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The Good, The Bad and The Impaired

A Credit Risk Model of the Irish Mortgage Market

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A Credit Risk Model of the Irish Mortgage Market*

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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 particular, the paper examines the progression of mortgages in arrears from 90 days to 360 days. This question is of major financial stability concern in an Irish context as the uncertainty concerning the quality of the loan books of the Irish financial institutions is due, in the main, to the perceived impaired nature of the residential mortgage book. Using this approach, default probabilities are shown to be "hump shaped" when conditioned on loan vintage, with loans originating between 2004 and 2006 are most likely to default.

JEL classification: G01, G12, G21.

Keywords: Probability of Default, Mortgages, Irish Banking System.

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*The views expressed in this paper are those of the authors and do not necessarily reflect those of the Central Bank and Financial Services Authority of Ireland.

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Non Technical Summary

Estimating the degree of impairment in the residential mortgage book of Irish financial institutions is of major policy importance. This paper outlines a framework to estimate default probabilities of individual mortgages in these institutions. Accurate assessment of this issue is essential for an informed provision of capital for these institutions.

To assess the credit risk and provide loss estimates for the mortgage book, three variables 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 repossession. The probability of default is given by the transition probabilities of loans between various states of delinquency.

A sample of 450,000 mortgages is taken from the loan books of the three largest Irish banks with an outstanding balance of €80 billion. The loans are then classified into one of three states; performing, impaired or in default. Performing loans are defined as having less than 90 days arrears, while impaired loans are between 90 and 360 days in arrears. Loans are classified in default whenever arrears exceed 360 days. The probability of loans moving between these states is then estimated, providing a probability of default (moving to state 3) for expected loss calculations.

To account for the exponential growth in mortgage debt in Ireland and the natural inflation driven reduction in repayment burden over the life of the mortgage, the probability of a mortgage facing delinquency is modelled to reflect the vintage of the loan. The result is a 'hump-shape' default curve peaking between 2002 and 2006 depending on institution. The peak of the 3 year default probabilities range between 4.5 and 7.75 per cent. The model is then extended to condition default probabilities on borrower type, interest rate type and the region in which the property is located. All of these factors are found to have a large effect on the future delinquency path of loans.

We generate expected loss estimates for the mortgages books over the three year horizon, 2011 to 2013 under differing scenarios for the housing market. The loss estimates are based on over 2,000 default probabilities, allowing for vintage, loan type, including btl and ftb

and finally lending institution. The forecast of the housing market conditions takes the baseline and the stressed cases as outlined in the macro scenarios for capital assessment published by the Central Bank of Ireland[1]. Based on house prices falls of 13.4 and 14.4 per cent in 2011 and 2012 and a small recovery of 0.5 per cent in 2013, the overall estimated loss on the mortgage book is 5.5 billion or 5.66 per cent of the book. Under a stressed scenario, the house price falls are more severe, losing 17.4 and 18.8 per cent of their value over the next 2 years and again a 0.5 per cent recovery in 2013. This results in higher losses of 6.8 billion or 6.95 per cent of the mortgage book. In comparison with the Financial Measures Programme (FMP), the baseline estimates are very similar (€5.684 bn or 5.8%) while the stressed estimates are considerable lower compared to the FMP estimates of €9.491 billion. This difference can be explained by the 'through-the-cycle' estimation of the default probabilities yielding the assumption of the macro environment remaining similar to 2010. If a longer time span of loan transitions were available, default probabilities could be calculated reflecting forecasts for the economy. While it would be beneficial to condition on the business cycle, there is merit in the through the cycle estimates as issues associated with measurement error and timing of default common in other approaches are avoided.

[1]See www.centralbank.ie

1 Introduction

The presence of significant housing booms and busts across many OECD countries such as Spain, Ireland and the United States has had profound financial stability concerns for the financial systems which serviced 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 credit risk and the pricing of future losses. In particular, a Markov chain transition model based on arrears profiles is used to estimate the probability of default for individual mortgage loans.

Ideally in addressing this issue of customer indebtedness, information would be available on the current economic circumstances and wealth of the individuals concerned. However, even comprehensive loan level datasets such as that extracted by BlackRock Solutions for PCAR 2011 do not provide this. For example, the arrears profile and outstanding balance reflect changes on a monthly basis but variables best suited to conditioning the probability of arrears are either recorded at loan origination, such as income and house price or not at all, e.g., current sector and status of employment. There are two solutions to this static problem. House prices and income at origination can be allowed to evolve using house price indices and more current estimates of income based on, say, income surveys[2]. This yields unbiased estimates of present values but lacks efficiency and makes no allowance for the discrete income shock caused by unemployment. Alternatively, one can aggregate up from the micro level information and condition on macro variables such as regional unemployment (See Lydon (2011)). This yields a superior conditioning state variable and provides a platform for forecasting trends but disregards the individual loan level information.

A series on loan level default probabilities are derived based on the probability a loan will move through three defined stages of delinquency - performing, impaired (90 - 360 day arrears) and default (360+ days in arrears). The timing of default is modelled without the need for conditioning variables such as LTV and income, both of which may be subject to

[2]See Lydon & McCarthy (2011).

measurement error. These estimates allow one to generate expected loss estimates for the mortgages books over the three year horizon, (2011 to 2013) under the same scenarios for the FMP project and provide an alternative framework for calculating expected losses. The expected losses range between 5.66 and 6.95 per cent of book value depending on the future path of the house prices and are below those estimated in the FMP.

In presenting this approach it is worth considering the scale of change in the Irish economy over the last two decades. The Irish mortgage market has evolved in a highly significant fashion, with rising incomes and house prices leading to a seismic growth in mortgage debt. The number of loans issued by Irish financial institutions between 2004 and 2007 was 330,000, for the 4 years before that it was 220,000[3]. Aside from these factors, other influences such as the development of a residential investment property market and the increased competition from foreign banks resulted in a mortgage book which is significantly different from anything that went before. Even ignoring this evolution, the natural inflation driven reduction in debt to income dictates that newer loans yield a higher risk of delinquency.

Given the increase in house prices and expansion in mortgage lending over the period post 2003, it is of paramount importance, in the Irish case, that the probability of mortgage default is conditioned on vintage. It can be shown that, given this vintage effect, the default probability of the Irish market peaks with mortgages issued between 2004 and 2006. Additionally, the probability of mortgage default is conditioned on factors such as borrower type, interest rate type and location of property. All of these factors have a significant role in determining if a mortgage survives its 30 or 40 year life.

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 the following section, we look at modelling the loan transitions in an Irish context. Section four provides estimates of the default probabilities and their sensitivity to a number of factors. The loss estimation section applies the default probabilities to the loan book yielding expected losses for 2011-2013 and a final section offers some concluding comments.

[3]From the Department of the Environment Housing Statistics, see http://www.environ.ie

2 Previous Literature

There have been a variety of different empirical approaches used to tackle the issue of mortgage arrears. 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 option on the house price with a strike price set equal to mortgage value. This pure-option based model assumes that the borrower will default immediately when the value of the property drops to the level of the mortgage value. Key to this framework is the non-recourse nature of US mortgages and the ruthless exercising of the option. Further, 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 & Muellbauer(2010) amongst others have shown default very often requires more than the household just experiencing negative equity.

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 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 first is similar to the option framework where 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. Lydon & McCarthy (2011) take a similar, although uni-variate approach to modelling delinquency in the Irish mortgage market. The probability of a loan entering into 90 day arrears is set as a function of house equity and MRTI. The MRTI is a repayment distress variable calculated as the ratio of mortgage repayment to current disposable income. The loan dataset provides income at loan origination, which is adjusted forward based on income trends in the SILC dataset[5].

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

[5]The SILC is the Standard of Living Survey by the Central Statistics Office (CSO), repeated yearly since 2004 and includes information on income and mortgage repayment burden. McCarthy and McQuinn(2011) provide a rigorous overview of the mortgage aspect of the SILC.

Although there are clear advantages to current repayment burden compared to that recorded at loan origination, there is the possibility of measurement error being introduced due to the discrete shock shock to income caused by unemployment. Further, scoring models ignore the timing of default and also fail to account for covariates changing over time.

Migration models provide another technique for modelling loan delinquency. These models form states based on delinquency status and default and estimate a multi-state time-consistent Markov model. 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)). It 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 Freddic 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 current as they age. More recently, focus has shifted to developing models of the sub-prime loan book(Grimshaw et al (2011)). Unlike the scoring models, the timing of default is modelled but these migration models do not incorporate predictive variables, providing a through the cycle approach concerning macroeconomic risk factors.

3 Modelling Loan Transitions

A scoring model framework is adopted in the expected loss calculations of the FMP. As a robustness check, we derive the same expected losses using the same scenarios but apply a migration model to the calculation of the default probabilities. This avoids the difficultly associated with conditioning variables but requires arrears to follow a Markov process, that is, future movements depend only on current arrears and have no memory. It is difficult to test the Markov assumption in practice but is usually accepted as having good local approximation for shorter samples and more problematic if estimating over several business cycles.

To assess the credit risk and provide loss estimates for the mortgage book, three variables 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 repossession. The probability of default is given by the transition probabilities of loans between various states of delinquency. These transition probabilities can then be conditioned on loan specific risk factors.

The approach is based on loan level data used in the review of capital and funding assessments of domestic Irish banks by the Central Bank of Ireland[6]. This is a unique dataset which includes 13 months of arrears balances for 550,000 mortgages of various vintage representing 85 per cent of the Irish mortgage market. Each loan is categorised into one of three states. The first is a performing loan, with arrears, if they exist of less than 90 days. The second is impaired loans, following the Basel definition of 90 days in arrears but less than 360 days and finally default. Default of a mortgage is difficult to define in an Irish context due to changes in the Code of Conduct on Mortgage Arrears (CCMA)[7] and forbearance. For ease of comparison, we adopt Moody's definition applied to securitised mortgage pools issued by Irish banks with default defined as a loan 360 days in arrears. The result is a sample of 5 million states over which loan level transitions can be estimated.

To summarise the evolution of the loan book, Table 1 presents the frequency of pairs of consecutive states. This counts for all loans, for each state r and s, the number of times a loan had an observation of state r followed by an observation of state s. There is clustering along the diagonal which indicates no movement between states. There are 3703 incidents of default from loans already impaired, but, interestingly a larger number 5494 recover to a performing classification. The 117 loans which moved straight from performing to default are unusual in that by definition they must go through the impaired state first.

We now specify a multi-state model to fit the data. Considering the evolution of arrears profile in the sample of loans described above, we assume that the underlying process is a Markov process $\{X(t), t \geq 0\}$ with state space $S = 1, 2, 3$ representing performing, impaired

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

[7]For more see www.centralbank.ie.

and default respectively. States 1 and 2 are transients and 3 is absorbent. By definition, we impose the restriction that a loan can advance or recover from impairment (state 2) but a performing (state 1) loan must pass through impairment (state 2) before default (state 3). Figure 1 illustrates the possible transition paths for a given loan and generates transition intensity matrix, Q, defined as,

$$Q = \begin{pmatrix} -q_{12} & q_{12} & 0 \\ q_{21} & -(q_{21} + q_{23}) & q_{23} \\ 0 & 0 & 0 \end{pmatrix}$$

There are two well known methods for estimating the elements of Q, the traditional, discrete, "cohort" or multinomial type estimator as well as the continuous "duration" estimator. The cohort approach estimates transition probabilities based on loan movements between December 2009 and December 2010, ignoring any transitions in the interim. The duration method, adopted here, uses all information available, taking account of loans which transition several times over the 13 month sample. This leads to more accurate and efficient estimates of rare event transitions, such as performing to default state and allows bootstrapping techniques to determine confidence intervals.[8] If we define T_r^n as the total time that loan n spends in state r , then T_r is the total time spent in state r, collectively by all loans. Further, if T_{rs}^n is the number of instances where loan n migrates from state r to s, the off diagonal elements of Q, are defined as,

$$q_{rs} = T_{rs}/T_r \quad r \neq s$$

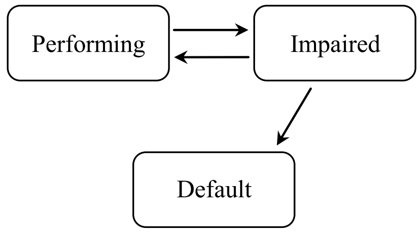
and the diagonal entries as,

$$q_{rr} = -\sum_{r \neq s} q_{rs}$$

The likelihood of a loan changing state is given by the transition probability matrix, $P(t)$. For a time-homogeneous process, the (r, s) entry of $P(t)$, $p_{rs}(t)$, is the probability of being in state s at a time $t + u$ in the future, given the state at time u is r,

[8]See Jafry & Schuermann, (2004) and Lando & Skdeberg (2002)

Figure 1: General Multi-State Model



$$p_{rs}(t) = P\left\{X(t+u) = s\,|X(t) = r\right\}$$

The timing of transitions from r to s are not specified, indeed the process may have entered other states between times u and $t+u$. $P(t)$ is defined as the matrix exponential of the time scaled transition intensity matrix, Q,

$$P(t) = Exp(tQ)$$

The elements in the right most column of $P(t)$ are the unconditional default probabilities. We are interested in the effects of additional risk factors on these probabilities. Explanatory variables for a particular transition intensity can be investigated by modelling the intensity as a function of these variables or covariates. The covariate vector is represented by $z^T = (z_1, z_2, z_3)$ where z_i are constant or time varying loan characteristics. Marshall and Jones (1995) derive a proportional hazards model, where the transition intensity elements of Q depend on z^T, are given as,

$$q_{rs}(z) = q_{rs}exp\left\{z^T \cdot \beta_{rs}\right\}$$

The new Q is used to determine the likelihood and estimates of default probabilities which reflect the loan characteristics defined in z^T.

4 Empirical Application

A sample of 450,000 mortgages is taken from the loan books of the three largest Irish banks with an outstanding balance of 80 billion. To maintain confidentiality, the banks are labeled A, B, and C with 150,000 mortgages randomly drawn from each[9]. A rigorous overview of the loan book is provided by Kennedy and McIndoe-Calder (2011), with focus here confined to transitions through the stages of delinquency. Table 2 presents a breakdown of the loan book by state, showing considerable variation across the banks. Bank B is an outlier recording the lowest number of accounts in delinquency at the end of 2009, but experiencing the largest growth rate through 2010. Across all banks there is a clear deteriorating trend with delinquency pools growing by an average of 76 per cent.

Applying the methodology outlined in Section 3 provides unconditional estimates of the generator matrix for each bank and the corresponding transition probabilities. Figure 2 shows the bank level mortgage survival probabilities for 2011 through 2020. The 95 per cent confidence intervals are calculated by non-parametric bootstrap refitting with 100,000 replications. Bank C has the best performing mortgage book with a three year survival probability of 97 per cent, significantly greater than the 94 per cent recorded for banks A and B. These are unconditional estimates of default probabilities - effectively applying the same risk profile to all loans from a given bank, with no control for differing loan portfolio composition. Therefore, while these results provide a good benchmark, the importance of loan vintage and other risk factors discussed above renders them unsuitable for expected loss estimates.

4.1 Vintage

Mortgage debt in Ireland grew significantly over the decade from 1997 to 2007. This was driven by a combination of factors including higher incomes, lower interest rates and growing house prices. It was further amplified by a loosening of credit standards[10]. Since 2007, house prices have fallen 45 per cent, while the unemployment rate has risen from 5 to 14 per cent.

[9]The total mortgage book contains 550,000 mortgages.

[10]McCarthy and McQuinn (2011) for example, estimate that income multiples, an obvious indicator of loosening credit standards, increased 50 per cent between 2000 and 2007.

This has resulted in a tranche of mortgages with high repayment burden and negative equity. Given the natural reduction in repayment burden over the life of the mortgage, it is highly likely that more recent mortgages would experience greater probability of default than mortgages issued ten or more years ago. The result is a 'hump - shape' expectation of mortgage default. To test this theory we estimate the mortgage default probabilities reflecting the vintage of the mortgage. Following the proportional hazards model in Section 3, transition intensities are regressed in a log linear model of the form,

$$Trans_{it} = \alpha + \beta_j Vint_{it} + \gamma_j Vint_{it}^2$$

where Vint_{it} is the number of months since origination for loan i for bank j. This equation is estimated for each transition intensity, q_{rs} in matrix Q[11]. Figure 3 shows a box plot across the institutions of how vintage effects the loan survival probability. From the median (red bar) and min/max(whiskers), the mortgage default probabilities are higher over the last 10 years compared to the 1990's.

The relatively low median through the house price peak shows how the default probabilities differs greatly across the institutions. There is an institution with a 3 year pd double that of best performing bank. More recently, one bank has a 3 year pd of less than one per cent compared to a median of greater than four per cent.

4.2 Type of Borrower

In the loan level data, the variety of borrower type is quite numerous with first-time, mover, switcher, equity release and buy-to-let being noted. It could be argued that first time buyers (FTB) and buy to let investors (BTL) carry the highest credit risk, due to the higher loan to value ratios associated with this proportion of the book. The residential investment loan book is also highly concentrated around the peak in house prices, with 75 per cent of the BTL mortgages issued between 2003 and 2007, compared to 58 per cent in the primary dwelling book. The sample allows for identification of FTB and BTL loans, allowing for estimation of the transition matrix conditional on both and to test for significant differences

[11] Due to the number of coefficients, estimates are available upon request from robert.kelly@centralbank.ie

from the unconditional. Borrower type is modeled as a binary dummy variable, yielding the log linear models,

$$Trans_{it} = \alpha + \chi_j BTL_i + \gamma_j Vint_{it} + \beta_j Vint_{it}^2 + \varphi_2 BTL_i * Vint_{it} + \phi_3 BTL_i * Vint_{it}^2$$

$$Trans_{it} = \alpha + \chi_j FTB_i + \gamma_j Vint_{it} + \beta_j Vint_{it}^2 + \varphi_2 FTB_i * Vint_{it} + \phi_3 FTB_i * Vint_{it}^2$$

where Vint_{it} is the number of months since origination for loan i and BTL_i (FTB_i) is a dummy variable identifying borrower type. This allows for a shift and change of slope for the default curve in section 4.1 to reflect borrower type.

Figure 4 presents the 3-year mortgage default probabilities conditioned on vintage and borrower type for the three institutions. All banks display a higher rate of delinquency for residential investments loans, with the default rate as high as 18.7 per cent. The peak in terms of vintage is slightly later, between 2006 and 2007, consistent with the relatively late growth of the investment mortgage market. The FTB element of the book also shows a higher 3 year pd, peaking in 2005 at 11.4 per cent.

4.3 Interest Rate Type

There are three ways in which interest rates are applied to mortgages in Ireland. The first is the standard variable rate (SVR), where rate changes are at the discretion of the bank but changes in the ECB prime rate are usually passed-on. A variant of the SVR is the tracker mortgage which gained popularity between 2003 and 2007. The distinguishing feature of the tracker is the automatic pass-through of ECB rate movements and the fixed nature of the banks margin, usually between 0.5 and 2 per cent. Lastly, there are the fixed rate mortgages, where repayments are independent of ECB rate movements. Unlike some Eurozone countries, the fixed rate is only for a short period of between 3 and 5 years and not the life of the loan. When the fixed period ends, some loans, mainly those fixed pre 2008 revert to tracker status and the remaining to the standard variable rate. Based on balances outstanding, trackers account for 62 per of the market, the SVR mortgages at 24 per cent and fixed rate the remaining 14 per cent, with only a small variation across the banks.

Interest rate type is modeled as a binary dummy variable, along with vintage and borrower type yielding the log linear models,

$$
\begin{aligned}
Trans_{it} = \quad & \alpha + \chi * Int_i +_i * Type_i + \gamma Vint_{it} + \beta Vint_{it}^2 + \varphi Int_i * Vint_{it} + \phi Int_i * Vint_{it}^2 \\
& + \kappa Int_i * Type_i * Vint_{it} + Int_i * Type_i * Vint_{it}^2
\end{aligned}
$$

where Int_i is a dummy variable picking up interest type for loan i, while Type_i is a dummy variable identifying borrower type as outlined in Section 4.2. Vint_{it} remains the number of months since origination.

Table 4 presents descriptive statistics based on interest rate type. In general, tracker loans are larger at an average of €189,968 compared to SVR(€91,562) and fixed(€142,850). The FTB segment of the book has a disproportionately high number of fixed rate loans reflecting the teaser rates offered at origination. The BTL book is dominated by high balance tracker mortgages, some 35 per cent greater than the average.

Figure 5 shows the non-linear mortgage default probabilities conditioned on loan vintage, borrower and interest rate type. There is clearly two very distinct pictures emerging depending on borrower type. In general, the fixed rate proportion of the book is the best performing. The FTB market shows small differences between SVR and fixed rate mortgages, with only a slight earlier peak in the SVR market in 2005/2006 compared to 2007. The tracker book is much poorer, with a 3 year default rate of almost 20 per cent for mortgages issued in 2004 and 2005. One interesting finding is that the BTL market shows trackers performing better than SVR loans. The poorest performing BTL mortgages are the SVR's issued late in the housing boom with 3 year default rates of 22 per cent. In general, with the exception of fixed rate loans, residential investment loans are much more likely to experience delinquency.

There are two possible explanations for this superior performance of fixed rate loans. Firstly, risk averse borrowers will opt for the higher but defined repayments offered by fixed rate loans. These people by definition are less risky. Secondly, most banks provide 2 to 3 year fixed teaser rates for first time buyers, reflected in the high proportion of fixed rate FTB loans. This yields temporarily lower repayments and hence a lower likelihood of repayment distress.

4.4 By Region

House prices, usually through the negative equity concept are a common conditioning variable in scoring models. However, recent house prices falls are not evenly distributed across the country, with Dublin prices falling almost 50 per cent from peak while non-Dublin properties dropping less, at 38 per cent.[12] If mortgage delinquency is closely related to these movements as the scoring models suggest, then one would expect variation in default probabilities based on property location. This variation by region is amplified by the timing of construction, with early building confined to the cities such as Dublin and Cork. Towards the end of the construction boom, development moved west to more rural areas. The net result is a concentration of properties in the midlands and border regions mortgaged as house prices peaked. This is coupled with a large dependence in these regions on the construction industry for employment.

Kennedy and McIndoe (2011) provide an overview of dwelling types, revealing, that apart from the Dublin region, property types are dominated by detached residencies. Dublin has a balanced mix between apartments, terraced, semi-detached and detach properties and a further reason to condition on property location. Figure 6 presents a regional breakdown of Irish mortgage lending by Eurostat NUTS3 regions. The bars show the relative size of the mortgage books, dominated by Dublin at twice the size of the mid-east, Dublin's own commuter belt and the south-west region which includes Cork city. The midlands have the smallest proportion of the mortgage lending, one tenth the size of the Dublin book. In terms of delinquency states, the highest proportion of under performing loans is in the Dublin region but all regions show a clear deteriorating trend since December 2009.

There is significant variation across the regions in terms of both peak and vintage of the loans most likely to enter default. Figure 8 shows loans in the border regions are of the poorest quality, with a 3 year pd of more than 10 per cent. Unsurprisingly, given its population, Dublin has the flattest distribution reflecting the relatively large number of loans originating in the late 1990's. In terms of credit quality, the capital is close to average, with a 2006 peak pd of 5.5 per cent. The best credit quality loans are in the mid

[12] Calculations based on CSO House Price Index, see www.cso.ie

and south west, with no loans having a default probability greater than 4 per cent. The evolution of construction from cites to rural areas is evident as the border, midland and Dublin commuter zone carry the highest risk of delinquency. This is particularly significant in the midlands, where if loans originating after 2008 are ignored, the region is among the best in terms of credit quality.

The Irish banks also extended a significant amount of mortgage credit, totalling 40 billion euro into the UK housing market. The macro conditions in the UK were a lot more favorable than Ireland for the period under review, with peak to trough house price falls of 18 per cent and an unemployment rate of 8 per cent in 2011 compared to 14 per cent in Ireland. Figure 7 compares the mortgage default probabilities for Ireland and the UK by vintage, with the 3 year rate of default five times greater for Ireland. The sale of this strong foreign lending portfolio may play a key part in the deleveraging process.

5 Expected Losses 2011-2013

The aim of this paper is to provide an alternative framework for estimating default probabilities avoiding the perceived shortcomings of the scoring models. The default probabilities are applied to the loan books of the four guaranteed banks[13,14]. We generate expected loss estimates for the mortgages books over the three year horizon, 2011 to 2013 under differing scenarios for the housing market.

The key components in calculating the expected loss from the mortgage book are,

- *The probability of a mortgage defaulting takes on one of 2,000 individual pd's accounting for vintage, loan type, including btl and ftb and lending institution.*
- *A mortgage is considered to default whenever it enters state 3.*
- *The loss given default (LDG) is calculated as negative equity proportion of the mortgage and a further 20 to 40 per cent of the current balance is factored into the loss*

[13]All estimation above is based on three institutions due to no time series dimension of arrears for one bank. Estimates of pd's based on the whole 450,000 sample are used for this fourth bank.

[14]These institutions are referred to as being covered as all of their assets and liabilities were guaranteed by the Irish State in September 2008.

estimates, dependent upon loan type and location of the property.

Negative equity in the LDG is calculated as the difference between current house price and the mortgage balance outstanding. As per Kennedy & McIndoe-Calder (2011), current house prices are calculated as the property valuation at origination brought forward using the PTSB index. The additional 20 to 40 percent losses are an allowance for legal/sale transaction costs and the inevitable downward pressure on house prices resulting from an increase in the supply of housing stock on to the market. Two different sets of estimates are provided dependent upon economic conditions prevailing in the housing market between 2011 and 2013. The forecast of the housing market conditions based upon the baseline and the stressed cases as outlined in the macro scenarios for capital assessment published by the Central Bank of Ireland[15].

All loans from the covered institutions is included, with a total balance of €97.8 billion. The lending into the UK is not analysised but the underlying framework could be extended to include foreign lending. Based on house prices falls of 13.4 and 14.4 per cent in 2011 and 2012 and a small recovery of 0.5 per cent in 2013, the overall estimated loss on the mortgage book is 5.5 billion or 5.66 per cent of the book. Under a stressed scenario, the house price falls are more severe, losing 17.4 and 18.8 per cent of their value over the next 2 years and again a 0.5 per cent recovery in 2013. This results in the higher losses of 6.8 billion or 6.95 per cent of the mortgage book. Reflecting the higher default probabilities in section 4.2, the residential property segment of the book accounts for 40 per cent of the expected loss but only 17 per cent of the outstanding balances.

Although not the purpose of this paper, these estimates can be compared to those estimated in the Financial Measures Programme (FMP). In the case of the baseline scenario, these estimates are very similar to those estimated in the FMP (€5.684 bn or 5.8%) while the stressed estimates are considerably lower compared to the FMP estimates of €9.491 billion. This difference can be attributed to the 'through-the-cycle' estimation of the migration matrices in section 4, resulting in the assumption of the macro environment remaining similar to 2010 over the 2011 to 2013 period whereas the FMP estimtes are conservative by design and take 69 per cent of BlackRock Solutions lifetime (30 year) stressed losses (after

[15]See www.centralbank.ie

the impact of deleveraging) into the 2011-2013 loss calculations. If significant economic recovery (deterioration) was to take place between now and 2013, the estimates presented here would be too pessimistic (optimistic).

If a longer time span of loan transitions were available, default probabilities could be calculated reflecting the forecasts for the economy. One could in principle introduce transition matrices specific to the current stage of the business cycle[16]. While it would be beneficial to condition on the business cycle, there is merit in the through the cycle estimates as the potential problems associated with measurement error and timing of default in the scoring models is avoided.

6 Conclusions

Estimating the degree of impairment in the residential mortgage book of Irish financial institutions is of major policy importance. This paper provides a framework for estimating default 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. Loan delinquency is modeled in a migration framework, where loans are classified into one of three states depending on current arrears. The probability of loans transitioning to the default state (loans with arrears greater than 360) is estimated in a multi-state Markov model. The mortgage default probabilities are found to exhibit a hump shape with vintage. This reflects the seismic growth in the Irish mortgage market and relaxing of credit standards through the housing price boom. There is a large variation across the banks with peaks occurring between 2002 and 2006 and 3-year default probabilities ranging between 4.5 and 7.75 per cent depending on institution. When we condition on variables such as borrower type, these 3-year default probabilities reach as high as 21.5 per cent. With a significant UK mortgage book (40 billion), comparison between UK and Irish lending show loans are up to 5 times more likely to default in Ireland. This can be explained by the more favourable macro conditions in the UK market but puts the credit quality of the Irish book

[16]For a discussion on the effects of business cycles on transition probabilities see Lucas and Lonski(1992), Carty and Fons(1993), Carty(1997) and Nickell, Perraudin and Varotto (2000).

into context.

These loan default probabilities allow for calculation of expected loss estimates for the mortgages books over the three year horizon, 2011 to 2013 under differing scenarios for the housing market. The loss estimates are based on over 2,000 default probabilities, allowing for vintage, loan type, including btl and ftb and finally lending institution. The forecast of the housing market conditions draws upon the baseline and the stressed cases as outlined in the macro scenarios for capital assessment published by the Central Bank of Ireland[17].Based on house prices falls of 13.4 and 14.4 per cent in 2011 and 2012 and a small recovery of 0.5 per cent in 2013, the overall estimated loss on the mortgage book is 5.5 billion or 5.66 per cent of the book. Under a stressed scenario, the house price falls are more severe, losing 17.4 and 18.8 per cent of their value over the next 2 years and again a 0.5 per cent recovery in 2013. This results in the higher losses of 6.8 billion or 6.95 per cent of the mortgage book. In comparison to the Financial Measures Programme (FMP), the baseline estimates are very similar (€5.684 bn or 5.8%) while the stressed estimates are considerably lower compared to the FMP estimates of €9.491 billion. This difference can be explained 'through-the-cycle' estimation of the default probabilities yielding the assumption of the macro environment remaining similar to 2010. If a longer time span of loan transitions were available, default probabilities could be calculated reflecting the forecasts for the economy. While it would be beneficial to condition on the business cycle, there is merit in the through the cycle estimates as the potential problems associated with measurement error and timing of default of other models is avoided.

[17]See www.centralbank.ie

References

[1] Aron, J., & Muellbauer J., 2010. Modelling and Forecasting UK Mortgage Arrears and Possessions, Discussion Paper Series No. 499, University of Oxford

[2] Bajari, Patrick, Chu, Chenghuan Sean & Park, Minjung., 2009. An Empirical Model of Subprime Mortgage Default from 2000 to 2007., NBER Working Paper 14625.

[3] Betancourt, L., 1999. Using Markov chains to estimate losses from a portfolio of mortgages., Review of Quantitative Finance and Accounting, 12, 303-317.

[4] Carty, L.V., 1997. Moody's Rating Migration and Credit Quality Correlations, 1920-1996, Special Comment, Moody's Investor Service, New York.

[5] Carty, L.V., Fons, J., 1993. Measuring Changes in Credit Quality, Special Comment, Moody's Investor Service, New York.

[6] Cyert R., Davidson H., & Thompson G., 1962. Estimation of the allowance for doubtful accounts by Markov chains. Management Science, 8, 287-303.

[7] Gupton G., Finger C., & Bhatia M., 1997. CreditMetrics Technical Document., J.P. Morgan & Co. Incorporated.

[8] Grimshaw, S., & Alexander W., 2011 Markov Chain Models for Delinquency: Transition matrix estimation and forecasting, Applied Stochastic Models in Business and Industry, 27, 267-279.

[9] Jafry, Y., Schuermann, T., 2004. Measurement, estimation and comparison of credit migration matrices. Journal of Banking and Finance 28, 2603-2639.

[10] Kau, J. B., Keenan, D. C., Muller, W. J. and Epperson, J. F., 1992. A Generalized Valuation Model for Fixed-Rate Residential Mortgages. Journal of Money, Credit and Banking, 24, 279-299.

[11] Kennedy, G., & McIndoe-Calder, T., 2011. Negative Equity and Irish Credit Institutions Residential Mortgage Books. Research Technical Paper XX/RT/11, Central Bank of Ireland.

[12] Lando, D., Skdeberg, T.M., 2002. Analyzing rating transitions and rating drift with continuous observations. Journal of Banking and Finance 26, 423-444.

[13] Lucas, D.J., Lonski, J.G., 1992. Changes in Corporate Credit Quality 1970-1990. Journal of Fixed Income, 7, 14.

[14] Lydon, R., & McCarty, Y., 2011. Modeling and Forecasting Irish Mortgage Arrears. Research Technical Paper XX/RT/11, Central Bank of Ireland.

[15] McCarthy, Y. & McQuinn, K., 2011. How are Irish households coping with their mortgage repayments? Information from the Survey on Income and Living Conditions, The Economic and Social Review, 42, 71-94

[16] McCarty, Y., & McQuinn, K. 2011. Decomposing Movements in Irish House Prices: 2000-2010. Research Technical Paper XX/RT/11, Central Bank of Ireland.

[17] Nickell, P., Perraudin, W., & Varotto, S. 2000. Stability of Ratings Transitions, Journal of Banking & Finance, 24, 203-227

[18] Vandell, K. 1995. How Ruthless Is Mortgage Default? A Review and Synthesis of the Evidence, Journal of Housing Research, 6, 245-264.

Table 1: Frequency of Pairs of Consecutive States, All Sample December 2009 - December 2010

	to		
from	Performing	Impaired	Default
Performing	6,365,654	21,161	117
Impaired	9,755	124,751	6,306
Default	0	0	169,475

Table 2: Descriptive Statistics by Delinquency State December 2009 and December 2010

	2010			2009		
	Number	Balance(€'mn)	Average Size(€)	Number	Balance(€'mn)	Average Size(€)
Bank A						
Performing	138,406	20,003	134,304	144,530	20,720	144,530
Impaired	6,081	1,125	204,751	4,359	660	184,913
Default	5,513	1,023	138,304	3,752	570	185,714
Bank B						
Performing	143,785	21,451	149,185	147,526	21,451	149,185
Impaired	2,306	496	214,891	1,299	226	174,090
Default	3,909	773	197,694	1,175	173	147,531
Bank C						
Performing	141,210	18,965	134,304	143,436	20,021	139,581
Impaired	3,274	670	204,751	2,637	496	188,269
Default	5,516	763	138,304	3,927	514	130,843

Note: These descriptive statistics reflect the randomly drawn sample of 450,000 mortgages and not the entire book (550,000 mortgages).

Table 3: Descriptive Statistics by Borrower Type

	All Loans	FTB	BTL	Other
No. of Loans	450,000	123,109	78,046	248,845
Current Balance (€'mn)	65,269	20,465	17,020	
Average Size (€)	145,042	166,237	218,090	
Average Length (months)	270	322	248	
Arrears				
No. of Loans				
Performing	423,401	116,825	72,673	
Impaired	11,661	3,137	2,771	
Default	14,938	3,147	2,602	
Current Balance (€'mn)				
Performing	61,411	19,421	15,849	
Impaired	1,691	521	604	
Default	2,167	523	567	

Note: These descriptive statistics reflect the randomly drawn sample of 450,000 mortgages and not the entire book (550,000 mortgages).

Table 4: Descriptive Statistics by Interest Rate Type

	All Loans			FTB			BTL		
	Fixed	Tracker	SVR	Fixed	Tracker	SVR	Fixed	Tracker	SVR
No. of Loans	60,397	208,758	169,935	24,145	57,471	36,744	4,632	50,213	22,371
Balance(€'mn)	8,628	39,657	15,468	3,939	11,566	4,131	758	12,893	3,230
Average Size(€)	142,850	189,968	91,562	163,133	201,248	112,414	163,752	256,757	144,377
Average Length (Months)									
Arrears									
No. of Loans									
Performing	56,471	198,161	157,536	23,541	54,697	34,105	4,466	46,999	20,436
Impaired	952	5,344	4,966	359	1,444	1,189	112	1,639	978
Default	2,974	5,253	6,433	245	1,330	1,450	54	1,575	957
Current Balance									
Performing	8,115	36,727	14,110	3,831	10,868	3,764	717	11,625	2,807
Impaired	160	1,465	609	69	366	171	31	624	205
Default	353	1,466	750	39	332	195	10	643	218

Note: These descriptive statistics reflect the randomly drawn sample of 450,000 mortgages and not the entire book (550,000 mortgages).

Table 5: Residential Mortgages Loan Loss Assessment Results (€'m)

	Baseline			**Stress**		
	Total	**PDH**	**BTL**	**Total**	**PDH**	**BTL**
Kelly(2011) Estimates	5,520	3,318	2,202	6,812	4,313	2,499
	5.6%	4.5%	9.43%	6.95%	5.85%	10.7%
FMP Estimates	5,684	3,465	2,219	8,997	5,668	3,330
	5.8%	4.7%	9.5%	9.2%	7.6%	14.3%

Figure 2
Unconditional Surival Probabilities

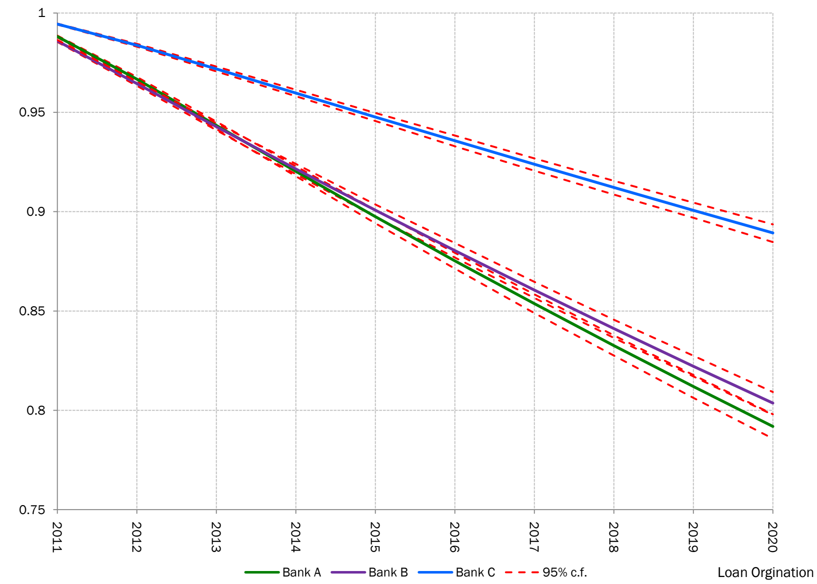


Figure 3

3 Yr Default Probability by Vintage

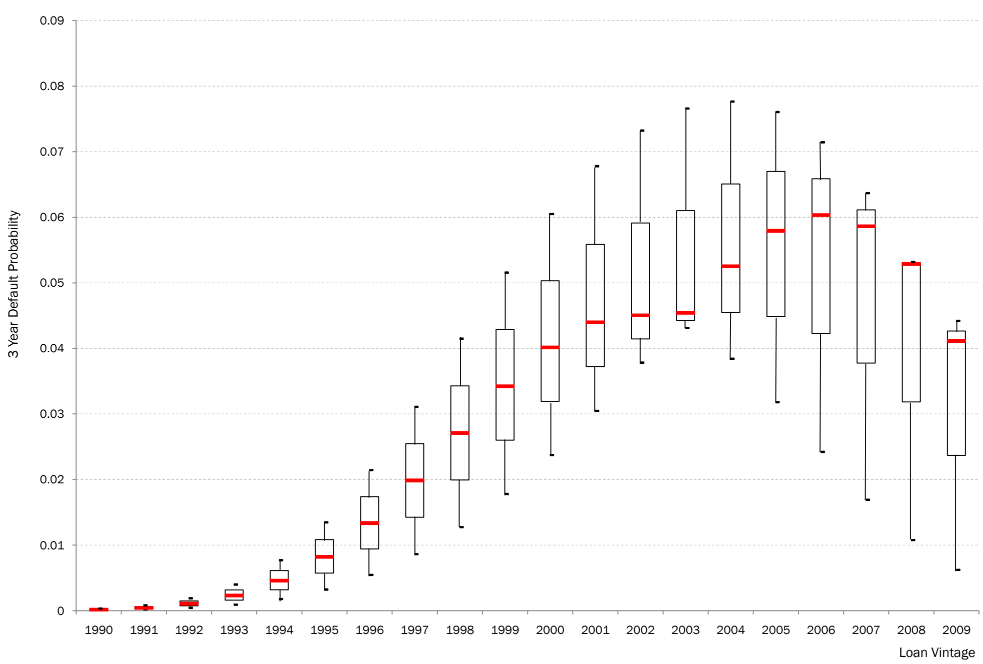


Figure 4

3 Yr Default Probabilities by Vintage and Borrower Type (FTB & BTL)

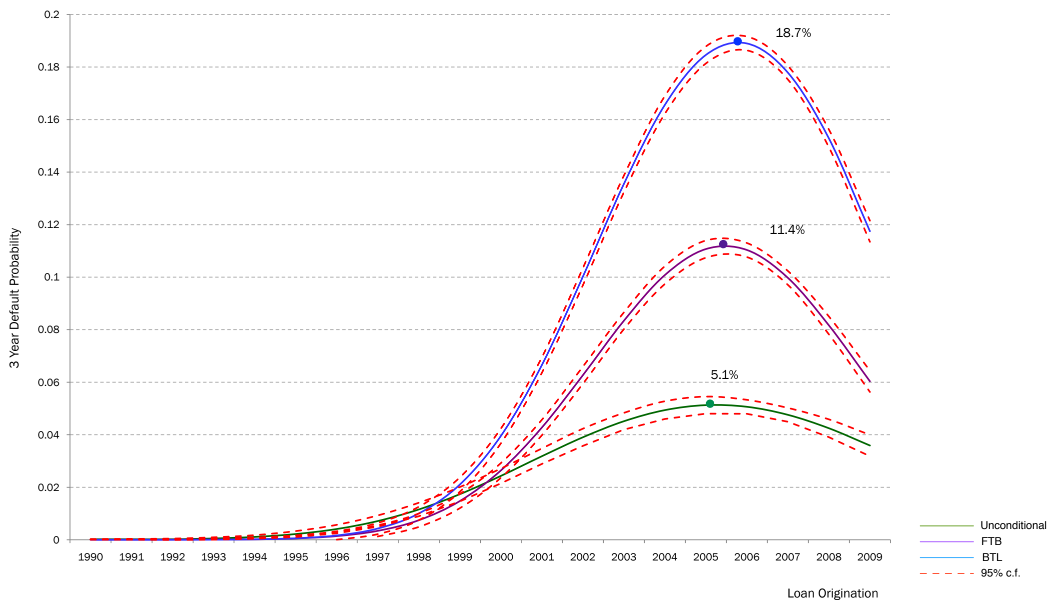
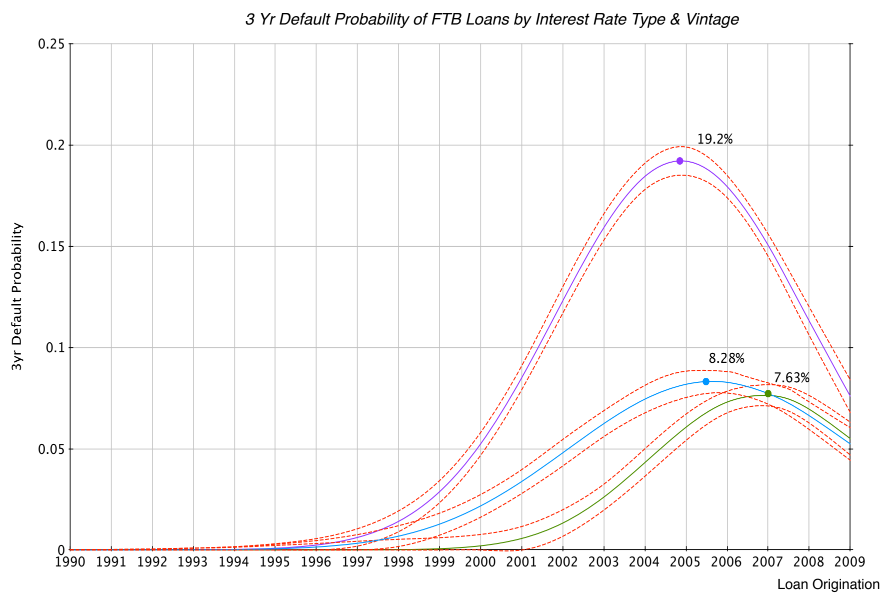


Figure 5


3 Yr Default Probability of FTB Loans by Interest Rate Type & Vintage
3yr Default Probability
0.25
0.2
0.15
0.1
0.05
0
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
Loan Origination
19.2%
8.28%
7.63%

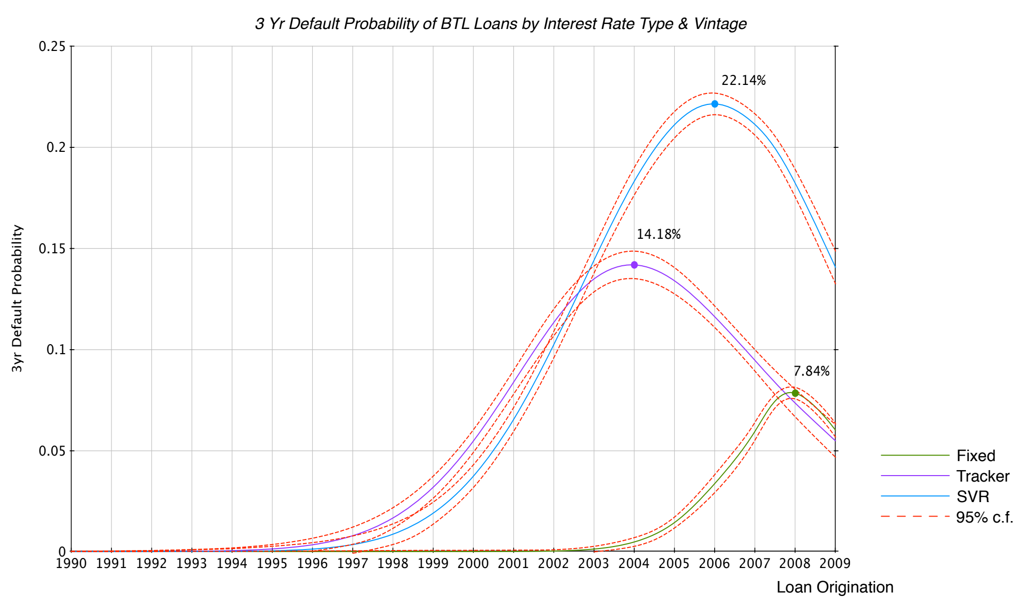

3 Yr Default Probability of BTL Loans by Interest Rate Type & Vintage
3yr Default Probability
0.25
0.2
0.15
0.1
0.05
0
1990 1991 1992 1993 1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009
Loan Origination
22.14%
14.18%
7.84%
Fixed
Tracker
SVR
95% c.f.

Figure 6
Regional Breakdown of Irish Mortgages by NUTS3 Regions

Regional map of Ireland showing the breakdown of mortgages by NUTS3 Regions. The relative height of the bars reflect the size of the mortgage market (based on current balance) for the region.

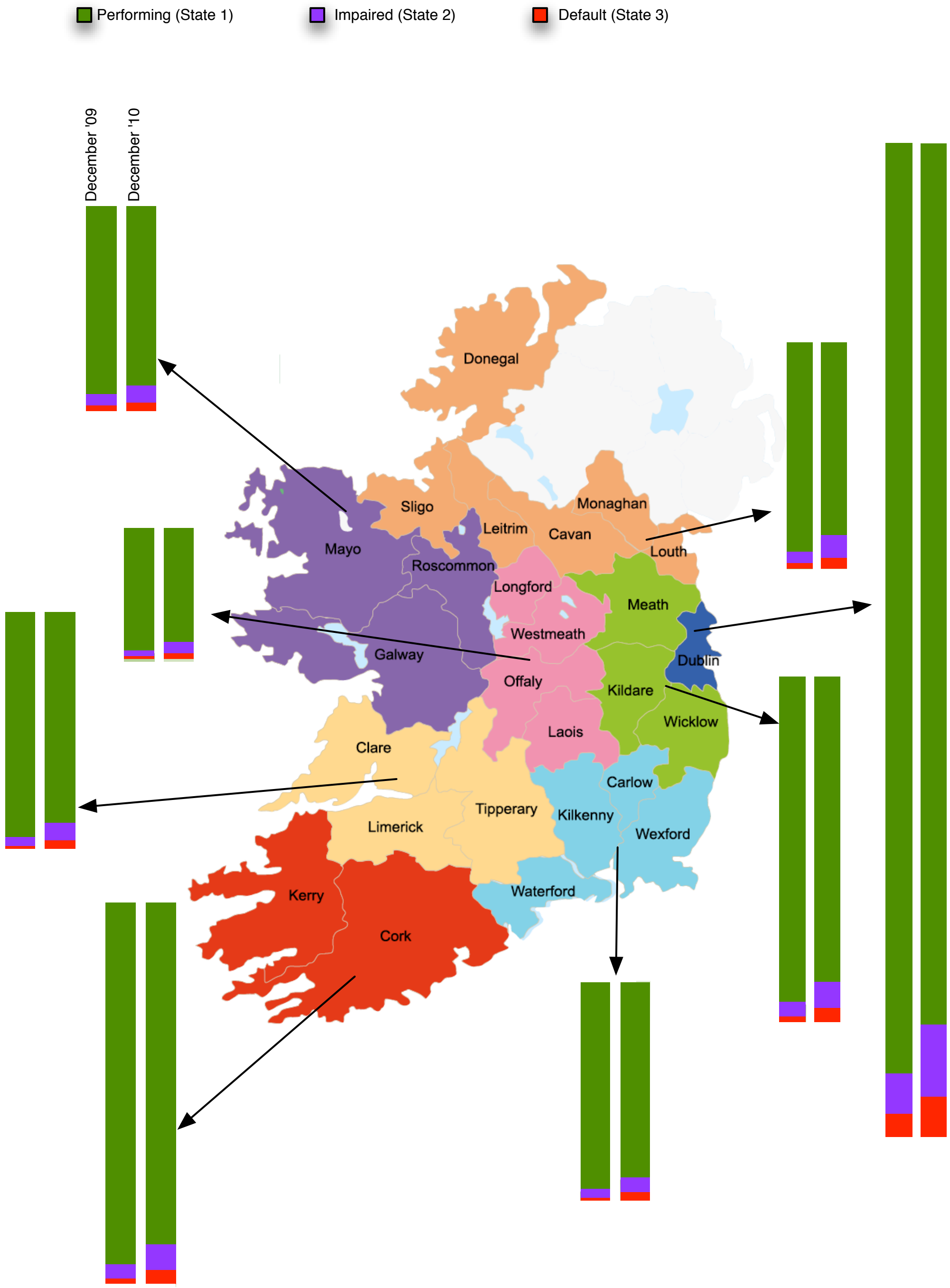


Figure 7

3 Yr Default Probabilities in Ireland and UK by Vintage

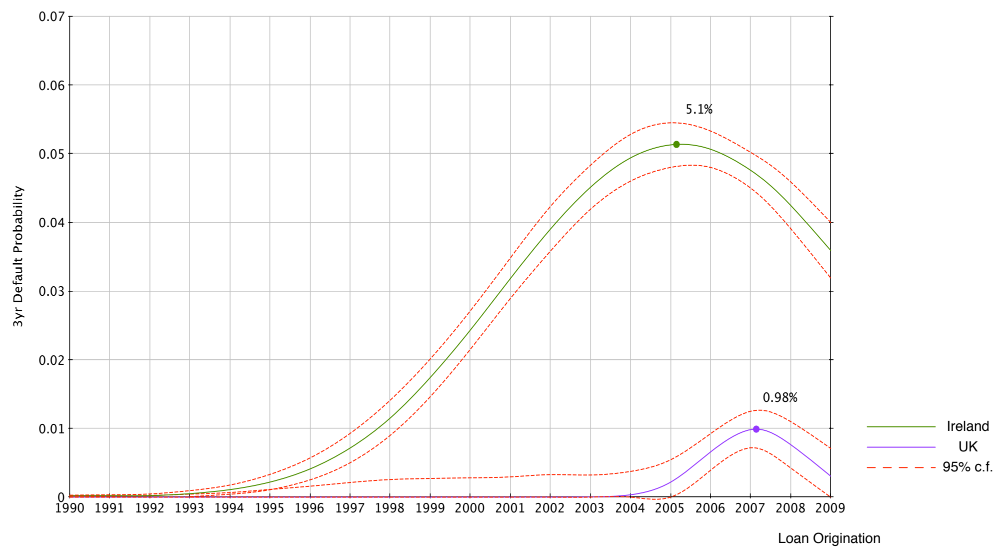


Figure 8

3 Yr Default Probabilities by Vintage and Region