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The cyclicality in SICR: mortgage modelling under IFRS 9

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Abstract

Banks must make forward-looking provisions for loan losses under new international accounting standards introduced in 2018. In Europe, banks will assign performing exposures to a new "Stage 2" category with a higher provisioning penalty, if they have experienced significant increase in credit risk (SICR). We use a loan-level credit risk model and Irish residential mortgage panel data to assign performing loans into the appropriate stage. Using this technique, we characterise approximately 30 per cent of the performing Irish mortgage portfolio at end-2015 as Stage 2. We then calculate backward-looking, static estimations of Stage 2 mortgages between 2008 and 2015. This exercise suggests that loan stage assignment can be highly pro-cyclical. The share of Stage 2 among performing mortgages rises during the economic downturn to peak in 2013, after which large transitions are assigned from Stage 2 into lower-risk performing loans, as the economy improves.
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1 Introduction

Banks provision for losses on impaired loans, bearing part of the cost of credit loss events before the final outcome. The treatment of provisions against credit losses changes fundamentally under International Financial Reporting Standard 9 (IFRS 9) for financial instruments, which became effective on 1 January 2018. IFRS 9 replaces *incurred loss* (IL) models with a forward-looking, *expected credit loss* (ECL) model. This follows evidence that during the recent crisis, impairment charges remained at low levels until the realization of sharp discontinuous growth in loan delinquencies (Chae, Sarama, Vojtech, and Wang, 2018). Large and discrete provision charges across the financial sector, at a time of significant volatility and stress, posed risks to financial stability. G20 leaders called for new models that use more information to recognise loss allowances on debt instruments earlier; among the other benefits of ECL models, they are expected to deliver more gradual changes in loss provisions across the economic cycle.

In the European Union, lenders now face higher provisioning requirements on performing loans that have experienced a significant increase in credit risk (SICR) since origination, which are known as Stage 2 (S2) exposures, while impaired exposures, now referred to as Stage 3 (S3), are treated in much the same way as under the previous regime. Provisions for S2 loans are calculated using *Lifetime ECL*, whereas provisions on other performing loans, known as Stage 1 (S1), are borne against *12-month ECL*.[1] This distinction poses conceptual and empirical challenges in finance and stress testing, not least of which is the data challenge to determine whether SICR has occurred.

In this paper, we deploy a loan-level Probability of Default (PD) modelling framework using quarterly information on Irish residential mortgage loans outstanding between 2008 and 2015. We fit current PDs (PD_C) to the population of loans at Ireland's five main mortgage lenders, comprising 90 per cent of the market at the end of 2015. We then highlight how this framework can be altered to fit PDs at origination (PD_O) for outstanding loans regardless of the loan's actual date of origination.[2].

We use our estimates of PD_C and PD_O to operationalize a three-step assignment procedure for delineating the Irish mortgage book into S1, S2 and S3. Under our approach, and in line with

[1] The time horizon signifies which default events to model, regardless of when the ensuing credit loss is realised. The staged approach contrasts with the Current Expected Credit Loss standard adopted in the United States, under which all performing loans bear forward-looking provisions based on Lifetime ECL.

[2] A similar approach for PD_O has been proposed by Joyce and McCann (2016), who assessed bank risk-taking around the introduction of macroprudential mortgage restrictions in Ireland in 2015 by measuring the fitted default probability of newly-issued loans

recent guidance from the European Banking Authority, loans have experienced SICR when in arrears of 31 and 90 days, when they have experienced forbearance or modification, or when PD_C is more than three times PD_O. Using this method, we estimate that 30 per cent of performing mortgage balances across our sample of Irish banks would have been characterised as S2, had our interpretation of the IFRS 9 standard been in place at 31 December 2015. Given the higher provisioning levels due to the Lifetime ECL calculation applied to these S2 loans, this suggests potential for substantial increases in provisioning levels relative to the situation under the IAS 39 incurred loss approach, where loans will generally be provisioned for upon a credit risk event.[3]

We then create a panel of mortgage loans observed at six-month intervals between June 2008 and December 2015, and calculate six-monthly matrices of transition rates across the three IFRS 9 states. These transition matrices may prove useful to policymakers and researchers calibrating provision and stress test models without the requisite data. We show that S2 loans have higher propensity to default than S1 throughout the entire 2008 to 2015 period. Six-monthly roll rates to default among S1 loans are typically between 0.5 and 1 per cent, whereas the roll rate for S2 loans is between 3 and 5 per cent during the 2009 to 2013 period, falling to between 2 and 3 per cent in 2014 and 2015, when the Irish economy was experiencing economic recovery.

Our calculations of half-yearly transition rates between the performing states S1 and S2 suggest a *regime switch*. Between June 2008 and December 2012, as the Irish economy entered crisis and experienced sustained increases in unemployment, 10 to 15 per cent of S1 loans transition to S2 every six months, while 2 to 5 per cent of S2 loans typically transition to S1. After June 2013, the order reverses. In a more benign economic environment, 0 to 5 per cent of S1 loans transition to S2, while the transition rates from S2 to S1 rise above 5 per cent and are as high as 30 per cent between 2013 and 2015.

Our work addresses concerns about unintended effects of IFRS 9 which may work against its stated aims. First, provisioning levels may rise sharply if a large share of performing loans falls into the newly-defined S2 category, which may harm the profitability of banks in certain circumstances; for instance, when beliefs about the future are pessimistic. Our results suggest

[3] In practice, there are numerous other factors that will be important in determining the net effect of the switch to IFRS 9 on provisioning. Provisions on all loan stages will be influenced by forward-looking estimates of macroeconomic and asset price outcomes. In cases where current estimates of house price growth, for example, are strong, the move to IFRS 9 may lead to reductions in provisions, particularly on defaulted S3 assets. Furthermore, any adverse change in capital adequacy will be mitigated by a phase-in period for S2 provisioning between 2018 and 2023.

that the potential size of the pool of S2 loans is likely to vary greatly across banks. In particular, propensity to fall into S2 will vary to the extent that origination conditions and standards differ across banks and markets.

Second, we address the debate about the new ECL framework and pro-cyclicality in bank capital ratios. Studies available so far can be placed into one of two categories. Firstly, there are studies that use backward-looking estimates of provisions and capital, had the new regime been in place in previous years, in a partial equilibrium setting where feedback loops from changes in provisions to the composition of the loan book are ignored (Kruger, Rosch, and Scheule, 2018; Chae, Sarama, Vojtech, and Wang, 2018). Secondly, there are studies that assess the effect of varying accounting regimes using simulated data and a simulated adverse shock, such as in Abad and Suarez (2017). Our paper falls into the former group, assigning loans as they appeared in the Irish data between 2008 and 2015 into an IFRS 9 stage. It should be pointed out that, even if provisioning becomes more closely related to the economic cycle under the new regime, it may still succeed in its goal of having smoother provisions, with less cliff-edged increases, than the previous incurred loss regime.

There are a range of views on pro-cyclicality emerging in the nascent literature. Kruger, Rosch, and Scheule (2018) infer from their counterfactual analysis of US corporate bond market data since 1990 that ECL provisioning leads to more severe reductions in CET1 ratios during downturns and in portfolios of lower credit quality; *prima facie* evidence of an increase in the sensitivity of bank capital to adverse economic events. They emphasize that the mechanism runs via the different provisioning concepts that exist in accounting regimes, where provisions are based on current economic conditions (Point in Time, PiT), as opposed to Basel capital regulation, where provisions are based on through-the-cycle (TTC) calculations. Where provisions under TTC are lower than those under PiT, as is more likely when current economic conditions are worse, the difference must be offset from regulatory capital, thus leading to pro-cyclical capital erosion. They conclude that during recessions, IFRS 9 would have had particularly sharp effects on provisioning due to the large volume of performing loans meeting the SICR criteria after turning points in the economic cycle. Due to the existence of differential provisioning treatment for S1 and S2 assets under IFRS 9, they also show that it is more pro-cyclical during downturns than the ECL regime implemented in the USA, GAAP 326, where all loans are subject to the same lifetime ECL provisioning treatment without the S1-S2 distinction. This underscores the importance of the SICR criteria in the debate on pro-cyclicality.

The findings of Chae, Sarama, Vojtech, and Wang (2018) are more nuanced; if banks made *perfect foresight* forecasts of the economy, then Current Expected Credit Loss provisioning in the

US mortgage market would have reduced the volatility of provisions during the last economic cycle. However, when forecasts use only recently available information, provisioning is much less smooth. We find this more realistic; evidence that banks successfully predicted the downturn of the cycle is scant. This finding supports the view that the expected credit loss concept may not be as successful in dampening the pro-cyclicality of bank provisions as has been hoped.

Finally, Abad and Suarez (2017) simulate euro area banks under both the IL and ECL approach. They show first that increased provisions during a contraction under IFRS 9 relative to IAS 39 stem from the treatment of S1 and S2 loans, i.e. that cyclicality in SICR is an important phenomenon. Second, bank profitability and provisioning rates respond more promptly to the economic cycle (both in good and bad times) under IFRS 9 than under IAS 39, implying pro-cyclicality via accelerator effects. Third, the probability that a bank would need to be recapitalised during a contraction increases under IFRS 9. They conclude that "the results of the analysis mean that it cannot be ruled out that, contrary to its intended purpose, IFRS 9 in certain circumstances amplifies rather than reduces the variability in capital pressures over the business cycle, with potential well-known implications for the cyclicality of credit supply".

In our paper, we stop short of assessing the pro-cyclicality of *provisions* under IFRS 9. Instead, we focus on *exposure assignment* into loan stages, with a particular focus on the close link between the economic cycle and the definition of SICR. As alluded to above, our exercise is static, in that we assign loans into each stage in each half-year from June 2008 to December 2015 based on the characteristics we observe in the data. We acknowledge possible general equilibrium effects on credit supply, lending standards and future loan defaults, bank capital markets and economic performance that may have resulted had a counterfactual provisioning regime been in place during our sample period; these are unobservable and their identification is beyond the scope of our study. Our study should also not be interpreted as taking a *normative* stance on whether the relative costs and benefits of the new accounting regime are likely to prevail; rather, we restrict our analysis to making a simple point about the relationship between loan stage assignment and the economic cycle.

Our results suggest loan stage assignment is highly sensitive to changes in the economic cycle. The share of S2 in the total loan book would have been less than 5 per cent in June 2008, just as the Irish economy was experiencing the first signs of distress. By June 2012, when unemployment rates were approaching their peak and house prices approaching their trough, the share of S2 in the loan book would have been close to 50 per cent. The close relationship between loan stage and the economic cycle is substantially explained by our use of current PD_C to define *significant increase in credit risk*: as the economy deteriorates, PD_C, which is a model estimate that relies on unemployment and house prices as explanatory factors, tends to rise. We see this as a potential conduit of pro-cyclicality between the real economy and loan-loss provisioning at banks. Given that IFRS 9 came into place in 2018, true empirical studies of the new standard will not be available for several years; for now, researchers can only speculate on the *possibility* of pro-cyclicality by using models, simulations or backward-looking calculations, while all empirical data ultimately arise from exposures accounted for under IAS 39.

The debate on pro-cyclicality in bank regulation pre-dates the introduction of IFRS 9. Laeven and Majnoni (2003) suggest an inherent pro-cyclicality in bank provisioning practices when banks delay provisioning until cyclical downturns have already set in, thereby magnifying the impact of the economic cycle on banks' income and capital. This pattern is corroborated by Bikker and Metzemakers (2005). More recently, Huizinga and Laeven (2018) demonstrate loan loss provision pro-cyclicality at euro area banks between 1996 and 2015; they are negatively correlated with GDP growth and explain two-thirds of the variation in bank capitalisation over the business cycle, both before and after the introduction of the euro. Olszak, Pipien, Kowalska, and Roszkowska (2017) show evidence that provisions are more pro-cyclical among large, publicly traded and commercial banks; restrictive capital standards can dampen such tendencies.

A more extensive economics literature identifies reductions in lending supply due to negative shocks to bank capital, particularly when banks are close to binding capital constraints. Researchers often identify capital-credit effects empirically using variation in regulatory capital requirements across banks and through time (Aiyar, Calomiris, and Wieladek, 2014; Fraisse, Le, and Thesmar, 2017; Gomez, Lizarazo, Mendoza, and Pabon, 2017; Gambacorta and Pabon, 2017; Jimenez, Ongena, Peydro, and Saurina, 2017). Banks may thus propagate and accelerate shocks from adverse economic events above and beyond the real economic cycle. Dynamic provisioning requirements introduced in Spain in the 2000s, studied by Jimenez, Ongena, Peydro, and Saurina (2017), and the countercyclical capital buffer (CCyB) now implemented by many countries, have at their heart the avoidance of such pro-cyclical loops. Tying together these strands of literature, it is clear that a negative relationship between provisioning and economic health has the potential to lead to a pro-cyclical loop between weak real economic performance, bank provisions, capital and lending supply, back to further harmful effects in the real economy.

We describe the loan stage concept in Section 2. Section 3 describes our model of significant increase in credit risk since origination. Section 4 calibrates the Stage 2 share using our credit risk measure. Section 5 extends the analysis to panel data, including transition rates. Section 6 concludes.

2 Explaining the IFRS 9 provisioning regime

The International Accounting Standards Board (IASB) has introduced IFRS 9 to replace IAS 39. IFRS 9 Financial Instruments (2014) includes three major changes in accounting for financial instruments to address weaknesses identified with IAS 39. The IFRS 9 simplifies asset accounting in financial statements and ongoing measurement, introduces a forward-looking impairment model, and incorporates new accounting requirements for recording profits and losses on derivatives and associated hedge instruments.

The magnitude of ECL recognition is based on a three-stage impairment approach:

- Stage 1 covers instruments that have not deteriorated significantly in credit quality since initial recognition or that have low credit risk. Provisions are calculated for such loans on the basis of expected defaults occurring in the next twelve months.
- Stage 2 covers instruments that have deteriorated significantly in credit quality since initial recognition, but which do not show objective evidence of a credit loss event. Impairment recognition is based on Lifetime ECL.
- Stage 3 covers instruments where one or more events have had a detrimental impact on the estimated future cash flows at the reporting date, e.g. if a borrower is in significant financial difficulty. Impairment recognition is based on Lifetime ECL.

Accordingly, under the IFRS 9 impairment model, the way in which provisions for ECLs are calculated changes as the credit risk of a financial instrument deteriorates significantly. Under the impairment approach in IFRS 9, many loans will bear small provisions from the day of origination, while loans that have had significant reductions in credit quality will incur larger provisions. For example, a performing mortgage loan will have a day-one provision based on its 12-month ECL. In most cases, the probability of this event would be expected to be very low. However, if the credit quality of the mortgage were to deteriorate, provisioning would increase to account for two factors: a higher probability of default and the possibility of a credit loss event at any time in the remaining lifetime of the loan, owing to the switch to the Stage 2 Lifetime ECL basis. This suggests that provisioning requirements may increase considerably as loan credit quality deteriorates. If the loan's credit risk were to return close to its initial level at a later date, the bank may return to using 12-month ECL to calculate its provision.

While the full impact of the introduction of IFRS 9 will not be known for some time, banks that participated in an EBA survey in 2017 expected their provisions to rise by an average of 18 per cent due to the treatment of non-defaulted loans with significant increases in credit risk. The lenders also expected greater provisioning volatility as the ECL forecasting horizon switches between 12 months and lifetime. A Deloitte survey of 54 global banks reported that most participants expect banking sector provisions to rise by up to 50 per cent, while 70 per cent expect their own provisions to be higher than current regulatory expected loss. By the end of 2018, large European banks will have undergone a European Banking Authority stress testing exercise, which will encompass the IFRS 9 reforms when assessing capital adequacy. Upon publication of these stress test results, along with half-year reporting for banks as of June 2018, the actual extent of provisioning changes resulting from these reforms will have become much clearer.

3 Methodology: Probability of default model

The probability of default (PD) module of the Central Bank of Ireland's Loan Loss Forecasting (LLF) model is used to inform this analysis. The model is an update of the PD model presented in Kelly and O'Malley (2016), which forms the basis for the PD-EAD-LGD engine described in Gaffney, Kelly, and McCann (2014), a framework that can be used to derive expected losses under user-specified macroeconomic scenarios.

We estimate a Markov Multi-State Model (MSM), which allows loans to transition in both directions between two states: Performing and Default. A loan is defined as Performing when it is not in arrears more than 90 days past due (DPD). Loans in arrears above 90 DPD are classified as being in default.[4] The MSM was first presented in Jackson (2011) with applications to biostatistics. It enables the estimation of the effect of a single set of covariates on the probabilities that loans transition from Performing to Default (the *PD equation*) and from Default to Performing (the *PCure equation*).

A random sample of 100,000 mortgages from the Private Dwelling Home (PDH) and Buy to Let (BTL) market segments is used in estimation. This is drawn from the Central Bank's mortgage panel data, which tracks loan performance on a quarterly basis from 2008 to 2015. One bank reports arrears information used in the sample between 2008 and 2009; from 2010 to 2015, the dataset contains information from three large lenders covering around two-thirds of the Irish mortgage market. Table 1 reports the set of covariates used in the Central Bank's PD model for Irish residential mortgages. Readers may notice that loan vintage effects are not included

[4] The definition of default for the purposes of the transition model does not include loans classified as "impaired but not above 90 DPD". This is due to data availability constraints in the quarterly estimation sample. For credit scoring and stage classification in this paper, the more comprehensive definition of default, in line with Basel guidelines, is used from 2012 H2 onwards.

TABLE 1. Explanation of PD Model Covariates

Coefficient	Comments
BTL	Intercept adjustment for buy-to-let mortgages. Base category is Private Dwelling Home mortgages.
Δ Install	Ratio of Current Instalment to Original Instalment, including impacts of changes to interest rates.
Modification	Intercept adjustment for any loan having ever received a modification, whether temporary or permanent in nature.
Multi-Loan	Intercept adjustment for loans secured on property with more than one loan.
SVR and Tracker	Intercept adjustments for interest rate type effects. Base category is fixed-rate mortgages.
Time in Default	Number of monthly repayments missed since loan entered into default state.
LTV	Current loan-to-value at the property level.
Unemployment	Unemployment rates, varying by region and quarter.
House Price Misalignment	Model average of quarterly estimates of over- or under-valuation of Irish house prices at the time of a loan's origination. This takes the place of loan age or vintage measures used in some other models.

in the model, despite being common to mortgage credit risk models. This is due to the strong correlation between Current LTV and vintage in the Irish mortgage market; the sharp house price falls experienced across the country from 2008 to 2012 mean that CTLV effects and vintage effects are not estimable in the same model using our methodology. To capture cohort origination effects, we include a model estimate of house price misalignment in the quarter in which the loan was originated. This allows for higher PD to be modelled for loans issued before 2008 relative to those issued subsequently.

The MSM model allows for the effect of any covariate to be disabled in one of the two equations. Our model allows the dummy variable for previous loan modification to enter only the default equation, where it signifies the difference between the re-default risks of previously troubled mortgages compared to performing loans with no modification history. Modification is not included as an explanatory variable in the cure equation, because its effect is purely mechanical in many cases where a loan is modified to have an arrears balance of less than 90 DPD. Similarly, we only allow Time in Default to affect the cure equation, since all performing loans should have a Time in Default equal to zero.

Table 2 reports the model coefficients, interpreted as percentage changes relative to the baseline hazard. The coefficients on the left hand side relate to the PD equation. BTL loans are shown to have greater credit risk than PDH loans. Multi-Loan facilities have greater credit risk than single-loan facilities. SVR and Tracker loans are higher risk relative to Fixed Rate

TABLE 2. Coefficient Estimates from Multi-State Model

	Performing to Default		Default to Performing	
	β	95% Confidence Interval	β	95% Confidence Interval
BTL	0.534	(0.489, 0.580)*	-0.058	(-0.116, -0.001) *
Rate: SVR	0.612	(0.536, 0.688)*	-0.186	(-0.285, -0.088) *
Rate: Tracker	0.272	(0.191, 0.353) *	-0.169	(-0.271, -0.067) *
Modification	1.576	(1.536, 1.616) *	n/a	n/a
Multi-Loan	0.064	(0.022, 0.105) *	0.032	(-0.016, 0.081)
Δ Install	0.473	(0.409, 0.536) *	-0.739	(-0.807, -0.672) *
Time in Default	n/a	n/a	-0.046	(-0.048, -0.044) *
Unemployment	0.093	(0.086, 0.100) *	-0.132	(-0.141, -0.123) *
CLTV	0.007	(0.006, 0.007) *	-0.003	(-0.004, -0.003) *
House Price Misalignment	0.016	(0.014, 0.018)*	0.000	(-0.806, -0.672)*

*indicates statistical significance at 5% level using bootstrapped confidence intervals loans, due in part to the popularity of introductory fixed rate offers in the first years of many mortgages. Previously-modified loans, loans with greater instalment growth since origination, loans in regions with higher unemployment, loans with a higher CLTV and loans issued in periods with greater house price misalignment are all also estimated to have a higher default risk.

Cure rate equation coefficients have the expected sign — the reverse of the default sign — except for the Multi-Loan dummy. The Time Since Default variable, which is excluded from the default equation, significantly affects probability of cure: the longer a loan has been in default, the lower the probability of a return to Performing status.

The economic magnitudes or *marginal effects* of each parameter reported in Table 1 are not immediately interpretable from an inspection of Table 2. In Table 3, we calculate the fitted PD for a loan moving from the median to the 75th percentile of its own in-sample distribution, holding other variables fixed. For categorical variables, we show the fitted value of moving from a reference category to the category of interest, while again fixing other input variables.

We observe the Modification variable to have the strongest prediction power in the default equation. A modified performing loan has a PD five times higher than a performing loan with no previous modification history, when we take other variables at their medians. In Ireland, re-default propensity of modified mortgages was high, and modification history may contain information about propensity to financial distress among borrowing households. Furthermore, many mortgage forbearance strategies in Ireland were temporary, short-term measures which did not lead to long-term financial sustainability. Households with this history are more vulnerable to adverse shocks than those with performing mortgages with no identifiable history of distress.

The loan type also reveals important information about credit risk. BTL mortgages have a one-quarter PD that is 0.37 per cent higher than a PDH mortgage; the SVR-fixed rate PD gap is similar. One-quartile increases in the three variables that link directly to the macroeconomic scenarios of stress testing exercises (Current LTV, Regional Unemployment and Δ Instalment) all have smaller magnitudes of impact on PDs. An increase in CLTV or unemployment from median to 75th percentile leads to an increase in PD of 0.15 and 0.12 per cent, respectively, while the effect is smaller again for Δ Instalment. Similarly small effects are found when observing the difference between multi-loan and single-loan facilities and the increase in origination house price misalignment from the median to the 75th percentile in our sample.

TABLE 3. Increase in PD for varying values of explanatory variables

Qualitative (move across categories)	
Never modified to modified	0.47% to 2.26%
Non-BTL to BTL	0.52% to 0.90%
Fixed to SVR	0.38% to 0.71%
Fixed to Tracker	0.38% to 0.50%
One-loan to Multi-loan	0.56% to 0.59%
Quantitative (move from median to 75th percentile)	
LTV	0.72%
Unemployment	0.68%
House price misalignment	0.64%
Change in instalment	0.61%

3 Calculation of PDs at Origination

Due to the focus on *significant deterioration in credit quality*, a vital calculation needed to complete provisioning exercises under IFRS 9 is the probability of default at the time of origination of each loan (PD_O). We use PD_O to ascertain which performing loans should be treated as Stage 2 loans, and should therefore incur a provisioning penalty relative to other performing loans, based on simulated rules to measure significant deterioration.

While the IFRS 9 regime endows importance on conditions at origination, lenders and regulators face the difficulty when categorising performing loans between Stages 1 and 2 that PD_O may not be available, particularly in legacy portfolios of longer-maturity assets. In particular, the lifetime PD concept is a novelty of IFRS 9 which was not calculated at the time of origination of legacy loans.

We propose a solution for our purposes borrowed from Joyce and McCann (2016), who calculate PD_O for cohorts of Irish mortgages to compare lending before and after the introduction of macroprudential mortgage restrictions in February 2015. The calculation takes loans outstanding at end-2015 and resets all covariates to their origination values, so that a fitted probability of default treats each loan as if it were at the point of origination. The transformations are outlined in Table 4. We additionally use our panel data to apply transformations to the *earliest available observation* per loan. By adopting the Joyce and McCann (2016) method, we can apply the coefficients of Table 2 to two sets of data:

1. Actual end-2015 records from five banks covering 90% of the Irish mortgage market;

2. Transformed end-2015 records to reflect conditions at origination, based on Table 4.

TABLE 4. Transformations of PD model covariates to origination values

Factor	Transformation from end-2015 data
Buy-to-Let	Assume no change before first observation date.
Δ Installment	Set to 1 for all mortgages.
Modification	Set to 0 for all mortgages, apart from cases where *split mortgages* are given an origination date corresponding to the date of modification.
Multi-Loan	Takes a 0 for the oldest loan on a multi-loan facility; takes a 1 for all loans apart from the oldest loan on a multi-loan facility.
Interest Rate Type	Infer or measure Interest Rate Type at Origination.
Time in Default	Set to zero on the basis that no loan can be in default at origination.
Loan-to-Value	Replaced with Origination LTV.
Unemployment	Choose the unemployment rate at the date of origination.
House Price Misalignment	This is already measured as at origination.

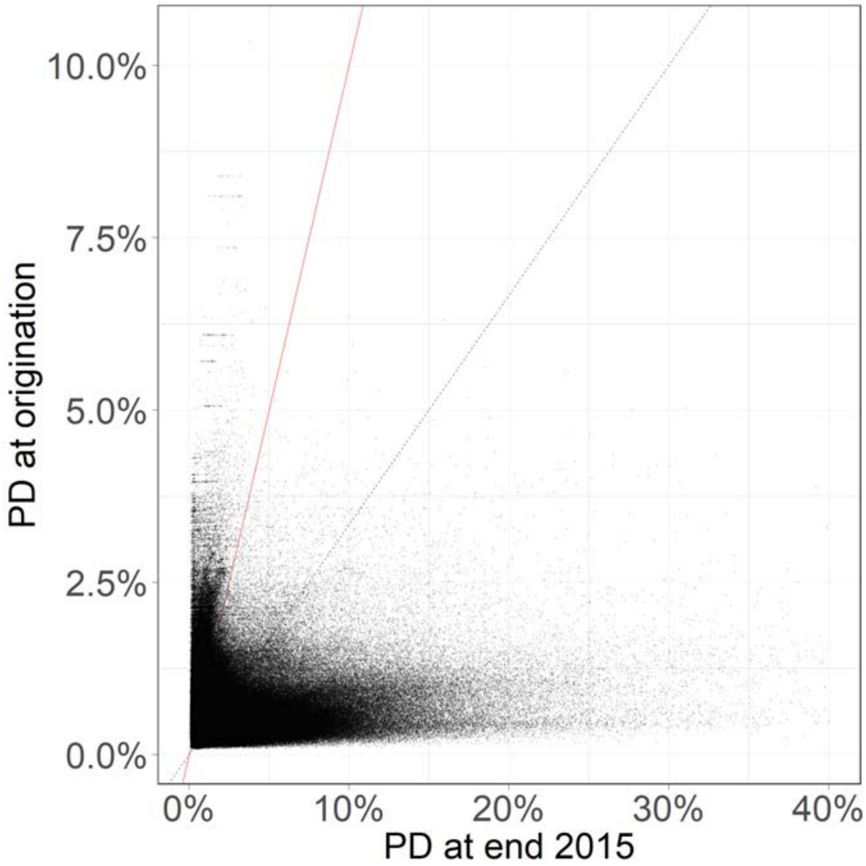
For every mortgage outstanding at end-2015, both PD_C and PD_O can now be calculated. Loans are likely to experience changes in PD from origination to the present day for a range of reasons:

- Macroeconomic changes between the point of origination and the present day; for example, changes in local unemployment.
- Interest rate changes, which will shift the Δ Instalment measure.
- Loan repayments and house price growth, which reduce LTV.
- Declining house prices, which raise LTV.
- The loan falling into difficulty and receiving a modification.
- The loan switching interest rate type (for example, by moving from fixed to variable).
- Additional loans being issued against the same collateral. All such loans secured on a property are marked as a *multi-loan* facility.

Figure 1 reports a scatter plot where each loan's PD_C is compared to its PD_O.[5] The solid red line shows where loans have $PD_C = PD_O$. The dashed black line shows the levels at which PD_C

[5]Fitted PD in the 2015 static analysis is expressed on a one-year basis, as recommended by the European Banking Authority as an appropriate proxy for Lifetime PD, which is a new concept introduced in the IFRS 9 standard. While the methodology can be applied to all exposures where information to calculate PD_O is available, we limit our exposition here to mortgages with collateral, excluding the warehoused balances of split mortgage restructures.

FIGURE 1. Scatter plot of PD at origination versus PD at end-2015

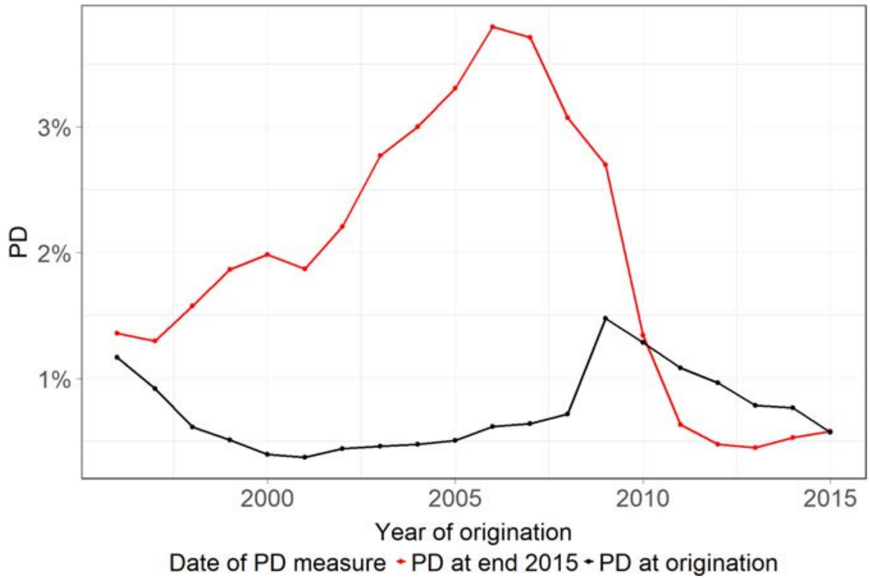


is three times as large as PD_O, i.e. where there has been 200% growth in PD since origination. This is the decision rule we apply to measure *significant deterioration in credit risk* since a loan's origination.

Credit quality deterioration may be due to idiosyncratic borrower factors, but it is also likely that economic and credit market conditions at origination play an important predictive role. For this reason, we report average PD_O and PD_C for year-cohorts of loans issued between 1995 and 2015 in Figure 2. We observe loans only during the estimation window of 2008 to 2015, introducing some *survivorship bias* to older cohorts of loans. For example, it excludes borrowers in the late 1990s and early 2000s who switched banks, prepaid or fully paid on schedule before 2008.[6] We expect these exit options to screen out high-quality loans over time. Loans issued during the period of rapid house price growth up to 2008 have the highest PD_C at end-2015.

[6] 12% of residential mortgages drawn down between 2003 and 2007 refinanced a change of lender (Banking and Payments Federation of Ireland, 2018). More recently, limited evidence from residential mortgage-backed securities suggests annual prepayment rates below 2.5% of balances; see, for instance, Moody's Investors Service (2018). The Irish Times (1998) reported that "Most homeowners in this State take out 20-year loans".

FIGURE 2. Average PD at origination and Average PD at end-2015 by Year of Origination



New loans since 2011 reduced in PD since origination, due in part to house price growth and improving regional employment.

Figure 3 presents the underlying distributions of PD_O and PD_C for loans grouped by years of origination. The one-for-one and 200% increase lines are again shown in red and black, respectively. For loans issued before 1998, the vast majority of loans have experienced reductions in PD (i.e. they sit to the left of the red degree line), thanks to households building up equity and Irish economic development since the 1990s. Between 1999 and 2007, a large right-tail of loans experienced more than a tripling in PD score between origination and end-2015. These loans were issued during a period of easier credit conditions, and are more likely to have been originated at high originating LTVs, especially in 2006-07; then the favourable economy reversed, and these households experienced the most adverse changes in house prices and unemployment since loan origination. By contrast, very few loans have deteriorated among the 2011-2015 cohort.

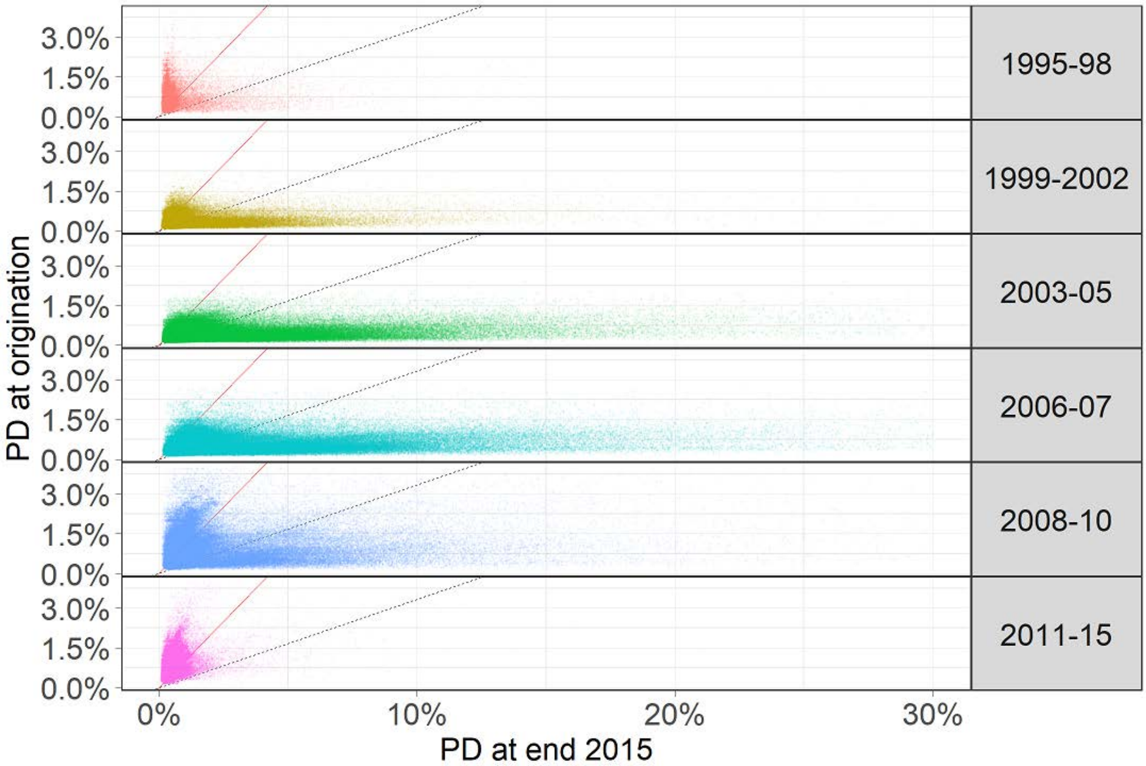
4 Stage 2 based on originated and current PDs

There are at least three methods of definition which have been proposed for assigning performing exposures into the IFRS 9 Stage 2 category:

1. Arrears between 31 and 90 days past due.

2. Current forbearance being applied.

FIGURE 3. Scatter plot of PD at origination and end-2015 by Years of Origination



3. Evidence of a significant increase in credit risk between origination and the measurement date, measured using lifetime PD, or a one-year PD proxy measure.

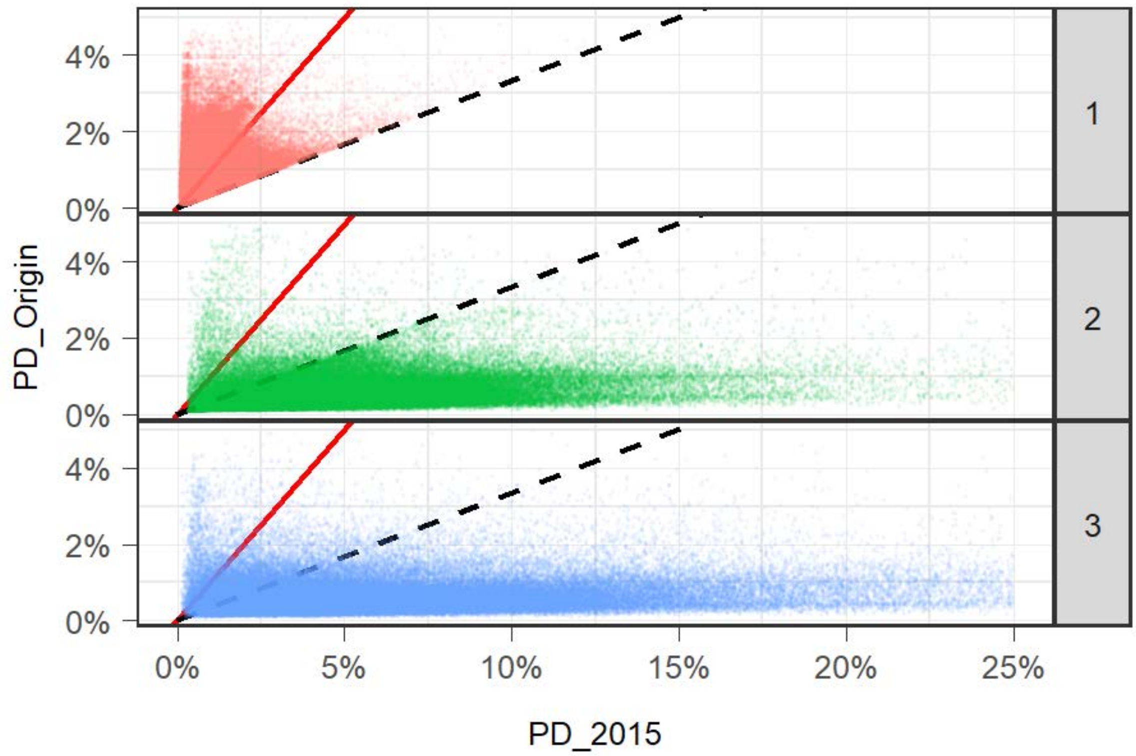
These definitions overlap to a great extent; for example, loans in early arrears may be more likely to receive forbearance or to exhibit high credit risk. Delineation of performing exposures is relatively straightforward with the first two definitions if data are available to the analyst. Definition 3 entails greater data requirements. In principle, we must estimate lifetime PD at time of origination. As this concept did not exist until recently, historic data will not list a value calculated at the time. At the very least, we require model-based estimates of the one-year PD proxy, i.e. both PD_O and PD_C described above.

For the purposes of this paper, we define Stage 2 loans to be any Performing loan (i.e. arrears less than 90 days past due and no impairment) that meets any of the above three criteria. Figure 4 describes the relative importance of S2 definition steps for our end-2015 sample from the five largest mortgage lenders in Ireland. If we begin by applying the *forbearance* definition, 11.8 per cent of performing balances are allocated to S2. Accounting for this, only 0.5 per cent of additional balances enter S2 due to *arrears between 31 and 90 DPD*. The chart underlines the importance of our calculation of PD_O: after having applied the previous two definitions, a further 17.5 per cent of performing balances are allocated to S2 due to the *significant deterioration*

FIGURE 4. “Waterfall”: assigning performing end-2015 mortgage balances into S2

Performing balances	100.0%			
1. Performing balances forborne	-11.8%	88.2%		
2. Other balances at 31-90 dpd		-0.5%	87.7%	
3. Other balances with PD 200% or more above origination			-17.5%	
Stage 1 Balance as % of Performing Balances				**70.2%**

FIGURE 5. Scatter plot of origination and current PDs for Stage 1, 2 and 3 loans.



criterion. In total, our estimate is that 29.8 per cent of performing balances in our mortgage sample would have been identified as S2, had IFRS 9 prevailed on 31 December 2015.

Figure 5 plots the relationship between PD_O and PD_C for loans classified into Stages 1, 2, and 3 using our definition. By definition, all Stage 1 loans must sit to the left of the *200% increase* black line. Among Stage 2 loans, the vast majority exhibit significant increase in PD, as would be expected given definition 3 above. However, the loans to the left of the black line are in Stage 2 due to early-stage arrears or currently forbearance, but have not experienced a tripling in PD score. Finally, Stage 3 contains loans on all sides of the red and black lines, as loans become non-performing due to a mix of modelled predictive factors and idiosyncratic features not captured by the PD equation. Thus, some have experienced less than a tripling in model-based PD between origination and end-2015.

5 Loan stage assignment, 2008 to 2015

We extend the analysis of end-2015 loans from Section 4 by asking the following question: if IFRS 9 accounting rules had been in place between 2008 and 2015, what share of performing mortgages in Irish banks' residential mortgage portfolios would have been classified as Stage 2 at each six-monthly interval? We follow closely the method from Section 4 for each loan in our panel, comparing PD_O and PD_C at six-monthly intervals, while also tracking non-performing and modification statuses. With these three pieces of information readily available for all loans in the portfolio on a quarterly basis from 2009, we are in a position to update our definitions of Stages 1, 2 and 3 throughout our panel.

We contribute to the pro-cyclicality debate by showing that transition rates between the three IFRS 9 stages react powerfully to changes in the state of the Irish economy. We do not model provisions or capital-lending feedback that may have resulted had the IFRS 9 provisioning regime been introduced at any of the six-monthly intervals in our sample period. For this reason, each half-yearly calculation should be thought of as a static, partial exercise that determines the stage split in the mortgage market at a given point in time, assuming no changes in the composition of the mortgage portfolios resulting from the hypothetical timing of reforms.

We begin by showing the three-by-three, six-monthly transition rate matrix among IFRS 9 states at three points in time: December 2008 to June 2009, December 2011 to June 2012, and June 2015 to December 2015 (Table 5).[7] As is common among credit risk transition matrices, the highest probabilities lie along the diagonal, signalling no move between states. Across the three periods, when loans leave S1, they are more likely to move to Stage 2 than to move into default (S3). Transitions from S2 appear to be cyclical, in that during the economic downturn (2009H1 and 2012H1), there are more S2 loans transitioning to default than returning to S1. During the economic recovery in 2015H2, however, 15 per cent of S2 loans return to S1 whereas only 3 per cent transition to default.

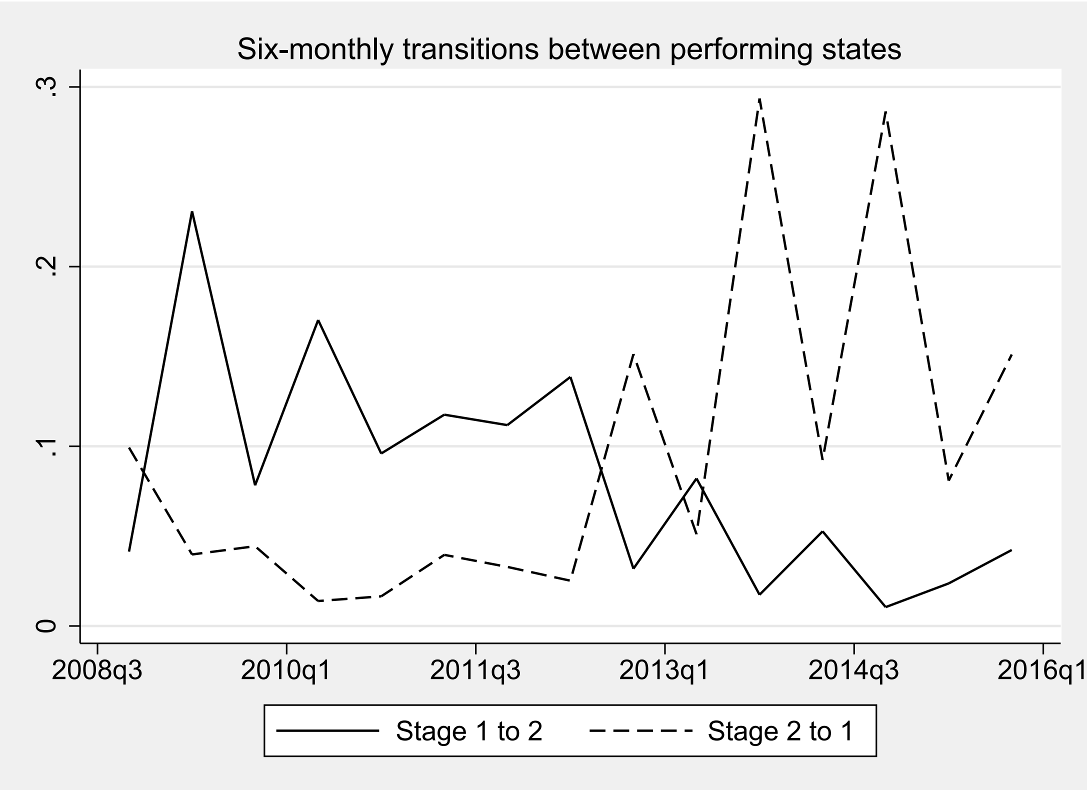
We now present the entire time series of transitions for selected states. In Figure 6 we see that there is something akin to a *regime switch* in the transition rates within the performing book. Prior to June 2012, the transition rate from S1 to S2 was generally between 10 and 15 per cent, while the transition rate from S2 to S1 was generally between 0 and 5 per cent. In the second half of 2012, however, at around the time that many economic indicators in Ireland hit their trough, we observe a sharp change: the probability of deterioration from S1 to S2 falls to the 0-5 per cent

[7] All calculations in this section refer to the number of loans transitioning between states, not weighted by loan balances. Please note that transitions to and from default are shown on a six-monthly basis in this section, to match the panel frequency.

TABLE 5. Six-monthly transition rates from December 2008, December 2011 and June 2015

	2009 H1			2012 H1			2015H2		
	1	2	3	1	2	3	1	2	3
from 1	76%	23%	1%	85%	14%	1%	96%	4%	0%
from 2	4%	89%	7%	2%	93%	4%	15%	83%	3%
from 3	4%	6%	90%	0%	3%	97%	1%	10%	89%

FIGURE 6. Six-monthly transition rates from between S1 and S2



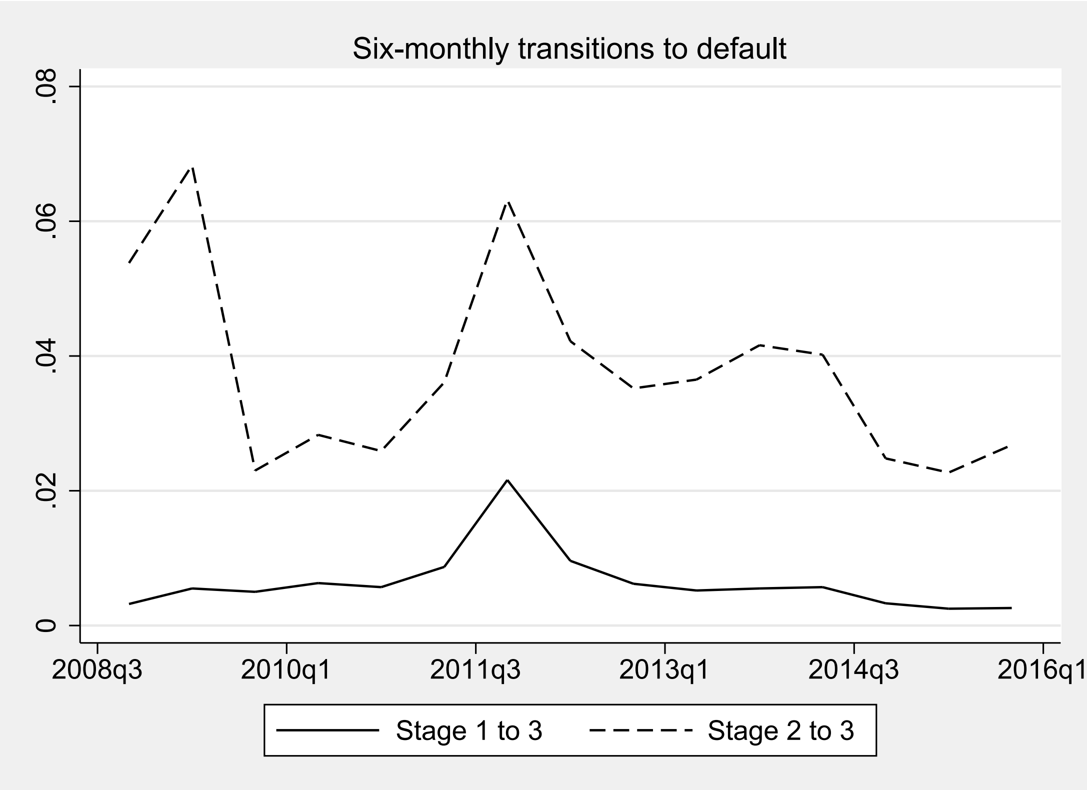
range, while the probability of an improving transition from S2 to S1 jumps above 10 per cent in most periods, and even rises close to 30 per cent in some periods.[8]

Figure 7 focuses on the default probabilities associated with S1 and S2 (performing) loans.[9] Figure 7 confirms that higher S2 provisions will partly reflect higher propensity to default; in all states of the economy, the six-monthly PD out of S2 (a six-monthly transition rate of 3 to 4 per

[8]The high degree of variability in the transition rates from Stage 2 to 1 from 2013 to 2015 relates to timing of forbearance, impairment and other loan quality classifications by some banks.

[9]In December 2011, our loan-level data introduces a broader definition of impairment to capture many loans that are not more than ninety days past due. It is not a reflection of a true deterioration in loan performance during this half-year.

FIGURE 7. Six-monthly transition rates into S3



cent between 2013 and 2015) is orders of magnitude larger than that from S1 (under 1 per cent during the same period).

Figure 8 displays transitions out of S3. Direct returns to S1 are rare, particularly from 2012 onwards as forbearance becomes more popular. The cure rate from S3 to S2 rises steadily from 2011, in line with economic developments and bank modification policies (McCann, 2017). We note that the tendency for modified loans to remain in S2 will limit the provision benefit that lenders can enjoy from engaging in such modifications.

We finally compare shares of loans per stage at each six-monthly interval with the national unemployment rate, a measure of Irish macroeconomic conditions, in Figure 9. The S2 share moves almost in lock-step with the national unemployment rate over the 2008 to 2015 period. Conversely, the correlation between the S1 share of the total mortgage book and the unemployment rate is strong and negative. This provides strong, direct evidence that the SICR concept is highly pro-cyclical, responding immediately to deteriorations in aggregate economic performance.

We explain this by noting that SICR is by definition partially driven by model assessments of credit risk, whereas a loan generally only enters S3 once a default event has occurred. Default events often lag behind the onset of financial distress, as households draw down liquid

FIGURE 8. Six-monthly transition rates from S3

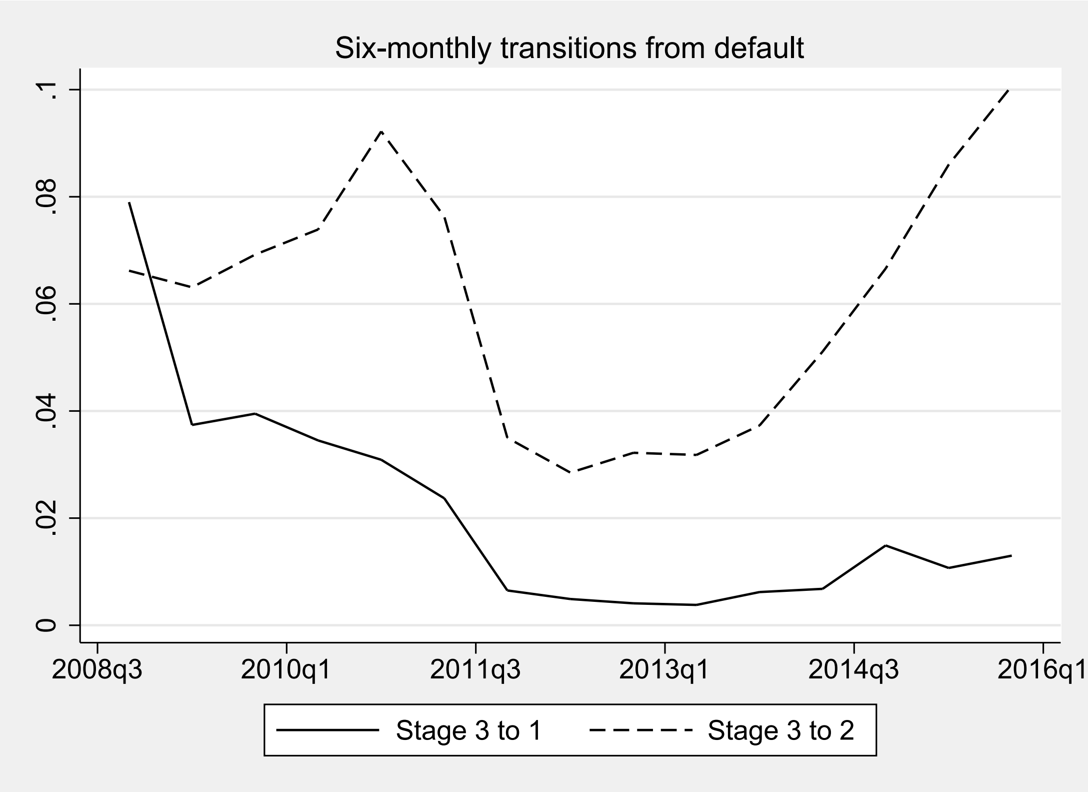
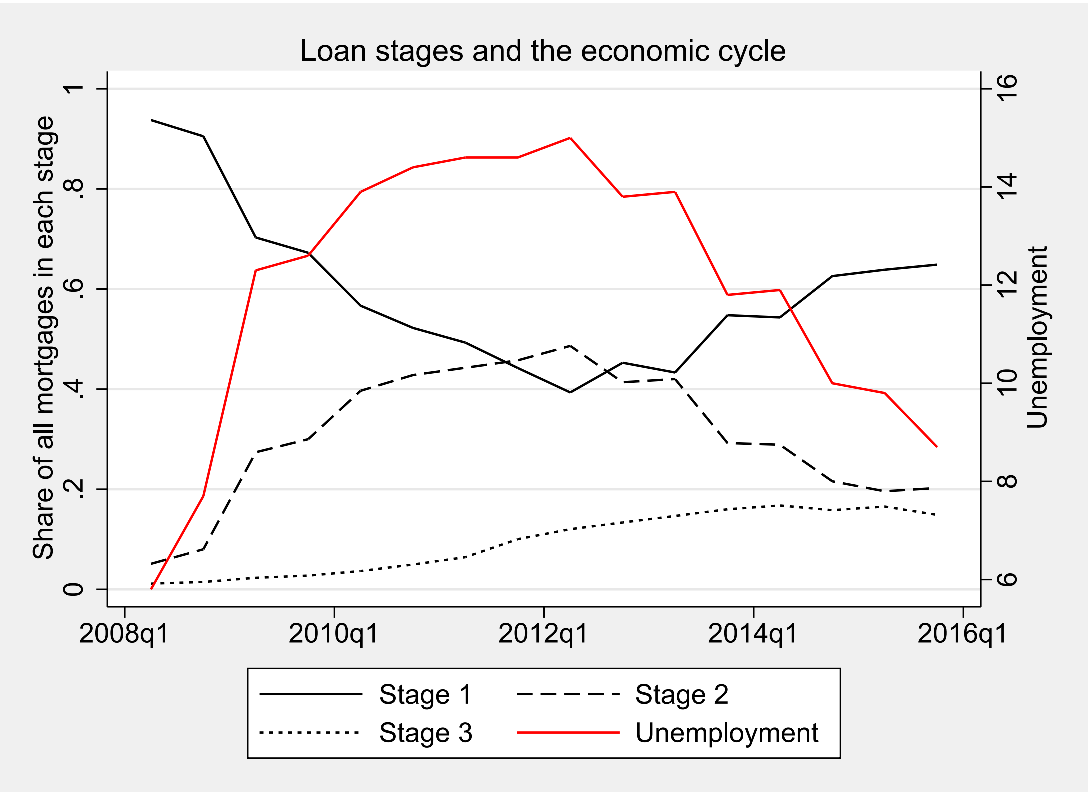


FIGURE 9. Cyclicality in SICR? Share of loans in each Stage and the national unemployment rate



asset buffers before risking a missed loan payment. The strong correlation therefore signifies earlier recognition of possible losses (and impairment charges), in line with the aims of the G20 leaders. In this sense, provisioning under IFRS 9 may be simultaneously smoother over the course of a downturn, as well as being more closely related to macroeconomic developments, than provisioning under IAS 39, which responded only to the occurrence of default events.

6 Conclusion

Using detailed loan-level data on the Irish mortgage market, we present a framework for assigning mortgage loans into the three stages defined under recent IFRS 9 accounting standards. Assignment of loans into these stages will be central to provision calculations and stress testing exercises from 2018 on, but data limitations will prevail for some time, particularly for credit risk at origination. The delineation of performing loans into Stage 1 and Stage 2 is new and important for loan provisions, with the latter group being distinguished from the former on grounds of significant build-ups in risk since loan origination.

Our analysis of our end-2015 data is that Stage 2 exposures could have comprised roughly 30 per cent of performing exposures in the Irish mortgage market. We contribute to the debate on provisioning pro-cyclicality by showing that the share of loans that would have been classified in the high-provision Stage 2 group rises from 5 per cent to 50 per cent of all mortgages over the period 2008 to 2012, in line with a sharp contraction in the Irish economy. Such a pattern suggests that a regime such as IFRS 9, relative to its IAS 39 predecessor, may lead to a smoother pattern for provisions during a downturn, while simultaneously having a higher correlation between provisions and the state of the economy. Further research is warranted on the exact mechanisms that underpin the pro-cyclicality, or otherwise, of bank provisioning under various regimes, as well as the general equilibrium effects on loan origination and bank capital.

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