International credit cycles: a regional perspective

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Abstract

I use credit/GDP ratio to construct stylized credit cycles at global and regional levels over 1980-2010. Their average duration is between 12 and 15 years and for all the regions there is “a ceiling” and “a floor” curbing the amplitude of credit cycles. They are also largely interconnected, with the US credit cycle being the most influential and autonomous at the same time. The relationship between credit cycles and intensity of banking crises is also discussed. It appears that the regions exerting predominant influence over their counterparts and having a higher number of total connections at the same time experience fewer banking crises.

Key words: *credit cycle, banking crisis, net spill-over index, Hodrick-Prescott filter, Poisson regression, macro-prudential regulation*

JEL Classification Number: *E50, F37, G15, G17*

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1. Introduction

The 2008-2009 global economic turmoil has translated into a growing number of research papers on the finance-business cycles nexus. Some authors argue that finance remains only a transmission mechanism of economic instability, triggered by real causes. The financial accelerator models illustrate this approach best (Coric, 2011). Others assert that finance has evolved into a self-sufficient determinant of business cycles. So, the tightening of financing conditions by itself may significantly exacerbate business cycle dynamics, as was the case with the 1990-91, 2001 and the past recessions in the US (Jermann, Quadrini, 2012).

Although financial situation is not the unique determinant of business cycles and the link between them is not unidirectional, cyclical patterns of financial variables have begun exerting overwhelming influence on overall economic performance. Thus, the notion “financial cycles” has come to the fore. They encompass credit, housing and equity cycles.

Certain work has been done to figure out stylized facts about them. First, all the three cycles are pretty well synchronized across developed countries. Second, there are feedback effects between them – between housing and credit cycles, in particular. Third, financial cycles are characterized by significant, though not complete, concordance with business cycles (Claessens, Kose, Terrones, 2011a). Credit cycles demonstrate the most pronounced co-movement with business cycles, with Harding-Pagan concordance index equal to 0,81 (Claessens, Kose, Terrones, 2011b).

These stylized facts are subject to criticism as they refer to financial cycles in advanced economies and embrace the period 1960:1-2007:4, leaving out the Great Recession impact. Some empirical studies also question high concordance between credit and business cycles, stating that both have a life of their own (Credit Cycles and their Role for Macro-prudential Policy, 2011). So, to come to more robust conclusions, it is necessary to increase the number of countries in the sample. Selection of cycle indicators also matter. In the papers cited aggregate claims on the private sector by deposit banks were used as a measure of credit cycles.

In this paper I rely on the so-called financial depth measures of financial cycles. Speaking about credit cycles, I mean the share of domestic credit to private sector (as % of GDP) (credit/GDP ratio). This ratio synthesizes cyclical properties of credit and GDP and is helpful in detecting excessive credit indebtedness, which is important from the macro-prudential regulation viewpoint. Recent papers on new approaches to macro-prudential regulation emphasize the feasibility of credit/GDP ratio as a potential anchor for the implementation of countercyclical capital buffers under Basle III. It outperforms such measures as real credit or money aggregates (Drehmann, Borio, Tsatsaronis, 2011) as a warning indicator of credit "overheating". Moritz Schularick and Alan M. Taylor (2012, *forthcoming*) also find that credit/GDP is a good predictor of financial crises in the long-run, as they rely on a dataset for 14 countries over the years 1870-2008. Moreover, they show that countries with high credit/GDP ratios are not only more prone to banking crises, but are also more likely to experience other types of financial turmoil, namely, more dangerous stock market busts.

I use credit relative to GDP to construct stylized credit cycles at global and regional levels over 1980-2010. The starting point of the time span is associated with the beginning of a mighty wave of financial globalization, according to Rajan and Zingales (2003). It turns out that there has actually been a single credit cycle over this period at global level (measured "from peak to peak"). It covered 1990-2005, with the downturn phase lasting from 1990 to 1997. The dating of regional credit cycles is not uniform, and I generalize the findings in Section 2 of the paper.

In addition to describing cyclical patterns of credit at global and regional dimensions, in Section 3 an attempt is made to evaluate the role of a given region and country in the transmission of credit cycles at cross- and intra-regional levels. To this end, I resort to computing the so-called *net spill-over index* (NSI), introduced in Credit Cycles and their Role for Macro-prudential Policy (2011). It measures a degree to what a region or a country is subject to credit cycle spillover from others or exerts predominant influence itself. I also focus on the components of this metric – the total number of counterparts to which a region or a country is connected, the number of exogenous (subject to influence from other countries' credit cycles) and endogenous (impact on other countries' credit cycles) links. To calculate NSI the methodology of vector auto-regressions (VAR) is applied. It ties the paper with a burgeoning literature on financial spillovers and contagion where such econometric techniques are used (Helbling et al., 2010; Xu, 2011).

At regional level the main finding is related to the US credit cycle, which proves to be the most influential in the world. It has directly led 3 other regional credit cycles in 1980-2010, experiencing exogenous influence of none itself. It again justifies the statement that when the US sneezes, the world catches cold! At country level I examine how individual NSIs and their components are related to the number of banking crises episodes in 1980-2010. A special dataset is created to reach the purpose, combining Reinhart-Rogoff (2011) and Laeven databases (2010). I establish that the regions exerting predominant influence over their counterparts and having a higher number of total connections at the same time experience fewer banking crises.

The paper is organized as follows: Section 2 describes the data, methodology and cyclical patterns of regional credit cycles; Section 3 introduces net-spillover indices at regional and country levels and studies the impact of its components on banking crises episodes; Section 4 concludes, indicating avenues for future research.

2. Global and regional credit cycles: methodology and properties

To extract global and regional credit cycles credit/GDP ratios for 94 countries are used. The source of information is World Development Indicators (WDI). The countries with missing values of this indicator for at least a single year in 1980-2010 have been eliminated from the initial sample, no interpolation has been carried out.

The global credit cycle is derived as follows. First, the credit/GDP series for all the countries are detrended. To this end, I employ Hodrick–Prescott filter (1997). So, I consider a credit cycle as a deviation from trend in a country's credit/GDP series. It is necessary to specify that relative deviation from trend is computed ($\frac{credit\ /GDP_i - credit\ /GDP_i\_trend}{credit\ /GDP_i\_trend}$). Second, the constructed series are normalized to obtain an individual country's stylized credit cycle: relative deviations from trend for each year less mean for 1980–2010 divided by standard deviation for 1980–2010. Finally, the first principal component for the series is extracted and normalized according to the described procedure. The result is a standardized global cycle presented below (figure 1).

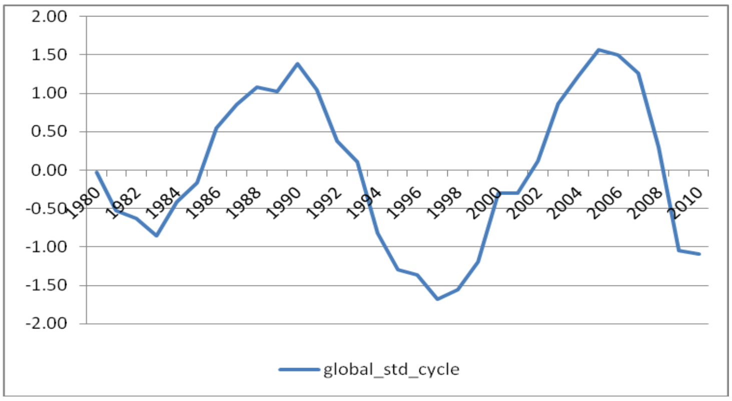
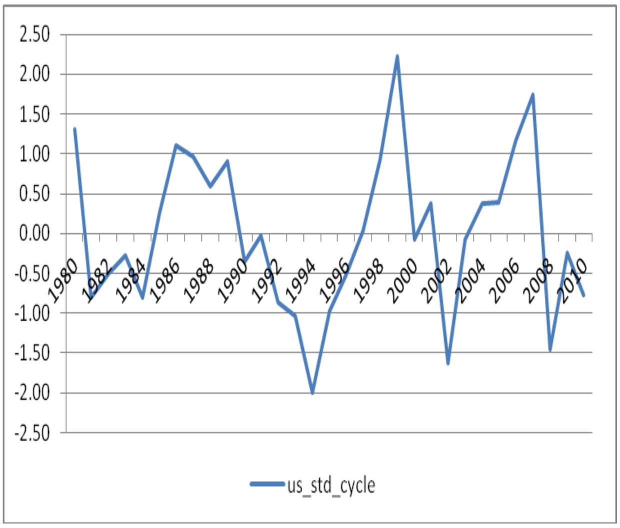


Figure 1. Global credit cycle.

It turns out that there has actually been a single credit cycle over this period at global level (measured "from peak to peak"). It covered 1990-2005, with the downturn phase lasting from 1990 to 1997. The beginning of the downturn meshes well with a burst of systemic financial crises in Latin America (Mexico, Brazil, etc.) and banking crises in Scandinavian countries. The trough of the cycle is associated with a number of serious financial crises in NICs. The upturn of the global credit cycle was resilient and almost unaffected by the 2001 dotcom crisis and US recession.

It is also noteworthy that both upper turning points of the cycle are reached at comparable level. It indicates that the 2008–2009 crisis was not preceded by any supernatural credit overhang, the global credit indebtedness in 2005 was 13% higher than in 1990. The upper turning point registered in 2005 and, say, not in 2006 or 2007, as one may intuitively have expected, seems an important empirical finding as well.

Now I turn to regional credit cycles. The names and county composition of regions are from WDI (Appendix 1). The methodology of cycle extraction is in line with the one used for the global credit cycle. Standardized regional credit cycles are displayed below (Figure 2a, b, c, d, e, f, g). In case of North America regional credit cycle is equivalent to the US, as Canada and Bermuda contain missing values in their series.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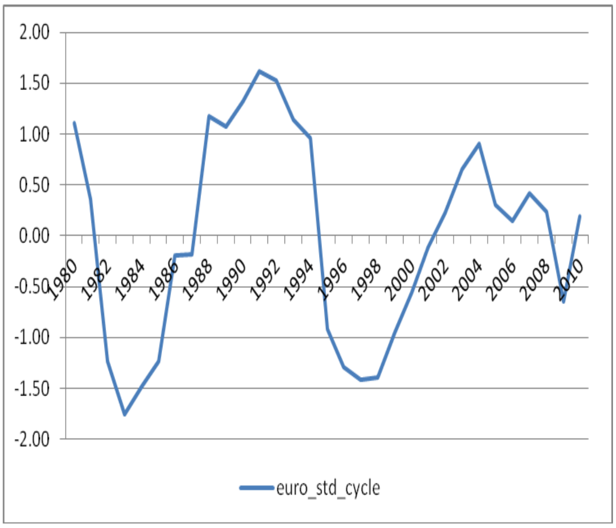
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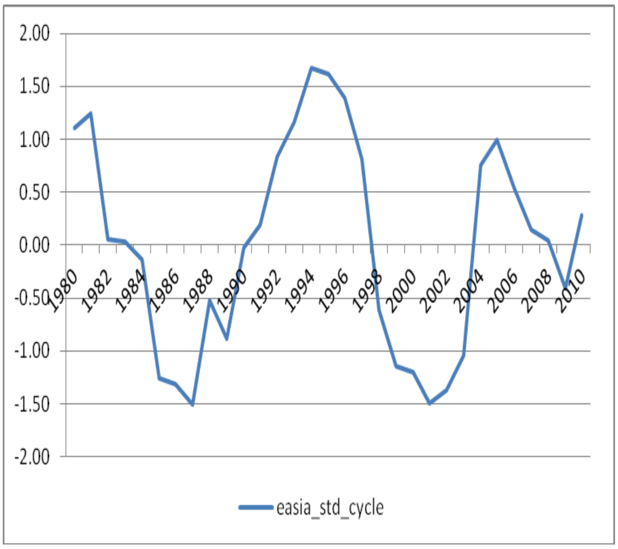
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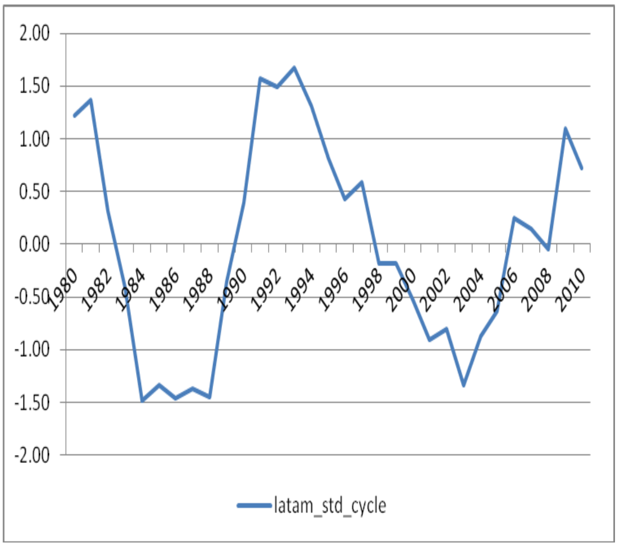
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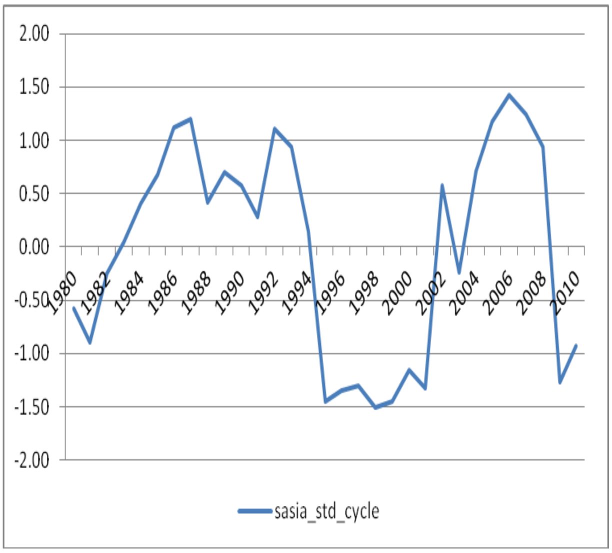
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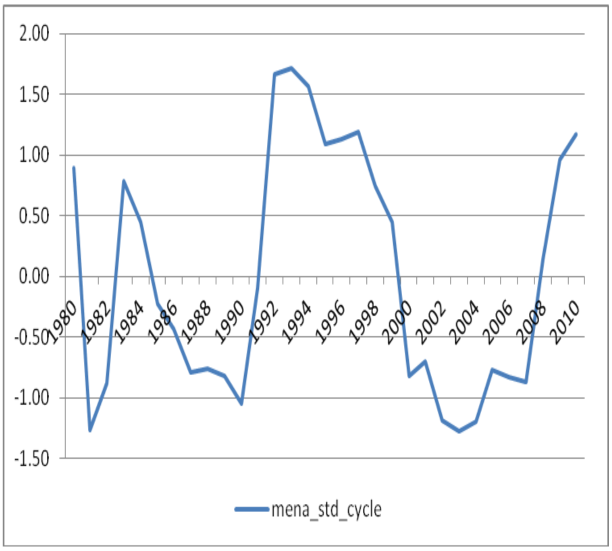
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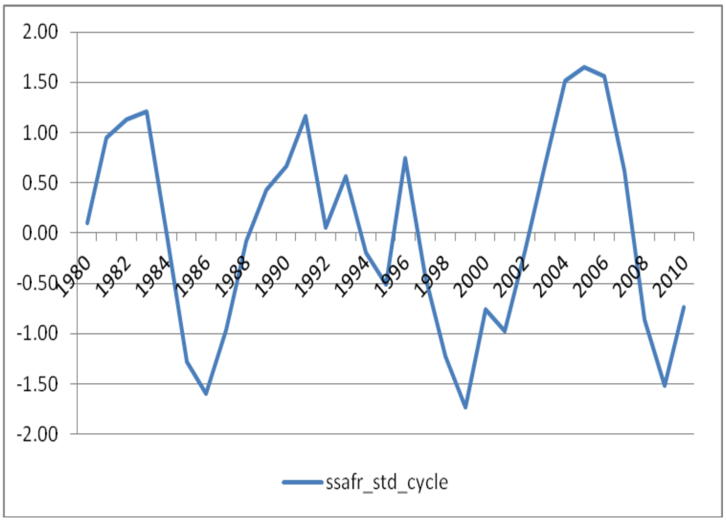


g

Figure 2. Regional credit cycle.

Regional credit cycles are far from being uniform in shape.

In case of the US one may decipher at least 2 cycles: from 1986 to 1999 and from 1999 to 2007 (measured "from peak to peak"). The upturns and downturns of the cycles adequately correspond to overall US macroeconomic performance, reflecting such episodes as the New Economy boom in 1996-2000, sub-prime mortgage expansion in 2003-2007 as well as busts of respective bubbles in 2001 and 2008-2009 with significant credit depth deterioration.

The European credit cycle lasted from 1991 to 2004, with 1997 being the trough. In 2004-2009 there was a clear downward trend with a local trough in 2009. Like in the US, the downturn in 2005-2009 in the European credit cycle was moderate. Two reasons may account for it. First, active bail-outs carried out by monetary authorities helped avoid massive write-offs in traditional loan portfolios. Second, the reduction in GDP partly ameliorated the shrinkage in credit volumes, as business and financial cycles in advanced economies are well synchronized.

As for East Asia, its credit cycle covered the span between 1994 and 2005, with 2001 being the trough. The downturn is completely associated with the crisis in the NICs. Again, the downturn in 2006-2009 was relatively mild.

In Latin America the credit cycle embraced 1993-2009. There was a steady and long downturn between 1993 and 2003. So, the 1990s could also be treated as a lost decade for Latin America from the financial development perspective, just like "flat" credit/GDP levels observed in the 1980s. But the 2008-2009 global recession passed unnoticed for Latin America with a pronounced upward trend in credit/GDP ratio. Almost identical cyclical pattern is found in case of Middle East and North Africa.

In South Asia the credit cycle lasted from 1992 to 2006. There was a protracted period of low credit/GDP levels between 1995 and 2001 which coincided with the financial disruption in the NICs.

Sub-Saharan Africa experienced a substantial upturn between 1999 and 2005 after mixed dynamics in the preceding years. Yet, it was reversed in 2006-2009.

To summarize the stylized facts about global and regional credit cycles, one may state that their average duration is 12-15 years, almost equally divided between upturns and downturns. Despite initial expectations that the downturn of the last credit cycle could be extremely deep, the empirics don't lend much support to them. For all the regions there is "a ceiling" and "a floor" curbing the amplitude of credit cycles. The first is a 1,5 standard deviation above the mean for 1980-2010, the second is the same value below the mean.

3. Cross- and intra-regional credit cycles' spillovers

Credit cycles in different regions and countries don't occur in vacuum. Modern banking systems are deeply interconnected, so credit cycles are sure to spill over both at cross- and intra-regional levels. My purpose in this section is to establish links between regional cycles, thus, finding out which of them strongly affect other regions' cycles and which are subject to external influence.

This analysis is helpful to evaluate risks of banking cycles' contagion. Its methodology rests on the use of vector auto-regressions (VARs). I use an unrestricted VAR model and treat all the standardized regional credit cycle time series as endogenous variables. I experiment with different number of lags, testing for optimal lag length and overall model stability. According to Akaike and Schwartz information criteria a model with a 2-period lag should be selected. It proves to be stable, as inverse roots of AR characteristic polynomial lie inside the unit circle (Appendix 2). Then I fill in a table displaying connections between the variables. The criterion is a t-statistic that is equal or exceeds 2 in respective regressions. The result is the following table.

t=2	US_STD_CYCLE	EURO_STD_CYCLE	EASIA_STD_CYCLE	LATAM_STD_CYCLE	SASIA_STD_CYCLE	MENA_STD_CYCLE	SSAFR_STD_CYCLE	**sub_to_infl**
US_STD_CYCLE								0
EURO_STD_CYCLE		+	+	+				3
EASIA_STD_CYCLE	+	+	+					3
LATAM_STD_CYCLE		+	+		+	+		4
SASIA_STD_CYCLE	2+				+			3
MENA_STD_CYCLE						2+		2
SSAFR_STD_CYCLE	2+	2+	2+		+			7
exert_infl	5	5	5	1	3	3	0	0

'+' denotes the presence of a link, '2+' means that both lags of the respective independent variable affect the given one. So, for example, in column 1 it is seen that the standardized US credit cycle takes a 2-year lead of the one of South Asia and Sub-Saharan Africa and a one-year lead of the credit cycle of East Asia. The last right-hand column contains information on the number of links a given country is subject to, whereas the lower line summarizes data on the number of links this country generates itself.

Consequently, one can conclude that the US credit cycle is the most influential, as it produces 5 links with 3 regions and remains totally unaffected itself. Then come Europe and East Asia. Europe receives feedback from itself, East Asia and Latin America. East Asia is affected by the US, European and its own credit cycles. Surprisingly, it seems that the US credit cycle affects Europe in a "roundabout" way – via East Asia. Thus, one may conjecture that a banking crisis (or any other financial turmoil) originated in the US will be particularly contagious for Europe if previously amplified in Japan and/or China that shape the credit cycle in East Asia.

Middle East and North Africa as well as South Asia are in neutral position in a sense that that the first exercises quite a limited influence and the second has a zero balance of links at all. Latin America and Sub-Saharan Africa are primarily subject to influence by other regions' credit cycles.

It is also interesting to evaluate the net influence effect for each region. To this end, I resort to the net spill-over index (NSI). It is calculated as the number of endogenous links less the number of exogenous ones divided by total sum of links attributed to the region. By definition it ranges from -1 to 1. The value of -1 indicates that the region only receives external impulses, i.e. its credit cycle is determined by developments in other regions. On the contrary, NSI equal to 1 means the region is absolutely independent of external influence and shapes credit cycles of its counterparts. So, I compute and visualize NSI values (Figure 3).

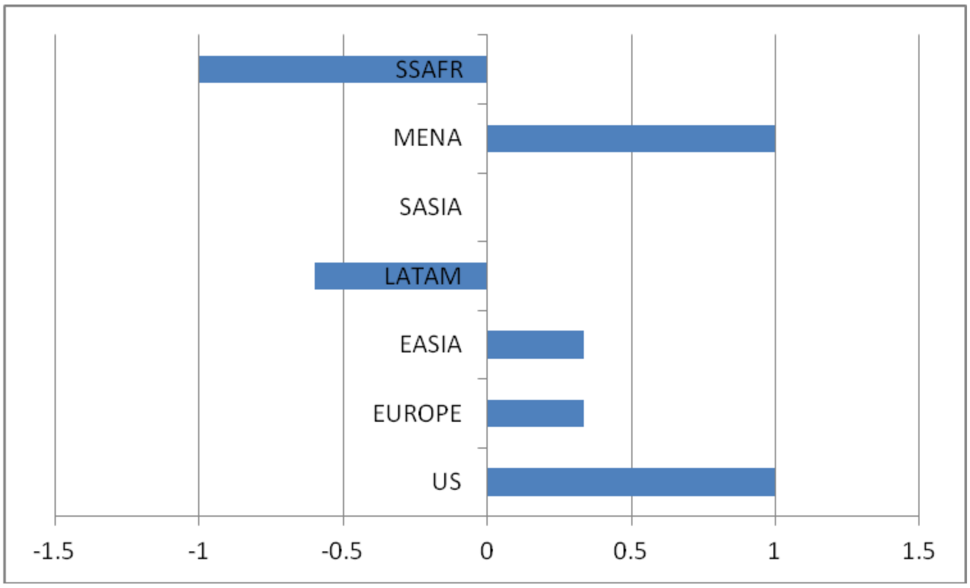
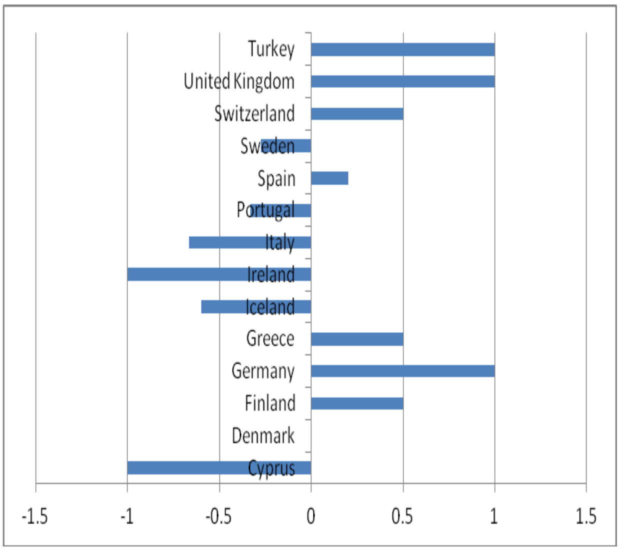


Figure 3. Regional NSI values.

Having NSI value significantly positive or close to1 makes the region almost immune to any banking shocks originated in other places. However, this position also transforms this region into a systemically important. It means that any significant shock generated within the region may be quickly propagated and amplified, undermining global financial stability. This fact imposes great responsibility over monetary authorities and banking regulators in the US, Europe and East Asia. It additionally points to the necessity of cooperation of these key regions in macro-prudential regulation of banking. The same is true for Middle East and North Africa, though this region has a much more "isolated" credit cycle.

The same approach to assessing credit cycle links could be applied at intra-regional level, as it helps identify countries disseminating their financial influence and those that only passively adjust to external impact. Again I report figures of NSIs values[2] (Figure 4a, b, c, d, e, f).

[2] The output of respective VAR models and proofs of their stability are available from the author upon request.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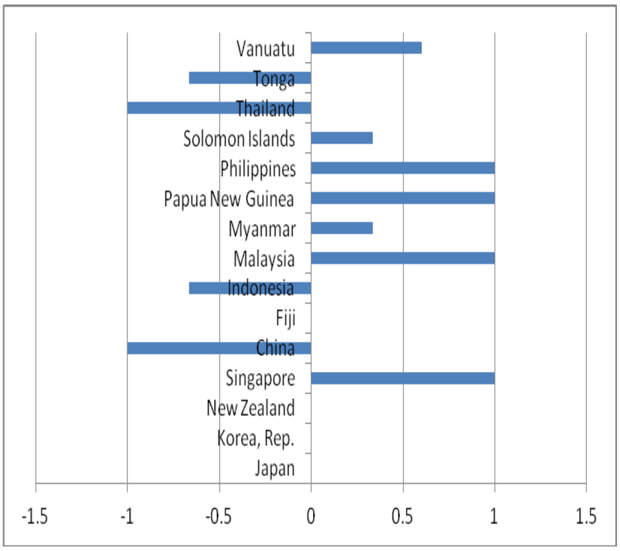
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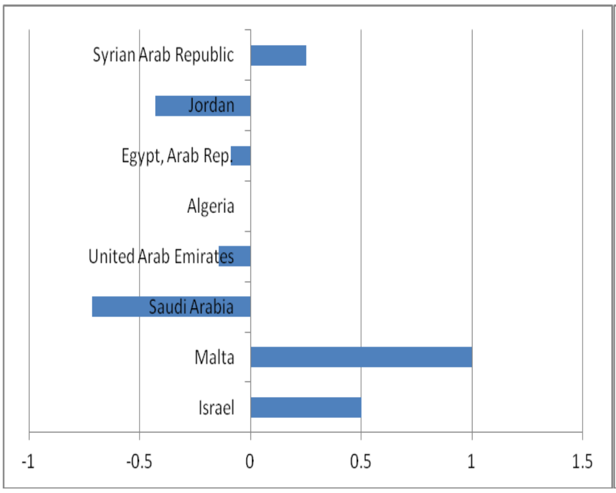
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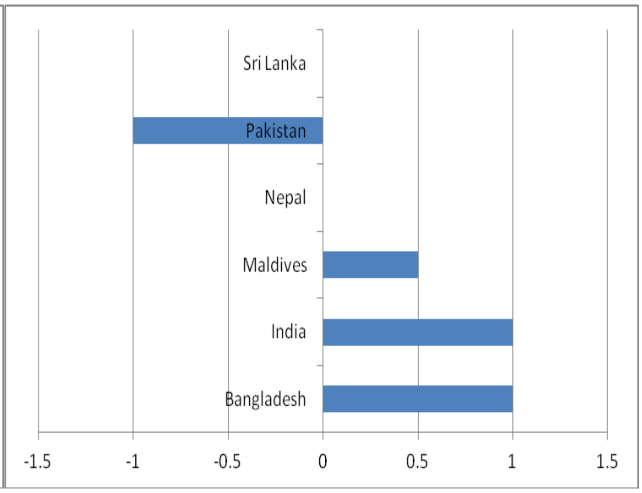
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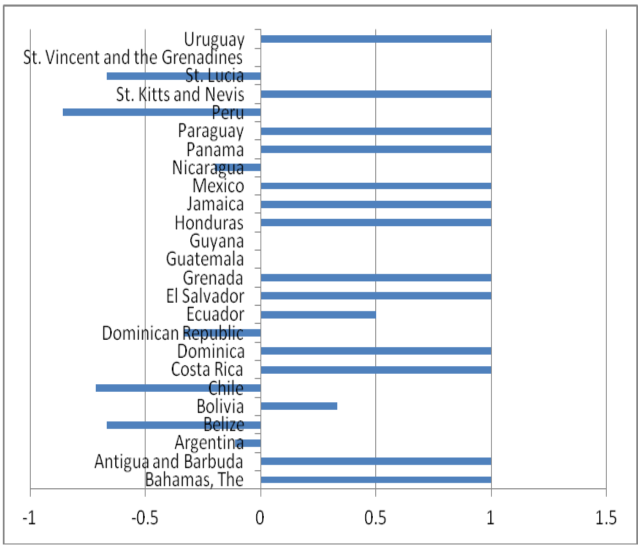
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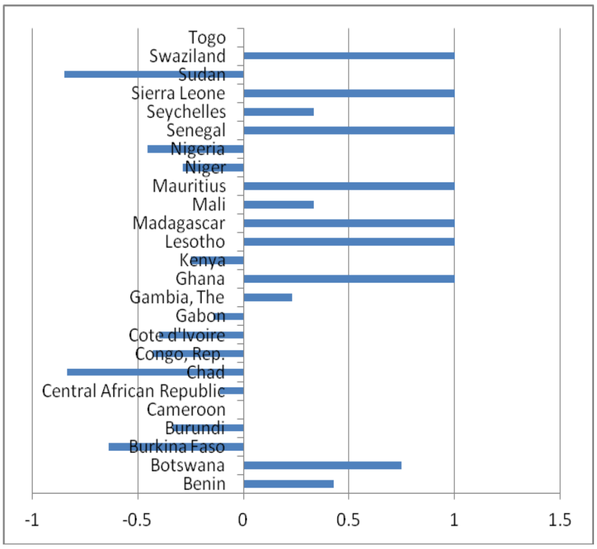
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Figure 4. Country-level net spill-over indices.

One should pay particular attention to country-level NSIs in Europe and East Asia because they have been found crucial in terms of influence on other regions' credit cycles. The countries characterized by positive NSI values in Europe and East Asia are not only resistant to financial shocks that may occur within the two regions, but also have significant potential to exert negative impact on other regions if a shock arises precisely in the given countries. So, the analysis provides preliminary guidelines for revealing countries with systemically important credit cycles[3].

In Europe and Central Asia the UK, Germany and Turkey are on the top-list with NSI value equal to 1. They are followed by Switzerland, Finland, Greece and Spain. The fact that Greece and Spain have positive NSI values means that financial conditions in the countries affect other countries' performance, both in Europe and beyond. So, this finding additionally explains why the 2010-2012 Greek crisis turned out to be so difficult to resolve. It is also worth mentioning that the Greek credit cycle leads the Spanish one, whereas the financial conditions in Spain directly affect Portugal, Ireland and Switzerland.

In East Asia the most striking thing is that China has an NSI equal to -1. This fact, however, doesn't necessarily imply that this country is easily affected by its regional counterparts' credit cycles. It is a significant financial power and links with other regions may be much more important for China. If extra-regional links are taken into consideration, NSI value may be quite different. A plausible explanation for the result obtained is that China experiences influence by the countries whose credit cycles may be particularly tied to the US and Europe (Korea, Rep., New Zealand, Malaysia). So, this could be an indirect impact of other regions' credit cycles. In other regions there are also some unexpected results of NSI computation, like Saudi Arabia in MENA or Chile in Latin America which have received negative scores. Nevertheless, the regions these countries belong to are not of systemic importance and the result changes little in global transmission of credit cycles, though really deserves further research and robustness checks.

Now I turn to examining a possible relationship between the computed NSIs at country level and the intensity of banking crises. I combine two special datasets on the incidence of banking crises that cover the period of 1980-2010 - Reinhart-Rogoff (2011) and Laeven (2010). They overlap to a great extent. In the cases they

[3] As the time-series in the analysis include only 31 observations, it is impossible to construct a genuinely global VAR model that would evaluate dependence of a given country on all other countries' or regions' credit cycles. So, the conclusions made may be subject to certain extensions given the suggested comprehensive analysis is conducted.

contradict, I rely on Reinhart-Rogoff database (2011) as a more recently updated data source. Thus, I assemble a sample of 65 countries in which at least one episode of banking crisis took place in 1980-2010. Figure 5 visualizes the data.

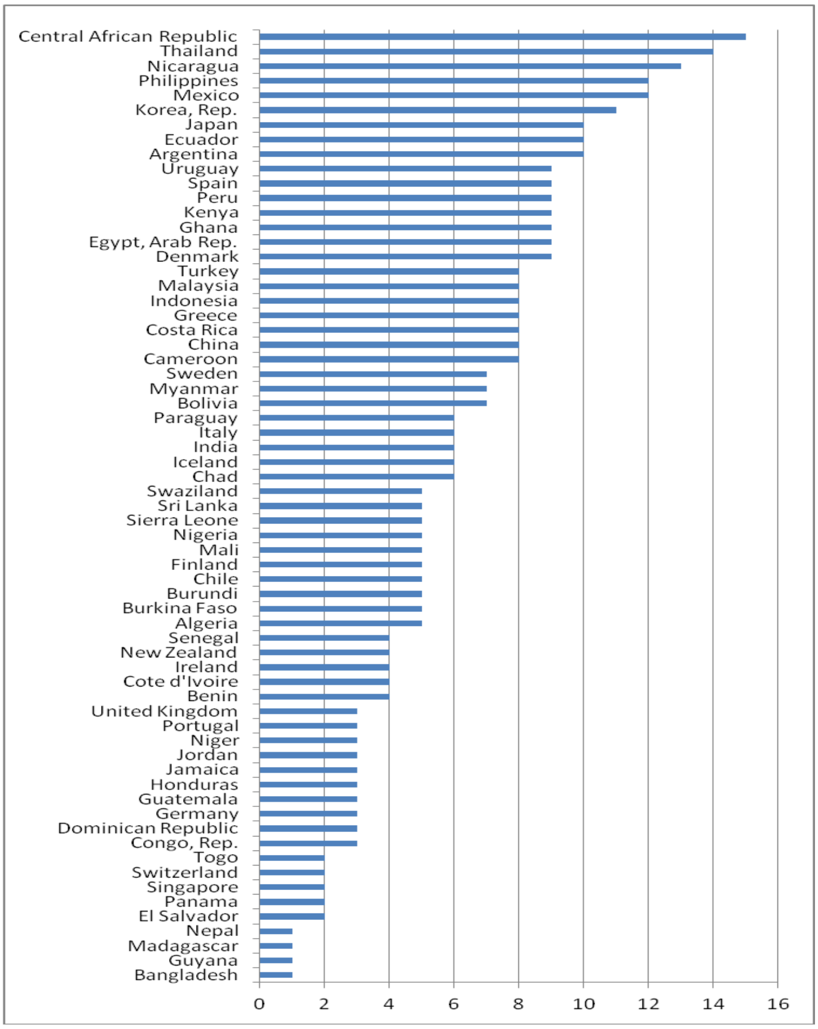

Figure 5. Number of banking crises per country, 1980-2010.

Then I make a regression of the number of banking crises (BANKCR) per country on a constant and two independent variables – the respective NSI of the country (NSI_c) and that of the region it belongs to (NSI_reg). As the dependent variable may take on only integer values, I use the so-called Poisson regression (Appendix 3a).

At first glance the formal result is that the regression is of acceptable quality as all the predictors are significant. The main qualitative conclusion based on the estimated equation is that the greater NSI a country has, the more prone to banking crises it is. Also, the number of banking crises seems inversely connected with regional NSI. So, having a high NSI value within a region may be a pro-crisis factor, whereas a high NSI value at regional level may be a buffer to financial turmoils.

However, the robustness of the results is to be checked as they may be biased due to overdispersion in the dependent variable, which means that the equality of the conditional mean and variance is broken. This is a typical problem with Poisson regressions. To establish if one can rely on the results, a goodness-of-fit test is carried out. Its idea is to regress residuals of the estimated regression on fitted values of the dependent variable (constant is suppressed). If the coefficient is significant, it means that the basic premise of Poisson regression is violated and its results are unreliable. The output of this auxilliary regression is presented in Appendix 3b. As t-statistic is not significant even at 10%-level, conditional mean and variance of the dependent variable can be considered equal and the obtained Poisson regression appropriate.

Anyway, I treat the qualitative conclusions with certain caution: the positive association between high NSI values within a region and the number of banking crises per country may be a mere reflection of the fact that such regions as Sub-Saharan Africa and Latin America have much higher average NSIs at country levels in comparison with Europe and East Asia (0,19 and 0,43 vs. 0,06 and 0,13). Further research is needed in this area.

As a starting point of it, I disaggregate the NSIs and use four predictors for banking crises – the difference between endogenous and exogenous links of a country's credit cycle at regional and country levels (i.e. the numerators of the respective NSIs – DIF_C, DIF_REG) and total sums of a country's credit cycles (i.e. the denominators of the respective NSIs – TOTINFL_C, TOTINFL_REG). The rest of the estimation is as described above. The result is presented in Appendices 3c, d. It sheds additional light on the connection between credit cycle links and banking crises. It is the cross–regional dimension that matters more than intra-regional interactions: the regions that exert predominant influence over their counterparts and have a higher number of total connections at the same time experience fewer banking crises.

4. Conclusions

In the paper standardized credit cycles were constructed for 7 regions and 94 countries. The cyclical patterns of the regional cycles have been studied and discussed and the notion of a global credit cycle have been introduced. Some regularities in their structure and duration have been discovered.

Regional cycles prove to be largely interdependent. The US credit cycle is the most influential and autonomous among them. Europe and East Asia come next. Other regions passively adjust to credit cyclicality of the mentioned regions. It has a direct implication for the conduct of economic policy. Macro-prudential measures should be coordinated and credit cycles should be carefully monitored precisely with respect to these three regions.

I have also studied the interdependence of country-level credit cycles and the impact of regional and country-level credit cycles on the intensity of banking crises. The regions that exert predominant influence over their counterparts and have a higher number of total connections at the same time experience fewer banking crises. Anyway, further effort is needed to verify these conclusions.

This quest could also be based on a different methodology. Using tools of network analysis looks quite promising in this respect. This approach may create additional value added as it is aimed at visualizing links between credit cycles. Some aspects of VAR models could also be developed. For example, general response functions could be estimated to study multilateral credit cycle links in more detail.

References

Coric, B., 2011. The Financial Accelerator Effect: a Survey. Financial Theory and Practice, Vol. 35 (2), 171-196.

Claessens, S., Kose, M.A., Terrones, M.E., 2011a. Financial Cycles: What? How? When? IMF Working Paper # 11/76.

Claessens, S., Kose, M.A., Terrones, M.E., 2011b. How Do Business and Financial Cycles Interact? IMF Working Paper # 11/88.

Credit Cycles and their Role for Macro-prudential Policy, 2011. European Banking Federation. Mimeo.

Drehmann, M., Borio, C., Tsatsaronis, K., 2011. Anchoring Countercyclical Capital Buffers: the Role of Credit Aggregates. International Journal of Central Banking, Vol. 7(4), 190-240.

Helbling, T., Huidrom, R., Kose, M.A., Otrok, C. 2010. Do Credit Shocks Matter? A Global Perspective. Mimeo.

Hodrick, R., Prescott, E., 1997. Postwar U.S. Business Cycles: An Empirical Investigation. Journal of Money, Credit, and Banking, Vol. 29 (1), 1–16.

Jermann, U., Quadrini, V., 2012. Macroeconomic Effects of Financial Shocks. The American Economic Review, Vol. 102 (1), 238-271.

Laeven, L., Valencia, F., 2010. Resolution of Banking Crises: the Good, the Bad, and the Ugly. IMF Working Paper # 11/88.

Rajan, R., Zingales, L., 2004 Saving Capitalism from the Capitalists: Unleashing the Power of Financial Markets to Create Wealth and Spread Opportunity. Princeton University Press.

Reinhart, C. M., Rogoff, K.S., 2011. From Financial Crash to Debt Crisis. The American Economic Review, 101(5): 1676–1706. Dataset.

Schularick, M., Taylor, A. M. 2012. Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. The American Economic Review, *forthcoming*.

Teng Teng Xu, 2011. The Role of Credit in International Credit Cycles. Mimeo.

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Appendix 2

VAR MODEL OF REGIONAL CREDIT CYCLE SPILLOVERS

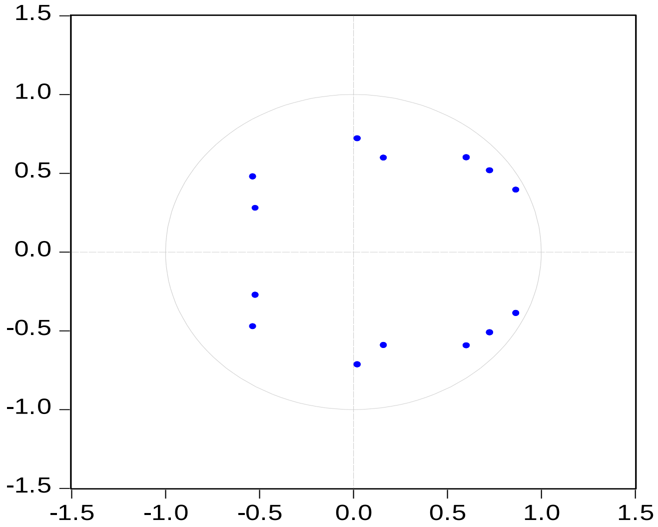
	US_STD_CYCLE	SSAFR_STD_CYCLE	SASIA_STD_CYCLE	MENA_STD_CYCLE	LATAM_STD_CYCLE	EURO_STD_CYCLE	EASIA_STD_CYCLE
US_STD_CYCLE(-1)	-0.019537	0.236139	0.339765	-0.141972	-0.121501	0.116950	0.144551
	(0.25902)	(0.11609)	(0.16489)	(0.13114)	(0.12201)	(0.11418)	(0.08908)
	[-0.07543]	[2.03407]	[2.06057]	[-1.08263]	[-0.99586]	[1.02430]	[1.62265]
US_STD_CYCLE(-2)	0.035311	-0.256298	-0.386742	-0.075254	0.232524	-0.019942	-0.286125
	(0.26024)	(0.11664)	(0.16566)	(0.13175)	(0.12258)	(0.11471)	(0.08950)
	[0.13569]	[-2.19740]	[-2.33451]	[-0.57118]	[1.89693]	[-0.17384]	[-3.19688]
SSAFR_STD_CYCLE(-1)	-0.111058	0.308055	0.181239	-0.068390	-0.049393	0.349148	0.278597
	(0.40911)	(0.18336)	(0.26043)	(0.20712)	(0.19270)	(0.18033)	(0.14070)
	[-0.27147]	[1.68006]	[0.69592]	[-0.33019]	[-0.25632]	[1.93613]	[1.98006]
SSAFR_STD_CYCLE(-2)	-0.181994	-0.099975	0.255133	-0.238816	0.016698	-0.048884	-0.180746
	(0.39740)	(0.17811)	(0.25298)	(0.20119)	(0.18719)	(0.17517)	(0.13667)
	[-0.45797]	[-0.56131]	[1.00852]	[-1.18700]	[0.08921]	[-0.27906]	[-1.32246]
SASIA_STD_CYCLE(-1)	0.064015	0.070400	0.573272	0.091523	-0.397663	0.026503	0.036083
	(0.39079)	(0.17515)	(0.24877)	(0.19785)	(0.18407)	(0.17226)	(0.13440)
	[0.16381]	[0.40194]	[2.30441]	[0.46259]	[-2.16033]	[0.15386]	[0.26847]
SASIA_STD_CYCLE(-2)	-0.168939	-0.309402	-0.056209	0.176694	0.122908	0.073062	0.103531
	(0.32727)	(0.14668)	(0.20834)	(0.16569)	(0.15416)	(0.14426)	(0.11256)
	[-0.51620]	[-2.10932]	[-0.26980]	[1.06641]	[0.79730]	[0.50645]	[0.91981]
MENA_STD_CYCLE(-1)	-0.135915	-0.285049	-0.252823	0.547303	0.450047	0.345156	0.212836
	(0.41883)	(0.18772)	(0.26662)	(0.21204)	(0.19728)	(0.18462)	(0.14405)
	[-0.32451]	[-1.51849]	[-0.94824]	[2.58109]	[2.28123]	[1.86955]	[1.47756]

MENA_STD_CYCLE(-2)	-0.067059	-0.017962	0.074749	-0.550669	-0.321354	0.143044	-0.001959
	(0.40503)	(0.18154)	(0.25784)	(0.20506)	(0.19078)	(0.17854)	(0.13930)
	[-0.16556]	[-0.09894]	[0.28990]	[-2.68542]	[-1.68439]	[0.80120]	[-0.01406]
LATAM_STD_CYCLE(-1)	-0.289642	-0.304186	0.035670	0.430913	0.333409	0.312394	-0.038833
	(0.49982)	(0.22402)	(0.31818)	(0.25305)	(0.23543)	(0.22032)	(0.17190)
	[-0.57949]	[-1.35786]	[0.11211]	[1.70290]	[1.41617]	[1.41791]	[-0.22590]
LATAM_STD_CYCLE(-2)	-0.653246	0.121966	0.070256	0.272107	-0.306584	-0.461788	0.136527
	(0.43792)	(0.19628)	(0.27878)	(0.22171)	(0.20628)	(0.19304)	(0.15061)
	[-1.49169]	[0.62140]	[0.25202]	[1.22731]	[-1.48629]	[-2.39225]	[0.90648]
EURO_STD_CYCLE(-1)	0.411891	-0.515730	0.065793	0.080229	0.651669	0.513157	-0.127176
	(0.54266)	(0.24322)	(0.34545)	(0.27473)	(0.25561)	(0.23920)	(0.18663)
	[0.75903]	[-2.12045]	[0.19046]	[0.29202]	[2.54948]	[2.14529]	[-0.68143]
EURO_STD_CYCLE(-2)	-0.469521	1.070260	-0.055128	-0.342069	0.069515	0.244328	0.544924
	(0.56092)	(0.25140)	(0.35708)	(0.28398)	(0.26421)	(0.24725)	(0.19291)
	[-0.83705]	[4.25712]	[-0.15439]	[-1.20454]	[0.26310]	[0.98817]	[2.82469]
EASIA_STD_CYCLE(-1)	0.134815	0.503279	-0.053700	0.090423	-0.099207	-0.654582	0.427332
	(0.55358)	(0.24811)	(0.35240)	(0.28027)	(0.26075)	(0.24402)	(0.19039)
	[0.24353]	[2.02842]	[-0.15238]	[0.32263]	[-0.38046]	[-2.68252]	[2.24451]
EASIA_STD_CYCLE(-2)	0.922586	-0.631274	-0.376378	0.223769	0.593986	-0.132177	-0.239575
	(0.61744)	(0.27673)	(0.39305)	(0.31259)	(0.29083)	(0.27216)	(0.21235)
	[1.49422]	[-2.28117]	[-0.95758]	[0.71585]	[2.04238]	[-0.48565]	[-1.12821]
C	-0.039760	-0.049840	0.018680	0.070903	-0.056490	-0.042513	-0.042033
	(0.18109)	(0.08116)	(0.11528)	(0.09168)	(0.08530)	(0.07982)	(0.06228)
	[-0.21956]	[-0.61406]	[0.16204]	[0.77336]	[-0.66226]	[-0.53259]	[-0.67489]
R-squared	0.554444	0.914981	0.826386	0.885836	0.900534	0.919197	0.946138
Adj. R-squared	0.108889	0.829962	0.652771	0.771672	0.801068	0.838395	0.892276
Sum sq. resids	12.30239	2.471303	4.985434	3.153274	2.729528	2.390380	1.455164
S.E. equation	0.937412	0.420145	0.596743	0.474588	0.441550	0.413209	0.322398
F-statistic	1.244388	10.76210	4.759889	7.759319	9.053673	11.37585	17.56600

Log likelihood	-28.71543	-5.442239	-15.61797	-8.975825	-6.883296	-4.959490	2.237348
Akaike AIC	3.014857	1.409810	2.111584	1.653505	1.509193	1.376517	0.880183
Schwarz SC	3.722079	2.117032	2.818806	2.360727	2.216415	2.083739	1.587405
Mean dependent	-0.017586	-0.035862	0.051379	0.012414	-0.089310	-0.050000	-0.080690
S.D. dependent	0.993035	1.018888	1.012697	0.993201	0.989982	1.027879	0.982282

Determinant resid covariance (dof adj.)	3.30E-06
Determinant resid covariance	2.02E-08
Log likelihood	-31.10513
Akaike information criterion	9.386561
Schwarz criterion	14.33711

Inverse Roots of AR Characteristic Polynomial



REGRESSION ANALYSIS OF BANKING CRISES

3a.

Dependent Variable: BANKCR
Method: ML/QML - Poisson Count (Quadratic hill climbing)
Sample: 1 65
Included observations: 65
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.654661	0.063686	25.98173	0.0000
NSI_C	0.163597	0.077761	2.103841	0.0354
NSI_REG	-0.304470	0.085987	-3.540890	0.0004

R-squared	0.160829	Mean dependent var	6.015385
Adjusted R-squared	0.133759	S.D. dependent var	3.384211
S.E. of regression	3.149755	Akaike info criterion	5.203372
Sum squared resid	615.0995	Schwarz criterion	5.303729
Log likelihood	-166.1096	Hannan-Quinn criter.	5.242970
Restr. log likelihood	-175.3187	LR statistic	18.41812
Avg. log likelihood	-2.555532	Prob(LR statistic)	0.000100

3b.

Dependent Variable: SRESID^2-1
Method: Least Squares
Sample: 1 65
Included observations: 65

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BANKCR_F	0.091053	0.056463	1.612608	0.1118

R-squared	-0.027194	Mean dependent var	0.720036
Adjusted R-squared	-0.027194	S.D. dependent var	2.763834
S.E. of regression	2.801161	Akaike info criterion	4.913210
Sum squared resid	502.1762	Schwarz criterion	4.946662
Log likelihood	-158.6793	Hannan-Quinn criter.	4.926409
Durbin-Watson stat	1.202063		

3c.

Dependent Variable: BANKCR
Method: ML/QML - Poisson Count (Quadratic hill climbing)
Sample: 1 65
Included observations: 65
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.164921	0.224057	9.662379	0.0000
DIF_C	0.021194	0.017598	1.204315	0.2285
DIF_REG	-0.074740	0.017337	-4.310933	0.0000
TOTINFL_C	-0.015909	0.017831	-0.892246	0.3723
TOTINFL_REG	-0.082218	0.042195	-1.948516	0.0514

R-squared	0.178384	Mean dependent var	6.015385
Adjusted R-squared	0.123610	S.D. dependent var	3.384211
S.E. of regression	3.168154	Akaike info criterion	5.196804
Sum squared resid	602.2319	Schwarz criterion	5.364065
Log likelihood	-163.8961	Hannan-Quinn criter.	5.262799
Restr. log likelihood	-175.3187	LR statistic	22.84505
Avg. log likelihood	-2.521479	Prob(LR statistic)	0.000136

3d.

Dependent Variable: SRESID^2-1
Method: Least Squares
Sample: 1 65
Included observations: 65

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BANKCR_F	0.084919	0.060028	1.414662	0.1620

R-squared	-0.023269	Mean dependent var	0.690398
Adjusted R-squared	-0.023269	S.D. dependent var	2.959604
S.E. of regression	2.993840	Akaike info criterion	5.046256
Sum squared resid	573.6371	Schwarz criterion	5.079708
Log likelihood	-163.0033	Hannan-Quinn criter.	5.059455
Durbin-Watson stat	1.230269		