TÜRKİYE CUMHURİYET MERKEZ BANKASI

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Abstract

Credit growth rate deviating from its long-run trend or equilibrium value holds importance for policymakers given the implications on economic activity and macro-financial interactions. In the first part of this study, the main aim is to construct indicators for determining the episodes of moderate-to-excessive credit slowdown and expansion by utilizing time-series filtering methods such as Hodrick-Prescott filter, Butterworth filter, Christiano-Fitzgerald filter and Hamilton filter over the time period 2007-2019. In addition to filtering choices, four different credit ratios (which are credit-to-GDP ratio, real credit growth, logarithm of real credit, credit impulse ratio) are included in the methodology to ensure the robustness. This framework enables one to generate monitoring tools for not only total loans, but also for financial intermediation activities with different loan breakdowns regarding type, sector and currency denomination. Moreover, industry-based dynamics of commercial loans are examined by using micro-level Credit Registry data set. In the following part, the credit cycle implied by macroeconomic dynamics are investigated by using factor-augmented predictive regression models. In this context, factors representing the global economic developments, banking sector outlook, local financial conditions and economic growth tendencies are created from large data set of 107 time series by utilizing principal component analysis. Analysis conducted for January 2009-April 2019 interval seems to be in line with exogenous shocks affecting the credit market in the corresponding period. To gain more knowledge about the predictive power of factor-augmented regression models, out-of-sample forecasting exercises are performed. It is found that global forces and economic activity provide substantial improvement in terms of predictive power over simple autoregressive benchmark models given low level of relative forecast errors.

Özet

İktisadi faaliyet ve makro-finansal etkileşimler dikkate alındığında, kredi büyüme oranlarının uzun vadeli eğiliminden ya da denge değerinden sapması politika yapıcılar açısından önem arz etmektedir. Bu çalışmanın ilk aşamasında Hodrick-Prescott, Butterworth, Christiano-Fitzgerald ve Hamilton filtrelerinin kullanıldığı zaman serisi analizleri yoluyla, 2007-2019 dönemi için aşırı kredi daralması ve genişlemesine işaret eden dönemleri takip eden göstergeler oluşturulmuştur. Filtreleme yöntemlerinin dışında sağlamlığı desteklemek için dört farklı kredi rasyosu (kredi/GSYİH oranı, reel kredi büyümesi, reel kredilerin logaritması, kredi etki oranı) metodolojiye dahil edilmiştir. Kullanılan yöntem çerçevesi toplam kredilere ek olarak, kredi türü, para birimi ve niteliği kırılımlarında finansal aracılık faaliyetlerinin sayısal takibine imkan sunmaktadır. Ek olarak, sektör bazlı ticari kredi dinamikleri Risk Merkezi mikro verisi kullanılarak analiz edilmektedir. Çalışmanın takip eden aşamasında, faktör eklenmiş regresyon modelleri kullanılarak makroekonomik ve finansal dinamiklerin ima ettiği kredi çevrimleri elde edilerek gerçekleşmelerle karşılaştırılmıştır. Faktörlerin oluşturulması adına küresel ekonomik gelişmeler, bankacılık sektörü görünümü, yurtiçi finansal koşullar ve iktisadi faaliyet dinamiklerini içeren 107 değişkenlik geniş bir veri setine temel bileşenler analizi uygulanmıştır. Ocak 2009-Nisan 2019 dönemine ilişkin bulgular modellerin ima ettiği kredi çevrimi ile gerçekleşmelerin seyrinin tarihsel olarak dışsal şokları yansıttığına işaret etmektedir. Faktör eklenmiş regresyon modellerinin açıklayıcılık gücü hakkında ek bilgiler elde etmek amacıyla tahmin egzersizleri yapılmıştır. Göreli tahmin hataları incelendiğinde, özellikle küresel gelişmeler ve yurtiçi iktisadi faaliyete ilişkin faktörlerin kredi çevriminin tahmininde baz modellere göre ek bilgi sağladığı gözlenmektedir.

JEL Classification: G21, E51, C38, C53

Keywords: Credit Cycle, Macroeconomic Dynamics, Filtering, Factor Models, Forecasting

Non-Technical Summary

Cyclical dynamics in financial intermediation activities holds importance for the course of economic activity in emerging markets. Particularly, in countries with banking sector-oriented financial structure, episodes characterized with drastic slowdown in credit allocation could hurt firm prospects, investment tendencies and economic growth. On the other hand, excessive credit growth periods are equivalently hazardous as it could lead to accumulation of financial risks, occurrence of asset price bubbles and emergence of current account imbalances. In fact, in the post-Global Financial Crisis era, constructed banking sector regulations on the global scale pay attention to some methods of quantifying the cyclical credit behavior.

In assessing the credit cycle dynamics, multiple parameters are crucial, as it is seen in the literature and practice. The statistical filtering method and credit ratio definition are two of such significant parameters. Our study aims to contribute to the existing literature by undertaking a comprehensive empirical analysis embodying four different time-series filters and four different credit ratios. In terms of aggregate banking sector analysis with nine credit sub-groups, we are able to monitor the moderate-to-excessive credit slowdown and expansion episodes in Turkey with monthly frequency for recent time period. Moreover, similar methodological framework is applied on sector-specific commercial loans retrieved from Credit Registry data to characterize the differentiation across sectors.

On the top of monitoring tasks, later parts of this study deal with predicting and forecasting credit cycle behavior in Turkey. To define the credit cycle level implied by macroeconomic and financial outlook, we utilize factor-augmented predictive regressions which summarize the informative content of a large data set. In particular, data set of 107 variables representing global economic developments, banking sector outlook, local financial conditions and economic growth tendencies are added to predictive models via principal component analysis. The relationship between in-sample fitted values and credit cycle realizations reflect the impact of exogenous shocks faced by our economic structure from historical perspective. Furthermore, out-of-sample forecasting exercises have yielded the conclusion that global and growth-related forces improve the forecasting accuracy in predicting credit cycle dynamics.

1. Introduction

Credit growth, as one of the prominent indicators to be monitored by the regulatory authorities, plays a critical role in macroeconomic dynamics of emerging markets. In the era of credit shrinkage, consumption and investment growth rates are expected to decline, and ultimately, leads to deceleration in economic activity and worsening in employment. On the other hand, excessive credit growth is expected to cause financial instabilities and macroeconomic imbalances such as bubbles in asset prices, deterioration in current account balance and inflationary pressures. The earlier studies in the literature of financial crisis also manifest that moderate-to-excessive credit expansion is associated with banking crisis episodes (Demirguç-Kunt and Detragiache, 1998; Borio and Lowe, 2002; Kaminsky and Reinhart, 1999; and Eichengreen and Arteta, 2002). In this context, regulatory authorities have been closely monitoring the abnormal credit developments. Particularly, in the aftermath of global financial crisis, excessive rise in credit use in emerging markets due to accommodative monetary policies in major central banks and drastic increase in capital inflows necessitated authorities to implement macro-prudential measures against credit booms.

For all these reasons, economists and policymakers have given particular attention to the determination of extreme movements in credits as well as equilibrium level of credit growth implied by macroeconomic fundamentals (Buncic and Melecky, 2013; Kiss et al., 2006; Jakubik and Moinescu, 2015; Drehmann et al., 2010). This is crucial in the sense that most policymakers are concerned with achieving credit growth rate being consistent with macro dynamics. For instance, for the countries that are in early phase of financial development, higher credit growth rates might not be sufficient given the fact that financial deepening process fundamentally requires even higher loan growth. And similarly, for others which have already had well-functioning financial markets, relatively low level of credit growth might be excessive.

The aim of this study is to create tools to determine the moderate-to-excessive credit growth or crunch periods for total loans and their breakdowns, e.g. commercial/consumer[1] and FX/TRY disaggregation, through implementation of econometric techniques. As a first

[1] Types of consumer loans used in this study are personal finance, vehicle and housing loans.

step, we are de-trending credit series by using statistical filters and obtain credit cycle realizations. Then, the boom/bust periods are determined by looking at the position of the cycle value with respect to the assigned certain threshold value. In the following step, we predict fair values for the cycle series of aggregate credits (and different types of credits) with macroeconomic variables via factor-augmented regressions. This will enable us to interpret the degree of compatibility between credit cycle realizations and what macroeconomic/financial fundamentals imply. As a last step of analysis, credit cycle is being forecasted with macroeconomic and financial factors.

The outline of the paper is as follows: In Section 2, we cover related literature by focusing on cycle measures, filtering techniques and widely used econometric methods. In Section 3, the methodology about cycle extraction, data compression technique (principle component), fair value estimation and out-of-sample forecasting framework are all explained. Section 4 presents the data concerning the credit indicators, several breakdowns of aggregate credits and macroeconomic variables used in the fair value estimations. In the following section, we provide and discuss the empirical results on de-trending, factor-augmented fair value regression models and forecasting exercises. In the final section, we will conclude the paper by summarizing the overall findings and policy implications derived from the paper.

2. Literature Review

Defining and quantifying financial cycle as a tool to monitor financial stability and direct macroprudential policies have been intensively focused in the finance and banking literature. In this section, we focus on the existing literature on credit indicators, filtering methodologies and macroeconomic determinants of credit indicators.

There exist several credit measures proposed in the literature so as to separate cyclical component from its trend. Calza et al. (2006); Eller et al. (2010), and IMF[2] (2004) utilize the level of real credit as an indicator for credit measure in their studies. While Utari et al. (2014) and Guo and Stepanyan (2011) prefer nominal credit growth rate in their boom-bust analyses, Elekdag and Wu (2011) use real credit growth rate as an indicator in their study

[2] Terrones, M., Mendoza E., Sutton Bennet.(2004). Are Credit Booms In Emergıng Markets A Concern?. IMF World Economic Outlook, April 2004: Advancing Structural Reforms, 147-166

on excess credit movements. Considering small sample size and the data with structural breaks, utilization of credit level and growth ratios have some drawbacks. To exemplify, if initial level of credit is small, the growth rate of credit level for the subsequent period may unusually high notwithstanding the credit measure returns its historical level in the following period. From the demand side perspective, the use of credit growth measures might be misleading if they do not taking into account the income levels of countries. In order to eliminate the abovementioned problems, several empirical studies propose aggregate credit level to be scaled by some macro level aggregates. In this case, the most preferred indicator is the ratio of credit level to gross domestic product (GDP) (Gourinchas et. al., 2001; Cottarelli et. al, 2005; Barajas, Dell'Ariccia, Levchenko, 2007; Dell'Ariccia et. al., 2016; Dell'Ariccia et. al., 2012; Ottens, Lambregts and Poelhekke, 2005; Castro and Martins, 2018; Hosszú et al., 2015; Kocsis and Sallay, 2018). Furthermore, Mendoza and Terrones (2008) focus on real credit per capita by scaling aggregate real credit by population, while Arena et al. (2015) suggest the logarithm of real credit per capita. In addition to these macro level aggregates, Kara and Tiryaki (2013, 2014) developed credit impulse ratio in order to comprise proper credit growth rate by using historical private loan growth paths for emerging economies. They propose the ratio of change in credit stock to GDP measure and exhibit it for Turkey in their research. With this calculation, stock credit data can be transformed into flow structure.

For seperating the cycle series from the trend series of the credit indicators mentioned above, there exist a variety of filtering methods in the literature. The most prominent methodology is Hodrick-Prescott (HP) filter developed by Hodrick and Prescott (1997) and further utilized by Hilbers et al. (2005), Drehman et al. (2010), Elekdağ and Wu (2011). Due to some drawbacks observed in the practice of HP filter such as sensitivity to smoothing parameter and end-point bias, some works in the literature choose to utilize other ones (Coşar et al., 2012). Hosszú et al. (2015), for instance, implement variety of univariate filtering methods such as HP, Christiano-Fitzgerald (CF), Beveridge-Nelson and complement their empirical approach with multivariate filtering methods such as multivariate HP filter in their studies on credit cycles. Furthermore, Kocsis and Sallay (2018) calculate credit-to-GDP gap by using multivariate HP method in terms of corporate, household and aggregate credits. In addition to these filtering methods, Schüler (2018) prefer Hamilton filter in his work for determining the de-trended credit-to-GDP ratio.

Another strand of the literature, related to abovementioned credit boom investigations, is estimating binary outcome models on a cross-country setting to analyze the impact of macroeconomic, global and banking sector-related variables on the probability of experiencing credit boom episodes. In this context, with logit models, Barajas et al. (2007) find that high inflation and bad quality banking supervision are coincided with credit boom episodes. Dell'Ariccia et al. (2016) estimate a probit model and show that stronger economic activity, surge in capital flows, financial reforms (liberalization) contribute to the probability of credit boom; while embracing flexible exchange rate regime and having less-oriented banking system are found to decrease the probability of booms. Arena et al. (2015) benefit from panel logit estimations to argue that capital flows, financial development and GDP growth increase the probability of credit booms, whereas global funding conditions (US Fed rate) and trade openness have negative impacts.

Third group of studies approaches the issue from equilibrium credit perspective. Kiss et al. (2006) analyze the long-run relationship between credit and GDP in Eastern European countries by using a system of equations and pooled mean group estimator. Guo and Stepanyan (2011) focus on a cross-country setup involving the estimation of credit growth rate with fixed effects panel regressions. Buncic and Melecky (2013) proceed with an error-correction form of ARDL model to determine the equilibrium credit level which is constructed with the inputs such as GDP, real interest rate, lending-deposit spread, inflation and cost of borrowing for banks by using pooled mean group estimator. Gersl and Seidler (2010) identify a similar framework by using financial development, GDP per capita and consumption to compose long-run equilibrium credit level, again by using pooled mean group estimator.

There is an extensive literature dealing with the determination of extreme and optimal credit cycles for advanced and emerging markets, whereas fewer studies exists for Turkish economy. As an early attempt to quantify credit gap developments, Binici and Köksal (2012) identify the phases of excessive credit movements in Turkish banking sector for the period covering December 2002-April 2012. Total credit extended in the sector is decomposed into cyclical part by utilizing three different indicators including credit/GDP ratio, nominal credit and real credit. Without resorting to statistical filters, Binici and Köksal (2012) employ 12-months moving average to isolate the deviations of amount of extended loans from the trend. Their results indicate that years like 2006, 2008 and 2011 are characterized by excessive credit movements. To complement their empirical investigation, they design binary variables taking value of 1 for identified episodes (in the first stage), and 0 otherwise. In the following step, they assess the impact of pre-selected global and local financial variables on the probability that credit dynamics display excessive movements. It is found that capital flows, US interest rates, real exchange rate and slope of the yield curve have statistically significant effects on credit cycle.

More recently, as an insightful study, Aydın and Yılmaz (2019) examine credit gap indicators for Turkish banking sector. In contrast to previous works for Turkey, this study implements univariate time-series filtering technique to calculate the credit gap indicators. Given the drawbacks of Hodrick-Prescott (HP) filter, they highlight the advantages of Hamilton filter, in terms of being independent of smoothing parameter determination and the ability to allow volatile trend structure, in the analysis. Their results show the existence of excess credit growth in the post-crisis period. The literature on the interaction between credit indicator and macroeconomic variables has evolved into three main categories. One group of studies in the literature is directly focusing on the credit boom episodes and provides descriptive measures about how macroeconomic variables behave around those accelerated credit dynamics. Hilbers et al. (2005) examine the average realizations of GDP, trade balance, inflation and current account around boom phases. Similarly, Dell'Ariccia et al. (2016) distinguish between boom and non-boom episodes of credit cycle by providing descriptive averaged economic performances in these two cases. Arena et al. (2015) apply event study analysis to examine the behavior of macroeconomic variables around the peak of credit boom episodes.

In our paper, we are choosing to use rather a flexible approach employing factor-augmented models. Instead of restricting our methodology to certain macroeconomic and financial variables, a broad data set incorporating 107 variables are pre-determined and the respective information is extracted through the application of factor models. Then, what this information implies is compared with credit cycle realizations through factor-augmented predictive regressions. This method is similar to equilibrium credit calculations (which we use rather loose term of fair value estimations) and it allows to identify credit cycle movements diverging from what local and global economic fundamentals imply.

3. Methodology

In this section, firstly, filtering methods for the extraction of credit cycle from its long-run trend are reviewed. Data compression technique applied on large macroeconomic/financial data set to form the factor-augmented regressions will also be discussed. In the last sub-section, forecasting framework utilized to assess predictive performance of macroeconomic/financial factors for credit cycle dynamics is explained.

3.1. Filtering Methods

We choose to proceed with four different statistical filters, namely HP filter, CF filter, Butterworth (BW) filter and lastly Hamilton filter. Use of multiple univariate time series filters is preferred to enhance the robustness of credit cycle calculation. HP filter, developed by Hodrick and Prescott (1997), has been widely used as a method in macroeconomic analysis to isolate smooth estimate of long-term trend, particularly with respect to business cycles. On the other hand, large number of empirical works use it to identify financial cycles determined by credit growth and asset prices[3].

Technically, two-sided HP filter technique is a frequency-pass filter taking the historic and future information on the time series into consideration. It assumes that a data series y_t can be separated into trend (τ_t) and cycle (c_t). In this context, HP filter computes the smoothed trend variable τ_t of y_t through minimizing the variance of original series around trend variable, which is also subject to a penalty term that contains the differenced values of τ_t. The difference between y_t and τ_t gives us the cyclical component termed as credit gap. By solving the following optimization of the loss function, HP filter can create de-trended series which is taken as an indicator of cyclical credit movements;

[3] Please see Harvey and Jaeger (1993), Kaiser and Maravall (1999), Canova (1998), Inklaar and De Haan (2001) for the applications in the case of business cycle; Borio (2014), Stremmel (2015) and Kollmann et al. (2011) for the applications in the case of financial cycle.

$$min_{\tau_1 \dots \tau_T} \sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} ((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2 \quad (1)$$

where λ stands for smoothing parameter. This parameter represents the ratio of the observed volatility in cyclical component over the volatility embedded in second difference of the trend component. While it takes values in $[0, \infty]$ interval, values closer to 0 corresponds to minimal cyclical movements in the series, and values closer to infinity are associated with the linear trend. Hodrick and Prescott (1997) recommends the value of 1600 as smoothing parameter for the quarterly data set. For this value, widely emphasizes the importance of the relationship between business cycle and credit cycle in terms of duration and the frequency to determine the smoothing parameter value. Ravn and Uhlig (2002) claim that the smoothing parameter can be adjusted accordingly by taking fourth power of frequency interval and multiply it with the basis lambda value of 1600[4]. In this manner, their calculation for the smoothing parameter is 129600. While this is the mainstream approach in treating the monthly data sets, there are some other values proposed for HP filter. For example, Drehman et al. (2010) use the value of 400000 for the smoothing parameter[5], since they assume that credit cycle is at least four time longer than the business cycle. They also utilize different smoothing parameters assuming the duration differential between business cycle and credit cycle. Consequently, the method of Ravn and Uhlig (2002) is employed for this study.

Even though HP filter is widely accepted methodology in the credit cycle literature, it has some deficiencies. For instance, there is no wide consensus on the optimal level of lambda as smoothing parameter. Moreover, the method is also remarkably sensitive to lambda parameter that can be subject to end-point bias. Therefore, we reinforce our empirical methodology by employing other filtering tools. CF filter is used as second tool in our study, which was introduced by Christiano and Fitzgerald (2003). Their work discusses optimal finite-sample approximations to the ideal band-pass filter and contains the description of

[4] In our case, we have data with monthly frequency. Standard lambda value is 1600 for quarterly frequencies. In order to calculate the smoothing parameter for monthly datasets, we need to multiply 1600 with 3^4, since frequency interval in a quarter is 3-months.

[5] If business cycle and credit cycle have the same length, smoothing parameter can be taken as the standard lambda value of 1600. In order to adjust smoothing parameter in accordance with the ratio of credit cycle length to business cycles length, we multiply fourth power of the ratio by 1600.

simple one-sided filtering. In particular, they argue that their filtering methodology provides an improvement over traditional HP filter, especially towards the end of sample period.

Unlike HP filter, CF filter formulates the de-trending optimization problem in frequency domain. As discussed by Christiano and Fitzgerald (2003)[6], in the hypothetical situation in which we are equipped with infinitely long data series, an “ideal” band-pass filter can be applied to extract cyclical component generated by stochastic cycles at the specified periodicities in a perfect manner. However, in finite samples, it would not be possible to conduct perfect frequency filtering. As explained by Nilsson and Gyomai (2011), CF filter overcomes this problem by approximating the ideal infinite band-pass filter. Although it has the simplifying assumption that underlying data series follow a random walk process, such an assumption is deemed to be reasonable given the empirical fact that many time series can be well-described by “random walk plus drift”. Furthermore, simulation evidence indicates that filter is performing well in the case that data generating process is not exactly random walk, but it exhibits “nearly random walk” tendencies. CF filter seems to have further advantages such as being designed to function well given larger classes of time series (compared to other band-pass filters such as the one outlined in Baxter and King (1999)), tackling the end-of-sample problem and converging to optimal filter in the long run (Nilsson and Gyomai, 2011).

Technically, CF filter composes the cyclical component by creating a weighting scheme applied to original data series as described in equation (2):

$$c_t = \sum_{j=-\infty}^{\infty} b_j y_{t-j} \tag{2}$$

where c_t, y_t and b_j represent cycle, original data series and weights respectively. The weights in the ideal band-pass filter are determined by the following processes in which p_l and p_h stand for minimum and maximum periods of the stochastic cycles of interest, respectively:

[6] In applying CF filter, we need to assign a minimum period as lower band and maximum period as upper band. In this study, 18 for the lower band and 120 for the upper band are determined as minimum and maximum periods, respectively.

$$b_j = \begin{cases} \pi^{-1}(\omega_h - \omega_l) & if\ j = 0 \\ (j\pi)^{-1}\{\sin(jw_h) - \sin(jw_l)\} & otherwise \end{cases} \tag{3}$$

where $\omega_l = 2\pi/p_l$ and $\omega_h = 2\pi/p_h$ represent the lower and higher cutoff frequencies.

Third filtering technique utilized in this study is Butterworth filter. This high-pass filter is also designed to disentangle cyclical component from trend component. One-sided version of it was introduced by Butterworth (1930) and is commonly employed in electrical engineering. The version of this filter as well as the computational procedure regarding econometric context is described in Pollock (2000). Its major difference from a closer counterparty Baxter-King filter is related to the de-trending properties. While Baxter-King filter depends on the de-trending properties of symmetric moving average filters whose coefficients add up to 0, Butterworth filter relies on de-trending properties influenced by filter's parameters itself.

Technically, filter has two parameters which are the cut-off frequency and the order of the filter denoted by Pollock (2000) which describe that the gain of the Butterworth high-pass filter can be expressed as follows:

$$\psi(\omega) = [1 + \left\{\frac{\tan(\frac{\omega_c}{2})}{\tan(\frac{\omega}{2})}\right\}^{2m}]^{-1} \tag{4}$$

In equation (4), *m* is defined as the order of the filter, $\omega_c = 2\pi/p_h$ is the cut-off frequency, and p_h corresponds to maximum period.

The model in this procedure represents the data series to be filtered,y_t, in terms of zero mean, covariance stationary as well as identically distributed shocks v_t and ε_t:

$$y_t = \frac{(1+L)^m}{(1-L)^m} v_t + \varepsilon_t \tag{5}$$

Within the framework of this model, Pollock (2000) demonstrate that the optimal estimate of the cyclical component is structured as in equation (6):

$$c = \lambda Q(\Omega_L + \lambda\Omega_H)^{-1}Q'y \tag{6}$$

where $var\{Q'(y-c)\} = \sigma_v^2\Omega_L$ and $var\{Q'c\} = \sigma_\varepsilon^2\Omega_H$. In this context, Ω_L and Ω_H are symmetric Toeplitz matrices with 2m+1 nonzero diagonal bands. They generate functions of $(1+z)^m(1+z^{-1})^m$ and $(1-z)^m(1-z^{-1})^m$ respectively.

The parameter λ can be defined as a function of maximum period of stochastic cycle that is being filtered out as well as the order of the filter:

$$\lambda = \{\tan(\pi/p_h)\}^{-2m} \tag{7}$$

The matrix Q' in this expression is a function of the coefficients in the polynomial $(1-L)^d = 1 + \delta_1 L + \cdots + \delta_d L^d$. It can be further shown that $\Omega_H = Q'Q$ and $\Omega_L = |\Omega_H|$. Thus, the extraction of cyclical component is transformed to be:

$$c = \lambda Q\{|Q'Q| + \lambda(Q'Q)\}^{-1}Q'y \tag{8}$$

The last statistical filter in separating cycle component of credit aggregates from their trend is Hamilton filter. As argued by Hamilton (2018), there are some drawbacks of HP filter. Firstly, HP filter is thought to produce cycle series with spurious dynamic relations with no meaningful attachment to data generating process. In other words, the cyclical components filtered out by HP method can contain richer dynamics including the high level of predictability from series' own lagged values since they are constructed as function of future values, while those components do not hint information regarding data generating process itself. The stock price series and consumption data are provided examples of such spurious relations in Hamilton (2018). Secondly, well-known end-point bias might be present which paves way for the substantial alterations of past estimates as new data is added to the end of sample. Last drawback is related to the determination of smoothing parameter in HP filter. Hamilton (2018) argue that smoothing parameter can be specified by using the Kalman filter to evaluate the likelihood function for the observed sample. In fact, for commonly studied macroeconomic series, this statistical formulation would produce parameter values that are opposing to the “rule of thumb” values employed in the literature.

As discussed by Schüler (2018), newly proposed method dealing with these isues is the Hamilton regression filter. Cyclical component is produced through an OLS regression of the observed time series y_t at date $t + h$ on a constant and four most recent lagged values as of date t. Then stationary cyclical component is obtained from the residuals as follows:

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + v_{t+h} \tag{9}$$

$$c_{t+h} = \hat{v}_{t+h} = y_{t+h} - \hat{\beta}_0 - \hat{\beta}_1 y_t + \hat{\beta}_2 y_{t-1} + \hat{\beta}_3 y_{t-2} - \hat{\beta}_4 y_{t-3} \tag{10}$$

3.2. Fair Value Estimations

Since our data set for tracking the banking sector conditions as well as local and global economic forces includes a large number of variables, standard least squares or other estimation methods seem to be infeasible given problems like multicollinearity and degrees of freedom. Considering the impact of this issue on inference, we choose to proceed with dimensionality-reduction technique.

Principal Component Analysis (PCA) is the most popular multivariate statistical method utilized for data reduction and size compression. Its aim is to extract the important information from a wide data set by expressing it as a set of new orthogonal variables called principal components. In this context, the factor representing the highest proportion of the total variation across variables is termed as first principal component which embodies the common movements. Technically, in PCA method, we identify the directions in the data with most variation (which are called eigenvectors) and project the data onto these directions.

PCA method handles this task by conducting spectral decomposition of the correlation (or covariance) matrix of the data. Let D represent the (pxp) correlation matrix to be analyzed. The eigen-decomposition of D can be illustrated as follows in which v_i terms represent eigenvectors (principal components):

$$D = V\Lambda V' = \sum_{i=1}^{p} \lambda_i v_i v_i' \tag{11}$$

$$v_i' v_j = \delta_{ij} \tag{12}$$

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0 \tag{13}$$

The widespread use of PCA method in financial economics and forecasting practices is discussed in Stock and Watson (2003), Bai and Ng (2007), Diebold and Li (2006) and Ludvingson and Ng (2009).

In this paper, this factor extraction procedure is applied to the large data set which covers the dimensions of global funding conditions/risk appetite, local financial situation, banking sector conditions and economic growth indicators, whose details are provided in Section 4.

After factors are produced, the fair value estimations are conducted for cyclical movements of aggregate credit growth ratios. To this end, a linear regression model is repeatedly estimated for each cycle indicator generated with varied credit growth definitions and different filters. Sample data for these regression estimations covers the period between January 2009 and April 201)[7]. The factor-augmented regressions specified in equation (14) are estimated by Ordinary Least Squares (OLS) with Newey and West (1986) heteroscedasticity and autocorrelation-consistent (HAC) errors. After the estimations, fitted values are obtained to compare with the realizations. Linear model specification can be described as follows:

$$\begin{aligned} C_t = \beta_0 + \beta_1 Banking_t + \beta_2 Global_t + \beta_3 Local\ Financial_t \\ + \beta_4 Economic\ Activity_t + e_t \end{aligned} \tag{14}$$

where C_t is credit cycle indicator and explanatory variables are the factors obtained from large data set of macroeconomic and financial variables.

It is known that real economic activity and aggregate credit fluctuations are closely linked through wealth effects and the financial accelerator mechanism as outlined in Bernanke

[7] This time interval is chosen given the data availability for factor construction.

and Gertler (1989), Kiyotaki and Moore (1997), Gilchrist and Zakrajsek (2008) among many others. During upturns of economic activity, better growth prospects improve borrowers' creditworthiness as well as the collateral values, which leads to robust supply of credit. In the case of downturns, the process is reversed with eventual depression in credit allocation.

The extension of credit is also naturally dependent on the internal conditions of banking sector. More specifically, liquidity, funding, leverage, asset quality and profitability all affect the credit extension capacity of banks in Turkey. The role of such dimensions in Turkish banking sector for credit creation is covered in studies like Binici and Köksal (2012), Alper et al. (2012) among others.

Banking sector in Turkey is characterized by closer connections with global economic factors since one of the most important funding source of credit activities in Turkish banking sector is cross-border bank liabilities. Considering that these types of cross-border bank liabilities have substantial sensitivities towards global factors such as risk appetite, policy uncertainties, liquidity conditions as well as monetary policy stance of advanced economies, we choose to combine local variables with the ones representing global forces (Cetorelli and Goldberg, 2011).

Lastly, the ability of banking sector to provide loans is associated with the local financial conditions. Cost of borrowing, exchange rate movements, risk premia developments, financial volatilities, bond yields and the course of stock markets are included with the local financial factor.

3.3. Forecasting Exercises

In order to evaluate the informative nature of economic and financial forces for credit cycle, we carry out pseudo out-of-sample forecasting experiments with expanding window strategy. In this context, initial estimation sample period is taken as January 2009-December 2014 and the models associating credit cycle with economic forces are estimated. Then, out-of-sample forecasts are produced for 6-months horizon including the period between January 2015 and June 2015. In the second step, estimation sample is extended by one month to cover January 2009-January 2015 to construct forecasts until July 2015. This procedure is repeated up to the end of whole sample (till April 2019).

To assess the relative predictive power of different factors, we utilize an incremental approach. In the first model, we augment the predictive regression with the factor representing the banking sector variables. Furthermore, second model incorporates the information related to global risk appetite, funding conditions and international economic developments. Third model is characterized with the factor tracking the local financial conjuncture, while fourth one includes the factor proxying local economic activity. On the other hand, last model stands as the most comprehensive one by spanning all the explanatory factors, corresponding to the broadest specification which is similar to the ones used in fair value estimations:

$$Model\ 1: C_{t+h} = \gamma_0 + \gamma_1 C_{t+h-1} + \gamma_2 Banking_t + e_{t+h} \tag{15}$$

$$Model\ 2: C_{t+h} = \gamma_0 + \gamma_1 C_{t+h-1} + \gamma_2 Global_t + e_{t+h} \tag{16}$$

$$Model\ 3: C_{t+h} = \gamma_0 + \gamma_1 C_{t+h-1} + \gamma_2 Local\ Financial_t + e_{t+h} \tag{17}$$

$$Model\ 4: C_{t+h} = \gamma_0 + \gamma_1 C_{t+h-1} + \gamma_2 Economic\ Activity_t + e_{t+h} \tag{18}$$

$$Model\ 5: C_{t+h} = \gamma_0 + \gamma_1 C_{t+h-1} + \gamma_2 Banking_t + \gamma_3 Global_t + \gamma_4 Local\ Financial_t + \gamma_5 Economic\ Activity_t + e_{t+h} \tag{19}$$

In this representation, C_t stands for credit cycle indicators obtained from BW, CF, HP and Hamilton filters applied on two credit ratios which are credit flow to GDP ratio and real credit growth rate (which are also the ones focused on sub-section 3.4) calculated for total loans, total commercial loans and TRY consumer loans. Hence, in total, 120 forecasting exercises with varied model specifications, filtering methods, cycle indicators and credit breakdowns are completed. In the equations (15) to (19), h symbolizes the forecast horizon up to 6 months ($h = 1, 2, 3, 4, 5, 6$) and e_t corresponds to the error term. In order to compare the forecast performance of the models, root mean squared error (RMSE) is used as a measure, as it is commonly preferred in the forecasting literature.[8] In this regard, relative RMSE statistics are calculated for each specifications in equations (20) to (21) with respect to baseline model which taken as AR model.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}({\zeta_i}^2)} \tag{20}$$

[8] Buchwalder et al.(2006), Wieland and Wolters (2013) and Ghysels et al. (2012) among others.

$$Relative\ RMSE = \frac{RMSE}{RMSE^*} \tag{21}$$

In equation (20), ζ_i refers to the differences between model predictions and realizations, while $RMSE^*$ indicates forecast errors of the base AR models.

4. Data

The selected credit indicators to be used for measuring the credit cycle series are credit to GDP, real credit growth, logarithm of real credit and credit impulse. As mentioned in the literature section, the ratio of total credit stock to GDP that is calculated in nominal term and natural logarithm of real credit are commonly used measures. Moreover, real credit growth that is measured by taking the annual growth rate of total credit in nominal terms divided by consumer price index is employed to identify credit cycle. Alongside with these three ratios, we utilize credit impulse ratio as a new indicator to define excessive credit movements in this study (Table 1).

Table 1: Description of Credit Ratios

Variables	Definition
Credit to GDP Ratio	The credit indicators are scaled with GDP.
Real Credit Growth	The credit indicators are adjusted by the CPI.
Logarithm of Real Credit	It represents the natural ogarithm of inflation adjusted credit indicators.
Credit Impulse Ratio	The difference in difference of credit stock which is scaled with GDP. (ΔCredit$_t$ - ΔCredit$_{t-1}$) / GDP

The aggregate credit data with breakdowns by loan type and currency denomination is derived from the Banking Regulation and Supervision Agency (BRSA) on a monthly basis for the period covered from 2007 to 2019 (Table 2). GDP data provided by TurkStat is retrieved quarterly and is transformed into monthly basis using interpolation technique developed by Fernandez (1981). In particular, our aggregate analysis comprises of the nine different credit breakdowns that are total banking sector loans (together with TRY and FX denomination sub-categorization), consumer loans along with vehicle and housing loans[9] as well as total, TRY and FX denominated commercial loans. Hence, 144 credit cycle

[9] The FX denominated consumer loans comprise considerably small amount of total loans. Therefore, they were excluded.

variables are obtained by the combination of four filtering methods and four credit ratios that are applied on these nine credit groups. [10]

Table 2: Summary Statistics of Aggregate Credits

Variables (Billion TRY)	Mean	St. Dev.	Min	Max
Total Loans*	959.1	537.9	232.4	1963
TRY Total Loans	703.4	433.5	153.7	1514
FX Total Loans*	255.6	107.2	78.6	454.9
Total Commercial Loans*	746.5	417.9	188.8	1544
TRY Commercial Loans	490.9	314.2	110.2	1106
FX Commercial Loans*	255.5	107.2	78.6	454.9
Total Consumer Loans	212.5	120.4	43.5	421.3
Housing Loans	98.4	57.6	21.0	200.3
Vehicle Loans	6.3	1.1	4.1	8.5

* The loans are adjusted for exchange rate effects.

Source: BRSA.

Together with the aggregate analysis, we calculate excessive credit movements on a sectoral basis by employing micro-level Credit Registry data provided by Bank Association of Turkey (Table 3). Credit Registry data encompasses the firm-level loan information including various categories such as currency, maturity and sectoral breakdowns. The data set involves the whole commercial loans universe provided by domestic banks as well as foreign banks operating through an intermediation of domestic banks. Due to unavailability of earlier data, the sample period covers 2007-2019, at monthly interval.

We use codes of financing issue, which are represented with 3-digit alphabetical characters, to aggregate firm-level data on sectoral-level. While first digit of financing issue codes exhibits the main industries such as manufacturing, utilities and construction, the second digit represents the sections of industries. The first aggregation procedure is formed for 2-digits corresponding to sub-sectors and, thereafter, with further aggregation we acquire the credit data of 16 main industries (see the Appendix). In order to adjust credit indicators against rapid depreciations, FX loans are calibrated to eliminate the impact of exchange rate changes.[11] Similar to aggregate analysis, same abovementioned credit ratios are considered for sectoral investigation.

[10] Four aggregate credit indicators were calculated for each of individual loan sub groups. Then, 16 credit cycle variables were generated by implementing HP filter, CF filter BW filter and Hamilton filter methods for each individual loans.

[11] In adjusting for exchange rate effects, we use a currency basket comprising USD and EUR with 70 % and 30 % weights, respectively.

Table 3: Summary Statistics of Sectoral Level Commercial Loans

Variables (Billion TRY)	Mean	St. Dev.	Min	Max
Agriculture and Forestry	38.7	27.4	5.4	93.3
Mining and Quarrying	12.6	9.1	2.3	33.8
Manufacturing	213.5	135.3	53.4	555.6
Utilities	59.4	58.0	2.0	217.4
Construction	81.9	68.4	9.1	249.8
Wholesale and Retail Trade	144.7	103.0	30.2	370.4
Hotel and Restaurants	30.3	24.2	4.5	92.6
Transportation and Communication	55.1	41.6	10.3	174.9

Source: Bank Association of Turkey.

After implementing filtering methods to extract cycle components as described in Section 3.1, we execute factor-augmented regression analysis to define excessive credit movements as well. Here, we define four factors which are related to banking sector, domestic financials, domestic economic activity as well as global risk and funding conditions. The data set for the domestic financial, economic activity, banking and global risk conditions contains 107 monthly time series (see the Appendix). Most of the global and financial variables are obtained from Bloomberg Terminal. The factor concerning banking sector data is derived from BRSA Monthly Bulletin. On the other hand, economic activity, foreign trade and employment data are retrieved from CBRT, BRSA and TurkStat databases. All non-stationary series are transformed to be stationary by taking difference or growth rates when needed. The data covers a period from the January 2009 to April 2019.

5. Empirical Results

In the first part of this section, the filtering results to obtain aggregate banking sector-level credit cycle indicators are presented. This analysis is not only performed for total loans, but also for several breakdowns depending on the loan type and currency of denomination. As a complementary analysis, cyclical dynamics are further investigated for commercial loans and sectoral-level cycle indicators are extracted from Credit Registry micro data. Following sub-section contains the findings for the interaction between credit cycle realizations at banking-sector level and macroeconomic/financial forces. In other words, we are exploring the role of local financial and growth factors as well as banking sector conditions and global forces in explaining the cyclical credit behavior in Turkish economy. In addition to gaining insights about in-sample fit of our factor-augmented predictive regression model, results in this part also enable us to reach fair value of de-trended credit indicators suggested by economic and financial conjuncture. Last sub-section indicates the results of conducted forecasting exercises.

5.1. Filtering Results

As it is discussed before, we choose to proceed with utilization of multiple filters in obtaining credit cycle to ensure robustness and benefit from the advantages of different filtering techniques. Together with several filters, inclusion of multiple ratios to track credit dynamics enables us to construct indicators to identify moderate-to-excessive credit slowdown and expansion. In particular, following results are based on four filters (HP, CF, BW and Hamilton) applied on four different proxy definitions (nominal credit to GDP ratio, credit flow to GDP ratio, logarithm of real credit and real credit growth rate) defined over nine different credit breakdowns. Hence, in total, 144 filtering tasks are performed.

After credit cycles are obtained, historical standard deviations of produced series are calculated. Another important point in filtering methodologies is the determination of threshold levels to categorize boom and bust periods. The general approach is to add / deduct a multiple of the standard deviation of the cycle to the trend and acquire the threshold for booms / busts. What values the standard errors are multiplied by differ across studies. While Mendoza and Terrones (2008) define the threshold as 1.75 times standard deviation of the gap. Elekdag and Wu (2011) use threshold of one times the cyclical standard deviation for busts and 1.55 times for booms. IMF[12] also define 1 standard deviation rule for determining the excessive real credit levels. Barajas et al. (2007) adopts relatively more conservative approach and proposes the threshold level as 0.75 standard deviation and the growth of credit to GDP ratio exceeds 5% simultaneously[13]. In our study, one standard deviation band for cyclical components of each credit indicator is assigned as a threshold value to define “moderate-to-excessive credit slowdown” and “moderate-to-excessive credit expansion”[14]. Chart 1 depicts one particular example of quantitative

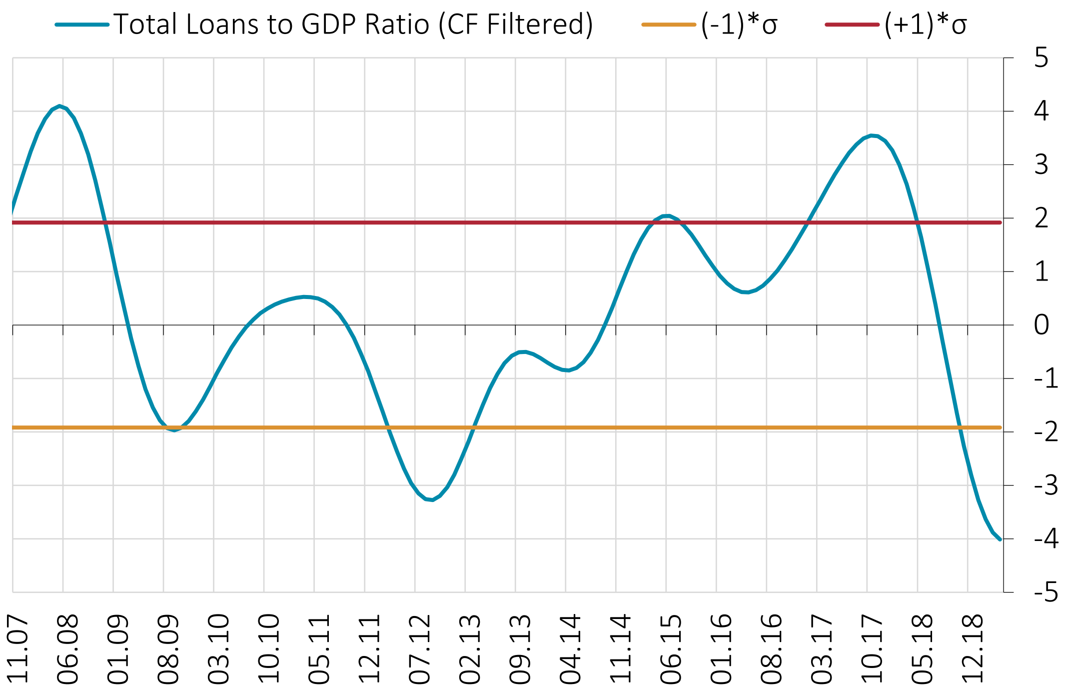
[12] Terrones, M., & Mendoza, E. (2004). Are credit booms in emerging markets a concern? IMF World Economic Outlook, 147-166.

[13] There are also some studies that identify thresholds as pre-defined and certain numbers or percentages. Gourinchas et. al. (2001) and BIS (2010) defines extreme credit period if the cycle exceeds the 2% of the credit-to-GDP Barajas et al. (2007) define if the credit-to-GDP increases more than 10 percent.

[14] To put it differently, if the value of credit cycle at a specified period is larger than the “plus one standard deviation” value of the whole cycle series, we conclude that this period can be associated with sizeable credit expansion. Similarly, if the cycle value stays below the “minus one standard deviation” value, we claim that dynamics are under the classification of considerable credit slowdown

assessment and categorization of historical episodes for which total loans to GDP ratio is preferred as credit measure and CF filter is the applied technique for de-trending.

Chart 1: An Example for Identification of Historical Credit Cycle Episodes



Source: BRSA, Authors' Calculations.

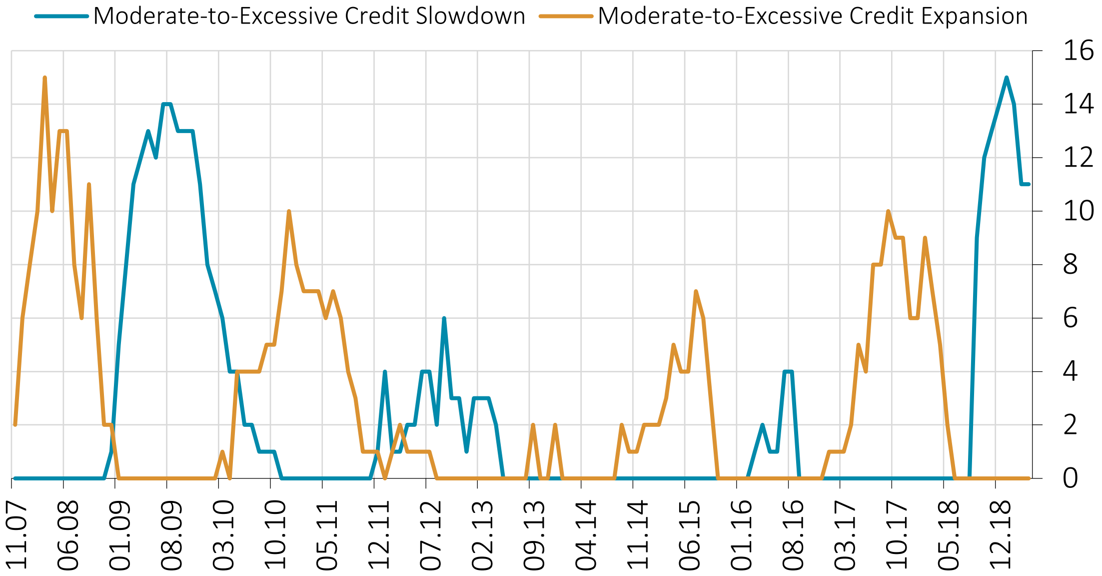
Chart 2 demonstrates the number of indicators pointing out the credit boom and bust phases for total loans, adjusted for FX effects. During the earlier periods of sample data, almost 14 out of 16 indicators exhibit moderate-to-excessive credit growth that can vastly be explained by the ongoing financial deepening process and overheating of financial markets in Turkey. With the outbreak of the Global Financial Crisis (GFC), it is know that outlook for credit facilities and domestic economic activity has been deteriorated severely; given the squeeze in external liquidity, surge in funding costs and depression in international commercial transactions [15]. Almost all of the indicators propose the occurrence of credit crunch in that particular time period. However, after GFC, coincided recovery in domestic and global economic activity becomes more visible. Implementation of unconventional monetary policies by monetary authorities in advanced countries has led

[15] Even though the symptoms of GFC have rested on the collapse of Lehman Brothers taking place in the second half of 2007, the direct impact of the crisis on Turkish economy and most of the emerging markets was detected with recessionary pressures in the third quarter of 2008.

to excessive liquidity flowing into emerging economies' financial systems. Relevant to these developments, easing in credit supply and demand for bank loans bounced back. During this period, number of indicators displaying moderate-to-excessive credit expansion has reached to level of 10, whereas positive tendencies of cycle dynamics had been sustained until the end of 2011.

Following this episode, macroprudential policies are introduced to restrain the considerable amount of current account deficit, overheating Turkish economy as well as unprecedented boost in credit allocation. In this context, with the utilization of policies such as reserve option mechanism, loan-to-value ratio, installment restrictions and reserve requirements; the momentum of excessive credit growth is decelerated, and thus, majority of the indicators do no hint excessive credit expansion during this time. On the other hand, from 2013 to 2016, a stable credit market has been observed where only a few number of indicators depict credit crunch. From the beginning of 2017 to the second half of 2018, new credit guarantees are introduced by the governmental authorities in coordination with Credit Guarantee Fund (CGF) as a counter-cyclical tool to support the economic activity. Banking system has extended nearly 300 billion TRY loans to non-financial corporations via this facility. Easier access to credit with the government-driven guarantees led to sizeable growth in commercial loans and almost 10 out of 18 indicators captured the significant credit expansion. Consequently, the turmoil occurred in local financial markets in mid-2018 is thought to cause worsening in credit conditions and number of indicators indicating excessive slowdown hiked to 15 in months.

Chart 2: Credit Cycle Results for Episodes of Moderate-to-Excessive Dynamics in Total Loans
(Number of Indicators)



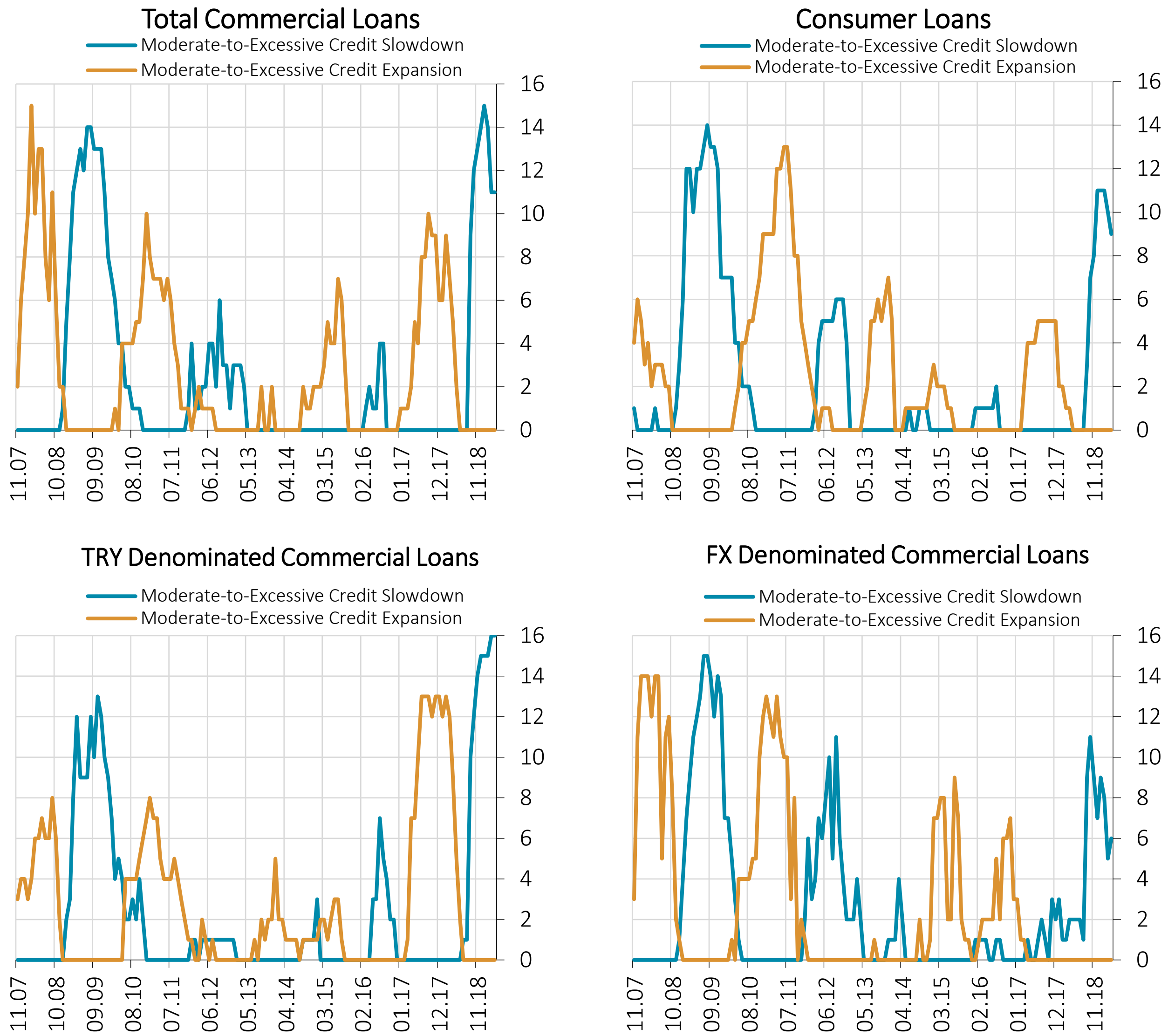
Source: BRSA, Authors' Calculations.

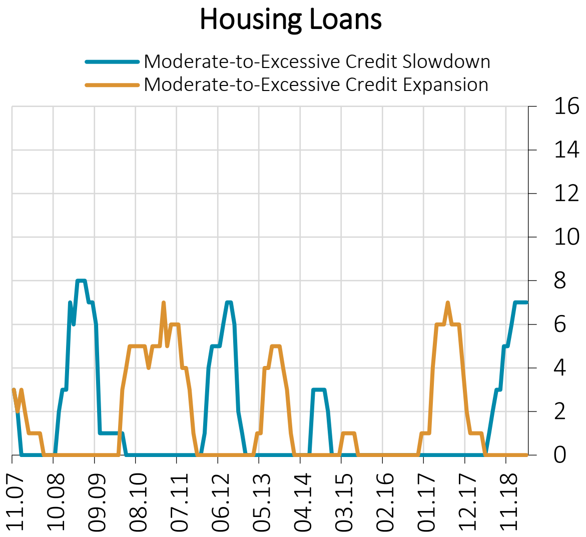
In order to classify credit cycle behavior in detail, we proceed with applying filtering methods on several breakdowns of total loans to obtain 16 indicators for each sub-category. Results belonging to some of those categories are depicted in Chart 3.

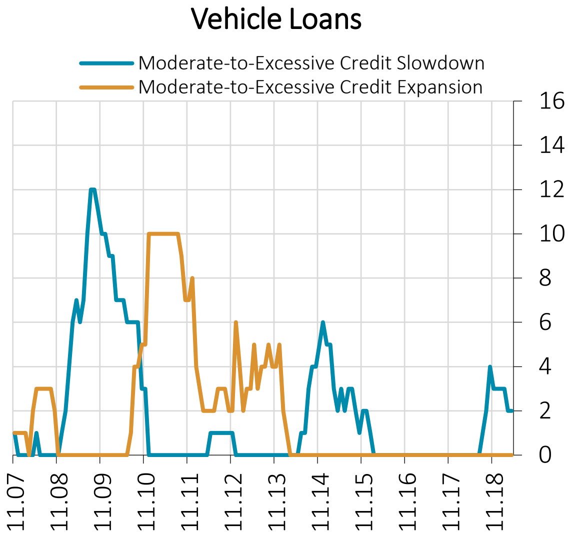
Extracted credit indicators for total commercial loans (adjusted for FX effects) and consumer loans appear to broadly capture historical trends. When we examine the dynamics in detail, we see that TRY-denominated commercial loans have accelerated after the introduction of CGF-related facilities to reverse the depressed economic activity in 2017. During that period, all indicators suggest the existence of moderate-to-excessive growth in loans. On the other hand, when FX commercial loans are considered, results somewhat differ from TRY commercial loans, especially towards the end of our sample. The time period pertaining 2017-2018 interval seems to be rather distinct episode in which FX commercial loan extension has been subject to great deal of volatility associated with recent regulations implemented to contain FX borrowing of corporates. Number of indicators showing credit bust has suppressed the level of 10 in that time period.

Towards the end of 2016, it is known that some incentives were provided for mortgage-financed house sales. Following this, there exists an upward trend in the cyclical behavior of housing loans, as demonstrated by the number of indicators for credit boom being reached almost to 8. Throughout the 2018, a sharp decline in mortgage-financed house sales is seen together with considerable increases in the interest rate of mortgage loans. In this context, almost 8 indicators depict the excessive slowdown in housing loans.

Chart 3: Credit Cycle Results for Episodes of Moderate-to-Excessive Dynamics in Different Loan Breakdowns
(Number of Indicators)





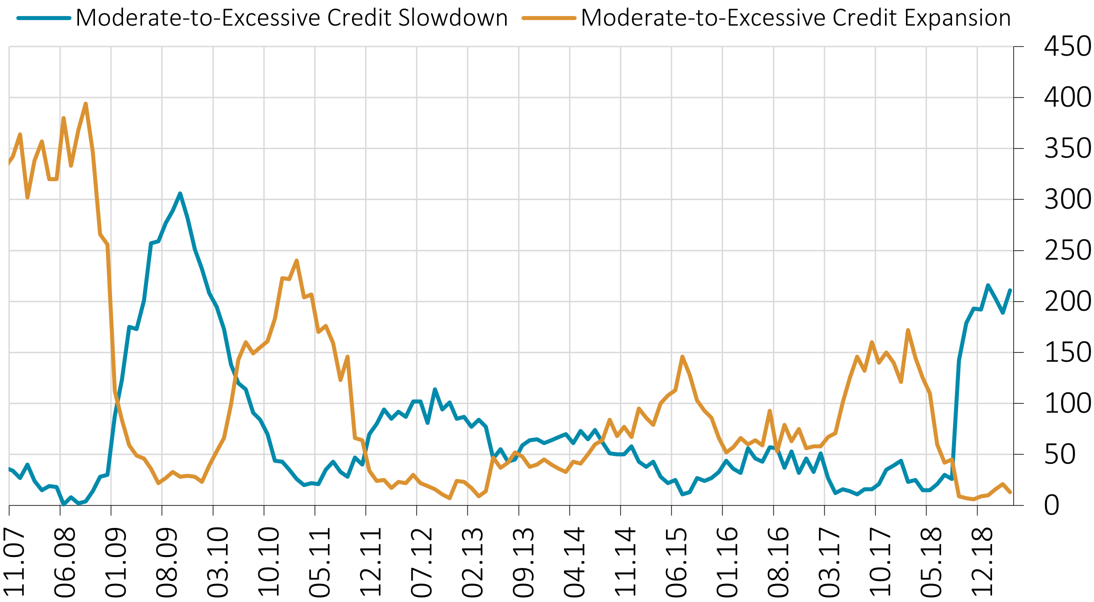


Source: BRSA, Authors' Calculations.

Apart from the aggregate analysis with several breakdowns, available data sets also allow use to decipher the sectoral-level commercial loan dynamics. In this way, we can provide quantitative tools to follow the credit developments particularly relevant to manufacturing, production and services sides of the economy. By using the empirical methodology similar to the aggregate analysis and the financing code classification of Credit Registry data, which is outline in Section 4, we obtain sector-specific credit cycle indicators. In particular, three filtering methods (HP, CF and BW) are applied to very same four credit gap ratios for 48 sectors and sub-sectors in 2-digit classification.[16] Hence, in total, 576 filtered credit indicators are produced. In the following step, again similar to aggregate analysis, credit boom and crunch episodes are identified under the scope of one standard deviation threshold rule defined from the historical time series of de-trended cyclical component of sectoral loans. Chart 4 demonstrates the number of indicators (out of total 576) pointing out "excessive-to-moderate credit slowdown" and "excessive-to-moderate credit expansion" episodes over the examine time period. The clustering of indicators seems to be compatible with overall economic outlook and to verify the pace of financial intermediation process from historical perspective.

[16] We discard the application of Hamilton filter just for the case of sectoral commercial loans from Credit Registry. This procedure is chosen since sectoral data is only available after 2007 and the use of Hamilton filter will cause the loss of some observations from the beginning of the sample period, in turn, diminishing the inference ability of our framework. Results do not change drastically when Hamilton filter is included in this analysis.

Chart 4: Clustering of Credit Cycle Results for Sectoral Commercial Loans
(Number of Indicators, 2-Digit Classification)



Source: Credit Registry, Authors' Calculations.

Earlier phases of sample period displays a robust tendency on the credit expansion front considering the rapid financial development during that period, especially in the case of banking sector. However, following the Global Financial Crisis, repercussions in domestic economic performance are experienced with global and local financial volatilities, erosion of market value in financial assets, sizeable hikes in credit risk and downturn in risk appetite leading less room for credit supply due to liquidity, funding, capital and profitability concerns. This process had also negative implications on loan demand across sectors given depressed fixed capital formation and weakened profitable investment opportunities. During this period, almost half of the indicators (306 out of total 576) signal moderate-to-excessive credit tightening.

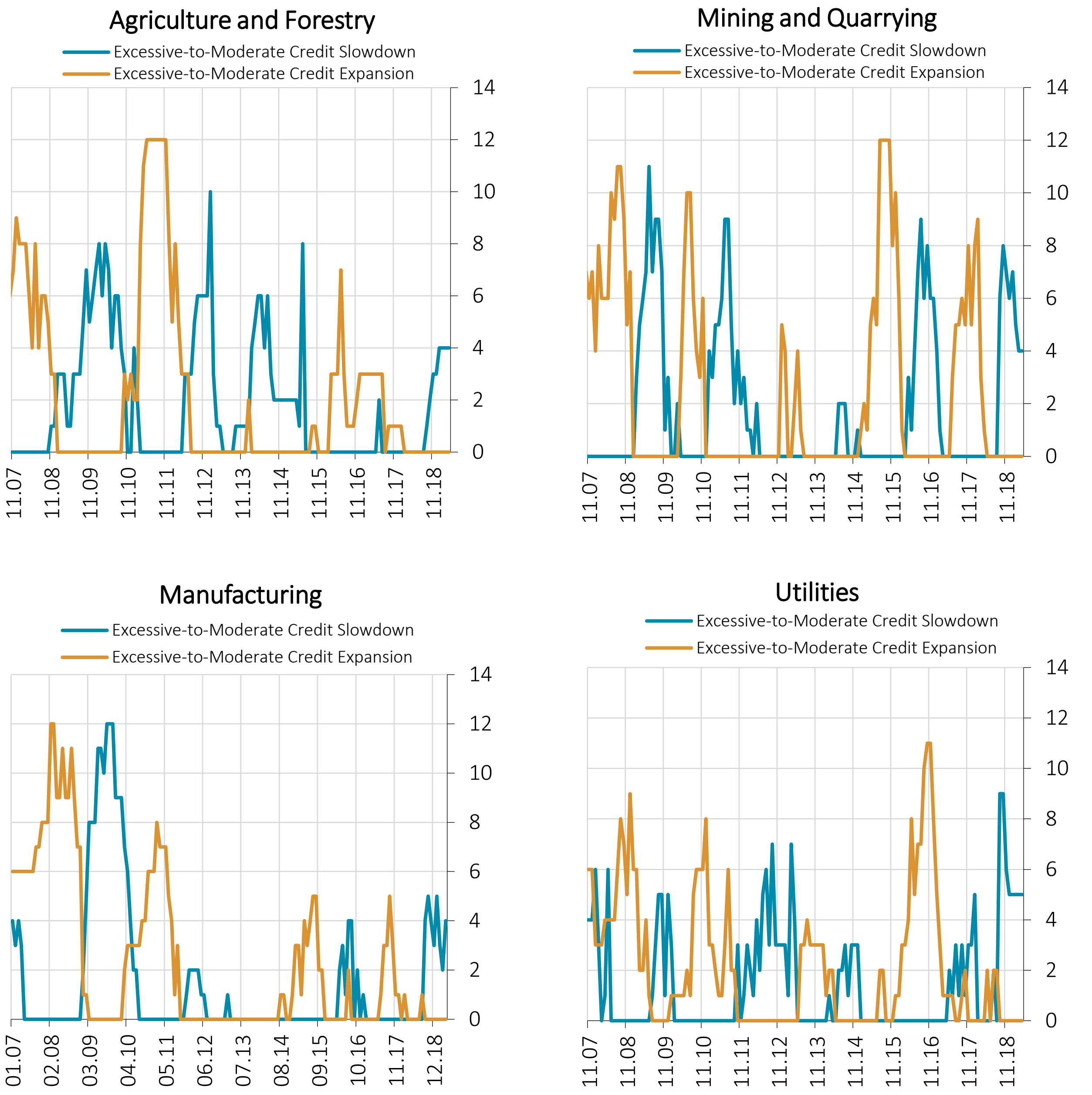
After this episode, the number of indicators hinting credit boom behavior seems to rebound again. It is argued that both loan demand and supply conditions have improved taking acceleration of economic growth performance into consideration. Quantitative easing programmes implemented by advanced economies and associated surge in capital flows to emerging markets are assessed to broaden the funding opportunities for banks to fuel local lending activities (Kara, 2015; Erdem et al., 2017). On the other hand, the number of sectoral indicators reflecting considerable credit growth declined in the following period on the back of normalization in economic activity towards historical trend and the utilization of set of macroprudential policies (Kara, 2016). More remarkably, our empirical tool appears to capture the recent adverse outlook in loan market as quantified by the number of credit bust indicators since the last quarter of 2018. Actually, number of excessive credit slowdown indicators has suppressed the level of 200, reaching to the levels comparable with crisis episodes.

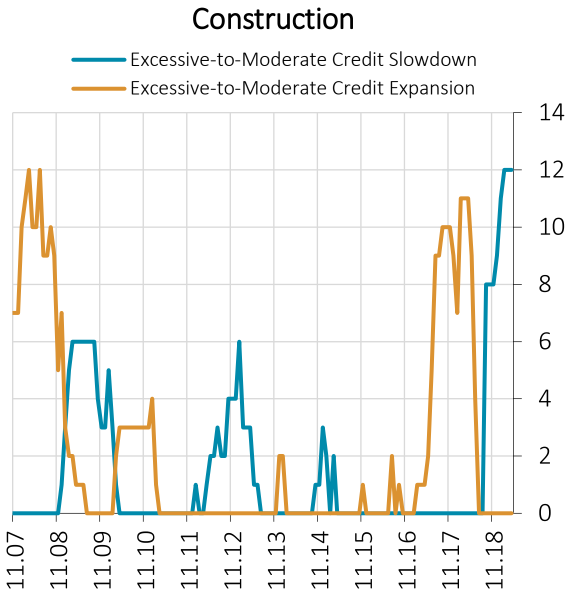
As a next step in our empirical analysis, in order to provide more plain insight, credit boom and bust indicators are also created for 16 sectors in 1-digit classification. Chart 5 shows the number of indicators depicting credit slowdown and expansion episodes for 8 prominent sectors. [17] Here, to exploit the informative nature of different ratios and filtering choices, we follow an empirical approach similar to aggregate analysis. Specifically, 12 indicators are calculated for all sectors in the form of three filters applied on four credit ratios.

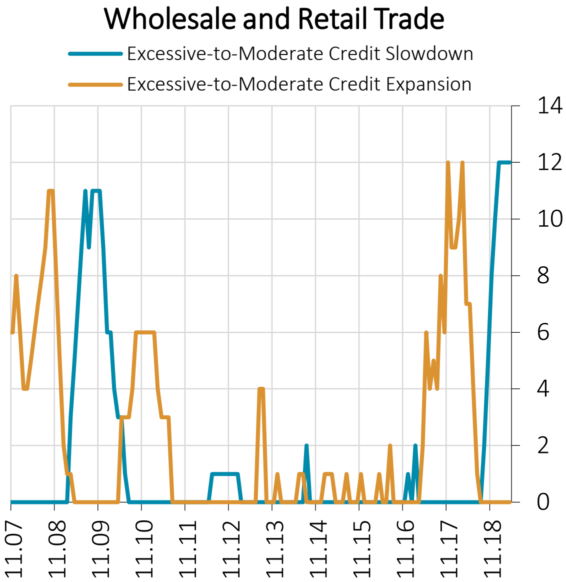
Results show that, during recent time, there exists a coincided weakening in commercial loans extended to prominent sectors as manifested by the hikes in the number of indicators signaling credit bust. The largest slowdown tendencies are observed for sectors such as construction, energy, wholesale and trade. Especially, the high share of FX debt in these sectors brings additional pressure on financial intermediation from supply side perspective. The tightening in credit supply for these sectors can be associated with the heightened credit risk due to the impairment of firm balance sheets caused by currency fluctuations and increasing financing expenses. While credit cycle indicators are presenting a tightening outlook for manufacturing industries, number of credit bust indicators is comparably less than other sectors, possibly thanks to the exporting capacity of this sector providing a buffer against decline in economic prospects.

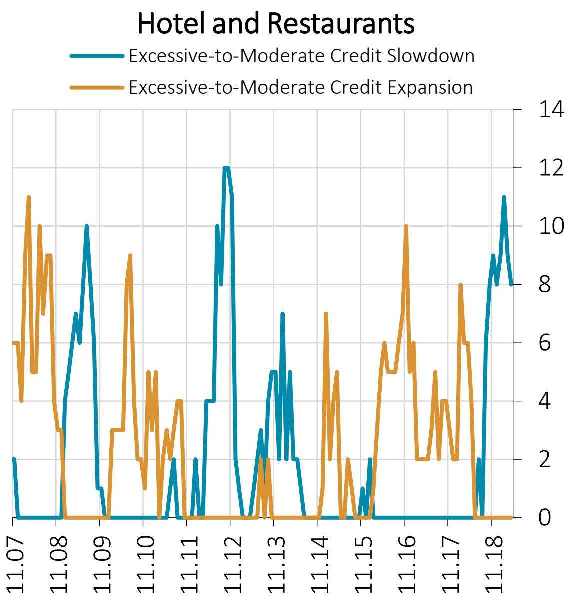
[17] Individual results belonging to other sectors can be provided by authors upon request.

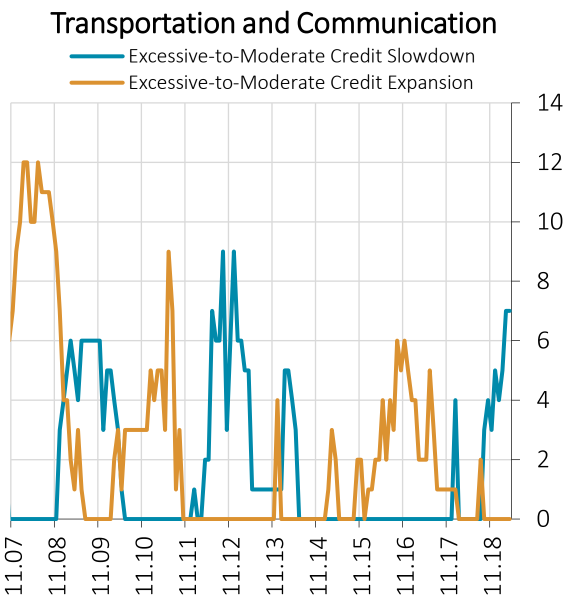
Chart 5: Individual Credit Cycle Results for Episodes of Moderate-to-Excessive Dynamics in 1-Digit Sectoral Loans
(Number of Indicators)











Source: Credit Registry, Authors' Calculations.

5.2. Fair Value Estimation Results

Given the multi-dimensional nature of our empirical framework, some descriptive information about in-sample fit of fair value estimations are provided before presenting fair value credit cycle tendencies implied by macroeconomic and financial factors. To this end, we specifically examine the in-sample predictive power of factor-augmented regressions by comparing the R-squared values with respect to choices of credit ratio definitions, statistical filtering methods and credit sub-categories. In addition to the descriptive statistics about differences in R-squared realizations across groups, we provide the results of parametric and non-parametric tests to enhance the arguments about heterogeneity regarding in-sample fit.

Filtering method to obtain credit cycle indicators seems to be associated with sizeable dispersion regarding R-squared values (Table 5). While predictive power of estimations involving CF and HP is somewhat concentrating on relatively low levels compared to other filtering methodologies as it is evident from the mean R-squared values. In fact, when Hamilton filter is chosen for cyclical identification, predictive regressions have the highest in-sample fit given the average explanatory power. To test the equality of R-squared means among four groups of models utilizing different filtering techniques, we perform multivariate test of means (which is the multivariate generalization of univariate t-test) and report Lawley-Hotelling trace test statistic. It is found that the heterogeneity across mean R-squared values is valid since we can reject the null hypothesis at conventional significance levels. Considering the fact that mean values can be affected by outliers and extreme observations, median R-squared values are also evaluated as another summary statistics. Median values are compatible with the findings that when BW and Hamilton filter are preferred, in-sample fit is better. To assess the differences of median R-squared values stemmed from varied filtering methods, we implement Kruskal-Wallis test which is the multiple sample generalization of Wilcoxon rank-sum test.

Table 5: Summary Statistics about R-square of Fair Value Estimations
(Classification Based on Filtering Method)

Method	Mean	Lawley-Hotelling Trace Test Statistic	p-value	Median	Kruskall-Wallis Test Statistic	p-value
HP	45.3	0.0517*	0.0693	44.1	8.3210**	0.0398
CF	41.1			28.6		
BW	46.6			45.4		
HM	53.3			54.6		

***, **, * represent statistical significance at 10%, 5% and 1% respectively.

Similar analysis is performed for ratio definitions used to extract credit cycle behavior (Table 6). When we consider the fair value estimations constructed with PCA factors, it appears that the inference is better in categories corresponding to definitions of real credit growth and credit impulse ratio. Here, the mean R-squared values for these two groups are considerably higher than others. Variation across credit definitions is statistically validated given the result of Lawley-Hotelling trace test statistic, pointing out the rejection of null hypothesis stating the equality of means. The median R-squared values obtained with real credit growth and credit impulse ratio show that the utilization of these ratio definitions in modeling credit cycle would result in cycle realizations compatible with macroeconomic and financial factors. Strong heterogeneity is further supported by the statistical significance of Kruskall-Wallis testing procedure.

Table 6: Summary Statistics about R-square of Fair Value Estimations
(Classification Based on Credit Ratio Definition)

Method	Mean	Lawley-Hotelling Trace Test Statistic	p-value	Median	Kruskall-Wallis Test Statistic	p-value
Credit to GDP Ratio	32.6	1.8856***	0.0000	29.6	92.2390***	0.0000
Real Credit Growth	69.1			73.1		
Logarithm of Real Credit	30.3			28.5		
Credit Impulse Ratio	54.2			54.6		

***, **, * represent statistical significance at 10%, 5% and 1% respectively.

Laslty, in-sample fit evaluation is done for different sub-categories depending on the type of the loans comprising the currency denomination and the purpose of loan usage (Table 7). Obtained mean values indicate that factor-augmented model is more successful in explaining credit cycle dynamics for sub-dimensions like total loans, TRY total loans, total commercial loans, total consumer loans and housing loans compared to other credit breakdowns. On the other hand, median values indicate somewhat similar picture as model predictions from these categories have higher R-squared statistics. Parametric and non-parametric tests are in line with the argument that there exists some degree of heterogeneity across credit breakdowns.

Table 7: Summary Statistics about R-square of Fair Value Estimations
(Classification Based on Credit Breakdown)

Method	Mean	Lawley-Hotelling Trace Test Statistic	p-value	Median	Kruskall-Wallis Test Statistic	p-value
Total Loans	50.7	2.8732***	0.0000	54.8	82.3890***	0.0000
TRY Total Loans	48.3			49.1		
FX Total Loans	41.5			45.6		
Total Commercial Loans	47.5			48.9		
TRY Commercial Loans	43.4			41.8		
FX Commercial Loans	41.5			45.6		
Total Consumer Loans	56.3			53.7		
Housing Loans	49.8			44.1		
Vehicle Loans	39.9			40.5		

***, **, * represent statistical significance at 10%, 5% and 1% respectively.

After covering the descriptive information about the in-sample fit of predictive regressions, we turn our focus on analyzing and interpreting the historical co-movements between actual and predicted credit cycle indicators. This will enable us to monitor the divergence between the fair values of credit cycle implied by macroeconomic factors and actual realizations during sample period. In Chart 6, fitted values constructed using all filtering methods are provided for total loans, total commercial loans and total consumer loans. Here, we restrict our analysis to two credit ratio definitions which are real credit growth and credit impulse ratio. [18]

In terms of the fitted values for the real credit growth definition, factor-augmented models appear to capture the cyclical movements in credit allocation from the historical perspective. When we focus on total loans, what local and global macroeconomic/financial conditions imply for credit cycle is broadly moving closely with realizations during crisis-related depression in financial intermediation activities as well as the post-crisis recovery period. However, in this context, there appears to be temporary periodical deviations of credit cycle realizations from model fitted values. Despite the fact that our large data set

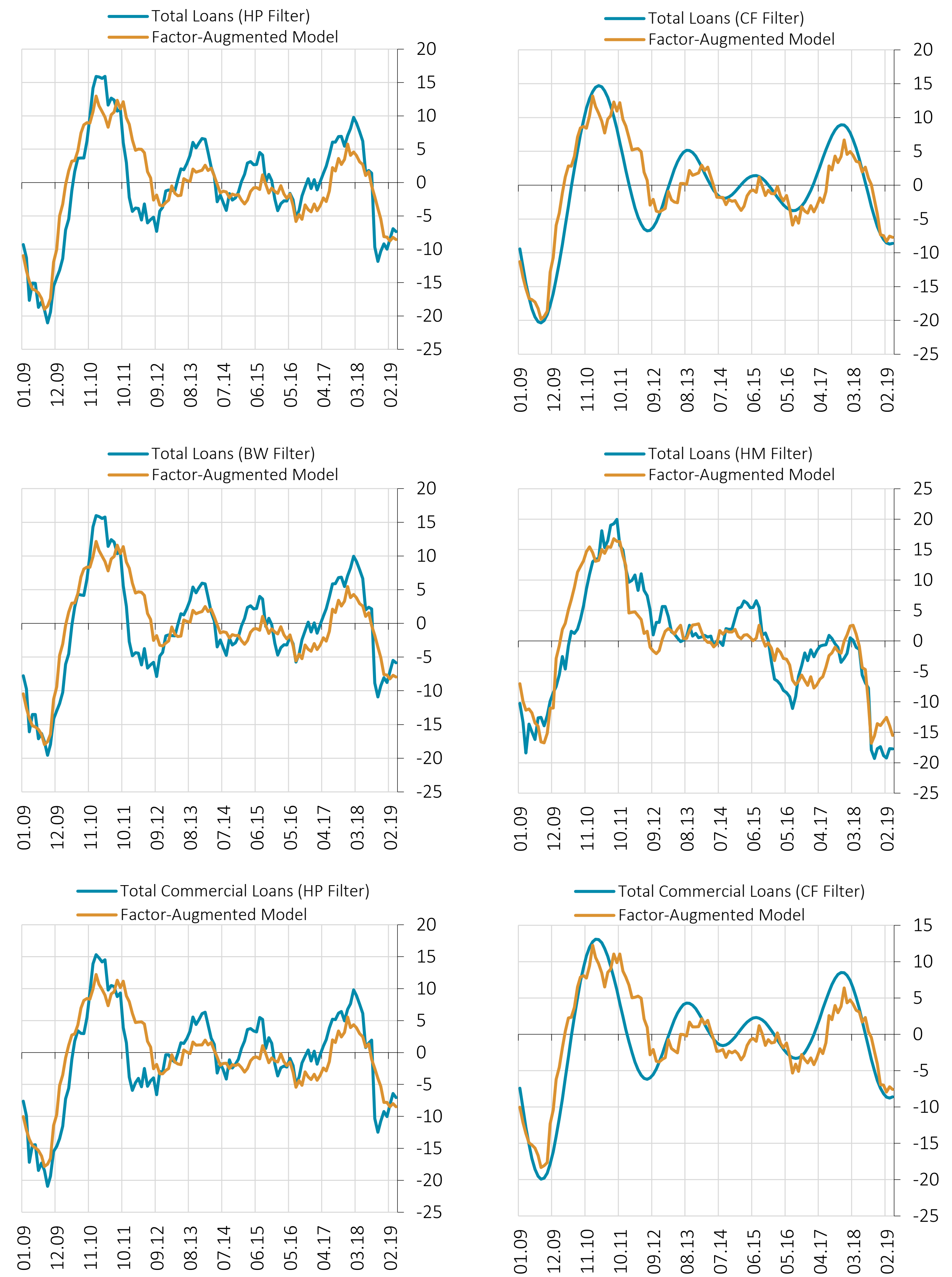
[18] Results belonging to other sub-dimensions like TRY total loans, FX total loans, TRY commercial loans, FX commercial loans, housing loans and vehicle loans as well as the results obtained from credit ratio definitons of credit-to-GDP ratio and logarithm of real credits can be provided by authors upon request.

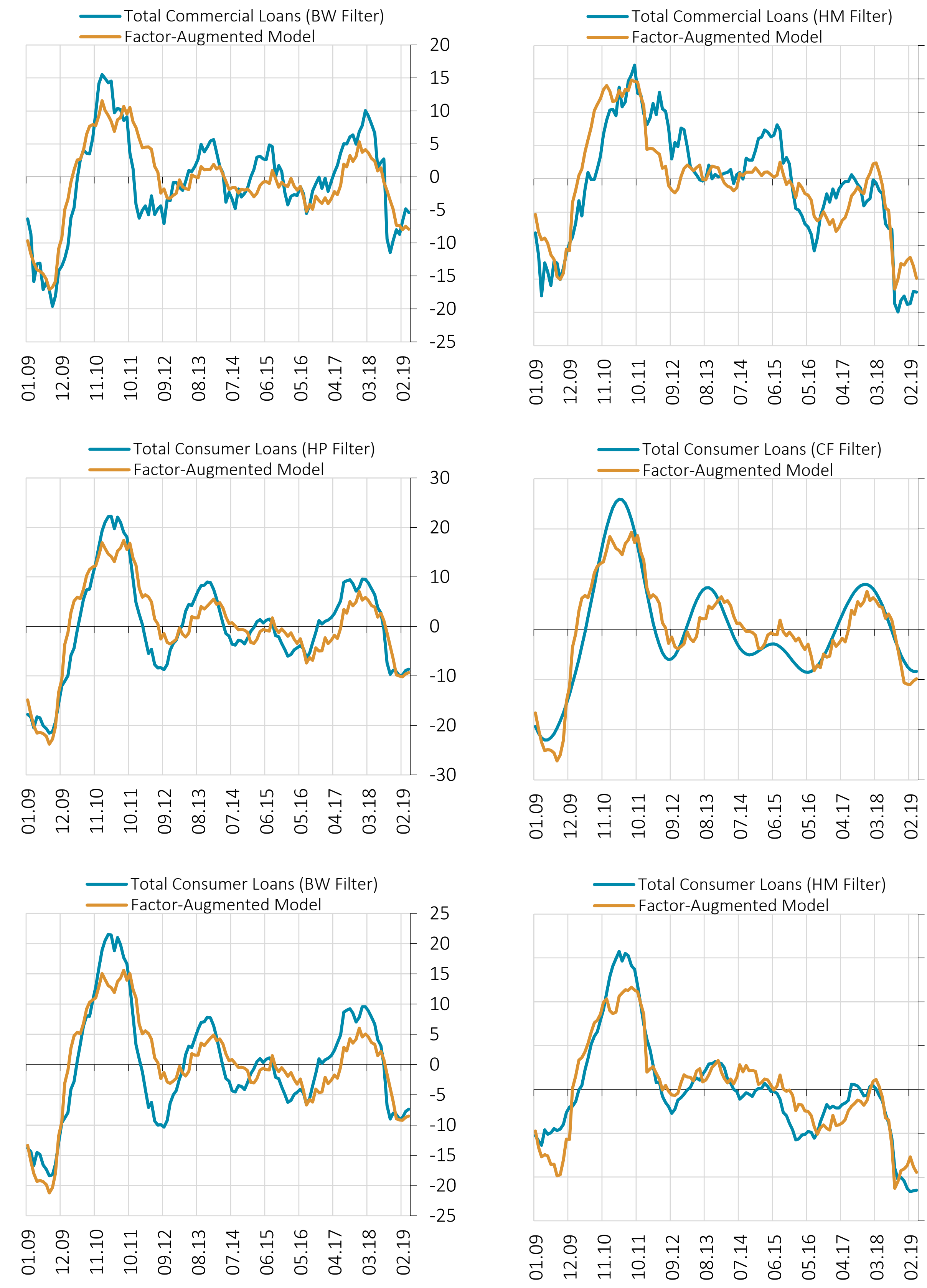
embodies the factor to control for banking sector conditions and peak-to-through movement in cyclical behavior in post-2011 period is captured by the predictive regression, the de-trended credit indicators stay below fitted values, probably reflecting the impact of introduction of macroprudential measures to sustain financial stability. This finding is not only specific to total loans, but also applicable to sub-categories of commercial and consumer loans. Moreover, factor-augmented model seems to be in line with the coincident worsening in credit supply and demand dynamics after 2016, mainly stemming from the local and international geopolitical events combined with the observed financial market volatilities.

However, as evident in Chart 6, model-implied credit cycle movements represented by total loans remain below the realizations, especially in 2017. This conclusion is thought to be associated with the pro-cyclical policy steps taken to improve the access to credit for real sector firms through credit guarantees by alleviating the collateral restrictions. The impact of such exogenous policy shocks cannot be captured by the model. This result is mostly same when when different filtering techniques are used, except for some cases of Hamilton filter. On the other hand, when further sub-categorization of credit breakdowns are considered, such a disaggregation reveals that the divergence is dramatically observed for loans denominated in TRY. In particular, the dispersion among model-implied and realized credit cycle is mostly seen in TRY commercial loans which point out the utilization of credit guarantee facilities regarding commercial loan category.

Abovementioned results are somewhat similar when we shift our focus to credit impulse ratio (Chart 7). The downward pressure on credit cycle and the ability of predictive regression to capture that effect is still evident. Albeit the closer co-movement in post-crisis recovery episode, the role of macroprudential measures is again influential given the fact that cycle realizations remain below the model-implied cycle dynamics. Lastly, more recent credit market related policy measures result in more amplified through-to-peak credit cycle dynamics. It should be further noted that, for this particular credit ratio definition, model implied values seem to perform poorly in terms of total consumer loans.

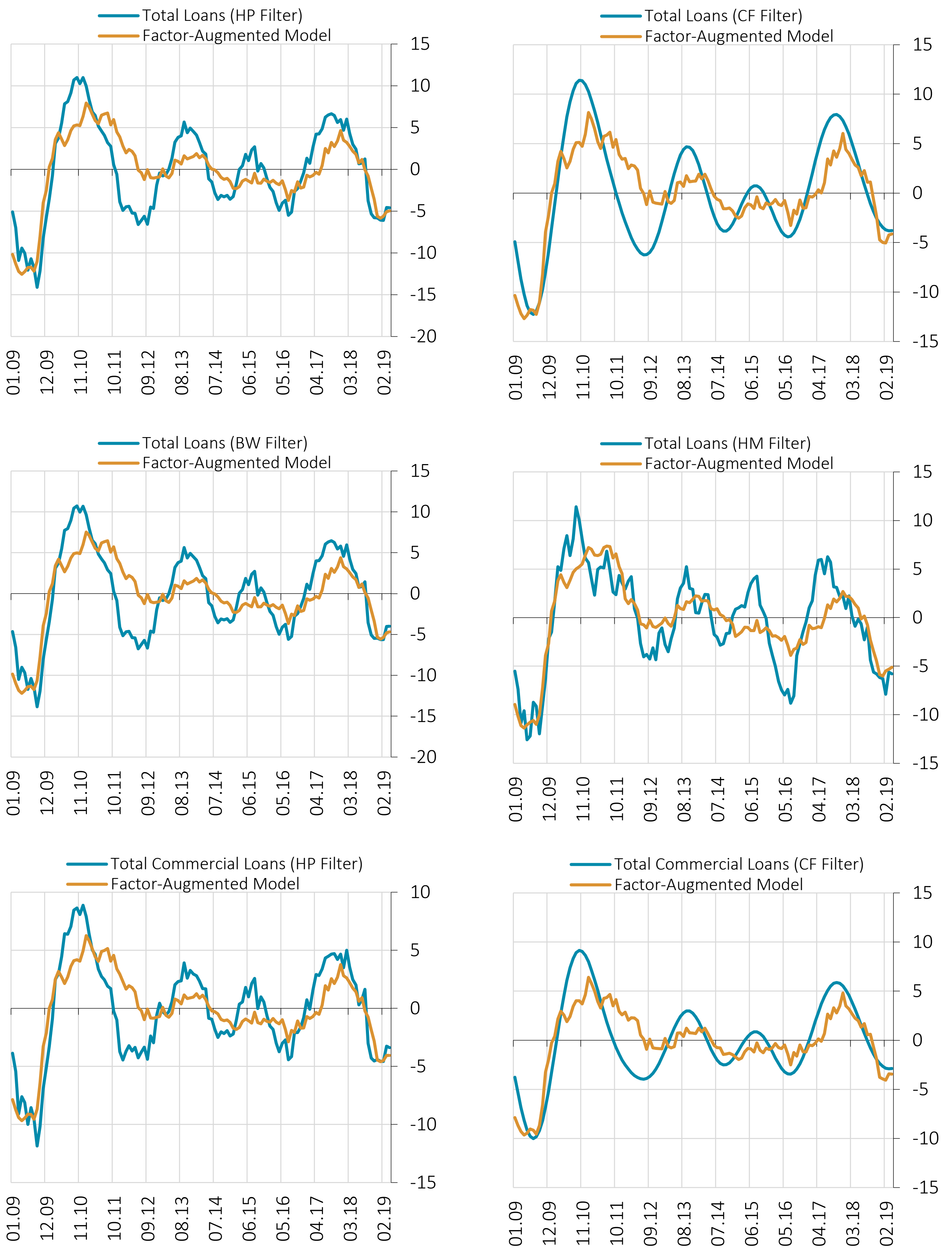
Chart 6: Fitted Values from Prdictive Regressions and Credit Cycle Realizations
(Real Credit Growth)

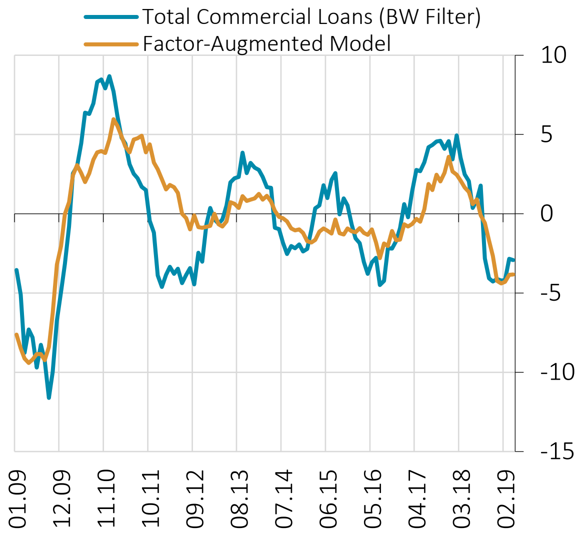


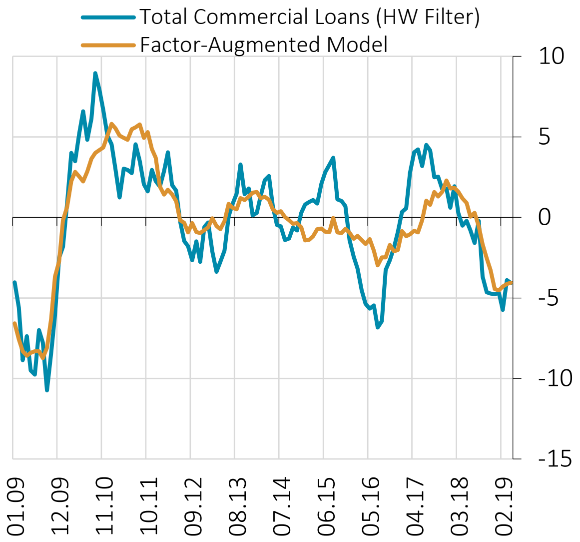


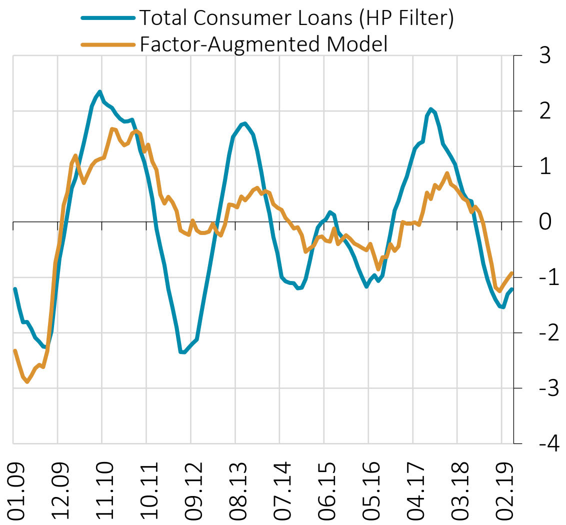
Source: Authors' Calculations.

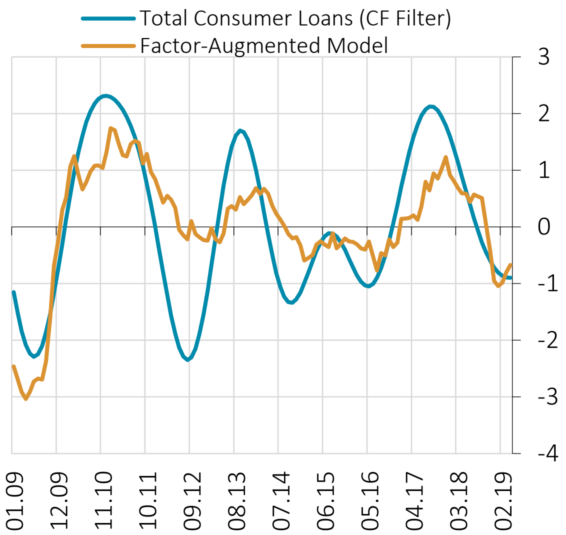
Chart 7: Fitted Values from Prdictive Regressions and Credit Cycle Realizations
(Credit Impulse Ratio)

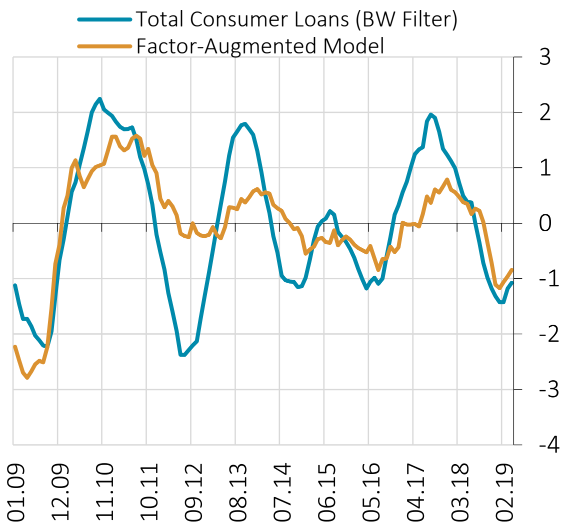


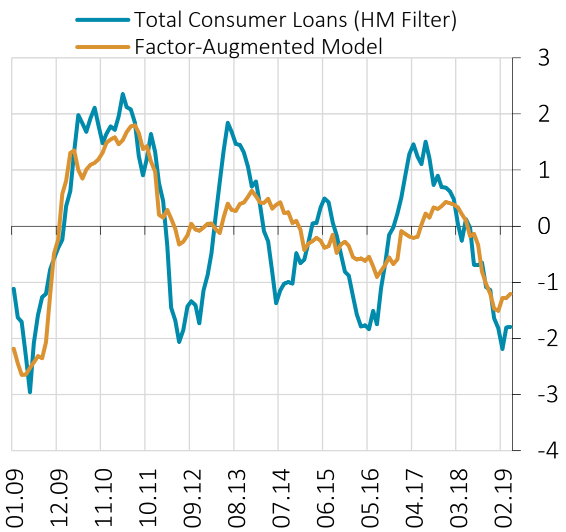












Source: Authors' Calculations.

5.3. Forecasting Results

The results of the forecasting exercises conducted for real credit growth rate indicator are given in Table 8. During the out-of-sample forecasting period, overwhelming majority of relative RMSE values are higher than unity for Model 1 including the banking sector conditions. This result does not change substantially when different credit breakdowns are considered or when de-trending procedure is based on varied filters, with few exceptions including the consumer loans with Hamilton filter. On the other hand, Model 2 incorporating the global factor is found to improve forecasting ability for all loan groups, regardless of the filtering method. This result is reinforced as forecast horizon enlarges. Largest forecasting accuracy on the top of baseline AR(1) model is achieved for consumer loans with CF filter. In fact, for this particular experiment, almost 30% decline in prediction errors is obtained compared to baseline model. Similar improvements are seen for total loans and commercial loans under different filtering strategies.

Results are mixed for the Model 3 involving local financial factor. Relative RMSE values in Table 8 display sizeable reduction in forecast errors for total, commercial and consumer loans given the condition that credit cycle is extracted with HP and Hamilton filter, while these findings are not robust for other filtering techniques. When local economic activity factor is considered with Model 4, informative nature of growth tendencies for credit cycle dynamics is revealed with lower than unity relative RMSE values in the case of HP and BW filters across all credit breakdowns. Similar to global factor-augmented model case, forecasting accuracy is enhanced as forecast horizon enlarges. These results further imply that the most profound upswing in forecast performance is seen when BW filter is applied on total commercial loans. Final panel of Table 8 provides results belonging to most comprehensive model specification. Here, it turns out that combining the inputs of all factors would result in successful forecast experiments across different credit categories and filters, except for few exceptions.

The robustness of this analysis is reviewed by applying same forecasting framework on another credit cycle definition with considerably well in-sample performance, which is credit impulse ratio (Table 9). In this context, the findings related to global factor and economic activity factor models stay mostly same, while forecasting performance is slightly diminished for local financial factor model.

Table 8: Relative RMSE for Forecasting Exercises with Real Credit Growth Rate

Model 1: Banking	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	1.016	1.039	1.072	1.121	1.175	1.234
Total Loans (CF Filter)	1.136	1.185	1.240	1.300	1.368	1.443
Total Loans (BW Filter)	1.017	1.041	1.077	1.130	1.188	1.253
Total Loans (HM Filter)	1.025	1.033	1.031	1.018	1.006	0.995
Total Commercial Loans (HP Filter)	1.007	1.016	1.028	1.052	1.079	1.108
Total Commercial Loans (CF Filter)	1.091	1.129	1.171	1.216	1.267	1.321
Total Commercial Loans (BW Filter)	1.008	1.017	1.030	1.056	1.085	1.117
Total Commercial Loans (HM Filter)	1.034	1.046	1.047	1.031	1.012	0.995
Total Consumer Loans (HP Filter)	1.088	1.185	1.316	1.470	1.645	1.842
Total Consumer Loans (CF Filter)	1.100	1.159	1.224	1.297	1.378	1.468
Total Consumer Loans (BW Filter)	1.095	1.202	1.346	1.519	1.716	1.940
Total Consumer Loans (HM Filter)	0.813	0.787	0.774	0.780	0.798	0.824
Model 2: Global	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	0.975	0.958	0.932	0.907	0.886	0.862
Total Loans (CF Filter)	0.876	0.857	0.842	0.830	0.821	0.814
Total Loans (BW Filter)	0.973	0.956	0.928	0.902	0.880	0.854
Total Loans (HM Filter)	0.970	0.953	0.934	0.920	0.909	0.899
Total Commercial Loans (HP Filter)	0.982	0.968	0.944	0.922	0.904	0.882
Total Commercial Loans (CF Filter)	0.895	0.877	0.864	0.854	0.847	0.842
Total Commercial Loans (BW Filter)	0.980	0.965	0.939	0.916	0.897	0.873
Total Commercial Loans (HM Filter)	0.976	0.960	0.943	0.929	0.921	0.913
Total Consumer Loans (HP Filter)	0.938	0.913	0.885	0.854	0.823	0.797
Total Consumer Loans (CF Filter)	0.771	0.753	0.737	0.725	0.715	0.706
Total Consumer Loans (BW Filter)	0.940	0.916	0.887	0.855	0.823	0.795
Total Consumer Loans (HM Filter)	0.948	0.932	0.915	0.897	0.883	0.871
Model 3: Local Financial	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	0.872	0.849	0.847	0.910	1.001	1.094
Total Loans (CF Filter)	1.078	1.093	1.106	1.119	1.138	1.163
Total Loans (BW Filter)	0.881	0.864	0.869	0.936	1.031	1.129
Total Loans (HM Filter)	0.837	0.766	0.709	0.691	0.693	0.701
Total Commercial Loans (HP Filter)	0.897	0.868	0.848	0.903	0.991	1.078
Total Commercial Loans (CF Filter)	1.056	1.072	1.088	1.103	1.125	1.152
Total Commercial Loans (BW Filter)	0.905	0.882	0.869	0.928	1.020	1.112
Total Commercial Loans (HM Filter)	0.882	0.818	0.759	0.741	0.747	0.755
Total Consumer Loans (HP Filter)	0.771	0.779	0.811	0.859	0.917	0.988

Total Consumer Loans (CF Filter)	1.067	1.063	1.056	1.051	1.052	1.058
Total Consumer Loans (BW Filter)	0.793	0.807	0.845	0.900	0.966	1.045
Total Consumer Loans (HM Filter)	0.671	0.616	0.580	0.564	0.562	0.576
Model 4: Local Economic Activity	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	0.969	0.934	0.899	0.852	0.809	0.771
Total Loans (CF Filter)	1.084	1.017	0.959	0.907	0.860	0.818
Total Loans (BW Filter)	0.963	0.926	0.890	0.844	0.805	0.769
Total Loans (HM Filter)	1.078	1.081	1.070	1.034	0.998	0.964
Total Commercial Loans (HP Filter)	0.969	0.936	0.904	0.855	0.811	0.772
Total Commercial Loans (CF Filter)	1.090	1.023	0.965	0.912	0.865	0.822
Total Commercial Loans (BW Filter)	0.961	0.924	0.889	0.841	0.798	0.762
Total Commercial Loans (HM Filter)	1.063	1.073	1.070	1.040	1.005	0.974
Total Consumer Loans (HP Filter)	0.980	0.951	0.918	0.885	0.854	0.825
Total Consumer Loans (CF Filter)	1.050	1.012	0.978	0.947	0.919	0.892
Total Consumer Loans (BW Filter)	0.981	0.961	0.938	0.914	0.892	0.871
Total Consumer Loans (HM Filter)	1.032	1.035	1.034	1.031	1.026	1.019
Model 5: All Factors	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	0.881	0.839	0.804	0.831	0.889	0.941
Total Loans (CF Filter)	0.908	0.931	0.954	0.977	1.002	1.030
Total Loans (BW Filter)	0.887	0.847	0.815	0.844	0.905	0.961
Total Loans (HM Filter)	0.849	0.783	0.731	0.694	0.667	0.644
Total Commercial Loans (HP Filter)	0.908	0.861	0.807	0.812	0.853	0.885
Total Commercial Loans (CF Filter)	0.893	0.912	0.931	0.951	0.974	0.999
Total Commercial Loans (BW Filter)	0.911	0.865	0.814	0.821	0.864	0.900
Total Commercial Loans (HM Filter)	0.892	0.834	0.784	0.748	0.724	0.703
Total Consumer Loans (HP Filter)	0.768	0.788	0.843	0.921	1.009	1.106
Total Consumer Loans (CF Filter)	1.046	1.069	1.087	1.104	1.124	1.146
Total Consumer Loans (BW Filter)	0.784	0.810	0.871	0.959	1.056	1.166
Total Consumer Loans (HM Filter)	0.714	0.679	0.662	0.663	0.670	0.688

Table 9: Relative RMSE for Forecasting Exercises with Credit Impulse Ratio

Model 1: Banking	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	1.059	1.104	1.166	1.245	1.331	1.427
Total Loans (CF Filter)	1.157	1.225	1.302	1.386	1.480	1.585
Total Loans (BW Filter)	1.055	1.097	1.156	1.232	1.314	1.407
Total Loans (HM Filter)	0.997	1.003	1.018	1.043	1.072	1.098
Total Commercial Loans (HP Filter)	1.040	1.065	1.103	1.161	1.222	1.290
Total Commercial Loans (CF Filter)	1.128	1.188	1.255	1.329	1.409	1.497
Total Commercial Loans (BW Filter)	1.038	1.061	1.096	1.152	1.211	1.276
Total Commercial Loans (HM Filter)	1.002	1.002	1.005	1.011	1.018	1.024
Total Consumer Loans (HP Filter)	1.108	1.180	1.267	1.365	1.476	1.599
Total Consumer Loans (CF Filter)	1.176	1.244	1.322	1.412	1.510	1.618
Total Consumer Loans (BW Filter)	1.097	1.165	1.250	1.346	1.453	1.570
Total Consumer Loans (HM Filter)	0.977	0.986	1.001	1.034	1.072	1.110
Model 2: Global	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**
Total Loans (HP Filter)	0.951	0.916	0.877	0.841	0.816	0.783
Total Loans (CF Filter)	0.888	0.861	0.839	0.816	0.795	0.774
Total Loans (BW Filter)	0.951	0.914	0.875	0.840	0.814	0.781
Total Loans (HM Filter)	0.944	0.900	0.871	0.847	0.830	0.805
Total Commercial Loans (HP Filter)	0.958	0.920	0.877	0.840	0.814	0.778
Total Commercial Loans (CF Filter)	0.879	0.851	0.828	0.806	0.784	0.763
Total Commercial Loans (BW Filter)	0.957	0.920	0.876	0.838	0.813	0.776
Total Commercial Loans (HM Filter)	0.951	0.908	0.877	0.854	0.840	0.817
Total Consumer Loans (HP Filter)	0.952	0.931	0.907	0.882	0.860	0.839
Total Consumer Loans (CF Filter)	0.926	0.903	0.882	0.865	0.845	0.828
Total Consumer Loans (BW Filter)	0.952	0.929	0.907	0.881	0.857	0.836
Total Consumer Loans (HM Filter)	0.930	0.889	0.861	0.842	0.826	0.806
Model 3: Local Financial	**h=1**	**h=2**	**h=3**	**h=4**	**h=5**	**h=6**
Total Loans (HP Filter)	0.978	0.993	1.038	1.085	1.141	1.197
Total Loans (CF Filter)	1.203	1.215	1.224	1.231	1.239	1.248
Total Loans (BW Filter)	0.984	1.004	1.055	1.106	1.167	1.228
Total Loans (HM Filter)	0.970	0.953	0.955	0.960	0.979	0.993
Total Commercial Loans (HP Filter)	0.976	0.980	1.014	1.057	1.112	1.165
Total Commercial Loans (CF Filter)	1.178	1.186	1.193	1.198	1.204	1.211
Total Commercial Loans (BW Filter)	0.981	0.990	1.030	1.077	1.136	1.194
Total Commercial Loans (HM Filter)	0.967	0.943	0.943	0.948	0.969	0.985
Total Consumer Loans (HP Filter)	1.069	1.095	1.130	1.172	1.222	1.273
Total Consumer Loans (CF Filter)	1.271	1.292	1.306	1.322	1.336	1.351
Total Consumer Loans (BW Filter)	1.079	1.108	1.152	1.199	1.255	1.311
Total Consumer Loans (HM Filter)	1.040	1.022	1.000	0.981	0.979	0.976

Model 4: Local Economic Activity	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	**0.999**	**0.996**	**0.991**	**0.982**	**0.972**	**0.963**
Total Loans (CF Filter)	**0.992**	1.007	1.022	1.037	1.053	1.069
Total Loans (BW Filter)	**0.998**	**0.995**	**0.990**	**0.981**	**0.971**	**0.962**
Total Loans (HM Filter)	1.075	1.068	1.038	**0.989**	**0.944**	**0.901**
Total Commercial Loans (HP Filter)	**0.989**	**0.980**	**0.971**	**0.949**	**0.929**	**0.908**
Total Commercial Loans (CF Filter)	1.002	1.009	1.016	1.024	1.032	1.040
Total Commercial Loans (BW Filter)	**0.988**	**0.980**	**0.970**	**0.949**	**0.930**	**0.910**
Total Commercial Loans (HM Filter)	1.103	1.100	1.057	**0.983**	**0.917**	**0.860**
Total Consumer Loans (HP Filter)	**0.987**	**0.998**	1.010	1.023	1.038	1.054
Total Consumer Loans (CF Filter)	**0.957**	**0.981**	1.005	1.032	1.059	1.085
Total Consumer Loans (BW Filter)	**0.991**	**0.998**	1.010	1.021	1.034	1.048
Total Consumer Loans (HM Filter)	**0.997**	**0.998**	1.001	1.008	1.014	1.020

Model 5: All Factors	h=1	h=2	h=3	h=4	h=5	h=6
Total Loans (HP Filter)	**0.949**	**0.915**	**0.904**	**0.917**	**0.947**	**0.970**
Total Loans (CF Filter)	**0.942**	**0.970**	**0.997**	1.022	1.047	1.071
Total Loans (BW Filter)	**0.953**	**0.921**	**0.913**	**0.928**	**0.959**	**0.984**
Total Loans (HM Filter)	**0.979**	**0.945**	**0.916**	**0.884**	**0.864**	**0.838**
Total Commercial Loans (HP Filter)	**0.965**	**0.927**	**0.896**	**0.886**	**0.897**	**0.898**
Total Commercial Loans (CF Filter)	**0.924**	**0.943**	**0.962**	**0.979**	**0.996**	1.012
Total Commercial Loans (BW Filter)	**0.968**	**0.933**	**0.904**	**0.896**	**0.909**	**0.913**
Total Commercial Loans (HM Filter)	1.021	1.001	**0.969**	**0.919**	**0.885**	**0.848**
Total Consumer Loans (HP Filter)	**0.991**	1.042	1.106	1.183	1.268	1.356
Total Consumer Loans (CF Filter)	1.101	1.164	1.219	1.275	1.326	1.377
Total Consumer Loans (BW Filter)	1.000	1.052	1.123	1.203	1.293	1.384
Total Consumer Loans (HM Filter)	1.060	1.062	1.061	1.064	1.080	1.093

6. Conclusion

In this paper, we aim to construct quantitative measures for monitoring the periods of moderate-to-excessive slowdown and expansion in credit cycle dynamics of Turkish banking sector. The methodological and data-related aspects of this study can contribute to the existing literature in Turkish case regarding several issues. Firstly, this happens to be the first study composing de-trended credit indicators in monthly frequency so that credit market can be monitored in higher frequency. Secondly, instead of relying on single filtering technique, this study extracts the credit cycle realizations with the help of multiple time series filters including HP, CF, BW and Hamilton. Thirdly, in addition to filtering choice, the inclusion of different credit ratios and breakdowns enable us to create clustered moderate-to-excessive slowdown and expansion proxies which can be collectively monitored in a historical manner. Fourthly, utilization of Credit Registy data allows us to decipher sectoral outlook in commercial loans which have important implications in terms of financial intermediation activities. Fifthly, unlike other studies in the literature, this work try to associate credit cycle realizations with credit dynamics implied by local and global macroeconomic/financial conditions via factor-augmented predictive regressions. Last contribution of the paper is related to forecasting exercise. On the top of in-sample evaluation, our framework appears to be the first attempt to forecast the credit cycle outlook in Turkish banking sector.

In particular, multiple indicators produced by filtering techniques applied on aggregate (banking sector-wide) loan data seems to be compatible with the historical course of credit market activities in Turkey. While number of indicators pointing out moderate-to-excessive credit slowdown are high during the Global Financial Crisis era, the post-crisis recovery period is also being captured by the number of indicators displaying moderate-to-excessive expansion. The implementation of macroprudential measures in post-2011 period to contain risks towards financial stability can also be explained by the course of our indicators. Moreover, the quantification of credit cycle by our methodology seems to be in line with sizeable boost in 2017, due to the counter-cyclical measures taken by policymakers. Especially, the stance of indicators for TRY commercial loans during 2017 validates this argument. More strikingly, our methodology is closely following the recent weakening in credit supply and demand dynamics as the number of indicators displaying moderate-to-excessive credit slowdown has reached to considerably high levels. Application on sectoral commercial loans has yielded similar conclusions about historical movements. Specific to recent weakening, sectors such as energy, construction, retail/wholesale trade and transportation/communication are the ones with worse credit allocation activities.

Following analyses in this paper have concluded that, based on R-squared values of predictive regressions, real credit growth rate and credit impulse ratio are the credit ratio definitions for which the in-sample explanatory power of macroeconomic/financial factors is highest. On the other hand, in terms of filtering techniques, BW and Hamilton filter are differentiated positively from others. In other words, when these filters are preferred for de-trending procedure, obtained cycle indicators are comparably more associated with macroeconomic/financial dynamics. Our fair value models also entail the better in-sample explanatory power for total loans, TRY total loans as well as commercial and consumer loans.

Forecasting exercises conducted for real credit growth and credit impulse ratio across several filters and credit breakdowns have brought useful insights as well. It is vastly seen that controlling for global and local economic activity factors have reinforced the forecasting performance compared to baseline univariate model. Hence, monitoring the global economic conditions and local growth tendencies turn out to be crucial for predicting future course of credit cycle dynamics in Turkish banking sector.

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Appendix

Table 10: Sectoral Classification based on Credit Registry Data

Sectoral Codes (1-digit)	Sectoral Codes (2-digit)	Name
A		Agriculture, Hunting, Forestry
	AA	Agriculture
	AB	Hunting
	AC	Lumber and Forestry
B		Fishery
C		Mining and Quarrying
	CA	Extraction of Energy-Producing Minerals
	CB	Extraction of Non-Energy-Producing Minerals
D		Manufacturing
	DA	Food, Beverages, Tobacco
	DB	Textiles
	DC	Leather Products
	DD	Wood Products
	DE	Paper Products
	DF	Nuclear, Refined Petroleum, Coke
	DG	Chemical Products
	DH	Rubber and Plastics Products
	DI	Other Non-Metallic Minerals
	DJ	Basic Metals
	DK	Machinery and Equipment
	DL	Electronic and Optical Products
	DM	Transport Equipment
	DN	Manufacturing N.E.C.
E		Utilities (Electricity, Gas and Water)
F		Construction
G		Wholesale and Retail Trade, Consumer Goods
	GA	Sales and Maintenance of Motor Vehicles
	GB	Wholesale Trade and Brokerage
	GC	Retail Trade and Consumer Goods
H		Restaurants and Hotels (Tourism)
	HA	Hotels
	HB	Restaurants
	HC	Other Tourism Activities
I		Transportation, Storage and Communication

	IA	Railroad Transportation
	IB	Land Route Passenger Transportation
	IC	Land Route Freightage Transportation
	ID	Sea Route Transporation
	IE	Air Route Transportation
	IF	Other Transportation Activities
	IG	Communication
K		Real Estate Brokerage, Rental and Administrative Activities
	KA	Real Estate Brokerage
	KB	Rental Activities
	KC	Computer and Related Activities
	KD	Research, Consulting and Advertising Activities
L		Defense Affairs and Public Administration
M		Education
N		Healthcare and Social Services
O		Other Social and Personal Services
	OA	Sewerage and Other Public Services
	OB	Union and Organziational Activities
	OC	Culture, Sport and Entertainment
	OD	Other Services
P		Employers (Natural Entities)
ZZ		Global

Source: Bank Association of Turkey.

Tablo 11: Description of Data Set for Factor Models

Number	Description	Data Class
1	FX Adjusted Total Deposits	Domestic Banking Sector
2	Non-core Liabilities	Domestic Banking Sector
3	Off-balance Sheet FX position	Domestic Banking Sector
4	Average Total Assets	Domestic Banking Sector
5	Credit-to-Deposit Ratio	Domestic Banking Sector
6	Capital Adequacy Ratio	Domestic Banking Sector
7	Return on Assets	Domestic Banking Sector
8	Return on Equity	Domestic Banking Sector
9	Leverage Ratio	Domestic Banking Sector
10	Non-Performing Loans (NPL)	Domestic Banking Sector
11	Profit (Loss) Before Tax to Average Total Assets	Domestic Banking Sector
12	Net Interest Revenue to Average Total Assets	Domestic Banking Sector
13	Non Interest Revenue to Average Total Assets	Domestic Banking Sector
14	Total Credit-to-Total Assets	Domestic Banking Sector
15	Liquidity Ratio	Domestic Banking Sector
16	Growth Rate of NPL	Domestic Banking Sector
17	NASDAQ 100 Stock Index	Global Risk and Funding Conditions
18	S&P 500 Index	Global Risk and Funding Conditions
19	Vstoxx Index	Global Risk and Funding Conditions
20	US Conference Board Consumer Confidence Index	Global Risk and Funding Conditions
21	US Industrial Production Index	Global Risk and Funding Conditions
22	EuroStoxx 50 Index	Global Risk and Funding Conditions
23	Eurozone industrial manufacturing production	Global Risk and Funding Conditions
24	S&P GSCI Spot Index	Global Risk and Funding Conditions
25	European Economic Policy Uncertainty Composite Index	Global Risk and Funding Conditions
26	US Economic Policy Uncertainty Composite Index	Global Risk and Funding Conditions
27	J.P. Morgan EMBI Global Spread	Global Risk and Funding Conditions
28	Bloomberg ECO US Surprise Index	Global Risk and Funding Conditions
29	Bloomberg ECO Euro Area Surprise Index	Global Risk and Funding Conditions
30	Citi Macro Risk Index	Global Risk and Funding Conditions
31	Citi Early Warning Signal Risk Index-All Emerging Markets	Global Risk and Funding Conditions
32	Bloomberg Emerging Markets Capital Flows Proxy Index	Global Risk and Funding Conditions
33	Chicago Board Options Exchange Market Volatility Index	Global Risk and Funding Conditions
34	Merrill Lynch MOVE Index	Global Risk and Funding Conditions
35	DXY Index	Global Risk and Funding Conditions
36	The JPMorgan Emerging Market Bond Index	Global Risk and Funding Conditions
37	The JPMorgan Emerging Market Bond Index Global	Global Risk and Funding Conditions
38	EURIBOR 3m	Global Risk and Funding Conditions
39	EURIBOR 6m	Global Risk and Funding Conditions
40	EURIBOR 12m	Global Risk and Funding Conditions

41	US 2 Year Bond Yield	Global Risk and Funding Conditions
42	US 10 Year Bond Yield	Global Risk and Funding Conditions
43	US 10 Year-2 Year Spread	Global Risk and Funding Conditions
44	US 5 Year-2 Year Spread	Global Risk and Funding Conditions
45	US LIBOR-OIS Spread	Global Risk and Funding Conditions
46	US Corporate BBB/10 Year Spread	Global Risk and Funding Conditions
47	US ISM Manufacturing PMI	Global Risk and Funding Conditions
48	Turkey 2 Year Bond Yield	Local Financial
49	Turkey 5 Year Bond Yield	Local Financial
50	BIST 100 Index	Local Financial
51	BIST Banks Index	Local Financial
52	BIST Industrials Index	Local Financial
53	USD/TRY 1-month Implied Volatility	Local Financial
54	USD/TRY 3-month Implied Volatility	Local Financial
55	USD/TRY 12-month Implied Volatility	Local Financial
56	Turkey 5 Year CDS	Local Financial
57	The JPMorgan Emerging Market Bond Index Turkey	Local Financial
58	The JPMorgan Emerging Market Bond Index + Turkey	Local Financial
59	BIST Interbank Overnight Interest Rate	Local Financial
60	Turkey Banking Sector Weighted Average Interest Rate for Consumer (Personal finance)	Local Financial
61	Turkey Banking Sector Weighted Average Interest Rate for Housing	Local Financial
62	Turkey Banking Sector Weighted Average Interest Rate for Vehicle	Local Financial
63	Turkey Banking Sector Total Deposit Rate	Local Financial
64	USD/TRY Spot Exchange Rate	Local Financial
65	EUR/TRY Spot Exchange Rate	Local Financial
66	Currency Basket	Local Financial
67	Turkey Real Effective Exchange Rate (CPI-Based)	Local Financial
68	USD/TRY 3-month Realized Volatility	Local Financial
69	USD/TRY 6-month Realized Volatility	Local Financial
70	USD/TRY 12-month Realized Volatility	Local Financial
71	USD/TRY 25 Delta-1-month Risk Reversal	Local Financial
72	USD/TRY 25 Delta-3-month Risk Reversal	Local Financial
73	USD/TRY 25 Delta-6-month Risk Reversal	Local Financial
74	USD/TRY 25 Delta-12-month Risk Reversal	Local Financial
75	Turkey Gross Foreign Exchange Reserves	Local Financial
76	Bloomberg Turkey Exchange Market Capitalization	Local Financial
77	Turkey Real GDP	Local Macro
78	Turkey Industrial Production	Local Macro
79	Turkey Industrial Production-Manufacturing	Local Macro
80	Turkey Industrial Production-Intermediate Goods	Local Macro
81	Turkey Industrial Production-Durable Consumer Goods	Local Macro
82	Turkey Industrial Production-Non-Durable Consumer Goods	Local Macro
83	Turkey Industrial Production-Capital Goods	Local Macro

84	Turkey PMI	Local Macro
85	Turkey Manufacturing PMI	Local Macro
86	Turkey Employment in Industry Sector	Local Macro
87	Turkey Employment in Services Sector	Local Macro
88	Turkey Employment in Construction Sector	Local Macro
89	Turkey Non-Agricultural Unemployment Rate	Local Macro
90	Turkey Unemployment Rate	Local Macro
91	Turkey Real Sector Confidence Index	Local Macro
92	Turkey Real Sector Confidence Index-Total Employment(Next 3 Months)	Local Macro
93	Turkey Real Sector Confidence Index-Total Amount of Orders (Next 3 Months)	Local Macro
94	Turkey Real Sector Confidence Index-Export Orders (Next 3 Months)	Local Macro
95	Turkey Business Tendency Survey-Expectations of Fixed Investment Expenditures over Next 12 Months (Increase-Decrease)	Local Macro
96	Turkey Capacity Utilization Rate	Local Macro
97	Turkey Primary Budget Balance as a Percentage of GDP	Local Macro
98	Turkey Budget Balance as a Percentage of GDP	Local Macro
99	Turkey Primary Expenditure as a Percentage of GDP	Local Macro
100	Turkey Exports-Intermediate Goods	Local Macro
101	Turkey Imports-Intermediate Goods	Local Macro
102	Turkey Total Exports	Local Macro
103	Turkey Total Imports	Local Macro
104	Turkey Exports-Capital Goods	Local Macro
105	Turkey Imports-Capital Goods	Local Macro
106	Turkey Exports-Consumer Goods	Local Macro
107	Turkey Imports-Consumer Goods	Local Macro

Sources: TurkStat, CBRT, Bloomberg, BRSA.

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