# Moving toward the Expected Credit Loss Model under IFRS 9:

# Capital Transitional Arrangement and Bank Systematic Risk

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ABSTRACT This paper examines banks' option to adopt the capital transitional arrangement (CTA) set out by the Basel Committee on Banking Supervision in response to the introduction of International Financial Reporting Standards 9 (IFRS 9), which requires the use of an expected credit loss model instead of an incurred loss model to estimate the impairment of financial assets. Using a sample of European publicly listed banks from 2016 to 2019, we find that bank CTA adoption choice is associated with neutral factors captured by bank-specific fundamental factors and potential opportunistic factors related to regulatory constraints implied by the application of IFRS 9. We further examine the association between the CTA adoption choice and bank risk taking. Our results show that banks that adopted the CTA (CTA adopters) decreased their exposure to systematic risk following the CTA adoption compared to the control group of CTA non-adopters. We find that such a relationship varies with the power of the banking authority, being more significant when the banking authority holds more power. Our study is the first academic work to address banks' voluntary choice to adopt the CTA policy under the mandatory application of IFRS 9.

**Keywords:** Systematic risk; Regulatory Capital; IFRS 9; Expected Credit Loss; Banks.

**JEL Classifications:** G21; G28; M41; M48.

*In Roman mythology, Janus was the god of transition and time. He was usually depicted as having two faces looking in opposite directions: one towards the past and the other towards the future.*

*https://www.greekmythology.com/Myths/Roman/Janus/janus.html*

## 1. Introduction

Accounting for credit losses was identified as one of the major accounting failures that exacerbated the 2007–2009 financial crisis by providing untimely information about banks' credit losses, creating financial instability and intensifying the procyclicality of bank lending (e.g. Financial Stability Forum 2009). In response to this criticism, the International Accounting Standards Board (IASB)[1] published the International Financial Reporting Standard (IFRS) 9 in 2014, which includes an expected credit loss (ECL) model for the impairment of financial assets.[2] Effective from the first fiscal quarter of 2018, the IFRS 9 ECL replaced the International Accounting Standard (IAS) 39 incurred loss (IL) model, with the objective of recognising credit losses earlier.

The IFRS 9 ECL model makes two fundamental changes with potential adverse consequences. First, the earlier recognition of credit losses is expected to increase loan loss allowance (LLA) and decrease regulatory capital, and as pointed out by the Basel Committee on Banking Supervision (BCBS), 'the impact could be significantly more material than currently expected and result in an unexpected decline in capital ratios' (BCBS 2017, p. 4). Second, the use of forward-looking information to measure the LLA under IFRS 9 introduces a significant amount of managerial discretion, which can also detrimentally affect financial stability (e.g. Novotny-Farkas 2016).

1 Appendix 2 provides a list of acronyms used in this paper.

2 Although the IASB and the Financial Accounting Standards Board (FASB) worked jointly on a converged standard on credit loss impairment, they ultimately failed to develop a single ECL model. In 2016, the FASB published the Accounting Standard Update (ASC) topic 326, which describes the new impairment model: the current expected credit loss (CECL) model. The FASB's CECL model standard takes effect in 2020 for listed companies and in 2021 for all other firms. For detailed discussions about the development of ECL models and differences between the IFRS 9 ECL model and the FASB CECL model, see for instance Giner and Mora (2019) and Hashim et al. (2016) .

Aiming to attenuate the perceived adverse consequence of the IFRS 9 ECL model (i.e. a potential 'capital shock'), the BCBS introduced a capital transitional arrangement (CTA) by providing banks an adjustment period to adapt their risk management to this new ECL model (BCBS 2017). Specifically, the CTA authorises banks to take up to five years to rebuild their necessary capital resources by allowing them to estimate their regulatory capital under the previous accounting regime (i.e. the IL model). The CTA reflects the different objectives of accounting standard and bank regulators.[3] Consequently, investigating how banks respond to these two relevant and interconnected but different policies is of great importance.

The primary purpose of this study is to examine bank-specific determinant factors that influence bank CTA adoption choice and consequences of this choice on bank risk taking. Specifically, we investigate several research questions in relation to the CTA: What are the determinant factors that affect bank CTA adoption choice? Do banks strategically select the CTA? Does the CTA adoption choice affect bank risk taking? To our best knowledge, no previous studies have addressed the economic consequences of the CTA option.

To address these research questions, we rely on a final sample of 101 banks drawn from all European publicly listed banks from 2016 to 2019. We hand-collected the data of bank CTA adoption choice and information related to the model used by the bank to estimate the risk-weighted assets (RWAs) (i.e. the internal rating-based (IRB) approach vs. the standardised approach (SA)).

Our first sub-hypothesis, H1a, examines whether banks' choice in applying advanced credit risk modelling (i.e. the IRB banks) is associated with CTA adoption choice. The relationship between these two choices, both of which are enabled by the Basel regulatory framework, is not straightforward. From a reporting practice perspective, since the estimation

[3] The general purpose of financial reporting is to provide 'true and fair' information to stakeholders to help them in decision-making. In contrast, the prime mission of banking regulators is to protect the financial system as a whole by avoiding bank failure and limiting the frequency and cost of systemic crises (e.g. Acharya et al. 2017, Barth and Landsman 2010).

of ECLs is more aligned with the IRB approach than with the SA approach (Novotny-Farkas, 2016) we would expect IRB banks to opt out of the CTA. From the bank supervision perspective, the IRB banks' motivation to opt out of the CTA might be influenced by the complexity in banks' supervision and regulatory environment. In light of the recent European financial and sovereign debt crises, the European Central Bank (ECB) created a common supervisory framework − the Single Supervisory Mechanism (SSM) − which has endowed the ECB with direct supervisory authority over European banks deemed 'significant'. In 2015, the ECB launched the Targeted Review of Internal Models (TRIM) project, which aims to assess whether the internal models currently used by SSM significant institutions comply with regulatory requirements. Thus, IRB banks' motivation to opt out of the CTA might be influenced by regulatory scrutiny over their use of internal models. Consistent with our prediction, we find that the use of the IRB approach does not drive banks' CTA opting-out choice unless IRB banks are directly supervised by the ECB under the SSM. These results reflect an interesting interplay between accounting practices and banking supervision. Indeed, the results suggest that 'significant' IRB institutions in the SSM are likely to be more prepared to adopt the IFRS 9 ECL model and to absorb the capital shock of day 1 application ECL.

In addition to considering bank-specific institutional factors such as the already-in-place use of advanced credit risk modelling (i.e. the IRB approach) and the regulatory framework (i.e. the SSM) under H1a, we develop our second sub-hypothesis, H1b, to examine whether banks' opportunistic behavior drives the CTA adoption choice. Consistent with prior literature on bank capital management (e.g. Ahmed et al. 1999, Efing 2019, Iannotta et al. 2019, Mariathasan and Merrouche 2014), we find that regulatory-capital constrained banks prior to the implementation of IFRS 9 are more likely to opt for the CTA. However, this result should be regarded as a double-edged sword. On one hand, this relationship might point to the efficacy of the CTA policy since these regulatory-constrained banks could benefit from the CTA to reduce their risk taking or to improve risk management, which corresponds exactly to the initiative of the BCBS for setting up the CTA. On the other hand, this relationship might highlight opportunistic behavior if regulatory-constrained banks have selected the CTA to delay compliance with the minimum regulatory capital requirement, which might lead to a critical situation regarding future financial stability.

To further examine banks' plausible CTA-related opportunistic choice underlying H1b results, we develop sub-hypothesis H2a, which investigates whether CTA choice changes banks' risk-taking behavior. By using CTA non-adopters (i.e. banks that did not adopt the CTA) as a control group, we conduct a difference-in-differences (DiD) analysis examining changes in risk exposure upon CTA adoption. We report that CTA adopters decrease their exposure to systematic risk following the CTA adoption, implying that the CTA adoption choice is not driven by opportunistic motives but is a consequence of regulatory compliance. In addition, following the line of analysis in H1a, we develop H2b to examine the influence of supervisory power on banks' risk taking. We find that the effect of reduced exposure to systematic risk by CTA adopters is more pronounced when banking authorities hold more power over banking activities. This relationship is robust when using two different measures of supervisory power: (1) a country-level indicator based on the 'official supervisory power' index (Barth et al. 2013) and (2) an indicator that captures significant institutions directly supervised by the ECB in the SSM.[4]

To ensure that our results are robust to different risk-taking measures and research designs and also capture banks' reaction to the CTA adoption choice (rather than other economic events or policy changes), we run a battery of robustness checks and sensitivity analyses. First, we focus on bank exposure to tail risk measured by the long-run marginal expected shortfall (LRMES) and report that CTA adopters decreased their tail risk exposure

[4] Loipersberger (2018) provides evidence consistent with market participants viewing the ECB as holding significant power over banking activities through the SSM.

following the CTA adoption. Second, we use average values instead of year-end values and employ different market indices (i.e. MSCI World index, MSCI Europe index and the Euro Stoxx 50 Index) for estimating bank risk taking. The post-CTA adoption risk reduction still holds using theses alternative measures. Third, to mitigate concerns surrounding changes in bank risk exposure due to bank-specific factors other than banks' CTA adoption choice, we employ entropy balancing (Hainmueller 2012) and report that differences in bank fundamentals across CTA adopters and non-adopters do not affect our inferences. Fourth, we apply an event study to test the parallel trend assumption underlying our DiD research design. In parallel, we also change our control group from CTA non-adapters to insurance companies. Both additional analyses validate our previous inferences. Finally, we perform a permutation test, which further confirms that the reported reduction in banks' risk taking following CTA adoption is not a random effect.

Our research contributes to the emerging literature on bank accounting and reporting in three key ways. First, given that the CTA aims to neutralise the effect of IFRS 9 on regulatory capital, we provide preliminary evidence that applying the new ECL model under IFRS 9 might influence bank risk taking. Indeed, instead of using the higher level of managerial discretions offered by IFRS 9 to manipulate the LLA, CTA adopters commit to decreasing their risk taking. Second, our study addresses an important interplay between accounting standards and Basel regulation policy. We provide the first empirical evidence of the effectiveness of the CTA policy, which allows banks to smooth the transition from the IL model to new ECL under IFRS, thereby avoiding a sharp impact on regulatory capital owing to the change of accounting standard. Third, the reported decrease in bank systematic risk exposure subsequent to the CTA adoption choice complements and softens the conclusion currently dominating the literature that banks often behave opportunistically in their use of internal models (e.g. Behn et al. 2016, Mariathasan and Merrouche 2014).

Our findings have timely implications for accounting standard setters, bank regulators, and other users of bank reporting. We show that the new IFRS 9 ECL model in conjunction with the CTA policy significantly changes banks' reporting choice as well as risk taking. Our results suggest that transitional policies such as the CTA are effective in bridging the regulation gap between the Basel rules and IFRS. While banks can select the CTA for opportunistic purposes, we find that (1) IRB-'significant' SSM institutions prefer opting out of the CTA and that (2) under strong supervision, CTA adopters do significantly reduce their risk exposure in subsequent CTA years. Both findings imply the crucial role of banking authorities in monitoring banks' practices. Finally, our study is relevant to several policies recently promulgated by banking authorities in reaction to the current COVID-19 crisis that aim to avoid excessive procyclicality of banks' regulatory capital. In March 2020, U.S. regulators authorised U.S. banks to delay for two years in implementing the new expected loss model (e.g. CECL) and extend the CTA duration.[5] Within its prudential remit, the ECB also took relief measures that give further flexibility to banks in provisioning loan losses. In addition to the CTA option, the ECB recommended that banks opt for the IFRS 9 transitional rules.[6] Our study suggests that, as long as banking authorities hold effective supervisory power, the increased tolerance through IFRS 9 for regulatory capital purposes will not incentivise banks to engage in opportunistic behavior.

The remainder of the paper proceeds as follows. In Section 2, we discuss the relevant background. In Section 3, we review prior literature and develop our hypotheses, and in Section 4 we present the research design. In Section 5, we discuss our main results and the robustness tests. Section 6 offers a summary and concluding remarks.

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[5] This Interim Final Rule permits U.S. banks that were required to implement the CECL model before the end of 2020 to have a five-year CTA period: https://www.occ.treas.gov/.

[6] https://www.bankingsupervision.europa.eu/

## 2. Background and related literature

### *2.1. Accounting for credit loss*

IAS 39 obliged firms to record impairment of financial assets conditional on the occurrence of an objective evidence of impairment, namely a 'trigger event'.[7] This restriction was criticised as being too little, too late (European Central Bank 2017) – a problem that IFRS 9 is designed to solve. Under IFRS 9, banks stop waiting for a trigger event and estimate a buffer to cover potential loan losses upon initial loan recognition. The IFRS 9 standard also differentiates the estimation ECLs according to credit risk into three stages. Financial assets for which credit risks are judged at a low level or that have not increased since the initial recognition are classified as Stage 1. Financial assets with a significant deterioration in credit quality since the initial recognition are recognised as Stage 2. Financial assets that are subject to incurred credit losses or are credit-impaired are designated as Stage 3. Banks report 12-month ECLs for Stage 1 but full-lifetime ECLs for Stages 2 and 3. Therefore, the ECL amounts depend on the loan-stage classification and subsequent change in credit risk. From the point when an ECL is initially recognised, any significant increase in credit risk on this loan requires a periodic update of additional provisions. Bank management should deal with various uncertainties in applying the new ECL model, including for instance the identification of change in credit risk and the lifetime estimate of ECLs.[8] Overall, IFRS 9 requires 'a significant increase in the role of risk management, data availability and expert judgment for accounting purposes, for which strong governance and clear internal processes have to be in place' (European Central Bank 2017, p. 5).

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7 See IAS 39 paragraph 59 for a list of trigger events.

8 Overall, the IFRS 9 impairment approach differs substantially from that under IAS 39. Only credit-impaired loans (Stage 3) are not modified since this category of exposures also requires the estimation of lifetime expected losses under IAS 39. Consequently, the estimation of ECLs for Stage 1 and Stage 2 financial assets should result in greater accounting loan loss provisions (BCBS 2017).

### 2.2. Basel rules on credit risk and capital adequacy

As credit risk is the largest risk exposure for the majority of banking institutions, the BCBS has issued a series of interconnected regulations embodying credit risk and capital requirements. In 1988, the Basel I accords introduced a capital adequacy ratio (CAR) based on a framework that required banks to hold regulatory capital in proportion to risk-weighted assets (RWA). In contrast to on-balance-sheet total assets that do not entail risk implication, the level of RWAs is sensitive to the level of banks' exposure to credit risk. Depending on the type of asset and the associated counterpart's riskiness, one of four possible risk weights (i.e. 0%, 20%, 50%, or 100%) associated with credit risk is assigned to each bank asset. RWAs are calculated by using the sum of all assets multiplied by the respective risk weights. Since the amount of RWAs is used as the denominator of the CAR, the higher the credit risk exposure, the higher the RWAs and consequently the lower the CAR and the higher the regulatory capital requirements. This risk-sensitive capital charge remains the fundamental principle of the Basel accords despite ongoing policy changes.[9]

In 2004, to enhance the stability of the financial sector by making capital charges more sensitive to banks' risk exposures, the Basel II framework extended the focus on credit risk to market risk and operational risk, and importantly allowed banks to calculate the RWAs associated with these risks using two different approaches: the advanced approach and the standardised approach (SA).[10] In contrast to using the SA, under which the risk weights are fixed and standardised, banks applying an advanced approach can use internally generated data and define different modelling processes to compute the RWAs. The advanced approach for credit risk, known as the IRB approach, allows banks to define either one or all three parameters

9 In 1996, the BCBS extended the RWA requirement from credit risk to market risk (BCBS 1996), but the minimum capital adequacy ratio (i.e. regulatory capital over RWAs) remained unchanged at 8%. In 2004, aiming to improve the risk sensitivity of capital requirements, the Basel II accords extended the risk-weight categories from credit risk and market risk to operational risks, and changed the rules for assigning risk weights to assets.

10 Under Basel I, internal models were already available to banks for estimating market risk.

for calculating credit risk: probability of default (PD), loss given default (LGD) and exposure at default (EAD).[11] In practice, the IRB approach is closely aligned with the new ECL model since the three similar parameters are used to estimate ECLs under IFRS 9 (see Novotny-Farkas (2016) for a detailed discussion). Unlike the SA, the IRB approach must be approved by the national banking supervisor. The approval of internal models is based on bank business models as well as on bank available resources: 'the process for determining which banks may be subject to the advanced approaches will require assessment of a number of factors, including a bank's risk profile, the nature of its operations, and its ability to meet the eligibility requirements for these approaches' (BCBS 2004, p. 11).[12] Since 2004, banks have increasingly implemented IRB models. However, these models have been widely criticised as banks seem to manipulate the estimated risk parameters to benefit from lower regulatory capital charges (e.g. Behn et al. 2016, Mariathasan and Merrouche 2014). Addressing those concerns, the ECB launched the Targeted Review of Internal Models (TRIM) initiative in 2015 to investigate whether the SSM-'significant' banks correctly apply the internal models (including the IRB approach), and report reliable and comparable risks estimates.[13]

Since Basel I, accounting for loan losses has consistently received attention from banking regulators because of banks' substantial exposure to credit risk and the required accounting provisioning for such risk that directly influences regulatory capital.[14] In October 2016, in reaction to the future introduction of ECL models by both the IASB and the FASB, the

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11 IRB yields two methods: the foundation internal ratings-based (F-IRB) and the advanced internal ratings-based (A-IRB) methods. Under the F-IRB method, banks are allowed to define only one parameter – probability of default – while under the A-IRB method, banks can use their own methodologies to estimate all three main parameters.

12 See the guidelines on the implementation, validation and assessment of Advanced Measurement (AMA) and Internal Ratings Based (IRB) Approaches (GL10) − https://eba.europa.eu/.

13 In its 2018 annual report on supervisory activities, available at www.bankingsupervision.europa.eu, the ECB notes, 'TRIM is the largest project that ECB Banking Supervision has launched so far' (p. 38).

14 The effect of accounting loan loss provisions on regulatory capital is conditional on whether the loan loss allowance is lower or higher than 1.25% of the risk-weighted asset since the introduction of the Basel framework. The inclusion of general provisions in Tier 2 capital is limited to 1.25% of credit RWAs. The regulatory capital treatment of provisions under the SA and IRB approaches differs slightly since the adoption of Basel II. For more information please refer to BCBS (2017).

BCBS started a consultation proposal on the policy considerations related to the regulatory treatment of accounting provisions under the new approach. Consistent with the accounting profession (Ernst & Young 2018) regarding the impact of the IFRS 9 ECL model, the BCBS 'acknowledges that the transition to ECL accounting will generally result in an increase in the overall amount of loan loss provisions, which in many cases will reduce the CAR of banks' (BCBS 2017, p. 4).

To address the perceived adverse impact on bank regulatory capital, the BCBS introduced the CTA policy (BCBS 2017). The primary objective of the CTA is to ensure a stable transition from the old incurred-based to the new expected-based models by adding back a transitional adjustment to regulatory capital. Broadly speaking, the authorised transitional adjustment under the CTA policy corresponds to the difference in required provisions under the IAS 39 incurred loss model and the IFRS 9 ECL model. This adjustment is phased out each year, allowing CTA adopters to absorb the day 1 capital impact of an IFRS 9 adoption over a five-year transitional period. For banks applying the IRB approach, the transitional adjustment needs to be adjusted for any existing IRB provisioning 'shortfall'.[15] The CTA aims at giving banks a protracted time of no more than five years to rebuild regulatory capital following the application of ECL accounting. Through the Pillar 3 framework, banks are required to disclose publicly whether this CTA is applied. Banks that adopt the CTA should also report publicly regulatory capital and leverage ratios in a 'fully loaded' basis, that is, without the impact of the CTA (BCBS 2017, p.6).

[15] It corresponds to the difference between accounting provisions under IAS 39 and prudential expected losses for portfolios under the IRB approach. If prudential expected losses under the IRB approach are higher than accounting provisions under IAS 39, the shortfall will absorb (totally or partially) the impact on CET1 of the increase in accounting provisions when IFRS 9 is first applied (which would not be the case for portfolios under the SA approach).

## 3. Review of the literature and hypothesis development

As our research questions reflect, this paper is relevant to two main streams of banking literature: (1) accounting and regulatory discretion in estimating credit losses, and (2) bank risk taking. Drawing on these two steams of research, we develop hypotheses related to banks' motives for adopting the CTA policy and subsequent consequences of this adoption on bank risk taking.

### *3.1. Non-opportunistic determinants of CTA adoption*

Although the BSBC does not require the bank CTA option to bond with the RWA reporting approach (SA or IRB), we might expect a strong association between these two regulatory choices for several reasons.

First, banks applying the IRB approach are more likely to have necessary regulatory capital resources, thereby supporting their choice of opting out of the CTA. Indeed, if a bank applies the IRB approach, any shortfall (i.e. a positive difference between prudential expected losses under the IRB approach and accounting provisions under IAS 39) is already deducted from regulatory capital prior to IFRS 9 adoption, which is not the case for SA banks (e.g. Novotny-Farkas 2016). Beyond necessary capital resources, banks with better management and an orientation toward credit intermediation are more likely to obtain the IRB validation by national supervisors (Cucinelli et al. 2018).

Second, as we mention in Section 2.2, the IRB approach requires the estimation of risk parameters, which are similar to those used in the IFRS 9 ECL model to estimate the LLA. Novotny-Farkas (2016) reports that the ECL model is more aligned with prudential expected losses estimated under the IRB approach than the SA approach. Since building an efficient internal system for estimating ECLs is key for implementing IFRS 9 properly (European Central Bank 2017), IRB banks have cost and experience advantages over SA banks. This discussion lead us to predict that IRB banks are better prepared to apply the IFRS 9 ECL model than SA banks. That is, IRB banks should be more likely to opt out of the CTA.

Third, in line with signalling theory, opting out of the CTA would signal that banks are ready to apply the new ECL model regardless of potentially adverse impacts on capital adequacy. Because IRB banks are larger (e.g. Cucinelli et al. 2018) and consequently face more regulatory scrutiny (e.g. Cheng et al. 2011, Vallascas and Hagendorff 2013), IRB banks have incentives to opt out of the CTA to avoid 'red flags' calling for further scrutiny. IRB banks could be inclined to opt out of the CTA to signal their good practices in managing and reporting credit risk.

However, IRB banks' ability and incentive to opt out of the CTA might depend on the ongoing evolution of banks' institutional framework and regulatory policies. As discussed in the introduction, the SSM framework is likely to influence IRB banks' CTA adoption choice since IRB-'significant' banks in the SSM are subject to higher regulatory scrutiny over their use of internal models because of on-site investigations under the TRIM project. In addition, estimating ECLs remains rather challenging for most banks (e.g. Gruenberger 2012). Moreover, as reported by prior research (i.e. Behn et al. 2016) and the ECB, IRB models might be applied improperly by some banks, even those under the SSM system (e.g. European Central Bank 2018).[16] Overall, these aspects might dilute the benefits for IRB banks of opting out of the CTA.

Considering these various aspects from the perspective of available resources and signalling theory, we expect that IRB banks are more likely to select opting out of the CTA than are SA banks. However, this response might be influenced by supervisory effectiveness. Thus, we develop our hypothesis as follows (in the null form):

> **H1a**: Banks that apply the IRB approach are not more likely to opt out of the CTA than banks applying the SA.

[16] See details on https://www.bankingsupervision.europa.eu/, 'Status update on TRIM: overview of outcome of general topics review and interim update on preliminary results of credit risk on-site investigations'.

### *3.2. Opportunistic determinant of CTA adoption*

Owing to the direct impact of loan impairment[17] on banks' net income and regulatory capital, accounting for loan losses has remained one of the dominant topics in bank accounting research (e.g. Beatty and Liao 2014, Ryan 2011). Indeed, loan impairment is the largest accrual for most banks, which gives rise to information asymmetry between bank managers and outsiders since compared to outsiders, bank managers have superior information about the credit quality of their loans. Beatty and Liao (2014) and Ryan (2011) provide recent surveys of the literature showing that, depending on their characteristics and economic condition, banks do exercise discretion over loan loss estimations in order to manage earnings and regulatory capital or to reduce taxes (e.g. Beatty et al. 1995, Collins et al. 1995, Liu and Ryan 2006).

Several early studies focus specifically on the capital management incentive and provide evidence showing that U.S. bank managers have exercised discretion over accounting provisions to manage regulatory capital, both before (e.g. Beatty et al. 1995, Moyer 1990) and after the Basel accords (e.g. Ahmed et al. 1999, Kim and Kross 1998). In contrast, recent studies using European data tend to fail to observe such opportunistic behavior (e.g. Curcio et al. 2017, Gebhardt and Novotny-Farkas 2011, Leventis et al. 2011).

In contrast to the accounting research that almost exclusively focuses on banks' accounting discretion in loan loss provisioning, banking research has examined bank managers' discretionary behavior over the calculation of the RWAs, in particular since 2004 when Basel II allowed for banks to use IRB approaches. The IRB approach provides bank managers more opportunities to manipulate the estimates of risk parameters (e.g. PD) as banks can use their own models and estimated parameters. Consistent with this opportunistic view, studies have documented evidence suggesting that as bank managers make strategic choices in modelling

[17] The literature often refers to loan impairment as loan loss provision, which is the term used in the prudential bank regulation but not in accounting standards. In this study, we refer to loan impairment as the loss recognised in the income statement in the reporting period, and LLA is the accumulated impairment that appears in the balance sheet at the end of the reporting period.

credit risk under the IRB framework, the required regulatory capital does not reflect banks' actual credit risk (e.g. Behn et al. 2016, Mariathasan and Merrouche 2014).

Further, unlike the IRB choice, for which banks should trade off between significant application costs and uncertainty of validation by supervisors, the CTA option is not subject to any validation process and thereby is not affected by potential application costs and regulatory process uncertainties. By providing only their CTA decision and related mandatory disclosures under the Pillar 3 framework, banks can immediately get the regulatory benefit of delaying the application of ECL.

Embracing this opportunistic view of bank managers' behavior, we predict that regulatory-constrained banks are more likely to select the CTA to benefit from temporarily lower capital charges.

**H1b:** Regulatory-constrained banks are more likely to opt for the CTA.

### *3.3. CTA adoption choice and bank risk taking*

Along with the research on bank regulatory incentives with regard to credit-risk reporting opportunistic choices, many studies have examined bank risk taking under the Basel frameworks.

Focusing on the discretion in estimation of RWAs, Behn et al. (2016) find that, compared to the SA banks, large banks are more likely to opportunistically benefit from lower capital charges under the IRB approach, subsequently expanding their risk taking in lending. Indeed, if regulation on credit risk assessment fails to capture bank risk taking, banks have incentives to take risks that they would not take with tighter and more efficient regulation (Iannotta et al. 2019). In contrast, other studies report improvement in risk management owing to the application of IRB models (e.g. Mascia et al. 2019). Cucinelli et al. (2018) provide evidence that IRB banks can curb the increase in credit risk driven by the macroeconomic slowdown more efficiently than the SA banks. ¸

Overall, the effect of bank CTA adoption choice on risk taking is likely to be influenced by intrinsic motivation (i.e. opportunistic or non-opportunistic). On one hand, empirical studies have reported consistently that regulatory-constrained banks are more likely to engage in opportunistic behavior (e.g. Ahmed et al. 1999, Efing 2019, Iannotta et al. 2019, Mariathasan and Merrouche 2014). From this perspective, banks that select the CTA might take advantage of the transitional period to take more risks than would be possible under a fully applied IFRS 9 framework. In contrast to this opportunistic view, banks opting for the CTA would use the transitional period to reduce risk taking in order to rebuild the necessary capital resources following a potentially negative impact arising from the application of the IFRS 9 ECL model. Given the competing arguments, we formulate the first sub-hypothesis of H2 (in the null form):

**H2a**: The choice of opting for CTA has no impact on banks' risk taking.

Following the line of reasoning in Section 3.1, we now hypothesise that institutional features influence the relationship between the CTA option and bank risk taking.

We focus on the power of the banking authority because it can influence banks' risk taking. Hoque et al. (2015) argue that the banking authority forms its assessments on bank risk on the basis of proprietary information and might ultimately use its power to affect bank risk taking. For instance, supervisors might adversely influence banks' risk taking by intervening in bank activities and forcing banks to issue risky loans to unqualified borrowers for private or political benefits. Fernández and González (2005) show that in the absence of strict accounting and auditing requirements, powerful supervisory authorities may reduce bank risk taking.

Recent studies have investigated how heterogeneity in the power of the banking authority drives the differences in bank opportunistic behavior that are likely to influence bank risk taking. For instance, Mariathasan and Merrouche (2014) report that a powerful banking authority reduces bank incentives, or ability, to opportunistically underreport RWAs. While acknowledging that banking authorities are influenced by their political connections, García

Osma et al. (2019) show that more politically independent supervisors moderate earnings smoothing in European banks, implying that politics are supportive of earnings smoothing as it creates an appearance of economic health and financial stability. On the other hand, banking supervisors seek an optimal balance between prudential regulation and economically detrimental volatility. As a result of this political influence over banking authorities, we predict that politicians and banking authorities have converged objectives over the CTA since this policy aims at enhancing financial stability upon an important accounting rule change.

Following these arguments, we expect that the risk consequence of CTA adapters varies with the power of the banking authority. We formulate our hypothesis without directional form:

**H2b**: The power of the banking authority affects CTA adopters' risk taking.

## 4. Research design

### *4.1. Sample and data*

Panel A of Table 1 summarises our sample selection process. We obtain our sample by identifying all European listed banks during the years 2016–2019 from S&P Global Market Intelligence.[18] This first screening yielded 174 banks across 26 European countries. We then exclude 23 sub-companies and include only the primary companies because management decisions are likely to be made at the level of the parent companies rather than at subsidiary levels. We also exclude 30 non-IFRS banks. We eliminate bank-year observations with missing data. As a final filter, we retain banks with at least 30 daily returns to compute market risk measures and banks with at least one observation in the pre- and post-IFRS 9 periods. Overall, this selection procedure yielded a final sample of 383 bank-year observations for 101 banks from 19 European countries.

[18] More precisely, we focus on operating banks as of 31.12.2018 from developed European countries that are fully covered by S&P Global Market Intelligence.

Panel B of Table 1 provides a breakdown of the sample composition by country and banks' fundamentals and institutional features: the 'official supervisory power' and the 'rule of law' scores. Our sample is dominated by banks operating in Norway (21) and Italy (16).[19] For the 101 banks that composed our sample, we hand-collected information related to the CTA adaptation decision. Within our sample, 38 banks opted for the CTA effective from the 2018 fiscal year.[20] All sample banks made a one-time decision (to adopt or to opt out) during the investigated IFRS 9 period. We also report that 43 institutions are under the umbrella of the SSM and 57 institutions have experience in advanced credit risk modelling with the use of the IRB approach.

**[Insert Table 1]**

Table 2 presents descriptive statistics of the main variables used in the analysis. The average market beta (*SYSTEMATIC RISK*) is 0.82. During the 2016–2019 period, banks had an average return on assets ($ROA$%) of 0.62%. The proportion of loans ($LOANS$) represents 66% of total assets, of which 6% are non-performing ($NPL$). Banks are well capitalised with an average regulatory capital ratio ($CAPITAL\ RATIO$) of 19%. Banks have a charter value ($CHARTER\ VALUE$) ranging from 0.95 (first quartile) to 1.00 (third quartile) and an average value of 0.98. Banks' average total assets ($SIZE$) is €39.34 billion (calculated as the exponential of 10.58 divided by 1000), indicating that the sample covers relatively large banks.

**[Insert Table 2]**

19 Our inferences remain qualitatively unchanged if we exclude banks operating in Norway or Italy (unreported).

20 Our sample is characterised by 38% of CTA adopters. The EBA reports that 43% of banks out of a sample of 54 (mostly) large banks opted for the CTA across 20 member states in 2018. Using all banks operating in the European Union, the percentage of CTA adopters increases to 57% (EBA 2018).

### *4.2. Empirical models*

We first investigate the determinants for a bank to adopt or opt out of the CTA. We then investigate the consequences of the CTA adoption on bank risk taking.

*Determinant analysis*: This section is exploratory in nature. As described in Sections 3.1 and 3.2, we rely on prior literature and use economic and institutional rationales to identify possible determinants: the neutral or the opportunistic motives. Our model follows previous studies that investigate the determinants of accounting and regulatory choices (e.g. Bischof et al. 2011, Fiechter et al. 2017, 2018). Specifically, we conduct a probit regression to identify the cross-sectional determinants to adopt the CTA at a given point in time. Our base model is as follows:

$$\begin{aligned} CTA\ ADOPTION_{it} = \ & \beta_0 + \beta_1 IRB_{it} \\ & + \beta_2 COST\ TO\ INCOME_{it} + \beta_3 ROA\%_{it} + \beta_4 LOANS_{it} \\ & + \beta_5 CAPITAL\ RATIO_{it} + \beta_6 SIZE_{it} + \beta_7 GDP\%_{it} \\ & + \beta_8 SSM_{it} + \beta_9 SP_{it} + \beta_{10} ROL_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

For CTA adopters, the dependent variable $CTA\ ADOPTION$ equals 1 in the year prior to the adoption of the CTA, and is missing in the years before and after. For CTA non-adopters, $CTA\ ADOPTION$ equals 0 in the fiscal years prior to the effective implementation of IFRS 9 and is missing in the years after. We exclude bank-year observations in the years post-IFRS 9 to ensure that our findings are not driven by the changes in bank fundamentals owing to the adoption of IFRS 9. Our main explanatory variable is $IRB$, an indicator variable that takes the value 1 if bank *i* uses the IRB approach to measure credit risk for estimating regulatory capital and 0 otherwise. In the estimation of Equation (1), $\beta_1 = 0$ would be consistent with H1a as IRB banks would not appear less likely to adopt the CTA.

As suggested by the relevant literature (e.g. Beatty et al. 2002, Bischof et al. 2011, Cucinelli et al. 2018, Fiechter et al. 2017, Lim et al. 2013), we control for several bank-specific fundamentals, such as managerial inefficiency using the ratio of operating expenses to operating income ($COST\ TO\ INCOME$), bank performance using the ratio of net income to total assets in percent ($ROA\%$), bank asset structure and business model using the ratio of total gross loans to total assets ($LOANS$), bank capitalization using the regulatory capital ratio ($CAPITAL\ RATIO$) and bank sophistication using the logarithm of total assets in € millions ($SIZE$). Second, we use the real GDP growth in percent ($GDP\%$) to control for economic conditions in the bank's home country. Finally, we control for two layers of institutional features that are likely to influence bank managerial decisions (e.g. Barth et al. 2004, García Osma et al. 2019, Loipersberger 2018). First, we control for bank-specific regulations related to the SSM, taking the value 1 for a bank categorised as a 'significant' institution in the SSM, and 0 otherwise. Second, we control for country-specific institutional environment. We use the rule of law ($ROL$) from Kaufmann et al. (2011) to capture the overall quality of the legal system, including the quality of contract enforcement, property rights, and the courts. We also consider the level of power of the banking authority − 'official supervisory power' ($SP$) (Barth et al. (2013)) – and use data from the 2019 Bank Regulation and Supervision Survey published by the World Bank. This index captures the power of the supervisor to demand information and/or take legal action against auditors, to restructure troubled banks and to require banks to provision for potential losses.

To test H1b, we include alternatively two additional variables in Equation (1) to capture banks that would operate with tight regulatory constraints under IFRS 9 because of higher credit risk. We first include $DIFF$ measured as the difference between the ratio of common equity to RWAs and the ratio of common equity to total assets. Banks with lower values of $DIFF$ are riskier, as the difference between the two ratios lies in the denominator (i.e. the risk-weighted assets and the total assets). Intuitively, $DIFF$ captures the margin in terms of bank risk exposure as measured by the RWAs between the regulatory capital ratio and the leverage ratio. Our second variable is $NPL$, measured by the ratio of non-performing loans to total gross loans. $NPL$ is a common measure of the level of credit risk in bank loan portfolios (e.g. Beatty and

Liao 2014, Beaver and Venkatachalam 2003, Bushman and Williams 2012, Cucinelli et al. 2018, Gebhardt and Novotny-Farkas 2011). In the estimation of Equation (1) a negative coefficient on $DIFF$ or a positive coefficient on $NPL$ would be consistent with H2b, as banks with a higher level of on-balance sheet credit risk should be more likely to adopt the CTA.

*Bank risk taking*: To investigate how bank risk taking evolved following the CTA adoption, we follow the banking literature (e.g. Flannery and James 1984, Haq and Heaney 2012, Hoque et al. 2015, Kane and Unal 1988) and focus on three measures of bank equity risk: total risk, idiosyncratic risk and systematic risk.

To measure total risk ($TOTAL\ RISK$), we refer to Haq and Heaney (2012) and take the standard deviation of bank stock returns. This measure is estimated each fiscal year for each bank using daily stock return data available in that fiscal year. It is defined as follows:

$$STD\ RISK = \sqrt{\frac{1}{n}\sum_{t=1}^{N}\left(R_{i,t} - \bar{R}_i\right)^2} \qquad (2)$$

where $R_{i,t}$= bank *i* return for day t, $\bar{R}_i$ = the average bank *i* return and *N* = the number of observations. $TOTAL\ RISK$ is the annualised standard deviation of bank stock returns ($STD\ RISK$).

We determine systematic risk and idiosyncratic risk using a market model regression of daily bank returns on daily market portfolio returns (Acharya et al. 2017, Beltratti and Stulz 2012, Bushman et al. 2016, Niu and Richardson 2006). The risk estimates are calculated each fiscal year for each bank using the following regression model:

$$R_{i,t} = \alpha_0 + \beta_{i,t} R\_MSCI_t + \varepsilon_{i,t} \qquad (3)$$

where $R_{i,t}$= bank *i* return for day t, and as the market portfolio return, $R\_MSCI_t$, we follow Beltratti and Stulz (2012) and Iannotta et al. (2019) and use the MSCI World index. Equation (3) is estimated at the end of the fiscal year using one year of data. The residual variance from the market model is used as an estimate of idiosyncratic risk ($IDIOSYNCRATIC\ RISK$)[21] and the equity market beta, $\beta_{i,t}$, is used as a proxy for systematic risk ($SYSTEMATIC\ RISK$).

To generate valid inferences, we implement a DiD design for H2a and H2b to remove the effects of contemporaneous changes in economic conditions affecting bank risk taking from the effects of adopting the CTA. This approach allows for a comparison of the differences in bank risk taking across a treatment group and a control group, before and after the CTA adoption. Specifically, we estimate the following model:

$$\begin{aligned} RISK_{it} = \ & \beta_0 + \beta_1 POST_{it} + \beta_2 CTA\ BANK_{it} + \beta_3 POST_{it} * CTA\ BANK_{it} \\ & + \beta_4 CHARTER\ VALUE_{it} + \beta_5 MB_{it} + \beta_6 ROA\%_{it} + \beta_7 ROA\ SD_{it} \\ & + \beta_8 CAPITAL\ RATIO_{it} + \beta_9 SIZE_{it} + \beta_{10} RISK\ FREE\ RATE_{it} \\ & + \beta_{11} GDP\%_{it} + \beta_{12} SSM_{it} + \beta Fixed\ Effects + \varepsilon_{it} \end{aligned} \tag{4}$$

where $RISK$ is $TOTAL\ RISK$, $IDIOSYNCRATIC\ RISK$ or $SYSTEMATIC\ RISK$. The main explanatory variables of interest are (a) $POST$, an indicator that equals 1 for years from the first fiscal year of IFRS 9 adoption and 0 otherwise, and (b) $CTA\ BANK$, an indicator that equals 1 for banks that opts for the CTA (i.e. CTA adopters) and 0 otherwise (i.e. CTA non-adopters). In the estimation of Equation (4), $\beta_3 \neq 0$ would be consistent with rejecting H2a as it indicates that CTA adopters changed their risk-taking behavior after adoption of the CTA.

To test H2b, we operationalise the power of the banking authority using the country-level 'official supervisory power' index (Barth et al. 2013). Although the Euro area introduced the SSM, this measure plausibly still captures heterogeneity in the power of the banking authority. First, the SSM regulation does not cover all European (member) states and only large banks are monitored in the SSM.[22] Second, some aspects of bank supervision that are not

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21 The variable $IDIOSYNCRATIC\ RISK$ is multiplied by 100 for expositional convenience.

22 Our sample comprises 42.6% of banks in the SSM. Amongst the 38 CTA adopters, 19 banks are operating in the SSM. Amongst those 19 banks, 13 banks are operating in countries characterised by a powerful banking authority as measured with the 2019 'official supervisor power' index (*SP*>=11). The correlation between the indicator variable *SSM* that captures banks in the SSM and *SP* is 0.34. It indicates that SSM banks are operating in countries with a more powerful national banking authority. Loipersberger (2018) shows that the stock market reacted more positively to announcements that regard the implementation of the SSM in countries with a less powerful banking authority suggesting that the SSM in providing the ECB with

deemed essential for financial stability (e.g. consumer protection) remain a task for national supervisors. Third, competent national authorities still have macro-prudential power and can impose stricter prudential requirements to banks in the SSM (Alexander 2016). On the basis of this index, we split the sample according to the median value of the 'official supervisory power' index ($SP$) and estimate Equation (4) for the two groups (i.e. strong supervisory power and weak supervisory power).

As prior research suggests (e.g. Haq and Heaney 2012, Hong and Sarkar 2007, Hoque et al. 2015, Iannotta et al. 2019), we control for characteristics that are potentially associated with bank risk taking. We include bank charter value ($CHARTER\ VALUE$) measured by the sum of the market value of equity and book value of liabilities divided by total assets, bank growth opportunity using the market to book ratio ($MB$), and bank earnings volatility ($ROA\ SD$) measured as the standard deviation of $ROA\%$ over the last five fiscal years. The other bank-level control variables – $CAPITAL\ RATIO$, $ROA\%$, $SIZE$ and $SSM$ – are defined as in Equation (1). We use two variables to control for the economic conditions of bank home country: $GDP\%$ and the risk free rate ($RISK\ FREE\ RATE$), measured by the country-specific money market interest rate as suggested by Hong and Sarkar (2007).

## 5. Results

### *5.1. Main results*

Table 3 reports the probit regression results based on Equation (1). In Column 1, the coefficients on $LOANS$ and $CAPITAL\ RATIO$ are significantly positive and negative at conventional levels, suggesting that banks with a higher proportion of loans are more likely to adopt the CTA. In

supervisory powers over individual banking institutions can influence the financial system stability. Overall, the country-level SP index might capture the effect of the SSM as suggested by the positive correlation between SP and SSM. However, our goal, here, is not to evaluate the efficacy of national versus supra-national supervisors, but rather to investigate the impact of the power of the banking authority as a whole.

other words, traditional lending activities drive the CTA adoption choice. This result is also supportive of the regulatory constraint hypothesis since traditional banks that are characterised by a higher proportion of loans are more likely to have higher regulatory capital charges (e.g. Mariathasan and Merrouche 2014). Thus the CTA would be an advantage for these banks in terms of lessening regulatory constraints. Larger banks are also more likely to adopt the CTA as suggested by the positive and significant coefficient on $SIZE$ at the 1% level. SSM-'significant' institutions are less likely to adopt the CTA ($\beta_8 = -1.77$; $p$-value <1 %), suggesting that SSM banks are relatively well prepared for the adoption of the IFRS 9 ECL model. Interestingly, the coefficient on $SP$ is statistically insignificant, which is consistent with the fact that the CTA adoption choice depends on the bank's own decisions and is independent of the power of the banking authority. On the other hand, banks operating in countries with a higher rule of law are less likely to adopt the CTA. Overall, institutional features in the form of bank-specific regulation through the SSM and the quality of domestic enforcement (measured by the rule of law) seem to influence bank choice to adopt the CTA. In Column 2, the insignificant coefficient on $IRB$ suggests that having experience with advanced credit risk modelling does not significantly influence the bank CTA adoption decision.[23] Notably, in Column 3, the negative and significant coefficient on the interaction term $IRB * SSM$ at the 1% level suggests that IRB-'significant' banks, under the umbrella of the SSM, are less likely to opt for the CTA. This result complements H1a and plausibly supports the TRIM project under the SSM regulation that aimed at strengthening the application of internal models for large European banks. Overall, our result is consistent with the ECB SSM thematic review on IFRS 9 showing that large IRB banks are better prepared for the implementation of IFRS 9 than are less significant institutions (European Central Bank 2017).

[23] To avoid selection bias, in an unreported analysis we exclude 6 IRB banks that adopted the IRB approach concurrently or after the publication of IFRS 9 in 2014. Overall, our conjecture is not affected by the exclusion of those banks.

**[Insert Table 3]**

Table 4 reports the results of investigating how regulatory constraints influence bank choice to adopt the CTA. In Column 1, we report that banks with a lower $DIFF$, a proxy for a bank's distance to regulatory constraints, are more likely to adopt the CTA, as suggested by the negative and marginally significant coefficient on $DIFF$.[24] In Column 2, we report that banks with a higher proportion of non-performing loans are more likely to adopt the CTA as shown by the positive and significant coefficient on $NPL$ at the 1% level. Both results are consistent with H1b, suggesting that banks characterised by tighter regulatory constraints under IFRS 9 are more likely to opt for the CTA owing to the incentive of smoothing the adverse impact of the transition from the incurred loss approach to the ECL model on regulatory capital. Because the IRB approach has been widely criticised as a means of regulatory capital arbitrage (e.g. Behn et al. 2016, Mariathasan and Merrouche 2014), we further investigate whether IRB banks, in particular those facing larger regulatory constraints, opt more aggressively for the CTA. However, the coefficients on the interaction term $DIFF * IRB$ in Column 3 and $NPL * IRB$ in Column 4 are statistically insignificant. This result implies that more regulatory-constrained banks select CTA, regardless of the approach used to measure the RWAs.

**[Insert Table 4]**

Table 5 reports the results of investigating how bank risk taking changed with the CTA adoption. Our main variable of interest is the interaction term $POST * CTA\ BANK$. Both the sign and statistical significance of the coefficients vary with different risk measures. Among the three market-based risk measures, the coefficient on $POST * CTA\ BANK$ is significant at

24 We acknowledge that we already control for bank capitalization with the variable $CAPITAL\ RATIO$. In an unreported robustness test, we exclude the variable $CAPITAL\ RATIO$ and we find that $DIFF$ remains negative and statistically significant at the 1% level. In addition, we replace $DIFF$ by the risk-weight density measured as in Vallascas and Hagendorff (2013) (i.e. using the ratio of the risk-weighted assets over total assets). Again, consistent with the level of bank credit risk influencing the choice to adopt the CTA, we find that the coefficient on the risk-weight density is positive and significant as long as we exclude the variable $CAPITAL\ RATIO$.

the 1% level only in Column 3. The negative sign on this coefficient suggests that CTA adopters decreased their exposure to systematic risk during the transitional period. In Column 1, we show the results investigating the impact on $TOTAL\ RISK$. The coefficient on $POST * CTA\ BANK$ is also negative but not significant. In Column 2, the coefficient on the interaction term $POST * CTA\ BANK$ is close to 0 and insignificant, suggesting that the choice of adopting the CTA does not change bank exposure to diversifiable risk ($IDIOSYNCRATIC\ RISK$).

These results can be explained as arising from two aspects: (1) during our sample period, systematic risk contributed less to total risk (in percent) than idiosyncratic risk[25] and (2) bank exposure to systematic risk is likely to increase significantly the ECLs in case of an adverse economic shock. Based on the Merton (1974) framework, Lönnbark (2017) incorporates economic outlooks to compute ECLs under IFRS 9 over a range of economic scenarios. The model specifies how systematic risk (and more generally the impact of a macro event) influences PD estimates. Importantly, it highlights that idiosyncratic risk is not necessarily independent from systematic factors. Consistent with this view, Bonfim (2009) provides empirical evidence showing that macroeconomic conditions do significantly affect loan default beyond firm-specific factors. Recently, Gaffney and Mccann (2019) report evidence showing that an economic downside shock can substantially increase the switch of financial assets from Stage 1 to Stage 2 under IFRS 9.[26] Overall, because exposure to systematic risk affects banks' overall portfolios and can trigger a large recognition of loan impairment in case of an expected adverse economic situation,[27] banks have incentives to decrease their exposure to this particular

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25 Using Equation (3), we decompose total risk (e.g. Holod et al., 2020) as: $\beta_i^2\sigma_{R\_MSCI}^2+\sigma_\varepsilon^2$. We find that systematic risk ($\beta_i^2\sigma_{R\_MSCI}^2$) represents 12.4% of total risk ($\beta_i^2\sigma_{R\_MSCI}^2+\sigma_\varepsilon^2$). Our inferences are qualitatively similar if we use this decomposition for total risk, systematic risk and idiosyncratic risk in our analysis.

26 This effect is likely to induce a 'cliff effect' in loan impairment (Novotny-Farkas, 2016). Moreover, the authors report that when the economy improves, it is likely that a large amount of loans that were transferred to Stage 2 are re-classified into Stage 1.

27 For instance, this effect is reflected in the UBS financial report of the second quarter 2020: 'Total net credit loss expenses were USD 272 million during the second quarter of 2020, compared with USD 12 million in the prior-year quarter, reflecting net expenses of USD 202 million related to stage 1 and 2 positions and net expenses of USD 70 million related to credit-impaired (stage 3) positions. Stage 1 and 2 net credit loss expenses of USD 202 million were primarily driven by a net expense of USD 127 million from an update to

risk under IFRS 9. On the other hand, exposure to idiosyncratic risk is less likely to affect as much as the volatility of loan impairment.

Overall, our results suggest that CTA adopters commit to decreasing their risk exposure by investing in assets less exposed to non-diversifiable risk. This result should be of interest to policy makers. Acharya et al. (2017) argue that systemic risk arises because banks have incentives to take risks that are borne by all, and therefore financial regulators should 'focus on limiting systemic risk[28] that is, the risk of a crisis in the financial sector and its spillover to the economy at large' (p. 35). Complementary to H1b, these results also suggest that the adoption of the CTA is not fully driven by opportunistic motives.

**[Insert Table 5]**

Panel A of Table 6 reports the results of investigating how the power of the banking authority influences bank risk taking following the adoption of the CTA (H2b). As discussed in Section 3.3, the banking authority is likely to play a role in how the bank reacts to the CTA policy. In fact, empirical studies provide evidence that the power of bank regulators over bank operations influences the degree of discretion used by managers (García Osma et al. 2019, Gebhardt and Novotny-Farkas 2011) as well as bank risk taking (e.g. Fernández and González 2005, Hoque et al. 2015). To investigate H2b, we split the sample into 'strong' versus 'weak' banking authority ($SP$) at the median and then we estimate Equation (4) for each group.[29] Banks operating in countries with an $SP$ score larger than (smaller than or equal to) 10 are classified into the strong (weak) group. In Columns 1 and 2, we find that overall risk slightly decreased for banks operating in countries with a powerful banking authority ($\beta_3 = -0.05$; $p$-value <10 %) while such an effect is not reported for banks operating in countries with a less powerful

the forward-looking scenarios, factoring in updated macroeconomic assumptions to reflect the effects of the COVID-19 pandemic, in particular updated GDP and unemployment assumptions. This also led to exposure movements from stage 1 to stage 2 as probabilities of default increased' (p. 12).

28 Systematic risk exposure can be key to bank contributions to systemic risk (e.g. Iannotta et al. 2019).

29 Alternatively, we also exclude banks operating in countries with an $SP$ score of 11. Our conjecture remains similar if we exclude those observations.

banking authority ($\beta_3 = 0.04$; $p$-value >10 %). In Columns 3 and 4, we do not report any changes in banks' idiosyncratic risk exposure following the adoption of the CTA for both groups. In Columns 5 and 6, results suggest that CTA adopters particularly commit to decreasing their systematic risk taking in countries with a powerful banking authority, as shown by the negative and significant coefficient on $\beta_3$ in Column 5 versus the insignificant coefficient on $\beta_3$ in Column 6.

Alternatively, we test whether the direct supervision power attributed to the ECB in the SSM context corroborates our main findings. We expect that 'significant' institutions in the SSM are more likely to decrease their risk exposures following CTA adoption than other banks that are arguably operating with a more lenient regulatory framework. To investigate this prediction, we split the sample into 'significant' institutions in the SSM ('SI-SSM banks') versus all other banks ('other banks') and then estimate Equation (4) for each group. Panel B of Table 6 presents results consistent with our expectations.

Overall, these results are consistent with the view that the banking authority might influence bank risk taking and the application of new policies. Although empowering the banking authority could hinder bank operations (Barth et al. 2004), our results suggest that powerful banking supervisors can have a positive influence as long as reducing banks' exposure to systematic risk is economically desirable.

**[Insert Table 6]**

### *5.2. Additional analysis*

Since banks' exposure to tail risk was an important driver of the severity of the 2007–2009 financial crisis (e.g. Acharya et al. 2012, Cohen et al. 2014, Laeven et al. 2016) and is not captured by the market beta (e.g. Acharya et al. 2017, De Jonghe 2010), we further investigate whether CTA adopters also decreased their exposure to this specific type of risk. We use the

LRMES (Brownlees and Engle 2017) as a proxy for banks' exposure to tail risk. LRMES is the fraction of the bank's loss when the MSCI World index declines 40% over a six-month window. Intuitively, if one multiplies the LRMES by the market value of equity, it would result in the absolute market value loss due to a systemic financial crisis in millions of euros. LRMES data are collected from V-Lab maintained by the NYU Stern School of Business.[30] We also retrieve the dynamic conditional beta (DCB) (Engle 2016) from V-Lab that is used in the computation of the LRMES. The use of the DCB allows us to assess the sensitivity of our results to an alternative estimate of market beta. [31]

Table 7 presents the results of investigating the impact of the adoption of the CTA on the DCB and LRMES measures. In Column 1, the negative coefficient on the interaction term $POST * CTA\,BANK$ is significant at the 5% level, suggesting that banks do decrease their exposure to systematic risk following the adoption of the CTA. This finding confirms that our main results are robust to alternative measurement of the market beta. In Column 2, we find that CTA adopters are less exposed to tail risk following the adoption of the CTA, as shown by the negative and significant coefficient on the interaction term $POST * CTA\,BANK$ ($\beta_3 = -0.04$; $p$-value <5 %), indicating that the commitment to the CTA policy decreases a bank's contribution to systemic risk. Again, our results remain robust, particularly for banks operating in countries with a strong banking authority, as suggested by the negative and significant coefficients on $\beta_3$ at a conventional level in Columns 3 and 5, while the coefficients on $\beta_3$ in Columns 4 and 6 are insignificant.

Despite the alternative measures of risk, our results remain consistent in indicating that CTA adopters have committed to decreasing their risk taking, at least during the first CTA adoption period covered by our sample.

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[30] The theoretical motivation of the measure is given in Acharya et al. (2012). For more information, please see https://vlab.stern.nyu.edu/welcome/srisk.

[31] The DCB is estimated using generalised autoregressive conditional heteroscedasticity and dynamic conditional correlation (Engle 2016).

**[Insert Table 7]**

### *5.3. Robustness checks*

We also perform a series of sensitivity tests to assess the robustness of our findings. First, in addition to the use of the MSCI World index, [32] we use alternative market portfolios to compute the systematic and idiosyncratic risk measures (i.e. $SYSTEMATIC\ RISK$ and $IDIOSYNCRATIC\ RISK$) that have been used in the literature (e.g. Ferreira and Orbe 2018, Haq and Heaney 2012). Specifically, we use the MSCI Europe index and the Euro Stoxx 50 index. Results displayed in Table 8 confirm our conjecture. Columns 1 and 3 present the results of using the MSCI Europe index as the market portfolio in the estimation of Equation (4), while Columns 2 and 4 show results of the Euro Stoxx 50 index. In Columns 1 and 2, the coefficient on the interaction term $POST * CTA\ BANK$ is insignificant, indicating that CTA adopters do not decrease their exposure to idiosyncratic risk. In Columns 3 and 4, we report that the observed decrease for CTA adopters is not affected by the choice of the market portfolio, as indicated by the negative and significant coefficient on the interaction term $POST * CTA\ BANK$ at a conventional level.

**[Insert Table 8]**

Second, we change the estimation procedure of the risk measures estimated with the market model (i.e. $SYSTEMATIC\ RISK$ and $IDIOSYNCRATIC\ RISK$). Specifically, we change the average value of risk measures over the fiscal period instead of the fiscal year-end value (e.g. Buch et al. 2019, Pagano and Sedunov 2016) and examine the sensitivity of our results to this measurement. Results displayed in Table 9 confirm that our inferences are not affected by such change. Consistently, we report a decrease in bank systematic risk for CTA adopters after the implementation of the CTA. The coefficient on $POST * CTA\ BANK$ is

[32] The use of the MSCI World index in our main tests should not bias our results because European countries did not experience a 'local' crisis during the period 2016-2019 (e.g. Engle et al. 2015).

negative and statistically significant at a conventional level in Columns 2, 4 and 6, in which we use the MSCI World index, the MSCI Europe index and the Euro Stoxx 50 index respectively as the market portfolio in the estimation of Equation (4).

**[Insert Table 9]**

Third, in Section 5.1, we report that CTA adopters and CTA non-adopters differ in their bank-specific characteristics. An alternative is that these bank characteristics, rather than the CTA policy, may contribute to the changes in bank risk taking. To mitigate this concern, we use entropy balancing (Hainmueller 2012). Entropy balancing is a quasi-matching technique that reweights control observations to ensure covariate balance between treatment and control banks. In other words, this technique ensures that CTA adopters and non-adopters are comparable in observable bank-specific variables. Only recently used in the accounting and finance literature (e.g. Boone et al. 2018, Gaver and Utke 2019), this technique has the advantage of preserving the sample size. To implement this procedure,[33] we specify the first and second moment as balance constraints, then match banks on the bank-specific variables (i.e. all control variables specified in Equation (4) except $RISK\ FREE\ RATE$ and $GDP\%$). Columns 1 to 3 in Table 10 show that the results are similar to those in Table 5. That is, we report that CTA adopters decrease their risk exposure to systematic risk but not to idiosyncratic risk and total risk.

Next, we validate the inferences drawn from the DiD approach. Similar to Chen and Garriott (2020), we employ an event-study approach to test the parallel trend assumptions underlying our research design. Specifically, we replace the $POST$ variable with a set of year dummies and re-estimate the model in Column 3, Table 10. Column 4 in Table 10 presents the result of this test using 2016 as a reference year. The coefficient on $2017 * CTA\ BANK$ is

[33] The implementation of this matching procedure is based on the *ebalance* command in Stata, further described in Hainmueller and Xu (2013).

insignificant, while the coefficients on the post-CTA period (i.e. $2018 * CTA\ BANK$ and $2019 * CTA\ BANK$) are negative and statistically significant at a conventional level, which mitigates the concerns about violations of the parallel-trends assumption.

**[Insert Table 10]**

Fourth, to ensure that our results do not capture strategic shifts in business models across CTA adopters and non-adopters unrelated to the CTA policy, we employ an alternative control group of insurance companies. In September 2016, the IASB issued an amendment to IFRS 4 introducing a temporary exemption from the adoption of IFRS 9 until 2021 for insurance companies that have not yet applied IFRS 9. The use of insurance companies as a control group is justifiable since the accounting environment (i.e. the application of IFRS) and the jurisdictional environment between treatment and control firms are constant but differ in the application of the CTA policy.[34] To select our alternative control group, we closely follow the original sample-selection procedure described in Panel A of Table 1.[35] The alternative control group includes 30 insurance companies.

To estimate Equation (4), we replace the variable $CTA\ ADOPTION$ by the variable $BENCHMARK,$ which takes the value 1 for CTA adopters and 0 for insurance companies. Because insurance companies are not subject to the Basel regulation, we follow Iannotta et al. (2019) and replace the variable $CAPITAL\ RATIO$ by $LEVERAGE\ RATIO$. The variable $LEVERAGE\ RATIO$ is the ratio of common equity to total assets. Table 11 reports the results. In Column 1, the coefficient on $POST * BENCHMARK$ is negative and significant. This result

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34 One might argue that the design does not entirely control for contemporaneous changes. Indeed, at the same time, firms reporting under IFRS had to implement IFRS 15. However, that should not influence the results in any analysis for at least three reasons. First, IFRS 15 explicitly excludes from its scope transactions governed by IFRS 9. Second, IFRS 15 does not apply to revenues relating to insurance contracts, lease contracts and financial instruments. Third, a review of banks’ and insurance companies’ annual reports reveals that IFRS 15 had an insignificant effect on financial statements.

35 We restrict our sample to insurance companies that are located within the 19 European countries analyzed in this paper. As additional criteria, we excluded insurance companies involved with banking through subsidiaries, companies that do not qualify for temporary exemption under IFRS 4, and companies that early adopted IFRS 9 with respect to the temporary exemption.

is consistent with the conclusion that CTA adopters decrease their exposure to systematic risk after the adoption of the CTA compared to the alternative control group (i.e. the insurance companies). In Column 2, we use entropy balancing and our conjecture holds.[36] Taken together, the results presented in this section reaffirm our findings and strengthen our confidence in the inferences from earlier analyses.

**[Insert Table 11]**

Finally, to assess whether the statistically significant effect that we report for the decrease in bank risk taking by CTA adopters is obtained by pure chance, we perform a permutation test to assess how likely a significant effect on bank risk taking is reported when the CTA option is randomly assigned. The purpose of this test is to minimise the probability of reporting a decrease (1) in bank systematic risk exposure and (2) in bank contributions to systemic risk while the effect is in fact nonexistent. To do so, we closely follow the methodology applied by Nagler et al. (2020) and use the randomization inference (Heß 2017). The randomization inference tests on systematic risk (LRMES) reveal that our estimated coefficient on the interaction term $POST * CTA\,BANK$ is statistically significant at the 1% (5%) level and larger in magnitude than almost all simulated effect sizes as seen in Figure 1 (Figure 2).

**[Insert Figure 1 & Figure 2]**

## 6. Conclusion

The application of the new ECL model under IFRS 9 and the possibility for banks to adopt in parallel the CTA set out by the BCBS represent the most important novelties in bank accounting

[36] We tried to match the first and second moment for all firm-specific covariates. However, the entropy balance maximum likelihood routine does not converge. Our analysis suggests that the lack of convergence is primarily driven by the earnings variables, which might highlight structural differences in reported earnings across banks and insurance companies. Consequently, we excluded $ROA\%$ and $ROA\ SD$ of the matching procedure.

and Basel regulation since the 2007–2009 financial crisis. The implementation of the new ECL models has raised several concerns (BCBS 2017, Giner and Mora 2019, Novotny-Farkas 2016), which have motivated regulators to provide banks with an opportunity to learn and adapt processes through the CTA policy. The aim of this paper is to investigate whether banks exercise a strategic choice in adopting the CTA.

Drawing on a sample of publicly traded European banks from 2016 to 2019, we provide four novel empirical analyses. First, we specify a determinant model to examine which bank-specific factors affect the CTA adoption choice. We provide consistent evidence that banks that use IRB approach under the SSM are more likely to opt out of the CTA. Second, we report that the CTA adoption choice is determined by regulatory constraints that would arise with the application of the IFRS 9 ECL model. This result raises red flags to regulators, as it could be consistent with opportunistic motives that drive the CTA adoption choice (i.e. to benefit temporarily from reduced capital charges without committing to decrease their risk exposure). Third, we examine banks' risk taking subsequent to the CTA adoption. We find that CTA adopters decreased their exposure to systematic risk during the transitional period. This result provides an encouraging sign that CTA adopters commit to decreasing their risk taking as they aim to meet the regulatory requirement targets. Finally, we show that the decrease in bank risk taking, measured by systematic risk and tail risk, is unambiguous when the banking authority holds more power. Our main findings remain robust to alternative tests. Overall, our study contributes to the literature investigating the impact of the institutional context on bank opportunistic choices and risk taking.

Our findings that (1) more regulatory-constrained banks are more likely to adopt the CTA and that (2) CTA adopters decreased their risk taking after the adoption of the CTA provide timely evidence for the debate on the implementation of the new ECL model. Our hand-collected data on the CTA adoption choice reveal that European banks, in particular non-IRB-

SSM European banks, have signaled their inability to absorb a ‘capital shock’ upon the application of ECL under IFRS 9. This finding is supportive of the need for the transitional policy set out by the BCBS (i.e. the CTA). Our results on the consequences of the CTA adoption on bank risk taking provide two main messages to policy makers. First, the CTA policy in conjunction with IFRS 9 has significantly incentivised banks to decrease their exposure to systematic risk. Second, more scrutiny over bank activities should be prioritised for CTA adopters operating in a weak supervisory environment.

As the present study is the first attempt to investigate bank CTA adoption choice, our empirical analysis is subject to several caveats. First, our institutional setting focuses on the IASB and the BCBS. We do not extensively address the role and function of other regional (i.e. European Banking Authority, EBA) and national regulators (e.g. FINMA [Swiss Financial Market Supervisory Authority] for the Swiss banks). For instance, the EBA intends to monitor the use of transitional provisions (EBA 2018), which will add one more layer of regulatory scrutiny. Second, our analysis addresses the CTA option only as a dummy variable without examining other CTA data, such as the magnitude of the actual transitional adjustment, as mandatorily disclosed under the Pillar 3 framework. For CTA adopters, we do not further distinguish their CTA reporting approach between the static, the dynamic or a combination of the two approaches. Third, this study is the first to specify a model conveying neutral (non-opportunistic) and opportunistic determinants to explain the CTA adoption choice. While our model includes bank-specific factors that are both theoretically justified and empirically consistent, it likely omits other (un)observable determinants.

This study is meant to provide preliminary evidence on the first transitional stage of the IFRS 9 ECL implementation, and deeper analysis is expected. Our study suggests several opportunities for future research. First, researchers could extend the CTA study by mitigating our caveats. Using disaggregated data on IFRS 9 application might provide more insights on banks' incentives to adopt the CTA. Second, as claimed by the EBA, 'given the complexity of the new standard and the challenges still being faced by banks (in particular during the first periods after implementation), it is expected that data accuracy will increase over time' (EBA 2018, p. 4), giving researchers the opportunity to assess how bank risk taking and risk management evolve over time in light of this new accounting paradigm. In addition, the recent COVID-19 crisis has led to several policy changes and it would be interesting to investigate bank reactions to critical events under the new IFRS 9 standard. Our results are built upon a 'normal' period and cannot accommodate such a crisis. Nevertheless, we are confident that our results can provide valuable insights into the effectiveness of the CTA policy.

## References


Acharya, V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, *102*(3), 59–64.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *Review of Financial Studies, 30*(1), 2–47.

Ahmed, A. S., Takeda, C., & Thomas, S. (1999). Bank loan loss provisions: a reexamination of capital management, earnings management and signaling effects. *Journal of Accounting and Economics*, *28*(1), 1–25.

Alexander, K. (2016). The European central bank and banking supervision: The regulatory limits of the single supervisory mechanism. *European Company and Financial Law Review*, *24*(13), 467–494.

Barth, J. R., Caprio, G., & Levine, R. (2004). Bank regulation and supervision: what works best? *Journal of Financial Intermediation*, *13*(2), 205–248.

Barth, J. R., Caprio, G., & Levine, R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011. *Journal of Financial Economic Policy*, *5*(2), 111–219.

Barth, M. E., & Landsman, W. R. (2010). How did financial reporting contribute to the financial crisis? *European Accounting Review*, *19*(3), 399–423.

BCBS. (1996). Amendment to the capital accord to incorporate market risks. In *Bank for International Settlements* (Issue January).

BCBS. (2004). Implementation of Basel II : Practical considerations. In *Bank for International Settlements* (Issue July).

BCBS. (2017). Regulatory treatment of accounting provisions – interim approach and transitional arrangements. In *Bank for International Settlements* (Issue March).

Beatty, A., Chamberlain, S. L., & Magliolo, J. (1995). Managing financial reports of commercial banks: The influence of taxes, regulatory capital, and earnings. *Journal of Accounting Research*, *33*(2), 231–261.

Beatty, A., Ke, B., & Petroni, K. R. (2002). Earnings management to avoid earnings declines across publicly and privately held banks. *The Accounting Review*, *77*(3), 547–570.

Beatty, A., & Liao, S. (2014). Financial accounting in the banking industry: A review of the empirical literature. *Journal of Accounting and Economics*, *58*(2–3), 339–383.

Beaver, W., & Venkatachalam, M. (2003). Differential pricing of components of bank loan fair values. *Journal of Accounting, Auditing & Finance*, *18*(1), 41–68.

Behn, M., Haselmann, R. F. H., & Vig, V. (2016). The limits of model-based regulation. *ECB Working Paper*, *1928*(July 4, 2016).

Beltratti, A., & Stulz, R. M. (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics*, *105*(1), 1–17.

Bischof, J., Brüggemann, U., & Daske, H. (2011). Asset reclassifications and bank recapitalization during the financial crisis. *SSRN Electronic Journal*, *May 31*, *2019*.

Bonfim, D. (2009). Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking & Finance*, *33*(2), 281–299.

Boone, A., Broughman, B., & Macias, A. J. (2018). Shareholder approval thresholds in acquisitions: Evidence from tender offers. *Journal of Corporate Finance*, *53*(December 2018), 225–245.

Brownlees, C., & Engle, R. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *Review of Financial Studies*, *30*(1), 48–79.

Buch, C. M., Krause, T., & Tonzer, L. (2019). Drivers of systemic risk: Do national and European perspectives differ? *Journal of International Money and Finance*, *91*(March 2019), 160–176.

Bushman, R. M., Hendricks, B. E., & Williams, C. D. (2016). Bank competition: Measurement, decision-making, and risk-taking. *Journal of Accounting Research*, *54*(3), 777–826.

Bushman, R. M., & Williams, C. D. (2012). Accounting discretion, loan loss provisioning, and discipline of Banks' risk-taking. *Journal of Accounting and Economics*, *54*(1), 1–18.

Bushman, R. M., & Williams, C. D. (2015). Delayed expected loss recognition and the risk profile of banks. *Journal of Accounting Research*, *53*(3), 511–553.

Chen, M., & Garriott, C. (2020). High-frequency trading and institutional trading costs. *Journal of Empirical Finance*, *56*(March 2020), 74–93.

Cheng, M., Dhaliwal, D. S., & Neamtiu, M. (2011). Asset securitization, securitization recourse, and information uncertainty. *The Accounting Review*, *86*(2), 541–568.

Cohen, L. J., Cornett, M. M., Marcus, A. J., & Tehranian, H. (2014). Bank earnings management and tail risk during the financial crisis. *Journal of Money, Credit and Banking*, *46*(1), 171–197.

Collins, J. H., Shackelford, D. A., & Wahlen, J. M. (1995). Bank differences in the coordination of regulatory capital, earnings, and taxes. *Journal of Accounting Research*, *33*(2), 263–291.

Cucinelli, D., Battista, M. L. Di, Marchese, M., & Nieri, L. (2018). Credit risk in European banks: The bright side of the internal ratings based approach. *Journal of Banking & Finance*, *93*(August 2018), 213–229.

Curcio, D., De Simone, A., & Gallo, A. (2017). Financial crisis and international supervision: New evidence on the discretionary use of loan loss provisions at Euro Area commercial banks. *The British Accounting Review*, *49*(2), 181–193.

De Jonghe, O. (2010). Back to the basics in banking? A micro-analysis of banking system stability. *Journal of Financial Intermediation*, *19*(3), 387–417.

EBA. (2018). First observations on the impact and implementation of IFRS 9 by EU Institutions. *European Banking Authority*.

Efing, M. (2019). Reaching for yield in the ABS market: Evidence from German bank investments. *Review of Finance*, *rfz013*(August 2019), 1–31.

Engle, R. (2016). Dynamic conditional beta. *Journal of Financial Econometrics*, *14*(4), 643–667.

Engle, R., Jondeau, E., & Rockinger, M. (2015). Systemic risk in Europe. *Review of Finance*, *19*(1), 145–190.

Ernst & Young. (2018). IFRS 9 expected credit loss: Making sense of the transition impact. *EY*.

European Central Bank. (2017). SSM thematic review on IFRS 9. *ECB*.

European Central Bank. (2018). Status update on TRIM: overview of outcome of general topics review and interim update on preliminary results of credit risk on-site investigations. *ECB*.

Fernández, A. I., & González, F. (2005). How accounting and auditing systems can counteract risk-shifting of safety-nets in banking: Some international evidence. *Journal of Financial Stability*, *1*(4), 466–500.

Ferreira, E., & Orbe, S. (2018). Why are there time-varying comovements in the European stock market? *The European Journal of Finance*, *24*(10), 828–848.

Fiechter, P., Halberkann, J., & Meyer, C. (2018). Determinants and consequences of a voluntary turn away from IFRS to Local GAAP: Evidence from Switzerland. *European Accounting Review*, *27*(5), 955–989.

Fiechter, P., Landsman, W. R., Peasnell, K., & Renders, A. (2017). The IFRS option to reclassify financial assets out of fair value in 2008: the roles played by regulatory capital and too-important-to-fail status. *Review of Accounting Studies*, *22*(4), 1698–1731.

Financial Stability Forum. (2009). Addressing procyclicality in the financial system. *FSB*.

Flannery, M. J., & James, C. M. (1984). The effect of interest rate changes on the common stock returns of financial institutions. *The Journal of Finance*, *39*(4), 1141–1153.

Gaffney, E., & Mccann, F. (2019). The cyclicality in SICR: mortgage modelling under IFRS 9. *European Systemic Risk Board (Working Paper Series)*, *May*(92), 1–26.

García Osma, B., Mora, A., & Porcuna-Enguix, L. (2019). Prudential supervisors' independence and income smoothing in European banks. *Journal of Banking & Finance*, *102*(May 2019), 156–176.

Gaver, J. J., & Utke, S. (2019). Audit quality and specialist tenure. *The Accounting Review*, *94*(3), 113–147.

Gebhardt, G., & Novotny-Farkas, Z. (2011). Mandatory IFRS adoption and accounting quality of european banks. *Journal of Business Finance & Accounting*, *38*(3–4), 289–333.

Giner, B., & Mora, A. (2019). Bank loan loss accounting and its contracting effects: the new expected loss models. *Accounting and Business Research*, *0*(0), 1–27.

Gruenberger, D. (2012). A rating migration model for loan loss provisions and credit cycles. *SSRN Electronic Journal*, *January 17, 2013*, 1–32.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. *Political Analysis*, *20*(1), 25–46.

Hainmueller, J., & Xu, Y. (2013). ebalance : A Stata package for entropy balancing. *Journal of Statistical Software*, *54*(7), 1–18.

Haq, M., & Heaney, R. (2012). Factors determining European bank risk. *Journal of International Financial Markets, Institutions and Money*, *22*(4), 696–718.

Hashim, N., Li, W., & O'Hanlon, J. (2016). Expected-loss-based accounting for impairment of financial instruments: The FASB and IASB proposals 2009–2016. *Accounting in Europe*, *13*(2), 229–267.

Heß, S. (2017). Randomization inference with Stata: A guide and software. *The Stata Journal*, *17*(3), 630–651.

Holod, D., Kitsul, Y., & Torna, G. (2020). Market risk-based capital requirements, trading activity, and bank risk. *Journal of Banking & Finance*, *112*(March 2020), 1–16.

Hong, G., & Sarkar, S. (2007). Equity systematic risk (beta) and its determinants. *Contemporary Accounting Research*, *24*(2), 423–466.

Hoque, H., Andriosopoulos, D., Andriosopoulos, K., & Douady, R. (2015). Bank regulation, risk and return: Evidence from the credit and sovereign debt crises. *Journal of Banking & Finance*, *50*(January 2015), 455–474.

Iannotta, G., Pennacchi, G., & Santos, J. A. C. (2019). Ratings-based regulation and systematic risk incentives. *Review of Financial Studies*, *32*(4), 1374–1415.

Kane, E. J., & Unal, H. (1988). Change in market assessments of deposit-institution riskiness. *Journal of Financial Services Research*, *1*(3), 207–229.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. *Hague Journal on the Rule of Law*, *3*(2), 220–246.

Kim, M.-S., & Kross, W. (1998). The impact of the 1989 change in bank capital standards on loan loss provisions and loan write-offs. *Journal of Accounting and Economics*, *25*(1), 69–99.

Laeven, L., Ratnovski, L., & Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking and Finance*, *69*(August 2016), S25–S34.

Leventis, S., Dimitropoulos, P. E., & Anandarajan, A. (2011). Loan loss provisions, earnings management and capital management under IFRS: The case of EU commercial banks. *Journal of Financial Services Research*, *40*(1), 103–122.

Lim, C. Y., Lim, C. Y., & Lobo, G. J. (2013). IAS 39 reclassification choice and analyst earnings forecast properties. *Journal of Accounting and Public Policy*, *32*(5), 342–356.

Liu, C., & Ryan, S. G. (2006). Income smoothing over the business cycle: Changes in banks' coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom. *The Accounting Review*, *81*(2), 421–441.

Loipersberger, F. (2018). The effect of supranational banking supervision on the financial sector: Event study evidence from Europe. *Journal of Banking & Finance*, *91*(June 2018), 34–98.

Lönnbark, C. (2017). Setting scenarios and assessing scenario probabilities under IFRS 9 accounting. *SSRN Electronic Journal*, *August 22*, 1–11.

Mariathasan, M., & Merrouche, O. (2014). The manipulation of basel risk-weights. *Journal of Financial Intermediation*, *23*(3), 300–321.

Mascia, D. V., Keasey, K., & Vallascas, F. (2019). Internal rating based models: Do they matter for bank profit margins? *SSRN Electronic Journal*, *June 26, 2019*, 1–58.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

Moyer, S. E. (1990). Capital adequacy ratio regulations and accounting choices in commercial banks. *Journal of Accounting and Economics*, *13*(2), 123–154.

Nagler, M., Piopiunik, M., & West, M. R. (2020). Weak markets, strong teachers: Recession at career start and teacher effectiveness. *Journal of Labor Economics*, *38*(2), 453–500.

Niu, F. F., & Richardson, G. D. (2006). Are securitizations in substance sales or secured borrowings? Capital-market evidence. *Contemporary Accounting Research*, *23*(4), 1105–1133.

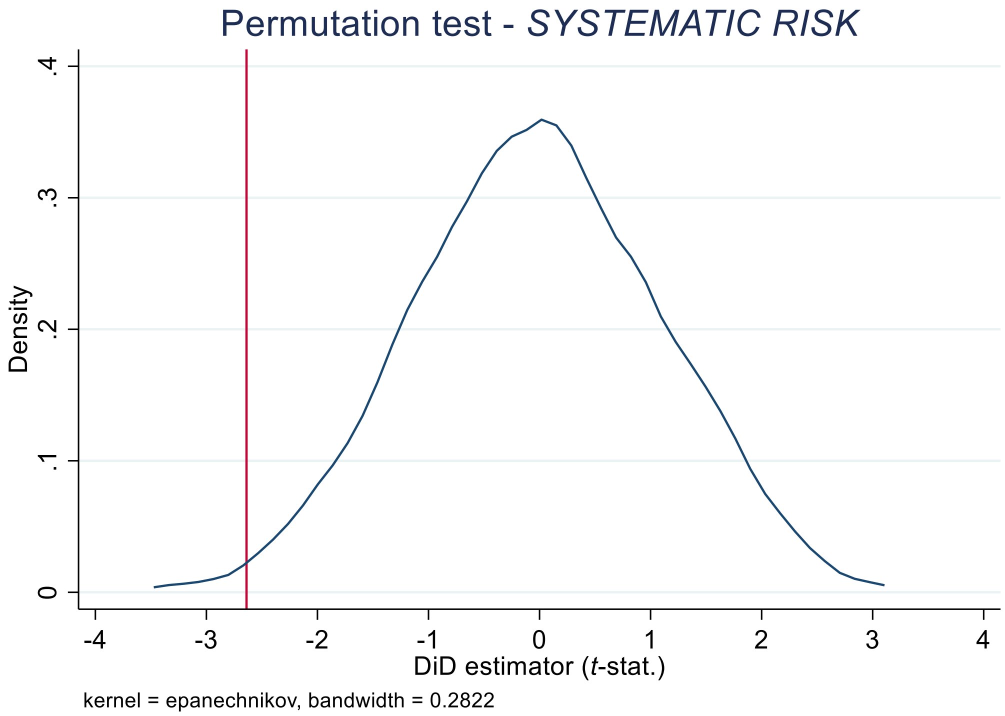
Novotny-Farkas, Z. (2016). The interaction of the IFRS 9 expected loss approach with supervisory rules and implications for financial stability. *Accounting in Europe*, *13*(2), 197–227.

Pagano, M. S., & Sedunov, J. (2016). A comprehensive approach to measuring the relation between systemic risk exposure and sovereign debt. *Journal of Financial Stability*, *23*(April 2016), 62–78.

Ryan, S. G. (2011). Financial reporting for financial instruments. *Foundations and Trends® in Accounting*, *6*(3–4), 187–354.

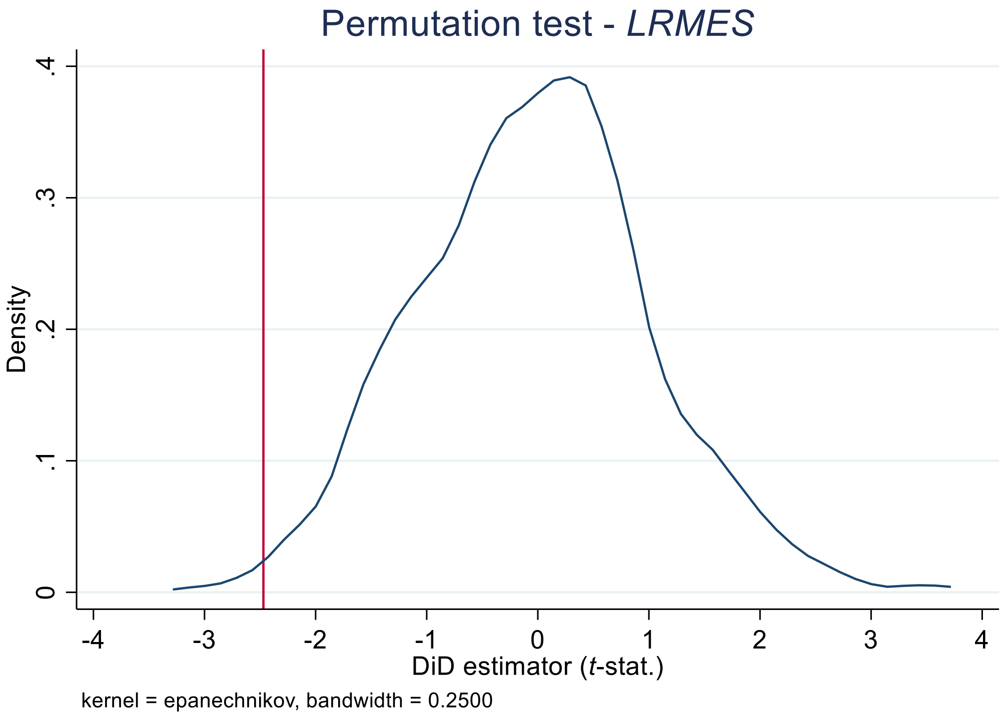
Vallascas, F., & Hagendorff, J. (2013). The risk sensitivity of capital requirements: Evidence from an international sample of large banks. *Review of Finance*, *17*(6), 1947–1988.

**Figure 1:** Placebo test—Systematic risk




Shown is a kernel density plot of a randomization inference test for simulated CTA adoption effect on systematic risk using 500 repetitions. The vertical line shows the CTA adoption effect (the robust $t$-statistic clustered by bank associated to the coefficient $POST * CTA\ BANK$) from Column 3 in Table 5.

**Figure 2:** Placebo test—Long-run marginal expected shortfall




Shown is a kernel density plot of a randomization inference test for simulated CTA adoption effect on LRMES using 500 repetitions. The vertical line shows the CTA adoption effect (the robust $t$-statistic clustered by bank associated to the coefficient $POST * CTA\ BANK$) from Column 2 in Table 7.

**Table 1:** Sample

| **Panel A: Sample selection** | Less | Remaining banks | Bank-year observations |
|---|---|---|---|
| Universe of listed European banks in SP Global Market Intelligence | | 174 | |
| Less sub-companies | −23 | 151 | |
| Less non-IFRS banks | −30 | 121 | |
| Less bank-year observations with missing data | −13 | 108 | 399 |
| Less bank-year observations with less than 30 daily returns to compute market risk measures | 0 | 108 | 395 |
| Less banks with not at least one observation in the pre- and post-IFRS 9 period | −7 | 101 | 383 |

**Panel B: Number of banks, Bank-years observations by country & Institutional features**

| | | Banks characteristics | | | | Institutional features | |
|---|---|---|---|---|---|---|---|
| Countries | Bank-year observations | # Banks | #CTA banks | # SSM banks | # IRB banks | *SP* | *ROL* |
| Austria | 19 | 5 | 0 | 3 | 3 | 11 | 1.84 |
| Belgium | 4 | 1 | 0 | 1 | 1 | 11 | 1.39 |
| Cyprus | 3 | 1 | 1 | 1 | 0 | 6 | 0.88 |
| Czech Republic | 4 | 1 | 0 | 0 | 0 | 9 | 1.09 |
| Denmark | 20 | 5 | 3 | 0 | 4 | 8 | 1.91 |
| Finland | 12 | 3 | 1 | 1 | 3 | 12 | 2.04 |
| France | 15 | 4 | 0 | 4 | 4 | 11 | 1.43 |
| Germany | 22 | 6 | 0 | 4 | 4 | 12 | 1.66 |
| Greece | 19 | 5 | 5 | 4 | 2 | 10 | 0.15 |
| Ireland | 8 | 2 | 1 | 2 | 2 | 8.5 | 1.55 |
| Italy | 58 | 16 | 11 | 11 | 8 | 13 | 0.29 |
| Malta | 11 | 3 | 1 | 1 | 0 | 13 | 1.08 |
| Netherlands | 10 | 3 | 0 | 2 | 3 | 11 | 1.87 |
| Norway | 83 | 21 | 1 | 0 | 7 | 8 | 2.01 |
| Portugal | 4 | 1 | 1 | 1 | 1 | 14 | 1.13 |
| Spain | 31 | 8 | 4 | 8 | 6 | 12 | 0.97 |
| Sweden | 11 | 3 | 0 | 0 | 3 | 14 | 1.97 |
| Switzerland | 15 | 4 | 1 | 0 | 1 | 14 | 1.94 |
| United Kingdom | 34 | 9 | 8 | 0 | 5 | 11 | 1.71 |

The 'official supervisory power' index ($SP$) is drawn from Barth et al. (2013) and is measured using the 2019 Bank Regulation and Supervision Survey from the World Bank. The rule of law index ($ROL$) from the World Bank captures the perception of the extent to which agents have confidence in and abide by the rules of society. The values displayed in the last column represent the average $ROL$ for the period 2016-2019 (using beginning-of-year estimates)

**Table 2:** Descriptive statistics

| Variable | N | Mean | SD | Q1 | Median | Q3 |
|---|---|---|---|---|---|---|
| *CTA ADOPTION* | 153 | 0.22 | 0.42 | 0.00 | 0.00 | 0.00 |
| *TOTAL RISK* | 383 | 0.32 | 0.18 | 0.21 | 0.26 | 0.35 |
| *IDIOSYNCRATIC RISK* | 383 | 0.05 | 0.08 | 0.02 | 0.02 | 0.04 |
| *SYSTEMATIC RISK* | 383 | 0.82 | 0.55 | 0.32 | 0.80 | 1.15 |
| *CTA BANK* | 383 | 0.37 | 0.48 | 0.00 | 0.00 | 1.00 |
| *IRB* | 383 | 0.57 | 0.50 | 0.00 | 1.00 | 1.00 |
| *DIFF* | 382 | 0.11 | 0.05 | 0.08 | 0.10 | 0.13 |
| *NPL* | 383 | 0.06 | 0.10 | 0.01 | 0.03 | 0.06 |
| *COST TO INCOME* | 383 | 0.60 | 0.15 | 0.48 | 0.58 | 0.71 |
| *ROA%* | 383 | 0.62 | 0.65 | 0.32 | 0.58 | 0.94 |
| *ROA SD* | 383 | 0.40 | 0.61 | 0.12 | 0.19 | 0.43 |
| *MB* | 383 | 0.96 | 0.77 | 0.55 | 0.83 | 1.08 |
| *LOANS* | 383 | 0.66 | 0.18 | 0.56 | 0.69 | 0.81 |
| *CHARTER VALUE* | 383 | 0.98 | 0.07 | 0.95 | 0.98 | 1.00 |
| *CAPITAL RATIO* | 383 | 0.19 | 0.04 | 0.16 | 0.18 | 0.21 |
| *SIZE* | 383 | 10.58 | 2.19 | 9.06 | 10.62 | 12.37 |
| *RISK FREE RATE* | 383 | 0.07 | 0.66 | −0.33 | −0.31 | 0.72 |
| *GDP%* | 383 | 1.96 | 1.32 | 1.25 | 1.73 | 2.39 |
| *SSM* | 383 | 0.42 | 0.49 | 0.00 | 0.00 | 1.00 |
| *ROL* | 383 | 1.41 | 0.67 | 0.98 | 1.69 | 1.97 |
| *DCB* | 260 | 1.12 | 0.47 | 0.85 | 1.11 | 1.36 |
| *LRMES* | 260 | 0.42 | 0.14 | 0.35 | 0.43 | 0.50 |

This table provides descriptive statistics for variables used in this study. All variables except dummies are winsorised at the 1 and 99 percentiles. The sample includes up to 101 banks for the period 2016-2019. See Appendix 1 for variable definitions.

**Table 3:** Bank institutional factors that may affect the CTA adoption choice: experience in advanced credit risk modelling (IRB) and the single supervisory mechanism (SSM)

| | Base Model | IRB | IRB & SSM |
|---|---|---|---|
| | (1) | (2) | (3) |
| Dependent Variable: *CTA ADOPTION* | | | |
| *IRB* | | −0.04 | 0.85 |
| | | (−0.09) | (1.51) |
| *IRB*SSM* | | | −2.24*** |
| | | | (−3.02) |
| *COST TO INCOME* | 1.68 | 1.69 | 2.08 |
| | (1.26) | (1.25) | (1.44) |
| *ROA%* | −0.07 | −0.07 | 0.20 |
| | (−0.28) | (−0.28) | (0.75) |
| *LOANS* | 2.81*** | 2.84*** | 3.23*** |
| | (2.69) | (2.63) | (2.91) |
| *CAPITAL RATIO* | −12.04** | −11.97** | −16.14*** |
| | (−2.09) | (−2.05) | (−2.82) |
| *SIZE* | 0.39*** | 0.39*** | 0.43*** |
| | (3.44) | (2.81) | (3.07) |
| *GDP%* | 0.20** | 0.21** | 0.23** |
| | (2.05) | (2.05) | (2.17) |
| *SSM* | −1.77*** | −1.76*** | −0.38 |
| | (−3.51) | (−3.51) | (−0.56) |
| *SP* | −0.13 | −0.13 | −0.09 |
| | (−1.16) | (−1.16) | (−0.86) |
| *ROL* | −1.42*** | −1.41*** | −1.46*** |
| | (−4.23) | (−4.25) | (−4.43) |
| *Constant* | −1.88 | −1.98 | −3.02 |
| | (−0.86) | (−0.81) | (−1.18) |
| Pseudo-R2 | 0.32 | 0.32 | 0.38 |
| N | 153 | 153 | 153 |

Columns 1 to 3 of the table report the estimation of variations of Equation (1) investigating whether banks with advanced credit risk modelling are more likely to adopt the CTA. On the basis of the definition of *CTA ADOPTION* in Section 4.2, the sample comprises bank-year observations one year prior to the CTA adoption choice for CTA adopters and bank-year observations prior to IFRS 9 adoption for CTA non-adopters. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses. See Appendix 1 for variable definitions.

**Table 4:** CTA and regulatory capital constraints, measured by the difference between the ratio of common equity to RWAs and the ratio of common equity to total assets (DIFF) as well as the proportion in non-performing loans (NPL), and both factors interacted with the IRB adoption choice

| | DIFF | NPL | DIFF & IRB | NPL & IRB |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable: *CTA ADOPTION* | | | | |
| *DIFF* | −10.13* | | −13.13** | |
| | (−1.87) | | (−2.28) | |
| *NPL* | | 8.98*** | | 9.25*** |
| | | (3.69) | | (3.32) |
| *IRB* | | | −0.64 | 0.13 |
| | | | (−0.71) | (0.23) |
| *DIFF*IRB* | | | 8.71 | |
| | | | (1.07) | |
| *NPL*IRB* | | | | −0.51 |
| | | | | (−0.16) |
| *COST TO INCOME* | 1.61 | 1.71 | 1.39 | 1.70 |
| | (1.15) | (1.18) | (0.96) | (1.16) |
| *ROA%* | −0.12 | 0.41 | −0.13 | 0.42 |
| | (−0.45) | (1.24) | (−0.49) | (1.27) |
| *LOANS* | 2.11* | 2.82** | 1.95 | 2.80** |
| | (1.73) | (2.33) | (1.47) | (2.24) |
| *CAPITAL RATIO* | −3.37 | −13.73** | −5.21 | −14.01** |
| | (−0.45) | (−2.46) | (−0.68) | (−2.45) |
| *SIZE* | 0.40*** | 0.50*** | 0.36** | 0.49*** |
| | (3.35) | (3.93) | (2.40) | (3.30) |
| *GDP%* | 0.19* | 0.03 | 0.18* | 0.03 |
| | (1.93) | (0.33) | (1.66) | (0.27) |
| *SSM* | −1.82*** | −1.93*** | −1.83*** | −1.95*** |
| | (−3.60) | (−3.86) | (−3.57) | (−3.73) |
| *SP* | −0.09 | −0.02 | −0.10 | −0.02 |
| | (−0.80) | (−0.20) | (−0.91) | (−0.16) |
| *ROL* | −1.46*** | −0.59 | −1.56*** | −0.61 |
| | (−4.08) | (−1.41) | (−4.29) | (−1.46) |
| *Constant* | −2.32 | −5.58** | −0.90 | −5.44** |
| | (−0.95) | (−2.29) | (−0.31) | (−2.12) |
| Pseudo-R2 | 0.35 | 0.40 | 0.35 | 0.40 |
| N | 153 | 153 | 153 | 153 |

Columns 1 to 4 of the table report the estimation of variations of Equation (1) investigating whether regulatory-constrained banks are more likely to adopt the CTA. Based on the definition of *CTA ADOPTION* in Section 4.2, the sample comprises bank-year observations one year prior to the CTA adoption choice for CTA adopters and bank-year observations prior to IFRS 9 adoption for CTA non-adopters. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses. See Appendix 1 for variable definitions.

**Table 5:** CTA and bank risk taking: total risk, idiosyncratic risk and systematic risk

| | Total risk | Idiosyncratic risk | Systematic risk |
|---|---|---|---|
| | (1) | (2) | (3) |
| Dependent Variable: | *TOTAL RISK* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* |
| *POST*CTA BANK* | −0.03 | −0.01 | −0.25*** |
| | (−1.43) | (−0.60) | (−2.64) |
| *CHARTER VALUE* | 0.15 | 0.13 | 0.65 |
| | (0.18) | (0.29) | (0.28) |
| *MB* | −0.14** | −0.06* | 0.03 |
| | (−2.11) | (−1.87) | (0.20) |
| *ROA%* | −0.06** | −0.03* | −0.13 |
| | (−1.99) | (−1.69) | (−1.55) |
| *ROA SD* | 0.03 | 0.00 | 0.28* |
| | (1.51) | (0.11) | (1.87) |
| *CAPITAL RATIO* | 0.56 | 0.32 | 2.00* |
| | (1.50) | (1.63) | (1.72) |
| *SIZE* | 0.09 | 0.04 | 0.76*** |
| | (1.08) | (0.92) | (2.76) |
| *RISK FREE RATE* | 0.03 | 0.03** | 0.26** |
| | (0.95) | (2.07) | (2.50) |
| *GDP%* | 0.00 | −0.00 | 0.05 |
| | (0.31) | (−0.41) | (1.24) |
| *SSM* | −0.06*** | −0.02 | 0.02 |
| | (−2.68) | (−1.50) | (0.07) |
| *Constant* | −0.70 | −0.43 | −8.21** |
| | (−0.57) | (−0.66) | (−2.09) |
| Time FE | yes | yes | yes |
| Bank FE | yes | yes | yes |
| Adj-R2 | 0.72 | 0.58 | 0.74 |
| N | 383 | 383 | 383 |

Columns 1 to 3 of the table report the estimation of variations of Equation (4) investigating changes in bank risk a consequence of the CTA adoption. Bank risk exposure is measured as *TOTAL RISK*, *IDIOSYNCRATIC RISK* or *SYSTEMATIC RISK*. The sample comprises all available bank-year observations of 101 banks from 2016 to 2019. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses See Appendix 1 for variable definitions.

**Table 6:** CTA and bank risk taking: total risk, idiosyncratic risk and systematic risk—The power of the banking authority

**Panel A: Official Supervisory Power**

| | Total risk | | Idiosyncratic risk | | Systematic risk | |
|---|---|---|---|---|---|---|
| Supervisory power | Strong | Weak | Strong | Weak | Strong | Weak |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dependent Variable: | *TOTAL RISK* | *TOTAL RISK* | *IDIOSYNCRATIC RISK* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* | *SYSTEMATIC RISK* |
| *POST*CTA BANK* | −0.05* | 0.04 | −0.01 | 0.01 | −0.22** | −0.00 |
| | (−1.94) | (0.62) | (−0.75) | (0.38) | (−2.00) | (−0.02) |
| *CHARTER VALUE* | −0.27 | 2.11 | −0.10 | 1.24 | −0.32 | 2.82 |
| | (−0.30) | (0.99) | (−0.21) | (1.02) | (−0.12) | (0.40) |
| *MB* | −0.11* | −0.20* | −0.05* | −0.11* | 0.06 | 0.49 |
| | (−1.84) | (−1.98) | (−1.68) | (−1.77) | (0.33) | (1.32) |
| *ROA%* | −0.09** | −0.07 | −0.04 | −0.03 | −0.19** | −0.09 |
| | (−2.02) | (−1.24) | (−1.62) | (−1.04) | (−2.44) | (−0.41) |
| *ROA SD* | 0.01 | 0.08 | −0.01 | 0.03 | 0.09 | 0.84** |
| | (0.22) | (1.46) | (−0.59) | (1.04) | (0.84) | (2.56) |
| *CAPITAL RATIO* | 0.59 | 1.90 | 0.29 | 1.19 | 0.61 | 5.98* |
| | (1.38) | (1.46) | (1.36) | (1.55) | (0.42) | (1.78) |
| *SIZE* | −0.02 | 0.21* | −0.02 | 0.12* | 0.31 | 0.76 |
| | (−0.16) | (1.82) | (−0.42) | (1.86) | (0.97) | (1.46) |
| *RISK FREE RATE* | 0.11** | 0.07 | 0.05** | 0.06 | 0.45** | −0.04 |
| | (2.23) | (0.70) | (2.47) | (1.07) | (2.03) | (−0.16) |
| *GDP%* | 0.01 | −0.01 | 0.00 | 0.00 | 0.15** | −0.05 |
| | (0.71) | (−0.45) | (0.21) | (0.39) | (2.47) | (−1.14) |
| *SSM* | −0.05 | −0.10 | −0.01 | −0.07* | −0.51*** | 0.46 |
| | (−1.65) | (−1.59) | (−0.95) | (−1.97) | (−4.60) | (1.40) |
| *Constant* | 0.89 | −3.80 | 0.45 | −2.37 | −2.05 | −10.75 |
| | (0.54) | (−1.44) | (0.50) | (−1.55) | (−0.43) | (−1.24) |
| Time FE | yes | yes | yes | yes | yes | yes |
| Bank FE | yes | yes | yes | yes | yes | yes |
| Adj-R2 | 0.65 | 0.79 | 0.46 | 0.70 | 0.73 | 0.78 |
| N | 246 | 137 | 246 | 137 | 246 | 137 |

**Table 6**: (Continued)

| **Panel B: Significant Institutions (SI) under the SSM** | | | | | | |
|---|---|---|---|---|---|---|
| | Total risk | | Idiosyncratic risk | | Systematic risk | |
| SSM | SI-SSM banks | Other banks | SI-SSM banks | Other banks | SI-SSM banks | Other banks |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dependent Variable: | *TOTAL RISK* | *TOTAL RISK* | *IDIOSYNCRATIC RISK* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* | *SYSTEMATIC RISK* |
| *POST*CTA BANK* | −0.02 | −0.01 | −0.00 | 0.01 | −0.30** | −0.14 |
| | (−0.42) | (−0.66) | (−0.07) | (0.69) | (−2.20) | (−1.23) |
| Control Variables | yes | yes | yes | yes | yes | yes |
| Time FE | yes | yes | yes | yes | yes | yes |
| Bank FE | yes | yes | yes | yes | yes | yes |
| Adj-R2 | 0.71 | 0.72 | 0.51 | 0.68 | 0.74 | 0.72 |
| N | 163 | 220 | 163 | 220 | 163 | 220 |

Columns 1 to 6 of both panels in the table report the estimation of variations of Equation (4) investigating how the power of the bank authority influences changes in bank risk as a consequence of the CTA adoption. Bank risk exposure is measured as *TOTAL RISK*, *IDIOSYNCRATIC RISK* or *SYSTEMATIC RISK*. The sample comprises all available bank-year observations of up to 101 banks from 2016 to 2019. In Panel A, we measure the power of the banking authority using the 'official supervisory power' index ($SP$) drawn from Barth et al. (2013) and measured using the 2019 Bank Regulation and Supervision Survey from the World Bank. In Panel B, we measure the power of the banking authority as whether the bank is a SSM-'significant' institution. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust $t$-statistics clustered by bank are shown in parentheses See Appendix 1 for variable definitions.

**Table 7:** CTA and bank risk taking: systematic risk and tail risk

| | DCB & LRMES | | DCB | | LRMES | |
|---|---|---|---|---|---|---|
| Supervisory power | | | Strong | Weak | Strong | Weak |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dependent Variable: | *DCB* | *LRMES* | *DCB* | *DCB* | *LRMES* | *LRMES* |
| *POST*CTA BANK* | −0.18** | −0.04** | −0.20** | −0.41 | −0.05*** | −0.08 |
| | (−2.43) | (−2.47) | (−2.53) | (−1.71) | (−2.68) | (−1.49) |
| *CHARTER VALUE* | −0.43 | −0.12* | −0.04 | −1.06*** | −0.01 | −0.25*** |
| | (−1.65) | (−1.77) | (−0.34) | (−2.95) | (−0.52) | (−3.26) |
| *MB* | 0.60 | 0.10 | 0.37 | 11.56 | 0.08 | 2.06 |
| | (0.23) | (0.18) | (0.14) | (1.02) | (0.16) | (0.80) |
| *ROA%* | −0.08 | −0.02 | 0.01 | −1.02 | 0.00 | −0.17 |
| | (−0.68) | (−0.64) | (0.07) | (−1.13) | (0.08) | (−0.83) |
| *ROA SD* | −0.16* | −0.03* | −0.21* | −0.17 | −0.05* | −0.04 |
| | (−1.81) | (−1.88) | (−1.78) | (−1.27) | (−1.97) | (−1.22) |
| *CAPITAL RATIO* | −0.03 | −0.02 | −0.04 | −0.26 | −0.02** | −0.05 |
| | (−0.61) | (−1.33) | (−0.74) | (−1.07) | (−2.12) | (−0.92) |
| *SIZE* | −2.46* | −0.58 | −1.40 | −1.58 | −0.31 | −0.82 |
| | (−1.70) | (−1.59) | (−1.06) | (−0.17) | (−0.90) | (−0.40) |
| *RISK FREE RATE* | 0.42* | 0.07 | −0.02 | 0.84* | −0.02 | 0.16 |
| | (1.81) | (1.39) | (−0.10) | (1.90) | (−0.36) | (1.68) |
| *GDP%* | 0.27 | 0.07* | 0.49** | 0.07 | 0.12** | 0.02 |
| | (1.54) | (1.94) | (2.08) | (0.23) | (2.39) | (0.25) |
| *SSM* | −0.05* | −0.01** | 0.07* | −0.11*** | 0.01 | −0.03*** |
| | (−1.77) | (−2.02) | (1.69) | (−3.19) | (1.44) | (−3.26) |
| *Constant* | −3.30 | −0.27 | 1.44 | −16.80 | 0.66 | −2.79 |
| | (−0.76) | (−0.28) | (0.34) | (−1.60) | (0.71) | (−1.20) |
| Time FE | yes | yes | yes | Yes | yes | yes |
| Bank FE | yes | yes | yes | Yes | yes | yes |
| Adj-R2 | 0.71 | 0.81 | 0.73 | 0.70 | 0.84 | 0.76 |
| N | 260 | 260 | 199 | 61 | 199 | 61 |

Columns 1 to 6 in the table report the estimation of variations of Equation (4) investigating changes in bank risk as a consequence of the CTA adoption (including the influence of the power of the banking authority on this relationship). Bank risk exposure is measured as either dynamic conditional beta (*DCB*) or the long-run marginal expected shortfall (*LRMES*). The sample comprises all available bank-year observations of up to 101 banks from 2016 to 2019. The sample size decreases because the V-Lab does not cover all the banks included in our main analysis. We measure the power of the banking authority using the 'official supervisory power' index (*SP*) drawn from Barth et al. (2013) and measured using the 2019 Bank Regulation and Supervision Survey from the World Bank. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses. See Appendix 1 for variable definitions.

**Table 8:** Sensitivity analysis to the choice of the market portfolio

| Market portfolio | MSCI Europe | Euro Stoxx | MSCI Europe | Euro Stoxx |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable: | *IDIOSYNCRATIC RISK* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* | *SYSTEMATIC RISK* |
| *POST*CTA BANK* | −0.01 | −0.00 | −0.15** | −0.15** |
| | (−0.49) | (−0.31) | (−2.17) | (−2.56) |
| *CHARTER VALUE* | 0.15 | 0.13 | 1.15 | −0.55 |
| | (0.33) | (0.31) | (0.53) | (−0.37) |
| *MB* | −0.07* | −0.06* | −0.11 | 0.03 |
| | (−1.90) | (−1.93) | (−0.65) | (0.25) |
| *ROA%* | −0.03* | −0.02 | −0.08 | −0.05 |
| | (−1.68) | (−1.51) | (−1.47) | (−0.99) |
| *ROA SD* | 0.00 | −0.00 | 0.12 | 0.12 |
| | (0.05) | (−0.04) | (1.50) | (1.43) |
| *CAPITAL RATIO* | 0.30 | 0.32* | 0.96 | 1.34 |
| | (1.61) | (1.70) | (1.00) | (1.57) |
| *SIZE* | 0.04 | 0.02 | 0.53*** | 0.39** |
| | (0.96) | (0.68) | (2.77) | (2.22) |
| *RISK FREE RATE* | 0.03* | 0.03** | 0.13 | 0.44*** |
| | (1.94) | (2.03) | (1.63) | (5.12) |
| *GDP%* | −0.00 | −0.00 | 0.03 | −0.00 |
| | (−0.33) | (−0.56) | (1.10) | (−0.07) |
| *SSM* | −0.02 | −0.02 | 0.04 | −0.03 |
| | (−1.65) | (−1.50) | (0.18) | (−0.46) |
| *Constant* | −0.45 | −0.32 | −5.95** | −3.17 |
| | (−0.71) | (−0.53) | (−2.15) | (−1.36) |
| Time FE | yes | yes | yes | yes |
| Bank FE | yes | yes | yes | yes |
| Adj-R2 | .59 | .57 | 0.77 | 0.75 |
| N | 383 | 383 | 383 | 383 |

Columns 1 to 4 of the table report the estimation of variations of Equation (4) investigating changes in bank risk a consequence of the CTA adoption. Bank risk exposure is measured as *IDIOSYNCRATIC RISK* or *SYSTEMATIC RISK*. Bank risk exposure is computed using the MSCI Europe index or the Euro Stoxx 50 index as the market portfolio. The sample comprises all available bank-year observations of 101 banks from 2016 to 2019. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses See Appendix 1 for variable definitions.

**Table 9.** Sensitivity analysis to using the average risk estimates from the market model over the fiscal year

| Market portfolio | MSCI World | | MSCI Europe | | Euro Stoxx | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Dependent Variable: *Average* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* |
| *POST*CTA BANK* | −0.03 | −0.39*** | −0.03 | −0.25*** | −0.03 | −0.27*** |
| | (−1.56) | (−3.60) | (−1.59) | (−3.65) | (−1.44) | (−3.52) |
| *CHARTER VALUE* | 0.05 | −0.50 | 0.05 | −0.41 | 0.05 | 1.02 |
| | (0.09) | (−0.22) | (0.09) | (−0.27) | (0.10) | (0.68) |
| *MB* | −0.03 | 0.04 | −0.03 | −0.03 | −0.03 | −0.14 |
| | (−0.82) | (0.24) | (−0.79) | (−0.28) | (−0.79) | (−1.47) |
| *ROA%* | −0.01 | −0.02 | −0.01 | −0.04 | −0.01 | −0.00 |
| | (−0.36) | (−0.32) | (−0.41) | (−1.00) | (−0.30) | (−0.06) |
| *ROA SD* | 0.01 | 0.18 | 0.01 | 0.15 | 0.01 | 0.10 |
| | (0.43) | (1.28) | (0.50) | (1.54) | (0.45) | (1.10) |
| *CAPITAL RATIO* | 0.76** | 3.33*** | 0.79** | 2.89*** | 0.77** | 2.27*** |
| | (2.08) | (2.86) | (2.08) | (3.47) | (2.08) | (2.74) |
| *SIZE* | 0.11* | 0.63** | 0.11* | 0.48*** | 0.10 | 0.49*** |
| | (1.68) | (2.57) | (1.69) | (2.77) | (1.56) | (3.05) |
| *RISK FREE RATE* | 0.02 | 0.15 | 0.02 | 0.21*** | 0.02 | 0.05 |
| | (1.59) | (1.43) | (1.61) | (2.72) | (1.59) | (0.70) |
| *GDP%* | −0.00 | 0.01 | −0.00 | 0.02 | −0.00 | 0.03 |
| | (−0.14) | (0.15) | (−0.11) | (0.39) | (−0.16) | (0.59) |
| *SSM* | −0.01 | 0.21** | −0.01 | 0.14** | −0.01 | 0.21 |
| | (−0.40) | (2.05) | (−0.38) | (2.28) | (−0.35) | (1.31) |
| *Constant* | −1.24 | −5.99 | −1.29 | −4.59* | −1.17 | −5.70** |
| | (−1.24) | (−1.63) | (−1.25) | (−1.78) | (−1.17) | (−2.37) |
| Time FE | yes | yes | yes | Yes | yes | yes |
| Bank FE | yes | yes | yes | Yes | yes | yes |
| Adj-R2 | 0.48 | 0.76 | 0.48 | 0.79 | 0.47 | 0.80 |
| N | 383 | 383 | 383 | 383 | 383 | 383 |

Columns 1 to 6 of the table report the estimation of variations of Equation (4) investigating changes in bank risk a consequence of the CTA adoption. Bank risk exposure is measured as *IDIOSYNCRATIC RISK* or *SYSTEMATIC RISK* using average values over the fiscal year. Bank risk exposure is computed using the MSCI Europe index, the MSCI Europe index or the Euro Stoxx 50 index as the market portfolio. The sample comprises all available bank-year observations of 101 banks from 2016 to 2019. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses See Appendix 1 for variable definitions.

**Table 10:** Entropy balancing and the parallel-trends assumption

| | Total risk | Idiosyncratic risk | Systematic risk | Systematic risk |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Dependent Variable: | *TOTAL RISK* | *IDIOSYNCRATIC RISK* | *SYSTEMATIC RISK* | *SYSTEMATIC RISK* |
| *POST*CTA BANK* | 0.04 | 0.03 | −0.24** | |
| | (0.61) | (0.79) | (−2.10) | |
| *2017*CTA BANK* | | | | −0.31 |
| | | | | (−1.65) |
| *2018*CTA BANK* | | | | −0.39* |
| | | | | (−1.97) |
| *2019*CTA BANK* | | | | −0.36** |
| | | | | (−2.47) |
| *CHARTER VALUE* | 1.94 | 1.10 | 1.05 | 1.35 |
| | (1.35) | (1.39) | (0.24) | (0.31) |
| *MB* | −0.29*** | −0.14** | −0.19 | −0.24 |
| | (−2.72) | (−2.38) | (−0.53) | (−0.70) |
| *ROA%* | −0.13** | −0.07** | −0.07 | −0.05 |
| | (−2.51) | (−2.34) | (−0.83) | (−0.54) |
| *ROA SD* | −0.06 | −0.05* | 0.37** | 0.41** |
| | (−1.43) | (−1.83) | (2.12) | (2.31) |
| *CAPITAL RATIO* | 2.70** | 1.76*** | −0.97 | −2.31 |
| | (2.51) | (2.78) | (−0.43) | (−0.90) |
| *SIZE* | −0.04 | −0.04 | 0.73** | 0.74** |
| | (−0.27) | (−0.43) | (2.17) | (2.22) |
| *RISK FREE RATE* | 0.20* | 0.14** | 0.18 | 0.17 |
| | (1.78) | (2.22) | (1.23) | (1.08) |
| *GDP%* | −0.01 | −0.01 | 0.08 | 0.06 |
| | (−0.95) | (−1.57) | (1.37) | (1.02) |
| *SSM* | −0.19*** | −0.11*** | 0.43*** | 0.45*** |
| | (−3.49) | (−3.48) | (2.85) | (2.97) |
| *Constant* | −1.08 | −0.68 | −8.00 | −8.11 |
| | (−0.50) | (−0.59) | (−1.53) | (−1.60) |
| Time FE | yes | yes | yes | yes |
| Bank FE | yes | yes | yes | yes |
| Adj-R2 | 0.75 | 0.62 | 0.81 | 0.81 |
| N | 383 | 383 | 383 | 383 |

Columns 1 to 4 of the table report the estimation of variations of Equation (4) investigating changes in bank risk a consequence of the CTA adoption by employing entropy balancing. Bank risk exposure is measured as *TOTAL RISK*, *IDIOSYNCRATIC RISK* or *SYSTEMATIC RISK*. The sample comprises all available bank-year observations of 101 banks from 2016 to 2019. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses See Appendix 1 for variable definitions.

**Table 11:** Alternative control group

| | DID | Entropy balancing |
|---|---|---|
| | (1) | (2) |
| Dependent Variable: | *SYSTEMATIC RISK* | *SYSTEMATIC RISK* |
| *POST*BENCHMARK* | −0.26** | −0.28** |
| | (−2.43) | (−2.22) |
| *CHARTER VALUE* | 1.32 | −3.29 |
| | (0.82) | (−0.45) |
| *MB* | −0.24 | −0.06 |
| | (−1.06) | (−0.11) |
| *ROA%* | −0.05 | 0.12 |
| | (−1.11) | (1.02) |
| *ROA SD* | 0.14 | 0.30 |
| | (1.39) | (1.36) |
| *LEVERAGE RATIO* | 3.08 | 0.48 |
| | (1.04) | (0.13) |
| *SIZE* | 0.43* | 0.41 |
| | (1.90) | (1.11) |
| *RISK FREE RATE* | 0.49*** | 0.86** |
| | (2.97) | (2.63) |
| *GDP%* | −0.01 | 0.05 |
| | (−0.24) | (0.65) |
| *SSM* | 0.33** | 0.51** |
| | (2.43) | (2.50) |
| *Constant* | −4.93** | −0.64 |
| | (−2.06) | (−0.11) |
| Time FE | yes | yes |
| Bank FE | yes | yes |
| Adj-R2 | 0.69 | 0.65 |
| N | 258 | 258 |

Columns 1 to 2 of the table report the estimation of variations of Equation (4) investigating changes in bank risk a consequence of the CTA adoption (by employing entropy balancing in column 2). Bank risk exposure is measured as *SYSTEMATIC RISK*. The sample comprises all available bank-year observations of 38 CTA adopters and 30 insurance companies from 2016 to2019. $BENCHMARK$ takes the value 1 for CTA adopters and 0 for insurance companies. $LEVERAGE\ RATIO$ is the ratio of common equity over total assets. *, **, and *** represent significance levels of 0.10, 0.05, and 0.01 (two-tailed), respectively. Robust *t*-statistics clustered by bank are shown in parentheses See Appendix 1 for variable definitions.

**Appendix 1:** Variable definitions

| | |
|---|---|
| *CTA ADOPTION* | Equals 1 in the year prior the adoption of the capital transitional arrangements, and is missing in the years before and after the year of the adoption. For non-adopters, *CTA ADOPTION* equals 0 throughout the pre-IFRS 9 period and is missing in the post-IFRS 9 period (hand-collected) |
| *TOTAL RISK* | Annualised standard deviation of the bank's daily stock return |
| *IDIOSYNCRATIC RISK* | Variance of the residuals from the market model multiplied by 100 |
| *SYSTEMATIC RISK* | Banks' systematic risk measured as the bank's market beta by regressing the bank's stock daily return on that of the market (MSCI world) over a one year period (i.e. the market model). |
| *CTA BANK* | Takes the value of 1 through the entire sample period if a bank opts for the capital transitional arrangements and 0 otherwise (hand-collected) |
| *POST* | Indicator variable that equals one for years 2018 and 2019, and 0 otherwise |
| *IRB* | Takes the value of 1 through the entire sample period if a bank applies the IRB approach and 0 otherwise (hand-collected) |
| *DIFF* | (Common equity divided over risk-weighted assets) minus (common equity over total assets) |
| *NPL* | Ratio of non-performing loans to total gross loans |
| *COST TO INCOME* | Operating expense over operating income |
| *ROA%* | Ratio of net income to beginning-of-year total assets in percent |
| *ROA SD* | Standard deviation of *ROA%* over the last 5 years |
| *MB* | Price to book value (common equity) per share |
| *LOANS* | Ratio of total gross loans to total assets |
| *CHARTER VALUE* | (Market value of equity plus the book value of liabilities) divided by total assets |
| *CAPITAL RATIO* | Total regulatory capital ratio |
| *SIZE* | Logarithm of total assets in € millions |
| *RISK FREE RATE* | Money Market Interest Rate (%) |
| *GDP%* | Real GDP growth in % |
| *SSM* | Indicator variable that equals one for banks categorised as a significant institution under the single supervisory mechanism, and 0 otherwise (hand-collected) |
| *SP* | Official supervisory power captures the power of the supervisor to demand information and/or to take legal actions against auditors, to restructure troubled banks and to require banks to provision for potential losses (World Bank) |
| *ROL* | The rule of law index (estimate) from the World Bank capturing perceptions of the extent to which agents have confidence in and abide by the rules of society. In our analyses, we employ the beginning-of-year estimate. |
| *DCB* | Dynamic conditional beta retrieved from V-Lab |
| *LRMES* | Long-run marginal expected shortfall retrieved from V-Lab |

Data are retrieved from S&P Global Market Intelligence unless explicitly mentioned.

**Appendix 2:** List of acronyms

| | |
|---|---|
| ASC | Accounting Standards Codification |
| BCBS | Basel Committee on Banking Supervision |
| CAR | Capital Adequacy Ratio |
| CECL | Current Expected Credit Loss |
| CTA | Capital Transitional Arrangement |
| DCB | Dynamic Conditional Beta |
| DiD | Difference-in-Differences |
| EAD | Exposure At Default |
| EBA | European Banking Authority |
| ECB | European Central Bank |
| ECL | Expected Credit Loss |
| FASB | Financial Accounting Standards Board |
| GDP | Gross Domestic Product |
| IAS | International Accounting Standard |
| IASB | International Accounting Standards Board |
| IFRS | International Financial Reporting Standards |
| IRB | Internal Ratings Based |
| LGD | Loss Given Default |
| LRMES | Long-Run Marginal Expected Shortfall |
| NPL | Non-Performing Loans |
| PD | Probability of Default |
| RWAs | Risk-Weighted Assets |
| SA | Standardised Approach |
| SSM | Single Supervisory Mechanism |
| TRIM | Targeted Review of Internal Models |