Financial Market Perception of Systemic Risk and Financial Stability

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ABSTRACT

This paper argues that during periods of boom in asset prices, investors, creditors and regulators of financial markets have a decreased perception of systemic risk. Therefore, they increase their indebtedness. In this way, by making financial decisions at a microeconomic level, they can increase the probability of the occurrence of episodes of financial instability at the aggregate level. Therefore, in this study, we analyzed the influence of the perception of systemic risk on private sector credit in the United States from 1970 based on co-integration VAR during boom in stock and real estate prices. The co-integration test suggested that long-term development of private sector credit could be explained by the perception of systemic risk during asset price boom. Impulse response analysis based on Cholesky's standard decomposition revealed that there was significant dynamic interaction between the perception of systemic risk in credit markets during asset prices boom and the level of private credit in the United States.

INTRODUCTION

In recent decades in many developed countries, there have been connected cycles in credit, asset prices and economic activity. A considerable amount of scientific and professional literature deals with the afore-mentioned events *(Mishkin and White, 2002; Adalid and Detken, 2007; Mendoza, 2008; Assenmacher-Wesche and Gerlach, 2008; Borio and Drehmann, 2009; ECB, 2010; Tarashev, Borio, Tsatsaronis, 2010).* However, only a small number of them try to model the movement of credit with asset prices (*Hofmann, 2004)*. With the model presented in this paper, we wanted to explore and explain these discrepancies, with particular emphasis on the analysis of perceptions of risk during the credit cycle. This paper starts with the basic assumption that agents of credit and asset markets incorrectly perceived systemic risk at a time of continued growth in asset prices. Therefore, by making rational microeconomic decisions, they created the risk of financial instability at the aggregate level. Namely, with an increase in stock and real estate prices, at the same time, increasing indebtedness and investments in the asset markets of private sectors was also evident. This made them vulnerable to adverse financial and real shocks. With the increasing value of assets owned by potential debtors, financial institutions were more willing to approve loans based on pledged assets *(Bernanke and Gertler, 1989),* thereby further exposing themselves to the fall in asset prices *(Herring and Watcher, 1999).* At the same time, there was an obvious decrease in financial market perception of systemic risk *(Rimac Smiljanić, 2011a).* During the time of growing asset prices, investors and creditors considered investment in assets and debts with pledged assets to be low-risk activities and they reduced their perception of risk. This risk perception decrease was reflected in the reduction of the risk premium that they were looking for in their investment. This was obvious in the growth of asset ownership and in the ratio between debt and assets in their balance sheets. Due to the increase in asset prices and a stimulated economic environment, microeconomic agents ignored the growing systemic risk and they reduced the risk premium that they demanded in their investments. Before the crisis, in times of the highest prices of assets, risk premiums were at the lowest levels, although the systemic risk was at its highest. When the asset prices started to fall, the risks which were accumulated during the boom cycle in asset prices become overly manifest. Namely, during the boom phase in asset prices, the net worth of potential borrowers grew also because of the

rising prices of stock and real estate in their possession. Therefore, the financial institutions were willing to grant them loans with lower interest rates due to a decrease in risk premium. It was also easier to borrow, so investors were encouraged with their "more valuable" asset, better financing terms and with expectations of retaining or a further increase in asset prices. The opposing events in the markets, i.e. the drop in asset prices, caused a withdrawal of lenders from the market due to increased problems of information asymmetry. In fact, the fall in asset prices caused a reduction in the net value of the debtor, and the creditor considered it to be more risky. This resulted in a rise in interest rates and the inability to gain new external financing. Quality investment projects were not undertaken because of the withdrawal of lenders from the financial markets. The problem of financial instability became visible. The financial system did not allocate savings surpluses to the most profitable projects, but directed them to the "safest" debtors. Starting from the basic theoretical hypotheses of this study, financial instability (stability) is defined as follows:

Financial instability is a phenomenon in the financial system, which is manifested by withdrawal of lenders from the financial markets due to increased distrust in the return of borrowed funds i.e. increased problems of information asymmetry among the participants in credit markets, which may be caused by internal or external events. It comes to disturbances in the functioning of the financial sector as an intermediary between savings-sufficed and savings-deficient subjects i.e. the financial sector allocates funds to the safest, not the most profitable borrowers. Financial stability is defined as the opposite phenomenon of financial instability.

By defining the financial stability (instability) in the above manner, we agree with the researchers that the causes of financial instability are seen in the phenomena of the strengthening problems of information asymmetry (*Mishkin, 1990; Mishkin and White, 2002*; *Borio and Drehmann, 2008*). The main difference between the proposed model in this paper compared to other previous studies is in the assumption that, during the boom phase in asset prices, macroeconomic subjects incorrectly perceived systemic risk and consequently their behavior created the threat of financial instability. Based on the described model, we set out two basic hypotheses that we seek to prove in the empirical part of research:

H1: Reduction of perception of systemic risk during the boom phase in asset prices encourages growth of borrowing.

H2: With longer duration of the boom phase in asset prices, the microeconomic agents are more prone to borrow or lend.

One of the few researchers who empirically tested supply and demand for credit with economic activity and asset prices is *Hofmann (2004).* He created a model that explains both the supply and demand for credit in the private non-financial sector with real GDP, real interest rates and the real price index of commercial and residential real estate weighted with their share in the wealth of private sectors. With the acceptance of Hofman's idea, the model presented in this paper will be upgraded with the stock, residential and commercial real estate price index, the aggregate asset price index and the indicators of financial markets perception of systemic risk. The proposed model represents a "reduce form" credit model that includes the supply and demand for loans to private non-financial sectors in a country. With the proposed model, we wanted to test how the perception of systemic risk, during boom phases in asset prices, affect the movement of the share of credit to private sectors in gross domestic product. It was tested as follows: during the boom phase in the aggregate asset price index, but also during the phase of the boom in stock prices, commercial and residential real estate

prices. By testing the model with perception of systemic risk during the boom phases in indexes of each type of assets included in aggregate price index - stocks, commercial and residential real estate gave us an answer to which particular type of asset price movements create the most dangerous "threats" to financial stability. In this study, we followed up the theoretical and empirical results presented in previous pieces of research presented in papers by *Rimac Smiljanić (2010, 2011a, 2011b)* about the connection between asset prices, systemic risk perception and financial stability.

The paper is organized as follows: Section 2 contains the methodological approach and the data used in the analysis are described. In Section 3 the empirical results are presented and discussed. Section 4 concludes the paper with a summary and states the potential benefits and costs from using the asset prices in forecasting future economic developments.

METHODOLOGY AND DATA

We analyzed and empirically tested the theoretical model on samples of data from the United States from 1970 to the end of 2008 using the quarterly data. The following data variables have been taken into consideration:

- Systemic risk perception (SRP): Systemic risk perception on credit markets is visible in interest rate risk premiums. Namely, when credit market participants are expecting an increase in systemic risk, the lower quality borrowers will be considered to be more risky than the high quality borrowers and therefore will pay higher interest rates than low risk borrowers. Considering the fact that there are no indicators at the aggregate level of the difference between interests on loans between high and low risk borrowers, the spread between low versus high quality bonds is taken. Precisely, the spread on Moody's Seasoned AAA and BAA Corporate Bond Yield is taken.
- Boom in asset prices (BAP), boom in stock prices (BSP), boom in residential real estate (BRREP) and boom in commercial real estate prices (BCREP): Dates of boom and bust phases in stock prices, residential and commercial real estate prices and aggregate price index's are taken from Rimac Smiljanić (2011b)[1].
- Gross domestic product (GDP): Data for gross domestic product in the US are taken from OECD Main Economic Indicators data base. We took the real GDP as the broadest aggregate measure of the real activity. The nominal data were transformed to the index with 1985 as the base year. Nominal data are transformed to the real using the 2005 CPI index.
- Inflation (CPI): data were taken from the OECD Main Economic Indicators data base.
- Real interest rate (RIR): As a proxy of the real cost of financing, the real interest rate was calculated. The three month short-interest rate was taken from the OECD Main Economic Indicators data base. The real interest rate was calculated by reducing this rate with annual CPI inflation.[2]
- Credit to the private sector/gross domestic product (CPS/GDP): Data for nominal credit to the private sector were taken from the base International Financial Statistics (IFS) International Monetary Fund. The levels of bank credit and credit of other financial institutions were used (line 22d + line 42d). After calculating the ratio to the GDP, the data were transformed to the index with 1985 as the base year.
- Stock price (SP): Data were taken from the base of Bank of International Settlements (BIS) in real terms and in index form with 1985 as the base year.

[1] More about methodology of determination boom and bust phases in asset prices in Rimac Smiljanić (2011b).
[2] More about the way this calculation for getting real interest rate on credit market in *Hofmann (2004).*

- Residential real estate prices (RREP): Data were taken from the base of the Bank of International Settlements (BIS) in real terms and in index form with 1985 as the base year.
- Commercial real estate prices (CREP): Data were taken from the base of Bank of International Settlements (BIS) in real terms and in index form with 1985 as the base year.
- Aggregate asset price index (AAPI): Data were taken from the base of the Bank of International Settlements (BIS) in real terms and in index form with 1985 as the base year.[3]

The results of the Standard argument Dickey-Fuller *(Dickey and Fuller, 1981)* unit tests reported in Table 1 suggested that all variables were integrated into the first level over the whole sample. Additionally, the ADF test was performed by considering trends and constants, and results indicated the same conclusion (Appendix Table 1-2). In the next step of empirical testing, the model of the multivariate approach to co-integration analysis was used.

Table 1 Augmented Dickey-Fuller

Variable	*H0: Variable has unit root*			
	Level		Change	
	t-Statistic	Prob	t-Statistic	Prob
AAPI	-2.349	0.158	-6.746	0.000
SP	-1.361	0.599	-7.699	0.000
REEP	-4.753	0.000	-4.466	0.000
CREP	1.207	0.669	-2.278	0.186
CPS/GDP	0.279	0.976	-13.230	0.000
GDP	-0.036	0.952	-4.194	0.000
CPI	-2.653	0.084	-5.190	0.000
RIR	-2.740	0.069	-3.766	0.021
SRP	-2.266	0.184	-11.444	0.000
COUNTER	-2.794	0.061	-12.367	0.000

*MacKinnon (1996) one-sided p-values.

Note: SRP - Systemic risk perception; GDP - Gross domestic product; CPI – Inflation; RIR - Real interest rate; CPS/GDP - Credit to the private sector/gross domestic product; SP - Stock price; RREP - Residential real estate prices; CREP - Commercial real estate prices; AAPI - Aggregate asset price index; COUNTER – duration of the boom phase in asset prices

In the next step, we designed the "interaction term" variable by using the movement of aggregate asset price index in the boom phase[4] and the financial markets perception of systemic risk. We believe that aggregate asset price index is the best indicator for the

[3] The aggregate asset price index is calculated and published by the Bank for International Settlements (BIS). Its components are stock, and commercial and residential real estate prices. Their weighting in the index are determined by the proportion of each asset in the portfolios of private investors, based on data from national accounts. Accordingly, residential and commercial real estate prices have the highest proportion in the index – an average of 80%. The lowest proportion is made up of stocks, because they still constitute a small fraction of total assets held by private investors. More about this index is in Arthur (2001).

[4] In this paper, we followed up methodology proposed in *Rimac Smiljanić (2011a).* Namely, we believe that this new methodology for ex post determination of the cycles in asset prices is more adequate than methodologies applied in previous studies *(Borio and Lowe, 2002; Adalid and Detken, 2007; Mendoza and Terrones, 2008; Borio and Drehmann, 2009)* in order to determine impact of asset prices on the level of credit in the country. Assuming that the level of indebtedness of the private sector is affected by their perception of systemic risk, which decreases with a longer continual growth in asset prices, we believe that it is necessary to determine the rising and falling phases in asset prices. In this paper we give strong arguments that the mentioned methodology can better determine the impact of asset prices on the occurrence of credit cycles in the country.

explanation of the movement ratio of credit/GDP. The index is formed based on the movement of stock, residential and commercial real estate prices weighted with shares of this type of asset in the wealth of private sectors. Perception of systemic risk in the times of this boom phase should be the best indicator of the willingness of households and businesses to borrow based on the pledge assets, as well as the indicator of preference for investing in certain types of assets of those sectors. Specifically, it is assumed to increase with the increase in asset prices. However, the proposed model was also tested with the "interaction term" variable formed on the basis of stock, commercial and residential real estate prices. The model was statistically significant and variables were marked with the expected sign for the "interaction term" variable formed on the basis of stock prices. The tested models with the "interaction term" variable formed on the basis of commercial and residential real estate prices were not statistically significant. The fact that the model is valid when we take the perception of systemic risk during the boom phase in the aggregate asset prices index, is not valid concerning the perception of systemic risk during the phase of the boom in real estate prices can be explained. Namely, in constructing the aggregate asset prices index, additionally the shares of these assets in the wealth of private sectors are taken into account. It is understandable that with greater or smaller share of ownership of a certain type of asset, its impact on the owners' willingness to borrow it increases or decreases as does their ability to obtain credit from commercial banks. Based on these results, we can conclude that the use of the aggregate asset price index for the formation of "interaction term" variable is justified because its value is affected by the share ownership of the certain type of asset and also with asset price movements. The afore-mentioned is in accordance with the assumptions of theoretical models. Following the model and research of *Hofmann (2004)*, we estimated an equation of the long-term relationship, because we cannot exclude the existence of a long-term relationship between variables, nor can the set of weakly exogenous variables be assumed. Therefore, in the first step, we estimated the initial VAR to be able to choose the optimal lag-length that is needed to construct the VECM model. The initial VAR model was reformulated in vector error-correction form:

$$D(Y_t) = \sum_{i=1}^{k-1} A * D(Y_{t-i}) + \alpha\beta' Y_{t-1} + \varepsilon_t \qquad (1)$$

Where:

Y_t – is a n*1 vector of endogenous variables, i.e. Y_t =[CPS/GDP RIR PSR AAP*PSR]'

- CPS/GDP – ratio of credit to the private sector to the GDP in the US
- RIR – short term interest rate in the US
- PSR – credit markets perception of systemic risk in the US
- AAP – asset prices in US;
- AAP*PSR – interaction term - perception of systemic risk during the growth of asset prices in the US

- K – optimal number of lags
- A – matrix of parameters
- ε_t – n x 1 vector of stochastic disturbance
- α - matrix of speed of adjustments
- β - co-integration parameters matrix = [n*r] = [5*1]

EMPIRICAL RESULTS

In the first step of the estimation VECM model with the associated co-integration vector, it was necessary to select the optimal lag length of the initial VAR. Results of order selection criteria are given in Table 2.

Table 2 VAR lag order selection criteria

Lag	*LogL*	*LR*	*FPE*	*AIC*	*SC*	*HQ*
0	-1180.187	NA	104.691	16.002	16.083	16.035
1	-504.466	1305.783	0.014*	7.087*	7.492*	7.251*
2	-493.624	20.365	0.015	7.157	7.886	7.453
3	-477.392	29.612	0.015	7.153	8.207	7.581
4	-465.635	20.813	0.015	7.211	8.588	7.770
5	-455.970	16.587	0.017	7.296	8.998	7.988
6	-436.909	31.682	0.016	7.255	9.280	8.078
7	-413.178	38.162*	0.015	7.151	9.500	8.105
8	-406.798	9.914	0.017	7.281	9.954	8.367

Note: * best lag order considering the criteria
LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion

Taking into account the Final Prediction Error, the Akaike, Schwarz and Hannan-Quinn information criterion, the information criterion for the lag length of VAR k = 1 was chosen. Diagnostic tests of vector auto-regression model in order of seven, according to the sequential modified LR test statistic criteria, were not significant.

In the next step, the Johansen co-integration test was implemented. Taking into account the result given in Table 3, it can be concluded that the H0 hypothesis can be rejected at the 5% level, i.e. Trace test and Max – eigenvalue test indicate a one co-integration vector.

Table 3 Johansen co- integration test

Maximum rank[a]	*Eigenvalue*	*Trace statistics*	*Eigenvalue*	*Max-Eigen statistic*[b]
0*	0.230	63.371	47.856	0.000
1	0.112	24.255	29.797	0.189
2	0.042	6.500	15.494	0.636
3	0.000	0.042	3.841	0.837

[a] Trace test and Max – eigenvalue test indicates one co-integrating equation at the 5% level (*)
[b] MacKinnon-Haug-Michelis (1999) p-values

From the VECM (1) system, the estimated function of private sector credit to gross domestic product can be written in the following form:

$$CPS/GDP = - 42.784\ RIR + 147.535\ SRP - 205{,}033\ SP*SRP + 281.290 \qquad (2)$$

T-statistic tests of estimated coefficients are presented in Table 4. According to the co-integrating coefficients in Table 4 in the long-term, we can expect that rise of real interest rates (RIR) by one percentage point will result with a decrease in the share of loans to private sectors in gross domestic product (CPS/GDP) by 42.784%. Reducing perception of systemic risk of one percentage point during the time of boom in asset prices (AAP*SRP) results in increasing the share of loans to private sectors in gross domestic product (CPS/GDP) for

205.03%. On the other hand, for the reducing perception of systemic risk (SRP) at a time when there is not a boom in asset prices the opposite effect is visible, i.e. reducing perception of systemic risk by one percentage point have effect to reduce the share of loans to private sectors in gross domestic product (CPS/GDP) for 145.54%.

Table 4 Co-integration vector coefficients

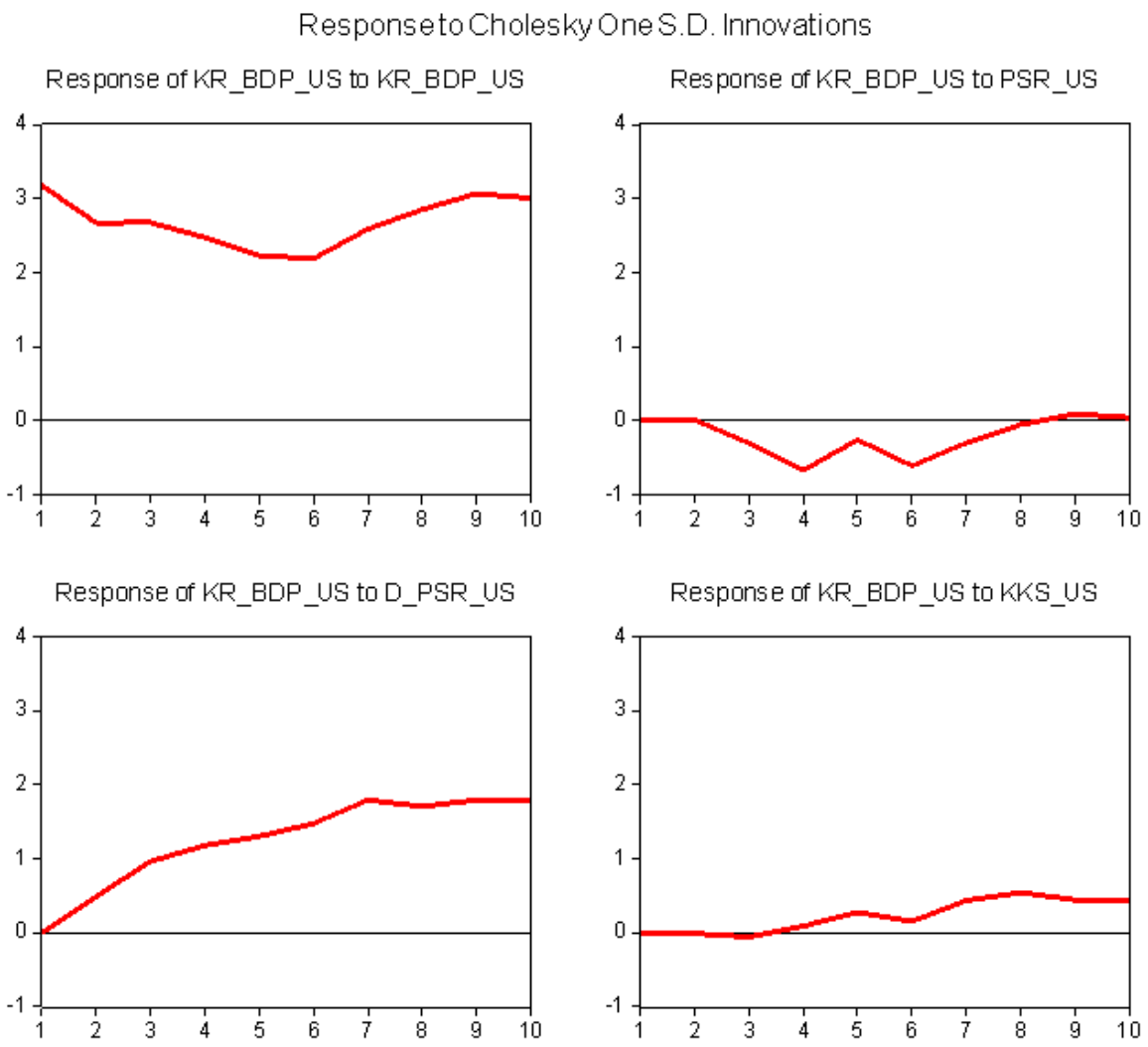
Variable	*Coefficient*	*Standard error*	*t-Statistic*
CPS/GDP	1		
RIR	42.784	9.793	4.369
SRP	-147.535	70.349	-2.097
AAP*SRP	352.568	63.606	5.119
C	-281.290		

Note: CPS/GDP - Credit to the private sector/gross domestic product; RIR - Real interest rate; SRP - Systemic risk perception; SP - Stock price; AAP*PSR – interaction term - perception of systemic risk during the growth of stock prices in the U.S.

The described model and its results confirm that we can accept hypothesis H1 i.e. that the reduced perception of systemic risk during boom phases in asset prices encouraged growth of indebtedness.

After evaluating the vector co-integration model of credit, an analysis of the dynamic interaction variables in the model follows. Cholesky's decomposition involves a recursive ordering of the variables *(Bahovec and Erjavec, 2009)*. The ordering adopted here is the following: share of credit to private sectors in gross domestic product, financial market perception of systemic risk during the boom phase in asset prices, perception of systemic risk when it is not the boom phase and the last real short-term interest rates on the interbank market. The real short-term interest rates are assumed to react first and their impact is transmitted to all other variables. Graph 1 shows how the ratio of credit in gross domestic product (CPS/GDP) reacts on the "shock" of one standard deviation in the values of other model variables. As can be seen in Graph 1, the share of loans to private sectors in gross domestic product responded with growth most strongly to the perception of systemic risk reduction during the phase of boom in asset prices. It is evident that the impact grows over time. In the first quarter, credit did not react to changes. In the next quarter, the "shock" of one standard deviation in the perception of systemic risk during the boom phase in asset prices led to the increase of ratio credit/GDP ratio by 48.55%. In the third quarter, after an initial increase in the perception of systemic risk during the boom phase in asset prices by one standard deviation, the credit/GDP remained a growth of 92.57% compared to the average level of movement of the ratio credit/GDP. In the following quarters, there was also visible growth of a shock effect on ratio credit/GDP relative to its average level. This trend went all the way to the eighth quarter, when it slightly fell, but was again restored in the ninth. In the tenth quarter, a small decline was visible, but the impact was still extremely strong. Namely, in the tenth quarter, after the "shock" of one standard deviation in the perception of systemic risk during the boom phase in asset prices, there remained a growth in ratio credit/GDP ratio by 177.6% compared to its average value. These facts support the theoretical thesis of the model that the impact of asset prices on the perception of systemic risk, and thus on financial stability is greater as time passes. Therefore, in the next step of the research, the model was upgraded with a variable COUNTER.

Graph 1 Standard Cholesky decomposition (+/- 95% bands)*



Note: SRP (QSABUS) - Systemic risk perception at a time when there is no boom in asset prices; APP*SRP (QDCSAAPRUS) - Systemic risk perception at a time where there is a boom in asset prices; GDP (BDP_US) - Gross domestic product; RIR (QSTIRRUS)- Real interest rate; CPS/GDP (QCRUS_QGDPUS) - Credit to the private sector/gross domestic product; AAPI - Aggregate asset price index; *Full Standard Cholesky decomposition (+/- 95% bands) in Appendix

In the next step, the model was upgraded with the variable COUNTER. We wanted to find the answer to the question of whether the duration of the boom phase in asset prices cycle affects the growth of private sector indebtedness in the country and thereby proves or disproves the second hypothesis. The new variable Counter was constructed. It counted how many successive quarters last boom phase in the asset prices cycle (ADF test results are in Table 1). We formed a new model by extending the existing with a new variable. The model was tested with VAR, because it was assumed that COUNTER influences in the short term. The variable

COUNTER was introduced into the model as an exogenous variable. VAR results are presented in Table 5.[5]

Table 5 Reduced results of VAR model variables counter effect on the ratio credit/GDP*

Vector Autoregression Estimates

Sample (adjusted): 8 156 Included observations: 149 after adjustments

Standard errors in ( ) & t-statistics in [ ]

	D(QCRUS_QGDPRUS)	D(QDCSAAPRUS)	D(QSABUS)	D(QSTIRRUS)
	⋮	⋮	⋮	⋮
BROJAC	**0.227167**	0.001616	-0.001755	-0.000519
	(0.06114)	(0.00299)	(0.00396)	(0.01929)
	[3.71577]	[0.54034]	[-0.44361]	[-0.02689]

Note: * Full result of VAR model with counter effect on the ratio credit/GDP can be found in appendix; BROJAC – is the symbol for the variable COUNTER

According to the results from empirical testing, the growth of variable COUNTER statistically significantly affected the growth of ratio credit/GDP. Therefore, hypothesis H2 can be accepted. That is, it can be said that with longer growth in asset prices, microeconomic agents are more willing to borrow and/or lend. Also, the result of the estimated VAR indicates that the variable COUNTER affects the perception of systemic risk during the boom phase in asset prices. The specified result is consistent with the theoretical hypothesis of the model. The effect of variable COUNTER on the perception of systemic risk in asset prices when there is not a boom phase is not statistically significant.

CONCLUSION

This article offers an overview of financial market perception of systemic risk role in private non-financial sector credit. Strong theoretical assumptions support the importance of financial markets systemic risk perception as determinate of supply and demand for credit. As was shown in this paper, the perception of systemic risk during the boom phase in asset prices had a significant influence on the credit/GDP ratio in the United Sates in the period between 1970-2008. Due to the lack of indexes included in this analysis, together with the absence of more adequate data, these finding needs to be further explored by more research. Despite these limitations, the results in this paper provide evidence about the role of financial market perception of systemic risk on credit movements. Therefore, the results provide a significant contribution to better credit and investment decision making, but also shed new light on ways to achieve financial stability. Therefore, the results have important implications for monetary policy and regulatory management. The fact that that the leaders of the leading financial regulatory institutions believe *(Caruana, 2010; Greenspan 2007 cited in Felsenthal, 2007)* that wrongly perceived systemic risk is a key cause of current financial crises certainly gives further significance to the results of this study.

[5] The selection criterions for optimal lag-length in the initial VAR are given in Appendix.

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APPENDIX

Table 1 Augmented Dickey-Fuller test with the constant and linear trend

Variable	*H0: Variable has unit root* Variable		Variable	
	t-Statistic	Prob*	t-Statistic	Prob*
AAPI	-3.083	0.114	-6.710	0.000
SP	-2.218	0.475	-7.693	0.000
REEP	-5.336	0.000	-4.467	0.002
CREP	-2.204	0.482	-2.281	0.440
CPS/GDP	-2.060	0.563	-13.269	0.000
GDP	-2.107	0.537	-5.568	0.000
CPI	-4.291	0.004	-5.214	0.000
RIR	-3.766	0.021	-12.379	0.000
SRP	-2.158	0.508	-11.434	0.000
COUNTER	-2.924	0.157	-12.336	0.000

*MacKinnon (1996) one-sided p-values.

Note: SRP - Systemic risk perception; GDP - Gross domestic product; CPI – Inflation; RIR - Real interest rate; CPS/GDP - Credit to the private sector/gross domestic product; SP - Stock price; RREP - Residential real estate prices; CREP - Commercial real estate prices; AAPI - Aggregate asset price index; COUNTER

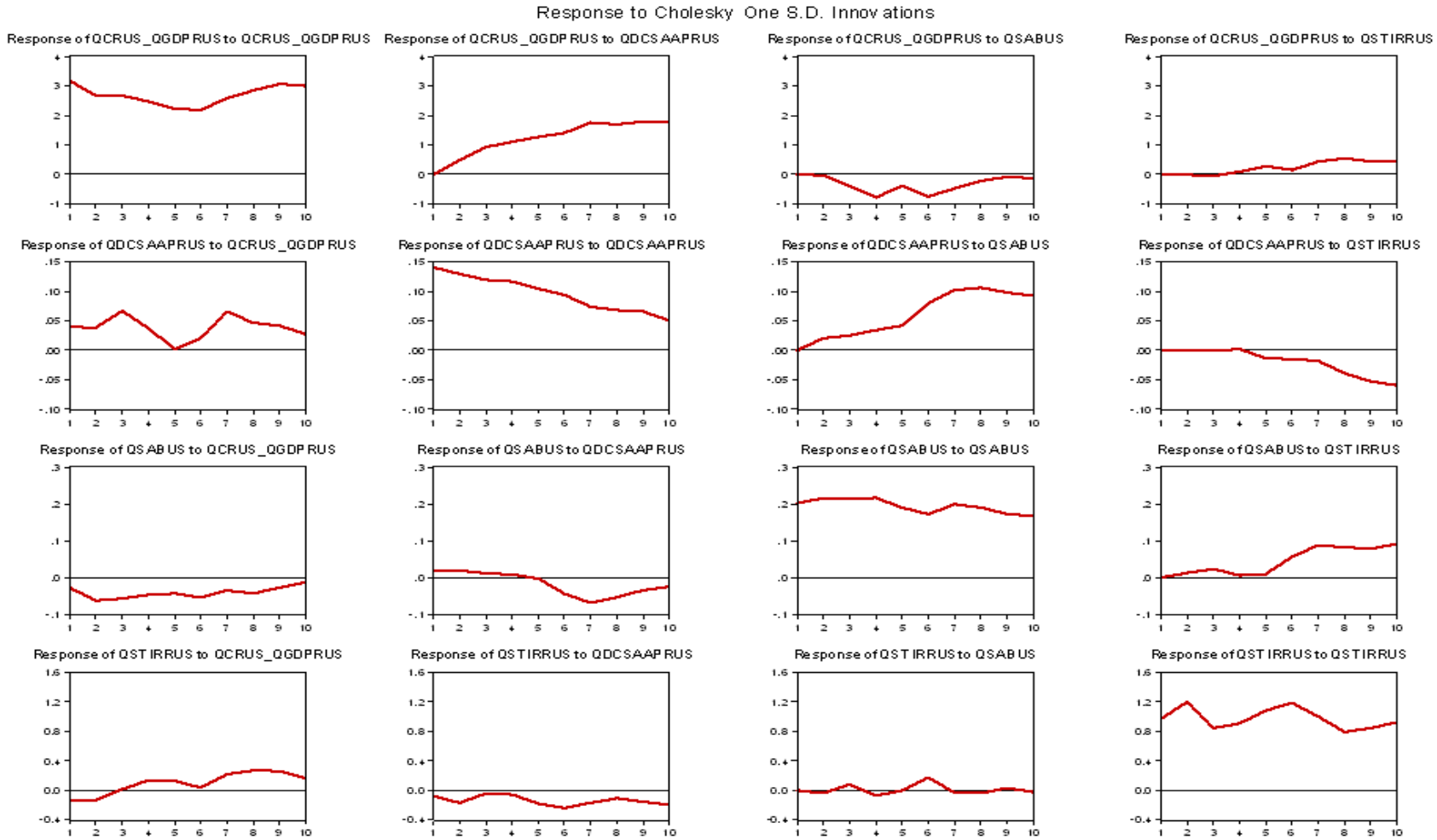
Table 2 Augmented Dickey-Fuller test without the constant and linear trend

Variable	*H0: Variable has unit root* Variable		Variable	
	t-Statistic	Prob*	t-Statistic	Prob*
AAPI	-0.216	0.606	-6.768	0.000
SP	-0.436	0.523	-7.716	0.000
REEP	0.952	0.909	-4.394	0.000
CREP	-2.142	0.031	-1.879	0.057
CPS/GDP	2.487	0.997	-12.704	0.000
GDP	3.278	0.999	-4.194	0.000
CPI	-1.762	0.074	-5.195	0.000
RIR	-1.182	0.216	-12.427	0.000
SRP	-0.311	0.571	-11.458	0.000
COUNTER	-2.441	0.014	-12.407	0.000

*MacKinnon (1996) one-sided p-values.

Note: SRP - Systemic risk perception; GDP - Gross domestic product; CPI – Inflation; RIR - Real interest rate; CPS/GDP - Credit to the private sector/gross domestic product; SP - Stock price; RREP - Residential real estate prices; CREP - Commercial real estate prices; AAPI - Aggregate asset price index; COUNTER

Graph 1 Full Standard Cholesky decomposition (+/- 95% bands)



Note: SRP (QSABUS) - Systemic risk perception in the time when is no boom in asset prices; APP*SRP (QDCSAAPRUS) - Systemic risk perception in the time when is boom in asset prices; GDP (BDP_US) - Gross domestic product; RIR (QSTIRRUS)- Real interest rate; CPS/GDP (QCRUS_QGDPUS) - Credit to the private sector/gross domestic product; AAPI - Aggregate asset price index

Table 3 VAR lag order selection criteria's - Results of VAR model with variable counter

VAR Lag Order Selection Criteria

Endogenous variables: QCRUS_QGDPRUS QSTIRRUS QDCSAAPRUS_
QSABUS

Exogenous variables: BROJAC

Date: 05/12/10 Time: 12:52

Sample: 1 158

Included observations: 148

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1350.392	NA	1044.284	18.30259	18.38360	18.33551
1	-497.4173	1648.316	0.012788	6.992125	7.397154*	7.156687*
2	-484.3033	24.63302	0.013303	7.031125	7.760177	7.327337
3	-468.8191	28.24812	0.013412	7.038096	8.091171	7.465958
4	-452.6266	28.66512	0.013408	7.035495	8.412592	7.595006
5	-442.2860	17.74668	0.014526	7.111973	8.813094	7.803135
6	-421.1745	35.09081	0.013629	7.042899	9.068042	7.865710
7	-398.9348	35.76387*	0.012621*	6.958578*	9.307744	7.913039
8	-393.1642	8.967825	0.014637	7.096813	9.770002	8.182924

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Note: BROJAC is a symbol for the variable COUNTER; SRP (QSABUS) - Systemic risk perception in the time when is no boom in asset prices; APP*SRP (QDCSAAPRUS) - Systemic risk perception in the time when is boom in asset prices; GDP (BDP_US) - Gross domestic product; RIR (QSTIRRUS)- Real interest rate; CPS/GDP (QCRUS_QGDPUS) - Credit to the private sector/gross domestic product; AAPI - Aggregate asset price index

Table 4 Results of VAR model with variable counter

Vector Autoregression Estimates

Date: 05/10/10 Time: 21:00

Sample (adjusted): 8 156

Included observations: 149 after adjustments

Standard errors in ( ) & t-statistics in [ ]

	D(QCRUS_QGDPRUS)	D(QDCSAAPRUS)	D(QSABUS)	D(QSTIRRUS)
D(QCRUS_QGDPRUS(-1))	-0.191030	-0.005535	-0.006918	-0.003598
	(0.09388)	(0.00459)	(0.00608)	(0.02963)
	[-2.03476]	[-1.20551]	[-1.13850]	[-0.12146]
D(QCRUS_QGDPRUS(-2))	-0.122852	0.003588	0.004482	0.001768
	(0.09934)	(0.00486)	(0.00643)	(0.03135)
	[-1.23663]	[0.73850]	[0.69697]	[0.05640]
D(QCRUS_QGDPRUS(-3))	-0.174753	-0.012827	0.004755	0.028668
	(0.09575)	(0.00468)	(0.00620)	(0.03022)
	[-1.82508]	[-2.73912]	[0.76726]	[0.94878]
D(QCRUS_QGDPRUS(-4))	-0.137252	-0.016214	0.002565	-0.008944
	(0.09566)	(0.00468)	(0.00619)	(0.03019)
	[-1.43481]	[-3.46571]	[0.41434]	[-0.29630]
D(QCRUS_QGDPRUS(-5))	-0.088970	0.001450	0.001594	0.000906
	(0.10240)	(0.00501)	(0.00663)	(0.03231)
	[-0.86883]	[0.28960]	[0.24051]	[0.02804]
D(QCRUS_QGDPRUS(-6))	0.029733	0.016395	0.013284	0.048931
	(0.09949)	(0.00487)	(0.00644)	(0.03140)
	[0.29884]	[3.36938]	[2.06281]	[1.55850]
D(QDCSAAPRUS(-1))	1.102936	0.011705	-0.027978	-0.153878
	(1.79411)	(0.08775)	(0.11613)	(0.56616)
	[0.61475]	[0.13340]	[-0.24093]	[-0.27179]

D(QDCSAAPRUS(-2))	2.123857	0.022016	-0.025035	0.988506
	(1.78170)	(0.08714)	(0.11532)	(0.56224)
	[1.19204]	[0.25266]	[-0.21708]	[1.75815]
D(QDCSAAPRUS(-3))	0.884924	0.086869	-0.051094	0.077775
	(1.73050)	(0.08463)	(0.11201)	(0.54608)
	[0.51137]	[1.02640]	[-0.45616]	[0.14242]
D(QDCSAAPRUS(-4))	1.015494	-0.009235	-0.099173	-0.333617
	(1.39416)	(0.06819)	(0.09024)	(0.43995)
	[0.72839]	[-0.13544]	[-1.09902]	[-0.75831]
D(QDCSAAPRUS(-5))	1.248056	0.041964	-0.262821	-0.456877
	(1.39724)	(0.06834)	(0.09044)	(0.44092)
	[0.89323]	[0.61407]	[-2.90608]	[-1.03619]
D(QDCSAAPRUS(-6))	2.281010	-0.030833	-0.191120	0.470729
	(1.49763)	(0.07325)	(0.09694)	(0.47260)
	[1.52308]	[-0.42096]	[-1.97162]	[0.99604]
D(QSABUS(-1))	0.282329	0.048610	0.076061	-0.340007
	(1.62070)	(0.07927)	(0.10490)	(0.51144)
	[0.17420]	[0.61326]	[0.72507]	[-0.66481]
D(QSABUS(-2))	-1.505410	-0.013928	-0.004361	0.573334
	(1.58183)	(0.07736)	(0.10239)	(0.49917)
	[-0.95169]	[-0.18003]	[-0.04259]	[1.14857]
D(QSABUS(-3))	-1.946625	-0.001427	0.011198	-1.230059
	(1.54345)	(0.07549)	(0.09990)	(0.48706)
	[-1.26122]	[-0.01890]	[0.11209]	[-2.52548]
D(QSABUS(-4))	1.576303	-0.007232	-0.120134	0.821318
	(1.60358)	(0.07843)	(0.10379)	(0.50603)
	[0.98299]	[-0.09221]	[-1.15743]	[1.62305]
D(QSABUS(-5))	-2.010338	0.142403	-0.007870	0.142807
	(1.60085)	(0.07829)	(0.10362)	(0.50517)
	[-1.25579]	[1.81881]	[-0.07595]	[0.28269]

D(QSABUS(-6))	0.190103	0.002095	0.149841	-0.763685
	(1.59599)	(0.07806)	(0.10330)	(0.50364)
	[0.11911]	[0.02684]	[1.45051]	[-1.51633]
D(QSTIRRUS(-1))	-0.176378	0.002010	0.012784	0.243660
	(0.29395)	(0.01438)	(0.01903)	(0.09276)
	[-0.60002]	[0.13982]	[0.67190]	[2.62673]
D(QSTIRRUS(-2))	-0.176037	0.001586	0.006991	-0.407276
	(0.28841)	(0.01411)	(0.01867)	(0.09101)
	[-0.61037]	[0.11241]	[0.37449]	[-4.47497]
D(QSTIRRUS(-3))	-0.026117	0.002646	-0.014941	0.251869
	(0.31302)	(0.01531)	(0.02026)	(0.09878)
	[-0.08344]	[0.17281]	[-0.73747]	[2.54987]
D(QSTIRRUS(-4))	0.144222	-0.015072	0.012338	-0.042191
	(0.30132)	(0.01474)	(0.01950)	(0.09509)
	[0.47864]	[-1.02277]	[0.63261]	[-0.44372]
D(QSTIRRUS(-5))	-0.204582	0.002807	0.039010	0.206598
	(0.29212)	(0.01429)	(0.01891)	(0.09218)
	[-0.70033]	[0.19647]	[2.06317]	[2.24116]
D(QSTIRRUS(-6))	0.319519	-0.012489	0.021392	-0.223512
	(0.29048)	(0.01421)	(0.01880)	(0.09166)
	[1.09999]	[-0.87907]	[1.13780]	[-2.43839]
BROJAC	**0.227167**	0.001616	-0.001755	-0.000519
	(0.06114)	(0.00299)	(0.00396)	(0.01929)
	[3.71577]	[0.54034]	[-0.44361]	[-0.02689]
R-squared	0.185522	0.250910	0.247652	0.342402
Adj. R-squared	0.027881	0.105925	0.102036	0.215125
Sum sq. resids	1246.548	2.981725	5.222364	124.1327
S.E. equation	3.170616	0.155068	0.205221	1.000535
F-statistic	1.176867	1.730594	1.700721	2.690208

Log likelihood	-369.6738	79.98077	38.22737	-197.8185
Akaike AIC	5.297634	-0.737997	-0.177549	2.990852
Schwarz SC	5.801652	-0.233979	0.326469	3.494870
Mean dependent	0.670744	-0.007696	0.012595	0.006798
S.D. dependent	3.215763	0.163997	0.216567	1.129359

Determinant resid covariance (dof adj.)	0.009422
Determinant resid covariance	0.004519
Log likelihood	-443.4334
Akaike information criterion	7.294408
Schwarz criterion	9.310479

Note: BROJAC is a symbol for the variable COUNTER; SRP (QSABUS) - Systemic risk perception in the time when is no boom in asset prices; APP*SRP (QDCSAAPRUS) - Systemic risk perception in the time when is boom in asset prices; GDP (BDP_US) - Gross domestic product; RIR (QSTIRRUS)- Real interest rate; CPS/GDP (QCRUS_QGDPUS) - Credit to the private sector/gross domestic product; AAPI - Aggregate asset price index