.year	-0.574**	(0.002)
2010.year	-0.225***	(0.000)
2011.year	-0.268***	(0.000)
2012.year	-0.418***	(0.000)
2013.year	-0.0478	(0.386)
2014.year	-0.187***	(0.000)
2015.year	-0.311***	(0.000)
_cons	0.191	(0.057)
N	250	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4.4: Banks: log returns and long-term interest rates



out which one of the static models is the best one because none of them are good. We will also not conduct any tests and diagnostics. We will achieve more interesting and well interpretable results using the Blundell-Bond system GMM estimator which we will employ during the dynamic panel data analysis. During the dynamic panel data analysis we will also attempt to determine whether the impact of interest rates on equity prices differs for life insurance companies and non-life insurance companies.

Now when the static analysis of insurance companies is finished, we can proceed to analyzing banks.

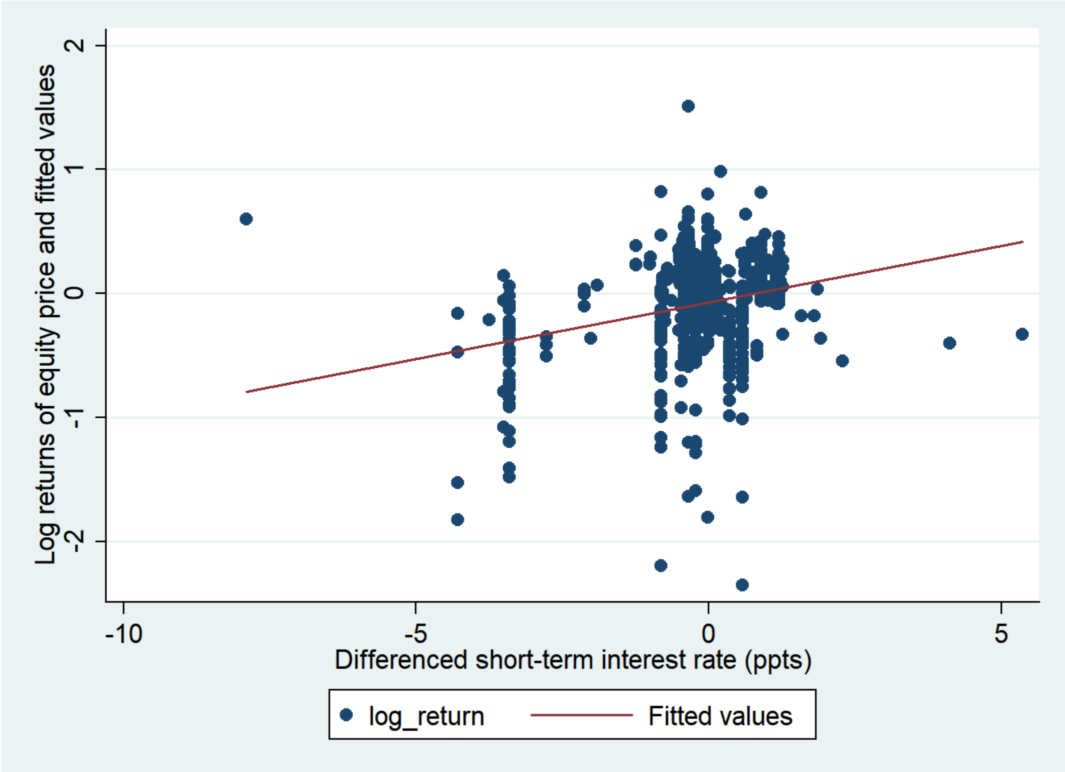
4.2 Banks

As before, let us first have a look at scatter plots depicting log returns against differenced long-term interest rates and differenced short-term interest rates, respectively. The scatter plot for long-term interest rates is in Figure 4.4.

Here the relationship of log returns and differenced long-term interest rates is rather negative.

The scatter plot for short-term interest rates is in Figure 4.5.

Figure 4.5: Banks: log returns and short term interest rates



This scatter plot shows a positive relationship between equity prices and short-term interest rates. However, we also need to control for other relevant explanatory variables to be able to make any conclusions.

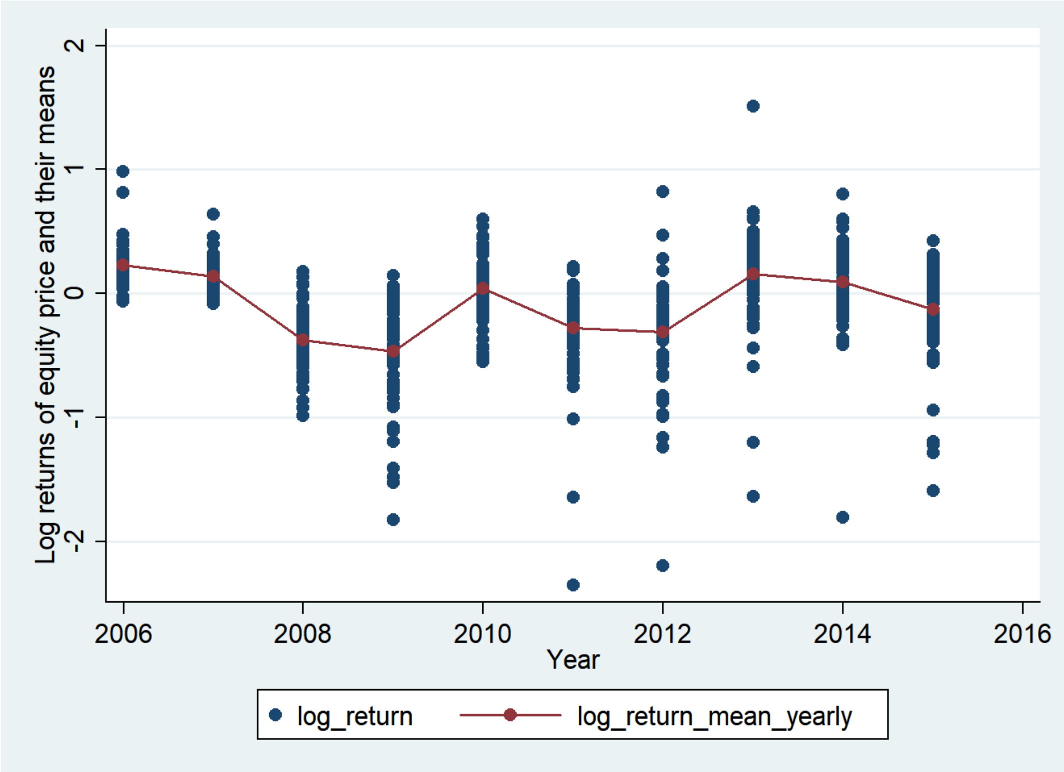
Another scatter plot in Figure 4.6 shows the development of log returns throughout the years.

The scatter plot looks almost identical with the scatter plot for all financial institutions, with the only difference that there are less points on the graph. The similarity is not surprising because we have already seen that the scatter plots looked very similar for insurance companies and all financial institutions. Another reason is that there are more banks in the sample than insurance companies.

Before we start the regression analysis, let us have a look at the patterns of unbalancedness.

```
     Freq.  Percent    Cum. |  Pattern
---------------------------+------------
        53    91.38   91.38 |  1111111111
         1     1.72   93.10 |  ......1111
         1     1.72   94.83 |  .....1...1
```

Figure 4.6: Banks: heterogeneity across years




```
          1       1.72    96.55 |   ..11111111
          1       1.72    98.28 |   11111.1111
          1       1.72   100.00 |   111111.111
 ----------------------------+------------
         58     100.00          |   XXXXXXXXXX
```

It turns out that there is not a single pattern that would cause unbalancedness and would appear more than once. The reason why some patterns appeared more frequently during the analysis of all financial institutions is that some more observations were dropped because of the missing value for the asset turnover variable. Here it turned out that the asset turnover was not significant so we decided to re-run the models without the asset turnover variable and with more observations.

Now we will start the regression analysis. The first model we will consider is the pooled OLS model. The results for banks where all variables are included and clustered standard errors are employed can be found in Table 4.6.

Again, description of the variables is in Table 2.1 at the end of Chapter 2. Through an F test we can exclude a set of jointly insignificant variables. Then we re-run the regression with the remaining variables, see Table 4.7.

Table 4.6: OLS for banks: all variables

	(1)	
	log_return	
shortterm_rate	0.0661	(0.118)
longterm_rate	-0.0137	(0.460)
gdp	0.0105	(0.529)
expected_gdp	0.0385*	(0.043)
inflation	0.0306	(0.241)
debt_to_gdp	-0.00466	(0.245)
eurozone	-0.0871	(0.103)
regional	-0.000226	(0.996)
2006.year	0	(.)
2007.year	-0.106*	(0.017)
2008.year	-0.435***	(0.000)
2009.year	-0.145	(0.389)
2010.year	-0.0138	(0.840)
2011.year	-0.324**	(0.001)
2012.year	-0.194	(0.083)
2013.year	0.131	(0.198)
2014.year	0.0730	(0.292)
2015.year	-0.155**	(0.008)
_cons	0.0107	(0.922)
N	562	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.7: OLS for banks: possibly significant variables

	(1) log_return	
shortterm_rate	0.0891	(0.053)
gdp	0.0118	(0.436)
expected_gdp	0.0681**	(0.005)
2006.year	0	(.)
2007.year	-0.119**	(0.008)
2008.year	-0.374***	(0.000)
2009.year	-0.108	(0.525)
2010.year	0.0125	(0.846)
2011.year	-0.276**	(0.001)
2012.year	-0.168	(0.054)
2013.year	0.148*	(0.038)
2014.year	0.0311	(0.622)
2015.year	-0.175	(0.093)
_cons	-0.0572	(0.362)
N	562	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

However, the short-term interest rate and GDP growth variables are not individually significant in the new model. Moreover, we can exclude them based on an F test. We are therefore left only with the expected GDP growth variable in the model. That means that the model is not very informative.

Let us move to the fixed effects model, whose results are in Table 4.8.

We exclude variables based on an F test. Results of the resulting model are in Table 4.9.

It is clear that the fixed effects model did not bring any interesting pieces of information, either.

The random effects model with all variables yields the following results, see Table 4.10.

We exclude some of them and arrive at the results in Table 4.11.

This model is already quite informative for us because it contains the short-term interest rate variable that is significant at the 5% significance level. The model also contains highly significant expected GDP growth. The last variable is the GDP growth which is insignificant but could not be excluded by the previous F test so we will keep the variable in the model.

The random effects model seems to be the best one but we will verify it

Table 4.8: Fixed effects for banks: all variables

	(1)	
	log_return	
shortterm_rate	0.0612	(0.170)
longterm_rate	-0.0118	(0.443)
gdp	0.0103*	(0.047)
expected_gdp	0.0385	(0.091)
inflation	0.0569*	(0.048)
debt_to_gdp	-0.00176	(0.616)
2006.year	0	(.)
2007.year	-0.106*	(0.013)
2008.year	-0.515***	(0.000)
2009.year	-0.175	(0.263)
2010.year	-0.0405	(0.493)
2011.year	-0.375***	(0.000)
2012.year	-0.256*	(0.011)
2013.year	0.135	(0.137)
2014.year	0.0823	(0.241)
2015.year	-0.116	(0.072)
_cons	-0.0735	(0.395)
N	562	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.9: Fixed effects for banks: significant variables

	(1)	
	log_return	
expected_gdp	0.0659***	(0.000)
inflation	0.0545	(0.057)
2006.year	0	(.)
2007.year	-0.0851**	(0.009)
2008.year	-0.536***	(0.000)
2009.year	-0.467***	(0.000)
2010.year	-0.106*	(0.042)
2011.year	-0.388***	(0.000)
2012.year	-0.346***	(0.001)
2013.year	0.0694	(0.333)
2014.year	0.0285	(0.709)
2015.year	-0.172**	(0.006)
_cons	-0.0508	(0.457)
N	562	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

using tests that will compare the random effects model to the pooled OLS model and to the fixed effects model.

The comparison to the pooled OLS model is done through the Breusch and Pagan Lagrangian multiplier test for random effects.

```
Breusch and Pagan Lagrangian multiplier test for random effects

log_return[institution,t] =
                       = Xb + u[institution] + e[institution,t]


        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
               log_re~rn |   .1649592       .4061518
                       e |   .0847648        .291144
                       u |   .0111852       .1057603

        Test:   Var(u) = 0
                            chibar2(01) =    67.53
                         Prob > chibar2 =   0.0000
```

Table 4.10: Random effects for banks: all variables

	(1)	
	log_return	
shortterm_rate	0.0653	(0.104)
longterm_rate	-0.0131	(0.456)
gdp	0.0104	(0.459)
expected_gdp	0.0382*	(0.037)
inflation	0.0348	(0.171)
debt_to_gdp	-0.00411	(0.281)
eurozone	-0.0921	(0.070)
regional	0.00652	(0.891)
2006.year	0	(.)
2007.year	-0.107**	(0.006)
2008.year	-0.450***	(0.000)
2009.year	-0.153	(0.340)
2010.year	-0.0194	(0.765)
2011.year	-0.334***	(0.000)
2012.year	-0.207*	(0.040)
2013.year	0.131	(0.170)
2014.year	0.0734	(0.275)
2015.year	-0.149**	(0.003)
_cons	0.00477	(0.965)
N	562	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.11: Random effects for banks: significant variables

	(1)	
	log_return	
shortterm_rate	0.0815*	(0.035)
gdp	0.0115	(0.150)
expected_gdp	0.0593***	(0.000)
2006.year	0	(.)
2007.year	-0.116**	(0.001)
2008.year	-0.399***	(0.000)
2009.year	-0.160	(0.312)
2010.year	-0.00921	(0.882)
2011.year	-0.302***	(0.000)
2012.year	-0.205**	(0.007)
2013.year	0.127	(0.061)
2014.year	0.0155	(0.809)
2015.year	-0.194*	(0.047)
_cons	-0.0255	(0.645)
N	562	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The p-value is extremely low which means that there are important random effects. The random effects model is therefore preferred to the pooled OLS model.

In order to test for whether the random effects model is better than the fixed effects model, we will use the Hausman test. To make the comparison, we will use a fixed effects model with the same set of variables that are contained in the last random effects model. That is, we will use the short-term interest rate, expected GDP growth, GDP growth and the time dummies as independent variables. The results of the Hausman test:

```
Test:  Ho:  difference in coefficients not systematic

                 chi2(12) =      3.77
                Prob>chi2 =      0.9872
```

The results clearly suggest that the random effects model is better because the p-value is really high. That is why we can take the random effects model and proceed to tests and diagnostics.

In order to test for stationarity, we conduct the Fisher-type unit-root tests which are based on augmented Dickey-Fuller tests. As before, we use two lags and the *drift* and *demean* Stata options. All of the tests suggest that the variables are stationary, including the dependent variable of log returns.

Another test is the Wooldridge test for autocorrelation in panel data.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,      56) =     16.796
           Prob > F =      0.0001
```

As in the case of all financial institutions, the test reveals that there is an issue with first-order autocorrelation. Torres-Reyna (2007) argues that autocorrelation brings about problems only in longer panels, with more than 20 periods. Anyways, we will address the issue when using the dynamic panel data model where a test will show that there is no autocorrelation in the model.

Let us present the results of the random effects model once more in Table 4.12, so that it is easier to make remarks about sizes of the effects.

Table 4.12: Random effects for banks: significant variables

	(1) log_return	
shortterm_rate	0.0815*	(0.035)
gdp	0.0115	(0.150)
expected_gdp	0.0593***	(0.000)
2006.year	0	(.)
2007.year	-0.116**	(0.001)
2008.year	-0.399***	(0.000)
2009.year	-0.160	(0.312)
2010.year	-0.00921	(0.882)
2011.year	-0.302***	(0.000)
2012.year	-0.205**	(0.007)
2013.year	0.127	(0.061)
2014.year	0.0155	(0.809)
2015.year	-0.194*	(0.047)
_cons	-0.0255	(0.645)
N	562	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

According to the model, a decrease in the expected GDP growth by 1 percentage point decreases the equity price of banks, *ceteris paribus*, by 5.9 % on average. In case of GDP growth it is 1.1 % and in case of the differenced short-term interest rate by 8.1 %.

Chapter 5

Dynamic Models

So far we have analyzed the relationship of financial institutions' stock prices with macroeconomic and institution-specific factors using the framework of static panel data models. But according to Dorofti and Jakubik (2015), a disadvantage of these static panel models is that they do not consider the possibility that both the dependent and independent variables can have a contemporaneous impact on each other. At the same time, especially when low-frequency data is analyzed, the possibility to take these contemporaneous impacts into account may be beneficial for the sake of results' accuracy.

If we want to consider these contemporaneous impacts, we can use a dynamic panel model. The dynamic panel model differs from the static panel model in that the dynamic panel model contains a lagged dependent variable, which serves as another independent variable. More lags of the dependent variable can also be included. The dynamic panel model helps us to deal with the omitted variable bias. This is also something very useful in our case because it will be possible to exclude the time dummy variables from the model and therefore obtain more interesting results even when insurance companies and banks are analyzed separately.

In order to estimate the parameters of our dynamic models, we will employ the Blundell and Bond's system GMM estimator. The Blundell and Bond's system GMM estimator is appropriate for short panels, i.e. data sets containing only a few time periods and many entities such as financial institutions in our case. Our data set contains 10 periods which is not many so the Blundell and Bond's estimator is appropriate. The estimator is sometimes called Arellano-Bover/Blundell-Bond estimator because Blundell and Bond built on the work of Arellano and Bover (1995) to construct the estimator.

The reason for why a special estimator, in this case the Blundell-Bond system GMM estimator, must be used in case of a dynamic panel model is that the unobserved panel-level effects, fixed or random, are by construction correlated with the lagged dependent variable, which makes standard estimators inconsistent.

The system GMM estimator assumes that there are weak correlations between the current and lagged levels of all variables (Dorofti and Jakubik 2015). Another assumption is that there is no autocorrelation in the idiosyncratic errors. It will be tested using the Arellano and Bond test of autocorrelation. We will be interested in whether there is second-order autocorrelation because we want to detect autocorrelation in terms of levels.

According to Griliches and Mairesse (1998), the application of traditional panel methods to microeconomic data produced unsatisfactory results in that the value of some coefficients differed a lot from expectations. It could be illustrated e.g. on the example of the Cobb-Douglas function. Blundell and Bond (2000) showed in their paper that their system GMM estimator produces results that are much more reasonable. The model underlying the Blundell and Bond's GMM estimation looks like this:

$$Y_{it} = \beta_1 Y_{i,t-1} + \beta_2 X_{it} + \beta_3 X_{i,t-1} + \eta_i + v_{it}.$$

Here the $\eta_i + v_{it}$ is the typical fixed effects decomposition of the error term.

The Blundell and Bond method lies in the fact that lagged first-differences are used as instruments for equations in levels, while lagged levels are used as instruments for equations in first-differences. The first-differenced equation and the levels equation are combined into a system which is a basis for the system GMM estimator. Nevertheless, all the explanatory variables do not have to be instrumented in this way. In case we can be sure an independent variable is exogenous, we do not have to instrument it. This was done e.g. by Garcia-Herrero *et al.* (2009) who used the Blundell and Bond's system GMM estimator to explain the low profitability of Chinese banks. The lagged independent variables denoted as $X_{i,t-1}$ in the equation above do not have to be included, either.

According to Garcia-Herrero *et al.* (2009), the Blundell and Bond's GMM estimator controls for unobserved heterogeneity, for persistence of the dependent variable and for potential endogeneity. Moreover, the estimator yields unbiased estimation of the parameters. The methodology should also yield consistent and asymptotically efficient results.

5.1 Banks and Insurers Together

First, we will analyze both banks and insurance companies at the same time. In Stata, the Blundell and Bond's system GMM estimation can be run using the command *xtdpdsys*. However, the command does not easily allow for various tests of the underlying assumptions, for example the Hansen test of overidentifying restrictions or the difference-in-Hansen tests of exogeneity of instrument subsets. In addition, the command does not support the clustered standard errors. Fortunately, there is an alternative command *xtabond2* created by Roodman (2009b) which allows for the tests of assumptions as well as for the clustered standard errors. With this alternative command it is also much easier to keep under control the instrumental variables that are used in the model.

We do not include lags of the independent variables into the regression because equity prices react to impulses almost immediately so that only the current changes in independent variables should matter for the dependent variable of log returns.

When running the *xtabond2* command, we will utilize several options of the command. First, we will make use of the *twostep* option. It means that the two-step estimator will be employed instead of the one-step estimator. The two-step estimator has an advantage that it is asymptotically efficient. However, as the number of instruments approaches the number of entities in the sample, the two-step GMM gets far from the efficient ideal. As Roodman (2009) argues, proliferation of instruments is an underappreciated problem. According to the paper, especially the system GMM estimator may generate suspect instruments. The problem is that a large number of instruments can overfit the endogeneous variables. As a result, the coefficient estimates are biased towards those from non-instrumenting estimators. That is why it is important to keep the number of instrumental variables rather low, even though a high number of instrumental variables does not cause inconsistency of the two-step GMM. It is particularly important to keep the number of instrumental variables lower than the number of entities. According to Roodman (2009), this is a key threshold for safe and reliable estimation.

Another problem caused by a high number of instrumental variables is that the coefficient standard errors in two-step GMM estimation tend to be downward biased (Roodman 2009). It can be prevented by employing the Windmeijer finite-sample correction for the two-step covariance matrix (Windmeijer 2005). Thanks to the correction, the two-step GMM estimation technique is preferred to the one-step GMM. In terms of the *xtabond2* command, the Windmeijer correction is run through the *robust* option or through the *cluster* option, if clustering of standard errors is necessary. In our case, clustering is indeed necessary because many variables in the sample are specific only for countries and not for financial institutions themselves. Thus we will employ the *cluster* option.

In addition, we use two lags of the dependent variable because it turned out that there was a problem with autocorrelation in the model when we used only one lag. Moreover, the second lag of the dependent variable will typically be statistically significant in the regressions. The results of the Blundell-Bond GMM estimation when all explanatory variables are included are in Table 5.1.

Table 5.1: System GMM for all institutions: all variables

	(1) log_return	
L.log_return	-0.107	(0.527)
L2.log_return	-0.167	(0.533)
shortterm_rate	0.131	(0.241)
longterm_rate	-0.0227	(0.784)
gdp	0.00816	(0.847)
expected_gdp	0.0736	(0.859)
inflation	-0.0772	(0.738)
debt_to_gdp	-0.00654	(0.721)
debt_crisis	-0.792	(0.614)
eurozone	0.177	(0.816)
turnover	0.0681	(0.374)
regional	-1.067	(0.762)
life	-1.855	(0.669)
nonlife	-2.947	(0.589)
_cons	0.869	(0.846)
N	579	
j	46	
ar2p	0.634	
hansenp	1.000	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The variables that appear in the regression are described in Table 2.1 at the end of Chapter 2. None of the variables are significant at this moment, although the short-term interest rate and inflation rate are not far. We will be able to see more after we drop a set of jointly insignificant variables and after we conduct necessary tests and diagnostics. Let us run an F test of joint significance where all the variables from the previous model except the short-term interest rate, the inflation rate, the expected GDP growth and the two lags of the dependent variable will be included.

```
 ( 1)  life = 0
 ( 2)  regional = 0
 ( 3)  nonlife = 0
 ( 4)  longterm_rate = 0
 ( 5)  eurozone = 0
 ( 6)  debt_crisis = 0
 ( 7)  debt_to_gdp = 0
 ( 8)  gdp = 0
 ( 9)  turnover = 0

           chi2(  8) =    5.07
         Prob > chi2 =    0.7501
```

With a light heart, we can exclude all of the variables that appeared in the F test from the model as the p-value is very high. Hence we will keep only the rest of variables in the model. We set the short-term interest rate and the lags of the dependent variable to be bases of the GMM-style instrument sets, which is done through the *gmmstyle* Stata option. This kind of instrument sets was described by Holtz-Eakin *et al.* (1998). Creating such GMM-style instrument sets helps to deal with possible endogeneity of the variables that are the bases of these instrument sets. The *gmmstyle* option has several suboptions. We use one of them, the *collapse* suboption. The suboption serves to reduce the number of instrument variables, by creating one instrument for each variable and lag distance, rather than one for each time period, variable, and lag distance. Inflation rate and expected GDP growth are set to be standard instrumental variables using the *ivstyle* Stata option. The option should be used only for exogeneous variables but has an important advantage that it does not create plenty of instrument variables like the *gmmstyle* option. The model with the rest of the variables yields the results shown in Table 5.2.

Table 5.2: System GMM for all institutions: significant variables

	(1)	
	log_return	
L.log_return	-0.0818	(0.226)
L2.log_return	-0.235***	(0.000)
shortterm_rate	0.106***	(0.000)
expected_gdp	0.106***	(0.000)
inflation	-0.0540*	(0.014)
_cons	-0.0829	(0.229)
N	579	
j	28	
ar2p	0.135	
hansenp	0.897	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The model yields very interesting results. All of the variables in the model are significant at the 5% significance level with the exception of the first lag of the dependent variable. Nevertheless, it definitely makes sense to keep the first lag in the model because it would be strange to have there only the second lag of the dependent variable. The reason why it is sensible to keep also the first lag in the model is that in the long-term it should not be true that the second lag is more significant that the first lag—here it was probably more by chance that it happened.

Anyways, both of the lagged dependent variables have a negative beta coefficient. That can be interpreted as follows: a 1% increase in the last year stock price would bring about a 0.08% decrease in the current year stock price. Additionally, a 1% increase in the stock price from two years ago would bring about a 0.24% decrease in the current year stock price. That would mean that over the period of our interest, it generally paid off to sell shares whose price grew in the previous two years and to buy shares whose price fell in the previous two years.

Most importantly, the differenced short-term interest rate is highly significant with a positive beta coefficient. The same is true for the expected GDP growth. Furthermore, the effect of the inflation rate is significant and negative. The justification of this influence of inflation rate on stock prices is different for banks, life insurance companies and non-life insurance companies. According to Wallich (1980), banks are net creditors, and creditors are born losers in inflation. Based on an article by Swiss Re (2010), for non-life insurers, unanticipated inflation leads to higher claims costs, thereby eroding profitability. Lower profitability then leads to lower equity prices. For life insurers, it is relevant that inflation is often accompanied by rising interest rates, which reduce the value of return guarantees. Rising inflation can also have a negative effect on demand, and may lead to policyholders cancelling their policies, and to increasing costs for insurers.

Now it is a good time to find out whether the effect of short-term interest rates on equity prices is more profound for banks or insurance companies. In order to answer the question, we will first create an interaction variable that will be the product of the differenced short-term interest rate variable and a dummy variable saying whether a given institution is an insurance company. Then we include this new variable, called *shortterm_rate_insurer*, in the previous regression, with the *ivstyle* option. The results are in Table 5.3.

Table 5.3: System GMM for all institutions: final results

	(1) log_return	
L.log_return	-0.0716	(0.317)
L2.log_return	-0.250***	(0.000)
shortterm_rate	0.118***	(0.000)
expected_gdp	0.102***	(0.000)
inflation	-0.0575**	(0.004)
shortterm_rate_insurer	-0.0620	(0.067)
_cons	-0.0795	(0.195)
N	579	
j	29	
ar2p	0.261	
hansenp	0.949	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The interaction term is significant at the 10% significance level and says that short-term interest rates have a larger impact on banks than on insurance companies. More specifically, an increase in the short-term interest rate by 1 percentage point will, *ceteris paribus*, increase stock prices of banks by 6.2 percentage points more on average than stock prices of insurance companies. An alternative interpretation is that a decrease in the short-term interest rate by 1 percentage point will decrease stock prices of banks by 6.2 percentage points more on average than stock prices of insurance companies. At the same time, the number of instruments, denoted as j in the tables with regression results, is much lower than the number of financial institutions in the sample, which equals 82. Hence this basic condition to keep the results reliable is met.

Nevertheless, our expectation is that life insurance companies should be influenced more by interest rates than banks. The reason is that the duration of life insurers' liabilities is typically very long and lowered interest rates therefore increase the value of liabilities really significantly. As we will see later, life insurance companies are indeed influenced more by interest rates than banks. But since non-life insurance companies are influenced by interest rates only mildly and there are more non-life insurance companies in the sample than life insurance companies, the overall effect of interest rates on insurance companies in the sample is lower than on banks.

For now, however, let us further examine the last regression results. It is important to check whether the key assumption underlying the Blundell-Bond system GMM estimation is met. We will check the Arellano-Bond test for zero autocorrelation in first-differenced errors. In the tables with regression results, the p-value of the Arellano-Bond test is denoted as ar2p. It is an important test because if there was autocorrelation of level 2 in the errors, the moment conditions of the Blundell-Bond GMM estimation would not be valid. Since the p-value for the autocorrelation of order 2 is higher than 0.05, we do not reject the null hypothesis that there is no autocorrelation of order 2 which means that the moment conditions are valid.

We also check the Hansen test of overidentifying restrictions and the difference-in-Hansen tests of exogeneity of instrument subsets. The p-value corresponding to the Hansen test is denoted as hansenp in the tables with regression results, while the difference-in-Hansen tests can be found below.

```
Difference-in-Hansen tests of exogeneity of instrument subsets:
  GMM instruments for levels
    Hansen test excluding group:
chi2(19)    =  12.62  Prob > chi2 =  0.857
    Difference (null H = exogenous):
chi2(3)     =  -0.22  Prob > chi2 =  1.000
  iv(inflation expected_gdp shortterm_rate_insurer)
    Hansen test excluding group:
chi2(19)    =  14.68  Prob > chi2 =  0.743
```

```
    Difference (null H = exogenous):
chi2(3)    =  -2.28  Prob > chi2 =  1.000
```

The p-values corresponding to these tests are high. In addition, the variables considered should be stationary because of the data transformations that were previously done, i.e. raw returns were transformed into log returns, interest rates in levels were transformed into differenced interest rates and so on. It means that the assumptions underlying the Blundell-Bond system GMM estimation technique are met and the regression results above can be considered reliable. If we included the interaction term variable *shortterm_rate_insurer* with the *gmmstyle* option instead of the *ivstyle* option, the results would be nearly the same.

5.2 Banks and Insurers Separately

Now we will conduct the same analysis for insurance companies and banks separately. During the analysis of insurance companies we will have a look at whether interest rates influence equity prices of life and non-life insurance companies in a different way. During the analysis of banks we will examine whether there is a difference between the impact of interest rates on banks that operate globally and banks that operate regionally, i.e. just in Europe.

Let us start with insurers. We follow the same procedure as when we analyzed all financial institutions. The results after we dropped jointly insignificant variables are in Table 5.4.

This model contains the same set of variables as the model for all financial institutions, only inflation rate is missing because the variable was insignificant. Expected GDP growth is the only variable that serves as the standard instrumental variables. The short-term interest rate and the lags of the dependent variables serve as bases for the GMM style instrument sets.

Hence, short-term interest rate turned out to be significant also in case of insurers. The corresponding beta coefficient is equal to 0.061, which means that an increase in the short-term interest rate by 1 percentage point brings about, *ceteris paribus*, 6.1% increase in insurers' stock prices on average.

In order to find out whether the effect of short-term interest rate is more profound in case of life or non-life insurance companies, we will add an interaction term between the differenced short-term interest rate variable and the dummy variable indicating whether the institution is a non-life insurance com-

Table 5.4: System GMM for insurers: significant variables

	(1)	
	log_return	
L.log_return	-0.0763	(0.613)
L2.log_return	-0.239**	(0.005)
shortterm_rate	0.0619*	(0.030)
expected_gdp	0.0991**	(0.003)
_cons	-0.117	(0.101)
N	200	
j	22	
ar2p	0.131	
hansenp	0.949	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

pany. The interaction term variable is called *shortterm_rate_nonlife*. See Table 5.5 for results.

Table 5.5: System GMM for insurers: final results

	(1)	
	log_return	
L.log_return	-0.179	(0.355)
L2.log_return	-0.248***	(0.001)
shortterm_rate	0.183*	(0.017)
expected_gdp	0.0792*	(0.038)
shortterm_rate_nonlife	-0.152*	(0.021)
_cons	-0.0756	(0.339)
N	200	
j	23	
ar2p	0.0489	
hansenp	0.990	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This time the interaction term is significant at the 5% significance level. It follows that life-insurance companies are effected much more by the short-term interest rates than non-life insurance companies, by 15.2 percentage points more on average. That is, the effect of short-term interest rates is really high for life insurance companies, estimated to 18.3 %, and quite low for non-life insurance companies, estimated to $18.3 - 15.2 = 3.1\%$. There are 23 instruments, so the number of instruments is slightly lower than the number of insurers in the sample, which is 25.

Let us also examine the results of the Arellano-Bond test for zero autocorrelation in first-differenced errors, the Hansen test of overidentifying restrictions and the difference-in-Hansen tests of exogeneity of instrument subsets. The Arellano-Bond test for zero autocorrelation in first-differenced errors, whose p-value is reported in Table 5.5 as *ar2p*, yields a p-value slightly lower than 0.049. Nevertheless, it is just microscopically lower than 0.05 and additionally, if the interaction term was not included, the p-value would be even higher than 0.10. So we will not consider it a big problem. The Hansen test and the difference-in-Hansen tests are not reported here but they do not reveal any problematic issues as their p-values are high. Stationarity should be secured by the way in which we transformed the data at the beginning. Hence the assumptions of the Blundell-Bond estimation technique are met.

Let us also have a look at banks. We will use the same procedure again. The results after excluding a jointly insignificant group of variables are in Table 5.6.

Table 5.6: System GMM for banks: significant variables

	(1) log_return	
L.log_return	-0.0757	(0.293)
L2.log_return	-0.273***	(0.000)
shortterm_rate	0.0785***	(0.000)
expected_gdp	0.125***	(0.000)
_cons	-0.258***	(0.000)
N	442	
j	23	
ar2p	0.314	
hansenp	0.816	

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The set of the variables that appear in the regression is the same as the set that appeared in the regression for insurance companies, with the same signs of the beta coefficients. An increase in the short-term interest rates by 1 percentage point leads, *ceteris paribus*, to an average increase in banks' stock prices by 7.9 %.

In Table 5.7 we add an interaction term, called *shortterm_rate_glob*, which is created as the product of the differenced short-term interest rate and the dummy variable saying whether an institution is a global bank.

Table 5.7: System GMM for banks: final results

	(1) log_return	
L.log_return	-0.0743	(0.330)
L2.log_return	-0.278***	(0.000)
shortterm_rate	0.0847**	(0.001)
expected_gdp	0.126***	(0.000)
shortterm_rate_glob	-0.0357	(0.534)
_cons	-0.261***	(0.000)
N	442	
j	24	
ar2p	0.382	
hansenp	0.814	

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Although the new variable is insignificant, it indicates that regional banks are influenced more by changes in short-term interest rates than global banks. It is intuitive because global banks are not so dependent on interest rates developments in the country of their headquarters. In case of a 1 percentage point decrease in short-term interest rates, equity prices of regional banks are estimated to decrease by 8.5 %, while equity prices of global banks by $8.5 - 3.6 = 4.9\%$. The number of instruments is 24 and this is much less than the number of banks which equals 57.

The Arellano-Bond test for zero autocorrelation in first-differenced errors, the Hansen test of overidentifying restrictions and the difference-in-Hansen tests of exogeneity of instrument subsets suggest that the underlying assumptions are not violated because their p-values are very high. Hence the estimation results can be considered reliable.

Chapter 6

Conclusion

In this thesis we analyzed how interest rates influence equity prices of banks and insurance companies in Europe. In the past years, central banks in Europe decreased policy rates and used quantitative easing to stimulate economic growth. However, both decreasing policy rates and using quantitative easing cause decreases in interest rates and therefore create a low yield environment. We employed static and dynamic panel data models in which we determined and quantified the effects of decreasing interest rates on life and non-life insurance companies, and on global and regional banks. In contrast with most of previous papers on this topic, we conducted the analysis using equity prices instead of profitability indicators. We also collected data for each individual institution rather than aggregate data for the whole sectors. Furthermore, we analyzed banks and insurers using the same methodology which makes direct comparisons possible.

Based on the models presented in the thesis, both banks and insurers are negatively influenced by decreases in short-term interest rates. On the other hand, decreases in long-term interest rates do not impact banks and insurers in a statistically significant way. Changes in short-term interest rates influence life insurers more than banks, and banks more than non-life insurers. The reason why life insurers are influenced more than banks and non-life insurers lies in the fact that life insurers operate with considerably negative duration gaps. So, when interest rates go down, investment opportunities become less profitable while the interest paid to the customers often stays at a high level. It has an adverse impact on profits, and lower expected profits are subsequently reflected in equity prices.

According to the results of the dynamic panel data models which were estimated using the Blundell-Bond system GMM estimaton technique, a decrease in the short-term interest rate by 1 percentage point leads, *ceteris paribus*, to an 8% average decrease in equity prices of banks. The impact of short-term interest rates does not differ significantly for global and regional banks—regional banks are effected only slightly more. On the other hand, the impact on life insurers is much bigger than the impact on non-life insurers. In case of life insurers a decrease in short-term interest rates leads to an 18% decrease, while in case of non-life insurers to a 3% decrease. Regarding the behaviour of control variables, expected GDP growth was shown to have positive impacts on both banks and insurers, while inflation rate had negative impacts based on the models.

The negative impact of decreasing short-term interest rates on equity prices of financial institutions was shown also by the random effects model, which turned out to be the best model out of static panel data models. However, the autocorrelation assumption was violated in case of the random effects model. In contrast, all of the underlying assumptions are met in case of the dynamic analysis. That is why we consider the dynamic panel data models based on the Blundell-Bond estimation technique more reliable. The technique was found appropriate also in papers dealing with similar topics, such as Dorofti and Jakubik (2015). In this paper by Dorofti and Jakubik, a positive relationship between interest rates and profitability of insurance companies was found, which is in accordance with results obtained in the thesis. The results obtained in the thesis are also in accordance with Moss & Moss (2010) who found a positive relationship between short-term interest rates and equity prices of banks, while they did not find a significant relationship between long-term interest rates and equity prices of banks. On the other hand, Akella & Chen (1990) found a positive relationship between long-term interest rates and bank equity prices, while they did not find a significant relationship between short-term interest rates and equity prices of banks. Hence, this thesis rather supports the conclusions of Moss & Moss (2010).

A policy implication is that when short-term interest rates are to be decreased by central banks through decreasing policy rates or through quantitative easing, the impacts on insurance companies and banks should be taken into account as a cost of these measures. Regarding a suggestion for future research, it would be interesting to examine whether the relationship of interest rates and equity prices of insurers has changed after the Solvency II Directive came into effect in January 2016. The Solvency II Directive is likely to influence the sensitivity of profitability to interest rates because insurance companies are forced to reflect more their risk profiles.

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Appendix

Figure A.1: Log returns by institutions