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Are risk weights of banks in the Czech Republic procyclical? Evidence from wavelet analysis

Abstract: We analyze the cyclicality of risk weights of banks in the Czech Republic from 2008 to 2016. We differentiate between risk weights under the internal ratings-based and those under the standardized approach, consider the financial cycle, and employ wavelet coherence as a means of dynamic correlation analysis. Our results indicate that the risk weights of exposures under the internal ratings-based approach, including risk weights related to exposures secured by real estate collateral, are procyclical with respect to the financial cycle. We also show that the effect of changing asset quality on risk weights is present for the internal ratings-based approach, in line with our expectations based on regulatory standards. Our results can be employed for the purposes of decision-making on the activation of supervisory and macroprudential instruments, including the countercyclical capital buffer.

Keywords: financial cycle, financial stability, internal ratings-based approach, risk weight.

JEL Classification: C14, E32, G21, G28, K23

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1. Introduction and motivation

In this paper, we analyse the cyclical behaviour of risk weights for credit exposures of banks in the Czech Republic. A risk weight is calculated as the ratio of risk-weighted exposures to total exposures and can be understood as a measure of the risk relevant to a particular exposure/exposure category (e.g., retail or corporate exposures). The amount of risk inherent to a bank's portfolio is then essential for calculating the capital requirement of the bank. Procyclical behaviour of risk weights magnifies the effect of the economic/financial cycle on the balance sheets of lending institutions and can undermine their resilience and stability when the cycle turns. The topic of procyclicality of risk weights is thus of utmost importance to prudential authorities on both the national and the global level (EBA, 2013a; CNB, 2015).

The topic of procyclicality of risk weights is also connected to the fact that banks can use two approaches to measure credit risk – the standardized (STA) approach and the internal ratings-based (IRB) approach (BCBS, 2013; EBA, 2013a).[1] This possibility was introduced by the Basel II regulatory package in 2004 (Resti, 2016). The calculation of risk weights is vastly different under the IRB and STA approaches. Under the STA approach, risk weights are derived directly based on regulatory rules; the bank simply applies the relevant regulatory standards. In contrast, using the IRB approach, banks determine risk weights on the basis of their own internal models, which are subject to the regulator's approval. The risk weights under the IRB approach are based on two parameters in particular: the probability of default (PD) of the counterparty and the loss given default (LGD). PD conveys the probability that the counterparty will be unable to meet its contractual obligations. LGD conveys the loss in the value of the asset if the counterparty defaults. Both parameters, along with the exposure at default (EAD), are key to the calculation of the expected loss stemming from a bank's operations. However, they can also be used for calculating risk-weighted exposures and the regulatory capital requirements intended to cover risks arising from unexpected losses (BCBS, 2005).

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[1] There are two types of IRB approach. In the basic approach (F-IRB), LGD is determined based on the regulatory rules and banks estimate PD themselves. In the advanced approach (A-IRB), banks set both PD and LGD based on their own estimates. The currently valid rules regarding the calculation of risk-weighted exposures can be found in the CRD IV/CRR regulatory framework. CRR (Capital Requirements Regulation) refers to the EU Regulation No. 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms. The CRD IV (Capital Requirements Directive) refers to the Directive 2013/36/EU of the European Parliament and of the Council of 26 June 2013 on access to the activity of credit institutions and the prudential supervision of credit institutions and investment firms.

Under the IRB approach, banks should set the risk weight of a given exposure according to its true riskiness, and the capital requirement of these banks should ultimately correspond to the riskiness of their business model. However, there are two reasons why the IRB approach, as outlined in the regulatory standards, might imply procyclical behaviour of risk-weighted exposures and thus also of the regulatory capital requirements. Both reasons are linked to the evolution of PD and the factors behind its evolution over the economic/financial cycle. The first reason reflects the fact that the impacts of defaulted exposures on risk weights are different under the IRB and STA approaches. On the one hand, the PD of defaulted exposures is by definition 100 percent for both regulatory approaches.[2] However, unlike for the STA approach, defaulted exposures under the IRB approach enter the bank's credit risk measurement model and thus affect the PD of the entire loan portfolio. In other words, the changing quality of the assets that banks hold might affect PD and thus also the level of risk weights. As asset quality typically increases during an expansionary phase of the economic/financial cycle, PD might decrease and so might risk weights. The opposite occurs during a downturn in the economic/financial cycle: asset quality deteriorares and risk weights increase. Moreover, the issue of procyclicality of risk weights under the IRB approach may be accentuated by too short a measurement of the actual cycle in banks' internal credit risk models. This applies especially to the financial cycle. While the CRR assumes that the cycle lasts for around 8 years, Borio (2014) shows that the duration of the financial cycle can be up to 20 years. PD gradually decreases in line with the decline in the non-performing loan ratio during the expansion phase of the financial cycle, so banks' internal models might estimate the lowest PD value at the peak of the financial cycle, especially in the case of a long-running boom. At the same time, however, new real risks emerge, based on the paradox of financial instability (Borio and Drehmann, 2011). Crucially, a bank cannot account for these new risks, as they have not materialized yet. Banks using the IRB approach may thus demonstrate the lowest risk weights and the lowest absolute capital requirement when real risks are at their highest.

The previous discussion aimed to clarify why prudential authorities should carefully assess the behaviour of risk weights over the cycle, along with their level and their heterogeneity across banks. Prudential authorities can respond with a number of instruments should they detect any potential risks linked to the evolution of risk weights. In particular, a supervisory and/or macroprudential authority may intervene if bank's internal risk model is incorrectly calibrated, if the levels of risk weights based on internal risk models do not match the underlying risks, or in a situation where banks show similar risk profiles. A supervisory authority

[2] According to Article 160(3) and Article 163(2) of the CRR.

may use a variety of microprudential tools based on Article 101 of the CRD and Article 103 of the CRD. A macroprudential authority can also intervene if low risk weights lead to the accumulation of systemic risk which cannot be restrained by other supervisory or macroprudential instruments. This includes the possibility to set minimum risk weights for banks using the IRB approach based on Article 458 of the CRR.

The objective of this paper is to analyse the cyclicality of risk weights of banks in the Czech Republic. Here, risk weights under both the IRB and STA approaches, including risk weights connected to exposures secured by real estate collateral, have been falling recently. At the same time, almost 75 percent of all the exposures of banks in the Czech Republic (CZK 4.1 trillion worth of exposures) fall under the IRB approach (CNB, 2017). We draw on a supervisory dataset of the Czech National Bank (CNB) and employ quarterly data from 2008 to 2016. In our analysis, we use the aggregate risk weights (for the entire banking sector) of total exposures as our default measure and complement them with risk weights of corporate and retail exposures. We distinguish between risk weights of exposures under the IRB approach and those under the STA approach and we are principally interested in checking for differences in the nature of the relationships of risk weights under the two regulatory techniques with respect to various variables connected to the financial cycle. Specifically, we construct a scheme capturing the effect of the financial cycle on risk weights through two asset channels: (i) the asset quality channel, accounting for the impact of change in the quality of banks' portfolios on risk weights, and (ii) the asset structure channel, which controls for the impact of change in the composition of banks' portfolios on risk weights. As our main analytical tool, we employ the wavelet coherence technique, which has recently started to be applied to financial stability topics (Altăr, Kubinschi, and Barnea, 2017; Ferrer et al., 2018). This tool reveals whether two time series are positively or negatively correlated in a certain time span and across several frequencies – which can be interpreted as procyclical or countercyclical behaviour.

Our contribution is threefold. First, we contribute to a growing stream of literature on financial stability topics which use wavelets. Second, we analyse the underresearched topic of cyclicality for the Czech banking sector Third, we explicitly distinguish between risk weights of exposures under the IRB approach and those under the STA approach. Our aim is to examine if the behaviour of risk weights with respect to the financial cycle differs along regulatory lines. This aspect is novel in the literature.

2. Literature review

To the best of our knowledge, our paper is the first to analyse the topic of cyclicality of risk weights in the academic literature. We can, however, review regulatory documents discussing the IRB approach, its advantages over the STA approach, and experiences with the IRB approach since its launch, including analyses of the cyclicality of risk weights and/or capital requirements. From the academic literature, we briefly review the literature on the procyclicality of capital requirements, which is closely related to the topic of procyclicality of risk weights. Furthermore, we review papers which analyse differences in the behaviour of risk weights under the IRB and STA approaches and the factors behind those differences. This stream of literature is directly related to our research objective, as we aim to analyse differences in the cyclical behaviour of risk weights under the IRB and STA approaches.

The IRB approach was first discussed in 1999 by the Basel Committee on Banking Supervision (BCBS) and introduced in the Basel II Accord in 2004 (BCBS, 2001; Resti, 2016). The objective of introducing the IRB approach was to ensure that the capital requirements for credit risk are more sensitive to the true underlying risks relevant to the assets banks hold. Overall, the EBA (2013a) claims that the IRB approach "has proven its validity, as the risk sensitivity in measuring capital requirements should be a key feature of prudential rules." Moreover, the official stance of the EBA on the IRB approach is positive, as "the EBA currently believes the IRB framework to be the most appropriate choice for prudential purposes." Using a variety of analyses, EBA (2013a) does not find any strong evidence of procyclicality of capital requirements: "a clear causal link between capital requirements and the economic cycle could not be established." On the other hand, the analysis finds that capital requirements differ among banks using the IRB approach. Still, the EBA (2013a) notes that it is hard to decide how much of the variation should be attributed to risk-based factors and how much to the non-risk-based ones (including different bank and supervisory practices). Next, the EBA (2013b) finds some evidence of procyclicality of capital requirements with respect to macroeconomic variables both at the bank level and at the portfolio level. However, the empirical analysis is tainted by a very short data sample, which, moreover, includes the aftermath of the global financial crisis and the anticipation of the implementation of the Basel III by banks (EBA, 2013b). Data availability is also a concern in the EBA (2016). Again, using a variety of analyses, the report finds very limited evidence in favour of procyclicality of capital requirements. In particular, PD and LGD are found to have been relatively stable since 2008 for a panel of European banks. The analysis concludes that the EU should retain the current regulatory framework for the calculation of regulatory capital, although the analyses of procyclicality should be regularly repeated (EBA, 2016).

Next, the BCBS (2013) analyses the variation of risk weights across major international banks. Similarly to EBA (2013a), it states that some of the variation in risk weights may be driven by bank and regulatory practices. The empirical analysis uncovers differences in the levels of estimated risks (as captured by PD and LGD) for corporate, sovereign, and bank exposures. The differences might stem from the relative infrequent occurrence of defaults, which translates into high variability of LGD estimates across banks. Also, the BCBS (2013) reports that banks might struggle to produce robust PD estimates. Altogether, the uncertainty associated with both parameters may affect the level of risk weights. Further, the BCBS (2016a) focuses on the factors behind the variability of risk-weighted assets for retail portfolios. It finds that actual defaults closely follow PD estimates, in contrast to LGD estimates Finally, the BCBS (2016b) proposes several changes to the IRB approach to reduce the heterogeneity of the capital requirements for credit risk across banks. Among other things, the BCBS proposes to exclude the option to use the IRB approach for certain exposure categories where there is significant uncertainty about model parameters stemming from a lack of data. Also, the concept of model-parameter floors is proposed "to ensure a minimum level of conservatism for portfolios where the IRB approaches remain available" (BCBS, 2016b).

In contrast to the regulatory documents, the academic literature finds persuasive evidence of procyclicality of capital requirements. That procyclicality is related to increased sensitivity to credit risk under the Basel II Accord (Kashyap and Stein, 2004; Heid, 2007; Andersen, 2011; Topbaş, 2018). As for cyclicality with respect to the business cycle, Zsámboki (2007) reports that the minimum capital requirements can fluctuate substantially over the business cycle – the difference between their levels in a recession and in a boom can easily be twofold. Further, Haubrich (2015) finds that cyclicality depends on the definition of capital ratio. While the ratio of Tier 1 capital to risk-weighted assets is moderately procyclical with respect to real GDP growth, the ratio of equity to total assets is not.

Next, several authors study the differences in the behaviour of risk weights under the IRB and STA approaches. Mariathasan and Merrouche (2014) examine the risk weights of 115 banks in 21 OECD countries and find that following the switch to the IRB approach, risk weights decrease mainly in banks in a worse capital position. However, the decrease in risk weights is not aligned with the development and management of credit risk in these banks. Behn, Haselmann, and Wachtel (2016) use data for German banks and report that PD and risk weights are significantly higher in portfolios continuously using the STA approach than in the portfolios of banks which switched to the IRB approach. However, the level of default in IRB portfolios does not sufficiently reflect that. Also, the interest rates of banks using the IRB approach are significantly higher than those of banks using the STA approach. This suggests that IRB banks are aware of the inherent riskiness of their loan portfolios. Next, Berg and Koziol (2017) use data from the German credit register and conclude that that the heterogeneity of PD is also sizable in the case of the same debtor across various IRB banks. This finding is linked with the criticism of the IRB approach's property of producing inconsistent results, i.e., of estimating different levels of risk weights under otherwise the same conditions (Danielsson et al., 2016). This characteristic can be attributed to the high granularity and complexity of internal ratings-based models (Montes et al., 2016).

Based on the literature reviewed above, it is unclear whether or not we should expect the risk weights of banks in the Czech Republic to behave in a procyclical manner. However, we might expect some differences in the behaviour of risk weights under the IRB and STA approaches.

3. Data, variables and hypotheses

3.1. Risk weights

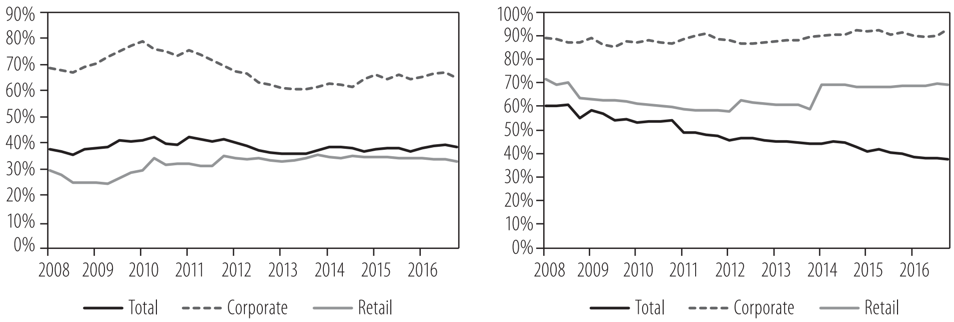
In our analysis, we work with quarterly data on implicit risk weights for credit exposures and balance sheet items only (2008 Q1 to 2016 Q4) from the CNB's supervisory databases. We assume aggregate risk weights – the risk weights of the entire Czech banking sector – throughout our analysis. We explicitly distinguish between risk weights under the IRB approach and those under the STA approach and consider three exposure categories – total, retail, and corporate.[3]

Graph 1 shows the evolution of the aggregate risk weights of total, retail, and corporate exposures under the IRB and STA approaches. While the risk weights of total exposures for the IRB approach are relatively stable over time, the risk weights of total exposures for the STA approach exhibit a substantial downward trend. Graph 1 also points to the fact that the risk weights under the STA approach are significantly higher than those of the same exposure categories under

[3] Corporate and retail exposures make up a decisive share of the loan portfolios of banks in the Czech Republic.

the IRB approach, except for the category of total exposures toward the end of the sample.

Graph 1: Aggregate risk weights according to exposure category and regulatory approach



(a) IRB approach

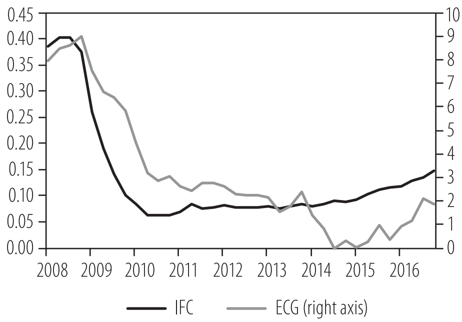
(b) STA approach

Source: CNB

3.2. Measures of the cycle

In our paper, we focus on the sensitivity of risk weights to the financial cycle which is novel in the literature. As a proxy for the financial cycle, we use the Financial Cycle Indicator (FCI) constructed by the Czech National Bank and regularly published in its Financial Stability Reports, such as CNB (2017). The FCI combines information about various cyclical risks in the economy, including credit growth and growth in residential property prices (Plašil et al., 2014). It takes values between 0 and 1. The evolution of the FCI in our sample period is shown in Graph 2: a rapid fall in the crisis period of 2008–2009 has been followed by a steady upward trend ever since. Graph 2 also displays the evolution of the expansive credit gap (ECG), another measure of the financial cycle, which has a similar profile as the FCI. The ECG is determined as the difference between the current

Graph 2: The financial cycle indicator and the expansive credit gap

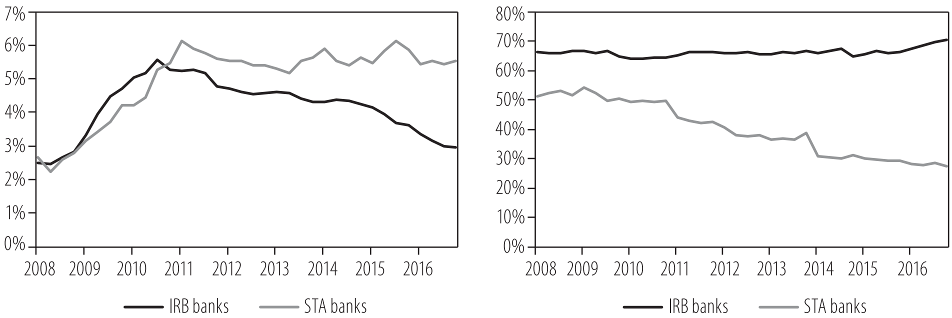


Source: CNB

bank credit-to-GDP ratio and its 8-quarter moving minimum and is regularly calculated by the CNB's staff. As such, it only captures the upward phase of the financial cycle, unlike the FCI, which captures both the upward and downward phases.

Further, the regulatory rules in the CRR and CRD imply that the financial cycle may induce a change in the quality and structure of the assets banks hold. In other words, the financial cycle might influence risk weights through two channels – the asset quality channel and the asset structure channel. The two asset channels are represented by the ratio of NPLs to total loans (the asset quality channel) and the share of client loans in total assets (the asset structure channel). These indicators are calculated separately for IRB and STA banks.[4] Graph 3 shows that a difference is apparent in the values of the two indicators across the two regulatory approaches. The ratio of NPLs to total loans of banks using predominantly the IRB approach has been decreasing since its peak in 2010, as their share of client loans in assets has been increasing moderately at the same time. On the other hand, the ratio of NPLs to total loans of banks using predominantly the STA approach has been relatively stable since its peak at the end of 2010. At the same time, the share of client loans has been decreasing constantly for STA banks.

Graph 3: Indicators for the asset quality channel and the asset structure channel



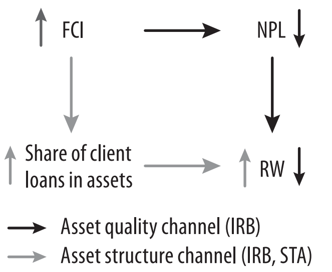
(a) IRB banks (b) STA banks

Source: CNB

[4] By IRB (STA) banks, we mean banks which use the IRB (STA) approach for the majority of their exposures at a given time. This approach is similar to the one used in Malovaná, Kolcunová, and Brož (2018).

In the case of the STA approach, the change in risk weights should be influenced predominantly by the change in the structure of assets. In contrast, for the IRB approach, the change in both the structure and quality of assets should matter. The effect of the expanding financial cycle on risk weights through the two asset channels is depicted in Graph 4. In the case of the asset structure channel, credit growth is induced by both demand and supply shocks during a financial boom. At the same time, this is generally reflected in an increasing share of client loans (retail and corporate exposures), and the asset structure of banks' loan portfolios changes toward riskier exposures (relative to exposures to central banks and governments) under both regulatory approaches. Finally, the fact that banks now hold riskier exposures should then translate into an increase of risk weights under both the IRB and STA approaches.

Graph 4: The effect of the financial cycle on risk weights through the asset quality and asset structure channels under the IRB and STA approaches



Next, the asset quality channel[5] should matter in different ways for the two regulatory approaches. For the IRB approach, defaulted exposures enter the internal ratings-based models and affect the PD of the entire loan portfolio, based on the CRR. By contrast, in the case of the STA approach, only the PD of defaulted exposures is impacted. During a financial boom, the ratio of non-performing loans (NPLs) to total loans – capturing the quality of the assets banks hold – typically falls, as does PD. As PD is an input to the calculation of risk weights under the IRB approach, it follows that risk weights should also decrease during a financial boom. The decline can become especially pronounced in the case of a long-running boom, as the financial cycle can last up to 20 years (Borio, 2014).

3.3. Cyclicality of risk weights

In our understanding, procyclicality means that a time series of risk weights co-moves with the measure of the cycle in such a way that this relationship magnifies both booms and busts. In other words, procyclicality of risk weights occurs when a decrease in the level of risk weights is accompanied by an increase in the

[5] Pfeifer and Pikhart (2019) describe the effect of asset quality channel on the capital and leverage ratio requirement.

value of the measure of the cycle. Thus, a negative correlation between the series of risk weights and the measure of the cycle is the evidence of procyclicality of risk weights.

The main goal of our empirical analysis is to determine (i) whether the cyclicality of risk weights is any different under the IRB and STA approaches, and (ii) whether the financial cycle indeed affects risk weights through two asset channels as shown in Graph 4. Therefore, Hypotheses #1, #2, and #3 are formulated as follows:

Hypothesis #1: *There is no difference in the behaviour of aggregate risk weights according to the IRB and STA approaches with respect to the proxy of the financial cycle.*
Hypothesis #2: *There is no difference in the behaviour of aggregate risk weights according to the IRB and STA approaches with respect to the measures capturing asset quality.*
Hypothesis #3: *There is no difference in the behaviour of aggregate risk weights according to the IRB and STA approaches with respect to the measures capturing the asset structure channel.*

We also employ aggregate risk weights for the corporate and retail exposures, but we focus predominantly on the aggregate risk weights of the total exposures. We test all four hypotheses using the wavelet coherence technique introduced in the following section.

4. Methodology

4.1. Wavelets and financial stability

The wavelet coherence technique belongs to the family of tools based on wavelets, which allow for analyses in both the time and frequency domain.[6] The frequency domain can also be understood in terms of cycles. Wavelet analysis decomposes a time series into several components which tell us which cycles (short or long) are essential to the behaviour of the analysed time series. Clearly, the time series can – with some information loss – be reconstructed using the components extracted. If there are two time series that we want to analyse, we can then study their

[6] Originally used mostly for applications in the natural sciences, wavelets have become increasingly popular in economics and finance recently (Hacker et al., 2014; Soares and Aguiar-Conraria, 2014; Baruník, Kočenda, and Vácha, 2016).

dependencies at various frequencies/cycles. Moreover, thanks to the frequency dimension, we can determine the phase difference between the two time series at various frequencies, and phase differences can be understood as correlations. That is why we use wavelet coherence as a suitable method to assess our hypotheses. While simple correlation produces a single number only, the output of the wavelet coherence technique is a Graph capturing the evolution of the correlation relationship between two series over time, across different frequencies, and at a certain level of confidence. Also, the graphical output is ideal for comparing the differences between the IRB and STA approaches.

Importantly, the wavelet coherence technique has recently been employed in two studies in the financial stability literature (Altăr, Kubinschi, and Barnea, 2017; Ferrer et al., 2018). Altăr, Kubinschi, and Barnea analyse the synchronization of financial cycles – proxied by the credit-to-GDP ratio – between selected members of the European Union (EU) and Germany. Similarly to Borio (2014), they show that financial cycles are longer than business cycles. Also, Altăr, Kubinschi, and Barnea find that the financial cycles of several EU member states (e.g., Italy, Portugal, and the United Kingdom) are synchronized with the financial cycle of Germany. Next, Ferrer et al. study the interaction between the financial stress index and several macroeconomic variables (industrial production, inflation, and unemployment). They find that financial stress negatively influenced the U.S. economy during the crisis years of 2007–2009. Finally, González-Concepción, Gil-Fariña, and Pestano-Gabino (2012) use wavelets to study the relationship between mortgages and GDP for Spain. They report that the series are negatively correlated at lower frequencies. Our paper contributes to the growing stream of literature using wavelets on monthly/quarterly data for financial stability topics.[7]

4.2. Theory of the wavelet coherence

Wavelet coherence analysis is based on the Morlet wavelet, defined as:

$$\psi = \pi^{-\frac{1}{4}} e^{i\omega t} e^{-\frac{t^2}{2}}, \tag{1}$$

where ω, the measure of central (angular) frequency, is set to 6 to achieve an optimal balance of the analysis (Rösch and Schmidbauer, 2014). Moreover, i reveals that the wavelet transform is complex-values and t denotes the time period. Essentially, the Morlet wavelet is a theoretically appealing function which is used

7 Moreover, Aloui et al. (2018) use yearly data to analyse the links between the GDP growth, the oil price, the inflation rate, and the exchange rate for Saudi Arabia also in the wavelet coherence framework.

as a tool to detect statistically significant frequencies across time that are instrumental in constituting the analysed time series. This is achieved by stretching and tightening the original function and moving it across different frequencies, in essence conducting a specific transformation of the original series. Using the wavelet jargon, the original "mother" wavelet is modified into a set of supplementary "daughter" wavelets. Formally, we have:

$$W(\tau,s) = \sum_t x_t \frac{1}{s}\psi^*\left(\frac{t-\tau}{s}\right), \qquad (2)$$

where W denotes the Morlet wavelet transform, x_t is the analyse d time series, τ is the localizing time parameter (that determines the time position of the daughter wavelet), and s the scale parameter (that determines the frequency coordinates of the daughter wavelet). Moreover, * hints at the use of the complex conjugate form to preserve the information content during the transformation (Filip et al., 2016).

Practically, in each position in the time-frequency domain, the algorithm checks the similarity of the Morlet wavelet with a certain segment of the analysed time series and reports the correlation between these two entities at a certain level of significance. The level of significance is obtained using 300 Monte Carlo simulations with 300 pairs of white noise processes.

Having established the basic notions associated with wavelets, we can now introduce wavelet coherence, which allows us to study the co-movement of two time series. Wavelet coherence is based on the cross-wavelet transform, which can be defined for two time series x and y as:

$$W_{xy}(\tau,s) = W_x(\tau,s)W_y^*(\tau,s). \qquad (3)$$

In essence, the cross-wavelet transform combines the wavelet transforms of the individual series. In the next step, after taking the modulus of the initial output, we obtain the cross-wavelet power:

$$P_{xy}(\tau,s) = |W_{xy}(\tau,s)|. \qquad (4)$$

With cross-wavelet power, we come closer to wavelet coherence. Still, cross-wavelet power has a significant drawback as far as its suitability for interpretation is concerned. Namely, it can only be understood as a measure of local covariance, which is misleading for different units of measurement (Rösch and Schmidbauer, 2014). These shortcomings are addressed by the concept of wavelet coherence, which is defined as:

$$C_{xy}(\tau,s) = \frac{|sW_{xy}(\tau,s)|^2}{sP_x . sP_y}, \qquad (5)$$

where we normalize the square of cross-wavelet power with the wavelet powers from the individual series. The letter s in front of the elements in Equation 5 reflects the need for a certain degree of smoothing in both the time and frequency domain to make the results meaningful (Rösch and Schmidbauer, 2014). Nevertheless, wavelet coherence can be finally perceived as a direct analogy to correlation analysis. Moreover, it can provide information about the direction of the relationship between two time series using the concept of phase difference, which can be defined as:

$$PD_{xy}(\tau, s) = Arg\,(W_{xy}(\tau, s)), \tag{6}$$

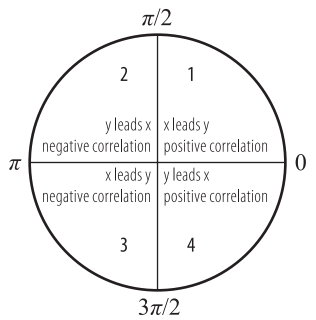
where Arg denotes an operation with both the real and imaginary parts of the cross-wavelet transform.

4.3. Interpretation of the wavelet coherence plots

In our analysis, we review the results from the wavelet coherence technique in a graphical way. Specifically, the Graphs in the Results section will contain several common features that need to be introduced in order to easily process the results.

First, the Graphs will contain two axes. The horizontal axis is the time axis, measured in years. The vertical axis is the frequency axis, measured in quarters. The bottom part of the frequency axis measures the dependencies at high frequencies. In other words, it points to short cycles. The upper part of the frequency axis measures the dependencies at low frequencies. In other words, it points to longer cycles. Inside the Graph, red colour shows the statistical significance of the dependencies at the 10 percent level of confidence, while the other colours (yellow, green, blue) indicate that there is no interaction between the given time series at the particular time and frequency. Next, Graph 5 provides a guide to the interpretation of phase differences between two time series. If there is a statistically significant dependence between two time series at some frequencies, the sign of this dependence can be determined. We can distinguish several patterns. If a black arrow appears in the areas denoted by

Graph 5: A guide to the interpretation of phase differences



1 and 4 (2 and 3), there is a positive (negative) correlation between the two series. Moreover, an arrow pointing exactly to 0 (π) signifies a perfect positive (negative) correlation. Next, there is the feature of one series leading the other. In areas 1 and 3 (2 and 4), the first series x (the second series y) is said to be leading. Moreover, an arrow pointing to $\pi/2$ ($3\pi/2$) reveals that x (y) is leading by exactly 1/4 of the cycle.[8] Finally, the shaded area at the edges indicates results that should be interpreted with caution.[9]

Regarding the practical implementation of the wavelet coherence technique, we employ the R package WaveletComp (Rösch and Schmidbauer, 2014; Mutascu, 2017). As we only have 36 quarterly observations, we need to carefully check the time series we aim to use for our analysis for periodicity. Graphs 1, 2, and 3 reveal that these series are driven rather by long-term trends. Although wavelets are a method that works locally and as such can be used to analyse non-stationary series, the lack of periodicity could make the results uncertain given the short data sample. We therefore employ differences on the analysed time series, similarly to González-Concepción, Gil-Fariña, and Pestano-Gabino (2012) and Ferrer et al. (2018).

5. Results

We derive three types of results about the evolution of risk weights of banks in the Czech Republic with respect to the financial cycle. Specifically, we analyse the co-movement of the aggregate risk weights of total exposures and (i) the FCI measure – an indicator of the financial cycle, (ii) the NPL ratio as a proxy for the asset quality channel, and (iii) the share of client loans in total assets, capturing the asset structure channel. Also, we separately study the issue of the cyclicality of aggregate risk weights of corporate and retail exposures.

We interpret the results from the wavelet coherence plot in a visual way, similarly to Ferrer et al. (2018). We are chiefly interested in the differences between the Graphs for the IRB and STA approaches, as stated in our working hypotheses.

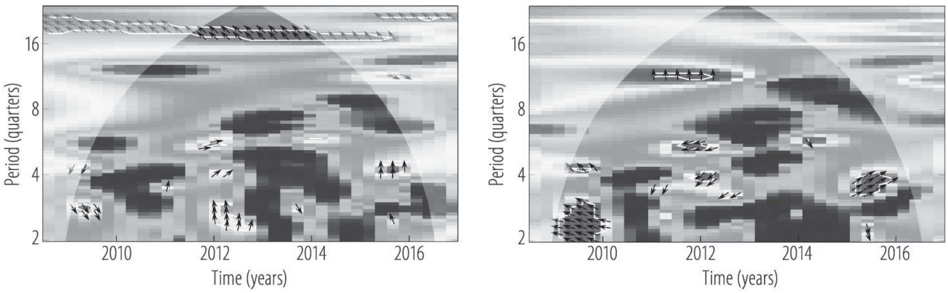
[8] The concept of one series leading the other means that the first one starts a movement and the other series follows it (in the same or the other direction) after some time has elapsed. In cases of perfect positive and negative correlation, the two series co-move without any delay.

[9] The reason why results at the edges are less reliable stems from the artificial extension of the time series in these areas. The time series is extended so that the wavelet of a certain width can analyse the segment of the time series in these areas in a similar way as in the middle of the sample (where there are easily as many observations as the width of the wavelet; however, at the edges the wavelet can be longer than the analysed segment of the time series).

In particular, we check for systematic dependencies (lasting for several years) at various frequencies and the sign of those dependencies, which can be interpreted as evidence of pro-/counter-cyclicality.

The first result concerns the co-movement of the aggregate risk weights of total exposures and the FCI and is captured in Graph 6. We obtain a stark contrast between the Graphs for the IRB and STA approaches and immediately reject Hypothesis #1. The risk weights under the STA approach are virtually insensitive to the financial cycle, which is in line with EBA (2013a, 2016). However, the risk weights for the IRB approach exhibit a negative dependence on the FCI measure at a frequency of around 16 quarters (4 years) over almost the entire sample period. The duration of the dependence reveals that the relationship between the two time series is longer-lasting, as it holds both for the period when the financial cycle was subsiding (until 2010) and for its expansionary phase (since 2011). Moreover, in the spirit of Graph 5, we can conclude that the financial cycle leads the risk weights under the IRB approach (as the arrows point to the second quadrant), which seems intuitive.

Graph 6: Wavelet coherence plots for the aggregate risk weights of total exposures and the financial cycle indicator



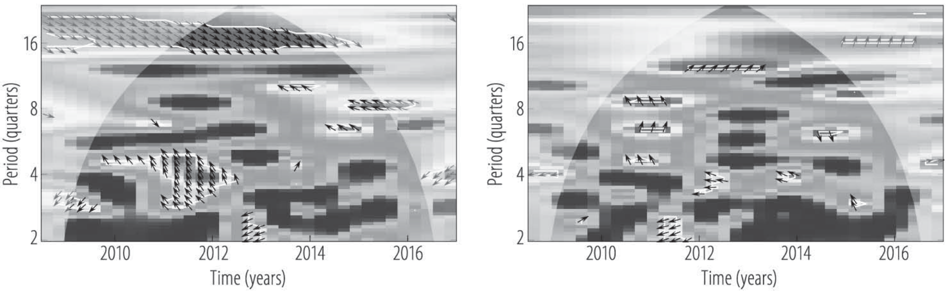
(a) IRB approach (b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

This procyclicality of the aggregate risk weights of total exposures under the IRB approach might be fostered by the fact that the asset quality channel dominates the asset structure channel in the case of the IRB approach. Graph 7 indeed shows that the asset quality channel is present only for the IRB approach and not for the STA approach. For the IRB approach, we obtain a positive dependence between the risk weights and the NPL ratio at a frequency of around 16 quarters – similarly to the case of the interaction of IRB risk weights and the FCI.

This means that there is a longer-lasting positive relationship between the risk weights and the NPL measure: they co-move in tandem over an extended period of time.[10] This indicates, in the spirit of Graph 4, that the asset quality channel must be dominant.

Graph 7: Wavelet coherence plots for the aggregate risk weights of total exposures and the NPL ratio



(a) IRB approach (b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

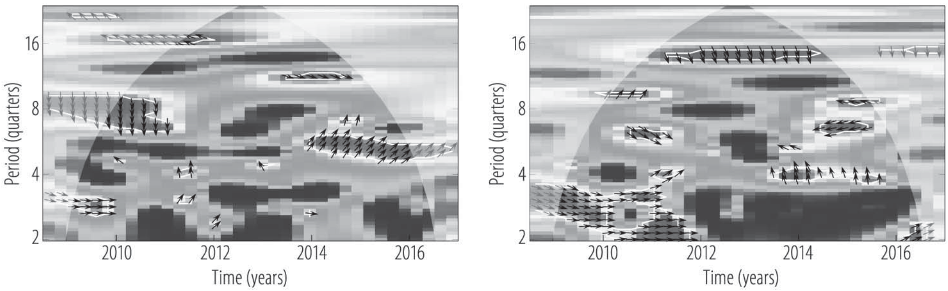
Indeed, for the IRB approach, the asset structure channel is much weaker than the asset quality channel, as Graph 8 reveals. There is some evidence of a positive dependence between the risk weights for the IRB approach and the share of client loans in assets, in line with our expectations captured in Graph 4. However, this positive correlation occurs only toward the end of the sample and at a higher frequency of around 6 quarters – implying that the relationship does not last that long. In contrast, Graph 8 shows that the asset structure channel is stronger for the STA approach compared to the IRB approach. For the STA approach, we obtain evidence of a positive dependence at a frequency of 16 quarters around the middle of our sample period. This hints that there was a longer-run relationship between the two series from 2011 to 2014.[11] Moreover, we obtain some evidence that the high-frequency components of the two series co-moved at the beginning of our sample period, which indicates a short-term relationship between the risk weights and the share of client loans in assets for the STA approach. Overall, we can reject Hypotheses #2 and #3, as we found distinct differences between the

[10] As the arrows point to the fourth quadrant, we can conclude in the spirit of Graph 4 that the NPL ratio leads the risk weights, which seems intuitive.

[11] As the arrows point to the fourth quadrant, we can conclude in the spirit of Graph 4 that the share of client loans in assets leads the risk weights, which seems intuitive.

Graphs showing the asset quality and asset structure channels for the IRB and STA approaches. Moreover, our results are in line with our expectations based on the CRR captured in Graph 4.

Graph 8: Wavelet coherence plots for the aggregate risk weights of total exposures and the share of client loans in total assets



(a) IRB approach (b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

We also analyse the interaction of the aggregate risk weights of the corporate/retail exposures and the FCI measure. The resulting wavelet coherence plots are shown in Graphs A1 and A2 (Appendix). Overall, we find little evidence of any dependencies for corporate exposures. However, Graph A2 shows persuasive evidence of a longer-lasting negative relationship between the risk weights of retail exposures under the IRB approach and the FCI measure. Moreover, the arrows pointing to the second quadrant indicate that the financial cycle leads the risk weights, which seems intuitive. From the point of view of financial stability, this result is intriguing, as retail exposures also include exposures secured by real estate collateral. In the Czech Republic, this category of exposures deserves increased scrutiny because of its recent evolution (CNB, 2017).

All in all, we found some differences in the behaviour of the aggregate risk weights of total exposures with respect to the FCI measure, the NPL ratio, and the share of client loans in assets under the IRB and STA approaches. This supports the findings of Mariathasan and Merrouche (2014), and Behn, Haselmann, and Wachtel (2016) that the behaviour of IRB and STA risk weights might generally differ. Also, our results reveal that the IRB approach might be inherently procyclical with respect to the financial cycle. This finding contrasts with the EBA (2013a, 2016).

Our results can contribute to the discussion on the nature and sustainability of the internal ratings-based risk models of banks. Moreover, they can be used for the purposes of decision-making on the activation of the supervisory and macroprudential instruments mentioned in the introduction. Procyclicality of risk weights can reduce the resilience of the banking sector during a period of accumulation of systemic risks. In this case, the macroprudential authority should take into account the option of increasing the countercyclical buffer which can increase resilience of the financial system to potential shocks during an economic downturn (Dumičić, 2017).

5.3. Robustness analysis

As a robustness check for the results concerning the financial cycle, we employ a different proxy for the financial cycle – the expansive credit gap (ECG). Thus, we analyse the interaction between the aggregate risk weights of total exposures, corporate exposures, and retail exposures with respect to the ECG measure. The aim is to compare the results based on the ECG to those based on the FCI.

Graph A3 shows that, similarly to the FCI case, the aggregate risk weights of total exposures for the IRB approach are negatively correlated with the ECG at a frequency of 16 quarters. There is also, however, a sign of positive dependence at higher frequencies. This indicates that the overall result about the procyclicality of risk weights under the IRB approach is less persuasive than in the case of the FCI. Next, we also obtain different conclusions for the risk weights under the IRB approach for the other exposure categories compared to the case when the FCI is used. In contrast to the FCI results (Graph A1), we obtain evidence of procyclicality of risk weights of corporate exposures with respect to the ECG (Graph A4). On the other hand, unlike for the FCI (Graph A2), we do not obtain any evidence of procyclicality of retail exposures (Graph A5). Overall, we note that the cyclicality of risk weights with respect to the financial cycle might depend on the choice of proxy for the financial cycle. We prefer the FCI, however, as it captures both the expansionary and contractionary phases of the financial cycle.

To put the wavelet analysis results into a familiar perspective, we also include a simple correlation analysis of our main results: the interaction of the aggregate risk weights of total exposures with respect to the financial cycle and the two asset channels. We expect that the two analyses should not give completely contrasting results. Table 1 shows the simple correlations corresponding to the wavelet coherence plots in Graphs 6, 7, and 8. We can see that the wavelet coherence plots and simple correlations generally give similar results. In line with

Graph 6, the simple correlation reveals a negative relationship between IRB risk weights and the FCI. Next, the lack of statistical significance in the result of the correlation analysis for the asset quality channel for the IRB approach might be caused by the fact that there is a negative correlation at various higher frequencies at some points in the sample period to counterbalance the positive dependence at low frequency (Graph 7). While the wavelet coherence output can distinguish between developments at lower and higher frequencies, the simple correlation cannot – resulting in a statistically insignificant positive correlation. Finally, the results of the simple correlation for the asset structure channel are entirely in line with the wavelet coherence outputs in Graph 8: the positive dependence is stronger for the STA approach. Overall, wavelet analysis seems to possess a superior property over simple correlation analysis in that it can distinguish relationships over a short period of time and at various frequencies. In other words, where the simple correlation produces an insignificant result – likely because the dependencies have various signs at various frequencies – wavelet coherence analysis can provide a more complete picture.

Table 1: Simple correlation of the aggregate risk weights of total exposures and the measures of the cycle

Graph (Indicator)	IRB approach	STA approach
Fig. 6 (FCI)	**-0.231**	-0.148
Fig. 7 (NPL ratio)	0.046	-0.078
Fig. 8 (Share of client loans in total assets)	**0.316**	**0.421**

Note: Numbers in bold indicate statistical significance at the 10% level.

6. Conclusion

Analyses of risk weights are essential for financial stability due to the direct interconnection of risk weights with the calculation of banks' capital requirements. In this paper, we cover the topic of the cyclicality of risk weights of banks in the Czech Republic in the period from 2008 to 2016. We primarily focus on the aggregate risk weights (for the entire banking sector) of total exposures, making use of a supervisory dataset available at the Czech National Bank (CNB). On the methodological level, we employ the wavelet coherence. This technique allows us to draw conclusions about the cyclicality of risk weights over the entire sample period and at different frequencies (cycles), including potential changes in the nature of the correlation relationship.

In our analysis, we adopt the approach to studying the cyclicality of risk weights of banks in the Czech Republic based on the financial cycle. We also introduce two channels through which the financial cycle influences risk weights: (i) the asset quality channel (proxied by the ratio of non-performing loans to total loans), and (ii) the asset structure channel (characterized by the share of client loans in total assets). The main goal of our empirical analysis is to check for potential differences between the behaviour of the aggregate risk weights of total exposures under the IRB and STA approaches with respect to the measures of the business/financial cycle.

The contribution of our paper is that we show that risk weights under the IRB approach might be inherently procyclical with respect to the financial cycle. The asset quality channel is relevant only for the IRB approach, and its dominance over the asset structure channel might foster procyclicality of IRB risk weights with respect to the financial cycle. This reasoning is in line with the discussion in the introduction, which is based on the Capital Requirements Regulation (CRR) and on Borio (2014). In contrast, the asset structure channel is stronger for the STA approach. However, as the asset quality channel is not relevant for the STA approach, risk weights under the STA approach are ultimately almost insensitive to the financial cycle. This conclusion is in line with EBA (2013a, 2016). Next, we find that the risk weights of retail exposures under the IRB approach – which also contain exposures secured by real estate collateral – are clearly procyclical with respect to the financial cycle. The different behaviour of the risk weights across the regulatory lines supports the findings of Mariathasan and Merrouche (2014), and Behn, Haselmann, and Wachtel (2016) that the behaviour of IRB and STA risk weights might generally differ. We also show that the finding of procyclicality with respect to the financial cycle depends to a certain extent on the choice of proxy for the financial cycle and that wavelet coherence analysis is a good complement to simple correlation analysis.

Our results might be employed for the purposes of decision-making on the use of supervisory and macroprudential instruments, including the countercyclical capital buffer. Also, they might contribute to the discussion on the nature and sustainability of the internal ratings-based models of banks.

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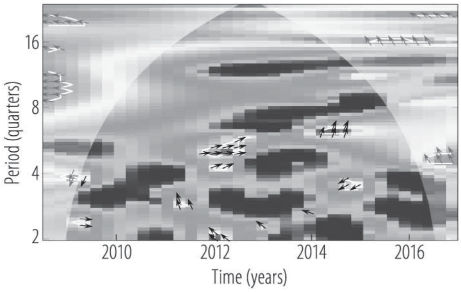
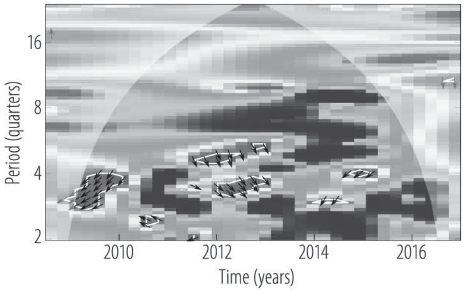
Appendix

Graph A1: Wavelet coherence plots for the aggregate risk weights of corporate exposures and the financial cycle indicator



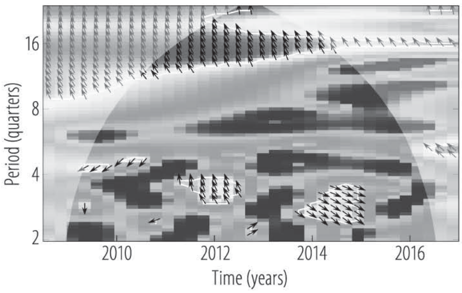
(a) IRB approach



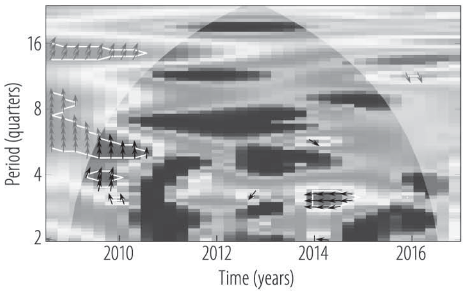
(b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

Graph A2: Wavelet coherence plots for the aggregate risk weights of retail exposures and the financial cycle indicator



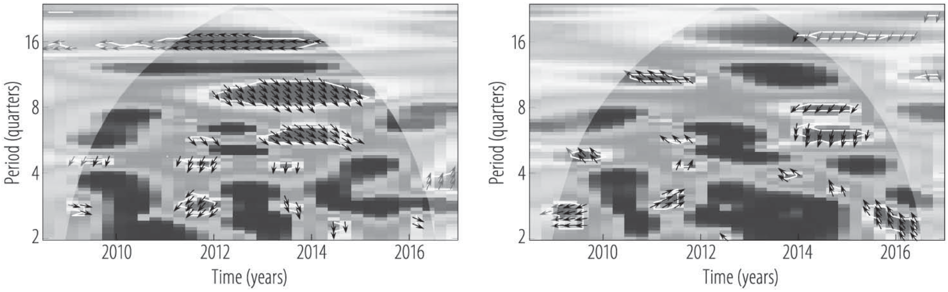
(a) IRB approach



(b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

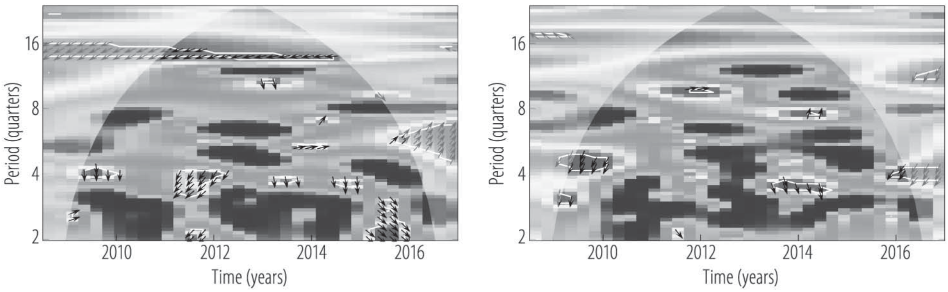
Graph A3: Wavelet coherence plots for the aggregate risk weights of total exposures and the expansive credit gap



(a) IRB approach (b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

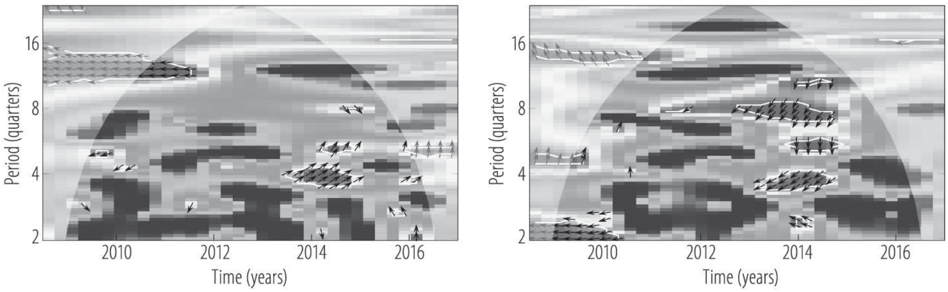
Graph A4: Wavelet coherence plots for the aggregate risk weights of corporate exposures and the expansive credit gap



(a) IRB approach (b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

Graph A5: Wavelet coherence plots for the aggregate risk weights of retail exposures and the expansive credit gap



(a) IRB approach

(b) STA approach

Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.