Relationship between the Credit-to-GDP Gap and Systemic Banking Crisis: The Case of Turkey

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Abstract

In this study, a two-step analysis has been done by using the annual data of Turkey's 1960-2013 periods. First, alternative credit-to-GDP gap calculations were made by using Hodrick-Prescott, Band-Pass filters, and Unobserved Components Model and their performances were compared. Reached findings showed that the credit-to-GDP gap estimations based on the Unobserved Components Model is more successful compared to others. In the second step, banking crisis experienced in Turkey in the studied period has been analysed based on Logit Model. Systemic crises and all banking crises defined as a binary variable were modelled separately. In these models, credit-to-GDP gap estimated in the first step were used as explanatory variable. The results show that the growth in the credit-to-GDP gap increases the probability of occurrence of both systemic and non-systemic banking crises.

Keywords: Credit-to-GDP Gap, Banking Crisis, Unobservable Component Models. **JEL Classification Codes:** C25, C32, E51, E58.

Kredilerin GSYİH'ye Oranı Açığı ve Sistemik Banka Krizleri Arasındaki İlişki: Türkiye Örneği

Öz

Çalışmada Türkiye'nin 1960-2013 dönemi yıllık verileri kullanılarak iki aşamalı bir analiz yapılmıştır. Önce Hodrick-Prescott, Band-Pass filtreleri ile Gözlenemeyen Değişken Modeli kullanılarak alternatif kredi açığı hesaplamaları yapılmış ve bunların performansları karşılaştırılmıştır. Ulaşılan bulgular, gözlenemeyen değişken modeline dayanan kredi açığının tahmininin diğerlerine oranla daha başarılı olduğunu göstermiştir. İkinci aşamada, logit kullanılarak ele alınan dönemde Türkiye'de yaşanmış bankacılık krizleri analiz edilmiştir. İkili değişken olarak tanımlanan sistemik krizler ve tüm bankacılık krizleri ayrı ayrı modellenmiş ve bu modellerde açıklayıcı değişken olarak ilk adımda tahmin edilmiş olan kredi açığı dizisi kullanılmıştır. Sonuçlar, kredi açığındaki artışların hem sistemik hem de sistemik olmayan bankacılık krizi meydana gelme olasılığını arttırdığı yönündedir.

Anahtar Kelimeler: Kredilerin GSYİH Oranı Açığı, Bankacılık Krizleri, Gözlenemeyen Değişken Modelleri.

JEL Sınıflandırma Kodları: C25, C32, E51, E58.

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1. Introduction

The global crisis has revealed the inadequacy of the current supervision and regulation activities and has led financial authorities to enter the quest for new and effective measures. The debates in the post-crisis period indicated that a series of macro prudential policy instruments are needed to reduce the systemic risk. The Basel Committee's recommendations on implementing the countercyclical capital buffer in the post-global crisis period has also brought up the issue of a measure of what proportion of capital should be allocated for this purpose.

In this context, the gap between the credit-to-GDP ratio with its long term backward-looking trend was foreseen as an appropriate measure for determining the amount of capital to be allocated and recommended to the relevant environments by Basel Committee. It is seen an increasing number of empirical studies in recent years about this measure named credit-to-GDP gap which might simply called as credit gap. The common goal of these studies is to identify whether the credit gap is a right measure as claimed to determine the optimal amount of capital buffers.

In many countries, there are empirical studies attempting to determine the performance of credit-to-GDP gap because of their own unique structure and conditions. The studies of researchers such as Edge & Meisenzahl (2011a, 2011b), Gersl & Seidler (2011), van Norden (2011), Mironchik & Demidenko (2012), De Bonis & Silvestrini (2013), Kelly et al. (2013), Farrell (2014), Giese et al. (2014) are some of them. Probably due to the differences between the countries' economic structures and banking systems, findings have also differed. These studies often test the performances of alternative measures based on historical data and experienced crisis events. Although the credit gap was tested successfully in these studies, it's not certain that its future performance will also be high. For these reasons, many researchers are approaching cautiously to credit gap and its performance. On the other hand, credit gap's explanatory power of systemic banking crises is also important. Except the De Bonis & Silvestrini (2013) studies, there is not enough work on this issue. Turkey has achieved a rapid economic growth with increased macroeconomic stability in the post 2003 period. With this feature, while indicated as one of the leading emerging markets, it is also stated as one of the most vulnerable economies for the reasons such as current account deficit and high dependence on fixed income inflows. Additionally, Turkey is one of the few countries experienced three major banking crisis in the last thirty to forty year period.

All these features make Turkey an ideal laboratory in terms of to test the credit gap measures and their explanatory power of systemic banking crises. In light of these findings and evaluations, in the study, credit gap estimations will be done with alternative methods and their performances will be compared for Turkey. Starting from the works of Edge & Meisenzahl (2011a, 2011b) with Mironchik &

Demidenko (2012), Unobservable Components Model which cannot be observed by Hodrick-Prescott and Band-Pass filters will be based on the estimations. Then, by following the De Bonis & Silvestrini (2013) approach, after specifying the measure which determined to be more successful than the alternatives, its explanatory power of experienced systemic banking crises will be analysed by using binary logit model.

2. Literature Review

The credit-to-GDP gap performance is measured stemming from the historical data. But when making decisions related to the real time countercyclical capital buffer, how reliable is the use of a measure based on the past? Economists know for a long while that the gaps that reflecting the changes in the volume of economic activity, such as output gap, cannot be reliable and they may cause problems when creating economic stability policies. Therefore, supervision and regulation authorities are concerned that the credit gap can also cause similar problems when creating and implementing of macro prudential policy.

Drehmann et al. (2011) and Van Norden (2011) indicated that value of the credit gap as a leading indicator cannot be denied and must be taken into account when making the policies. According to Drehmann et al. (2011), the reason for that is; aforementioned variable can reflect systemic vulnerabilities caused by the bank crises. Alternative indicators such as credit spreads are also successful as synonymous signals of the problems that may lead to credit crunch in banking sector. But they are not considered successful enough to identify the problem in advance.

Van Norden (2011) indicates that credit gap can help to estimate the systemic financial risk periods but it's not the perfect measure. The criticisms about this measure are gathered under three points. These are; they are not suitable for buffer target which received data from, they don't have an early warning signal feature especially for banking crisis in emerging economies and there are measurement problems in the implementing. Despite the fact that these criticisms has justified, Drehmann & Tsatsaronis (2014) argue that the role of the credit gap as a measure is expressed wrong. According to them, in many crises occurred in the historically different countries, credit gap is the only indicator for the financial vulnerabilities. Hence, its role should provide information rather than dictating the decision when making decisions about what should be the appropriate level of countercyclical capital buffer.

In United Kingdom sample, Giese et al. (2014) researched the performance of credit gap and test it for the periods of which the British banking system fell into distress during the last fifty years. Findings showed that the measure demonstrated successful signals in terms of past events. However, Giese et al. (2014) stated that this successful performance of the measure doesn't guarantee its success for

future forecasts. According to them, during the decision making process of the countercyclical capital buffer, flow based and market based measures must be used. For example; the measures such as property prices and credit rates can be helpful estimating the credit cycles, at least exclusively in England/ UK. In the other hand, monitoring the indicators based on bank balancesheet such as leverage ratio and credit to deposit ratio can be beneficial on tracking the funding in the period of experienced excess expansion in credit volume.

Edge & Meisenzahl (2011a) analysed the credit gap in USA by Unobserved Components method. They have determined that; credit gap volume can change, estimations on gap's trend might be unreliable and the costs that may arise from incorrect measurement of the gap can reduce the credit volume in the current period. Even though the credit interest rates showed a moderate increase, they have observed that the credit volume can be narrowed due to incorrect measurement of the gap. Findings of Gersl & Seidler (2011), Kelly et al. (2013), Farrell (2014)'s studies on different countries are also similar.

For some Middle East and Eastern Europe countries, Gersl & Seidler (2011) have researched how to determine whether the volume of the credits to the private sector is excessive in terms of countercyclical capital buffer. They have concluded that the calculation based on Hodrick-Prescott filter recommended by Basel Committee is not an appropriate measure for evaluating the excessive credit growth. In their study on Ireland, Kelly et al. (2013); indicates that the measure to be used for capital buffer must be flexible in a way that reflects the alternative situations. On the other hand, Farrell (2014) examining the South African banking system stated that implementing of credit gap in a mechanical manner is not a reasonable option for determining the capital buffer. The lower and upper thresholds of the capital buffer can vary outside of Basel Committee's expectations about their usage durations. In summary, the structural differences of the countries require also a review of the structures of the credit gap for an accurate measurement. In this context, to calculate the credit gap in a more accurate way reflecting the characteristics of the countries analysed and take this into consideration in the analysis is important.

3. Empirical Method

It's assumed that the ratio of the commercial banks' credits to private sector to GDP is consist of two components which are trend (τ_t) and cycle (c_t)

$$Crd_t = \tau_t + c_t \tag{1}$$

If the cyclical component will be drawn from the above equation, a nominal credits to GDP ratio deviates from its trend and in fact this represents the credit gap.

$$c_t = Crd_t - \tau_t \tag{2}$$

If the credit-to-GDP ratio trend is estimated, the cycle component or the gap can easily be calculated.But the trend is not an observable variable. Therefore for estimating the unobservable components, it must be used an improved method. For this purpose, filters are used commonly in practice and calculations can be made with univariate or multivariate filters according to the type of analysed variable. Most widely used filters are Hodrick-Precott and Band-Pass filters. Hodrick-Prescott (1980, 1997) filter parses the Crd_t in equation (1) as trend or cyclical component with the help of below minimization:

$$\min: \sum_{t=1}^{T} \left(Crd_t - \tau_t \right)^2 + \lambda \sum_{t=2}^{T-1} \left(\left(\tau_{t+1} - \tau_t \right) - \left(\tau_t - \tau_{t-1} \right) \right)^2$$
(3)

Strength of this filter is that it is flexible and the weak side of it is that responsiveness of the results is depending upon the value of λ parameter. Because of the frequency of the economic cycle is generally considered to be 7.5 years, in the analyses on 3 months frequency, lamda parameter is filtered by equalized to 1.600. The frequency structure for the credit cycles is also considered similar and lamda parameter is equated to 1.600 commonly. When the lamda value dicreases, the trend of the credit gap will show a more variable structure and when this value increases, it will be transformed into a linear trend (Edge & Meisenzahl, 2011a, 2011b). Band-pass filters are also used in the analysis of time series. Baxter-King and Christiano-Fitzjerald filters are more commonly used Band-Pass filters in economic analysis. The main difference of these two is in determining the polynomial weight. Band-pass filter is a symmetric linear filter and can transform Crdt into xt time series:

$$x_{t} = \sum_{j=-\infty}^{\infty} \psi_{j} Crd_{t-j} = \psi(L)Crd_{t}$$

$$\tag{4}$$

In equation (4), L is the lag processor. In this method, precise time series are converted into cyclical components and deterministic trend to make filtering.

Both Hodrick-Prescott and Band-Pass filters are quite easy to use but sometimes it can be seen significant deficiencies, depending on the variable they implemented. For example, results in the Band-Pass filter are sensitive to the number of observations and cannot calculate the cyclical component for the most recent observations as future values of the time series. It means, the use of this method is limited in the real time and this situation is called "endpoint problem". Since December 2010, Hodrick-Prescott filter is used for the measurement of the credit gap and recommended to banking environments by Basel Committee. Even though this filter is successful in both measuring the trends of macroeconomic variables and the calculation of potential output level in industrialized countries, it doesn't show the same high performance in emerging economies. Because excessive rise and fall in the volume of economic activity is rarely seen in industrial countries, whereas macroeconomic variables show high volatility in emerging economies.

Unobserved components model and the Kalman filter used in their estimation, provide significant advantages over the other two methods. This method is more conducive for credit gap estimation consistent with structural model of the economy. Its sensitivity to the length of the observation period and the possibility of uncertainty in end-point estimates of time-series are much lower compared to alternative methods. (Özbek & Özlale, 2005; Proietti & Luati, 2012; Johnson, 2013).

For estimating the credit gap with Unobserved Components Model, the problem must be defined as a state-space model. The researchers such as Edge & Meisenzahl (2011a), Mironchik and Demidenko (2012), De Bonis and Silvestrini (2013) have used a model similar to the following structure:

$$Crd_t = \tau_t + c_t + \varepsilon_t$$
 (5)

In the equation (5), ε_t , which its average is zero, variance σ_{ε}^2 is independent and normally distributed temporary error term. Trend (τ_t) and cycle (c_t) cannot be directly observed but can be expressed parametrically. Stochastic trends can be defined in the framework of local linear trend as follows (Harvey & Koopman 2009, De Bonis & Silvestrini (2013):

$$\tau_t = \tau_{t-1} + \beta_{t-1} + \eta_t$$

$$\beta_t = \beta_{t-1} + \xi_t$$
(6)

In the equation (6), β_t symbolizes the stochastic slope. Trend is affected from both slope and irregular disturbances. η_t and ξ_t which their averages are zero and variances are σ_{η}^2 and σ_{ξ}^2 are independent and normally distributed error terms (De Bonis ve Silvestrini 2013). When $\sigma_{\xi}^2 = 0$, the slope becomes stable and trend decreases with random walk with drift. If $\sigma_{\xi}^2 > 0$ and $\sigma_{\eta}^2 = 0$, integrated random walk trend is obtained. The estimation realized by signal extraction will slowly change over time (Harvey & Koopman, 2009; Commandeur et al., 2011).

Stochastic cycle in equation (1) is stationary and it develops by following the bivariate AR (1) process below:

$$\begin{bmatrix} c_t \\ c_t^* \end{bmatrix} = \begin{bmatrix} 1 - \rho \cos \lambda_c L & -\rho \sin \lambda_c L \\ \rho \sin \lambda_c L & 1 - \rho \cos \lambda_c L \end{bmatrix}^{-1} \begin{bmatrix} \kappa_{1t} \\ \kappa_{2t} \end{bmatrix}$$
(7)

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In equation (7), κ_{1t} and κ_{2t} are the joint independent white noise terms distributed with the same variance (σ^2). ρ is damping factor and assumed $0 < \rho < 1$. λ_c which measures the cycle frequency in radians is considered as $0 < \lambda_c < \pi$ (Harvey & Koopman 2009, De Bonis & Silvestrini 2013). Based on the equation (7), cycle can be expressed as follows:

$$(1 - 2\rho\cos\lambda_c L + \rho^2 L^2)c_t = (1 - \rho\cos\lambda_c L)\kappa_{1t} + (\rho\sin\lambda_c L)\kappa_{2t}$$
(8)

Right side of the equation (8) is equal to MA(1) process. Thus the cycle, together with the root complex described below, defined as ARMA(2,1) process:

$$\left(1 - 2\rho\cos\lambda_{c}L + \rho^{2}L^{2}\right)c_{t} = \left(1 + \theta L\right)\kappa_{t}$$

$$\tag{9}$$

In equation (9), κ_t which its variance is σ_{κ}^2 is the white noise term. When $\theta = 0$, ARMA(2,1) representation will return to AR(2) cycle (De Bonis & Silvestrini 2013). In the light of these statements, alternative estimations can be made, such as, Harvey's (1989) local linear trend model, smooth trend model that based on the adoption of $\sigma_{\xi}^2 > 0$ and $\sigma_{\eta}^2 = 0$ and local linear trend model containing stochastic cycle that based on equations (7) and (9), and local linear trend model containing a stationary AR(2) component. It is also possible to estimate the combinations thereof (De Bonis & Silvestrini 2013). Which one of the different representations of the cyclical component will be prefered for the analysis is decided by estimating them separately and then looking at the diagnostic statistics of the obtained residue.

The impact of the credit gap on bank crisis can be analyzed by using the De Bonis & Silvestrini (2013) approach with logit models. The occurrence of banking crises can be defined as "1" and non-occurrence of banking crises can be defined as "0". In this binary response process, probability of occurrence of crises will be π_t and probability of non-occurrence of crises will be $(1-\pi_t)$. Logit model for π_t probability can be defined as follows:

$$\pi_{t} = \frac{\exp\left\{\alpha + \sum_{i=0}^{T} \beta_{i} c_{t-i}\right\}}{1 + \exp\left\{\alpha + \sum_{i=0}^{T} \beta_{i} c_{t-i}\right\}}$$
(10)

In equation (10), c_t is the credit gap, α and β are the coefficients.

In the first stage of analysis, credit gap will be estimated based on unobservable component model. In the second stage of analysis, alternative calculations of the credit gap will be made based on Hodrick-Prescott and Christiano-Fitzjerald filters and the alternative estimations will be compared. In the last stage, both systemic and all bank crises (systemic and non-systemic) will be analysed by Logit models where the most successful credit gap estimation compared to alternatives and its lags are the exogeneous variables.

4. Data

In the study, domestic credit to private sector % of GDP has been compiled from the World Development Indicators in the Worldank's official web site and comprised of annual data of the period 1960-2013. The systemic banking crises occurred in Turkey are based on the works of researchers such as Caprio & Klingebiel (1999, 2003), Laeva & Valencia (2008, 2010, 2012). According to these studies, in the 1982-1984 periods, three banks were merged with the largest public bank of Turkey "T.C. Ziraat Bankası" and additional resources have been transferred to this bank. The two big banks were also restructured during this period. In 2000-2001 periods two banks went bankrupt and 19 banks have been transferred to Savings Deposit Insurance Fund. Caprio & Klingebiel (1999, 2003) qualified the crisis occurred in 1994 as a small scale and "non-systemic". It has started as a currency crisis and has evolved to banking crisis. As a result, the three banks have been transferred to Saving Deposits Insurance Fund and the liquidation process has been initiated. Because of these three banks are medium and small scales, the realization of a systemic crisis was prevented. In addition to these, in 1997, another bank has voluntarily entered into liquidation process. In the study 1982-84, 1994, 2000-2001 periods are taken into account, 1997 which a single bank closed were ignored.

5. Result

First, stationaries of the data has been analysed by unit root tests. In this context, augmented unit root tests were calculated. Lag lengths were determined according to Schwartz information criterion. The summary results of the tests are presented in Table 1. The test showed that credit to GDP ratio is non-stationary. Therefore, test was repeated with the first difference of the variable and the differenced variable are valid for the level of 1%, ensure the stationary condition.

In equation (5), (6) and (7), Unobserved Component Model is estimated for alternative local linear trend models in the framework of Harvey and Koopman (2009), Commandeur et al. (2011). Diagnostic checking of these fitted models' residuals are presented in Table 2. Standard descriptive statistics were used in this table. In this context, standart error, normality test, Box-Ljung serial correlation test, log likelihood and coefficient of determination, R^2_D are calculated. Generally these diagnostics are successful. Obtained results have determined that LLT(S) + Stochastic Cycle model is better on reflecting the long term and cyclical properties of credit-to-GDP ratio in Turkey, compared to other models. Maximum likelihood (ML) estimation results of this model are given in Table 3- panel I.

	Intercept	Lag*	Intercept and Trend	Lag*
Credit/GDP	1.9212	5	0.1071	5
	[0.9998]		[0.9970]	
Δ (Credit/GDP)	-2.6290	3	-4.1870	4
	[0.0904]		[0.0066]	
Critical Values**				
1%	-3.493		-4.047	
5%	-2.889		-3.453	
10%	-2.581		-3.152	

Table 1: Augmented Dickey-Fuller Unit Root Tests

(*) Lags are calculated according to Schwarz information criterion.

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

			LLT(S)+	LLT +	LLT(S)
	LLT	LLT(S)	Stoch.Cyc.	AR(2)	+ AR(2)
Std. Error	2.810	3.224	2.708	2.800	2.824
Normality	19.137	23.185	18.093	19.799	21.604
Box-Ljung	6.159	10.667	4.597	9.094	7.862
Log. Likelihood	-55.000	-61.850	-53.171	-54.790	-55.251
R^2_D	0.285	0.058	0.335	0.289	0.277

 Table 2: Diagnostic Checking for Alternative Model Spesifications

Since there is a smooth trend and there is no irregular component in LLT(S) + Stochastic Cycle model, their variances are equal to zero. Damping factor is $\rho = 0.697$ and cyclical component can be assumed stationary. The period of the stochastic cycle is approximately 4.5 years. This period is very close to Turkey's average business cycle which is around five years.

Drehman et al. (2012) study in USA and some developed countries, De Bonis & Silvestrini (2013) study in Italy showed that the financial cycles in these countires ranged from 10 to 20 years. This period varies depending on the liberalization of the economy. Findings from Turkey do not conform to this pattern. As an emerging market, in Turkey where economic conditions are more variable and financial indicators have high volatility, it is normal that the stochastic cycle period to be short-term. During the period examined, Turkey has experienced more frequent financial crises compared to other countries. Therefore, level breaks and outliers in LLT(S) + Stochastic Cycle model were studied. Intervened model's estimates presented in Table 3 (panel II), the coefficient estimates of the breaks are presented in Table 4. Results in the Table 3 shows that the average of the stochastic cycle period reaches almost 9 years (8.96) but stationary value of the stochastic cycle of this new model is close to the first one. ($\rho = 0.720$). σ_{η}^2 decreased, σ_{ξ}^2 and σ_{κ}^2 increased compared to the first model. LLT(S) + Stochastic

Cycle model's trend and cyclical components with residuals analyses presented in Figure 1 and 2, Intervened Model's are presented in Figure 3 and 4.

Panel I - Base Mo	odel			
Variance estimati	ons			
	σ_{ϵ}^2	σ_{ξ}^2	σ^2	σ_η^2
Coefficients	0.000	1.524	1.215	0.000
q Ratios	0.000	1.000	0.7971	0.000
Parameter estima	tions			
	σ_{κ}^2	$2\pi/\lambda_c$	$\lambda_{ m c}$	ρ
Coefficients	2.365	4.535	1.386	0.697
Panel II- Interven	tion Model			
Variance estimati	ons			
	σ_{ϵ}^2	σ_{ξ^2}	σ^2	σ_{η}^2
Coefficients	0.000	1.051	1.644	0.000
q Ratios	0.000	0.643	1.000	0.000
Parameter estima	tions			
	σ_{κ}^2	$2\pi/\lambda_c$	$\lambda_{ m c}$	ρ
Coefficients	3.396	8.960	0.701	0.720

 Table 3: Parameter Estimates: LLT(S) + Stoch. Cyc.

 $\sigma_{\kappa}{}^2$ cycle variance, $2\pi/\lambda_c$ period, λ_c frequency, ρ damping factor



Figure 1: LLT(S) +Stochastic Cycle Model



Figure 2: LLT(S) +Stochastic Cycle Model Residuals



Figure 3: LLT(S) +Stochastic Cycle Intervention Model



Figure 4: LLT(S) +Stochastic Cycle Intervention Model Residuals

The results in Table 4 show that, there are significant outliers in 1983, 1994 and 2001. They are matched with the bank crises in 1982-84, 1994 and 2000-2001 periods. On the other hand, the significant level breaks were also determined in 1998 and 2009. 1998 was a year of considerable political difficulties in Turkey, but more importantly, there was a continued turmoil in the banking sector caused by medium scale "Turkbank" entering the liquidation process in 1997. After September 2008, Turkey has started to feel the effects of economic recession caused by the 2007-2008 Global Crises. Since there were not serious vulnerabilities in the banking system, this recession was short term and economy has entered a rapid recovery.

 Table 4: Estimates of Intervention Variables: LLT(S) + Stoch.Cyc.

	Coefficients	RMSE	t Tests	
Level breaks				
1998	-10.47226	2.07087	-5.05693	*

Credit-to-GDP gap in Turkey is also calculated by Hodrick-Prescott and Band-Pass filters. Then, as presented in Table 5, these with LLT(S) + Stochastic Cycle model and its intervened version were subjected to diagnostic checking. Within this framework, again conventional descriptive statistics, normality and serial correlation tests were used. The test results showed that the intervened model is

more successful compared with the alternative models. Figure 5 shows the course of alternative Credit-to-GDP gap measures.

	LLT(S) + Stoch.Cyc.	Intervention Model	HP Gap	BP Gap
Mean	0.021	-0.073	-0.201	-0.092
Std. Deviation	1.272	1.351	2.335	1.436
Skewness	0.534	-0.384	1.096	1.013
Kurtosis	1.974	-0.324	3.699	2.831
Jarque-Bera Test	10.071	1.565	36.973	24.244
	(0.007)	(0.457)	(0.000)	(0.000)
Normality Test	10.210	1.904	14.222	10.830
	(0.006)	(0.386)	(0.001)	(0.004)
Portmanteau Test	35.421	24.634	21.976	20.868
	(0.000)	(0.000)	(0.001)	(0.002)

Table 5: Diagnostic Checking for Alternative Credit-to-GDP Gaps



Figure 5: Alternative Credit-to GDP Gap Measures

In the last stage of the analyses, effect of the Credit-to-GDP gap obtained from the intervened model on all the banking crises and systemic bank crises experienced in Turkey is researched. Based on equation (10), contemporaneous and lagged logit estimation has been made and result of the most significant estimates is presented in Table 6. The results show that, with a consistent manner with the findings of De Bonis & Silvestrini (2013), in the models analyse both all the crises and systemic crises, one lagged credit gap and stationary are highly significant. It was also determined that the credit gap has a positive impact on the

entire banking crises in Turkey. However, financial cycle coefficient estimate is 0.98 in systemic banking crises and 0.8 in all crises which is well above than 0.5 that De Bonis & Silvestrini (2013) had found for Italy. Accordingly, 1% increase in the credit gap in t-1 time, will increase the probability of occurance of systemic banking crisis by about 10%, and the probability of any bank crisis occurance by 8%, in t time. These results indicate the credit gap can be used as an indicator of banking crises. Moreover, it might be an indicator that shows a stronger signal in an emerging economy.

6. Conclusion

In this study, credit-to-GDP gap estimation has been done by alternative models in Turkey as an emerging economy and the probability of this gap turning into a banking crisis has been researched. In this regard, all the experienced crises and specifically systemic crises have been studied. Findings show that, for Turkey, an unobservable component model in the structure of LLT(S) + Stochastic Cycle is more successful for estimating the credit gap than the alternatives. It's determined that the credit gap obtained from this model is explaining both systemic and nonsystemic bank crises with high significance. %1 increase in the credit gap increases the probability of systemic bank crisis by %10, probability of any bank crisis by %8 which can be considered high rates. On the other hand, the period of the financial cycle was determined to be about 9 in Turkey. This is slightly lower than the industrialized countries value of ten to twenty years. It is also longer than the business cycles in Turkey which is around 5 years. The results show that the credit gap can be use as an indicator of bank crises in emerging economies. Moreover, it might be an indicator showing a stronger signal compared to industrialized countries.

	All Crisis			Systemic Crisis		
	Coefficient	z-Statistic		Coefficient	z-Statistic	
constant	-2.3899	-4.3868	*	-2.7699	-4.0685	*
gap(-1)	0.8085	2.1413	**	0.9805	2.0768	**
McFadden R ²	0.1204			0.1565		
Log likelihood	-16.4635			-13.9693		
LR statistic (1 df)	4.5090	(0.0337)		5.1825	(0.0228)	
A.I.C.	0.6967			0.6026		
Total obs.	54			54		

Table 6: Probability of Banking Crisis in Turkey (1960-2013): Logit Model^(β)

 (β) Estimation method is ML - Binary Logit (Quadratic hill climbing) with QML (Huber/White) standard errors amd covariance.

The symbols (*),(**),(***) mean statistically significant at the 1 %, 5 % and 10 % levels, respectively.



Figure 6: Binary Choice (Logit) Model for Banking Crisis

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