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Elena Deryugina [*]**, *Maria Guseva*** [**]**,**
Alexey Ponomarenko [***]

The Credit Cycle and Measurement of the Natural Rate of Interest[1]

* *Bank of Russia, Moscow, Russian Federation*

E-mail: DeryuginaEB@cbr.ru

** *Bank of Russia, Moscow, Russian Federation*

E-mail: GusevaME@cbr.ru

*** *Bank of Russia, Moscow, Russian Federation*

E-mail (corresponding author): PonomarenkoAA@cbr.ru

Abstract: We conduct a Monte Carlo experiment using an ad-hoc New Keynesian model and a tractable agent-based model to generate artificial credit cycle episodes. We show that fluctuations in the implicit measures of the natural rate of interest obtained using a conventional trivariate Kalman filter on these artificial datasets occur in the vicinity of credit cycle peaks without any underlying changes in fundamentals (that is the agents' type or their behaviour). The empirical analysis confirms that the measures of the natural interest rate tend to increase prior to a credit cycle peak and decrease afterwards. We conclude that a decline in the estimated natural rates of interest does not necessarily indicate changes in macroeconomic fundamentals. Instead, it may simply reflect the innate properties of the measurement technique in the vicinity of credit cycle peaks.

Keywords: natural rate of interest, credit cycle, Kalman filter, agent-based models.

JEL codes: C32, C63, E43, E44, E51.

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1. Introduction

Global real interest rates have remained exceptionally low since the Great Financial Crisis, triggering a debate about the causes and consequences of the decline. The usual presumption is that the evolution of real interest rates reflects structural changes in the underlying consumption and investment determinants. These are seen to govern variations in a notional 'equilibrium' or natural real rate, most commonly estimated using semi-structural filtering methods[2] in the spirit of Laubach and Williams (2003). A large number of recent economic research papers[3] endeavour to estimate the current level and trend in the equilibrium real interest rate, and a common finding of these studies is that the equilibrium real interest rate has declined in recent years to a level that has not been seen in decades.

In these models, the natural rate measure is anchored to theory-prescribed relationships, such as the Phillips curve and aggregate demand (IS), that govern the joint dynamics of the interest rate, output and inflation (in general, rising inflation indicates that the output is above the potential and, correspondingly, that the actual interest rate is below the natural rate; falling inflation and lower output indicate the reverse). The changes in the observed relationships are accommodated by the changes in the implicitly estimated natural rate of interest. The variability of the natural rate is usually interpreted as an indication of undergoing structural developments. The potential explanations include a persistently weak demand for capital and a rising propensity to save (Summers, 2014, 2015), investors' growing preference for safe assets (Bernanke, 2005; Caballero, Farhi, and Gourinchas, 2008; Broadbent, 2014) and demographic changes (Carvalho, Ferrero, and Nechio, 2016; Gagnon, Johannsen, and Lopez-Salido, 2016; Rachel and Smith, 2017). See also Borio et al. (2017, 2018, 2019) for a critical assessment of these hypotheses.

The objective of this paper is to show that the fluctuations of the estimated natural rates of interest do not necessarily indicate changes in macroeconomic fundamentals. Note that the standard filters assume a constant linear relationship

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2 The alternative concept of natural interest rate that may be estimated using structural economic models (i.e. the rate that would prevail if the price level were flexible (Woodford, 2003) does not correspond to the long run equilibrium rate that appears as a reference point in the Taylor rule and, therefore, is rarely used in the policy discussions. In this paper we also do not discuss the TVP-VAR-based estimates of the natural rate of interest (Lubik and Matthes 2015) that may be regarded as a close alternative (although with fewer theoretical restrictions) to the state-space model approach.

3 See e.g. Justiniano and Primiceri (2010), Laubach and Williams (2016) and Holston, Laubach, and Williams (2017).

between interest rate, inflation, and output. Therefore, if this is not the case and the models are misspecified, the standard approach will give indication of changes in the unobserved trend value of the interest rate even when there is no change in the true data generating process. Interestingly, there is ample evidence on instability of the relationship between the main macroeconomic variables depending on the state of financial conditions (Silvestrini and Zaghini, 2015, Metiu, Hilberg and Grill, 2015, Gross, Henry J, Semmler, 2017, Carriero, Galvao and Marcellino, 2018, Asanović, 2020, Peña, 2020, Nain and Kamaiah, 2020). Such instability cannot be captured by a simple linear relationship between output, inflation and observed interest rate and will be accommodated by the fluctuations in the natural interest rate estimate.

These concerns are not unprecedented. In a related strand of research, Juselius, Borio, Disyatat and Drehmann (2017), Krustev (2018), and Belke and Klose (2019) also claim that conventional models for natural interest rate estimation may be misspecified and augment them with financial variables. We contribute to this type of analysis by examining the properties of conventional natural interest over different phases of the credit cycle.

Admittedly, this task is extremely data demanding. We therefore augment purely empirical analysis with Monte Carlo experiments, which are commonly applied in the analysis of trend/cycle decomposition (Nelson, 1988, Basistha, 2007, and Gonzalez-Astudillo and Roberts, 2016). This approach allows us to generate a large number of artificial credit cycles and examine the fluctuations of the natural rate of interest in the proximity of credit cycle peaks. Therefore, our contribution to the literature in this regard is that instead of augmenting an ad-hoc filter model with financial variables, we employ a tractable theoretical model that is arguably well suited to credit cycle modelling.

The rest of the paper is structured as follows. Section 2 describes the Monte Carlo experiments. Section 3 examines the developments of empirical measures of the natural rate of interest in proximity to credit cycle peaks. Section 4 concludes.

2. Monte Carlo experiments

Reproducing endogenous credit cycles is not an easy task for standard macroeconomic models such as DSGE models.

Notably, the theory of cycles embedded in DSGE models is exogenous: the economy rests in the steady state unless it is hit by a stream of exogenous stochastic shocks. As a consequence, even the DSGE models specifically developed for the financial sector analysis (e.g. Jakab and Kumhof, 2015) do not explain the emergence cycles, having instead to generate them with some sorts of ad-hoc mechanisms. For example, Curdia, Del Negro and Greenwald (2014) estimate the Smets and Wouters (2007) model assuming the Student's t-distributed shocks. They find that the fit of the model improves and rare deep downturns are relevant (see also Fernandez-Villaverde and Levintal, 2016, for a DSGE model with exogenous time-varying rare disaster risk). A similar strategy is employed to Canzoneri, Collard, Dellas and Diba (2016) to allow the effects of fiscal policies to change over time. Gerba and Żochowski (2017) rely of an adaptive learning set-up.

We therefore employ several two-alternative approaches in our paper.

2.1. New Keynesian framework

We set up a conventional New Keynesian model that is line with the traditional Laubach and Williams (2003) approach:

$$y_t = y_t^* + \alpha_1(y_{t-1} - y_{t-1}^*) + \alpha_2(r_{t-1} - r_{t-1}^*) + e_t^y \tag{1}$$

$$\pi_t = \beta_1\pi_{t-1} + \beta_2(y_{t-1} - y_{t-1}^*) + (1 - \beta_1)\pi^* + e_t^\pi \tag{2}$$

$$i_t = \rho_1 i_{t-1} + (1 - \rho_1)(\rho_2 + \pi^* + \rho_3(\pi_{t-1} - \pi^*)) \tag{3}$$

$$r_t = i_t - \gamma\pi_{t-1} - (1 - \gamma)\pi^* \tag{4}$$

$$y_t^* = y_{t-1}^* + g_t + e_t^* \tag{5}$$

$$g_t = g_{t-1} + e_t^g \tag{6}$$

$$r_t^* = 400(g_{t-1} + z_{t-1}) \tag{7}$$

$$z_t = z_{t-1} + e_t^z \tag{8}$$

where y_t is the log of output, π_t is the quarterly inflation rate and i_t is the short-term nominal interest rate and r_t represents the real interest rate. y_t^* and r_t^* are the respective unobserved trends. The respective e are disturbances. One period represents one quarter.

We follow Ajello, Laubach, Lopez-Salido and Nakata (2019) and add several ad-hoc elements to the model in order to introduce the credit cycle into the model. First we add

$$L_t = \varphi_1 L_{t-1} + \varphi_2 (y_t - y_t^*) + \varphi_3 r_t + \varphi_4 (1 - \varphi_1) \quad (9)$$

where L_t is real credit growth that is driven by fluctuations in output and interest rate.

We also add several ad-hoc shocks generating processes that represent booms and busts phases of the cycle. We assume that the economy may switch into a boom state with probability P^B. In this case, the series of expansionary shocks in output are generated as follows:

$$e_t^y = \begin{cases} B, & if\ "boom"\ event\ occured\ 15\ or\ less\ quarters\ earlier \\ u_t^y, & otherwise \end{cases} \quad (10)$$

The economy may also switch to the crisis state with probability:

$$P_t^C = \frac{\exp(h_0 + h_1 L_t)}{1 + \exp(h_0 + h_1 L_t)} \quad (11)$$

In this case, the contractionary shocks in output and inflation are generated as follows:

$$e_t^y = \begin{cases} \delta_y, & if\ "crisis"\ event\ occured\ 3\ or\ less\ quarters\ earlier \\ u_t^y, & otherwise \end{cases} \quad (12)$$

$$e_t^\pi = \begin{cases} \delta_\pi, & if\ "crisis"\ event\ occured\ 3\ or\ less\ quarters\ earlier \\ u_t^\pi, & otherwise \end{cases} \quad (13)$$

Note that while expansionary booms are associated with higher output growth, they also fuel credit growth via equation (9). This in turn leads to higher crisis probability (equation 11). Accordingly, the booms followed by busts pattern emerge.

Disturbances are generated as $u_t^y \sim N(0, \sigma_y^2),\ u_t^\pi \sim N(0, \sigma_\pi^2),\ e_t^* \sim N(0, \sigma_{y^*}^2),$ $e_t^g \sim N(0, \sigma_g^2),\ e_t^z \sim N(0, \sigma_z^2)$.

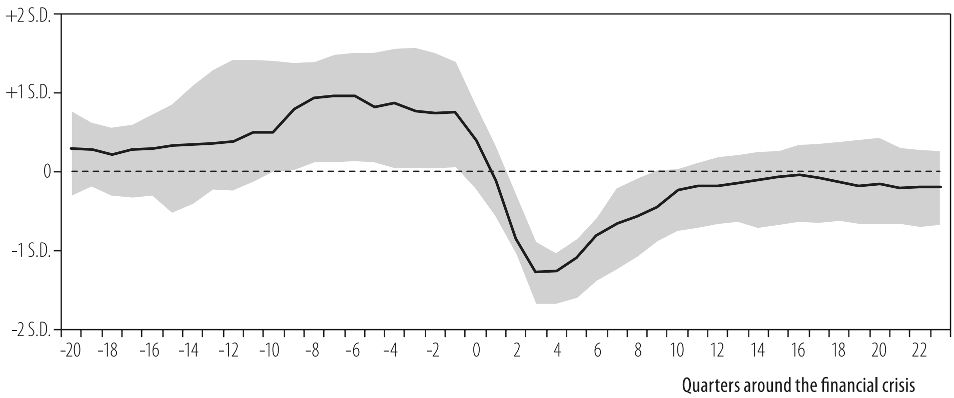
The parameters of the model are reported in Table 1 in the Annex.

We design the Monte Carlo experiment as follows.

The full model (i.e. equations (1)-(13)) is used to generate the artificial dataset (i.e. the observable output, inflation and interest rates) that contains 10000 observations and 139 crisis occurrences.

We proceed by setting up a state-space model comprising only equations (1)-(8) that represent a conventional trivariate New Keynesian model in the spirit of Laubach and Williams (2003). This misspecified model is applied to the artificial dataset and unobserved states are estimated using one-sided Kalman filter. The developments of the r_t^* estimates in the vicinity of the crisis occurrences are presented in Figure 1.

Figure 1: Natural interest rate measures in the vicinity of the crisis occurrences (standardised four-quarter moving averages) based on the artificial dataset generated by the New Keynesian model



The results indicate that the boom and bust developments are accommodated by the fluctuations in the natural interest rate measure. Namely, the estimates obtained during the boom phase of the cycle associated with output expansion are systematically higher and decline rapidly after the crisis events take place.

2.2. Agent-based framework

Admittedly, the outcome obtained in Section 2.1 may seem to be predetermined by the ad-hoc approach to the credit cycle modelling. We therefore employ an alternative agent-based modelling approach where the cyclical fluctuations are fully endogenous. The merits of agent-based models (ABMs) are discussed in detail by Caiani et al. (2016), Fagiolo and Roventini (2017), and Haldane and Turrell (2018). The literature has showed that endogenous credit cycles and debt deflation are a robust emerging feature of fully-fledged macro ABMs, almost independently from the exact micro assumptions (see e.g. Raberto, Tegli and

Cincotti, 2012, Dosi, Fagiolo, Napoletano and Roventini, 2013, Caiani et al., 2016, to name just a few).

In our paper we use the JAMEL model developed by the Seppecher, Salle and Lang (2019) that provides an evolutionary characterization of an economy.[4] This model is able to account for behavioural heterogeneity which, together with full decentralization, produces the resulting co-evolution between micro behaviours and macro outcomes and the fully endogenous emergence of cyclical developments and economic crises.

This modelling approach is conceptually different from the benchmark model and does not explicitly rely on the natural rate of interest concept. But does not mean that an implicit measure of this indicator may not be estimated.

The model is used to generate an artificial dataset containing 250 observations output, inflation and interest rate and 12 financial cycle peaks (defined as local maxima of debt to assets ratio).

We employ the trivariate model outlined by Holston, Laubach, and Williams (2017) to estimate the natural interest rate for this dataset. The model governs the joint dynamics of output, inflation and real interest rates. Its main assumptions are that negative deviations of the real[5] interest rate from the unobserved trend (which is interpreted as the natural rate of interest) result in larger output and that positive deviations of output from the trend are associated with higher inflation. Specifically, the state–space model consists of the following equations:

$$(y_t - y_t^*)*100 = \alpha_{1,y}(y_{t-1} - y_{t-1}^*) + \alpha_{2,y}(y_{t-1} - y_{t-1}^*) + \frac{\alpha_r}{2}\sum_{j=1}^{2}(r_{t-j} - r_{t-j}^*) + \varepsilon_{y,t}$$

$$\pi_t = \beta_\pi\, \pi_{t-1} + (1-\beta_\pi)\, \pi_{t-2,4} + \beta_y\, (y_{t-1} - y_{t-1}^*)*100 + \varepsilon_{\pi,t}$$

$$r_t^* = g_t + z_t$$

$$y_t^* = y_{t-1}^* + g_t + \varepsilon_{y*,t}$$

$$g_t = g_{t-1} + \varepsilon_{g,t}$$

$$z_t = z_{t-1} + \varepsilon_{z,t}$$

where y_t is the log of output, π_t is the quarterly inflation rate ($\pi_{t-2,4}$ is the average of its second to fourth lags) and r_t is the short-term interest rate. y_t^* and r_t^* are the

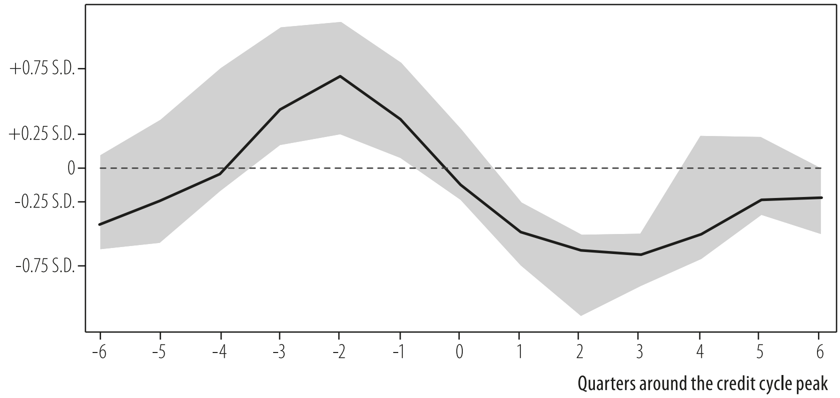
4 The model files were obtained from http://p.seppecher.free.fr/jamel/

5 We use a four-quarter moving average of past inflation as a proxy for inflation expectations to construct the ex-ante real interest rates.

respective unobserved trends. The respective ε are disturbances with zero mean and σ standard deviation.

We use the parameters reported by Holston, Laubach, and Williams (2017) (see Table 2 in the Annex for details). We apply one-sided Kalman filtering to calculate r_t^* and regard these estimates as the natural rate of interest indicators. The developments of the r_t^* estimates in the vicinity of the crisis occurrences are presented in Figure 2.

Figure 2: Natural interest rate measures in the vicinity of the credit cycle peaks (standardised four-quarter moving averages) based on the artificial dataset generated by the JAMEL model



The model predicts that the measures of the natural interest rate will fluctuate during the transition between credit cycle phases. Specifically, the natural interest rates increase prior to the credit cycle peak and decrease as the economy enters the deleverage phase. Notably, these fluctuations are purely endogenous and are not associated with any underlying changes in fundamentals (e.g. in the long-term growth potential or consumer preferences). Rather, these results simply reflect the time-varying relationship between output growth and interest rates in different phases of the credit cycle that is inherent to the agent-based model.

3. Empirical analysis

We proceed by examining the properties of empirical measures of the natural rate of interest.

We use the measures of the natural rate of interest reported by Holston, Laubach and Williams (2017) for Canada, and the natural interest rate measures are estimated for each data set using the UK and the US.[6] For other countries (see Table 3 in the Annex for a description of the data set), the measures of the natural rate of interest are estimated using the trivariate state–space model described in Section 2.2.[7] These measures are standardized using the mean and the standard deviation over the 65-quarter-long period around the credit peaks.[8] The developments of these measures in the vicinity of credit cycle peaks are presented in Figure 3. Note that besides the median of the whole distribution, we separately plot the median of the natural interest rate developments around the credit cycle peaks that occurred after 2005.[9]

The empirical analysis generally confirms the predictions of the theoretical model. The measures of the natural interest rate tend to increase prior to credit cycle peaks and decrease afterwards. The difference between the highest and the lowest value of the median natural interest rates amounts to 0.5 of a standard deviation (about 1 p.p. on average). Interestingly, the drop in the natural interest rates after the Great Financial Crisis does not appear to be dramatically different from those observed during previous credit crunch episodes.[10]

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[6] Obtained from https://www.frbsf.org/economic-research/publications/working-papers/2016/11/ on 20 July 2018. We cross-check our findings using only these natural interest measures (Figure 4 in the Annex).

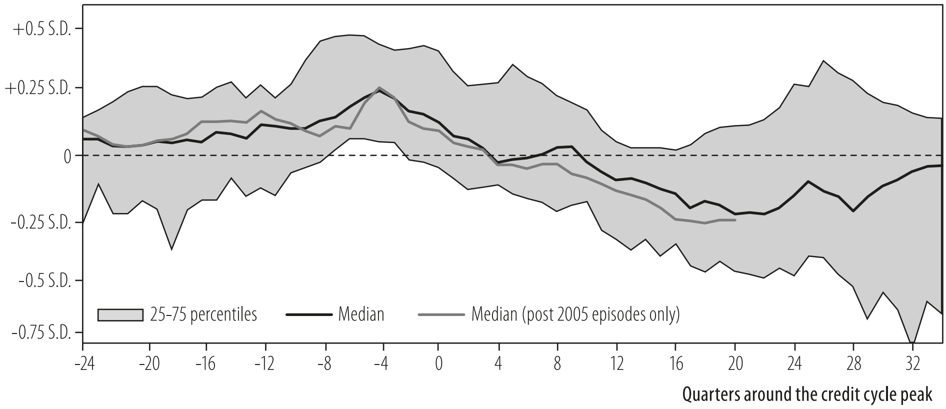
[7] We do not re-estimate the parameters, as the goal of empirical verification of this set-up is beyond the scope of the paper. Note that using a calibrated (i.e. 'based on economic and not econometric considerations') version of such models is far from unprecedented and is in fact recommended in a number of papers (see e.g. Berg, Karam and Laxton, 2006). Nevertheless, we crosscheck our findings using only the natural interest measures obtained with estimated versions of the state–space model (Figure 4 in the Annex).

[8] Credit cycle peaks are identified as local maxima of a credit-to-GDP ratio over a 9-quarter window and set the minimum cycle length equal to 30 quarters. The identified dates are reported in Table 3 in the Annex.

[9] There are 12 such episodes out of 33 in total.

[10] A thorough empirical analysis of whether the credit cycle theory is sufficient to explain all recent fluctuations of the natural rate of interest is beyond the scope of this paper, although Belke and Klose (2019) confirm that this may be the case in the euro area.

Figure 3: Empirical standardized natural interest rate measures in the vicinity of credit cycle peaks (four-quarter moving averages)



4. Conclusions

Estimation of implicit measures of the natural rate of interest is a conventional tool for macroeconomic analysis. Numerous research papers published after the Great Financial Crisis report a decline in such measures, triggering a debate about the causes and consequences of these findings. The usual presumption is that they reflect structural changes in underlying consumption and investment determinants (such as consumers' and investors' preferences and demographic changes).

We believe that there is a more parsimonious interpretation of these findings that is underpinned by the same mechanisms that account for the existence of the credit cycle.[11] To illustrate our point, we set up an ad-hoc New Keynesian model and a tractable agent-based model. This allows our model to generate realistic credit cycles. It also means that the relationship between the interest rate and aggregate macroeconomic variables (e.g. output and inflation) varies across different phases of the credit cycle. Accordingly, the fluctuations in the implicit measures of the natural rate of interest (obtained using a simple linear model) may occur without any underlying changes in fundamentals (e.g. in the long-term growth potential or consumer preferences). In fact, the model predicts the

[11] In this regard, our concept echoes the discussion presented by Borio and Disyatat (2014).

existence of a certain pattern in the developments of natural interest rate measures in the vicinity of credit cycle peaks.

The empirical analysis generally confirms the predictions of the theoretical model. The measures of the natural interest rate tend to increase prior to a credit cycle peak and decrease afterwards. The drop in the natural interest rates after the Great Financial Crisis does not appear to be dramatically different from those observed during previous credit crunch episodes. We conclude that the current decline in the measures of the natural rate of interest does not necessarily indicate changes in the macroeconomic fundamentals. Instead, it may simply reflect the innate properties of the measurement technique in the vicinity of credit cycle peaks.

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Annex

Table 1: Augmented New Keynesian model parameters (used in Section 2.1)

Parameters	Value
α_1	0.85
α_2	-0.03
β_1	0.6
β_2	0.5
ρ_1	0.7
ρ_2	2
ρ_3	1.5
Υ	0.75
φ_1	19/20
φ_2	0.3
φ_3	-0.005
φ_4	0.3
h_0	-6
h_1	3
σ_y	0.000009
σ_π	0.62
σ_{y*}	0.000032
σ_g	0.0000001
σ_z	0.0000002
δ_y	-0.1
δ_π	-1
P^B	0.01
B	0.1
π^*	2

Table 2: Trivariate model parameters (used Section 2.2 and Section 3)

Parameter	European countries	Other countries and artificial series
$\alpha_{1,y}$	1.675	1.648
$\alpha_{2,y}$	-0.725	-0.709
α_r	-0.036	-0.045
δ_π	0.721	0.623
δ_y	0.721	0.188
σ_y	0.354	0.277
σ_π	0.787	1.459
σ_{y*}	0.566	0.610
σ_g	0.125	0.096
σ_z	0.158	0.210

σ_g is expressed as an annual rate. We use the parameters reported by Holston, Laubach, and Williams (2017)[12] for the euro area to compute the natural interest rate for European countries and the averaged (across the estimates for Canada, the euro area, the UK and the US) parameters to compute the natural interest rate for other countries and artificial data sets.

[12] Obtained from https://www.frbsf.org/economic-research/publications/working-papers/2016/11/ on 20 July 2018.

Table 3: Empirical data set

Country	Time sample		Identified credit cycle peaks
	From	To	
Australia	1Q 1968	Q3 2016	4Q1989, 1Q2010
Austria	1Q 1960	Q4 2016	2Q2012
Belgium	3Q 1970	Q3 2016	3Q1979, 4Q2001
Canada	1Q 1960	Q3 2016	2Q1981, 2Q2002
Denmark	1Q 1967	Q3 2016	1Q1976, 1Q1991
Finland	3Q 1970	Q3 2016	3Q1992
France	1Q 1970	Q3 2016	3Q1984
Germany	1Q 1960	Q3 2016	3Q1973, 1Q2003
Greece	2Q 1984	Q3 2016	1Q2010
Japan	3Q 1964	Q3 2016	3Q1995, 3Q2008
Korea	1Q 1964	Q3 2016	3Q1974, 4Q2002
Netherlands	1Q 1982	Q3 2016	1Q2012
Norway	1Q 1979	Q3 2016	1Q1989
Portugal	4Q 1985	Q3 2016	3Q2012
Spain	4Q 1969	Q3 2016	3Q1993, 1Q2010
Sweden	4Q 1960	Q3 2016	1Q1969, 4Q1989
Switzerland	1Q 1960	Q3 2016	3Q1972, 1Q1990, 4Q1999
United Kingdom	4Q 1962	Q3 2016	2Q1973, 1Q1991, 3Q2008
United States	4Q 1951	Q3 2016	2Q1990, 2Q2008

We use the BIS database as the source of credit series (adjusted for breaks; all sectors' credit to the private non-financial sector). The availability of these data determines the composition of the data set. We use the OECD database for the GDP and price (the GDP deflator if available and consumer prices otherwise) series. These series are seasonally adjusted using the X-12 procedure. We use the short-term interest rates from the OECD and FRED databases (in the cases in which money market interest rates are unavailable, we use the interest rates of the respective central bank's instrument).

Figure 4: Empirical standardized natural interest rate measures in the vicinity of credit cycle peaks for Canada, the UK and the US (four-quarter moving averages)