LAZARSKI UNIVERSITY

Faculty of Economics and Management

RELATION BETWEEN HOME BIAS AND FINANCIAL STABILITY OF EUROPEAN UNION COUNTRIES

Związek między uprzedzenie krajowe i stabilność finansową krajów Unii Europejskiej

International Business Economics

REUTOV OLEKSII
38285

Master Thesis
Professor Bogna Gawrońska-Nowak

Warsaw 2016

Statement of originality

DECLARATION

This work has not previously been accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

Signed (Reutov Oleksii)

Date

STATEMENT

I, being aware of all the applicable consequences, declare that the submitted dissertation, titled in

English and Polish, is the result of my own work and research.

Additionally, I declare that the dissertation does not infringe on any copyrights in accordance with the act on copyright and neighboring rights, nor does it infringe on any personal rights as protected by civil law.

I also declare that the submitted work does not contain data and information obtained by me in a forbidden manner.

I also confirm that the submitted dissertation is identical with the attached electronic version of it.

Signed (Reutov Oleksii)

Date

Abstract

In this thesis, the relation between home bias and financial stability of countries of the European Union is analyzed. The investigated hypothesis is as follows: the relation between home bias and financial stability is statistically significant after taking into account some controllable variables' influence. As it is shown in this work, home bias is not simply the difference between actual and optimal portfolio held, as it was seen sometimes by rational economists, but it is also a profound and complex feature of the modern financial world that can be influenced by other economic processes and can influence them too. For example, home bias and its changes are influenced by financial stability, and financial stability is influenced by home bias (financial stability changes are not influenced by home bias). To testify the hypothesis, home bias and financial indexes are developed because the existing home bias measure and exchange market pressure index do not satisfy requirements of this work. The following variables are components of indexes: assets and liabilities of the international investment position, the interest rate, the interest rate spread, the secondary income account balance, and the real exchange rate. The aggregation of appropriate variables into one index variable is done by principal component analysis (PCA) methodology, while the statistical significance of the relation is tested on a panel data of ten countries of the European Union that have the consistent data: Austria, Czech Republic, German, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and the United Kingdom. The hypothesis is proved showing that the relation between home bias and financial stability indexes is usually positive. However, it is also demonstrated that the strength of the relation depends on groups of countries, and there is a possibility that it can be even negative in some cases.

Table of Contents

List of Tables and Figures

Key to Abbreviations

AIIP – Assets of international investment position.

HB – home bias.

HBI – home bias index.

FSI – financial stability index.

IMF – International Monetary Fund.

IR – interest rate.

LIIP – liabilities of international investment position.

OECD – the Organization for Economic Cooperation and Development.

PCA – principal component analysis.

PIGS – the group of follows countries: Portugal, Ireland, Greece, Spain.

RER – real exchange rate.

SI – secondary income account.

SP – interest rate spread.

UK – the United Kingdom.

Introduction

Home bias has been investigated very carefully, but it is still not well researched. The issue is complex and requires considering the decision-making process of portfolio investments, the rational behavior of investors, and the development of economic crises. There is no even a single formula for home bias estimation that should be the first step to be taken in any research. However, the home bias paradox and effective allocation of resources became important economic processes after the global financial crisis in 2008. It caused the introducing of austerity programs whose goals are to balance the fiscal budget and to lower the government debt that raised the question about possibility of foreign investments in such tough times for domestic countries. Such processes are closely connected with home bias which could be one of the crises causes due higher level of foreign investment. At the same time, home bias could be also the instrument to lower the spillover effect from external financial shocks through lowering financial interaction with foreign markets (Shinagawa 2014).

The proof for the existence of this relation is determined as the main goal of the thesis investigation, while the investigated hypothesis is described as follows: the relation between home bias and financial stability is statistically significant after taking into account some control variables. Additionally to existence of statistical significance between two processes, it is also important to identify the prevailing sign of the relation between home bias and financial stability: whether it is positive and the home bias and financial stability are moving in one direction or it is negative and home bias and financial stability are moving in different directions (home bias grows while financial stability falls or vice versa). To investigate the statistical significance of the relation, the indexes of home bias and financial stability are designed. The home bias index aims to estimate the relative level of investments into foreign assets and their profitability, while financial stability index is to estimate the relative level of stability from financial exogenous shocks.

European countries and theirs home bias and financial stability are identified as the subject of research due to historical and geographical connections between countries. However, a lot of countries have inconsistence in the data; thereby, the analysis is done only for ten countries of the European Union that have the consistent data: Austria, the Czech Republic, German, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and the United Kingdom. For indexes' calculations, the data from EUROSTAT and OECD databases and data from Bloomberg terminal are used. From the first database the following data are used: assets and liabilities of the international investment position, real exchange rate, interest rate, and secondary income account balance, while from the second database are taken quarter and annual changes of real gross domestic product changes. Bloomberg is used for stock exchange index information. The data is used on quarterly basis from first quarter of 2014 till the third quarter of 2015 (the last datapoint for real exchange rate).

The work has four chapters. In the first chapter, general issues that are connected with home bias index (definitions, trends, advantages and disadvantages of measure etc.) are described. The second chapter presents home bias and financial stability indexes. They have been designed using principal component analysis methodology due to problems of the existing measures of home bias and exchange market pressure – it is used for crisis' identification. In the third chapter, the analysis of designed home bias and financial stability indexes is presented and it is identified that they have positive correlation. Thereby, the hypothesis is modified for checking a strictly positive relation between designed indexes. In the fourth and final chapter, the hypothesis is verified on a panel data of the ten European countries.

Chapter 1. Home Bias: Definition, Measuring, and Impacts

1.1 Home bias concepts and trends

The market portfolio theory is based on the conception of diversification and that investors -versify their investments efficiently (Cooper & Kaplanis 1994; Gruber 2003). According to diversification conception, it is possible to minimize the risk of individual assets through systematic risk reduction or, in other words, to minimize the risk that is not unique for the securities from investors' portfolio. It is possible due to different covariation[1] between assets that will lower the risk of portfolio (while risk of assets and portfolio is measured by standard deviation[2]), if the covariation between assets is mostly negative. The main goal of the market portfolio theory is the determination of assets weights for investors' optimal portfolio. In this case, the optimal portfolio implies the portfolio which can generate proper expected return with the lowest risk or standard deviation. In general, it is understandable that each investor should have the own portfolio structure; however, it is theoretically possible to create methodology that should help to determine the weights in an optimal way due to obscurity of people's decision that is proper for an average or a rational investor.

The same conception can be applied not only to general asset combination but also to allocation between portfolios of domestic and foreign assets – this task can also be optimized. Fig. 1.1shows the artificial market portfolio of two assets: the foreign portfolio with 2% expected return and 1%

---

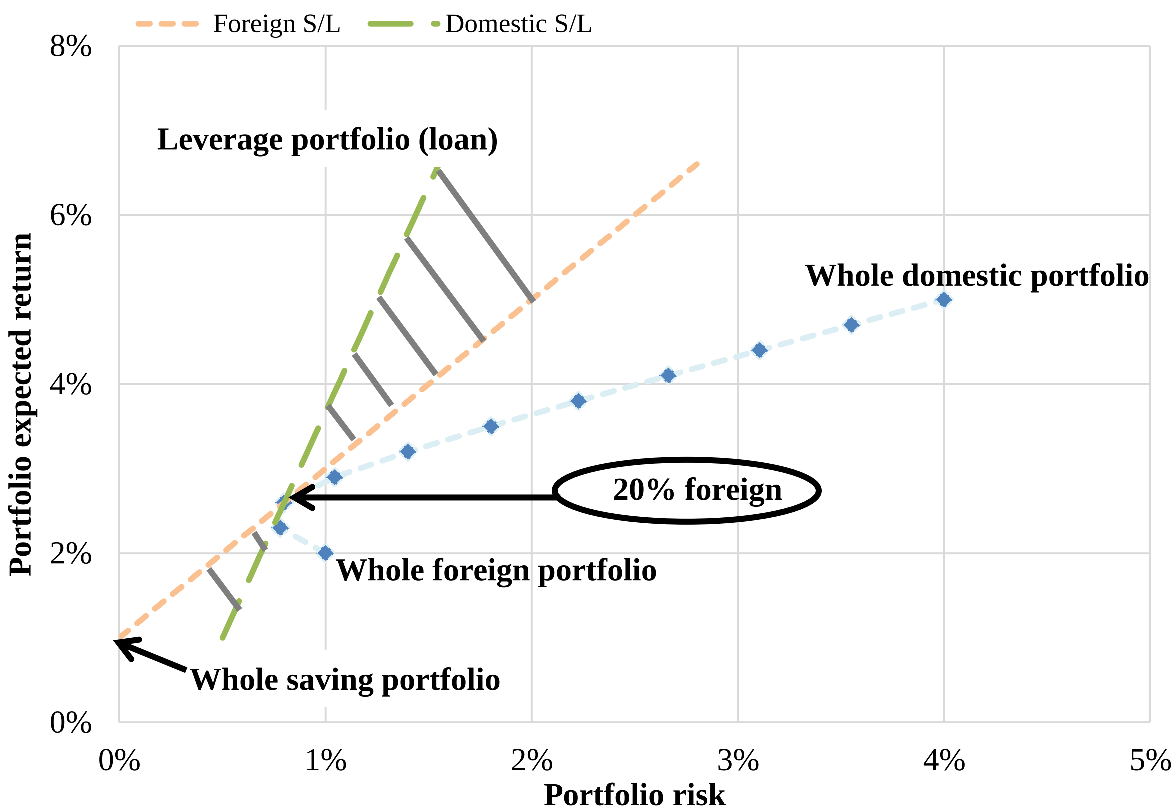
[1] $Covariance\ between\ two\ assets = \mathrm{cov}_{ij} = \frac{1}{n-1}\sum_{t=1}^{n}(x_{it} - \bar{x}_i)(x_{jt} - \bar{x}_j).$

[2] $Standard\ deviation\ of\ asset = \sigma_i = \frac{1}{n-1}\sum_{t=1}^{n}(x_{it} - \bar{x}_i)^2\ ;$

$$Standard\ deviation\ of\ portfolio = \sigma_{por} = \sqrt{\sum_{i=1}^{n} w_i^2\sigma_i^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \mathrm{cov}_{ij}}.$$

standard deviation and the domestic portfolio with 5% expected return and 4% standard deviation. As it could be seen in this artificial example, the whole foreign portfolio is the worst possible portfolio to choose because there is one more portfolio that generates higher expected return with the same risk (standard deviation) that can be reached through including domestic assets into whole foreign portfolio (in this example, it is assumed that correlation between two portfolio is equal to minus 0.5 or, in other words, it is negative but domestic and foreign portfolios are not fully uncorrelated).

Fig. 1.1 Portfolio theory description.



Source: author’s calculations.

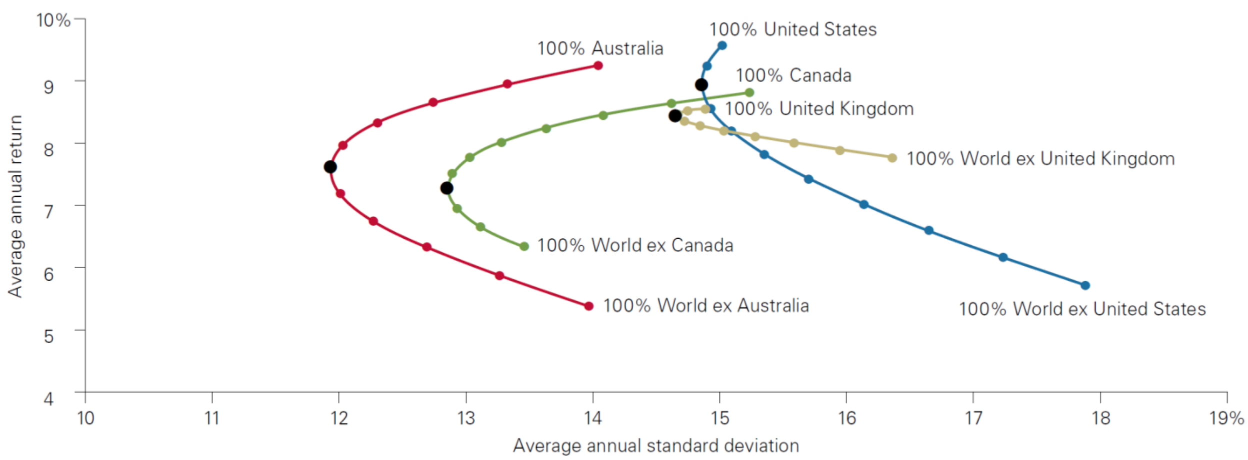
However, even the whole domestic portfolio is also the sub-optimal portfolio (portfolio that is worse than optimal) in the case, if there is possibility to take loans or make deposits (Omisore, Yusuf & Christopher 2012). Loans create additional possibilities to earn higher expected return with a usage of leverage, investing with borrowed capital. There are some implicit assumptions about deposits and loans for this artificial example. At first, the interest rate on deposits and loans is the same and is equal to risk-free rate and deposits and loans are not part of decision process about portfolio creation. Secondly, the free-risk interest rate is the same in any country (whether domestic or foreign). Finally, there are no limitations in making deposits or taking loans and a higher level of leverage increases risk linearly, even though de Martel, Holmes, and Gemelou (2015) showed that in some conditions is not so, and risk function from leverage has rather exponential function dynamics.

As it is shown in Fig. 1.1, the whole sets of risk and expected return of portfolio can be found between the “Foreign S/L” and “Domestic S/L” lines. It is the solution, of course, if the assumptions about the same interest rate for loans and deposits inside one country and linear risk function for savings/loans portfolio remain relevant. From this theoretical and artificial example, it can be assumed that saving is better to do in foreign countries, but the loans are better to take in a domestic country. As it can be seen from Fig. 1.1, “Foreign S/L” line is higher than “Domestic S/L” line to the left side of the portfolio with the lowest risk and it implies that it is possible to get the higher interest rate with the same standard deviation, if savings are done in foreign markets; however, the situation is different to the right side of the minimal risk portfolio and, thereby, loans are better to take on domestic markets. All that leads to *home bias paradox*[3]*:* the weights of domestic assets in portfolio are not equal to optimal worldwide portfolio weights because, due to some circumstances in environment (like discussed above for loans and deposits), domestic investors look for domestic assets in a more preferable way than foreign investors. Thereby, the global fully-diversified portfolio is not reachable: without foreign assets, it is

[3] It is a phenomenon or puzzle from the perspective of the market portfolio theory).

impossible to diversify foreign systemic risk and investors lose money from missed opportunities.

However, the allocation of portfolio on foreign and domestic that was described above is not actually artificial because the same results were received on the basis of the actual data for different countries (Philips, Kinniry & Donaldson 2012). As it is shown in Fig.1.2, the whole foreign portfolio is actually less risky than the whole domestic portfolio, but it is not the best option. In this graph, domestic returns are represented by the MSCI USA Index, MSCI U.K. Index, MSCI Australia Index. Foreign ex-domestic returns are represented by MSCI All Country World ex country indexes for the United States, U.K., and Australia. Because a comprehensive index for global equities ex Canada is not available from Thomson Reuters, the MSCI EAFE Index with the MSCI Emerging Markets Index and the MSCI USA Index (all indexes are presented in Canadian dollars) were used to get the data for Canada. Black point in each series in Fig.1.2 represents the portfolio with the lowest average volatility from 1988 through 2011.



Sources: Philips, Kinniry & Donaldson (2012).

However, it is not the best option according to market-capitalization optimality weights approach – in this case, investors should construct their portfolio in line with the global market capitalization. For example, UK equities accounted for 8.6% of the global equity market as of 31 December 2011 (Philips, Kinniry & Donaldson 2012); however, Fig.1.2 shows that the best option according to risk-minimization measure is closer to 100% domestic portfolio than to 100% foreign portfolio, as it can be assumed from market-capitalization measure. The historical minimum-variance allocation into foreign equity portfolio (using 1988-2011 period) should be equal to 20% for UK investors (Philips, Kinniry & Donaldson 2012), the same 20% foreign allocation is enough for US investors, while the foreign allocation should be equal to 50% for Australia investors and 70% for Canadian investors (black points). The work of Foad (2012) also shows differences in results from two approaches, but data only till 2004 are used and his results are incomparable with the last results.

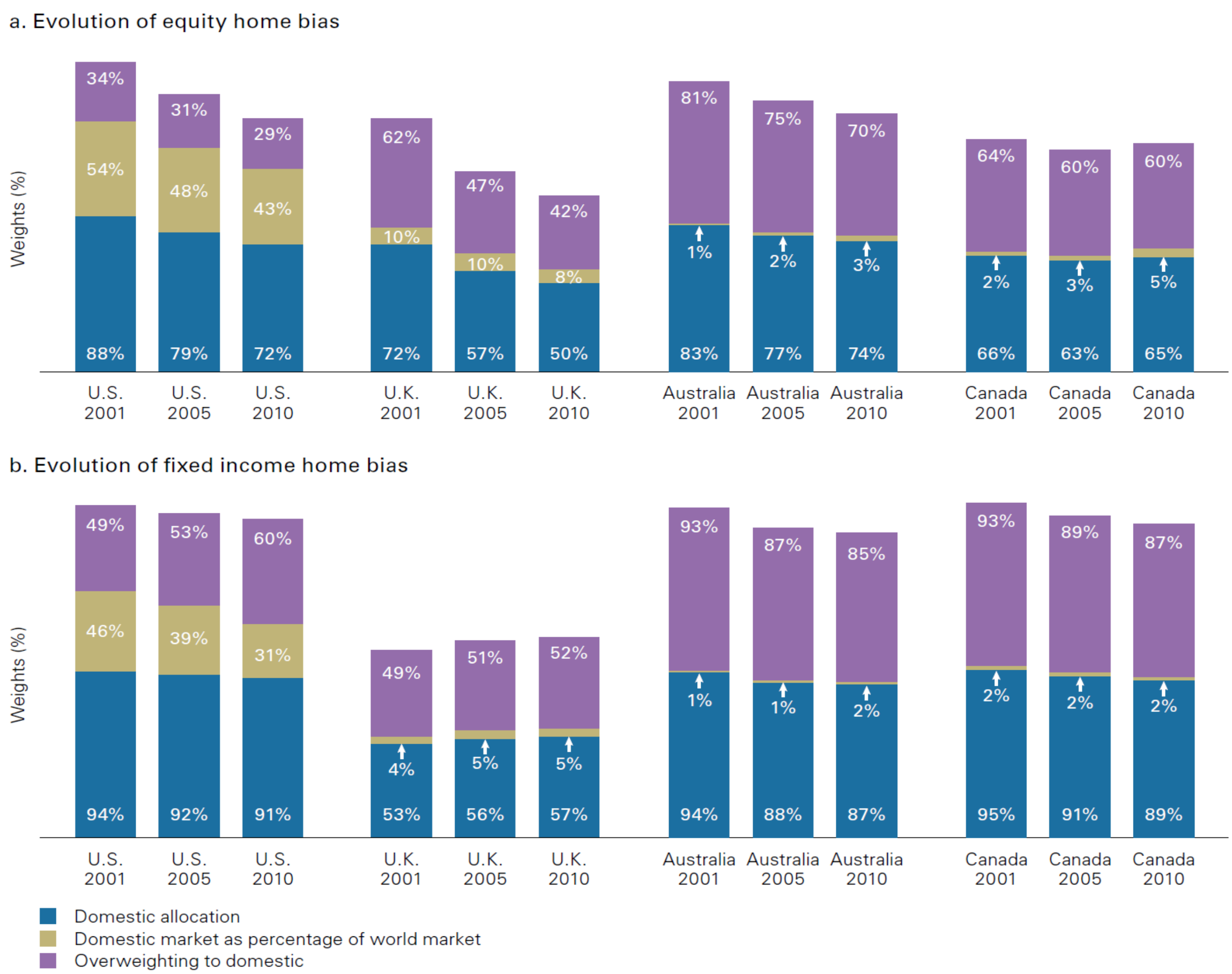
Table.1.1Evolution of Equity home bias.

Countries	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Belgium	73.3	72.1	70.9	69.4	49.1	47.6	42.3	38.2	40.5	42.6	44.2	45.1
Denmark	65.2	64.3	63.1	64.3	62.2	58.9	56.5	56.1	55.4	54.8	55.9	57.2
Finland	97.5	97.4	96.8	97.9	97.8	93.4	94.2	58.8	54.0	47.5	49.3	55.2
France	92.9	93.3	94.9	86.1	85.3	89.5	90.2	60.8	62.1	64.5	65.1	66.0
Germany	81.9	83.7	84.2	85.4	54.6	52.3	49.2	51.1	50.3	49.9	51.1	53.2
Italy	97.3	84.6	82.2	84.7	87.4	88.1	89.7	50.6	52.9	54.2	55.3	57.9
Netherland	56.6	52.1	49.4	43.3	30.8	38.5	43.5	12.2	23.7	34.0	35.8	38.7
Portugal	94.1	89.3	87.1	85.3	77.7	70.1	52.9	27.9	40.2	55.8	57.1	59.2
Spain	98.1	96.2	95.6	95.6	95.5	95.2	92.1	81.3	85.3	89.0	89.9	91.3
Sweden	86.3	82.7	78.3	73.8	58.4	57.6	56.4	52.1	53.6	55.1	57.1	58.2
UK	32.9	39.7	52.0	48.4	48.1	49.2	52.7	53.1	55.9	58.7	60.4	62.1
US	49.8	52.3	55.7	57.2	58.8	59.7	62.8	55.2	59.5	66.9	67.4	68.6

Sources: Othmani, Saanoun, Garali, and Arab (2014).

More detailed trends of home bias measures are presented in Fig.1.3 and in Table 1.1. As it can be seen from Fig. 1.3, equity home bias lowered in all investigated countries from 2001 till 2010 while fixed income home bias has different trends in different countries. USA and UK are characterized by growing fixed income home bias, while Australia and Canada are characterized by lowering fixed income home bias. At the same time, the data from Table 1.1 show mostly the same trend; however, some data are not correlated with data from Fig. 1.2. This could be due to different datasets. Kim et al. (2014) show the same general trend as other works.

Fig.1.3 Trends in home bias.



Sources: Philips, Kinniry, and Donaldson (2012).

Nevertheless, the trend is not the most important issue. The ratio of domestic allocation to domestic capitalization is very high. The same issue is raised by Kim et al. (2014). For example, the best case is for USA which had the ratio close to 2 in 2001 and close to 3 in 2010 (a higher ratio implies higher home bias). At the same time, the UK, Australia, and Canada have higher ratios due to lower domestic market share as percentage of world market; nevertheless, even developed countries with free capital movement make higher allocation to their domestic portfolio. Additionally, it is necessary to mention that fixed income home bias for the analyzed countries is higher than equity home bias. However, it does not refer only to these countries. In Switzerland, some insurance companies have also higher allocation in foreign equity markets than in the domestic market but lower allocation in foreign fixed income markets than in the domestic ones (PPCMetrics 2015). Moreover, Kim et al. (2014) suggest that the policy for reducing home bias should be more concentrated on fixed-income securities markets because the performance of these markets has higher influence on equity home bias than the performance of equity markets has on fixed income home bias.

1.2 Defining home bias measures

The weights according to market-capitalization approach imply the comparison of the actual foreign portfolio weight of the countries with markets capitalization share of other countries and, thereby, the simplest formula for the equity and debt securities home bias measurement is as follows (Shinagawa 2014):

$$Home\ bias\ of\ i's\ country = HB_i = 1 - \frac{actual\ weights}{optimal\ weights} =$$

$$1 - \frac{share\ of\ country\ i's\ holding\ of\ foreign\ \ security\ in\ country\ i's\ total\ portfolio\ investment}{country\ i's\ market\ share\ of\ the\ world} = \qquad (1.1a)$$

$$1 - \frac{\frac{total\ foreign\ security\ held\ by\ country\ i}{domestic\ equity\ holding\ in\ country\ i + total\ equity\ holding\ in\ country\ i - amount\ of\ country\ i's\ equity\ held\ by\ foreigners}}{1 - \frac{equity\ market\ capitalization\ of\ a\ country\ i}{equity\ market\ capitalization\ of\ the\ world}}.$$

$$Home\ bias\ of\ i's\ country = HB_i = 1 - \frac{actual\ weights}{optimal\ weights} =$$

$$1 - \frac{share\ of\ country\ i's\ holding\ of\ foreign\ debt\ security\ in\ country\ i's\ total\ portfolio\ investment}{country\ i's\ market\ share\ of\ the\ world} = \qquad (1.1b)$$

$$1 - \frac{\frac{total\ foreign\ debt\ security\ held\ by\ country\ i}{domestic\ debt\ security\ outstanding\ in\ country\ i + total\ foreign\ debt\ securities\ in\ country\ i}}{1 - \frac{debt\ security\ market\ capitalization\ of\ a\ country\ i}{debt\ security\ market\ capitalization\ of\ the\ world}}.$$

If actual weights of foreign portfolio are equal to market-capitalization weights (optimal weights), then the home bias will be equal to 0, which implies the absence of home bias. If the actual weights are higher than optimal weights, then the home bias does not exist and the measure according to the equations (1.1a and 1.1b) will take the negative values from 0 to infinity; however, it is the sign of data problem because such situations mostly cannot be met in real world data. The home bias is presented when the actual weights are lower than optimal weights. In this case, home bias measure will take the value between 0 and 1, where the value of 1 implies that the country has no foreign investments and its investors are concentrated only on domestic investments (full home bias). For example, if the actual foreign weight is equal to 40% and the optimal weight is equal to 40%, then the home bias will be equal to 0 (no home bias). Or if actual foreign weight is equal to 50% as for the United Kingdom in 2010 (Fig. 1.3) and optimal foreign weight is equal to 92% (Fig. 1.3, 100% minus 8% where 8% is domestic share in world markets), then home bias measure will be equal to 0.46.

The measures according to (1.1a and 1.1b) estimate home bias only through comparing weights of actual and optimal foreign portfolios (i.e. 40% actual foreign portfolio and 50% optimal foreign portfolio). However, some researches need a more precise measure that will compare not only home bias estimation as a whole but also its measure across the industries. Such home bias measure is called the industry concentration index by Brushko and Hashimoto (2014):

$$\mathrm{CI}_{i,t} = \sum_{j=1}^{N} (w_{i,j,t} - \overline{w}_{j,t})^2,$$

where

$w_{i,j,t}$ – share of total portfolio investment assets of country *i* invested in country *j* in year *t*;

$\overline{w}_{j,t}$ – region average share of total portfolio investments assets invested in country j.

This equation has one disadvantage: it compares the investment into industries of a country with average across region, and it does not show if the investments are higher or lower than average (it is so due to the presence of squares in formula). Thereby, this equation usage is rather limited for research purposes.

However, optimal weights could be calculated not only through market-capitalization approach. Generally, the formula for home bias measure is as follows (Mishra 2015):

$$Home\ bias\ of\ i's\ country = HB_i = 1 - \frac{Actual_i}{Optimal_i}, \tag{1.2}$$

$$Actual_i = \frac{Foreign\ Assets_i}{Foreign\ Assets_i - Foreign\ Liabilities_i + Market\ Capitalization_i}. \tag{1.3}$$

Equations (1.2) and (1.3) are the same as the first half of equations (1.1a) and (1.1b) and, thereby, it has the same logic behind values. However, the optimal weights for equation (1.2) could be identified through other methods, i.e. minimum-variance allocation, capital asset pricing model, or international capital asset pricing model.

According to international capital asset pricing model approach, the optimal weights should be calculated from the coefficients of the following equation (Mishra 2015):

$$R_D - R_f = \beta_0 + \beta_{MR}(R_F - R_f) + \beta_{FR}(E_F - E_D) + \varepsilon, \tag{1.4}$$

where

ε – error term;

R_D, R_F, and R_f – expected returns for domestic portfolio, foreign portfolio, and free-risk return;

β_0, β_{MR}, and β_{FR} – coefficients that described the risk differentiation: general risk, market risk, exchange rate risk accordingly.

The β-coefficients of equation (1.4) are estimated using ordinary least-square method. Through these coefficients, the optimal weights (β-coefficient shows the ratio between foreign and domestic portfolios) are calculated to be used in equation (1.2).

However, if the optimal foreign portfolio is calculated according to some mathematical algorithms, then there is the risk of receiving a low value of optimal weights or even a negative value (the investors should take a short-position). In this case, actual weights will exceed the optimal value and it will appear that the country is not home-biased, but, on the contrary, it is overinvesting in foreign countries. For example, if the actual foreign portfolio is 50% (the UK case in 2010 according to Fig. 1.3.) and the optimal weight is equal to 20% (due to minimum-variance allocation), then home bias measure according to equation (1.2) will be equal to -1.5 (minus one and half), which is much lower than home bias measure value according to equation (1.1a) and it misleads. To solve this issue, Baele, Pungulescu and Ter Horst (2007) proposed to use the following formula:

$$Home\ bias\ of\ i's\ country = HB_i = \frac{\min(|Optimal_i|Actual_i)}{\mathrm{sign}(Optimal_i)\max(|Optimal_i|Actual_i)} - 1. \quad (1.5)$$

This measure will be equal to 0 when optimal foreign weights are equal to actual foreign weights, the same as in equations (1.1a), (1.1b), and (1.2). But it will be equal to -1 not +1 if there is the full home bias situation (no foreign portfolio). According to equation (1.5), the value of home bias measure in the presented example will be equal to -0.6 (minus zero point six) that is closer by module to 0.46, the initial UK's case calculations. Additionally, formulae (1.5) will return results lower than -1 (full home bias), if the short-position is assumed by optimal weight calculation. For example, if optimal weight is equal to -5% (the country should take loan and invest more in domestic portfolio) and actual weight is equal to 50%, then home bias measure according to equation (1.5) will be equal to -1.1, which gives more consistency than home bias measure according to equation (1.2).

Kim et al. 2014 propose one more approach to calculate actual weights instead of equation (1.1a), (1.1b), and (1.3):

$$Actual_i = \frac{Market\ Capitalization_i - Capital\ Inflow_i}{Market\ Capitalization_i - Capital\ Inflow_i + Capital\ Outflow_i}.$$

The home bias should not be measured only through above-mentioned approaches. Collard, Dellas, Diba, and Stockman (2007) show that foreign equity shares in an economy are highly correlated with import to gross domestic product share for the period from 1995 till 2004: the correlation is equal to 92.2%. Thereby, foreign investments can be also measured through international trade. In this case, it is possible to use the following formula for home bias benchmark estimation (Balta & Delgado, 2007):

$$Frictionless\ Economy\ Benchmark_i = \frac{Production_i - Exports\ to\ non\ OECD\ countries_i}{Total\ OECD\ production - Total\ exports\ to\ non\ OECD}. \quad (1.6)$$

If $Frictionless\ Economy\ Benchmark_i$ from equation (1.6) that describes the share of the country production in OECD production is equal to domestic share of good and services consumption, then the country is not home biased (the difference cannot be higher than 1 and cannot be lower than -1). If the value is negative, then foreign bias exists, while positives values imply home bias. Such a relation exists due to the indirect connection between home bias and costs of trading: if a country is not home-biased then there are no trade frictions and no additional costs from trading, and all customers have equal access to markets and have no preferences for origin country of goods. Under this assumption, it is possible to approximate the country's share in consumption basket of any country by the share of its goods in the production basket of the OECD countries.

$$Frictionless\ Economy\ Benchmark_i = \frac{Market\ capitalisation_{\ i}}{\sum_{j \in OECD} Market\ capitalisation_{\ j}} \tag{1.7}$$

The same conception can be used for equity market too (Balta & Delgado, 2007). The equation (1.7) is similar to optimal weights calculation in equation (1.1) but only for the OECD countries. Then $Frictionless\ Economy\ Benchmark_i$ must be compared with actual equity domestic share as it was done for equation (1.6) – negative values also imply foreign bias, while positive values imply home bias.

However, there is also Integrated Economic Benchmark that is the more profound version of Frictionless Economy Benchmark. At first, it is necessary to estimate a standard gravity trade equation (Balta & Delgado, 2007) according to which the trade volume between two countries is related to the economic size of countries (nominal gross domestic product, GDP) and the distance between two countries. Additionally, it is possible to use other factors as input for model. For example, in equation (1.8), home bias "dummy"-variable is used. The variable takes value 1 for domestic trade and value 0 for the trade of other countries.

$$X_{ij} = \alpha_1 + homebias + \alpha_2 GDP_i + \alpha_3 GDP_j + \alpha_4 dist_{ij} + u_{ij}, \tag{1.8}$$

where

X_{ij} – trade volume between *i*-th and *j*-th countries;

α_i – *i*-th coefficient of the model that can be estimated by ordinary least-square method;

GDP_i – nominal gross domestic product of *i*-th country;

$dist_{ij}$ – distance between *i*-th and *j*-th countries;

u_{ij} – error term of trade value estimation between i-th and j-th countries.

Using the coefficients estimated from equation (1.8), it is possible to estimate the home products demand in the absence of home bias according to equation (1.9) and Integrated Economic Benchmark according to equation (1.10).

$$Estimated\ demand\ of\ home\ products\ in\ the\ absence\ of\ home\ bias =$$

$$= X_{ij} = \hat{\alpha}_1 + \hat{\alpha}_2 GDP_i + \hat{\alpha}_3 GDP_j + \hat{\alpha}_4 dist_{ij} \tag{1.9}$$

Actually, equation (1.9) is the same equation as (1.8) from which estimated home bias influence is deleted. That gives the possibility to estimate the share that is missing after home bias effect exclusion.

$$Integrated\ Economic\ Benchmark = \frac{Value\ from\ equation\ (1.9)}{Value\ from\ equation\ (1.8)} \tag{1.10}$$

Integrated Economic Benchmark estimates the level of home bias: value 0 implies the extreme home bias level while value 1 implies the absence of home bias. The same calculation can be done for investment home bias, when the cross-border equity holdings are used instead of the trade volume (Balta & Delgado, 2007) in equation (1.8). In this case, the equation (1.8)-(1.10) will take the form of equation (1.11)-(1.13).

$$E_{ij} = \alpha_1 + homebias + \alpha_2 GDP_i + \alpha_3 GDP_j + \alpha_4 dist_{ij} + u_{ij} \tag{1.11}$$

$$Estimated\ holdings\ of\ home\ equity\ in\ the\ absence\ of\ home\ bias =$$

$$= X_{ij} = \hat{\alpha}_1 + \hat{\alpha}_2 GDP_i + \hat{\alpha}_3 GDP_j + \hat{\alpha}_4 dist_{ij} \tag{1.12}$$

$$Integrated\ Economic\ Benchmark = \frac{Value\ from\ equation\ (1.12)}{Value\ from\ equation\ (1.11)} \tag{1.13}$$

The last but not least important option to measure home bias is the method that relies on usage of return differences. The main idea of the method is to separate individual country's effect that is not related with the effect of the other countries (Maier & Scholz, 2016). This methodology recalls the methodology behind event studies. At first stage, it is necessary to estimate the model of excess stock-market returns of each country with ten industries excess returns as model inputs:

$$r_{d,t} = \alpha_d^{10F} + \sum_{j=1}^{10} \beta_{d,j} r_{j,t}^{E} + \varepsilon_{d,t}^{10F}, \tag{1.14}$$

where

$r_{d,t}$ – the excess return of country index *d* in month *t*;

$r_{j,t}^{E}$ – the excess return of European industry *j* in month *t*;

α_d^{10F} – the abnormal performance of a country index against the ten European industries (coefficients, can be estimated using ordinary least-square method);

$\beta_{d,j}$ – sensitivity of country index *d* to *j*-th European industry (coefficients, can be estimated using ordinary least-square method);

$\varepsilon_{d,t}^{10F}$ – error term of country index *d* in month *t*.

At the second stage, the country factor C_t^0 is calculated by adding α_d^{10F} and $\varepsilon_{d,t}^{10F}$. Then, the follow model is used to estimate the coefficient near country factor:

$$r_{c,t} = \alpha_c^{20F} + \beta_c^{MKT} MKT_t + \beta_c^{SMB} SMB_t + \beta_c^{HML} HML_t + \beta_c^{MOM} MOM_t + \sum_{d=1}^{16} \gamma_{c,d} C_{d,t}^0 + \eta_{c,t}^{20F}, \tag{1.15}$$

where

$r_{c,t}$ – excess return of fund portfolio *c* in month *t*;

MKT_t – excess return of the European market factor in month *t*;

SMB_t – return of the European size factor in month *t*;

HML_t – return of the European value factor in month *t*;

MOM_t – return of the European momentum factor in month *t*;

$\eta_{c,t}^{20F}$ – error term of fund portfolio *c* in month *t*.

Coefficient of the model $\gamma_{c,d}$ describes the fund portfolio *c* relation to the European market *d*. The positive coefficient $\gamma_{c,d}$ implies the overweighting of the European market *d*. According to Maier and Scholz (2016), "if *d* is fund portfolio *c*'s domicile, we interpret the overweighting of the domestic market – in the spirit of the existing home bias literature – as home bias index and label it with $\gamma_{c,d}^{HB}$". It is one of the most sophisticated methods of home bias estimation that can give interesting results that would not be possible to calculate by any other measure.

1.3 Research results on home bias

There are a lot of studies that investigated home bias paradox from different sides in one or another way. Generally, the results are not unanimous because each country has differences and it is possible to identify only one cause of home bias existence in each case. Nevertheless, it is possible to see some trends in home bias analysis through systematization of studies.

Home bias is simply excessive investments in domestic markets in comparison to its share of global market capitalization (French & Poterba, 1991) that has negative influence on the economic development. According to the financial theory, home bias leads to lower ratio expected return by standard deviation due to lack of international diversification (Sharpe 1964, Lintner 1965, French & Poterba 1991). For example, LaBarge (2008) found that diversification is still relevant across countries and sectors. At the same time, according to the macroeconomic theory, home bias implies sub-optimal international risk-sharing for investments (Lewis 1991). Thereby, studies of home bias had been done mostly in this direction with the following possible solutions of this puzzle:

- ✓ Higher return explanations (French & Poterba 1991; Fidora, Fratzscher & Thimann, 2006). It is possible to expect that higher expected returns on domestic market will influence investor's decision about investing level in domestic markets. Nevertheless, it is necessary to see also risk-measures for expected return adjusting and not to forget about diversification of systemic risk: domestic securities cannot diversify country risk.
- ✓ Hedging possibilities against domestic risk (Adler & Dumas 1983; Sercu & Vanpée 2007). Very often, investors do not believe in possibilities to hedge domestic risk or even do not want to take model-risk: risk of potential loss that is caused from models that was used for hedging strategy designing. Thereby, investors must make higher investments into domestic markets to replace lost opportunities from diversification absence.
- ✓ Trading costs, taxes, and border control barriers (Glassman & Riddick 2001; Warnock &Cleave 2002; Jeske 2001). The limitations of capital movements influence hugely the investments in foreign countries. It is possible to expect that higher limitation implies higher home bias; however, it is not so generally (Gordon & Gaspar 2001): higher costs imply lower home bias because more investors try to avoid investment in local markets due to government's constraints that are caused by accumulated imbalances in economic.
- ✓ Governance (Dahlquist, Pinkowitz, Stulz & Williamson 2003). Bad governance of companies must divert investor from these companies. However, it is also possible that bad governance is accompanied with low transparency and low information quality. In this case, bad governance could not be estimated correctly, and that will lead to bad investors' decision.
- ✓ Information asymmetries (Ahearne, Griever & Warnock 2004). Information asymmetries have generally the same effects on investors' decision as if they are made in environment with limited or low-quality information: higher asymmetries lead to "bad" decisions and, therefore, it can lead to higher home bias.

- ✓ Behavioral explanations and expectations (Coval & Moskovitz 1999, Magi 2008). There are a lot of different behavioral biases that can be found in investors' decision-making process, and they are often connected with expectations. For example, investors tend to be more optimistic about their domestic economies than foreign investors (Strong & Xu 2003). Nevertheless, there are issues with estimation of their influence on home bias because behavioral biases and expectations are generally non-measurable variables and their effect is often obscure.
- ✓ Exchange rate volatility (Fidora, Fratzscher & Thimann 2006). Higher exchange rate risk implies high volatility of profitability for companies that are working in different countries. Thereby, exchange rate risk can harm expected return of investors indirectly through the companies that are influenced by the risk or directly through the re-evaluation of foreign portfolio in domestic currency. The same situation as it was described with hedging, investors may not take additional (obscure and often not understandable for them) risk at all instead of looking for a trade-off between diversification advantages and additional risks disadvantages.
- ✓ Cross-border factors and multinational companies (Berill & Kearney 2008). Cross-border factors can be represented by historical or cultural deep connection between two countries along their border line. It can explain partly the home bias puzzle, but this influence is hard to be measured and it seems like it can explain the home bias puzzle only partly. At the same time, investments in multinational companies can be felt by investors as investments in other countries and, thereby, it is possible to diversify portfolio without foreign investments but it is not always so. According to Philips (2012), there is historical evidence that company's performance has been more strongly correlated to domestic market, regardless of the fact where business is conducted.

Some studies of home bias provide us with the following important observations that can be used in actual context:

- *Home bias* is significantly declining due to globalization processes, mutual and index funds, and technological progress (Amadi 2005; Philips, Kinniry & Donaldson 2012; Kim et al. 2014; Foad 2012).
- *Home bias* is higher for fixed income financial instruments than for equities (Fidora, Fratzscher & Thimann 2006; Kim et al. 2014).
- *Home bias* is larger for investors from emerging countries than from developed countries for equities as well as for fixed income financial instruments due to economic development and market performance differences (Coeurdacier & Rey 2013; Kim et al. 2014).
- *Home bias* is larger in countries with larger (real and nominal) currency volatility (Fidora, Fratzscher & Thimann 2006).
- *Home bias* is also the feature for pension funds from the USA and European Union (Hochberg, Rauh & Andonov 2013, Bakker 20013, PPCMetrics 2015).
- *Home bias* is larger in countries with poorer corporate governance (Dahlquist, Pinkowitz, Stulz & Williamson 2003).
- *Home bias* is seen as the instrument to lower spillover effect (and damage, of course) from external financial shock spillovers through lowering financial interaction with foreign markets (Shinagawa 2014) that is very important results for further investigation within this thesis.
- *Home bias* is influenced negatively by market returns, negatively by real GDP growth that confirms size bias, and positively by country leverage that confirms flight to quality (Berill & Kearney 2008).

- *Home bias* of equities market is influenced strongly by bond market performance than vice versa; the policy to build up market efficiency should be conducted mainly around the bond market in order to reduce home bias (Kim et al. 2014).
- *Home bias* lowering can differently influence countries depending on investment types: high-concentration investment type countries (which invest heavily in a particular subset of countries) may look for more profitable opportunities and are more inclined to tolerate risk while low-concentration investment type counties (which invest in a broader set of countries) may look for diversification in the first place (Brushko & Hashimoto 2014).
- *Home bias* in the countries of the Asia region is lowering due to greater financial integration and better regulatory quality (Park & Mercado 2014). In their research, it is also shown that home bias measure according to equations (1.2) and (1.3) lowered with delay home bias against global and regional equities while foreign exchange rate volatility increases equity home bias against regional stocks but not against global stocks.

In Fig.1.4, the influence from home bias factors with their potential impact on individual investors' decision from the United States, the United Kingdom, Canada, and Australia is presented (Philips, Kinniry & Donaldson 2012). The United States is the only country that has only low impact from all investigated factors. But even in this case, investors from the United States invested 28% of equity portfolio as of 2010 into foreign assets (Fig.1.3a), while they should allocate only 20% of their portfolio. They could invest less in foreign assets without high negative effects on profits. UK investors have high potential impact from domestic-issuer concentration and domestic liquidity and moderate impact from domestic-sector concentration and domestic taxes. Therefore, UK's investors invested 50% of equity portfolio into foreign assets in 2010 (Fig.1.3) while, according to minimum-variance allocation, the share should be only 20%. They try to reap the benefits from foreign markets due to issues on domestic markets. At the same time, Canada and Australia invested less than the level provided by minimum-variance allocation (70% and 50% respectively), even though there are the factors with the negative impact (Fig.1.4). Both countries have the low potential impact only from taxes, and Canada has the low potential impact from other domestic market-risk factors. It is obvious that investors from both countries should redesign their portfolio to maximize profitability.

Fig.1.4 Summary of quantitative factors affecting asset allocation.

Sources: Philips, Kinniry, and Donaldson (2012).

Conclusion:

In this chapter, different nuances that are connected with home bias definition and measurement were discussed. Mostly, home bias is defined through differences between actual and optimal investments in foreign countries. For example, if optimal weights of investments into foreign countries are equal to 80%, while actual investment weights are equal to 50% then home bias exists. However, the measure of home bias is not unambiguous due to the following difficulties. At first, the optimal weights can be measured according to market-capitalization approach, minimum-variance allocation, geographical distance between countries, capital asset pricing model etc. Some methods could even imply the negative share for optimal foreign portfolio investments, which means taking a short-position on foreign investments: selling foreign investment without collateral and buying domestic investments on the money inflow from selling. Secondary, home bias can be measured through investment return differences because, if foreign investments are lower in the amount but higher in profitability, then it should be also incorporated into home bias measure; however, it is the more complex task to be solved. Despite all difficulties, there are important results of the studies: home bias has mostly been lowering in the last fifteen years, fixed income home securities home bias is higher than equity home bias, local investors are more optimistic about domestic economies, the performance of fixed income markets has higher influence on equity home bias then the performance of equity markets has influence on fixed income home bias, and higher home bias keeps spillover from external shocks under control. The last result is not investigated enough and, thereby, it was chosen as the topic for this thesis.

Chapter 2. Data and Methodology

The European Union, in particular, and Europe, in general, is interesting for home bias and financial stability relation analysis due to historical and geographical tight connections between countries. However, there are only ten countries from the European Union for which there are no issues[4] with data and home bias and financial stability indexes are calculated: Austria, the Czech Republic, Germany, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and the United Kingdoms. The analysis is made on the basis of quarterly data from the first quarter of 2004, the biggest expansion of European Union, till third quarter of 2015, the last published data for the real exchange rate that is component of financial stability index from the EUROSTAT database[5]. From this database, the following data are taken: assets and liabilities of international investment position, interest rates and interest rate spreads, secondary income account inflow/outflow, and real exchange rate.

For model estimation, the following stock exchanges indexes will be used: WIG[6] for Poland, DAX 30 for German, FTSE 100 for United Kingdom, PX for Czech Republic, RIGSE for Latvia, VILSE for Lithuania, LUXXX for Luxembourg, BUX for Hungary, ATX for Austria, and PSI 20 for Portugal. For example, WIG (Warszawski Indeks Giełdowy) is stock exchange index of income type that is calculated for the longest period on Warsaw Stock Exchange; it is calculated from 16th April 1991. At the same time, DAX 30 (Deutscher Aktienindex) is a blue chip stock market index of the 30 major, in terms of order book volume and market capitalization, German companies that are traded on Frankfurt Stock Exchange; DAX 30 is calculated from 30 th December 1987. And, the stock exchange index of global financial "hub" is called FTSE 100

[4] Detailed information about missing data is presented in Appendix 1.
[5] http://ec.europa.eu/eurostat/data/database
[6] All information about indexes was taken from Bloomberg Terminal due to limited access from free sources.

(Financial Times Stock Exchange). It is the index of 100 companies with the highest capitalization that is traded on London Stock Exchange; the index is calculated from third January 1984[7].

The second control variable is real gross domestic product. Its data source is the site of the OECD[8]. For models estimation, quarter changes of real domestic product (short-term data trend) and annual changes (long-term data trend) will be used.

2.1 Financial stability index

One of most used measures of financial stability is exchange market pressure that is calculated according to the following formula (Heinz & Rusinova 2015):

$$EMP_{i,t} = \gamma_1 \left(\frac{ER_{i,t} - ER_{i,t-1}}{ER_{i,t-1}}\right) + \gamma_2 \left(\overline{IR}_{i,t} - \overline{IR}_{i,t-1}\right) - \gamma_3 \left(\frac{R_{i,t} - R_{i,t-1}}{R_{i,t-1}}\right),$$

where

$\overline{IR}_{i,t}$ – international reserves of country *i* in moment of time *t*;

$ER_{i,t}$ – nominal exchange rate of country *i* in moment of time *t*;

$R_{i,t}$ – money market interest rate of country *i* in moment of time *t*;

$\gamma_1, \gamma_2, \gamma_3$ – weights for the individual components of exchange market pressure.

One of important questions for exchange market pressure is the weighting scheme or, in other words, how the weights for individual components are identified. There are following main weighting schemes: equal weighting schemes (Aizenman, Lee & Sushko 2012, Heinz & Rusinova 2015) and precision weighting scheme (inversely proportional to the variances of components) that are used to prevent the domination of more volatile components (Girton & Roper 1977, Eichengreen et al. 1994). According to Li, Rajan and Willet (2006), the equal

[7] General information about others indexes is presented in Appendix 2.
[8] http://stats.oecd.org/OECDStat_Metadata/ShowMetadata.ashx?Dataset=QNA&ShowOnWeb=true&Lang=en

weighting scheme is recommended to use as an optimal approach reflecting the ignorance on the correct weighting scheme. Heinz and Rusinova (2015) mention that precision weighting scheme also eliminates the effect of cross-countries differences in volatility which could be important for pooled data. At the same time, Pentecost, Van Hooydonk and Van Poeck (2001) use the principal component analysis to estimate the weights of exchange market pressure. They mention two arguments in favor of principal component analysis usage: the signs are not imposed in accordance with a priori beliefs and weights are chosen "to deliver the largest proportion of the system variance" or to aggregate the most information quantity of components comovement in the designed index. Due to the same arguments, the principal component analysis was chosen as the main algorithm for the calculations of financial stability and home bias indexes.

There is one additional problem with exchange market pressure. The international reserves of central banks are used for each country because the exchange rate peg should be abandoned when reserves are depleted (Eichengreen, Rose & Wyplosz 1997). According to Gadanecz and Jayaram (2009), foreign exchange reserves are used for financial stability measurement because it estimates the ability of the country to resist external shocks. For Euro zone countries, there is no possibility to abandon peg because the euro is not pegged to any other foreign currency and has no possibility to use foreign reserves to resist external shocks because foreign exchange policy is in the competence of the European Central Bank. Poland and the United Kingdom can use foreign exchange reserves to resist external shock but there is no consistency to use these components of exchange market pressure for all countries. Therefore, it is necessary to use another component that is suitable to all countries. Such components can be liabilities of international investment position that estimates the capital that is invested by nonresidents in the domestic country. According to Eurostat (2015), international investment position figures are important for financial stability analysts.

The financial stability index is measured as follows:

$$FSI_t^{Pl} = \alpha_{LIIP} \frac{LIIP_t^{Pl}}{GDP_t^{Pl}} + \alpha_{IR} IR_t^{Pl} + \alpha_{RER} RER_t^{Pl}, \tag{2.1}$$

where

FSI_t^C – financial stability index of a country in moment of time *t*;

$LIIP_t^C$ – liabilities of international investment position (normalized value) for a country in *t*;

IR_t^C – interest rate (normalized value) for a country in *t*;

RER_t^C – real foreign exchange rate (normalized value) for a country in *t;*

α_{LIIP}, α_{IR}, $and\ \alpha_{RER}$ – weights of the index that are calculated using principal component analysis methodology – first principal component or eigenvector of covariance matrix that is corresponded with the highest eigenvalue by absolute value.

The last important issue for financial stability index identification is the signs determination. The higher liabilities of international investment position imply lower financial stability because the higher level of debt means higher potential outflow stock in time of crises. At the same time, the interest rate component sign could be positive and negative. The higher interest rate could imply higher financial stability due to the fact that investors will take money from countries with the lowest interest rate in crisis time. But the interest rate could also have negative contributions in financial stability index. If the interest rate is higher due to negative expectations, then it will be incorrect to expect higher financial stability in the time when interest rate already incorporates information about bad economic stance. The direction of relation between real exchange rate and financial stability is not obvious too. Generally, the higher real exchange rate implies stronger domestic currency, which implies higher financial stability because stronger economy that has no problems with financial stability attracts foreign capital that must be sold on foreign exchange market. However, the negative relation between financial stability and real exchange rate is also possible: if the country has negative current account, then the lower exchange rate is less risky for its future stability because weaker currency makes import more expensive for domestic consumers and export less expensive for foreign consumers that should balance current account.

2.2 Home bias index

The existing measure of home bias is not sufficiently complex to describe its different tendencies. For example, market-capitalization approach (i.e. Philips, Kinniry & Donaldson 2012) compares only foreign and domestic shares of portfolio investments while return-based approach compares return differences (Maier & Scholz, 2016). Therefore, it was decided to use the more complex approach as it is used for exchange market pressure and aggregate more components in home bias measure. Assets of international investment position are mostly used to calculate home bias measure, i.e. equations (1.1a), (1.1b) and (1.3), and, thereby, it should be presented in aggregated measure too. As the interest rate differential, it was decided to use interest rate spread and secondary income account balance. Interest rate spread is important because investors are interested not only in domestic interest rates but also in the difference between interest rates. At the same time, secondary income account balance[9] contributes to home bias index additional information about actual foreign investments profitability (not expected profitability as interest rate spread) on accumulated international investments position.

Home bias index can be defined in the following way:

[9] According to IMF (2013), the secondary income account shows "current transfers between residents and nonresidents. Various types of current transfers are recorded in this account to show their role in the process of income distribution between the economies. Transfers may be made in cash or in kind."

$$HBI_t^{Pl} = \alpha_{AIIP} \frac{AIIP_t^{Pl}}{GDP_t^{Pl}} + \alpha_{SP} SP_t^{Pl} + \alpha_{SI} \frac{SI_t^{Pl}}{GDP_t^{Pl}} \; ; \qquad (2.2)$$

where

HBI_t^C – home bias index for a country in *t*;

$AIIP_t^C$ – assets of international investment position (normalized value) for a country in *t*;

SP_t^C – interest rate spread (normalized value) for a country in *t*;

SI_t^C – secondary income account inflow or outflow (normalized value) for a country in *t;*

$\alpha_{AIIP}, \alpha_{\,SP},\ and\ \alpha_{SI}$ – weights of the index that are calculated using principal component analysis methodology – first principal component or eigenvector of covariance matrix that is corresponded with the highest eigenvalue by absolute value.

The assets of international investment position describes the financial assets of residents that are claims on non-residents (the liabilities of international investment positions describes claims in other direction). Thereby, higher assets of international investment position imply lower home bias because the capital that is claimed from nonresidents is the money that has been invested in other countries. Contributions into home bias index from interest rate spread should be negative: higher interest rate spread implies more domestic investments due to higher opportunity costs and implies higher home bias. But if the dependence on foreign credits exceed some critical value, then it will be hard to expect positive relation between home bias and interest rate spread due to inversed environment; thereby, for some countries, the interest spread contribution into home bias index could be positive. At the same time, it is also possible to expect that higher secondary income implies lower home bias if the next argumentation chain is used: higher secondary income implies higher accumulated foreign investment position that implies lower home bias. But it is not always so because the secondary income shows the inflow (or outflow if it is negative) from non-residents that has been earned from all types of operations (not only interest income); therefore, if the non-interest income is too high then the relation should be inversed: higher secondary income implies higher home bias because such transfers are substituents of other investments that could be done into foreign countries.

2.3 Principal component analysis

The index creation is one of possible mechanisms to lower the dimension of data. For example, if there is the database with one hundred variables which have more than one thousand points of measurement, then it will be very hard to analyze such huge array of the data. In this case, it is necessary to lower the number of the variables to ten or even one. There are a lot of methods to aggregate the data to lower its dimension, but they could be divided on two sets: weighting algorithms and aggregating algorithms. The ideologies of first sets of algorithms are to give all variables the same weights and save only one variable, i.e. $\frac{1}{N}$ as weight for each variable as it was used for exchange market pressure calculation in the work of Heinz and Rusinova (2015). At the same time, aggregating algorithms use decomposition method to identify the best weights for each variable through an optimization task. The major known algorithms from aggregation sets are principal component analysis and factor analysis. They have mostly the same foundation, but they are different in calculation approach. In this thesis, principal component analysis algorithm is used.

The formulation of the problem can be described in next steps. At first, there is a multidimensional observation:

$$X_i = \begin{pmatrix} x_i^{(1)} \\ \vdots \\ x_i^{(p)} \end{pmatrix}, i = 1, \dots, n. \tag{2.1}$$

These multidimensional observations are subjected to some statistical analysis. However, the number of objects that were observed is very huge – the number of objects is described in equation (2.1) by variable p, while n describes the number of observations that were taken only for separated object. The goal of data investigator is to lower dimension of the data (as it was already mentioned) to p' where the next inequality is fulfilled: $p' < p$. To lower the dimension, it is important to have some criterion which can estimate the quality of dimension squeezing. Investigators want to save the highest level of information that was presented in p-vectors of observation in new created p'-vector of observation. Therefore, the criterion has the following structure generally (Ayvazian, Buchstaber, Yenyukov & Meshalkin 1989)[10]:

$$I_{p'}\left(\tilde{Z}(X)\right) = \max_{Z \in F}\{I_{p'}(Z(X))\}. \tag{2.2}$$

The equation (2.2) means that it is necessary to find the number of features $\tilde{Z}(.)$ from class F of possible transformation functions of raw data in such way that the criterion $I_{p'}(Z(X))$ is maximized. This criterion is called the measure of information and its form determines the algorithm that is actually used, principal component or factorial analysis.

The principal components p' can be calculated, if the sets of linear orthogonal combinations of raw data are used as class F of possible transformation functions or in the mathematical form:

$$z^{(j)}(X) = c_{j1}\left(x^{(1)} - \mu^{(1)}\right) + \cdots + c_{jp}\left(x^{(p)} - \mu^{(p)}\right), \tag{2.3}$$

while the following conditions are fulfilled:

I condition: $\sum_{v=1}^{p} c_{jv}^2 = 1,\ j = 1, \dots, p;$ (2.3a)

II condition: $\sum_{v=1}^{p} c_{jv}c_{kv} = 0,\ j = 1, \dots, p, j \neq k;$ (2.3b)

where $\mu^{(p)}$ is expected value of $x^{(p)}$.

[10] The PCA methodology is mostly presented according to book of Ayvazian, Buchstaber, Yenyukov, and Meshalkin (1989); however, it is reworked and simplified by author.

As information criterion of p'-dimensional system of raw data is used the follow equation:

$$I_{p'}\big(Z(X)\big) = \frac{Dz^{(1)} + \cdots + z^{(p')}}{Dx^{(1)} + \cdots + x^{(p)}}, \qquad (2.4)$$

where D is the dispersion function for corresponding variable.

The equation (2.3) and (2.4) with two conditions (2.3a) and (2.3b) are the principal component analysis foundations. However, it is only the theoretical way of material presentation, and it is also necessary to take a look at methodology how to find the number of features $\tilde{Z}(.)$ that will give the investigator the weights for index calculations.

From the definition of principal component that was discussed above, it is followed that to find first principal component, it is necessary to solve the next optimization task:

$$\begin{cases} D(l_1 X) \to \max_{l_1}; \\ \quad l_1 l_1' = 1. \end{cases} \qquad (2.5)$$

Consequently, the equation (2.5) can be presented in the next way:

$$\begin{cases} l_1 \Sigma l_1' \to \max_{l_1}; \\ \quad l_1 l_1' = 1. \end{cases} \qquad (2.6)$$

As the next step, the Langrage function is written on the basis of equation (2.6):

$$\varphi(l_1, \lambda) = l_1 \Sigma l_1' - \lambda(l_1 l_1' - 1). \qquad (2.7)$$

Differentiating equation (2.7) by l_1' gives the next result:

$$\frac{\partial \varphi(l_1, \lambda)}{\partial l_1'} = 2\Sigma l_1' - 2\lambda l_1'. \qquad (2.8)$$

After equating (2.8) to zero and making mathematical transformation, the system of equations takes the form as follows:

$$(\Sigma - \lambda I) l_1' = 0. \qquad (2.9)$$

$$|\Sigma - \lambda I| = 0. \qquad (2.10)$$

Equation (2.9) has the non-zero solution only if the condition (2.10) is fulfilled or, in other words, matrix $|\Sigma - \lambda I|$ is singular. Equation (2.10) is the first part of solution for index creation task. The equation has p – the dimension of raw data – different values for λ that is called as eigenvalues of covariance matrix, Σ. In this case, the quality of factor's reduction can be described as the following information criterion:

$$I_{p'}\big(Z(X)\big) = \frac{\lambda_1 + \cdots + \lambda_{p'}}{\lambda_1 + \cdots + \lambda_p}, \tag{2.11}$$

where p' is the dimension of new data that must be lower than p.

But the equation (2.11) shows only the level of the information that is saved after matrix squeezing; however, it does not show how to calculate p' indexes for the new dataset. To fulfill the second part of the task, it is necessary to remember that λ is the eigenvalues of the covariance matrix, and there should also be the eigenvector for each eigenvalue that is calculated as follows:

$$\Sigma u_i = \lambda_i I, i = 1, \dots, p; \tag{2.12}$$

where u_i is i-th eigenvector that correspond to the eigenvalue λ_i.

After getting $u_i, i = 1, \dots, p$, from equation (2.12), it is possible to calculate p' indexes using the following information:

I. The components of u_i is the weights for the i-th index.

II. The quantity of information that is described by i-th index is equal to $\frac{\lambda_i}{\sum_{j=1}^{p} \lambda_j}$.

III. For index calculation, data are used in the normalized way (with substracted expected value and divided on standard deviation). The necessity of average substraction can be seen from equation (2.3), while division on standard deviation is important due to information criterion dependence on dispersion calculation. Generally, it is always preferable to use normalized data, if there is the task to aggregate data with different dimensions to delete redundant information about them.

IV. Each additional index describes the information that was not described from the previous indexes; therefore, it is necessary to have very strong arguments to use the vectors not one by one according to their information criterion, i.e. as Hausmann et al. (2014).

As it was shown above, principal component analysis is, generally, the very simple algorithm. However, it has some assumptions as any mathematical algorithm. The first assumption is the identification of the number of sufficient cases. From the huge number of different rules that were created for different tasks, three rules are most interesting:

I. *Rule of 10.* For each variable, it should be at least ten points of data (OECD Methodology and User guide 2008).

II. *5:1 ratio.* The points to variables ratio should be at least five (Bryant & Yarnold 1995, Gorsuch 1983, Nunnaly 1978).

III. *Significance rule.* There should be at least 51 more points of data than variables to support chi-square testing (Lawley & Maxwell 1971).

The second assumption is the absence of biases in individually selected factors. The main issue is located in the information criterion that will give very biased results, if it gets biased data as input. Therefore, the best way is to use so many variables as it is possible, but they should be relevant and unbiased, and they must carry different information. Also, data with unexplained outliers influence hugely the results of index calculations, and it is much more preferable to delete unexplained outliers from the raw data.

The next assumption is about data interval. Kim and Mueller (1978) mentioned that ordinal data can be used, as if they do not distort the variables scaling. But it is not so. Ordinal data are hard to understand and hard to normalize. Therefore, it is preferable not to use ordinal data. According to Gorsuch (1983), the categorical variables with similar splits will necessarily correlate with each other, regardless of the information that is presented in these variables; therefore, it will be difficult to divide “informative” information and “uninformative” that is carried due to similar categorization of data.

The fourth assumption is connected with data linearity. The issue is connected with the identification algorithm of principal components. It is linear decomposition of covariance matrix; therefore, if information about data co-movements is lying not in linear dimension, then this information will be missed. The smaller the sample size of the data is, the more critical the problem of the data linearity is.

One more assumption can be formulated as “garbage in, garbage out”. The dimension of data should have one dimension, it is important to remember one more time about normalization, because usage of data with different dimension creates something non-interpretable. Principal component analysis algorithm cannot create the underlying dimension of data; therefore, it is necessary to create it before. Additionally, it should be mentioned that there is no necessity for input data to have the same distribution; however, it is preferable to have normal distribution to save more quantity of information in designed indexes errors (OECD Methodology and User guide 2008).

The last but, of course, not least assumption is about strong inter-correlations of the data. This assumption is not connected with mathematic calculations directly but the usage of the data with low inter-correlations will require nearly as many factors as there are in raw dataset and will lower the added value of index creation process. At the same time, high correlation should also be checked due to possible issue of multicollinearity. The highly correlated data is better to delete from initial dataset because PCA algorithm is used to reduce the dataset dimension that has different information and the influence from the same information is obscure, assumption “garbage out, garbage in”. Also, the principal component analysis (the same as factor analysis and Cronbach’s alpha) assume uncorrelated measurement errors (OECD Methodology and User guide 2008).

Conclusion:

In this chapter, the problems, which are connected with development of financial stability and home bias measurement, were discussed. Foreign exchange reserves that are component of exchange market pressure were changed on liabilities of international investment positions as component of financial stability index. The change was done because the currencies of investigated countries are not pegged to foreign currencies (actually, almost all countries share one common currency, euro) and the usage of foreign exchange reserves is limited for the Euro zone countries. Due to this, foreign exchange index uses liabilities of international investment position instead of foreign exchange reserves. At the same time, the existing measurements of home bias are not used due to their simplicity: they estimate only differences between foreign and domestic investment portfolios or the difference in investment returns. It was decided to develop home bias measure that would estimate both differences at once. Therefore, the aggregated measure that consists of three components: assets of the international investment position, the interest rate spread, and the secondary income account balance, was created. The principal component analysis was decided as best option for index weights estimation due to the following arguments. At first, the signs are estimated by the mathematical algorithm, and they are not influenced with a priori beliefs. Secondly, weights are chosen by optimization task solving that uses information measure as the criterion of optimality. According to the criterion, the weights are calculated to save the highest quantity of information from covariance matrix or, in other words, information about joint changes of index components.

Chapter 3. Home Bias and Financial Stability Indexes Calculations

The financial stability and home bias indexes are calculated for ten countries: Austria, the Czech Republic, Germany, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and United Kingdom. Weights of indexes are calculated using programming code for Python (see Appendix 3) according to equations (2.1) and (2.2) presented for all investigated countries in the last sub-chapter of this chapter (3.4 Indexes weights comparison analysis), while three countries with the higher level of interest: Germany, Poland, and the United Kingdom, are analyzed more deeply before that. These countries have been chosen to analyze the behavior of home bias and financial stability indexes more deeply. For example, Poland is one of countries (or even only one) that has reaped the highest benefits from entering the European Union in 2004. This country could be interesting for the analysis due to dependence on foreign capital and foreign technologies for catching-up with more developed countries. At the same time, Germany could be perceived as "safe heaven" country[11] from the European Union; moreover, Germany is the source of foreign capital for other countries, i.e. Poland, at a more stable time on financial markets. Finally, United Kingdom is the "hub" for global finances and foreign capital.

3.1 Poland

The equations of home bias and financial stability indexes (56% and 58% of initial information is presented in indexes) for Poland are as follows:

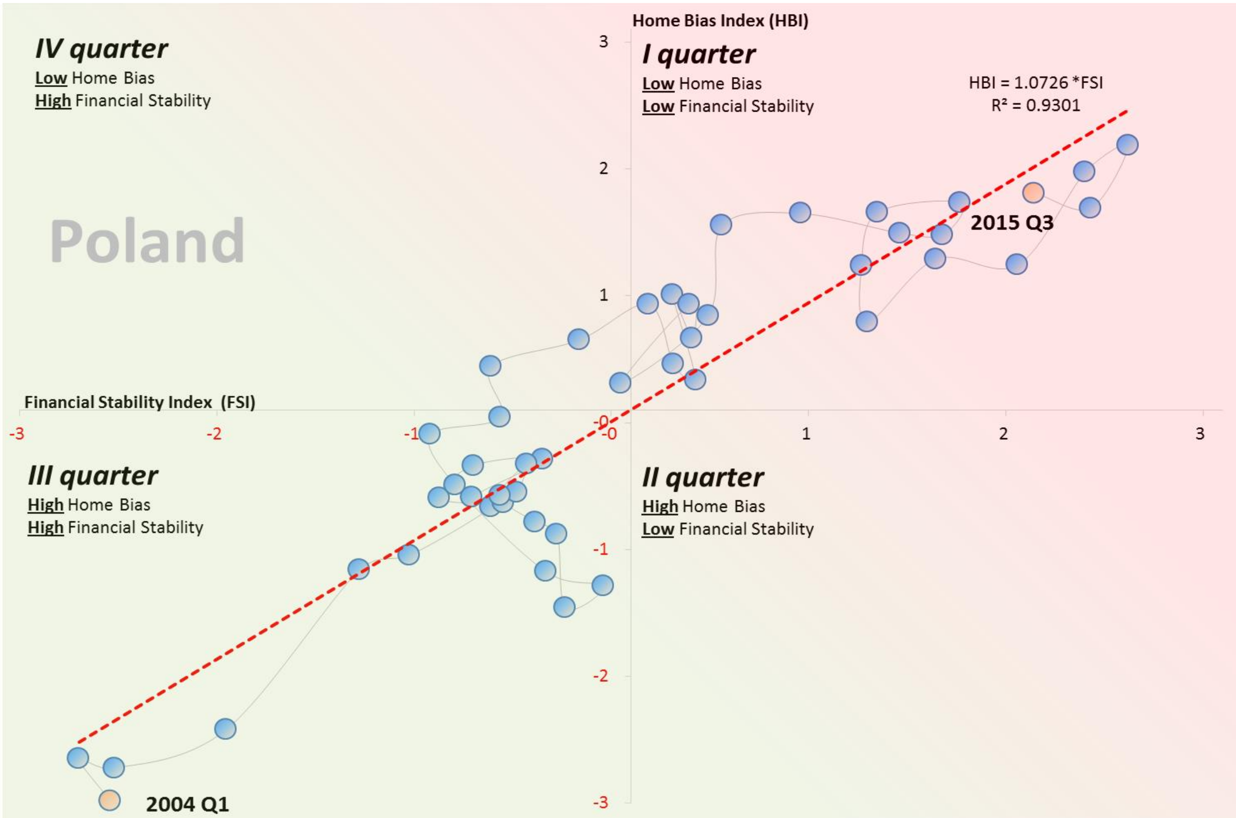
$$HBI_t^{Pl} = 0.69\,\frac{AIIP_t^{Pl}}{GDP_t^{Pl}} - 0.37SP_t^{Pl} - 0.62\,\frac{SI_t^{Pl}}{GDP_t^{Pl}}\ ; \tag{3.1}$$

$$FSI_t^{Pl} = 0.68\,\frac{LIIP_t^{Pl}}{GDP_t^{Pl}} + 0.67IR_t^{Pl} + 0.29RER_t^{Pl}, \tag{3.2}$$

where all marks are the same as in the second chapter.

[11] "Safe heaven" country is the country that has additional inflow of capital due to lower expected risk in crisis time.

.
Fig.3.1 Poland’s home bias and financial stability indexes.



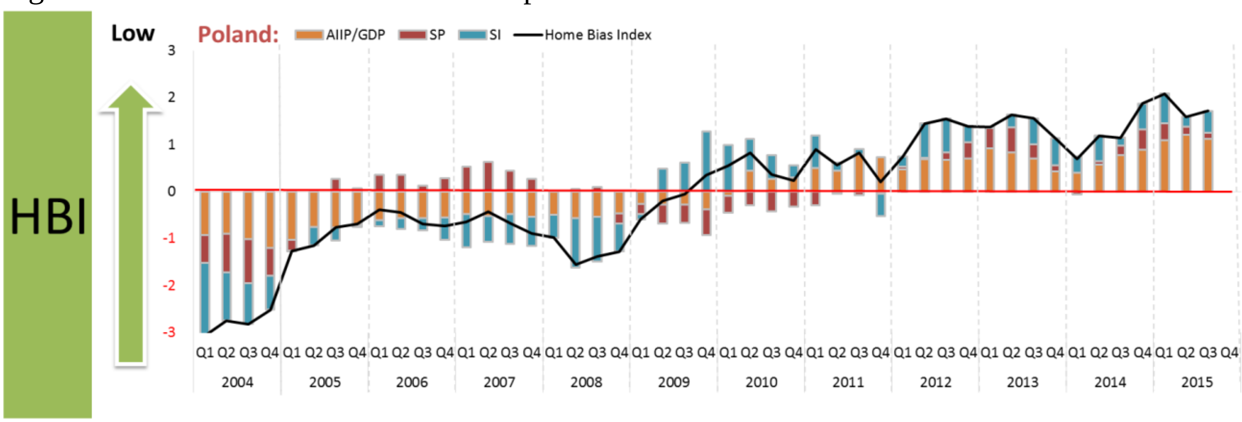
Sources: author’s calculations

As it can be seen from equation (3.1) and (3.2), the influence of international investment position assets is almost equal to the influence of liabilities and is about 70% of its normalized amount[12]. Additionally, the contributions from assets and liabilities of investment international position are positive as it was expected according to the preliminary analysis – the higher assets and liabilities of the international investment position implies the higher home bias and financial stability indexes (home bias and financial stability are lower). At the same time, the signs of interest rate and interest rate spread contribution were not obvious from the preliminary analysis :there were identified two options: negative and positive sign, due to different possible influence on people’s expectations from these variables that it is hard to estimate directly. As it was seen from (3.1) and

[12] As it was mentioned in Chapter 3, all the factors for index calculations are used in normalized way (with substracted expected value and divided on standard deviation).

(3.2), both coefficients are negative and implicate the following conclusions: higher spread means higher domestic bias because there are less opportunities to invest money in foreign countries; the higher local interest rate means higher financial stability due to lower dependence on foreign capital for financial system development. The higher secondary income also implicates higher home bias, while a stronger real exchange rate implicates lower financial stability – it would be possible due to exchange rate overvaluation that causes the negative impact on export and current account inflow.

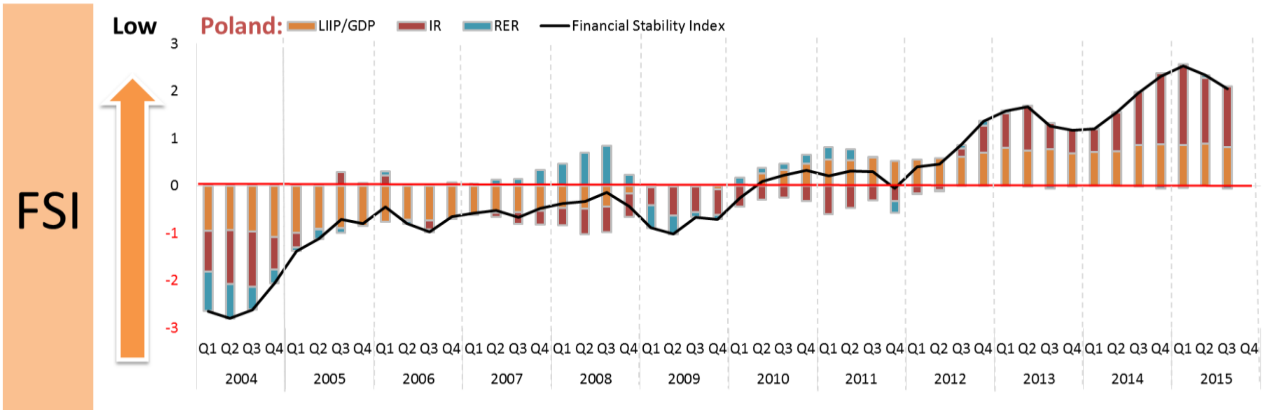
Fig.3.2 Poland’s home bias index decomposition.



Sources: author’s calculations.

As it can be seen from Fig.3.1, home bias and financial stability were lowering through the investigated period in synchronous way generally. The main exception was in 2008-2009, at the time of the global financial crisis. But it was almost impossible to identify a causal relation between home bias and financial stability indexes because it could exist in both directions: home bias influences financial stability and financial stability influences home bias. It is similar to the “chicken and egg” problem or, in other words, the identification issue of what was created at first. Mathematically, this issue will be solved in the next chapter while, currently, the financial stability index influence on home bias index is assumed without proof.

Fig.3.3 Poland's financial stability index decomposition.



Sources: author's calculations.

In Fig.3.2 and Fig.3.3, the contribution of each index components into the value of home bias and financial stability indexes are shown[13]. From these graphs, it is possible to see that secondary income was the main component that implies the higher home bias level (the lower home bias index value) in the first quarter of 2004 but it was already assets of investment international positions that led home bias index value in the third quarter of 2015. Interest rate spread has low influence; however in some years, it fulfilled the balancing functions, i.e. it lowered home bias level, while the other two components increased their values. The low interest rate is the main driver of financial stability index changing from lower to higher levels (decrease of financial stability) from the first quarter of 2004 till third quarter of 2015. The lower interest rate has lower attraction for foreign investors and gives them stimulus to take out capital in some critical situations (that mostly coincide with crisis). And finally, the real exchange rate had contribution into financial stability index value only in financial global crisis time (2008-2009) and at the beginning of 2004, the time of European Union entering.

Real exchange rate contribution in Poland's financial stability index is interesting due to higher than in average deviation between HBI and FSI in 2008-2009. While home bias increased

[13] It will be called decomposition hereafter

(Fig.3.2) due to higher level of secondary income, financial stability index decreased due to real exchange rate contribution. Later, home bias index also changed the direction and began to grow (home bias was lowering). It is an example of the situation when changes in financial stability lead to changes in home bias – local investors can think that the crisis is only local or, in other words, they can lose confidence in local markets.

3.2 Germany

The equations of home bias and financial stability indexes (70% and 87% % of initial information is presented in indexes) for Germany are as follows:

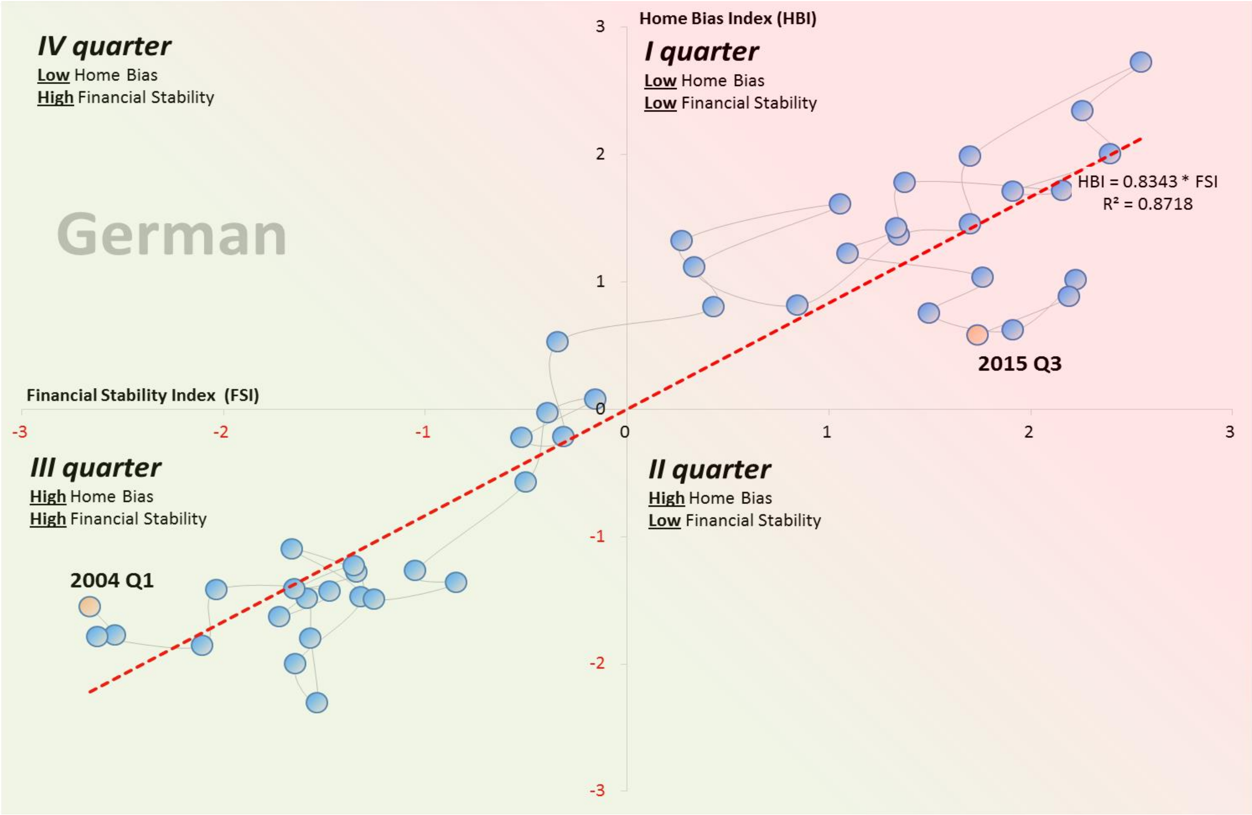
$$HBI_t^G = 0.62\,\frac{AIIP_t^G}{GDP_t^G} - 0.63SP_t^G - 0.48\frac{SI_t^G}{GDP_t^G}; \tag{3.3}$$

$$FSI_t^G = 0.59\,\frac{ALIIP_t^G}{GDP_t^G} - 0.56IR_t^G - 0.58RER_t^G, \tag{3.4}$$

where all marks are the same as in the second chapter.

Except for the real exchange rate, the relation between German indexes and its components is the same as in Poland's case because the signs of components weights are the same. The situation with the real exchange rate is different because German shares one currency with other countries of the Euro zone. It is possible to assume that Germany has high influence on monetary policy of the Euro zone because it is the biggest country from the Euro-zone, but it could not be the same as to have an own currency. Thereby, the real exchange rate could have the different effect on financial stability index of Germany as it is calculated by principal component analysis: a stronger currency may imply higher financial stability or, in other words, the capital inflow in the country is stable and not speculative.

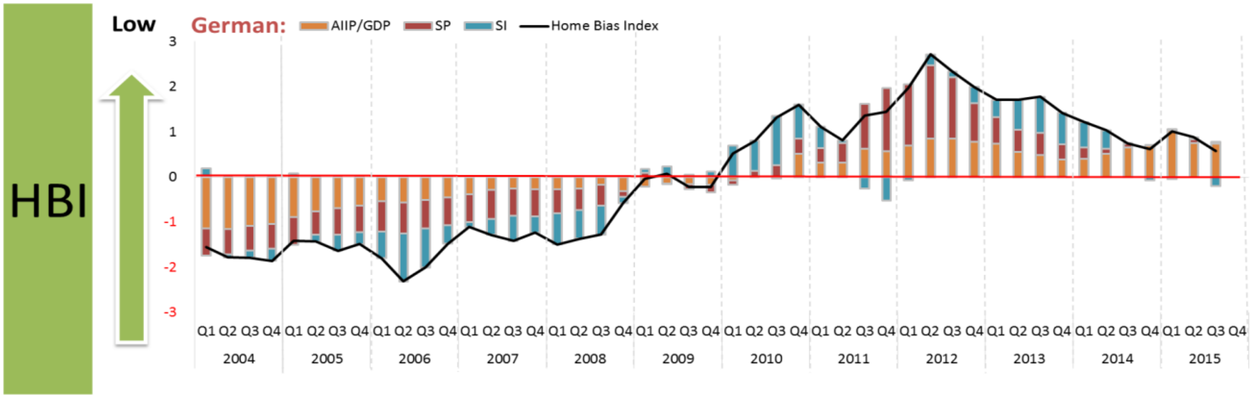
Fig.3.4 German's home bias and financial stability indexes.



Sources: author's calculations.

As it is shown in Fig.3.4, the relation between home bias and financial stability indexes is also positive in the long run: lower financial stability implies lower home bias. The same relation between indexes was seen for Poland's calculations. However, general dynamic of both indexes is different: there is no deviation between the two indexes at the time of global financial crisis, but there are deviations in other periods. For example, the home bias increased from second quarter of 2012, while the financial stability showed the same trend only till the first quarter of 2013, when it began to fall again (Fig.3.5 and Fig.3.6). It seems that financial stability started to grow again after the second quarter of 2015, but this trend is too short to say something about it strength. Also, there are deviations between the two indexes in 2010: home bias decreased with higher rate than financial stability, and home bias grew in 2006, while financial stability was mostly stable.

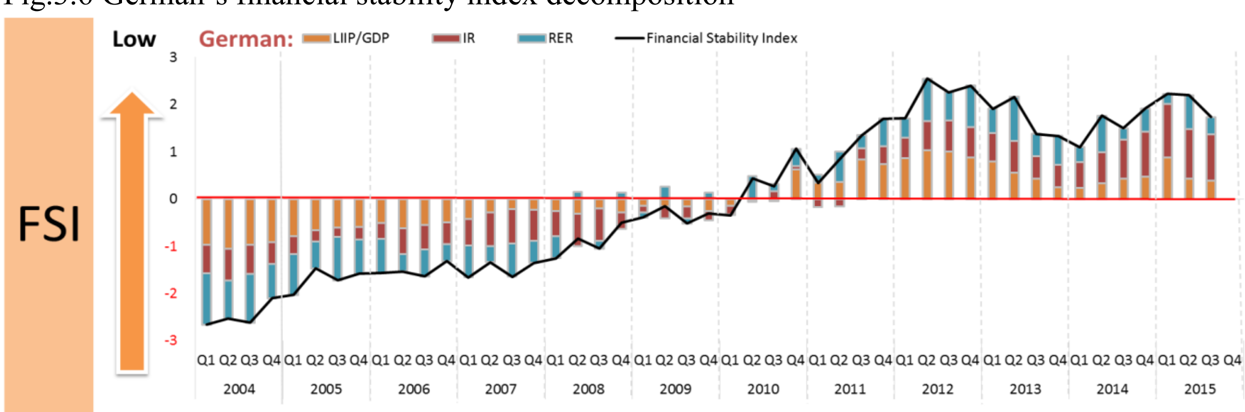
Fig.3.5 German’s home bias index decomposition.



Sources: author’s calculations.

The decomposition (components contribution) of home bias and financial stability indexes that is shown in Fig.3.5 and Fid.3.6 also presented important results. At first, the main component of German home bias strengthening from the second quarter of 2011 was interest rate spread that lowered to the average levels and made German assets interesting only from the perspective of “safe heaven” assets. Additionally, international investment position assets are the main contributor in the high level of home bias in the first quarter of 2004 and in low home bias in the third quarter of 2015, foreign investments increased from 621% of GDP to 1047% of GDP in the investigated period.

Fig.3.6 German’s financial stability index decomposition



Sources: author’s calculations.

At the same time, international investment position liabilities increased only to 854% of GDP as of the third quarter of 2015 from 615% of GDP as of the first quarter of 2004 (the liabilities were almost equal to assets in the first quarter of 2004). Therefore, the place of the main contributor is occupied by interest rate component in the third quarter of 2015, while the main contributor in the high level of financial stability index in the first quarter of 2004 (in comparison with current situation) was real exchange rate. Finally, it is necessary to stress on the fact that the interest rate makes high contribution in financial stability index currently, the interest rate is lower than average level, but the interest rate spread has almost no effect on home bias index.

3.3 United Kingdom

The equations of home bias and financial stability indexes (75% and 72% of information is saved) for the United Kingdoms are as follows:

$$HBI_t^{UK} = 0.59\,\frac{AIIP_t^{UK}}{GDP_t^{UK}} - 0.61SP_t^{UK} - 0.53\,\frac{SI_t^{UK}}{GDP_t^{UK}}; \tag{3.5}$$

$$FSI_t^{UK} = 0.65\,\frac{LIIP_t^{UK}}{GDP_t^{UK}} - 0.49IR_t^{UK} - 0.59RER_t^{UK}, \tag{3.6}$$

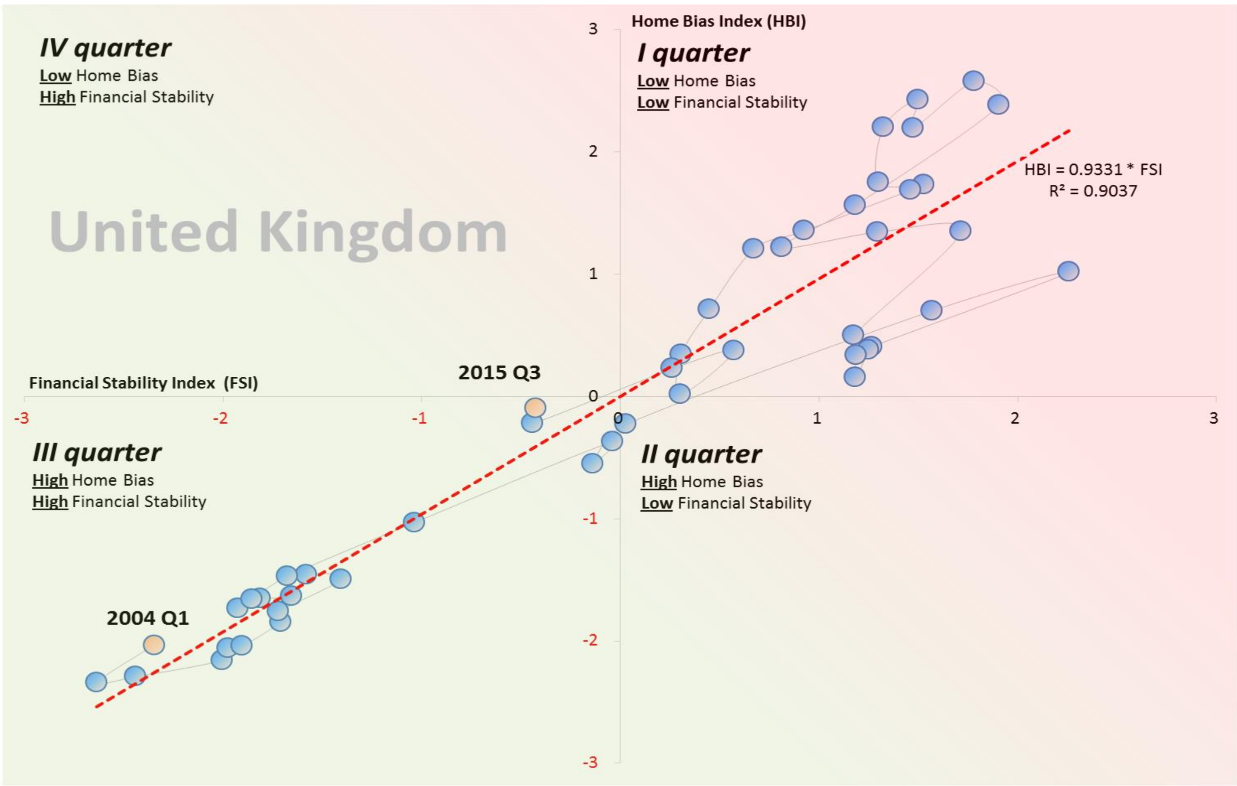
where all marks are the same as in the second chapter.

The signs of all indexes' weights are the same as for Germany. However, the negative sign of real exchange rate weight in financial stability index should be explained in the other way than for German because the United Kingdom has its own currency: the pound. However, it is possible to assume that the pound is hugely dependent on financial global trends because London is the financial "hub"; therefore, stronger real exchange rate could imply higher financial stability. If investors think that the United Kingdom economy is strong, then its exchange rate should also be stronger due to higher demand for foreign currency and, vice versa, if investors think that the

United Kingdom economy is weak, and then pound could lose their position due to lower demand.

As it can be seen in Fig.3.7, the home bias and financial stability indexes of the United Kingdom have changed more dynamically than the same indexes of Poland and Germany. In the third quarter of 2015, the indexes were in the same quarter: quarter III, with high home bias and high financial stability, as in first quarter of 2004. Germany had the same situation: home bias index also showed dynamics toward tightening of home bias from the second quarter of 2012, but financial stability was loose in this period (with a short-term exception); therefore, it seems that the United Kingdom heads towards IV quarter of the graph, with low (actually moderate) home bias and high financial stability.

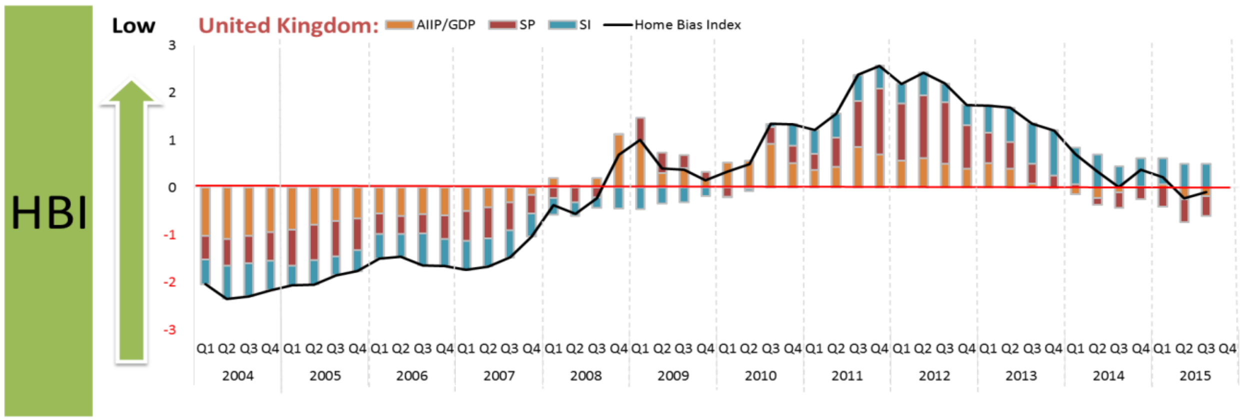
Fig.3.7 UK’s home bias and financial stability indexes



Sources: author’s calculations.

Also, as it can be seen from Fig.3.8 and Fig.3.9, the relation between home bias and financial stability indexes was not very coordinated after the financial global crisis of 2008 started (from the third quarter of 2008) and till the second half of 2013 or, in other words, home bias index had higher volatility then financial stability index from the third quarter of 2008 till the third quarter of 2013, for 5 years. In this period, the financial stability index was stable on the average after it showed huge increase in the fourth quarter of 2008 and the first quarter of 2009. Lehman Brother's collapse influenced strongly the United Kingdom because London is the global financial "hub" and a lot of global financial institutions had headquarters in London, capital of United Kingdom. At the same time, home bias index fluctuated a lot: home bias index increased in the fourth quarter of 2008 and the first quarter of 2009 then it fell a little; it began to grow again in the first quarter of 2010: Greece crisis pushed investors to take capital from the European Union at all. The growing trend was reversed finally in the second quarter of 2012 when the home bias started to gain back the positions that had been lost in the crisis time.

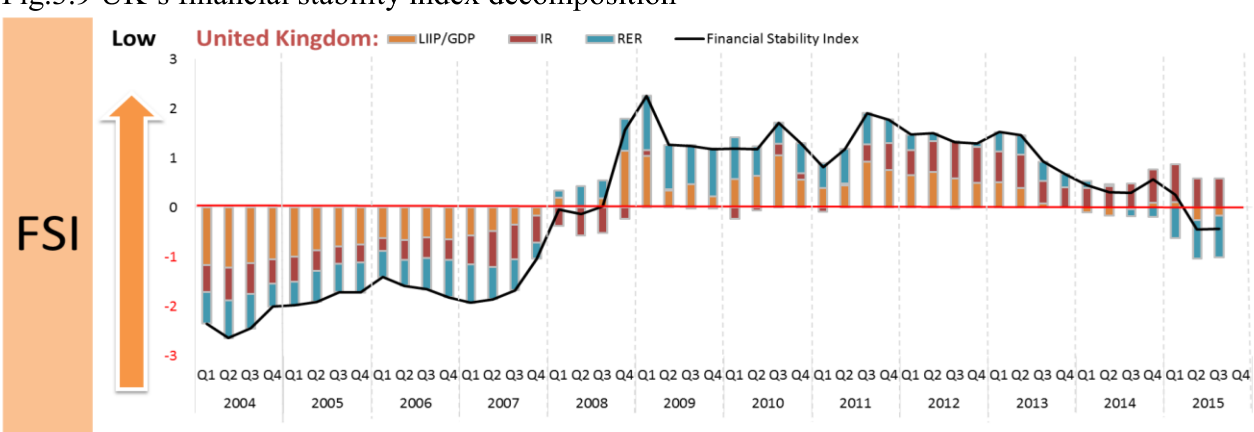
Fig.3.8 UK's home bias index decomposition.



Sources: author's calculations.

From the decomposition of home bias and financial stability indexes (Fig.3.8 and Fig.3.9), it is possible to see the main differences in components of indexes that have made such differences possible. At first, the influence from the real exchange rate is very important for UK financial stability index and its dynamics is very different from the dynamics of this component in German financial stability index: UK real exchange rate had negative influence on financial stability index in 2015, while German's real exchange rate makes financial stability index higher (financial stability is lower). At the same time, the dynamics of the other two components of financial stability index is not cardinally different. The deviation in UK's and German's real exchange rate contribution started to differentiate in 2014, at that time, the pound started to increase from low levels, while German real exchange rate (whose dynamics is connected to the euro) stayed on the same levels as before due to weak European economies as a whole. For home bias indexes, the main contributor to differences between Germany and the United Kingdom is interest rate spread. It seems that for home bias the independent monetary policy is also important. In this case, it is possible to influence with higher flexibility on investors' expectations: though German's home bias index is not influenced at all from the interest rate spread in 2015 because interest rate spread is on average level, the UK home bias index is lower due to interest rate spread contribution. Also, there is the difference in secondary income contribution into home bias index: its contribution for the UK case is more stable than for the German case.

Fig.3.9 UK's financial stability index decomposition



Sources: author's calculations.

3.4 Indexes weights comparison analysis

In the aggregated way, the information about indexes weights for investigated countries is presented in Table 3.1. As it can be seen, the signs of weights for assets and liabilities of international investment position are always positive as it should be according to the preliminary analysis, while all other weights have positive or negative signs which depend on the countries and their reaction for crises. There are some groups of similar countries according to weights signs. For example, Austria, the Czech Republic, and Poland have the same signs of weights. However, the value of coefficient is very different: Austria's weights for liabilities of international investment position is cardinally different from the other countries and is equal only to 0.13, while mean for nine other countries is equal to 0.67 (the mean for weights of international investment position assets is equal to the same 0.67). It means that the contribution from this variable is much lower for Austria than for other countries. There are two more groups of countries according to signs of indexes weights: Germany and the United Kingdom, and Hungary and Lithuania. Nevertheless, it does not mean that these countries are similar. They are similar only in accordance with the direction of variable contribution into indexes or, in other words, according to the connection between macroeconomic variables and their influence on home bias and financial stability indexes.

It is necessary to make an additional comment about the difference between weight signs of real exchange rate. The weight of real exchange rate, generally, should be negative (higher real exchange rate implies stronger currency, which implies higher financial stability) because investors can expect on this influence on the demand-led markets while positive weight is a nice indicator of supply-led foreign exchange market that is the case for Germany, Portugal, and the United Kingdom. Also, it is important that Poland's real exchange rate weight is half as much as for the other nine countries. It is hard to identify the causes for such differences but, in any case, it is the important feature of Poland's economic.

Table 3.1 Weights of indexes for countries.

Country / ***Coefficient***	**Austria**	**Czech Republic**	**German**	**Hungary**	**Latvia**	**Lithuania**	**Lux.**	**Poland**	**Portugal**	**United Kingdom**
α_{AIIP}	0.55	0.68	0.62	0.71	0.73	0.71	0.71	0.69	0.66	0.59
α_{SP}	-0.59	-0.68	-0.63	0.71	0.18	0.33	-0.26	-0.37	0.65	-0.61
α_{SI}	-0.59	-0.26	-0.48	0.01	-0.67	0.62	0.66	-0.62	-0.38	-0.53
α_{LIIP}	0.13	0.68	0.59	0.66	0.66	0.68	0.68	0.68	0.72	0.65
α_{IR}	-0.71	-0.51	-0.56	0.27	0.36	0.34	0.34	-0.67	0.31	-0.49
α_{RER}	0.70	0.52	-0.58	0.71	0.66	0.65	0.65	0.29	-0.62	-0.59
Information Criteria										
HBI	55%	54%	70%	39%	51%	54%	44%	58%	59%	75%
FSI	64%	68%	87%	45%	68%	67%	67%	56%	57%	72%

Sources: author's calculations.

Conclusion:

In this chapter, the results of home bias and financial stability indexes were calculated for ten countries of European Union: Austria, the Czech Republic, Germany, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and the United Kingdom. Other countries of European Union have different problems with data and have been excluded from the calculation part. Mostly, the home bias and financial stability index changed jointly in the investigated period; however, each country had some feature differences in contributors of index changes. There was presented deep analysis of indexes comovement for three countries: Germany, Poland, and the United Kingdom, which also showed divergent dynamics of indexes in short-term periods, especially, at the time of crisis. Additionally, three groups of countries that have same signs of weights (the structure of both indexes is similar) were identified. Poland, the Czech Republic, and Austria belong to the first group, while Germany and the United Kingdom, and Hungary and Lithuania belong to the second and third groups accordingly. Nevertheless, all countries have features if the positive contribution of international investment position assets and liabilities into both indexes is not taken into account: this contribution is the same for all the investigated countries.

Chapter 4. Relation between Home Bias and Financial Stability Indexes

After having calculated indexes, it is time to return to the hypothesis which has to be testified and is formulated as follows: the *positive* relation between home bias and financial stability is statistically significant after taking into account changes of some control variables. At the stage of hypothesis formulation, it was not assumed that the relation between home bias and financial stability from the foreign connection perspective is positive for all countries; however, it seems that, generally, home bias and financial stability indexes for the investigated countries move mostly together. Due to these additional results, it is necessary to include the word "positive" into hypothesis to toughen conditions. To testify the hypothesis, the models on panel data from 10 countries, the same list that was used for index calculations, is developed and their coefficients are estimated. Additionally to the macroeconomic variables that were discussed before, the "dummy" variables for the distinction of groups of countries are used for panel data models.

"Dummy" variable for countries' groups' distinction is used to estimate additional effects from variables that are used in the model: financial stability index, stock index exchanges, and real gross domestic product changes, on home bias index of countries with different economic features. For example, there are different countries according to the economic size, the political system, the political decision at the crisis time, or place in the global financial system. The pool of ten countries was divided into four groups: financial countries, the Baltic countries, other countries that have tight connections with the USSR, and others. Germany, the United Kingdom, Luxembourg, and Austria belong to financial countries due to existence of important stock exchanges or financial institutions within these countries. Latvia and Lithuania belong to Baltic countries due to geographical place, high interconnectedness, and sharp reduction of real gross domestic product at the time of the global financial crisis. Poland, Hungary, and the Czech Republic were assigned to the third group due to high relatedness to the USSR before 1990 and presence of additional relation within the Visegrád Group. Only Portugal was assigned to the fourth group as part of so-called PIGS-countries: Portugal, Ireland, Greece, and Spain, which were harmed hard at the time of the global financial crisis of 2008 and the European Union debt crisis afterwards. All other countries from this group have different problems with data and cannot be used; therefore, Portugal is the only country in the fourth group and should be interpreted as the redundant group.

4.1 Causation between home bias and financial stability indexes

The direction of influence between home bias and financial stability indexes may be different. For example, at the crisis times, investors generally try to take money away from the epicenter of problems; therefore, they are biased from the perspective of the rational decision-making process. However, investors could also be biased in "tranquility period" (without crisis) because of lowering risk estimations or increasing expectations of investment profitability. Moreover, all investment decisions influence financial stability due to changes in home-foreign allocation; and it is generally hard to distinguish between a cause and a result.

Nevertheless, the causation effect between home bias and financial stability indexes can be checked through Pairwise Granger Causality Test. It tests two null-hypotheses for home bias and financial stability indexes: FSI does not Granger cause HBI and HBI does not Granger cause HBI. With 450 estimations, F-statistic (for detailed results from EViews see Appendix 4) for the first null-hypothesis is equal to 5.46 (Table 4.1) and it is possible to decline the hypothesis that FSI does not Granger cause HBI at 1% significance level. At the same time, F-statistic for the second hypothesis is equal only to 1.46 and it is not possible to decline the hypothesis that HBI does not Granger cause FSI even at 5% level of significance (the significance level is equal to 23%).

Table 4.1 Pairwise Granger Causality Test results.

Null Hypothesis:	Observations	F-Statistic	Probability of significance
FSI does not Granger Cause HBI	450	5.46	0%
FSI does not Granger Cause HBI Changes	440	3.53	3%
HBI does not Granger Cause FSI Changes	440	3.27	4%
HBI does not Granger Cause FSI	450	1.46	23%
FSI Changes does not Granger Cause HBI	440	0.06	94%
FSI Changes does not Granger Cause HBI Changes	440	0.05	95%
HBI Changes does not Granger Cause FSI Changes	440	0.02	98%
HBI Changes does not Granger Cause FSI	440	0.00	100%

Source: EViews calculations.

However, there is no significant statistical causation effect between the changes of home bias and financial stability indexes. Therefore, it is necessary to be very careful with causation direction interpretations. It is possible to say that home bias index is caused by financial stability index in general; however, it is not possible to say that financial stability index changes (without the information about the current level of financial stability index) Granger caused home bias index changes. Deeper analysis shows that it is possible to reject only three hypotheses: FSI does not cause HBI, FSI does not cause HBI changes, and HBI does not cause FSI changes. And it is very important for the whole analysis. It is shown mathematically that home bias index and its changes are influenced by financial stability index, while home bias index influences only financial stability index changes. The last two hypotheses describe the issue that was mentioned above about two-way influence, but the first null-hypothesis can be interpreted as the prime cause of the variable identification: in this case, it is financial stability index that has the prime effect on home bias index.

4.2 Models specification

One more step should be made before the model specification would be possible to identify. It is also important to check the null-hypotheses about stationarity of all variables and, especially, of home bias and financial stability indexes. Panel Unit Root Test shows that home bias and financial stability indexes are stationary if the common unit root processes are assumed. But it is known that there is the individual unit root process for each country from the panel data, and the indexes are unstationary for this case. Therefore, the first differences of indexes are used for panel model estimations. The short-form model has the following structure:

$$HBI_t^C - HBI_{t-1}^C = \alpha + \beta_{FSI}^0(FSI_t^C - FSI_{t-1}^C) + \beta_{FSI}^1(FSI_{t-1}^C - FSI_{t-2}^C) + \beta_{QQ}^0 QQ_t^C + \beta_{QQ}^1 QQ_{t-1}^C + \beta_{YY}^0 YY_t^C + \beta_{YY}^1 YY_{t-1}^C + \beta_{IND}^0 IND_t^C + \beta_{IND}^1 IND_{t-1}^C + [CX = R/F] + [PER = R/F]\,, \qquad (4.1)$$

where

C – one of countries from the above-mentioned list: Austria, the Czech Republic, German, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and the United Kingdom;

$(HBI_t^C - HBI_{t-1}^C)$ – change of home bias index of the specific country from the moment of time *t-1* till the moment of time *t*;

$(FSI_t^C - FSI_{t-1}^C)$ – change of financial stability index of the specific country from the moment of time *t-1* till the moment of time *t*;

QQ_t^C – quarter to previous quarter change of real gross domestic products of the specific country in the moment of time *t*;

YY_{t-1}^C – quarter to the same quarter of previous year change of real gross domestic products of specific country in moment of time *t-1*;

$[CX = R/F]$ –cross-section effect can be random or fixed;

$[PER = R/F]$ – time-period effect can be random or fixed;

$\beta^0_{\mathrm{FSI}}, \dots, \beta^1_{\mathrm{IND}}$ – is the coefficients of the model that are estimated by ordinary least square method in EViews.

The short-form model estimates the same coefficients for all countries from the panel data. This feature is an advantage and a disadvantage of the model in accordance with the equation (4.1) at the same time. It is important to testify the hypothesis and estimate the coefficients for all countries at once, but, in this case, the coefficients describe only the average relation between the two variables. For example, if the coefficient near current changes of financial stability index is equal to 0.2, then it is possible to assume that the financial stability index changes at1 point will cause home bias change at 0.2 point on the average. When the average reaction for all countries is not precise enough due to differences in country's reaction, then short-form model will give misleading or biased results. Mostly, it is the feature of economic problems because every answer depends on different factors. For example, "small" (according to gross domestic product) countries are dominated by "big" countries, "open" economies (according to foreign trade) are more influenced by endogenous shocks than "closed" economies, countries with the floating exchange rate are more influenced by foreign environment than countries with the fixed exchange rate. All these differences cannot be estimated by short-form model according to equation (4.1); therefore, the long-form model, in which the relation between variables should be estimated also for each group separately, should be also designed. Actually, the reaction is estimated only for three groups of countries due to technical reasons, and Portugal can be perceived as the neutral country that has no additional features. The long-form model has the following structure:

$$HBI_t^C - HBI_{t-1}^C = \alpha + \sum_{L \in \{All,BC,VC,FC\}} L * \Big(\beta_{FSI}^{0L}(FSI_t^C - FSI_{t-1}^C) + \beta_{FSI}^{1L}(FSI_{t-1}^C - FSI_{t-2}^C) + \beta_{QQ}^{0L} QQ_t^C + \beta_{QQ}^{1L} QQ_{t-1}^C + \beta_{YY}^{0L} YY_t^C + \beta_{YY}^{1L} YY_{t-1}^C + \beta_{IND}^{0L} IND_t^C + \beta_{IND}^{1L} IND_{t-1}^C\Big) + \left[CX = \frac{R}{F}\right] + [PER = R/F]\,, \tag{4.2}$$

where

VC – “dummy” variable for the countries of the Visegrád Group;

BC – “dummy” variable for the Baltic countries;

FC – “dummy” variable for the financial center countries;

All – is the sign of short-form model,

other marks are the same as for equation[14] (4.1).

4.3 Empirical results

In short- and long-form model, both random and fixed parameters are used for cross-section effect and time-period effect to check which option is better. According to Hausman test, there is evidence against the null-hypothesis that there is no misspecification in the model for time-period effect but not for cross-section effect. It means that random cross-section and fixed time-period effects should be used. Additionally, Redundant Fixed Effects test supports the result of Hausman test and shows that the fixed time-period effect is not redundant, while the fixed cross-section effect is redundant. Additionally, both forms of the model have the better adjusted r-square measure with the fixed time-period effect than without the fixed time-period effect. Therefore, short- and long-form models are estimated with random and fixed time-period effect to testify the stability of coefficients (and with the random cross-section effect).

[14] It should be mentioned that all coefficients is estimated separately; thereby β_{FSI}^{0VC} may not be equal to β_{FSI}^{0BC}, etc.

Table 4.2 Coefficients value and significance level for short-form model.

		C	ΔFSI	ΔFSI(-1)	QQ	QQ(-1)	YY	YY(-1)	IND	IND(-1)
All countries		With fixed time-period effect								
	Coefficient	0.03	0.11***	-0.00	-0.06*	-0.01	-	0.03*	0.20	0.02
	Std. error	0.02	0.06	0.06	0.02	0.02	-	0.01	0.21	0.21
		Without fixed time-period effect								
	Coefficient	0.04	0.16***	0.03	-0.05*	0.01	-	0.01*	-0.07	-0.02
	Std. error	0.02	0.06	0.06	0.02	0.02	-	0.01	0.15	0.15

* - 1% significance level, ** - 5% significance level, *** - 10% significance level, and **** - 15% significance level.
Source: EViews calculations.

The Durbin Watson statistics for all forms and structure of models is about 1.7, and it means that positive autocorrelation is present. However, it is not the critical issue because the Durbin-Watson statistic is higher than the critical value (that is equal to 1.6 for positive autocorrelation) and it is possible to decline null-hypothesis about the presence of positive autocorrelation. The multicollinearity problem is also not present because uncentered variance inflation factors for all variables that are presented in Table 4.2 and Table 4.3 are lower than the critical value (that is equal to 5) – actually, the coefficients that are missed in these tables for models with fixed time-period effect are excluded due to multicollinearity problem's presence. The main issue of designed models is low adjusted r-square statistic: 10.0% and 11.2% for short- and long-form models with the fixed time-period effect and 4.3% and 8.3% for short- and long-form model without the fixed time-period effect. However, low adjusted r-square statistic implies only that there are other variables that also influence home bias index, but they are not used in the current structure. Thereby, the coefficients according to Table 4.1 and Table 4.2 are best linear unbiased estimators.

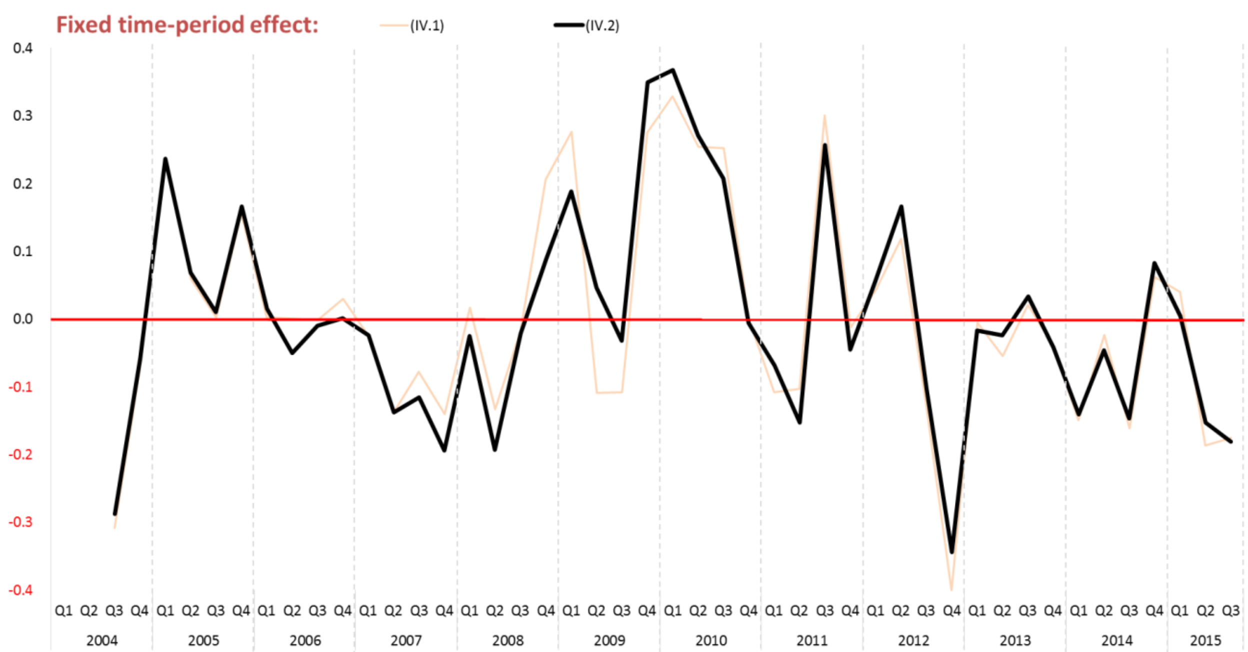
Table 4.3 Coefficients value and significance level for long-form model.

		C	ΔFSI	ΔFSI(-1)	QQ	QQ(-1)	YY	YY(-1)	IND	IND(-1)
All countries		With fixed time-period effect								
	Coefficient	0.03	0.21**	-	-	-	-	-	-	-
	Std. error	0.03	0.08	-	-	-	-	-	-	-
		Without fixed time-period effect								
	Coefficient	0.02	0.14**	-	-	-	-	-	-	-
	Std. error	0.03	0.06	-	-	-	-	-	-	-
Financial centers countries		With fixed time-period effect								
	Coefficient	-	-	0.04	-0.06** *	0.02	-	0.054*	0.25	0.14
	Std. error	-	-	0.09	0.03	0.04	-	0.02	0.33	0.34
		Without fixed time-period effect								
	Coefficient	-	-	-	-0.05***	-	-	0.03*	-	-
	Std. error	-	-	-	0.03	-	-	0.01	-	-
Baltic countries		With fixed time-period effect								
	Coefficient	-	0.48**	-0.24	-0.01	-0.03	-	0.01	0.25	0.09
	Std. error	-	0.23	0.21	0.03	0.04	-	0.01	0.26	0.27
		Without fixed time-period effect								
	Coefficient	-	0.54**	-	-	-	-	-	-	-
	Std. error	-	0.15	-	-	-	-	-	-	-
Visegrád group countries		With fixed time-period effect								
	Coefficient	-	-0.18	0.03	-0.07****	0.04	-	0.02	-0.37	-0.54****
	Std. error	-	0.14	0.11	0.04	0.06	-	0.02	0.34	0.34
		Without fixed time-period effect								
	Coefficient	-	-	-	-0.08**	-	-	-	-	-0.44***
	Std. error	-	-	-	0.04	-	-	-	-	0.26

* - 1% significance level, ** - 5% significance level, *** - 10% significance level, and **** - 15% significance level.
Source: EViews calculations.

As it is showed in Fig.4.1, the fixed time-period effect values are stable and do not differ too much for short- and long-form of models. For example, home bias index for all countries was higher (home bias was lower) than it was implied by models from the middle of 2008 (Lehman Brother’s collapse was in the third quarter of 2008) till the middle of 2012 with exceptions for the first half of 2011. At the same time, home bias index was lower (home bias was higher) than it was implied by models in 2004 after the expansion of the European Union. The same situation was in the second and third quarters of 2015, in the first three quarters of 2014, and from the first quarter of 2006 till the middle of 2008. It is important that the fixed time-period effect does not influence coefficients of the model (Table 4.2 and Table 4.3), and it is possible to assume that this effect is connected with additional control variables that are missed from the consideration in this thesis and it is not connected with the hypothesis of this thesis.

Fig.4.1 Fixed time-period effect.



Sources: author's calculations.

4.4 Interpretation of results

The values of coefficient near current financial stability changes from Table 4.2 imply that home bias index changes in the same direction as financial stability index at 0.11 point for each 1 point change of financial stability index. But it is average influence according to short-form model. At the same time, the influence according to long-form model is different for different groups of countries (Table 4.3): 0.21 for Portugal and the financial center countries, 0.69 for the Baltic countries, and only 0.03 for the Visegrád group countries. But it is very important to say that the relation between home bias and financial stability indexes for the Visegrád group countries is equal to 0.03, only if the statistical insignificant especial coefficient of financial stability index changes for the Visegrád group countries is taken into account. Otherwise, the relation between the two indexes is the same as for Portugal and the financial center countries. Also, there are influences on home bias index from financial stability changes one quarter ago for all the groups of countries, but it is not statistically significant.

There is also the significant statistical influence on home bias index from current quarter changes of real gross domestic product, from annual changes of real gross domestic product that is delayed on one quarter, and from the previous quarter changes of stock exchange indexes. According to Table 4.2, the stock index changes do not influence home bias index, but it means only that there are no statistical significant coefficients for all the countries simultaneously. According to short- and long-form model, the higher quarter changes of real gross domestic products imply lower home bias index, while higher annual changes of real domestic products imply higher home bias index. It seems that annual changes fulfill the role of smoothing for quarter changes in turbulent periods, while quarter changes imply that higher economic growth leads to lower home bias due to the higher level of expected return. The stock exchange index changes for the Visegrád group have the same influence. For other groups of countries, the influence on home bias index from stock index changes is positive, but it is not statistically significant; thereby, there is no confidence in the sign of this influence. It is possible that the positive value was received only due to the chance. Additionally, it is necessary to mention that quarter changes of real domestic product are statistically significant only for the financial center countries and the Visegrád group countries, while annual changes of real domestic product are statistically significant only for the financial center countries; therefore, it is possible to assume that long-form model is more precise than short-form model due to differences between the groups of countries.

The more critical problem for the results of the investigation is the standard errors of coefficients that are presented in Table 4.2 and Table 4.3 in general and the standard errors of coefficients for financial stability changes in particular. The standard errors are very high: sometimes, the standard error is even equal to coefficient or even higher, and, thereby, the confidence intervals are very wide. For example, the financial stability index changes can influence home bias index in the range from -1.2% till 23.7% for short-form model according to equation (4.1). For the long-form model, the range of possible coefficient values is from 5.0% till 37.6%. In any case, it does not influence the confirmation of the hypothesis that was testified in this thesis: the relation between home bias and financial stability indexes is positive and statistically significant at least for the countries and groups of countries that were investigated.

Conclusion:

In this chapter, the hypothesis about the relation between home bias and financial stability was testified: the relation between home bias and financial stability indexes is positive after taking into account some control variables. Before the hypothesis was verified, the problem of causation between home bias and financial stability indexes was investigated. It was shown that financial stability index Granger causes home bias index and its changes, while home bias index only Granger causes financial stability index. That gives arguments to consider financial stability index as the prime cause in home bias and financial stability feedback loop. Then two models that confirmed the hypothesis were designed. It was also shown that the relation between home bias and financial stability indexes could also depend on environment; however, the relation between home bias and financial stability indexes is positive and statistically significant for ten European countries that were investigated: Austria, the Czech Republic, Germany, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and United Kingdom. This positive relation is statistically significant after taking into account economic growth, stock exchange index growth, and differences between groups of countries.

Summary and conclusions

The main conclusion from the thesis would be possible describe in one sentence: the relation between home bias and financial stability is statistically significant after taking into account influence of some control variables. However, it is not the only result that has been received in this thesis.

In the first chapter, the problems with home bias definitions and measurement were discussed. The home bias means differences between actual weights of foreign investments and optimal weights that are determined in some way. However, home bias should measure not only differences between accumulated investments stocks, but also the profitability of foreign investments because there will be no paradox in higher domestic investments, if they are more profitable than foreign inverstments. Thereby, there are two types of home bias measurement: the measure of difference between foreign actual and optimal portfolios allocation and the measure of difference between returns on investments for some period – the second measure is harder to calculate and, generally, it is not possible to present its dynamics. According to the first type of measures (difference between actual and optimal weights), investors invest much more in domestic markets than it is assumed by optimal weights. Due to home bias presence, investors have lost money because the optimal portfolio generally is designed according to profitability ideas, i.e. to minimize risk and to earn the highest expected return. But home bias has been decreasing for the last fifteen years –the causes of this process is not known precisely but it can be the globalization of financial markets or creation of European Union – that is mostly good for the global economy due to better allocation of financial resources. However, it is also terrible in some circumstances because foreign investments are highly connected with crisis spillover effect: a lower level of home bias implies a higher level of connections with foreign countries, which causes a higher pace of exogenous shock spreading across the domestic country (and contagion spreading across the world too). Because this issue has not been investigated in depth, it was used as the topic of this thesis.

In the second chapter, the construction of home bias and financial stability indexes which are the important parts of hypothesis checking were discussed. As it was shown, the index weights of components that can be positive or negative give additional information about the economic stance of investigated countries. For example, real exchange rate weights present information whether domestic foreign exchange is demand-led (a negative value) or supply-led (a positive value). At the same time, the relation between home bias index and assets of investment international position and financial stability index and liabilities of international investment position is univocal: a higher level of assets and liabilities of international investment position implies a higher level of home bias and financial stability indexes accordingly (home bias and financial stability are lower for the higher level of assets and liabilities of international investment positions).

The more profound analysis of home bias and financial stability indexes was made in third chapter. It was shown that the indexes have the positive relation: a higher financial stability implies a higher level of home bias and vice versa. However, generally at the crisis time, home bias and financial stability indexes show divergent dynamics. Additionally, the three groups of countries that have the same weight signs and the three separated countries that have no similarities with other countries are identified. The exceptions are Latvia, Luxemburg, and Portugal while the three groups are as follows: Austria, the Czech Republic, and Poland; Germany and the United Kingdom; Hungary and Lithuania. The countries from the groups have commonalities between economies that is caused not by geographical or political tendencies, but by the reaction for contagion spillover after Lehman Brothers' collapse and general economic environment.

The last but the most important chapter is the fourth chapter that tested the hypothesis. As it was investigated, the home bias and financial stability indexes have the positive correlation; therefore, the hypothesis was modified to testify exactly positive relation between home bias and financial stability indexes. The stronger version of hypothesis was verified by panel model results where panel model was estimated on data of the ten European Union countries that have no problems with data. According to results, it is possible to conclude the following results. At first, the relation between home bias and financial stability indexes are statistically significant and the relation is positive. Secondly, even though home bias index influences changes of financial stability index, the "prime" cause, more probably, is financial stability index that caused the home bias index changes and also the level of home bias index. Finally, different groups of countries has different strength of relation between home bias index and financial stability.

To summarize the whole thesis, it is necessary to mention the importance of the identified relation. It was shown that financial stability index changes are influenced by home bias index, while home bias index value and changes are influenced by financial stability index. Thereby, it is explainable why it is hard to limit the spillover and contagion effects. The abstract example can be as follows. In the beginning, a crisis starts in some country. Then the event causes changes of financial stability of this country and the financial stability of other countries afterwards. Further, that causes changes already in home bias index of these countries and financial stability of other countries is caused one more time afterwards. Such the negative feedback spiral can be repeated many times, if the feedback loop is not identified. But if the process behind the negative feedback spiral is identified, then it is possible to limit its strength beforehand to limit the contagion spreading inside the country through supporting financial stability index or to limit the relation between home bias and financial stability indexes through additional mechanisms that should still be developed. The first step of this negative feedback spiral identifying was done in this work, but more steps should have been made because, as it was shown, the relation between home bias and financial stability indexes is different for different groups of countries. The next step should be identifying the causes of these differences because it can show more instruments that can be used to stabilize a domestic economy after exogenous shocks.

Bibliography

1. Adler, M. & Dumas, M., 1983. ‘International Portfolio Choice and Corporation Finance: A Synthesis’. *The Journal of Finance*, vol. 38, no. 3, pp. 925-984.
2. Ahearne, A. G., Griever, W. L. & Warnock, F.E., 2004. ‘Information costs and home bias: an analysis of US holdings of foreign equities.’ *Journal of International Economics*, vol. 62, no. 2, pp. 313-336.
3. Aizenman, J., Lee, J. & Sushko, Vl., 2012. ‘From the Great Moderation to the Global Crisis: Exchange Market Pressure in the 2000s.’ *Open Economies Review*, vol. 23, no. 4, pp. 597-621.
4. Amadi, A. A., 2005. *Equity Home Bias: A Disappearing Phenomenon?* Davis: University of California.
5. Ayvazian, S.A., Buchstaber, V.M., Yenyukov, I.S. & Meshalkin, L.D., 1989. *Applied statistics. Classification and Reduction of Dimensionality.* Moscow: Finansy i statistika (in Russian).
6. Baele, L., Pungulescu, Ch. & Ter Horste, J., 2007. ‘Model uncertainty, financial market integration and the home bias puzzle.’ *Journal of International Money and Finance*, vol. 26, no. 4, pp. 606-630.
7. Bakker, Melle, 2013. ‘European Union Pension Funds and Home Bias. Geographical Asset Allocation in Light of the Three Goals Set by the European Commission‘. *MSc Thesis*, Rotterdam: Erasmus University.
8. Balta, N. & Delgado, J., 2007. ‘Home Bias and Market Integration in the EU’. *CESifo Economic Studies*, vol.55, no. 1, pp. 110-144.

9. Berill, J. & Kearney, C., 2008. ‘Firm-level internationalisation and the home bias puzzle’. *Journal of Economics and Business*, vol.62, no. 4, pp. 235-256.

10. Brushko, I. & Hashimoto, Y., 2014. *The Role of Country Concentration in the International Portfolio Investment Positions for the European Union Members*. IMF Working Paper No. 14/74, International Monetary Fund.

11. Bryant, F. B., and Yarnold, P. R., 1995. *Principal components analysis and exploratory and confirmatory factor analysis. In L. G. Grimm & P. R. Yarnold (Eds.), Reading and understanding multivariate analysis.* Washington, DC: American Psychological Association.

12. Coeurdacier, N. & Rey, H., 2013. *Home Bias in Open Economy Financial Macroeconomics.* NBER Working Paper No. 17691, National Bureau of Economic Research.

13. Collard, F., Dellas, H., Diba, B. & Stockman, A., 2007. *Goods Trade and International Equity Portfolios.* NBER Working Paper No. 13612, National Bureau of Economic Research.

14. Cooper, I. & Kaplanis, E., 1994. ‘The Implications of the Home Bias in Equity Portfolios’. *Business Strategy Review*, vol.5, no.2, pp. 41-53.

15. Coval, J. D. & Moskovitz, T. J., 1999. ‘Home Bias at Home: Local Equity Preference in Domestic Portfolios’. *The Journal of Finance*, vol. 54, no. 6, pp. 2045-2073.

16. Dahlquist, M., Pinkowitz, L., Stulz, R. M. & Williamson, R., 2003. ‘Corporate Governance and the Home Bias’. *Journal of Financial and Quantitative Analysis*, vol. 38, no. 1, pp. 87-110.

17. De Martel, V., Holmes, R. & Gemelou, R., 2015. *Leverage in Risk Parity. A Means to a More Diversified End.* BlackRock report. US: BlackRock Inc.

18. Eichengreen, B., Rose, A. & Wyplosz Ch., 1994. *Speculative Attacks on Pegged Exchange Rates: An Empirical Exploration with Special Reference to the European Monetary System.* NBER Working Paper No. 4898, National Bureau of Economic Research.

19. Eichengreen, B., Rose, A. & Wyplosz Ch., 1997. *Contagious Currency Crises.* NBER Working Paper No. 5681, National Bureau of Economic Research.

20. Eurostat, 2015. *International investment position statistics.* Review, viewed 18 April 2016, <http://ec.europa.eu/eurostat/statistics-explained/index.php/International_investment_position_statistics>.

21. Fidora, M., Fratzscher, M. & Thimann, Ch., 2006. *Home Bias in Global Bond and Equity Markets: The Role of Real Exchange Rate Volatility.* ECB Working Paper No. 685, European Central Bank.

22. Foad, H. S., 2012. 'Equity Home Bias and the Euro'. *Quarterly Journal of Finance*, vol. 2, no.1, p.29.

23. French, K.R. & Poterba, J.M., 1991. *Investor Diversification and International Equity Markets.* NBER Working Paper No. 3609, National Bureau of Economic Research.

24. Gadanecz, B. & Jayaram, K., 2009. 'Measures of financial stability – a review.' IFC Bulletin, no. 31, pp. 365-380.

25. Girton, L. & Roper, D., 1977. 'A monetary model of exchange market pressure applied to the postwar Canadian experience', *American Economic Review*, vol. 67, no. 4, pp. 537-548.

26. Glassman, D. A. & Riddick, L. A. 'What causes home asset bias and how should it be measured?' *Journal of Empirical Finance*, vol. 8, pp. 35-54.

27. Gordon, R. & Gaspar, V., 2001. *Home Bias in Portfolios and Taxation of Asset Income.* NBER Working Paper No. 8193, National Bureau of Economic Research.

28. Gorsuch, R. L., 1983. *Factor Analysis, second edition.* Hillsdale: Lawrence Erlbaum Associates.

29. Gruber, M.J., 2003. *Modern Portfolio Theory.* Essay, viewed 18 April 2016, < http://www1.law.nyu.edu/ncpl/pdfs/2003/Conf2003_Gruber_Final.pdf>.

30. Hausmann, R., Hidalgo, C. A., Stock, D. P. & Yildirim, M. A., 2014. *Implied Comparative Advantage.* Working Paper Series rwp14-003, Harvard University, John F. Kennedy School of Government.

31. Heinz, F. F. & Rusinova, D., 2015. *An alternative view of exchange market pressure episodes in emerging Europe: an analysis using Extreme Value Theory (EVT).* ECB Working Paper No. 1818, European Central Bank.

32. Hochberg, Y. V., Rauh, J. D. & Andonov, A., 2013. *Pension Fund Board Composition and Investment Performance: Evidence from Private Equity.* Working Paper, viewed 18 April 2016, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2754820>.

33. IMF, 2013. *Sixth Edition of the IMF's Balance of Payments and International Investment Position Manual (BPM6).* Manual, viewed 18 April 2016, < https://www.imf.org/external/pubs/ft/bop/ 2007/bopman6.htm>.

34. Jeske, K., 2001. *Private International Debt with Risk of Repudiation.* Working Paper No. 16a, Federal Reserve Bank of Atlanta.

35. Kim, J. O., & Mueller, C. W., 1978. *Factor Analysis: Statistical methods and practical issues.* Newbury Park, CA: Sage Publications.

36. Kim, B.J., Yun, Y. S., Cin, B. Ch. & Kim, Y. J., 2014. ‘Home Bias in Emerging Bond and Stock Markets’. *Emerging Markets Finance and Trade*, vol. 50, no. 4, pp. 95-124.

37. LaBarge, Karin Peterson, 2008. *Diversification by Country and Global Sector: Considerations for Portfolio Construction.* Vanguard report. Valley Forge, Pa.: The Vanguard Group.
38. Lawley, D. N. & Maxwell., A. E., 1971. *Factor Analysis as a Statistical Method. Second ed.* London: Butterworths.
39. Lewis, K. K., 1991. 'Should the Holding Period Matter in Tests of the Intertemporal Consumption-based CAPM?' *Journal of Monetary Economics*, vol. 28, pp. 365 - 389.
40. Li, J., Rajan, S. R. and Willet, Th., 2006. *Measuring currency crises using exchange market pressure indices: the imprecision of precision weights.* Working Paper, viewed 18 April 2016, < http://cgu.edu/PDFFiles/SPE/workingpapers/econ/2006-09.pdf>.
41. Lintner, J., 1965. 'The valuation of risky assets and the selection of risky investment in stock portfolio and capital budgets.' *Review of Economics and Statistics*, vol. 47, pp. 103 – 124.
42. Magi, A., 2008. 'Portfolio choice, behavioral preferences and equity home bias.' *The Quarterly Review of Economics and Finance*, vol. 49, no. 2, pp. 501-520.
43. Maier, M. & Scholz, H., 2016. *A Return-Based Approach to Identify Home Bias of European Equity Funds.* Working Paper, viewed 18 April 2016, <http://papers.ssrn.com/sol3/ papers.cfm?abstract_id=2738035>.
44. Mishra, A.V., 2015. 'Measures of equity home bias puzzle'. *Journal of Empirical Finance*, vol. 34, pp. 293–312.
45. Nunnally, J. C. (1978). *Psychometric theory. Second edition.* New York: McGraw-Hill.
46. OECD, 2008. *Handbook on Constructing Composite Indicators.* Methodology and User Guide, viewed 18 April 2016, < http://www.oecd.org/std/42495745.pdf>.

47. Omisore, I., Yusuf, M. & Christopher, Nw., 2012. ‘The modern portfolio theory as an investment decision tool’. *Journal of Accounting and Taxation*, vol.4, no.2, pp. 19-28.
48. Othmani, S., Saanoun, I. B., Garali, W. & Arab, M. B., 2014. ‘Determinants of Home Bias Puzzle in European Countries.’ *International Review of Management and Business Research*, vol.3, no. 1, pp. 182-198.
49. Park, C. Y. & Mercado, R. V. Jr., 2014. *Equity Home Bias, Financial Integration, and Regulatory Reforms: Implications for Emerging Asia.* Working paper Series on Regional Economic Integration No. 133, Asian Development Bank.
50. Pentecost, E. J., Van Hooydonk, Ch. & Van Poeck, A., 2001. ‘Measuring and estimating exchange market pressure in EU.’ *Journal of International Money and Finance*, vol. 20, pp. 401-418.
51. Philips, Christopher B., 2012. *Considerations for Investing in Non-U.S. Equities.* Vanguard report. Valley Forge, Pa.: The Vanguard Group.
52. Philips, C. B., Kinniry, F. M. Jr. & Donaldson, S. J., 2012. *The role of home bias in global asset allocation decisions.* Vanguard report. Valley Forge, Pa.: The Vanguard Group.
53. PPCMetrics, 2015. *Home Bias – Swiss Pension Fund Experience.* Presentation, viewed 18 April 2016, <http://www.ppcmetrics.ch/files/publications/files/2015_06_Home_Bias_Swiss_Pension_ Fund_Experience_EPFIF_DL.pdf>.
54. Sercu, P. & Vanpée, R., 2007. *Home Bias in International Equity Portfolios: A Review.* Working Paper, viewed 18 April 2016, <http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1025806>.
55. Sharpe, W. F., 1964. ‘Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk’. *The Journal of Finance*, vol. 19, no. 3, pp. 425-442.

56. Shinagawa, Y, 2014. *Determinants of Financial Market Spillovers: The Role of Portfolio Diversification, Trade, Home Bias, and Concentration.* IMF Working Paper No. 14/187, International Monetary Fund.

57. Strong, N. C. & Xu, X., 2003. 'Understanding the equity home bias: evidence from survey data'. *The Review of Economics and Statistics*, vol. 85, no. 2, pp. 307–312

58. Warnock, F. E. & Cleave, Ch., 2002. *Financial Centers and the Geography of Capital Flows.* International Finance Discussion Papers No. 722, Board of Governors of the Federal Reserve System.

Appendix 1. Data Inconsistencies for European Countries

Table A1.1 Weights of indexes for countries.

	Issues	Data					
	Countries	Real Exchange Rate	Interest Rate	International investment position	Secondary income	Nominal or Real GDP	Stock indexes
1	*Austria*						
2	*Belgium*						
3	*Bulgaria*						
4	*Croatia*						
5	*Cyprus*						
6	*Czech Republic*						
7	*Denmark*						
8	*Estonia*						
9	*Finland*						
10	*France*						
11	*Germany*						
12	*Greece*						
13	*Hungary*						
14	*Iceland*						
15	*Ireland*						
16	*Italy*						
17	*Latvia*						
18	*Lithuania*						
19	*Luxembourg*						
20	*Malta*						
21	*Netherlands*						
22	*Norway*						
23	*Poland*						
24	*Portugal*						
25	*Romania*						
26	*Serbia*						
27	*Slovakia*						
28	*Slovenia*						
29	*Spain*						
30	*Sweden*						
31	*Switzerland*						
32	*United Kingdom*						

Source: author's findings.

All the data was checked from the left one by one and, if some data were missed, then all other data would not be checked later (gray color of the cells). The problem for a country is marked by red, while all green cells mean that the country has no problems with data and is used for all following calculations. There are ten such countries: Austria, the Czech Republic, Germany, Hungary, Latvia, Lithuania, Luxembourg, Poland, Portugal, and the United Kingdom.

Appendix 2. Stock Exchange Indexes

Table A2.1 General information about stock exchange indexes.

Country	Index	Index name	Companies[15]	Initial date	Short description
Poland	WIG	Warszawski Indeks Giełdowy	482	16 April 1991	Stock exchange index of income type.
German	DAX 30	Deutscher Aktienindex	30	30 December 1987	Major (capitalization and book value) German companies.
United Kingdom	FTSE 100	Financial Times Stock Exchange	100	3 January 1984	Companies with the highest capitalization
Czech Republic	PX	Prague Stock Exchange Index	50	4 May 1994	Capitalization-weighted index of major stocks
Latvia	RIGSE	OMX Riga Index	26	31 December 1999	All-share index consisting of all the shares listed on the Main & Secondary lists.
Lithhuania	VILSE	OMX Vilnius Index	10	31 December 1999	All-share index consisting of all the shares listed on the Main & Secondary lists.
Luxembourg	LUXXX	Luxembourg Stock Exchange Index	9	4 January 1999	Weighted index of the most capitalized (by free-float) and liquid
Hungary	BUX	Budapest Stock Exchange Index	25	2 January 1991	Capitalization-weighted total return index adjusted for free float.
Austria	ATX	Austrian Traded Index	20	2 January 1991	Capitalization-weighted index of the most heavily traded stocks.
Portugal	PSI 20	Portuguese Stock Index	20	31 December 1992	Capitalization-weighted index of the top 20 stocks by free-float.

Source: Bloomberg Terminal, stock exchange's sites.

[15] The information is presented as of 13 April 2016.

Appendix 3. Python Program Code For Index Coefficient Calculations

```
import numpy as np

import csv

from sklearn.decomposition import PCA

from sklearn.preprocessing import StandardScaler


#=============CZECH===========================================

home_bias_data_str = np.loadtxt('CzechHomeBias.csv',

               dtype = 'S12',

               skiprows = 1,

               delimiter = ';',

               usecols = (1,2,3))


home_bias_data = home_bias_data_str.astype(np.float)


home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)


pca_home_bias = PCA(n_components = 1)

home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)

print("Czech's Home bias index explained %d%% of volatility!"

     % (pca_home_bias.explained_variance_ratio_*100))

print("Czech's Home bias index coefficients are follows: %f, %f, %f."
```

```
    % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1], pca_home_bias.components_[0,2]))


exchange_rate_data_str = np.loadtxt('CzechFinancialStability.csv',
             dtype = 'S10',
             skiprows = 1,
             delimiter = ';',
             usecols = (1,2,3))


exchange_rate_data = exchange_rate_data_str.astype(np.float)


exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)


pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("Czech's Financial Stability index explained %d%% of volatility!"
    % (pca_exchange_rate.explained_variance_ratio_*100))
print("Czech's Financial Stability index coefficients are follows: %f, %f, %f."
    % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1], pca_exchange_rate.components_[0,2]))


with open('Results/Czech.csv', 'w') as csvfile:
   fieldnames = ['HBI', 'FSI']
   writer = csv.DictWriter(csvfile, fieldnames=fieldnames)


   writer.writeheader()
```

```
    for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
        writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})
#====GERMAN=================
home_bias_data_str = np.loadtxt('GermanHomeBias.csv',
                dtype = 'S12',
                skiprows = 1,
                delimiter = ';',
                usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)

pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("German's Home bias index explained %d%% of volatility!"
     % (pca_home_bias.explained_variance_ratio_*100))
print("German's Home bias index coefficients are follows: %f, %f, %f."
     % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1],
pca_home_bias.components_[0,2]))

exchange_rate_data_str = np.loadtxt('GermanFinancialStability.csv',
                dtype = 'S10',
                skiprows = 1,
                delimiter = ';',
```

```
                usecols = (1,2,3))

exchange_rate_data = exchange_rate_data_str.astype(np.float)

exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)

pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("German's Financial Stability index explained %d%% of volatility!"
     % (pca_exchange_rate.explained_variance_ratio_*100))
print("German's Financial Stability index coefficients are follows: %f, %f, %f."
     % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1],
pca_exchange_rate.components_[0,2]))

with open('Results/German.csv', 'w') as csvfile:
    fieldnames = ['HBI', 'FSI']
    writer = csv.DictWriter(csvfile, fieldnames=fieldnames)

    writer.writeheader()
    for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
        writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})

#============LATVIA===========================
home_bias_data_str = np.loadtxt('LatviaHomeBias.csv',
                dtype = 'S12',
```

```
            skiprows = 1,
            delimiter = ';',
            usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)

pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("Latvia's Home bias index explained %d%% of volatility!"
    % (pca_home_bias.explained_variance_ratio_*100))
print("Latvia's Home bias index coefficients are follows: %f, %f, %f."
    % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1], pca_home_bias.components_[0,2]))

exchange_rate_data_str = np.loadtxt('LatviaFinancialStability.csv',
            dtype = 'S10',
            skiprows = 1,
            delimiter = ';',
            usecols = (1,2,3))

exchange_rate_data = exchange_rate_data_str.astype(np.float)

exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)
```

```
pca_exchange_rate = PCA(n_components = 1)

exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)

print("Latvia's Financial Stability index explained %d%% of volatility!"
    % (pca_exchange_rate.explained_variance_ratio_*100))

print("Latvia's Financial Stability index coefficients are follows: %f, %f, %f."
    % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1],
pca_exchange_rate.components_[0,2]))


with open('Results/Latvia.csv', 'w') as csvfile:
  fieldnames = ['HBI', 'FSI']
  writer = csv.DictWriter(csvfile, fieldnames=fieldnames)


  writer.writeheader()
  for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
    writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})


#==============LITHUANIA====================================
home_bias_data_str = np.loadtxt('LithuaniaHomeBias.csv',
          dtype = 'S12',
          skiprows = 1,
          delimiter = ';',
          usecols = (1,2,3))


home_bias_data = home_bias_data_str.astype(np.float)
```

```
home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)


pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("Lithuania's Home bias index explained %d%% of volatility!"
    % (pca_home_bias.explained_variance_ratio_*100))
print("Lithuania's Home bias index coefficients are follows: %f, %f, %f."
    % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1],
pca_home_bias.components_[0,2]))


exchange_rate_data_str = np.loadtxt('LithuaniaFinancialStability.csv',
            dtype = 'S10',
            skiprows = 1,
            delimiter = ';',
            usecols = (1,2,3))


exchange_rate_data = exchange_rate_data_str.astype(np.float)


exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)


pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("Lithuania's Financial Stability index explained %d%% of volatility!"
    % (pca_exchange_rate.explained_variance_ratio_*100))
```

```
print("Lithuania's Financial Stability index coefficients are follows: %f, %f, %f."
    % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1],
pca_exchange_rate.components_[0,2]))

with open('Results/Lithuania.csv', 'w') as csvfile:
    fieldnames = ['HBI', 'FSI']
    writer = csv.DictWriter(csvfile, fieldnames=fieldnames)

    writer.writeheader()
    for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
        writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})

#====================LUXEMBOURG======================
home_bias_data_str = np.loadtxt('LuxembourgHomeBias.csv',
                dtype = 'S12',
                skiprows = 1,
                delimiter = ';',
                usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)

pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
```

```
print("Luxembourg's Home bias index explained %d%% of volatility!"
    % (pca_home_bias.explained_variance_ratio_*100))
print("Luxembourg's Home bias index coefficients are follows: %f, %f, %f."
    % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1],
pca_home_bias.components_[0,2]))

exchange_rate_data_str = np.loadtxt('LithuaniaFinancialStability.csv',
            dtype = 'S10',
            skiprows = 1,
            delimiter = ';',
            usecols = (1,2,3))

exchange_rate_data = exchange_rate_data_str.astype(np.float)

exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)

pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("Luxembourg's Financial Stability index explained %d%% of volatility!"
    % (pca_exchange_rate.explained_variance_ratio_*100))
print("Luxembourg's Financial Stability index coefficients are follows: %f, %f, %f."
    % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1],
pca_exchange_rate.components_[0,2]))

with open('Results/Luxembourg.csv', 'w') as csvfile:
  fieldnames = ['HBI', 'FSI']
```

```
    writer = csv.DictWriter(csvfile, fieldnames=fieldnames)

    writer.writeheader()
    for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
        writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})

#=======HUNGARY========================================
home_bias_data_str = np.loadtxt('HungaryHomeBias.csv',
                dtype = 'S12',
                skiprows = 1,
                delimiter = ';',
                usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)

pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("Hungary's Home bias index explained %d%% of volatility!"
     % (pca_home_bias.explained_variance_ratio_*100))
print("Hungary's Home bias index coefficients are follows: %f, %f, %f."
     % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1],
pca_home_bias.components_[0,2]))
```

```
exchange_rate_data_str = np.loadtxt('HungaryFinancialStability.csv',
                dtype = 'S10',
                skiprows = 1,
                delimiter = ';',
                usecols = (1,2,3))

exchange_rate_data = exchange_rate_data_str.astype(np.float)

exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)

pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("Hungary's Financial Stability index explained %d%% of volatility!"
     % (pca_exchange_rate.explained_variance_ratio_*100))
print("Hungary's Financial Stability index coefficients are follows: %f, %f, %f."
     % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1], pca_exchange_rate.components_[0,2]))

with open('Results/Hungary.csv', 'w') as csvfile:
   fieldnames = ['HBI', 'FSI']
   writer = csv.DictWriter(csvfile, fieldnames=fieldnames)

   writer.writeheader()
   for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
      writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})
```

```
#================AUSTRIA=================================

home_bias_data_str = np.loadtxt('AustriaHomeBias.csv',
                dtype = 'S12',
                skiprows = 1,
                delimiter = ';',
                usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)

pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("Austria's Home bias index explained %d%% of volatility!"
     % (pca_home_bias.explained_variance_ratio_*100))
print("Austria's Home bias index coefficients are follows: %f, %f, %f."
     % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1],
pca_home_bias.components_[0,2]))

exchange_rate_data_str = np.loadtxt('AustriaFinancialStability.csv',
                dtype = 'S10',
                skiprows = 1,
                delimiter = ';',
                usecols = (1,2,3))
```

```
exchange_rate_data = exchange_rate_data_str.astype(np.float)


exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)


pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("Austria's Financial Stability index explained %d%% of volatility!"
    % (pca_exchange_rate.explained_variance_ratio_*100))
print("Austria's Financial Stability index coefficients are follows: %f, %f, %f."
    % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1], pca_exchange_rate.components_[0,2]))


with open('Results/Austria.csv', 'w') as csvfile:
   fieldnames = ['HBI', 'FSI']
   writer = csv.DictWriter(csvfile, fieldnames=fieldnames)


   writer.writeheader()
   for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
      writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})


#==================POLAND========================
home_bias_data_str = np.loadtxt('PolandHomeBias.csv',
            dtype = 'S12',
            skiprows = 1,
            delimiter = ';',
```

```
            usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)

pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("Poland's Home bias index explained %d%% of volatility!"
    % (pca_home_bias.explained_variance_ratio_*100))
print("Poland's Home bias index coefficients are follows: %f, %f, %f."
    % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1], pca_home_bias.components_[0,2]))

exchange_rate_data_str = np.loadtxt('PolandFinancialStability.csv',
            dtype = 'S10',
            skiprows = 1,
            delimiter = ';',
            usecols = (1,2,3))

exchange_rate_data = exchange_rate_data_str.astype(np.float)

exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)

pca_exchange_rate = PCA(n_components = 1)
```

```
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("Poland's Financial Stability index explained %d%% of volatility!"
     % (pca_exchange_rate.explained_variance_ratio_*100))
print("Poland's Financial Stability index coefficients are follows: %f, %f, %f."
     % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1], pca_exchange_rate.components_[0,2]))

with open('Results/Poland.csv', 'w') as csvfile:
    fieldnames = ['HBI', 'FSI']
    writer = csv.DictWriter(csvfile, fieldnames=fieldnames)

    writer.writeheader()
    for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
        writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})

#=================PORTUGAL=====================================
home_bias_data_str = np.loadtxt('PortugalHomeBias.csv',
                dtype = 'S12',
                skiprows = 1,
                delimiter = ';',
                usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)
```

```
pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("Portugal's Home bias index explained %d%% of volatility!"
    % (pca_home_bias.explained_variance_ratio_*100))
print("Portugal's Home bias index coefficients are follows: %f, %f, %f."
    % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1],
pca_home_bias.components_[0,2]))


exchange_rate_data_str = np.loadtxt('PortugalFinancialStability.csv',
            dtype = 'S10',
            skiprows = 1,
            delimiter = ';',
            usecols = (1,2,3))


exchange_rate_data = exchange_rate_data_str.astype(np.float)


exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)


pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("Portugal's Financial Stability index explained %d%% of volatility!"
    % (pca_exchange_rate.explained_variance_ratio_*100))
print("Portugal's Financial Stability index coefficients are follows: %f, %f, %f."
    % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1],
pca_exchange_rate.components_[0,2]))
```

```
with open('Results/Portugal.csv', 'w') as csvfile:
    fieldnames = ['HBI', 'FSI']
    writer = csv.DictWriter(csvfile, fieldnames=fieldnames)

    writer.writeheader()
    for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
        writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})

#==================UK================================
home_bias_data_str = np.loadtxt('UKHomeBias.csv',
                  dtype = 'S12',
                  skiprows = 1,
                  delimiter = ';',
                  usecols = (1,2,3))

home_bias_data = home_bias_data_str.astype(np.float)

home_bias_data_norm = StandardScaler().fit_transform(home_bias_data)

pca_home_bias = PCA(n_components = 1)
home_bias_index_data = pca_home_bias.fit_transform(home_bias_data_norm)
print("UK's Home bias index explained %d%% of volatility!"
      % (pca_home_bias.explained_variance_ratio_*100))
print("UK's Home bias index coefficients are follows: %f, %f, %f."
```

```
    % (pca_home_bias.components_[0,0], pca_home_bias.components_[0,1], pca_home_bias.components_[0,2]))


exchange_rate_data_str = np.loadtxt('UKFinancialStability.csv',
            dtype = 'S10',
            skiprows = 1,
            delimiter = ';',
            usecols = (1,2,3))


exchange_rate_data = exchange_rate_data_str.astype(np.float)


exchange_rate_data_norm = StandardScaler().fit_transform(exchange_rate_data)


pca_exchange_rate = PCA(n_components = 1)
exchange_rate_index_data = pca_exchange_rate.fit_transform(exchange_rate_data_norm)
print("UK's Financial Stability index explained %d%% of volatility!"
    % (pca_exchange_rate.explained_variance_ratio_*100))
print("UK's Financial Stability index coefficients are follows: %f, %f, %f."
    % (pca_exchange_rate.components_[0,0], pca_exchange_rate.components_[0,1], pca_exchange_rate.components_[0,2]))


with open('Results/UK.csv', 'w') as csvfile:
  fieldnames = ['HBI', 'FSI']
  writer = csv.DictWriter(csvfile, fieldnames=fieldnames)


  writer.writeheader()
```

```
for hbi, fsi in zip(home_bias_index_data, exchange_rate_index_data):
    writer.writerow({'HBI': float(hbi), 'FSI': float(fsi)})
```

Appendix 4. EViews Result Tables

Table A4.1 Unit root test for financial stability index.

Panel unit root test: Summary
Series: FSI
Date: 04/20/16 Time: 16:36
Sample: 2004Q1 2015Q3
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.33930	0.0097	10	450
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.15475	0.5615	10	450
ADF - Fisher Chi-square	15.5476	0.7443	10	450
PP - Fisher Chi-square	13.7821	0.8414	10	460

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Source: EViews calculations.

Table A4.2 Unit root test for home bias index.

Panel unit root test: Summary
Series: HBI
Date: 04/20/16 Time: 16:36
Sample: 2004Q1 2015Q3
Exogenous variables: Individual effects
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.49227	0.0063	10	450

Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.58781	0.2783	10	450
ADF - Fisher Chi-square	19.0629	0.5177	10	450
PP - Fisher Chi-square	13.0781	0.8740	10	460

** Probabilities for Fisher tests are computed using an asymptotic Chi
-square distribution. All other tests assume asymptotic normality.

Source: EViews calculations.

Table A4.3 Pairwise Granger Causality Test.

Pairwise Granger Causality Tests
Date: 04/20/16 Time: 16:38
Sample: 2004Q1 2015Q3
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
FSI does not Granger Cause HBI	450	5.46147	0.0045
HBI does not Granger Cause FSI		1.46347	0.2325
FSI-FSI(-1) does not Granger Cause HBI	440	0.05762	0.9440
HBI does not Granger Cause FSI-FSI(-1)		3.27126	0.0389
HBI-HBI(-1) does not Granger Cause FSI	440	0.00208	0.9979
FSI does not Granger Cause HBI-HBI(-1)		3.53057	0.0301
FSI-FSI(-1) does not Granger Cause HBI-HBI(-1)	440	0.04664	0.9544
HBI-HBI(-1) does not Granger Cause FSI-FSI(-1)		0.02154	0.9787

Source: EViews calculations.

Table A4.4 Short-form model.

Dependent Variable: HBI-HBI(-1)
Method: Panel EGLS (Cross-section random effects)
Date: 04/23/16 Time: 15:23
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	0.027504	0.023884	1.151571	0.2502
FSI-FSI(-1)	0.112238	0.063226	1.775195	0.0766
FSI(-1)-FSI(-2)	-0.008280	0.062668	-0.132125	0.8950
QQ	-0.035355	0.030847	-1.146126	0.2524
QQ(-1)	-0.000795	0.024087	-0.033016	0.9737
YY	-0.019232	0.023429	-0.820870	0.4122
YY(-1)	0.037998	0.018126	2.096286	0.0367
IND	0.204759	0.214185	0.955989	0.3397
IND(-1)	0.016805	0.218459	0.076928	0.9387

Effects Specification

	S.D.	Rho
Cross-section random	0.000000	0.0000
Period fixed (dummy variables)		
Idiosyncratic random	0.382296	1.0000

Weighted Statistics

R-squared	0.203439	Mean dependent var	0.059541
Adjusted R-squared	0.099104	S.D. dependent var	0.398638
S.E. of regression	0.378369	Sum squared resid	56.83587
F-statistic	1.949860	Durbin-Watson stat	1.707384
Prob(F-statistic)	0.000207		

Unweighted Statistics

R-squared	0.203439	Mean dependent var	0.059541
Sum squared resid	56.83587	Durbin-Watson stat	1.707384

Source: EViews calculations.

Table A4.5 Redundant Fixed Effects Test for short-form model.

Redundant Fixed Effects Tests
Equation: MODELFUL
Test period fixed effects

Effects Test	Statistic	d.f.	Prob.
Period F	1.565053	(44,397)	0.0149

Period fixed effects test equation:
Dependent Variable: HBI-HBI(-1)
Method: Panel EGLS (Cross-section random effects)
Date: 04/23/16 Time: 15:25
Sample (adjusted): 2004Q3 2015Q3

Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450
Use pre-specified random component estimates
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.036901	0.021358	1.727719	0.0847
FSI-FSI(-1)	0.170194	0.056648	3.004387	0.0028
FSI(-1)-FSI(-2)	0.041353	0.056172	0.736185	0.4620
QQ	-0.066893	0.028792	-2.323275	0.0206
QQ(-1)	0.013817	0.021819	0.633251	0.5269
YY	0.016945	0.020768	0.815937	0.4150
YY(-1)	-0.000346	0.015025	-0.023060	0.9816
IND	-0.114407	0.132786	-0.861591	0.3894
IND(-1)	-0.025633	0.142063	-0.180435	0.8569

Effects Specification

	S.D.	Rho
Cross-section random	0.000000	0.0000
Idiosyncratic random	0.382296	1.0000

Weighted Statistics

R-squared	0.065271	Mean dependent var	0.059541
Adjusted R-squared	0.048314	S.D. dependent var	0.398638
S.E. of regression	0.388889	Sum squared resid	66.69444
F-statistic	3.849284	Durbin-Watson stat	1.670993
Prob(F-statistic)	0.000214		

Unweighted Statistics

R-squared	0.065271	Mean dependent var	0.059541
Sum squared resid	66.69444	Durbin-Watson stat	1.670993

Source: EViews calculations.

Table A4.6 Hausman Test for short-form model.

Correlated Random Effects - Hausman Test
Equation: Untitled
Test cross-section and period random effects

Test Summary	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000000	8	1.0000

Period random	19.279387	8	0.0134
Cross-section and period random	18.569011	8	0.0173

* Cross-section test variance is invalid. Hausman statistic set to zero.
** WARNING: estimated cross-section random effects variance is zero.

Cross-section random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
(FSI-FSI(-1))	0.157599	0.160879	0.000009	0.2746
(FSI(-1)-FSI(-2))	0.029546	0.033440	0.000011	0.2390
QQ	-0.063301	-0.061974	-0.000001	NA
QQ(-1)	0.012075	0.012065	-0.000002	NA
YY	0.011198	0.011303	-0.000002	NA
YY(-1)	0.004405	0.005242	0.000001	0.2602
IND	-0.087426	-0.085570	-0.000021	NA
IND(-1)	-0.014424	-0.019531	-0.000028	NA

Cross-section random effects test equation:
Dependent Variable: HBI-HBI(-1)
Method: Panel EGLS (Period random effects)
Date: 04/23/16   Time: 15:25
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.039353	0.021969	1.791272	0.0739
FSI-FSI(-1)	0.157599	0.058029	2.715858	0.0069
FSI(-1)-FSI(-2)	0.029546	0.057582	0.513115	0.6081
QQ	-0.063301	0.029211	-2.166992	0.0308
QQ(-1)	0.012075	0.022200	0.543891	0.5868
YY	0.011198	0.021198	0.528227	0.5976
YY(-1)	0.004405	0.015552	0.283206	0.7772
IND	-0.087426	0.141686	-0.617042	0.5375
IND(-1)	-0.014424	0.150176	-0.096046	0.9235

Effects Specification		
	S.D.	Rho

Cross-section fixed (dummy variables)		
Period random	0.061729	0.0254
Idiosyncratic random	0.382296	0.9746

Weighted Statistics

R-squared	0.063161	Mean dependent var	0.059541
Adjusted R-squared	0.026294	S.D. dependent var	0.392106
S.E. of regression	0.386917	Sum squared resid	64.67246
F-statistic	1.713232	Durbin-Watson stat	1.683315
Prob(F-statistic)	0.037692		

Unweighted Statistics

R-squared	0.067392	Mean dependent var	0.059541
Sum squared resid	66.54307	Durbin-Watson stat	1.671893

Period random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
(FSI-FSI(-1))	0.112238	0.160879	0.000639	0.0544
(FSI(-1)-FSI(-2))	-0.008280	0.033440	0.000623	0.0945
QQ	-0.035355	-0.061974	0.000097	0.0068
QQ(-1)	-0.000795	0.012065	0.000085	0.1633
YY	-0.019232	0.011303	0.000097	0.0019
YY(-1)	0.037998	0.005242	0.000087	0.0005
IND	0.204759	-0.085570	0.025780	0.0706
IND(-1)	0.016805	-0.019531	0.025144	0.8187

Period random effects test equation:
Dependent Variable: HBI-HBI(-1)
Method: Panel EGLS (Cross-section random effects)
Date: 04/23/16 Time: 15:25
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450
Swamy and Arora estimator of component variances

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.027504	0.023884	1.151571	0.2502
FSI-FSI(-1)	0.112238	0.063226	1.775195	0.0766
FSI(-1)-FSI(-2)	-0.008280	0.062668	-0.132125	0.8950
QQ	-0.035355	0.030847	-1.146126	0.2524

QQ(-1)	-0.000795	0.024087	-0.033016	0.9737
YY	-0.019232	0.023429	-0.820870	0.4122
YY(-1)	0.037998	0.018126	2.096286	0.0367
IND	0.204759	0.214185	0.955989	0.3397
IND(-1)	0.016805	0.218459	0.076928	0.9387

Effects Specification	S.D.	Rho
Cross-section random	0.000000	0.0000
Period fixed (dummy variables)		
Idiosyncratic random	0.382296	1.0000

Weighted Statistics

R-squared	0.203439	Mean dependent var	0.059541
Adjusted R-squared	0.099104	S.D. dependent var	0.398638
S.E. of regression	0.378369	Sum squared resid	56.83587
F-statistic	1.949860	Durbin-Watson stat	1.707384
Prob(F-statistic)	0.000207		

Unweighted Statistics

R-squared	0.203439	Mean dependent var	0.059541
Sum squared resid	56.83587	Durbin-Watson stat	1.707384

Cross-section and period random effects test comparisons:

Variable	Fixed	Random	Var(Diff.)	Prob.
(FSI-FSI(-1))	0.108450	0.160879	0.000681	0.0446
(FSI(-1)-FSI(-2))	-0.012288	0.033440	0.000666	0.0764
QQ	-0.036033	-0.061974	0.000101	0.0099
QQ(-1)	-0.000892	0.012065	0.000086	0.1632
YY	-0.019778	0.011303	0.000098	0.0017
YY(-1)	0.037454	0.005242	0.000093	0.0008
IND	0.209675	-0.085570	0.026359	0.0690
IND(-1)	0.025727	-0.019531	0.025686	0.7776

Cross-section and period random effects test equation:
Dependent Variable: HBI-HBI(-1)
Method: Panel Least Squares
Date: 04/23/16 Time: 15:25
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10

Total panel (balanced) observations: 450

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.030606	0.024903	1.229016	0.2198
FSI-FSI(-1)	0.108450	0.063558	1.706308	0.0888
FSI(-1)-FSI(-2)	-0.012288	0.063015	-0.194998	0.8455
QQ	-0.036033	0.030916	-1.165507	0.2445
QQ(-1)	-0.000892	0.024112	-0.036984	0.9705
YY	-0.019778	0.023441	-0.843761	0.3993
YY(-1)	0.037454	0.018283	2.048592	0.0412
IND	0.209675	0.215534	0.972816	0.3313
IND(-1)	0.025727	0.219697	0.117104	0.9068

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.205254	Mean dependent var	0.059541
Adjusted R-squared	0.080306	S.D. dependent var	0.398638
S.E. of regression	0.382296	Akaike info criterion	1.042072
Sum squared resid	56.70641	Schwarz criterion	1.608235
Log likelihood	-172.4663	Hannan-Quinn criter.	1.265218
F-statistic	1.642723	Durbin-Watson stat	1.711443
Prob(F-statistic)	0.003012		

Source: EViews calculations.

Table A4.7 Variance Inflation Factors for short-form model.

Variance Inflation Factors
Date: 04/23/16 Time: 15:23
Sample: 2004Q1 2015Q3
Included observations: 450

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.000570	1.756351	NA
(FSI-FSI(-1))	0.003997	1.127328	1.063570
(FSI(-1)-FSI(-2))	0.003927	1.125138	1.057609
QQ	0.000952	4.017533	3.312175
QQ(-1)	0.000580	2.481150	2.030583
YY	0.000549	21.00643	13.70685
YY(-1)	0.000329	12.77208	8.258673
IND	0.045875	1.089517	1.077818
IND(-1)	0.047724	1.099585	1.084509

Source: EViews calculations.

Table A4.8 Long-form model.

Dependent Variable: HBI-HBI(-1)
Method: Panel Least Squares
Date: 04/23/16 Time: 15:38
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003319	0.028293	0.117308	0.9067
FSI-FSI(-1)	0.213079	0.082797	2.573524	0.0105
FC*(FSI(-1)-FSI(-2))	0.040151	0.088021	0.456158	0.6485
FC*QQ	-0.063304	0.034636	-1.827696	0.0684
FC*QQ(-1)	0.021136	0.040460	0.522408	0.6017
FC*YY(-1)	0.048408	0.016772	2.886194	0.0041
FC*IND	0.250667	0.326419	0.767929	0.4430
FC*IND(-1)	0.143711	0.344571	0.417072	0.6769
BC*(FSI-FSI(-1))	0.484511	0.230431	2.102627	0.0362
BC*(FSI(-1)-FSI(-2))	-0.238521	0.208143	-1.145949	0.2525
BC*QQ	-0.013215	0.030416	-0.434465	0.6642
BC*QQ(-1)	-0.025325	0.035120	-0.721103	0.4713
BC*YY(-1)	0.014691	0.012079	1.216217	0.2247
BC*IND	0.246426	0.258932	0.951702	0.3419
BC*IND(-1)	0.094122	0.276807	0.340027	0.7340
QC*(FSI-FSI(-1))	-0.182089	0.138521	-1.314526	0.1895
QC*(FSI(-1)-FSI(-2))	0.029484	0.111860	0.263581	0.7922
QC*QQ	-0.070732	0.046042	-1.536260	0.1253
QC*QQ(-1)	0.037480	0.057169	0.655597	0.5125
QC*YY(-1)	0.021034	0.019321	1.088677	0.2770
QC*IND	-0.367127	0.337837	-1.086700	0.2779
QC*IND(-1)	-0.534270	0.343757	-1.554206	0.1210

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.258399	Mean dependent var	0.059541
Adjusted R-squared	0.112056	S.D. dependent var	0.398638
S.E. of regression	0.375640	Akaike info criterion	1.030639

Sum squared resid	52.91442	Schwarz criterion	1.715513
Log likelihood	-156.8937	Hannan-Quinn criter.	1.300573
F-statistic	1.765712	Durbin-Watson stat	1.727074
Prob(F-statistic)	0.000343		

Source: EViews calculations.

Table A4.9 Redundant Fixed Effects Test for long-form model.

Redundant Fixed Effects Tests
Equation: MODELLONGFUL
Test cross-section and period fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	0.322423	(9,375)	0.9675
Cross-section Chi-square	3.468766	9	0.9428
Period F	1.441228	(44,375)	0.0394
Period Chi-square	70.306971	44	0.0071
Cross-Section/Period F	1.273323	(53,375)	0.1057
Cross-Section/Period Chi-square	74.467363	53	0.0275

Cross-section fixed effects test equation:
Dependent Variable: HBI-HBI(-1)
Method: Panel Least Squares
Date: 04/23/16 Time: 15:50
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003299	0.025421	0.129786	0.8968
FSI-FSI(-1)	0.195315	0.080870	2.415179	0.0162
FC*(FSI(-1)-FSI(-2))	0.014145	0.084997	0.166415	0.8679
FC*QQ	-0.073940	0.033351	-2.217028	0.0272
FC*QQ(-1)	0.017959	0.040053	0.448382	0.6541
FC*YY(-1)	0.043204	0.015630	2.764124	0.0060
FC*IND	0.257120	0.322130	0.798186	0.4253
FC*IND(-1)	0.169324	0.339096	0.499339	0.6178
BC*(FSI-FSI(-1))	0.523237	0.222806	2.348403	0.0194
BC*(FSI(-1)-FSI(-2))	-0.201546	0.198746	-1.014088	0.3112
BC*QQ	-0.010311	0.029681	-0.347404	0.7285

BC*QQ(-1)	-0.022914	0.034569	-0.662866	0.5078
BC*YY(-1)	0.014672	0.011932	1.229604	0.2196
BC*IND	0.256353	0.255768	1.002287	0.3168
BC*IND(-1)	0.092097	0.274146	0.335943	0.7371
QC*(FSI-FSI(-1))	-0.148963	0.134651	-1.106291	0.2693
QC*(FSI(-1)-FSI(-2))	0.044248	0.109107	0.405549	0.6853
QC*QQ	-0.064273	0.044455	-1.445810	0.1490
QC*QQ(-1)	0.033255	0.056575	0.587796	0.5570
QC*YY(-1)	0.027214	0.017370	1.566707	0.1180
QC*IND	-0.348810	0.333253	-1.046681	0.2959
QC*IND(-1)	-0.550133	0.338195	-1.626675	0.1046

Effects Specification

Period fixed (dummy variables)

R-squared	0.252660	Mean dependent var	0.059541
Adjusted R-squared	0.126158	S.D. dependent var	0.398638
S.E. of regression	0.372645	Akaike info criterion	0.998347
Sum squared resid	53.32388	Schwarz criterion	1.601037
Log likelihood	-158.6281	Hannan-Quinn criter.	1.235889
F-statistic	1.997270	Durbin-Watson stat	1.723911
Prob(F-statistic)	0.000034		

Period fixed effects test equation:
Dependent Variable: HBI-HBI(-1)
Method: Panel Least Squares
Date: 04/23/16 Time: 15:50
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.026411	0.023217	1.137589	0.2559
FSI-FSI(-1)	0.274917	0.076908	3.574642	0.0004
FC*(FSI(-1)-FSI(-2))	0.094367	0.082856	1.138918	0.2554
FC*QQ	-0.049366	0.032093	-1.538215	0.1248
FC*QQ(-1)	0.046150	0.037270	1.238281	0.2163
FC*YY(-1)	0.024082	0.013456	1.789742	0.0742
FC*IND	0.014636	0.259002	0.056511	0.9550
FC*IND(-1)	0.218117	0.283315	0.769874	0.4418
BC*(FSI-FSI(-1))	0.487909	0.220231	2.215446	0.0273
BC*(FSI(-1)-FSI(-	-0.221241	0.194583	-1.137001	0.2562

2))				
BC*QQ	-0.007642	0.029266	-0.261129	0.7941
BC*QQ(-1)	-0.001142	0.033980	-0.033607	0.9732
BC*YY(-1)	-0.001800	0.011258	-0.159885	0.8730
BC*IND	0.124610	0.223174	0.558355	0.5769
BC*IND(-1)	0.199103	0.245343	0.811528	0.4175
QC*(FSI-FSI(-1))	-0.259584	0.131141	-1.979427	0.0484
QC*(FSI(-1)-FSI(-2))	0.029463	0.103953	0.283423	0.7770
QC*QQ	-0.073968	0.043173	-1.713301	0.0874
QC*QQ(-1)	0.042904	0.053951	0.795238	0.4269
QC*YY(-1)	0.006759	0.016939	0.399015	0.6901
QC*IND	-0.533977	0.272858	-1.956977	0.0510
QC*IND(-1)	-0.367370	0.281230	-1.306299	0.1922

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.132991	Mean dependent var	0.059541
Adjusted R-squared	0.070914	S.D. dependent var	0.398638
S.E. of regression	0.384244	Akaike info criterion	0.991321
Sum squared resid	61.86246	Schwarz criterion	1.274402
Log likelihood	-192.0472	Hannan-Quinn criter.	1.102894
F-statistic	2.142358	Durbin-Watson stat	1.657099
Prob(F-statistic)	0.000561		

Cross-section and period fixed effects test equation:
Dependent Variable: HBI-HBI(-1)
Method: Panel Least Squares
Date: 04/23/16 Time: 15:50
Sample (adjusted): 2004Q3 2015Q3
Periods included: 45
Cross-sections included: 10
Total panel (balanced) observations: 450

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.022686	0.022410	1.012309	0.3120
FSI-FSI(-1)	0.253497	0.075206	3.370705	0.0008
FC*(FSI(-1)-FSI(-2))	0.067140	0.080147	0.837709	0.4027
FC*QQ	-0.058005	0.031160	-1.861498	0.0634
FC*QQ(-1)	0.044077	0.037002	1.191184	0.2342
FC*YY(-1)	0.019166	0.012894	1.486445	0.1379
FC*IND	0.005919	0.256766	0.023053	0.9816
FC*IND(-1)	0.223929	0.279948	0.799895	0.4242

BC*(FSI-FSI(-1))	0.533839	0.213965	2.494983	0.0130
BC*(FSI(-1)-FSI(-2))	-0.186043	0.187360	-0.992972	0.3213
BC*QQ	-0.004028	0.028634	-0.140666	0.8882
BC*QQ(-1)	0.001974	0.033503	0.058917	0.9530
BC*YY(-1)	-0.001709	0.011190	-0.152768	0.8787
BC*IND	0.132636	0.221325	0.599281	0.5493
BC*IND(-1)	0.197574	0.243673	0.810814	0.4179
QC*(FSI-FSI(-1))	-0.216826	0.128028	-1.693589	0.0911
QC*(FSI(-1)-FSI(-2))	0.050966	0.102122	0.499070	0.6180
QC*QQ	-0.061967	0.042077	-1.472690	0.1416
QC*QQ(-1)	0.039027	0.053506	0.729400	0.4662
QC*YY(-1)	0.015219	0.015606	0.975236	0.3300
QC*IND	-0.528456	0.270479	-1.953777	0.0514
QC*IND(-1)	-0.403368	0.277572	-1.453201	0.1469

R-squared	0.124938	Mean dependent var	0.059541
Adjusted R-squared	0.082003	S.D. dependent var	0.398638
S.E. of regression	0.381944	Akaike info criterion	0.960566
Sum squared resid	62.43705	Schwarz criterion	1.161463
Log likelihood	-194.1274	Hannan-Quinn criter.	1.039747
F-statistic	2.909921	Durbin-Watson stat	1.651217
Prob(F-statistic)	0.000022		

Source: EViews calculations.

Table A4.10 Variance Inflation Factors for long-form model.

Variance Inflation Factors
Date: 04/23/16 Time: 15:51
Sample: 2004Q1 2015Q3
Included observations: 450

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
C	0.000800	2.552818	NA
(FSI-FSI(-1))	0.006855	1.985611	1.872364
FC*(FSI(-1)-FSI(-2))	0.007748	1.093246	1.069237
FC*QQ	0.001200	1.502857	1.390550
FC*QQ(-1)	0.001637	2.052351	1.896306
FC*YY(-1)	0.000281	2.517834	2.075162
FC*IND	0.106549	1.402914	1.398904
FC*IND(-1)	0.118729	1.529869	1.521428
BC*(FSI-FSI(-1))	0.053099	2.058251	2.031376

BC*(FSI(-1)-FSI(-2))	0.043323	1.695266	1.671086
BC*QQ	0.000925	2.684796	2.627153
BC*QQ(-1)	0.001233	3.618682	3.534581
BC*YY(-1)	0.000146	4.049429	3.855255
BC*IND	0.067046	1.339565	1.337489
BC*IND(-1)	0.076622	1.499336	1.497951
QC*(FSI-FSI(-1))	0.019188	1.754308	1.721810
QC*(FSI(-1)-FSI(-2))	0.012513	1.151697	1.126304
QC*QQ	0.002120	1.738694	1.515856
QC*QQ(-1)	0.003268	2.705719	2.352835
QC*YY(-1)	0.000373	3.044442	2.353175
QC*IND	0.114134	1.509144	1.504944
QC*IND(-1)	0.118169	1.558664	1.553484

Source: EViews calculations.