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Measuring the procyclicality of
impairment accounting regimes:
a comparison between
IFRS 9 and US GAAP

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Abstract

The purpose of this paper is to compare the cyclical behavior of various credit impairment accounting regimes, namely IAS 39, IFRS 9 and US GAAP. We model the impact of credit impairments on the Profit and Loss (P&L) account under all three regimes. Our results suggest that although IFRS 9 is less procyclical than the previous regulation (IAS 39), it is more procyclical than US GAAP because it merely requests to provision the expected loss of one year under Stage 1 (initial category). Instead, since US GAAP prescribes that lifetime expected losses are fully provisioned at inception, the amount of new loans originated is negatively correlated with realized losses. This leads to relatively higher (lower) provisions during the upswing (downswing) phase of the financial cycle. Nevertheless, the lower procyclicality of US GAAP seems to come at cost of a large increase in provisions.

Non-technical summary

The purpose of this paper is to present an assessment of the cyclical implications of various accounting regimes for credit instruments. We elaborate on the recent evolution of accounting standards, namely International Accounting Standard 39 (IAS 39), International Financial Reporting Standards 9 (IFRS 9) and the US Generally Accepted Accounting Principles (US GAAP). The latter two have implied a shift from the incurred loss to the expected loss paradigm.

The different approaches followed have a significant impact on the timing with which credit losses are recognized in the profit and loss account (P&L), thus potentially hampering hamper a financial institution's viability and credit supply. IFRS 9 recognizes the expected credit loss (ECL) based on the degree of credit deterioration (one year for Stage 1 and lifetime expected loss for Stages 2 and 3); under US GAAP, since for each loan the provisions made at the origination date account for its lifetime ECL, overall provisions tend to increase with the flow of newly originated loans, *ceteris paribus*. Given that the latter is negatively correlated with default rates, two opposite effects influence the dynamics of provisions: on the one hand, a higher new loans origination rate tends to increase provisioning during the credit cycle's boom phases (and vice versa during crises); on the other hand, it is possible that lifetime ECL be underestimated during credit booms, leading to insufficient provisioning at inception and therefore to subsequent adjustments in the provisions held for loans originated in previous periods. The degree of cyclicality of the impact on P&L under different accounting regimes, therefore, cannot be told beforehand and depends crucially on how financial institutions are assumed to incorporate information in the expectations of lifetime losses.

In order to simulate the effect of P&L accounts we use a database of Italian mortgages from 2006 to 2018. We model the impact of credit impairments on P&L under different accounting regimes in a historical scenario for default rates and newly originated loans, under different assumptions on how financial institutions incorporate information on varying loss rates.

We obtain the following results: Firstly, as expected, provisions under IFRS 9 forecast default approximately one year in advance, with provisions for loans in Stage 1 accounting for the greatest share of the impact on P&L; Stage 2 loan provisions do not have a meaningful effect. The impact on P&L under IFRS 9 is, therefore, much less procyclical than under the previous regime (IAS 39, where it just coincided with realized losses, which occur well after the default), but still substantially more procyclical than US GAAP.

Secondly, provisions under US GAAP appear to be less cyclical than those required under IFRS 9 under different assumptions on how financial institutions incorporate information in the expectations of lifetime losses. The lower procyclicality of US GAAP, however, comes at the cost of holding a larger stock of provisions at all times.

We perform several robustness checks relaxing our methodological assumptions as well as comparative statics on the parameters of the model; for instance, we explore alternative mechanisms of migrations from and to Stage 2 for the IFRS 9 regime.

Finally, it is worth mentioning that our results have relevant implications for supervisors and policymakers. Although the aim of accounting regulation is not to tackle procyclicality, the latter requires attention from a financial stability standpoint.

1 Introduction

In the early years of the 21st century, the accounting of financial assets was still guided by International Accounting Standard 39 (IASB, 2004), which prescribed the use of the incurred loss model for the recognition of credit losses in the profit and loss (P&L) account. If there was objective evidence that an impairment loss on a loan had been incurred, the amount of the loss needed to be calculated; however, losses expected as a result of future events were not recognized. As stated by the Basel Committee on Banking Supervision in BCBS (2015a), following the financial crisis of the late 2000s, concerns were raised about this method, particularly about the timeliness of banks'recognition of loan loss expenses. More concretely, recognizing losses after they have been incurred on a financial asset has been widely criticized for being "too little, too late", as detailed in Gaston and Song (2014).

Procyclicality in banks'financial soundness and credit supply is a well-known issue with many roots, such as the tendency to make a more lenient assessment of risk in good times than in bad ones, the amplification of shocks led by varying collateral valuations, the inclination of financial institutions to show herd behavior, and deterioration in managerial ability; A non-exhaustive set of references is Rajan (1994), Berger and Udell (2004), Lepetit et al. (2008), Jiménez and Saurina (2006) or Kiyotaki and Moore (1997), among others. Moreover, an extensive literature stresses the links between the accounting treatment of credit portfolios and procyclicality in lending and risk-taking[1]. Moreover, Stoian and Norden (2013), Wall and Koch (2000), Laeven and Majnoni (2003), Bushman and Williams (2015) and Ahmed et al. (1999) argue that banks have incentives for using discretion in establishing loan loss provisions to manage reported capital and earnings.

In response to such concerns, the G20 leaders issued a clear mandate to reform international prudential and accounting standards, reducing complexity and procyclicality and increasing coordination among the various standards used, as stated in G20 (2009). The G20 endorsed the Financial Stability Forum's report on addressing procyclicality in the financial system (FSF, 2009), according to which *"earlier recognition of loan losses could have dampened cyclical moves"* and *"earlier identification of credit losses is consistent both with financial statement users'needs for transparency regarding changes in credit trends and with prudential objectives of safety and soundness"*. The report also recommended the International Accounting Standards Board (IASB) and the Financial Accounting Standards Board (FASB) to replace the incurred loss method of loan loss provisioning with alternative approaches that *"incorporate a broader range of available credit information"*, i.e. with a more forward-looking expected loss method using statistical information to identify probable future losses. The result has been the publication of International Financial Reporting Standards 9 (IFRS 9) "Financial Instruments" in July 2014 (IASB, 2014) and the US GAAP in July 2016 (FASB, 2016). The primary difference between the two approaches is the method for impairment calculation (full lifetime in US GAAP vs staging in IFRS 9)

This paper contributes to the literature that aims at establishing whether forward-looking accounting standards are actually more procyclical. There is a lack of consensus among the research conducted so far on this issue. Earlier literature as well as policymakers agreed on the

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[1]See, for example, BCBS (2015), Beatty and Liao (2011), Schwartz et al. (2014) or Bushman and Williams (2012).

fact that forward-looking provisioning would reduce procyclicality; some examples are Balla and McKenna (2009), Laeven and Majnoni (2003), Wezel et al. (2012), FSF (2009) and BCBS (2009). Conversely, more recent contributions point in the opposite direction: Two prominent examples are Barclays (2017) and Abad and Suárez (2017). In particular, the latter find that under the two forward-looking accounting standards, the impact of an exogenous increase in substandard loans on P&L and capital is greater than under the incurred loss approach (with the IFRS 9 impact being the greatest). They conclude, therefore, that forward-looking approaches may amplify the effect of an unexpected increase in risk, since they concentrate the impact on P&L of future losses at the beginning of a contractionary phase of the credit or business cycle, possibly determining negative feedback effects on credit supply just as economic conditions start to worsen.

In this paper, we will focus exclusively on the dynamics of P&L impact under different accounting standards (IAS 39, IFRS 9 or US GAAP) with a simulated mortgage portfolio. More precisely, we investigate the degree of contemporaneous correlation with GDP as well as realized losses. Our results suggest that, in order to reduce the cyclicality of impairments, it is preferable to use an accounting method that takes into consideration the expected loss of credit portfolios over the entire lifetime of the asset, i.e., the approach followed by US GAAP.

In the latter case, since for each loan provisions made at the origination date account for its lifetime expected credit loss (ECL), overall provisions tend to increase with the flow of newly originated loans, *ceteris paribus*. Given that the latter is negatively correlated with default rates, two opposite effects influence the dynamics of provisions: While a higher new loan origination rate tends to increase provisions during credit cycle's boom phases (and vice versa during crises), it is also possible that lifetime ECL is underestimated during credit booms, leading to insufficient provisioning at inception and subsequent adjustments in the provisions held for loans originated in previous periods. Thus, the degree of cyclicality (in the sense previously defined of contemporaneous correlation with the evolution of credit quality) of the impact on P&L under the US GAAP framework, and how it compares with IFRS 9, cannot be disentangled beforehand but depends on which effect is empirically greater.

We model the impact of credit impairments on P&L under different accounting regimes in a historical scenario for default rates and newly originated loans, under different assumptions on how financial institutions incorporate information in the expectation for lifetime losses. We alternatively assume that (a) financial institutions are able to correctly forecast future defaults, so that no underestimation of ECL is possible; (b) their perfect forecasting ability is limited to a one-year horizon, after which the loss rate is assumed to revert to the sample's average value; (c) after one year of perfect forecast loss rates revert to the average of the previous five years. Under (b) and (c), therefore, underestimation of ECL at inception is possible and implies adjustments in the provisions for older loans as new information becomes available.

As expected, provisions under IFRS 9 forecast realized losses approximately one year in advance, with the provisions for loans in Stage 1 accounting for the greatest share of the impact on P&L: provisions for Stage 2 loans do not have a significant effect. The impact on P&L under IFRS 9, therefore, appears less procyclical than under the previous regime (IAS 39, where it just coincided with realized losses), but still likely to hit financial institutions when a contractionary phase of the credit or business cycle has already started. Provisions under US GAAP appear to

be less cyclical then those required under IFRS 9 under all the scenarios considered. The lower procyclicality of US GAAP, however, comes at the cost of holding a larger stock of provisions at all times. In contrast with Abad and Suárez (2017), we find that forward-looking impairment accounting systems may allow to build up provisions in advance, smoothing out the impact of losses[2].

The remainder of this paper is structured as follows: Section 2 presents a brief review of the most important accounting regimes for credit instruments; in Section 3, we describe our data sources. The methodology used in the paper is detailed in Section 4. Our aim results as well as robustness checks constitute Section 5. Finally, Section 6 concludes.

2 Regulation

In this section, we present a brief review of alternative accounting treatments — IAS 39, IFRS 9 and US GAAP — for credit portfolios.

2.1 IAS 39

IAS 39 adopts an incurred loss approach for impairment accounting, i.e. after the initial recognition of the asset it requires, at least, a loss event to occur for any impairment to be recognized (IASB, 2004). A non-comprehensive list of loss events is provided, but the crucial aspect is that expected losses stemming from future events cannot be accounted for. IAS 39 also allows to recognize collective provisioning or "incurred but not reported" (IBNR) losses[3]: Statistical evidence can be used to work out the level of loss events already incurred, although not yet recognized, in a loan portfolio. However, this proved insufficient both because of the divergent application across countries and because the use of statistical evidence was limited to the existence of trigger events after origination (ECB, 2014). Following the distress unleashed by the financial crisis in the late 2000s, the incurred loss approach was broadly deemed "too little, too late" (BCBS, 2015b). Among the measures adopted to mitigate the procyclicality of IAS 39, it is worth to mention the generic provision scheme adopted in Spain, implemented in Banco de España (2004)[4] . This approach stemmed from IBNR collective provisioning (Saurina, 2009) and its objective was to accumulate allowances in the boom years of the cycle for subsequent use during crises[5]. However, it did not cover the full amount of specific provisions accumulated

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[2]Differently from Abad and Suárez (2017), we do not make assumptions on neither dividend distribution policies nor capital injections or net interest income. Their conclusions, however, follow mainly from the results on the impact on P&L under the different regimes, on which we concentrate our analysis.

[3]See IAS 39, AG 89 and 90.

[4]Prior to the modification via CBE 4/2016, which increased alignment with IAS 39.

[5]This was done determining generic provisions via the following formula:

$$\Delta Generic\,provision_t = \sum_{k=1}^{N} \left(\alpha_t^k \Delta c_t^k + \beta^k C_t^k - Specific\,provision_t^k \right)$$

where C_i is the stock of loans in portfolio k at time t. The coefficients α and β represent respectively the rate of credit losses in a cyclically neutral year and the average specific provision for loans in a specific portfolio k, estimated on the basis of historical data for Spanish banks.

by banks during crisis years, as detailed in Trucharte and Saurina (2013) and Banco de España (2017).

2.2   IFRS 9 and Current Expected Credit Loss (CECL)

IASB published its final IFRS 9 implementation guidelines in July 2014 after several reviews and failed efforts to converge with US GAAP. The most fundamental change concerned the impairment accounting regime for financial instruments, which implies a shift in paradigm moving from incurred to expected losses.

According to the new standard, the bank needs to recognize the expected loss for any financial asset valued at amortized cost or fair value through other comprehensive income. The degree to which the expected credit loss (henceforth, ECL) has to be recognized depends, however, on the severity of credit quality deterioration. At origination or purchase of the asset, and as long as the condition for classification other stages does not subsist, the value correction has to account for the expected loss for the following 12 months (Stage 1). However, if there has been a significant increase in the risk of the financial instrument from inception (Stage 2) or default (Stage 3), the institution will recognize the expected loss for the full expected lifetime[6].

A generalized significant increase in risk due, for example, to a deterioration of the economic cycle, may determine a sharp rise (*"cliff effect"*) in the required provisions (IASB, 2013). Although there is a certain degree of discretion in the recognition of a significant increase in risk, some indications are provided; in particular, there is an assumption (rebuttable by the financial institution) that a significant increase in risk exists in case of exposures which are past due for more than 30 days. Additionally, IFRS 9 enumerates a non-exhaustive list of example criteria to recognize increases in risk, notably the criterion based on loan pricing, which suggests a comparison between the prices of existing and new portfolios as a proxy for risk increases[7].

As previously noted, after several failed attempts at convergence the FASB published its own financial instrument accounting standard, which is known as Current Expected Credit Loss (CECL) and tries to prevent under-provisioning by immediately recognizing, at the moment of origination or purchase of the asset, the full amount of credit losses expected over the assets'foreseeable lifetime (FASB, 2016 and European Parliament, 2015a). In terms of IFRS 9, this would be similar to recognizing every asset directly in Stage 2. The FASB approach would also be conceptually close to the late Spanish collective provision with the only nuance of the automatic mechanism both for accumulating and releasing provisions, as explained in Trucharte and Saurina (2013).

The updated weighted averages of the expected credit losses (with the weights being the respective probabilities of default) are defined as the updated differences between expected and contractual payments. The expected loss must be estimated taking into account the weighted probability of default, the expected recovery rate, the time value of money and all the available information. The proceeds from collateral must be included when calculating the expected cash

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[6]In order to move an asset from Stage 1 to Stage 2, thus recognizing a significant increase in default risk, the entity should evaluate the variation in the probability of default (PD) for the asset's lifetime. However, an increase in the twelve-month PD might be a good proxy for lifetime PD (IFRS 9, B5.5.13).

[7]Also mentioned in EBA (2017), paragraph 107.

flows once execution costs have been deducted. Finally, the rate used to actualize shortages in payments will be the original rate at inception; thus, subsequent changes in interest rates after a loan's inception are not relevant for the calculation of provisions.

2.3 Linkages between accounting and regulatory provisions

The main goal of accounting standards is not to reduce procyclicality but to depict a truthful representation of the company's financial condition. This is the reason why the cyclicality of the provisioning regime is mitigated via prudential capital requirements. Nevertheless, the results of accounting and regulatory provisions are not independent from each other and the FSF (2009) report recommended accounting standard setters to replace the incurred losses approach with an expected losses one, arguing that *"earlier identification of credit losses is consistent both with financial statement users'needs for transparency (...) and with prudential objectives"*.

Accounting and regulatory provisions, however, still differ under several perspectives, and to avoid any undue shock in solvency, the first implementation of the ECL approaches is to be mitigated via transitional arrangements (see BCBS, 2017). In this section, we explore the primary differences between accounting and regulatory expected losses from the P&L perspective. In this line, it is reasonable to expect that credit parameters used for regulatory purposes be the basis for calculating accounting parameters; however, these parameters will be adjusted for the different purposes of each view (as mentioned in both the EBA and Basel guidelines).

For prudential purposes, the probabilities of default (PD) estimates are based on long-run averages (through the cycle approach, TTC) of one-year default rates. For accounting purposes, the PD is the point-in-time (PiT) value appropriate for each reporting period. As we have seen, the time horizon greatly depends on the accounting standard, full lifetime for US GAAP and the three-stage approach of IFRS 9.

In the same manner, for regulatory purposes, loss given default (LGD) estimates are expected to consider an economic downturn if this leads to more conservative estimates than the long-run average. However, for accounting purposes the best point-in-time estimation is chosen to avoid any bias.

Prudential regulation might be able to partly mitigate procyclicality. Firstly, discrepancies in accounting and regulatory expected losses will be considered in regulatory capital[8]. Besides, the level of provisions must be factored in during the Supervisory Review and Evaluation Process to determine Pillar 2 capital requirements (EBA, 2014). These elements might be used to mitigate the potentially procyclical impact of the new accounting regime. However, one should bear in mind that accounting is crucial for incentives to managers (impact on dividends, bonuses, reputation in the market...); for this reason, it is of utmost importance to assess the cyclical aspects of accounting regimes.

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[8] According to the CRR, for banks following the internal ratings-based (IRB) approach, deficits in accounting provisions will be deducted from Core Equity Tier 1 (CET1) capital while surplus will be included as Tier 2 capital (with a cap of 1.25% of the total risk exposure amount stemming from credit risk).

2.4 Comparison between the different methods

One of the main issues that we want to address is the procyclicality of conditions for moving from Stage 1 to Stage 2. Most of the events that may trigger the reclassification from Stage 1 to Stage 2, such as changes in internal and external ratings, value of collateral, pricing of the credit risk or financial soundness of the borrower, are highly correlated with the business cycle. A widespread concern is that the "cliff effect" may exacerbate the increases in provisions due to the simultaneous deterioration of credit quality for a significant portion of the portfolio. Abad and Suárez (2017) find that the impact on P&L of an exogenous increase in substandard loans under an IFRS 9 regime would be particularly concentrated at the beginning of a contractionary phase of the credit or business cycle, with negative feedback effects on credit supply. In the next sections, we conduct a similar analysis showing that, while IFRS 9 does not seem to be able to decisively solve the issue of procyclicality, in contrast with the results of Abad and Suárez (2017) the impact of the "cliff effect" is likely to be small and not determine an excessive concentration of provisions at the turning point of the cycle. The other framework we study, US GAAP, seems better suited to smooth future losses over time.

We share some of the criticisms on the FASB accounting approach. The CECL approach, by frontloading all the future expected losses, implies the recognition of a significant amount of day-one losses. This also reduces comparability among portfolios and institutions since riskier loans will present higher initial losses, while their net present value is not lower if risk premiums are correctly set. However, in this paper we analyze only the cyclical behavior of the two methods, disregarding the comparison from a pure accounting perspective.

3 Data

In Section 5, we will propose an exercise which simulates provisions and losses under different regimes for a fictional portfolio composed only of mortgages with 20-year maturity over the years 2006-2018. This section describes the data used to feed the simulation, its sources and some methodological choices.

Average default rates for mortgages are estimated from the Italian central credit register (*Centrale dei Rischi*, CR). We consider loans with a predetermined maturity granted to households: given the minimum threshold of 30,000 euros for inclusion in the dataset, these loans are mostly constituted by mortgages. In order to estimate default rates, we divide the amount of loans in default at the end of each period by the amount that were performing at the beginning of the quarter. Quarterly default rates are then seasonally adjusted through the X-13 procedure. Information on defaulted loans compatible with the current harmonized EBA definition of non-performing loans is available from 2006 (Figure 1).

The probability of default, however, is not constant over the life of a loan; while various idiosyncratic events may intervene, default probability tends to be lower at the very beginning of a loan's lifecycle (when the information under which it was granted is more likely to still hold true) and for older loans (i.e. 'survivors' are likely to have idiosyncratic characteristics that make them more resilient). We are particularly interested in modeling the dependence between default

rates and the age (i.e., the time since origination) of a loan, for it strengthens the link between credit dynamics and credit risk.
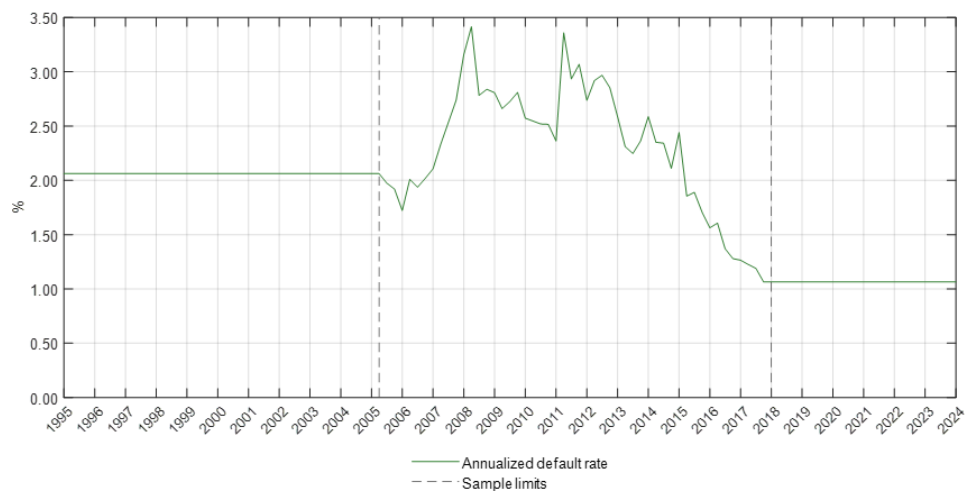

Figure 1: Annualized default rates for mortgage loans

In our Italian data from the CR, unfortunately, it is not possible to separately identify multiple exposures toward the same subject nor the contractual maturity of mortgages at origination, which makes it difficult to estimate the relation between default rates and loan age. We therefore obtain the latter using data from the *European Data Warehouse (EDW)*, composed of more than 9 million loans that are part of residential mortgage-backed securities (RMBS) from several European countries. For each loan, the dataset contains the date of origination, the date of maturity, and where applicable, the date of default[9].

The EDW dataset has the benefit of providing a wide cross-country sample for European loans but also some shortcomings that can introduce bias in the estimation of default probabilities (PDs). The reason is twofold: First, even though the available evidence does not clearly point to a systematic presence or even a clear direction of a selection bias in securitized pools of loans in Europe[10], we reckon that its existence is plausible. Second, the EDW dataset does not include a complete history for each cohort of loans originated at a given date (origination cohort) since institutions can start reporting the status of the loans included in a securitization well after the date when it was initially created. When this is the case, information on loans initially included in the securitized pool but defaulted or matured before the first date of reporting is generally not reported, since it is not mandatory.

Because of the potential presence of these two biases, we will only use this sample to characterize the relative PD level changes as a function of the age of a loan because we assert that it is not affected by these biases, even if the average PD is over- or underestimated. However,

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[9]Institutions report information on securitisation deals that have not reached maturity (as is usually the case) and begin reporting significantly after the creation of the product, providing only information on the current status of the underlying pool of loans (i.e., omitting information on loans originally included in the pool but that have since reached maturity, or that have defaulted and all the recovery procedures have been concluded so that no further cash flows are expected). This creates some issues in the estimation of probability of default, as explained in Section 4.

[10]For an analysis of the impact of securitization on screening and monitoring activity and a summary of the relevant literature, see Salleo et al. (2011).

since the PD for a given age must be estimated using default rates from cohorts whose origination date is not successive to the current date minus the specific age, the PD for higher age buckets would be affected by a downward survivorship bias. This effect can be removed by excluding from the sample those loans originated before the first date of information reporting of the securitisation deal to which they belong. However, this solution is unsuitable for our purposes, since it would leave us with the possibility of studying the evolution of PD only within a small number of years from origination. Instead, we decided to accept the presence of some bias but, to mitigate the problem, we exclude from the sample the loans originated before 2000 or after 2010, for which underestimation of PD is more likely.

In a nutshell, we will use the Italian credit register to obtain the average PD for each period and the EDW database for establishing the relationship between the age of a loan (i.e., the time from origination) and its probability of default[11].

According to the IFRS 9 dispositions, a rebuttable presumption exists that the 30-day past due status represents a significant increase in the risk qualifier for loans. Unfortunately, this information is not available. However, we know the share of non-performing loans that are 90-days past due at the end of each quarter; if payments stop with uniform probability within each quarter, approximately two thirds of the 90-day past due loans at the end of the quarter would already be 30-days past due by the end of the previous quarter. Therefore, we approximate the amount of loans with significant risk increase in t[12] with

$$SRI_t = \frac{2}{3} PastDue90_{t+1} \qquad (1)$$

Data on new loans for house purchases in Italy is extracted from the MFI Interest Rate Statistics (MIR), available at the European Central Bank's Statistical Data Warehouse[13]. In our simulation exercise, in each period new loans are originated for a normalized amount that tracks the historical series of new loans for house purchases, as depicted in Figure 2.

The dynamics of the overall stock of (performing) loans are therefore determined by the difference between the speed at which new loans are originated, which is inversely correlated with credit quality, the outflows deriving from regular repayments, following the amortization schedule in equation (2) below, and defaults[14].

Other relevant information for modeling the effect of various impairment accounting rules is represented by the residual maturity of the loans in the portfolio. Impairment accounting rules indeed differ regarding the moment at which provisions must be made: under US GAAP, provisions are set aside at origination so that they tend to increase during credit cycle upswings

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[11]Notice that if the PD is estimated conditional on the number of years from origination, right-censoring is not a source of bias: loans for which, at the sample cut-off date, neither default has been observed nor maturity has been reached are not considered part of the pool of loans alive at ages above the age they possess at the cut-off date. This is not true for the average default rate, which must be calculated removing from the sample right-censored observations to avoid a downward bias.

[12]This proxy is likely to slightly underestimate the amount of 90-day past due loans, since it excludes those exposures which enter and exit the status within the 90 days.

[13]More precisely, the series contains new business related to *"lending for house purchase, excluding revolving loans and overdrafts, convenience and extended credit card debt"* (MIR.M.IT.B.A2C.A.B.A.2250.EUR.N).

[14]Notice that the overall stock of outstanding loans reported in aggregate statistics such as MIR includes NPLs instead.

when the portfolio contains younger loans and vice versa[15]. In addition, both the PD and the LGD, as detailed in Section 4, depend on the age of the loan measured since its origination. For loss given default, we model this dependence deterministically.
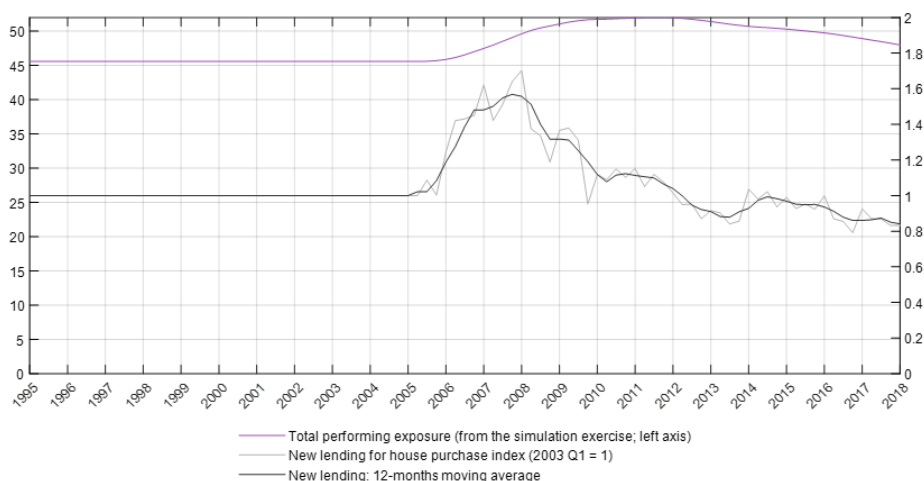
The dynamics of the overall stock of performing loans (left axis), which is an index, are determined by the difference between the speed with which new loans are originated and the outflows deriving from regular repayments and defaults.

Figure 2: New loans and simulated stock of loans

4 Methodology

In this section, we model a simplified version of the accounting regimes detailed in the previous part. For simplification purposes, we will not allow for multiple default events or the possibility that defaulted exposures return to performing status[16]. In addition, once the default status is triggered, the LGD is deterministic and depends on the loan-to-value (LTV) ratio. Finally, to focus on the differences between accounting regimes, we remove uncertainty from the model by assuming that credit models are perfect in the sense that they can exactly predict future outcomes.

4.1 Parameters

We construct provisions and realized losses through the computation of PD, LGD and exposure at default (EAD) for the various years. In this subsection, we explain the assumptions made to calculate these parameters.

With a slight abuse of notation, we use a single subscript t to denote the one-period time span $[t-1, t]$. PD_t and LGD_t are, respectively, the probability of default and the applicable loss

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[15]This effect can be compensated by lower estimates for PD and LGD during credit cycle upswings. In the following, we will in fact analyse both the case of perfect forecasting ability for all future periods — where the underestimation of risk parameters is absent by assumption — and the case where the forecast horizon is limited to one year forward, where underestimation of future risk at origination is possible. We also introduce stochastic forecast errors in Section 5.3.

[16]This simplification assumptions have been chosen in line with standard practices; see, for example, the stress testing methodology in EBA (2016).

given default between $t-1$ and t. For simplicity we assume that the exposure does not change between t and the moment of default, so that EAD_t is constant throughout the period.

4.1.1 Exposure at default

We model the evolution of EAD according to a constant annuity amortization schedule with a fixed interest rate and annual coupon payments. The residual exposure EAD_t is[17]:

$$EAD_t = L \cdot \big[\frac{(1+r)^M - (1+r)^t}{(1+r)^M - 1} \big] \tag{2}$$

where L is the loan amount at inception, r is the interest rate and M is the original maturity of the loan. Figure 3 shows the EAD variation with the age of the loan, assuming $r = 3\%$ and M equal to 20 years for all loans.

4.1.2 Loss given default

Following the literature[18], in modeling loss given default we use a simplified structural model that represents LGDs as a deterministic function of the loan-to-value (LTV) ratio, that is, the ratio of the exposure value (EXP) to the value of the collateral C, and the residual exposure at a given time. Clearly, there is a positive relation in time between recovery rates and the reduction of LTV following the progressive reimbursement of the loan. If the LTV ratio is smaller than the sales ratio SR (which is the quotient between the present value of the sale price and the value C of the collateral), the entire value of the exposure can be recovered. In addition, we introduce a cost of recovery procedures CR that is proportional to EAD and equal to 5%. This effectively imposes an LGD floor of 5% even when $LTV_t \leq SR$. Our formula for LGD reads as follows[19]:

$$LGD_t \equiv LGD\left(EXP_t\right) = CR + \max\left\{0, \frac{EXP_t - C \cdot SR}{EXP_t}\right\} = CR + \max\left\{0, \frac{LTV_t - SR}{LTV_t}\right\} \tag{3}$$

We make the simplifying assumptions of no uncertainty and no changes along the life horizon of the loan for recovery costs CR, the collateral value C and the sales ratio SR: Fixing these variables, the LTV ratio is just a constant share of the residual exposure at time t, and LGD a deterministic concave function of it. Since the loan is progressively reimbursed during his lifetime, given the assumptions LTV ratios and LGD will progressively decrease with the age of the loan, as shown in Figure 3.

We have set the SR value to 50% in this exercise and the initial LTV at 80% to obtain an average LGD of 16.8%, which is broadly in line with historical empirical values for residential mortgages[20].

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[17] The proof of this result can be found in standard financial mathematics textbooks.

[18] See, for example, Qi and Yang (2009), Greve and Hahnenstein (2014) or Ross and Shibut (2015).

[19] We consider loan-to-value ratios within the $(0, 1]$ range, which is a reasonable modelling assumption, though not crucial to any of the results presented.
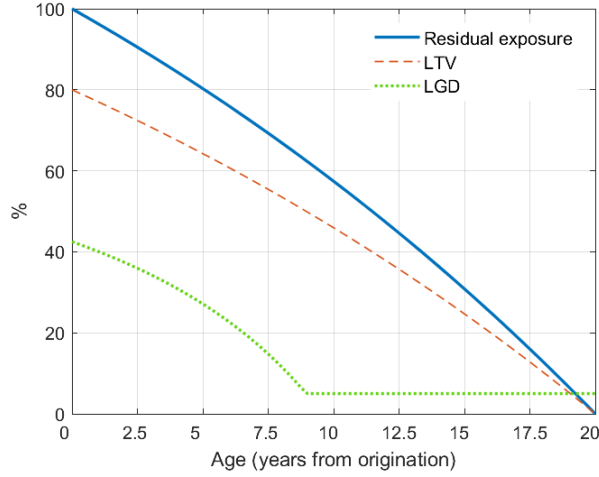
[20] see, for example, EBA (2013).

Figure 3: EAD and LGD vs. age of the loan.

4.1.3 Probability of default

As explained above, we need to estimate the relationship between the age of a loan (i.e., the time from origination) and its probability of default. To do so, we need to observe cohorts of loans with the same origination date over their entire lifetime (i.e., until each of them defaults or comes to maturity).

With this information, we can estimate the probability of default PD_t for each year following origination using the default rate for age t, calculated as the number of defaults in the period over the number of loans that either have not yet reached maturity or have defaulted at the beginning of the period:

$$\hat{PD}_t = \frac{1}{N_t} \sum_{i=1}^{N_t} D_{i,t} \tag{4}$$

$$N_t = N_{t-1} - \sum_{i=1}^{N_{t-1}} D_{i,t-1} - \sum_{i=1}^{N_{t-1}} M_{i,t-1} \tag{5}$$

where $D_{i,t}$ and $M_{i,t}$ are binary variables for the default and maturity of loan i at age t and N_t is the number of loans survived.

In order to be consistent with the IFRS 9 framework and the rationale behind expected loss provisioning, we have also included forward-looking information in the calculation of PDs using information from the ECB's Bank Lending Survey. The series BLS.Q.IT.ALL.Z.H.H.F3.ST.S.FNET is available from 2003Q1 and collects the answers to the question *"Please indicate how you expect your bank's credit standards as applied to the approval of loans to households to change over the next three months"*; a negative (positive) value implies a perceived net easing (tightening) of credit standards. If BLT_t is the value of the bank lending tightening series in period t, we rescale PDs so that

$$PD_t^* = \hat{PD}_t \times \left(1 + \frac{BLT_t}{BLT_{max} - BLT_{min}} \right) \tag{6}$$

Moreover, in the calculation of default probabilities, Krüger, Rösch and Scheule (2018) account for macroeconomic information for the US economy using the VIX volatility index as a proxy, owing to its leading nature for the economic juncture[21]. We mimic this approach using the VSTOXX time series which is the VIX equivalent built upon the Dow Jones EUROSTOXX 50 Index.

Using the historical average $\overline{V}$ and the volatility σ_V of the VSTOXX from 2006 to 2018, we rescale the PDs so that both the magnitude and the sign of the index influence the probability of default:

We illustrate the effect of applying this correction by looking at the 1-year PD curves as a function of the age of the loan in two different points of the sample: on one hand, a moment of economic bliss (2006Q4) at which the value of the volatility index was below its historical average (but not further away than one standard deviation); on the other, we choose 2008Q4 as an example of severe economic downturn as the VSTOXX reached its maximum value within the time span considered. Figure 4 confirms that the inclusion of macroeconomic information has non-negligible effects on the calculation of expected losses. Note that linking the calculation of losses to the evolution of a macroeconomic variable in such a way implicitly introduces some degree of procyclicality, although not linked to the nature of impairment accounting regime, as we will discuss in subsequent sections of this paper.
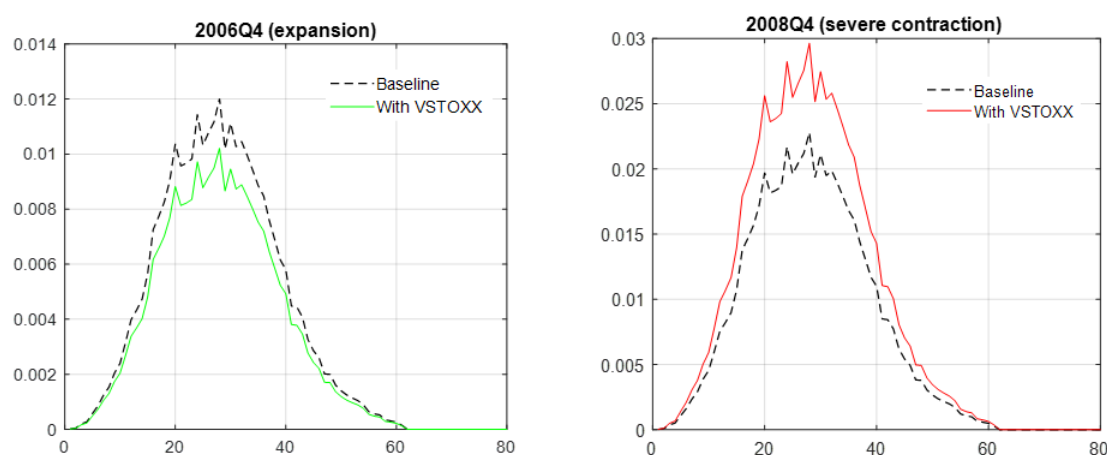
PD curves assuming loans with 20-year maturity for two different points of the economic cycle.

Figure 4: Effect of macroeconomic information on 1-year PDs.

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[21] As detailed, among other works, in Bloom (2009) and Jo and Sekkel (2017).

To calculate the lifetime expected loss in t we need, for each future period s until maturity, the probability of default conditional on a unique non-default event in previous periods between t and s. Indicating with D_k a default event in period k, the probability of a default in a future period s conditional on the information set $\mathcal{F}_t$ available at time $t < s$ is as follows:

$$PD_{s|\mathcal{F}_t} = p\left(D_s = 1, D_k = 0; t \leq k \leq s\right) = PD_s \prod_{k=t}^{s-1} \left(1 - PD_k\right) \tag{7}$$

The lifetime PD in t is simply the probability of observing a default in any of the future time periods, conditional on the information in t:

$$PD_t^{Life} = \sum_{s=t}^{M} PD_{s|\mathcal{F}_t} = PD_t + \sum_{s=t+1}^{M} PD_s \prod_{k=t}^{s-1} \left(1 - PD_k\right) \tag{8}$$

It follows immediately that the lifetime PD is always higher than the single-period PD and converges to it as the loan approaches maturity.

Following the logic explained above, PD_t is calculated for each age of a loan using EDW data (as in Figure 5). Given the limited number of defaults in the EDW dataset, we lack the amount of data necessary to calculate how this relation changed over time and assume a single curve for all periods.

The PDs for each age are subsequently multiplied in each period by a coefficient which ensures that the weighted average PD of the portfolio equals the default rate calculated from the Italian credit register.
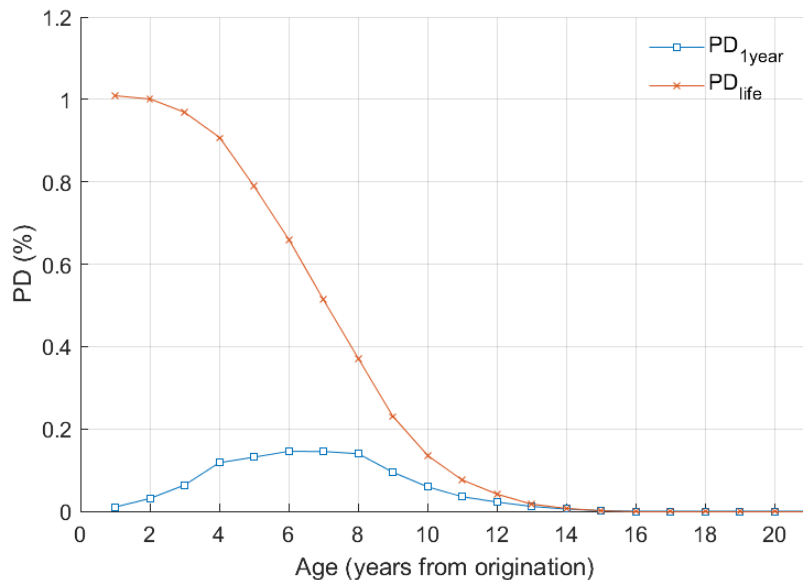

Figure 5: Lifetime versus one-period PD.

4.1.4 Expected loss

The one-period expected loss is defined as the product of the exposure times the PD and the LGD. However, in calculating lifetime provisions, the lifetime expected loss (using the proper discount rate) is the suitable measurement. Following the same logic as in the PD case, the lifetime expected loss in period t for a loan with contractual maturity M is merely defined as the sum of current and future one-period expected losses.

To calculate the lifetime expected loss in t we need, for each future period s until maturity, the probability of default conditional on no default event in previous periods between t and s[22]. The formula for the expected loss over the residual lifetime of the loan can then be written as:

$$
\begin{aligned}
EL_{t+1,M} &\equiv \sum_{s=t+1}^{M} EL_s = \sum_{s=t+1}^{M} EAD_s \cdot LGD_s \cdot PD_{s|\mathcal{F}_t} \cdot (1+r)^{-(s-t)} \\
&= \sum_{s=t+1}^{M} EAD_s \cdot LGD_s \cdot PD_s \prod_{k=t}^{s-1} (1-PD_k) \cdot (1+r)^{-(s-t)}
\end{aligned}
\tag{9}
$$

As in the case of the PD, compared to the one-period EL, the lifetime EL not only is higher but monotonically decreasing as the loan ages (see Figure 6).
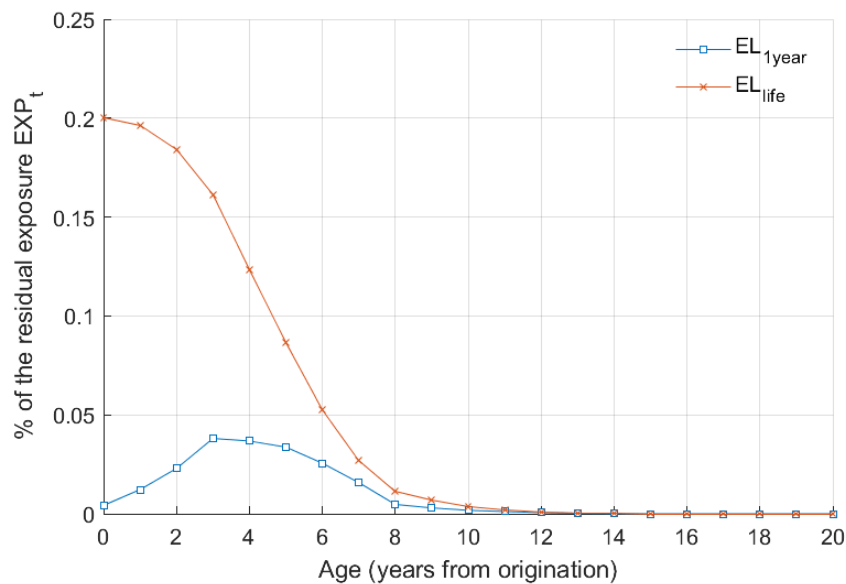

Figure 6: Lifetime versus one-period expected loss.

4.2 Impact on P&L: provisions and realized losses

In calculating the impact on the profit and loss account we follow the approach defined by the accounting practice (GPPC, 2016), that is, we calculate provisions and realized losses through the PD, LGD and EAD for each year. In this section, the basis time unit t is the quarter and financial institutions are supposed to account for provisions and losses on a quarterly basis.

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[22]Here again, we exclude the possibility of multiple defaults.

4.2.1 IAS 39

Under IAS 39 there are no provisions, neither at inception nor for any given year; each period's total negative impact on the profit and loss account (PL_t) is required to equal realized losses. Assuming that the loss appears when there is a default, the P&L under IAS 39 would be:

$$PL_t^{IAS\,39} = EAD_t \cdot DR_t \cdot LGD_t \tag{10}$$

where DR_t is the realized default rate in t. However, since the loss appears well after the default, this formula is just an approximation. As we will state afterwards, for simplicity in this paper we will assume that the loss from a default is split equally across the following six years.

4.2.2 IFRS 9

Under the perfect forecast assumption, losses in each period are fully compensated with previous year provisions. Again, assuming the loss appears when there is a default, the negative impact on P&L from Stage 1 loans would be just equal to the losses expected for the following year:

$$PL_t^{S1} = EL_{t+1,t+4}^{S1} = \sum_{s=t+1}^{t+4} EL_s^{S1} = \sum_{s=t+1}^{t+4} EAD_s^{S1} \cdot LGD_s \cdot PD_{s|\mathcal{F}_t} \cdot (1+r)^{-(s-t)} \tag{11}$$

As in the previous case, since the loss appears well after default this formula is just an approximation.

If there is a significant risk increase, loans pass to Stage 2 status and the full lifetime expected loss must be recognized. We use a proxy of the 30-day past due status as a trigger for the transition from Stage 1. According to IFRS 9 dispositions, a (rebuttable) presumption exists that 30-days past due status represents a significant increase in the risk qualifier for loans. Unfortunately, data on payments past due less than 90 days is not available from the Italian Credit Register. However, assuming that payments become past due with uniform probability within each quarter, approximately two thirds of the 90-day past due loans at the end of a quarter would already be 30-day past due by the end of the previous quarter. We assume as a rough approximation that two thirds of the loans to be defaulted in $t+1$ show a significant risk increase in t, that is:

$$EAD_t^{S2} = \frac{2}{3} \cdot EAD_{t+1}^{S3}$$

However, this assumption does not embrace loans that temporarily shift from Stage 1 to Stage 2 and vice-versa; in subsequent sections of the paper, we explore alternative formulations that account for migrations from and to Stage 2. Assuming the loss is discovered when there is a default, the impact on P&L from loans in Stage 2 is:

$$PL_t^{S2} = \sum_{s=t+1}^{M} EL_s^{S2} = \sum_{s=t+1}^{M} EAD_s^{S2} \cdot LGD_s \cdot PD_{s|\mathcal{F}_t} \cdot (1+r)^{-(s-t)}$$

$$= \sum_{s=t+1}^{M} EAD_s^{S2} \cdot LGD_s \cdot PD_s \prod_{k=t}^{s-1} (1 - PD_k) \cdot (1+r)^{-(s-t)}$$

(12)

where M is the exposure maturity and $\mathcal{F}_t$ the information set in t.

The impact on P&L from Stage 1 and Stage 2 exposures comes therefore in terms of provisions for future losses:

$$PL_t^{S1} + PL_t^{S2} = Prov_t^{IFRS\,9}$$

For loans in Stage 3 default is certain ($PD_t = 1$), and a loss must be accounted for in P&L. The corresponding provisions already made in the previous periods, on the other hand, must be cancelled. Under the assumption of perfect forecast, in every period realized losses correspond to the expectations of the previous periods and the two quantities offset each other.

$$PL_t^{S3} = Loss_t - Prov_{\text{Previous periods}}^{IFRS\,9} = 0$$

(13)

Since we have assumed perfect forecasting ability, the sum of losses realized in any period will exactly offset previous year's provisions, short of a difference due to discount unwinding. For the sake of simplicity, we assume that there is no flow of loans back from Stage 2 to Stage 1. Under these assumptions the impact in P&L from Stage 3 is zero.

Summing up, under our assumption the impact on P&L in each period under IFRS 9 is therefore equal to the sum of one-year expected losses for loans in Stage 1 and of lifetime expected losses for loans in Stage 2:

$$PL_t^{IFRS\,9} = Prov_t^{IFRS\,9} + \left(Loss_t - Prov_{\text{Previous periods}}^{IFRS\,9} \right) = PL_t^{S1} + PL_t^{S2}$$

(14)

4.2.3 US GAAP

In order to replicate the approach devised by the FASB we recognize the full lifetime expected loss of each loan at inception. We model the impact on P&L under US GAAP under three different assumptions on how financial institutions incorporate new information in the estimates for lifetime ECL:

1. Future loss rates are known ("perfect forecast");

2. Future loss rates are known up to a one-year horizon in the future, after which they are assumed to revert to the sample average;

3. Future loss rates are known up to a one-year horizon in the future, after which they are assumed to revert to the average of the previous five years.

When we assume that financial institutions can perfectly forecast future losses, the sum of realized losses in the subsequent periods will exactly offset the provisions in year one. Therefore, the impact on P&L in each period will equal to the lifetime expected loss for the newly originated loans and is obtained by replacing the EAD with the volume of new loans in equation (10).

Under the alternative assumptions where the perfect forecast horizon is limited to one year[23] (after which financial institutions either assume that PD will revert to the historical sample average levels or to the average of the last five years), in addition to the provisions for new loans in each period there will be a positive or negative impact from the provisions on older loans, for which the expectation on the loss for the residual lifetime changes in response to the new information available. The new value of the lifetime ECL for old loans tends to increase during crisis times, partially offsetting the reduction in overall provisions implied by the lower flow of new loans.

Which of the two effects will prevail is crucially contingent upon how financial institutions update their expectations on future losses. Under our assumption an increase in loss rates is seen as transitory and the latter are assumed to revert to some average value, which results in a limited effect that only partially offset the opposite dynamic driven by the provisions on new loans. If financial institutions assume longer persistence of loss rates values, the changes in provisions for old loans tend to prevail.

4.3 Methodological assumptions

In order to calculate the impact on procyclicality we were forced to make a number of assumptions to simplify our model. Although some of them have already been mentioned, in this section we explore the most relevant ones trying to highlight their potential impact. Besides, we would like all these restrictions to be borne in mind when extrapolating policy conclusions from our paper.

Stage 2 and "cliff effect"

As mentioned, when designing the impact of the significant increase in credit risk and its cliff effect we were forced to make two consecutive simplifications. We link the Stage 1 to Stage 2 transition to the 30-day past due rebuttable assumption. This simplification is heavily rooted on the IFRS 9 being the only common and purely objective criterion. Thus, regulation itself assumes the delay in payments as the most evident predictor of the rest of triggers (e.g. forbearance, increase in PD...).

Since our database did not have any information on which loans were 30 days past due we were forced to use a proxy. We assumed an even distribution of the 90 days past due loans as described in the previous section. This is another difference with respect to Abad and Suárez (2017) since they model the cliff effect by means of the transition matrix. Based on their data we have every reason to believe that the delay in payment will be even more procyclical than default itself.

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[23]We keep one year of perfect forecast in order to ease the comparison with the results for IFRS 9.

Perfect forecast

Since we use an *ex post* database including observations from the latest economic crisis, one of the modelling options we compare is based on perfect forecast. That is, we test the different accounting regimes assuming that provisioning models can exactly predict future outcomes. We fully acknowledge that actual models will be subject to real data availability and thus, perfect forecast is not compatible with "real life". However, for comparison purposes we see merit in removing all other practical considerations from credit risk models.

Lag between default events and loss recognition

The timing with which credit losses are recognized can be constrained to a varying degree by accounting rules, but also depends on the actual speed with which the loss associated with a non-performing exposure becomes known, on the length of recovery procedures, and to some extent on discretion. There is abundant evidence in the literature on the tendency for financial intermediaries to procrastinate loss recognition in the context of crises, as shown in Stoian and Norden (2013), Basel Committee on Banking Supervision (2015a) and IMF (2015).

Modelling how these factors affect the timing of loss recognition is beyond the scope of this paper. For simplicity, we assume that it takes some time to realise the full extent of the loss on a non-performing loan (this can be interpreted as a progressive deterioration in credit quality): if required to recognise realised losses, under this assumption a financial intermediary would split the loss equally across the six years following the default event[24].

Independence between accounting regime and loan supply

For modelling purposes, we assume independence between the accounting regime and loan supply. This hypothesis is established in order to be able to compare the two models and because there is no clear knowledge on how much the accounting model will impact credit supply. However, we fully acknowledge that the different P&L impacts might tailor banks'behavior. In fact, one of the conclusions of this paper is the different cyclical impact of the accounting regimes.

5   Results

Based on the methodology and parameters described, in this section we have simulated what the shapes of provisions plus realized losses would have been for a simulated portfolio of Italian mortgages from 2006 to 2018. We do not assess the impact of regulatory changes given the current conditions of the financial system; instead, we study the dynamics of provisions and losses in a scenario where the effects of the transition to the new rules have been completely absorbed[25].

Assumptions on the exposures at default, LGDs and loan-to-value ratios were already detailed in the previous section. Related to PD, we will use average default rates from the Italian credit

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[24]This number of years is roughly coherent with evidence on the average time needed to obtain the recoverable value in foreclosures procedures in Italy; see Carpinelli et al. (2016).

[25]In this spirit, Figure 7 does not show the provisions made in the first period of existence of the fictional portfolio, which correspond to the initial value of the stocks of provisions in Figure 6.

register as averages for each period, whereas the relationship between the PD and the age of the loan is estimated from the European Data Warehouse (EDW).

Using this fictional portfolio, Figure 7 depicts the sum of realized losses plus net provisions, i.e. the impact on P&L in each period under all three accounting regimes (IAS 39, IFRS 9 and US GAAP). For US GAAP, we show the result for the three alternative assumptions presented in the previous section.

Under the perfect forecast assumption, for US GAAP realized losses are always provisioned in advance (at loan origination). If there were no delay between default and write-off, the realised losses curve also would correspond to the total impact on P&L in each period under IAS 39. However, since this delay exists and we have assumed that the loss from a default is split equally across the following six years, under IAS 39 losses are recognized well after default.
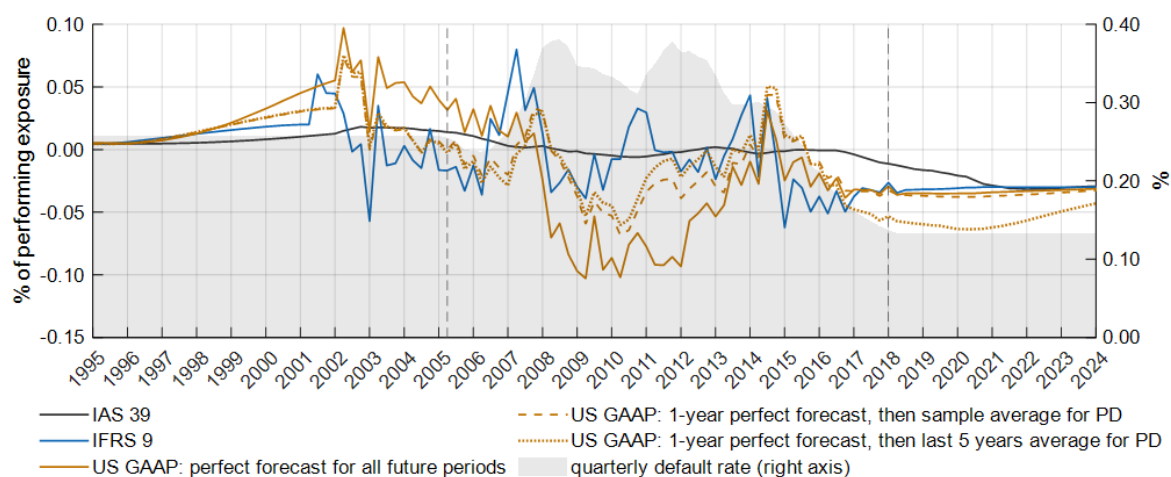
Variation of P&L (realized losses plus net provisions) under the different accounting regimes, over an historical scenario for mortgage defaults and new loan volumes

Figure 7: Impact on P&L.

With IFRS 9, provisions anticipate default by one year (Figure 7). Under the perfect forecast assumption, in fact, Stage 1 provisions represent exactly the following year's realized losses if losses took place at the same time of default, whereas under our assumptions the amounts of exposure in Stage 2 have a relatively small effect[26]. In other words, as we will analyze below, IFRS 9 seems much less procyclical than the previous IAS 39 regime (in the sense of contemporaneous correlation with realized losses). This is a major improvement with respect to IFRS 9 since under IAS 39 losses are recognized once they take place, sometimes too long *after* default, whereas under IFRS 9 they are recognized one year *before* default. However, the impact on P&L barely anticipates actual losses by one year, which may be an insufficient amount of time to build up reserves and the business cycle may already have entered the downturn phase.

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[26]This point marks a significant difference with respect to the results of Abad and Suárez (2017). We use quarterly frequency in the model and assume that uncertainty on the status of assets classified into Stage 2 is solved (with passage to default) within one quarter. Since Stage 1 provisions account for the expected loss over the next four quarters, provisions for Stage 2 loans tend to be much less than those for loans in Stage 1. Abad and Suárez (2017), instead, divide time in discrete periods which implicitly represent years, assuming *de facto* that loans stay in Stage 2 for at least one year. In addition, their model allows a prolonged permanence in that status. The "cliff effect" from Stage 2 loans in their model is therefore much bigger and determines a strong response of IFRS 9 provisions to shifts in credit quality.

Our set of assumptions entails that the impact of the "cliff effect" from Stage 2 provisions is almost negligible, since the assets migrate toward a different stage within one quarter. More conservative assumptions about the conditions to classify assets in Stage 2 may lead to a higher amount of provisions being frontloaded when credit quality starts deteriorating. However, to the best of our knowledge, it seems that the cliff effect will always be close in time to defaults, which may worsen rather than reduce the procyclical effects of losses. So, based on these results it appears that while IFRS 9 is an advance with respect to previous regulation (IAS 39), there could be some room for improvement.

Under US GAAP, due to the fact that we have assumed independence between the accounting regime and loan supply, since provisions are granted at inception and there is a clear negative correlation between volumes of new granted loans and default rates, the impact on P&L is negatively related to contemporaneous default rates. The reason behind this result is that under US GAAP provisions tend to be accumulated during boom phases of the credit cycle, when new loans volumes are higher: losses that will occur during crises are recognized in advance and provisions are progressively released when credit quality deteriorates.

The effect described above is stronger with perfect forecast, while when loss rates are estimated to be more persistent in time (the other two cases for US GAAP, indicated by the dotted and the dashed line in Figure 7) the effect of updating expectations on future losses for older loans tends to compensate the decrease in new loans. Without perfect forecast, in fact, losses in times of crisis could exceed provisions granted at inception based on the lifetime expected loss, if the future default and recovery rates were severely underestimated. Nevertheless, even if the perfect forecast horizon is limited to one-year, cyclicality under US GAAP is much lower than under IFRS 9. The results, thus, appear still valid under the assumption that expectations are overly optimistic in risk assessments during boom times.

Finally, notice that the level of provisions (see Figure 8) is much higher under US GAAP (between 1.5% and 2.5% of performing exposure) than under IFRS 9 (approximately 0.25%). This is not surprising since under US GAAP the entire expected lifetime loss is provisioned at inception, whereas in IFRS 9 financial institutions are required to provision only the following year expected loss plus the lifetime expected loss for the loans that show a significant increase in risk.
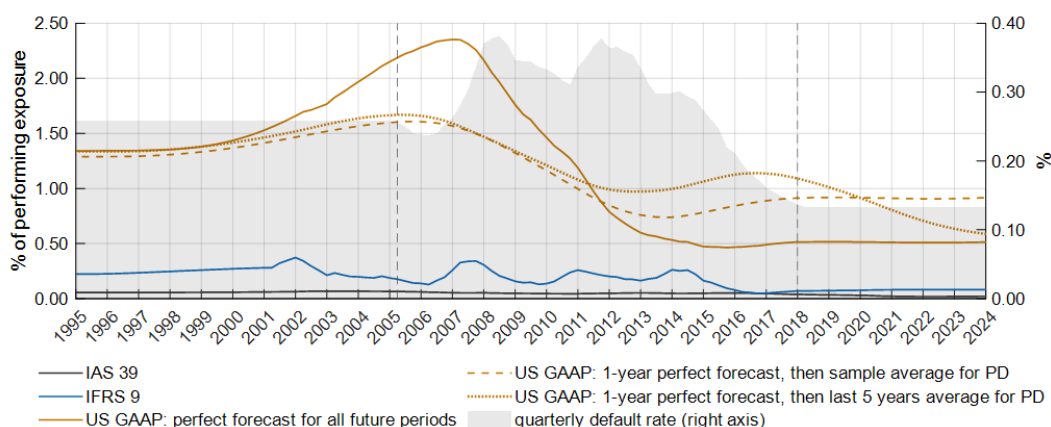

Figure 8: Stock of provisions.

To confirm these intuitions about procyclicality that we draw from the previous graphs, in the following subsection we present a statistical procedure to measure procyclicality. However, it is worth noting that our results are based on our assumptions and, although these are reasonable and robustness checks will be carried out below, we should be cautious about the policy conclusions that can be extracted from these results.

5.1 Procyclicality

In the context of this paper, procyclicality is defined as the correlation with the contemporaneous evolution of credit quality, proxied by realised losses. However, procyclicality can also be defined in terms of correlation with macroeconomic variables, usually with GDP. Credit quality, in turn, tends to be strongly related to credit supply and the business cycle so we do not expect significant differences in both calculations, which justifies our use of the word "procyclical" in the former sense.

Following Paredes et al. (2014), we use dynamic cross-correlation functions to measure procyclicality. Tables 1 and 2 report the unconditional correlations between the impact on P&L and the realized losses as well as Italian GDP under different accounting regimes. Following standard practice, we measure the comovement between two series using the cross-correlation function (henceforth CCF). Each row of Tables 1 and 2 displays the CCF between the impact on P&L (net provisions and realized losses) under different accounting regimes at time $t \pm k$, and, realized losses as well as Italian GDP at time t.

Lags/Leads	IFRS 9	US GAAP (a)	US GAAP (b)	US GAAP (c)
-8	45.2	6	16.6	34.8
-7	48.4	5	17.9	36.6
-6	51.6	3.9	19.8	38.8
-5	53.9	2.8	21.8	41.1
-4	55.3	1.9	24.1	43.6
-3	56.1	1.2	26.6	46.3
-2	55.5	0.4	29	48.8
-1	53.7	-0.6	30.6	50.6
0	52.3	-0.9	31.9	51.9
1	50.3	-2.3	31.1	51.5
2	48.8	-3.1	30	50.8
3	48.1	-3.2	29.1	50
4	48.1	-3.2	28.4	49.3
5	48.2	-2.8	28	48.6
6	48.7	-2	28	48.1
7	50.2	-0.8	28.7	48.2
8	50.3	-0.1	29.6	48.2

Unconditional correlations between the impact on P&L and losses. For US GAAP: (a) Future loss rates are known ("perfect forecast"); (b) Future loss rates known up to a one-year horizon in the future, then revert to the sample average; (c) Future loss rates known up to a one-year horizon in the future, then revert to the average of the previous five years.

Table 1: Cross-correlation functions: P&L with realized losses.

It can be inferred from the previous section that the impact in P&L from IFRS 9 presents positive and strong contemporaneous correlation with realized losses and increases to roughly 55% with four lags (one year). Table 1, therefore, confirms the intuition that IFRS 9 provisions input future realized losses to P&L approximately four quarters in advance: the impact of Stage

2 provisions is minimal, under our assumptions[27]. Consequently, as stated above, IFRS 9 appears less procyclical than the previous IAS 39 regime, which is perfectly correlated with realized losses by construction, but — even with perfect forecasting ability — provisions start rising only one year before actual defaults. Thus, the impact on P&L is still likely to exert negative effects on banks'balance sheets at a point when the business cycle is starting to deteriorate.

Instead, confirming the previous section results, the impact in P&L from US GAAP and realized losses present negative and non-negligible contemporaneous correlation in case (a), entailing a negative correlation with the business cycle, which is a desirable property. In cases (b) and (c) contemporaneous correlations are positive, but still significantly lower than under IFRS 9 except for some leads in (c). These results are not totally unexpected since the purpose of the introduction of ECL was to reduce procyclicality and US GAAP requires fully ECL recognition since inception[28].

We mentioned that credit quality tends to be strongly related to the business cycle; therefore, if we repeat the exercise using Italian GDP instead of realized losses, we expect no major differences. In general terms, Table 2 confirms this intuition. Firstly, taking into account lags and forwards, IFRS 9 tends to be procyclical in the sense that realized losses net of provisions tend to be higher when GDP is lower (negative, or almost zero, correlation). However, as expected, in the case of US GAAP with perfect forecast, realized losses net of provisions tend to be higher when GDP is higher (positive correlation), which is a desirable property.

Lags/Leads	IFRS 9	US GAAP (a)	US GAAP (b)	US GAAP (c)
-8	-23.5	43.3	19.3	2.6
-7	-29	38.2	11.3	-4.6
-6	-31.9	33.8	3.1	-12
-5	-31.6	30.3	-4.3	-18.8
-4	-29.2	26.3	-11.9	-25.8
-3	-22	23.2	-17.7	-31.1
-2	-14.5	20.1	-21.6	-34.8
-1	-6.2	17.4	-22.6	-35.8
0	0.6	13.9	-21.1	-34.2
1	3.6	9.1	-19	-31.8
2	5.1	3.4	-17.2	-29.2
3	4.9	-3.7	-16.7	-27.3
4	3.4	-11.3	-18	-26.5
5	1.3	-18.1	-20.2	-26.5
6	-1.1	-23.9	-22.8	-26.6
7	-2.8	-28.8	-25.6	-26.8
8	-4.2	-33.8	-29.3	-27.8

Table 2: Cross-correlation functions: P&L with GDP.

Results related to US GAAP cases (b) and (c) are not totally unexpected considering what is stated above. The effect of updating expectations on future losses for older loans in bad times compensates the fact that during bad times banks grant less loans, creating a situation in which realized losses net of provisions tend to be higher when GDP is lower.

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[27] However, recall that our baseline assumption does not consider loans that temporarily shift from S1 to S2 and later on, instead of defaulting, recover their S1 status. Rating migrations data show that a non-negligible amount of rated entities improve their rating every period, which would qualify for an S2 to S1 transition. Thus, any results regarding the procyclicality induced by S2 loans should be understood as only a lower bound of the potential, actual effects.

[28] See, for example, FSF (2009).

5.2 Robustness checks

The previous sections have clarified that, in order to calculate the impact on procyclicality, we were forced to make several assumptions to simplify our model. Although all the assumptions are reasonable and in line with regulation, we present a set of robustness checks in order to understand how results depend on the assumptions.

5.2.1 Allowing for forecast errors in expected losses

The first assumption that we will challenge is the ability of credit institutions to perfectly forecast expected losses up to a one-year horizon. In the alternative setup, 1-year-ahead PDs across the sample span are subject to a stochastic forecast error drawn from a uniform distribution over the interval $(75\%, 105\%)$. It is reasonable to assume that, in general, there is a tendency to underestimate the probability of default more often than being overly cautious, hence the choice of the interval. Introducing such biased noise in the computations results in lower expected losses, which ultimately entails a reduction of the stock of provisions, as illustrated by Figure 9. However, the main conclusion of the paper would not have changed had this effect been in place.
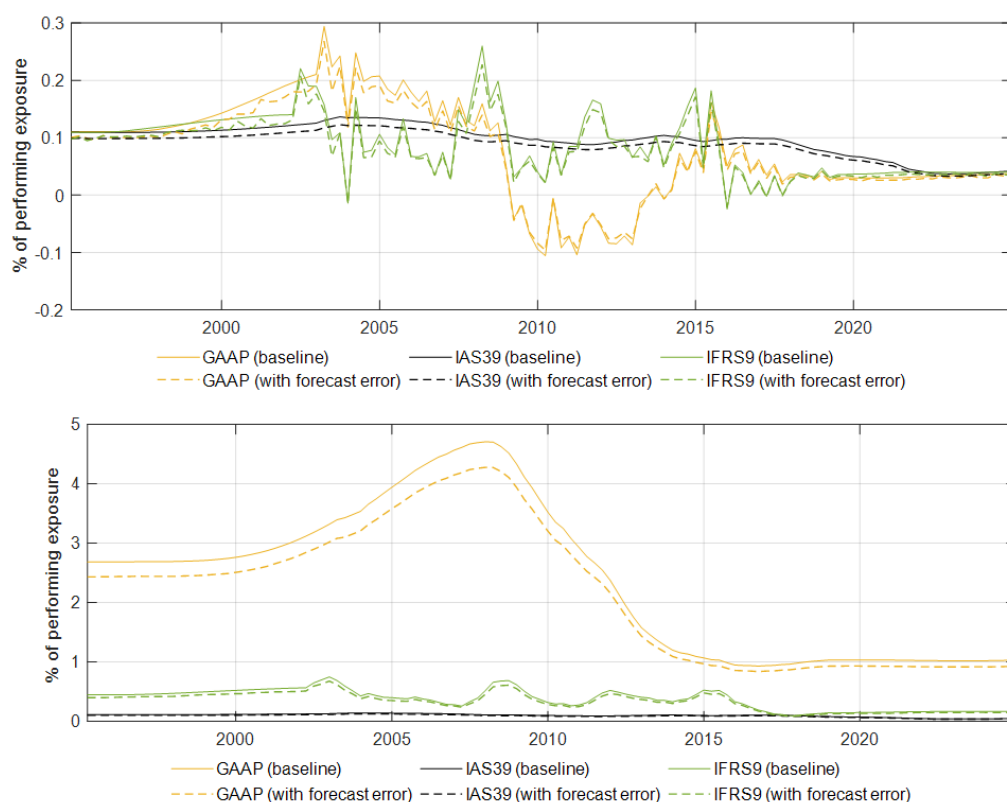
Profit and Loss (upper panel), stock of provisions (lower panel).

Figure 9: Effect of the inclusion of stochastic forecast errors.

5.2.2 Ruling out macroeconomic information

The simulations conducted in our baseline specification account for the interaction of default probabilities with the economic cycle, the latter proxied through the VSTOXX index. In previous sections, we have pointed out that this feature implicitly introduces some procyclicality in the calculation of loan losses. Figure 10 plots the cross-correlation functions from Table 1 in the baseline and "no macro" scenario; it appears that discarding macroeconomic information reduces the procyclicality of P&L with respect to GDP in both the IFRS 9 and GAAP accounting regimes, in line with our intuition.
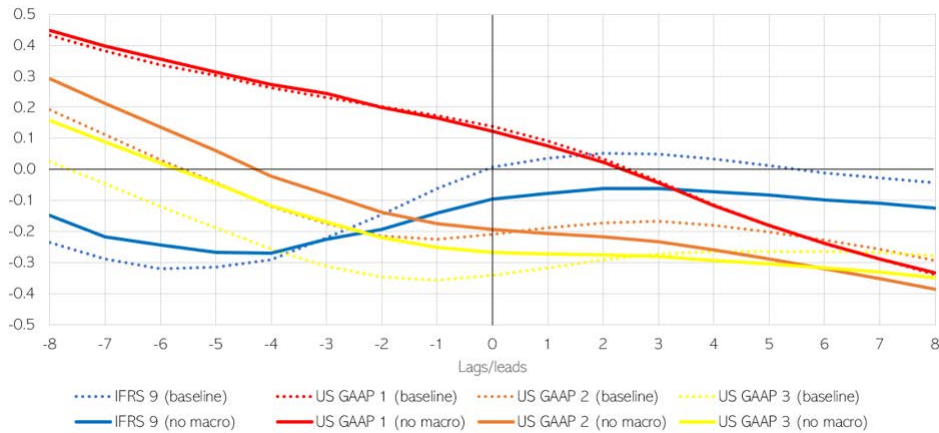
GAAP 1: Future loss rates are known ("perfect forecast"); GAAP 2: Future loss rates known up to a one-year horizon in the future, then revert to the sample average; GAAP 3: Future loss rates known up to a one-year horizon in the future, then revert to the average of the previous five years.

Figure 10: Cross-correlation function of P&L and GDP: Effect of macroeconomic information.

Regarding the ultimate impact on provisions, where we also look at the IAS 39 case, Figure 11 illustrates that the shape of the series varies notably; for IFRS 9, in particular, the reduction in procyclicality can also be observed in the more moderate oscillations in the neighbourhood of the 2008 recession.
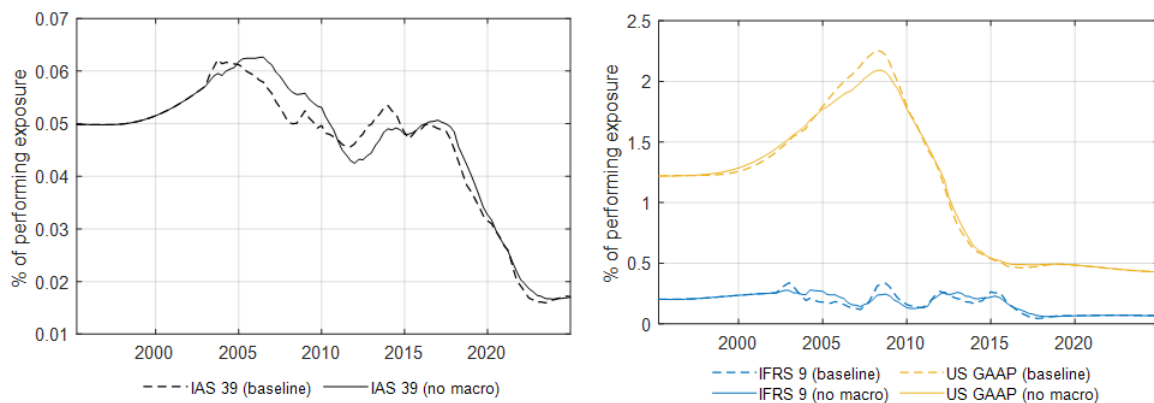
The US GAAP series refers to the perfect forecast case.

Figure 11: Stock of provisions: Effect of macroeconomic information.

5.2.3 Comparative statics on key parameters

As an additional check on the suitability of our approach, we perform two sensitivity exercises: Firstly, we gauge the responsiveness of loss given default to different values of the loan-to-value ratio (LTV in our equations) and the sales ratio SR, that is, the ratio between the present value of the sale price and the value of the collateral; secondly, we depart from a loan maturity of 20 years to evaluate the consequences in the profit and loss account and the stock of provisions.

Starting with loan-to-value ratios, it is straightforward that a higher exposure-to-collateral value induces greater losses through the LGD identity and, hence, provisions will also increase. The opposite occurs with the sales ratio: If the (discounted) sale price represents a large share of the collateral, losses will be more contained and so LGD is decreasing in SR. Figure 12 shows how loss given default, plotted against the age of the loan, varies for different values of the two parameters of reference; the effects, as expected, are not linear. In terms of impact on provisions and the P&L account, we provide the full set of time series for each of the accounting regimes in the Appendix.
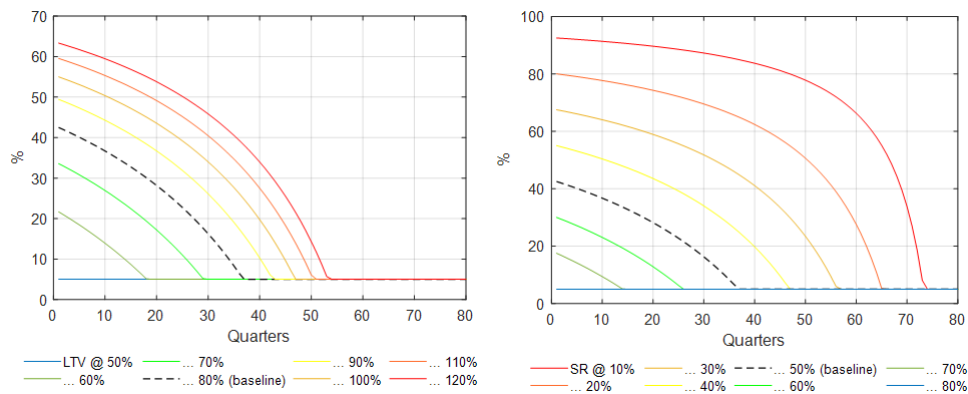
The dashed black line represents the baseline for the simulations.

Figure 12: LGD (%) vs. loan age for selected LTV (left panel) and SR (right panel) values.

Regarding the effects of loan maturity M in our results, we relax the 20-year assumption to allow for shorter and longer mortgage horizons. The results are plotted in Figures 13 and 14: longer-term loans imply a larger stock of provisions for all the maturities considered.
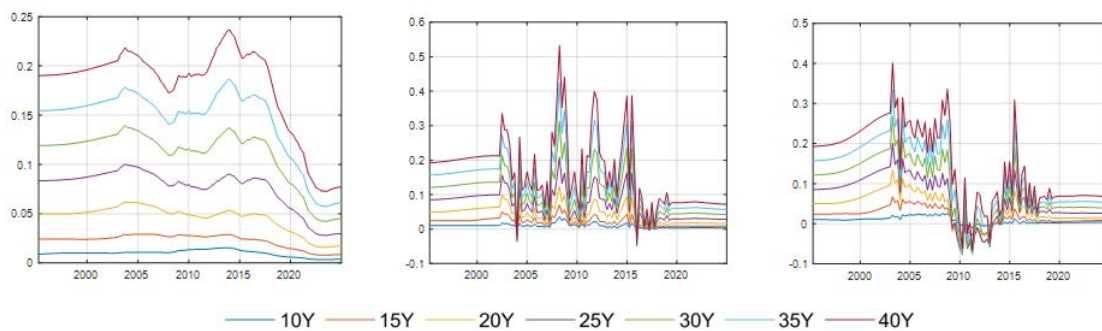
IAS 39 (left panel), IFRS 9 (center panel), US GAAP (right panel).

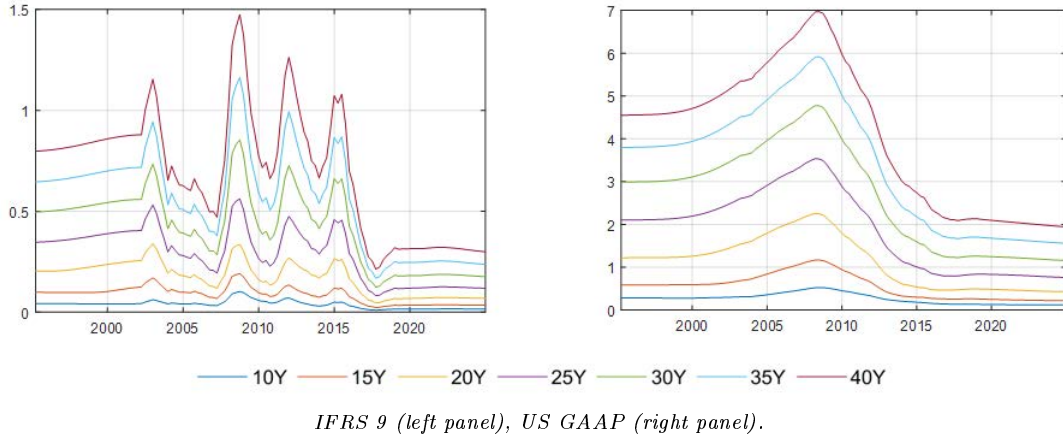Figure 13: P&L as a percentage of performing exposure for different loan maturities.

IFRS 9 (left panel), US GAAP (right panel).

Figure 14: Stock of provisions as a percentage of performing exposure for different loan maturities.

5.2.4 A second look at Stage 2 transitions

In our baseline simulations, we link the Stage 1 to Stage 2 transition to the 30-day past due rebuttable assumption. Exploring the existing literature along with other data sources has provided us with two alternatives for the modelling of $S1 \leftrightarrow S2$ transitions.

The work by Abad and Suárez (2017) is our first source of inspiration as the authors compute transition probabilities from S1 to S2 (TR_{12}) and from S2 to S1 (TR_{21}) in expansions and contractions of the economic cycle. We take the averages in both points to obtain proxies of the two TRs. With this information, we can calculate the Stage 1 and Stage 2 exposures at default accounting for migrations within both states:

$$
\begin{aligned}
EAD_{t+1}^{S1} &= (1 - TR_{12}) \times EAD_t^{S1} + TR_{21} \times EAD_t^{S2} \\
EAD_{t+1}^{S2} &= (1 - TR_{21}) \times EAD_t^{S2} + TR_{12} \times EAD_t^{S2}
\end{aligned}
\tag{15}
$$

In this case we obtain $TR_{12} = 5.65\%$ and $TR_{21} = 8.8\%$.

Besides, the European Central Bank's Household Finance and Consumption Survey (HFCS) contains information on late or missed payments on loans and mortgage payments from households across the euro area. In particular, variable HNC0125 collects the answers to the question *"Thinking of all the various loan or mortgage payments due in the last twelve months: were all the payments made the way they were scheduled, or were payments on any of the loans sometimes made later or missed?"*. The possible answers are: 1 (All payments as scheduled), 2 (It happened once or more that I was late with or missed some of the payments) and 3 (Household did not have loans in the last 12 months). We use this variable as a proxy for the transition probability TR_{12} with the intuition (and the strong assumption) that impaired repayments imply a deterioration in the credit quality of the loan:

$$
TR_{12}^{HFCS} = \frac{\sum \left(\text{HNC0125} = 2 \mid \text{Italian household} \right)}{\sum \left(\text{Italian household} \right)} = \frac{1274}{8156} = 15.62\%
\tag{16}
$$

To the best of our knowledge, however, none of the survey variables sheds any light on how to approximate the transition probability from S2 to S1; therefore, we decide to use the same value for TR_{21} than in the previous case.

Both the effect on P&L and the differences in provisioning under the three migration regimes are shown in Figure 15. While similar in shape, provisions are higher when one allows for loans switching between Stage 1 and Stage 2.
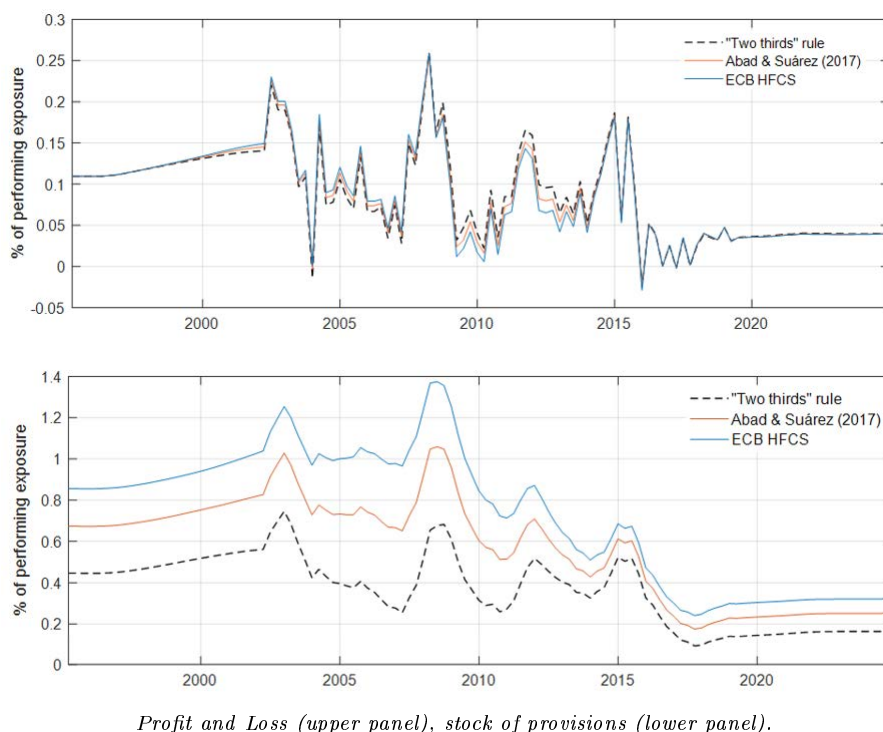

Profit and Loss (upper panel), stock of provisions (lower panel).

Figure 15: Comparison of different Stage 2 migration assumptions.

6   Conclusions

The purpose of this paper is to present an assessment of the procyclicality of credit impairments under various accounting regimes. We elaborate on the recent evolution of financial instrument accounting systems, namely, IAS 39, IFRS 9 and US GAAP. Under IAS 39, expected losses stemming from future events cannot be recognized. Consequently, under this accounting regime financial institutions are required to deal with losses only when a negative turn in the business cycle is already affecting credit quality.

The recently introduced IFRS 9 and US GAAP mark a paradigm shift from incurred loss to expected loss but differ in the moment at which expected losses are recognized. While US GAAP requires the recognition of lifetime losses at origination or purchase of an asset, IFRS 9 only demands to account for the expected losses in the next 12 months as long as the asset does not show a significant increase in risk, which triggers the recognition of the ECL for the remaining lifetime.

We model the impact of credit impairments on P&L under different accounting regimes in an historical scenario under different assumption on the how financial institutions estimate ECL. Our results indicate that IFRS 9 is much less procyclical than the previous regulation (IAS 39). The reason behind it is that under IAS 39 losses are recognized once the write-off takes place whereas under IFRS 9 losses are recognized one year before default, and default takes place some time before the write-off (sometimes too early); thus, from that point of view it is a step in the right direction.

Nevertheless, it presents a substantial degree of procyclicality because, even if financial institutions had the ability to exactly forecast future losses, their impact would be anticipated by just one year, and therefore would still be likely to hit financial institutions when a contractionary phase of the credit or business cycle is already started. Under US GAAP, since future expected losses are fully provisioned from inception, the realized impact on P&L instead tends to be anticipated and smoothed out in time. The US GAAP therefore seems more likely to reduce the procyclical effects of credit quality deterioration.

However, the level of provisions is much higher under US GAAP than under IFRS 9. Therefore, the lower procyclicality of US GAAP seems to come at the cost of holding a larger stock of provisions.

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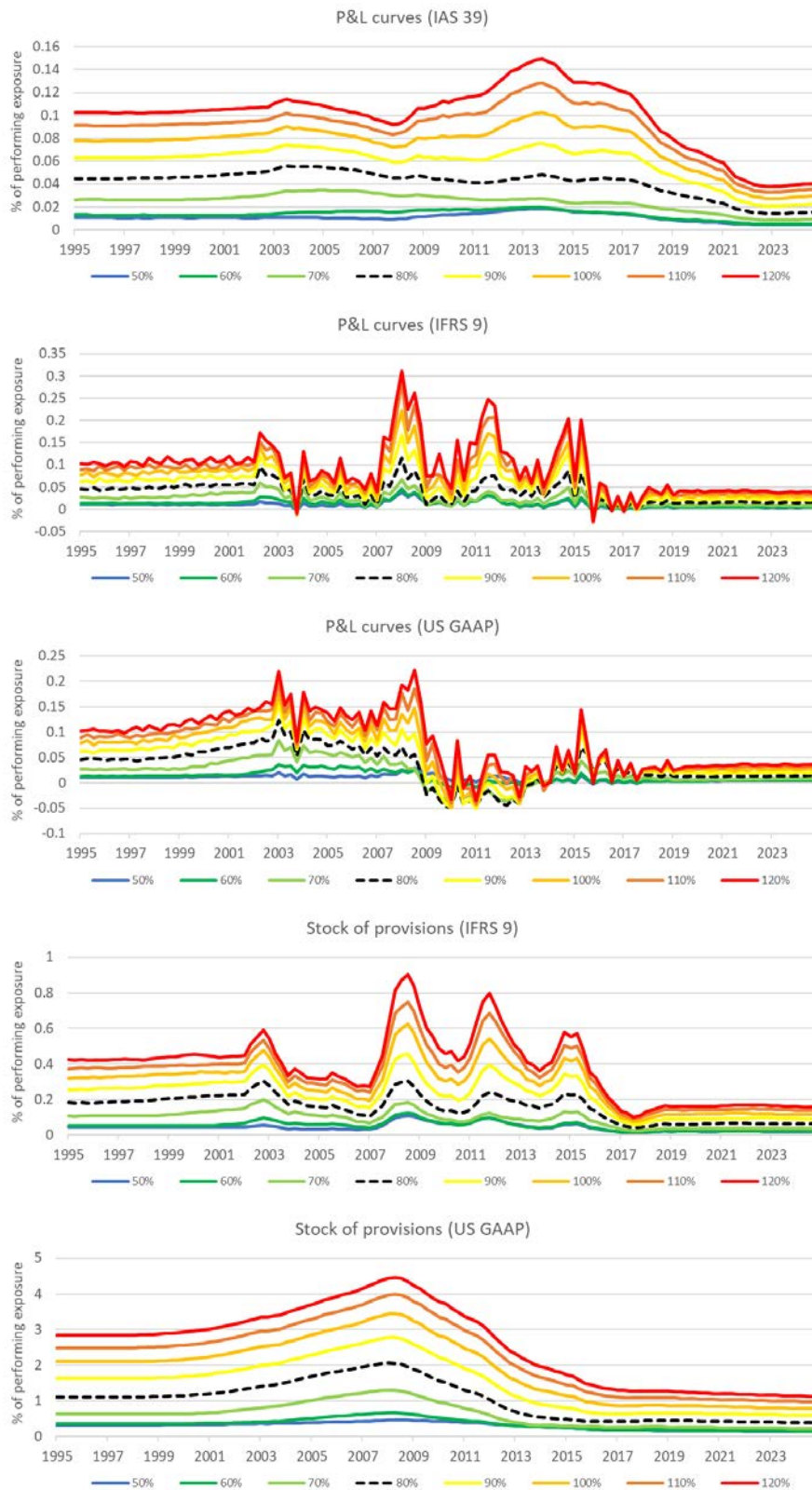
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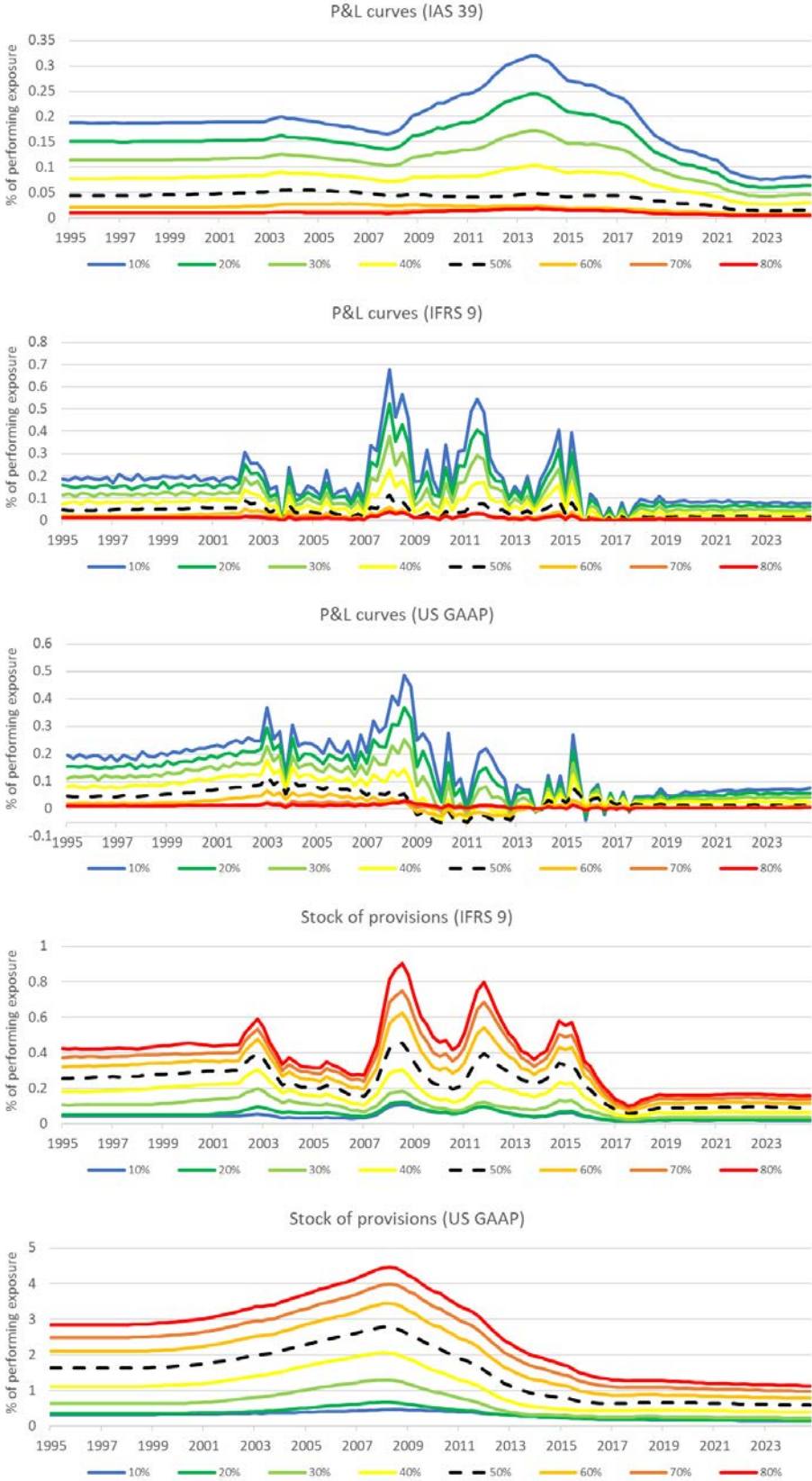
A Robustness checks: Detailed results

Comparative statics on the loan-to-value ratio, *LTV*

(The black dashed line represents the baseline for our simulations)

P&L curves (IAS 39)

P&L curves (IFRS 9)

P&L curves (US GAAP)

Stock of provisions (IFRS 9)

Stock of provisions (US GAAP)

Comparative statics on the sales ratio, SR

(The black dashed line represents the baseline for our simulations)

P&L curves (IAS 39)

P&L curves (IFRS 9)

P&L curves (US GAAP)

Stock of provisions (IFRS 9)

Stock of provisions (US GAAP)

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