DEUTSCHE BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 07/2023

The rollout of internal credit risk models: Implications for the novel partial-use philosophy

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Internet http://www.bundesbank.de

ISBN 978–3–95729–938–3
ISSN 2749–2958

Non-technical summary

Research Question

Recently, one of the most fundamental requirements for banks using the internal ratings-based approach (IRBA) to determine their regulatory capital charges for credit risk was the obligation to roll it out across all exposures subject to credit risk. However, with the novel partial-use philosophy, the Basel Committee on Banking Supervision initiates a paradigm shift, allowing banks to permanently apply the IRBA for only parts of their exposures. The objective of this paper is to reveal what the effects of the novel partial-use philosophy may be. For that purpose, we examine, first, the trade-off for banks between costs of the IRBA rollout and a possible reduction in risk-weighted assets (RWA). Second, we analyze whether the risk management of banks improves with a progressing rollout.

Contribution

The topic of the gradual introduction of internal risk models in general and, in particular, of the IRBA rollout in banks has so far hardly been discussed in the literature. However, this topic is important in the light of the novel partial-use philosophy. Hesitant rollouts with little progress over time, as have often been observed, could possibly give rise to opportunistic behavior of banks and may ultimately lead to insufficient bank capital. This, in turn, may exacerbate the already existing criticism toward internal risk models for determining regulatory capital charges.

Results

We demonstrate that, on the one hand, banks' annual cost growth rate is lower for banks with a hesitant rollout compared to similar banks with a clear rollout progress over time. On the other hand, we observe that the first IRBA implementation steps lead to the greatest RWA reductions for banks. Thus, the incentive to incur costs to fully carry out the rollout diminishes with higher rollout levels. We also provide initial evidence that bank risk management, as measured by loan portfolio quality and credit risk prediction accuracy, improves with a progressing IRBA rollout.

Nichttechnische Zusammenfassung

Fragestellung

Bisher galt für Banken, die ihre regulatorischen Eigenmittelanforderungen für das Kreditrisiko anhand des auf internen Ratings basierenden Ansatzes (IRBA) bestimmen, die grundlegende Anforderung, diesen Ansatz für alle dem Kreditrisiko unterliegenden Positionen anzuwenden. Die neue Partial-Use-Philosophie des Baseler Ausschusses für Bankenaufsicht leitet nun einen Paradigmenwechsel ein, der es den Banken ermöglicht, den IRBA dauerhaft nur für einen Teil ihrer Kreditportfolios einzuführen. Unsere Analyse identifiziert mögliche Auswirkungen dieser neuen Partial-Use-Philosophie. Hierfür untersuchen wir zum einen den Zielkonflikt für Banken zwischen den Kosten einer Implementierung des IRBA (dem sog. „Rollout“) und einer dadurch möglichen Reduktion von risikogewichteten Aktiva (RWA). Zum anderen analysieren wir, ob sich das Risikomanagement der Banken mit einem fortschreitenden Rollout verbessert.

Beitrag

Die Thematik der schrittweisen Einführung bankinterner Risikomodelle im Allgemeinen und insbesondere des IRBA-Rollouts in Banken wird in der Literatur bisher kaum diskutiert. Dieses Thema ist jedoch vor dem Hintergrund der neuen Partial-Use-Philosophie von Bedeutung. So könnten womöglich zögerliche Rollouts mit wenig Fortschritt im Zeitverlauf, wie häufig beobachtet, auf opportunistisches Verhalten durch Banken zurückgehen und letztlich auch zu unzureichenden Eigenmitteln führen. Dies wiederum könnte die bereits bestehende Kritik an internen Risikomodellen zur Bestimmung der regulatorischen Eigenmittelanforderungen noch verstärken.

Ergebnisse

Wir zeigen, dass zum einen die jährliche Wachstumsrate der Kosten für Banken mit zögerlichem Rollout niedriger ist als bei ähnlichen Banken mit im Zeitverlauf deutlichem Fortschritt bei der Einführung des IRBA. Zum anderen beobachten wir, dass die ersten Implementierungsschritte des IRBA in Banken zu den größten RWA-Reduktionen führen. Der Anreiz, Kosten für die vollständige Implementierung des IRBA zu tragen, nimmt somit mit fortschreitendem Rollout ab. Darüber hinaus liefern wir erste Hinweise dafür, dass sich das Bankrisikomanagement, gemessen an der Kreditportfolioqualität und der Kreditrisikoprognosegenauigkeit, mit einem fortschreitenden Rollout verbessert.

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The Rollout of Internal Credit Risk Models: Implications for the Novel Partial-Use Philosophy *

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Abstract

The novel partial-use philosophy by the Basel Committee on Banking Supervision initiates a paradigm shift for banks, allowing them to permanently partially apply the internal ratings-based approach (IRBA) and not having to fully roll it out across the overall bank anymore. This raises the questions of how banks roll out the IRBA and what the consequences of partial use may be. We reveal that banks with little rollout progress over time can keep annual cost growth comparatively low. Furthermore, we find that the first implementation steps lead to the greatest risk-weighted assets reductions, which indicates that banks benefit from "cherry-picking" by not fully rolling out the IRBA. However, we also provide tentative evidence that bank risk management improves with a progressing rollout.

Keywords: Costs, Internal Ratings-Based Approach, Partial Use, Risk Management, Risk-Weighted Assets, Rollout

JEL Classification: G21, G28, G32

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*We thank participants at the 2021 Research Workshop at the Deutsche Bundesbank, the 2019 Paris Financial Management Conference, the 2019 German Finance Association Annual Meeting, the 2019 European Accounting Association Annual Congress, the 2018 German Academic Association for Business Research Annual Conference, the 2018 Financial Management Association Annual Meeting, the 2018 Doctoral Seminar at the German Finance Association Annual Meeting, the 2017 Doctoral Workshop sponsored by Unicredit at the University of Oldenburg, the Finance Center Münster Research Seminar, as well as Stefan Blochwitz, Victoria Böhnke, Philipp Klein, Andreas grosse Kohorst, Michael Kötter, Thomas Langer, Andreas Pfingsten, Jan Riepe, Nicolas Rudolf, Christian Schlam, Judith C. Schneider, Michael Semenischev, Heiko Vay, Lisa Van den Branden, Anna Sophie Wupper, as well as an anonymous referee for helpful comments and suggestions. The views expressed are those of the authors and do not necessarily reflect those of the Deutsche Bundesbank or the Eurosystem.

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1 Introduction

Recently, one of the most important requirements for using the internal ratings-based approach (IRBA) was the obligation to apply it not only partially but at the overall bank level. To prevent "cherry-picking",[1] banks applying the IRBA obtained only in exceptional cases, and exclusively for immaterial business units and insignificant asset classes, the supervisory approval to also use the standardized approach (SA) (BCBS, 2004). Conversely, as of 2022, the novel permanent partial-use philosophy by the BCBS will allow banks to roll out the IRBA across exposures within a single asset class[2] (BCBS, 2017). This constitutes a so far little discussed paradigm shift for banks. With this novel BCBS philosophy in place, the European Banking Authority (EBA) argued that a permanent partial use is reasonable because for some portfolios, especially those less suited for modeling, IRBA implementation may be counterproductive from a supervisory perspective and costly for the banking system (EBA, 2019).

So far, in most member states of the Basel Committee on Banking Supervision (BCBS), including all European countries, but excluding the United States, supervisors permitted banks to adopt a phased rollout across all exposures within a reasonably short period only, generally referred to as temporary partial use (BCBS, 2004). The BCBS does not further specify what it expects by a reasonably short period. However, national supervisory authorities sometimes define an entry and exit threshold for the IRBA rollout, as well as a period in which the latter has to be achieved. Nevertheless, many banks remained at low levels of partial use for several years. For instance, the "United Kingdom's initial policy for rollout was that IRB[A] banks could have no more than 15 percent of their portfolio on standardized approach within three years of first use. Currently, for the major banks the range on IRB[A] is 67 percent to 89 percent"[3] (IMF, 2011).

Hesitant rollouts with little progress over time give rise to "cherry-picking" opportu-

[1] Under "cherry-picking", we understand that banks only roll out the IRBA on portfolios that promise RWA reductions, while they keep less promising portfolios under the standardized approach. In contrast, "regulatory arbitrage" refers to strategically exploiting modeling choices.

[2] Asset classes are banks, corporates, specialized lending, corporate purchased receivables, qualifying revolving retail exposures, retail residential mortgages, other retail, and retail purchased receivables (BCBS, 2017).

[3] The United Kingdom adopted the IRBA under Basel II in 2007.

nities and may ultimately lead to insufficient bank capital. This, in turn, may exacerbate the already growing criticism toward internal credit risk models, allowing to engage in regulatory arbitrage by underreporting risk-weighted assets (RWA) (e.g., Vallascas and Hagendorff, 2013; Mariathasan and Merrouche, 2014). A recent initiative by the EBA to "repair"[4] internal models picks up this criticism and addresses concerns about undue RWA variability between banks to restore trust in those models (EBA, 2019). However, in the context of these discussions as well as in the literature in general, the IRBA rollout remains largely unexplored.

The objective of this paper is to reveal what the consequences of the novel partial-use philosophy may be. Due to the low levels of partial use, the clear distinction between a temporary and a permanent partial use was obscured. Banks were not prevented from a permanent partial use already recently, which provides us with the possibility to derive implications from our analysis for the novel partial-use philosophy by the BCBS. Therefore, we examine, first, the trade-off for banks between costs and RWA reductions during the rollout process and second, whether bank risk management improves with a progressing rollout. For this purpose, we construct a unique sample of 386 large banks covering the period from 2007 to 2016.[5] This period is very suitable to analyze the rollout process since most countries adopted the IRBA under Basel II in 2007 and accordingly many banks started to roll out the IRBA in the subsequent years. By manually screening banks' annual reports and pillar 3 reports, we collect the exact IRBA coverage ratios for each bank in each year, which are the percentages of the loan portfolio covered by internal credit risk models.

Based on this rich and comprehensive sample, we investigate the phased rollout using dynamic panel data models to address the likely endogeneity between bank risks and the IRBA coverage ratio. Piecewise regression models are considered to detect possible non-linear relationships. In addition to investigating the effects of a phased rollout, we divide the banks in our sample into two groups depending on whether they show a more or less hesitant rollout process and conduct several propensity score matching analyses. While a phased rollout is intended originally by supervisors, this does not apply to a

[4] The EBA introduced the term "repair", referring to the recent IRBA revisions (EBA, 2019).

[5] The phase-in period for the output floor starts only in 2022 and thus does not affect our findings.

hesitant rollout. Therefore, undesirable effects arising from either dimension may be addressed differently by supervisors, which demonstrates the necessity of disentangling those two dimensions in our analyses.

In a nutshell, we provide evidence that, on the one hand, the annual cost growth rate is lower for banks with a hesitant rollout. On the other hand, as anticipated above, we observe that the first IRBA implementation steps lead to the greatest RWA reductions. Thus, the incentive to incur costs to fully carry out the rollout diminishes with higher rollout levels. However, we also demonstrate that bank risk management, as measured by loan portfolio quality and credit risk prediction accuracy, improves with a progressing rollout. These findings persist under a broad variety of robustness checks.

The remainder of this paper is organized as follows. Section 2 reviews the literature and develops our hypotheses. Section 3 describes the data sources and sample selection procedure. Section 4 presents our identification strategy and defines the variables used. Section 5 explains the empirical design and Section 6 discusses our findings. Section 7 contains robustness checks and Section 8 concludes.

2 Literature review and hypotheses development

2.1 Internal credit risk models as drivers for RWA variability

The literature on internal credit risk models as drivers for RWA variability can broadly be categorized into two main subgroups. Whereas some papers explore RWA heterogeneity at the loan level, most studies address this topic at the bank level.

At the loan level, Behn et al. (2022) find that internal credit risk models significantly underestimate actual default rates. At the same time, their study indicates that banks price loans originated under the IRBA with higher interest rates compared to those originated under the SA. This reveals that they are aware of the true loan risk and price those loans accordingly. Additionally, Berg and Koziol (2017) highlight wide variations in default probability estimates across German banks applying the IRBA. They provide evidence that weakly capitalized banks report lower default probabilities for comparable loans than strongly capitalized ones. In accordance, Plosser and Santos

(2018), using data on U.S. syndicated loans, investigate bank incentives to bias their internal credit risk model estimates. They show that weakly capitalized banks aiming to improve their capital ratios are more likely to engage in regulatory arbitrage. Building on that and exploring interdependencies between different asset categories, Abbassi and Schmidt (2018) reveal that banks report lower risk weights for credit risk exposures when facing higher risk exposures in the trading book, particularly when regulatory capital constraints are binding.

At the bank level and based on an international sample of large banks, Le Leslé and Avramova (2012) point to significant RWA divergences across and within jurisdictions. Additionally, Vallascas and Hagendorff (2013) provide evidence for an asymmetric risk sensitivity of bank RWA densities under the IRBA. According to their findings, banks with riskier asset portfolios, measured by asset volatility, especially reduce their capital requirements through IRBA adoption. Furthermore, Mariathasan and Merrouche (2014) demonstrate a decline in bank RWA densities following the IRBA introduction, which is even more pronounced in weak supervisory regimes and for weakly capitalized banks. Beltratti and Paladino (2016) show that the cost of equity is a significant factor in explaining RWA reductions, suggesting that banks optimize their capital ratios particularly when equity capital is costly. Montes et al. (2018) provide more recent evidence for a negative relationship between the IRBA use and RWA densities after controlling for portfolio and bank characteristics.

In summary, all these findings support the view that some banks strategically exploit discretionary leeway provided by the IRBA framework, such as modeling choices, to optimize their own fund requirements.[6] Banks can estimate main risk parameters themselves since the IRBA introduction in the course of the Basel II implementation in 2007, which substantially raised the level of sophistication and complexity for both banks and supervisors.[7] Thus, information asymmetries between banks and supervisors regarding

[6] This is also evident in other internal models. For instance, Dal Borgo (2022) show that banks opt for an internal model for deposit maturity to measure interest rate risk if they can obtain capital savings, considering that the adoption is costly.

[7] In contrast to the IRBA, the SA relies on external ratings to determine risk weights. Banks can seek approval either for the foundation IRBA or the advanced IRBA. The foundation IRBA only allows for internally estimating probabilities of default while the advanced IRBA permits banks to additionally estimate the loss given default and the exposure at default (BCBS, 2004).

internal credit risk models are intentionally high (Mariathasan and Merrouche, 2014; Colliard, 2019). Due to the opaqueness and complexity of internal credit risk models, IRBA rollout is considered to be particularly challenging to supervise, while at the same time, it provides opportunities to engage in "cherry-picking" (e.g., IMF, 2011). Aiming at reducing "cherry-picking" opportunities, banks have to present an IRBA implementation plan, which is verified and monitored by the national supervisory authorities. This plan specifies the phased rollout across different loan portfolios over time by determining fixed and reasonable time periods with regard to the IRBA implementation of all types of exposures (EBA, 2016).

However, none of the studies presented above consider the effects of the rollout of internal credit risk models. To the best of our knowledge, Cannata et al. (2012), Bruno et al. (2015), and Ferri and Pesic (2017) are the only papers so far indirectly addressing the rollout process.[8] All three studies focus on disentangling the IRBA rollout process from RWA variability. For instance, Cannata et al. (2012) use a sample of 36 European banks and find that the "SA share", computed as the ratio of the exposure at default (EAD) under the SA divided by the total EAD, explains a large part of observed interbank RWA dispersion. Bruno et al. (2015) and Ferri and Pesic (2017) consider temporary partial use by applying the IRBA coverage as independent variable for explaining RWA densities. Both studies provide an initial empirical indication that the rollout process may give rise to strategic leeway. Our paper contributes to the literature by explicitly addressing the effects of gradually adopting internal credit risk models.

2.2 The potential effects of the IRBA rollout

Following studies on RWA variability under the IRBA presented in Section 2.1, we suppose that banks strategically choose the sequence and timing of extending the IRBA across portfolios. The effects of IRBA adoption on annual costs[9] and effective risk man-

[8] Ferri and Pesic (2017) provide a tabular overview of the most important studies analyzing RWA dispersion, also indicating whether rollout effects are considered.

[9] "Annual costs" refer to the costs indicated in the profit and loss account, which is prepared on an annual basis. These costs need to be distinguished from the totoal costs arising from the rollout process.

agement are not extensively explored in the literature. Therefore, we do not summarize the few relevant studies in a separate section but rather incorporate them below. Banks face a trade-off because, on the one hand, the IRBA adoption involves costs (e.g., Giles and Milne, 2004), but on the other hand, it also usually lowers the capital burden at the bank level (e.g., Mariathasan and Merrouche, 2014). Eventually, the IRBA rollout may affect bank risk management (e.g., Cucinelli et al., 2018). In the following, we develop hypotheses for all these three fields of analysis, namely costs,[10] RWA reductions, and improved risk management.

Costs:

The implementation of internal credit risk models is often carried out by management consultants and usually entails adjustments to banks' IT systems. Both non-recurring and recurring costs may be affected during the rollout process, such as consulting costs for the initial design of an appropriate internal model and for periodic reviews of this model. Industry experts estimate that the costs of fully implementing the IRBA amount up to five basis points of the asset base for large banks (Giles and Milne, 2004). Banks may be reluctant to fully carry out the rollout process and particularly may avoid implementing exposures, for which the costs are not (over-)compensated by RWA savings. In recent years, these considerations have become particularly important in Europe since generally, profitability is low and cost pressure is high in the banking sector. We hypothesize that if banks decide to roll out the IRBA very stringently, that is, with a clear progress over time, those banks exhibit higher annual cost growth rates than similar banks with a more hesitant IRBA rollout. The reason for this is that banks with a clear rollout progress implement the IRBA more quickly for a larger part of their loan portfolio, requiring more resources for model design and IT implementation in the short term. In contrast, banks with a more hesitant IRBA rollout may stretch costs over a longer time horizon.

RWA reductions:

Beyond analyzing RWA dispersion as in prior studies described in Section 2.1, it is of particular interest for supervisors to examine the sequence and timing of extending the

10 Somewhat imprecisely, we simply refer to costs in the following, although we mean actual costs as opposed to hypothetically necessary costs.

IRBA to assess the effect of the rollout on RWA reductions. In general, assuming similar costs for each portfolio, banks are incentivized to firstly implement those portfolios that lead to the greatest RWA reductions before considering portfolios that either promise only little RWA savings or even result in increasing RWA compared to the SA. This reasoning is in line with the BCBS, which originally expressed the concern that adopting the IRBA partially could lead to minimized capital requirements (BCBS, 2001). Thus, we hypothesize that the first implementation steps lead to the greatest RWA reductions and that less promising portfolios are implemented in a second step, or only when explicitly required by supervisors. Meanwhile, such portfolios remain under the SA.

Improved risk management:

The introduction of sophisticated and risk-sensitive internal credit risk models originally aimed at implementing superior risk management practices, enabling banks to model risk more precisely (BCBS, 2004; EBA, 2015). Cucinelli et al. (2018) reveal that banks applying the IRBA can manage their credit risk more effectively than SA banks, leading to a lower deterioration of their loan portfolio, as measured by non- performing loans (NPL) to total loans ratio, in the aftermath of the financial crisis. However, they do not consider the IRBA rollout but rather apply a dummy variable to differentiate between SA and IRBA banks. To receive IRBA approval from supervisors, banks generally undergo high investments in terms of comprehensive data collection, novel risk management tools and procedures, as well as highly educated human capital (Hakenes and Schnabel, 2011; Cucinelli et al., 2018). Moreover, banks already applying the IRBA are required to regularly validate their internal credit risk models and compare estimates with realized default rates (e.g., Art. 185 Regulation (EU) No 575/2013). As a result, IRBA banks are expected to have a deeper understanding of specific portfolio risk drivers. However, only partially applying the IRBA may hamper this positive effect because risk drivers are only comprehensively examined for a part of the portfolios. Thus, we presume that banks with higher levels of IRBA rollout can manage their loan portfolios more effectively.

3 Data sources and sample selection

3.1 Main sample

We present our sample selection procedure in detail in Table A.1 in the appendix and summarize the most important steps below. We consider all 15 countries included in the most recent EBA stress test in 2021, which covers about 70% of total banking assets in the European Union (EBA, 2021). Our observation period ranges from 2007 to 2016. The year 2007 is the natural starting point for our analysis since the IRBA was introduced in the course of the Basel II implementation in 2007. Moreover, it is to be expected that within a period of 10 years after this introduction most of the rollout processes can be observed.

In each country, we consider the largest banks because IRBA implementation requires a sophisticated risk management system, which must be certified by the supervisory authorities. Consequently, larger banks are more likely to opt for the IRBA and to make information on the applied risk measurement approach publicly available (Behn et al., 2022). We manually screen bank annual reports and pillar 3 reports to collect the exact levels of the loan portfolio covered by the IRBA, the IRBA coverage ratio, for each bank in each year. Additionally, we get most of our bank-specific information from Fitch Connect. Only the information on bank business models[11] is derived from Bankscope. We supplement our sample with macro-financial information from the World Bank Database as well as information on country-specific supervisory strength provided by Barth et al. (2013).

Although our main focus of analysis is on European IRBA banks, we both include U.S. and SA banks in our sample to explore the full IRBA rollout process from a coverage of 0% to 100%. First, similar to Begley et al. (2017), we supplement U.S. banks since they are forced by national supervisors to implement the IRBA for all loan portfolios at the same time, leading to an IRBA coverage ratio of either 0% or 100%. This approach assures full use at any time, which U.S. supervisors consider to be particularly necessary for an appropriate risk management of large, internationally

[11] Although business models do not necessarily have to be constant over time, that is the case in our data set.

active banks (BCBS, 2014a; BCBS, 2014b). For our sample, we select the 25 largest SA banks from the United States at the beginning of our observation period, of which 12 obtain the IRBA approval between 2007 and 2016. To ensure that our results are not driven by the U.S. banks in our sample, we also conduct each analysis based on our *European subsample*, which excludes U.S. banks (see Section 3.2).

Second, we also include European banks using the SA in our sample because IRBA first-time adopters start with an average IRBA coverage ratio of around 60%, whereas SA banks show no partial use at all, translating into an IRBA coverage ratio of 0%. Since bank size appears to be one of the main drivers of IRBA adoption as explained in Table A.2 in the appendix, we only maintain the largest SA banks in our sample and restrict the number of observations referring to SA banks as best as possible to the number of observations relating to banks already applying the IRBA at the start of our observation period or obtaining approval during our observation period (IRBA banks). The total assets threshold of USD 896 million results in an almost balanced final sample of 46% of observations referring to IRBA banks and 54% to SA banks.

Nevertheless, IRBA banks still tend to be generally larger than SA banks in our sample (see Table A.3, upper panel, in the appendix). Therefore, we control for bank size in our regression analyses and also conduct each analysis based on our *IRBA subsample*, which excludes SA banks (see Section 3.2). This ensures that our findings are not driven by systematic differences between larger IRBA and smaller SA banks.

In addition, we drop banks from our main sample for which major variables, such as RWA and total assets, are predominantly missing since we require banks to exhibit more than two observations for these major variables. Furthermore, to calculate the Z-score, a bank economic risk measure explained in more detail in Section 4.4, and to implement the system generalized method of moments (GMM) estimator as described in Section 5, we only keep banks with strictly consecutive observations, hence exhibiting no gaps in the time series.

Eventually, our main sample comprises 3,639 bank-year observations and 386 banks representing about 170 IRBA and 216 SA banks. This corresponds to one of the most comprehensive samples applied in studies analyzing RWA dispersion, both with regard to the number of banks as well as to the length of the observation period (Ferri and Pesic, 2017). In several ways, our sample appears to be representative for the European banking market. For instance, the average annual decline of bank total assets in Europe[12] between 2008 and 2016 was around 1.4%. In our main sample, this decrease is at a similarly low level and amounts to around 3.0%. We refer to Tables A.4, A.5, and A.6 in the appendix for a more detailed representation of our sample distribution.

3.2 Subsamples

We create three subsamples to assure robustness of our findings. First, we exclude all U.S. banks from our main sample and generate a solely *European subsample* consisting of 3,389 observations and 361 banks. Second, we drop all observations referring to SA banks from our main sample, which by definition exhibit an IRBA coverage ratio of 0%, and create an *IRBA subsample*. This subsample contains 1,261 observations and 170 banks. Third, in our *Partial-use subsample*, we focus on banks during their rollout process and exclude observations relating to banks with an IRBA coverage ratio of either 0% or 100%, basically comprising SA and U.S. banks but also European banks with a full IRBA rollout. In this subsample, we retain 1,182 observations and 150 banks.

4 Variable construction

4.1 Overview

Section 4 describes the variables used in the empirical analysis. Variable definitions as well as descriptive statistics are collected in Tables 1 and 2. The descriptive statistics are largely in line with other studies (e.g., Vallascas and Hagendorff, 2013; Mariathasan and Merrouche, 2014). Table A.7 in the appendix contains the variables' pairwise correlations. All non-binary variables are winsorized at the 1% and 99% levels.

12 The average annual decline of bank total assets in Europe is calculated based on consolidated banking data from the ECB Statistical Data Warehouse.

Table 1: Variable descriptions.

Variable	Description	Data source
Costs:		
COSTS	Other operating expenses over total assets (%).	Fitch Connect
$\Delta\,COSTS$	Annual growth rate of other operating expenses (%).	Fitch Connect
RWA reductions:		
RWATA	RWA density, computed as RWA over total assets (%).	Fitch Connect
$\Delta\,RWA$	Annual growth rate of RWA (%).	Fitch Connect
Improved risk management:		
NPL	Non-performing loans over total loans (%).	Fitch Connect
$NPL_t - LLP_{t-1}$	Difference between non-performing loans over total loans at time t and loan loss provisions over total loans at time $t-1$ (%).	Fitch Connect
Phased and hesitant IRBA rollout:		
IRBA_COV	IRBA coverage ratio, calculated as the percentage of the loan portfolio under the IRBA (%).	Annual reports and pillar 3 reports
SQ_IRBA_COV	Squared values of the IRBA coverage ratio.	Own calculation
D_HESITANT	Binary variable, which considers both the absolute level of the IRBA coverage ratio and the observed rollout progress over time (see Section 4.2) and which is equal to one if a bank is categorized as a *hesitant rollout bank* and zero otherwise.	Own calculation
Bank-specific control variables:		
D_MODEL	Categorical variable capturing ten different bank business models.	Bankscope
Z_SCORE	Natural logarithm of the sum of the return on assets and the equity to assets ratio, divided by the two-year standard deviation of the return on assets.	Fitch Connect
ROA	Net income over total assets (%).	Fitch Connect
NII	Net interest income over operating income (%).	Fitch Connect
LOANS	Total loans over total assets (%).	Fitch Connect
DEPOSITS	Total deposits over total assets (%).	Fitch Connect
SIZE	Natural logarithm of total assets in millions of USD.	Fitch Connect
D_JST	Dummy variable equal to one if a bank is supervised by a joint supervisory team in the relevant reporting year and zero otherwise.	ECB
D_M&A	Dummy variable equal to one if a bank experiences a merger or acquisition event during our observation period and zero otherwise.	Bankscope and annual reports
Country-specific control variables:		
GDP_GR	Annual growth rate of the gross domestic product (%).	World Bank Database
INFLATION	Annual growth rate of the consumer price index (%).	World Bank Database
SUP_STR	Index measuring supervisory stringency ranging from 0 to 14, where higher index values indicate higher supervisory stringency.	Barth et al. (2013)

This table describes the variables used in our empirical analysis and indicates the relevant data sources.

Table 2: Descriptive statistics.

Variable	N	Mean	SD	p10	p50	p90
Costs:						
COSTS	3,617	0.86	0.86	0.15	0.71	1.56
$\Delta\,COSTS$	3,577	5.05	31.08	-19.62	0.35	29.85
RWA reductions:						
RWATA	3,073	49.96	22.03	20.93	48.69	79.90
$\Delta\,RWA$	2,870	0.05	18.99	-18.97	-2.32	21.27
Improved risk management:						
NPL	2,757	5.58	7.07	0.41	3.26	13.83
$NPL_t - LLP_{t-1}$	2,439	5.10	6.68	0.21	2.99	12.99
Phased and hesitant IRBA rollout:						
IRBA_COV	3,429	22.48	35.74	0.00	0.00	87.38
SQ_IRBA_COV	3,429	1,782.49	3,102.18	0.00	0.00	7,634.56
D_HESITANT	3,639	0.11	0.31	0.00	0.00	1.00
Bank-specific control variables:						
D_MODEL	3,639	2.66	2.52	0.00	2.00	7.00
Z_SCORE	3,532	4.30	1.73	2.24	4.16	6.52
ROA	3,639	0.34	0.87	-0.16	0.31	1.08
NII	3,616	69.12	29.83	37.68	67.82	96.68
LOANS	3,623	60.27	23.56	24.97	64.88	86.98
DEPOSITS	3,622	66.13	21.98	33.73	70.49	90.12
SIZE	3,639	10.25	1.85	8.03	9.98	12.87
D_JST	3,639	0.06	0.23	0.00	0.00	0.00
D_M&A	3,639	0.06	0.25	0.00	0.00	0.00
Country-specific control variables:						
GDP_GR	3,639	0.96	2.67	-2.82	1.45	3.40
INFLATION	3,639	1.64	1.27	0.05	1.61	3.29
SUP_STR	3,639	9.87	2.19	7.00	10.00	13.00

This table reports, based on our main sample, the descriptive statistics for the variables used in our analysis. To retain the largest possible number of observations for our regression analysis, we do not standardize the number of observations for each variable. Variables are described in Table 1. N refers to the number of observations, SD means standard deviation. p10, p50, and p90 represent the tenth, fiftieth, and the ninetieth percentile.

4.2 Identification strategies for a phased and a hesitant rollout

The IRBA rollout process encompasses two dimensions: the absolute level of partial use at a specific date, in the sense of a *phased rollout*, and the partial-use progress over time, implying a *hesitant rollout* when progress is comparatively little as time goes on. Aiming to capture both dimensions, we create two different measures.

Phased rollout:

The most straightforward way to measure the rollout level represents the IRBA coverage ratio ($IRBA\_COV$), which is calculated as the percentage of the loan portfolio volume under the IRBA. On average, we observe an IRBA coverage ratio of about 22% in our main sample, also including observations referring to SA banks with an IRBA coverage ratio of 0% (see Table 2). In our *IRBA subsample*, the mean IRBA coverage ratio amounts to about 73%. Based on this subsample, Tables A.8 and A.9 in the appendix present the IRBA coverage ratio distributions across countries and over time. They reveal that the IRBA coverage ratio varies somewhat between countries and that it steadily increases during our observation period. The latter may be partially due to the ongoing rollout progress of banks in our subsample over time but also due to additional first-time adopters with high initial coverage levels since the total number of observations per year rises. To determine whether the first implementation steps lead to the greatest RWA reductions, we check for a possible non-linear and non-monotonic relationship in the rollout process and compute the squared IRBA coverage ratio (SQ_IRBA_COV).

As an alternative for this squared term, we apply a piecewise regression model because it has the advantage of not predetermining a strictly quadratic, that is, a non-monotonic, relationship. The piecewise regression model may either reveal a linear, a non-linear and non-monotonic, or a non-linear and monotonic relationship. We explain the procedure and interpretation of this piecewise regression model in more detail in Section 5. For now, it is sufficient to know that for each knot value applied in our piecewise regression model and defined as the value at which the different segments of the model connect, we create two new variables ($IRBA\_COV^{low}$ and $IRBA\_COV^{high}$), which are defined as follows:

$$
\begin{aligned}
IRBA\_COV^{low}_{i,t,KV} &= IRBA\_COV_{i,t}, \\
IRBA\_COV^{high}_{i,t,KV} &= \max[IRBA\_COV_{i,t} - KV; 0],
\end{aligned} \tag{1}
$$

where i indexes banks, t indexes years, and KV refers to the knot value.

Hesitant rollout:

As illustrated in Figure 1, plotting the IRBA coverage ratio over time reveals that the rollout process substantially differs across banks in our sample. On the one hand, the left panel shows three exemplary banks from our sample, which either observe a very high IRBA coverage ratio directly after the first adoption or the rollout progress is clearly visible as the IRBA coverage ratio considerably increases over time and quickly exceeds the mean of 73% observed in our *IRBA subsample*. On the other hand, the exemplary banks in the right panel exhibit IRBA coverage ratios well below this percentage as well as considerably less rollout progress over time.

To capture these differences, which go beyond a phased rollout measured solely by the absolute level of the IRBA coverage ratio, we classify each bank either as a *hesitant rollout bank* or *non-hesitant rollout bank*. Therefore, we create a dummy variable ($D\_HESITANT$), considering the absolute level of the IRBA coverage ratio ($IRBA\_COV$) <u>and</u> the observed rollout progress over time (ΔCOV). The latter is calculated as the percentage points (pp) difference between the IRBA coverage ratio in the current period and the previous period. We categorize a bank as *hesitant rollout bank* and set the dummy variable equal to one if *one* of the following criteria is met for at least two years:[13]

$$
\begin{gathered}
IRBA\_COV_{i,t} \leq 50\% \wedge \Delta COV_{i,t} \leq 10\,\text{pp} \\
\vee \\
IRBA\_COV_{i,t} \leq 60\% \wedge \Delta COV_{i,t} \leq 8\,\text{pp} \\
\vee \\
IRBA\_COV_{i,t} \leq 70\% \wedge \Delta COV_{i,t} \leq 6\,\text{pp}.
\end{gathered}
$$

[13] U.S. banks are naturally classified as *non-hesitant rollout banks* because they need to extend the IRBA across all exposures at the same time. If we do not classify them as *non-hesitant rollout banks* but exclude them from our analyses, our results remain the same.

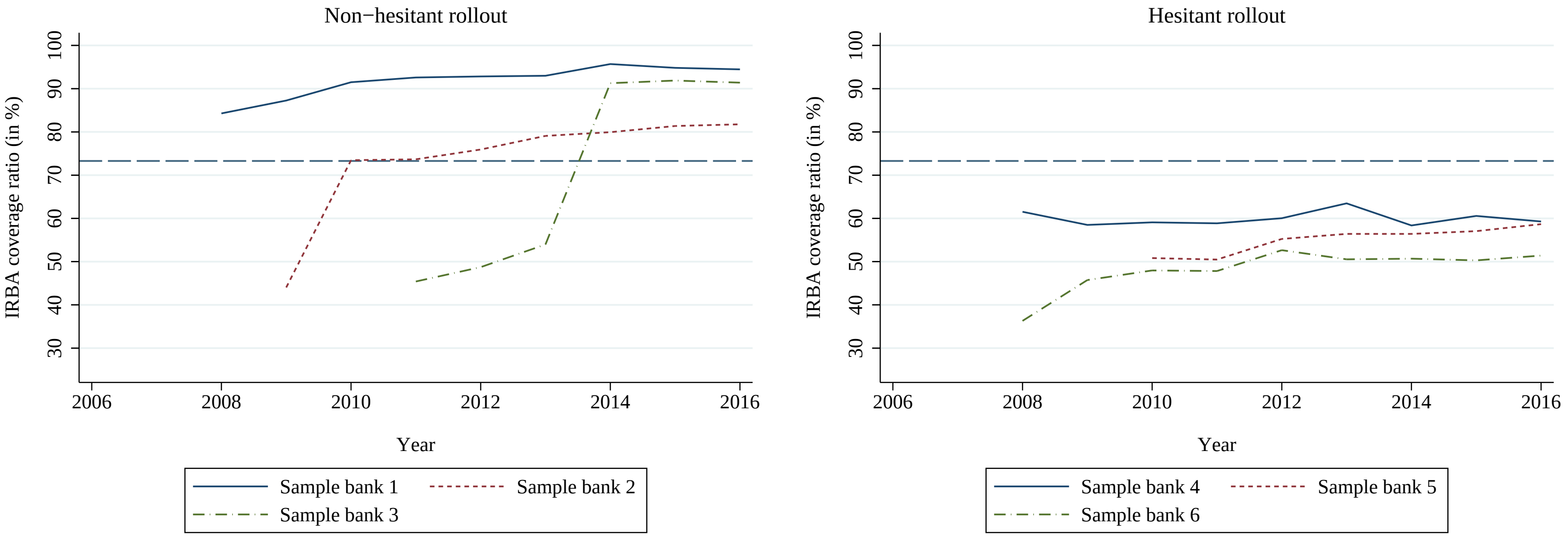

Figure 1: Annual IRBA coverage ratio (%) for typical banks in our sample with a non-hesitant rollout (left panel) and hesitant rollout (right panel) process. The blue dashed line marks the average IRBA coverage ratio in our *IRBA subsample*.

By requiring different levels of ΔCOV at various values of $IRBA\_COV$, we consider that the rollout progress tends to diminish with an increasing IRBA coverage ratio (see Figure 1). Thus, we make banks, which adopt the IRBA at different points in time, comparable throughout our observation period. We choose 50% as a first important mark for the IRBA coverage ratio since the ECB and some national supervisors specify entry thresholds for the IRBA rollout approximately at this level (e.g., § 10, Solvency Regulation in Germany; ECB, 2019a). Additionally, national supervisors usually define a period of around five years in which the IRBA has to be fully rolled out (e.g., § 8, Solvency Regulation in Germany). Consequently, we select the values of ΔCOV just high enough that banks reach an IRBA coverage ratio of 100% within five years. We vary our classification approach in several ways in our robustness checks in Section 7.

In our sample, 45 of 386 banks are *hesitant rollout banks*, which account for 11% of observations in our main sample (see Table 2). In our *IRBA subsample*, these 45 *hesitant rollout banks* refer to 31% of observations. When we compare SA banks which are categorized as *hesitant rollout banks* after their IRBA adoption with SA banks obtaining the IRBA approval and then fulfilling the criteria to be classified as *non-hesitant rollout banks*, we find no significant differences between these groups regarding bank profitability, as measured by the return on equity, and NPL ratios.[14] Solely, we observe that, before their IRBA approval, *hesitant rollout banks* are significantly larger and exhibit higher RWA densities than *non-hesitant rollout banks* (see Table A.3, bottom panel, in the appendix).

4.3 Dependent variables

In our analysis, we examine the trade-off for banks between costs and RWA reductions during the IRBA rollout process, as well as its effect on improved risk management. We explain our measures to quantify these three fields below.

Costs:

We quantify the annual costs of the IRBA rollout by using the ratio of other operating expenses divided by total assets ($COSTS$), which amounts to around 1% on average in

[14] We consider financial statement positions prior to the first IRBA usage for both groups.

our main sample. Other operating expenses predominantly consist of costs for consulting and advisory, legal as well as IT and data processing services (Kovner et al., 2015). These expenses are closely related to the implementation of internal credit risk models, usually carried out by management consultants[15] and often entailing adjustments to banks' IT systems.[16] We compute the annual growth rate of other operating expenses ($\Delta\, COSTS$), which is equal to around 5% on average in our main sample.

RWA reductions:

Following Le Leslé and Avramova (2012) and Mariathasan and Merrouche (2014), we apply the RWA density[17] ($RWATA$), calculated as RWA divided by total assets, to estimate the RWA reduction pattern during the IRBA rollout. On average, we observe a RWA density of around 50% in our main sample. We also determine the annual RWA growth rate ($\Delta\, RWA$) amounting to about 0.1% on average in our main sample.

Improved risk management:

To detect improved risk management practices, we first follow Cucinelli et al. (2018) and examine the risk management output, particularly the NPL ratio (NPL). This ex post, standard measure of bank credit risk in loan portfolios has also been frequently used in other studies (e.g., Louzis et al., 2012). Second, we proxy banks' credit risk prediction accuracy. Beatty and Liao (2011) argue that loan loss provisions (LLP) exhibit explanatory power of future non-performing loans. Thus, we compute the difference between NPL ratios at time t and LLP ratios at time $t-1$ ($NPL_t - LLP_{t-1}$). If this difference becomes smaller, risk management is expected to improve since banks can predict future non-performing loans more accurately.[18] The mean NPL ratio is around 6%,[19] and the mean difference between the NPL ratio at time t and LLP ratio at time $t-1$ around 5 pp in our main sample. Overall, measuring improved risk management

[15] Due to the fact that the implementation of internal credit risk models is usually carried out by management consultants, we do not expect a substantial increase in banks' personnel expenses.

[16] More granular information on costs that can be allocated more precisely to the implementation of internal credit risk models is not publicly available. Furthermore, we are aware that expenses and costs are not completely congruent, but to the best of our knowledge, other operating expenses represent the most appropriate proxy in Fitch Connect.

[17] RWA density is sometimes also referred to as "reported riskiness" or "average risk weights" (Mariathasan and Merrouche, 2014).

[18] Of course, the levels of NPL and LLP are also the result of banks' strategic decisions. We consider this in the best possible way by controlling for many different bank characteristics (see Section 4.4).

[19] Cucinelli et al. (2018) report a similar mean NPL ratio of 5.2%.

is much more challenging than quantifying reductions in RWA. Therefore, we interpret our findings on risk management more tentatively than the ones on RWA reductions.

4.4 Control variables

We incorporate differences between banks and countries by applying bank- and country-specific controls in our analysis. Multicollinearity is not an issue in our sample, since, considering all of our bank- and country-specific controls as well as the time-fixed effects, the highest variance inflation factor (VIF) amounts to 2.87.

Bank-specific controls:

At first, we consider ten different bank types to control for various business models (D_MODEL).[20] Closely related and as originally suggested by Roy (1952), the Z-score (Z_SCORE) captures bank economic risk by measuring the distance to default. A higher Z-score indicates lower bank risk and vice versa. Following Imbierowicz and Rauch (2014), we calculate the Z-score as the sum of the return on assets (ROA) and the equity to total assets ratio ($EQUITY$), divided by the two-year standard deviation of the return on assets ($\sigma(ROA)$):

$$Z\_SCORE = \frac{ROA + EQUITY}{\sigma(ROA)}. \tag{2}$$

Because of its high skewness, it is recommended to use the natural logarithm of the Z-score (e.g., Laeven and Levine, 2009; Anginer et al., 2014; Imbierowicz and Rauch, 2014; Hoque et al., 2015). For simplicity, we refer to the Z-score although we use the logarithmized Z-score.

As further measures for risk-taking behavior and profitability, we apply the return on assets (ROA) and the ratio of net interest income divided by the operating income (NII). Additionally, we incorporate the bank asset structure by the ratio of total loans over total assets ($LOANS$), which typically strongly contributes to bank RWA densities and NPL ratios (Mariathasan and Merrouche, 2014; Cucinelli et al., 2018). The ratio of total deposits divided by total assets ($DEPOSITS$) considers the bank liability

[20] The distinct categorization into ten bank types, listed in Table A.6 in the appendix, is conducted by Bankscope.

structure. We account for bank size ($SIZE$) by the natural logarithm of total assets.

Country-specific controls:

We consider the impact of economic growth and business cycle in each country by computing the annual gross domestic product growth rate (GDP_GR) and the annual change rate of the consumer price index ($INFLATION$). In the literature, there is broad support that the business cylce affects bank risk (e.g., Shim, 2013). Furthermore, we control for supervisory stringency (SUP_STR) by using the index from the survey of Barth et al. (2013) ranging from 0 to 14, where higher index values indicate higher supervisory stringency. Following Vallascas and Hagendorff (2013), Mariathasan and Merrouche (2014), and Wengerek et al. (2022), we include, in addition to macroeconomic variables, time-fixed effects ($YEAR$) to control for unobserved macroeconomic changes over time.

5 Estimation procedures

Our main empirical analysis is based on three major methods: dynamic panel data regression models for analyzing the effects of a phased rollout, piecewise regression models for detecting any non-linearities during the phased rollout, and propensity score matching for comparing *hesitant rollout banks* and similar *non-hesitant rollout banks*. We briefly describe these approaches below.

5.1 System GMM estimation: Phased rollout

For our phased rollout analysis, we use the system GMM estimator by Arellano and Bover (1995) and Blundell and Bond (1998) representing a dynamic panel model and, for the purpose of our paper, a particularly suitable estimation procedure.[21] The system GMM estimator is designed to address two econometric issues in an empirical model.[22] First, it considers a possible persistence in the time series of the dependent variable, which may depend on its own past realizations. Second, the system GMM estimator

[21] Using the system GMM estimator is in line with the two closely related papers by Vallascas and Hagendorff (2013) and Cucinelli et al. (2018). In our robustness checks, we also apply fixed effects panel regressions (see Section 7).

[22] Whereas we describe these issues very briefly, Roodman (2009a,b) explains them in great detail.

addresses the likely endogeneity between bank risks ($RWATA$, NPL, and $NPL_t - LLP_{t-1}$) on the one hand and the IRBA coverage ratio ($IRBA\_COV$) on the other hand. To investigate the effects of a phased rollout, measured by the IRBA coverage ratio, we estimate the following system GMM regression model on annual data and with robust standard errors clustered at the bank level:

$$\begin{aligned} Y_{i,t,k} &= \alpha_k + \beta_{1,k} \cdot Y_{i,t-1,k} + \beta_{2,k} \cdot IRBA\_COV_{i,t} \\ &+ \gamma_k' \cdot BANK\ CHARACTERISTICS_{i,t} \\ &+ \tau_k' \cdot MACROS_{c,t} + \omega_k' \cdot YEAR_t + \xi_{i,t,k}, \end{aligned} \tag{3}$$

where i indexes banks, c indexes countries, t indexes years, and ξ is the error term. k indexes our dependent variables indicating that Y_k refers either to $RWATA$, NPL, or $NPL_t - LLP_{t-1}$. $BANK\ CHARACTERISTICS$ aim to capture major bank specifics and include D_MODEL, Z_SCORE, ROA, NII, $LOANS$, $DEPOSITS$, and $SIZE$. $MACROS$ consist of GDP_GR, $INFLATION$, and SUP_STR.[23] $YEAR$ represents time-fixed effects. We apply this system GMM regression model to our main sample, our *IRBA subsample*, our *European subsample*, as well as our *Partial-use subsample* (see Section 3.2).

To specify our system GMM model, we follow Louzis et al. (2012) and Wengerek et al. (2022). First, we consider the country-specific controls ($MACROS$) as strictly exogenous. We apply the same approach for D_MODEL because the choice of the business model is a long-term strategic decision. Second, the remaining bank-specific controls reflect financial statement positions and can be considered as forward-looking and decision-making instruments for banks. This indicates that the management of these financial statement positions may be affected by the expected future values of our dependent variables, namely, $RWATA$, NPL, and $NPL_t - LLP_{t-1}$, while future random, and thus unpredictable, shocks may not be considered. Accordingly, we define the bank-specific controls as weakly exogenous and instrument them by using their lagged values. Eventually, we allow for feedback effects from our dependent variables

[23] Following Vallascas and Hagendorff (2013) and Wengerek et al. (2022), we include macroeconomic variables instead of country-fixed effects in our system GMM estimations to limit instrument proliferation.

to the IRBA coverage ratio and treat the IRBA coverage ratio as a strictly endogenous variable. We use lags 3 and longer for the transformed equation and lag 1 for the levels equation. Moreover, we collapse the instrument set to limit instrument proliferation and report the Hansen test of overidentifying restrictions (Roodman, 2009b). To control for the consistency of the system GMM estimations, we provide the Arellano–Bond tests for first-order, AR(1), and second-order, AR(2), autocorrelation of the residuals.

5.2 Piecewise regression model: Non-linearity during the phased roll-out

To check how the RWA reduction pattern is characterized, we employ piecewise regression models since they have the advantage of not predetermining a strictly quadratic relationship between the IRBA coverage ratio and RWA densities. We use a locally weighted smoother, also called lowess, to identify an appropriate knot for our regression model (see Figure 2, upper-left panel). The lowess graph reinforces that the relationship between the IRBA coverage ratio and RWA densities is indeed non-linear.[24] RWA densities seem to decrease clearly with an increasing IRBA coverage ratio until about 60%, at which point the RWA density reductions substantially diminish. Thus, as indicated by the red vertical line in Figure 2 (upper-left panel), a knot at 60% seems most suitable for our sample. Of course, we vary this specification and also apply knots at 50% and 70%.

We use these three knots to calculate $IRBA\_COV^{low}$ and $IRBA\_COV^{high}$ (see Equation 1). Subsequently, we replace the IRBA coverage ratio ($IRBA\_COV$) in our regression model specified in Equation 3 by these two variables. Thus, our piecewise regression model estimates the slope of RWA density changes before the knot ($IRBA\_COV^{low}$), and the change in the slope after the knot compared to the slope before the knot ($IRBA\_COV^{high}$).

[24] In addition, the lowess graph does not provide any evidence for two or more knots in the relationship between the IRBA coverage ratio and RWA densities.

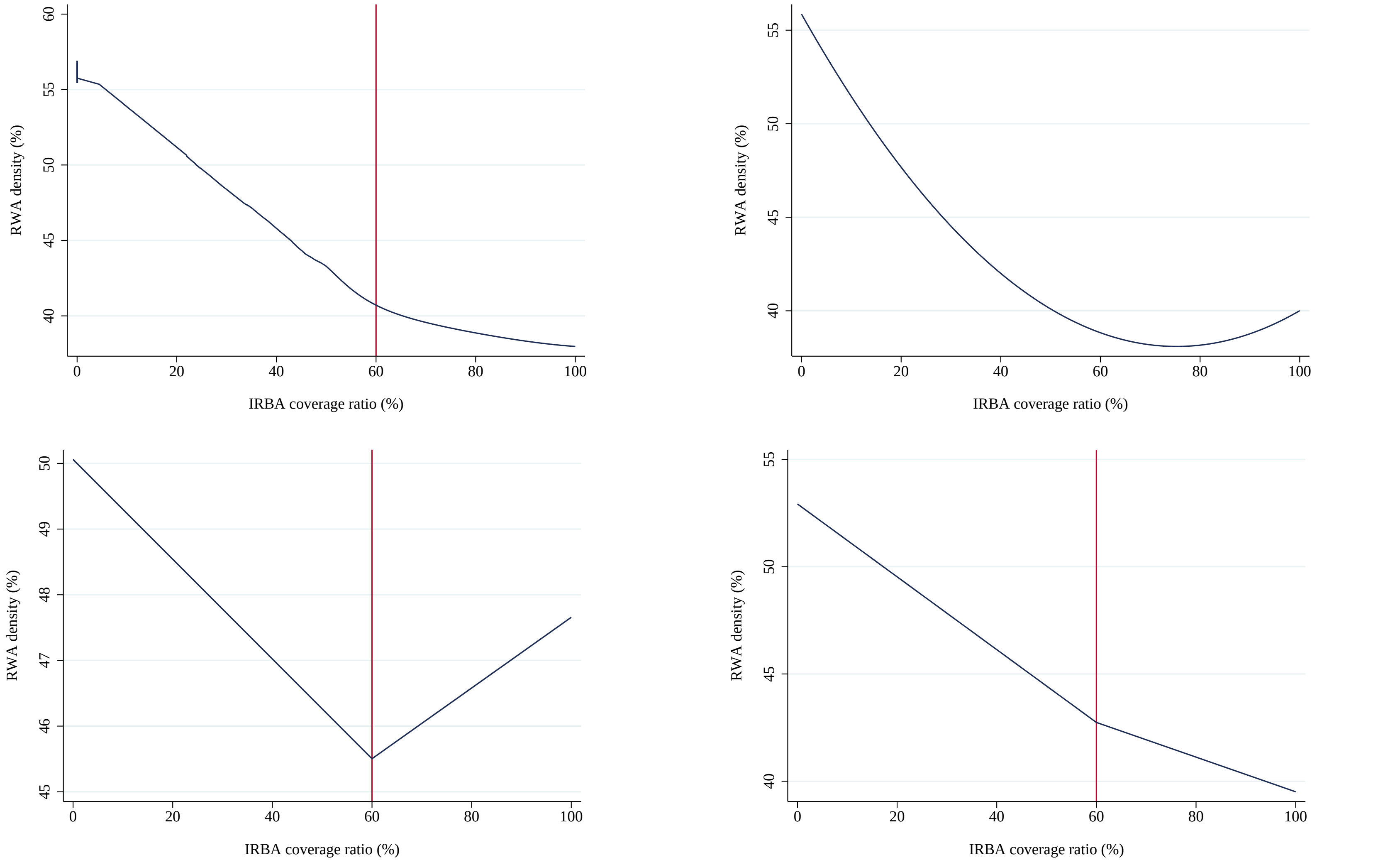

Figure 2: Non-linear relationship between the IRBA coverage ratio and RWA density. Locally weighted regression of RWA density by IRBA coverage ratio (upper-left panel), quadratically fitted values (upper-right panel), and fitted values from piecewise regression models (knot at 60%) based on a system GMM estimation (bottom-left panel) and on a fixed effects panel estimation (bottom-right panel).

5.3 Propensity score matching: Hesitant rollout

To explore differences between *hesitant rollout banks* and similar *non-hesitant rollout banks*, we apply several propensity score matching analyses, originally developed by Rosenbaum and Rubin (1983). We distinguish *hesitant rollout banks* and *non-hesitant rollout banks* by our dummy variable created according to Section 4.2 ($D\_HESITANT$). Further, we use our *IRBA subsample*[25] and compute the propensity scores based on the following logit regression model:[26]

$$\begin{aligned} D\_HESITANT_{i,t} &= \alpha + \gamma' \cdot BANK\ CHARACTERISTICS_{i,t} + \tau' \cdot MACROS_{c,t} \\ &+ \varphi' \cdot COUNTRY_c + \omega' \cdot YEAR_t + \xi_{i,t}, \end{aligned} \tag{4}$$

where i indexes banks, c indexes countries, t indexes years, and ξ is the error term. $BANK\ CHARACTERISTICS$ and $MACROS$ include the aforementioned bank and country specifics (see Equation 3). $COUNTRY$ and $YEAR$ represent country- and time-fixed effects. The results of the logit regression model, specified in Equation 4, are reported in Table A.10 in the appendix. They reveal that the probability to be classified as a *hesitant rollout bank* is significantly higher for larger as well as for economically riskier banks, that is, banks with lower Z-scores.

Following Heckman et al. (1998) and Hellmann et al. (2007), we apply different matching algorithms. At first, we implement the most commonly used, nearest-neighbor ($N-N$) matching algorithm (e.g., Stuart, 2010). It compares each *hesitant rollout bank* with the arithmetic average of n *non-hesitant rollout banks* showing the closest propensity scores and allows for replacement. We assume n = 1, 5, 10, 20, or 50. Additionally, we implement both the Gaussian kernel estimator and local linear matching. The Gaussian kernel estimator assigns greater weight to those *non-hesitant rollout banks* with particularly close propensity scores to those of *hesitant rollout banks.* Local linear matching is similar to the Gaussian kernel estimator but additionally includes a linear term in the weighting function.

[25] Using the *IRBA subsample* is necessary since SA banks cannot be classified as *hesitant rollout banks* or as *non-hesitant rollout banks.*

[26] The propensity scores can be estimated by either using a logit or a probit model (Hellmann et al., 2007). We employ a probit model in our robustness checks in Section 7.

6 Empirical results

6.1 Costs

Below, we analyze whether *hesitant rollout banks* exhibit significantly different cost growth rates as opposed to similar *non-hesitant rollout banks.* Table 3 (upper panel) provides the estimates of the mean difference tests of $\Delta\, COSTS$ between *hesitant rollout banks* and similar *non-hesitant rollout banks* based on propensity score matching (see Section 5.3). In five of seven specifications, we provide evidence that *hesitant rollout banks* show significantly lower cost growth rates than *non-hesitant rollout banks.* In the remaining two specifications, the coefficients are negative as well but lack significance. In terms of economic magnitude, according to the second specification ($n = 5$), *hesitant rollout banks* exhibit around 9 pp lower annual cost growth rates than *non-hesitant rollout banks.*

Overall, these results support our hypothesis that banks deciding to roll out the IRBA very stringently require more resources for model design and IT implementation in the short term, thus exhibiting higher cost growth rates. In contrast, banks with a more hesitant IRBA rollout are able to stretch costs over a longer time horizon and show lower cost growth rates on average. Importantly, because of the reduced pace of their rollout progress, *hesitant rollout banks* remain at lower levels of partial use for a longer period. Aside from costs, the incentive to fully roll out the IRBA may further diminish if the exposures with the potentially highest RWA reductions have already been rolled out with the first implementation steps. We explore this issue below.

6.2 RWA reductions

Next, we address the other side of the coin when adopting the IRBA and focus on RWA. We first concentrate on the phased rollout and analyze the RWA reduction pattern with an increasing IRBA coverage ratio. Second, we look into differences in RWA reduction rates between *hesitant rollout banks* and similar *non-hesitant rollout banks.*

Phased rollout:

We present the findings of our system GMM estimations (see Equation 3), applying

Table 3: Test for mean differences in annual cost growth rates and RWA growth rates between *hesitant rollout banks* and similar *non-hesitant rollout banks* based on propensity score matching.

Estimator	**Differences in $\Delta\, COSTS$ between *hesitant* and *non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	-4.36	(-0.91)
Nearest neighbor ($n = 5$)	-8.60**	(-2.38)
Nearest neighbor ($n = 10$)	-7.40**	(-2.20)
Nearest neighbor ($n = 20$)	-7.32**	(-2.24)
Nearest neighbor ($n = 50$)	-7.79**	(-2.55)
Gaussian kernel	-6.67**	(-2.11)
Local linear regression	-5.85	(-1.22)
N		1,060
Hesitant rollout banks		323
Non-hesitant rollout banks		737

Estimator	**Differences in $\Delta\, RWA$ between *hesitant* and *non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	-2.79	(-1.15)
Nearest neighbor ($n = 5$)	-3.21*	(-1.65)
Nearest neighbor ($n = 10$)	-3.14*	(-1.71)
Nearest neighbor ($n = 20$)	-4.38**	(-2.49)
Nearest neighbor ($n = 50$)	-4.07**	(-2.46)
Gaussian kernel	-2.83	(-1.63)
Local linear regression	-2.69	(-1.11)
N		983
Hesitant rollout banks		299
Non-hesitant rollout banks		684

This table provides estimates of the mean differences in annual cost growth rates ($\Delta\, COSTS$) and RWA growth rates ($\Delta\, RWA$) between *hesitant rollout banks* and similar *non-hesitant rollout banks* based on propensity score matching. In the bottom panel, the RWA growth rates are negative for both matched groups on average. The estimation of propensity scores is based on a logit regression, reported in Table A.10 in the appendix, where the dependent variable is the dummy $D\_HESITANT$, as described in Section 4.2. Variables are described in Table 1. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

$RWATA$ as the dependent and $IRBA\_COV$ as the main independent variable, in Table 4. Across all specifications, the positive and significant coefficients on the lagged dependent variable, $RWATA_{i,t-1}$, confirm the expected autoregressive process of banks' risk-weighted assets, underlining the need for applying a dynamic panel data model. The coefficients on the IRBA coverage ratio are significantly negative using our *European subsample* in specification (2), our *IRBA subsample* in specification (3), as well as our *Partial-use subsample* in specification (4). Applying our main sample in specification (1), the coefficient is also negative but insignificant. These results provide tentative evidence for RWA reductions with an increasing IRBA coverage ratio.

To check for a possible non-linear relationship, we add the squared term of the IRBA coverage ratio (SQ_IRBA_COV) to Equation 3 and report our results in Table 5. Whereas the coefficients on the IRBA coverage ratio are now significantly negative across all specifications, we additionally observe a significantly positive effect of the squared term of the IRBA coverage ratio on RWA densities in three out of four specifications. This indicates a non-linear and non-monotonic relationship. Figure 2 (upper-right panel) plots the quadratically fitted values suggesting that banks adopt the IRBA for exposures promising the highest RWA savings at first. Furthermore, the derived quadratic relationship indicates that the lastly adopted portfolios do not seem to promise RWA reductions under the IRBA at all, but rather lead to an increase in RWA densities, although RWA densities are, at a full IRBA rollout, still lower as opposed to very low IRBA rollout levels.[27]

To provide further evidence that the non-linear and non-monotonic relationship is not forced by adding the squared term of the IRBA coverage ratio to our regression model, we employ piecewise regression models (see Section 5.2) and report our findings in Table 6. Across all three specifications referring to different knot values (50%, 60%, 70%), we find significantly negative coefficients on $IRBA\_COV^{low}$, meaning that banks can substantially reduce their RWA densities during the early IRBA implementation steps, that is, before reaching an IRBA coverage ratio higher than the knot value. Conversely, the significantly positive coefficients on $IRBA\_COV^{high}$ provide evidence that the slope after the specified knot increases compared to the slope before. As a result, early implementation steps seem to be clearly more rewarding than later ones. Since the coefficients on $IRBA\_COV^{high}$ are absolutely higher than those of $IRBA\_COV^{low}$, the lastly adopted portfolios do not seem to promise RWA reductions under the IRBA at all. This is in line with our findings when applying the quadratic term of the IRBA coverage ratio. We plot the estimated relationship between the IRBA coverage ratio

[27] Our results are reinforced when we replace $IRBA\_COV$ and SQ_IRBA_COV by the natural logarithm of $IRBA\_COV$. Since we predominantly gain significantly negative coefficients but the overall significance level decreases in this specification, the relationship appears to be indeed non-monotonic.

Table 4: Phased IRBA rollout and RWA densities.

	(1)	(2)	(3)	(4)
	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$
$RWATA_{i,t-1}$	0.798***	0.767***	0.934***	0.876***
	(0.0732)	(0.0735)	(0.0921)	(0.0984)
$IRBA\_COV_{i,t}$	-0.0153	-0.0557*	-0.124**	-0.112*
	(0.0252)	(0.0299)	(0.0569)	(0.0625)
D_MODEL_i	-0.779**	-0.716**	0.329	0.375
	(0.338)	(0.295)	(0.375)	(0.458)
$Z\_SCORE_{i,t}$	0.773	0.345	-0.492	-0.364
	(0.484)	(0.426)	(0.510)	(0.494)
$ROA_{i,t}$	-2.035	-2.869*	1.518	1.319
	(1.648)	(1.496)	(1.381)	(1.380)
$NII_{i,t}$	0.0864**	0.0737*	0.0151	0.00226
	(0.0395)	(0.0376)	(0.0516)	(0.0450)
$LOANS_{i,t}$	-0.0196	-0.0120	0.0183	0.0423
	(0.0520)	(0.0591)	(0.0850)	(0.102)
$DEPOSITS_{i,t}$	0.0845	0.0408	0.109	0.108
	(0.0848)	(0.0854)	(0.0777)	(0.100)
$SIZE_{i,t}$	-0.843	-0.810	0.0720	0.424
	(0.931)	(1.042)	(1.085)	(1.296)
$GDP\_GR_{c,t}$	0.225**	0.133	0.123	0.0884
	(0.113)	(0.125)	(0.104)	(0.0851)
$INFLATION_{c,t}$	0.0295	-0.0235	0.0109	0.188
	(0.220)	(0.237)	(0.297)	(0.316)
$SUP\_STR_{c,t}$	0.279	-0.0745	0.249	0.210
	(0.176)	(0.163)	(0.275)	(0.272)
Time-fixed effects	Yes	Yes	Yes	Yes
N	2,440	2,230	857	796
Number of groups	373	348	150	134
Number of instruments	45	45	45	45
AR(1)-p	0.000	0.000	0.001	0.001
AR(2)-p	0.989	0.810	0.568	0.478
Hansen-p	0.202	0.318	0.776	0.582

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$) in the period from 2007 to 2016. We apply a system GMM estimation, as specified in Section 5.1. Specification (1) uses our main sample, specification (2) uses our *European subsample*, specification (3) uses our *IRBA subsample*, and specification (4) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations and p to the p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

and RWA densities, based on our piecewise regression model with a knot at 60%, in Figure 2 (bottom-left panel).

We conclude that the RWA reduction pattern is characterized by first, diminishing

Table 5: Phased IRBA rollout and RWA densities, additionally controlling for the squared term of the IRBA coverage ratio.

	(1)	**(2)**	**(3)**	**(4)**
	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{RWATA_{i,t}}$
$RWATA_{i,t-1}$	0.796^{***}	0.773^{***}	0.891^{***}	0.823^{***}
	(0.0622)	(0.0688)	(0.0894)	(0.0885)
$IRBA\_COV_{i,t}$	-0.180^{***}	-0.144^{*}	-0.436^{**}	-0.393^{*}
	(0.0661)	(0.0834)	(0.204)	(0.203)
$SQ\_IRBA\_COV_{i,t}$	0.00188^{***}	0.00116	0.00278^{*}	0.00252^{*}
	(0.000601)	(0.000781)	(0.00155)	(0.00147)
D_MODEL_{i}	-0.907^{***}	-0.775^{***}	0.199	0.0829
	(0.314)	(0.295)	(0.338)	(0.351)
$Z\_SCORE_{i,t}$	0.773	0.342	-0.349	-0.131
	(0.480)	(0.421)	(0.480)	(0.440)
$ROA_{i,t}$	-2.089	-2.579^{*}	1.529	1.562
	(1.539)	(1.508)	(1.445)	(1.595)
$NII_{i,t}$	0.0928^{**}	0.0816^{**}	0.0305	0.0240
	(0.0362)	(0.0369)	(0.0436)	(0.0397)
$LOANS_{i,t}$	-0.0308	-0.0250	-0.0326	-0.0245
	(0.0495)	(0.0583)	(0.0688)	(0.0756)
$DEPOSITS_{i,t}$	0.0721	0.0497	0.119^{*}	0.109
	(0.0754)	(0.0827)	(0.0702)	(0.0962)
$SIZE_{i,t}$	-0.914	-0.973	0.371	0.283
	(0.899)	(0.995)	(1.116)	(1.217)
$GDP\_GR_{c,t}$	0.186	0.0977	0.0799	0.0739
	(0.119)	(0.124)	(0.122)	(0.0984)
$INFLATION_{c,t}$	-0.0814	-0.117	-0.0618	0.153
	(0.228)	(0.248)	(0.317)	(0.349)
$SUP\_STR_{c,t}$	0.233	-0.0640	0.263	0.323
	(0.172)	(0.153)	(0.231)	(0.224)
Time-fixed effects	Yes	Yes	Yes	Yes
N	2,440	2,230	857	796
Number of groups	373	348	150	134
Number of instruments	49	49	49	49
AR(1)-p	0.000	0.000	0.001	0.001
AR(2)-p	0.993	0.833	0.588	0.562
Hansen-p	0.355	0.447	0.892	0.703

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$) in the period from 2007 to 2016, additionally controlling for the squared term of the IRBA coverage ratio (SQ_IRBA_COV). We apply a system GMM estimation, as specified in Section 5.1. Specification (1) uses our main sample, specification (2) uses our *European subsample*, specification (3) uses our *IRBA subsample*, and specification (4) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations and p to the p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table 6: Phased IRBA rollout and RWA densities, applying a piecewise regression model.

	(1)	(2)	(3)
	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{RWATA_{i,t}}$
$RWATA_{i,t-1}$	0.808***	0.804***	0.789***
	(0.0617)	(0.0608)	(0.0613)
$IRBA\_COV^{low}_{i,t,KV}$	-0.0947**	-0.0760**	-0.0657*
	(0.0427)	(0.0381)	(0.0342)
$IRBA\_COV^{high}_{i,t,KV}$	0.194***	0.206***	0.264***
	(0.0662)	(0.0713)	(0.0838)
D_MODEL_i	-0.879***	-0.871***	-0.903***
	(0.312)	(0.320)	(0.330)
$Z\_SCORE_{i,t}$	0.696	0.678	0.703
	(0.485)	(0.485)	(0.485)
$ROA_{i,t}$	-1.987	-1.796	-1.735
	(1.560)	(1.557)	(1.562)
$NII_{i,t}$	0.0993***	0.0971***	0.0870**
	(0.0356)	(0.0368)	(0.0372)
$LOANS_{i,t}$	-0.0357	-0.0388	-0.0337
	(0.0500)	(0.0505)	(0.0497)
$DEPOSITS_{i,t}$	0.0758	0.0774	0.0762
	(0.0773)	(0.0800)	(0.0807)
$SIZE_{i,t}$	-0.863	-0.895	-1.057
	(0.897)	(0.897)	(0.902)
$GDP\_GR_{c,t}$	0.179	0.175	0.198*
	(0.114)	(0.115)	(0.118)
$INFLATION_{c,t}$	-0.0644	-0.0739	-0.0816
	(0.221)	(0.228)	(0.232)
$SUP\_STR_{c,t}$	0.209	0.224	0.261
	(0.169)	(0.173)	(0.179)
Time-fixed effects	Yes	Yes	Yes
N	2,440	2,440	2,440
Number of groups	373	373	373
Number of instruments	49	49	49
AR(1)-p	0.000	0.000	0.000
AR(2)-p	0.986	0.984	0.945
Hansen-p	0.331	0.265	0.218

This table reports the piecewise regression analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$) in the period from 2007 to 2016, based on our main sample. We apply a system GMM estimation, as specified in Section 5.1. Specification (1) assumes a knot at 50%, specification (2) at 60%, and specification (3) at 70%. Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations, and p to the p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

positive and finally, negative marginal benefits. Hence, our results point to "cherry-picking" opportunities during a phased IRBA rollout. Banks seem to choose the sequence of the IRBA adoption for certain portfolios strategically and implement the most RWA density-reducing exposures at first. Thus, beyond previous findings, we provide initial evidence that banks seem to have an incentive to not fully roll out the IRBA since they achieve the highest possible RWA reduction at lower rollout levels. Although this explanation is in line with previous studies pointing to overall reduced RWA densities and underreporting of RWA under the IRBA (e.g., Mariathasan and Merrouche, 2014; Montes et al., 2018; Behn et al., 2022), we cannot entirely rule out other explanations for deferred IRBA rollouts. For instance, banks may decide to remain at low levels of partial use because the remaining portfolios under the SA are less suited for modelling or supervisors do not approve the models required for the completion of the rollout.

Hesitant rollout:

We examine below whether *hesitant rollout banks* not only show significantly lower cost growth rates during the IRBA rollout compared to similar *non-hesitant rollout banks* but also exhibit significant differences in RWA growth rates. Table 3 (bottom panel) presents the estimates of the mean difference tests of $\Delta\, RWA$ between *hesitant rollout banks* and similar *non-hesitant rollout banks* based on propensity score matching (see Section 5.3). Across all specifications, we observe negative coefficients and in four out of seven specifications, those are significant. Given the fact that the RWA growth rates are negative for both matched groups on average, our results indicate that *hesitant rollout banks* can reduce their RWA to a greater extent as opposed to similar *non-hesitant rollout banks*. For instance, according to the second specification ($n = 5$), *hesitant rollout banks* exhibit higher RWA reduction rates of around 3 pp than *non-hesitant rollout banks*. This may be attributed to differences in credit risk exposures and corresponds to our previous finding that before their IRBA approval, *hesitant rollout banks* exhibit significantly higher RWA densities than *non-hesitant rollout banks*, leaving them with a higher potential for RWA reductions during the IRBA rollout (see Table A.3, bottom panel, in the appendix).

6.3 Improved risk management

In the last step, we build on our previous finding that, due to their trade-off between costs and RWA reductions, banks seem to have the incentive to not fully roll out the IRBA. Aiming to derive implications for the novel permanent partial-use philosophy recommended by the BCBS (BCBS, 2017), we investigate below whether an incomplete IRBA rollout negatively affects bank risk management. Building on Cucinelli et al. (2018), which focus on differences in risk management between SA and IRBA banks, we add results on risk management differences between IRBA banks with different levels of rollout. Accordingly, we use $IRBA\_COV$ as the main independent variable and exclude SA banks in our analysis in order to particularly examine banks rolling out the IRBA. Thus, we apply our *IRBA subsample*, our *European subsample* excluding observations referring to SA banks, and our *Partial-use subsample*.

Initially, following Cucinelli et al. (2018), we use NPL as the dependent variable in our system GMM estimations (see Equation 3). As presented in Table 7, the IRBA coverage ratio significantly negatively affects NPL ratios across all specifications. This suggests that bank risk management improves with a progressing IRBA rollout after controlling for bank risk-taking by the Z-score, the ROA, and the net interest income over operating income.[28] Thus, not only do SA banks improve their risk management by adopting the IRBA as required by the regulatory authorities to obtain approval and as shown by Cucinelli et al. (2018), but IRBA banks seem to benefit also from further rolling out their internal credit risk models.[29] By applying bank NPL ratios as ex post output measure for effective risk management and identifying the IRBA rollout as one of its determinants, we also contribute to previous literature which points to several other bank-specific and macroeconomic determinants (e.g., Ghosh, 2015; Dimitrios et al., 2016).

To underpin our finding that supervisory approval to apply the IRBA is merely

[28] In the literature, various studies consider the NPL ratio also as a proxy for bank risk-taking behavior (e.g., Agoraki et al., 2011; Jiménez et al., 2013). We disentangle banks' general risk appetite from effective risk management by controlling for bank risk-taking.

[29] Importantly, this result is not driven by a common trend of improved risk management over time because we incorporate time-fixed effects in our regressions. Moreover, we observe on average positive growth rates of NPL ratios, that is, increasing NPL ratios over time, in our sample.

Table 7: Phased IRBA rollout and NPL ratios.

	(1)	(2)	(3)
	$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t}}$
$NPL_{i,t-1}$	0.986***	0.955***	0.951***
	(0.0940)	(0.0787)	(0.0753)
$IRBA\_COV_{i,t}$	-0.0372*	-0.0465**	-0.0405*
	(0.0205)	(0.0233)	(0.0222)
D_MODEL_{i}	0.134	0.204	0.230*
	(0.136)	(0.131)	(0.135)
$Z\_SCORE_{i,t}$	-0.632***	-0.577**	-0.599**
	(0.238)	(0.258)	(0.251)
$ROA_{i,t}$	-0.628	-1.218	-1.212
	(1.112)	(1.022)	(0.899)
$NII_{i,t}$	-0.00662	-0.0126	-0.0204
	(0.0263)	(0.0190)	(0.0184)
$LOANS_{i,t}$	0.0614	0.0730*	0.0817**
	(0.0450)	(0.0388)	(0.0369)
$DEPOSITS_{i,t}$	0.0504	0.0377	0.0442
	(0.0442)	(0.0436)	(0.0474)
$SIZE_{i,t}$	0.341	0.640	0.741
	(0.430)	(0.404)	(0.472)
$GDP\_GR_{c,t}$	-0.165**	-0.167**	-0.165**
	(0.0693)	(0.0736)	(0.0766)
$INFLATION_{c,t}$	0.0526	0.0712	0.0323
	(0.153)	(0.149)	(0.145)
$SUP\_STR_{c,t}$	0.0537	0.0219	0.0183
	(0.0858)	(0.0866)	(0.0863)
Time-fixed effects	Yes	Yes	Yes
N	812	792	757
Number of groups	136	125	121
Number of instruments	45	45	45
AR(1)-p	0.013	0.002	0.002
AR(2)-p	0.103	0.135	0.127
Hansen-p	0.242	0.299	0.331

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects the ratio of non-performing loans divided by total loans (NPL) in the period from 2007 to 2016. We apply a system GMM estimation, as specified in Section 5.1. Specification (1) uses our *IRBA subsample*, specification (2) uses our *European subsample* excluding observations referring to SA banks, and specification (3) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations and p to the p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

the first step to improve risk management and that banks significantly deepen their understanding of portfolio risk drivers during the rollout process, we additionally analyze whether bank credit risk prediction becomes more accurate during the rollout process. Therefore, we apply $NPL_{i,t} - LLP_{i,t-1}$ as our dependent variable and $IRBA\_COV$ as our main independent variable. As reported in Table 8, we strengthen our previous finding by observing significantly negative coefficients on the IRBA coverage ratio across all specifications. This underlines that banks seem to improve their credit risk prediction accuracy during the rollout process.

In additional analyses reported in Tables A.11 and A.12 in the appendix, we lag our explanatory variables by one period, most importantly $IRBA\_COV$, to incorporate that NPLs usually take some time to materialize. Across all specifications, our results are consistent with previous findings.

In conclusion, we add to the result by Cucinelli et al. (2018) that bank risk management not only improves through the IRBA adoption per se but also particularly through the further IRBA rollout process. We also point to a potential conflict of interest since banks, according to their cost-benefit trade-off, seem to have incentives to not fully rollout the IRBA, but at the same time a full rollout appears to ensure effective risk management practices and bank resilience.

7 Robustness checks

We perform additional analyses to verify whether our results are robust to changes of our econometric approaches. None of the modifications lead to qualitatively different outcomes.

7.1 Phased rollout

Fixed effects panel estimations and additional fixed effects:
Following Mariathasan and Merrouche (2014), we apply a simpler, static econometric panel model, in addition to the dynamic panel data model (see Section 5.1), to analyze the effects of a phased rollout. Consequently, we perform several fixed effects panel

Table 8: Phased IRBA rollout and bank credit risk prediction accuracy.

	(1)	**(2)**	**(3)**
	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$NPL_{i,t-1} - LLP_{i,t-2}$	0.940***	0.936***	0.939***
	(0.0655)	(0.0671)	(0.0656)
$IRBA\_COV_{i,t}$	-0.0549***	-0.0547***	-0.0514***
	(0.0156)	(0.0156)	(0.0157)
D_MODEL_i	0.0639	0.0678	0.0838
	(0.115)	(0.102)	(0.0949)
$Z\_SCORE_{i,t}$	-0.281	-0.230	-0.197
	(0.252)	(0.237)	(0.232)
$ROA_{i,t}$	-0.859	-1.326	-1.297
	(0.965)	(1.013)	(0.979)
$NII_{i,t}$	0.0117	0.0127	0.00805
	(0.0168)	(0.0151)	(0.0151)
$LOANS_{i,t}$	0.0298	0.0355	0.0354
	(0.0324)	(0.0335)	(0.0321)
$DEPOSITS_{i,t}$	0.0217	0.00431	0.0146
	(0.0266)	(0.0254)	(0.0248)
$SIZE_{i,t}$	0.253	0.447	0.404
	(0.304)	(0.312)	(0.339)
$GDP\_GR_{c,t}$	-0.121**	-0.107*	-0.108*
	(0.0584)	(0.0585)	(0.0578)
$INFLATION_{c,t}$	0.0624	0.113	0.0496
	(0.105)	(0.115)	(0.102)
$SUP\_STR_{c,t}$	0.111	0.104	0.0862
	(0.0743)	(0.0707)	(0.0653)
Time-fixed effects	Yes	Yes	Yes
N	767	751	718
Number of groups	133	124	119
Number of instruments	36	36	36
AR(1)-p	0.000	0.001	0.001
AR(2)-p	0.272	0.273	0.281
Hansen-p	0.109	0.128	0.170

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects the difference between the NPL ratio at time t and the LLP ratio at time $t-1$ ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2016. We apply a system GMM estimation, as specified in Section 5.1. Specification (1) uses our *IRBA subsample*, specification (2) uses our *European subsample* excluding observations referring to SA banks, and specification (3) uses our *Partial-use subsample* (see Section 3.2). In all specifications, we use lags 2, instead of 3, and longer for the transformed equation because otherwise, the Hansen test of overidentifying restrictions is significant. Variables are described in Table 1. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations and p to the p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

estimations[30] and report the results in Tables A.13 to A.17 in the appendix. In summary, across all specifications, our findings are very similar compared to the previous system GMM estimations. Additionally, again applying fixed effects panel estimations, we also replace our time-fixed effects by the interaction of time- and country-fixed effects and report the results using our main sample in Table A.18 in the appendix.

Competing explanations:

As illustrated in Figure 1, the rollout process usually takes several years. Thus, the phased rollout contains a strong time component. Since our observation period lasts from 2007 to 2016 and comprises different events, we want to make sure that our findings are indeed driven by the rollout process. Therefore, we collect several important events during our observation period that potentially alter our findings and accordingly create five different subsamples. Our first subsample covers the period before the adoption of Basel 2.5 in Europe in 2010 and consists of observations from 2007 to 2009.[31] Our second subsample refers to the period before the adoption of Basel III in Europe in 2014. Thus, we only retain observations from 2007 to 2013. As a counterpart, we build our third subsample by focusing on the period since the adoption of Basel III in Europe in 2014 and drop all observations, except the ones from 2014 to 2016. Beside important regulatory developments in the European banking sector, we also incorporate major macroeconomic events. In our fourth subsample, we exclude the period of the financial crisis and only analyze observations from 2010 to 2016. In order to take the subsequent Eurozone crisis into account, we concentrate on the period from 2011 to 2016 in our fifth subsample.

Based on these five subsamples, we reestimate our main regression models. Since dynamic panel models are particularly suited for longer observation periods as opposed to shorter ones, we again perform fixed effects panel estimations. Our results are reported separately for each subsample in Tables A.19 to A.23 in the appendix. We also compare our results based on our five subsamples with our baseline results based on the original observation period in Table A.24 in the appendix. Even if the significance

[30] In our fixed effects panel estimations, we cannot apply D_MODEL as control variable since this variable is time invariant for each bank and is thus omitted.

[31] Basel II was adopted in Europe in 2007, which corresponds to the start of our observation period.

level drops in individual subsamples, our findings are robust overall. This is remarkable since our smallest subsample only contains three years as opposed to ten years in our main analysis.

Moreover, we control for the presence of joint supervisory teams (JSTs), which comprise staff from both the ECB and national central banks and oversee the most important banks in Europe (ECB, 2014). A JST was established for each significant institution in Europe after the introduction of the single supervisory mechanism (SSM) in 2014. Haselmann et al. (2022) provide evidence that banks under the SSM are supervised more strictly compared to those surveyed by national regulators, which affects risk weight reporting and bank risk-taking behavior. Since this may also alter our findings, we create a dummy variable (D_JST), which is equal to one if a bank is supervised by a JST in a specific year and zero otherwise. When reestimating our main regression analyses with this dummy as an additional control variable, our results remain robust (see Table A.25 in the appendix).

Finally, we account for bank mergers and acquisitions. Following Lepetit et al. (2015), we create a dummy variable ($D\_M\&A$), which is equal to one for those banks that experience a merger or acquisition event during our observation period, and zero otherwise. Taking advantage of data from Bankscope and banks' annual reports, we identify 131 banks with a merger or acquisition event in our main sample. We add $D\_M\&A$ as an additional control variable and report our results in Table A.26 in the appendix. Overall, our findings are consistent with previous results.

7.2 Hesitant rollout

Alternative thresholds for hesitant rollout bank:

We test for the robustness of our categorization as *hesitant rollout bank* and *non-hesitant rollout bank*. Instead of the thresholds presented in Section 4.2, we choose lower values for $IRBA\_COV$ since many national supervisors do not require a full rollout but rather define an exit threshold below a 100% coverage. For instance, the Solvency Regulation in Germany defines an exit threshold of 92% (see § 10). Lowering the IRBA coverage ratio thresholds in our definition of a *hesitant rollout bank* by 10 pp, banks still require, based on the defined $\Delta\, COV$ values, five years to reach the exit threshold. Our new categorization leads to fewer *hesitant rollout banks* in our *IRBA subsample*, now accounting for only 24% instead of 31% of our observations, which translates to a reduction of 23%:

$$IRBA\_COV \leq 40\% \wedge \Delta\, COV \leq 10\,\text{pp}$$
$$\vee$$
$$IRBA\_COV \leq 50\% \wedge \Delta\, COV \leq 8\,\text{pp}$$
$$\vee$$
$$IRBA\_COV \leq 60\% \wedge \Delta\, COV \leq 6\,\text{pp}.$$

Based on these alternative thresholds, we reestimate our logit regression model (see Equation 4) and propensity score matching analyses and summarize our results in Table A.27 in the appendix. We still yield significantly lower annual cost growth rates for *hesitant rollout banks* compared with similar *non-hesitant rollout banks* in six out of seven specifications. We even gain higher significance levels than in our main analysis. Furthermore, we observe that *hesitant rollout banks* exhibit significantly higher RWA reduction rates as opposed to similar *non-hesitant rollout banks* across all specifications, which strengthens our previous finding.

Alternative categorization as hesitant rollout bank:
To further underpin the validity of our findings, we additionally use an alternative categorization approach and create a very simple measure of rollout progress to classify *hesitant rollout banks* and *non-hesitant rollout banks*. For that purpose, we restrict our sample to banks that start their IRBA rollout early enough to have at least five years for the completion of the rollout process during our observation period. We define banks as *non-hesitant rollout banks* that reach an IRBA coverage ratio of at least 90% over time, reflecting the usual exit threshold by national supervisors below a 100% coverage. We again reestimate our logit regression model (see Equation 4) and propensity score matching analyses and present our results in Table A.28 in the appendix. Although our results are slightly weaker than previously in terms of statistical significance, they are overall consistent, which indicates the robustness against a modified classification approach for *hesitant rollout banks* and *non-hesitant rollout banks*.

Binary regression:

We reestimate our binary regressions with our dummy variable ($D\_HESITANT$) as the dependent variable (see Equation 4) to calculate propensity scores and apply a probit instead of a logit regression model, which we report in Table A.10, specification (2), in the appendix. The probit estimation leads to qualitatively and quantitatively similar findings as the logit estimation. Building on this, we reconduct our propensity score matching analyses and illustrate our findings in Table A.29 in the appendix. Even if the significance levels drop slightly, we still yield qualitatively the same findings as in our main analysis.

Panel estimations:

Instead of using propensity score matching, we apply linear panel data estimations using $\Delta COSTS$ and ΔRWA as dependent variables and $D\_HESITANT$ as our main independent variable. In addition, we control for the bank- and country-specific variables specified in Equation 3, apply time- and country-fixed effects, and cluster the standard errors at the bank level. As reported in Table A.30 in the appendix, we still provide evidence that *hesitant rollout banks* exhibit significantly lower annual cost growth rates as well as significantly higher RWA reduction rates, which reinforces our findings based on the propensity score matching.

8 Conclusions and policy implications

In most BCBS member states, supervisors permit banks to adopt a phased IRBA rollout across credit risk exposures within a reasonably short period (BCBS, 2004). Under the novel permanent partial-use philosophy recommended by the BCBS, banks no longer need to fully roll out the IRBA at the overall bank level. This paper reveals what potential consequences of this novel philosophy may be. In particular, we examine the trade-off for banks between annual costs and RWA reductions during the rollout process. Additionally, we aim to understand the effect of the rollout process on effective risk management, as measured by loan portfolio quality and credit risk prediction accuracy.

We cover the period with the most rollout processes to be observed, from 2007 to 2016, and construct a unique sample of 386 large banks. Our data set contains the manually collected, exact IRBA coverage ratios for each bank in each year. We use several dynamic panel data models to account as best as possible for the fact that we are only able to observe endogenous decisions taken by banks. We also apply piecewise regression models and propensity score matching to conduct our analyses and modify our models in a broad variety of robustness checks.

We provide evidence that banks rolling out the IRBA hesitantly, that is, with only little progress over time, exhibit significantly lower *cost* growth rates than similar banks with less hesitant IRBA rollouts. Furthermore, we observe that the first implementation steps lead to the greatest *RWA reductions*. Less promising portfolios seem to be implemented in a second step. Although we cannot completely rule out the possibility that less promising portfolios are also not very well suited for modelling and thus remain under the SA, the incentive to fully carry out the rollout still diminishes with higher IRBA coverage ratios, particularly if the RWA savings do not (over-)compensate for the costs. If supervisors do not enforce the full IRBA rollout, banks may thus take advantage of "cherry-picking" opportunities.

However, this conflicts with the original objective of policy makers, requiring a full implementation to introduce internal credit risk models as a comprehensive risk governance tool at the overall bank level (BCBS, 2004). Therefore, we analyze whether a full IRBA implementation is useful at all from a supervisory perspective, and find initial evidence that bank *risk management* improves with increasing IRBA coverage ratios. Nevertheless, if the novel permanent partial use reduces the IRBA entry barrier for SA banks, which would not have considered the IRBA adoption under the requirement of a full rollout at the overall bank level, it may at least induce improved risk management practices for this group.

References

Abbassi, P. and M. Schmidt (2018). A comprehensive view on risk reporting: Evidence from supervisory data. *Journal of Financial Intermediation 36*, 74–85.

Agoraki, M.-E. K., M. D. Delis, and F. Pasiouras (2011). Regulations, competition and bank risk-taking in transition countries. *Journal of Financial Stability 7*, 38–48.

Anginer, D., A. Demirgüc-Kunt, and M. Zhu (2014). How does deposit insurance affect bank risk? Evidence from the recent crisis. *Journal of Banking and Finance 48*, 312–321.

Arellano, M. and O. Bover (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics 68*, 29–51.

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

Basel Committee on Banking Supervision (BCBS) (2001). The internal ratings-based approach: Consultative document. Bank for International Settlements, January 2001.

Basel Committee on Banking Supervision (BCBS) (2004). Basel II: International convergence of capital measurement and capital standards: A revised framework. Bank for International Settlements, June 2004.

Basel Committee on Banking Supervision (BCBS) (2014a). Basel capital framework, National discretions. Bank for International Settlements, November 2014.

Basel Committee on Banking Supervision (BCBS) (2014b). Regulatory consistency assessment programme (RCAP): Assessment of Basel III regulations – United States of America. Bank for International Settlements, December 2014.

Basel Committee on Banking Supervision (BCBS) (2017). Basel III: Finalising post-crisis reforms. Bank for International Settlements, December 2017.

Beatty, A. and S. Liao (2011). Do delays in expected loss recognition affect banks' willingness to lend? *Journal of Accounting and Economics 52*, 1–20.

Begley, T. A., A. Purnanandam, and K. Zheng (2017). The strategic underreporting of bank risk. *The Review of Financial Studies 30*, 3376–3415.

Behn, M., R. Haselmann, and V. Vig (2022). The limits of model-based regulation. *The Journal of Finance 77*, 1635–1684.

Beltratti, A. and G. Paladino (2016). Basel II and regulatory arbitrage. Evidence from financial crises. *Journal of Empirical Finance 39*, 180–196.

Berg, T. and P. Koziol (2017). An analysis of the consistency of banks' internal ratings. *Journal of Banking and Finance 78*, 27–41.

Blundell, R. and S. Bond (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87*, 115–143.

Bruno, B., G. Nocera, and A. Resti (2015). The credibility of European banks' risk-weighted capital: Structural differences or national segmentations? *BAFFI CAREFIN Centre Research Paper 2015-9,* June 2015.

Cannata, F., S. Casellina, and G. Guidi (2012). Inside the labyrinth of Basel and risk-weighted assets: How not to get lost. *Banca di Italia, Questioni di Economia e Finanza (Occasional Papers),* September 2012.

Colliard, J.-E. (2019). Strategic selection of risk models and bank capital regulation. *Management Science 65*, 2591–2606.

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

Dal Borgo, M. (2022). Internal models for deposits: Effects on banks' capital and interest rate risk of assets. *Journal of Banking and Finance 135*, 105940.

Dimitrios, A., L. Helen, and T. Mike (2016). Determinants of non-performing loans: Evidence from Euro-area countries. *Finance Research Letters 18*, 116–119.

European Banking Authority (EBA) (2015). Future of the IRB approach. *EBA Discussion Paper*, March 2015.

European Banking Authority (EBA) (2016). Final draft regulatory technical standards on the specification of the assessment methodology for competent authorities regarding compliance of an institution with the requirements to use the IRB approach in accordance with Articles 144(2), 173(3) and 180(3)(b) of Regulation (EU) No 575/2013, July 2016.

European Banking Authority (EBA) (2019). Policy advice on the Basel III reforms: Credit risk, August 2019.

European Banking Authority (EBA) (2021). 2021 EU-wide stress test: Results, 30 July 2021.

European Central Bank (ECB) (2014). Guide to banking supervision. ECB Banking Supervision, November 2014.

European Central Bank (ECB) (2019). ECB guide to internal models. ECB Banking Supervision, October 2019.

Ferri, G. and V. Pesic (2017). Bank regulatory arbitrage via risk weighted assets dispersion. *Journal of Financial Stability 33*, 331–345.

Ghosh, A. (2015). Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states. *Journal of Financial Stability 20*, 93–104.

Giles, T. and A. Milne (2004). Basel II and UK banks: What are the costs and benefits of IRB qualification. *Charles River Associates EU Practitioner Papers,* March 2004.

Hakenes, H. and I. Schnabel (2011). Bank size and risk-taking under Basel II. *Journal of Banking and Finance 35*, 1436–1449.

Haselmann, R., S. Singla, and V. Vig (2022). Supranational supervision. *LawFin Working Paper No. 46,* November 2022.

Heckman, J. J., H. Ichimura, and P. Todd (1998). Matching as an econometric evaluation estimator. *The Review of Economic Studies 65*, 261–294.

Hellmann, T., L. Lindsey, and M. Puri (2007). Building relationships early: Banks in venture capital. *The Review of Financial Studies 21*, 513–541.

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

Imbierowicz, B. and C. Rauch (2014). The relationship between liquidity risk and credit risk in banks. *Journal of Banking and Finance 40*, 242–256.

International Monetary Fund (IMF) (2011). United Kingdom: Basel core principles for effective banking supervision detailed assessment of compliance, financial sector assessment program, August 2011.

Jiménez, G., J. A. Lopez, and J. Saurina (2013). How does competition affect bank risk-taking? *Journal of Financial Stability 9*, 185–195.

Kovner, A., J. Vickery, and L. Zhou (2015). Do big banks have lower operating costs? *Journal of Financial Perspectives 3*, 157–196.

Laeven, L. and R. Levine (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics 93*, 259–275.

Le Leslé, V. and S. Avramova (2012). Revisiting risk-weighted assets. *IMF Working Paper WP/12/90,* March 2012.

Lepetit, L., N. Saghi-Zedek, and A. Tarazi (2015). Excess control rights, bank capital structure adjustments, and lending. *Journal of Financial Economics 115*, 574–591.

Louzis, D. P., A. T. Vouldis, and V. L. Metaxas (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking and Finance 36*, 1012–1027.

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

Montes, C. P., C. T. Artigas, M. E. Cristófoli, and N. L. S. Segundo (2018). The impact of the IRB approach on the risk weights of European banks. *Journal of Financial Stability 39*, 147–166.

Plosser, M. C. and J. A. Santos (2018). Banks' incentives and the quality of internal risk models. *The Review of Financial Studies 31*, 2038–2079.

Roodman, D. (2009a). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics 71*, 135–158.

Roodman, D. (2009b). How to do xtabond2: An introduction to difference and system GMM. *Stata Journal 9*, 86–136.

Rosenbaum, P. R. and D. B. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika 70*, 41–55.

Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica 20*, 431–449.

Shim, J. (2013). Bank capital buffer and portfolio risk: The influence of business cycle and revenue diversification. *Journal of Banking & Finance 37*, 761–772.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science 25*, 1–21.

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

Wengerek, S. T., B. Hippert, and A. Uhde (2022). Risk allocation through securitization – Evidence from non-performing loans. *The Quarterly Review of Economics and Finance 86*, 48–64.

A Appendix

The Rollout of Internal Credit Risk Models: Implications for the Novel Partial-Use Philosophy

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Guide to the appendix:

This appendix provides additional information and analyses for "The Rollout of Internal Credit Risk Models: Implications for the Novel Partial-Use Philosophy." It is divided into the following five categories:

Sample selection:

First, we present our sample selection procedure in Table A.1.

IRBA adoption drivers:

Second, while analyzing the IRBA adoption drivers in the main body is beyond the scope of our paper, we provide some background information on this topic in Tables A.2 and A.3.

Sample description:

Third, we provide some more details on our samples. In Tables A.4 to A.6, we present the distribution by country, year, and bank type for our main sample. The variables' pairwise correlations are shown in Table A.7. In Tables A.8 and A.9, we illustrate the distribution by country and year for our *IRBA subsample*.

Determinants of the classification as a *hesitant rollout bank*:

Fourth, we report the logit and probit models to estimate propensity scores in Table A.10.

Robustness checks:

Fifth, in Tables A.11 to A.30, we provide the results of various robustness checks, which are mainly described in Section 7 in the main body of the paper.

Table A.1: Overview of our sample selection procedure.

Sample selection procedure		**Number of banks**
Initial sample		**554**
Adjustments to effectively suit the research purpose at hand:		
Add additional European IRBA banks available in Fitch Connect	+	86
Collect U.S. banks	+	25
Drop smaller SA banks to arrive at an almost balanced panel	−	261
Drop banks for which main variables are predominantly missing (e. g., RWA, IRBA coverage ratio, total assets)	−	15
Drop banks for which observations contain gaps	−	3
Main sample		**386**

This table reports the sample selection procedure for our main sample covering the observation period from 2007 to 2016. The initial sample is based on Bankscope and covers the observation period from 2007 to 2014. It includes about 30% of observations relating to IRBA banks. We extend the original observation period until 2016 in order to capture possible effects from introducing the Single Supervisory Mechanism (SSM) in Europe in 2014 (ECB, 2014). For the purpose of extending our sample to 2016, we had to switch from Bankscope to Fitch Connect, which was launched in 2015. Moreover, we drop smaller SA banks to arrive at an almost balanced panel because our research questions focus on IRBA banks.

Table A.2: IRBA adoption drivers.

As we observe major differences in the IRBA rollout process across banks (see Figure 1 in the main body of the paper), it is of particular interest to explore the key drivers for banks to adopt the IRBA. Thus, Table A.3, upper panel, in the appendix compares SA banks that do not implement the IRBA and SA banks that obtain IRBA approval during our observation period. In the latter case, we consider financial statement positions prior to the first IRBA usage since the change in risk measurement approach may affect those positions.

First, not surprisingly, we find that banks prior to starting their IRBA rollout are significantly larger than those that continue to apply the SA. Even though we only consider SA banks with total assets above USD 896 million, it seems that the adoption of complex internal credit risk models only pays off for larger banks, possibly because of higher economies of scale. Second, banks, before their first IRBA usage, are significantly more profitable, measured by the ROE, than those continuously relying on the SA. This may be because IRBA implementation is costly and only affordable for banks showing solid profitability. Third, contrary to our expectations, banks prior to starting their IRBA implementation show significantly lower RWA densities than those continuously applying the SA. Consequently, high RWA densities do not seem to be the major motive for switching the risk measurement approach. Lastly, banks with IRBA approval have significantly lower NPL ratios than those without approval. Following Cucinelli et al. (2018), banks with higher NPL ratios benefit the most from applying internal credit risk models because they can improve their risk management and consequently decrease NPL ratios. However, IRBA applications from banks with poor risk management, and thus with high NPL ratios, may be rejected by supervisors.

Table A.3: Results of univariate tests to compare SA and IRBA banks as well as *hesitant rollout banks* and *non-hesitant rollout banks*.

	No IRBA approval ***(SA banks)***	**Before IRBA approval** ***(IRBA banks)***	**Difference between these groups**
SIZE			
Mean	9.35	11.11	1.77^{***}
N (t-statistics)	1,982	377	(-22.12)
ROE			
Mean	3.33	8.08	4.75^{***}
N (t-statistics)	1,982	377	(-5.71)
RWATA			
Mean	56.25	53.53	-2.72^{*}
N (t-statistics)	1,562	318	(1.95)
NPL			
Mean	5.85	3.19	-2.66^{***}
N (t-statistics)	1,368	286	(6.61)

	Before IRBA approval ***(Non-hesitant rollout banks)***	**Before IRBA approval** ***(Hesitant rollout banks)***	**Difference between these groups**
SIZE			
Mean	10.98	11.90	0.92^{***}
N (t-statistics)	323	54	(-3.33)
ROE			
Mean	8.01	8.06	0.05
N (t-statistics)	323	54	(-0.03)
RWATA			
Mean	52.80	58.20	5.41^{*}
N (t-statistics)	275	43	(-1.86)
NPL			
Mean	3.06	3.83	0.77
N (t-statistics)	237	49	(-1.42)

This table reports tests on the mean differences between SA banks without IRBA approval and SA banks obtaining the IRBA approval later on during our observation period (upper panel), as well as tests on the mean differences between *hesitant rollout banks* and *non-hesitant rollout banks* before their IRBA approval (bottom panel). We consider financial statement positions prior to the first IRBA usage since the change in risk measurement approach may affect those positions. Variables are described in Table 1 in the main body of the paper. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.4: Sample distribution by country.

Country	**Number of observations**	**Number of banks**	**% of total assets in the sample**
Austria	310	33	2.23
Belgium	88	9	4.00
Denmark	165	18	1.83
Finland	76	9	0.46
France	157	16	17.31
Germany	718	72	12.47
Hungary	40	4	0.13
Ireland	91	10	1.38
Italy	594	64	6.37
Netherlands	165	17	5.31
Norway	270	32	1.68
Poland	83	9	0.39
Spain	150	18	6.69
Sweden	169	18	3.68
United Kingdom	313	32	15.63
United States of America	250	25	20.46
Total	**3,639**	**386**	**100.00**

This table presents the distribution by country for our main sample during the observation period from 2007 to 2016. Due to rounding errors, the sum in the forth column is not exactly 100.

Table A.5: Sample distribution by year.

Year	**Number of observations and banks**	**% of total assets in the sample**
2007	348	9.96
2008	358	10.49
2009	367	10.67
2010	374	10.39
2011	374	10.40
2012	371	10.49
2013	372	10.24
2014	363	9.74
2015	361	8.94
2016	351	8.68
Total	**3,639**	**100.00**

This table presents the distribution by year for our main sample during the observation period from 2007 to 2016. The numbers of observations and banks coincide because we observe each bank once every year.

Table A.6: Sample distribution by bank type.

Bank type	**Number of observations**	**Number of banks**	**% of total assets in the sample**
Bank holdings	479	49	41.46
Commercial banks	1,326	143	38.69
Cooperative banks	404	41	8.38
Savings banks	505	55	2.65
Finance companies	146	16	0.46
Investment banks	119	14	0.78
Private banking	40	4	0.09
Real estate banks	388	40	3.03
Specialized governmental credit institutions	180	18	4.33
Other banks	52	6	0.14
Total	**3,639**	**386**	**100.00**

This table presents the distribution by bank type for our main sample during the observation period from 2007 to 2016. The distinct categorization into 10 bank types is conducted by Bankscope. Due to rounding errors, the sum in the forth column is not exactly 100.

Table A.7: Pairwise correlations of all non-binary variables.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
(1) $COSTS$	1.000															
(2) $\Delta COSTS$	0.079	1.000														
(3) $RWATA$	0.364	0.030	1.000													
(4) ΔRWA	0.037	0.287	0.157	1.000												
(5) NPL	0.098	-0.004	0.166	-0.162	1.000											
(6) $NPL_t - LLP_{t-1}$	0.044	0.021	0.138	-0.136	0.954	1.000										
(7) $IRBA\_COV$	-0.159	-0.031	-0.344	-0.155	-0.046	-0.070	1.000									
(8) Z_SCORE	-0.087	-0.067	0.048	0.065	-0.241	-0.215	-0.064	1.000								
(9) ROA	0.181	0.000	0.196	0.192	-0.362	-0.347	-0.037	0.213	1.000							
(10) NII	-0.272	0.029	-0.107	0.007	-0.068	-0.064	0.084	0.044	-0.130	1.000						
(11) $LOANS$	-0.090	0.035	0.363	0.024	0.115	0.126	0.014	0.089	-0.033	0.341	1.000					
(12) $DEPOSITS$	0.154	-0.031	0.169	0.006	0.141	0.136	-0.220	0.170	-0.018	-0.184	0.006	1.000				
(13) $SIZE$	-0.125	-0.016	-0.216	-0.059	-0.106	-0.133	0.441	-0.161	-0.037	-0.073	-0.197	-0.317	1.000			
(14) GDP_GR	0.021	-0.027	-0.022	0.011	-0.052	-0.025	0.065	0.116	0.141	0.007	-0.039	-0.000	0.007	1.000		
(15) $INFLATION$	0.023	0.063	0.109	0.137	-0.113	-0.105	-0.131	-0.096	0.010	0.012	0.015	-0.019	-0.007	0.036	1.000	
(16) SUP_STR	0.194	-0.029	0.208	-0.053	0.156	0.143	-0.057	-0.022	-0.026	-0.179	-0.081	0.103	0.146	-0.081	-0.079	1.000

This table reports the pairwise correlations of all non-binary variables used in our analysis. Variables are described in Table 1 in the main body of the paper.

Table A.8: Distribution of the IRBA coverage ratio (%) by country in our *IRBA subsample.*

Country	**N**	**Mean**	**SD**	**p10**	**p50**	**p90**
Austria	71	72.38	24.28	41.28	73.63	100.00
Belgium	40	79.09	19.94	48.89	87.72	99.08
Denmark	48	82.18	13.95	68.84	85.27	95.00
Finland	28	66.13	30.60	23.72	83.93	94.86
France	64	65.40	14.51	47.95	62.13	83.39
Germany	174	78.08	15.12	57.60	82.37	93.43
Hungary	6	92.13	1.60	90.31	91.84	94.12
Ireland	37	63.89	25.19	32.55	58.74	94.89
Italy	108	59.56	18.93	37.71	56.56	84.28
Netherlands	47	84.84	14.11	74.84	88.28	96.54
Norway	82	74.90	26.14	48.47	85.56	100.00
Poland	18	64.69	17.91	46.59	59.71	86.73
Spain	57	50.10	13.66	28.99	50.16	68.12
Sweden	132	83.41	15.76	56.29	86.60	99.95
United Kingdom	107	69.26	16.07	43.31	69.70	89.66
United States of America	32	100.00	0.00	100.00	100.00	100.00
Total	**1,051**	**73.25**	**20.98**	**44.12**	**77.64**	**97.94**

This table presents the distribution of the IRBA coverage ratio (%) by country in our *IRBA subsample* during the observation period from 2007 to 2016. N refers to the number of observations, SD means standard deviation. p10, p50, and p90 represent the tenth, fiftieth, and the ninetieth percentile. The total number of observations reported in this table does not coincide with the number reported in the main body of the paper since for some observations, we do not observe the IRBA coverage ratio. We do not drop those observations from our sample because they are useful with respect to our propensity score matching. Due to rounding errors, the sum of the columns does not always match the totals line.

Table A.9: Distribution of the IRBA coverage ratio (%) by year in our *IRBA subsample*.

Year	N	Mean	SD	p10	p50	p90
2007	29	66.05	26.60	24.65	60.98	100.00
2008	78	67.13	22.10	35.70	67.97	97.54
2009	84	68.53	22.83	41.57	70.57	95.19
2010	95	69.80	22.50	35.41	72.69	97.44
2011	103	71.27	20.90	43.18	72.47	96.18
2012	112	72.59	20.30	41.93	78.10	95.90
2013	116	74.01	19.67	45.62	80.05	94.89
2014	134	76.29	19.25	48.38	79.91	100.00
2015	150	77.06	19.61	50.32	80.77	100.00
2016	150	77.42	19.86	48.30	82.07	100.00
Total	**1,051**	**73.25**	**20.98**	**44.12**	**77.64**	**97.94**

This table presents the distribution of the IRBA coverage ratio (%) by year in our *IRBA subsample* during the observation period from 2007 to 2016. N refers to the number of observations, SD means standard deviation. p10, p50, and p90 represent the tenth, fiftieth, and the ninetieth percentile. The total number of observations reported in this table does not coincide with the number reported in the main body of the paper since for some observations, we do not observe the IRBA coverage ratio. We do not drop those observations from our sample because they are useful with respect to our propensity score matching. Due to rounding errors, the sum of the columns does not always match the totals line.

Table A.10: Determinants of the classification as a *hesitant rollout bank*.

	(1)	**(2)**
	$\boldsymbol{D\_HESITANT_{i,t}}$	$\boldsymbol{D\_HESITANT_{i,t}}$
D_MODEL_i	0.00392	0.00297
	(0.0161)	(0.0167)
$Z\_SCORE_{i,t}$	-0.0249**	-0.0275**
	(0.0119)	(0.0116)
$ROA_{i,t}$	-0.00103	0.00140
	(0.0338)	(0.0349)
$NII_{i,t}$	-0.000525	-0.000574
	(0.000825)	(0.000853)
$LOANS_{i,t}$	0.00154	0.00180
	(0.00176)	(0.00171)
$DEPOSITS_{i,t}$	-0.00115	-0.00167
	(0.00266)	(0.00251)
$SIZE_{i,t}$	0.0878***	0.0788***
	(0.0299)	(0.0287)
$GDP\_GR_{c,t}$	-0.00143	-0.00196
	(0.00267)	(0.00270)
$INFLATION_{c,t}$	0.00175	0.00112
	(0.00533)	(0.00522)
$SUP\_STR_{c,t}$	-0.00550	-0.00543
	(0.00805)	(0.00806)
Time-fixed effects	Yes	Yes
Country-fixed effects	Yes	Yes
N	1,066	1,066
Pseudo R^2	0.2125	0.2014
Estimation method	Logit	Probit

This table reports the marginal effects of the logit, specification (1), and probit regression, specification (2), on the determinants of being classified as a *hesitant rollout bank* ($D\_HESITANT$). Variables are described in Table 1 in the main body of the paper. N refers to the number of observations. Robust standard errors clustered at the bank level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.11: Phased IRBA rollout and NPL ratios (Robustness: Fixed effects panel regression with lagged explanatory variables).

	(1)	(2)	(3)
	$\boldsymbol{NPL}_{i,t}$	$\boldsymbol{NPL}_{i,t}$	$\boldsymbol{NPL}_{i,t}$
$IRBA\_COV_{i,t-1}$	-0.0399**	-0.0399**	-0.0422***
	(0.0154)	(0.0154)	(0.0158)
$Z\_SCORE_{i,t-1}$	-0.384**	-0.382**	-0.400**
	(0.148)	(0.148)	(0.156)
$ROA_{i,t-1}$	-1.811***	-1.815***	-1.781***
	(0.489)	(0.491)	(0.492)
$NII_{i,t-1}$	-0.0167	-0.0167	-0.0167
	(0.0140)	(0.0140)	(0.0141)
$LOANS_{i,t-1}$	0.0568**	0.0567**	0.0564**
	(0.0267)	(0.0266)	(0.0268)
$DEPOSITS_{i,t-1}$	0.0134	0.0134	0.0153
	(0.0198)	(0.0198)	(0.0206)
$SIZE_{i,t-1}$	-2.287***	-2.292***	-2.210***
	(0.786)	(0.786)	(0.787)
$GDP\_GR_{c,t-1}$	0.0217	0.0228	0.0226
	(0.0735)	(0.0735)	(0.0751)
$INFLATION_{c,t-1}$	0.289*	0.297*	0.322**
	(0.150)	(0.151)	(0.160)
$SUP\_STR_{c,t-1}$	0.194	0.194	0.197
	(0.228)	(0.228)	(0.227)
Time-fixed effects	Yes	Yes	Yes
N	787	767	730
R^2	0.301	0.301	0.305

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects the ratio of non-performing loans divided by total loans (NPL) in the period from 2007 to 2016, applying fixed effects panel regression models with lagged explanatory variables. Specification (1) uses our *IRBA subsample*, specification (2) uses our *European subsample* excluding observations referring to SA banks, and specification (3) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.12: Phased IRBA rollout and bank credit risk prediction accuracy (Robustness: Fixed effects panel regression with lagged explanatory variables).

	(1)	(2)	(3)
	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$IRBA\_COV_{i,t-1}$	-0.0415***	-0.0415***	-0.0439***
	(0.0151)	(0.0151)	(0.0155)
$Z\_SCORE_{i,t-1}$	-0.332**	-0.332**	-0.351**
	(0.130)	(0.130)	(0.137)
$ROA_{i,t-1}$	-1.209***	-1.210***	-1.173***
	(0.418)	(0.420)	(0.421)
$NII_{i,t-1}$	-0.0123	-0.0123	-0.0123
	(0.0125)	(0.0125)	(0.0126)
$LOANS_{i,t-1}$	0.0599**	0.0599**	0.0596**
	(0.0239)	(0.0239)	(0.0241)
$DEPOSITS_{i,t-1}$	0.00873	0.00868	0.0108
	(0.0194)	(0.0194)	(0.0202)
$SIZE_{i,t-1}$	-2.508***	-2.511***	-2.430***
	(0.762)	(0.762)	(0.761)
$GDP\_GR_{c,t-1}$	0.0653	0.0659	0.0660
	(0.0748)	(0.0748)	(0.0767)
$INFLATION_{c,t-1}$	0.234	0.239	0.259*
	(0.144)	(0.145)	(0.154)
$SUP\_STR_{c,t-1}$	0.150	0.150	0.153
	(0.222)	(0.222)	(0.220)
Time-fixed effects	Yes	Yes	Yes
N	780	764	727
R^2	0.282	0.282	0.286

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects the difference between the NPL ratio at time t and the LLP ratio at time $t-1$ ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2016, applying fixed effects panel regression models with lagged explanatory variables. Specification (1) uses our *IRBA subsample*, specification (2) uses our *European subsample* excluding observations referring to SA banks, and specification (3) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.13: Phased IRBA rollout and RWA densities (Robustness: Fixed effects panel regression).

	(1)	**(2)**	**(3)**	**(4)**
	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$
$IRBA\_COV_{i,t}$	-0.0882***	-0.139***	-0.137***	-0.144***
	(0.0180)	(0.0198)	(0.0356)	(0.0338)
$Z\_SCORE_{i,t}$	-0.0805	-0.136	-0.270	-0.394
	(0.139)	(0.149)	(0.287)	(0.291)
$ROA_{i,t}$	1.228***	1.363***	-0.225	0.0684
	(0.356)	(0.403)	(0.722)	(0.659)
$NII_{i,t}$	0.00911	0.0106	0.00942	0.0127
	(0.0133)	(0.0137)	(0.0250)	(0.0250)
$LOANS_{i,t}$	0.315***	0.329***	0.450***	0.451***
	(0.0613)	(0.0652)	(0.115)	(0.115)
$DEPOSITS_{i,t}$	-0.136***	-0.137***	-0.156	-0.119
	(0.0458)	(0.0475)	(0.118)	(0.119)
$SIZE_{i,t}$	-3.060*	-3.648*	-4.799	-4.352
	(1.743)	(1.938)	(3.844)	(3.828)
$GDP\_GR_{c,t}$	0.0474	0.0460	0.0721	0.0518
	(0.0861)	(0.0829)	(0.111)	(0.112)
$INFLATION_{c,t}$	1.068***	0.902***	0.615*	0.732**
	(0.201)	(0.196)	(0.333)	(0.350)
$SUP\_STR_{c,t}$	-0.379*	-0.223	0.216	0.227
	(0.198)	(0.201)	(0.287)	(0.288)
Time-fixed effects	Yes	Yes	Yes	Yes
N	2,802	2,566	979	902
R^2	0.225	0.260	0.249	0.260

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$) in the period from 2007 to 2016, applying fixed effects panel regression models. Specification (1) uses our main sample, specification (2) uses our *European subsample*, specification (3) uses our *IRBA subsample*, and specification (4) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.14: Phased IRBA rollout and RWA densities, additionally controlling for the squared term of the IRBA coverage ratio (Robustness: Fixed effects panel regression).

	(1)	**(2)**	**(3)**	**(4)**
	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$
$IRBA\_COV_{i,t}$	-0.297***	-0.263***	-0.223*	-0.185*
	(0.0512)	(0.0498)	(0.123)	(0.111)
$SQ\_IRBA\_COV_{i,t}$	0.00232***	0.00144**	0.000710	0.000337
	(0.000601)	(0.000611)	(0.00111)	(0.000956)
$Z\_SCORE_{i,t}$	-0.0962	-0.143	-0.271	-0.394
	(0.138)	(0.148)	(0.287)	(0.291)
$ROA_{i,t}$	1.137***	1.291***	-0.220	0.0689
	(0.347)	(0.397)	(0.724)	(0.662)
$NII_{i,t}$	0.00900	0.0105	0.00930	0.0126
	(0.0130)	(0.0135)	(0.0250)	(0.0251)
$LOANS_{i,t}$	0.309***	0.324***	0.448***	0.450***
	(0.0604)	(0.0644)	(0.116)	(0.115)
$DEPOSITS_{i,t}$	-0.137***	-0.139***	-0.156	-0.119
	(0.0462)	(0.0479)	(0.118)	(0.120)
$SIZE_{i,t}$	-3.223*	-3.667*	-4.623	-4.266
	(1.706)	(1.902)	(3.840)	(3.854)
$GDP\_GR_{c,t}$	0.0399	0.0428	0.0726	0.0521
	(0.0843)	(0.0819)	(0.111)	(0.112)
$INFLATION_{c,t}$	1.003***	0.874***	0.631*	0.741**
	(0.203)	(0.199)	(0.335)	(0.347)
$SUP\_STR_{c,t}$	-0.347*	-0.213	0.222	0.229
	(0.193)	(0.199)	(0.286)	(0.288)
Time-fixed effects	Yes	Yes	Yes	Yes
N	2,802	2,566	979	902
R^2	0.237	0.265	0.249	0.260

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$) in the period from 2007 to 2016, applying fixed effects panel regression models and additionally controlling for the squared term of the IRBA coverage ratio (SQ_IRBA_COV). Specification (1) uses our main sample, specification (2) uses our *European subsample*, specification (3) uses our *IRBA subsample*, and specification (4) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.15: Phased IRBA rollout and RWA densities, applying a piecewise regression model (Robustness: Fixed effects panel regression).

	(1)	(2)	(3)
	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$
$IRBA\_COV_{i,t}^{low}$	-0.178***	-0.170***	-0.165***
	(0.0283)	(0.0220)	(0.0198)
$IRBA\_COV_{i,t}^{high}$	0.210***	0.259***	0.368***
	(0.0659)	(0.0667)	(0.0829)
$Z\_SCORE_{i,t}$	-0.0908	-0.0953	-0.101
	(0.138)	(0.138)	(0.138)
$ROA_{i,t}$	1.159***	1.152***	1.140***
	(0.350)	(0.349)	(0.346)
$NII_{i,t}$	0.00928	0.00909	0.00857
	(0.0131)	(0.0130)	(0.0129)
$LOANS_{i,t}$	0.310***	0.310***	0.310***
	(0.0606)	(0.0604)	(0.0603)
$DEPOSITS_{i,t}$	-0.136***	-0.137***	-0.137***
	(0.0460)	(0.0461)	(0.0463)
$SIZE_{i,t}$	-3.140*	-3.152*	-3.222*
	(1.718)	(1.717)	(1.719)
$GDP\_GR_{c,t}$	0.0416	0.0423	0.0497
	(0.0850)	(0.0853)	(0.0848)
$INFLATION_{c,t}$	1.022***	1.022***	1.018***
	(0.204)	(0.204)	(0.202)
$SUP\_STR_{c,t}$	-0.358*	-0.341*	-0.314
	(0.193)	(0.193)	(0.193)
Time-fixed effects	Yes	Yes	Yes
N	2,802	2,802	2,802
R^2	0.233	0.236	0.242

This table reports the piecewise regression analysis on whether the IRBA coverage ratio (IRB_COV) affects RWA densities ($RWATA$) in the period from 2007 to 2016, based on our main sample and applying fixed effects panel regression models. Specification (1) assumes a knot at 50%, specification (2) at 60%, and specification (3) at 70%. Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.16: Phased IRBA rollout and NPL ratios (Robustness: Fixed effects panel regression).

	(1)	**(2)**	**(3)**
	$\boldsymbol{NPL}_{i,t}$	$\boldsymbol{NPL}_{i,t}$	$\boldsymbol{NPL}_{i,t}$
$IRBA\_COV_{i,t}$	-0.0235**	-0.0239**	-0.0256**
	(0.00996)	(0.00995)	(0.0101)
$Z\_SCORE_{i,t}$	-0.320**	-0.328**	-0.350**
	(0.146)	(0.150)	(0.157)
$ROA_{i,t}$	-1.641***	-1.642***	-1.596***
	(0.459)	(0.462)	(0.463)
$NII_{i,t}$	-0.0170	-0.0170	-0.0170
	(0.0141)	(0.0141)	(0.0143)
$LOANS_{i,t}$	0.0357	0.0351	0.0352
	(0.0377)	(0.0376)	(0.0378)
$DEPOSITS_{i,t}$	0.0397	0.0395	0.0442
	(0.0278)	(0.0279)	(0.0292)
$SIZE_{i,t}$	-2.424**	-2.467**	-2.372**
	(1.074)	(1.082)	(1.077)
$GDP\_GR_{c,t}$	0.173***	0.177***	0.178***
	(0.0624)	(0.0635)	(0.0650)
$INFLATION_{c,t}$	0.172	0.173	0.189
	(0.157)	(0.160)	(0.169)
$SUP\_STR_{c,t}$	-0.0402	-0.0400	-0.0388
	(0.256)	(0.256)	(0.254)
Time-fixed effects	Yes	Yes	Yes
N	919	887	849
R^2	0.280	0.282	0.287

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects the ratio of non-performing loans divided by total loans (NPL) in the period from 2007 to 2016, applying fixed effects panel regression models. Specification (1) uses our *IRBA subsample*, specification (2) uses our *European subsample* excluding observations referring to SA banks, and specification (3) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.17: Phased IRBA rollout and bank credit risk prediction accuracy (Robustness: Fixed effects panel regression).

	(1)	(2)	(3)
	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$IRBA\_COV_{i,t}$	-0.0360***	-0.0360***	-0.0379***
	(0.0122)	(0.0122)	(0.0125)
$Z\_SCORE_{i,t}$	-0.249*	-0.256*	-0.275*
	(0.131)	(0.134)	(0.140)
$ROA_{i,t}$	-1.350***	-1.347***	-1.307***
	(0.436)	(0.437)	(0.438)
$NII_{i,t}$	-0.0179	-0.0180	-0.0180
	(0.0132)	(0.0132)	(0.0134)
$LOANS_{i,t}$	0.0433	0.0432	0.0429
	(0.0315)	(0.0315)	(0.0315)
$DEPOSITS_{i,t}$	0.0128	0.0127	0.0161
	(0.0241)	(0.0241)	(0.0254)
$SIZE_{i,t}$	-3.068***	-3.099***	-2.964***
	(1.099)	(1.107)	(1.102)
$GDP\_GR_{c,t}$	0.220***	0.222***	0.224***
	(0.0676)	(0.0682)	(0.0701)
$INFLATION_{c,t}$	0.128	0.128	0.155
	(0.153)	(0.156)	(0.165)
$SUP\_STR_{c,t}$	-0.00863	-0.00814	-0.00706
	(0.241)	(0.241)	(0.239)
Time-fixed effects	Yes	Yes	Yes
N	881	855	819
R^2	0.308	0.309	0.314

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects the difference between the NPL ratio at time t and the LLP ratio at time $t-1$ ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2016, applying fixed effects panel regression models. Specification (1) uses our *IRBA subsample*, specification (2) uses our *European subsample* excluding observations referring to SA banks, and specification (3) uses our *Partial-use subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.18: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Fixed effects panel regression using the interaction of time- and country-fixed effects).

	(1)	**(2)**	**(3)**	**(4)**
	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{NPL}_{i,t}$	$\boldsymbol{NPL}_{i,t} - \boldsymbol{LLP}_{i,t-1}$
$IRBA\_COV_{i,t}$	-0.0770***	-0.258***	-0.0249***	-0.0259**
	(0.0162)	(0.0541)	(0.00932)	(0.0104)
$SQ\_IRBA\_COV_{i,t}$		0.00202***		
		(0.000591)		
$Z\_SCORE_{i,t}$	-0.176	-0.179	-0.183*	-0.117
	(0.132)	(0.131)	(0.107)	(0.0973)
$ROA_{i,t}$	1.138***	1.077***	-1.062**	-0.943**
	(0.404)	(0.396)	(0.441)	(0.475)
$NII_{i,t}$	0.00728	0.00726	-0.00246	-0.00512
	(0.0136)	(0.0134)	(0.0113)	(0.0110)
$LOANS_{i,t}$	0.295***	0.290***	-0.00577	0.00620
	(0.0627)	(0.0616)	(0.0363)	(0.0353)
$DEPOSITS_{i,t}$	-0.105**	-0.106**	-0.0101	-0.0193
	(0.0482)	(0.0486)	(0.0246)	(0.0217)
$SIZE_{i,t}$	-3.876**	-3.909**	-0.881	-1.584
	(1.929)	(1.883)	(1.404)	(1.394)
$GDP\_GR_{c,t}$	0.217	0.425	-0.0111	0.262
	(0.896)	(0.847)	(0.160)	(0.187)
$INFLATION_{c,t}$	-0.330	-0.157	0.0736	0.186
	(0.975)	(0.908)	(0.117)	(0.154)
$SUP\_STR_{c,t}$	-4.333***	-3.915***	-0.389*	-0.259
	(1.402)	(1.297)	(0.233)	(0.247)
Time- x country-fixed effects	Yes	Yes	Yes	Yes
N	2,802	2,802	919	881
R^2	0.369	0.376	0.641	0.625

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2016, applying fixed effects panel regression models as well as the interaction of time- and country-fixed effects instead of time-fixed effects. Specifications (1) and (2) use our main sample, specifications (3) and (4) use our *IRBA subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.19: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Subsample from 2007 to 2009).

	(1)	(2)	(3)
	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{NPL}_{i,t}$	$\boldsymbol{NPL}_{i,t} - \boldsymbol{LLP}_{i,t-1}$
$IRBA\_COV_{i,t}$	-0.133**	-0.00541	-0.0172
	(0.0527)	(0.00660)	(0.0167)
$SQ\_IRBA\_COV_{i,t}$	0.000634		
	(0.000633)		
$Z\_SCORE_{i,t}$	-0.00249	0.229**	0.193**
	(0.246)	(0.0950)	(0.0832)
$ROA_{i,t}$	0.302	-1.210**	-1.481***
	(0.594)	(0.490)	(0.434)
$NII_{i,t}$	-0.00456	0.000666	-0.00113
	(0.0136)	(0.00421)	(0.00342)
$LOANS_{i,t}$	0.426***	0.00332	0.0685**
	(0.0557)	(0.0297)	(0.0333)
$DEPOSITS_{i,t}$	-0.255**	0.00831	0.0229
	(0.113)	(0.0263)	(0.0173)
$SIZE_{i,t}$	-6.443***	1.506	2.461***
	(2.046)	(1.175)	(0.731)
$GDP\_GR_{c,t}$	-0.0526	-0.0130	-0.126
	(0.229)	(0.0874)	(0.0999)
$INFLATION_{c,t}$	-0.291	0.0640	-0.00833
	(0.223)	(0.0642)	(0.0793)
Time-fixed effects	Yes	Yes	Yes
N	700	160	135
R^2	0.310	0.567	0.581

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2009, applying fixed effects panel regression models. Specification (1) uses our main sample, specifications (2) and (3) use our *IRBA subsample* (see Section 3.2). Due to the reduced numbers of observations in our subsamples, the variable SUP_STR is omitted. Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.20: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Subsample from 2007 to 2013).

	(1)	**(2)**	**(3)**
	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$IRBA\_COV_{i,t}$	-0.227***	-0.0427***	-0.0448**
	(0.0562)	(0.0162)	(0.0194)
$SQ\_IRBA\_COV_{i,t}$	0.00132**		
	(0.000660)		
$Z\_SCORE_{i,t}$	-0.147	-0.189	-0.138
	(0.167)	(0.119)	(0.110)
$ROA_{i,t}$	1.044***	-1.332**	-0.871
	(0.395)	(0.648)	(0.602)
$NII_{i,t}$	-0.00262	-0.00553	-0.00879
	(0.0111)	(0.00944)	(0.00815)
$LOANS_{i,t}$	0.325***	0.0577*	0.0583*
	(0.0700)	(0.0308)	(0.0295)
$DEPOSITS_{i,t}$	-0.112*	0.0234	0.000118
	(0.0636)	(0.0241)	(0.0164)
$SIZE_{i,t}$	-2.561	-2.369	-2.569
	(2.277)	(1.524)	(1.686)
$GDP\_GR_{c,t}$	0.132	0.136	0.165
	(0.139)	(0.116)	(0.111)
$INFLATION_{c,t}$	-0.0709	0.508***	0.413***
	(0.221)	(0.149)	(0.147)
$SUP\_STR_{c,t}$	-0.353*	-0.425**	-0.335*
	(0.198)	(0.204)	(0.195)
Time-fixed effects	Yes	Yes	Yes
N	1,868	531	500
R^2	0.288	0.472	0.457

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2013, applying fixed effects panel regression models. Specification (1) uses our main sample, specifications (2) and (3) use our *IRBA subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.21: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Subsample from 2014 to 2016).

	(1)	(2)	(3)
	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$IRBA\_COV_{i,t}$	-0.197*	-0.0110	-0.0362**
	(0.103)	(0.0191)	(0.0177)
$SQ\_IRBA\_COV_{i,t}$	0.00178		
	(0.00109)		
$Z\_SCORE_{i,t}$	-0.197	-0.192*	-0.120
	(0.128)	(0.0996)	(0.0852)
$ROA_{i,t}$	0.388	-0.0160	-0.681*
	(0.323)	(0.429)	(0.410)
$NII_{i,t}$	0.0353*	0.0108	0.00465
	(0.0196)	(0.0103)	(0.00866)
$LOANS_{i,t}$	-0.0174	-0.0292	-0.0618
	(0.178)	(0.0636)	(0.0559)
$DEPOSITS_{i,t}$	-0.0720	-0.150	-0.100
	(0.0491)	(0.105)	(0.0894)
$SIZE_{i,t}$	-10.20**	3.738**	1.542
	(5.011)	(1.485)	(1.352)
$GDP\_GR_{c,t}$	0.0186	-0.0864**	-0.0584
	(0.0549)	(0.0401)	(0.0356)
$INFLATION_{c,t}$	0.317	0.359**	0.299**
	(0.414)	(0.146)	(0.128)
Time-fixed effects	Yes	Yes	Yes
N	934	388	381
R^2	0.164	0.211	0.174

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2014 to 2016, applying fixed effects panel regression models. Specification (1) uses our main sample, specifications (2) and (3) use our *IRBA subsample* (see Section 3.2). Due to the reduced numbers of observations in our subsamples, the variable SUP_STR is omitted. Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.22: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Subsample from 2010 to 2016).

	(1)	(2)	(3)
	$\boldsymbol{RWATA}_{i,t}$	$\boldsymbol{NPL}_{i,t}$	$\boldsymbol{NPL}_{i,t} - \boldsymbol{LLP}_{i,t-1}$
$IRBA\_COV_{i,t}$	-0.199**	-0.0338**	-0.0361***
	(0.0845)	(0.0142)	(0.0132)
$SQ\_IRBA\_COV_{i,t}$	0.00210**		
	(0.000856)		
$Z\_SCORE_{i,t}$	0.116	-0.268**	-0.174
	(0.121)	(0.118)	(0.106)
$ROA_{i,t}$	0.468	-1.095**	-0.897**
	(0.415)	(0.465)	(0.423)
$NII_{i,t}$	0.0108	-0.0180	-0.0165
	(0.0183)	(0.0143)	(0.0131)
$LOANS_{i,t}$	0.262***	0.0375	0.0362
	(0.0854)	(0.0454)	(0.0383)
$DEPOSITS_{i,t}$	-0.0887*	0.0362	0.0226
	(0.0532)	(0.0328)	(0.0287)
$SIZE_{i,t}$	-6.505***	-2.216*	-3.042**
	(2.293)	(1.304)	(1.254)
$GDP\_GR_{c,t}$	0.120	0.0435	0.103
	(0.0810)	(0.0779)	(0.0740)
$INFLATION_{c,t}$	0.456*	-0.0292	-0.108
	(0.253)	(0.187)	(0.167)
$SUP\_STR_{c,t}$	-0.104	0.0857	0.102
	(0.180)	(0.232)	(0.216)
Time-fixed effects	Yes	Yes	Yes
N	2,102	759	746
R^2	0.194	0.179	0.206

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2010 to 2016, applying fixed effects panel regression models. Specification (1) uses our main sample, specifications (2) and (3) use our *IRBA subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.23: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Subsample from 2011 to 2016).

	(1)	**(2)**	**(3)**
	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$IRBA\_COV_{i,t}$	-0.182**	-0.0305	-0.0290*
	(0.0838)	(0.0209)	(0.0170)
$SQ\_IRBA\_COV_{i,t}$	0.00188**		
	(0.000845)		
$Z\_SCORE_{i,t}$	0.0698	-0.219**	-0.143
	(0.116)	(0.104)	(0.0939)
$ROA_{i,t}$	0.124	-1.046**	-0.849**
	(0.436)	(0.483)	(0.427)
$NII_{i,t}$	0.0103	-0.00530	-0.00740
	(0.0199)	(0.00963)	(0.00909)
$LOANS_{i,t}$	0.193**	-0.0100	-0.00433
	(0.0896)	(0.0489)	(0.0434)
$DEPOSITS_{i,t}$	-0.0935*	0.0240	0.0126
	(0.0533)	(0.0355)	(0.0304)
$SIZE_{i,t}$	-6.460**	-1.835	-2.391*
	(2.618)	(1.371)	(1.247)
$GDP\_GR_{c,t}$	-0.0180	-0.0470	0.0165
	(0.0706)	(0.0719)	(0.0680)
$INFLATION_{c,t}$	0.982***	-0.216	-0.244*
	(0.223)	(0.150)	(0.138)
$SUP\_STR_{c,t}$	-0.420***	0.196	0.162
	(0.156)	(0.211)	(0.204)
Time-fixed effects	Yes	Yes	Yes
N	1,845	680	669
R^2	0.137	0.149	0.146

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2011 to 2016, applying fixed effects panel regression models. Specification (1) uses our main sample, specifications (2) and (3) use our *IRBA subsample* (see Section 3.2). Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.24: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Overview of subsamples).

	(1)		(2)	(4)	
Endogenous variable	$\boldsymbol{RWATA_{i,t}}$		$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$	
Exogenous variable	$\boldsymbol{IRBA\_COV_{i,t}}$	$\boldsymbol{SQ\_IRBA\_COV_{i,t}}$	$\boldsymbol{IRBA\_COV_{i,t}}$	$\boldsymbol{IRBA\_COV_{i,t}}$	
Main sample: 2007 – 2016	- - -	+ + +	- -	- - -	Tables A.13 – A.17
Subsample 1: 2007 – 2009	- -	o	o	o	Table A.19
Subsample 2: 2007 – 2013	- - -	+ +	- - -	- -	Table A.20
Subsample 3: 2014 – 2016	-	o	o	- -	Table A.21
Subsample 4: 2010 – 2016	- -	+ +	- -	- - -	Table A.22
Subsample 5: 2011 – 2016	- -	+ +	o	-	Table A.23

This table reports the summary of the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$), when applying several subsamples. Specification (1) uses our main sample, specifications (2) and (3) use our *IRBA subsample* (see Section 3.2). +, ++, and +++ denote significantly positive coefficients at the 10%, 5%, and 1% levels, -, - -, and - - - denote significantly negative coefficients, respectively. o refers to insignificant coefficients. Variables are described in Table 1 in the main body of the paper.

Table A.25: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Additionally controlling for the presence of joint supervisory teams).

	(1)	(2)	(3)	(4)
	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$RWATA_{i,t-1}$	0.799***	0.794***		
	(0.0726)	(0.0620)		
$NPL_{i,t-1}$			0.971***	
			(0.0811)	
$NPL_{i,t-1} - LLP_{i,t-2}$				0.921***
				(0.0710)
$IRBA\_COV_{i,t}$	-0.0102	-0.199***	-0.0356*	-0.0497***
	(0.0226)	(0.0681)	(0.0196)	(0.0154)
$SQ\_IRBA\_COV_{i,t}$		0.00199***		
		(0.000615)		
$D\_JST_{i,t}$	0.189	-0.413	-0.367	-0.718
	(1.217)	(1.170)	(0.684)	(0.513)
D_MODEL_i	-0.794**	-0.887***	0.157	0.0479
	(0.340)	(0.314)	(0.147)	(0.105)
$Z\_SCORE_{i,t}$	0.751	0.810*	-0.599**	-0.142
	(0.490)	(0.489)	(0.268)	(0.266)
$ROA_{i,t}$	-1.993	-2.187	-0.851	-1.498
	(1.664)	(1.543)	(1.128)	(1.145)
$NII_{i,t}$	0.0856**	0.0954***	-0.00971	0.00866
	(0.0388)	(0.0361)	(0.0240)	(0.0160)
$LOANS_{i,t}$	-0.0193	-0.0309	0.0650*	0.0409
	(0.0527)	(0.0478)	(0.0367)	(0.0311)
$DEPOSITS_{i,t}$	0.0883	0.0666	0.0507	0.0153
	(0.0832)	(0.0722)	(0.0396)	(0.0256)
$SIZE_{i,t}$	-1.096	-0.435	0.523	0.455
	(0.913)	(0.892)	(0.524)	(0.348)
$GDP\_GR_{c,t}$	0.230**	0.172	-0.165**	-0.0952
	(0.113)	(0.121)	(0.0719)	(0.0640)
$INFLATION_{c,t}$	-0.00275	-0.0332	0.0370	0.105
	(0.208)	(0.218)	(0.145)	(0.115)
$SUP\_STR_{c,t}$	0.298	0.190	0.0507	0.120
	(0.182)	(0.178)	(0.0904)	(0.0739)
Time-fixed effects	Yes	Yes	Yes	Yes
N	2,440	2,440	812	767
Number of groups	373	373	136	133
Number of instruments	46	50	45	37
AR(1)-p	0.000	0.000	0.013	0.001
AR(2)-p	0.988	0.988	0.103	0.281
Hansen-p	0.209	0.355	0.244	0.155

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2016, additionally controlling for the presence of joint supervisory teams (D_JST). We apply a system GMM estimation, as specified in Section 5.1. D_JST is treated as strictly exogenous. Specifications (1) and (2) use our main sample, specifications (3) and (4) use our *IRBA subsample* (see Section 3.2). In specification (4), we use lags 2, instead of 3, and longer for the transformed equation because otherwise the Hansen test of overidentifying restrictions is significant. Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations and p to the p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.26: Phased IRBA rollout and RWA densities, NPL ratios, and bank credit risk prediction accuracy (Robustness: Additionally controlling for bank mergers and acquisitions).

	(1)	(2)	(3)	(4)
	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{RWATA_{i,t}}$	$\boldsymbol{NPL_{i,t}}$	$\boldsymbol{NPL_{i,t} - LLP_{i,t-1}}$
$RWATA_{i,t-1}$	0.799***	0.796***		
	(0.0731)	(0.0622)		
$NPL_{i,t-1}$			0.989***	
			(0.0936)	
$NPL_{i,t-1} - LLP_{i,t-2}$				0.944***
				(0.0651)
$IRBA\_COV_{i,t}$	-0.0154	-0.193***	-0.0354*	-0.0533***
	(0.0252)	(0.0665)	(0.0209)	(0.0156)
$SQ\_IRBA\_COV_{i,t}$		0.00203***		
		(0.000614)		
$D\_M\&A_i$	0.527	1.198	0.277	0.311
	(0.728)	(0.740)	(0.411)	(0.352)
D_MODEL_i	-0.787**	-0.937***	0.128	0.0646
	(0.339)	(0.316)	(0.137)	(0.115)
$Z\_SCORE_{i,t}$	0.795	0.815*	-0.605**	-0.279
	(0.487)	(0.481)	(0.238)	(0.254)
$ROA_{i,t}$	-2.100	-2.265	-0.620	-0.802
	(1.662)	(1.559)	(1.090)	(0.930)
$NII_{i,t}$	0.0869**	0.0933**	-0.00585	0.0122
	(0.0393)	(0.0363)	(0.0267)	(0.0175)
$LOANS_{i,t}$	-0.0191	-0.0296	0.0597	0.0270
	(0.0520)	(0.0497)	(0.0451)	(0.0324)
$DEPOSITS_{i,t}$	0.0823	0.0664	0.0479	0.0218
	(0.0846)	(0.0747)	(0.0444)	(0.0266)
$SIZE_{i,t}$	-0.849	-0.939	0.321	0.231
	(0.931)	(0.900)	(0.453)	(0.316)
$GDP\_GR_{c,t}$	0.230**	0.198	-0.160**	-0.120**
	(0.115)	(0.121)	(0.0676)	(0.0588)
$INFLATION_{c,t}$	0.0315	-0.0782	0.0572	0.0583
	(0.220)	(0.228)	(0.152)	(0.103)
$SUP\_STR_{c,t}$	0.284	0.240	0.0553	0.109
	(0.177)	(0.173)	(0.0859)	(0.0735)
Time-fixed effects	Yes	Yes	Yes	Yes
N	2,440	2,440	812	767
Number of groups	373	373	136	133
Number of instruments	46	50	46	37
AR(1)-p	0.000	0.000	0.018	0.000
AR(2)-p	0.993	0.982	0.102	0.286
Hansen-p	0.212	0.398	0.218	0.140

This table reports the analysis on whether the IRBA coverage ratio ($IRBA\_COV$) affects RWA densities ($RWATA$), bank NPL ratios (NPL), and bank credit risk prediction accuracy ($NPL_{i,t} - LLP_{i,t-1}$) in the period from 2007 to 2016, additionally controlling for bank mergers and acquisitions ($D\_M\&A$). We apply a system GMM estimation, as specified in Section 5.1. $D\_M\&A$ is treated as strictly exogenous. Specifications (1) and (2) use our main sample, specifications (3) and (4) use our *IRBA subsample* (see Section 3.2). In specification (4), we use lags 2, instead of 3, and longer for the transformed equation because otherwise the Hansen test of overidentifying restrictions is significant. Variables are described in Table 1 in the main body of the paper. Robust standard errors clustered at the bank level are in parentheses. N refers to the the number of observations and p to the p-value. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.27: Test for mean differences in annual cost growth rates and RWA growth rates between *hesitant rollout banks* and *non-hesitant rollout banks* based on propensity score matching (Robustness: Alternative thresholds).

Estimator	**Differences in $\Delta\, COSTS$ between *hesitant* and *non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	-11.95^{**}	(-2.27)
Nearest neighbor ($n = 5$)	-8.43^{**}	(-2.14)
Nearest neighbor ($n = 10$)	-12.07^{***}	(-3.18)
Nearest neighbor ($n = 20$)	-9.42^{***}	(-2.71)
Nearest neighbor ($n = 50$)	-6.41^{**}	(-2.03)
Gaussian kernel	-8.11^{**}	(-2.36)
Local linear regression	-7.48	(-1.42)
N		1,058
Hesitant rollout banks		295
Non-hesitant rollout banks		763

Estimator	**Differences in $\Delta\, RWA$ between *hesitant* and *non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	-5.69^{**}	(-2.27)
Nearest neighbor ($n = 5$)	-4.59^{**}	(-2.23)
Nearest neighbor ($n = 10$)	-5.16^{***}	(-2.66)
Nearest neighbor ($n = 20$)	-4.82^{**}	(-2.57)
Nearest neighbor ($n = 50$)	-3.13^{*}	(-1.84)
Gaussian kernel	-4.74^{**}	(-2.57)
Local linear regression	-4.73^{*}	(-1.89)
N		981
Hesitant rollout banks		273
Non-hesitant rollout banks		708

This table provides estimates of the mean differences in annual cost growth rates ($\Delta\, COSTS$) and RWA growth rates ($\Delta\, RWA$) between *hesitant rollout banks* and similar *non-hesitant rollout banks*, based on propensity score matching and applying an alternative categorization approach (see Section 7.2). In the bottom panel, the RWA growth rates are negative for both matched groups on average. The estimation of propensity scores is based on a logit regression, reported in Table A.10 in the appendix, where the dependent variable is the dummy $D\_HESITANT$, as described in Section 4.2. Variables are described in Table 1 in the main body of the paper. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.28: Test for mean differences in annual cost growth rates and RWA growth rates between *hesitant rollout banks* and *non-hesitant rollout banks* based on propensity score matching (Robustness: Alternative categorization approach).

Estimator	**Differences in $\Delta\, COSTS$ between** ***hesitant*** **and** ***non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	0.30	(0.15)
Nearest neighbor ($n = 5$)	1.26	(0.55)
Nearest neighbor ($n = 10$)	-5.64**	(-2.25)
Nearest neighbor ($n = 20$)	-7.24***	(-2.78)
Nearest neighbor ($n = 50$)	-4.94**	(-2.19)
Gaussian kernel	-2.00	(-0.81)
Local linear regression	-3.35	(0.15)
N		906
Hesitant rollout banks		517
Non-hesitant rollout banks		389

Estimator	**Differences in $\Delta\, RWA$ between** ***hesitant*** **and** ***non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	-1.33	(-1.10)
Nearest neighbor ($n = 5$)	-0.49	(-0.44)
Nearest neighbor ($n = 10$)	-2.65**	(-2.11)
Nearest neighbor ($n = 20$)	-3.46***	(-2.78)
Nearest neighbor ($n = 50$)	-2.59**	(-2.21)
Gaussian kernel	-2.14*	(-1.79)
Local linear regression	-2.27	(-1.10)
N		844
Hesitant rollout banks		486
Non-hesitant rollout banks		358

This table provides estimates of the mean differences in annual cost growth rates ($\Delta\, COSTS$) and RWA growth rates ($\Delta\, RWA$) between *hesitant rollout banks* and similar *non-hesitant rollout banks*, based on propensity score matching and applying an alternative categorization approach (see Section 7.2). In the bottom panel, the RWA growth rates are negative for both matched groups on average. The estimation of propensity scores is based on a logit regression, where the dependent variable is the dummy $D\_HESITANT$, as described in Section 4.2. Variables are described in Table 1 in the main body of the paper. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.29: Test for mean differences in annual cost growth rates and RWA growth rates between *hesitant rollout banks* and similar *non-hesitant rollout banks* based on propensity score matching (Robustness: Probit regression).

Estimator	**Differences in $\Delta\,COSTS$ between *hesitant* and *non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	-3.70	(-0.87)
Nearest neighbor ($n = 5$)	-4.82	(-1.42)
Nearest neighbor ($n = 10$)	-6.06*	(-1.86)
Nearest neighbor ($n = 20$)	-6.89**	(-2.23)
Nearest neighbor ($n = 50$)	-8.10***	(-2.72)
Gaussian kernel	-6.19**	(-2.04)
Local linear regression	-5.94	(-1.40)
N		1,060
Hesitant rollout banks		323
Non-hesitant rollout banks		737

Estimator	**Differences in $\Delta\,RWA$ between *hesitant* and *non-hesitant rollout banks***	**(t-value)**
Nearest neighbor ($n = 1$)	-1.94	(-0.77)
Nearest neighbor ($n = 5$)	-2.71	(-1.47)
Nearest neighbor ($n = 10$)	-3.25*	(-1.86)
Nearest neighbor ($n = 20$)	-3.92**	(-2.31)
Nearest neighbor ($n = 50$)	-4.27***	(-2.64)
Gaussian kernel	-2.80*	(-1.68)
Local linear regression	-2.80	(-1.10)
N		983
Hesitant rollout banks		299
Non-hesitant rollout banks		684

This table provides estimates of the mean differences in annual cost growth rates ($\Delta\,COSTS$) and RWA growth rates ($\Delta\,RWA$) between *hesitant rollout banks* and similar *non-hesitant rollout banks* based on propensity score matching. In the bottom panel, the RWA growth rates are negative for both groups on average. The estimation of propensity scores is based on a probit regression, reported in Table A.10 in the appendix, where the dependent variable is the dummy $D\_HESITANT$, as described in Section 4.2. Variables are described in Table 1 in the main body of the paper. N refers to the number of observations. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Table A.30: Hesitant rollout and annual cost growth rates and RWA growth rates.

	(1)	**(2)**
	$\Delta\, COSTS_{i,t}$	$\Delta\, RWA_{i,t}$
$D\_HESITANT_{i,t}$	-4.356**	-2.207*
	(2.072)	(1.202)
D_MODEL_{i}	0.523	0.0858
	(0.386)	(0.281)
$Z\_SCORE_{i,t}$	-1.308**	-0.101
	(0.639)	(0.427)
$ROA_{i,t}$	-1.229	0.630
	(1.877)	(1.793)
$NII_{i,t}$	0.00251	0.00291
	(0.0364)	(0.0202)
$LOANS_{i,t}$	0.0388	0.0805*
	(0.0660)	(0.0422)
$DEPOSITS_{i,t}$	-0.0838	-0.0102
	(0.0701)	(0.0359)
$SIZE_{i,t}$	-0.762	0.127
	(0.865)	(0.428)
$GDP\_GR_{c,t}$	2.367**	0.620**
	(1.064)	(0.277)
$INFLATION_{c,t}$	0.831	1.427**
	(1.526)	(0.715)
$SUP\_GR_{c,t}$	-0.0722	0.808*
	(0.882)	(0.467)
Time-fixed effects	Yes	Yes
Country-fixed effects	Yes	Yes
N	1,211	1,122
R^2	0.1468	0.2163

This table reports the analysis on whether a hesitant rollout ($D\_HESITANT$) affects annual cost growth rates ($\Delta\, COSTS$) and RWA growth rates ($\Delta\, RWA$), based on our *IRBA subsample* and using a linear panel regression model. RWA growth rates are negative on average. Variables are described in Table 1 in the main body of the paper. N refers to the number of observations. Robust standard errors clustered at the bank level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.