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MASTER'S THESIS

The Effects of Monetary Policy on Real Estate Market: a SVAR Analysis

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Declaration of Authorship

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

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Prague, June 1, 2019

Signature

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Abstract

This thesis empirically investigates the effects of monetary policy instruments on the real estate market for the following countries: Germany, France, the Netherlands, Spain and the United Kingdom, using a Structural Vector Autoregression model (SVAR) with Choleski recursive identification. This was done from the three different aspects: interest rate, scale of credit, and output. The covered period lasts from the first quarter of 2005 and then varies, depending on the country. The Wu-Xia shadow rate was used as a proxy for the interest rate, households' debt was used as a proxy for scale of credit, and real GDP was used as a proxy for the output. As the output of the analysis, we used the impulse response functions (IRF) and forecast errors variance decomposition (FEVD). The results suggest that the Residential Property Prices (RPPI) in every country react positively to an output shock and negatively to interest rates (except Spain). The effect of household debt on RPPI and statistical significance of intervals depend on the country observed.

Keywords monetary policy, real estate, SVAR

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Table of Contents

List of Tables

List of Figures

Acronyms

CPI	Consumer Price Index
ECB	European Central Bank
EMF	European Mortgage Federation
EU	European Union
EUR	Euro
FAVAR	Factor augmented VAR
FEVD	Forecast Error Variance Decomposition
FRED	Federal Reserve Economic Data
GBP	Great British Pound
GDP	Gross Domestic Product
OECD	Organization for Economic Co-operation and Development
RPPI	Residential Property Price Index
SVAR	Structural Vector Autoregression
UK	United Kingdom
VAR	Vector Autoregression

Master's Thesis Proposal

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Proposed Topic:

The Effects of Monetary Policy on Real Estate Market: a SVAR Analysis

Motivation:

Other the last years, property prices have climbed to dangerous levels in several advanced economies, raising the risk of massive price falls if markets overheat. According to IMF Q2 2017 Report, the IMF's Global House Price Index, a simple average of real house prices for 57 countries, is now almost back to its level before the crisis. Taking into consideration the recent global financial crisis and the role that asset bubble played in it, it is very important to understand the connection between the housing price fluctuations and monetary policy in order to prevent future housing prices shocks and to maintain financial stability.

According to ECB reports and market analyses, the quantitative easing monetary policy served as the main reason that led to artificially inflated asset prices. In this thesis I will focus on analyzing the effects of transmission mechanism of monetary policy on the real estate market for France, Germany, Spain, the Netherland, and the UK. A structural vector autoregression model will be employed to examine monetary policy's influence on the real estate market from three different aspects: interest rate, scale of credit, and output.

Hypotheses:

1. Hypothesis #1: Interest rate has a significant influence over real estate prices.
2. Hypothesis #2: The scale of credit has a significant influence over real estate prices.
3. Hypothesis #3: The output has a significant influence over real estate prices.

Methodology:

In the first part of the thesis, I am going to review and analyze the empirical literature conducted so far on the influence of monetary policy on house prices in the selected EU economies. The theoretical analysis will also include a detailed description of the main characteristics and specifics of the EU housing and mortgage markets.

To test our hypotheses, a Structural VAR model will be used in the second part of the thesis. The data for the empirical investigation will be obtained through the publicly available databases, such as The Federal Reserve Bank of St. Louis (FRED) and The Organization for Economic Co-operation and

Development (OECD).
I will test each hypothesis by analyzing the output of Structural VAR's impulse response functions. The house Residential Property Price Index (RPPI) will be used as a proxy for the price dynamics of real estate purchased by different agents. This variable will be used for every hypothesis.
In case of the first hypothesis, the existing literature suggests that the effect of interest rates on real estate market is statistically significant, I will be checking that statement individually for each of the selected countries. The interest rate will be used as a shock to see its influence on the real estate prices. To test the second hypothesis, the shock of the amount of credit will be used to see and analyze the results from the response functions.
Regarding the third hypothesis, there exists as well major amount of empirical investigations on the of effect of the output on real estate prices, I intend to make my own conclusion from observing the results of the impulse response functions. Data for these variables will be accessed from the sources mentioned above. The impulse response functions are expected to be different from country to country.

Expected Contribution:

Even through, the literature on the proposed topic has grown very rapidly in the recent years, most of the current studies focus on the UK and the US markets, yet, little is known about the effects of monetary policy on house prices in each EU member states (Nocera & Roma, 2017). My first contribution of this paper is to try fill this gap by analyzing the real estate market of France, Germany, Spain the Netherlands, and the UK .
Also, one of the main contribution of the paper will be the empirical study, which will answers the questions set in the hypothesises by examining monetary policy's influence on the real estate market from three different aspects: interest rate, scale of credit, and output.

Outline:

1. Introduction
2. Theoretical Background
3. Literature review of monetary policy transmission mechanism on RE prices
4. Characteristics of the EU housing and mortgage markets
5. Empirical Investigation
6. a. Description of the Data
7. b. SVAR Model
8. c. Discussion of the Results
9. Conclusions
10. References / Bibliography

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Author **Supervisor**

Chapter 1

Introduction

In recent years, the evolution of housing and mortgage markets has received a considerable attention from the economists and the monetary policy makers. The European Central Bank papers[1] highlight several reasons for this: (1) variations in household wealth, income, and expenditure can lead to changes in house prices, rents, and interest rates of mortgage that might have a significant impact on demand and inflation, and play an important role in the transmission mechanism of monetary policy (2) rents represent an important component of the consumer price index (CPI), thus need to be closely monitored when assessing the risks to price stability; (3) as seen from recent financial crisis, the boom in houses and other assets prices can play an important role in shaping the financial and business cycles and influence financial stability; (4) functioning of the housing market may also have implications for the supply side of the economy, especially labor mobility in the EU.

[1] Structural factors in the EU housing market (2003) ECB

Other the last years, property prices have climbed to dangerous levels in several advanced economies, raising the risk of massive price falls if markets overheat. According to International Monetary Fund Q2 2017 Report, the IMF's Global House Price Index, a simple average of real house prices for 57 countries, is now almost back to its level before the crisis. Taking into consideration the recent global financial crisis and the role that asset bubble played in it, it is very important to understand the connection between the housing price fluctuations and monetary policy in order to prevent future housing prices shocks and to maintain financial stability.

According to ECB reports and market analyses, the quantitative easing monetary policy served as the main reason that led to artificially inflated asset prices. In this thesis I will focus on analyzing the effects of monetary policy instruments on the real estate market for the following EU member states: Germany, France, the Netherlands, and Spain. The United Kingdom will be part of analysis as well.

There are several reasons why this paper is focused on particularly these countries. According to 2017 European Mortgage Federation report prepared by Hypostat, in terms of size, the EU mortgage market is currently dominated by these five countries, which accounted for 81% of the overall outstanding residential mortgages in the EU in 2016 and 72% in 2017. In addition, most of the literature review on this topic is focused on United States, while little is known about the effects of monetary policy on house prices in each EU member states (Nocera & Roma, 2017). Thus, this paper is trying to fill the gap by analyzing the real estate market of these five European countries.

Also, one of the main contributions of the paper will be the empirical study. A Structural Vector Autoregression model (SVAR) will be employed to examine monetary policy's influence on the prices in the real estate market from three different aspects: interest rate, scale of credit, and output. The central issues addressed by our hypotheses will be to investigate whether the interest rate has a significant influence over real estate prices; scale of credit has a significant influence over real estate prices; and output has a significant influence over real estate prices.

Furthermore, it is very important to mention that, by understanding and studying the role of monetary policy on real estate prices, this thesis attempts to contribute to the existing literature that may serve as a useful prerequisite for the implementation of an efficient monetary policy strategy in the future.

Overall, the thesis is structured as follows. Chapter 2 comprises the literature review on the effects of monetary policy on real estate prices as well as a detailed description on the characteristics on the EU housing and mortgage markets. The analysis of literature review is, in particular, focused on the papers which investigated the monetary policy shocks through vector autoregression models. Chapter 3 represents the methodological section where are presented the hypotheses that are aimed to be tested and a detailed description of the SVAR applied econometric model. In the chapter are defined the variables that are used in the econometrics analysis, explaining the rationale behind them and contrasting with the previous researches and the availability of data. Next, Chapter 4 will provide with discussion of the estimated results for each particular country: France, Germany, Spain, the Netherlands, and the UK. Finally, Chapter 5 includes the concluding remarks.

Chapter 2

Theoretical Background

2.1 Chaper Overview

This chapter presents a comprehensive review on the existing literature review on effects of monetary policy on real estate prices. The final section of this chapter is devoted to a detailed description on the characteristics on the EU housing and mortgage markets. In addition, this section describes macroeconomic, housing and mortgage indicators of selected countries.

2.2 Literature review of monetary policy transmission mechanism on real estate prices

There is a considerable amount of studies examining the impact of monetary policy on real estate prices. This section provides an overview of the most recent existing literature on this topic.

The most common and suitable procedure used by economists for analyzing the effect of monetary policy on house prices is usually the structural VAR approach. VAR models were applied by Sims (1980), Tan and Chen (2013), Robstad (2014), Nocera and Roma (2017), and many others in their analysis on same topic. For my research I intend to use a SVAR model to investigate this process for selected EU countries. One of the main contribution of this paper is the empirical study, which will answer the questions set in the hypothesizes by examining monetary policy influence on the real estate market from three different aspects: interest rate, scale of credit, and output.

Given its important role in the economy, the real estate market is of central concern to monetary policy makers. As emphasized by Matalík et. al (2005), growing importance of asset prices for central banks' monetary policy represents the consequence of the ongoing liberalization of the economic environment and the ensuing globalization of the world economy. Nowadays, the primary goal of the European Central Bank (ECB) is to maintain price stability to contribute towards economic growth and job creation. However, changing global economic environment has moved the perception of a central bank's fundamental role towards that of securing financial stability (Matalík et. al, 2005).

Each country has its specific institutional features and circumstances that determine how monetary policy decisions are formulated and implemented in order to achieve set objectives. Williams (2015), in his research, is asking the question, which currently is of great importance for central banking: Should monetary policy be used to foster financial stability, even at the expense of achieving other macroeconomic goals such as inflation and employment? Author states that in many circumstances, macroeconomic and financial stability goals may be well aligned. However, he brings the example of Sweden where the costs of higher interest rates in terms of higher unemployment exceed the benefits in terms of reducing financial stability risks. Lastly, he affirms that when macroeconomic and financial stability goals do not coincide, it is crucial to estimate the costs and benefits of using monetary policy to impact house prices. Williams' results were based on an empirical analysis of a sample of 17 countries over the past 140 years. In his paper the author draws two main conclusions:

(1) Monetary policy actions have substantial effects on house prices in advanced economies - a rise in interest rates is likely to lower real inflation-adjusted house prices;

(2) The trade-off of using monetary policy to influence house prices, when macroeconomic and financial stability goals are in conflict, is very pricey.

In order to achieve its monetary policy objectives, the ECB uses short-term interest rates as the main policy instrument to influence economic developments. House prices are rising or stable in all major European economies thanks to ultra-low interest rates, according to S&P European housing market 2018 report. Real estate tends to do well when interest rates are low, because homeowners and investors will take advantage of low mortgage rates to acquire properties. It is widely recognized that the low level of U.S. real interest rates during 2001-2004 years served as one of the main reasons for real estate bubble during financial crisis in 2007. On the other side, when interest rates are rising, it costs more to service mortgage debt, which leads to a decline in demand among homeowners and investors.

Many researchers are stating that interest rate has a strong influence on house price dynamics. Bjornlanda and Jacobsen (2010) in their paper find interest rate to respond systematically to changes in house prices and that house prices react immediately and strongly to a monetary policy shock. For Bjornlanda and Jacobsen the major issue was when incorporating asset prices like housing into a VAR model is how to identify the system because both the interest rate and asset prices may respond simultaneously to news. Their finding was that house prices react immediately and strongly to a monetary policy shock. In addition, Mishkin (2007) argues that there are at least six channels through which by raising or lowering short-term interest rates, monetary policy affects the housing market, in a direct: the user cost of capital, expectations of future house-price movements, and housing supply; or indirect manner: standard wealth effects from house prices, balance sheet, credit-channel effects on consumer spending, and balance sheet, credit-channel effects on housing demand. Furthermore, same author in a later paper (Boivin and Mishkin, 2010), adds that when monetary policy raises the short-term interest rates, the long-term interest rates also tend to rise because they are connected to expected future short-term rates. Thus, the user cost of capital rises and the demand for housing falls.

Same logic underlies Sutton et al. (2017) in their research. The authors were estimating the response of house prices to changes in short-term and long-term interest rates in 47 advanced, including the U.S. and emerging market economies over the period from 1970 to 2015. The authors identified that short-term interest rates are an important driver of house prices, especially outside the U. S. Moreover, they discovered that changes in short-term interest rates from up to five years in the past can have a strong influence on changes in house prices today. Therefore, it is of vital importance to study the relationship among monetary policy and house prices in more depth.

The effect of monetary policy on house prices was also investigated and discussed in Eickmeier and Hofmann (2010) paper. Authors used a Factor augmented VAR (FAVAR) model to analyze role of monetary policy in the three imbalances that were observed prior to the global financial crisis: high house price inflation, strong private debt growth and low credit risk spreads. They used a quarterly data sample for the period starting 1987 to 2007 and explored the interaction between monetary policy and over 200 financial and asset variables in the U.S. Eickmeier and Hofmann findings showed that monetary policy shocks affected property prices, real estate wealth and private sector debt in a strong and constant manner. On the other side, Jordà et. al (2015) are investigating whether interest rate is the most effective monetary tool in regulating house prices. The author tries to answer the following question: how much interest rates would have had to rise to keep housing prices under control? The author highlights that a considerable increase in interest will cost us in terms of higher unemployment and lower inflation. For instance, Gupta and Kabundi (2009), by examining the effect of monetary policy on U.S. house price inflation, found that housing price inflation negatively responded by positive monetary shocks. They were using a FAVAR model for their research. However, this paper only considers house price inflation and ignores other housing market variables.

It is also of great importance what sub-segment of the real estate sector is analyzed in the research. Particularly, Berleman (2010) conducted a detailed analysis of real estate market by studying various sub-segments in Switzerland and concluded that commercial property prices do not react on interest rate variations. While the author found substitution effects between house and apartment prices on the one hand and rental prices on the other, commercial property prices show no significant reaction to interest rate variations. Therefore, this affirms that various sub-markets might react differently to monetary policy shocks.

About similar findings, but for the Euro area, Zammit (2010) is relating in his research on the asymmetries in the monetary transmission mechanism. He found that the strength and timing of the effects of monetary policy shocks on house prices and consumption in euro area countries is correlated by different mortgage market characteristics and tends to be stronger in countries with more flexible and highly developed mortgage market.

Lastly, Zhao and Sun (2014) were using a SVAR model to test the effect not only of interest rates but also of money supply on real estate price. Their results have shown that interest rates have a negative impact on real estate price in short-term and medium-term, but regulation effect is more significant in medium-term; while money supply has a positive impact on real estate price in short-term and medium-term, and a negative one in long-term.

2.2 Characteristics of the EU housing and mortgage markets

According to the European Mortgage Federation 2017 report, the 2016 year marked the first year since the financial crisis in which all 28 Member States were not in recession and the EU as a whole had a growth of 1,9% year-over-year (y-o-y). What concerns mortgage market, the 2016 total outstanding lending in the EU decreased by 1,4% with respect to 2015, mainly due to the depreciation of the GBP. For Euro area the outstanding mortgage market increased by more than 2% in 2016, while for the non-Euro area decreased by 7%.

In 2017, the rate of mortgage lending recovered the positive trend. Contrary to 2016, the total outstanding lending in the EU in 2017 increased by 2,24% with respect to 2016. Also, in 2017, the European economy registered its strongest growth in the last 10 years and the European Union economy as a whole grew by 2,4% y-o-y (EMF, Hypostat 2018).

In terms of size, the EU mortgage market is dominated by five countries: the UK, Germany, France, the Netherlands, and Spain, which accounted for 81% of the overall outstanding residential mortgages in the EU in 2016 year (EMF, Hypostat 2017) and 72% of the overall outstanding residential mortgages in the EU in 2017 year (EMF, Hypostat 2018). This makes examination of the factors affecting housing prices interesting and comfortable for these selected countries. For this thesis I selected these countries to test the monetary policy transmission mechanism on real estate prices.

According to 2017 EMF Report, 2016 was another year when the residential investment and construction activities in Germany kept growing. Encouraging financing conditions and the stability of households' income, kept the solid demand for residential properties. Prices for residential property were still on the growing pace in 2016. Mean price increase in home owners 'houses climbed by 6% the same year, in contrast to 2015, when the rise was only 4,5%. Mean mortgage interest rates, in 2016 were lower than a year before. The average mortgage rate decreased to 1,8% from 2% in 2015. The sequence of rising rents, low interest rates and the deficit of profitable alternative investments noticeably increased the demand for houses, especially in the larger dynamic cities. In 2017 year, according to 2018 EMF Report, the gross residential lending, and especially the volume of mortgage loans outstanding, follows a steady upward trend. However, from Table 1 we can see that the nominal house price growth slightly decreased to 5,8% in 2017 compared to 6% in 2016.

Table 1: Macroeconomic, housing and mortgage indicators of selected countries

	Germany		**France**		**The Netherlands**		**Spain**		**The UK**	
	2016	**2017**	**2016**	**2017**	**2016**	**2017**	**2016**	**2017**	**2016**	**2017**
Real GDP growth (%)	1,9	2,2	1,2	2,2	2,2	3,2	3,3	3,1	1,8	1,7
Unemployment Rate, annual average (%)	4,1	3,8	10,1	9,4	6,0	4,9	19,6	17,2	4,8	4,4
HICP inflation (%)	0,4	1,7	0,3	1,2	0,1	13	-0,3	2,0	0,7	2,7
Outstanding Residential Loans (mn EUR)	1 326 901	1 378 810	899 358	954 226	664 416	672 235	511 253	497 711	1 546 503	1 539 979
Outstanding Residential Loans to disposable income ratio (%)	66,9	67,3	63,1	65,4	197,1	193,4	73,0	69,7	94,7	98,7
Gross residential lending, annual growth (%)	0,4	2,3	12,8	13,9	27,6	24,7	5,0	3,7	-1,5	-2,6
Typical mortgage rate, annual average (%)	1,8	1,8	1,6	1,6	2,6	2,4	2,0	2,0	2,3	2,0
Nominal house price growth (%)	6,0	5,8	1,6	1,6	5,0	7,5	1,9	2,4	7,0	4,6

Note: *The table provides the latest figures for macroeconomic, housing and mortgage dynamics for the selected countries in years 2016 and 2017.*

Source: *European Mortgage Federation; Eurostat*

The French housing market has been driven for a long period by a solid demand for new dwellings. Continuous decline of interest rates, incentives to first-time home buyers (zero interest rate loans) and tax cuts for buy-to-let investors initiated the vivid recovery of the housing market in 2016. The home loans market has been very active since the end of 2014. The drop of interest rates fueled the recovery of French real estate market in 2016, thus feeding the housing credit market throughout the year. According to EMF Report 2018, for the housing market, 2017 year was a record year. A historical record volume of new loans was granted this year, as a result of both the real estate market activity and persistent low interest rates. Also, the nominal house price growth climbed to 3,3% in 2017, compared to 2016, when it was 1,6%.

There is an increase in the number of housing transactions in Netherlands by 24,7% in 2017 compared to 2016 and the origination volume was the highest since the financial crisis. The post crisis effect has faded. The amount of housing transactions exceeds the amount in 2007. In 2017 the nominal house price growth climbed to 7,5% compared to 5% in 2016. Currently, the main driver of mortgage market is low interest rates.

Spanish housing market is being characterized as market with increased demand for dwellings, slow developments in supply, in which house prices in some areas of the country experience an increase. In 2017 the number of housing transactions in Spain went up by 16,3%, comparing to last year's. Housing market price improved by 2,4% y-o-y nationally and it can be considered the best figure seen since 2007. (EMF, Hypostat 2018).

According to 2018 EMF Report, the UK housing market remains unbalanced in 2017, with the long term gap between demand and supply of housing continuing to place upwards pressure on prices and rents. From Table 1 below we can see that the nominal house price growth for UK slightly decreased to 4,6% in 2017 compared to 7% in 2016. Mortgage interest rates in the UK fell in 2016, reaching new historic lows. The average mortgage interest rate on new lending was 2,2 % in 2017. This was driven by improvements in funding conditions, a fall in swap rates, increased competition amongst lenders as they looked to increase their market shares, and monetary policy easing (EMF, Hypostat 2018).

Chapter 3

Empirical Investigation

3.1 Chapter Overview

This chapter is dedicated to description of the theoretical and empirical methodology employed to test the factors influencing housing prices in the selected countries of interest, in the period from year 1997 till 2017. The detailed description of models used, as well as inspection of data and working variables, is parts of the current chapter. The working hypotheses are included in this chapter, so are their tests and comments on testing results.

3.2 Assumptions and Hypotheses

The following part introduces the working hypotheses and the approach to testing them. The first hypothesis we would like to test states:

Hypothesis 1: Interest rate has a significant influence over real estate prices.

Following the discussion on the effects of monetary policy on real estate market literature review from Chapter 2, we can notice already several existing researches suggesting that, indeed, there is a significant relationship between short-term interest rates and real estate prices.

The second working hypothesis is:

Hypothesis 2: The scale of credit has a significant influence over real estate prices.

Intuition behind this hypothesis is that loans provided are expected to increase the prices for housing via demand- supply relationship. This hypothesis is to be tested on each country individually. The result is expected to fluctuate, depending on the country's ownership preferences, that is, whether country-specific preference is to take a mortgage or purchase real estate with accumulated funds.

The third working hypothesis is:

Hypothesis 3: The output has a significant influence over real estate prices.

There exists as vast amount of empirical investigations on the of effect of the GDP growth on real estate prices. GDP growth influences morgage market and house prices. For example, with higher economic growth and rising incomes, people will be able to spend more on houses. Thus, this will increase demand and push up prices.

3.3 Data description

The set of data used for this paper contains quarterly time-series data for the periods described in Table 2 below. The data set is obtained via collecting sample observations from FRED database (The Federal Reserve Bank of St. Louis) and The Organization for Economic Co-operation and Development (OECD). Where possible, seasonally adjusted data was collected, otherwise the X-12 ARIMA method was deployed for seasonal adjustment. In the X-12 ARIMA method, the seasonally adjusted series is obtained by dividing the original series by the estimated seasonal component, which, in turn, is a twelve-term centered moving average.[2]

Table 2: The covered period of dataset for each country of interest

Country	Covered Period
France	2005-Q1 - 2017-Q4
Germany	
The UK	
The Netherlands	2005-Q1 - 2017-Q3
Spain	2005-Q4 - 2017-Q4

Note: *The table provides information on the covered period for each of the observed countries. The periods vary because of the unavailability of data, however, insignificantly.*

Source: *Author's computations.*

3.4 Brief model and methodology discussion

As mentioned earlier, this thesis employs A Structural Vector Auto Regression (SVAR) model for the observation of the joint dynamics of multiple time series. According to Zivot and Wang (2003), VAR models are convenient to use as they

[2] For more information, please refer to https://www.census.gov

represent a very powerful tool for “describing the dynamic behavior of economic and financial time series and for forecasting”. The authors further claim that VAR models are also used for policy analysis and structural inference, where the impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarized by impulse response functions and forecast error variance decompositions (Zivot and Wang, 2003). Del Negro and Schorfheide (2009) claims that VARs appear to be straightforward multivariate generalizations of univariate autoregressive models, but turn out to be one of the key empirical tools in modern macroeconomics.

Let us introduce VAR with a simple example of two – variable VAR with lag order 1, VAR(1):

$$y_{1,t} = g_{10} + g_{11}y_{1,t-1} + g_{11}y_{1,t-1} + e_{1,t} \tag{3.1}$$

$$y_{2,t} = g_{20} + g_{21}y_{1,t-1} + g_{22}y_{2,t-1} + e_{2,t} \tag{3.2}$$

and in matrix notation:

$$\boldsymbol{y_t} = \boldsymbol{G_0} + \boldsymbol{G_1 y_{t-1}} + \boldsymbol{e_t} \tag{3.3}$$

Where,

$$\boldsymbol{y_t} = \begin{pmatrix} y_{1,t} \\ y_{2,t} \end{pmatrix}, \boldsymbol{G_0} = \begin{pmatrix} g_{10} \\ g_{20} \end{pmatrix}, \boldsymbol{G_1} = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}, \boldsymbol{e_t} = \begin{pmatrix} e_{1,t} \\ e_{2,t} \end{pmatrix} \tag{3.4}$$

And the general form of VAR(p):

$$\boldsymbol{y_t} = \boldsymbol{G_0} + \boldsymbol{G_1 y_{t-1}} + \boldsymbol{G_2 y_{t-2}} + \cdots + \boldsymbol{G_p y_{t-p}} + \boldsymbol{e_t} \tag{3.5}$$

The above can be rewritten as:

$$(I_n - G_1L - G_2L^2 - \cdots - G_pL^p)y_t = G_0 + e_t \tag{3.6}$$

$$G(L)y_t = G_0 + e_t \tag{3.7}$$

where $G(L)$ is lag polynomial.

Stationarity is an important feature of the model for this thesis. If VAR process is stationary, y_t is well defined stochastic process and its moving - average (MA) representation exists:

$$y_t = \sum_{i=0}^{\infty} G_1^i e_{t-i} \tag{3.8}$$

For VAR process of order p, to be stationary, the roots modulo of the characteristic polynomial (the determinant of the lag polynomial) must be greater than 1 (lie outside of unit imaginary circle) or similarly all eigenvalues of G must have modulus less than 1:

$$det(I_n - G_1L - G_2L^2 - \cdots - G_pL^p) = 0 \tag{3.9}$$

where I_n is identity matrix.

In this paper we employ a Structural Vector Auto Regression model. In the recent years, SVAR models have become a popular tool, in particular, for the analysis of the monetary transmission mechanisms and the origination of business cycle fluctuations. To describe the distinctiveness of SVAR model compared to a VAR model, we will refer to Lütkepohl, et al, (2004) Applied Time Series Econometrics book that states that the difference between simple VAR and structural VAR is that instead of identifying the coefficients, in SVAR we focus on identifying the errors of the system, which are interpreted as the linear combinations of exogenous shocks. In structural VAR firstly the restrictions are imposed on the variable dynamics while the rest is recognized as exogenous shocks. In a simple VAR no restrictions are imposed in advance and the coefficients of the lagged values of the variables included are identified.

Furthermore, as described by Sims (2002), a model is structural if it allows us to predict the effect of interventions - deliberate policy actions, or changes in the economy or in nature of known types.

According to Sims (2011), let us define VAR model in the following form:

$$A(L)Y_t = e_t \tag{3.10}$$

where $A(L)$ is a matrix lag polynomial of order p, e_t are innovations and $Y_t = \binom{y_{1,t}}{y_{2,t}}$ from formula 3.4.

Let us now define structural shock as:

$$\in_t = \left[\in_{1,t} \in_{2,t}\right] \tag{3.11}$$

And the link between structural shocks and innovations will be:

$$e_t = B \in_t \tag{3.12}$$

We can now rewrite the above in the following form:

$$A(L)Y_t = B \in_t \tag{3.13}$$

inverting the AR component and pre-multiplying both sides by $C(L) = A(L)^{-1}B,$ we get:

$$Y_t = C(L) \in_t \tag{3.14}$$

A tool for examining SVAR dynamics, once the model has been fitted, is variance decomposition of forecast errors (FEVD). When forecast errors are known in dynamics of a variable evolution, variance decomposition shows the shocks to this variable and shocks to other variables as proportion of movement of this variable. With help of this tool, it will be possible to see the proportion of monetary policy tools contribution to the movement of house prices.

The forecast error variance at horizon h = 0 for a two - variable system $(x_t\,, z_t)$ is:

$$E_t x_t - E_{t-1} x_t = C_{1,1}(0) \in_{1,t} + C_{1,2}(0) \in_{2,t} \quad (3.15)$$

$$E_t z_t - E_{t-1} z_t = C_{2,1}(0) \in_{1,t} + C_{2,2}(0) \in_{2,t} \quad (3.16)$$

Since forecast error variance is square of forecast errors, defining $\Omega_i(h)$ as forecast error variance of variable i at horizon h, we have the total forecast error variance of variable i at horizon h in a n variable system:

$$\Omega_i(h) = \sum_{k=0}^{h} \sum_{j=1}^{n} C_{i,j}\,(k)^2 \quad (3.17)$$

Forecast error variance decomposition shows contribution of each variable in variance of forecast error of other variables and itself. Let us define $\omega_{i,j}(h)$ as forecast error variance of variable i due to shock j at horizon h:

$$\omega_{i,j}(h) = \sum_{k=0}^{h} C_{i,j}\,(k)^2 \quad (3.18)$$

To identify fraction of a variable in explaining total variance, we can define this fraction as:

$$\varphi_{i,j}(h) = \frac{\omega_{i,j}(h)}{\Omega_i(h)} \quad (3.19)$$

When dealing with a set of multiple variables, it is of particular interest to observe a response of one variable to a shock to the other variable. In this thesis we want to use impulse response function to see the evolution of house prices when there is a monetary policy shock.

Let us formally introduce the IRF, starting with the moving - average (MA) representation of VAR, which has the following form:

$$\boldsymbol{y_t} = \sum_{\boldsymbol{i=0}}^{\infty} \boldsymbol{G_1^i e_{t-i}} \tag{3.20}$$

The matrix G_i has the interpretation and is the impulse response matrix:

$$\frac{\boldsymbol{\partial y_{t+s}}}{\boldsymbol{\partial e_t}} = \boldsymbol{G_i} \tag{3.21}$$

Now the row j, column k element of $\boldsymbol{G_i}$ identifies the consequences of a unit increase in the k^{th} variable's innovation at time t for the value of the j^{th} variable at time $t+s$, holding all other innovations constant.

We will use the CUSUM (Cumulative Sum of Recursive Residuals) to test for presence of structural break. Structural break is unexpected change of parameters in model with time, which can lead to time-variance of coefficients.

According to Lütkepohl et al. (2006), CUSUM test plots statistic within boundaries, and the place where statistic penetrates those boundaries is point in time where structural break occurs. The statistic computes as follows:

$$CUSUM_\tau = \sum_{T=M+1}^{\tau} {}^{\hat{u}_t}/_{\hat{\sigma}_u} \tag{3.22}$$

where τ = M+1,..,T periods in time, $\hat{u}_t$ is recursive residuals, which is standardized 1-step forecast errors from a model estimated on the basis of data up to period τ−1, $\hat{\sigma}_u^2$ is residual variance estimator.

Bounding lines (upper and lower) are drawn as follows:

$$\pm C_\gamma\left[\sqrt{T-M} + 2(\tau - M)/\sqrt{T-M}\right] \tag{3.23}$$

where coefficient $C_\gamma$depends on test's level of significance.

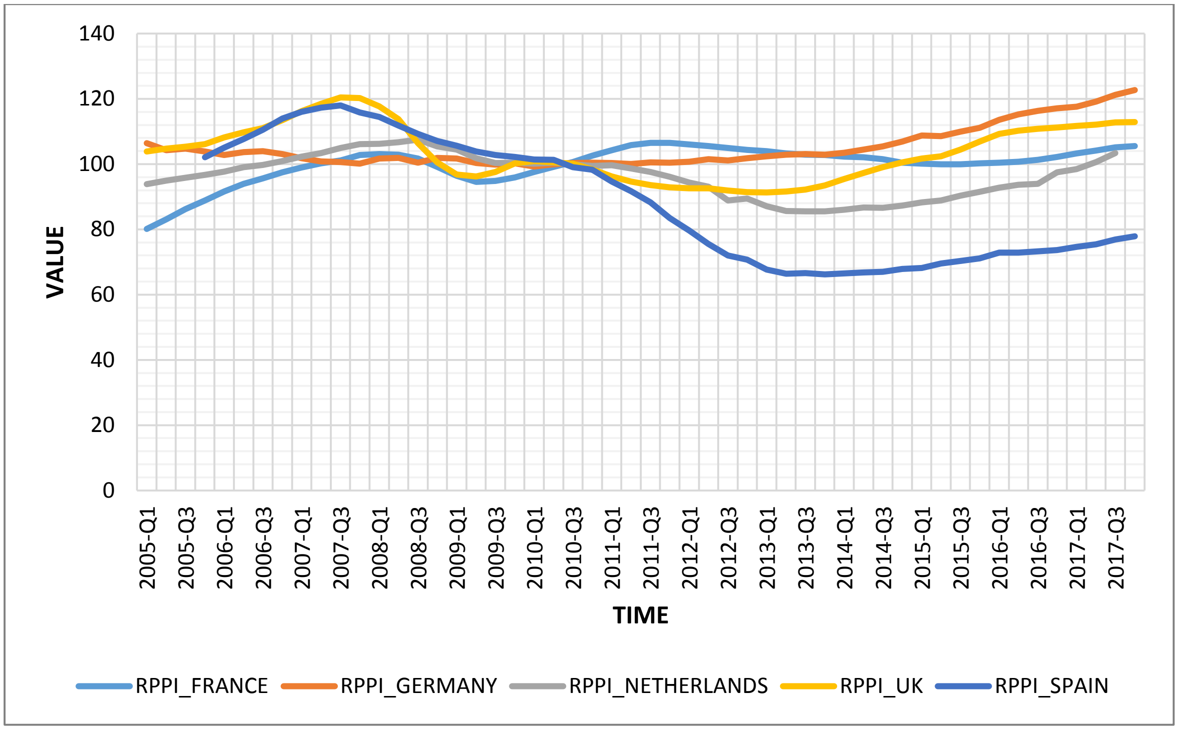
3.5 Dependent variable

To see the impact of monetary policy on housing prices, we set housing prices as the dependent variable. The proxy for housing prices will be *Residential Property Price Index*. Similar approach, where RPPI was used as proxy for housing prices, we can meet in Kalra et al. (2000), Sutton et al. (2017) works. This variable covers all types of owner-occupied and existing dwellings. The series is deflated using CPI and covers dwellings in the whole country. The data for the dependent variable is obtained from FRED database and contains quarterly observations for the period described in Table 2 above. Index base year is 2010 (2010 = 100).

Residential property price indices in developed countries have a strong correlation between economic growth and growth in house prices. Goodhart and Hofmann (2008) found a strong link between housing prices and macroeconomic variables in 17 industrialized countries. They also found that shock to money and credit led to stronger effect in the periods of peaking housing prices.

Increase in house prices and possibilities for increasing returns on building new dwellings encourages more constructions to take place, which positively affects stakeholders. Economic stimulus (increase in government spending) is created on taxes of higher amounts and values of real estate property deals. Another important channel through which increase in housing prices influences economy is the increase of spending and investment of households. Primarily, in times of observing the rise of real estate prices, households tend to spend on renewal of their dwellings, other areas, however, also take a portion of households' spending. As mentioned in the Eurostat Research Handbook concerning Residential Property Prices Indices (2013), often majority of households have dwelling a s their largest part of wealth, making their quality of life and consumption very tight to housing price. Increase in wealth in times of rise of dwellings, can actually lead to price inflation at local stores. For instance, Stroebel and Vavra (2014) found that sometimes households can experience periods of "relaxed" spending behavior, meaning that households reduce the role of commodity price markup and are paying higher price than it was before the increase of household's wealth. Whereas decline in house prices is observed when economy stagnates, which makes it extremely important for the policy makers the precise following of housing prices up-to-date fluctuations. Making right decisions, basing on dwellings price fluctuation might prevent economic crises, which happened several times in past, when real estate bubble burst, and this is certainly another motivation for policy makers to keep an eye on development of real estate prices.

Figure 1: The evolution of Residential Property Price Index - RPPI



Note: *The figure shows the evolution of Residential Property Price Index over time in the selected countries of interest. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*

Source: *Author's computations.*

The evolution of the Residential Property Price Index variable for each country we analyze in this paper is displayed in Figure 1. As we can see in Figure 1, in four (France, the United Kingdom, the Netherlands and Spain) out of five observed countries residential property prices begin to rise immediately at the start of interval. The price rise continues approximately until the end of year 2007 – mid 2008. Sharpest dynamics can be observed in France, the United Kingdom and Spain data. Next comes the period of property price decline for the 4 mentioned above countries. Interestingly, those countries, which showed fastest growing dynamics at the beginning of observed period, show similar dynamics, but this time - in an opposite direction. The United Kingdom and

France reach a local minimum at approximately end of year 2008 – mid 2009, whereas property prices in Spain keep falling until mid-2013, and manage to recover, starting from the end of 2014. Until the end of observed interval, the RPPI in Spain grows. The property prices in United Kingdom create a local maximum soon in the middle of 2008, after which prices slowly decrease until mid of 2013, and then keep rising until the end of observed interval. The local maximum of property prices in France is at the end of 2014. From there RPPI very slowly decreases until the end of 2015, and with very similar dynamics, follows the opposite – growing direction until the end of observed interval. RPPI of the Netherlands reaches peak at the end of 2008, after which the property prices slowly go down until the end of 2013. From the beginning of 2014 and on, RPPI of the Netherlands keeps growing until the end of observed interval. The dynamics of RPPI in Germany are relatively weak in the periods before the financial crisis of 2008, period during financial crisis itself, and period following it. From mid of 2011, the property prices start rising, and keep this direction until the end of observed period.

3.6 Independent variables

For the SVAR model employed in this paper, there will be several independent variables:

- **Household Debt**

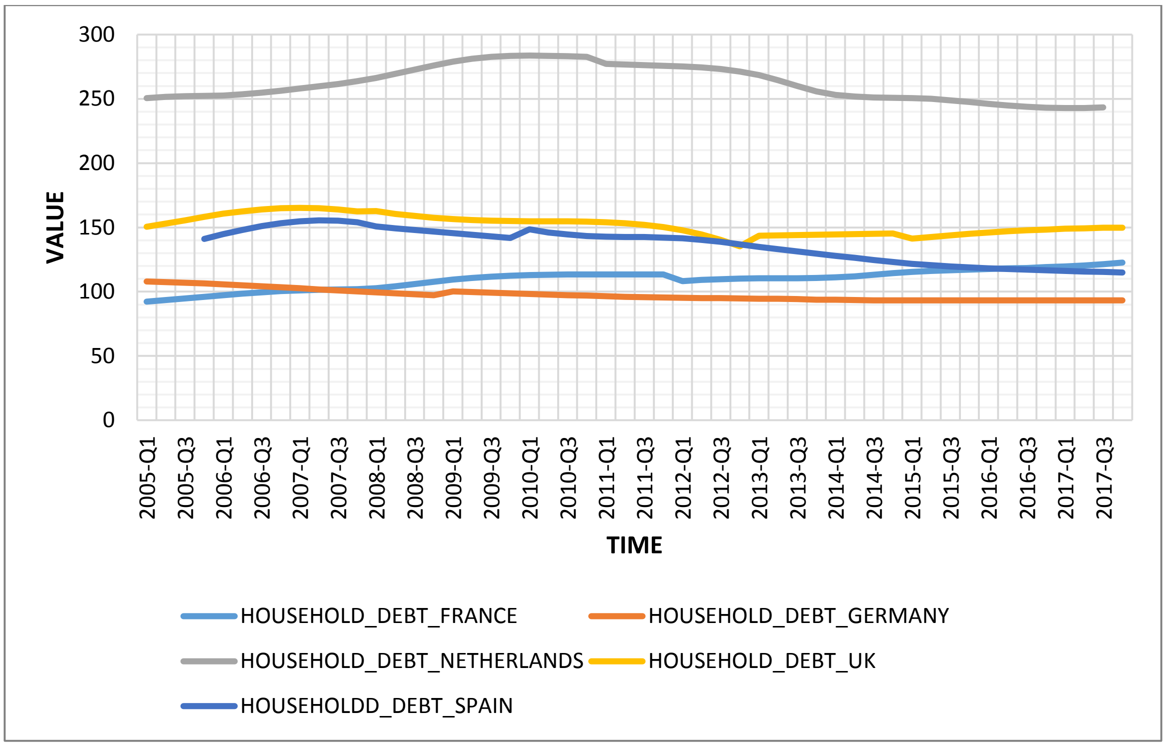
As proxy variable for the scale of credit, *Household Debt* variable will be used. The observations for this variable were obtained from the OECD database.

The household debt is widely used in analyzing the economic situation and taking appropriate actions in order to control the flow of economic development. When the debt to GDP ratio increases, this might be a warning sign, because the recent financial crisis of 2008 had shown what unpleasant consequences for the economy can over-indebtedness of subprime households' initiate. At first glance, it might appear to be fine when a household increases its borrowings for some needs, but the problems come when household is unable to meet its timely obligations because of decline in level of income (due to job loss, for example). To repay the loan, household will probably cut consumption, which on the level of the whole economy can lead to recession and downturn. Another way the households can negatively impact economy is through financial institution. If households with low repaying capability defaults on a loan, this might put whole financial institution, which in turn will hurt economy, as we've seen during the 2008 financial crisis (Lombardi, et al. 2017).

On the other hand, an increase in borrowing from households for investing in financial or capital assets, or education – this might mean that in future the GDP will actually rise, since these investments will in future contribute to the economy. Despite this can be the case, the borrowed finance will have a negative on GDP growth, once these funds, borrowed by private sector reach a certain threshold, and this negative affect is associated with rising financial stability risks and misallocation of resources (Alter et al, 2018).

In general, household debt includes two main categories within it, which are consumer debt and mortgage debt. Consumer debt usually equals to smaller portion of total household debt, and typically, as the names suggests, is used to purchase items that can be consumed during relatively short time in nearest future, like food, clothes, consumer electronics, paying for car repair, paying electricity bills, etc. Much larger portion of household debt is covered by property loans – mortgages. As previously mentioned, the data for this variable were obtained from the OECD database, where this indicator is measured as a percentage of net disposable income.

Figure 2: The evolution of Household Debt



Note: *The figure shows the evolution of household debt over time in the selected countries of interest. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*

Source: *Author's computations.*

Figure 2 above visualize the dynamics of evolution of the household debt variable for each country. As we can see from Figure 2, the household debt of the Netherlands increases almost exponentially since the first observed quarter and until the second quarter of 2009 with average increase of 0,68% per quarter. From the last quarter of 2009 and until the last quarter of 2010, we can observe period of household debt remaining unchanged. Next, we observe a drop from the fourth quarter of 2010 to the first quarter of 2011 by almost 2%. Period from the beginning of 2011 and lasting until the third quarter of 2012 can be characterized as still, where average change per quarter was equal to –0,24%.

The period following was, in contrast, more dynamic, and here the average change in household debt per quarter of –1,15% is observed since the third quarter of 2012 and until the first quarter of 2014. From there and until the last observed quarter, the household debt of the Netherlands dynamics remains relatively smooth with an average per-quarter change of –0,28% The household debt of the United Kingdom shows a slow increase of 1,02% per quarter since the last observed interval and until the second quarter of 2007. A period since the beginning of 2008 and until the end of 2011 can be characterized as slow decrease, with average change of –0,49% per quarter. Next follows a drop of –2,57% until the end of 2012. Immediately after that, household debt increases by 6,04% next quarter. As till period, lasting from the beginning of 2013 and until the end of 2014 shows an average increase of 0,17% per quarter. Next, we observe a drop by –2,74% at the beginning of 2015, following with a slow increase of household debt, which started increasing thereafter, averaging 0,54% percent per quarter, until the of observed interval. The household debt of Spain starts increasing since the beginning of observed interval and reaches its highest observed value in the second quarter of 2007. Next follows a drop (sharp at the begging), which lasts until the end of 2009 and amounts in average –0,92% drop per quarter. Immediately next quarter the household debt of Spain jumps by 4,7%. From there and until the end of observed interval the household debt keeps falling with speed in average –0,82% per quarter. France's household debt graph can be divided in two parts. The first interval is an increase in average by 0,77% per quarter, which lasts since the beginning of observed interval and until the end of year 2011. The second interval is an increase in average of 0,54% per quarter, which last since the beginning of 2012 and until the end of observed interval. There is a drop by –4,54% between the end of 2011 and beginning of 2012. Similarly, household debt of Germany can also be divided in two intervals. Since the beginning of the observed interval, there is a decreasing pattern in household debt, which lasts until the end of 2008 and equals in average –0,7% per quarter. The household debt decreases in the second in the second interval as well (since the beginning of 2009 and until the end of observed interval) in average by –0,21% per quarter, after a jump of 3,15% in the between the end of 2008 and the beginning of 2009 year.

- **Wu-Xia shadow rate**

As proxy variable for the interest rates *Wu-Xia shadow rate (%)* variable will be used. We use this variable instead of short-term interest rates because of Zero Lower Bound (ZLB) policy of central banks. In this case our results would have values for long periods equal 0 percent. In contrast to short-term interest rate, Wu-Xia shadow rate, introduced by Wu and Xia (2016), can take values below zero and shows what short-term interest rate could equal if it could take negative values. Because of the nature of Wu-Xia shadow rate, it is very convenient to use it in this analysis[3].

Interest rate is one of the conventional monetary policy instruments of country's central bank to achieve monetary goals. The central bank of England calls it the "Bank Rate" and adjust the interest rate accordingly, in order to meet its current goal: the 2% inflation rate. The European Central Bank has the same goal, its current target is to keep inflation at 2% rate as well, the ECB calls interest rate the "Marginal lending facility".

In general, interest rate is a conventional monetary policy instrument, used by central banks. The interest rate defines a fee the central bank charges when providing funds to the other banks. This rate, for example, generally sets a base when commercial banks compute consumers' lending rate. Commercial banks will benefit from lending funds from the central banks and then lend to consumers with some extra margin. In times when commercial banks find it difficult to lend to consumers, they might benefit from depositing their extra funds within the central bank, however, earning a lower interest.

Depending on the current economic target, the country's central bank can rise or decrease interest rate, to slow down or stimulate the country's economy, respectively. A decrease in central banks' interest rate means that the other banks can borrow for a lower fee, and thus provide the funds to final consumers for a lower fee as well, this will make borrowing cheaper. Cheaper funds will stimulate borrowing for whatever needs.

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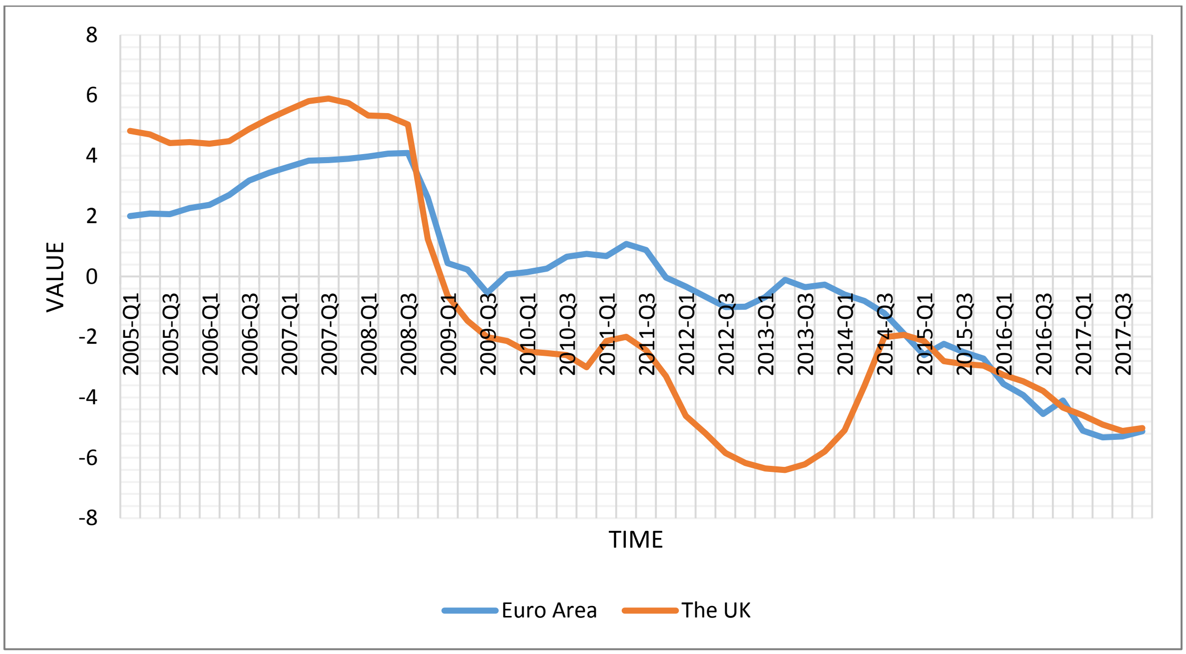
[3] For more information about Wu-Xia shadow rate and access to dataset itself see (https://sites.google.com/view/jingcynthiawu/shadow-rates)

As a result of people borrowing cheaper money, consumption will increase, what will in turn increase the country's output. Cheaper funds will be appreciated by firms as well, who will likely invest in development, what will in turn increase the country's output as well. The downside of cheaper funds, and as a result increased consumption, is also a rise in prices, which will follow the growth of economy (Alvarez et al, 2001).

On the other hand, a rise in interest rate will lead to decreased consumption. Households will have to cut their consumption to pay their loans, whose instalment will rise together with interest rates. The interest rate offered on saving account at the commercial bank will look attractive for many households, thus many will deposit their funds within bank to earn some additional money. Firms will find it more difficult to lend and invest into development. As a consequence of list above, the country's output will fall, and inflation will decrease.

As we can see from Figure 3 below, Wu-Xia shadow rate for the Euro Area starts growing right from the beginning of observed interval and until the third quarter of 2008. This growth can be further divided into three sub-intervals. The first one lasts for the first three quarters of 2005 with average pace of 1,52% percent growth per quarter. Next comes period with substantially higher growth speed (in average 9,33% per quarter), which lasts since the third quarter of 2005 until second quarter of 2007. And finally, last sub-interval is showing weak growing dynamics with average growth speed of 1,31% per quarter. Since the third quarter of 2008 follows a period of decline, which lasts until the third quarter of 2009, where Wu-Xia shadow rate firstly decreases below zero. This decline in average was -73,1% per quarter. Since the third quarter of 2009 and until the second quarter of 2011, we can observe an increase in rates, whose increase shows in average 20,78% growth per quarter. Since the third quarter of 2011 and until the second quarter of 2013 we can see a j-curve with left end higher than right end by 1,18 units. Last part of Euro Area Wu-Xia shadow rate (from second quarter of 2013 and until the last quarter of 2017) shows a decline trend with several small increases. In average, the decline amounts -21,18% decrease per quarter.

Figure 3: The evolution of Wu-Xia shadow rate



Note: *The figure shows the evolution of Wu-Xia shadow rate over time in the selected countries of interest. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*

Source: *Author's computations.*

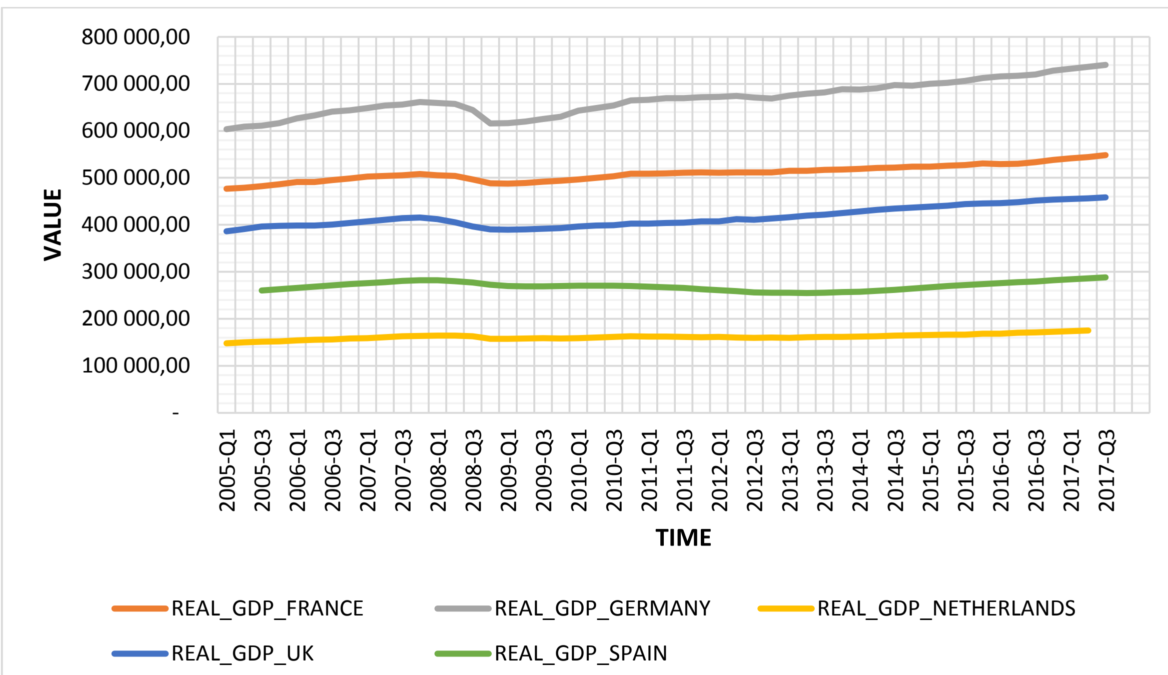
Wu-Xia shadow rate shows a period of little change in the first six quarters since the beginning of observed interval (since the first quarter of 2005 and until the second quarter of 2006). From here and until the third quarter of 2007 we can observe increase in Wu-Xia shadow rate up to the absolute maximum of 5,89 in the third quarter of 2007, the increase has an average growth of 5,67% per quarter. Next there is short period of decline down to 5,03 units in the third quarter of 2008. The first j-curve can be seen from the third quarter of 2008 and until second quarter of 2011 (with few small sharp increases and decreases at the end of j-curve), where the Wu-Xia shadow rate went down from 5,03 units to -1,99 units in the second quarter of 2011. Second j-curve can be observed since the second quarter of 2011 and until the third quarter of 2014. The difference in values between left peak and right peak is 0,43 units increase. Since the last quarter of 2014 and until the end of observed interval, Wu-Xia shadow rate for the United Kingdom keeps decreasing with average speed of -7,6% per quarter.

- **Real GDP**

GDP is an important indicator of economic health. It can say much about the unemployment, the consumption and the welfare of country's residents. Despite having downsides, as mentioned by Dynan and Sheiner (2018), gross domestic product is widely used in economic analysis. Policy makers collect data and see how changes in monetary policy affect economy. Depending on the numbers, policy makers see if economy is on the rise, whether recession is taking place, or whether economy stagnates. Various monetary policy instruments then are employed, depending on the target of the central bank. For example, if the aim is to boost economic growth, policy maker must make sure that prices are stable. This is also case for European Central Bank (ECB), as its aim is "to maintain price stability, i.e. to safeguard the value of the euro. Price stability is essential for economic growth and job creation – two of the European Union's objectives – and it represents the most important contribution monetary policy can make in that area"[4]. ECB suggests[5] that prices are stable at level "below, but close to, 2% over the medium term" and tries to keep it there, setting it as ECB's primary goal.

A much more precise picture of economic performance can be achieved when using real gross domestic product instead of nominal. The difference is that real GDP is adjusted for year-to-year price changes, using a GDP deflator, which takes into account movements in prices. Therefore, despite nominal GDP might look higher, compared to another period's, the true story can be read when transforming nominal GDP to real.

Figure 4: The evolution of real GDP



Note: *The figure shows the evolution of real GDP over time in the selected countries of interest. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*

Source: *Author's computations.*

[4] European Central Bank website www.ecb.europa.eu *ECB Tasks*
[5] European Central Bank website www.ecb.europa.eu *Monetary policy: Definition of price stability*

For our SVAR model we use *real GDP* independent variable. The data for this variables are taken from FRED database. The units of real GDP are millions.

Figure 4 above shows the dynamics of evolution of the real GDP variable for each country. As we can see from Figure 4, at the very beginning of observed interval, each country's real GDP is growing until approximately mid of 2008, where consequences of global financial crisis started taking place. In the period prior to global financial crisis, the pace of quarter-to-quarter growth was approximately 0,55% in average for France, 0,82% for Germany, 0,86% for the Netherlands 0,7% for the United Kingdom, and 0,81% for Spain. The negative real GDP growth can be observed from second quarter of 2018 until the second quarter of 2009 and averaging –0,79% growth per quarter in France. In Germany, the average negative growth of real GDP, amounting –1,77% per quarter is observed from second quarter of 2008 until the thirst quarter of 2009. The negative mean growth of real GDP, which amounts –1,1% per quarter, lasted from third quarter of 2008 until the second quarter of 2009 in the Netherlands. The United Kingdom shows a mean negative growth of real GDP, amounting –1,28% per quarter and lasting from second quarter of 2008 and until the second quarter of 2009. In case of Spain, we observe an average of –0,78% per quarter negative growth of real GDP, lasting from the third quarter of 2008 and until the last quarter of 2009. After recovering from the period of negative real GDP growth, the visualized in Figure 2 data for the Netherlands look almost like a slowly rising straight line until the end of observed period. Similar can be said about graphs of France and the United Kingdom real GDP, which both, however, have some peaks in the dynamics. The dynamics of real GDP in Spain are moving slowly in both directions: firstly, after the negative growth during the financial crises, real GDP starts growing for 3 quarters, after which we again observe negative growth, averaging -0,53% per quarter from first quarter of 2011 until the third quarter of 2013; starting from the last quarter of 2013 and until the end of observed interval, we see a constant increase in real GDP, averaging 0,72% per quarter. The real GDP of Germany managed to recover from the financial crisis the fastest. First part of the growth is observed from the second quarter of 2009 until the first quarter of 2011. Starting from the second quarter of 2011 and until the third quarter of 2012, real GDP is growing at a much slower pace (0,45% per quarter). Starting from the last quarter of 2012 and until the end of the observed interval, real GDP of Germany mainly grows with an average speed of 0,45% per quarter.

3.7 Brief descriptive statistics of the data

In this section we will summarize our data that we gathered in statistical tables of means, counts, standard deviations, etc. This helps us to communicate the largest amount of information as simply as possible.

Table 3: Brief descriptive statistics of real GDP

real GDP					
	FRANCE	**GERMANY**	**NETHERLANDS**	**UK**	**SPAIN**
min	475 699,10	599 750,90	146 954,30	381 950,30	254 950,00
max	548 307,90	740 025,70	174 905,70	458 033,10	288 064,00
average	509 009,16	666 347,63	161 227,40	414 984,51	269 477,88
s.d.	17 589,26	37 078,06	5 957,02	21 494,07	8 958,30

Note: *The table provides the brief descriptive statistics of real GDP on the covered period for each of the observed countries. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*

Source: *Author's computations.*

Tables 3, 4, 5 and 6 report the data descriptive statistics as means, standard deviations, and definitions for our independent variables, such as real GDP, RPPI, Household Debt, and Wu-Xia shadow rate for each country in part.

Table 4: Brief descriptive statistics of RPPI

RPPI					
	FRANCE	**GERMANY**	**NETHERLANDS**	**UK**	**SPAIN**
min	80,18	99,23	85,52	91,30	66,26
max	106,57	122,68	107,55	120,43	118,02
average	99,91	105,07	96,40	103,48	88,40
s.d.	5,69	6,21	6,53	8,57	18,39

Note: *The table provides the brief descriptive statistics of Residential Property Price Index on the covered period for each of the observed countries. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*
Source: *Author's computations.*

As we can read in Table 4 above, RPPI in Spain has the highest standard deviation among all other countries and at the same time the lowest average value. This shows that there've been large fluctuations in housing prices taking place during selected period for observation.

Table 5: Brief descriptive statistics of Household Debt

Household Debt					
	FRANCE	**GERMANY**	**NETHERLANDS**	**UK**	**SPAIN**
min	92,31	93,24	242,83	135,31	114,97
max	122,60	108,06	283,70	165,18	155,51
average	109,67	97,47	262,17	151,90	136,34
s.d.	7,63	4,50	13,64	7,54	13,15

Note: *The table provides the brief descriptive statistics of household debt on the covered period for each of the observed countries. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*
Source: *Author's computations.*

Table 6: Brief descriptive statistics of Wu-Xia shadow rate

Wu-Xia shadow rate		
	EURO	GBP
min	-5,32	-6,40
max	4,09	5,90
average	-0,02	-1,04
s.d.	2,73	4,21

Note: *The table provides the brief descriptive statistics of Wu-Xia shadow rate on the covered period for each of the observed countries. The covered period for France, Germany and the United Kingdom is from 2005 Q1 until 2017 Q4, for the Netherlands – from 2005 Q1 until 2017 Q3, for Spain – 2005 Q4 until 2017 Q4. The periods vary because of the unavailability of data, however, insignificantly.*

Source: *Author's computations.*

Chapter 4

Results and Interpretation

4.1 Chapter Overview

In this chapter we will construct Structural VAR models using Choleski decomposition and interpret the results for each country individually. We will choose the best lag length to have most stable and well fitted. Considering our number of observations and variables, we are going to limit amount of suggested by software lag length to 3, using the rule of thumb. All variables are used logarithmic form. We follow Choleski recursive identification with variables ordered as below (as suggested by Mojon and Peersman (2001) :

$$\begin{bmatrix} \varepsilon_{GDP} \\ \varepsilon_{RPPI} \\ \varepsilon_{HD} \\ \varepsilon_{WX} \end{bmatrix} = \begin{vmatrix} 1 & 0 & 0 & 0 \\ a_{21} & 1 & 0 & 0 \\ a_{31} & a_{32} & 1 & 0 \\ a_{41} & a_{42} & a_{43} & 1 \end{vmatrix} \begin{bmatrix} e_{GDP} \\ e_{RPPI} \\ e_{HD} \\ e_{WX} \end{bmatrix} \tag{4.1}$$

Where, *GDP* stands for real GDP, *HD* stands for Household Debt and WX stands for Wu-Xia shadow rate.

4.2 France

The first step would be the selection of lag lengths. The suggested by the software optimal lag lengths and selected lag lengths are depicted in Table 7 below. The lag lengths for each country of interest were chosen, based on stability tests[6] and Ventzislav and Kilian (2005).

Table 7: Optimal suggested lag length and chosen lag length for every country of interest

	France	The UK	Germany	The Netherlands	Spain
Akaike Info Criterion	2	2	2	2	2
Hannan-Quinn Criterion	2	1	2	2	2
Shwarz Criterion	1	1	1	1	1
Chosen	1	1	1	1	1

Note: *The table provides information on lag lengths suggested by the software JMulTi and lag lengths selected by the author, for each country of interest.*

Source: *Author's computations in JMulTi*

The resulting impulse response functions of RPPI together with confidence bands for France are shown in Figure 5 below.

[6] Stability tests for each country of interest can be found in appendix.

Figure 5: Impulse Response Function of Residential Property Price Index in Structural VAR for France

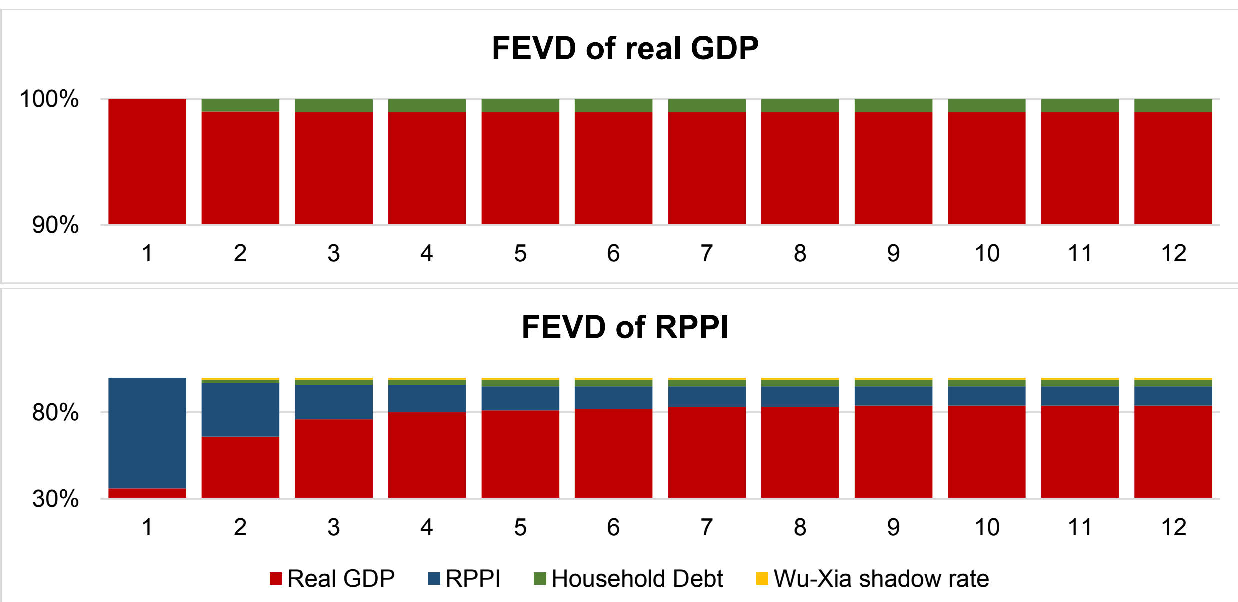
Note: *The figure provides visualization of Residential Property Price Index response to shock of real GDP, household debt and Wu-Xia shadow rate (left to right, up to down) for the period of 12 quarters in France.*

Source: *Author's computations in JMulTi*

As we can see in Figure 5, one standard deviation shock of real GDP, amounting 17589,26 units, makes RPPI react immediately with an increase, which lasts up to the fourth quarter, where the maximum value of 0,01 is reached. After that, RPPI impulse response slowly attempts to return to its initial state up to the end of observed quarter.

In the last, twelfth, quarter we can observe the value of 0,0008 units. The impulse response of RPPI to real GDP shock is statistically significant from the first and until the seventh quarter. RPPI impulse response reacts with a decrease to 7,63 units shock (one standard deviation) of household debt. The decrease lasts since the beginning of observed interval and until the fifth quarter, where impulse response reaches its lowest value of -0,0041 units. RPPI impulse response then slowly increases until the end of observed interval. The impulse response is statistically insignificant for the whole observed interval. One standard deviation shock of Wu-Xia shadow rate (2,73 units) forces RPPI impulse response to decrease since the first quarter until the fifth quarter, where it reaches lowest value of -0,006 units and keeps it until the sixth quarter. The impulse response then tries to return to its initial state until the end of last observed quarter. The results are statistically significant from the second and until the seventh quarter.

Figure 6: Forecast Error Variance Decomposition of Real GDP and RPPI for France



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in France. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

Source: *Author's computations.*

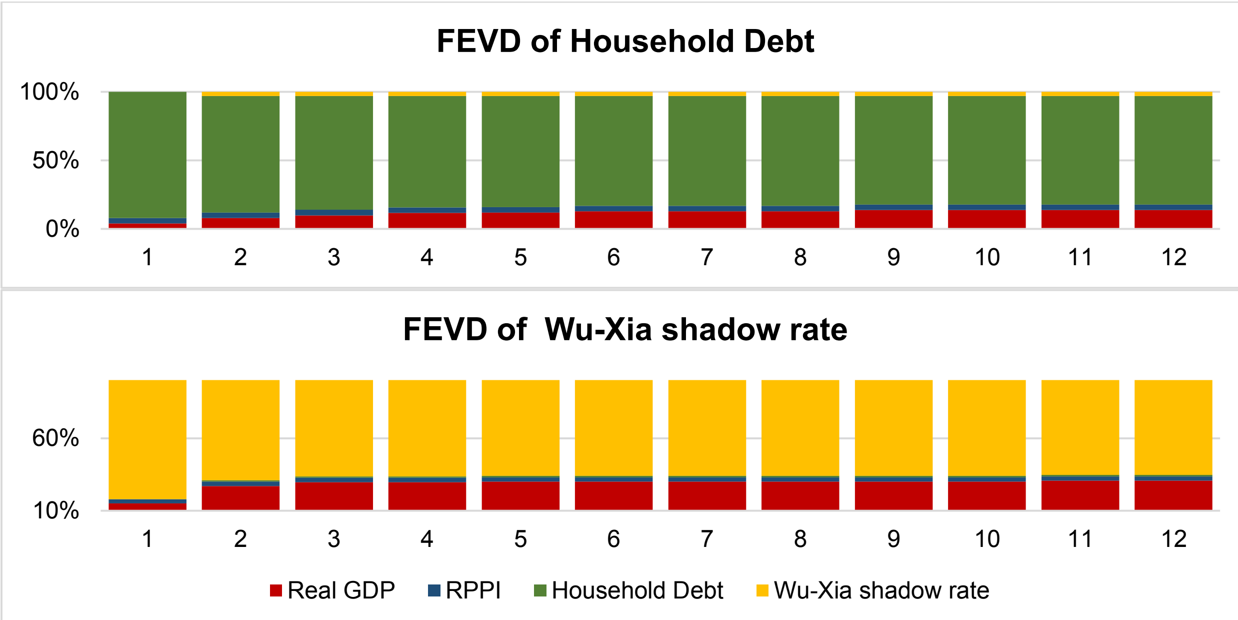
The above results of Forecast Error Variance Decomposition for France SVAR, shown in Figure 6 and Figure 7, tell that almost each variable’s future value forecast errors are mainly explained by past values of themselves.

As we can see, FEVD of real GDP in France is mainly explained by itself. Real GDP takes a 100 percent proportion of FEVD in the first lag, slightly drops to 99 percent in the second lag and then again drops by 1 percent to 98 percent in the third lag, where it stays until the last lag. Household debt takes explaining power of real GDP forecast error variance only in the second lag with 1 percent proportion, where it stays constant until the last lag. As we can see, household debt and Wu-Xia shadow rate do not take part in explaining real GDP forecast error variance.

The forecast error variance of RPPI has real GDP with the largest proportion of 84 percent in seventh and all subsequent lags. The role of GDP increases since the first lag, where it only can explain 36 percent of RPPI forecast error variance. It increases significantly right in the second lag up to 66 percent, and then with slower pace increases to it maximum in seventh lag. RPPI manages to explain up to 64 percent of itself forecast error variance. This largest proportion RPPI has in the first lag. It then decreases sharply in the second lag to 31 percent, and much slower reaches its minimum of 11 percent in ninth lag, since which it remains constant until the last lag.

Household debt manages to explain the major portion of itself forecast error variance in all lags, having largest proportion in the first lag 92 percent and lowest of 80 percent in seventh and all subsequent lags. The major change is observed in second lag, where the jump from 92 down to 85 percent is observed. Further declines are rather smooth. The second largest proportion in the household debt FEVD takes real GDP, which has only 4 percent explaining power in the first lag, but then quickly increases to 8 percent in the second lag and reaches its maximum of 14 percent in the ninth lag, after which remains constant up to the last lag. RPPI only has 4 percent explaining power in the household forecast error variance in every lag. Wu-Xia shadow rate does not take part in FEVD in the first lag, but in second and all subsequent lags takes 3 percent proportion.

Figure 7: Forecast Error Variance Decomposition of Household Debt and Wu-Xia Shadow Rate for France



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in France. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

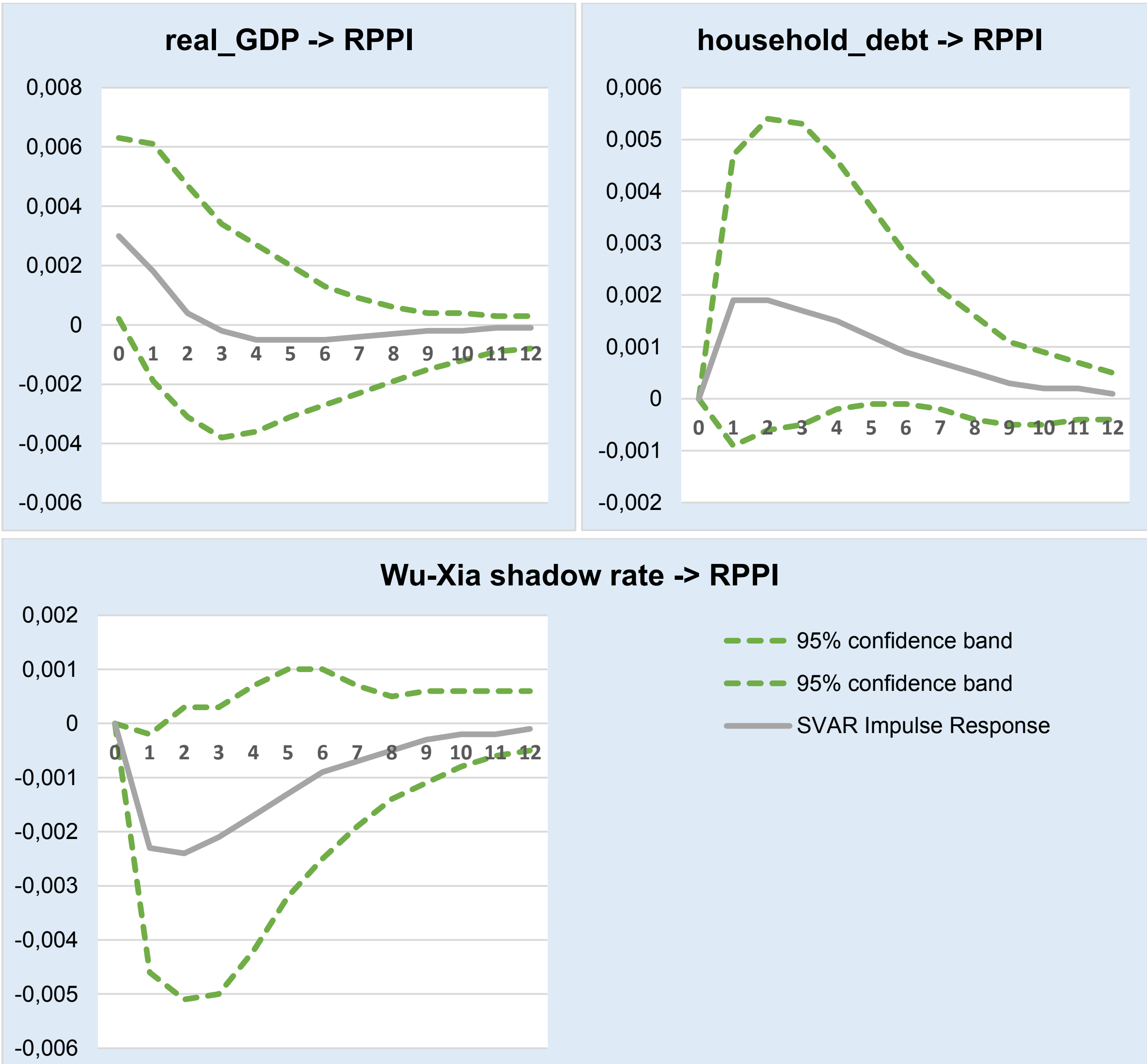
Source: *Author's computations.*

Wu-Xia shadow rate takes a major role in itself FEVD with the largest proportion of 82 percent in the first lag and lowest of 66 percent in fifth and all subsequent lags. A major drop is observed in the second lag, where proportion of Wu-Xia shadow rate drops from 82 to 69 percent. Later drops are smaller. The household debt has the largest proportion of 1 percent in the second and all subsequent lags. In the first lag, the household debt does not participate in Wu-Xia shadow rate FEVD. RPPI keeps a constant proportion of 3 percent for all of the lags.

4.3 The UK

After employing Structural VAR for the UK with one lag, the following results on impulse response and FEVD where achieved and shown in Figures 8, Figure 9 and Figure 10 below.

Figure 8: Impulse Response Function of Residential Property Price Index in SVAR for the UK



Note: *The figure provides visualization of Residential Property Price Index response to shock of real GDP, household debt and Wu-Xia shadow rate (left to right, up to down) for the period of 12 quarters in the United Kingdom.*

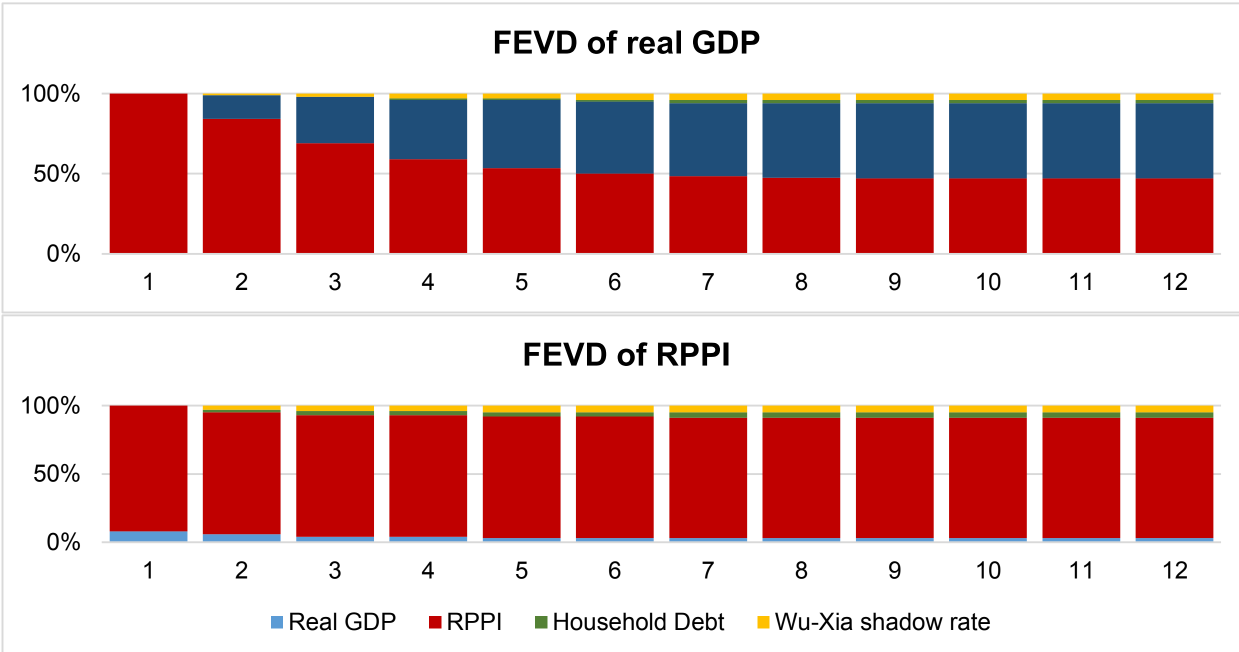
Source: *Author's computations in JMulTi*

Despite neither of the resulting impulse responses on the UK model are not statistically significant for at least a short interval, it might be still interesting to examine and interpret them. In the case of the UK, we can see impulse response of RPPI to one standard deviation shock (21494,07 units) of real GPD increasing immediately in the beginning of the observed interval to its highest value of 0,003 units in the first quarter already. After that, RPPI attempts to return to its initial state until the end of the observed interval, passing below zero between second and third quarters. A household debt shock of one standard deviation, amounting 7,54 units, makes RPPI impulse response increase from the beginning of the observed interval until the first quarter, where it reaches its highest value of 0,0019 units and keeps it until the second quarter. Next follows a decline trend until the end of the observed period, where RPPI impulse response tries to return to its initial state. A decline can be observed, resulting 4,21 units (one standard deviation) shock from Wu-Xia shadow rate. The impulse response drops rapidly in the first quarter and reaches its lowest point of -0,0024 units in the second quarter. Next follows a period when RPPI attempts to return to its initial state, which lasts until the end of the observed interval. The results of neither RPPI impulse response of the UK are statistically significant.

Following is interpretation of the UK Structural VAR FEVD with variance with FEVD itself shown in Figure 9 and Figure 10 below.

In the UK, real GDP has a 100 percent proportion in explaining forecast error variance of itself in the first lag. With each next lag, the proportion decreases and reaches its lowest value of 47 percent in the tenth lag, since which it remains constant until the last lag. RPPI is the second largest contributor to the UK real GDP forecast error variance. Starting from the second lag with 15 percent proportion, it then grows with each next lag until the eighth lag, since which it remains constant at its largest value of 47 percent. The household debt comes into action at the fourth lag with proportion of 1 percent, which remains constant until the sixth lag. In the second lag we can see household debt’s contribution increasing to the maximum value of 2 percent, which remains unchanged until the last lag. Wu-Xia shadow rate has 1 percent proportion in explaining household debt’s FEVD in the second lag. Until the sixth lag, it reaches its maximum of 4 percent, which remains unchanged until the last lag.

Figure 9: Forecast Error Variance Decomposition of Real GDP and RPPI for the UK

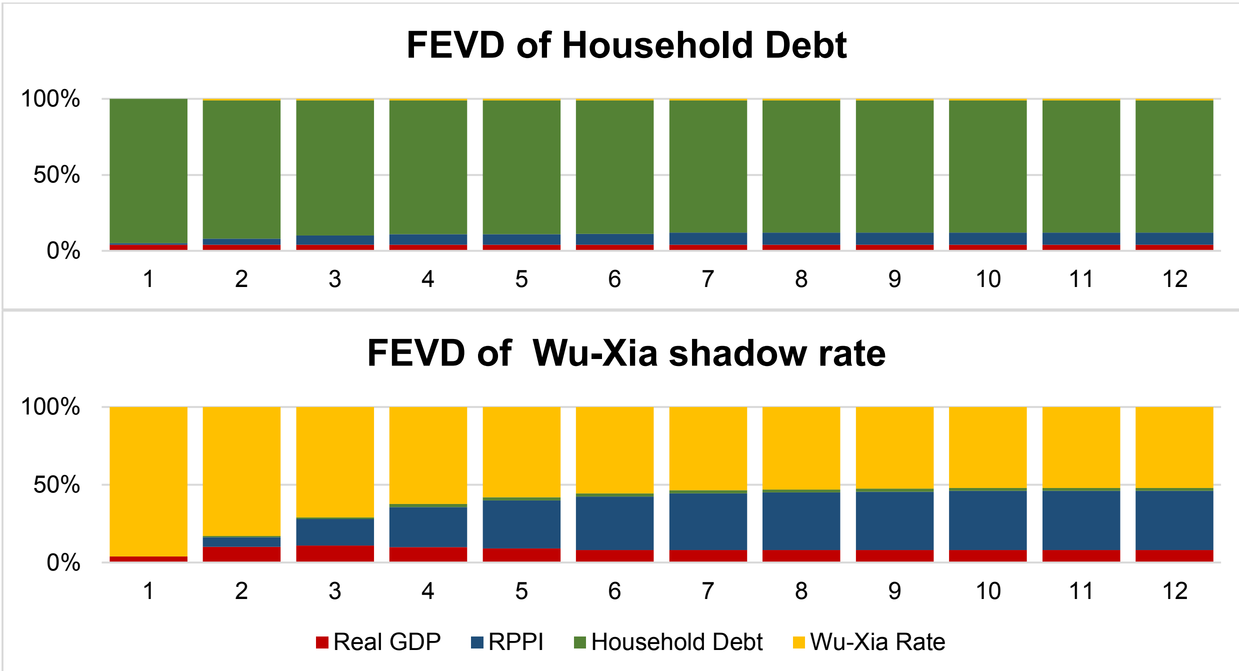


Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in the UK. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

Source: *Author's computations.*

In case of the UK, RPPI manages to explain the largest portion of itself forecast error variance. The largest proportion of 92 percent is observed in the first lag, which drops down to 89 percent at the third lag, where it remains constant until the fifth lag. Since the sixth lag and until the end of the observed interval, we can see RPPI's proportion at its lowest value of 88 percent. Household debt only has minor contribution to RPPI's FEVD. Starting with 2 percent at the second lag, it grows to 3 percent in the next lag and until the sixth lag remain constant. From the seventh and until the last lag, we see household debt having a 4 percent proportion in RPPI FEVD. Wu-Xia shadow rate enters into action with 3 percent explaining power in the second lag, then it grows to 4 percent in the next lag and remain constant until the fourth lag. Since the fifth lag and until the last lag, Wu-Xia shadow rate remains constant at its maximum value of 5 percent.

Figure 10: Forecast Error Variance Decomposition of Household Debt and Wu-Xia Shadow Rate for the UK



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in the UK. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

Source: *Author's computations.*

Household debt of the UK mainly explains alone itself forecast error variance. Starting from the largest value of 95 in the first lag, the proportion in FEVD of household debt drops to 87 percent in the sixth lag, where it stays constant until the last lag. Wu-Xia shadow rate only has 1 percent contribution to the household debt FEVD from the second and until the last lag. Real GDP has a 4 percent proportion in the FEVD in all of the lags. RPPI starts its explaining power with 1 percent at the first lag, grows to 7 percent in the fourth lag, where it keeps its value until the sixth lag. RPPI has its maximum proportion of 8 percent in the seventh until the twelfth quarter.

Wu-Xia shadow rate explains itself forecast error variance with the highest proportion at every lag. Starting with its highest proportion of 96 percent in the first lag, its quickly decreases to 53 percent in the seventh lag, and keeps its value until the eighth lag. Since the ninth lag and until the last lag we observe a lowest value of 52 percent. Second largest contributor to Wu-Xia shadow rate's FEVD is RPPI with the highest value of 38 percent in the last three lags. It enters into action at the second lag with 6 percent contribution, which then grows to 37 percent at the eighth lag and remain constant until the ninth. Real GDP's proportion quickly grows to its maximum of 11 percent in the third lag, but then drops to 8 percent until the sixth lag, where its value remains constant until the last lag. Household debt's contribution to Wu-Xia shadow rate's FEVD is the lowest of 1 percent at the second and third lag, and highest of 2 percent from the fourth until the twelfth lag.

4.4 Germany

Following is the Structural VAR model for Germany. Impulse response function and FEVD for Germany SVAR are shown in Figure 11, Figure 12 and Figure 13, respectively.

As in previous cases, we are going to interpret results for each impulse response function; despite they are not statistically significant in some cases for major portion of the observed interval.

In case of Germany, we can see the impulse response of RPPI increasing as a result to one standard deviation shock of real GDP, amounting 37078,06 units. The values impulse response value keeps growing until the end of observed interval; thus, the highest value is observed at the twelfth quarter. The results are statistically insignificant for the whole observed interval. RPPI impulse response grows as well to one standard deviation shock of household debt (4,5 units) until the seventh quarter, where it reaches its highest value of 0,0021 units and keeps it until the ninth quarter. Impulse response then slowly decreases until the twelfth quarter. The results are statistically insignificant for the whole interval. We can see a decrease of RPPI impulse response as a result of one standard deviation (2,73 units) shock from Wu-Xia shadow rate. At first, impulse response decreases on a fast pace until the eighth quarter, where it reaches value of -0,0047 units, but then decrease becomes slower since the eighth quarter and until the end of observed interval. The results are statistically significant since the second quarter and until the end of observed interval.

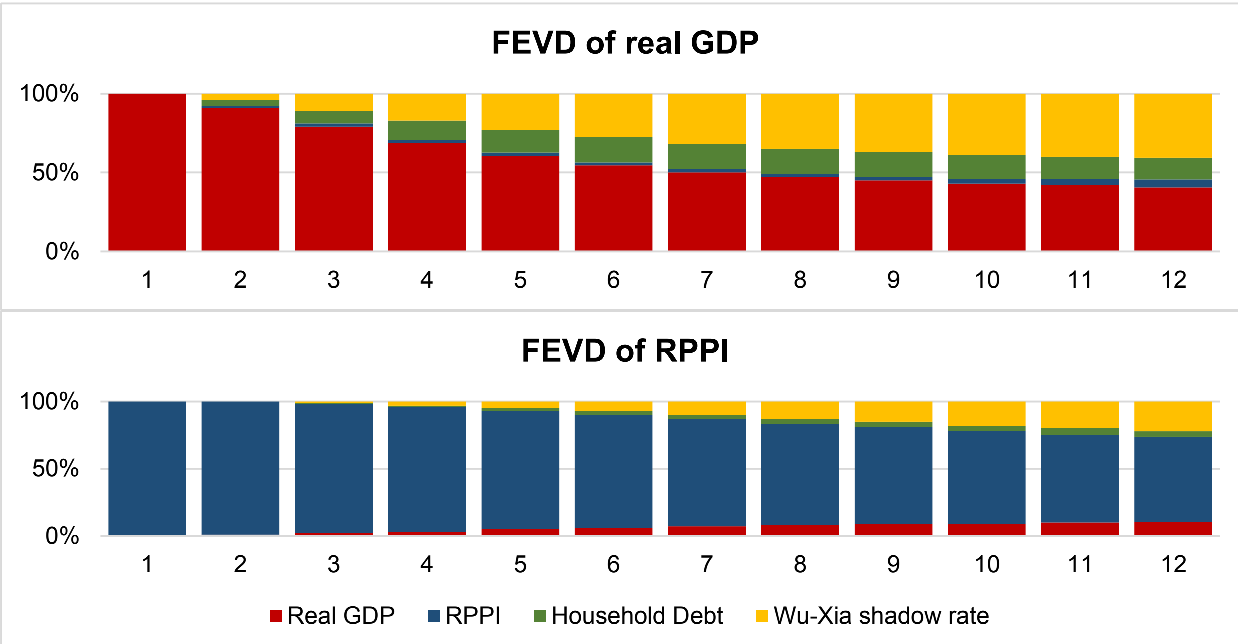
Figure 11: Impulse Response Function of Residential Property Price Index in SVAR for Germany

Note: *The figure provides visualization of Residential Property Price Index response to shock of real GDP, household debt and Wu-Xia shadow rate (left to right, up to down) for the period of 12 quarters in Germany.*

Source: *Author's computations in JMulTi*

The interpretation of Germany SVAR FEVD is shown in Figure 12 and Figure 13 below.

Figure 12: Forecast Error Variance Decomposition of Real GDP and RPPI for Germany



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in Germany. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

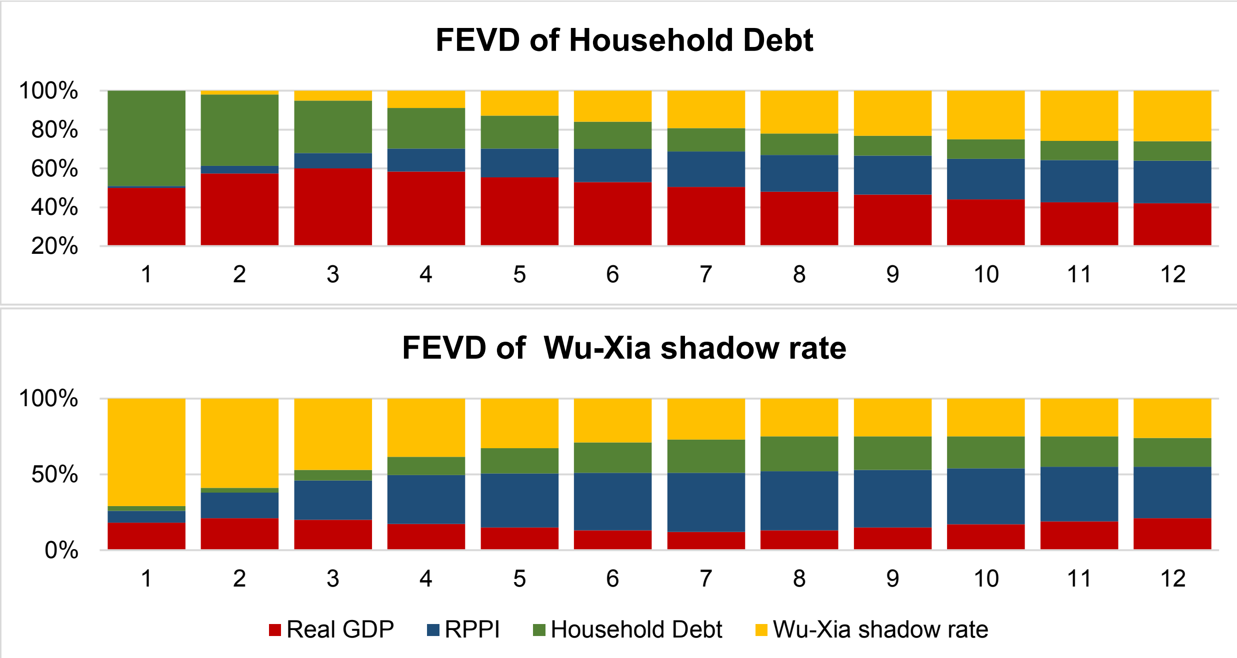
Source: *Author's computations.*

The real GDP in Germany explains a major part of forecast error variance in itself for the first six lags with largest proportion of 100 percent in the first lag and lowest of 55 percent in the sixth lag. In the seventh lag real GDP takes 50 percent proportion in itself FEVD, and in the subsequent lags the proportion keeps dropping to the lowest of 41 percent in the twelfth lag. Wu-Xia shadow rate is the second largest influencer of real GDP forecast error variance. In the first lag it does not appear, but in the second lag it reaches value of 4 percent, after what with a slowing pace increases up to the last lag, where it reaches 40 percent proportion. The household debt's contribution increases from 4 percent in the second lag up to its maximum of 16 percent in the sixth lag. It stays constant until the ninth lag, but then drops to 15 percent in the tenth lag, and again to 14 percent in eleventh and twelfth lag. RPPI has the lest contribution to real GDP FEVD. It starts with 1 percent in the second lag, grows to 2 percent in the third lag, where in remain constant up to the ninth lag, and then increases to its maximum of 15 percent in the last lag.

RPPI is able to explain the major part of itself FEVD in every lag, with highest proportion of 100 percent in the first lag and lowest of 63 in the last lag. Wu-Xia shadow rate is the second largest RPPI FEVD contributor, which comes into action only in the third lag with 1 percent proportion. It then increases with constant speed to it maximum value of 22 percent at the last lag. Real GDP is the third largest RPPI FEVD contributor. It starts with 1 percent proportion in the second lag and grows to its largest value of 10 percent in the eleventh lag, where it stays constant in the twelfth lag as well. Household debt only in the third lag contributes to RPPI FEVD with 1 percent proportion, stays constant at 1 percent at fourth lag, grows to 4 percent in eighth lag, where it stays unchanged up to tenth lag. In the eleventh lag RPPI proportion grows again to 5 percent, but in the eleventh lag drops back to 4 percent.

In household debt, the proportion of real GDP starts with 50 percent in the first lag, but then grows to its highest value of 60 percent in the third lag. Next follows a slow decrease, which lasts up to the twelfth lag, where real GDP proportion only has 42 percent. Household debt in the first lag influences itself forecast error variance with 49 percent in the first lag. The proportion then keeps dropping to the minimum value of 10 percent in the ninth lag, since which and up to the twelfth lag, its contribution remains unchanged. RPPI's proportion grows from 1 percent in the first lag until 22 percent in the eleventh lag, where it keeps its value until the final lag. Wu-Xia shadow rate comes into action at second lag 2 percent contribution, and keeps a slow growth up the eleventh lag, where it reaches its maximum value of 26 percent. At the twelfth lag the proportion remains unchanged.

Figure 13: Forecast Error Variance Decomposition of Household Debt and Wu-Xia Shadow Rate for Germany



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in Germany. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

Source: *Author's computations.*

The proportion of real GDP in Wu-Xia shadow rate FEVD changed several times. Since the first lag, the proportion grows from 18 percent to its maximum of 21 percent in the second lag. The proportion then keeps decreasing up to the seventh lag, where it reaches 12 percent proportion – its lowest observed proportion. Since the eighth lag, percentage grows again to a value of 21 in the last lag. The role of RPPI quickly grows from 8 percent in the first lag to its maximum of 39 percent in the seventh lag, where it stays constant until the eighth lag. Since the ninth lag and until the last lag, the role of RPPI drops to 34 percent in the last lag. Household debt's proportion quickly grows from 3 percent in the first and second lag up to maximum of 23 percent in eighth lag. The proportion then decreases with each next lag down to 19 percent in the twelfth lag. Wu-Xia shadow rate has major proportion in itself forecast error variance in the first (71 percent) and second (59 percent) lags. The proportion then slowly decreases to 25 percent in the eighth lag, where it stays constant until the eleventh lag. At the last lag we see percentage again increased to 26.

4.5 The Netherlands

In case of the Netherlands, one standard deviation (5957,0 units) of real GDP forces the Netherlands RPPI impulse response to increase until the fourth quarter, where it reaches its maximum value of 0,0036 and keeps it until the fifth quarter. RPPI then slightly decreases to 0,0035 units in sixth and seventh quarter, but after that tries to return to its initial state until the end of observed interval. The results are statistically significant only for up to the fourth quarter. We can see a drop in RPPI impulse response after 13,64 units (one standard deviation) household debt shock. The impulse response keeps decreasing until the end of observed interval. The results are statistically significant for the whole observed interval.

RPPI impulse response decreases as well to one standard deviation (2,73 units) shock from Wu-Xia shadow rate. The impulse response keeps decreasing until the end of observed interval. The results are statistically insignificant for the whole observed interval.

Figure 14, Figure 15 and Figure 16 below show impulse response functions of RPPI and FEVD of all variables, respectively.

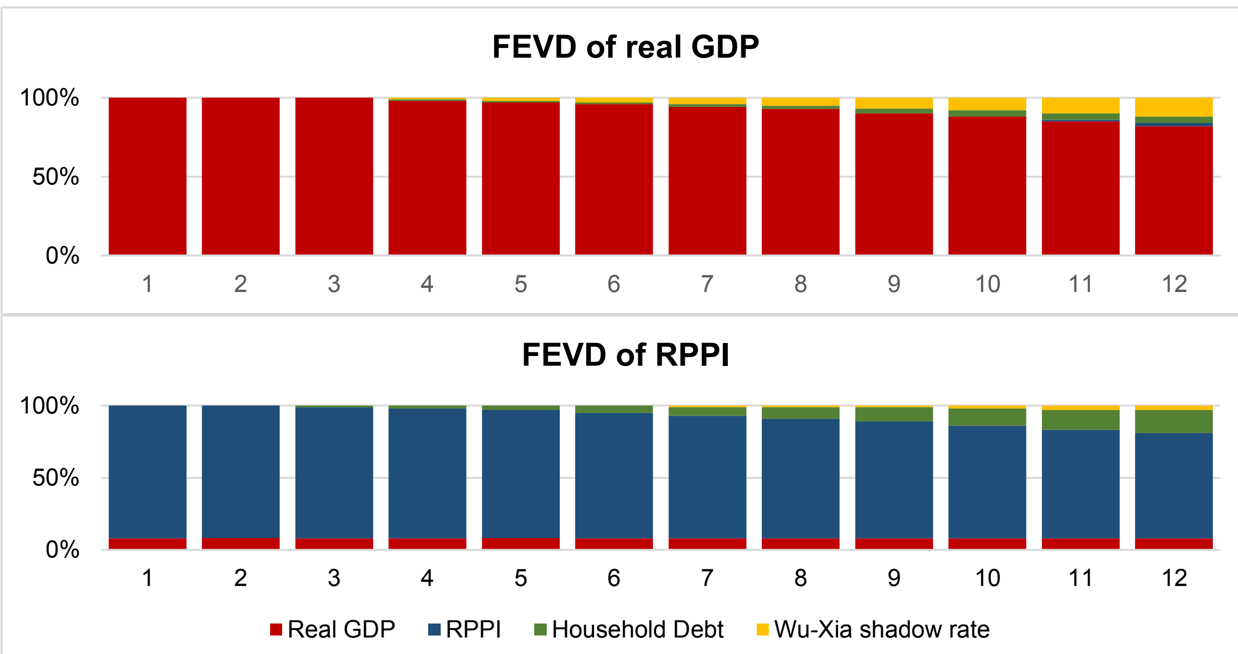
Figure 14: Impulse Response Function of Residential Property Price Index in SVAR for the Netherlands

Note: *The figure provides visualization of Residential Property Price Index response to shock of real GDP, household debt and Wu-Xia shadow rate (left to right, up to down) for the period of 12 quarters in the Netherlands.*

Source: *Author's computations in JMulTi.*

As we can see from Figure 15, real GDP has significant power in explaining the forecast error variance of itself for all of twelve lags. Highest values of 100 percent are observed in the first two lags. The proportion then gradually drops to the lowest of 82 percent in the twelfth lag. RPPI does not participate in explaining real GDP forecast error until the eleventh lag, where it has a proportion of 1 percent. In the twelfth lag RPPI reaches its maximum value of 2 percent. For the first three lags, household debt does not explain forecast error variance of real GDP, but only starts doing so since the fourth lag, where its proportion equals 1 percent until the sixth lag. In the seventh and eighth lag we can see a value of 2 percent, in ninth it increases to 3 percent, and in the tenth to twelfth it stays at its maximum of 4 percent. Wu-Xia shadow rate comes into action at the fourth lag with proportion of 1 percent, which increases with each next lag to the maximum of 12 percent in the twelfth lag.

Figure 15: Forecast Error Variance Decomposition of Real GDP and RPPI for the Netherlands

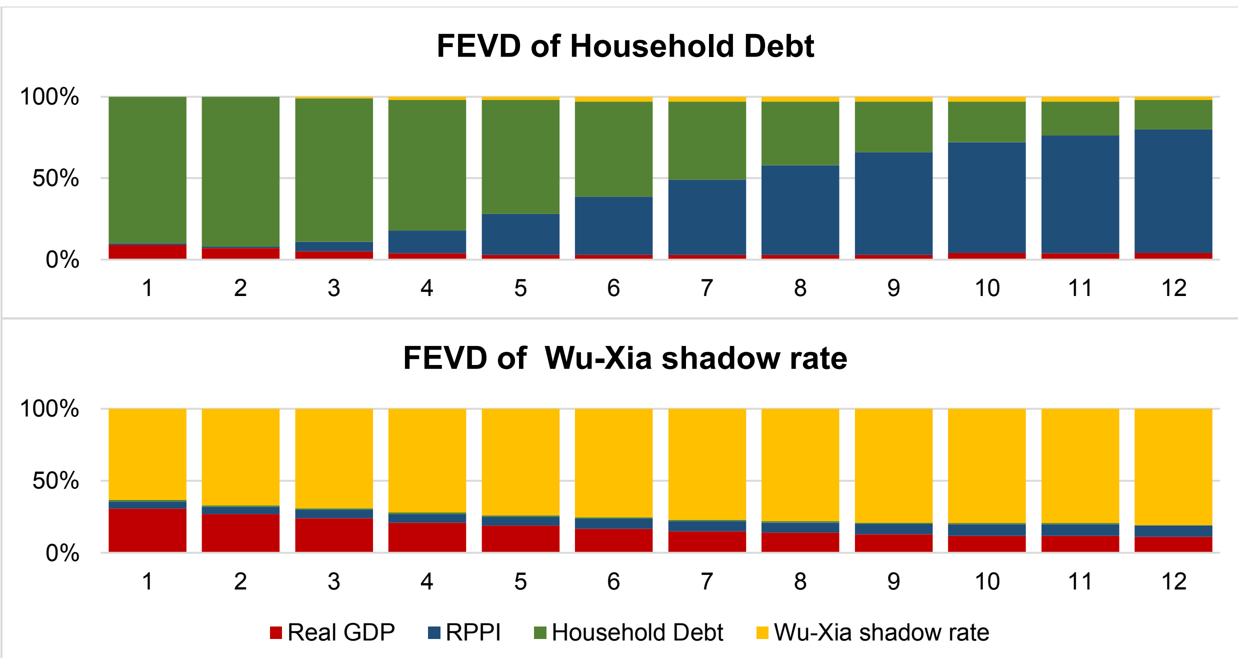


Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in the Netherlands. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

Source: *Author's computations.*

When looking at the RPPI FEVD, we can observe that the real GDP's contribution stays constant at 8 percent for every lag. RPPI's contribution to itself forecast error variance is the largest in every lag. In the first lag, it has the highest proportion of 92 percent, in the second and third it amounts 91 percent. It then keeps decreasing until the last lag, where it reaches its lowest value of 73 percent in the twelfth lag. Household debt starts its contribution to RPPI FEVD with 1 percent at the third lag and gradually increases to its largest value of 16 percent in the last lag. Wu-Xia shadow rate only enters into action at the seventh lag with 1 percent proportion, which stays constant until the ninth lag. At tenth lag we see its proportion increased up to 2 percent, and at the eleventh lag and the twelfth lag, Wu-Xia shadow rate's contribution to RPPI FEVD increases the maximum value of 3 percent.

Figure 16: Forecast Error Variance Decomposition of Household Debt and Wu-Xia Shadow Rate for the Netherlands



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in the Netherlands. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

Source: *Author's computations.*

In the FEVD of household debt, the real GDP plays a minor role. In the first lag, real GDP takes 9 percent proportion (its largest contribution), which then quickly drops to a minimum of 3 percent in the fifth lag, where it stays constant until the ninth lag.

From the tenth and until the last lag, we can observe household debt's stake amounting 4 percent. RPPI's contribution to the household debt's FEVD starts at 1 percent at the first and second lags, but then quickly grows to the maximum of 76 percent at the last lag. Wu-Xia shadow rate's power in explaining the household debt's FEVD, on the other hand, does not grow fast. It starts at 1 percent at the third lag, reaches a value of 2 percent at the fourth lag, which it keeps until the fifth lag, then grows to 3 percent at the sixth lag. Since the sixth lag and until the eleventh lag, percentage remains constant. At the last lag, we observe a drop down to 2 percent.

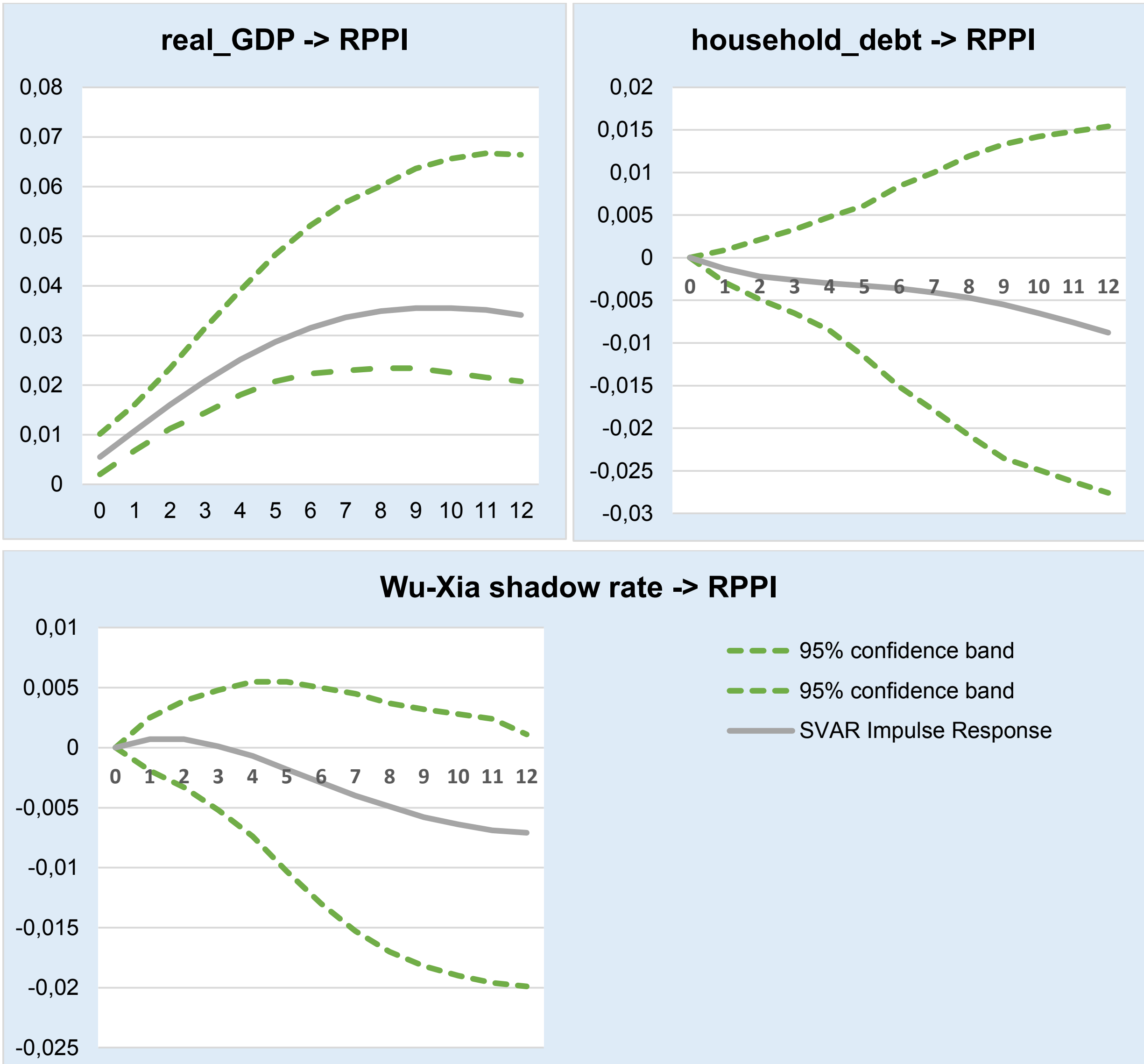
Wu-Xia shadow rate explains up to 80 percent of the forecast error variance in itself. Starting from the first lag with 64 percent proportion, Wu-Xia shadow rate's contribution to FEVD of itself grows with each lag, reaching a maximum of 80 percent in the tenth lag, where it remains constant until the last lag. The second largest contributor to Wu-Xia shadow rate FEVD is real GDP with its maximum of 31 percent in the first lag, which decreases with each lag until down to 11 percent at the last lag. RPPI's proportion grows very slowly. It starts with 5 percent at the first and second lags, grows to 6 percent in the third and fifth lag, grows again to 7 percent at sixth lag, where remains constant until the ninth lag. At the last three lags we observe a maximum value of 8 percent. Household debt has 1 percent explaining power of Wu-Xia shadow rate's FEVD in the first and until the eleventh lag.

4.6 Spain

The last country following is Spain. Figures 17, Figure 18 and Figure 19 show impulse response functions of RPPI and FEVD of each variable, respectively.

RPPI impulse response of Spain starts increasing as a result of one standard deviation (8958,3 units) of real GDP since the beginning of the observed interval and reaches its maximum of 0,0355 units in ninth quarter. Next quarter we can see impulse response staying at its maximum value, but then starts decreasing since the eleventh quarter to its initial state.

Figure 17: Impulse Response Function of Residential Property Price Index in SVAR for Spain



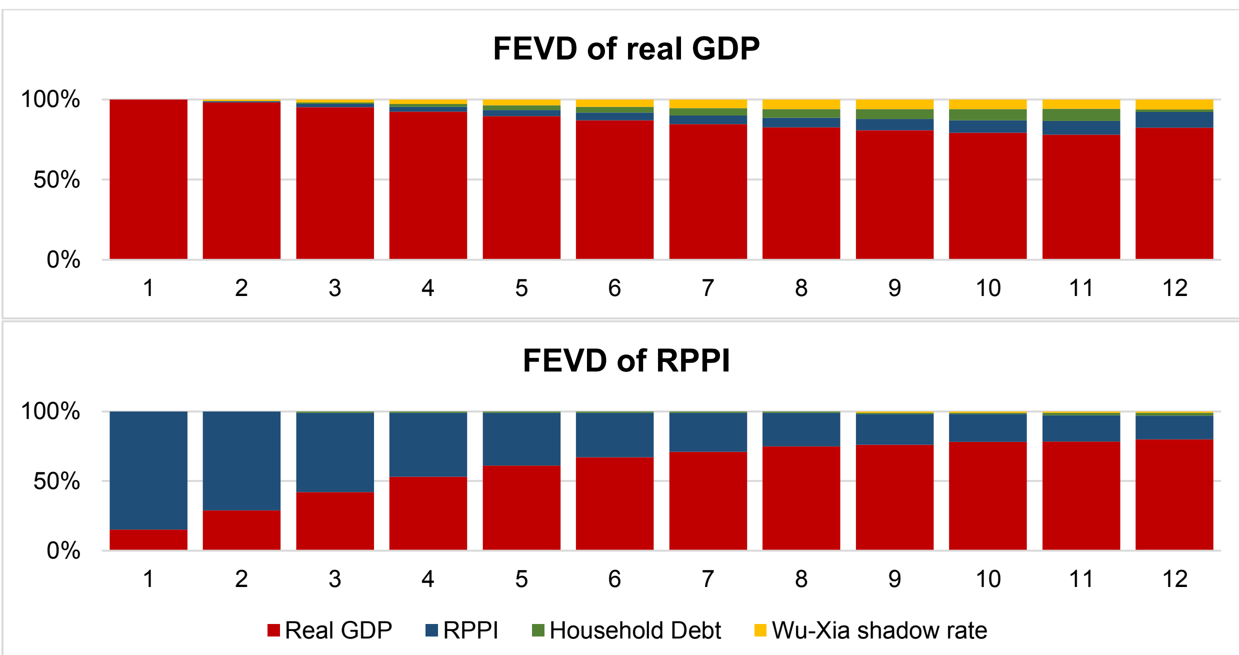
Note: *The figure provides visualization of Residential Property Price Index response to shock of real GDP, household debt and Wu-Xia shadow rate (left to right, up to down) for the period of 12 quarters in Spain.*

Source: *Author's computations in JMulTi*

The results are statistically significant for the whole observed horizon. We can see a decrease in RPPI impulse response after a one standard deviation shock of household debt, amounting 13,15 units. Since the beginning of the observed interval and until the second quarter, the decrease is faster. RPPI impulse response here reaches value of -0,0022. Next follows a period with a decrease not so rapid, lasting until the eighth quarter. In the eighth quarter we see the value of -0,0047. The last period of decline is again fast, it lasts since the eighth and until the last observed quarter. The results of impulse response to household debt shock are statistically insignificant for the whole observed horizon. A short period of increase is following a 2,73 units one standard deviation shock of Wu-Xia shadow rate. The impulse response reaches its maximum value of 0,0007 units right in the first quarter and keeps it value until the second quarter. Next follows a decrease, which lasts until the end of the observed interval. The results of impulse response to Wu-Xia shadow rate shock are statistically insignificant for the whole observed horizon.

Figure 18 and Figure 19 below shows FEVD of each variable of the model.

Figure 18: Forecast Error Variance Decomposition of Real GDP and RPPI for Spain



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in Spain. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

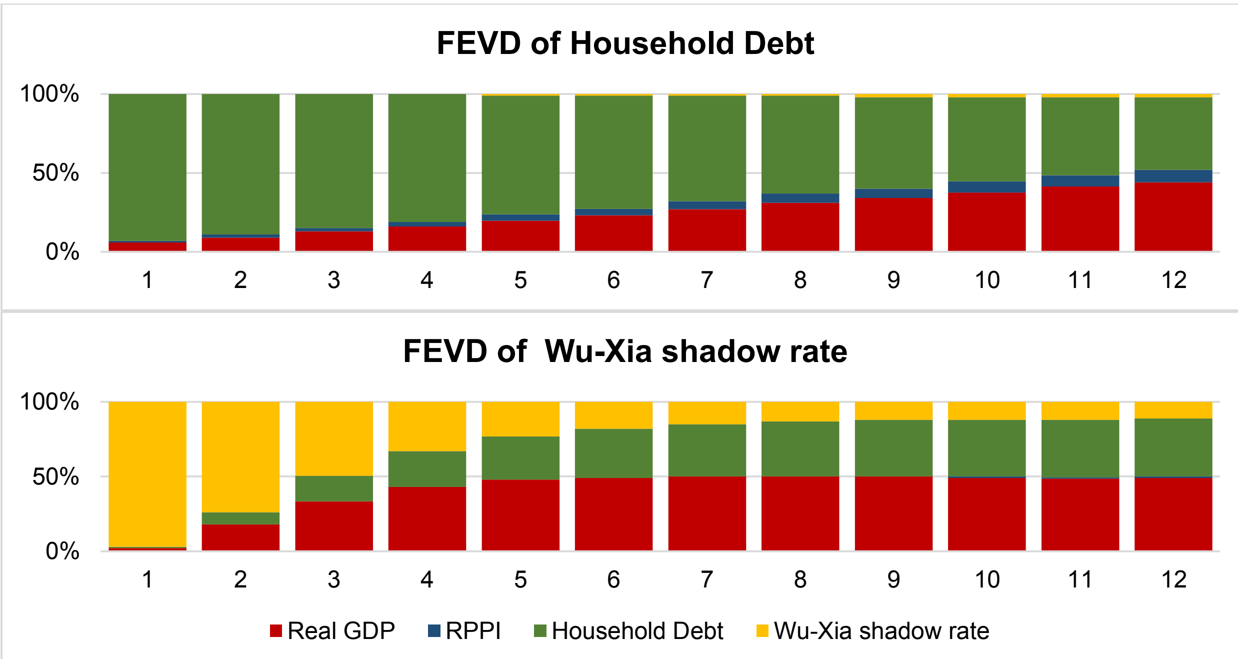
Source: *Author's computations.*

In the case of Spain, we can see that real GDP takes the largest proportion in explaining forecast error variance of itself. In the first lag, the proportion is 100 percent, slowly dropping down to 93 in the seventh lag. In the eighth lag real GDP again gains 94 percent proportion, drops to 91 until the tenth lag and grows again to 93 until the twelfth lag. RPPI's greatest proportion in real GDP FEVD equals 11 percent in the twelfth lag, which it reaches after slowly growing from 1 percent in the second lag. Household debt comes into explaining of real GDP forecast error variance at the third lag with 1 percent proportion, which slowly grows up to 9 percent in the twelfth lag. In the last lag, we can see 2 percent value. Wu-Xia shadow rate's proportion appears in the second lag with value of 1 percent, which then grows up to 7 percent in the eighth lag. The value remains unchanged a 7 percent until the last lag.

Real GDP takes a major part in explaining RPPI's forecast error variance, starting at the fourth lag. In the first lag we see 15 percent proportion of real GDP, which then grows to its maximum of 79 percent in the last two lags. In the first three lags, RPPI plays a major role in explaining forecast error variance of itself. The largest proportion of 85 percent is observed in the first lag. The percentage drops to the lowest value of 17 percent in the twelfth lag. Household debt and Wu-Xia shadow rate only have minor influence on RPPI FEVD. Household debts has influence, starting from the third lag with value of 1 percent, which lasts until the tenth quarter. In the last two quarters, the proportion increases to 2 percent. Wu-Xia shadow rate comes into action only at the ninth lag with 1 percent contribution, which it keeps until the last lag.

In the household debt's FEVD, proportion of real GDP grows with each following lag, starting from 6 percent in the first lag and reaching maximum of 44 percent in the twelfth lag. RPPI's proportion starts with 1 percent at the first lag, stays constant at 2 percent in the second and third lags, grows to 4 and stays constant at fifth and sixth lags, grows to 6 percent and stays at this value in the eighth to ninth lags, grows again to 7 percent at tenth and eleventh lag, then reaches its highest value of 8 percent in the last lag. Household debt has a major part in explaining the forecast error variance of itself in the first ten lags. Starting at its largest value of a 93 percent, household debt's proportion slowly drops to 46 percent in the last lag. Wu-Xia shadow rate only comes into action at fifth lag with 1 percent contribution. It remains constant until the eighth lag. At the ninth lag we already see it increased to 2 percent, which it keeps until the last lag.

Figure 19: Forecast Error Variance Decomposition of Household Debt and Wu-Xia Shadow Rate for Spain



Note: *The figure provides visualization of Forecast Error Variance Decomposition in real GDP (red color), Residential Property Price Index (blue), household debt (green) and Wu-Xia shadow rate (yellow) - up to down, in Spain. On the vertical axis we can see cumulative percentage, amounting 100 percent in total, on the horizontal axis are the lags from 1 to 12.*

Source: *Author's computations.*

Real GDP takes a 2 percent proportion in explaining the forecast error variance of Wu-Xia shadow rate in the first lag. The proportion of real GDP then quickly grows to a maximum of 50 percent at seventh to ninth lag. From tenth to twelfth lag we see percentage drop to a value of 49. RPPI is only able to explain forecast error variance of Wu-Xia shadow rate with 1 percent proportion, starting from tenth lag and until the twelfth lag. Household debt is significant in this case. Its explaining power starts with 1 percent in the first lag, which then grows to its maximum of 39 percent at last two lags.

Wu-Xia shadow rate has a major power of explaining power in the forecast error variance of itself. In the first lag it reaches 97, but then quickly drops to 23 percent at the fifth lag. Wu-Xia shadow rate's proportion keeps decreasing, however, much slower, since the sixth lag and until the last lag, where it reaches its minimum of 11 percent. The proportion of Wu-Xia shadow rate stays at 12 percent at ninth through eleventh lag.

Chapter 5

Conclusion

The aim of this thesis was to analyze the effects of transmission mechanism of monetary policy on the real estate market for the following countries: Germany, France, the Netherlands, Spain and the United Kingdom, using a Structural Vector Autoregression model (SVAR) with Choleski recursive identification. This was done from the three different aspects: interest rate, scale of credit, and output. We used the Wu-Xia shadow rate as a proxy for the interest rate, households' debt was used as a proxy for scale of credit, and real GDP was used as a proxy for the output. During our investigation, we were trying to access the latest data available from different sources.

After constructing Structural VAR models for each country, we see that for France every variable, real GDP, household debt and Wu-Xia shadow rate, has substantial effect on RPPI. Real GDP forces RPPI to increase at maximum of 0,96 units in fourth quarter, after which RPPI tries to return to its initial state. The results are statistically significant for the first eight lags. Household debt pushes RPPI down to its minimum of -0.34 units in fifth quarter, after which RPPI tries to return to its initial value. The results are statistically insignificant for the whole observed horizon. Wu-Xia shadow rate also forces RPPI to decrease, to a minimum of -0,64 units in fifth quarter, after which RPPI tries to return to its initial value. The results are statistically significant for second till eighth quarter. FEVD of RPPI in case of France contains 25 to 42 percent proportion of real GDP, RPPI itself makes 34 to 75 percent proportion, household debt and Wu-Xia shadow rate make together from 0 to 24 percent proportion.

In case of the UK, RPPI reacts with a decrease to a shock of real GDP for four quarters, where RPPI reaches its lowest value of -0,079, and after which RPPI tries to return to its initial value. RPPI sharply increases in reaction to shock of household debt to maximum of 0,24 units in second quarter, after what RPPI slowly returns to its initial value. Wu-Xia shadow rate quickly pushes RPPI down to its minimum of -0,24 units in second quarter, after what RPPI slowly returns to its initial value. The results for all of Impulse Response Functions are statistically insignificant for the whole observed interval. FEVD of RPPI in case of the UK is heavily dependent on RPPI itself (88-93 percent), the role of other variables combined is only minor – 7 to 12 percent.

Germany's Structural VAR shows an increase of RPPI in reaction to shock of real GDP. RPPI grows for the whole observed interval, reaching highest value of 0,41 units at twelfth quarter. Results become statistically significant at approximately sixth quarter. RPPI increases as well to a shock of household debt, but only until the ninth lag, where value reaches its maximum of 0,26 units. After that RPPI slowly decreases. The results are statistically significant for about tenth to eleventh lag. Wu-Xia shadow rate forces RPPI to decreases for the whole observed interval. Results are statistically significant since about third lag. FEVD of RPPI in case of the UK is very much dependent on RPPI itself (60 to 100 percent), Wu-Xia shadow rate's proportion varies from 0 to 24 percent, the role of other variables combined makes from 0 to 17 percent.

The RPPI of the Netherlands reacts with an increase to a maximum of 0,36 units in the fifth lag to a shock of real GDP, and then keeps slowly decreasing up to the last observed quarter. The results are statistically significant for about the first five observed quarters. Household debt's shock pushes RPPI down for the whole observed interval. The lowest point of -0,73 units is observed at the last quarter. The results are statistically significant for the whole interval. RPPI reacts with a decrease as well to a shock of Wu-Xia shadow rate for the whole observed horizon. The lowest point of -0,44 units is reached in the twelfth quarter. Results are statistically significant for approximately tenth to twelfth quarter. The Netherlands FEVD of RPPI is explained mainly by RPPI itself (71 to 90 percent). The proportion of real GDP varies from 9 to 10 percent, proportion of household debt – from 0 to 16 percent and of Wu-Xia shadow rate – from 0 to 4 percent.

Spain RPPI reacts with increase to shock of real GDP, reaching maximum value of 3,09 units at ninth lag. Results are statistically significant for the whole observed horizon. A decrease in RPPI follows a shock of household debt. RPPI slowly decreases, reaching lowest value of -0,81 units at twelfth quarter. The results are statistically insignificant for the whole observed interval. RPPI decreases as well in response to Wu-Xia shadow rate shock. Lowest observed point of -0,73 units is observed at the twelfth quarter. The results are statistically insignificant for the whole interval. FEVD of Spain RPPI almost evenly distributed between RPPI itself (19 to 83 percent) and other variables combined (17 to 80 percent), where highest proportion takes real GDP (17 to 78 percent).

Despite only some of the results having statistical significance for the whole observed interval of the impulse response, this work can contribute to understanding the latest relationship between monetary policy instruments and the housing prices. Of particular interest this might be for the policy makers, who are currently aiming at price stability, including the prices for housing. This work can be extended with further analysis, like, for example the inverse relationship – the effect of housing prices on the economy with empirical proof, extending the model with another macro and microeconomic variables, or grouping different types of dwellings for a detailed sectoral analysis. For any type of purpose, further research is more than welcome.

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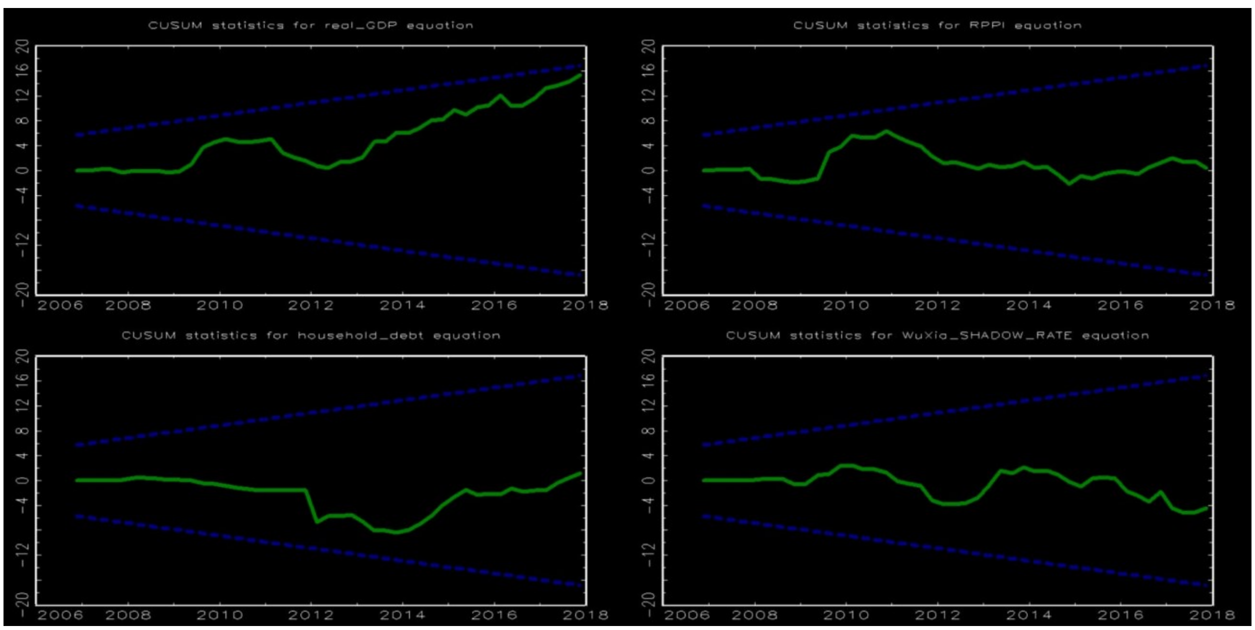
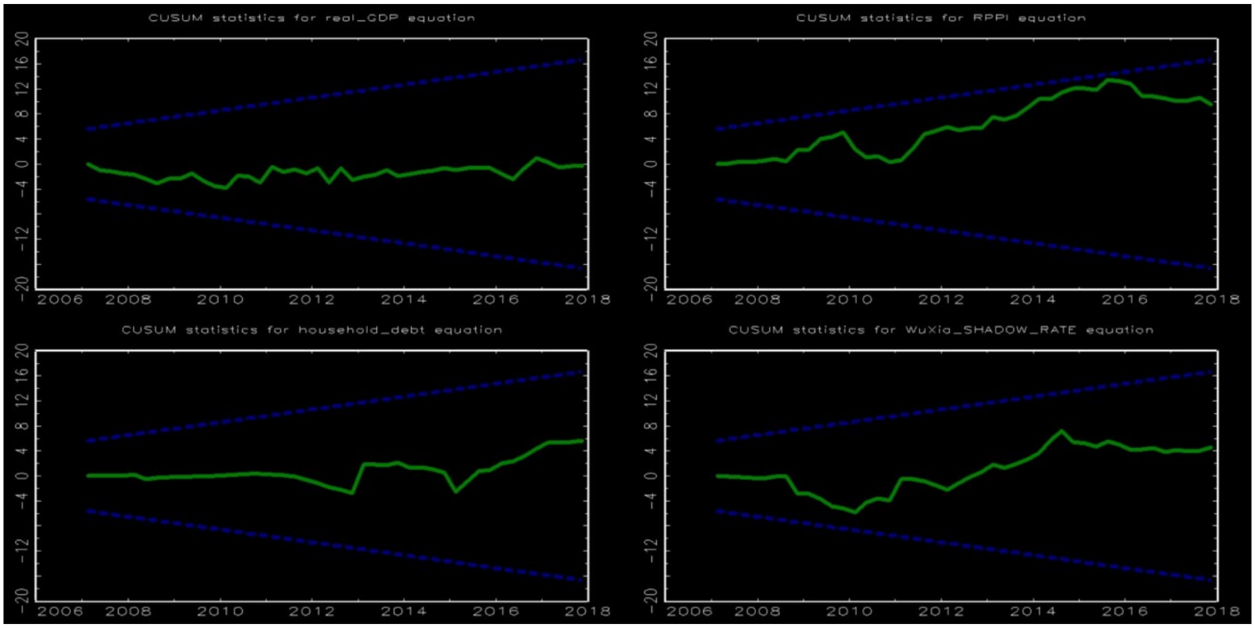
Appendix

Figure 20: CUSUM test of stability for the Structural VAR, France



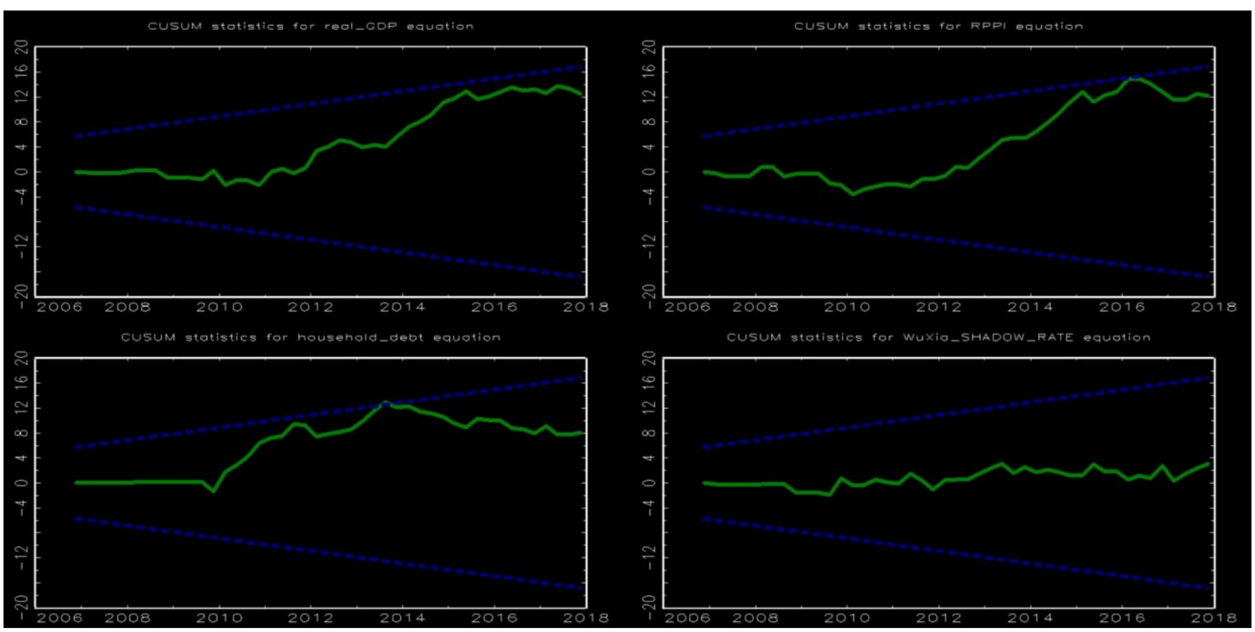
Source: *Author’s computations in JMulTi.*

Figure 21: CUSUM test of stability for the Structural VAR, the United Kingdom



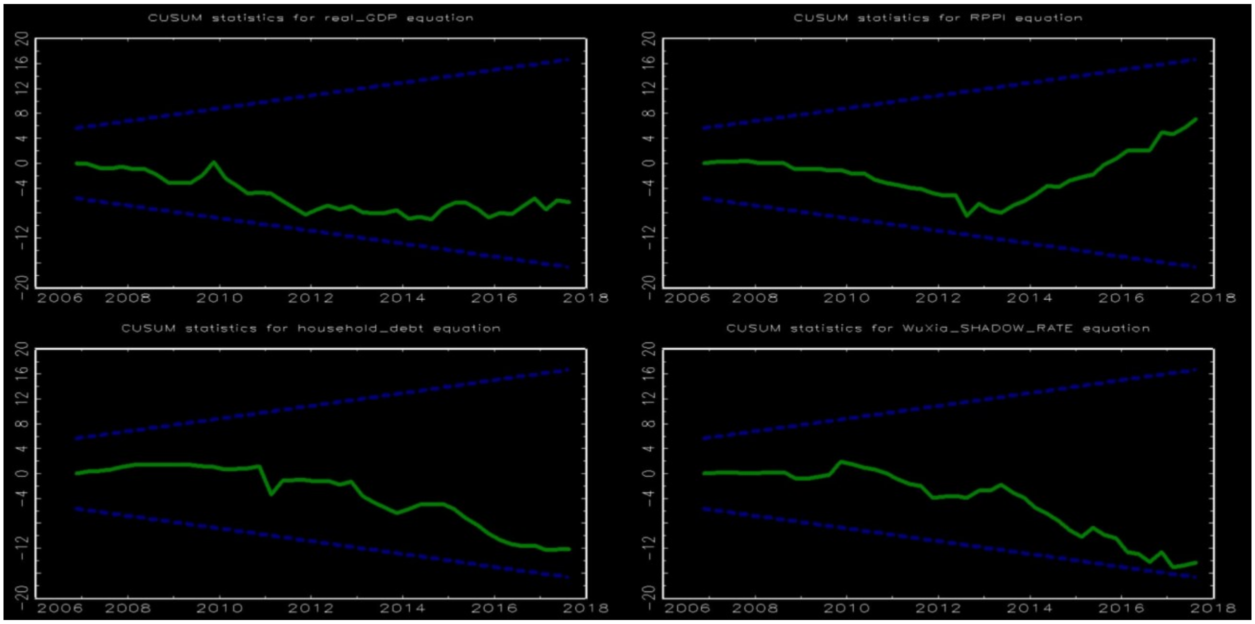
Source: *Author's computations in JMulTi.*

Figure 22: CUSUM test of stability for the Structural VAR, Germany



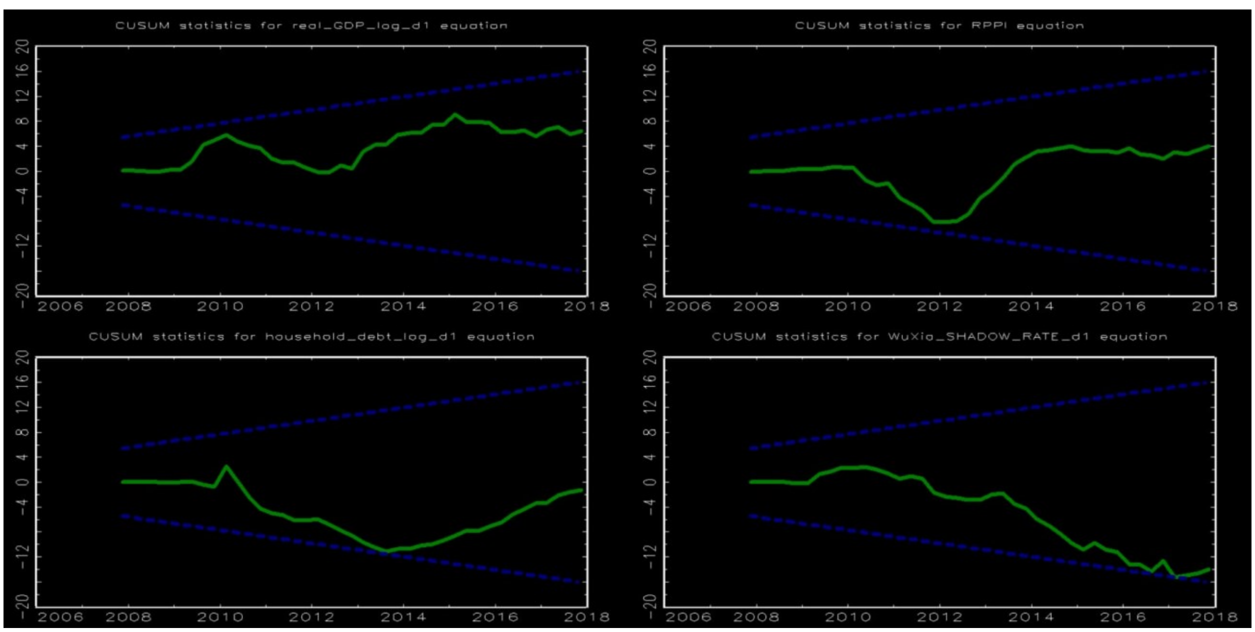
Source: *Author's computations in JMulTi.*

Figure 23: CUSUM test of stability for the Structural VAR, the Netherlands



Source: *Author's computations in JMulTi.*

Figure 24: CUSUM test of stability for the Structural VAR, Spain



Source: *Author's computations in JMulTi.*