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Financial and Business Cycles: Shall We Dance?

An Application to Kazakhstan

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ABSTRACT: This paper examines the role of financial cycle proxies in refining available estimates of the business cycle in Kazakhstan. It contributes to the existing literature by introducing a formal test for the stability of the mean of exogenous variables in the estimation set up, and by developing a self-contained statistical package to streamline the whole estimation process. The empirical strategy is designed to be parsimonious, aiming to avoid the pitfalls associated with overly complex models while achieving comparable results. Results have implications for the extent with which the authorities should manage the business and financial cycles, with which policies, for macroprudential policy calibration, and for the usefulness for policymaking of end-sample estimates of the cycle.

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WORKING PAPERS

Financial and business cycles: shall we dance?

An application to Kazakhstan

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Content

Glossary

ARDFM	Agency for Regulation and Development of Financial Markets
BNS	Bureau of National Statistics
CB	Central Bank
CPI	Consumer Price Index
CUSUM	Cumulative Sum Test
DSGE	Dynamic Stochastic General Equilibrium
FDI	Foreign Direct Investment
FX	Foreign exchange
GFC	Global Financial Crisis
GG	General Government
HH	Households
HP	Hodrick Prescott
IT	Inflation Targeting
LC	Local currency
LCR	Liquidity Coverage Ration
NBK	National bank of Kazakhstan
NFC	Non-Financial Corporations
NSFR	Net Stable Funding Ratio
ODC	Other Depository Corporations
OFC	Other Financial Corporations
OLS	Ordinary Least Squares
RMSE	Root Mean Square Error
ROW	Rest of the World

Executive Summary

The financial cycle in Kazakhstan has a small but significant contribution to the business cycle. The impact of the financial cycle on business fluctuations primarily occurs through consumption (credit to individuals) and construction (housing prices), rather than through investment (long-term credit and corporate credit). Financial shocks have a persistent and amplifying impact on the business cycle, and this impact is similar during both expansion and contraction phases of the economy. The influence of the financial cycle on the business cycle highlights the relevance of using macroprudential policy to manage the financial cycle and preserve financial stability, and macroeconomic policies to manage the business cycle and preserve macroeconomic stability. The symmetric impact of financial shocks on the economy during both expansion and contraction phases suggests a need for symmetric calibration of macroprudential policy. While the methodological approach used in this paper significantly reduces the confidence interval around cyclical component estimates, caution should be exercised in relying exclusively on real-time estimates for policy setting. The inherent limitations in end-sample estimates mean that policymakers should consider a range of indicators and analyses when making policy decisions.

A. Motivation and Introduction

This paper examines the role of financial cycle proxies in refining available estimates of the business cycle[1] in Kazakhstan. It is part of a concerted effort to promote macro-financial integration in IMF surveillance. It uses a parsimonious estimation approach that does neither require a detailed understanding of the intricate structure of the economy to estimate its trend and cycle, nor of the nature of financial frictions.

Financial sector fluctuations in Kazakhstan are expected to have a small impact on the business cycle for several reasons:

- Kazakhstan is an upper middle-income open economy with a large extractive industry largely financed by foreign direct investment (FDI) with marginal intermediation through the domestic financial system. The country produces and exports primarily oil and raw materials and it imports higher value-added goods.

- The banking sector is relatively small, with traditional funding and business models (Table 1). Total financial assets amount to 47 percent of GDP and credit penetration accounts for only 25 percent of GDP, mainly consisting of local currency (LC) loans to individuals in the form of mortgage and other retail loans. LC and foreign exchange (FX) loans to corporates are less important and primarily used to finance working capital and some investments. Banks are primarily funded by deposits in LC and deposit dollarization, which has been decreasing, remains at 25 percent of total deposits.

- The state retains a large footprint in the economy. Large infrastructure investments tend to be financed by SOEs and funded by issuance of FX debt securities, bypassing the domestic banking sector. Pervasive credit subsidies and significant dollarization weaken the interest rate channel of monetary policy.

- The banking sector is highly capitalized, with some liquidity imbalances and FX imbalances, suggesting that financial frictions have a limited amplifying impact on the business cycle. The average capital adequacy ratio exceeded 19 percent at end-2023. The local currency liquidity ratio suggests some liquidity imbalances stemming mainly from the household sector and less so from the nonfinancial and other financial corporate sectors. Banks are also exposed to some FX liquidity imbalances, at least indirectly. Monetary data report a long foreign currency position of about 11 percent of capital for the sector, but this position is for the most part closed through off-balance sheet items (e.g., derivatives), so that banks comply with prevailing regulation in this area.[2]

Assessing the extent to which the financial cycle impacts the business cycle is important for many reasons, including to: (i) refine the assessment of the monetary and fiscal policy stances; (ii) support the role of macroprudential policy as an integral part of the countercyclical policy toolkit to preserve financial stability; (iii) gauge the strength of the interest channel of monetary policy transmission; and (iv) inform the calibration of

[1] In this paper, we use interchangeably the terms “busyness cycle” and “cyclical component of GDP”.

[2] Notice that monetary data and the ad hoc definition of liquid assets adopted here convey only a partial (accounting) information of banks’ liquidity imbalances. The more comprehensive liquidity coverage ratio (LCR), net stable funding ratio (NSFR), and other regulatory provisions aimed at mitigating liquidity risk provide a more benign picture.

macroprudential policy tools.

The remainder of this paper is structured as follows: section B selectively summarizes the vast theoretical and empirical literature in this area to put the approach followed in this paper in perspective. Section C discusses the empirical set-up used in this paper. Section D presents the data used and discusses estimation results with particular emphasis on the pros and cons of the chosen methodology. Conclusions follow in section E.

B. Select Literature Survey

A vast body of literature has by now established that financial and business fluctuations interact through multiple channels. For instance, asset prices (like equity prices, house prices and exchange rates) can influence consumption through their impact on household wealth and they can affect investment by altering a firms' net worth and the market value of the capital stock relative to its replacement value. The extension of credit and its dynamics are the manifestation of such interactions. Key insights from this literature[3,4] include:

- **Credit and asset price cycles are procyclical relative to the business cycle**. According to Borio *et al.* (2001) and Claessens *et al.* (2010), credit and asset price cycles are typically procyclical with respect to the business cycle. This means that during periods of economic expansion, credit availability and asset prices tend to rise, contributing to economic expansion. However, they tend to peak before the business cycle, thus contributing to its mean reversion.

- **With financial frictions, shocks can have persistent and amplifying effects on the business cycle**. In the presence of financial frictions, such as the costly state verification of idiosyncratic temporary shocks to entrepreneurs' net worth, shocks show a persistent impact on the business cycle. Bernanke and Gertler (1989) use a business cycle model to show that persistence can be the result of a *linear* changes in borrower-lender agency costs associated with changes in the net-worth of the borrower, which affect lending and therefore investment. Financial frictions can have also amplifying effects on the business cycle if shocks to entrepreneurs' net worth cause a *convex* increase in the cost of capital as in the financial accelerator Bernanke *et al.* (1999). Financial frictions can take many other forms. Kiyotaki and Moore (1997) show that the amplifying effect can stem from fire sales of capital used as collateral from more productive to less productive sectors. This further depresses collateral values and amplifies feedback loops.

- **Financial busts can have severe economic consequences**. Financial system exhibits inherent instability due to possibly non-linear effects explained through mechanisms such as liquidity mismatches, spirals, and margin calls justifying (*inter alia*) monitoring by the IMF through its Global Financial Stability Reports. Without government intervention, the system can remain in crisis state for a long time (Gertler and Kiyotaki 2010, Brunnermeier *et al.* 2013, and Borio 2014). This has severe economic ramifications, including profound declines in output and employment as well as sharp increases in the real value of government debt, as documented by Reinhart and Rogoff (2009). In

[3] A comprehensive review of the vast body of literature on the subject is beyond the scope of this paper. Useful starting points for reviewing the theoretical literature is Brunnermeier *et al.* (2013).

[4] The literature focusing on commodity rich countries is thinner and mainly concerned with the impact of the oil price and international cycles, the countercyclical role of fiscal policy, and the role of domestic supply chains (see Bergholt *et al.*, 2017, for the case of Norway, and Baldini, 2005, for the case of Venezuela).

particular, Dell'Ariccia *et al*. (2016) suggest that sectors that are less tradable, more labor-intensive, and more dependent on external finance are more sensitive to the credit cycle

The empirical literature on assessments of financial cycles/frictions can be divided in two main strands:

- **The "structural literature**." The first strand of the literature is based on structural and semi structural general equilibrium models. It exploded around the time of the GFC modelling various forms of financial frictions and identifying the channels through which these frictions impact the business cycle. For instance,[5] Iacoviello (2005) identifies collateral constraints linked to house values as the amplifying mechanism of monetary policy on economic activity. Cúrdia and Woodford (2010) identify credit spreads with heterogenous borrowers as the mechanism through which financial shocks can amplify the business cycle and useful operational target for monetary policy rules. Gelain *et al.* (2021), Taheri Sanjani (2014a, 2014b) identify lending spreads, default, and liquidity risks associated with maturity mismatches as the amplifying channels of monetary policy transmission. Rabanal and Taheri Sanjani (2015) identify the decline of risk premia and the financial accelerator a la Bernanke *et al.* (1999) as key mechanisms explaining macroeconomic fluctuations in the euro area around the GFC. Abilov (2021), the only known study in this strand of the literature applied to Kazakhstan, estimates a DSGE model a la Gerali *et al.* (2010) and identifies financial frictions in the form borrowing constraints associated to the value of housing and entrepreneurs' capital as amplifying mechanisms of monetary, technology, and banks' net worth shocks.

- **The "parsimonious literature**" The other strand of the literature does not delve into specific channels and financial frictions affecting the business cycle but focuses on empirically measuring the impact of the financial cycle on the business cycle. In general, research under this approach starts with the estimation of the business cycle and imposes varying degrees of structure in the estimation, depending on the specific objective of the paper. For instance, Laxton and Tetlow (1992) modify the HP filter by adding information about prices and unemployment to identify demand and supply shocks that could have different impacts on inflation. They argue that this approach is a valid semi-structural compromise between agnostic detrending and fully structural estimations of potential outputs in the case of Canadian data. Similarly, Kuttner (1994) extends the HP filter with a Phillips curve and applies it to Canadian data to estimate the different impact on inflation of shocks coming from the cycle and trend components. Mohr (2005) extends the HP filter by explicitly modeling the cyclical and the seasonal component, thereby reducing the pro-cyclical bias in end-of-sample trend estimates of the HP filter. Benes *et al.* (2010) focus on the calibration of macroprudential policies to mitigate the impact of the housing market cycle. They argue that a combination of loan-to-value limits for mortgages and countercyclical capital buffers would moderate the credit cycle and therefore, its impact on the business cycle. Jönsson (2010) introduces additional information in the HP filter by using judgement to values for the trend or cyclical component at specific points in time, thereby improving some properties of the filter. Borio *et al.* (2013 and 2014) find that proxies for the credit cycle and unemployment contain significant information in the case of the US to help generate robust real-time output gap estimates. Blagrave *et al.* (2015) extend the model by Benes *et al.* (2010) by adding a Phillips curve equation for inflation and an Okun law equation for unemployment to help identify demand and supply

[5] Again, a comprehensive review of the vast body of the empirical literature focusing on the different types of financial frictions is beyond the scope of this paper. Useful starting points for such exercise are papers mentioned in this section and in the introduction.

shocks. They find that the end-sample estimates are improved but remain too imprecise for policy setting. Berger *et al.* (2015) apply the approach of Borio *et al.* (2013 and 2014) to a set of Euro-area countries and find that sustainable output adjusted for the ups and downs of financial variables moves more steadily during financial “boom and bust” periods than implied by conventional estimates such as univariate HP filters (which instead tend to move more closely to actual GDP).

C. Empirical Framework

This paper follows this second strand of the literature by extending the univariate Hodrick and Prescott (1982 and 1997) (HP) filter to capture information contained in proxies for the financial cycle. The empirical strategy has two key objectives: (i) to improve on the HP filter estimates of the Kazakhstan business cycle; and (ii) to remain parsimonious in order to facilitate its applicability to a variety of countries/situations. As such, it falls in the “as-parsimonious-as-it-gets” spectrum of this strand of the literature.

The natural starting place for this empirical strategy is the HP filter in its state space representation. Given T observations of GDP in logs y, the HP filter separates each y_t into a trend τ_t and a cyclical component $c_t = y_t - \tau_t$ by minimizing the following problem:

$$\min_{\tau_1 \dots \tau_T} \left[\sum_{t=1}^{T} (y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} (\Delta\tau_{t+1} - \Delta\tau_t)^2 \right] \quad \text{s.t.}\ \sigma_0^2 \lambda = \sigma_1^2 \tag{1}$$

where λ is the smoothing parameter that penalizes the acceleration in the trend τ relative to the cyclical component $(y_t - \tau_t)$. This is set at 1600 for quarterly data following Ravn and Uhlig (2002) and it constrains the estimated variance ratio of σ_0^2 (the estimated variance of the change in the slope of the trend $(\Delta\tau_{t+1} - \Delta\tau_t)$) over σ_1^2 (the estimated variance of the business cycle $(y_t - \tau_t)$).[6]

Notice that (1) is a second order difference equation which can be re-cast in its state space representation and transformed into a system of two first order linear equations[7] as follows:

$$\begin{bmatrix} \tau_t \\ \tau_{t-1} \end{bmatrix} = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ \tau_{t-2} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{0,t} \\ \varepsilon_{0,t-1} \end{bmatrix}$$
$$y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_t \\ \tau_{t-1} \end{bmatrix} + \varepsilon_{1,t} \tag{2}$$

where the first two equations are the first order difference *state equations* for the unobserved trend and its lag, the third equation is the *observation equation* for the log of GDP y, $\varepsilon_{0,t}$ is the error term of the state equations, and $\varepsilon_{1,t}$ is the error term of the observation equation assumed to be both white noise and non-correlated with all own and cross leads and lags. Using the Kalman filter on (2) with $1600 = \lambda = \sigma_1^2/\sigma_0^2$ yields the estimated HP trend τ_t and the estimated cyclical component $c_t = y_t - \tau_t$. In what follows, I denote estimates using (2) with

[6] The higher λ, the smoother is the estimated trend. When $\lambda \to \infty$, the estimated cycle would have a lower degree of mean reversion and approximate a random walk.

[7] A state space representation is simply the transformation of an n^th order difference equation into a system of n first order difference equations.

"static" HP filter estimates.

In what follows, I augment (2) to include an $AR(1)$ process for the cycle $(y_t - \tau_t) = \beta(y_{t-1} - \tau_{t-1}) + \varepsilon_{1,t}$ in the observation equation[8] and exogenous variables that potentially contain information about the status of the business cycle.[9] More formally, I use Impavido (2024) to estimate:

$$\begin{bmatrix} \tau_t \\ \tau_{t-1} \end{bmatrix} = \begin{bmatrix} 2 & -1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ \tau_{t-2} \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_{0,t} \\ \varepsilon_{0,t-1} \end{bmatrix}$$
$$y_t = \begin{bmatrix} 1 & -\beta \end{bmatrix} \begin{bmatrix} \tau_t \\ \tau_{t-1} \end{bmatrix} + \begin{bmatrix} \beta & \boldsymbol{\gamma} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ \boldsymbol{\xi_t} \end{bmatrix} + \varepsilon_{1,t} \tag{3}$$

subject to the constraints $(1 - \beta^2)\delta\lambda\sigma_0^2 = \sigma_1^2$ and $\lambda = 1600$.[10] In this representation, τ_t is the unobserved trend that needs to be estimated, β is the $\mathrm{AR}(1)$ parameter of the business cycle $(y_t - \tau_t)$, $\boldsymbol{\gamma}$ is a vector of parameters in front of the vector of exogenous variables $\boldsymbol{\xi_t}$ measuring the contribution of such variables to the business cycle, δ is a scaling factor calibrated so as to preserve in (3) the same cyclicality assumed by the static HP filter in (2). Estimation is conducted via maximum likelihood, using the Kalman Filter.[11] In what follows, I denote estimates using in (3) as "dynamic" HP filter estimates to distinguish them from the static HP filter estimates using (2).

This empirical framework closely follows, but it is not the same as, Borio *et al.* (2013 and 2014) and Berger *et al.* (2015). In particular:

- Similarly to these papers, I correct for the small sample problem that results from the introduction of the AR process for the business cycle.[12]
- Similarly to Berger *et al.* (2015) and differently from Borio *et al.* (2013 and 2014), I estimate the autoregressive parameter outside the state space model[13] and I do not use a Bayesian estimation

[8] The rationale is that the estimated HP filter cycle tends to follow an $AR(p)$ process, violating the assumptions of the error terms in (2). While we fail to accept the hypothesis that $p > 1$ for Kazakhstan, a more general $ARMA(p, q)$ may be needed for other countries but this increase in generality would come at the costs of additional parameters to be estimated and not drastically different qualitative results in simulated data.

[9] The rationale for introducing exogenous variables in the observation equations and not in the state equation is closely linked to the title of the paper. In addition, while the literature acknowledge that financial crises can have an impact on potential GDP, it is an empirical issue whether such impact works through the business cycle or directly on the trend.

[10] While the Kalman filter could be used to estimate λ, this is imposed following Ravn and Uhlig (2002) to avoid the "pile-up" problem discussed in Stock and Watson (1988). The Kalman filter would yield an upward biased estimate of λ reducing the degree of mean reversion in the cycle.

[11] The maximum likelihood estimation assumes that the model is identified. I.e., that a change in parameters would imply a different probability distribution for τ_t. Hamilton (1994) shows that the ML estimator is consistent and asymptotically normal when the model is stationary. Model (3) is clearly non-stationary with $\tau_t \sim I(2)$. Schneider (1988) shows that the ML estimator is consistent and asymptotic normally distributed when also when the model is nonstationary, and when the transition matrix has eigenvalues lying on the unit circle and with no unknown parameters.

[12] The inclusion of the $AR(1)$implies that that the smoothing parameter λ should be set such that $\lambda = (1 - \beta^2)1600$ for quarterly data. This, however, reduces the weight on the variability of the trend τ relative to what done by the HP filter resulting in an estimated cycle that is less mean reverting. Hence, an adjustment factor δ needs to be introduced in the corresponding variance ratio constraint $(1 - \beta^2)\delta\lambda\sigma_0^2 = \sigma_1^2$ such that the sample variance of the HP cycle is equal to the sample variance of the cycle estimated with the $AR(1)$process. See Borio ***et al.*** (2014) for details.

[13] This is because the Kalman filter in STATA cannot jointly estimate β and the other parameters as it cannot handle linear restrictions of the form $(1 - \beta^2)\delta\lambda\sigma_0^2 = \sigma_1^2$ required here.

method.

- Differently from Berger *et al.* (2015), I use a state space representation that allows me to impose restrictions on the variance-covariance matrix of the equations' residuals rather than on the equations' parameters.

- Differently from all these papers, I propose a formal test for stability in the means of the exogenous variables.

- Other technical differences include: (i) using the Kalman filter, rather than the OLS estimator, to estimate the autoregressive parameter β also so as to ensure that the same sample is used to estimate the impact of the financial cycle γ and the autoregressive parameter β; and (ii) a lower threshold is used to estimate δ to increase the extent with which the cyclicality in (3) matches the cyclicality assumed in (2).

D. Data, Estimation Strategy, and Results

Data

Table 2 reports the data used in this note, their availability, and sources. Our observed endogenous variable is the log of quarterly real GDP. Data used to construct financial cycle proxies inlcude:[14]

- **Headline inflation**. I take the one and four quarter difference of the log of the CPI index. I expect inflation to be positively correlated with the cycle and with its contribution being a function of the reaction function of the monetary authority.[15]

- **Real interest rates**. I take the annual real rate banks apply to loans in Tenge to individuals and non-financial corporates. I do not take the rate applied to FX loans as individuals are barred from borrowing in FX from banks and the volume of FX loans to corporates is small. I expect the interest rate to be negatively correlated with the cycle and with its contribution being a function of the reaction function of the monetary authority.

- **Short term real credit**. I take the one and four quarter difference in the log of the short-term banking sector loans deflated by the CPI. I expect short term credit to be positively correlated with the cycle and primarily with real consumption.

- **Long term real credit**. I take the one and four quarter difference in the log of the long-term banking sector loans deflated by the CPI. I expect this type of credit to be positively correlated with the cycle and primarily with real investment.

[14] Given that the primary objective of this paper is to establish a link between the financial cycle and the business cycle, I limit the analysis to financial cycle proxies. An exhaustive explanation of the business cycle should clearly extend the structure imposed in the model and include other determinants.

[15] I do not consider core inflation as published data do not exclude energy prices.

- **Total real credit**. I take the one and four quarter difference in the log of the sum of short- and long-term banking sector loans deflated by the CPI. I expect this type of credit to be positively correlated with the business cycle.

- **Real credit to individuals**. I take the one and four quarter difference in the log of the banking sector loans extended to individuals deflated by the CPI. I expect this type of credit to be positively correlated with the business cycle and primarily with consumption.

- **Real credit to nonfinancial corporates**. I take the one and four quarter difference in the log of the banking sector loans extended deflated by the CPI. I expect this type of credit to be positively correlated with the business cycle and primarily with real investment.

- **House price inflation**. I take the one and four quarters difference in the log of the CPI index. I expect the house price inflation to be positively correlated with the business cycle.

All these variables are demeaned to avoid a parallel shift in the estimated trend and that a mean different from zero appear in the estimated cycle.[16] Variables are also detrended to avoid that a linear trend appears in the estimated cycle. In a similar vein, and in order to avoid that a stochastic trend appears in the estimated business cycle, I also include among our exogenous variables ξ_t their cyclical components estimated with the HP filter. A full list of variables used as alternative proxies for the financial cycle is contained in Table 3.

Empirical strategy and results

I then proceed to estimate equation (3) by successively including these variables separately and I assess whether they contain information about the business cycle on the basis of their statistical significance in the estimation. Table 3 reports the estimation results: $\hat{\gamma}$ is the estimated parameter in front of the exogenous variable, w is the value of the Wald statistics for the null $H_0: \hat{\gamma} = 0$, and $\chi(1)$ is the corresponding p-value. Other information reported includes the number of observations contained in the sample and its span. Results are as follows:

- **Real interest rates**. I fail to reject the null for real lending rates to individuals and reject it for real lending rates to corporates but only at a seven percent confidence level. Results may be partly a reflection of the weight of inflation in the reaction function of the central bank over the sample: for instance, during the period 2021-23, the ex-ante real policy rate drifted into negative territory (especially in late 2022) while inflation surged above 20 percent. More likely, they confirm the fact that the interest rate channel of the monetary policy in Kazakhstan is weak as noted already in Zhou (2022), that there is a low pass through from the policy to the lending rates, and that such pass through is stronger for credit to corporates than to individuals.

- **Headline inflation**. I fail to reject the null that annual headline inflation contains no information about the cycle, while we reject it for quarterly inflation; but only at a high six-seven percent confidence level and with the wrong sign. Results suggest that inflation does not contain any meaningful information

[16] Besides, it is not possible to identify a constant in the observation equation as the initial value of τ already plays this role when the Kalman filter is initialized.

about the business cycle and/or that the Phillips curve in Kazakhstan is rather flat. They also confirm the results in Hajdenberg (2024) that inflation in Kazakhstan is mostly externally determined. They are supported by the observation that unemployment barely moves during recessions.

- **Housing price inflation**. I fail to reject the null for quarterly house price inflation but reject it for annual house price inflation. Results suggest that house prices behave procyclically: i.e., while they co-move with output gaps on average, they peak before the output gap peaks. The significance of house prices for the business cycle is not surprising given the large share of construction in supply GDP.

- **Short- and long-term real credit**. Long term real credit has a larger and more significant contribution than short term credit, driving the behavior of total credit in explaining the business cycle. For all these three variables, I fail to reject the null at five percent confidence level for quarterly growth while I reject it for annual growth suggesting that these variables behave procyclically (like housing prices) relative to the business cycle.

- **Real credit to individuals and corporates**. Credit to individuals appears to be highly correlated with the business cycle and to contain the largest information among our variables. Thes results seem to confirm our priors that the financial cycle impacts the business cycle more through consumption than investment. Indeed, the Kazakhstani oil economy is largely financed from abroad through FDIs and the domestic banking sector primarily lends to households. In 2021, credit to individuals accounted for about 13 percent of GDP, or 54 percent of credit portfolio. Its contribution has been increasing since 2022 due to a boom in loans to individuals while the share of credit to non-financial corporates has been decreasing.

On the basis of the Wald statistics reported in Table 3, I select six variables as best candidates to explain the business cycle: short-term, long-term, and total credit, credit to individuals, credit to non-financial corporates, and house prices.

Structural breaks and other non-linearities

Caution in interpretation is needed when there are substantial changes in the underlying data generating processes. For this reason, I check for stability in the variable means and for other non-linearities in two ways:

- **Visual inspection** of Figure 2 which plots each variable together with its recursive mean. This is obtained by extending the sample successively by one observation starting from an initial period of five years of observations.[17] This initial period is long enough to obtain a meaningful starting estimate of the underlying mean and let it stabilize. Visual inspections suggests that means are stable as long as we ignore for the moment the initial instability around the global financial crisis (GFC). A similar conclusion can be drawn from Figure 3 that plots the recursive $\hat{\gamma}$ obtained from estimating (3) by extending the sample successively by one observation starting from an initial period of five years of observations.

[17] 2010q1 for the house price variable for which we have data only starting in 2007q1.

- **Formal testing**. Borio *et al.* (2014) acknowledge that they were unable to find a test that works well in their set up. Here, I use the cumulative sum (CUSUM) test for parameter stability proposed by Brown *et al.* (1975). I regress each exogenous variable on a constant and test whether the estimated mean is constant over time. The null hypothesis for the test of parameter stability is $H_0 : \beta_t = \beta$. The CUSUM statistics is based on recursive OLS residuals and is constructed using the one-step-ahead standardized forecast error. Inference is based on the path of the sequence of the CUSUM statistics crossing a theoretical boundary of a Brownian motion with given probability. Figure 4 reports the sequences of these tests and the linear approximation for the boundaries of the Brownian motion at 95 percent confidence level. Only for ST credit do I fail to reject the null of absence of structural breaks at the 95 percent confidence level. For all other variables, a structural break exists in the mean primarily around the GFC. In addition, the mean of the house price series appears to be strongly trended, especially before 2011, while it appears to be quite stable after then.

The analysis of means stability suggests the presence of structural breaks and possibly other non-linearities. In order to account for structural breaks, I interact our exogenous variables with four dummies: one for each recession period in our sample (Figure 5). Table 4 reports the estimated parameters for average contributions $(\hat{\gamma})$, the deviations from such averages for four recessions periods: (i) 2008q3-q4, at the onset of GFC $(\mathrm{d08})$, (ii) 2015q1-q2, soon after the 2014 financial crisis $(\mathrm{d15})$, (iii) 2016q1-q2, soon after the floating of the Tenge in 2015 $(\mathrm{d16})$, and (iv) 2020q2-q3, at the onset of COVID-19 $(\mathrm{d20})$. Results based on the significance of such deviations from average contributions suggest that the recessions during the GFC and COVID-19 are the largest source of non-linearities.

Conditioning on these two periods, I also test whether contributions to the business cycle differ:

- Before and after the floating of the Tenge. Given the importance of the external sector in the Kazakhstani economy, we expect that the choice of exchange rate regime affects significantly the international transmission mechanism, potentially affecting the contribution of financial cycle proxies to the business cycle.

- During positive versus negative output gap periods. Asymmetric contributions over the business cycle would suggest temporal agglomeration (or bunching) and have a direct implication on the design and application of macroprudential tools along different phases of the business cycle.

Table 5 and Table 6 report the estimated average contributions $(\hat{\gamma})$ and deviations from such averages for the period after the float of the Tenge (dIT) or for positive output gap periods (dpos). I conclude that the adoption of the flexible exchange rate regime might have affected the business cycle but not the contribution of the financial cycle proxies. The most plausible rationale for this is that banks in Kazakhstan are not funded from abroad and are required to close their net open FX positions by regulation, which minimizes potential balance sheet effects from exchange rate volatility. Also, the financial cycle does not seem to impact the business cycle differently in positive or negative output gap periods. This argues for a symmetric calibration of macroprudential policies aimed at managing the financial cycle.

Static and dynamic cycle estimates

Figure 6 compares the static HP business cycle estimate derived from equation (2) and the six dynamic cycle estimates derived from equation (3) by successively including each of the six exogenous variables together with their interaction dummies for the recessions during the GFC and COVID-19. Proxies for the financial cycle yield notably significantly different output gap estimates in three distinct periods:

- **1999-2007**. In the run up to the GFC, dynamic estimates are notably higher than static HP filter estimates. During this period, real GDP grew on average by about 10 percent per year, real credit and house prices grew on average by about 39 percent per year (with real credit reaching an astonishing 67 percent annual growth rate in 2007q2).

- **2008-19**. During this period, dynamic estimates are notably lower than static HP filter estimates. This period is characterized by the GFC in 2008, a financial crisis in 2014, the floating of the Tenge and adoption of inflation targeting in 2015, three recessions, a high level of nonperforming loans, and a slow process of cleaning up bank balance sheets. Real GDP grew on average by 4 percent per year, house prices by 5 percent per year and real credit contracted on average by 2 percent per year.

- **2020-23**. During this period, dynamic estimates are notably higher than static HP filter estimates. This period is characterized by the COVID-19 global pandemic. Real GDP grew on average 2 percent per year, house prices by 14 percent, and real credit by 6 percent.

The difference in the static and dynamic estimates is due to the fact that static estimates fail to capture the amplifying impact of the financial cycle. When financial cycles proxies are above their trends, the static HP filter overestimates potential GDP and output gaps are lower. Conversely, when financial cycle proxies are below their trend, the static HP filter fails to capture the extent with which the financial sector is holding back the economy. It yields lower trend estimates and more optimistic output gap estimates. Instead, dynamic estimates capture the amplifying effect of the financial cycle and better reflect the sustainability of economic growth.

Notice that that the amplification effect of the financial cycle proxies did not take place during and after the COVID-19 shock. The financial cycle did not contribute to the economic recession in 2020, which was caused primarily by a demand shock induced by measures such as school and workplace closures, restrictions on public gatherings, public transport closures, and stay-at-home requirements. Both cyclical and structural factors contributed to keeping financial cycle proxies above trend during this period. From a cyclical perspective (i) monetary policy remained loose especially in 2022 and the first half of 2023; (ii) the authorities subsidized local currency deposits, the key source of local currency lending, limiting depositors' switch into FX deposits (which would have amplified exchange rate pressures); (iii) pension fund contributors were allowed to use cash balances to purchase houses, inflating house prices; and (iv) a large influx of Russian citizens also contributed to keeping high house prices after the invasion of Ukraine. Finally, from a structural perspective, the increasing state footprint in the economy and financial sector since the 2014 financial crisis progressively weakened the link between business and financial cycles.

The confidence interval around the cycle estimated with equation in (3) is much narrower than the HP filter estimates. Figure 7 plots the cycle estimated using financial cycle proxies, its 95 percent confidence interval, and the confidence interval of the HP filter estimates. Confidence intervals are constructed using the RMSE of the one step-ahead forecast from the Kalman filter. Both sets of confidence intervals display the typical end-sample problem when the RMSE tends to increase. However, confidence intervals using (3) are considerably narrower than the confidence intervals estimated with the HP filter. This suggests that accounting for autocorrelation in the HP filter cycle and for the impact of the financial cycle, drastically reduces the imprecision with which the business cycle is estimated. However, the exclusive use of these real-time estimates of the economy's cyclical position to set policy continues to be problematic. A more granular modelling of the various contributions to the business cycle is necessary to further reduce the estimates' imprecision.[18]

Weak exogeneity

Ultimately, I assess the direction or extent of causality between our proxies of the financial cycle and the estimated business cycles. Because house prices, credit and monetary variables, and macroeconomic aggregates also move in response to other shocks hitting the economy, the direction or extent of causality between these variables can be difficult to disentangle. For instance, in a typical open-economy Phillips curve, inflation is positively related to its own expectation and its lag, the output gap, and other factors. Depending on the lag structure it is possible to assume weak contemporaneous exogeneity and still maintain that inflation contain information about the status of the business cycle. Similarly, one can think that the output gap evolves according to a typical IS-type curve and is positively related to its own expectation and its lag, and negatively related to the real interest rate and deviations from its trend. Again, depending on the lag structure and the sequence of shocks assumed, it is possible to see the interest rate as weakly exogenous relative to the output gap. Finally, whether credit drives or responds to changes in demand remains an empirical question. In order to avoid issues associated with endogeneity, we: (i) assume that our variables contain information about the *contemporaneous* state of the business cycle but react to *past or expected* values of the business cycle or are generated by something exogenous to the business cycle;[19] (ii) test this assumption by using lagged values of ξ_t in (3) and yielding results that are qualitatively very similar to what reported in Table 3; and (iii) test whether the cycle Granger-causes the exogenous variables. Results reported in Table 7 suggest that we always reject the null hypothesis that the exogenous variable does not Granger cause the business cycle while we always fail to reject that the cycle does not Granger cause the exogenous variable.[20]

Contemporaneous and historical contribution of financial cycle proxies

The observation equation in (3) can be used to estimate both the contemporaneous and historical contribution of financial cycle proxies to the business cycle. Figure 8 reports the contemporaneous contribution simply calculated as $\hat{\boldsymbol{\gamma}}\boldsymbol{\xi}_{\mathbf{t}}$. The procyclical behavior and the persistent and amplifying effect of financial cycle proxies are now more obvious than what was possible by simply comparing the static HP with the dynamic cycles in Figure 6. This is especially noticeable around the GFC and less so (if at all) during the COVID-19 recession which, as discussed above, was of a different nature. Towards the end of 2023, short term credit and housing prices had a negative or trivial contribution to the business cycle as they were growing at or below trend.

[18] But not a sufficient condition, as the large confidence intervals shown in IMF (2023), table A2.3 "output gaps", suggest.

[19] For credit, one could think of net worth shocks affecting future production; in the case of inflation, one could think of changes in the monetary base.

[20] It is important to recognize that the Granger causality test is a test for strict, not weak, exogeneity. Weak exogeneity by itself does not supply enough restrictions that can be subjected to statistical tests. A test of strict exogeneity can be interpreted as joint tests of strict exogeneity and the assumptions that link weak exogeneity to strict exogeneity.

Figure 9 plots the historical contributions[21] of short-term and long-term credit to the business cycle. Several things can be observed. The initial condition component ($\hat{\beta}^t(y_0 - \hat{\tau}_0)$) is practically zero already around 2003, confirming what already suggested by the low estimated $AR(1)$ parameter ($\hat{\beta} = 0.672$) that series have short memory.[22] The historical contributions of both ST and LT credit ($\sum_{j=1}^{t} \hat{\beta}^{t-j}\, \hat{\boldsymbol{\gamma}}\boldsymbol{\xi}_j$) display a clearly procyclical behavior: they tend peak before recessions and revert to their means before the business cycle. LT credit has the largest amplifying effect on the cycle during expansion and contractions periods. ST credit appears to have the largest contribution during recessions, likely because ST credit matures earlier than LT credit and banks can stop rolling over this type of credit earlier to improve their balance sheets. The unexplained component ($\sum_{j=1}^{t} \hat{\beta}^{t-j}\, \hat{\boldsymbol{\varepsilon}}_{1,j}$) is particularly large around the COVID-19 pandemic. If anything, financial cycle proxies supported growth during the recession in 2020q2-q3 instead of amplifying the recession. In 2023, the historical contribution of LT credit was around two percentage points of potential GDP while ST credit had reverted to its mean.

E. Conclusions

The financial cycle in Kazakhstan has a small but significant contribution to the business cycle. Banking sector credit to individuals and housing prices contribute on average more to the business cycle than long-term and credit to corporates. This suggests that the financial cycle in Kazakhstan affects the business cycle more through consumption and construction than through investment.

Headline inflation contains no information about the business cycle. This weak relationship between the output gap and inflation (flat Phillips curve) may reflect the large state footprint in the economy, a rigid labor market (with unemployment barely moving between cyclical peaks and troughs), price controls and subsidies. This confirms that inflation in Kazakhstan is primarily imported.

Real interest rates contain limited information about the business cycle. Rates on loans to individual contain no information about the cycle while rates on loans to corporates have a small impact but different from zero only with a high p-value. This suggests that the interest rate channel of monetary policy works primarily through credit to corporates.

The financial cycle displays procyclicality and persistence, and it has an amplifying effect on the business cycle. In the run up to recession periods, the static HP filter overestimates potential GDP as it fails to capture the divergence of financial proxies from their trend. Consequently, output gaps are lower. Conversely, after financial busts, the static HP filter fails to capture the extent to which the financial sector is holding back the economy, yielding optimistic output gap estimates. It is worth noticing that the amplification effect of the financial cycle proxies did not take place before or after the COVID-19 recession: during this period, the financial sector actually supported growth. Likely explanations for this include: (i) the relative loose monetary policy in 2022-23; (ii) the increasing state footprint in the financial sector and growing reliance on subsidized credit; (iii) policy responses that included subsidizing LC deposits and allowing pensioners to use their cash balances to buy houses; and (iv) increased housing demand from Russian citizens following the invasion of

[21] See Appendix II for calculation details.

[22] The initial condition is set at $(y_0 - \hat{\tau}_0) = (y_1 - \hat{\tau}_1)/\hat{\beta}$ where $(y_1 - \hat{\tau}_1)$ is the first observation of the natural cycle estimated with (3).

Ukraine.

The impact of the financial cycle suggests that macroprudential policy has a significant role in helping to manage Kazakhstan's economic cycle while preserving financial stability, complementing macroeconomic policies. This highlights the importance of preserving significant buffers in bank balance sheets and implementing any needed balance sheet repair swiftly. In addition, since the impact of the financial cycle on the economy appears similar in both periods of expansion and contraction, macroprudential policy should be calibrated in a symmetric fashion in both periods.

Finally, this paper contributes to the literature on financial and business cycles in two ways. It proposes a formal test for the stability of the mean of the exogenous variables to limit the likelihood that cycle estimates contain low frequency cycles that should instead be captured in the trend estimates. It also makes available a self-contained statistical software that drastically simplifies the estimation strategy followed in the paper.

The parsimonious approach used in the paper produces comparatively good results, as it significantly reduces the confidence interval around the estimates of the cyclical component, while not requiring a detailed understanding of the intricate structure of the economy to estimate its trend and cycle or of the nature of financial frictions. This method contrasts with more complex structural approaches that attempt to jointly estimate multiple economic trends and cycles based on a deeper understanding and modeling of the economy. Still, caution should be exercised in relying exclusively on these real-time estimates for policy setting. The inherent limitations in end-sample estimates of the filter mean that policymakers should consider a range of indicators and analyses when making policy decisions.

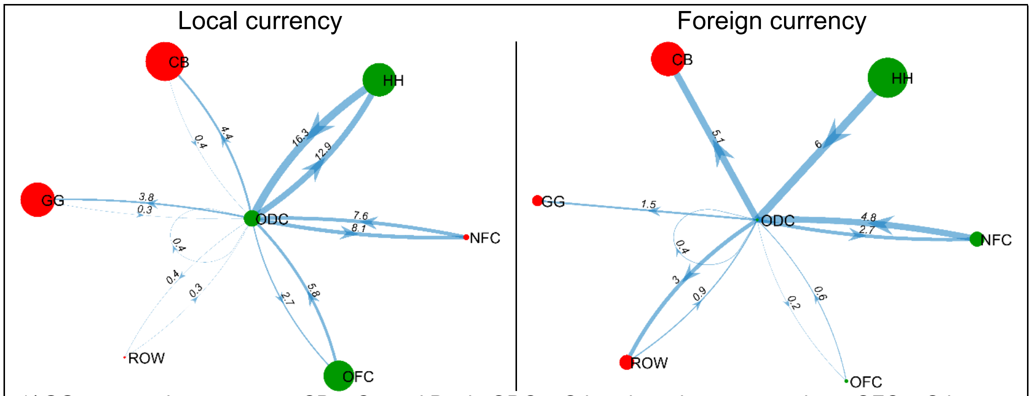
Appendix I. Tables and Figures

Table 1. Balance sheet of commercial banks
(Percent of 2021 GDP)

Assets	**46.6**	**Liabilities**	**46.6**
FX Assets	13.1	FX Liabilities	12.4
Cash	0.4	Cash	0.0
Deposits	6.7	Deposits	11.8
Debt	2.8	Debt	0.2
Loans	2.9	Loans	0.1
Shares & Equity	0.0	Shares & Equity	0.0
Other 1/	0.3	Other 2/	0.3
LC Assets	33.6	LC Liabilities	34.2
Cash	0.5	Cash	0.0
Deposits	2.2	Deposits	19.3
Debt	7.0	Debt	2.5
Loans	21.6	Loans	2.9
Shares & Equity	0.7	Shares & Equity	5.5
Other 1/	1.5	Other 2/	4.0
Memorandum items			
Liquidity Ratio (percent) 3/		57.8	
LC Liquidity Ratio (percent) 3/		44.4	
FX Liquidity Ratio (percent) 3/		82.3	
FX Ratio (percent)		104.9	
FX Funding Ratio (percent)		26.7	
FX Net Open Position (percent)		11.2	
Leverage (percent)		50.0	

Sources: National Bank of Kazakhstan and Fund staff calculations.
1/ Including insurance technical reserves, financial derivatives, other accounts receivable, and non financial assets.
2/ Including insurance and technical reserves, financial derivatives, and other accounts payable.
3/ Liquid assets include cash, deposits, and debt. Liquid liabilities include cash, deposits, and debt.

Figure 1. Gross claims of the banking sector
(Percent of 2021 GDP 1/)



1/ GG = general government, CB = Central Bank; ODC = Other depository corporations; OFC = Other financial corporations; HH = household sector; NFC = nonfinancial corporations; ROW = rest of the world.
Source: National authorities' data and authors' calculations.

Table 2. Data and sources

Variable	Min	Max	Source
Gross Domestic Product (SA, Mil.2005.KZT)	1999q1	2023q3	BNS
Credit			
Loans to the Economy - Medium & Long Term (EOP, NSA,Mil.KZT)	1996q1	2023q4	NBK
Loans to the Economy - Short Term (EOP, NSA,Mil.KZT)	1996q1	2023q4	NBK
Loans to individuals (EOP, NSA,Mil.KZT)	1996q1	2023q4	NBK
Loans to non-financial corporates (EOP, NSA,Mil.KZT)	1996q1	2023q4	NBK
Prices			
New Housing prices (NSA, Thou.KZT/Sq.m)	2006q1	2023q4	BNS
Consumer Price Index (SA, Dec. 2020 = 100)	1993q1	2023q4	NBK
Interest rates			
Loans to individuals (KZT, percent)	1997q1	2023q4	NBK
Loans to corporates (KZT, percent)	1997q1	2023q4	NBK

Table 3. Significance of exogenous variables

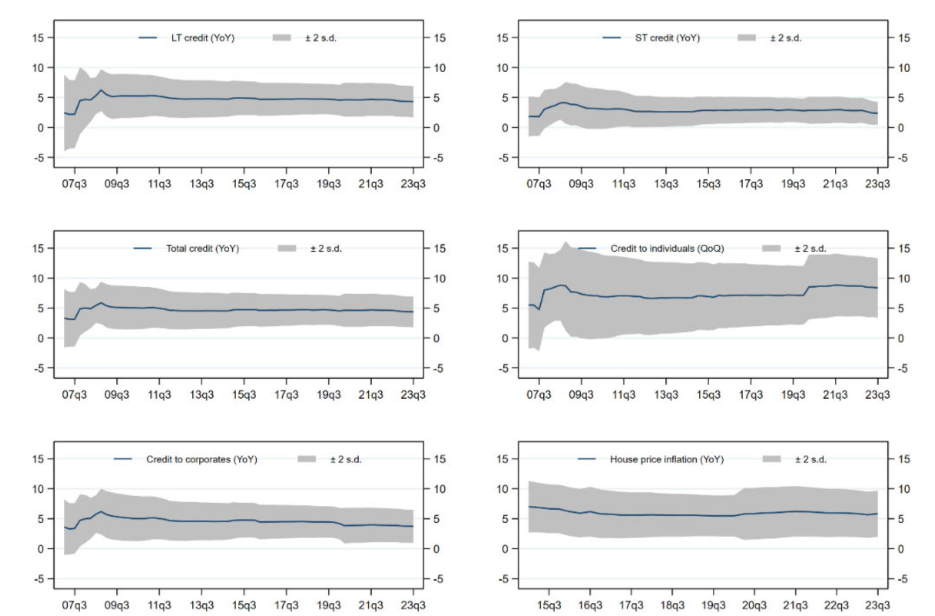
Variable	$\hat{\beta}$	$\hat{\gamma}$	w	χ(1)	1/	N	Min	Max
Real Lending Rate to Individuals (HP filter, cycle)	0.672	0.012	0.050	0.823		98	1999q2	2023q3
Real Lending Rate to Individuals (annual)	0.672	0.009	0.034	0.853		98	1999q2	2023q3
Real Lending Rate to Corporates (HP filter, cycle)	0.672	-0.100	2.407	0.121	*	98	1999q2	2023q3
Real Lending Rate to Corporates (annual)	0.672	-0.112	3.332	0.068	**	98	1999q2	2023q3
CPI Inflation (QoQ, HP filter, cycle)	0.672	-0.217	3.249	0.071	**	98	1999q2	2023q3
CPI Inflation (QoQ)	0.672	-0.213	3.471	0.062	**	98	1999q2	2023q3
CPI Inflation (YoY, HP filter, cycle)	0.672	0.014	0.055	0.814		98	1999q2	2023q3
CPI Inflation (YoY)	0.672	0.006	0.016	0.899		98	1999q2	2023q3
House Prices Inflation (QoQ, HP filter, cycle)	0.701	0.063	1.426	0.232		70	2006q2	2023q3
House Prices Inflation (QoQ)	0.701	0.071	2.090	0.148	*	70	2006q2	2023q3
House Prices Inflation (YoY, HP filter, cycle)	0.702	0.074	10.199	0.001	***	67	2007q1	2023q3
House Prices Inflation (YoY)	0.702	0.058	9.089	0.003	***	67	2007q1	2023q3
Long Term Real Credit (QoQ, HP filter cycle)	0.672	0.042	1.680	0.195		98	1999q2	2023q3
Long Term Real Credit (QoQ)	0.672	0.046	2.276	0.131	*	98	1999q2	2023q3
Long Term Real Credit (YoY, HP filter cycle)	0.672	0.047	10.874	0.001	***	98	1999q2	2023q3
Long Term Real Credit (YoY)	0.672	0.043	10.744	0.001	***	98	1999q2	2023q3
Short Term Real Credit (QoQ, HP filter cycle)	0.672	0.014	0.409	0.522		98	1999q2	2023q3
Short Term Real Credit (QoQ)	0.672	0.016	0.611	0.434		98	1999q2	2023q3
Short Term Real Credit (YoY, HP filter cycle)	0.672	0.024	5.204	0.023	***	98	1999q2	2023q3
Short Term Real Credit (YoY)	0.672	0.024	6.205	0.013	***	98	1999q2	2023q3
Total Real Credit (QoQ, HP filter cycle)	0.672	0.046	1.992	0.158		98	1999q2	2023q3
Total Real Credit (QoQ)	0.672	0.052	2.776	0.096	**	98	1999q2	2023q3
Total Real Credit (YoY, HP filter cycle)	0.672	0.047	11.207	0.001	***	98	1999q2	2023q3
Total Real Credit (YoY)	0.672	0.044	11.601	0.001	***	98	1999q2	2023q3
Real Credit to Individuals (QoQ, HP filter, cycle)	0.672	0.087	9.949	0.002	***	98	1999q2	2023q3
Real Credit to Individuals (QoQ)	0.672	0.084	11.276	0.001	***	98	1999q2	2023q3
Real Credit to Individuals (YoY, HP filter, cycle)	0.672	0.044	12.829	0.000	***	98	1999q2	2023q3
Real Credit to Individuals (YoY)	0.672	0.035	11.660	0.001	***	98	1999q2	2023q3
Real Credit to NFCs (QoQ, HP filter, cycle)	0.672	0.020	0.444	0.505		98	1999q2	2023q3
Real Credit to NFCs (QoQ)	0.672	0.026	0.755	0.385		98	1999q2	2023q3
Real Credit to NFCs (YoY, HP filter, cycle)	0.672	0.037	6.012	0.014	***	98	1999q2	2023q3
Real Credit to NFCs (YoY)	0.672	0.037	7.208	0.007	***	98	1999q2	2023q3

Sources: Authors' calculations.
1/ *** $0 < p \leq 0.05$, ** $0.05 < p \leq 0.10$, * $0.10 < p \leq 0.15$.

Figure 2. Rolling mean of exogenous variables 1/

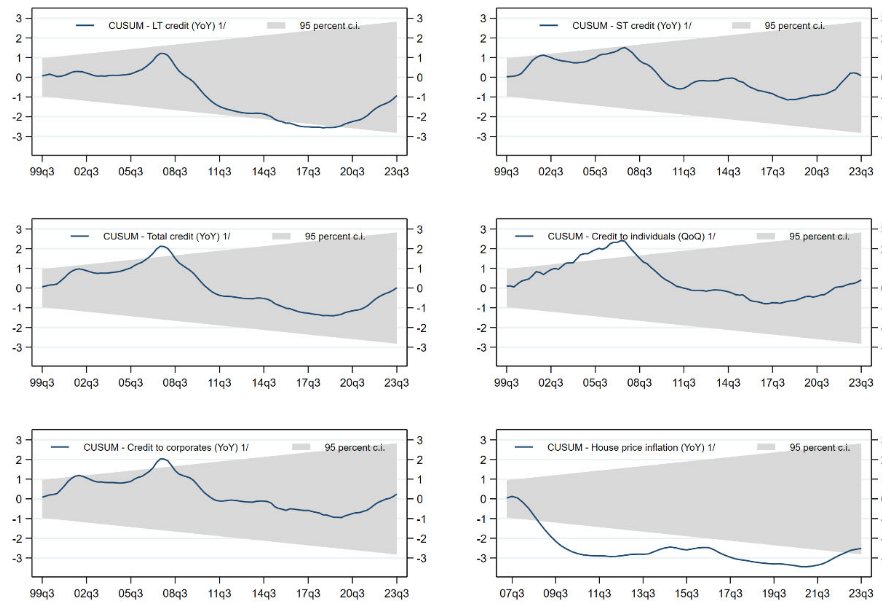
Sources: Authors' calculations.
1/ Percent, demeaned and detrended.

Figure 3. Parameter stability 1/ 2/



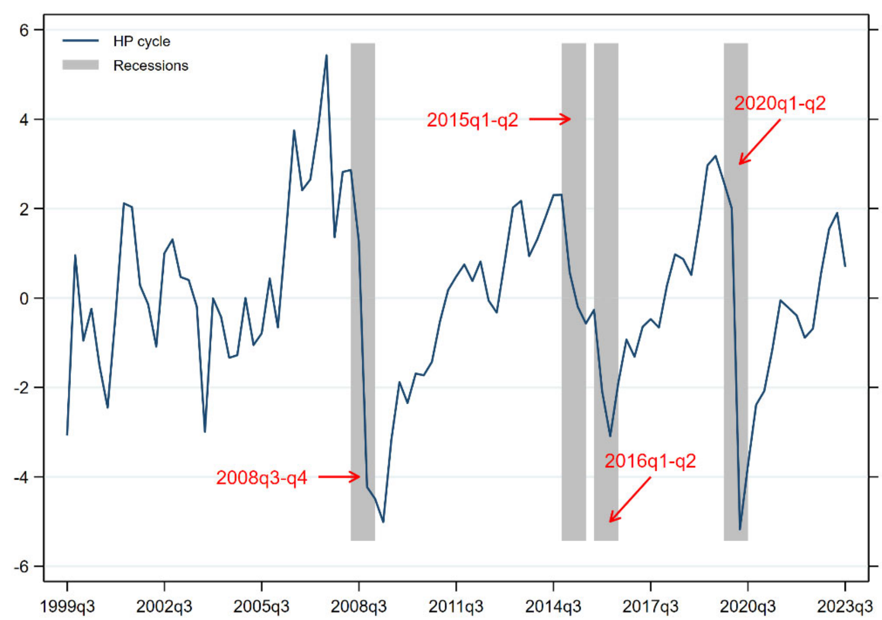
Sources: Authors' calculations.
1/ Percent. 2/ Rolling estimates for γ with sample ending as reported on the x axis.

Figure 4. CUSUM test for mean stability



Sources: Authors' calculations.
1/ Based on recursive residuals using the one-step-ahead standardized forecast error.

Figure 5. Recession episodes 1/



Sources: Authors' calculations.
1/ Percent.

Table 4. Significance of exogenous variables during recession episodes

Variable		ξ	d08 1/	d15 1/	d16 1/	d20 1/
Long Term Real Credit (YoY)	$\hat{\theta}$	0.031	0.052	0.028	0.159	-0.515
	w	5.420	3.254	0.332	2.771	14.686
	χ(1)	0.020	0.071	0.565	0.096	0.000
Short Term Real Credit (YoY)	$\hat{\theta}$	0.019	0.084	0.044	0.103	-1.658
	w	4.792	5.067	0.598	3.845	25.081
	χ(1)	0.029	0.024	0.439	0.050	0.000
Total Real Credit (YoY)	$\hat{\theta}$	0.032	0.060	0.030	0.150	-0.800
	w	6.337	3.505	0.337	3.134	17.102
	χ(1)	0.012	0.061	0.561	0.077	0.000
Real Credit to individuals (QoQ)	$\hat{\theta}$	0.058	0.213	0.170	0.181	1.093
	w	6.326	7.450	0.890	2.698	15.782
	χ(1)	0.012	0.006	0.346	0.100	0.000
Real Credit to NFCs (YoY)	$\hat{\theta}$	0.031	0.076	0.009	-0.026	-0.573
	w	4.916	2.976	0.029	0.058	11.773
	χ(1)	0.027	0.085	0.864	0.809	0.001
House Prices Inflation (YoY)	$\hat{\theta}$	0.038	0.187	0.185	-0.561	0.850
	w	4.325	10.931	1.006	7.792	21.344
	χ(1)	0.038	0.001	0.316	0.005	0.000

Sources: Authors' calculations.
1/ deviations from average contribution.

Table 5. Switch to the IT regime

Variable		ξ	d08 1/	d20 1/	dIT 1/
Long Term Real Credit (YoY)	$\hat{\theta}$	0.040	0.052	-0.518	-0.010
	w	4.944	3.162	14.419	0.280
	χ(1)	0.026	0.075	0.000	0.597
Short Term Real Credit (YoY)	$\hat{\theta}$	0.021	0.083	-1.657	-0.001
	w	3.389	4.623	23.942	0.005
	χ(1)	0.066	0.032	0.000	0.942
Total Real Credit (YoY)	$\hat{\theta}$	0.043	0.062	-0.801	-0.014
	w	6.251	3.539	16.677	0.527
	χ(1)	0.012	0.060	0.000	0.468
Real Credit to individuals (QoQ)	$\hat{\theta}$	0.057	0.207	1.091	0.014
	w	3.951	6.803	15.185	0.166
	χ(1)	0.047	0.009	0.000	0.683
Real Credit to NFCs (YoY)	$\hat{\theta}$	0.041	0.082	-0.577	-0.016
	w	4.167	3.319	11.951	0.453
	χ(1)	0.041	0.068	0.001	0.501
House Prices Inflation (YoY)	$\hat{\theta}$	0.041	0.201	0.844	-0.014
	w	2.396	10.607	18.495	0.142
	χ(1)	0.122	0.001	0.000	0.706

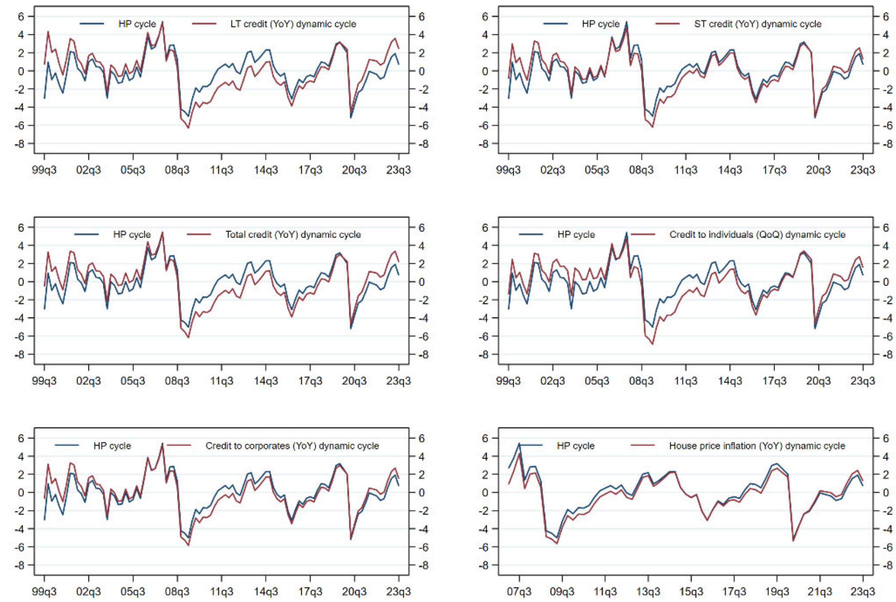
Sources: Authors' calculations.
1/ deviations from average contribution.

Table 6. Contribution in distinct phases of the cycle

Variable		ξ	d08 1/	d20 1/	dpos 1/
Long Term Real Credit (YoY)	$\hat{\theta}$	0.040	0.052	-0.518	-0.010
	w	4.944	3.162	14.419	0.280
	χ(1)	0.026	0.075	0.000	0.597
Short Term Real Credit (YoY)	$\hat{\theta}$	0.021	0.083	-1.657	-0.001
	w	3.389	4.623	23.942	0.005
	χ(1)	0.066	0.032	0.000	0.942
Total Real Credit (YoY)	$\hat{\theta}$	0.043	0.062	-0.801	-0.014
	w	6.251	3.539	16.677	0.527
	χ(1)	0.012	0.060	0.000	0.468
Real Credit to individuals (QoQ)	$\hat{\theta}$	0.057	0.207	1.091	0.014
	w	3.951	6.803	15.185	0.166
	χ(1)	0.047	0.009	0.000	0.683
Real Credit to NFCs (YoY)	$\hat{\theta}$	0.041	0.082	-0.577	-0.016
	w	4.167	3.319	11.951	0.453
	χ(1)	0.041	0.068	0.001	0.501
House Prices Inflation (YoY)	$\hat{\theta}$	0.041	0.201	0.844	-0.014
	w	2.396	10.607	18.495	0.142
	χ(1)	0.122	0.001	0.000	0.706

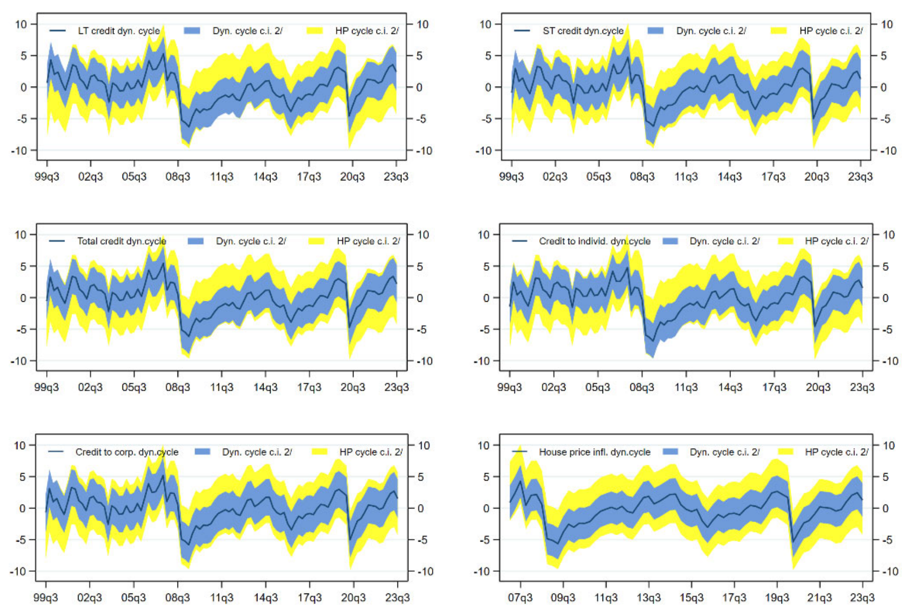
Sources: Authors' calculations.
1/ deviations from average contribution.

Figure 6. HP and dynamic cycles 1/



Sources: Authors' calculations.
1/ Percent.

Figure 7. Confidence intervals of HP and dynamic cycles 1/



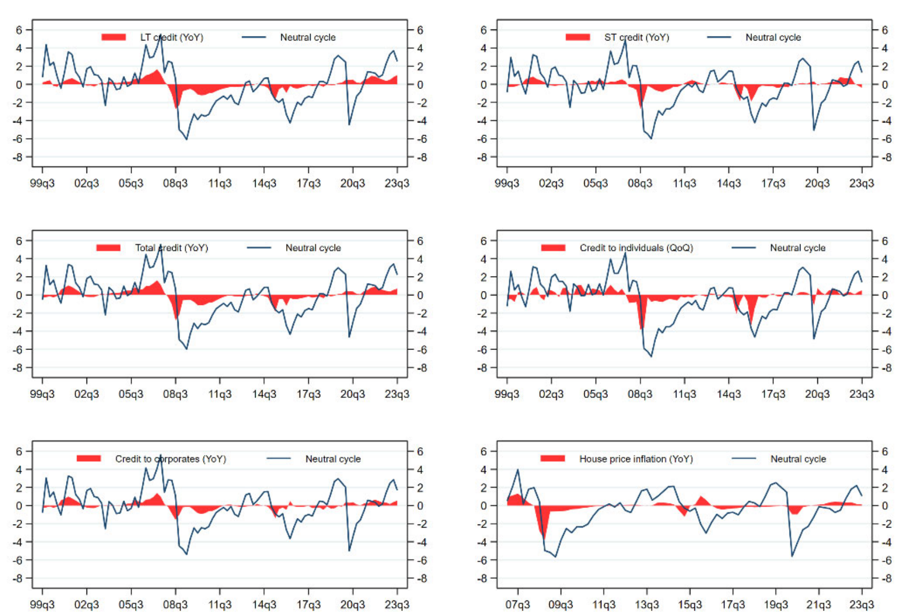
Sources: Authors' calculations.
1/ Percent; 2/ ± 1.96√MSE}

Table 7. Granger causality tests

H0	w	χ(2)
Long Term Real Credit (YoY) does not GC Cycle	19.360	0.000
Cycle does not GC Long Term Real Credit (YoY)	1.170	0.557
Short Term Real Credit (YoY) does not GC Cycle	11.238	0.004
Cycle does not GC Short Term Real Credit (YoY)	0.319	0.852
Total Real Credit (YoY) does not GC Cycle	17.544	0.000
Cycle does not GC Total Real Credit (YoY)	1.988	0.370
Real Credit to individuals (QoQ) does not GC Cycle	7.057	0.029
Cycle does not GC Real Credit to individuals (QoQ)	1.157	0.561
Real Credit to NFCs (YoY) does not GC Cycle	9.672	0.008
Cycle does not GC Real Credit to NFCs (YoY)	2.258	0.323
House Prices Inflation (YoY) does not GC Cycle	7.827	0.020
Cycle does not GC House Prices Inflation (YoY)	0.436	0.804

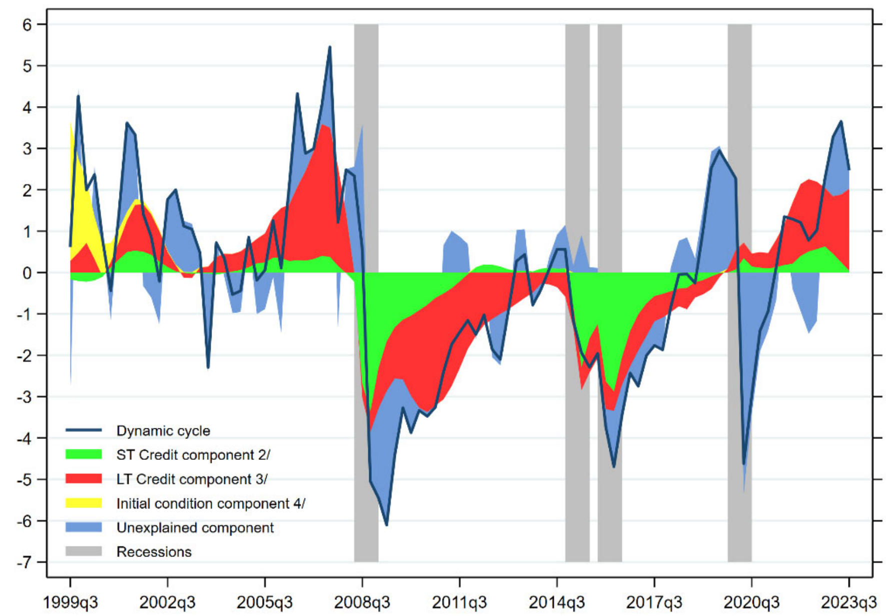
Sources: Authors' calculations.

Figure 8. Contemporaneous contribution to the business cycle 1/



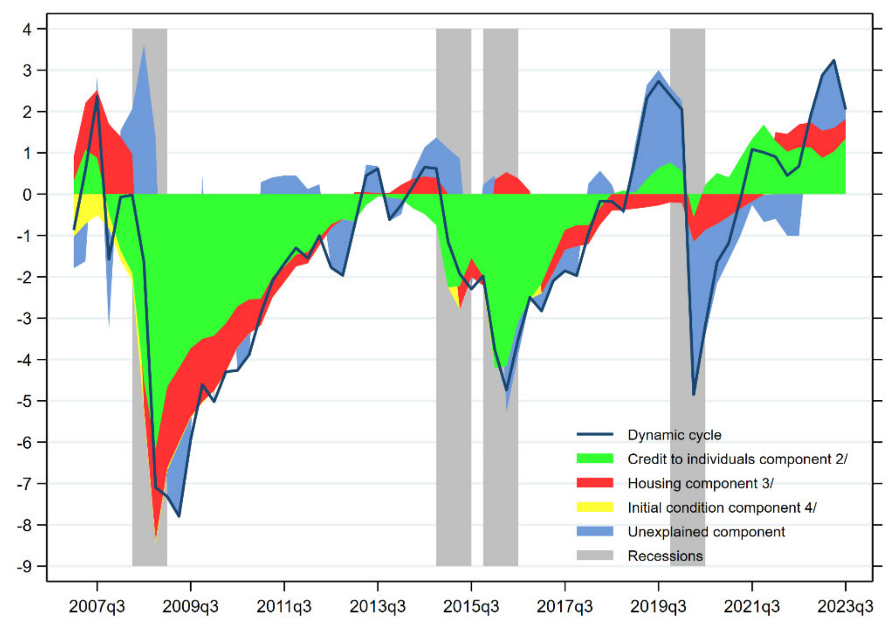
Sources: Authors' calculations.
1/ Percent.

Figure 9. Historical contribution of short- and long-term credit 1/



Sources: Authors' calculations.
1/ Percent; 2/ Annual growth rate of ST real credit; 3/ Annual growth rate of LT real credit; 4/ y_0-τ_0=(y_1-τ_1)/β.

Figure 10. Historical contribution of credit to individuals and housing 1/



Sources: Authors' calculations.
1/ Percent; 2/ Quarterly growth rate of real credit to individuals; 3/ Annual new housing inflation; 4/ y_0-τ_0=(y_1-τ_1)/β.

Appendix II. Derivation of the Historical Decomposition

A linear, first order autonomous difference equation has the general form:

$$y_{t+1} = ay_t + b, \text{ for } t = 0,1,\cdots \tag{A.1}$$

Where a and b are known constants. (A.1) can be solved forward by iteration if we know the initial condition y_0. The solution for $a \neq 1$ is:

$$\begin{aligned}
y_0 &= y_0 \\
y_1 &= ay_0 + b \\
y_2 &= \text{a}(ay_0 + b) + \text{b} \\
y_3 &= a[a(ay_0 + b) + b] + b \\
&\cdots \\
y_t &= a^t y_0 + \sum_{j=0}^{t-1} a^j\, b \\
&= a^t y_0 + b\left(\frac{1 - a^t}{1 - a}\right) \\
&= a^t\left(y_0 + \frac{b}{1 - a}\right) + \frac{b}{1 - a}
\end{aligned} \tag{A.2}$$

Where $\frac{b}{1-a}$ is the steady state value of y.

A linear, first order non-autonomous difference equation has the general form:

$$y_{t+1} = a_{t+1}y_t + b_{t+1}, \text{ for } t = 0,1,\cdots \tag{A.3}$$

The solution via forward iteration is given by:

$$\begin{aligned}
y_0 &= y_0 \\
y_1 &= a_1 y_0 + b_1 \\
y_2 &= \text{a}_2(a_1 y_0 + b_1) + \text{b}_2 \\
y_3 &= a_3[a_2(a_1 y_0 + b_1) + b_2] + b_3 \\
&\cdots \\
y_t &= \prod_{i=0}^{t} a_i\, y_0 + \sum_{j=0}^{t-1}\left(\prod_{i=j+1}^{t} a_i\right) b_j + b_t
\end{aligned} \tag{A.4}$$

The observation equation in (3) is a "partial" non-autonomous difference equation. It has a constant coefficient (the autoregressive parameter) but variable intercepts (the exogenous variables and error term).

$$y_t = [1 \quad -\beta]\begin{bmatrix}\tau_t \\ \tau_{t-1}\end{bmatrix} + [\beta \quad \boldsymbol{\gamma}]\begin{bmatrix}y_{t-1} \\ \boldsymbol{\xi_t}\end{bmatrix} + \varepsilon_{1,t} \tag{A.5}$$

$$(y_t - \tau_t) = \beta(y_{t-1} - \tau_{t-1}) + \boldsymbol{\gamma}\boldsymbol{\xi}_{\mathbf{t}} + \varepsilon_{1,\text{t}}$$

Hence, its solution is a combination of the solutions of autonomous and non-autonomous difference equations just derived. Starting from (A.4) and taking $a_i = a \;\; \forall i$:

$$\begin{aligned} y_t &= \prod_{i=0}^{t} a_i \, y_0 + \sum_{j=0}^{t-1} \left(\prod_{i=1+1}^{t} a_i \right) b_j + b_t \\ &= a^t y_0 + \sum_{j=0}^{t-1} a^{t-j} \, b_j + b_t \\ &= a^t y_0 + \sum_{j=1}^{t} a^{t-j} \, b_j \end{aligned} \tag{A.6}$$

Therefore, by substituting the relevant in the observation equation (A.5) into (A.6):

$$\begin{aligned} (y_t - \tau_t) &= \beta(y_{t-1} - \tau_{t-1}) + \boldsymbol{\gamma\xi_t} + \varepsilon_{1,t} \\ &= \beta^t (y_0 - \tau_0) + \sum_{j=1}^{t} \beta^{t-j} \, b_j \\ &= \beta^t (y_0 - \tau_0) + \sum_{j=1}^{t} \beta^{t-j} \left(\boldsymbol{\gamma\xi_j} + \varepsilon_{1,j} \right) \end{aligned} \tag{A.7}$$

Which can be rearranged into:

$$\underbrace{(y_t - \tau_t)}_{\textit{Neutral cycle}} = \underbrace{\beta^t (y_0 - \tau_0)}_{\textit{Initial condition}} + \underbrace{\sum_{j=1}^{t} \beta^{t-j} \, \boldsymbol{\gamma\xi_j}}_{\textit{Exogenous component(s)}} + \underbrace{\sum_{j=1}^{t} \beta^{t-j} \, \varepsilon_{1,j}}_{\textit{Unexplained residual}} \tag{A.8}$$

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