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Are the Risk Weights of Banks in the Czech Republic Procyclical? Evidence from Wavelet Analysis

Václav Brož, Lukáš Pfeifer, and Dominika Kolcunová *

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 both the business cycle and 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.

Abstrakt

V článku analyzujeme cykličnost rizikových vah bank působících v České republice mezi lety 2008 a 2016. Rozlišujeme mezi rizikovými váhami pro přístup na základě interních modelů bank a na základě standardizovaného přístupu, uvažujeme jak cyklus hospodářský, tak cyklus finanční a používáme vlnkovou koherenci jako prostředek dynamické korelační analýzy. Naše výsledky ukazují, že rizikové váhy expozic spadající pod přístup založený na interních modelech bank jsou procyklické ve vztahu k finančnímu cyklu, a to včetně rizikových vah spjatých s expozicemi zajištěnými nemovitostmi. Také ukazujeme, že pro přístup založený na interních modelech bank je relevantní vliv měnící se kvality aktiv na rizikové váhy, což je v souladu s našimi očekáváními na základě regulatorních standardů. Naše výsledky mohou být použity pro účel rozhodování o aktivaci dohledových a makroobezřetnostních nástrojů včetně proticyklické kapitálové rezervy.

JEL Codes: C14, E32, G21, G28, K23.
Keywords: Financial cycle, financial stability, internal ratings-based approach, risk weight.

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Nontechnical Summary

Analyses of risk weights are essential for financial stability due to the direct interconnection of risk weights with the calculation of banks' capital requirements. The need for such analyses is amplified by the use of internal ratings-based (IRB) models by banks. Prudential authorities should carefully assess potential differences in risk weights under the IRB approach with respect to those based on the standardized (STA) approach as well as their behavior during the cycle. Procyclicality of risk weights might amplify the effect of the cycle on the balance sheets of lending institutions and may negatively influence their resilience when the cycle turns. If deemed necessary, supervisory/macroprudential authorities may respond with a number of instruments to influence the internal models of banks, including the minimum risk weights for banks using the IRB approach.

In this paper, we analyze 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. On the methodological level, we employ wavelets. This technique allows us to draw conclusions about the cyclicality of risk weights over the entire sample period, including potential changes in the nature of the correlation relationship. In our analysis, we adopt two approaches to studying the cyclicality of risk weights of banks in the Czech Republic, one based on the business cycle and the other one the financial cycle. The former is represented by real GDP growth and the latter by the Financial Cycle Indicator (FCI) constructed by the Czech National Bank. We also introduce two channels through which the financial cycle might influence 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 goal of our empirical analysis is to check for potential differences between the behavior 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 main 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. At the same time, however, they are not procyclical with respect to the business 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. 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. 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. This finding might be of policy relevance for the Czech National Bank. All in all, we find some differences in the behavior of the aggregate risk weights of total exposures with respect to real GDP growth, the FCI measure, the NPL ratio, and the share of client loans in assets under the IRB and STA approaches.

Our results can be used in several ways. First, they might be employed for the purposes of decision-making on the use of supervisory and macroprudential instruments, including the countercyclical capital buffer. Second, they might contribute to the discussion on the nature and sustainability of the internal ratings-based models of banks. And third, they might provide a basis for assessing the impact of the regulatory changes associated with risk weights which are under way, including the leverage ratio and the output floor based on the revised Basel III STA approach.

1. Introduction and Motivation

In this paper, we analyze the cyclical behavior 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 behavior 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, banks using the IRB approach 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).

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 behavior 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

[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 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. CRD IV (Capital Requirements Directive) refers to 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.
[2] According to Article 160(3) and Article 163(2) of the CRR.

during a downturn in the economic/financial cycle: asset quality worsens 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 behavior of risk weights over the cycle, along with their level and their heterogeneity across banks.[3] 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 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 analyze the cyclicality of risk weights of banks in the Czech Republic. In the case of the Czech Republic, 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 in some cases. We distinguish between the 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 cyclical variables. Specifically, we adopt two approaches to studying the cyclicality of risk weights of banks in the Czech Republic. First, we apply the business cycle approach, where we inspect the interaction of risk weights and real GDP growth. Second, we construct a scheme capturing the effect of the financial cycle – represented by the Financial Cycle Indicator (FCI) constructed by the CNB – on risk weights through two asset channels. These are: (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. The former channel is proxied by the ratio of non-performing loans to total loans, while the latter one is represented by the share of client loans in total assets. As our main

[3] The importance of such analyses for the stability of the banking sector is highlighted by the creation of the European Central Bank's (ECB) project TRIM (Targeted Review of Internal Models). This project aims to analyze unjustified differences in the internal models of banks. The ECB included this project among its supervisory priorities for 2017. The conclusions of the TRIM project should be available in 2019.

analytical tool, we employ wavelets, which have recently started to be applied to financial stability topics (Altăr et al., 2017; Ferrer et al., 2018). Wavelets – or, more precisely, the wavelet coherence technique – enable us to draw conclusions about the nature of the comovement of two series over time, including changes in the relationship. In other words, 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 behavior.

Our contribution is threefold. First, we contribute to a growing stream of literature on financial stability topics which uses wavelets. Second, we analyze the topic of cyclicality for the Czech banking sector, something which has never been done before on such a scale.[4] Third, we explicitly distinguish between the risk weights of exposures under the IRB approach and those under the STA approach. Our aim is to examine if the behavior of risk weights with respect to the business/financial cycle differs along regulatory lines. This aspect is novel in the literature.

The paper is structured as follows. The second section offers a literature review of the IRB approach based on both regulatory documents and academic papers. The third section describes our data and variables and presents our working hypotheses. The fourth section introduces wavelets as our main methodological approach and provides the intuition behind the wavelet coherence technique. In the fifth section, the results of our analysis are summarized and their policy implications are discussed. The last, sixth, section provides concluding remarks.

2. Literature Review

To the best of our knowledge, our paper is the first to analyze 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 analyze differences in the behavior 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 analyze differences in the cyclical behavior 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. If the PD of a counterparty increases marginally, so will the capital requirement under the IRB approach. The STA approach, in contrast, is susceptible to abrupt changes (Resti, 2016). Another goal of the proposed IRB approach was to provide an incentive for banks to improve their risk management practices, as they would naturally aim to minimize the capital requirements demanded by prudential authorities (BCBS, 2001). The BCBS stated that it expected most banks to eventually move from the STA to the IRB approach as they gradually improved their risk management techniques. And indeed, around one half of all the capital requirements of banks in the EU are currently based on the IRB approach, with corporate and retail exposures accounting for a sizable share (Resti, 2016). Third, the introduction of the IRB approach reflected the fact that internal models were routinely being used by banks in credit management practice. The extension of internal models into the credit risk management area

[4] In some sense, we draw inspiration from Box 2 in CNB (2015).

thus seemed natural to align regulatory standards more closely with practice (Resti, 2016). Finally, the IRB approach also allows banks to better adapt to local conditions and to use their knowledge of customers (EBA, 2013a).

Overall, 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, 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 non-risk-based ones (including different bank and supervisory practices). Next, 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 Basel III by banks (EBA, 2013b). Data availability is also a concern in EBA (2016). Again, using a variety of analyses, the report finds very limited evidence in favor 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, BCBS (2013) analyzes 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, 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, 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. One of the sources of the variation in risk weights for retail exposures is *"methodologies for applying cyclicality adjustments to PD estimates"* (BCBS, 2016a). There are two possible approaches – point-in-time (PIT) and through-the-cycle (TTC). The TTC approach produces PD estimates that are inherently more stable and less cyclical. This means that in periods of stress, it generates capital requirements well below those based on the PIT approach to estimating PD. On the other hand, if economic conditions improve, the capital requirements calculated using PD based on the PIT approach decline much more, while PD based on the TTC approach remains relatively stable (BCBS, 2016a). Finally, 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). Regarding 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 behavior 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 et al. (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 (Haldane, 2011; Montes et al., 2016). Finally, Cizel et al. (2017) uncover a statistically significant relationship between risk weights and the evolution of risk in individual institutions only in the case of banks that do *not* use IRB models. In other words, under the IRB approach, unlike for the STA approach, the risk a bank reports and the risks it faces differ.

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 behavior of risk weights under the IRB and STA approaches.

3. Data, Variables, and Hypotheses

In our analysis, we work with quarterly data from two main sources: (i) the CNB's internal database on supervisory data ICD, and (ii) the CNB's public repository of economic time series ARAD. The dataset spans from 2008 Q1 to 2016 Q4 and consists of 36 observations.

First and foremost, it is important to define what we consider to be pro-/countercyclicality of risk weights. In our understanding, procyclicality means that a time series of risk weights comoves 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 value of the measure of the cycle. Thus, a negative correlation between the series of risk weights and the measure of the cycle is evidence of procyclicality of risk weights.

3.1 Variables

3.1.1 Risk Weights

Throughout the analysis, we use implicit risk weights for credit exposures and balance sheet items only.[5] These can be retrieved from the CNB's internal database ICD. We consider aggregate risk weights – the risk weights of the entire Czech banking sector – throughout our analysis, while we also use risk weights of building societies for a part of our analysis. We explicitly distinguish between risk weights under the IRB approach and those under the STA approach.[6]

We consider three exposure categories – total, retail, and corporate.[7] Corporate and retail exposures make up a decisive share of the loan portfolios of banks in the Czech Republic. Figures A1 and A2 indicate that under the IRB approach, these two exposure categories clearly have the highest share on both an unweighted and weighted basis. As for the STA approach, exposures to central banks and central governments exhibit the highest share of the unweighted amount of exposures. However, their share in risk-weighted exposures is by definition zero (as they carry a zero risk weight), so corporate and retail exposures are again the dominant categories on a risk-weighted basis. The shares of the individual exposure categories are relatively stable over time under the IRB approach, unlike for the STA approach. There, the structure of exposures has been changing significantly. Most notably, the share of exposures to central banks and governments has increased from around 20 percent to more than 50 percent over the last 10 years.

A risk weight can be intuitively perceived as a measure of the risk corresponding to a particular exposure/exposure category. As such, it can attain any non-negative value. Figure 1 shows the evolution of the aggregate risk weights of total, retail, and corporate exposures and building societies' risk weights of retail exposures under the IRB and STA approaches.[8]

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. This is clearly caused by an increasing share of zero risk exposures to central banks and central governments, as depicted in Figure A1. Figure 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 the IRB approach, except for the category of total exposures toward the end of the sample.

3.1.2 Measures of the Cycle

We use two approaches to analyze the cyclicality of risk weights of banks in the Czech Republic. First, we inspect the comovement of the aggregate risk weights of total exposures and a measure of the business cycle. We take real GDP growth as our business cycle indicator, similarly to Brei

[5] We do not consider the Czech Export Bank and the Czech-Moravian Guarantee and Development Bank, as these two banks are wholly owned by the Czech state (providing implicit state guarantees for their liabilities) and have different business models and volatile credit portfolios.

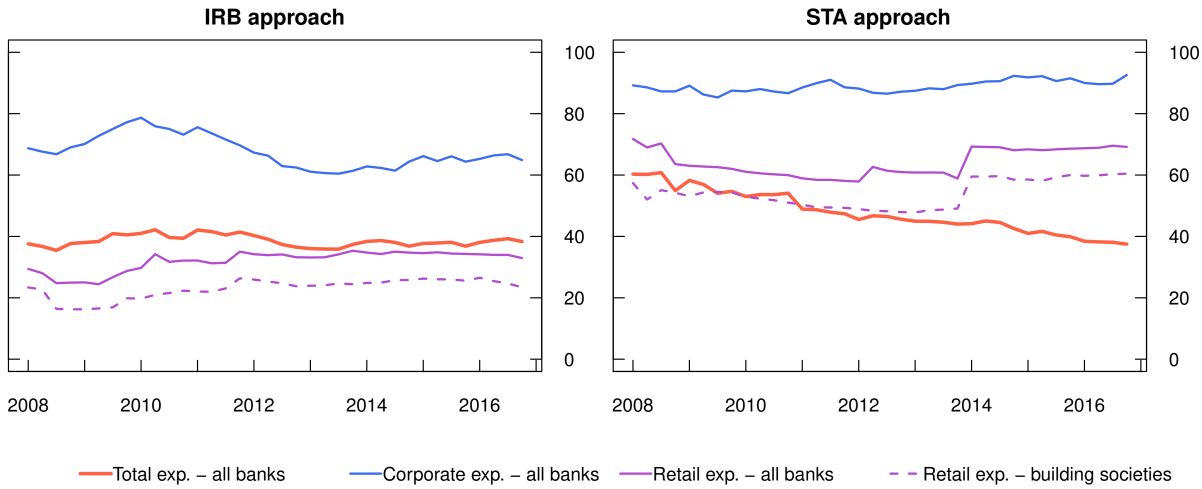
[6] It is debatable how comparable risk weights are under the IRB and the STA approaches. This uncertainty reflects the different regulatory treatment of the two types of risk weights. For example, for the STA approach, the net exposure (after taking loan loss provisions into account) is risk weighted, whereas for the IRB approach, the gross exposure is risk weighted. However, we find that the difference between the net and gross exposure is negligible for the STA approach over time. Also, for the STA approach, defaulted exposures are used in the calculation of the aggregate risk weights. However, we again find that the difference between the risk weights with and without defaulted exposures under the STA approach is minimal.

[7] Thus, in the end, we use the aggregate risk weights of total/corporate/retail exposures under the IRB/STA approach.

[8] For building societies, we only use the risk weights of retail exposures, as they form the most significant part of their portfolios.

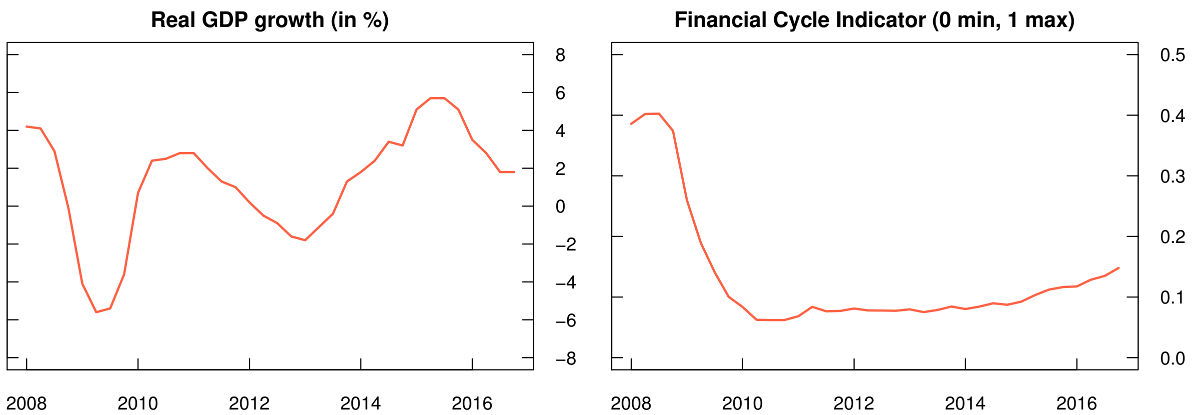
and Gambacorta (2014) and Malovaná et al. (2018). The evolution of real GDP growth is shown in Figure 2(a): the Czech economy was hit by a double recession in 2009 and 2012–2013 but has enjoyed a resurgence recently.

Figure 1: Aggregate Risk Weights according to Exposure Category and Regulatory Approach (in %)



The second approach to analyzing the cyclicality of risk weights concerns the financial cycle. This perspective 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 Figure 2(b): a rapid fall in the crisis period of 2008–2009 has been followed by a steady upward trend ever since.

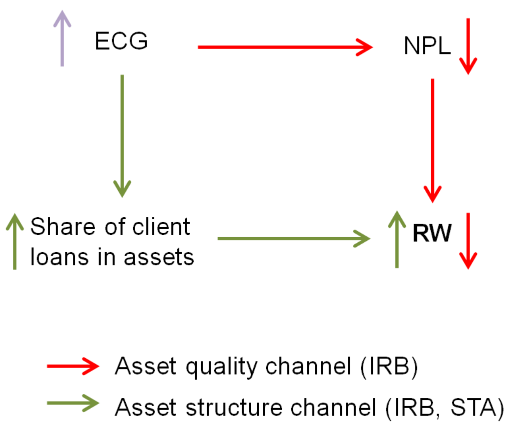
Figure 2: Measures of the Business and Financial Cycles



(a) (b)

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. 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 Figure 3.

Figure 3: The Effect of the Financial Cycle on Risk Weights through the Asset Quality and Asset Structure Channels under the IRB and STA Approaches



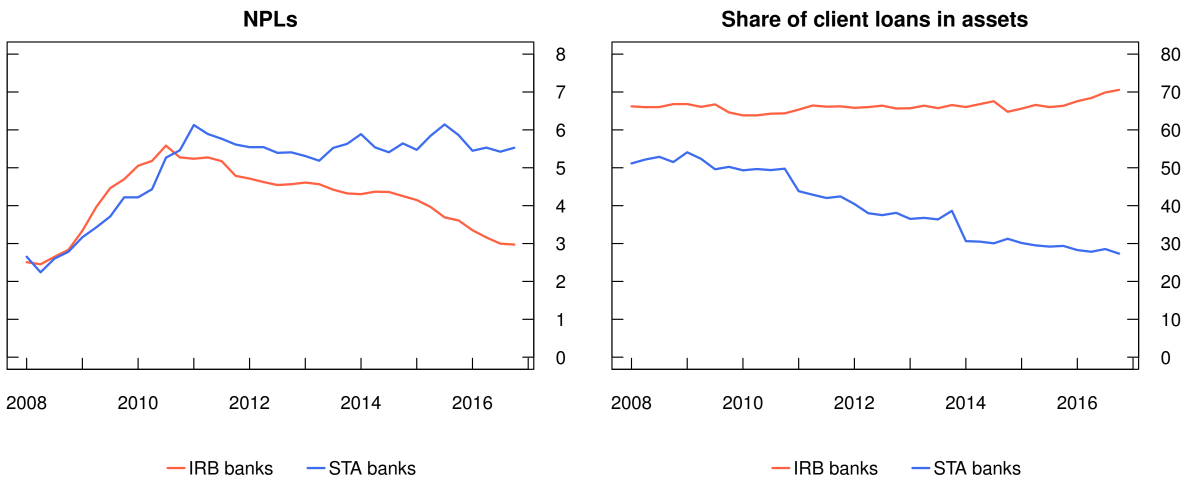
In the case of the asset structure channel, credit growth is induced by both demand and supply shocks during a financial boom. At the same time, this is generally reflected in an increasing share of client loans (retail and corporate exposures), and the asset structure of banks' loan portfolios changes 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. Next, the asset quality channel 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, and so 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).

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.[9] Figure 4 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

[9] 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 et al. (2018).

client loans in assets has been increasing moderately at the same time.[10] 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, in accordance with the change in the structure of assets under the STA approach indicated by Figure A2.

Figure 4: Indicators for the Asset Quality Channel and the Asset Structure Channel (in %)



(a) (b)

3.2 Hypotheses

As indicated in the previous sections, we aim to study the issue of the cyclicality of risk weights of banks in the Czech Republic using the business cycle and financial cycle approaches. 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 Figure 3. We also employ risk weights for the corporate and retail exposures of all banks and the retail exposures of building societies, but we focus predominantly on the risk weights of the total exposures of all banks. First, we study the interaction of risk weights and the business cycle, which is the traditional approach used in the literature to analyze this issue (Brei and Gambacorta, 2014). This leads us to the formulation of the following hypothesis:

Hypothesis #1: There is no difference in the behavior of aggregate risk weights according to the IRB and STA approaches with respect to the measure of the business cycle.

As our business cycle indicator, we use real GDP growth measured as year-on-year changes. Next, we test the validity of the scheme indicated by Figure 3. We are interested in particular in uncovering potential differences between the results for the IRB and STA approaches in any of the links of the scheme (risk weights–FCI, risk weights–NPLs, risk weights–share of client loans in assets). Therefore, Hypotheses #2, #3, and #4 are formulated as follows:

[10] The decrease in the ratio of NPLs to total loans was achieved through a combination of growth in total loans and an absolute decline in the NPL ratio (CNB, 2017).

Hypothesis #2: There is no difference in the behavior of aggregate risk weights according to the IRB and STA approaches with respect to the proxy of the financial cycle.

Hypothesis #3: There is no difference in the behavior of aggregate risk weights according to the IRB and STA approaches with respect to the measures capturing asset quality.

Hypothesis #4: There is no difference in the behavior of aggregate risk weights according to the IRB and STA approaches with respect to the measures capturing the asset structure channel.

We test all four hypotheses using the wavelet coherence technique introduced in the following section.

4. Methods

In our empirical analysis, we aim to study potential differences in the cyclicality of risk weights (i.e., the correlation between risk weights and a measure of the cycle) for the IRB and STA approaches. Moreover, we are interested in more than just "one number," which would be the result of a simple correlation analysis. An analysis able to capture changes in the relationship between risk weights and the measure of the cycle would be a further improvement.

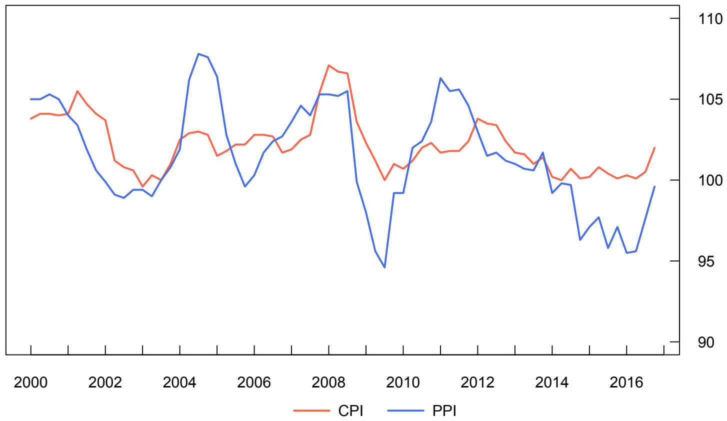
The wavelet coherence technique satisfies all these criteria. It belongs to the family of tools based on wavelets, which allow for analyses in both the time and frequency domain.[11] The frequency domain can also be understood in terms of cycles. Wavelet analysis decomposes a time series into several components which tell us which cycles (short or long) are essential to the behavior of the time series analyzed. 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 analyze, we can then study their 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 figure 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. For example, we can claim that at the 10 percent level of statistical significance, there is an apparent long-term negative relationship between the time series of the aggregate risk weights for corporate exposures according to the IRB approach and real GDP growth, indicating procyclicality of these risk weights with respect to the business cycle, over the entire sample period from 2008 to 2016.

A formal introduction to the wavelet coherence technique, along with the definitions of the terms wavelet (transform) and phase difference, can be found in the Appendix.[12] Here in the main text, we provide an illustrative example that will explain all the features needed to interpret our results and assess our hypotheses. We use the Consumer Price Index (CPI) and the Producer Price Index (PPI) for the Czech Republic from 2000 Q1 to 2016 Q4, which provides 64 observations in total. The evolution of both time series is shown in Figure 5.

[11] 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 et al., 2016)

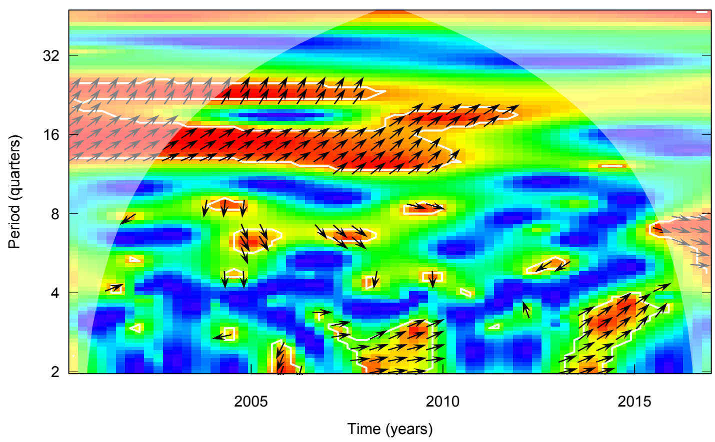
[12] More information on the theory and empirics of wavelets can be found, for example, in Rösch and Schmidbauer (2014) and references therein.

Figure 5: The CPI and PPI for the Czech Republic (2000–2016)



We can see that both the CPI and the PPI fluctuate. Moreover, until around 2009, the series comoved in a synchronized fashion: when one series was decreasing, the other was also decreasing, and when one series was increasing, the other was also increasing. In other words, the series seem to be dependent, and this dependence lasted for roughly the first half of the sample, from 2000 to 2009/2010. After 2010, this long-term dependence is broken. However, after a drop in the PPI in 2014, there seems to be evidence for renewed synchronization between the two series since then. However, this dependence is a short-term one, unlike that in 2000–2009/2010. An alternative to this verbal description is provided by the output of the wavelet coherence method. The wavelet coherence between the CPI and the PPI from 2000 Q1 to 2016 Q4 is shown in Figure 6.

Figure 6: An Example of a Wavelet Coherence Analysis Output: the CPI and PPI for the Czech Republic (2000–2016)



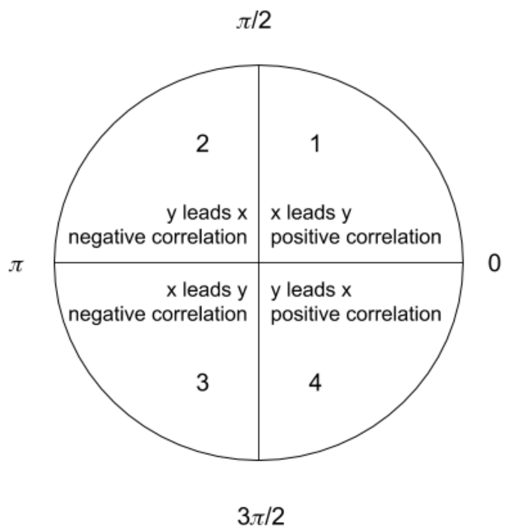
Note: Arrows to the right (left) = positive (negative) correlation, red areas = statistical significance at the 10% level.

The figure contains two axes. Inside the figure, we can see arrows, several colors, and a shaded area at the edges, which contrasts with the non-shaded cone in the middle. 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 figure, red color shows the statistical significance of the dependencies at the 10 percent level of confidence, while the other colors (yellow, green, blue) indicate that there is no interaction between the CPI and the PPI at the particular time and frequency.[13] As for the arrows, those pointing to the right show that the time series are positively correlated at the particular time and frequency, while those pointing to the left show that they are negatively correlated. The shaded area at the edges indicates results that should be interpreted with caution, as will be explained below.

The results of the wavelet coherence technique are in line with the previous verbal discussion of the dependencies between the CPI and the PPI. We can see that the wavelets detect a positive correlation between the CPI and the PPI at a frequency of 16 quarters (4 years) from 2000 to 2009/2010. After 2010, this dependence disappears, but in 2013, a new dependence on higher frequencies emerges (the bottom right corner). This is line with the observed short-term dependence between the CPI and the PPI in Figure 5. To sum up, we find evidence of a positive dependence between the low-frequency components of the CPI and the PPI between 2000 and 2009/2010 (hinting at a longer-term relationship) and a positive dependence between the high-frequency components of the CPI and the PPI since 2013 (hinting at a short-term relationship). As such, this example illustrates that wavelet coherence can be employed as a means of dynamic correlation analysis.

Next, Figure 7 provides a more precise guide to the interpretation of phase differences between two time series.

Figure 7: A Guide to the Interpretation of Phase Differences



[13] The statistical significance at the 10 percent level is based on 300 Monte Carlo simulations against white noise processes.

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 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.[14]

The issue of the shaded area at the edges also needs to be discussed. The mechanics of the wavelet method rely on an auxiliary function – the wavelet – which can have a certain width and is used to determine which components constitute the time series analyzed. The wavelet compares itself to a certain part of the actual time series and records the similarity. The flexible width of the wavelet obviously allows us to detect components of different lengths that drive the behavior of the time series. However, 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 analyze 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 analyzed segment of the time series).[15]

Finally, wavelets have recently been employed in two studies in the financial stability literature (Altăr et al., 2017; Ferrer et al., 2018). More precisely, both studies use the wavelet coherence technique, similarly to our case. Altăr et al. (2017) analyze 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 et al. (2017) 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. (2018) 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 et al. (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.

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. Figures 1, 2, and 4 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 analyze non-stationary series, the lack of periodicity could make the results uncertain given the short data sample. We therefore employ differences on the analyzed time series, similarly to González-Concepción et al. (2012) and Ferrer et al. (2018).

[14] 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 comove without any delay.
[15] The extension is typically conducted by adding zeros before or after the analyzed segment of the time series, depending on whether the analysis is conducted at the beginning or the end of the sample. The non-shaded cone of influence is rounded because the time series is extended by less – the wavelet function is tighter – at higher frequencies than at lower frequencies.

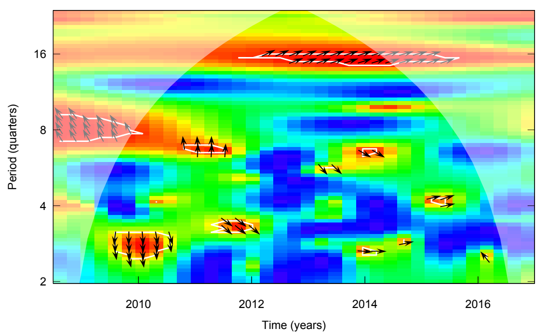
5. Results

We derive two types of results about the cyclicality of risk weights of banks in the Czech Republic using the wavelet coherence technique. First, we follow the "business cycle" approach: we examine the comovement of the aggregate risk weights (for the entire banking sector) of total exposures and real GDP growth in the time span from 2008 to 2016. Second, we introduce the "financial cycle" approach: we analyze the comovement 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. Moreover, we separately study the issue of the cyclicality of aggregate risk weights of corporate and retail exposures and building societies' risk weights of retail exposures.

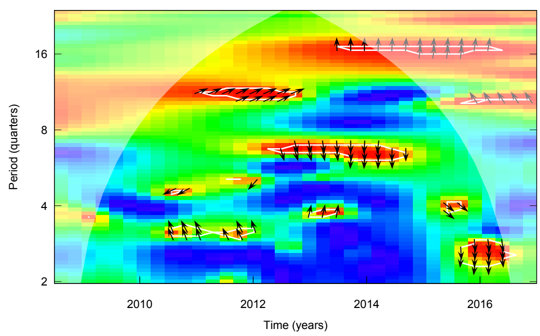
We interpret the results from the wavelet coherence plot in a visual way, similarly to Ferrer et al. (2018). We are chiefly interested in the differences between the figures for the IRB and STA approaches, as stated in our working hypotheses. In particular, we check for systematic dependencies (lasting for several years) at various frequencies and the sign of those dependencies, which can be interpreted as evidence of pro-/countercyclicality.

5.1 The Business Cycle Approach

Figure 8: Wavelet Coherence Plots for the Aggregate Risk Weights of Total Exposures and Real GDP Growth



(a) IRB approach



(b) STA approach

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

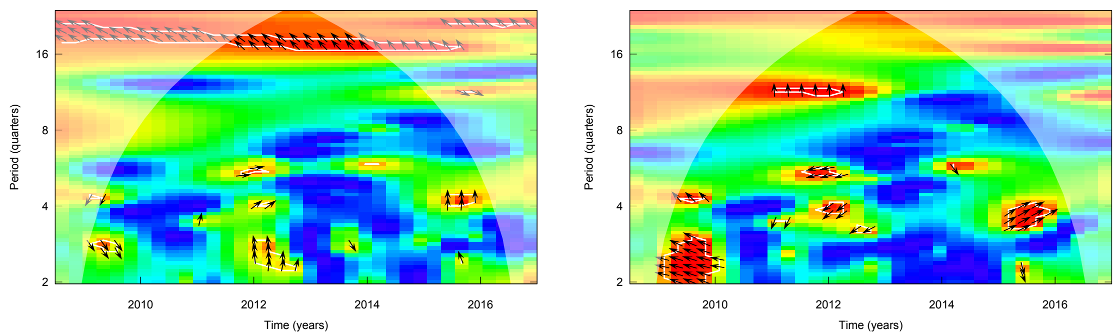
First, Figure 8 shows the interaction of the aggregate risk weights of total exposures and real GDP growth for the IRB and STA approaches. For the IRB approach, we obtain some evidence of a longer-lasting positive dependence – indicating countercyclicality – at a frequency of 16 quarters after 2012. The picture for the STA approach contains fewer systematic relationships and overall conveys that the risk weights under the STA approach are not very sensitive to the business cycle. Thus, we can reject Hypothesis #1.

However, similarly as for the case of total exposures under the STA approach, the supporting analyses for corporate and retail exposures (for all banks) and the retail exposures of building societies on average show little interaction between risk weights and the business cycle measure (Figures A3, A4, and A5). These conclusions are generally in line with EBA (2013a) and EBA (2016): most risk weights, regardless of whether they are related to the IRB or the STA approach, are not very sensitive to the business cycle. The exceptions are the risk weights of total exposures under the IRB approach. They show some evidence of countercyclical behavior, which is the desirable outcome for prudential authorities.

5.2 The Financial Cycle Approach

Next, we analyze the interaction of the aggregate risk weights of total exposures with the three measures connected to the financial cycle – the FCI, the NPL ratio, and the share of client loans in total assets. Here, we cannot rely on any references, as the cyclicality of risk weights with respect to the financial cycle is not explicitly covered in the literature. We can, however, build our expectations around the literature describing the different behavior of risk weights under the IRB and STA approaches (Mariathasan and Merrouche, 2014; Behn et al., 2016; Cizel et al., 2017). The first result concerns the comovement of the aggregate risk weights of total exposures and the FCI and is captured in Figure 9.

Figure 9: Wavelet Coherence Plots for the Aggregate Risk Weights of Total Exposures and the Financial Cycle Indicator



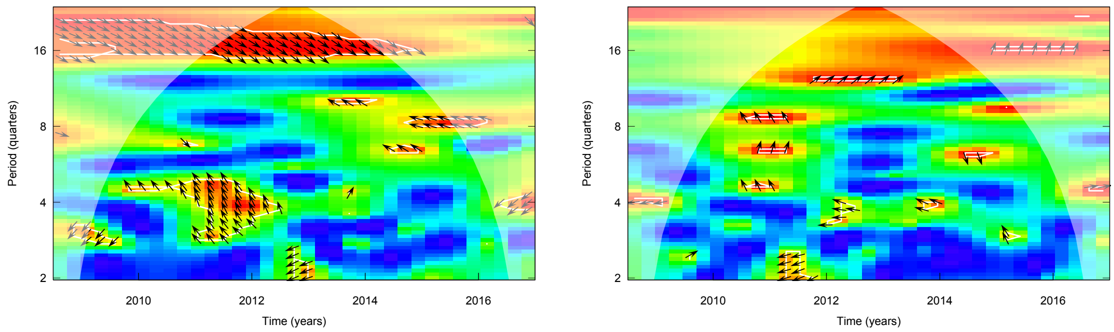
(a) IRB approach (b) STA approach

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

We obtain a stark contrast between the figures for the IRB and STA approaches and immediately reject Hypothesis #2. The risk weights under the STA approach are very insensitive to the financial cycle, which is again 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 Figure 7, 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.

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. We explore this in Figures 10 and 11.

Figure 10: Wavelet Coherence Plots for the Aggregate Risk Weights of Total Exposures and the NPL Ratio

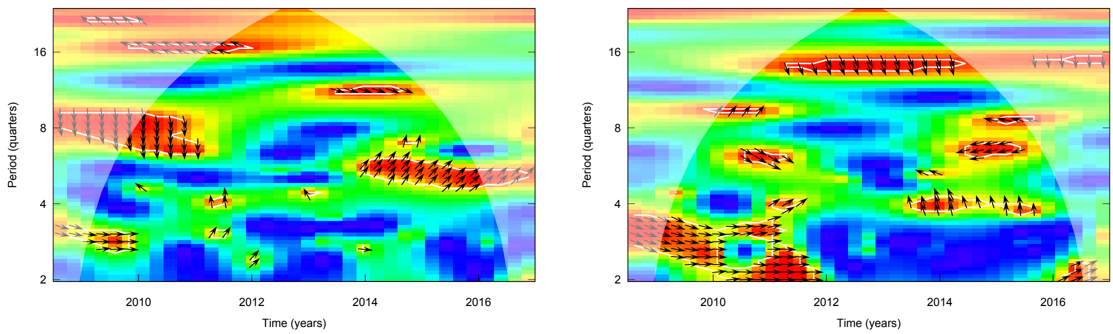


(a) IRB approach

(b) STA approach

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

Figure 11: 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.

Figure 10 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 comove in tandem over an extended period of time.[16] This indicates, in the spirit of Figure 3, that the asset quality channel must be dominant. Indeed, for the IRB approach, the asset structure channel is much weaker than the asset quality channel, as Figure 11 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 Figure 3. 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, Figure 11 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.[17] Moreover, we obtain some evidence that the high-frequency components of the two series comoved 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 #3 and #4, as we found distinct differences between the figures 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 Figure 3.

We also analyze the interaction of the risk weights of the corporate exposures of all banks, the retail exposures of all banks, and the retail exposures of building societies and the FCI measure for the financial cycle. The resulting wavelet coherence plots are shown in Figures A6, A7, and A8. Overall, we find little evidence of any dependencies for corporate exposures and for retail exposures of building societies. However, Figure A7 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 behavior of the aggregate risk weights of total exposures with respect to real GDP growth, 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), Behn et al. (2016), and Cizel et al. (2017) that the behavior of IRB and STA risk weights might generally differ. Although we find that the aggregate risk weights of total exposures for the IRB approach are countercyclical with respect to the business cycle, we conclude that they behave procyclically with respect to the financial cycle. In contrast, the aggregate risk weights of total exposures for the STA approach are not very sensitive to either the business or the financial cycle. These results are in line with EBA (2013a, 2016). Regarding the asset channels introduced in Figure 3, we obtain results that are consistent with our expectations. The asset quality channel is relevant only for the IRB approach, and its dominance over the asset structure channel might foster

[16] Moreover, as the arrows point to the fourth quadrant, we can conclude in the spirit of Figure 7 that the NPL ratio leads the risk weights, which seems intuitive.
[17] Moreover, as the arrows point to the fourth quadrant, we can conclude in the spirit of Figure 7 that the share of client loans in assets leads the risk weights, which seems intuitive.

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 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. Synthesizing the results from the analysis of the asset channels for the IRB and STA approaches, we can claim that the asset quality channel seems to be the one fostering the procyclicality of risk weights with respect to the financial cycle. Finally, 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. Overall, our results reveal that the IRB approach might be inherently procyclical with respect to the financial cycle. This finding contrasts with 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. However, BIS (2017) – which evaluates practices in implementing the countercyclical buffer on the global scale – does not indicate its use for the purpose of risk weights in any of the 24 countries analyzed. Our results can also be used in discussions about the impact of the regulatory changes associated with risk weights which are under way. These include the output floor and the leverage ratio. The proposed output floor is based on the fact that the aggregate risk-weighted assets generated by the IRB approach cannot fall below the 72.5 percent threshold of risk-weighted assets computed by the STA approach (BCBS, 2017). The leverage ratio, i.e., the capital requirement that does not take into account asset risk, should complement the risk-weighted capital requirement as from 2018. The numerator of the leverage ratio represents total exposures instead of risk-weighted assets, so the leverage ratio should be less procyclical (Brei and Gambacorta, 2016).[18]

5.3 Robustness Analysis

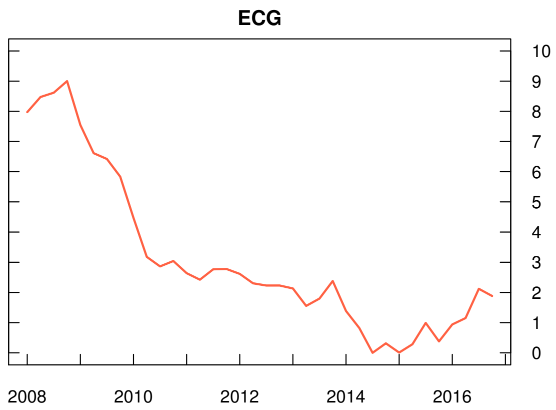
As a robustness check for the results concerning the financial cycle, we employ a different proxy for the financial cycle – the expansive credit gap (ECG). The ECG is determined as the difference between the current bank credit-to-GDP ratio and its 8-quarter moving minimum and is regularly calculated 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. Figure 12 shows that the Czech Republic has been in an expansionary phase of the financial cycle recently.

Next, we analyze the interaction between the aggregate risk weights of total exposures, corporate exposures, retail exposures, and retail exposures of building societies with respect to the ECG measure. The aim is to compare the results based on the ECG to those based on the FCI. Figure A9 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

[18] In addition, the capital requirement based on the leverage ratio can take into account the level of capital reserves and act in a macroprudential way. Pfeifer et al. (2017) state that the introduction of a macroprudential leverage ratio could, under certain circumstances, enhance the effectiveness of macroprudential policy.

exposure categories compared to the case when the FCI is used. In contrast to the FCI results (Figure A6), we obtain evidence of procyclicality of risk weights of corporate exposures with respect to the ECG (Figure A10). Also, again in contrast to the FCI results (Figure A8), we obtain evidence of procyclicality of risk weights of building societies' retail exposures with the ECG (Figure A12). On the other hand, unlike for the FCI (Figure A7), we do not obtain any evidence of procyclicality of retail exposures (Figure A11). 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.

Figure 12: Expansive Credit Gap (in %)



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 business and 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 Figures 8, 9, 10, and 11.

Table 1: Simple Correlation of the Aggregate Risk Weights of Total Exposures and the Measures of the Cycle

	(a) IRB approach	(b) STA approach
Fig. 8	0.052	0.006
Fig. 9	**-0.231**	-0.148
Fig. 10	0.046	-0.078
Fig. 11	**0.316**	**0.421**

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

We can see that the wavelet coherence plots and simple correlations generally give similar results. As for the interaction with respect to real GDP growth, the simple correlation reveals that the relationship is stronger for the IRB approach. This is in line with Figure 8, although the simple correlation does not produce statistically significant results. Similarly, the simple correlation reveals a negative relationship between IRB risk weights and the FCI, in line with Figure 9. 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 (Figure 10). 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 Figure 11: 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.

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. The need for such analyses is amplified by the use of internal ratings-based (IRB) models by banks. Prudential authorities should carefully assess potential differences in risk weights under the IRB approach with respect to those based on the standardized (STA) approach as well as their behavior during the cycle. Procyclicality of risk weights might amplify the effect of the cycle on the balance sheets of lending institutions and may negatively influence their resilience when the cycle turns. If deemed necessary, supervisory/macroprudential authorities may respond with a number of instruments to influence the internal models of banks, including minimum risk weights for banks using the IRB approach.

In this paper, we analyze 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 wavelets. 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 two approaches to studying the cyclicality of risk weights of banks in the Czech Republic, one based on the business cycle and the other on the financial cycle. The former is represented by real GDP growth and the latter by the Financial Cycle Indicator (FCI) constructed by the Czech National Bank. 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 behavior 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 main 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. At the same time, however, they are not procyclical with respect to the business 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. This finding might be of policy relevance for the CNB. All in all, we found some differences in the behavior of the aggregate risk weights of total exposures with respect to real GDP growth, 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), Behn et al. (2016), and Cizel et al. (2017) that the behavior 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 can be used in several ways. First, they might be employed for the purposes of decision-making on the use of supervisory and macroprudential instruments, including the countercyclical capital buffer. Second, they might contribute to the discussion on the nature and sustainability of the internal ratings-based models of banks. And third, they might provide a basis for assessing the impact of the regulatory changes associated with risk weights which are under way, including the leverage ratio and the output floor based on the revised Basel III STA approach.

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Appendix

A.1 Shares of Exposure Categories in Total Unweighted/Risk-weighted Exposures (in %)

Figure A1: Shares of Exposure Categories in Total Original (Unweighted) Exposures (in %)

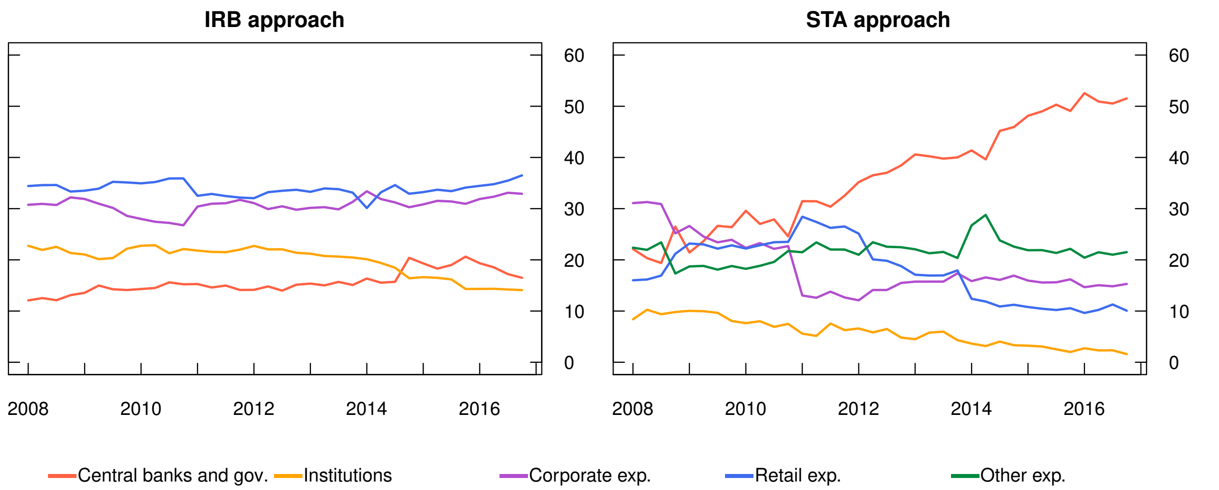
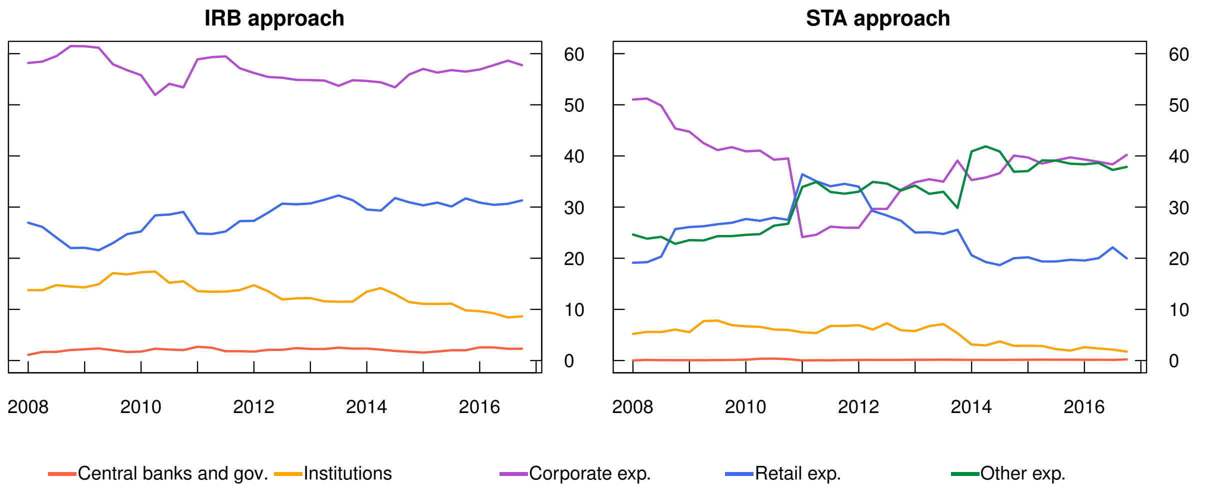


Figure A2: Shares of Exposure Categories in Total Risk-weighted Exposures (in %)



A.2 Theory of Wavelet Coherence

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

$$\psi = \pi^{-\frac{1}{4}} e^{i\omega t} e^{-\frac{t^2}{2}}, \tag{A1}$$

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 as a tool to detect statistically significant frequencies across time which are instrumental in constituting the analyzed 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:

$$W(\tau, s) = \sum_t x_t \frac{1}{s} \psi^* \left(\frac{t-\tau}{s} \right), \tag{A2}$$

where W denotes the Morlet wavelet transform, x_t is the analyzed time series, τ is the localizing time parameter (that detemines 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).[19]

Practically, in each position in the time-frequency domain, the algorithm checks the similarity of the Morlet wavelet with a certain segment of the analyzed time series and reports the correlation between these two entities at a certain level of significance. The level of significance is obtained using 300 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 comovement 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:

$$W_{xy}(\tau, s) = W_x(\tau, s) W_y^*(\tau, s). \tag{A3}$$

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:

$$P_{xy}(\tau, s) = |W_{xy}(\tau, s)|. \tag{A4}$$

[19] To be precise, W is a convolution of the time series at hand and a set of daughter wavelets, where convolution can be intuitively understood as a complex multiplication or combination.

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:

$$C_{xy}(\tau,s) = \frac{|sW_{xy}(\tau,s)|^2}{sP_x \cdot sP_y}, \tag{A5}$$

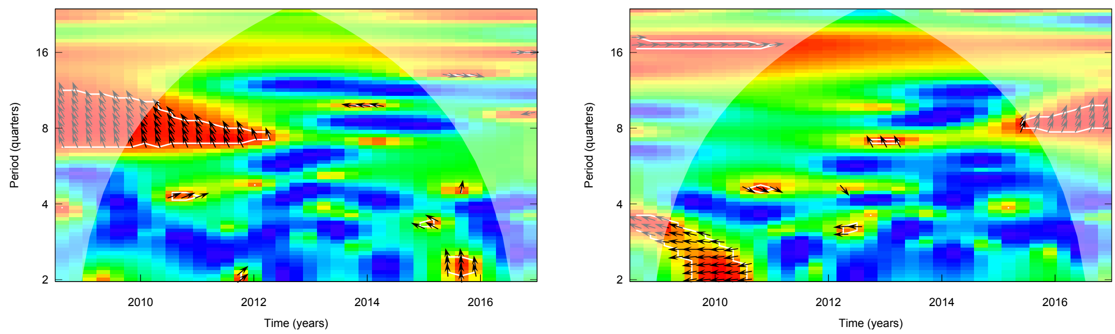
where we normalize the square of cross-wavelet power with the wavelet powers from the individual series. The letter *s* in front of the elements in Equation A5 reflects the need for a certain degree of smoothing in both the time and frequency domain to make the results meaningful (Rösch and Schmidbauer, 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:

$$PD_{xy}(\tau,s) = Arg(W_{xy}(\tau,s)), \tag{A6}$$

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

A.3 Wavelet Coherence Plots

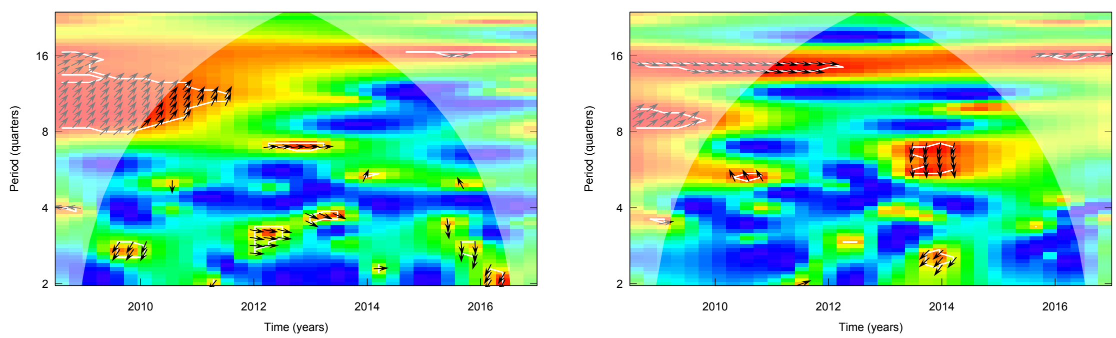
Figure A3: Wavelet Coherence Plots for the Aggregate Risk Weights of Corporate Exposures and Real GDP Growth



(a) IRB approach (b) STA approach

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

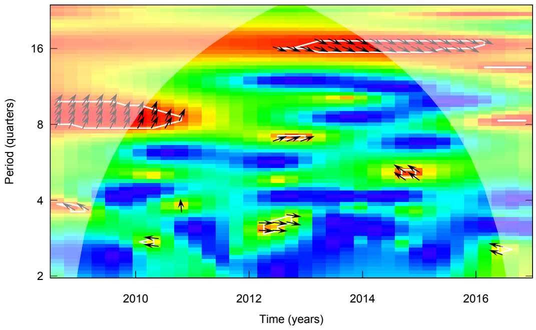
Figure A4: Wavelet Coherence Plots for the Aggregate Risk Weights of Retail Exposures and Real GDP Growth



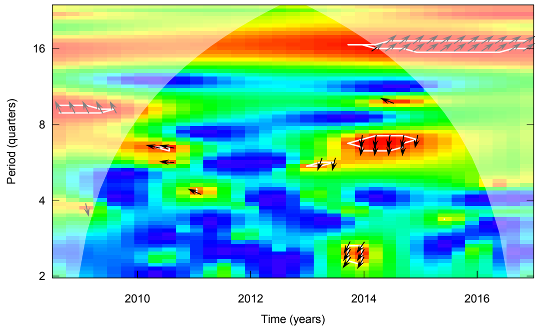
(a) IRB approach (b) STA approach

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

Figure A5: Wavelet Coherence Plots for Building Societies' Risk Weights of Retail Exposures and Real GDP Growth



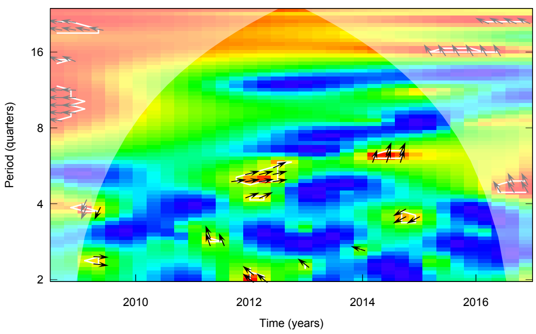
(a) IRB approach



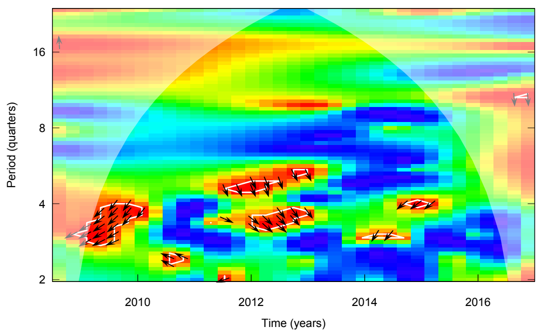
(b) STA approach

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

Figure A6: Wavelet Coherence Plots for the Aggregate Risk Weights of Corporate Exposures and the Financial Cycle Indicator



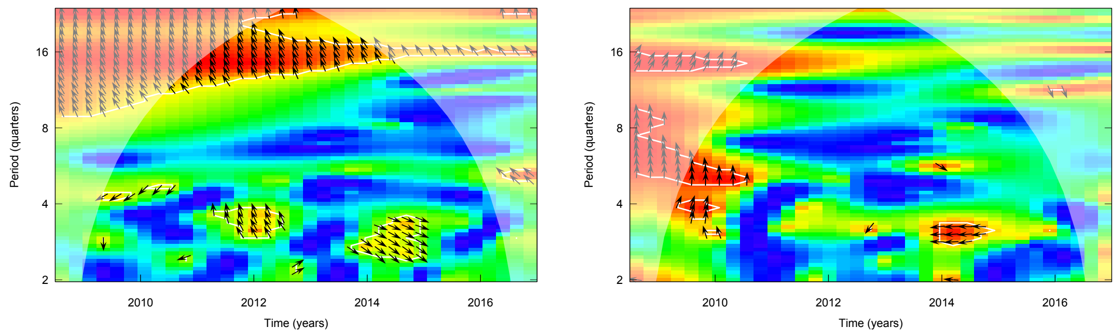
(a) IRB approach



(b) STA approach

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

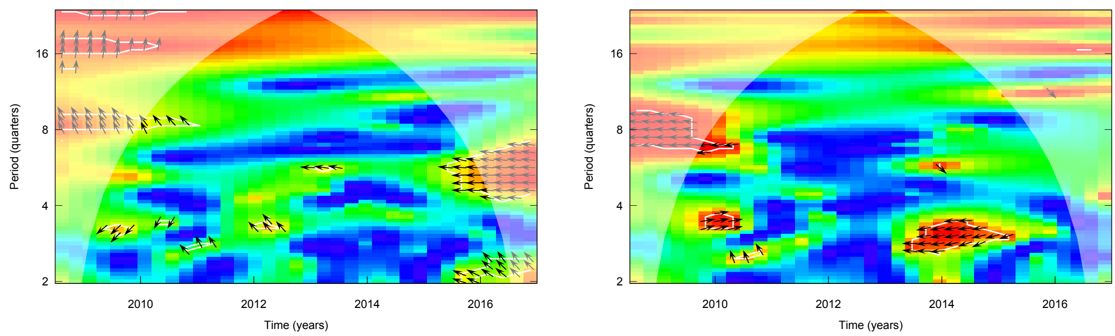
Figure A7: Wavelet Coherence Plots for the Aggregate Risk Weights of Retail Exposures and the Financial Cycle Indicator



(a) IRB approach (b) STA approach

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

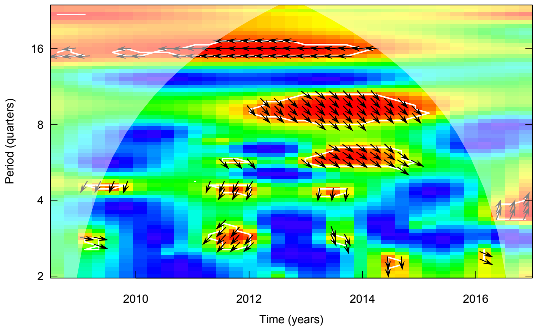
Figure A8: Wavelet Coherence Plots for Building Societies' Risk Weights of Retail Exposures and the Financial Cycle Indicator



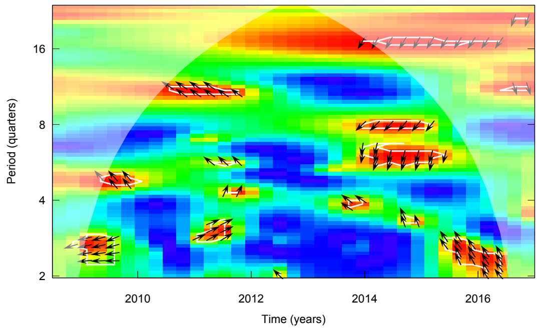
(a) IRB approach (b) STA approach

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

Figure A9: Wavelet Coherence Plots for the Aggregate Risk Weights of Total Exposures and the Expansive Credit Gap



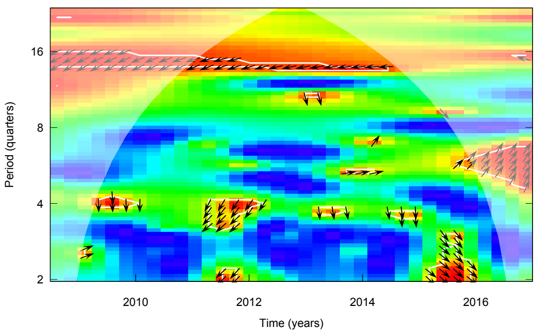
(a) IRB approach



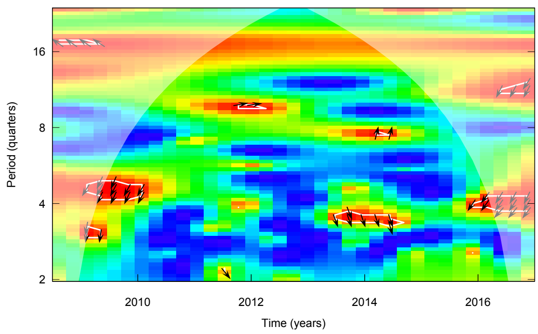
(b) STA approach

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

Figure A10: Wavelet Coherence Plots for the Aggregate Risk Weights of Corporate Exposures and the Expansive Credit Gap



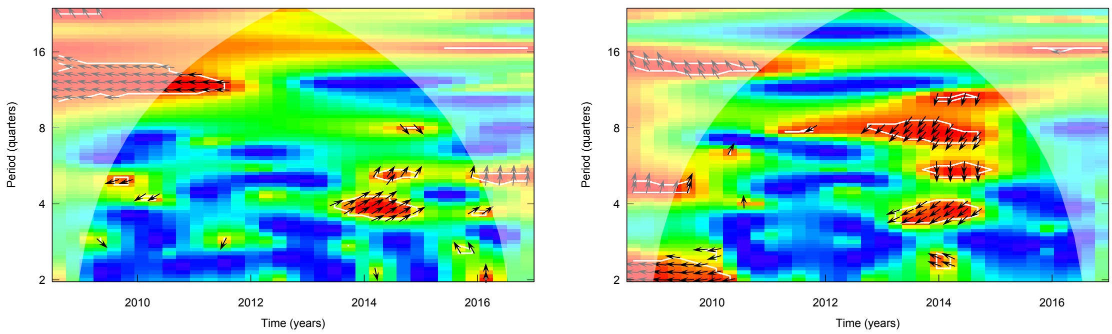
(a) IRB approach



(b) STA approach

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

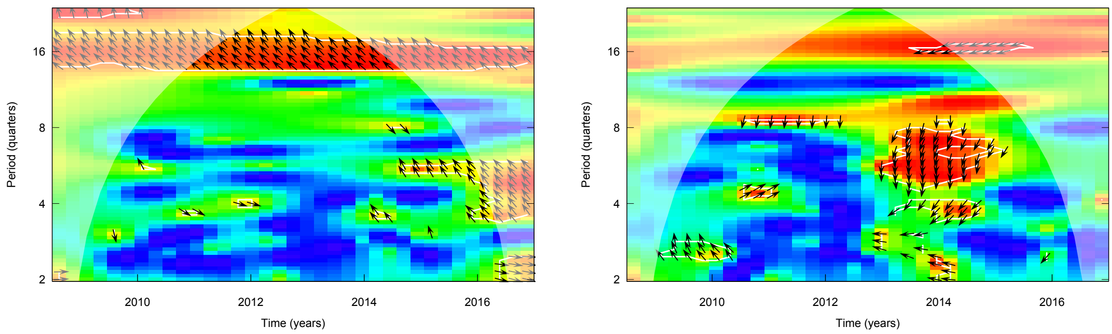
Figure A11: Wavelet Coherence Plots for the Aggregate Risk Weights of Retail Exposures and the Expansive Credit Gap



(a) IRB approach (b) STA approach

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

Figure A12: Wavelet Coherence Plots for Building Societies' 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.

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