Business and Financial Cycles in Romania: An Empirical Investigation

Cristina-Elena BEJENARU*
The Bucharest University of Economic Studies, Bucharest, Romania
**Corresponding author, bejenarucristina@yahoo.com*

Abstract. *In this paper we study the relationship between business and financial cycles in Romania, highlighting their distinct characteristics and interactions. The global financial crisis highlighted the role of financial factors in shaping macroeconomic dynamics, especially in developing countries which are more vulnerable to foreign credit reversals. While the business cycle is well-defined, financial cycles are less "standardized" because of their longer duration and greater amplitude. Using quarterly data from 2005 to 2024, this study applies turning-point analysis, band-pass filtering, and finance-neutral output-gap estimation to highlight the key traits of Romania's business and financial cycles. The results show these cycles rarely align, though GDP and real house prices move together more closely than credit measures. Real credit and property prices prove to shape the output gap significantly: booms in credit and housing push standard methods to overstate potential output, while financial contractions deepen downturns beyond what trend filters suggest. These insights underscore the value of weaving financial-cycle signals into macroeconomic analysis and help illuminate the unique dynamics of emerging economies.*

Keywords: Business cycles, financial cycles, output gap, macroeconomics, financial stability, credit market, housing market, turning point analysis.

Introduction

The global financial crisis prompted an increased focus on the role of financial factors in driving real economic fluctuations. Recent studies have emphasized the significant economic effect of boom-bust cycles in credit and the overall importance of credit to the macro-economy, including Reinhart and Rogoff (2009), Claessens, Kose and Terrones (2011), Borio (2012) and Aikman, Haldane and Nelson (2015). Broadly speaking, all advanced economies and many emerging markets have experienced recessions during the past years. There were common features of these, such various types of financial disruptions, including contractions in the supply of credit and sharp declines in asset prices. Above mentioned developments have led to an intensive debate about the links between macroeconomics and finance, and have propelled the study of interactions between business cycles and financial cycles to the forefront of research.

However, the comparative studies reveal a different impact of financial crisis on emerging countries than developed countries, the main aspect that stands out is that declines in real GDP were smaller for advanced economies than for emerging market economies. A pertinent explanation would be that severe contractions in emerging market economies are prone to abrupt reversals in the availability of foreign credit (when no foreign financing is possible, emerging markets have seen consumption and investment implode during severe financial crises)1. When foreign capital comes to a "sudden stop," to use the phrase coined by Guillermo Calvo et al. (2006), economic activity heads into a downward spiral. According with Reinhart and Rogoff (2008b) defaults in emerging economies tend to grow sharply when many countries are simultaneously experiencing domestic banking crises. On the other hand, intolerance to debt is manifested in the

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extreme constraint of many emerging markets with debt experience that would seem to be fairly manageable by advanced countries.

The concept of business cycle has received various definitions in literature. The formal definition of business cycle was only presented in 1946 by Burns and Mitchell, which is used as standard definition even today and described business cycle "as type of fluctuations found in aggregate economic activity of nations that organize their work mainly in business enterprises: cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of next cycle; this sequence of changes is recurrent but not periodic". Business cycles are identified as having four distinct phases: expansion, peak, contraction, and trough. The business cycle it is generally measured by upward and downward movements of GDP around the trend. As traditionally measured, the business cycle involves frequencies from 1 to 8 years - this being the range that statistical filters target when seeking to distinguish the cyclical from the trend components in GDP. Considering the financial cycle there is no consensus on the definition. An explanation is that financial cycles refer to interactions between perceptions of value and risk, attitude towards risk and financial constraints, which translate to booms followed by busts (Borio et al. 2012). These interactions can have important effects on business cycles, amplifying economic fluctuations and leading to serious financial constraints and economic imbalances.

Borio et al. (2012) showed that there are five distinctive features of financial cycles2. One of the features is that they are best described by the evolution of credit and property. These variables seem to have about the same evolution, especially regarding their low frequencies, emphasizing the role of credit for financing the construction and acquisition of properties (by contrast, equity prices don't evolve like them). Another feature of financial cycles is that they last longer than business cycles; thus, financial cycles last on average 16 years, while business cycles, between 1 and 8 years. Peaks in the financial cycle are closely associated with systemic banking crises - this connection helps explain a feature often observed in reality, which is the fact that busts that coincide with the contraction phase of financial cycles are much more abrupt. GDP drops on average 50% more compared to the times when the two busts do not coincide (Drehmann et al, 2012). The amplitude and duration of financial cycles vary, depending on the political regime of the analysed country. In this respect the most important triggers are the monetary policy, the fiscal policy and the real economy policy (Borio and Lowe, 2002). Financial liberalization is associated with increasing the amplitude of financial cycle. A monetary regime focused on short term will not respond to financial booms. Positive shocks on the supply side, like those related to the globalization of the real economy, amplify financial booms, increasing the growth potential of credit and asset prices, while putting downward pressure on inflation, lowering furthermore the possibility of intervention through the monetary policy.

The interactions between business and financial cycles cannot be limited to a single process. The relationships between them are the result of dynamic interactions, derived from the influence that different segments in the financial cycle have on dynamics of the business cycle (e.g. real estate, credits). The financial cycle plays a significant role in the business cycle, and that financial cycle shock has become a main driving force for macroeconomic fluctuations, especially during times of financial instability.

This study focuses on Romania as an emerging market economy. Romania's economic recent history, characterized by severe housing price booms and financial volatility, provides a strong case for the study of interactions between financial and business cycles. The following sections the review of the relevant literature, the section after that describes the methodology, Section 4 details the data used, while Section 5 presents the empirical findings. Finally, Section 6 synthesizes the results and discusses their implications for economic policymaking.

Literature review

Much of the recent literature on financial cycles builds on the arguments presented as early as the 1930s (Fisher 1933; Gurley and Shaw 1955; Minsky 1977; Kindleberger 1978). In contrast with the mainstream economic literature of the second half of the 20th century, which argued that there was no role for finance in determining economic conditions (e.g. Modigliani and Miller 1958), these papers suggest that the financial system can propagate shocks as well as be the source of shocks that lead to economic instability. Over the next decades, literature has continued to separate finance from the economy.

In the 1990s and early 2000s, new research appeared with focusing on the pro-cyclicality of the financial system and the concept of a "financial cycle" was introduced. Bernanke and Gertler (1989), Kiyotaki and Moore (1997) and Bernanke, Gertlerand Gilchrist (1999) develop theoretical frameworks that explicitly allow financial frictions to amplify and propagate shocks to the economy (commonly referred to as the 'financial accelerator' mechanism FA).

Borio et al. (2001) motivated that an additional source of financial pro-cyclicality is market participants' inappropriate responses to changes in risk, which can result in significant financial and economic instability. Borio suggested that policymakers should consider promoting a better understanding of risk and ensure supervisory rules promote better measurement of risk by using supervisory instruments in a countercyclical manner. In another related paper Borio and Lowe (2002), finds credit growth and asset price inflation to be the best predictors of financial crises, reliefing that financial imbalances can be developed in relatively weak economic conditions. Fostel and Geanakoplos (2008), Adrian and Shin (2010) and Geanakoplos (2010) highlight the importance of collateral rates (or 'leverage') for the economy. In particular, the pro-cyclical variation in leverage can significantly affect asset prices, which can subsequently influence the behavior of economic agents.

After the financial crisis, it became clear that connections between financial developments and business cycles are still poorly understood. Claessens et al. (2011) are among the first authors to analyse the financial cycle and the interactions with the business cycles. In their research thy used an extensive database of 44 countries for the period 1960-2007 finding two main results. First, the relationships between different phases of business and financial cycles are strong, and recessions associated with financial disruption episodes, notably house price falls, tend to be longer and deeper than other recessions. Second, recoveries associated with rapid growth in credit and house prices tend to be stronger.

Borio (2012) has also studied the main characteristics of the financial cycle in advanced economies, finding that the credit gap - meaning the difeerence between the actual credit-to GDP ratio and its long-term trend (Drehmann and Tsatsaronis, 2014) is an useful tool for the prediction of financial crises and for evaluotion of risks of systemic banking crises. In another paper, Borio, Disyatat, and Juselius (2013) propose a framework to estimate the output gap and potential output by embedding financial cycle information into their model. They demonstrated that financial cycles contain information relevant to the estimation of output gaps and potential output. Recent studies have also explored the interactions between business and financial cycles either across countries (Claessens, Kose, and Terrones, 2012) or on a country-by-country basis (Galati et al., 2016; Runstler and Vlekke, 2016).

Jorda et al. (2011) argued the role of credit in the recessions. If the recession coincides with a financial crisis, these effects are compounded and typically accompanied by pronounced deflationary pressures. Generally speaking, a credit build-up in the boom seems to heighten the vulnerability of economies. In a very recent study Borio (2017) revealed that central banks need to adjust monetary policy frameworks by putting less weight on inflation and more weight on the longer-term real effects of monetary policy through its impact on financial stability.

Building on these insights, the present study examines the interplay of Romania's business and financial cycles, using a combination of turning-point analysis, band-pass filtering, and finance-neutral output-gap estimation. In doing so, it contributes to the growing strand of literature illustrating that standard approaches to measuring economic slack may underestimate risks if financial variables are omitted. By focusing on Romania - an emerging market economy marked prominently by housing price booms in the GFC- the study underscores how property price swings, credit booms, and financial frictions can shape both short-term fluctuations and longer-term potential output. Such findings hold clear implications for macroeconomic and macroprudential policymaking, reinforcing the consensus that finance can no longer be relegated to the periphery of economic analysis.

Methodology

Turning point analysis (BBQ algorithm)

In this section the methodology used for computing business and financial cycles and analyzed their interactions is presented as it follows. In the first part is presented the turning point algorithm introduced by Bry and Boschan (1971) and extended by Harding and Pagan (2002) for quarterly data. In the second part, the band-pass filter is presented and in the third part Borio's model for measuring the output gap by embedding information about financial indicators.

I employ the algorithm introduced by Harding and Pagan (2002a), which extends the so-called BB algorithm developed by Bry and Boschan (1971), to identify the turning points in the log-level of a series. We search for maxima and minima over a given period of time. Then, we select pairs of adjacent, locally absolute maxima and minima that meet certain censoring rules, requiring a minimal duration for cycles and phases. In particular, the algorithm requires the duration of a complete cycle and of each phase to be at least five quarters and two quarters, respectively.

Specifically, a peak in a quarterly series yt occurs at time t if:

$$[(yt - yt - 2) > 0, (yt - yt - 1) > 0] and [(yt + 2 - yt) < 0, (yt + 1 - yt) < 0]$$

And a cyclical trough occurs at time t if:

$$[(yt - yt - 2) < 0, (yt - yt - 1) < 0] and [(yt + 2 - yt) > 0, (yt + 1 - yt) > 0]$$

A complete cycle typically comprises two phases, the recession phase (from peak to trough) and the expansion phase (from trough to the next peak). The recovery is the early part of the expansion phase and is usually defined as the time it takes for output to rebound from the trough to the peak level before the recession.

Main features of cycles

The characteristics that are of main interest are the duration and amplitude of the cycle and phases, cumulative movements within phases and asymmetries between the phases (Harding and Pagan, 2002).

The duration of a recession/downturn (D) is the number of quarters between a peak and the next trough of a variable (the lenght). The amplitude refers to the depth of expansions and contractions (average rise or decline of activity). Cumulation refers to cumulated gains or losses and represents the sum of the amplitudes for each period of the phase. As a way to analyze asymmetries, the excess movements metrics capture the divergences from a triangle which is used as an approximation of a typical phase with the height being the amplitude and the base being the duration. Given that the triangle approximation measures the cumulative change in the level of the variable, if it changed at a constant rate over a phase, the excess metrics is able to capture the shape of the cycle compared to this triangle approximation. In order to calculate the measures of these characteristics, one should first transform the original series containing the turning points into binary variables. The followed methodolody in defining binary variables St is the one computed by Harding and Pagan (2002). St take values of 1 when the series is in expansionary phase and 0 when the series is in contractionary phase.

The average duration (1) and amplitude (2) of expansions can be calculated as:

$$D = \frac{\sum_{t=1}^{T} S_t}{\sum_{t=1}^{T-1}(1 - S_{t+1})S_t} \qquad (1)$$

$$A = \frac{\sum_{t=1}^{T} S_t \Delta y_t}{\sum_{t=1}^{T-1}(1 - S_{t+1})S_t} \qquad (2)$$

where the denominator in (1) and (2) represent number of peaks, the numerator in (1) represents the total time spent in expansions and the numerator in (2) represents sum of the changes in the level of the variable in the expansionary phases.

Cumulative movements and excess movements, respectively, are given by:

$$C = \sum_{t=1}^{T} r_t - \frac{1}{2}A \qquad (3)$$

$$E = \frac{1}{D}\left(\frac{1}{2}DA - \sum_{t=1}^{T} r_t + \frac{1}{2}A\right) \qquad (4)$$

where $\sum rt$ =1 is the sum of the areas of t rectangles, with each rectangle referring to the log difference between the level of the variable in each quarter during the phase and the level of the variable at the beginning of the phase

Measuring cycles synchronization

In order to analyze the degree of synchronization between classical business and financial cycles we use the concordance index established by Harding and Pagan (2002). The concordance index is a descriptive statistic which specifies the average amount of time in which two variables are found to be in the same phase of their cycles. It can take any number between 0 and 1, with 1 representing perfect overlap of the two cycles and 0 indicating that the series are always in opposite phases of the cycle. The index has the advantage in that it does not require the two variables to be stationary. In order to compute the index, Harding and Pagan (2002) apply the following formula:

$$\hat{I} = \frac{1}{T}\left(\sum_{t=1}^{T} S_{xt}S_{yt} + \sum_{t=1}^{T}(1 - S_{xt})(1 - S_{yt})\right) \qquad (5)$$

Given the two series x_t and y_t, S_{xt} and S_{yt} are the binary variables obtained from the nonparametric BBQ algorithm which, as mentioned previously, are defined as:

- S_{xt} = {1 if x is in expansionary phase at time t, 0 otherwise}
- S_{yt} = {1 if y is in expansionary phase at time t, 0 otherwise}
- T is the number of time periods in the sample.

Frequency-based filter analysis – Band-Pass Filter

Introduced by Marianne Baxter and Robert King (1999) and Christiano and Fitzgerald (2003), the band pass filter is an approximation, in the time domain and using a finite terms centred moving average, of the ideal band pass. It is based on the Spectral Representation Theorem, according to which time series are composed of different frequency components. What the band pass filter does, is to isolate those components that have a frequency within a certain range.

The use of the band-pass filter is based on the idea that fluctuations in a time series are composed of fluctuations from different sources. The filter largely removes the high or low frequency components of a series, leaving the fluctuations that can be interpreted as cyclical fluctuations. In a nutshell this is a two-sided moving average filter isolating certain frequencies in the time series.

The financial cycle has a much lower frequency than the traditional business cycle (Drehmann et al (2012)). As traditionally measured, the business cycle involves frequencies from 1 to 8 years: this is the range that statistical filters target when seeking to distinguish the cyclical from the trend components in GDP. Recent literature argues that the length of the financial cycle is four times the length of a business cycle (Ravn and Uhlig (2002), Gerdrup et al. (2013), Detken et al. (2014)). Therefore, the duration of a financial cycle spans from 32 to 120 quarters (or 8 to 30 years) using this band -pass methodology.

Medium-Term Business and Financial Cycles

Using univariate filtering methods, Drehmann et al. (2012) and Aikman et al. (2015) find evidence of large medium-term cycles in credit volumes and house prices series, while Claessens et al. (2012) reach similar conclusions using turning point analysis. Comin and Gertler (2006) have already reported important medium-term fluctuations in US GDP. In their study Drehmann et al. (2012) compare the behavior of the short-term and medium-term cycles in individual variables (as GDP, credit volumes, credit to GDP ratio and house prices), considering that the two components are independent of each other.

Working Group on Econometric Modelling from European Central Bank show the importance of applying a bandpass filter, using the same frequency bands for all series saying that the fact that filter bands must be chosen in advance naturally introduces a certain arbitrariness in the results. In general, pre-specified filter bands imply the risk of missing parts of cyclical dynamics or, conversely, obtaining spurious cycles (Murray, 2003). In particular, if the frequency bands used to extract cycles in real GDP and financial variables do not overlap, the resulting estimates of cycles will be uncorrelated by construction. Hence, the conclusion of Drehmann et al. (2012) that "business and financial cycles are independent phenomena" may well be induced by their choice of filter bands. They propose extraction of cycles from the bandpass filter with a frequency band of 8-80 quarters. This choice captures both traditional business cycle fluctuations and medium-term frequencies and is therefore neutral on whether they should be distinguished. The upper bound of 80 quarters is lower than that used by Drehmann et al. (2012), as the samples in this study are shorter.

Chen and Svirydzenka (2021) provide additional insights, examining the duration and amplitude across various financial variables. Their findings indicate that the length of financial cycles is equal or even shorter than, business cycles, depending on the variable analized. Equity cycles are the shortest (averaging 3-4 years) and have a larger amplitude, reflecting the volatility of stock markets. Bank credit and GDP cycles are the longest, with build-up phases lasting 5-6 years and downturns lasting 1-1.5 years. Cycles in loan-to-deposit ratios, real estate prices, and equity prices display relatively symmetrical peaks and troughs, lasting 3-5 years on average. These findings emphasize the variability in financial cycles across different variables, highlighting the importance of identifying the specific dynamics of each indicator to derive important insights.

Building on this literature, I will estimate both business and financial cycles for Romania using a band-pass filter with a frequency range of 8-40 quarters. This decision reflects the specific characteristics of Romania as an emerging economy and aligns with the findings of studies such as Drehmann et al. (2012) and Chen and Svirydzenka (2021). The choice of the 8-40 quarters frequency band enables the capture of key cyclical properties while addressing the shorter data samples available for Romania. This empirical approach will allow for an examination of the basic properties of the estimated cycles and their correlations, contributing to the ongoing discussion on the interplay between business and financial cycles. By focusing on emerging economies, the study complements the broader literature and provides valuable insights into the cyclical dynamics that shape macroeconomic and financial stability in such contexts.

The impact of financial factors on the output gap

Economic growth displays irregular fluctuations along business cycles, periods of economic expansion alternating with those of stagnation or even contraction. The fact that economies have a central long-term growth tendency has prompted economists to formulate the concept of potential GDP. Starting from the potential output concept, we can define the component that indicates the cyclical position of an economy, ie the output gap, the latter representing the percentage deviation of the actual GDP from its potential. The output gap measures the degree of utilisation of production factors in the economy and is often regarded, among others, as an indicator of possible inflationary pressures - when the actual level of output is above the potential output, inflation tend to rise due to inflationary pressures and vice versa.

Borio et al. (2013) developed measures of potential output and output gaps in which financial factors play a central role. Their point of departure is the conviction that financial factors are critical for economic activity, for the evolution of output over time, and for which of its paths are sustainable and which are not. Computing the so-called "finance-neutral output gap" Borio et al. contributes to the expansion of the burgeoning literature on the link between financial and business cycles.

Borio's approach is meant to be transparent, without constraining the data, while at the same time incorporating information regarding financial cycles. 9 The point of departure is a purely statistical approach, the Hodrick-Prescott filter, cast in state space form by specifying the state and measurement equations as :

$$\Delta y_t^* = \Delta y_{t-1}^* + \varepsilon_{0,t} \quad (6)$$

$$y_t = y_t^* + \varepsilon_{1,t} \quad (7)$$

where $y_t = ln(Y_t)$, Y_t is the real GDP, $\varepsilon_{i,t}$ for *i=0,1*, represents the normal and independent distributed error, with zero mean and variance σ_i^2. The first equation is the state equation, which represents the variation of potential GDP and the second is the measurement equation of the deviation of GDP from its potential, also known as the output gap.

For the state equation, the parameter $\lambda_1 = \sigma_1^2/\sigma_0^2$ (noise-to-signal ratio) determines the relative change of the estimated potential output. When the parameter is too big, the estimated series follows the linear trend very closely. However, if the parameter tends towards zero, potential GDP mimics the actual GDP. The used value is the one that corresponds to the duration of an estimated output gap of up to 8 years, which is the duration considered in the literature for the business cycle. This implies a value of λ_1 of 1600 for a quarterly database. The functional form of the state equation and the noise to signal ratio determines the relative change of the potential GDP estimates. As shown by Borio et al. (2013), the recommended method for incorporating additional information regarding financial cycles in the estimates of output gap is by introducing variables in the measurement equation:

$$y_t - y_t^* = \gamma' x_t + \varepsilon_{2,t} \quad (8)$$

where x_t is a vector of economic variables, with the possibility of including lags of the output gap itself, and $\varepsilon_{2,t}$ is the error term, which is independent and normal distributed, with zero mean and variance σ_2^2. To preserve the same duration of the business cycle as implied by the standard HP filter when extending (7) to (8), we use a state equation of the form (6) and set the signal-to-noise ratio $\lambda_2 = \sigma_2^2/\sigma_0^2$ such that:

$$\frac{\operatorname{var}\left(y_t - y_{(2),t}^*\right)}{\operatorname{var}\left(\Delta^2 y_{(2),t}^*\right)} = \frac{\operatorname{var}\left(y_t - y_{(3),t}^*\right)}{\operatorname{var}\left(\Delta^2 y_{(3),t}^*\right)} \quad (9)$$

where $y_{(2),t}^* *$ and $y_{(3),t}^*$ are the potential output series from equations (7) and (8), respectively.

This approach by using the equations (6) and (8) is a compromise between the statistical and theoretical methods for the estimation of potential GDP, without relying on a fully specified model of general equilibrium. Therefore, the parameters estimators in equation (8) will imply zero weight to elements in x_t that do not contain information about the cyclical fluctuations, which represents a relaxation of the methodology.

As can be seen from equation (6), financial factors do not influence potential output directly, rather it is assumed that they contain information only about the cyclical component of production. Financial variables included in the model are: credit to the private sector and real property prices. I also introduced an autoregressive component of output gap, in order to capture the dynamic behavior of the indicator. Therefore, equation (8) becomes:

$$y_t - y_t^* = \beta(y_{t-1} - y_{t-1}^*) + \gamma_r r_{t-k_r} + \gamma_{cr}\Delta cr_{t-k_{cr}} + \gamma_{ph}\Delta ph_{t-k_{ph}} + \varepsilon_{3,t} (10)$$

where $r_t = i_t - \Delta p_t$ is the ex-post real interest rate, Δp_t is consumer price inflation, Δcr_t represents the relative growth of real credit, Δph_t represents the relative growth of property prices, k_{cr} and k_{ph} represent the optimal lag with which each variable in included in the model and $\varepsilon_{2,t}$ is the error term with zero mean and variance σ_2^2. Variables are mean adjusted, since they present a high degree of cyclicality. The method used for adjustment is with Cesaro means, which consists of the calculation of the average of the series of averages obtained by adding an observation to the database successively, starting with the initial data. This helps reduce pro-cyclicality in the adjusted data series.

Intuitive Overview of Methods

The methodologies employed in this study - turning point detection, band-pass filtering, and finance-neutral output gap estimation - are each designed to capture cyclical fluctuations from different angles. Turning point detection through the Bry-Boschan/Harding-Pagan (BBQ) approach finds local peaks and troughs in the series, showing a segmentation of expansions and contractions without reliance on structural assumptions. This helps identify the duration, amplitude, and timing of each cycle phase, but it can occasionally miss short-lived cycles that do not meet the minimum phase length imposed by the censoring rules.

The band-pass filter serves as a more continuous technique, isolating particular frequency components of a time. In this study, we consider cycles between 8 to 40 quarters, a choice guided by findings in the literature for measuring the medium-term financial cycles, found especially in emerging economies. The selection of the frequency introduces though some arbitrariness and may exclude certain cyclical patterns that fall near the chosen thresholds. To address end-point bias, which can distort the filtered series near the edges of the sample, we extrapolate the data by twelve quarters using an AR(1) model, a standard practice that allows the filter to operate on an extended dataset and mitigates artificial shifts at the boundaries.

Finally, the finance-neutral output gap approach incorporates key financial variables into a traditional Hodrick-Prescott framework by treating them as additional signals of cyclical imbalances. At its core, this framework assumes that rapid changes in credit and asset prices often reflect shifts in the broader economy that conventional tools can miss. By blending elements of statistical filtering with structural modeling - yet remaining agnostic to any particular financial theory - it finds a middle ground that's both flexible and insightful. Of course, its results hinge on the parameters you choose and the fact that financial markets can jump around unpredictably. When you stack this alongside the other two approaches, you get three different—but mutually reinforcing—ways to explore how real and financial cycles interact, and how credit surges and asset-price spikes can fuel booms yet deepen busts.

Data description

In order to study the business cycle for Romania's economy I use real GDP, since this is the best available measure of the aggregate economic activity typically used in the literature, sourced from the Eurostat database. To measure the financial cycle, I used the credit extended to non-financial corporations and households, and fixed-base index of residential property prices. These datasets are from the National Committee for Macroprudential Oversight (NCMO), which have the source the data from the National Bank of Romania (NBR) and the National Institute of Statistics (INSSE). Both series are in real terms (adjusted with HICP index), from Eurostat. To measure the financial cycle, I also included the credit-to-GDP ratio as a variable. To calculate the real interest rate, I used the nominal interest rate, represented by the 3-month ROBOR rate (ROBOR3M) from the NBR database, extracting the inflation rate based on the HICP index. All data were collected for the period 2005Q1 to 2024Q3, with quarterly frequency.

For the turning-point analysis and the estimation of the output gap, I used MATLAB[1]. The band-pass filtering of variables was performed in EViews. To avoid losing observations due to the band-pass filtering process, the data series were extended by 12 periods through extrapolation using an AR(1) model.

Results and discussions

Turning-point analysis

Business and financial cycles characteristics

I will start my analysis with a description of the main features of business and financial cycles, since I consider this as a necessary step before going into investigation about the relations between them. In Table 1 are presented the main features of the different phases of the business and financial cycles: the average duration of the cyclical phases, amplitude, average cumulative movements and

[1] The BBQ code was written by James Engel and is available on the National Bureau of Economic Research website. The code implementing Borio's methodology was kindly provided by the authors of the paper *"The Impact of Financial Factors on the Output Gap and Estimates of Potential Output Growth,"* Jesus Felipe, Noli R. Sotocinal, and Connie Bayudan-Dacuycuy, whom I would like to thank for sharing their work.

excess for the business and financial cycles. All of these measures are in terms of percentages, with the exception of duration which is in quarters. Same as Harding and Pagan, I work with the natural logarithm of the variables, excepting the credit to GDP ratio.

Table 1: Characteristics of business and financial cycles

	Mean duration Contraction/Expansion (quarters)	Amplitude Contraction/Expansion (%)	Avg. cumulative movement Contraction/Expansion (%)	Excess movements Contraction/Expansion (%)
GDP	3.5 / 11.5	-7.5 / 15.2	-23 / 128.6	22.1 / 14.6
Credit/GDP	18.7 / 2.0	-10 / 1.5	-165 / 2	-38.1 / -25
Real credit	5.7 / 5.2	-7.1 / 6	-26.4 / 21	-4.5 / 12.3
Real house prices	9.3 / 5.8	-30.6 / 6.9	-495.9 / 44.7	3.4 / 18.3

Source: Authors' calculation. Cumulative movements combine information about duration, amplitude and the shape of cyclical phases and are represented as a percentage of the variables in the first quarter of phase. Excess movements show the percentage gain or loss of the analyzed variable per quarter during an expansion or contraction in comparison with the constant growth scenario.

Our examination of Romania's cycles brings out some striking contrasts between the business and financial sides of the economy. On the business front, expansions last on average nearly three years (11.5 quarters), while downturns are relatively short, at about a year (3.5 quarters)—a pattern you often see in fast-growing, emerging markets. Financial cycles, by comparison, follow a very different rhythm. Credit booms are fleeting (just two quarters long), but credit squeezes drag on for nearly five years (18.7 quarters), pointing to deep-seated constraints in Romania's lending markets. The housing market tells a similar story: once prices fall, they stay down for over two years (9.3 quarters), underlining how slowly this sector heals.

When we dig into the size of these swings, the differences become even more pronounced. GDP jumps by roughly 15 percent during expansions—accumulating more than 128 percent in gains over the cycle—whereas contractions shave off about 7.5 percent, shrinking total output by around 23 percent. House prices, however, plunge by over 30 percent in downturns, with a cumulative loss approaching 50 percent, making them a key driver of financial volatility. Credit-to-GDP shifts are more muted: expansion s only nudge the ratio up by 1.5 percent, and contractions pull it down by about 10 percent, amounting to a total slide of 165 percent over the cycle.

Finally, by looking at "excess" measures—how actual cycle shapes deviate from symmetrical or "ideal" forms—we see clear asymmetries. Credit falls accelerate sharply in downturns (concave losses), while GDP, housing, and overall credit show convex patterns, meaning they drop off more steeply than they recover. During up-swings, both house prices and credit surge beyond what a simple model would predict. These dynamics echo findings from Drehmann et al. (2012), underscoring that Romania's business and financial cycles not only move in different tempos but also in very different ways—especially given the unusually brief credit booms and deep, prolonged housing slumps that characterize its financial system.

Table2: Business and financial cycles dates of peaks and troughs

GDP		Credit/GDP		Real Credit		Real House Prices	
Peak	Trough	Peak	Trough	Peak	Trough	Peak	Trough
2008Q4	2010 Q3	2009Q1	2011 Q1	2009Q1	2011 Q1	2008Q4	2014 Q3
2012 Q2	2013 Q1	2011Q3	2014 Q4	2012 Q3	2014 Q2	2018 Q2	2019 Q2
2018Q3	2019 Q1	2015 Q2	2024Q1	2015 Q3	2016 Q4	2020 Q1	2020 Q3
2019 Q4	2020 Q2			2017 Q3	2018 Q1	2021 Q2	2023 Q2
				2019 Q4	2020 Q2	2023 Q4	
				2021 Q1	2024 Q1		

Source: Authors' calculation.

Table 2 presents the timing of peaks and troughs for GDP, Credit/GDP, real credit, and real house prices in Romania. By employing the BBQ dating algorithm, the analysis identifies distinct phases of expansions and contractions across the variables.

Over the period we studied, Romania's GDP went through four downturns and three upswings, each closely tied to major economic shocks. You can clearly see the fallout from the 2008 global financial crisis and the 2020 COVID-19 slump in those contraction phases.

Looking at the credit-to-GDP ratio, there are three distinct wipe-outs where lending retrenched sharply. The first, from Q1 2009 to Q1 2011, tracks the immediate aftermath of the financial crisis, while the later downturn—from Q2 2015 all the way to Q1 2024—shows how long it took Romania's banks and businesses to rebuild leverage, hinting at deeper structural hurdles.

Real credit and real house prices tell a similar story of boom and bust. Credit peaked in Q1 2009 and hit its low in Q1 2011 as the economy retrenched, and house prices topped out in Q4 2008 before sliding steadily until Q3 2014. After those dramatic swings, both metrics settled into a quieter pattern: credit recovered only slowly, and housing prices flattened out, suggesting that post-crisis growth has been steadier but a lot more muted than the heady pre-2008 expansion.

Table 3: Synchronization of cycles: concordance index

	GDP	Credit/GDP	Real Credit	Real House Prices
GDP	1	0.4	0.6	0.7
Credit/GDP	0.4	1	0.7	0.7
Real Credit	0.6	0.7	1	0.7
Real House Prices	0.7	0.7	0.7	1

Source: Authors' calculation.

The synchronization index in Table 3 shows that GDP and real house prices move in step quite closely, suggesting that housing-market swings are tightly linked to overall economic activity. Real house prices also line up strongly with both real credit and the credit-to- GDP ratio, underlining the housing sector's central role in financial cycles. By contrast, GDP's tie to other financial measures is much looser: its synchronization with real credit is only marginally significant, and there's essentially no statistical link between GDP and the credit-to- GDP ratio over our sample. In other words, while housing prices track the economy and broader financial trends very well, credit-to- GDP shifts d on't consistently mirror GDP movements[2].

[2] To ensure the robustness of these findings, a statistical test was conducted to assess the significance of the synchronization indices. The results confirm that the observed concordance between certain variables, such as real

Frequency-based filter analysis – Band-Pass Filter
For our financial-cycle measures, we looked at real total credit, the credit- to- GDP ratio, and real house prices, while the business cycle is captured by real GDP. Except for the credit-to- GDP ratio, every series was transformed into natural logs.
To pull out the cyclical swings, we applied the Baxter–King filter with a 12-quarter symmetric window and isolated movements lasting between 8 and 40 quarters. Because filters struggle at the sample edges, we padded each series by forecasting 12 extra quarters with an AR(1) model, which gave us cleaner estimates of the most recent cycles. As a reality check, we also ran the Hodrick–Prescott filter—using the standard λ values of 1,600, 125,000, and 400,000 that Drehmann and Yetman (2018) suggest.

Both filters tell essentially the same story. The peaks and troughs line up, and the magnitudes of the swings are very similar. That agreement gives us confidence that our cyclical profiles are both robust and reliable.

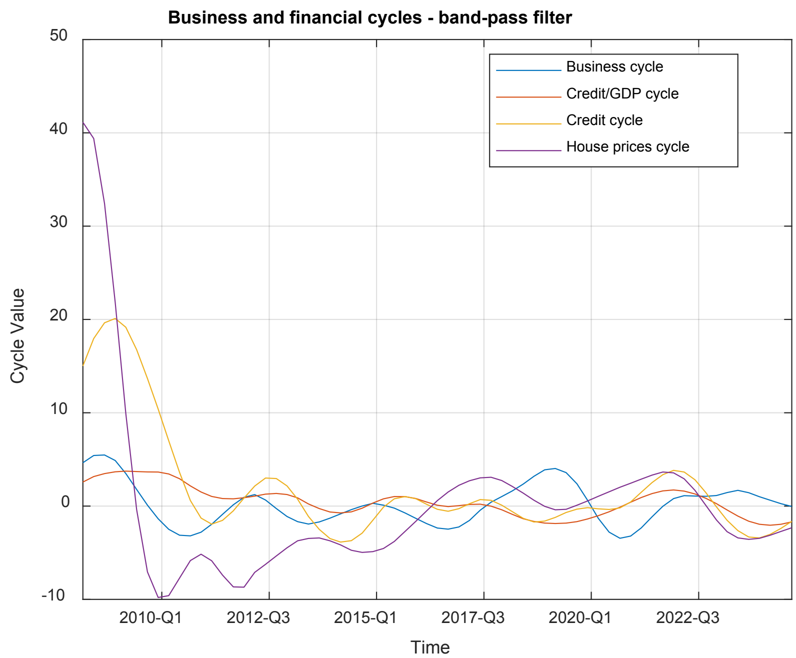

Figure 1. Bandpass filtered business and financial cycles (frequency band 8-40 quarters)
Source: Authors' calculation.

Figure 1 traces Romania's business and financial rhythms from the start of 2008 through the third quarter of 2024. At the height of the global financial crisis, real estate was the most overheated: house prices swung up to 41 percent above trend before plunging back as the market corrected itself. Credit followed a similar, if milder, pattern—peaking around 20 percent above its long-run path by late 2008 and then collapsing through 2009 as banks pulled back amid uncertainty.

house prices and the other financial variables, is statistically significant. In contrast, other relationships, such as between GDP and the credit-to-GDP ratio, do not show significant alignment. This variation underscores the complex and nuanced relationships between economic and financial cycles, reflecting the different dynamics driving these variables. The significance of the synchronization indices was tested by comparing the observed concordance to a null hypothesis of no synchronization. This was achieved by computing the probability (p-value) that the observed concordance could occur by chance. The test involved evaluating the proportion of matching phases between pairs of variables, relative to the total number of observations.

On the GDP side, you can see the raw impact of the Great Recession in 2009, when output contracted sharply before tentatively rebounding. What's striking is that lending stayed weak even as growth edged upward. From roughly 2009 to 2015, credit barely budged or drifted lower even while GDP recovered, underlining how the financial sector trailed the broader economy.

More recently, all three series have calmed down. The housing cycle now shows only modest swings, with a small dip during the first waves of COVID-19 (2020 Q1–Q3) and a steady pickup afterward. Credit-to-GDP remains subdued, reflecting tighter lending standards, while GDP itself has posted steady, moderate gains in the post-pandemic era. Altogether, the figure illustrates how Romania weathered two major shocks and has gradually settled into a more stable—but still cautious—economic pattern.

The impact of financial factors on the output gap

I estimated Romania's output gap from Q1 2005 through Q3 2024 using a Bayesian state-space framework. In practice, that meant writing down equation (5), feeding it into a Kalman filter to build the likelihood, and then combining that with our chosen priors to maximize the posterior. For every parameter, I picked a Gamma prior with a standard deviation of 0.3 - wide enough to let the data speak but tight enough to keep estimates sensible.

To avoid pathological results, I bounded the key parameters: the persistence term, β, could only sit between 0 and 0.95 (with a prior mean of 0.7), ruling out unit-root behavior in the gap and the financial-channel weights (the γ_r, γ_{cr} and γ_{ph}) were each limited to [0, 1] and centered on 0.3 a priori. I also tuned the λ_2 scaling factor so that our cyclical estimates would look roughly like those from a standard Hodrick–Prescott filter. A quick line-search over possible λ_2 values got us there. Next, I explored how adding financial indicators one by one (via equation 10) affected the gap estimate. That step-by-step inclusion reveals which variables really move the needle.

Table 4 lays out the regression results for two sets of output gaps: the "classical" HP-filtered gap and the gaps augmented with financial information. All series enter the regressions as log-differences - so we're modeling percentage changes, not levels, ensuring stationarity and consistency with the theory. The top panel of the table shows the coefficients on the lagged output gap and whichever financial variable is in the model; the bottom panel reports each variable's own lags from 0 up to 5 quarters. I've only shown coefficients that turned out statistically significant—and I've put the t-stat in parentheses below each one. You won't see the real interest rate in the table because it never reached significance at any lag.

Table 4: regressions results

	Models estimated for Romania			
	1	**2**	**3**	**4**
$\boldsymbol{\beta}$	0.95	0.67	0.66	0.78
	(30.17)	(5.14)	(5.61)	(8.64)
$\boldsymbol{\Delta cr}$	-	0.19	0.22	-
	-	(2.00)	(2.32)	-
$\boldsymbol{\Delta ph}$	-	-	-	0.12
	-	-	-	(3.05)
$\boldsymbol{k_{cr}}$	-	0	3	
$\boldsymbol{k_{ph}}$	-	-	-	4

Source: Authors' calculation.

The regressions were estimated by including only one explanatory variable at a time. This approach allows us to assess the individual effect of each variable in isolation on the estimated output gap. Four models are presented: a benchmark specification (Model 1) and three extended models that include financial variables (Models 2, 3, and 4).

The coefficients on the lagged output gap (β) are sizable and highly statistically significant in all models, ranging from 0.66 to 0.95. This indicates a high degree of persistence in the Romanian output gap behavior. Turning to the financial variables, the coefficients associated with real credit and real property prices are both economically and statistically significant. Specifically, Model 2 includes real credit, with a coefficient of 0.19 ($t = 2.00$) at lag 0, while Model 3 also includes real credit (0.22; $t = 2.32$) but operates with a different lag structure (lag 3). By contrast, Model 4 focuses on real property prices, yielding a coefficient of 0.12 ($t = 3.05$) at lag 4.These results underscore the importance of financial cycle indicators -especially credit and property prices - in explaining cyclical fluctuations in Romanian output. They also corroborate findings in the broader literature that financial variables often provide superior insight into the amplitude and duration of business cycle swings.

Figure 2 compares the evolution of the output gap as estimated by three approaches: the Hodrick-Prescott (HP) filter, the credit-neutral method, and the property price-neutral method. The latter two yield noticeably different outcomes from the simple HP-based estimate, particularly around the 2008 boom and its aftermath. During the economic boom that peaked in Q3/Q4 of 2008, surging property prices contributed to a higher property price-neutral (PPN) gap, suggesting that part of the observed growth may have been overstated by excessive financial exuberance. In contrast, in the post-crisis period, both financially augmented measures produce more negative readings than the HP filter, indicating that tighter credit conditions and weakened balance sheets have dampened real output growth. Currently, all methods imply that Romania's output remains below its potential, with the credit-neutral measure being the most negative.

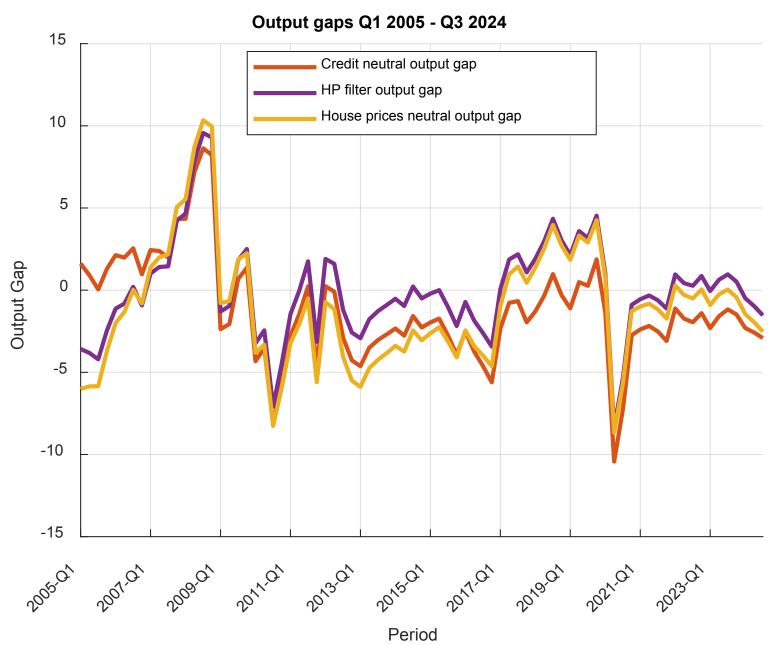

Figure 2. Hodrick-Prescott and finance neutral output gaps

Source: Authors' calculation.

From a policy perspective, weaving financial data into estimates of potential output gives a truer sense of how sustainable growth really is. In Romania's case, the pre-2009 period showed a sizable positive output gap—driven by easy credit, foreign-bank entry, and favorable global conditions—whereas the post-2009 negative gap reflects a deliberate but drawn- out pullback in bank lending. This pattern echoes broader research showing that filters adjusted for credit and property-price swings can spot imbalances that the standard HP filter misses. By baking in financial-cycle dynamics, these enhanced measures paint a more detailed picture of whether the economy is running "hot" or "cold," information that policymakers need to temper risks in booms and bolster support during busts.

Looking at Figure 2, you can see how output gaps that adjust for property prices run above the plain HP estimate in boom times, and both the credit-neutral and price- neutral gaps fall below HP during downturns. These gaps highlight just how much financial variables shape the size and persistence of business-cycle swings —and why it matters to include them when assessing an economy's true capacity.

Policy Implications

The findings presented in this paper have clear practical relevance for policymakers, particularly central banks and supervisory authorities charged with safeguarding economic stability in emerging markets like Romania. hen we pit the classic Hodrick–Prescott filter against versions that incorporate credit and house-price data, a clear lesson emerges: overlooking financial booms and busts can leave you thinking the economy is stronger than it really is during upswings—and dismissing lingering slack when markets unwind. Think back to the run-up to 2008. Easy money from abroad and lax lending rules sent credit surging and house prices sky-high. On the surface, it looked like Romania was powering ahead on its own steam. But once banks pulled in their horns, it became obvious that much of that "growth" was really a bubble waiting to burst—not long-term investment or productivity gains.

In practice, feeding real-time credit and property indicators into your standard toolbox can make policy both more precise and more proactive. For example, central banks could tweak countercyclical capital buffers or adjust loan-to-value and debt-to-income limits based on house-price inflation and credit growth. And when the cycle turns down, spotting the squeeze early could trigger targeted relief measures to prevent a drawn-out slump. Of course, the exact settings will vary by country and by institution. But Romania's experience shows that leaning against financial excesses doesn't just soften recessions—it reduces the odds of banking crises and lays the groundwork for a stronger rebound. By embedding these financial signals into everyday policymaking, authorities can identify risks sooner, tailor their responses more effectively, and ultimately nurture steadier, more inclusive growth.

Conclusion

This study explored Romania's business and financial cycles and examined how financial factors reshape our view of the output gap. To do this, we combined three methods: a turning-point algorithm (Bry-Boschan/Harding-Pagan) to pinpoint peaks and troughs in logged data and chart the length, magnitude, and cumulative shifts of each cycle; a band-pass filter isolating movements lasting eight to forty quarters to capture medium-term financial swings alongside traditional business-cycle rhythms; and a finance-neutral approach that weaved credit and housing-price indicators into an HP-style filter.

The turning-point analysis showed that financial cycles - especially in house prices and credit - often march to a different beat than GDP. House-price downturns last much longer than typical economic contractions, signaling drawn-out real-estate corrections after a boom, while credit-to-GDP expansions fade quickly, hinting at structural limits in domestic lending. Synchronization metrics confirmed that housing and GDP move more closely together than GDP and other financial gauges, although even that link is only partial.

Our band-pass results echoed this: the financial cycle pulses over a broader, slower rhythm than the classic business cycle, yet it still jumps sharply in crises—house prices, in particular, swung wildly around 2008. When we folded these financial indicators into our output-gap estimates, the impact was clear: surging credit and housing prices made the pre-crisis gap look larger than the plain HP filter would suggest, while post-crisis deleveraging drove a deeper, more persistent negative gap. Real interest rates barely registered, but credit and property-price shifts explained a substantial share of the swings.

For policymakers, the takeaway is straightforward: keeping an eye on credit and housing cycles alongside GDP gives a sharper, timelier read on where the economy really stands. In an emerging market like Romania—where foreign capital flows and bank behavior can pivot quickly - embedding financial signals into potential-output models helps spot imbalances sooner and fine-tune macro and macroprudential tools. Ultimately, recognizing that business and financial cycles each have their own tempo—and that credit or housing booms can paint an overly rosy picture of capacity while busts can drag output down harder than a simple trend implies - is key to better forecasting, stronger analysis, and more effective policy interventions.

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