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# The Pro-Cyclicality of Risk Weights for Credit Exposures in the Czech Republic

Simona Malovaná *

## Abstract

This paper studies the pro-cyclicality of risk weights with respect to the business, credit and financial cycles using data for the Czech Republic. The empirical results indicate that risk weights behave pro-cyclically under the IRB approach and acyclically under the STA approach. The pro-cyclical behaviour of IRB risk weights for credit exposures is caused primarily by the pro-cyclicality of risk weights for retail credit exposures, the strongest effects being in the highest and lowest quantiles of risk weights. The risk weights for retail exposures behave pro-cyclically not only with regard to the business cycle, but also with respect to the financial cycle and house price growth.

## Abstrakt

Tento článek s využitím dat pro Českou republiku zkoumá procyklický charakter rizikových vah ve vztahu k hospodářskému, úvěrovému a finančnímu cyklu. Empirické výsledky ukazují, že rizikové váhy působí procyklicky v rámci přístupu IRB a acyklicky v rámci přístupu STA. Procyklické působení rizikových vah úvěrových expozic v přístupu IRB je způsobeno především procykličností rizikových vah retailových úvěrových expozic, přičemž nejsilnější efekt je pozorován v nejvyšším a nejnižším kvantilu rizikových vah. Rizikové váhy retailových expozic působí procyklicky nejen ve vztahu k hospodářskému cyklu, ale také ve vztahu k finančnímu cyklu a růstu cen rezidenčních nemovitostí.

**JEL Codes:** C22, E32, G21, G28.
**Keywords:** Housing market, internal ratings-based approach, procyclicality, quantile regression, risk weights.

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## Nontechnical Summary

There is a general belief among many academics and policy-makers that some features of the Basel II regulatory framework have contributed to strengthening the inherent pro-cyclicality of bank behaviour. This paper studies the pro-cyclicality of risk weights with respect to the business, credit and financial cycles using data for the Czech Republic. Distribution analysis and the quantile regression method are employed in order to explore the heterogeneity in banks' behaviour, allowing us to study the effect in different quantiles of risk weights.

The contribution of the paper is threefold. First, we contribute to a growing stream of literature showing that risk-sensitive capital regulation may reinforce the pro-cyclicality of banks' behaviour. Second, using a granular dataset, we are able to distinguish between credit exposures under the IRB approach and the STA approach at quarterly frequency. Third, we empirically analyse the whole distribution of risk weights for different credit exposure categories under the IRB approach. This is important because there is significant heterogeneity of risk weights even in individual exposure categories.

In general, the distribution of banks' implicit risk weights seems to be far from normal. This is caused by a combination of at least three factors – the regulatory approach, banks' credit exposure structure and the financial cycle. Further empirical investigation reveals that risk weights seem to behave pro-cyclically under the IRB approach and counter-cyclically under the STA approach. The seemingly counter-cyclical behaviour of STA risk weights can be attributed to change in the credit exposure structure. Taking this change into account, STA implicit risk weights behave acyclically rather than counter-cyclically, i.e. they are generally stable over time. The pro-cyclical behaviour of IRB risk weights cannot be explained solely by such change; rather, it is a result of a combination of change in the credit exposure structure and decreasing or increasing risk weights in good or bad times.

Estimating the model separately for different credit exposure categories reveals the pro-cyclicality of risk weights for retail exposures under the IRB approach. The pro-cyclicality with respect to the business cycle seems to be strongest in the highest quantiles of risk weights, while the pro-cyclicality with respect to the credit cycle seems to be strongest in the lowest quantiles of risk weights. The pro-cyclicality with respect to the financial cycle is strong in both the lowest and higher quantiles of risk weights for retail exposures. In particular, an upward shift in the financial cycle leads to a further decrease in the lowest retail risk weights and the highest retail risk weights, shifting the whole distribution to lower values. The opposite is true for a downward shift of the financial cycle. This indicates that risk-sensitive capital regulation increases the inherent pro-cyclicality of the banking sector.

The effect of monetary policy easing on risk weights is statistically significant only for retail credit exposures under the IRB approach. In particular, this effect is statistically significant only in higher quantiles of risk weights, i.e. risk weights for retail exposures which are considered more risky (usually unsecured consumer loans). The effect in lower quantiles of risk weights (i.e. usually for secured retail exposures) is not statistically significant. The main reason for that may be different speeds of transmission and/or different channels of transmission of monetary policy to secured and unsecured retail credit exposures.

# 1. Introduction

**There is a general belief among many academics and policy-makers that the Basel II regulatory framework has contributed to strengthening the inherent pro-cyclicality of bank behaviour.** Under Pillar 1, banks' risk weights are related to the credit risk of the underlying assets, which varies with the business and financial cycle. During economic and financial booms, the favourable economic situation and low default rates are reflected in lower risk estimates, prompting lower minimum capital requirements per unit of risk-weighted assets. This gives banks an opportunity to use the resulting capital surplus for credit expansion. This credit expansion is usually accompanied by rising asset prices and easing of lending conditions, which might be desirable in a phase of economic recovery. Once the credit growth becomes excessive and asset prices reach levels far from economic fundamentals, the lower capital requirements may cause financial imbalances to emerge. During an economic downturn, banks' capital may be insufficient for them to manage unanticipated loan losses and asset writedowns. Rising default risk will lead to higher risk estimates and risk weights, which will in turn raise the minimum capital requirements, further adding to this strain. Since it can be very expensive for banks to raise new capital at short notice in this situation, they may respond by restricting credit supply in order to meet the regulatory requirements. The credit reduction accompanied by falling asset prices will further aggravate the economic downturn and increase the risks to financial stability (Acharya and Richardson, 2009).[1]

**While this behaviour may seem rational from the perspective of a single bank, it poses a significant threat to the stability of the financial system if pursued by all banks collectively.** Microprudential policy views the stability of the financial system as the sum of the soundness of its individual institutions. It does not usually take into account problems that may arise when all banks engage in similar behaviour which overexposes the system to the same risk – be it credit risk (debtors do not repay), market risk (collateral values decline) or other risk. The global financial crisis demonstrated that microprudential policy is not sufficient to safeguard the stability of the financial system as a whole. A consensus has emerged on the need to establish macroprudential policy as an essential addition to microprudential regulation and supervision.

**This paper studies the pro-cyclicality of risk weights with respect to the business, credit and financial cycles using data for the Czech Republic.** The analysis draws on a unique supervisory panel dataset covering 20 banks between 2004 Q1 and 2017 Q4. The detailed information on individual banks allows us to investigate the pro-cyclicality of risk weights under the IRB and STA approaches and for different asset classes. In addition, house price growth and the monetary conditions are considered as potential factors contributing to the pro-cyclicality. Distribution analysis and the quantile regression method are employed in order to explore the heterogeneity in banks' behaviour, allowing us to study the effect in different quantiles of risk weights.

The contribution of the paper is threefold. First, we contribute to a growing stream of literature showing that risk-sensitive capital regulation may reinforce the pro-cyclicality of banks' behaviour (see section 2).[2] Second, using a granular dataset, we are able to distinguish between credit ex-

[1] A risk-sensitive regulatory framework is not the only factor that can amplify the pro-cyclicality of bank behaviour. Other factors include accounting standards (especially fair-value accounting), different provisioning regimes and executive remuneration schemes (for a detailed discussion and literature review see BCBS, 2015; Athanasoglou et al., 2014).

[2] Another paper dealing with the pro-cyclicality of risk weights in the Czech Republic has recently been published (see Brož et al., 2017). Using wavelet analysis, the authors show that implicit risk weights under the IRB approach behave pro-cyclically with respect to the financial cycle, in line with the results of this paper. Even though the two papers deal with a very similar topic, they differ in many ways are thus complements rather than substitutes. They

posures under the IRB approach and the STA approach at quarterly frequency. Such a distinction would not be possible using the BankScope database, for example. Third, we empirically analyse the whole distribution of risk weights for different credit exposure categories under the IRB approach. This is important because there is significant heterogeneity of risk weights even in individual exposure categories. In addition, the non-normality of the distribution of risk weights identified highlights the importance of using quantile regression analysis instead of mean regression, which is an additional novelty of this paper.

The Czech Republic seems to be an ideal candidate for this analysis for at least two reasons in addition to data granularity. First, the Czech banking sector is homogeneous, consisting mainly of universal banks with a business model focusing on providing loans to the private sector (risk-weighted exposures for credit risk accounted for almost 90% of total risk-weighted exposures as of 2017 Q4). We can therefore focus our attention fully on credit exposures. Second, the IRB approach has been adopted by a large part of the sector (approximately 83% as of 2017 Q4) and the Czech Republic has one of the largest shares of capital requirements for credit risk originated by internal models in the EU (Resti, 2016).

The remainder of this paper is organised as follows. Section 2 provides a short literature review. Sections 3 and 4 present the empirical model and describe the data. Section 5 reports the estimation results and discusses policy implications. Section 6 concludes.

## 2. Literature Review

**The Basel II accord is aimed at making banks' capital requirements more sensitive to the underlying asset portfolio risk, i.e. at maintaining more capital for higher-risk assets but less for assets that are deemed safer.** Under Pillar I, banks can use three different approaches for calculating the risk-weighted value of credit exposures held in the banking book: the Standardised (STA) approach, the Foundation Internal Ratings-Based (F-IRB) approach and the Advanced Internal Ratings-Based (A-IRB) approach.[3] Implementation of the IRB approach is subject to approval and a thorough validation review by the regulator. Under the two IRB approaches, risk-weighted assets are calculated using four risk inputs for each asset – the probability of default (PD), the loss given default (LGD), the exposure at default (EAD) and the maturity (M)[4] – and a specific formula proposed by the Basel Committee on Banking Supervision (BCBS, 2005).[5] Under the F-IRB approach, banks are permitted to estimate their own PD value, while the LGD, EAD and M values are

use very different methodologies and analyse different channels of transmission and factors influencing implicit risk weights.

[3] The current rules for determining risk-weighted exposures can be found in the implementing act of Basel III in Europe – the CRD IV/CRR regulatory framework. CRD IV – the 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; CRR – the Capital Requirements Regulation – refers to Regulation (EU) No 575/2013 of the European Parliament and of the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms.

[4] PD – the likelihood that the obligor will default in the course of one year. Default occurs when either or both of the following conditions have been met: (i) the obligor is unlikely to pay its credit obligations in full, (ii) the obligor is past due more than 90 days on any material credit obligation. For more details, see Article 178(1) of the CRR. LGD – the percentage of the exposure the bank might lose in the event of default. EAD – an estimate of the outstanding amount in the event of default. M – the effective maturity of the exposure.

[5] The formula varies depending on the exposure category. Under the IRB approach, banks allocate their exposures into the following categories – central governments and central banks, institutions, corporates, retail and equity.

determined by the regulator. Under the A-IRB approach, banks provide their own estimates of PD, LGD and EAD and M is calculated using the formula provided by the regulator.[6]

The main goal of introducing risk-sensitive capital regulation – the IRB approach – was to increase the sensitivity of the capital requirements for credit risk to the underlying risks of banks' assets, in the belief that the newly proposed approach would provide incentives for banks to improve their credit risk management (BCBS, 2001). It was also believed that banks' could utilise their knowledge of customers and local conditions to further improve risk management (EBA, 2013).The European Banking Authority (EBA) concludes that the IRB approach is still the most appropriate approach for determining capital requirements for credit risk and does not express concerns about it introducing additional pro-cyclicality into the banking sector (EBA, 2013, 2016).

**Risk estimates generally vary over time, being lower in booms and higher in busts, which may lead to underestimation of a portfolio's real loss potential.** As argued by Amato and Furfine (2004), Drumond (2009) and Lowe (2002), among others, the banking sector is inherently pro-cyclical regardless of the capital regulation design.[7] The losses gradually decrease as the economic conditions improve, reaching their lowest level at the point of highest systemic risk. Under the IRB approach banks can use as little as five years of data when calculating their estimates (Articles 180 and 181 of the CRR).[8] Such a short historical series cannot capture the full business or financial cycle. The average length of the financial cycle in advanced economies is estimated at around 15 years, with the upward phase making two-thirds of the cycle (see e.g. Drehmann et al., 2012, 2013). Thus, at the peak of the financial cycle the risk estimates are based entirely on its upward-sloping part. Such estimates, which exclude any adverse period, cannot provide an accurate indicator of the future losses the economy will face in a downturn and will underestimate the portfolio's real loss potential. Consequently, the risk weights calculated under the IRB approach can be lowest at the time of highest risks. In fact, the inability of risk-sensitive capital regulation to reflect banks' portfolio risk seems to have caused an increase in systemic risk over the last two decades (Vallascas and Hagendorff, 2013). A number of studies have shown that IRB risk weights are systematically lower than in the case of STA banks, while this does not necessarily reflect lower or better-managed credit risk. For instance, Behn et al. (2016a) document that the internal risk estimates of banks which switched to the IRB approach systematically underpredict actual default rates. Mariathasan and Merrouche (2014) analyse a panel of 115 banks from 21 OECD countries and find that once regulatory approval for the IRB approach was granted the risk-weight density became lower. The effect persists when the authors control for asset structure, and they provide evidence showing that this phenomenon cannot be explained by modelling choices, or improved risk-measurement alone.

**Numerous studies have confirmed the inherent pro-cyclicality of bank behaviour and the contribution of risk-sensitive bank regulation.** The Basel II regulatory framework has received significant criticism regarding its contribution to strengthening the pro-cyclicality of bank behaviour (see the de Larosière Report, 2009). This issue has been widely discussed by academics and policy-makers over the years (see e.g. Borio et al., 2001; Lowe, 2002; Goodhart et al., 2004; Gordy and Howells, 2006; Rochet, 2008; Repullo et al., 2010) and studied both theoretically and empirically. The related literature can be divided into two broad categories. The first stream analyses the effect of banks' capital ratios on the credit supply, generally concluding that low-capitalised banks restrict

[6] See Article 162 of the CRR.

[7] Much of this pro-cyclicality can be explained by the existence of asymmetric information and market imperfections (ECB, 2010; Drumond, 2009; VanHoose, 1989, 2007).

[8] In the case of LGD for exposures other than retail exposures, the minimum period is seven years.

lending during recessions (Peek and Rosengen, 1995; Peek and Rosengren, 1996; Gambacorta and Mistrulli, 2004). However, these studies are based on the experience prior to the introduction of the IRB approach. In a more recent paper, Behn et al. (2016b) find evidence that German bank regulation amplifies the inherently pro-cyclical nature of bank lending behaviour after 2008. Unlike the previous studies, the authors provide direct empirical estimates of the effect of the internal risk-sensitive model-based approach on the supply of loans to firms.

The second stream of literature investigates the effect of economic fluctuations on banks' capital buffers and capital requirements. Studies conducted on samples prior to the implementation of the IRB approach find evidence of a negative relationship between business cycle fluctuations and capital buffers (Ayuso et al., 2004; Lindquist, 2004; Bikker and Metzemakers, 2005; Stolz and Wedow, 2011; Jokipii and Milne, 2008, 2011). These patterns are found for both Western European banks and U.S. banks. Some other earlier studies focusing specifically on the consequences of risk-sensitive Basel II capital regulation are based on theoretical models (Catarineu-Rabell et al., 2005; Angelini et al., 2010) or numerical simulations on hypothetical and real world portfolios (Kashyap and Stein, 2004; Goodhart et al., 2004; Andersen, 2011; Saurina and Trucharte, 2007). In general, these studies document the tendency of Basel II to increase pro-cyclicality. A few recent studies utilise existing data from the period after the introduction of Basel II. For instance, Cannata et al. (2011) document pro-cyclicality of risk weights for credit risk under the IRB approach using supervisory data for Italian banks. On the other hand, Baule and Tallau (2016), using a comprehensive data set covering 200 large banks from 28 countries, find no indication that Basel II has increased cyclicality.

**Housing prices and residential mortgage credit are particularly prone to cyclical behaviour.** Historically, the worst financial crises have begun with a housing bubble combined with loose mortgage-lending conditions (Reinhart and Rogoff, 2009; Schularick and Taylor, 2012). Housing is closely linked to credit markets, simply because of the need to finance home purchases. Credit expansion and softer credit standards foster growth in property prices, which is then reflected in the size of the loans needed to finance property purchases. This can lead to the creation of a spiral between property prices and property purchase loans. As such, house price bubbles go hand in hand with credit bubbles, reinforcing each other (Wachter, 2015). Bubbles on real estate markets are particularly devastating because the majority of homes are financed by mortgage loans, which form the largest liability of a debtor throughout his or her life.

**These concerns have motivated several measures, the first of which were already incorporated into Basel II and were then followed by others in Basel III.** The adjustments in Basel II include a recommendation to calculate so-called through-the-cycle PD (rather than point-in-time PD) and downturn LGD (rather than simple LGD).[9] Gordy and Howells (2006) and Repullo et al. (2010) confirm the usefulness of through-the-cycle PD in limiting the pro-cyclicality inherent in the IRB calculation method. Under Basel III, two new capital measures intended specifically to reduce the cyclicality of risk-sensitive regulation were proposed – the counter-cyclical capital buffer and the leverage ratio. The counter-cyclical capital buffer imposes a capital surcharge on banks when credit

[9] In addition to obligor-specific information, the through-the-cycle PD estimate should reflect long-run macroeconomic factors. It should be unaffected by the current state of the economy and stay very similar throughout the business cycle. In contrast, the point-in-time PD estimate varies with the cycle, as it is based on current macroeconomic and obligor-specific information. Analogously, downturn LGD should reflect the losses occurring during a business downturn, i.e. it should include the downward-sloping phase of the cycle.

over-expands, i.e. it should build up banks' resilience in good times;[10] the leverage ratio sets a percentage limit on the ratio of minimum capital to non-risk-weighted assets.[11]

# 3. Methodology

The relationship between banks' risk weights and cycle variables is examined using two, conceptually connected approaches. First, simple distributional analysis is employed. This helps us to analyse differences in the distribution of risk weights of different credit exposure categories and changes in the distribution over time. The results of the distributional analysis can help us to decide whether the estimated mean effects are representative of the behaviour of risk weights or whether quantile effects should be considered. The distribution is estimated using Epanechnikov kernel density estimation; the bandwidths were chosen using the rule of thumb.[12]

Second, the dynamic panel data quantile and mean regression models are used. The quantile regression model is more flexible than statistical techniques focusing solely on mean effects; it allows us to study the effects of a covariate on the whole conditional distribution of the dependent variable. In the next section the methodology is described in more detail.

## 3.1 Dynamic Panel Data Quantile and Mean Regression

Two empirical models are constructed for bank $i$ at time $t$:

$$RW_{i,t} = \alpha_0 + \alpha_1 trend + \alpha_2 RW_{i,t-1} + \beta Cycle_t + \gamma X_{i,t-1} + \delta RegPress_t + v_{1,i} + \varepsilon_{1,i,t} \qquad (1)$$

where $RW_{i,j,t}$ is the implicit risk weight, $Cycle_{j,t}$ is a proxy for either the business, credit or financial cycle, $X_{i,j,t}$ are bank-specific control variables and $RegPress_{i,j,t}$ is a dummy for regulatory pressures which takes the value of 1 if banks' regulatory capital ratio is less than 1.5 pp above the minimum of 8% plus capital buffers.[13] The set of bank-specific characteristics $X_{i,j,t}$ includes a proxy for bank size (the natural logarithm of total assets), a proxy for bank credit risk profile (cost of risk; the ratio of the four-quarter moving sum of impairment losses on loans to total loans[14]) and a proxy for bank profitability (ROA). Bank-specific control variables are included in lags in order to eliminate the potential endogeneity problem. In addition, the model contains the intercept, fixed effects $v_{1,i}$ and the time trend; the time trend is included because there is a clear downward-sloping trend in risk weights over the period analysed (see Figure 1).

**The model is estimated using the penalised quantile regression (QR) method with fixed effects as proposed by Koenker (2004).** Quantile regression allows us to examine how covariates influence the location, scale and shape of the response distribution, revealing important heterogeneity. A problem of QR without penalisation is the large number of "fixed effects" introduced, which significantly increases the variability of the estimates of the covariate effects. The penalty parameter

[10] BCBS (2010) contains the regulatory framework and BCBS (2011) further specifies details on how banks should calculate the counter-cyclical buffer.

[11] BCBS (2016) contains a revised methodology for calculating the leverage ratio. Generally, it should be set at 3%, with higher requirements for global systemically important banks.

[12] For more details see the documentation on the R function *density*.

[13] The Czech National Bank currently applies three capital buffers – a conservation buffer (2.5% since July 2014), a systemic risk buffer (1%–3% for some banks since October 2014) and a counter-cyclical capital buffer (0.5% since January 2017). A rate of 0.5% is applied at the end of 2017 Q4, i.e. the end of our estimation sample. It will move to 1.0% as from July 2018, 1.25% as from January 2019 and 1.5% as from July 2019.

[14] Cost of risk is used rather than loan loss provisions so as to eliminate the impact of the different approaches to write-offs among banks.

helps to shrink the fixed effects towards a common value (i.e. zero) and to reduce the variability. The degree of this shrinkage is controlled by a penalty parameter $\lambda$ (for more details, see Koenker, 2004). The estimation method is implemented using the R package *rqpd* developed by Koenker and Bache (2011).

**Penalised QR is suitable for both static and dynamic panel data models.** The penalty term reduces the potential bias arising in short and wide dynamic panels and increases the efficiency of the estimators (Galvao and Montes-Rojas, 2010).[15] However, given that our panel has T=56 and only N=20, the bias itself should not be of great concern. Simulations by Judson and Owen (1999) show that for panel data with T=30 a standard fixed-effects estimator seems to performs just as well or better than most of alternatives, including various types of generalised method of moments estimators and corrected fixed-effects estimators. The penalty term shrinks the individual effects towards a common value. The underlying intuition is that there is no need to use instruments for a lagged dependent variable in a dynamic panel data model that does not have any individual effects. In fact, with shrinkage the model without instrumental variables performs just as well as the model with instrumental variables (Galvao and Montes-Rojas, 2010).[16]

**The mean effects are estimated using the bootstrap-based bias-corrected LSDV estimator by De Vos et al. (2015) to mitigate potential Nickell bias.**[17] Bias-corrected LSDV estimators, pioneered by Kiviet (1995), are shown to have superior small-sample properties compared to GMM estimators; they maintain relatively small coefficient uncertainty while removing most of the bias. Soon after, a few modifications to the Kiviet (1995) estimator emerged, allowing for heteroscedasticity (Bun, 2003; Bun and Carree, 2005; Everaert and Pozzi, 2007; De Vos et al., 2015).[18] We do not consider using GMM estimators as is usual in many other panel data studies, because it is suitable for panels with very large N and small T. One particular weakness of GMM estimators (especially the System-GMM) is that when T is large relative to N, the huge number of instruments produced may render the GMM estimator invalid even though the individual instruments may be valid (Roodman, 2009). Some studies also show that using the instrumental variables technique to avoid bias often leads to poor small-sample properties (Kiviet, 1995; Bun and Windmeijer, 2010). Nevertheless, as argued earlier, the bias should not be of great concern in our case, because our panel is relatively long and narrow. Therefore, we compare the mean effects estimated by the bootstrap-based bias-corrected LSDV and the simple "non-corrected" LSDV.

# 4. Data

The full sample covers 56 quarters from 2004 Q1 to 2017 Q4 and 20 banks, giving an unbalanced panel of 1,067 observations in total. The sample of banks using the IRB approach covers 41 quarters from 2007 Q4 to 2017 Q4 and 9 banks, giving an unbalanced panel of 354 observations (see below). Implicit risk weights are calculated as risk-weighted exposures for credit risk divided by the

[15] It is widely acknowledged that a bias arises in dynamic panel data models with a large number of individuals (N) and a small number of time periods (T) (Nickell, 1981); in such case a standard fixed-effects estimator is inconsistent. But this bias shrinks substantially with higher T.
[16] For more details on the methodology, see Appendix B.
[17] De Vos et al. (2015) build on the model by Everaert and Pozzi (2007); instead of analytical expressions for the bias, usually derived under strict assumptions, they make use of numerical evaluation by bootstrap resampling. This procedure is far simpler and turns out to perform well.
[18] Implemented using the Stata routine *xtbcfe* For each model, 1,000 iterations are produced and 800 enter the final inference. For more details on the implementation of this routine and a description of the methodology, see De Vos et al. (2015).

exposure value, as defined by the regulations.[19] We work with exposures for credit risk, which accounted for about 85% of total risk-weighted exposures as of 2017 Q4. We consider unconsolidated bank statements.[20]

According to CRD IV, banks' credit exposures under the IRB approach can be divided into four main exposure classes: (i) exposures to central governments and central banks, (ii) exposures to institutions, (iii) exposures to corporates and (iv) retail exposures. The remaining credit exposure categories under the IRB approach are equity exposures, items representing securitisation positions and other non credit-obligation assets; all these exposures are categorised as "other credit exposures". The categorisation of banks' credit exposures under the STA approach is more complicated because there are 17 different credit exposure categories (as compared to seven under the IRB approach; for more detail see Appendix A). To simplify the analysis and make the credit exposure classes more or less comparable under the two approaches, we categorise the STA credit exposures as follows: (i) exposures to central governments or central banks,[21] (ii) exposures to institutions, (iii) exposures to corporates, (iv) retail exposures,[22] (v) exposures secured by mortgages on immovable property, (vi) exposures in default and (vii) other exposures.

Nevertheless, the credit exposure categories and corresponding implicit risk weights are not fully comparable under the two approaches. The main differences are as follows. First, under the STA approach there is a separate category for exposures in default, while under the IRB approach exposures in default are part of other categories. Second, under the STA approach there is a separate category for exposures secured by mortgages on immovable property containing only that part of an exposure which is fully secured by a mortgage on immovable property; the part of the exposure that exceeds the mortgage value of the property is categorised as an unsecured exposure of the counterparty involved. Under the IRB approach, the whole exposure is categorised according to

[19] The exposure value is the fully adjusted exposure value adjusted for the effect of conversion factors for off-balance sheet items. The data are from the Common Reporting (COREP) standardised reporting framework issued by the European Banking Authority for Capital Requirements Directive (CRD) reporting. COREP is used by credit institutions and investment firms when reporting their solvency ratios to supervisory authorities under the CRD. For more information see EBA (2010) and further revisions of these guidelines.
Under the STA approach, the total implicit risk weights are calculated as risk-weighted exposures divided by total assets; total assets are used instead of the exposure value, because exposure value data are not available for the period 2004–2007. The difference between the implicit risk weights calculated using total assets and the exposure value is negligible in the period after 2007; we therefore consider this approximation to be appropriate. In all other cases except for the total implicit risk weights under the STA approach, the exposure value is used in the denominator.

[20] The Czech Export Bank and the Czech-Moravian Guarantee and Development Bank are excluded from the analysis; these banks are wholly owned by the Czech state (providing implicit state guarantees for their liabilities) and have different business models and volatile credit portfolios. ERB bank is also excluded due to its insolvency. Bank-level data are obtained from the CNB's internal supervisory database.

[21] Exposures to central governments or central banks consist of exposures to central governments or central banks, exposures to regional governments or local authorities, exposures to public sector entities, exposures to multilateral development banks and exposures to international organisations as defined by Article 112 of CRR/CRD IV. This is in line with the categorisation under the IRB approach (see Article 147(3) and (4) of CRD IV).

[22] Retail exposures comprise exposures to natural persons and exposures to SMEs, which are treated by the institution in its risk management consistently over time and in a similar manner. They are not managed just individually as exposures in the corporate exposure class and they each represent one of a significant number of similarly managed exposures. In addition, the total amount of exposures to an SME owed to the institution and parent undertakings and its subsidiaries cannot exceed EUR 1 million (see Article 146(5) of CRD IV for IRB retail credit exposures and Article 123 of CRD IV for STA retail credit exposures. With respect to that, the retail exposure category usually consists of special-purpose and non-special-purpose consumer loans, mortgage loans, credit card loans and loans to SMEs which meet the aforementioned conditions.

the counterparty involved. A detailed description of the exposure categories and their shares in the Czech banking sector is presented in Appendix A.

***Table 1: Aggregate Implicit Risk Weights and Exposure Shares in Different Credit Exposure Categories (%)***

| | | Implicit risk weights | | | Shares | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | RWE | | | Exposures | | |
| | Category | Q1/08 | Q4/14 | Q4/17 | Q1/08 | Q4/14 | Q4/17 | Q1/08 | Q4/14 | Q4/17 |
| | CGCB | 0.2 | 0.1 | 0.3 | 0.0 | 0.0 | 0.2 | 6.3 | 12.1 | 17.6 |
| STA | Institutions | 33.2 | 36.8 | 22.9 | 1.9 | 0.9 | 0.7 | 2.5 | 1.0 | 0.9 |
| approach | Corporate | 98.7 | 99.1 | 93.9 | 24.3 | 12.4 | 11.6 | 10.5 | 4.8 | 3.7 |
| | Retail | 74.0 | 73.4 | 71.5 | 7.8 | 5.8 | 5.4 | 4.5 | 3.0 | 2.2 |
| | Secured | 37.5 | 36.2 | 36.5 | 1.5 | 2.2 | 2.6 | 1.7 | 2.3 | 2.1 |
| | In default | 141.0 | 124.8 | 129.9 | 0.7 | 1.0 | 1.0 | 0.2 | 0.3 | 0.2 |
| | Other | 83.1 | 97.1 | 94.9 | 7.0 | 7.4 | 6.6 | 3.6 | 2.9 | 2.0 |
| | CGCB | 2.3 | 2.9 | 2.4 | 0.6 | 1.1 | 1.5 | 11.9 | 14.6 | 18.5 |
| IRB | Institutions | 19.4 | 25.6 | 16.8 | 7.6 | 8.3 | 6.3 | 16.8 | 12.3 | 11.0 |
| approach | Corporate | 66.3 | 64.2 | 60.0 | 35.4 | 40.9 | 41.3 | 22.8 | 24.3 | 20.3 |
| | Retail | 29.1 | 33.8 | 30.3 | 13.1 | 20.0 | 21.7 | 19.2 | 22.5 | 21.1 |
| | - of which BSMBs | 24.2 | 27.8 | 24.6 | 4.0 | 5.9 | 6.3 | 7.1 | 8.2 | 7.6 |
| | Other | - | - | 97.3 | 0.0 | 0.0 | 1.2 | 0.0 | 0.0 | 0.4 |

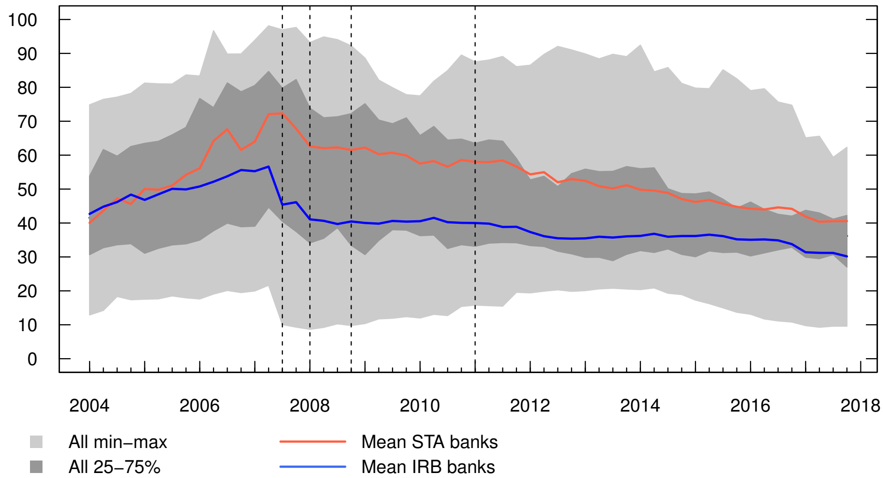
***Note:*** Aggregate implicit risk weights are calculated as the sum of risk-weighted exposures divided by the sum of the fully adjusted exposure value in each credit exposure category. There was a change in the classification of some exposure categories in 2014. CGCB – central government and central bank. BSMBs – building societies and mortgage banks.

**In the Czech Republic, the IRB approach is used by all large banks and several medium-sized banks and some of their subsidiary building societies , with a combined market share of approximately 80%.** Five large or medium-sized banks started to use the IRB approach in 2007 Q3; three others followed a few quarters later; the last bank started to use the IRB approach in 2011 Q1. Figure 1 shows that implicit risk weights started falling simultaneously with the switch to the IRB approach. The difference between the risk weights of banks using solely the STA approach (the blue line) and those of banks using the IRB approach for at least some part of their exposures (the purple line) is striking. The effect is even more pronounced when one takes into account IRB exposures only (the red line).[23] The implicit risk weights of banks using solely the STA approach started to decrease slowly a few quarters later than those of banks using the IRB approach. In the case of STA banks, the decline can be explained by a fall in the ratio of generally more risky credit exposures and a rise in the ratio of generally less risky credit exposures. In particular, the aggregated balance sheet of STA banks saw an increase in the share of exposures to central governments or central banks of 40 pp and decreases in the shares of exposures to corporates of 23 pp, exposures to institutions of 5.5 pp and exposures to retail of 7.5 pp between 2008 Q1 and 2017 Q4 (see Table 1). The fall in the implicit risk weights of IRB banks, on the other hand, cannot be explained solely by a change in the asset structure, so migration to the IRB approach also played a role. The aggregated balance sheet of IRB banks saw an increase in the share of exposures to central governments or central banks of only 9 pp and decreases in the shares of exposures to corporates of only 4 pp and exposures to

[23] All banks using the IRB approach also use the STA approach for a certain (usually small) portion of their exposures. The purple line represents the total implicit risk weights of banks using the IRB approach, while the red line represents the implicit risk weights calculated using IRB exposures only.

institutions of 8 pp between 2008 Q1 and 2017 Q4; moreover, the share of retail exposures increased by 2.5 pp in the given period (see Table 1).

***Figure 1: Implicit Risk Weights under the STA and IRB Approaches (%)***



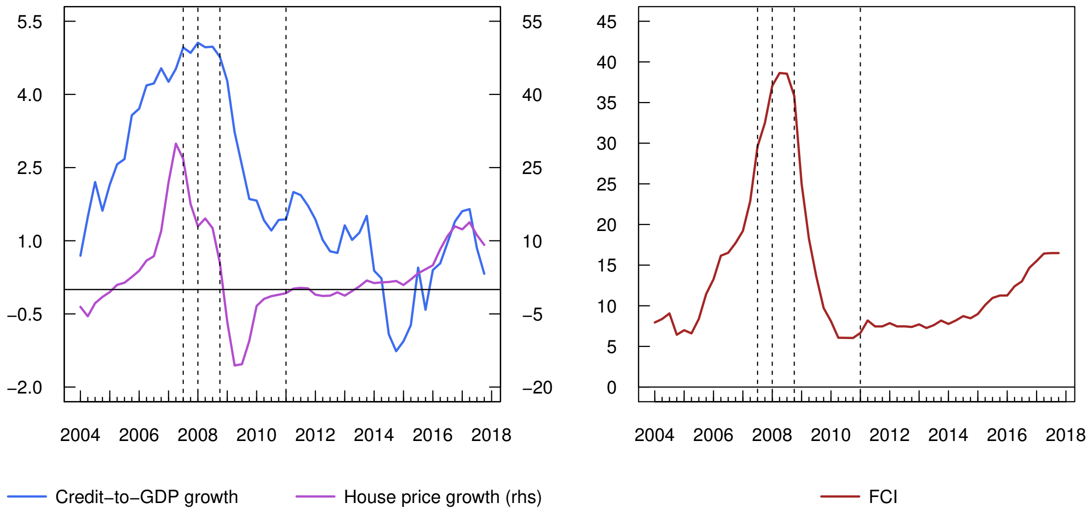

***Note:*** Shaded areas show the variance in implicit risk weights for the total exposures of all banks; coloured lines refer to the average implicit risk weights of banks using solely the STA approach or the IRB approach as of 2017 Q4. Vertical lines – banks' switches to the IRB approach (nine banks in four waves).

**The cycle is proxied by four indicators – annual real and nominal GDP growth as proxies for the business cycle and the annual credit-to-GDP growth ratio of the private non-financial sector and the financial cycle indicator (FCI) as proxies for the credit and financial cycle (see Figures 2–3).**[24] The credit-to-GDP ratio may not seem an optimal proxy for the credit cycle for a converging economy with financial deepening. The gap between the ratio and its long-term trend can be suggested instead. However, the Czech economy entered into transition in the 1990s with a very high level of corporate debt. As a result, there has been no upward-sloping trend so far. Moreover, the credit-to-GDP gap is affected by a fall in the credit volume in 1998–2002 caused by a banking crisis in the late 1990s and the clean-up of bank balance sheets ahead of the privatisation of large banks. The fact that the evolution of credit in this period is a result of economic transformation and institutional changes rather than a reflection of the credit cycle prevents any meaningful estimation.[25] For this and other reasons,[26] the long-term trend in the ratio of total credit to GDP is not suitable for obtaining robust information. Therefore, the simple credit-to-GDP change may be a good proxy for the credit cycle. The FCI is constructed by Plašil et al. (2014) and used by the Czech National Bank as an indicator of the financial cycle (see e.g. CNB, 2017) which is intended to signal the emergence of future problems in timely fashion and to capture the individual phases of the financial cycle (see CNB, 2013). The FCI is estimated using a factor model and selected variables tracking risks in the financial sector and the real economy.[27] One of the variables entering the FCI estimation is house price growth; we use house price growth in addition to the four

[24] We use both nominal and real GDP growth to provide comprehensive results. The empirical results are very similar for both these proxies. This is due to the small difference between nominal and real GDP growth in the Czech Republic given by low and stable consumer price inflation.
[25] For more details, see Frait et al. (2011) and Gersl and Seidler (2011).
[26] The reasons were described in detail in CNB (2015b, 2016).
[27] Credit, the FCI and the RMCI are obtained from the CNB's internal database and GDP from the Czech Statistical Office.

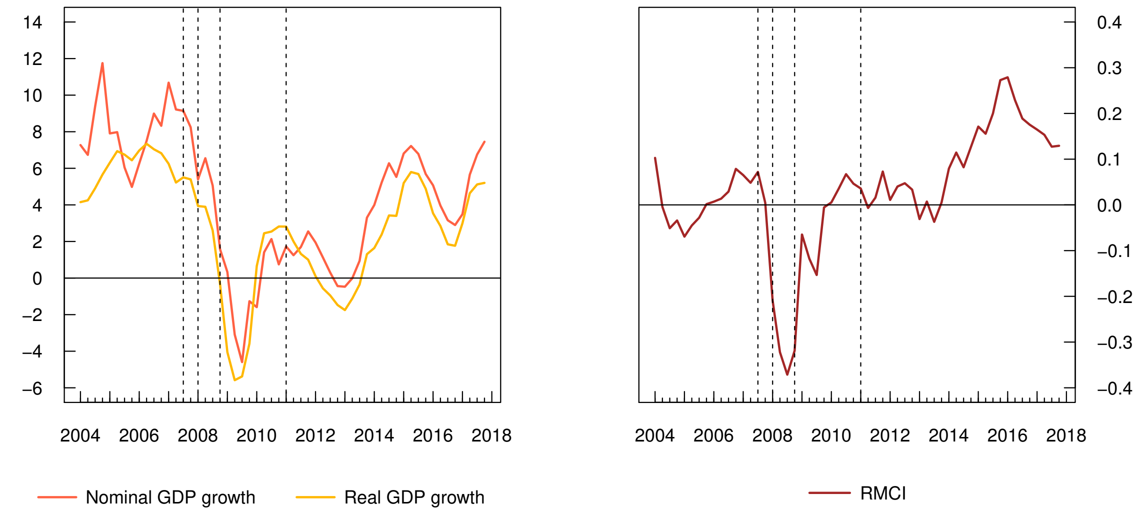
cycle variables in the regression analysis. Specifically, we use year-on-year growth in apartment prices as published by the Czech Statistical Office.

***Figure 2: House Price Growth and Proxies for the Financial and Credit Cycle***




***Note:*** Vertical lines – banks' switches to the IRB approach (nine banks in four waves).

***Figure 3: Business Cycle Proxies and Monetary Policy Variables***




***Note:*** Vertical lines – banks' switches to the IRB approach (nine banks in four waves).

**Monetary conditions are proxied by the real monetary conditions index (RMCI), which captures the effect of unconventional monetary policy alongside conventional policy and the period of prolonged monetary easing at the zero lower bound on policy rates.** The CNB operated with its monetary policy rates at the zero lower bound between November 2012 and August 2017. It started to use the exchange rate as an unconventional monetary policy instrument within its inflation targeting regime in the form of a publicly declared, one-sided exchange rate commitment in November 2013 and decided to discontinue its use in April 2017. In the baseline analysis we use the real monetary conditions index (RMCI) constructed and used by the Czech National Bank (CNB, 2015a). The RMCI is calculated as a weighted average of deviations of domestic ex ante real interest rates and the real exchange rate from their equilibrium levels. A positive value of the RMCI refers to easy monetary conditions and a negative value to tight monetary conditions. As for the interest rate component, the 3-month Pribor adjusted for financial market inflation expectations one year ahead was chosen. The exchange rate component was proxied by the effective real exchange rate. The right panel of Figure 3 shows the path of the RMCI.

# 5. Results

## 5.1 Distribution Analysis

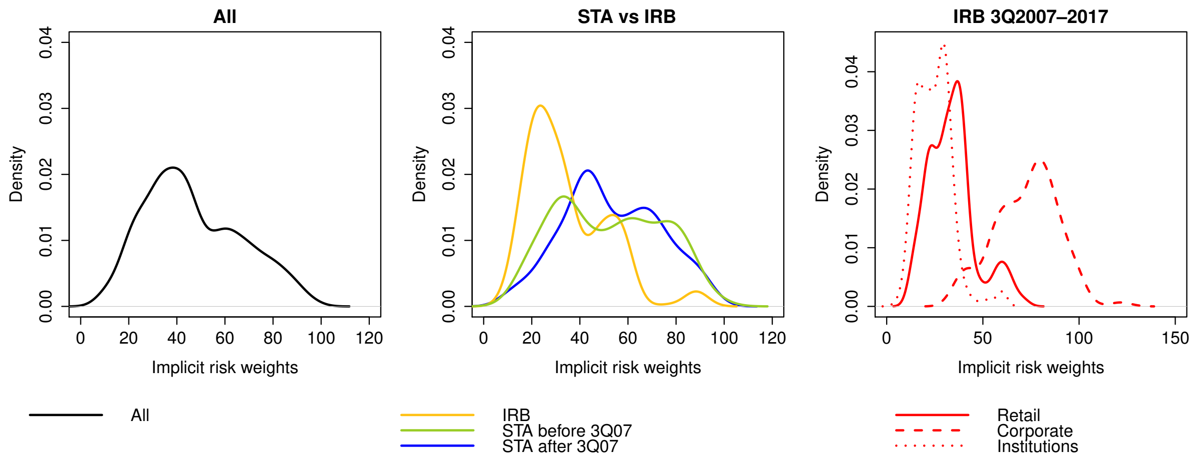
**The distribution of banks' implicit risk weights is not normal – it differs significantly with respect to regulatory approach, credit exposure category and time.** The distribution of banks' implicit risk weights is right-skewed (with mean > median > mode) under both the IRB and STA approaches (Figure 4); in addition, there are still significant differences between these two distributions. As expected, the distribution under the IRB approach is shifted towards lower values, ranging between 9% and 91% (after we exclude one particular bank the range is even narrower, at 9%–60%). On the other hand, the implicit risk weights under the STA approach reach up to 100 and their location parameters and dispersion are much higher. In particular, the mean and the standard deviation of the implicit risk weights under the IRB approach is, respectively, 35% and 17% (31% and 13% after excluding the bank), while under the STA approach it is 53% and 20% (considering the same time period 2007 Q3–2017 Q4).

**The distribution of the implicit risk weights is bimodal under both regulatory approaches in the period after 2007 Q3 due to the different distributions of the implicit risk weights for different credit exposure categories.** Banks' credit exposures are classified into four main categories: (i) exposures to central governments and central banks, (ii) exposures to institutions, (iii) corporate exposures and (iv) retail exposures; under the STA approach, remaining exposures which do not belong to any category are reported as "others".[28] The riskiness of exposures in different categories usually differs; for example, retail credit exposures secured by property will be considered less risky than unsecured loans to non-financial corporations, so the associated risk weights will be lower. The right panel of Figure 4a) illustrates the differences in the distributions under the IRB approach. Under the STA approach the risk weights in different credit exposures classes are defined by regulation. Even though banks can differentiate between counterparties within the same loan category with respect to their external credit rating, the dispersion is usually small. The shape of the distribution of total implicit risk weights under the STA approach is thus given mainly by the credit exposure structure, i.e. by the relative share of each exposure category.

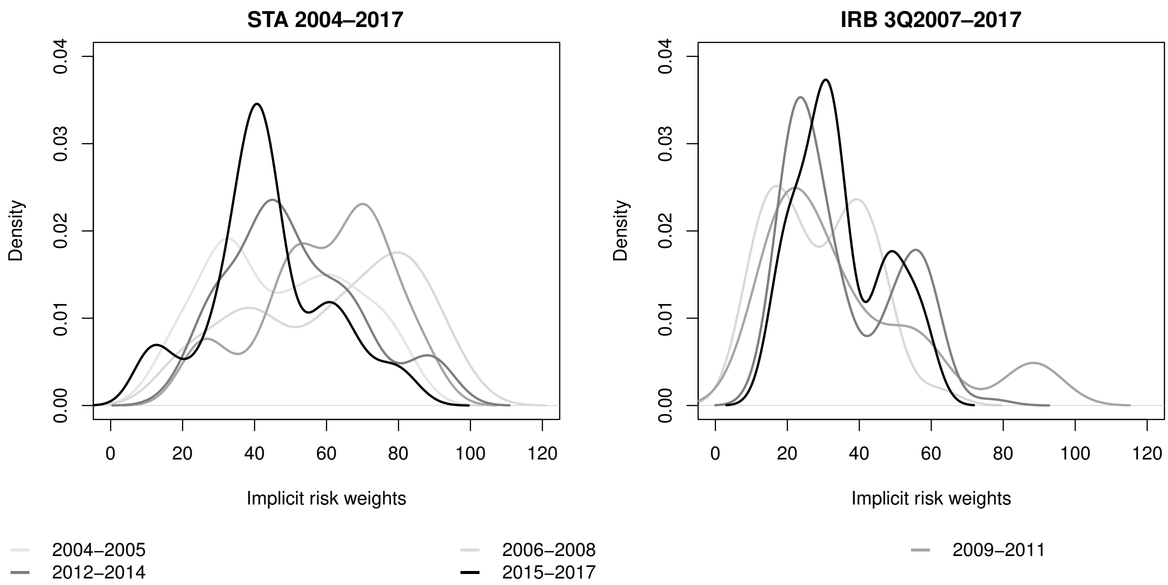
[28] The classification differs slightly between STA and IRB banks. While for IRB banks we can distinguish only these four asset classes, for STA banks exposures are classified into a large number of classes. To be able to compare between STA and IRB banks, for STA banks we report the four main classes and refer to the remaining exposures as "others"; these include exposures to regional governments or local authorities, public sector entities, multilateral development banks, international organisations, exposures secured by residential property, exposures in default, exposures associated with particularly high risk, exposures in the form of covered bonds, items representing secularisation positions, exposures to institutions with a short-term credit assessment and in collective investment undertakings, equity exposures and other items.

***Figure 4: Distribution of Implicit Risk Weights by Regulatory Approach and Credit Exposure Category***

*(a) Differences in the Distribution by Regulatory Approach and Credit Exposure Category*




*(b) Differences in the Distribution by Regulatory Approach and Time*




***Note:*** Implicit risk weights under the STA approach are calculated as the ratio of risk-weighted credit exposures to total assets; implicit risk weights under the IRB approach are calculated as the ratio of risk-weighted credit exposures to the non-risk-weighted credit exposure value fully adjusted for the effect of conversion factors for off-balance sheet items. Under the STA approach total assets are used because the adjusted non-risk-weighted credit exposure value is not available before 2007 Q3; however, the difference between the implicit risk weights calculated using total assets and the fully adjusted non-risk-weighted credit exposure value is small, as indicated by a comparison of the two in the period after 2007 Q3. The distribution is estimated using Epanechnikov kernel density estimation; the bandwidths were chosen using the rule of thumb. For more details see the documentation on the R function *density*.

**The distribution of implicit risk weights under both regulatory approaches changes significantly over time, too (Figure 4).** Between 2004 and 2017, the distribution under the STA approach changes from right-skewed to left-skewed and then back to right-skewed. The average risk weight under the STA approach increases from 42% to 68% between 2004 Q1 and 2007 Q3 and then goes back to 41% in 2017 Q4.[29] The change in the credit exposure structure towards less risky assets is an important factor explaining the decline in risk weights. The total credit exposures of STA banks saw an increase in the share of generally less risky exposures (to central government and the central bank) of 30 pp and a decrease in the share of generally more risky exposures (to institutions, corporates and retail) of 35 pp between 2008 Q1 and 2017 Q4 (see Table 1). The distribution under the IRB approach remains right-skewed and bimodal in the whole period between 2008 Q1 and 2017 Q4, while the importance of the mode at a lower level of implicit risk weights increases significantly over time. This change, however, cannot be explained solely by change in the balance-sheet structure; rather, it is a result of a combination of a higher share of less risky exposures and lower implicit risk weights (see Table 1).

**The distribution of implicit risk weights is quite distinct between different phases of the financial and credit cycle.** Figures 5 displays the kernel density estimates for risk weights conditional on the credit cycle, doing so separately for the individual credit exposure categories and regulatory approaches. The conditional distribution with respect to the financial cycle is presented in Appendix C; the results are similar. We distinguish between two phases. The first phase – let's call it the near-peak phase of the cycle – refers to a period of high financial imbalances, excessive lending and optimism and a high level of systemic risk; the second phase – the near-trough phase of the cycle – refers to a completely opposite situation characterised by low financial imbalances, subdued lending activity, pessimistic expectations and a low level of systemic risk. These two phases are approximated by the upper and lower quartile of the credit-to-GDP growth ratio and the FCI (see Figure 5a)). For the sake of brevity, only results with the credit-to-GDP growth ratio are presented; however, the results with the FCI are analogous (see Figure C1 in Appendix C).

Neither of the estimated conditional distributions seems Gaussian. Under the IRB approach, the distribution in the near-peak phase of the cycle is characterised by higher right-skewness, i.e. the distribution is clustered more around lower values. This is given primarily by the distribution of risk weights for retail exposures. For retail exposures the location parameters (mean, median and mode) of the distribution are lower in the near-peak phase, while for corporate exposures and exposures to institutions they remain very similar in both phases. In contrast, under the STA approach the distribution is left-skewed in the near-peak phase and right-skewed in the near-trough phase. This corresponds to the change in the credit exposure structure of STA banks towards more risky exposures between 2002–2007 and then back towards less risky exposures between 2008–2016, as discussed above.

Figure 5c) shows the conditional distributions of the average total PD and LGD parameters for individual banks (without breakdown by exposure type). It reveals that the difference between the distributions of IRB risk weights in the near-peak and near-trough phases of the cycle is determined mainly by the distribution of the PD parameter. The PD distribution in the near-peak phase is clustered around much lower values relative to the distribution in the near-trough phase. On the other hand, the distribution of the LGD parameter exhibits a similar mean and dispersion in both

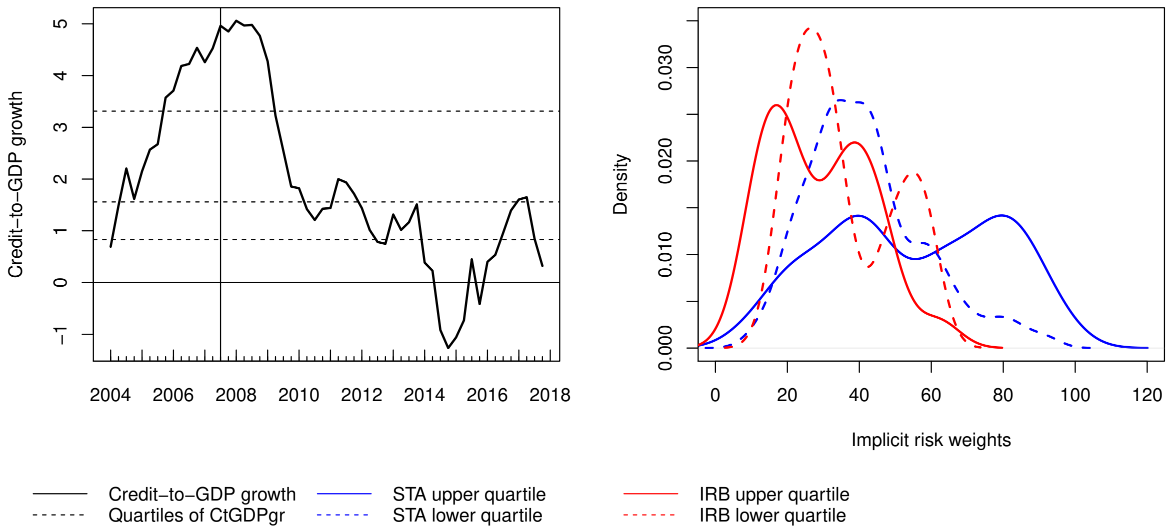
[29] The average is calculated as the average value across risk weights for individual STA banks. The aggregate implicit risk weights (calculated as the sum of risk-weighted exposures divided by the sum of total assets) give similar information – the implicit risk weights increase from 41% to 68% and then drop back to 40%. This is not surprising, as the Czech banking sector is relatively homogeneous (consisting mainly of universal banks with similar business models).

phases. Even so, the distribution in the near-trough phase is left-skewed while that in the near-peak phase is right-skewed, i.e. the distribution in the near-peak phase is more clustered around lower values, similarly to PD. The bimodal shape of the PD and LGD distributions corresponds to the different credit exposure structures of individual banks (see Figure 6).

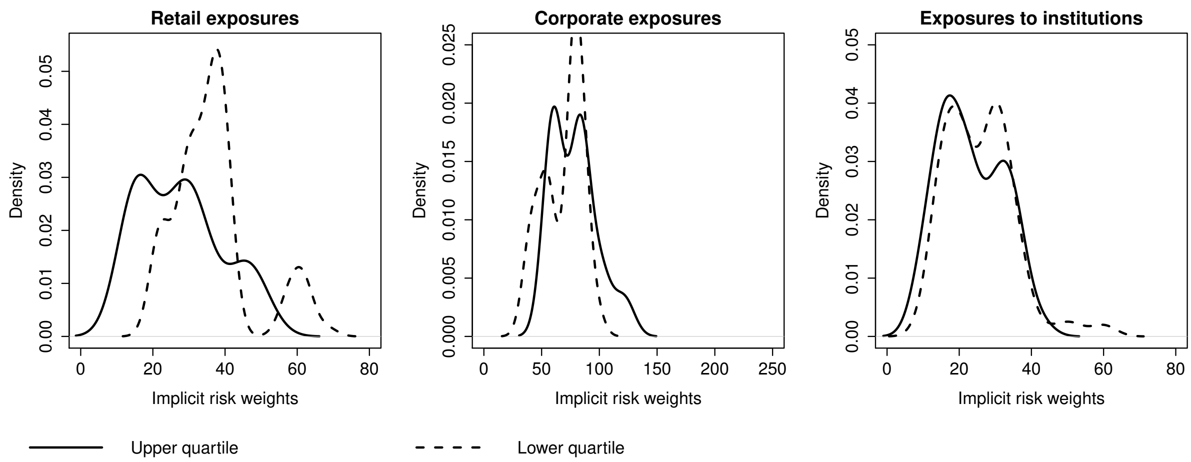
An analogous exercise performed with the business cycle proxies – nominal and real GDP growth – reveals that the conditional distribution is very similar in the upper and lower quartiles of the cycle proxies (see Appendix C).

***Figure 5: Distribution of Implicit Risk Weights and Risk Parameters Conditional on the Credit Cycle***

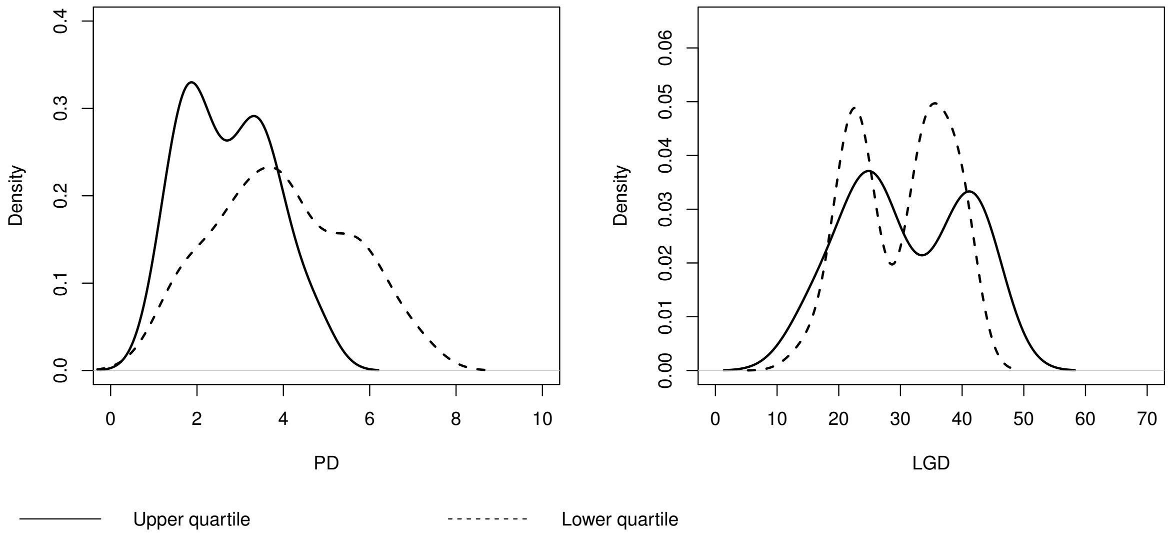
*(a) STA vs IRB Approach*




*(b) Credit Exposure Categories under the IRB Approach*



*(c) Probability of Default and Loss Given Default under the IRB Approach*

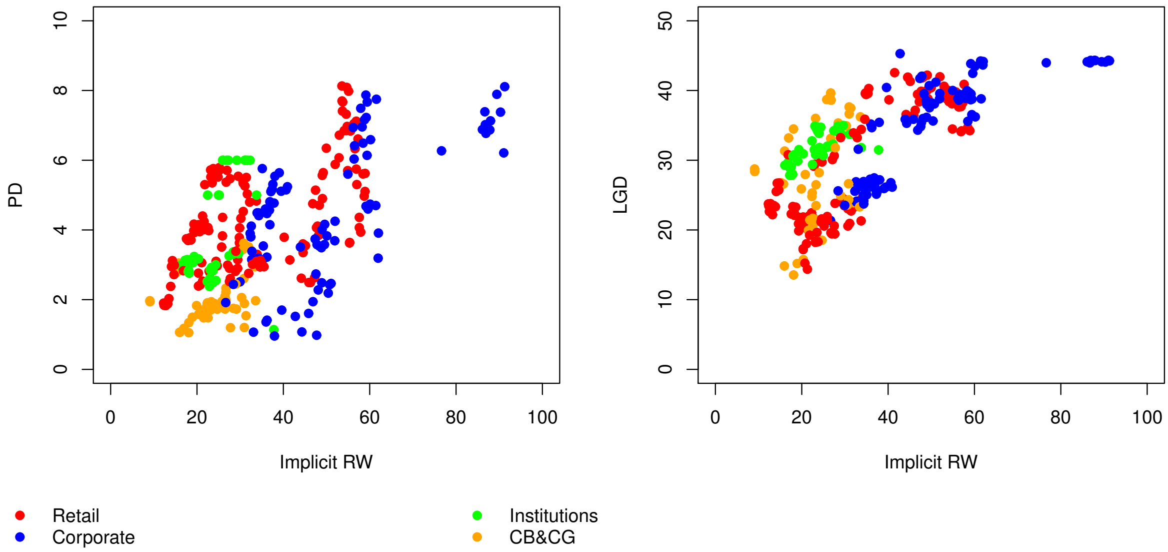



***Note:*** The distribution is estimated using Epanechnikov kernel density estimation; the bandwidths were chosen using the rule of thumb. For more details see the documentation on the R function *density*. CtGDPgr – credit-to-GDP growth.

**To sum up, the distributions of banks' implicit risk weights seem to be far from normal. This is caused by a combination of at least three factors – the regulatory approach, banks' credit exposure structure and the financial cycle.** First, under the IRB approach the implicit risk weights are clustered around much lower values than under the STA approach. This is due to the nature of the IRB approach.[30] Second, the distribution is bimodal under both regulatory approaches. This is caused by different riskiness of different asset classes and therefore different associated risk weights. Third, under the IRB approach, the implicit risk weights are lower in the near-peak phase of the financial and credit cycle compared to the near-trough phase of the cycle. At the peak of the cycle the level of credit risk is usually lowest. This affects the estimates of the risk parameters (PD and LGD) entering the calculation of the capital requirements for credit risk and consequently the implicit risk weights under the IRB approach. All in all, the distributional analysis shows that the impact of cycle variables on risk weights is probably more complex than a simple mean effect. This justifies the choice of quantile regression as the estimation method (see the next subsection).

[30] When using the IRB approach, the bank implicitly derives risk weights based on its own assessment of the riskiness of the portfolio, i.e. on the basis of its own model estimates of the PD and LGD parameters.

***Figure 6: Relationship between Implicit Risk Weights and Risk Parameters by Prevailing Credit Exposure Categories under the IRB Approach***




***Note:*** The prevailing credit exposure category is determined based on the fully adjusted exposure value adjusted for the effect of conversion factors for off-balance sheet items.

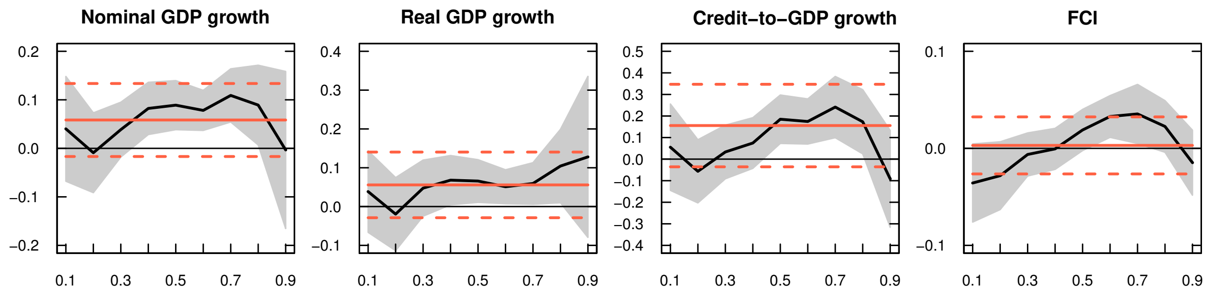
## 5.2 Quantile Regression Analysis

The estimation results for equation (1) are reported in Figures 7–11. The model is estimated separately for banks using solely the STA approach and banks using the IRB approach.[31] For the sake of brevity, only the coefficients on the cycle variables and 90% confidence intervals are reported. The mean effects are shown in red. Complete estimation results are presented in Appendix C. As for the interpretation, a negative sign on the coefficient indicates that the implicit risk weights are pro-cyclical and a positive sign indicates that they are counter-cyclical. In other words, the implicit risk weights tend to be lower in booms and higher in busts if the coefficient is negative and vice versa if the coefficient is positive. As for the STA approach, the whole business and financial cycle enters the analysis (2004–2016); as for the IRB approach, the cycles are incomplete (2007 Q3–2016). This might seem to be a limitation; however, even the analysis under the IRB approach takes into account a significant part of both cycles – the peak of the financial and business cycles in 2007–2009, the descending phase of both cycles in the years afterwards and the recovery in recent years (see Figures 2–3). Nevertheless, we should keep in mind the time span entering the analysis under both regulatory approaches. In terms of size, a coefficient equal to 0.1 implies that if the cycle variable increases by 1 pp, then the implied risk weights increase by 0.1 pp.

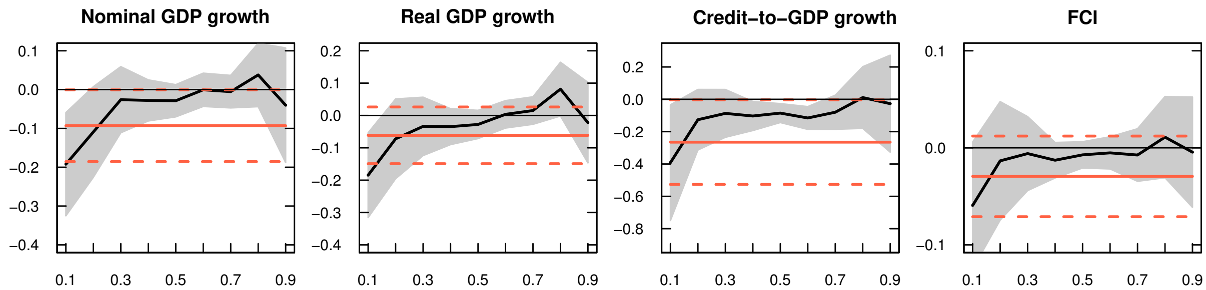
[31] Because banks started to switch to the IRB approach in 2007 Q3 the sample of IRB banks is for the period 2007 Q3–2016 Q4, while the sample of STA banks is for the whole period 2004 Q1–2016 Q4. It is common for banks using the IRB approach also to use the STA approach for some part of their exposures; nevertheless, the dependent variables entering the analysis are either implicit risk weights of STA banks (i.e. determined solely under the STA approach) or implicit risk weights of IRB banks calculated solely under the IRB approach. Implicit risk weights of IRB banks determined under the STA approach do not enter the analysis; this should not be of great concern, as their share is relatively small.

***Figure 7: Effect of an Increase in the Cycle Variable on Implicit Risk Weights (pp)***

*(a) Dependent Variable – Implicit Risk Weights of Banks Using Solely the STA Approach in the Given Quarter*




*(b) Dependent Variable – Implicit Risk Weights under the IRB Approach*




***Note:*** X-axis – quantiles, y-axis – coefficient size; red lines refer to mean effect; 90% confidence intervals reported.

**The implicit risk weights seem to behave pro-cyclically under the IRB approach and counter-cyclically under the STA approach.** There is a predominantly positive relationship between the implicit risk weights under the STA approach and the cycle variables; this relationship is stronger and statistically significant in higher quantiles of risk weights. Under the IRB approach, the relationship between the implicit risk weights and the cycle variables is negative. The strength of this relationship increases in lower quantiles; however, most of the results are not statistically significant at the 10% level.

The direction of the estimated effects is in line with the conclusions drawn in the distributional analysis in the previous subsection. It was shown that under the STA approach the distribution of the implicit risk weights is right-skewed in the lower quartile of the financial and credit cycle and left-skewed in the upper quartile of the cycle, pointing to potentially counter-cyclical behaviour of STA risk weights. The opposite relationship was identified under the IRB approach, pointing to potentially pro-cyclical behaviour of IRB risk weights. The counter-cyclical behaviour of STA implicit risk weights can be attributed to change in the credit exposure structure (see paragraph 3 of section 4 for more details). Taking this change into account, STA implicit risk weights behave acyclically rather than counter-cyclically, i.e. they are generally stable over time, because only very few Czech corporates have been assigned an external rating and exposures in default are treated in a separate exposure class. The pro-cyclical behaviour of IRB risk weights cannot be explained solely by such change; rather, it is a result of a combination of change in the credit exposure structure and decreasing risk weights, especially in the category of retail exposures. To distinguish between these two effects, the model is re-estimated separately for the individual exposure categories under the IRB approach.[32]

**Estimating the model separately for different credit exposure categories confirms the pro-cyclical behaviour of implicit risk weights for retail exposures, revealing a statistically significant hump-shaped effect with respect to the credit and financial cycle variables and a statistically significant effect with respect to the business cycle variables in higher quantiles of risk weights (see Figure 8).** The pro-cyclicality of risk weights for retail exposures with respect to the financial cycle is in line with another recent empirical study conducted using data for the Czech Republic (Brož et al., 2017). The relationship between cycle variables and corporate risk weights remains statistically insignificant in all quantiles and also at the mean. Risk weights in the category of exposures to institutions indicate some signs of pro-cyclicality, but the effects are mostly statistically insignificant. The results show that implicit risk weights for retail exposures react to change in the cycles most prominently in the lowest and highest quantiles of risk weights. Generally, the prevailing exposures in the lowest quantiles of risk weights are exposures secured by property (i.e. mortgages) and those in the highest quantiles are consumer loans.[33] With respect to time, the risk weights in the lowest quantiles correspond to the period of the peak of the financial cycle and the subsequent sharp decline (2007Q4–2010Q4) and to the recent period of a further upward shift in the growth phase of the financial cycle (2016Q4–2017Q4). The risk weights in the highest quantiles, on the other hand, do not correspond to any specific time period.

To sum up, the pro-cyclicality seems to be strongest for the lowest and highest risk weights of retail exposures. In particular, an upward shift in the financial cycle leads to a further decrease in the lowest retail risk weights and a decrease in the highest retail risk weights, shifting the whole distribution to lower values. The opposite is true for a downward shift of the financial cycle.

**The relatively low indebtedness and conservative nature of Czech households, together with the fall of lending rates to historical lows in a prolonged period of easy monetary conditions, led to a significant increase in bank loans to households, especially mortgage loans, but recently also consumer loans.** The Czech private non-financial sector has always been less indebted compared to a number of other European countries (see Figure 9). This has created potential for its future growth. On top of that, Czech households are very conservative in terms of the sources of external financing they use. Bank loans are their major source of external finances. According to available data, bank loans accounted for 95% of the total external sources of financing of Czech households in 2017, while the share is rising constantly over time due to an increasing volume of bank loans and a decreasing volume of non-bank loans. Non-financial corporation, on the other hand, are less conservative – their external sources of financing consist of bank loans (35% as of 2017), non-bank loans (53% as of 2017) and debt securities (12% as of 2017). Czech households are also known for a large share of owner-occupied housing as compared to renting (80% vs 20%; Eurostat, 2017).

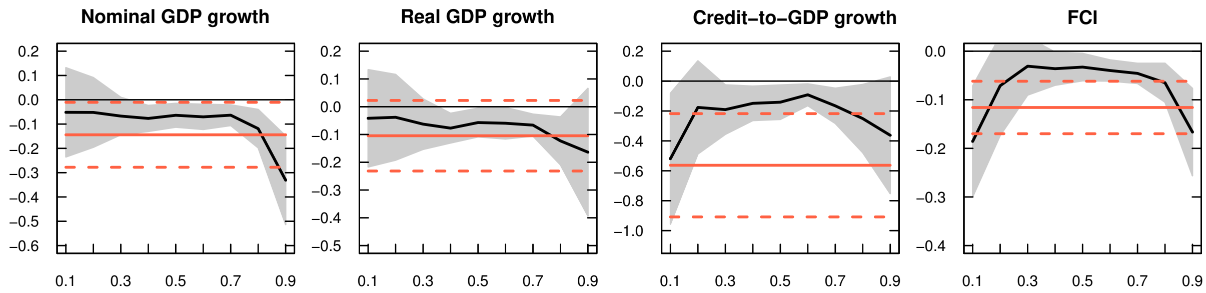
Lending rates on new loans for house purchase declined by 3.5 pp to 2.1% between 2009 and 2016 and started to increase slowly in 2017. Lending rates on new loans for consumption started to

[32] The estimation is done separately for retail exposures, corporate exposures and exposures to institutions. The implicit risk weights on exposures to central banks and central governments are zero or near-zero, so they are not assumed in the regression analysis.
[33] This is supported by the fact that the risk weights in the lowest quantiles are those on retail exposures of banks whose business model focuses primarily on providing loans for house purchase, while the risk weights in the highest quantiles are those on retail exposures of banks whose retail business model focuses on other retail loans, i.e. consumer loans or credit cards.

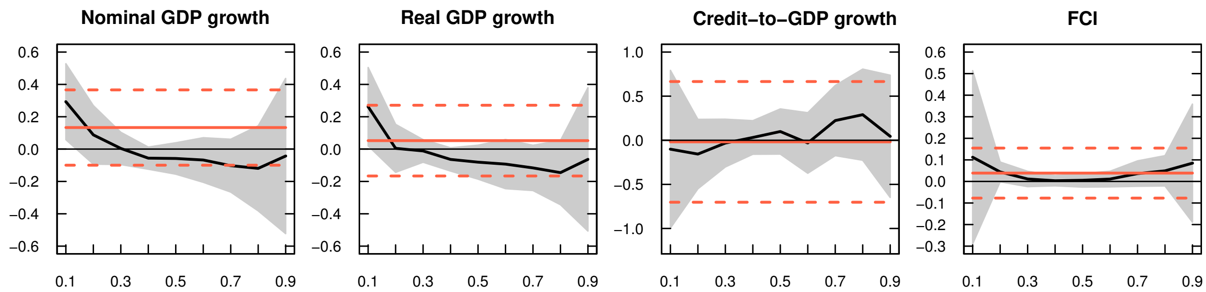
decline a few years later – they fell by about 6 pp between 2013 and 2017. Bank loans for house purchase and consumer bank loans increased by 85% and 36% respectively between 2009 and 2017, while the year-on-year growth rate in both loan categories has been increasing continuously over the last few years (CNB, 2018). A significant increase in the volume of mortgage loans and other retail loans granted is also apparent from the COREP report. It shows that the absolute volume of retail credit exposures under the IRB approach has increased substantially over the last four years.[34] In particular, the absolute volume of total retail exposures rose by 44% and the volume of retail exposures secured by property by 71% between 2014 Q1 and 2017 Q4. Their share in total IRB credit exposures also increased (see Table 1).[35]

***Figure 8: Effect of an Increase in the Cycle Variable on IRB Implicit Risk Weights (pp)***

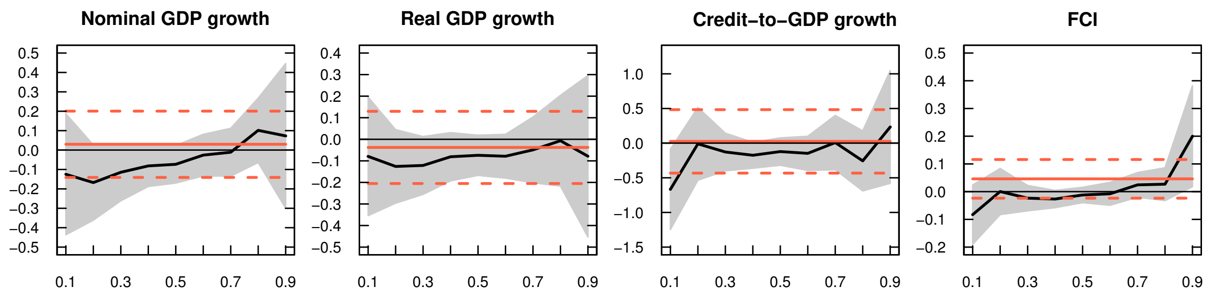
*(a) Dependent Variable – Implicit Risk Weights for Retail Exposures under the IRB Approach*




*(b) Dependent Variable – Implicit Risk Weights for Corporate Exposures under the IRB Approach*




*(c) Dependent Variable – Implicit Risk Weights for Exposures to Institutions under the IRB Approach*

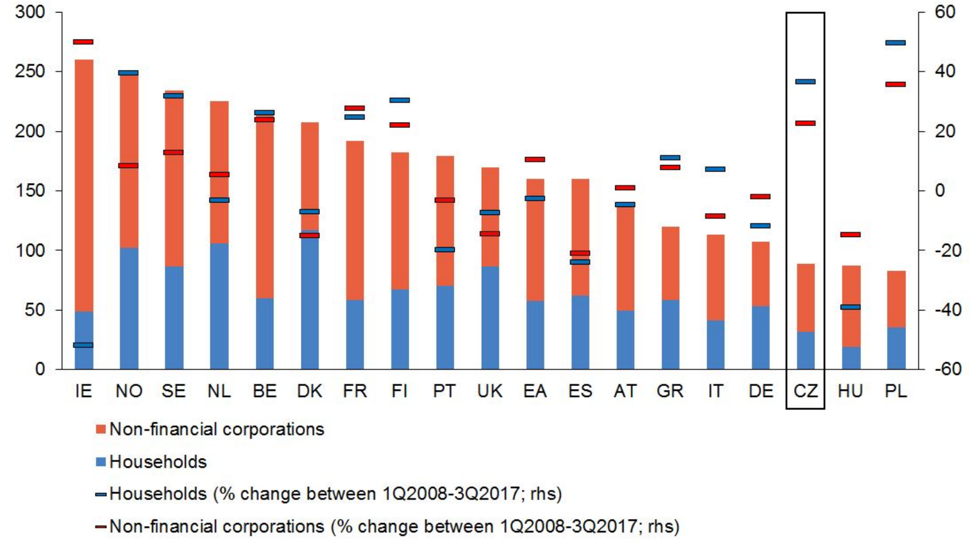



***Note:*** X-axis – quantiles, y-axis – coefficient size; red lines refer to mean effect; 90% confidence intervals reported.

[34] Data on retail exposures secured by property have been available since 2014 Q1.

[35] Under the STA approach, the absolute volume of total retail exposures increased by 17% and the volume of retail exposures secured by property by 53% in the given period.

***Figure 9: Credit to Households and Non-Financial Corporations in Per Cent of GDP***




***Source:*** BIS, data for 2017 Q3

**The growing volume of retail credit exposures, especially mortgage loans, has contributed to the upward shift of the financial cycle, amplifying the inherent pro-cyclicality of the housing market.**[36] The upward shift in the financial cycle in recent years, together with favourable economic conditions, has led to a decrease in credit risk.[37] This has been reflected in a decrease in implicit risk weights (see Table 1). The prolonged period of low interest rates might also have contributed to the decrease in implicit risk weights in recent years. Low interest rates can affect risk estimates – which enter the calculation of risk weights and capital requirements – either directly or indirectly through their impact on collateral value. For instance, low interest rates and increasing asset prices tend to reduce asset price volatility and increase collateral value, which in turn reduces PD and LGD estimates (see Gambacorta, 2009; Jiménez et al., 2014; Dell'Ariccia et al., 2017, among others). The impact of monetary policy on the implicit risk weights of IRB banks in the Czech Republic was identified by Malovaná et al. (2017).

To analyse these effects we propose two extensions of the baseline specification. First, equation (1) is extended to include a proxy for the monetary conditions while simultaneously controlling for cycle variables (both the financial and the business cycle). The effect of the monetary conditions is captured by the real monetary conditions index (RMCI) proposed by CNB (2015a). In addition, alternative measures of monetary policy (the MCI, the shadow rate and the short-term interbank rate; see section 4) were used, but the main message remained the same; therefore, only the results for the RMCI are reported and the other results are available upon request. Second, change in collateral value is proxied by house price growth, which is used instead of the cycle indicators in equation 1. The results of both extensions are presented in Figures 10–11.

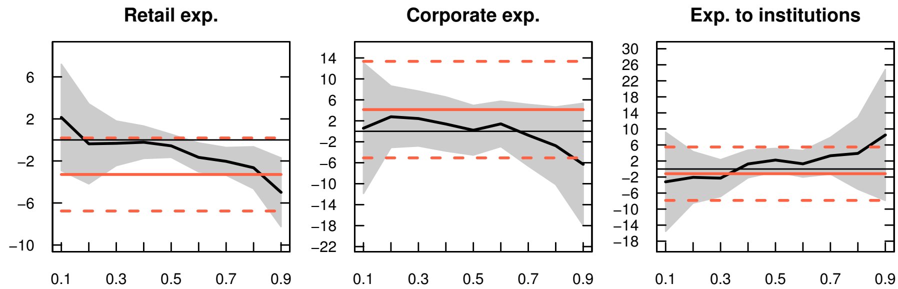
**The effect of monetary policy easing (an increase in the RMCI) on the implicit risk weights of retail exposures under the IRB approach is statistically significant and negative in higher quantiles of risk weights (Figure 10).** In other words, monetary policy easing leads to a decrease

[36] For a discussion of the financial cycle in the Czech Republic, see section 2 and CNB (2017).
[37] The non-performing loans ratios for bank loans to households and non-financial corporations decreased to their pre-crisis levels or even lower in 2017 (CNB, 2018).

in the risk weights of retail exposures which are considered more risky, i.e. usually unsecured consumer loans. The effect on the risk weights of retail exposures in lower quantiles (i.e. secured retail exposures) is not statistically significant. The main reason for the difference in the response may be different speeds of transmission and/or different channels of transmission of monetary policy to secured and unsecured retail credit exposures.

Consumer loans generally have shorter maturity and interest rate fixation periods than mortgages, so they also have the potential to respond more quickly to monetary policy changes. As a consequence, the stock of consumer loans rolls over much faster than the stock of mortgage loans, hence new consumer loans can influence the overall stock much faster than mortgage loans. If, for example, the lending rate on new loans decreases and lending standards become highly relaxed in response to monetary policy easing, this would be reflected more quickly in the stock of consumer loans than mortgage loans. In addition, the credit risk premium on consumer loans is generally much higher than that on mortgage loans, which creates more space for it to decrease during a prolonged period of monetary policy easing.

***Figure 10: Effect of Monetary Policy Easing on Implicit Risk Weights under the IRB Approach while Simultaneously Controlling for Cycle Variables (pp)***



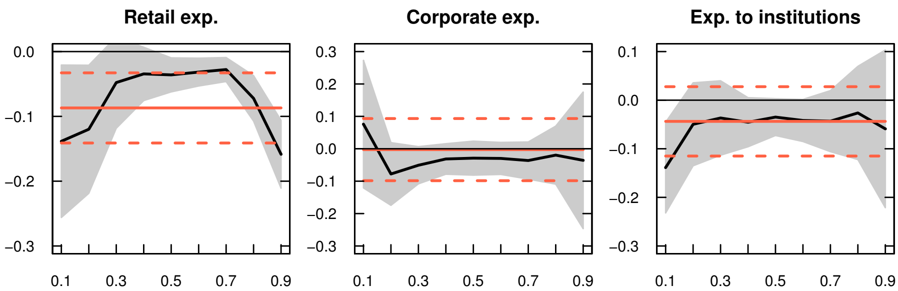

*Note:* X-axis – quantiles, y-axis – coefficient size; red lines refer to mean effect; 90% confidence intervals reported.

**The risk weights for retail exposures under the IRB approach are negatively associated with faster house price growth, with a pronounced effect in the lowest and highest quantiles (Figure 11).** This is not surprising, as the development of house prices is in line with the development of the credit cycle and the financial cycle. As discussed in section 2, property prices and credit usually evolve in tandem, reinforcing each other. At first sight, the relationship might seem logical – secured loans are generally less risky; with higher collateral value the riskiness should decrease further. This, though, would be problematic in at least three situations: (i) if LTV is higher than 100% (i.e. the principal of the loan is not fully covered by the collateral) while the principal increases at the same pace or even faster than the collateral value; (ii) if house prices are not evolving in line with economic fundamentals, i.e. they are overvalued, and (iii) if banks' property valuation methodology is not in line with the market development of property prices. The latter two could either reinforce or dampen each other. In the worst-case scenario, both would lead to overvaluation of property prices and their effect would multiply, prompting the emergence of a property price bubble.[38] The potential for a spiral between property prices and property purchase loans is currently the most significant risk to the financial stability of the Czech banking sector (for more details see CNB, 2017).

[38] The effects are insignificant when estimating for STA banks.

It is worth noting that the transmission of changes in the financial and business cycle or monetary policy changes might also depend on the type of model used to estimate PD and LGD. For instance, the pro-cyclicality of retail exposures could be partly explained by more frequent application of behavioural models in comparison with corporate exposures. Due to limited data availability we cannot verify this hypothesis empirically.

***Figure 11: Effect of an Increase in House Price Growth on Implicit Risk Weights under the IRB Approach (pp)***




***Note:*** X-axis – quantiles, y-axis – coefficient size; red lines refer to mean effect; 90% confidence intervals reported.

## 5.3 Coefficients on the Control Variables

The sign and statistical significance of the coefficients on the control variables differ with respect to credit exposure category. Table 2 provides a simple summary of the signs on the statistically significant coefficients on the control variables in the quantile regressions across all estimated models and quantiles. The complete results are presented in Appendix C.

***Table 2: Signs on the Statistically Significant Coefficients on the Control Variables in the Quantile Regressions across All Models and Quantiles***

| Dependent variable: | IRB RW for retail exp. | IRB RW for corporate exp. | IRB RW for exp. to institutions |
|---|---|---|---|
| Log(assets) (t-1) | . | - | - |
| ROA (t-1) | +/- | + | + |
| Cost of risk (t-1) | + | + | + |
| Regulatory pressures dummy | + | + | +/- |

***Note:*** Full regression results are presented in Tables C1–C21 in Appendix C.

Cost of risk – which is supposed to control for bank credit risk – is associated with higher implicit risk weights of each credit exposure category, suggesting that IRB banks reflect a recognised deterioration in loan quality in their risk-weighted exposures.

Size receives a negative and significant coefficient in the specifications with corporate exposures and exposures to institutions, implying that larger banks tend to hold lower risk weights. The negative sign is intuitive – larger banks usually face lower risk and have better access to funding (which may be reflected in lower risk weights). This is due to the fact that smaller IRB banks include building societies. They specialise mainly in providing loans for house purchase secured by property, which are generally less risky and bear lower risk weights.

The proxy for profitability – ROA – has a positive and significant coefficient in most of the specifications. Banks may achieve higher profitability by investing in more risky assets, i.e. assets which might exhibit a higher probability of unexpected losses based on the historical data estimated; this may be reflected in higher risk weights.

The dummy for regulatory pressures has a positive and significant coefficient in all the specifications with the small exception of the risk weights of exposures to institutions in the highest quantile. This suggests that regulatory restrictions do seem to be binding in a way that affects banks' implicit risk weights.

## 5.4 Robustness and Sensitivity Analysis

In the baseline analysis, we use various proxies for the business and financial cycles (nominal and real GDP growth, the FCI and the credit-to-GDP growth ratio), house price growth, a proxy for monetary policy and different methodological approaches (quantile regression, mean regression and distributional analysis). In addition, we use different values for the penalty parameter $\lambda$ to test the sensitivity of the regression results. Overall, we consider the presented results to be robust. In addition, we test the robustness of the baseline regression results in several other ways.

One potential issue with the estimation results presented is the limited sample size and number of quantiles. Data are usually sparser at the extremes of the distribution; modelling extreme quantiles (for example the 10th or 90th) might therefore have lower precision than modelling the median. With a relatively small sample size and a high number of quantiles the possibility of Type II errors increases, that is, the results may turn out to be statistically insignificant even if they are actually significant. This keeps us on the relatively safe side, as we should not be able to identify a non-existent relationship as statistically significant. It is also important to note that quantile regression uses the full distribution for every quantile. As we are not able to increase the sample size, we check the sensitivity of the results by altering the number of quantiles estimated, i.e. we reduce the number of quantiles estimated from nine to five (15th, 35th, 50th, 65th and 85th) and four (20th, 40th, 60th and 80th) and the results remain both quantitatively and qualitatively similar to the baseline results. The results are not presented here, but are available upon request.

Another potential issue is the coefficient on the lagged dependent variable, which is close to unity in some specifications and for some quantiles. This may give rise to some concerns about the stationarity of the panel data (even though the model includes the time trend) and about the behaviour of the risk weights at the extremes of the distribution. First of all, the panel is tested for the presence of unit roots using various statistical tests designed for unbalanced panels.[39] All these tests lead to the same conclusion – rejection of the null hypothesis stating that all the panels contain unit roots at the 5% significance level. In general, stationarity seems not to be a problem, but we might be concerned about the behaviour at the extremes of the distribution. The coefficient on the lagged dependent variable is close to unity in the highest quantiles of the distribution. This is more or less consistent with the findings of the distribution analysis, that is, the whole distribution of risk weights shifts to lower values, while the dispersion also decreases over time (i.e. higher risk weights decrease by more than lower risk weights).

As an additional exercise we use the change in the risk weights instead of their level as a dependent variable and we exclude the time trend. The change is calculated as the difference between the cur-

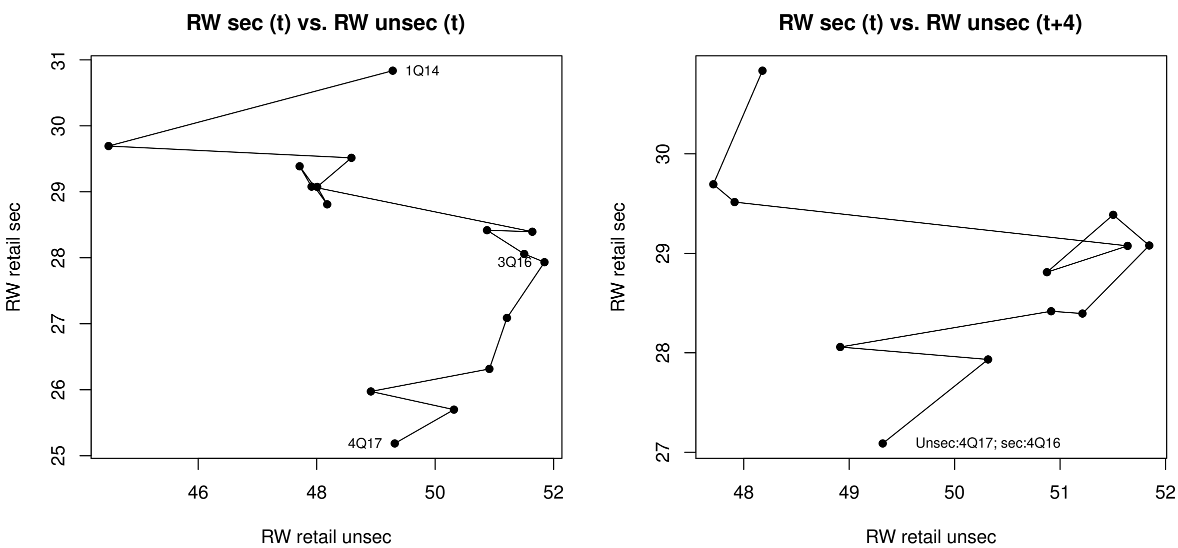
[39] We use the Augmented Dickey-Fuller unit-root test, the Phillips-Perron unit-root tests and the Im-Pesaran-Shin test with drift or a time trend and with up to 6 lags.

rent value of a risk weight and its value in the previous quarter; the resulting change is in percentage points. The pro-cyclicality of retail credit exposures remains strong and statistically significant with respect to the business cycle in higher quantiles of risk weights and with respect to the financial cycle in the highest and lowest quantiles of the risk weights (see Tables C19–C21 in Appendix C).

One possible reason for this, especially in the category of retail exposures, is the relation between secured and unsecured credit exposures. Historically, consumer loans (i.e. usually unsecured loans) in the Czech Republic were characterised by relatively high interest rate margins, high perceived riskiness and low volumes provided. This has changed significantly in recent years in an environment of a prolonged period of accommodative monetary policy and low margins on mortgage loans and loans to non-financial corporations. These lower margins have exerted pressure on the overall profitability of banks, which have started to provide larger volumes of consumer loans at lower lending rates. We hypothesise that *changing* credit market conditions in the market for housing loans and mortgages might have influenced the market for consumer loans, which might consequently have reacted more by change in the risk parameters and implicit risk weights.

Data for retail exposures secured by property are available only since 2014 Q1, so we cannot do the empirical analysis separately for secured and unsecured retail credit exposures. However, a simple scatter plot indicates that the relationship between the risk weights for secured and unsecured retail credit exposures has changed (see Figure 12). Until 2016 the relationship seems to be predominantly negative, while since then it has been positive. The negative relationship is even more apparent if lagged risk weights are used for secured exposures, which supports the aforementioned hypothesis. Nevertheless, the period analysed is still very short.

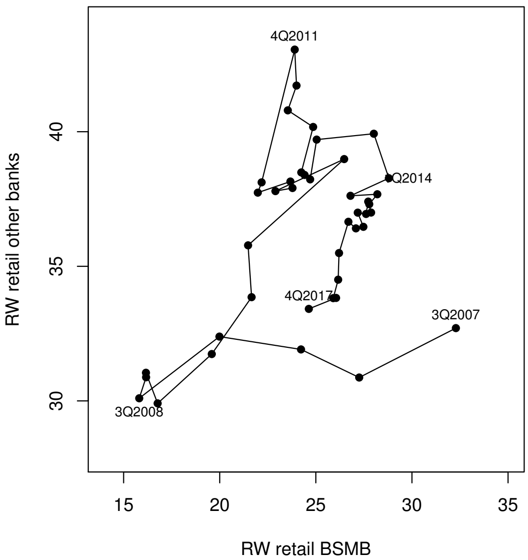
***Figure 12: Aggregate Implicit Risk Weights for Secured and Unsecured Retail Credit Exposures***




In addition, we can differentiate between the risk weights for the retail credit exposures of building societies and mortgage banks on the one hand and the risk weights for the retail credit exposures of other banks on the other hand. This allows us to differentiate the retail segment by the business model of the bank – building societies and mortgage banks focus exclusively on providing secured housing loans, while the remaining banks in the retail segment also provide consumer loans alongside mortgage loans.

Figure 13 illustrates the relationship between the aggregate risk weights for the retail credit exposures of building societies and mortgage banks and those of remaining banks in the segment. There is a clear negative relationship – the risk weights in the two sub-categories decline or rise at the same time over most of the period analysed. The relationship is also negative in both sub-categories with respect to the financial and credit cycle (see Figure 13).

***Figure 13: Aggregate Implicit Risk Weights for Retail Credit Exposures – BSMBs vs Other Banks***




***Note:*** BSMBs – building societies and mortgage banks

As an additional exercise we control for lags of the cycle variables and monetary policy variables. The lags between the variables describing the business/financial cycle and risk weights could be several months or even more than a year, depending on the exposure category. For instance, for corporate exposures the lag could be longer if the rating is updated based on the end-of-year financial statements. In the robustness analyses we control for four lags of the variables and test for the statistical significance of their sum. The results are reported in Tables C12–C18 in Appendix C. The results for retail credit exposures remain very similar to the baseline analysis. The results for corporate exposures indicate pro-cyclical behaviour in higher lags of real GDP growth. There are also some signs of pro-cyclicality of risk weights for exposures to institutions in lower quantiles of risk weights and counter-cyclicality in higher quantiles of risk weights. Controlling for different lags of the real monetary conditions index and house price growth confirms the baseline results, that is, monetary policy easing and growth of house prices contribute to lower risk weights under the IRB approach.

## 6. Conclusions

This paper studies the pro-cyclicality of risk weights under the STA and IRB approaches and for different credit exposure categories with respect to the business, credit and financial cycles using data for the Czech Republic. In addition, it analyses the impact of changing monetary conditions on risk weights under the IRB approach.

**In general, the distribution of banks' implicit risk weights seems to be far from normal.** This is caused by a combination of at least three factors – the regulatory approach, banks' credit exposure structure and the financial cycle. Further empirical investigation reveals that risk weights seem to behave pro-cyclically under the IRB approach and counter-cyclically under the STA approach. The seemingly counter-cyclical behaviour of STA risk weights can be attributed to change in the credit exposure structure. Taking this change into account, STA implicit risk weights behave acyclically rather than counter-cyclically, i.e. they are generally stable over time. The pro-cyclical behaviour of IRB risk weights cannot be explained solely by such change; rather, it is a result of a combination of change in the credit exposure structure and decreasing risk weights.

**Estimating the model separately for different credit exposure categories reveals the pro-cyclicality of risk weights for retail exposures under the IRB approach.** The pro-cyclicality with respect to the business cycle seems to be strongest in the highest quantiles of risk weights, while the pro-cyclicality with respect to the credit cycle seems to be strongest in the lowest quantiles of risk weights. The pro-cyclicality with respect to the financial cycle is strong in both the lowest and higher quantiles of risk weights for retail exposures. In particular, an upward shift in the financial cycle leads to a further decrease in the lowest retail risk weights and the highest retail risk weights, shifting the whole distribution to lower values. The opposite is true for a downward shift of the financial cycle. This indicates that risk-sensitive capital regulation increases the inherent pro-cyclicality of the banking sector.

**The effect of monetary policy easing on risk weights is statistically significant only for retail credit exposures under the IRB approach.** In particular, this effect is statistically significant only in higher quantiles of risk weights, i.e. risk weights for retail exposures which are considered more risky (usually unsecured consumer loans). The effect in lower quantiles of risk weights (i.e. usually for secured retail exposures) is not statistically significant. The main reason for that may be different speeds of transmission and/or different channels of transmission of monetary policy to secured and unsecured retail credit exposures.

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## Appendix A: Risk-Weighted Exposure Categories

According to CRD IV, banks' total risk-weighted exposures can be divided as follows:

(i) risk-weighted exposures of firms providing investment services and activities according to Articles 95(2) and 98 CRR;

(ii) risk-weighted exposures of firms providing investment services and activities according to Articles 96(2) and 98 CRR;

(iii) risk-weighted exposures for credit risk, counterparty risk, dilution risk and free deliveries;

- (iii-a) risk-weighted exposures for credit risk under the STA approach;
- (iii-b) risk-weighted exposures for credit risk under the IRB approach;
- (iii-c) risk-weighted exposures for contributions to the default fund of a central counterparty;

(iv) risk-weighted exposures for settlement risk;

(v) risk-weighted exposures for position risk, foreign-exchange risk and commodities risk;

(vi) risk-weighted exposures for operational risk;

(vii) additional risk-weighted exposures due to the application of overhead costs;

(viii) risk-weighted exposures for credit valuation adjustment risk to reduce risk-weighted exposures for credit risk;

(ix) risk-weighted exposures for large exposures in the trading portfolio;

(x) other risk-weighted exposures.

As of 2017 Q4, more than 85% of total risk-weighted exposures are risk-weighted exposures for credit risk ((iii-a) and (iii-b); see Figure A1). The other two significant categories are risk-weighted exposures for operational risk (11%) and risk-weighted exposures for position risk, foreign-exchange risk and commodities risk (4%). The risk-weighted exposures for credit risk can be further divided as follows:

(i) risk-weighted exposures for credit risk under the STA approach

- (i-a) exposures to central governments or central banks;
- (i-b) exposures to regional governments or local authorities;
- (i-c) exposures to public sector entities;
- (i-d) exposures to multilateral development banks;
- (i-e) exposures to international organisations;
- (i-f) exposures to institutions;
- (i-g) exposures to corporates;
- (i-h) retail exposures;
- (i-i) exposures secured by mortgages on immovable property;
- (i-j) exposures in default;
- (i-k) exposures associated with particularly high risk;
- (i-l) exposures in the form of covered bonds;
- (i-m) exposures to institutions and corporates with a short-term credit assessment;
- (i-n) exposures in the form of units or shares in collective investment undertakings;
- (i-o) equity exposures;

(i-p) other exposures;
(i-q) items representing securitisation positions;

(ii) risk-weighted exposures for credit risk under the IRB approach;

(ii-a) exposures to central governments or central banks;
(ii-b) exposures to institutions;
(ii-c) exposures to corporates;
(ii-d) retail exposures;
(ii-e) equity exposures;
(ii-f) items representing securitisation positions;
(ii-g) other non credit-obligation assets.

For the purposes of the analysis, the credit exposure categories listed above are aggregated as follows:

(i) risk-weighted exposures for credit risk under the STA approach

(A) exposures to central governments or central banks;
(B) exposures to institutions;
(C) exposures to corporates;
(D) retail exposures;
(E) exposures secured by mortgages on immovable property;
(F) exposures in default;
(G) other exposures ((i-b)–(i-e) and (i-k)–(i-q));

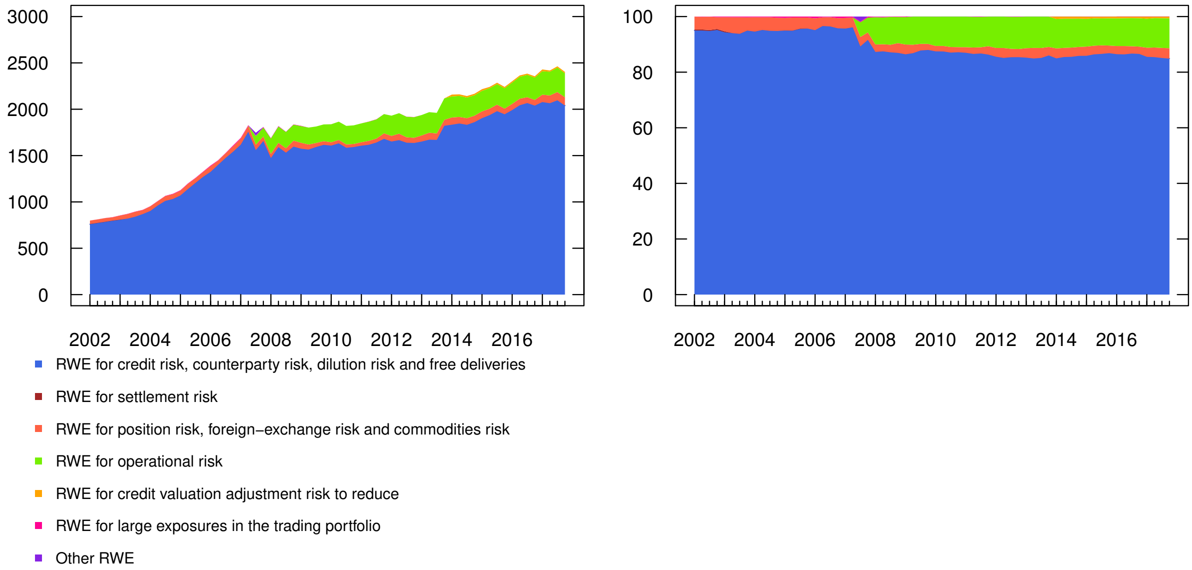
(ii) risk-weighted exposures for credit risk under the IRB approach;

(A) exposures to central governments or central banks;
(B) exposures to institutions;
(C) exposures to corporates;
(D) retail exposures;
(E) other exposures ((ii-e), (ii-f) and (ii-g)).

More than 70% of both risk-weighted and non-risk-weighted credit exposures are under the IRB approach as of 2017 Q4 (see Figures A2 and A3). The most significant risk-weighted credit exposure category is the IRB corporate exposure category (more than 41% of total credit exposures); the most significant non-risk-weighted credit exposure category is the IRB retail exposure category (more than 21% of total credit exposures). Securitised exposures and equity exposures account for only 2% of non-risk-weighted credit exposures and 5.6% of risk-weighted credit exposures as of 2017 Q4.

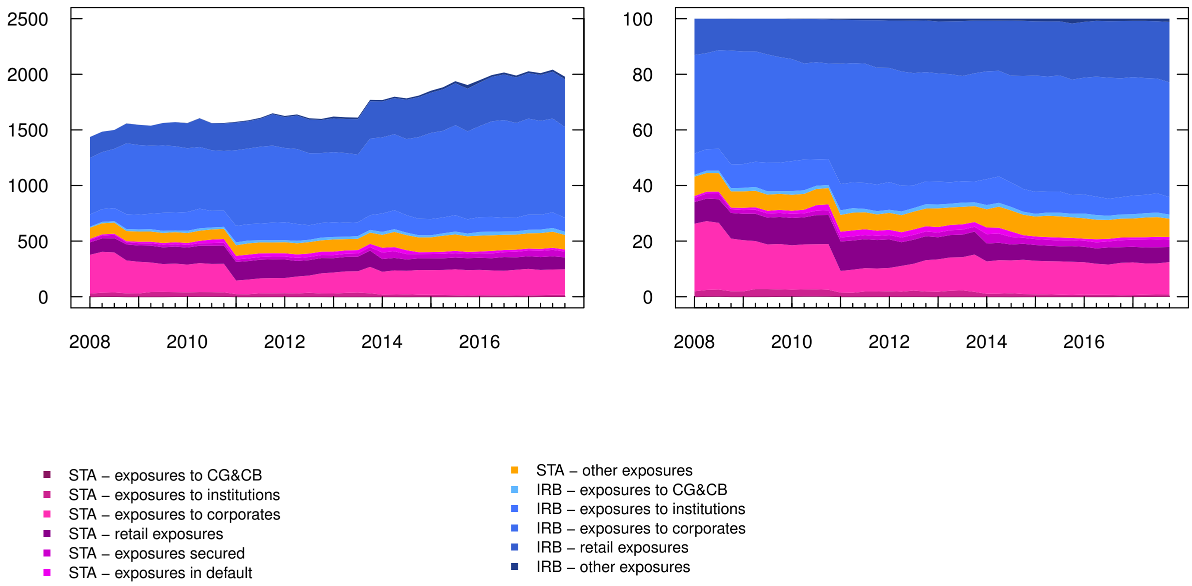
It should be noted that there are differences between the credit exposure categories under the STA and IRB approaches. First, under the STA approach there is a separate category for exposures in default, while under the IRB approach exposures in default are part of other categories. Second, under the STA approach there is a separate category of exposures secured by mortgages on immovable property containing only that part of an exposure which is fully secured by a mortgage on immovable property; the part of the exposure that exceeds the mortgage value of the property is categorised as an unsecured exposure of the counterparty involved. Under the IRB approach, the whole exposure is categorised according to the counterparty involved. For these reasons, the exposure categories and corresponding implicit risk weights are not fully comparable.

***Figure A1: Total Risk-Weighted Exposures of Banks in the Czech Republic (CZK Billions; Share in %)***



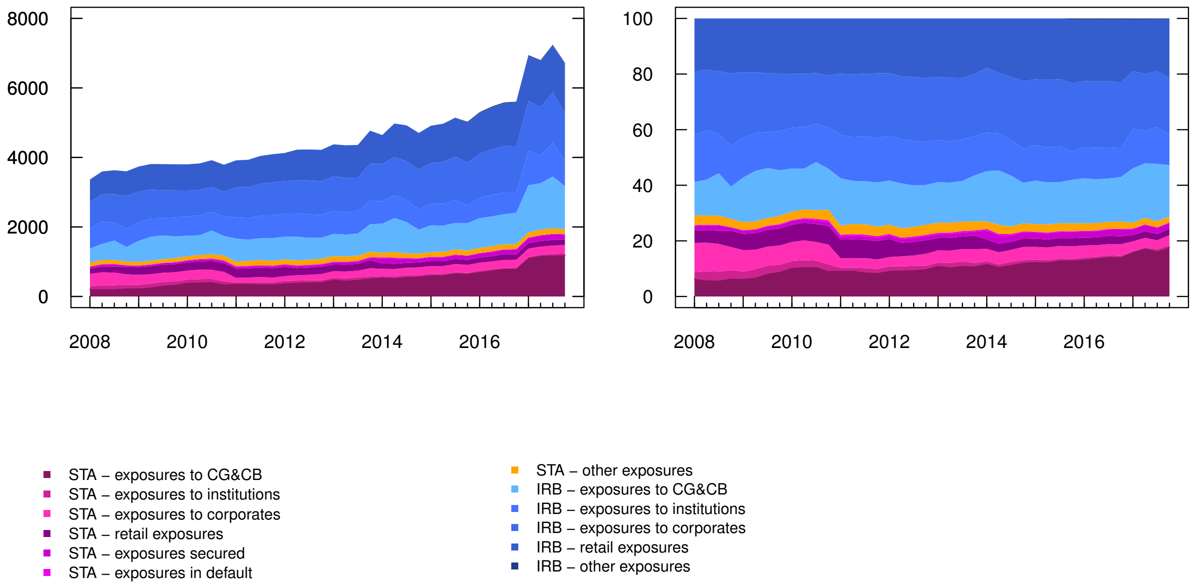

***Note:*** Risk-weighted exposures are calculated as the sum of the risk-weighted exposures of banks and their subsidiaries active in the given quarter on a solo basis.

***Figure A2: Risk-Weighted Exposures for Credit Risk of Banks in the Czech Republic (CZK Billions; Share in %)***




***Note:*** See the note to Figure A1.

***Figure A3: Non-Risk-Weighted Exposures for Credit Risk of Banks in the Czech Republic (CZK Billions; Share in %)***




***Note:*** See the note to Figure A1.

# Appendix B: Methodology

## B.1 Penalised Quantile Regression for Dynamic Panel Data

When using the dynamic panel data quantile regression model without penalisation, we face two possible identification problems. First, the large number of fixed effects introduced significantly increases the variability of the estimates of the covariate effects. Second, in the context of dynamic panel data models we can face endogeneity bias (Nickell, 1981). Koenker (2004) shows that introducing a penalty term helps in both cases – it improves the properties of the estimator, reduces the possible bias and increases the efficiency. The penalty parameter $\lambda$ helps to shrink the fixed effects towards a common value (i.e. zero) and to reduce the variability.

Consider the following model for the $\tau$th conditional quantile functions of the response of the $t$th observation on the $i$th individual $yit$,

$$Q_{y_{i,t}}(\tau|\eta_i, y_{i,t-1}, x_{i,t}, z_t) = \eta_i + \alpha(\tau)y_{i,t-1} + x'_{i,t}\beta(\tau) + z'_t\delta(\tau) \qquad \text{(B1)}$$

where $y_{i,t}$ is the dependent variable, $x_{i,t}$ are exogenous individual-specific variables, $z_t$ are exogenous macro (individual-invariant) variables and $\eta_i$ are individual specific effects or intercepts. The effects of the covariates $(y_{i,t-1}, x_{i,t}, z_t)$ are permitted to depend on the quantile of interest, $\tau$, but the fixed effects, $\eta_i$, do not. With respect to the model specification presented in section 3, $y_{i,t}$ are the risk-weights $RW_{i,t}$, $x_{i,t}$ are the bank-specific control variables $X_{i,t}$ and $z_t$ are the cycle variables $Cycle_t$, the monetary policy proxy $MP_t$ and the volatility index $VIX_t$.

Next, we define the piecewise linear loss function $\rho_\tau(u) = u(\tau - I(u < 0))$, where I is an indicator function, and introduce the penalty term $\lambda$, which only affects fixed effects (Koenker and Bassett, 1978). Then the model can be estimated for a specific quantile by solving

$$\min_{(\alpha,\beta,\delta)} \sum_{k=1}^{q} \sum_{i=1}^{N} \sum_{t=1}^{T} w_k \rho_\tau (y_{i,t} - \eta_i - \alpha(\tau_k) y_{i,t-1} - x'_{i,t} \beta(\tau_k) - z'_t \delta(\tau_k)) + \lambda \sum_{i=1}^{N} |\eta_i| \tag{B2}$$

where $w_k$ are the weights for the $k = 1,...,q$ quantiles, which are jointly estimated. Note that if $\lambda \to \infty$, $\hat{\eta}_i \to 0$, while if $\lambda \to 0$, the penalised QR fixed-effects estimator becomes the standard QR fixed-effects estimator. For a more detailed discussion of the methodology and the theoretical and empirical properties of the proposed estimator, see Koenker (2004); Galvao and Montes-Rojas (2010).

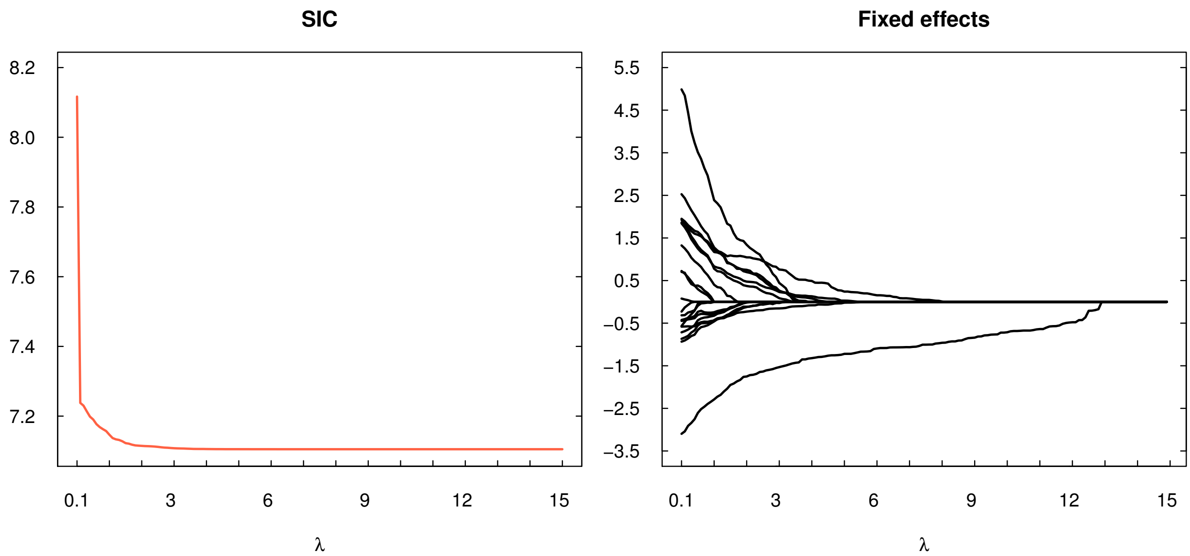
## B.2 Penalty Selection

The penalty parameter $\lambda$ is selected by minimising the high-dimensional Schwartz information criterion (SIC) for the quantile regression model:

$$SIC(\lambda) = log(checkloss) + |S| log(log(n)) C_n / n \tag{B3}$$

where $S$ is the selected model, $n$ is the number of observations and $C_n = log(p)/const$ is a positive constant diverging to infinity as $n$ increases. We compare the SIC for models with $\lambda = seq(0.1, 15, by = 0.1)$; the results are plotted in Figure B1. The most significant drop in the SIC can be seen at the beginning of the sample, while it stabilises at around 7.105, corresponding to $\lambda$=5. This value is used in the following analysis. The right panel of the figure shows how increasing $\lambda$ penalises fixed effects, i.e. shrinks them towards zero. At $\lambda$=5 the individual fixed effects are still non-zero even if their value is significantly lower compared to $\lambda$=0.1.

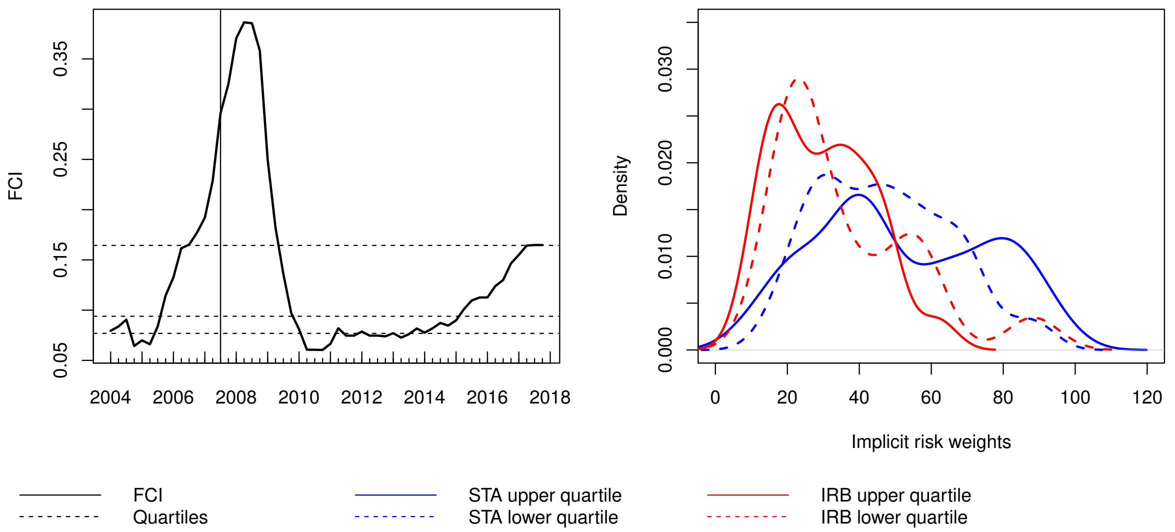
***Figure B1: Penalty Selection***



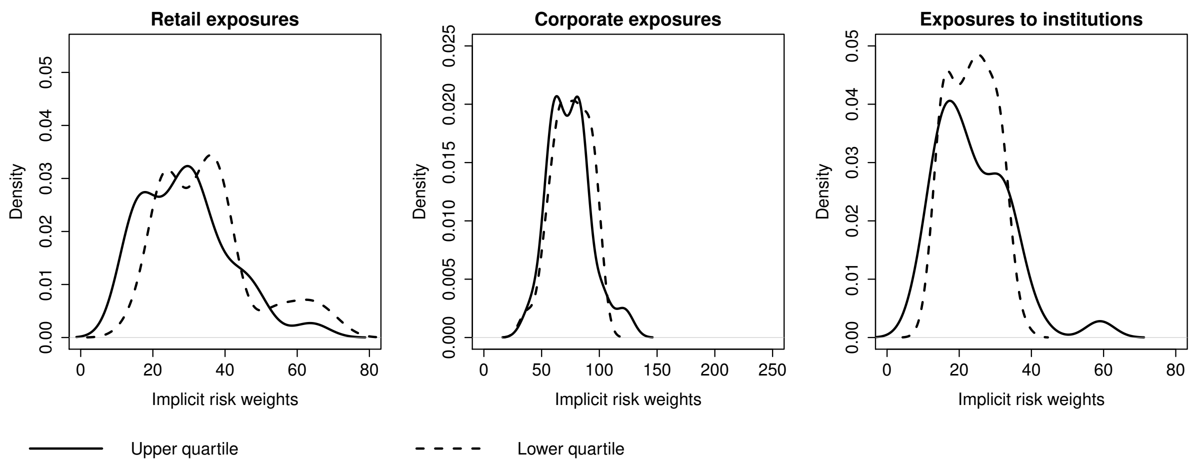
# Appendix C: Data and Full Regression Results

***Figure C1: Distribution of Implicit Risk Weights and Risk Parameters Conditional on the Financial Cycle***

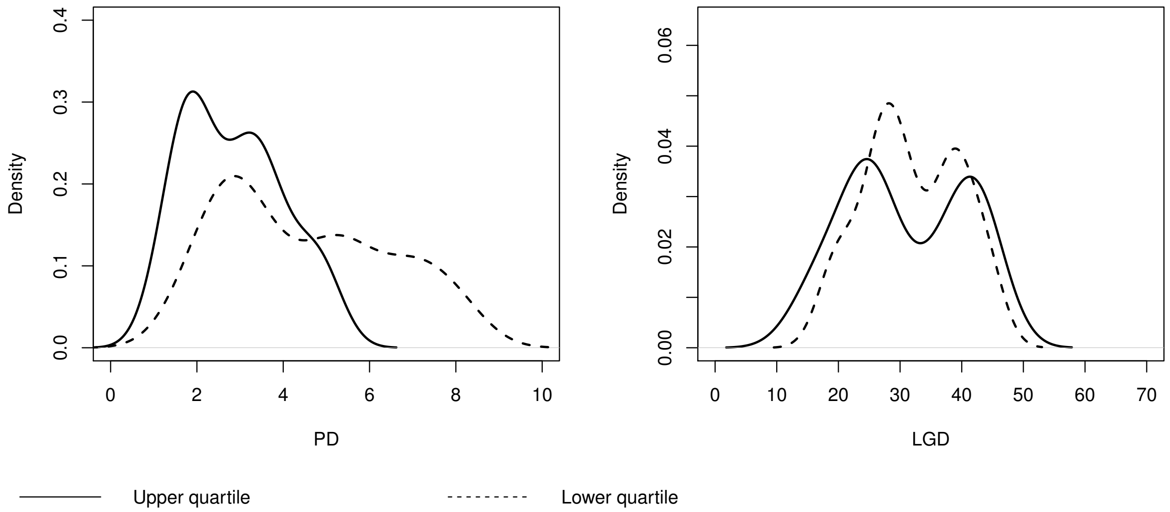
*(a) STA vs IRB Approach*




*(b) Credit Exposure Categories under the IRB Approach*



*(c) Probability of Default and Loss Given Default under the IRB Approach*




***Note:*** The distribution is estimated using Epanechnikov kernel density estimation; the bandwidths were chosen using the rule of thumb. For more details see the documentation on the R function *density*.

***Table C1: Regression Results – Risk Weights for Credit Exposures under the STA Approach***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -13.249 *** | -8.689 * | -3.994 | -2.313 | -0.346 | -2.150 | -1.713 | 0.574 | 5.373 |
| Nominal GDP growth | 0.040 | -0.009 | 0.039 | 0.082 ** | 0.089 ** | 0.078 ** | 0.109 *** | 0.089 | -0.003 |
| Dependent variable (t-1) | 0.921 *** | 0.943 *** | 0.975 *** | 0.993 *** | 0.994 *** | 1.004 *** | 1.014 *** | 1.029 *** | 1.035 *** |
| Log(assets) (t-1) | 0.764 ** | 0.536 * | 0.230 | 0.125 | 0.044 | 0.150 | 0.147 | 0.051 | -0.099 |
| ROA (t-1) | -0.153 | 0.081 | 0.113 | 0.058 | 0.048 | 0.021 | -0.034 | -0.122 | -0.232 |
| Cost of risk (t-1) | 0.298 | 0.049 | -0.054 | 0.054 | 0.038 | 0.181 | 0.060 | -0.001 | -0.428 |
| Regulatory pressures dummy | 0.666 | 0.452 | 0.909 | 0.619 | 0.731 | 0.897 * | 0.313 | 0.043 | -0.866 |
| Trend | -0.031 | -0.028 * | -0.026 ** | -0.025 ** | -0.025 *** | -0.026 *** | -0.035 *** | -0.040 ** | -0.034 |
| Intercept | -12.846 ** | -8.480 * | -3.140 | -1.587 | -0.098 | -1.332 | -1.338 | 2.190 | 4.440 |
| Real GDP growth | 0.039 | -0.019 | 0.047 | 0.068 | 0.066 | 0.051 | 0.059 | 0.104 | 0.128 |
| Dependent variable (t-1) | 0.920 *** | 0.943 *** | 0.974 *** | 0.990 *** | 0.993 *** | 1.003 *** | 1.011 *** | 1.028 *** | 1.037 *** |
| Log(assets) (t-1) | 0.751 ** | 0.526 * | 0.192 | 0.109 | 0.048 | 0.117 | 0.161 | -0.010 | -0.096 |
| ROA (t-1) | -0.099 | 0.106 | 0.105 | 0.053 | 0.063 | 0.045 | 0.011 | -0.151 | -0.235 |
| Cost of risk (t-1) | 0.296 | 0.021 | -0.110 | 0.017 | 0.013 | 0.161 | 0.072 | -0.011 | -0.384 |
| Regulatory pressures dummy | 0.726 | 0.513 | 0.867 | 0.569 | 0.737 | 0.831 | 0.127 | 0.000 | -0.863 |
| Trend | -0.034 | -0.027 * | -0.026 ** | -0.027 ** | -0.026 *** | -0.026 *** | -0.039 *** | -0.046 *** | -0.028 |
| Intercept | -13.312 ** | -7.686 | -2.813 | -1.260 | -1.048 | -1.468 | 0.268 | 0.503 | 6.244 |
| Credit-to-GDP growth | 0.055 | -0.056 | 0.033 | 0.075 | 0.185 ** | 0.175 ** | 0.241 ** | 0.173 | -0.092 |
| Dependent variable (t-1) | 0.920 *** | 0.945 *** | 0.973 *** | 0.989 *** | 0.992 *** | 0.998 *** | 1.009 *** | 1.029 *** | 1.034 *** |
| Log(assets) (t-1) | 0.790 *** | 0.491 * | 0.184 | 0.103 | 0.091 | 0.128 | 0.042 | 0.040 | -0.126 |
| ROA (t-1) | -0.069 | 0.117 | 0.112 | 0.063 | 0.065 | 0.083 | -0.035 | -0.079 | -0.146 |
| Cost of risk (t-1) | 0.277 | 0.020 | 0.053 | -0.100 | -0.101 | 0.084 | 0.189 | 0.007 | -0.491 ** |
| Regulatory pressures dummy | 1.303 | 0.571 | 0.696 | 0.689 | 0.653 | 0.862 | 0.468 | 0.047 | -0.799 |
| Trend | -0.047 | -0.033 | -0.028 ** | -0.027 * | -0.018 | -0.019 * | -0.026 | -0.027 | -0.039 ** |
| Intercept | -14.898 *** | -8.853 * | -3.700 | -1.594 | -0.985 | -1.314 | -0.473 | 0.738 | 5.320 |
| FCI | -0.036 | -0.028 | -0.006 | -0.001 | 0.019 | 0.033 ** | 0.035 | 0.023 | -0.015 |
| Dependent variable (t-1) | 0.922 *** | 0.946 *** | 0.974 *** | 0.988 *** | 0.991 *** | 0.999 *** | 1.010 *** | 1.029 *** | 1.034 *** |
| Log(assets) (t-1) | 0.902 *** | 0.555 ** | 0.236 | 0.137 | 0.111 | 0.124 | 0.091 | 0.048 | -0.081 |
| ROA (t-1) | -0.212 | 0.108 | 0.112 | 0.036 | 0.049 | 0.042 | -0.059 | -0.061 | -0.195 |
| Cost of risk (t-1) | 0.112 | 0.010 | 0.001 | -0.077 | 0.044 | 0.164 | 0.167 | -0.011 | -0.458 ** |
| Regulatory pressures dummy | 0.762 | 0.644 | 0.798 | 0.562 | 0.707 | 0.921 | 0.673 | 0.022 | -0.787 |
| Trend | -0.032 | -0.029 | -0.029 ** | -0.032 *** | -0.029 *** | -0.030 *** | -0.036 ** | -0.040 ** | -0.035 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C2: Regression Results – Risk Weights for Credit Exposures under the IRB Approach***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.079 | 6.131 | 4.697 | 1.691 | 1.031 | 0.467 | -1.057 | -2.855 | -0.894 |
| Nominal GDP growth | -0.192 ** | -0.109 | -0.026 | -0.028 | -0.029 | -0.001 | -0.005 | 0.038 | -0.040 |
| Dependent variable (t-1) | 0.893 *** | 0.932 *** | 0.966 *** | 0.970 *** | 0.974 *** | 0.981 *** | 0.980 *** | 0.978 *** | 0.992 *** |
| Log(assets) (t-1) | -0.200 | -0.416 | -0.283 | -0.102 | -0.050 | -0.007 | 0.089 | 0.205 | 0.204 |
| ROA (t-1) | 1.553 | 0.939 | 0.742 ** | 0.413 | 0.317 | 0.095 | 0.066 | 0.249 | -0.448 |
| Cost of risk (t-1) | 3.117 *** | 1.846 * | 0.587 | 0.712 | 0.694 * | 0.697 | 0.634 | 0.939 | 0.817 |
| Regulatory pressures dummy | -2.950 | -0.884 | -1.705 | 2.506 | 2.243 *** | 1.869 ** | 3.426 *** | 3.072 | 5.892 *** |
| Trend | 0.089 ** | 0.048 | 0.004 | 0.006 | 0.004 | 0.002 | 0.010 | -0.004 | -0.009 |
| Intercept | 0.124 | 4.625 | 4.579 | 1.529 | 1.070 | 0.362 | -1.386 | -0.552 | -3.317 |
| Real GDP growth | -0.185 * | -0.072 | -0.034 | -0.035 | -0.028 | 0.004 | 0.015 | 0.081 | -0.022 |
| Dependent variable (t-1) | 0.889 *** | 0.929 *** | 0.966 *** | 0.971 *** | 0.974 *** | 0.979 *** | 0.980 *** | 0.979 *** | 0.983 *** |
| Log(assets) (t-1) | -0.217 | -0.347 | -0.280 | -0.095 | -0.055 | -0.002 | 0.112 | 0.107 | 0.352 |
| ROA (t-1) | 1.682 * | 1.018 | 0.733 *** | 0.429 | 0.328 | 0.116 | 0.102 | 0.201 | -0.832 |
| Cost of risk (t-1) | 3.277 *** | 2.120 ** | 0.632 | 0.720 | 0.732 * | 0.742 * | 0.677 | 1.062 | 1.418 ** |
| Regulatory pressures dummy | -3.413 | -0.952 | -1.806 | 2.522 | 2.214 *** | 1.877 ** | 3.442 *** | 2.950 | 5.644 ** |
| Trend | 0.085 * | 0.043 | 0.005 | 0.005 | 0.005 | 0.003 | 0.003 | -0.020 | -0.007 |
| Intercept | 5.178 | 7.102 | 4.704 | 1.163 | 0.100 | 0.071 | -1.250 | -3.227 | -2.466 |
| Credit-to-GDP growth | -0.392 | -0.126 | -0.087 | -0.103 | -0.085 * | -0.116 ** | -0.080 | 0.011 | -0.027 |
| Dependent variable (t-1) | 0.886 *** | 0.930 *** | 0.966 *** | 0.968 *** | 0.973 *** | 0.984 *** | 0.982 *** | 0.979 *** | 0.982 *** |
| Log(assets) (t-1) | -0.444 | -0.425 | -0.270 | -0.033 | 0.013 | 0.040 | 0.108 | 0.241 | 0.317 |
| ROA (t-1) | 1.893 | 0.834 | 0.751 * | 0.226 | 0.339 | 0.064 | 0.165 | 0.117 | -0.804 |
| Cost of risk (t-1) | 3.448 *** | 1.947 ** | 0.509 | 0.582 | 0.624 | 0.507 | 0.556 | 0.644 | 1.412 * |
| Regulatory pressures dummy | -1.318 | -0.639 | -1.528 | 2.242 | 2.111 *** | 1.832 ** | 3.373 *** | 3.122 | 5.691 ** |
| Trend | 0.050 | 0.015 | -0.006 | -0.012 | -0.005 | -0.012 | -0.001 | -0.002 | -0.015 |
| Intercept | 3.655 | 6.757 | 4.941 | 1.411 | 1.366 | 0.579 | -1.217 | -1.290 | -2.827 |
| FCI | -0.059 | -0.013 | -0.006 | -0.013 | -0.007 | -0.005 | -0.007 | 0.011 | -0.004 |
| Dependent variable (t-1) | 0.898 *** | 0.932 *** | 0.966 *** | 0.969 *** | 0.975 *** | 0.981 *** | 0.980 *** | 0.980 *** | 0.982 *** |
| Log(assets) (t-1) | -0.343 | -0.404 | -0.295 | -0.058 | -0.064 | -0.009 | 0.101 | 0.119 | 0.337 |
| ROA (t-1) | 1.372 | 0.771 | 0.787 * | 0.281 | 0.365 | 0.120 | 0.116 | 0.241 | -0.853 |
| Cost of risk (t-1) | 2.994 ** | 1.771 ** | 0.596 | 0.585 | 0.622 | 0.700 * | 0.650 | 0.730 | 1.423 * |
| Regulatory pressures dummy | -2.062 | -0.782 | -1.530 | 2.428 | 2.239 *** | 1.897 ** | 3.451 *** | 3.129 | 5.706 ** |
| Trend | 0.063 | 0.015 | 0.001 | -0.002 | -0.001 | 0.001 | 0.008 | 0.002 | -0.011 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C3: Regression Results – Risk Weights for Retail Credit Exposures under the IRB Approach***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.079 | 6.131 | 4.697 | 1.691 | 1.031 | 0.467 | -1.057 | -2.855 | -0.894 |
| Nominal GDP growth | -0.192 * | -0.109 | -0.026 | -0.028 | -0.029 | -0.001 | -0.005 | 0.038 | -0.040 |
| Dependent variable (t-1) | 0.893 *** | 0.932 *** | 0.966 *** | 0.970 *** | 0.974 *** | 0.981 *** | 0.980 *** | 0.978 *** | 0.992 *** |
| Log(assets) (t-1) | -0.200 | -0.416 | -0.283 | -0.102 | -0.050 | -0.007 | 0.089 | 0.205 | 0.204 |
| ROA (t-1) | 1.553 | 0.939 | 0.742 ** | 0.413 | 0.317 | 0.095 | 0.066 | 0.249 | -0.448 |
| Cost of risk (t-1) | 3.117 *** | 1.846 ** | 0.587 | 0.712 | 0.694 | 0.697 | 0.634 | 0.939 | 0.817 |
| Regulatory pressures dummy | -2.950 | -0.884 | -1.705 | 2.506 | 2.243 *** | 1.869 ** | 3.426 *** | 3.072 | 5.892 ** |
| Trend | 0.089 ** | 0.048 | 0.004 | 0.006 | 0.004 | 0.002 | 0.010 | -0.004 | -0.009 |
| Intercept | 0.124 | 4.625 | 4.579 | 1.529 | 1.070 | 0.362 | -1.386 | -0.552 | -3.317 |
| Real GDP growth | -0.185 * | -0.072 | -0.034 | -0.035 | -0.028 | 0.004 | 0.015 | 0.081 | -0.022 |
| Dependent variable (t-1) | 0.889 *** | 0.929 *** | 0.966 *** | 0.971 *** | 0.974 *** | 0.979 *** | 0.980 *** | 0.979 *** | 0.983 *** |
| Log(assets) (t-1) | -0.217 | -0.347 | -0.280 | -0.095 | -0.055 | -0.002 | 0.112 | 0.107 | 0.352 |
| ROA (t-1) | 1.682 * | 1.018 | 0.733 *** | 0.429 * | 0.328 | 0.116 | 0.102 | 0.201 | -0.832 |
| Cost of risk (t-1) | 3.277 *** | 2.120 ** | 0.632 | 0.720 | 0.732 ** | 0.742 * | 0.677 | 1.062 | 1.418 * |
| Regulatory pressures dummy | -3.413 | -0.952 | -1.806 | 2.522 | 2.214 *** | 1.877 ** | 3.442 *** | 2.950 | 5.644 ** |
| Trend | 0.085 * | 0.043 | 0.005 | 0.005 | 0.005 | 0.003 | 0.003 | -0.020 | -0.007 |
| Intercept | 5.178 | 7.102 | 4.704 | 1.163 | 0.100 | 0.071 | -1.250 | -3.227 | -2.466 |
| Credit-to-GDP growth | -0.392 | -0.126 | -0.087 | -0.103 | -0.085 * | -0.116 ** | -0.080 | 0.011 | -0.027 |
| Dependent variable (t-1) | 0.886 *** | 0.930 *** | 0.966 *** | 0.968 *** | 0.973 *** | 0.984 *** | 0.982 *** | 0.979 *** | 0.982 *** |
| Log(assets) (t-1) | -0.444 | -0.425 | -0.270 | -0.033 | 0.013 | 0.040 | 0.108 | 0.241 | 0.317 |
| ROA (t-1) | 1.893 | 0.834 | 0.751 ** | 0.226 | 0.339 | 0.064 | 0.165 | 0.117 | -0.804 |
| Cost of risk (t-1) | 3.448 *** | 1.947 ** | 0.509 | 0.582 | 0.624 | 0.507 | 0.556 | 0.644 | 1.412 ** |
| Regulatory pressures dummy | -1.318 | -0.639 | -1.528 | 2.242 | 2.111 *** | 1.832 ** | 3.373 *** | 3.122 | 5.691 ** |
| Trend | 0.050 | 0.015 | -0.006 | -0.012 | -0.005 | -0.012 | -0.001 | -0.002 | -0.015 |
| Intercept | 3.655 | 6.757 | 4.941 | 1.411 | 1.366 | 0.579 | -1.217 | -1.290 | -2.827 |
| FCI | -0.059 | -0.013 | -0.006 | -0.013 | -0.007 | -0.005 | -0.007 | 0.011 | -0.004 |
| Dependent variable (t-1) | 0.898 *** | 0.932 *** | 0.966 *** | 0.969 *** | 0.975 *** | 0.981 *** | 0.980 *** | 0.980 *** | 0.982 *** |
| Log(assets) (t-1) | -0.343 | -0.404 | -0.295 | -0.058 | -0.064 | -0.009 | 0.101 | 0.119 | 0.337 |
| ROA (t-1) | 1.372 | 0.771 | 0.787 * | 0.281 | 0.365 | 0.120 | 0.116 | 0.241 | -0.853 |
| Cost of risk (t-1) | 2.994 *** | 1.771 ** | 0.596 | 0.585 | 0.622 | 0.700 | 0.650 | 0.730 | 1.423 * |
| Regulatory pressures dummy | -2.062 | -0.782 | -1.530 | 2.428 | 2.239 *** | 1.897 ** | 3.451 *** | 3.129 | 5.706 *** |
| Trend | 0.063 | 0.015 | 0.001 | -0.002 | -0.001 | 0.001 | 0.008 | 0.002 | -0.011 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

## *Table C4: Regression Results – Risk Weights for Retail Credit Exposures under the IRB Approach (2)*

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -11.911 | -1.255 | -0.859 | -2.367 | -2.160 | -2.828 | -4.222 | -4.445 | 0.808 |
| House price growth | -0.138 * | -0.120 ** | -0.048 | -0.034 | -0.036 ** | -0.032 ** | -0.028 ** | -0.072 *** | -0.159 *** |
| Dependent variable (t-1) | 0.871 *** | 0.943 *** | 0.974 *** | 0.975 *** | 0.983 *** | 0.993 *** | 0.998 *** | 1.016 *** | 1.035 *** |
| Log(assets) (t-1) | 0.482 | -0.034 | 0.053 | 0.133 | 0.126 | 0.191 | 0.274 | 0.332 | 0.196 |
| ROA (t-1) | 0.969 | 0.607 | -0.132 | -0.003 | -0.063 | -0.393 | -0.380 | -0.707 | -1.289 |
| Cost of risk (t-1) | 0.348 | -0.065 | -0.495 | -0.063 | 0.022 | 0.231 | 0.224 | -0.206 | -0.745 |
| Regulatory pressures dummy | 1.339 | 3.259 | 0.391 | 2.250 | 1.971 *** | 1.308 | 1.601 | 0.838 | 5.785 |
| Trend | 0.141 *** | 0.086 ** | 0.020 | 0.014 | 0.011 | -0.002 | -0.010 | -0.020 | -0.049 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

## *Table C5: Regression Results – Risk Weights for Retail Credit Exposures under the IRB Approach (3)*

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -19.229 | -5.694 | -2.012 | -1.961 | -2.019 | -3.163 | -3.192 | -4.780 | -4.275 |
| RMCI | 2.140 | -0.372 | -0.323 | -0.220 | -0.563 | -1.660 | -2.038 ** | -2.647 * | -4.985 ** |
| FCI | -0.173 *** | -0.072 | -0.031 | -0.018 | -0.029 * | -0.045 ** | -0.060 *** | -0.084 ** | -0.215 *** |
| Real GDP growth | -0.005 | -0.094 | -0.043 | -0.069 * | -0.031 | -0.024 | -0.022 | -0.057 | 0.049 |
| Dependent variable (t-1) | 0.826 *** | 0.907 *** | 0.963 *** | 0.978 *** | 0.982 *** | 0.994 *** | 1.009 *** | 1.018 *** | 1.014 *** |
| Log(assets) (t-1) | 1.199 | 0.345 | 0.152 | 0.130 | 0.160 | 0.261 | 0.289 | 0.466 * | 0.716 |
| ROA (t-1) | 0.217 | 0.257 | -0.101 | -0.038 | -0.185 | -0.541 * | -0.675 ** | -1.166 ** | -1.784 * |
| Cost of risk (t-1) | -0.751 | 0.107 | -0.514 | -0.063 | 0.040 | -0.044 | -0.236 | -0.539 | -0.649 |
| Regulatory pressures dummy | 3.578 ** | 3.819 | 0.780 | 2.205 | 1.921 *** | 1.536 | 1.270 | 0.817 | 5.520 |
| Trend | 0.037 | 0.055 | 0.012 | 0.008 | 0.000 | -0.009 | -0.021 | -0.044 ** | -0.103 *** |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C6: Regression Results – Risk Weights for Corporate Credit Exposures under the IRB Approach***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 9.185 | 37.626 *** | 22.043 *** | 17.069 *** | 10.912 | 2.313 | -3.844 | -6.779 | 17.789 |
| Nominal GDP growth | 0.293 ** | 0.088 | 0.004 | -0.056 | -0.058 | -0.068 | -0.102 | -0.119 | -0.043 |
| Dependent variable (t-1) | 0.906 *** | 0.956 *** | 0.972 *** | 0.990 *** | 0.991 *** | 0.992 *** | 1.007 *** | 1.013 *** | 0.981 *** |
| Log(assets) (t-1) | -0.489 | -1.922 ** | -1.071 *** | -0.868 *** | -0.525 | -0.026 | 0.221 | 0.374 | -0.613 |
| ROA (t-1) | 0.765 | 1.412 | 0.654 | 0.786 * | 0.591 | -0.149 | 0.069 | -0.054 | -0.421 |
| Cost of risk (t-1) | 3.152 ** | -0.012 | -0.339 | -0.669 * | -0.591 | -0.495 | -0.062 | 0.106 | -0.049 |
| Regulatory pressures dummy | 2.001 | 1.521 * | 1.495 *** | 1.236 * | 1.858 * | 2.206 ** | 1.858 * | 1.374 | -0.512 |
| Trend | 0.017 | -0.002 | -0.019 | -0.005 | -0.012 | -0.007 | 0.003 | 0.022 | -0.010 |
| Intercept | 13.804 | 34.446 *** | 22.182 *** | 17.491 *** | 10.328 | 2.260 | -3.526 | -13.958 | 18.926 |
| Real GDP growth | 0.262 * | 0.005 | -0.011 | -0.064 | -0.081 | -0.093 | -0.116 | -0.146 | -0.064 |
| Dependent variable (t-1) | 0.907 *** | 0.962 *** | 0.972 *** | 0.990 *** | 0.991 *** | 0.989 *** | 1.011 *** | 1.011 *** | 0.980 *** |
| Log(assets) (t-1) | -0.681 | -1.756 *** | -1.067 *** | -0.888 *** | -0.474 | -0.032 | 0.170 | 0.805 | -0.669 |
| ROA (t-1) | 0.526 | 1.234 | 0.550 | 0.749 | 0.268 | -0.064 | 0.220 | -0.838 | -0.434 |
| Cost of risk (t-1) | 2.876 * | -0.138 | -0.380 | -0.707 * | -0.600 | 0.047 | 0.160 | 0.196 | 0.145 |
| Regulatory pressures dummy | 2.587 | 1.764 *** | 1.404 *** | 1.194 * | 1.513 | 1.863 | 1.729 * | -0.178 | -0.706 |
| Trend | 0.023 | 0.000 | -0.017 | -0.003 | -0.008 | -0.006 | 0.009 | 0.007 | -0.006 |
| Intercept | 8.806 | 29.929 ** | 21.463 *** | 16.394 *** | 15.125 ** | 1.039 | -6.906 | -7.044 | 20.062 |
| Credit-to-GDP growth | -0.101 | -0.157 | -0.032 | 0.032 | 0.099 | -0.031 | 0.224 | 0.290 | 0.045 |
| Dependent variable (t-1) | 0.911 *** | 0.952 *** | 0.975 *** | 0.987 *** | 0.984 *** | 0.999 *** | 1.002 *** | 1.015 *** | 0.980 *** |
| Log(assets) (t-1) | -0.436 | -1.435 ** | -1.032 *** | -0.828 *** | -0.765 * | -0.016 | 0.344 | 0.290 | -0.768 |
| ROA (t-1) | 0.038 | 0.534 | 0.509 | 0.582 | 0.746 | 0.023 | 0.069 | 0.311 | -0.071 |
| Cost of risk (t-1) | 2.916 | 0.161 | -0.442 | -0.331 | -0.337 | -0.095 | 0.549 | 0.706 | 0.116 |
| Regulatory pressures dummy | 4.339 | 1.932 ** | 1.451 ** | 1.130 * | 2.159 *** | 2.685 *** | 1.603 * | 1.690 | 0.100 |
| Trend | 0.058 | -0.015 | -0.022 | -0.008 | 0.007 | -0.009 | 0.010 | 0.030 | -0.001 |
| Intercept | 16.248 | 35.312 ** | 23.547 ** | 16.150 | 16.030 | 1.004 | -4.522 | -5.213 | 24.647 |
| FCI | 0.112 | 0.044 | 0.011 | 0.003 | 0.005 | 0.011 | 0.036 | 0.049 | 0.085 |
| Dependent variable (t-1) | 0.894 *** | 0.944 *** | 0.972 *** | 0.987 *** | 0.987 *** | 1.000 *** | 1.002 *** | 1.006 *** | 0.983 *** |
| Log(assets) (t-1) | -0.878 | -1.813 ** | -1.172 ** | -0.814 * | -0.821 | -0.066 | 0.232 | 0.218 | -1.231 |
| ROA (t-1) | 0.553 | 1.245 | 0.764 | 0.621 | 1.006 | 0.246 | 0.171 | 0.533 | 1.044 |
| Cost of risk (t-1) | 3.552 ** | 0.851 | -0.175 | -0.341 | -0.389 | 0.167 | 0.285 | 0.836 | 1.150 |
| Regulatory pressures dummy | 1.191 | 1.031 | 1.487 ** | 1.092 | 2.371 ** | 2.893 ** | 1.680 * | 1.796 | 1.578 |
| Trend | 0.063 | 0.013 | -0.010 | -0.015 | -0.004 | 0.006 | -0.006 | 0.019 | 0.055 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

### *Table C7: Regression Results – Risk Weights for Corporate Credit Exposures under the IRB Approach (2)*

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 8.137 | 25.111 ** | 21.577 *** | 19.438 ** | 13.524 | -0.994 | -6.200 | -6.106 | 11.378 |
| House price growth | 0.076 | -0.078 | -0.051 | -0.031 | -0.029 | -0.030 | -0.036 | -0.020 | -0.036 |
| Dependent variable (t-1) | 0.904 *** | 0.957 *** | 0.971 *** | 0.985 *** | 0.989 *** | 1.000 *** | 1.010 *** | 1.011 *** | 0.992 *** |
| Log(assets) (t-1) | -0.360 | -1.214 * | -1.069 *** | -0.954 ** | -0.651 | 0.116 | 0.336 | 0.293 | -0.272 |
| ROA (t-1) | 0.450 | 0.474 | 0.732 * | 0.651 | 0.567 | -0.273 | -0.075 | 0.375 | -0.857 |
| Cost of risk (t-1) | 3.093 | -0.304 | -0.366 | -0.898 ** | -0.598 | -0.410 | -0.008 | 0.646 | -0.333 |
| Regulatory pressures dummy | 1.834 | 2.459 *** | 2.107 *** | 1.223 | 1.904 | 1.976 * | 1.559 | 1.804 | -1.584 |
| Trend | 0.004 | 0.010 | 0.000 | -0.009 | -0.011 | -0.011 | -0.007 | 0.022 | -0.029 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

### *Table C8: Regression Results – Risk Weights for Corporate Credit Exposures under the IRB Approach (3)*

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 23.322 | 28.469 ** | 23.690 ** | 17.293 ** | 10.738 | 2.716 | -3.706 | -8.742 | 25.493 |
| RMCI | 0.588 | 2.776 | 2.437 | 1.391 | 0.205 | 1.420 | -0.749 | -2.752 | -6.299 |
| FCI | 0.081 | 0.070 | 0.045 | 0.029 | 0.023 | 0.025 | 0.033 * | 0.049 | 0.059 |
| Real GDP growth | 0.211 | -0.064 | -0.076 | -0.119 * | -0.095 | -0.125 | -0.165 | -0.060 | -0.022 |
| Dependent variable (t-1) | 0.904 *** | 0.937 *** | 0.971 *** | 0.988 *** | 0.990 *** | 0.992 *** | 0.997 *** | 1.008 *** | 0.961 *** |
| Log(assets) (t-1) | -1.262 | -1.407 * | -1.214 ** | -0.912 ** | -0.546 | -0.085 | 0.197 | 0.373 | -1.191 |
| ROA (t-1) | 1.301 | 0.855 | 1.012 | 0.885 * | 0.543 | 0.002 | 0.080 | 0.159 | 0.393 |
| Cost of risk (t-1) | 2.960 * | 0.940 | -0.104 | -0.596 | -0.554 | 0.010 | 0.498 | 0.979 * | 1.711 * |
| Regulatory pressures dummy | 1.285 | 0.755 | 1.566 ** | 1.144 * | 1.579 | 1.657 | 1.033 | 1.228 | 0.573 |
| Trend | 0.041 | -0.013 | -0.008 | 0.007 | 0.008 | -0.005 | 0.029 | 0.061 | 0.116 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C9: Regression Results – Risk Weights for Credit Exposures to Institutions under the IRB Approach***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 18.429 * | 16.323 ** | 10.995 * | 11.805 ** | 8.848 ** | 6.035 | 4.701 | 2.603 | 16.938 |
| Nominal GDP growth | -0.125 | -0.167 | -0.115 | -0.082 | -0.073 | -0.026 | -0.011 | 0.102 | 0.073 |
| Dependent variable (t-1) | 0.750 *** | 0.825 *** | 0.884 *** | 0.919 *** | 0.951 *** | 0.961 *** | 0.942 *** | 0.940 *** | 0.886 *** |
| Log(assets) (t-1) | -1.007 | -0.849 ** | -0.489 | -0.524 ** | -0.366 * | -0.234 | -0.057 | 0.053 | -0.492 |
| ROA (t-1) | 2.707 ** | 1.154 | 0.269 | -0.012 | -0.271 | -0.152 | -0.790 | -0.474 | -1.670 |
| Cost of risk (t-1) | 1.692 | 1.814 *** | 1.119 * | 0.840 * | 0.751 * | 0.921 ** | 0.518 | 0.795 | 1.222 |
| Regulatory pressures dummy | 1.067 | 0.553 | 0.003 | -0.433 | 0.108 | 0.635 | -0.372 | -0.934 | -2.039 |
| Trend | 0.010 | 0.066 ** | 0.029 | 0.028 | 0.021 | 0.026 | 0.024 | 0.042 | 0.103 |
| Intercept | 20.312 * | 16.685 * | 10.993 * | 11.947 ** | 9.879 ** | 5.488 | 3.959 | 0.782 | 8.037 |
| Real GDP growth | -0.079 | -0.126 | -0.121 | -0.081 | -0.074 | -0.079 | -0.049 | -0.007 | -0.079 |
| Dependent variable (t-1) | 0.735 *** | 0.809 *** | 0.882 *** | 0.921 *** | 0.950 *** | 0.962 *** | 0.947 *** | 0.940 *** | 0.864 *** |
| Log(assets) (t-1) | -1.126 * | -0.913 ** | -0.513 | -0.532 ** | -0.438 ** | -0.196 | -0.020 | 0.161 | 0.121 |
| ROA (t-1) | 2.776 ** | 1.503 | 0.336 | -0.034 | -0.097 | -0.283 | -0.919 | -0.452 | -2.944 |
| Cost of risk (t-1) | 2.222 | 2.488 *** | 1.454 ** | 0.894 * | 0.897 ** | 0.851 ** | 0.534 | 0.517 | 0.322 |
| Regulatory pressures dummy | 1.122 | 0.487 | -0.131 | -0.495 | 0.078 | 0.255 | -0.597 | -1.246 | -3.545 |
| Trend | 0.012 | 0.078 ** | 0.037 | 0.024 | 0.024 | 0.027 | 0.031 | 0.049 | 0.107 |
| Intercept | 19.569 | 18.299 * | 11.278 | 11.070 ** | 8.501 * | 6.610 | 3.538 | -0.581 | 6.204 |
| Credit-to-GDP growth | -0.667 * | -0.010 | -0.128 | -0.175 | -0.122 | -0.147 | 0.008 | -0.256 | 0.233 |
| Dependent variable (t-1) | 0.726 *** | 0.810 *** | 0.887 *** | 0.918 *** | 0.953 *** | 0.961 *** | 0.948 *** | 0.950 *** | 0.875 *** |
| Log(assets) (t-1) | -0.888 | -1.019 ** | -0.505 | -0.469 * | -0.352 | -0.227 | -0.005 | 0.296 | 0.112 |
| ROA (t-1) | 2.432 * | 1.780 ** | 0.421 | 0.258 | -0.070 | -0.207 | -0.784 | -0.755 | -3.079 |
| Cost of risk (t-1) | 1.394 | 2.571 *** | 1.136 | 0.730 | 0.671 | 0.563 | 0.419 | 0.255 | 1.441 |
| Regulatory pressures dummy | 1.111 | 0.218 | -0.678 | -0.791 | 0.093 | 0.796 | -0.474 | -1.335 | -3.356 |
| Trend | -0.078 | 0.059 | 0.012 | -0.003 | 0.008 | 0.005 | 0.020 | 0.013 | 0.138 |
| Intercept | 19.297 * | 18.689 ** | 11.153 | 11.120 ** | 9.169 ** | 6.040 | 3.598 | 2.902 | -3.870 |
| FCI | -0.083 | 0.000 | -0.023 | -0.027 | -0.012 | -0.008 | 0.024 | 0.027 | 0.200 * |
| Dependent variable (t-1) | 0.728 *** | 0.810 *** | 0.896 *** | 0.912 *** | 0.952 *** | 0.964 *** | 0.942 *** | 0.934 *** | 0.901 *** |
| Log(assets) (t-1) | -0.911 | -1.048 ** | -0.473 | -0.462 * | -0.397 * | -0.233 | -0.033 | 0.003 | 0.519 |
| ROA (t-1) | 2.353 * | 1.861 * | 0.244 | 0.180 | -0.041 | -0.088 | -0.704 | -0.305 | -3.008 |
| Cost of risk (t-1) | 1.353 | 2.527 *** | 0.905 | 0.597 | 0.724 | 0.762 | 0.674 | 0.924 | 1.680 |
| Regulatory pressures dummy | 1.742 | 0.260 | -0.453 | -0.485 | 0.247 | 0.745 | -0.579 | -1.010 | -5.821 ** |
| Trend | -0.042 | 0.063 | 0.002 | 0.005 | 0.014 | 0.018 | 0.029 | 0.065 | 0.113 * |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

### *Table C10: Regression Results – Risk Weights for Credit Exposures to Institutions under the IRB Approach (2)*

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 10.070 | 15.865 * | 9.718 | 9.774 ** | 8.254 ** | 4.790 | 4.144 | -0.502 | 8.586 |
| House price growth | -0.139 ** | -0.050 | -0.037 | -0.045 | -0.035 | -0.042 | -0.043 | -0.026 | -0.059 |
| Dependent variable (t-1) | 0.761 *** | 0.803 *** | 0.886 *** | 0.920 *** | 0.949 *** | 0.964 *** | 0.948 *** | 0.947 *** | 0.903 *** |
| Log(assets) (t-1) | -0.542 | -0.844 * | -0.438 | -0.405 | -0.354 * | -0.153 | -0.049 | 0.250 | 0.115 |
| ROA (t-1) | 1.682 | 1.371 | 0.361 | -0.119 | -0.081 | -0.306 | -0.869 | -0.674 | -3.758 |
| Cost of risk (t-1) | 1.384 | 2.295 *** | 1.059 | 0.625 | 0.706 | 0.508 | 0.500 | 0.104 | 0.741 |
| Regulatory pressures dummy | 2.245 * | 0.481 | -0.466 | -0.560 | 0.051 | 0.045 | -0.496 | -1.775 | -4.066 |
| Trend | 0.033 | 0.057 ** | 0.030 | 0.018 | 0.023 | 0.023 | 0.041 | 0.042 | 0.077 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

### *Table C11: Regression Results – Risk Weights for Credit Exposures to Institutions under the IRB Approach (3)*

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 16.354 | 16.810 * | 12.318 | 11.626 ** | 9.958 ** | 6.646 | 3.988 | 3.136 | -1.188 |
| RMCI | -3.195 | -2.081 | -2.276 | 1.266 | 2.231 | 1.289 | 3.311 | 3.892 | 8.484 |
| FCI | -0.105 | -0.008 | -0.027 | -0.004 | 0.008 | 0.008 | 0.063 * | 0.073 | 0.289 * |
| Real GDP growth | -0.107 | -0.115 | -0.068 | -0.082 | -0.083 | -0.097 | -0.076 | -0.088 | -0.118 |
| Dependent variable (t-1) | 0.760 *** | 0.820 *** | 0.888 *** | 0.916 *** | 0.943 *** | 0.965 *** | 0.928 *** | 0.933 *** | 0.902 *** |
| Log(assets) (t-1) | -0.767 | -0.919 * | -0.554 | -0.486 | -0.406 * | -0.264 | -0.078 | 0.025 | 0.332 |
| ROA (t-1) | 2.078 | 1.272 | 0.203 | -0.055 | -0.227 | -0.139 | -0.480 | -0.622 | -2.251 |
| Cost of risk (t-1) | 1.215 | 2.378 *** | 1.237 | 0.731 | 0.839 | 0.820 | 0.973 | 0.639 | 0.250 |
| Regulatory pressures dummy | 1.762 | 0.165 | -0.364 | -0.439 | -0.012 | 0.158 | -0.547 | -1.922 | -5.230 ** |
| Trend | -0.022 | 0.093 * | 0.037 | 0.007 | 0.001 | 0.021 | 0.033 | 0.037 | 0.079 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C12: Robustness Analysis – Risk Weights for Retail Credit Exposures under the IRB Approach – Controlling for Lags of Cycle Variables***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -1.639 * | 0.056 | 0.007 | 0.235 | 0.220 | 0.417 | 0.863 *** | 1.168 | 4.070 *** |
| Nominal GDP growth (t-1) | -0.928 *** | -0.206 | -0.133 | -0.153 ** | -0.102 * | -0.164 ** | -0.118 * | -0.230 ** | -0.156 |
| Nominal GDP growth (t-2) | 1.200 ** | 0.211 | 0.135 | 0.104 | 0.070 | 0.197 ** | 0.116 | 0.165 | 0.266 |
| Nominal GDP growth (t-3) | -0.627 ** | -0.151 | -0.147 | -0.046 | -0.100 | -0.210 ** | -0.143 | -0.007 | -0.392 |
| Nominal GDP growth (t-4) | 0.006 | 0.081 | 0.078 | 0.000 | 0.055 | 0.073 | 0.032 | -0.091 | -0.115 |
| Dependent variable (t-1) | 0.913 *** | 0.950 *** | 0.973 *** | 0.982 *** | 0.994 *** | 1.009 *** | 1.013 *** | 1.025 *** | 1.036 *** |
| Trend | 0.127 *** | 0.031 | 0.019 | 0.013 | 0.003 | -0.008 | -0.018 ** | -0.019 | -0.068 ** |
| Nominal GDP growth (sum) | -0.349 ** | -0.065 | -0.068 | -0.096 *** | -0.077 *** | -0.104 *** | -0.114 *** | -0.163 * | -0.398 *** |
| Intercept | -0.949 | 0.003 | -0.078 | 0.165 | 0.214 | 0.297 | 0.656 ** | 0.817 | 4.581 *** |
| Real GDP growth (t-1) | -0.828 ** | -0.074 | -0.091 | -0.046 | -0.012 | 0.047 | 0.117 | 0.156 | 1.029 * |
| Real GDP growth (t-2) | 0.705 | -0.240 | -0.078 | -0.053 | -0.151 | -0.273 * | -0.441 ** | -0.517 * | -2.029 * |
| Real GDP growth (t-3) | -0.162 | 0.461 | 0.159 | 0.009 | 0.142 | 0.219 | 0.411 * | 0.290 | 1.006 |
| Real GDP growth (t-4) | -0.217 | -0.287 | -0.105 | 0.003 | -0.056 | -0.072 | -0.199 | -0.120 | -0.340 |
| Dependent variable (t-1) | 0.905 *** | 0.947 *** | 0.973 *** | 0.980 *** | 0.992 *** | 1.004 *** | 1.015 *** | 1.031 *** | 1.023 *** |
| Trend | 0.106 ** | 0.041 | 0.022 | 0.013 | 0.004 | -0.006 | -0.018 ** | -0.022 ** | -0.081 *** |
| Real GDP growth (sum) | -0.502 *** | -0.140 | -0.115 | -0.087 * | -0.078 ** | -0.079 ** | -0.112 *** | -0.191 ** | -0.334 ** |
| Intercept | 1.906 | 0.982 | 0.394 | 0.525 | 0.401 | 0.783 * | 0.466 | 0.784 | 3.244 |
| Credit-to-GDP growth (t-1) | -1.076 *** | -0.391 * | -0.268 | -0.207 | -0.126 | -0.056 | -0.096 | 0.020 | -0.747 |
| Credit-to-GDP growth (t-2) | 0.304 | 0.149 | 0.059 | -0.070 | -0.092 | -0.093 | -0.247 | -0.329 | 0.290 |
| Credit-to-GDP growth (t-3) | 0.409 | 0.126 | 0.194 | 0.218 | 0.197 | 0.151 | 0.191 | 0.263 | 0.248 |
| Credit-to-GDP growth (t-4) | -0.498 * | -0.110 | -0.078 | -0.044 | -0.018 | -0.057 | 0.107 | 0.043 | 0.094 |
| Dependent variable (t-1) | 0.889 *** | 0.947 *** | 0.970 *** | 0.978 *** | 0.986 *** | 0.999 *** | 1.019 *** | 1.023 *** | 1.032 *** |
| Trend | 0.008 | 0.000 | 0.001 | -0.003 | -0.002 | -0.022 ** | -0.023 ** | -0.028 | -0.079 ** |
| Credit-to-GDP growth (sum) | -0.862 *** | -0.226 | -0.093 | -0.104 | -0.039 | -0.055 | -0.046 | -0.003 | -0.115 |
| Intercept | 1.058 | 0.591 | -0.325 | 0.307 | 0.472 * | 0.821 *** | 0.972 * | 1.012 | 5.352 ** |
| FCI (t-1) | -0.459 *** | -0.142 | 0.005 | 0.006 | -0.035 | -0.023 | 0.009 | -0.022 | -0.386 * |
| FCI (t-2) | 0.149 | -0.022 | -0.155 | -0.141 | -0.106 | -0.101 | -0.134 | -0.075 | 0.315 |
| FCI (t-3) | 0.285 | 0.185 * | 0.201 | 0.191 | 0.214 | 0.133 | 0.115 | 0.004 | 0.005 |
| FCI (t-4) | -0.141 | -0.080 | -0.055 | -0.068 | -0.087 | -0.029 | -0.009 | 0.072 | -0.053 |
| Dependent variable (t-1) | 0.910 *** | 0.952 *** | 0.982 *** | 0.978 *** | 0.992 *** | 1.001 *** | 1.018 *** | 1.034 *** | 1.022 *** |
| Trend | 0.072 *** | 0.025 | 0.014 | 0.008 | -0.005 | -0.019 ** | -0.035 *** | -0.038 * | -0.091 *** |
| FCI (sum) | -0.166 *** | -0.059 | -0.003 | -0.012 | -0.015 | -0.020 * | -0.020 | -0.021 | -0.119 ** |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C13: Robustness Analysis – Risk Weights for Corporate Credit Exposures under the IRB Approach – Controlling for Lags of Cycle Variables***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.218 | 1.151 | -0.185 | 1.049 | 0.601 | 1.639 | 2.224 ** | 1.996 | 4.564 |
| Nominal GDP growth (t-1) | -0.040 | -0.184 | -0.079 | -0.128 | -0.204 | -0.340 | -0.346 | -0.260 | -0.305 |
| Nominal GDP growth (t-2) | -0.314 | 0.230 | 0.047 | 0.103 | 0.272 | 0.399 | 0.393 | 0.385 | 0.486 |
| Nominal GDP growth (t-3) | 0.947 | 0.204 | 0.217 | -0.066 | -0.244 | -0.271 | -0.249 | -0.239 | -0.687 |
| Nominal GDP growth (t-4) | -0.611 | -0.220 | -0.139 | 0.082 | 0.141 | 0.165 | 0.168 * | 0.156 | 0.439 |
| Dependent variable (t-1) | 0.953 *** | 0.970 *** | 0.988 *** | 0.989 *** | 1.000 *** | 0.988 *** | 0.984 *** | 0.998 *** | 0.997 *** |
| Trend | -0.009 | -0.029 | -0.011 | -0.024 *** | -0.017 | -0.010 | -0.002 | -0.008 | -0.033 |
| Nominal GDP growth (sum) | -0.018 | 0.029 | 0.046 | -0.009 | -0.035 | -0.046 | -0.034 | 0.042 | -0.067 |
| Intercept | 0.812 | 1.776 | 0.644 | 1.326 | 0.024 | 0.901 | 1.646 | 1.012 | 2.707 |
| Real GDP growth (t-1) | -0.742 | -1.024 *** | -0.652 *** | -0.617 *** | -0.404 ** | -0.455 *** | -0.582 *** | -0.608 *** | -0.456 |
| Real GDP growth (t-2) | 1.765 ** | 1.368 *** | 1.011 *** | 0.978 *** | 0.568 ** | 0.627 *** | 0.875 *** | 1.042 *** | 0.667 |
| Real GDP growth (t-3) | -1.161 | -0.292 | -0.360 ** | -0.453 *** | -0.231 | -0.292 | -0.628 ** | -0.933 *** | -0.909 |
| Real GDP growth (t-4) | 0.239 | -0.197 | -0.095 | -0.008 | -0.007 | 0.053 | 0.231 | 0.394 ** | 0.485 |
| Dependent variable (t-1) | 0.951 *** | 0.954 *** | 0.983 *** | 0.981 *** | 1.005 *** | 0.991 *** | 0.988 *** | 1.010 *** | 0.993 *** |
| Trend | -0.031 | -0.009 | -0.013 | -0.016 | -0.011 | 0.003 | 0.004 | 0.002 | 0.026 |
| Real GDP growth (sum) | 0.101 | -0.145 | -0.096 * | -0.100 *** | -0.074 | -0.068 | -0.105 | -0.106 | -0.213 |
| Intercept | 2.274 | 1.474 | 2.137 | 2.203 * | 0.518 | -0.366 | -1.094 | -3.373 | -3.246 |
| Credit-to-GDP growth (t-1) | -0.227 | -1.299 *** | -0.922 ** | -0.659 ** | -0.452 | -0.275 | -0.448 | -0.291 | -0.278 |
| Credit-to-GDP growth (t-2) | 0.348 | 0.950 *** | 0.841 *** | 0.857 ** | 0.386 | 0.257 | 0.187 | -0.160 | -0.472 |
| Credit-to-GDP growth (t-3) | 0.465 | 0.271 | -0.433 | -0.485 * | 0.190 | -0.028 | 0.479 | 0.200 | -0.028 |
| Credit-to-GDP growth (t-4) | -0.788 | -0.248 | 0.250 | 0.187 | 0.003 | 0.293 | 0.090 | 0.954 | 1.459 |
| Dependent variable (t-1) | 0.954 *** | 0.976 *** | 0.980 *** | 0.984 *** | 0.988 *** | 0.993 *** | 0.997 *** | 0.998 *** | 1.018 *** |
| Trend | -0.057 | -0.036 | -0.045 | -0.043 ** | -0.002 | 0.021 | 0.046 | 0.114 ** | 0.103 |
| Credit-to-GDP growth (sum) | -0.201 | -0.326 | -0.265 | -0.101 | 0.127 | 0.248 | 0.308 | 0.703 | 0.681 |
| Intercept | 0.549 | -0.775 | 0.043 | 0.485 | 0.222 | 0.026 | -1.114 | -0.942 | -1.988 |
| FCI (t-1) | -0.281 | -0.223 * | -0.261 ** | -0.150 | -0.137 | -0.175 | -0.133 | -0.034 | 0.212 |
| FCI (t-2) | 0.915 | 0.395 | 0.466 * | 0.295 | 0.102 | 0.169 | 0.167 | -0.017 | -0.654 |
| FCI (t-3) | -0.998 | -0.153 | -0.198 | -0.152 | 0.134 | 0.072 | -0.032 | -0.024 | 0.463 |
| FCI (t-4) | 0.350 | 0.004 | -0.003 | 0.031 | -0.070 | -0.036 | 0.059 | 0.163 | 0.102 |
| Dependent variable (t-1) | 0.947 *** | 0.979 *** | 0.985 *** | 0.983 *** | 0.994 *** | 1.001 *** | 0.998 *** | 0.997 *** | 1.012 *** |
| Trend | -0.011 | 0.002 | -0.009 | -0.008 | -0.006 | -0.004 | 0.036 | 0.046 * | 0.063 |
| FCI (sum) | -0.014 | 0.022 | 0.004 | 0.024 | 0.028 | 0.031 | 0.061 | 0.088 | 0.122 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C14: Robustness Analysis – Risk Weights for Credit Exposures to Institutions under the IRB Approach – Controlling for Lags of Cycle Variables***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 5.133 ** | 2.248 | 1.217 | 1.532 * | 1.454 | 1.676 | 1.738 | 2.144 | 4.120 |
| Nominal GDP growth (t-1) | 0.006 | -0.099 | -0.054 | 0.046 | 0.062 | 0.066 | 0.112 | 0.200 | 0.239 |
| Nominal GDP growth (t-2) | -0.004 | 0.099 | 0.035 | 0.035 | -0.035 | 0.018 | 0.093 | 0.076 | 0.346 |
| Nominal GDP growth (t-3) | -0.560 | -0.365 | -0.232 | -0.273 ** | -0.087 | -0.191 | -0.293 | -0.398 * | -0.640 |
| Nominal GDP growth (t-4) | 0.220 | 0.140 | 0.142 | 0.131 | 0.006 | 0.083 | 0.130 | 0.265 ** | 0.404 |
| Dependent variable (t-1) | 0.768 *** | 0.838 *** | 0.924 *** | 0.944 *** | 0.964 *** | 0.964 *** | 0.951 *** | 0.940 *** | 0.863 *** |
| Trend | -0.066 | 0.013 | 0.005 | -0.008 | -0.006 | -0.003 | 0.020 | 0.037 | 0.082 |
| Nominal GDP growth (sum) | -0.338 *** | -0.225 ** | -0.110 | -0.061 | -0.053 | -0.023 | 0.041 | 0.143 | 0.349 |
| Intercept | 3.457 | 2.380 | 1.200 | 1.269 | 1.263 | 1.231 | 1.320 | 1.860 | 4.675 * |
| Real GDP growth (t-1) | -0.567 | -0.157 | 0.026 | -0.008 | 0.060 | 0.048 | 0.183 | 0.253 | 0.378 |
| Real GDP growth (t-2) | 0.550 | 0.040 | -0.062 | 0.010 | -0.156 | -0.057 | -0.182 | -0.483 | -0.148 |
| Real GDP growth (t-3) | -0.046 | -0.039 | -0.140 | -0.115 | 0.075 | -0.092 | -0.132 | 0.349 | -0.245 |
| Real GDP growth (t-4) | -0.329 | -0.075 | 0.071 | 0.025 | -0.048 | 0.037 | 0.149 | -0.108 | 0.319 |
| Dependent variable (t-1) | 0.765 *** | 0.838 *** | 0.919 *** | 0.945 *** | 0.969 *** | 0.971 *** | 0.959 *** | 0.960 *** | 0.860 *** |
| Trend | -0.033 | 0.002 | 0.007 | 0.000 | -0.003 | 0.005 | 0.028 | 0.043 | 0.087 |
| Real GDP growth (sum) | -0.392 | -0.230 | -0.105 | -0.088 | -0.069 | -0.064 | 0.018 | 0.012 | 0.303 |
| Intercept | 10.502 *** | 6.226 * | 0.709 | 1.064 | 1.046 | 0.802 | -0.751 | 0.173 | -11.704 *** |
| Credit-to-GDP growth (t-1) | -0.766 | -0.438 | 0.353 | 0.221 | -0.118 | -0.236 | -0.546 | -0.171 | -0.258 |
| Credit-to-GDP growth (t-2) | -0.235 | 0.134 | -0.489 | -0.334 | 0.082 | 0.354 | 1.039 | 1.358 * | 3.191 *** |
| Credit-to-GDP growth (t-3) | 0.835 | -0.060 | -0.415 | -0.318 | -0.115 | -0.290 | -0.516 | -1.492 ** | -2.836 *** |
| Credit-to-GDP growth (t-4) | -1.068 | -0.274 | 0.588 | 0.458 | 0.146 | 0.270 | 0.272 | 0.691 | 1.948 ** |
| Dependent variable (t-1) | 0.758 *** | 0.829 *** | 0.930 *** | 0.948 *** | 0.968 *** | 0.969 *** | 0.965 *** | 0.950 *** | 0.964 *** |
| Trend | -0.177 ** | -0.083 | 0.006 | -0.003 | 0.000 | 0.012 | 0.070 * | 0.078 | 0.385 *** |
| Credit-to-GDP growth (sum) | -1.234 ** | -0.639 | 0.037 | 0.028 | -0.005 | 0.098 | 0.249 | 0.386 | 2.045 *** |
| Intercept | 7.453 *** | 4.656 ** | 2.039 | 1.732 | 1.373 | 0.944 | 0.448 | 0.031 | -4.771 |
| FCI (t-1) | -0.453 *** | -0.345 *** | -0.056 | -0.090 | -0.116 | -0.112 | -0.025 | -0.025 | 0.025 |
| FCI (t-2) | 0.266 | 0.244 | -0.105 | -0.030 | 0.036 | 0.104 | -0.050 | -0.228 | -0.126 |
| FCI (t-3) | 0.359 | 0.252 | 0.189 | 0.149 | 0.088 | -0.018 | 0.077 | 0.399 | 0.399 |
| FCI (t-4) | -0.313 | -0.232 | -0.043 | -0.046 | -0.020 | 0.038 | 0.031 | -0.090 | -0.085 |
| Dependent variable (t-1) | 0.750 *** | 0.824 *** | 0.904 *** | 0.935 *** | 0.962 *** | 0.961 *** | 0.938 *** | 0.937 *** | 0.951 *** |
| Trend | -0.093 | -0.037 | -0.005 | -0.002 | 0.002 | 0.017 | 0.057 * | 0.087 * | 0.230 *** |
| FCI (sum) | -0.141 ** | -0.081 ** | -0.015 | -0.017 | -0.011 | 0.011 | 0.033 * | 0.056 | 0.212 ** |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

**Table C15: Robustness Analysis – Risk Weights for Retail Credit Exposures under the IRB Approach – Controlling for Lags of the RMCI**

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -3.096 * | -0.157 | -0.466 | -0.278 | 0.041 | 0.019 | -0.094 | 0.493 | 2.728 * |
| RMCI (t-1) | 6.002 | -1.172 | -2.205 | -1.836 | -1.157 | -0.714 | 0.129 | -0.831 | -0.543 |
| RMCI (t-2) | 3.021 | 2.467 | 2.447 | 1.979 | 0.974 | 0.428 | -0.975 | 0.565 | 6.943 |
| RMCI (t-3) | -12.189 | -1.989 | -0.948 | -0.530 | 0.207 | 0.997 | 1.599 | 0.547 | -6.670 |
| RMCI (t-4) | -2.370 | -1.065 | -2.010 * | -1.752 | -1.642 | -2.757 ** | -3.029 ** | -3.751 | -3.508 |
| Dependent variable (t-1) | 0.898 *** | 0.956 *** | 0.979 *** | 0.985 *** | 0.987 *** | 1.001 *** | 1.025 *** | 1.022 *** | 1.029 *** |
| Trend | 0.169 *** | 0.029 | 0.028 ** | 0.022 ** | 0.017 | 0.010 | -0.003 | -0.002 | -0.045 |
| RMCI (sum) | -5.536 * | -1.759 | -2.717 ** | -2.140 ** | -1.618 | -2.047 | -2.276 * | -3.470 | -3.778 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

**Table C16: Robustness Analysis – Risk Weights for Corporate Credit Exposures under the IRB Approach – Controlling for Lags of the RMCI**

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 1.543 | -1.779 | 0.245 | 1.472 | 0.892 | -0.261 | -1.545 | -1.507 | 0.952 |
| RMCI (t-1) | 9.901 | 2.545 | 1.316 | 1.449 | -2.349 | -3.797 | -3.554 | -8.588 | -21.656 |
| RMCI (t-2) | -17.878 | -7.148 | -5.906 | -0.381 | 4.001 | 4.073 | 2.665 | 1.254 | 21.131 |
| RMCI (t-3) | 20.620 | -0.047 | 0.064 | -3.830 | -6.686 | -7.131 | -5.085 | 4.295 | -8.974 |
| RMCI (t-4) | -11.349 * | -1.628 | -0.680 | 1.167 | 0.616 | 0.991 | -0.115 | -5.239 | -7.540 |
| Dependent variable (t-1) | 0.933 *** | 0.979 *** | 0.973 *** | 0.982 *** | 0.988 *** | 0.995 *** | 1.009 *** | 1.013 *** | 0.994 *** |
| Trend | -0.019 | 0.041 | 0.014 | -0.019 | 0.001 | 0.035 * | 0.058 ** | 0.076 *** | 0.104 |
| RMCI (sum) | 1.293 | -6.277 | -5.206 | -1.595 | -4.419 | -5.864 *** | -6.089 *** | -8.278 *** | -17.039 *** |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

**Table C17: Robustness Analysis – Risk Weights for Credit Exposures to Institutions under the IRB Approach – Controlling for Lags of the RMCI**

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.299 | -0.269 | -0.097 | -0.230 | 0.351 | 0.204 | 0.099 | -0.372 | -0.566 |
| RMCI (t-1) | 2.133 | 0.920 | -2.505 | -1.623 | 0.191 | 0.323 | 0.329 | 1.004 | -18.186 * |
| RMCI (t-2) | 0.398 | 3.177 | 3.647 | 2.700 | 0.528 | 0.557 | -1.568 | -4.056 | 15.626 |
| RMCI (t-3) | -7.635 | -12.534 * | -4.186 | -5.004 | -3.021 | -2.366 | -2.205 | 0.832 | -13.251 |
| RMCI (t-4) | -3.996 | 4.719 | -1.728 | -0.713 | -1.299 | -2.034 | -2.249 | -5.046 | 1.076 |
| Dependent variable (t-1) | 0.751 *** | 0.870 *** | 0.915 *** | 0.940 *** | 0.968 *** | 0.973 *** | 0.954 *** | 0.949 *** | 0.931 *** |
| Trend | 0.052 | 0.048 | 0.045 | 0.046 | 0.024 | 0.035 | 0.070 * | 0.122 ** | 0.219 *** |
| RMCI (sum) | -9.101 ** | -3.718 | -4.773 | -4.639 | -3.601 | -3.520 | -5.693 ** | -7.265 | -14.735 * |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

### *Table C18: Robustness Analysis – Risk Weights for Retail Credit Exposures under the IRB Approach – Controlling for Lags of House Price Growth*

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -1.471 | -0.463 | -0.125 | 0.038 | 0.394 | 0.487 | 0.770 * | 1.200 * | 2.881 |
| House price growth (t-1) | -0.304 ** | -0.009 | 0.011 | 0.008 | 0.032 | 0.045 | 0.061 | 0.073 | 0.112 |
| House price growth (t-2) | 0.169 | -0.220 | -0.139 | -0.098 | -0.147 ** | -0.185 *** | -0.202 *** | -0.263 *** | -0.224 |
| House price growth (t-3) | -0.010 | 0.263 *** | 0.138 ** | 0.098 * | 0.134 ** | 0.170 *** | 0.179 *** | 0.197 * | 0.074 |
| House price growth (t-4) | -0.079 | -0.114 | -0.047 | -0.030 | -0.044 | -0.058 ** | -0.067 * | -0.061 | -0.072 |
| Dependent variable (t-1) | 0.898 *** | 0.951 *** | 0.970 *** | 0.982 *** | 0.987 *** | 0.997 *** | 1.005 *** | 1.017 *** | 1.038 *** |
| Trend | 0.127 *** | 0.048 | 0.022 | 0.012 | 0.003 | -0.006 | -0.015 * | -0.021 ** | -0.061 * |
| House price growth (sum) | -0.224 *** | -0.080 | -0.037 | -0.022 | -0.025 * | -0.028 ** | -0.029 ** | -0.054 *** | -0.110 ** |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C19: Robustness Analysis – Risk Weights for Retail Credit Exposures under the IRB Approach – Change in Risk Weights***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 4.798 | 3.544 | 0.788 | 0.408 | -0.879 | -1.526 | -3.815 | -5.265 | -9.025 |
| Nominal GDP growth | 0.110 | -0.019 | -0.038 | -0.062 *** | -0.055 ** | -0.075 *** | -0.093 *** | -0.140 ** | -0.382 *** |
| Dependent variable (t-1) | 0.043 | 0.026 * | 0.030 * | 0.011 | 0.004 | 0.027 | 0.017 | -0.030 | -0.153 ** |
| Log(assets) (t-1) | -0.395 | -0.224 | -0.048 | -0.011 | 0.055 | 0.114 | 0.253 | 0.351 | 0.669 |
| ROA (t-1) | 0.834 | 0.084 | -0.153 | -0.152 | -0.090 | -0.288 | -0.437 ** | -0.163 | -0.305 |
| Cost of risk (t-1) | -0.312 | -0.403 * | -0.475 * | -0.610 * | -0.104 | 0.174 | 0.352 | 0.018 | -0.182 |
| Regulatory pressures dummy | 0.203 | 0.066 | -0.520 | 1.411 | 1.523 *** | 1.505 | 1.587 | 1.847 | 8.047 ** |
| Intercept | 4.702 | 3.833 | 1.135 | 0.141 | -0.031 | -1.927 | -3.298 | -4.716 | -8.217 |
| Real GDP growth | 0.099 | -0.028 | -0.038 | -0.046 * | -0.058 ** | -0.078 *** | -0.091 *** | -0.117 * | -0.396 *** |
| Dependent variable (t-1) | 0.039 | 0.027 | 0.029 * | 0.019 | 0.011 | 0.031 | 0.015 | -0.034 | -0.112 |
| Log(assets) (t-1) | -0.361 | -0.232 | -0.060 | -0.002 | 0.006 | 0.135 | 0.221 | 0.303 | 0.623 |
| ROA (t-1) | 0.597 | 0.012 | -0.234 | -0.148 | -0.034 | -0.381 | -0.428 | -0.016 | -0.376 |
| Cost of risk (t-1) | -0.528 | -0.426 ** | -0.484 * | -0.593 | 0.052 | 0.233 | 0.315 | 0.140 | -1.171 |
| Regulatory pressures dummy | 0.061 | -0.011 | -0.605 | 1.262 | 1.401 ** | 1.200 | 1.563 | 1.775 | 7.333 * |
| Intercept | 3.513 | 3.799 | 2.681 | 2.408 | 0.876 | -1.437 | -1.032 | -1.534 | -0.287 |
| Credit-to-GDP growth | -0.470 | -0.070 | -0.005 | -0.013 | 0.002 | 0.046 | 0.047 | 0.078 | 0.324 |
| Dependent variable (t-1) | 0.055 | 0.019 | 0.029 * | 0.021 | 0.029 | 0.032 | 0.026 | -0.024 | -0.040 |
| Log(assets) (t-1) | -0.274 | -0.233 | -0.162 | -0.130 | -0.048 | 0.090 | 0.066 | 0.106 | 0.039 |
| ROA (t-1) | 0.454 | 0.096 | 0.072 | 0.040 | 0.038 | -0.215 | -0.027 | 0.289 | 0.992 |
| Cost of risk (t-1) | -0.108 | -0.348 * | -0.403 | -0.580 * | -0.141 | 0.429 | 0.488 | 0.105 | 1.507 |
| Regulatory pressures dummy | 0.399 | 0.328 | -0.285 | 1.264 | 1.361 ** | 1.629 | 1.570 | 1.730 | 7.810 * |
| Intercept | -0.071 | 3.370 | 2.279 | 2.474 | 1.559 | 0.792 | -0.675 | -1.381 | -2.370 |
| FCI | -0.194 * | -0.018 | -0.010 | -0.013 | -0.016 | -0.009 | -0.014 | -0.031 * | -0.073 ** |
| Dependent variable (t-1) | 0.019 | 0.019 | 0.026 | 0.006 | 0.038 | 0.016 | 0.006 | -0.014 | -0.178 |
| Log(assets) (t-1) | 0.096 | -0.186 | -0.132 | -0.123 | -0.068 | -0.029 | 0.058 | 0.135 | 0.200 |
| ROA (t-1) | -0.828 | -0.157 | 0.024 | 0.030 | 0.015 | -0.001 | 0.056 | 0.165 | 1.215 |
| Cost of risk (t-1) | -0.450 | -0.445 | -0.430 | -0.673 * | -0.210 | 0.266 | 0.371 | -0.085 | 1.583 |
| Regulatory pressures dummy | -0.594 | 0.330 | -0.109 | 1.550 | 1.459 *** | 1.641 | 1.861 | 1.475 | 7.147 ** |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C20: Robustness Analysis – Risk Weights for Corporate Credit Exposures under the IRB Approach – Change in Risk Weights***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | -2.770 | 18.713 | 15.915 *** | 9.775 ** | 4.870 | -0.429 | -2.558 | -11.188 | 17.538 |
| Nominal GDP growth | 0.446 *** | 0.079 | -0.060 | -0.095 * | -0.095 | -0.089 | -0.092 | -0.054 | 0.061 |
| Dependent variable (t-1) | -0.164 *** | -0.013 | -0.001 | 0.001 | -0.002 | -0.050 | -0.037 | -0.030 | -0.008 |
| Log(assets) (t-1) | -0.299 | -1.138 | -0.862 *** | -0.527 ** | -0.240 | 0.071 | 0.162 | 0.650 | -0.810 |
| ROA (t-1) | 1.676 | 1.278 | 0.604 | 0.583 ** | 0.220 | -0.091 | 0.309 | -0.310 | 1.074 |
| Cost of risk (t-1) | 1.979 ** | 0.027 | -0.798 ** | -0.775 *** | -0.727 ** | -0.690 * | -0.017 | 0.662 | 0.122 |
| Regulatory pressures dummy | 2.525 *** | 1.888 *** | 1.785 *** | 1.137 *** | 1.822 *** | 2.451 *** | 2.167 *** | 0.905 | 1.752 |
| Intercept | -7.932 | 19.365 | 14.703 ** | 9.644 * | 2.989 | -2.993 | -4.129 | -13.597 | 16.504 |
| Real GDP growth | 0.193 | 0.042 | -0.057 | -0.093 | -0.106 | -0.108 | -0.146 | -0.129 | 0.008 |
| Dependent variable (t-1) | -0.169 ** | -0.017 | 0.004 | 0.010 | 0.001 | -0.036 | -0.033 | -0.038 | -0.006 |
| Log(assets) (t-1) | 0.077 | -1.135 | -0.791 *** | -0.513 * | -0.122 | 0.194 | 0.259 | 0.822 | -0.700 |
| ROA (t-1) | 0.753 | 1.093 | 0.472 | 0.420 | -0.141 | -0.172 | 0.032 | -0.819 | 0.573 |
| Cost of risk (t-1) | 1.722 | -0.213 | -0.809 ** | -0.775 *** | -0.639 * | -0.178 | 0.146 | 0.252 | -0.084 |
| Regulatory pressures dummy | 3.461 *** | 1.868 *** | 1.587 *** | 0.972 *** | 1.315 ** | 1.890 * | 1.261 | -0.158 | 0.886 |
| Intercept | -13.814 | 19.791 | 16.473 ** | 13.414 *** | 9.558 | 0.190 | -0.481 | -15.306 | 11.440 |
| Credit-to-GDP growth | -0.643 | -0.092 | 0.062 | 0.069 | 0.030 | 0.073 | 0.236 | 0.243 | 0.249 |
| Dependent variable (t-1) | -0.200 ** | -0.035 | -0.004 | 0.003 | -0.001 | -0.033 | -0.036 | -0.017 | -0.032 |
| Log(assets) (t-1) | 0.429 | -1.154 | -0.922 *** | -0.733 *** | -0.533 * | -0.016 | 0.017 | 0.839 | -0.411 |
| ROA (t-1) | 0.663 | 1.191 | 0.824 * | 0.523 * | 0.789 * | 0.350 | 0.491 | -0.361 | -0.395 |
| Cost of risk (t-1) | 1.794 | -0.205 | -0.698 ** | -0.519 *** | -0.575 | -0.208 | 0.088 | 0.645 | -0.153 |
| Regulatory pressures dummy | 6.135 *** | 2.295 ** | 1.844 ** | 1.216 *** | 2.356 *** | 2.770 *** | 1.835 ** | 0.480 | -0.111 |
| Intercept | -10.963 | 15.144 | 16.676 ** | 14.241 *** | 9.012 | 1.537 | -4.726 | -10.935 | 17.527 |
| FCI | -0.003 | -0.015 | 0.010 | 0.010 | 0.003 | 0.013 | 0.070 * | 0.070 * | 0.106 |
| Dependent variable (t-1) | -0.136 | -0.023 | -0.006 | 0.002 | -0.001 | -0.025 | -0.009 | -0.018 | -0.137 |
| Log(assets) (t-1) | 0.277 | -0.890 | -0.935 *** | -0.777 *** | -0.497 * | -0.095 | 0.233 | 0.564 | -0.837 |
| ROA (t-1) | 0.594 | 0.819 | 0.858 * | 0.536 * | 0.704 * | 0.447 | 0.104 | 0.026 | 0.605 |
| Cost of risk (t-1) | 1.414 | -0.345 | -0.652 ** | -0.436 * | -0.556 | -0.045 | 0.274 | 0.818 ** | 0.348 |
| Regulatory pressures dummy | 3.593 | 2.206 * | 1.842 *** | 1.239 *** | 2.297 *** | 2.902 *** | 1.106 * | 0.916 | 0.771 |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

***Table C21: Robustness Analysis – Risk Weights for Credit Exposures to Institutions under the IRB Approach – Change in Risk Weights***

| | q0.1 | q0.2 | q0.3 | q0.4 | q0.5 | q0.6 | q0.7 | q0.8 | q0.9 |
|---|---|---|---|---|---|---|---|---|---|
| Intercept | 25.618 ** | 12.642 ** | 7.335 ** | 6.012 ** | 1.738 | 1.529 | 0.601 | -5.596 | -5.644 |
| Nominal GDP growth | -0.095 | -0.096 | -0.093 | -0.034 | -0.039 | 0.012 | 0.030 | 0.146 | 0.158 |
| Dependent variable (t-1) | -0.283 *** | -0.171 * | -0.118 *** | -0.102 *** | -0.081 * | -0.076 | -0.032 | 0.064 | -0.005 |
| Log(assets) (t-1) | -1.728 *** | -0.814 ** | -0.426 ** | -0.336 ** | -0.077 | -0.064 | 0.058 | 0.455 | 0.861 |
| ROA (t-1) | 2.631 | 1.326 | 0.174 | 0.087 | -0.095 | 0.001 | -0.622 | -0.991 | -4.975 ** |
| Cost of risk (t-1) | 1.802 | 0.534 | 0.529 | 0.456 *** | 0.139 | 0.301 | 0.273 | 0.139 | -0.141 |
| Regulatory pressures dummy | 2.108 | 1.340 | 0.200 | -0.101 | 0.213 | 0.664 | -0.288 | -2.220 * | -7.014 *** |
| Intercept | 25.108 ** | 12.205 ** | 8.270 ** | 5.596 ** | 2.369 | 0.743 | -0.136 | -8.628 | 0.289 |
| Real GDP growth | -0.087 | -0.091 | -0.082 | -0.035 | -0.057 | -0.034 | 0.000 | 0.057 | -0.134 |
| Dependent variable (t-1) | -0.284 *** | -0.168 ** | -0.121 *** | -0.110 *** | -0.078 * | -0.080 | -0.039 | 0.066 | -0.004 |
| Log(assets) (t-1) | -1.726 *** | -0.795 ** | -0.483 ** | -0.315 ** | -0.118 | -0.001 | 0.099 | 0.635 * | 0.647 |
| ROA (t-1) | 2.840 | 1.240 | 0.225 | 0.051 | -0.015 | -0.220 | -0.589 | -1.239 | -5.334 ** |
| Cost of risk (t-1) | 1.988 | 0.527 | 0.517 | 0.498 *** | 0.254 ** | 0.266 | 0.099 | 0.130 | -0.964 |
| Regulatory pressures dummy | 1.960 | 1.181 | -0.028 | -0.153 | 0.162 | 0.185 | -0.307 | -2.412 * | -7.782 *** |
| Intercept | 25.127 ** | 17.154 ** | 9.354 ** | 6.843 ** | 2.878 | 1.969 | -0.160 | -3.131 | -1.744 |
| Credit-to-GDP growth | 0.030 | -0.182 | -0.024 | -0.027 | -0.082 | -0.104 | -0.055 | -0.404 * | -0.046 |
| Dependent variable (t-1) | -0.271 *** | -0.159 * | -0.126 ** | -0.114 *** | -0.091 * | -0.073 | -0.018 | 0.055 | 0.038 |
| Log(assets) (t-1) | -1.762 *** | -1.047 *** | -0.559 ** | -0.386 ** | -0.146 | -0.095 | 0.110 | 0.395 | 0.645 |
| ROA (t-1) | 3.160 | 1.126 | 0.426 | 0.164 | 0.054 | 0.253 | -0.643 | -1.181 | -4.284 ** |
| Cost of risk (t-1) | 1.913 | 0.860 | 0.703 *** | 0.499 *** | 0.263 *** | 0.232 | 0.123 | -0.163 | -0.378 |
| Regulatory pressures dummy | 1.888 | 0.367 | -0.178 | -0.316 | 0.260 | 1.162 | -0.399 | -1.586 | -7.146 *** |
| Intercept | 26.278 ** | 14.074 * | 9.412 ** | 6.535 ** | 1.227 | 1.011 | -0.335 | -6.156 | -9.745 |
| FCI | -0.006 | -0.055 | -0.014 | -0.006 | -0.010 | -0.009 | 0.009 | -0.008 | 0.217 |
| Dependent variable (t-1) | -0.298 *** | -0.133 | -0.121 ** | -0.113 *** | -0.086 * | -0.075 | -0.042 | 0.050 | -0.051 |
| Log(assets) (t-1) | -1.791 ** | -0.838 * | -0.554 ** | -0.376 ** | -0.058 | -0.035 | 0.100 | 0.531 | 1.036 |
| ROA (t-1) | 2.985 | 0.793 | 0.392 | 0.237 | 0.021 | 0.000 | -0.592 | -1.360 | -5.714 *** |
| Cost of risk (t-1) | 1.197 | 0.553 | 0.639 | 0.474 *** | 0.128 | 0.353 ** | 0.240 | -0.248 | -0.172 |
| Regulatory pressures dummy | 2.017 | 0.470 | -0.229 | -0.230 | 0.298 | 0.752 | -0.381 | -2.557 *** | -7.412 *** |

***Note:*** This table presents the estimates based on the penalised quantile regression for dynamic panel data with fixed effects. The regression was implemented using the *rqpd* R function. ***, ** and * denote the 1%, 5% and 10% significance levels.

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