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A transitions-based model of loan default for Irish mortgages

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A Transitions-Based Model of Default for Irish Mortgages

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Abstract

Using a uniquely constructed loan-level dataset of the residential mortgage book of Irish financial institutions, this paper provides a framework for estimating default probabilities of individual mortgages. In contrast to the popular stock delinquency approach, this model provides estimates of default and cure flows: a requirement of the stress test approach adopted by the European Central Bank's comprehensive assessment. In addition, both default and cure transitions are modelled as functions of micro- and macro-covariates including loan characteristics and current macroeconomic conditions such as house prices and unemployment. When comparing the competing equity and affordability effects, labour market deterioration played a stronger role than house equity in the rise of Irish default rates. For cures, a scarring effect of default is identified and estimated with the probability of a loan returning to performing reducing by 25 per cent each quarter a loan remains delinquent.

JEL classification: G01, G12, G21.

Keywords: Mortgage Default Modelling, Irish Banks, ECB Comprehensive Assessment.

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1 Introduction

The presence of significant housing booms and busts across many OECD countries such as Spain, Ireland and the United States has profound financial stability concerns for the financial systems which service these markets. In light of the considerable uncertainty surrounding the “health” or otherwise of financial institutions in these countries, the optimal response of policy makers is guided by an accurate estimate of the presence of loan impairment on the mortgage books. Motivated by studies in corporate credit risk, this paper provides a framework for assessing the credit risk of residential-property lending. In particular, the model is based on transition matrix framework, allowing for estimates of default and cure flows: a key advantage over a standard stock delinquency model. Indeed, this is a requirement under the new split stress testing framework comprising asset quality review (AQR) informed test of losses on the stock of default loans and a forward looking piece on the future flow of new defaults. The European Central Bank’s (ECB) comprehensive assessment¹ of 127 banks across Europe adopts this approach.

In Ireland, driven by almost a decade of historically low unemployment levels, double digit annual house price growth, development of a residential investment property market and lower interest margins due to increased competition from foreign banks resulted in a mortgage book with a credit risk profile unlike anything that went before. Two models are presented for both the traditional owner occupier (OO) mortgages and loans for investment properties, commonly known as Buy-to-Let (BTL) loans. Both models condition defaults and cures on loan characteristics and macro factors such as house prices and labour market conditions. Support is found for the equity (measured by the Current Loan to Value (CLTV) ratio) and affordability (measured by regional unemployment and loan-level interest rates) hypotheses² and their role in the probability of loans default and curing. For an unemployment (CLTV) increase of one percentage point, the likelihood of a default increases by 7 (0.5) per cent. Because the model is linked on the log function, there is a non-linearity between CLTV and default probabilities. Comparing a house with positive

¹See <https://www.ecb.europa.eu/ssm/assessment/html/index.en.html> for further information.

²This is commonly referred to as the “double-trigger” hypothesis in the literature. For example, see Bajari et al. (2008) and Foote et al. (2008, p.241).

equity (CLTV of 50 per cent) to the case with negative equity (CLTV of 150 per cent), the one year probability of a loan moving to default is twice as high in the latter (1.9% compared to 4.1%)³. When comparing the competing equity and affordability effects, labour market deterioration played a stronger role than house equity in the rise of Irish default rates.

Due to changes in the conduct of banks in the cases of delinquent loans and a legal case impeding the repossession of property, the loan books of Irish banks provide a unique dataset to investigate the determinants of loans curing, as the number of repossessions were insignificant during the period under investigation. As in the case of default modelling, macro conditions and loan characteristics play an important role. In addition -and to the authors' knowledge the first time - a scarring effect of delinquency is found to be one of the strongest influences on the probability of a loan curing, decaying with every quarter a loan is in arrears. Both the OO and BTL markets show a similar trend with the likelihood of a cure falling 25 per cent for each additional quarter a loan remains in default. This identifies the importance of early engagement with borrowers in the design of any framework aimed at altering loan terms in the hope of loan recovery.

The rest of the paper is structured as follows; in the next section we look at the previous literature on modelling loan arrears, while in section three we outline a transition-based method to estimate default and cure probabilities of loans. Section four provides estimates of the default and cure probabilities in an Irish residential property lending context and their sensitivity to macro factors and a final section offers some concluding comments.

2 Previous Literature

There are a variety of different empirical approaches used to tackle the issue of estimating mortgage default. For example, the early literature investigating delinquency in the US mortgage market derived an option based model of default. [Kau et al. \(1992\)](#) view default as an American put option on the house price with a strike price set equal to mortgage value.

³1 year transition probability for a variable rate performing loan, with all covariates except CLTV set to their mean.

This pure-option based model assumes that the borrower will default immediately when the value of the property drops below the mortgage value. Key to this framework is the non-recourse nature of some mortgages and the ruthless exercising of the option. Furthermore, the substantial transaction costs of moving property are ignored.⁴ The greatest strength of this model, the independence from borrower’s solvency is also its greatest weakness as [Aron and Muellbauer \(2010\)](#), amongst others, have shown default very often requires more than the household just experiencing negative equity.

[Schwartz and Torous \(1993\)](#) using a Poisson regression framework find evidence of significant differences in default behaviour. The main drivers are found to be vintage of loan and volatility of housing index returns. More recently, [Mayer et al. \(2009\)](#) provide a detailed overview of loan performance by credit quality for mortgages originating between 2003 and 2007. Although not explicitly modelled, the drivers of delinquency rates are regional unemployment and house prices. House prices played a particularly important role as the sub-prime model involved re-financing after improvement in an individual’s credit score before the “teaser” rate period expired. Once these borrowers entered negative equity, re-financing to a lower rate was not possible.

Scoring models provide the most popular framework for conditioning the probability of delinquency on borrower solvency. These models tend to use single-period classification (Logit and variations) techniques to assess the probability of default (PD) for a loan. [Bajari et al. \(2008\)](#) develop a US sub-prime market scoring model using a bi-variate Probit or “double trigger” framework, requiring two conditions to be satisfied for default to occur. The dual conditions that result in hypothesised mortgage default are: the mortgage to equity ratio exceeds a certain threshold and the second is a function of credit worthiness of the household, its employment status and its expected income growth. The literature is mixed in terms of the dominant effect, with [Foote et al. \(2008\)](#) and [Goodman et al. \(2010\)](#) citing negative equity as the primary influence while [Gerardi et al. \(2013\)](#) show unemployment to be the strongest predictor. [Elul et al. \(2010\)](#) introduces a measure of illiquidity; the utilization of credit card which has a positive impact on default probabilities. In the

⁴See [Vandell \(1995\)](#) for a review of cases where the borrower will not default even with non-recourse mortgages

Irish case, [Lydon and McCarthy \(2013\)](#) take a similar approach to modelling delinquency. Housing equity is found to be a main determinant of default along with a proxy for current repayment burden; originating income adjusted for aggregate changes. [McCarthy \(2014\)](#) estimates a probability of arrears model with a cleaner version of current income, gained from a survey of mortgage holders, which allows for disaggregation of house equity, unemployment and income shocks on the probability of loan arrears. While all three effects have a significant impact, estimates show unemployment has a three times larger effect than an income shock (without job loss) on the probability of arrears.

While stock delinquency models address the causes of arrears and default, they lack a time structure framework; excluding them from use when the flows of default and cures are required, such as in the current ECB led comprehensive assessment (CA). The first component of the CA involves testing of adequate collective provision coverage. This is the equivalent of modelling the loss outcome for the current stock of defaulted loans. The second element involves calculating the future defaults of currently performing loans. A stock delinquency model, with 0 and 1 defined as performing and default, will estimate the stock of defaulted loans both in the current and future time periods, but because each loan takes an expected default probability at each time period, the identification of new defaults and cures is not possible.

Migration models provide another technique for modelling loan delinquency. These models form states based on delinquency status and link directly to the cashflows of individual loans and hence allow for default and cure flow estimation. [Cyert et al. \(1962\)](#) first proposed a Markov model for estimating the loss on accounts receivable, but this type of modelling gained popularity in the fixed income market with CreditMetrics in 1997 (See [Gupton et al. \(1997\)](#)). The approach takes historical credit ratings and estimates a transition matrix through which the migration probability of any bond rating to default could be estimated. [Betancourt \(1999\)](#) develop a migration model of Freddie Mac prime mortgages and concluded that unconditional models provide poor forecasting ability. He proposed two observations which greatly improved the forecasting ability. Firstly, it is advantageous to divide the loan book into portfolio's reflecting loan characteristics such as fixed or floating interest rates. Secondly, loans are more likely to remain performing as they age. More

recently, focus has shifted to developing models of the sub-prime loan book. [Grimshaw and Alexander \(2011\)](#) use covariates to augment transition-matrix estimates of the transition probabilities between states for sub-prime mortgages; prediction is improved when repayment behaviour, interest rates and CLTV are introduced into the model.

Independent of the methodology used to estimate the default probabilities, an important consideration is the dependence between the default probability and the loss given default (LGD). Due to unobservable asset correlations, modelling this dependence is conceptually very difficult. Standard capital calculation formula under Basel II assumes a fixed correlation of 15 per cent. [Altman et al. \(2005\)](#) show for the corporate bond market, that recovery rates can be modelled as a function of the demand and supply for the underlying asset with default rates also playing a pivotal role. More recently, [Frye and Jacobs \(2012\)](#) show only small efficiency gains to modelling dependence and finds support for the Basel model. However, if LGD is modelled as a function of negative equity, and the PD depends on CLTV, a natural correlation between PD, LGD and the house price cycle will occur in loan level loss models. Similar to the findings of [Acharya et al. \(2007\)](#) in the corporate market, when estimated PDs are elevated, creditors recover significantly less.

3 Modelling Loan Transitions

To assess the credit risk and provide loss estimates for the mortgage book, three components are required; (i) the size of exposure, (ii) probability of default and (iii) loss given default. The first is simply the sum of the current balances outstanding. The last is the proportion of the current balance the bank can recover through repossession - approximated through negative equity and the costs associated with a forced sale. The probability of default is modelled in a transition framework where each performing loan has a probability of staying in its current state; performing or default and a likelihood of defaulting or curing. In addition, both the default and cure probabilities can then be individually conditioned on loan specific risk factors.

Transition matrices are central to modern risk management. Industry leading tools in the fixed income market, such as JP Morgan's Creditmetrics and McKinsey's CreditPortfo-

lioView have rating migration probabilities at their core. In essence, these models define a number of states, bond ratings in the case of fixed income markets, with one state defined as default, where upon entering, a loss will be realised. The transition matrix can then be used to assign a probability that a bond, currently not in default, will migrate towards default over a given time horizon. Traditionally, these models use a ‘discrete time’ framework and rely on the ‘cohort’ method, where transitions are estimated using a simple summing technique - if there are N_A loans in rating A at time t and one year later at time $t + 1$ out of this group N_{AB} have migrated to rating B , then the one year transition probability is given as,

$$p_{AB} = \frac{N_{AB}}{N_A} \quad (1)$$

The major weakness of this method is apparent in the case when the stocks of loans in ratings A and B do not change over the year, then p_{AB} is zero. However, it is possible that a loan in A migrated to B and then back to A within the year, yielding a non-zero true transition probability. The framework adopted in this paper, does not apply the ‘cohort’ method but instead adopts the continuous method outlined by [Lando and Skødeberg \(2002\)](#). This method still requires pre-defined states and estimates the probability of migration between said states. It differs in that the probability of migration at time t , $P(t)$ are not calculated by (1) above but instead depends on a generator matrix, Λ and takes the form,

$$P(t) = \exp(\Lambda t) \quad (2)$$

Here, the transition probabilities for all time horizons are a function of the generator matrix, Λ . Therefore, obtaining maximum likelihood estimates of the generator matrix, applying the matrix exponential function on this estimate and scaling by the time horizon t yields continuous time estimates of the transition probabilities.

It is possible to extend this framework to allow transition intensities between states A and B , $\lambda_{A,B}$ i.e. to allow elements of the generator matrix Λ to depend on certain covariates. Covariates are entered into the model similar to the proportional hazards model proposed by [Cox \(1972\)](#). First, we take a baseline transition intensity, $\lambda_{A,B,0}(t)$, similar to

the elements of equation (2) above and model the influence of covariates on this baseline intensity. Due to the zero lower bound of transition intensities, the covariates are entered into the model as a linear model for the log-hazard or as a multiplicative model for the hazard. For example, if the covariate vector is represented by $z^T = (z_1, z_2, z_3)$ where z_i are constant or time varying explanatory variables, the transition intensities are given as

$$\lambda_{A,B}(t, z) = \lambda_{A,B,0}(t) \exp \{ z^T \cdot \beta_{A,B} \}$$

In this case, the vector β provides estimates of the sensitivity of transitions to the elements in z^T . This allows the transition probabilities in (2) to reflect business cycle effects and different portfolio characteristics.

When comparing this methodology to the scoring model, the system-wide estimation of all possible migrations is a much richer specification than modelling a single transition. However, at the core of migration models is the assumption that transitions follow a first order Markov chain. This requires the probability of migrating between two states to be dependent only on the present state and not on the manner in which the current state was reached. In the case of a model with covariates, this Markov assumption takes a different form. The transition probability matrix $P(t, t+1)$, cannot be calculated in closed form if Λ varies over the interval $(t, t+1)$. An exception is if Λ is piecewise-constant. The effect of time-dependent variables, including time itself, on the transition intensities can be modelled under this assumption. In general, suppose a covariate varies continuously through time, but is only observed at the same times as the state of the Markov process. The effect of that covariate can be estimated assuming that it is constant in between the times that it is observed⁵.

4 Empirical Application

Loan delinquency estimates are based on loan-level data used in the review of capital and funding assessments of domestic Irish banks by the Central Bank of Ireland⁶. The data are a

⁵For a detailed discussion, see [Jackson \(2011\)](#).

⁶See the Financial Measures Programme at www.centralbank.ie

point-in-time view of the current stock of mortgages held on the books of the banks as of 31st December 2013, containing micro-level information mainly recorded at loan origination⁷. In addition, data are also provided on the quarterly arrears balances between December 2008 and December 2013. In each time period, a loan can be categorised as performing or in default. We follow the standard Basel III definition of loan delinquency in defining defaulted loans as those with arrears in excess of 90 days.

A rigorous overview of the loan book is provided by [Kennedy and McIndoe-Calder \(2012\)](#); focus here is confined to loan delinquency. Figure 1 shows the number and balance of loans in default since 2010 for owner occupier mortgages. There is a sharp rise in delinquency levels through 2011 and 2012, with the balance of loans in arrears doubling. Through 2013, the level of arrears stabilised at 17 per cent of balance outstanding. Estimation of the transition probabilities depends on upgrades (mortgages with decreasing arrears moving into the performing pool) and downgrades (mortgages with growing levels of arrears migrating toward default). Figure 2 shows the proportion of the book moving states through the sample period. The number of loans moving into default grew sharply to a peak of 3 per cent of performing balance quarterly in early 2012. This is consistent with the sharp growth in the delinquency pools in Figure 1. Comparing the number and the value of migrating loans, there is evidence that on average larger loans are moving into default while smaller loans are more likely to cure, implying loan balance has a significant impact on migration.

4.1 Unconditional Probabilities of Default and Cure

A feature of the house price growth between 2003 and 2007 was a sharp increase in the number of loans for investment properties, commonly known as Buy-to-Let (BTL) loans. BTL loans account for 22 per cent of outstanding balance and compared to Owner Occupier (OO) loans on average exhibit larger balances, longer terms, higher interest rates and a large

⁷The methodology used to estimate the probability of default/cure poses extreme computational challenges. There are 648,091 loans in the June 2013 data set and each loan can be represented up to 21 times if present in every quarter in the data from June 2008 to June 2013. For this reason, a stratified sample of the loan book is taken at June 2013, and for this sub-sample, statistically representative of the population, loans are linked across data drops to form an estimation data set which is a 10% panel of 64,669 loans.

amount were originated around peak house prices resulting in high levels of negative equity. All of these factors suggest a higher risk profile and a benefit from being modelled separately to the OO segment of the book.

Applying the methodology without covariates outlined in Section 3, Table 1 shows the one year transformation matrix for OO and BTL loans. The superior credit quality of the OO loans is evident with one year default rate of 3.6 per cent compared to 6.8 per cent for BTL loans. There is no significant difference between loan types for the probability of curing from default. These are unconditional estimates of default probabilities - effectively applying the same risk profile to all loans, with no control for differing loan portfolio composition. While these results provide a benchmark, the importance of loan characteristics and macro risk factors discussed earlier renders them unsuitable for application in a credit risk model.

4.2 Factors Affecting the Probability of Default

Estimating accurate expected loss figures requires conditioning default probabilities on time invariant borrower factors and time-varying macroeconomic factors. The coupling of domestic demand factors, such as higher incomes and growing house prices; with domestic and international supply factors, such as a loosening of credit standards⁸, lower interest rates and Irish banks financing of lending through wholesale money markets fuelled a significant growth in Irish mortgage debt over the decade 1997-2007. Between 2007-2012, house prices fell 50 per cent, while the unemployment rate rose from 5 to 15 per cent. The net effect is a tranche of mortgages with a high repayment burden and negative equity. To capture these effects three macro factors are considered - regional unemployment, house prices through CLTV and interest rate type/level.

House prices, usually through the negative equity concept, are a common conditioning variable in default models. In the Irish case, there are two important regional aspects to house prices. Firstly, house price falls were not evenly distributed across the country, with Dublin prices falling almost 55 per cent from peak while non-Dublin properties dropping

⁸Hallisey et al. (2014) show how loan to income ratios at origination- an obvious indicator of loosening lending standards- increased significantly during the Irish property boom.

less, at 43 per cent⁹. Secondly, regional variation is amplified by the timing of construction, with early building mainly confined to cities such as Dublin and a progressive movement toward more rural areas such as the West and Midland regions. While original external expert valuation is available at the loan level, the current value of the collateral is most important for assessing credit risk. House prices are adjusted to current levels based on regional house price changes. Since no official price indices are available at the regional level, regional house price changes are estimated through quarterly changes in the median valuation on more recently issued loans in that region¹⁰.

The second well accepted determinant of mortgage default is the borrowers' capacity to repay. Although household disposable income has fallen since 2007 (8.1 per cent from peak), studies have shown it is the discrete shock caused by unemployment which has the largest effect on arrears rates¹¹. Current employment status is not available at the loan level, therefore regional unemployment is linked to loan book based on borrower location. Figure 4 presents the unemployment rate by region, with significant variation across unemployment rates with Midlands region (19.5 per cent) 1.5 times that of the Mid-East (12.9 per cent) in 2011.

Both regional unemployment and current LTV are therefore important variables to condition transition probabilities on. Given the large differences in unconditional default probabilities (Section 4.1), OO and BTL loans are modelled separately with transition intensity given as,

$$\begin{aligned} \lambda_{P,D}(t, z) = \lambda_{P,D,0}(t) \exp \{ & \beta_{P,D,1} \text{OB}_i + \beta_{P,D,2} \text{Int Type}_i + \beta_{P,D,3} \text{Int Rate}_i + \\ & \beta_{P,D,4} \text{Loan Vintage}_i + \beta_{P,D,5} \text{CLTV}_i + \beta_{P,D,6} \text{Un}_i + \\ & \beta_{P,D,7} \text{TinD}_i \} \end{aligned}$$

where $\lambda_{P,D}$ is the transition intensity between states performing and default. Deviations

⁹Calculations based on CSO House Price Index, see www.cso.ie

¹⁰Regional breakdown is based on the EuroStat NUTS3 classification.

¹¹See [Ehul et al. \(2010\)](#) & [McCarthy \(2014\)](#).

from the baseline hazard function, $\lambda_{P,D,0}(t)$ are explained by outstanding balance (OB_i), interest rate type ($Int\ Type_i$), interest rate level ($Int\ Rate_i$), number of months since origination ($Loan\ Vintage_i$), current loan to value ratio ($CLTV_i$) and regional unemployment (Un_i) for loan i . There are two intensity equations for OO and BTL loans, one estimating the default transition and the other the probability of curing, allowing for different coefficient effects, with the exception of time in default ($TinD_i$) which is only applicable to cures.

Table 2 shows the coefficient hazard ratios. The hazard ratio can be interpreted as the increase in the probability of a transition from a one unit increase in the covariate. For example, the probability of default for a OO performing loan increases by 0.13 per cent for each 1,000 euro in outstanding balance. In comparison, BTL default transitions are 4.7 times more sensitive to an increase of 1,000 euro in outstanding balance. Both interest rate type and level are found to have a significant impact for both loan groups; variable rate loans - in particular tracker loans¹² - show significantly higher default risk. Two possible explanations for this interest effect are: (i) fixed rate loans appeal to risk adverse individuals as they are willing to pay a premium to avoid changes in repayment burden caused by rate movements and (ii) banks provide 1 to 3 year teaser rates for first-time buyers, with lower repayments compared to variable rate loans.

In general, LTV and unemployment have positive (negative) coefficients on the deteriorating (improving) transitions. Estimates show a 1 per cent increase in unemployment levels is associated with a 7.5 per cent increase in the risk of a performing loan entering default. Delinquency rates in the BTL book are even more closely linked to unemployment levels with a 9.7 per cent increase in default risk for a percentage point increase in unemployment rates. Unemployment also plays an important role in the cure rates for delinquent loans. There is a 4 per cent increase in the OO cure rate for a 1 percentage point fall in unemployment levels. With almost one quarter of BTL borrowers also having an OO loan, these results are consistent with the behavioural hypothesis whereby individuals prioritise payment of OO loans over those for investment purposes. This higher sensitivity could also be

¹²A tracker mortgage is similar to a variable-rate mortgage with the exception that the interest rate tracks the ECB base rate, thereby forcing the lender to maintain a constant margin.

explained by weaker demand for rental properties due to deteriorated economic conditions in the region.

While significant, the effect of house price movements, through current LTV is weaker. An increase of one percentage point in the current LTV level results in a 0.6 per cent increase in the hazard rate of loans from performing to default for both OO and BTL loans. This must be considered in the context of higher variance in the CLTV variable than in regional unemployment. In the debate of the competing house equity and employment effects, the default probabilities for each can be isolated and measured. In Dublin, the unemployment rate more than tripled from 4.5 to 17 per cent during the crisis. The effect of this is a 2.4 times increase in the one-year default probability. Over the same period, peak-to-trough fall in house prices was 57 per cent. Figure 5 shows how the CLTV affects default probabilities non-linearly, therefore house price falls for individuals with higher LTVs have a greater effect compared to lower LTV levels. Using the 57 per cent fall figure, for an individual with an LTV of 100 per cent at the peak (232 at the trough), the comparable one-year default probability is 2.2 times greater. In comparison, an LTV of 50 at the peak would see an increase of 57 per cent in default probability. With the exception of extreme LTVs (greater than 110) issued in 2007, results show the labour market effect is stronger than the house equity effect. In addition, [Gyourko and Tracy \(2014\)](#) show that regional unemployment rates as a proxy for employment status provide a lower bound for the role of unemployment in default.

The scarring effect of default has a strong influence on the probability of curing in both OO and BTL markets. Figure 4 shows the one year cure probability drops from 45 per cent just after a loan enters default to 15 per cent if a loan remains in default for a year. The cure rate converges to below 1 per cent after 3 years in default. The “scarring effect” is the leading determinant of recovery from default, with estimates showing a 5 times greater significance compared to unemployment and CLTV. This highlights the importance of banks early interaction with distressed borrowers.

4.3 Model Validation

While Section 4.1 and 4.2 develop our understanding of the factors which determine loan default in a Irish context, for credit risk application the accuracy of the model's predictions is paramount. The predictive power of a panel-data model such as ours can be tested along two criteria; (i) the ability to rank borrowers in the cross section and (ii) the ability to produce accurate time series forecasts of the default rates. The most common way to test cross sectional discrimination is the receiver operating characteristic (ROC) curve, which plots the model performance in terms of true and false positives. Figure 6 shows the ROC curve for the OO and BTL loan books, with loans classified by the model at December 2013. The curve shows both models to have a high degree of cross sectional discrimination. A commonly used measure of performance is the area under the curve (AUC)¹³, with OO and BTL models scoring 0.85 and 0.83 respectively. An AUC greater than 0.7 is generally accepted as a well performing model.

A key advantage of modelling the macro drivers of mortgage default is to accurately assess the impact of changes in economic conditions. For example, if house prices and the labour market were to have an improved pace of recovery, there would be a significant decrease in default levels, but a model is required to disentangle the effects and calculate the pace of loan book recovery. The accuracy of the time series fit of default rates across the loan book can be used to assess the model's effectiveness in this type of scenario evaluation. Figure 7 presents the actual and predicted values of the levels of default, with 95 per cent confidence intervals generated from boot-strapping with 100,000 replications. For each quarter the model predicts the expected number of cures and default over the next quarter. The in-sample fit provides an accurate estimate of the arrears trends from 2008 to 2013 with only a small level of forecast error, which - except in the early sample period - always remains within the 95 per cent confidence bands.

¹³A model with no predictive power in terms of ranking cross-sectionally has an area of 0.5. A perfect model (one that has zero false positives and zero false negatives) has an area of 1.00.

5 Conclusions

Estimating the degree of impairment in the residential mortgage book of Irish financial institutions is of major policy importance. In November 2010, Ireland agreed a programme of support from the EU, ECB & IMF. This support was mainly required because of the highly impaired nature of the loan books of the Irish financial institutions. This paper provides a framework for estimating default and cure probabilities of individual mortgages in the Irish mortgage market. Accurate assessment of this issue is essential for an informed provision of capital for these institutions. This paper outlines a transitions based model to estimate the level of defaults/cures under various scenarios for the housing and labour markets.

In contrast to the widely used stock delinquency based approach, this transition model provides for the estimation of default and cure flow. Such is a requirement for new stressing models such as the ECB comprehensive assessment, which involves assessing losses on stock and new flows separately gaining from the use of an asset quality review. Further advantages include an intuitive method to model potential loan modifications, which could be modelled as an additional state and linked directly to loan cashflows.

Crucially in this framework, the transition probabilities are a function of loan characteristics and macro factors such as house prices and unemployment. Support is found for the two central hypotheses of loan default; (i) equity effect, whereby the borrower views the mortgage as a put option with a payoff when in negative equity and (ii) affordability, measure in the model by regional unemployment rates and burden through balance and interest rates at the loan level. For an unemployment (CLTV) increase of one percentage point, the likelihood of a default increases by 7 (0.5) per cent. Because the model is linked on the log function, there is a non-linearity between CLTV and default probabilities. Comparing a house with equity (CLTV of 50 per cent) to the case with negative equity (CLTV of 150 per cent), the one year probability of a loan moving to default twice as high in the latter (1.9% compared to 4.1%)¹⁴. When comparing the competing equity and affordability effects, since

¹⁴1 year transition probability for a variable rate performing loan, with all covariates except CLTV set to their mean.

2008 in Ireland labour market deterioration played a stronger role than house equity in the rise of default rates. This suggests policies aimed at stimulating the domestic economy, and hence lowering unemployment will yield a more efficient outcome than policy aimed at debt reduction (lowering current LTV), although the large number of unemployed construction workers may suggest both are linked.

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Table 1: Unconditional 1 Year Transition Probabilities for Irish Mortgages by Type

PDH			BTL		
	Perform	Default		Perform	Default
Perform	96.40 <i>(96.32,96.48)</i>	3.59 <i>(3.52,3.68)</i>	Perform	93.23 <i>(92.97,93.47)</i>	6.77 <i>(6.53,7.02)</i>
Default	16.40 <i>(15.74,17.03)</i>	83.60 <i>(82.97,84.27)</i>	Default	16.93 <i>(15.91,17.92)</i>	83.07 <i>(82.08,84.09)</i>

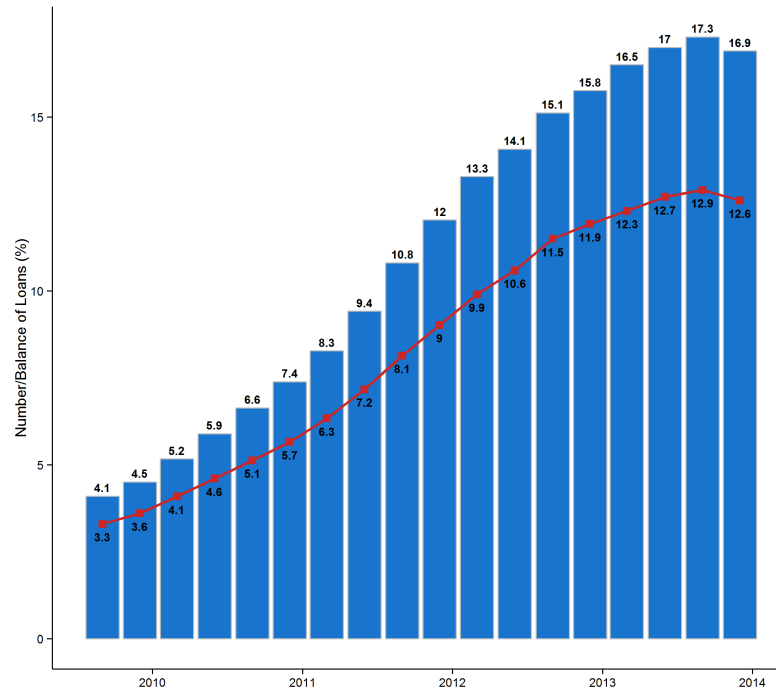
Notes: 1 year transition probabilities estimates using the continuous method outlined by Lando & Skødeberg (2002). The 95 per cent confidence intervals are in parenthesis.

Table 2: Coefficient Estimates for Macro Effects on Transition Intensities

		PDH		BTL	
Interest Rate Type	Fixed	To Default	To Performing	To Default	To Performing
		1.0013*** (1.0010,1.0014)	0.9993*** (0.999,0.9996)	1.0061*** (1.0009,1.001)	0.999 (0.998,1.000)
Outstanding Balance	SVR	Omitted	Omitted	Omitted	Omitted
		3.2046*** (2.8089,3.656)	0.9577 (0.7501,1.223)	1.5422*** (1.2024,1.9780)	0.5565*** (0.3464,0.8941)
Current Interest Rate	Tracker	6.5707*** (5.246,8.229)	0.8046 (0.529,1.224)	1.7141*** (1.2085,2.4312)	0.4399*** (0.2142,0.9035)
		1.426*** (1.352,1.5043)	0.852*** (0.7663,0.9473)	1.1695*** (1.0884,1.2567)	0.7698*** (0.6594,0.8986)
Loan Vinatge		1.0399*** (1.0309,1.049)	0.9698*** (0.9538,0.986)	1.020*** (1.001,1.039)	1.038*** (0.998,1.080)
		NA	0.7455*** (0.7309,0.7604)	NA	0.7625*** (0.7371,0.7888)
Time in Default	CLTV	1.0063*** (1.0057,1.0069)	0.9935*** (0.9935,0.9947)	1.0069*** (1.0061,1.0078)	0.9971*** (0.9953,0.9989)
		1.0752*** (1.0652,1.0853)	0.9618*** (0.9452,0.9786)	1.0969*** (1.0808,1.1133)	0.9414*** (0.9115,0.9722)

Notes: This table shows the hazard rates for the transition probabilities described by the matrix, $P(t) = \exp(t)$ with the elements, $\lambda_{P,D}$ of the generator matrix Λ given as, $\lambda_{P,D}(t, z) = \lambda_{P,D,0}(t) \exp\{z^T \cdot \beta_{P,D}\}$ with $\beta_{P,D}$ as a vector of covariate estimates (displayed as hazard rates to aid interpretation) presented above. The 95 percent confidence interval for hazard rates are given in parenthesis. * * * denotes significance with 95 per cent confidence.

Figure 1: Time Series of Loans in Default for Owner Occupier Properties



Notes: Time series from September 2009 to December 2013 of arrears rates (blue by balance, red by count) of owner occupied mortgages in Ireland. Source: Central Bank of Ireland Official Statistics

Figure 2: Time Series of Quarterly Transitions

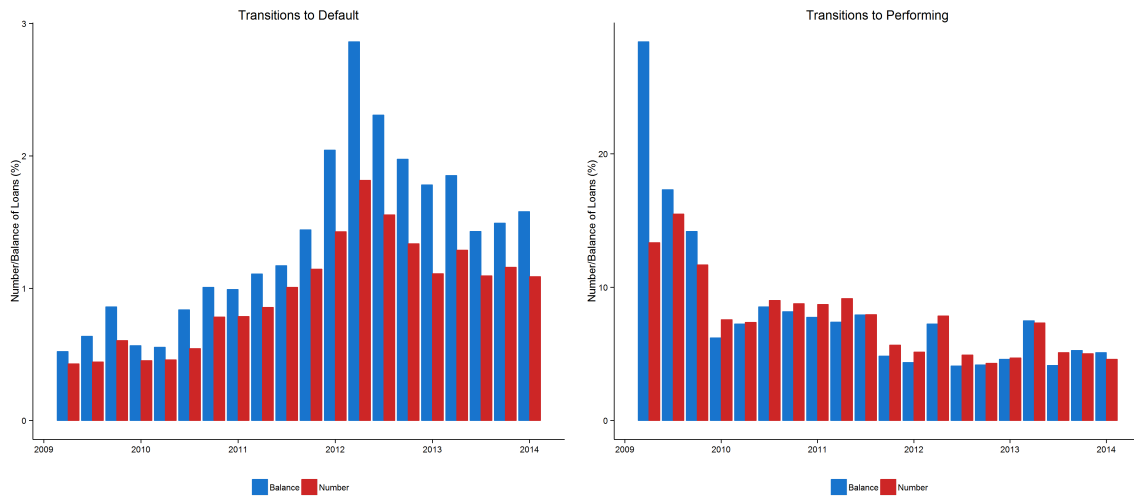


Figure 3: Regional Unemployment from Quarterly National Household Survey (QNHS)

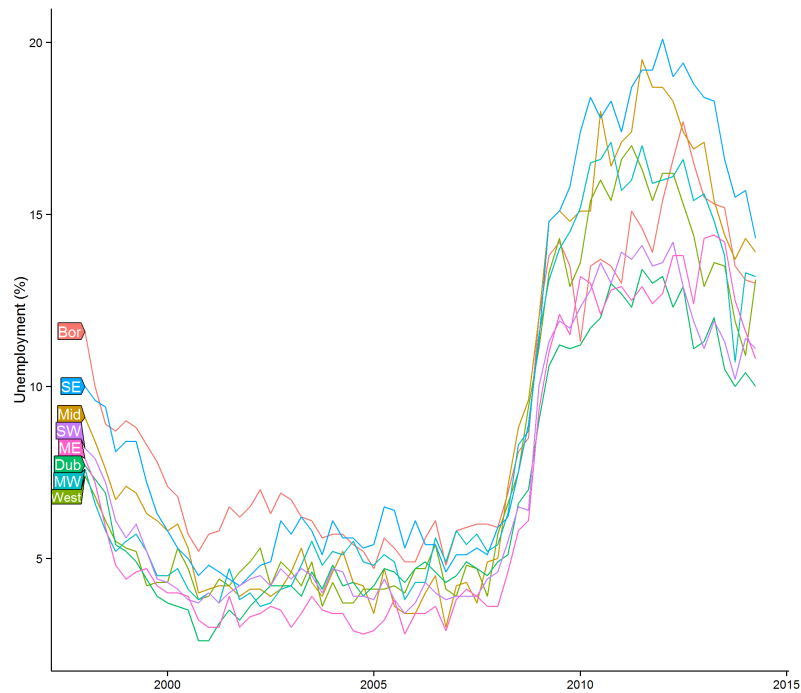
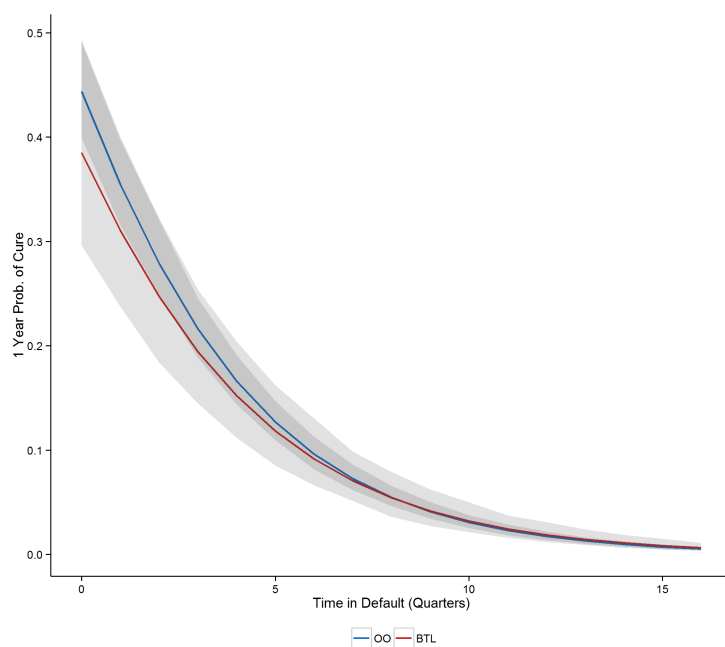


Figure 4: Non Linear Effect of Time in Default on 1 Year Probability of Cure



Notes: 95 per cent confidence intervals shown in shaded regions.

Figure 5: Non Linear Effects of CLTV on 1 Year Probability of Default and Cure

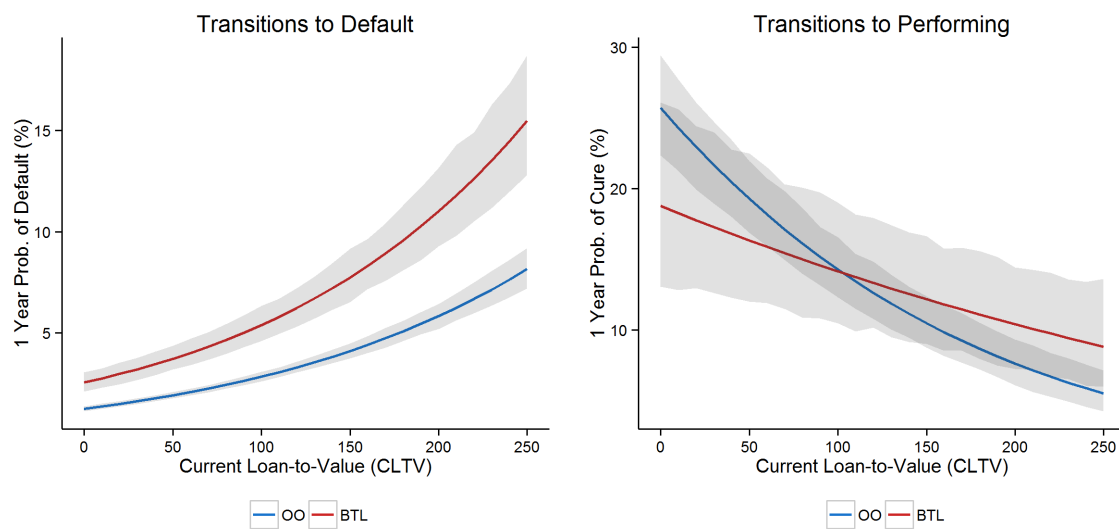
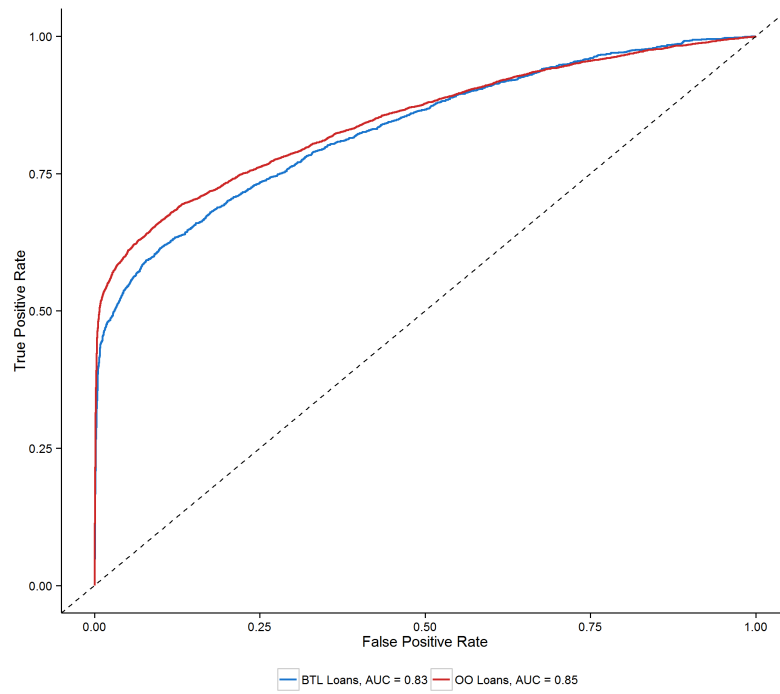
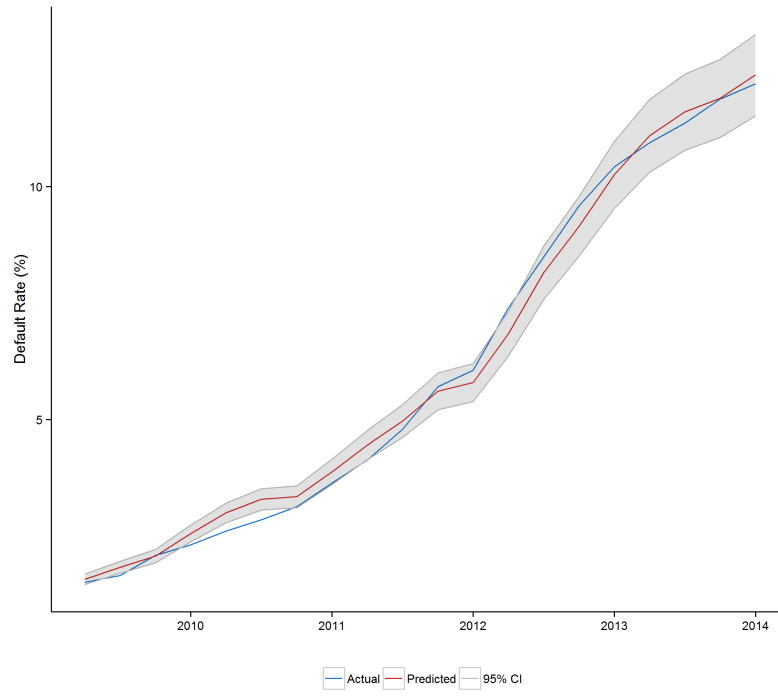


Figure 6: ROC Curve (with AUC) by Loan Type



Notes: Receiver Operating Curve (ROC) is commonly used to test a model's ability to discriminate in the cross section. The Area Under the Curve (AUC) is a measure of performance with a value of 0.5 showing no difference to a randomness and a value of 1 to a model perfectly ranking the predicted probabilities and actual defaults.

Figure 7: In Sample Fit of Predicted and Actual Default Levels



Notes: Actual and predicted levels of default, with 95 per cent confidence intervals generated from boot-strapping with 100,000 replications. For each quarter the model (hazard rates presented in Table 2) predicts the expected number of cures and default over the next quarter.