House Prices, Unemployment & Irish Mortgage Losses

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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. The default probabilities depend on loan characteristics such as the vintage of the loan and current macroeconomic conditions such as house prices and unemployment. This is an issue of major financial stability concern in an Irish context as the uncertainty concerning the quality of the loan books of Irish financial institutions is due, in the main, to the perceived impaired nature of the residential mortgage book. Default probabilities are found to be non-linear with vintage, peaking with loans issued between 2006 and 2007. Changes in unemployment rates are found to have a stronger influence on default probabilities compared to house price movements - showing ability to pay considerations have a stronger influence than house equity for delinquency rates. This provides a platform for sophisticated stress scenarios and the final section presents estimates of expected loss figures for 2011-2013.

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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 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.

The last decade saw a seismic shift in the Irish mortgage market, with rising incomes and house prices coupled with Irish banks access to European capital markets, after the advent of the Euro, resulting in a large 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[1]. 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 reduction in repayment burden due to loan seasoning 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, given this vintage effect, the default probability of the Irish market peaks with mortgages issued between 2004 and 2006.

In addition, there are two well-formed hypotheses as to the cause of mortgage delinquency and ultimately default. The first is the equity effect, whereby an individual will not continue servicing a mortgage due to negative equity. This is similar to viewing a mortgage as an American option with strike price equal to mortgage value. This effect will be strongest in non-recourse markets, such as some US states. The second factor is the

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

ability to repay. This occurs whenever falls in income, usually through an unemployment shock, leaves the individual unable to meet the repayment burden of the mortgage. The Irish mortgage market provides a unique opportunity to investigate these effects having experienced one of the largest international house price falls in recent history.

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 under the Financial Measures Programme (FMP) 2011 do not provide for 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. Therefore, to model delinquency and arrears rates accounting for the macro considerations above, loan level data must be augmented to include measures of unemployment and current house prices. Regional unemployment is matched to the loan book using borrower location information and is calculated as the proportion of the labour force availing of work-related benefits. Original house price valuations are updated to current using an index derived from valuations of similar properties issued later in the loan book.

A series of loan level default probabilities are derived based on the probability that a loan will move through five defined stages of delinquency towards default. The rate at which loans transition through these states is modelled as a function of loan characteristics such as vintage and time varying macro factors such as current LTV and regional unemployment. The default probabilities are found to be significantly more sensitive to unemployment compared to house price changes. This could be related to the recourse nature of Irish mortgages. These estimates allow one to generate expected loss estimates for the mortgage books over the three year horizon, (2011 to 2013), under the same scenarios outlined under the FMP programme and thus provide an alternative framework for calculating expected losses. The expected losses range between 4.6 and 6 per cent of owner occupier book value depending on the future path of the house prices and unemployment rates.

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 macro 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.

2 Previous Literature

There is 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 some mortgages and the ruthless exercising of the option. Furthermore, the substantial transaction costs of moving property are ignored.[2] 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.

Schwartz and Torous (1993) using a Poisson regression framework find evidence of significant regional 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 the US sub-prime and Alt-A 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

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

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[3].

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 adjusting origination income due to the asymmetric income shock caused by rising unemployment rates. 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. 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.

[3]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.

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)).

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. 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. Acharya et al. (2007) show that in a down-cycle, when industry pd's are elevated, the creditors recover significantly less. More recently, Frye et al (2011) show only small efficiency gains to modelling dependence and finds support for the Basel model.

3 Modelling Loan Transitions

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.

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 CreditPortfolioView 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 firms 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

$$p_{AB} = \frac{N_{AB}}{N_A} \tag{1}$$

The major weakness of this method is if no migrations from A to B take place over the year, p_{AB} is zero. However, it is possible that 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 Skodeberg (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,

$$P(t) = exp(\Lambda t) \tag{2}$$

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 and 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,

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

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 this framework is the assumption that migrations 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. It is difficult to test the Markov assumption in practice, but it is usually accepted as having good local approximation for shorter samples and more problematic if estimating over several business cycles.

4 Empirical Application

Loan delinquency and potential loss 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 Ireland[4]. This unique dataset includes 25 months of arrears balances over the period December 2009 to December 2011 for 550,000 mortgages of various vintage, representing 85 per cent of the Irish mortgage market. Each loan is categorised into one of five states. The first is a performing loan, with no arrears. The next three states capture the stages of delinquency; 30-60, 60-90, 90-360 days in arrears and finally a default state. Default of a mortgage is difficult to define in an Irish context due to changes in the Code of Conduct on Mortgage Arrears (CCMA) and forbearance[5]. For ease of comparison, we adopt the Moody's definition applied to securitised mortgage pools issued by Irish banks with default defined as a loan 360 or more days in arrears. The result is a sample of 13.75 million loan migrations over which transition intensities can be estimated.

The possible transitions paths is an important issue. The transitions which are modelled, A-G, are outlined in Figure 1 below. The shaded squares are impossible transitions as a

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

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

mortgage can only deteriorate by one months payment at a time. The only other possible transitions are from 90-360 DPD to 60-90DPD and/or performing and 60-90DPD back to performing, which all total to less than 0.01 per cent of all transitions. Accurate estimation of the covariate effect is not feasible with such small numbers. However, thee transitions are not ignored. It is assumed that loans deep in delinquency pass-through the mild delinquency states on the way to recovery. For example the 60-90DPD to performing is assumed to move unobserved through 30-60DPD.

A rigorous overview of the loan book is provided by Kennedy and McIndoe-Calder (2011), therefore, focus here is confined to loan delinquency and potential losses. Figure 2 shows the evolution of the states through the sample period. There is a clear deteriorating trend with delinquency pools more than doubling over the sample period. The stabilisation of the 30 day arrears pool in the last quarter is positive and if maintained will feed into the other pools over time. Expected losses will depend on the intersection of these arrears with mortgages in negative equity. As of December 2011, 74 per cent of mortgages in the 90 day arrears pool are also in negative equity.

Estimation of the transition probabilities in Section 3 depends on upgrades (mortgages with decreasing arrears moving states toward the performing pool) and downgrades (mortgages with growing levels of arrears migrating toward default). Figure 3 shows the proportion of the book moving states through the sample period. The number of moving loans, both upgrades and downgrades grew sharply to a peak in mid-2011, with the number of downgrades on average twice that of upgrades. This is consistent with the sharp growth in the delinquency pools in Figure 2. Comparing the number and the value of migrating loans, there is evidence that on average larger loans are moving states.

4.1 Primary Dwelling and Investment Mortgages

The loan book can be decomposed into investment properties (BTL), accounting for 22 per cent of outstanding balances and primary dwelling household (PDH) mortgages. The residential investment loan book is highly concentrated around the peak of house prices, with 75 per cent of the BTL mortgages issued between 2003 and 2007, compared to 58 per cent in the PDH book. The average balance of an investment mortgage is €218,090, 68 per cent greater than the average of the PDH book. This suggests investment loans pose a higher credit risk and benefit from being modelled separately to the PDH segment of the book.

Applying the methodology without covariates outlined in Section 3, Table 1 shows the one year transformation matrix for PDH and BTL loans. The probability, over one year that a currently performing loan will be 360 days in arrears is less than one per cent in both the PDH and BTL portfolios. The superior credit quality of the PDH loans is evident with default almost three times more likely in the BTL market. The tipping point for PDH loans is 60 day arrears - after this point the likelihood of progression toward default (78 per cent) is far greater than recovery (22 per cent). Loans for investment are more likely to continue to deteriorate than recover even if just 30 days in arrears. 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.

While these results provide a good benchmark, the importance of loan vintage and other macro risk factors discussed above renders them unsuitable for generating expected loss estimates.

4.2 Factors affecting the Probability of Default

Estimating accurate expected loss figures requires conditioning default probabilities on time invariant borrower factors and and time varying macro-economic factors. Betancourt(1999) shows mortgages are more likely to remain performing as they age. This effect is particularly relevant for Ireland. 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 standards[6], 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. Since 2007, house prices have fallen 50 per cent, while the unemployment rate has risen from 5 to almost 15 per cent. The net effect is a tranche of mortgages with high repayment burden and negative equity. This amplifies the natural reduction in repayment

[6]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.

burden due to loan seasoning generating a 'hump-shape' expectation of mortgage default peaking toward the end of the house price boom.

While vintage attempts to capture the evolution of Irish mortgage market in terms of more accommodating credit standards and the change in funding source for lending, the current performance of the domestic economy will have a large impact on the performance of these loans. To capture these effects two further factors are considered - regional unemployment and house prices through current LTV.

House prices, usually through the negative equity concept are a common conditioning variable in scoring models. 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 less, at 43 per cent[7]. These peak-to-through house price falls are second only to Japan as the largest ever recorded, and continue to fall in excess of 14 per cent annually.

With mortgage delinquency closely related to house price movements as scoring models suggest, one expects variation in default probabilities based on property location. This variation by region is amplified by the timing of construction, with early building mainly in cities such as Dublin and Cork and a progressive movement toward more rural area's such as the West and Midland regions. The dataset provides information on the property valuation at mortgage origination. 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 region[8]. These indices are shown in Figure 4, with a similar trend across regions but significant variation in level, with peak Dublin price of €420,000, 47 per cent greater than the Midland peak of €285,000. These regional price indices are used to adjust original valuations from those recorded at origination to current on a loan level basis.

The second main potential determinant in mortgage defaults 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

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

[8]Regional breakdown is based on the EuroStat NUTS3 classification.

largest effect on arrears rates[9]. The current employment status of an individual is not available in the loan level dataset. However, it is possible to compute the regional level of unemployment and link it to the loan book through the borrower location[10]. Figure 4 presents the unemployment rate by region. There is large variation across unemployment rates with Border region (30.1 per cent) almost double that of the MidEast (15.7 per cent).

Although there is a significant body of evidence showing unemployment has a significant impact on an individual's ability to repay (Elul et al (2010)), there is less conclusive evidence on the lag between income shock caused by unemployment and the start of loan delinquency. The level of unobserved personal savings and wealth will have a large impact on lag length. To determine the best specification in terms of unemployment, goodness-of-fit tests determine the lag length which best fits the observed transitions. For models with observations at arbitrary times and not on the exact transition times, the formal test by Aguirre-Hernandez and Farewell (2002) provides a test of fit adequacy. Currently, no formal test exists for models with directly observable transitions such as those found in the loan level data. Therefore, best fit is determined by estimating the observed numbers of loans occupying each state on a monthly basis, and comparing these with forecasts from the fitted models. The superior model is determined as the specification with the smallest error in predicting the number in the default (360+DPD) state.

Table 2 shows the fit across a number of unemployment lag specifications; contemporaneous, 3, 6, 9, 12 and 24 month lags, with the 12 month lag providing the best fit for both PDH and BTL books. Specifying separate models for the PDH and BTL books, the effects of these covariates are estimated using the panel of 550,000 loans in the proportional hazard model,

[9] See Elul et al. (2010)

[10] Regional unemployment rates are not published on a monthly basis in Ireland. There is a dataset with regional monthly information on the number of individuals claiming work seeking benefits. This is expressed as a proportion of the labour force which is recorded as part of the Quarterly National Household Survey (QNHS). This will be higher than the official unemployment rate as part-time workers will, in some cases receive welfare benefits but are not considered officially unemployed. This rate could be a more accurate measure for repayment distress as reduced working hours will have a significant impact on repayment capacity.

$$\lambda_{A,B}(t,z) = \lambda_{A,B,0}(t) exp\{\beta_{A,B,1} Vint_i + \beta_{A,B,2} Vint_i^2 + \beta_{A,B,3} LTV_i + \beta_{A,B,4} UN_i\} \quad (3)$$

where $\lambda_{A,B}$ is the transition intensity between states A and B, for example from performing to 30-60DPD. Deviations from the baseline hazard function, $\lambda_{A,B,0}(t)$ are explained by the number of months since origination ($Vint_i$), number of months since origination squared ($Vint_i^2$), current loan to value ratio (LTV_i) and regional unemployment (UN_i) for loan i.

To allow for the investigation of the vintage effect in isolation, Figure 5 presents default probabilities across a range of vintages with house prices and unemployment assuming a zero value. This allows for investigation of the vintage effect in isolation. There is a higher rate of delinquency for residential investments loans, with a high of 7.4 per cent compared to 4.7 per cent for the PDH loans. The BTL peak is also later, in early 2007, consistent with the relatively late growth of the investment mortgage market.

Table 3 shows the coefficients for LTV and unemployment at each transition intensity for both BTL and PDH 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 1.2 per cent increase in the risk of a performing loan missing a payment in the PDH book. Delinquency rates in the BTL book are even more closely linked to unemployment levels with a 2.8 per cent increase in performing to 30-60DPD hazard for a percentage point increase in unemployment rates. Unemployment also plays an important role in the cure rates for delinquent loans. There is a 2 per cent increase in the cure rate for 90-360DPD to 60-90DPD for a 1 percentage point fall in unemployment levels. This effect is weaker for the BTL segment with a 1.2 per cent increase in the same cure rate. With almost one quarter of BTL borrowers also having a PDH loan, these results are consistent with the behavioural hypothesis whereby individuals prioritise payment of PDH loans over those for investment purposes. In the event of job loss, these individuals are more likely to service the mortgage on their primary dwelling and are more likely to cure arrears on the PDH loan upon re-entry to the labour market.

While significant, the effect of house price movements, through current LTV is weaker.

An increase of one in the current LTV level results in a 0.5 per cent increase in the hazard rate of loans from performing to 30-60DPD. If part of the loan delinquency rates can be explained by borrowers behaviour when the loan enters negative equity, default probabilities could exhibit a non-linear relationship with LTV ratios. Although the hazard rates are modelled as a linear function in LTV, due to the complex number of possible transitions, the overall effect of house prices on default probabilities may not remain linear.

Figure 6 presents the convex relationship between default probabilities and LTV levels. For PDH mortgages, increasing LTV by 10 per cent from 50 to 55 yields a 6.9 per cent increase in 3 year default probabilities while the same 10 per cent increase from a LTV of 150 to 165 causes a 17.2 percent increase in default probabilities. There is an expectation that mortgages for investment purposes are more sensitive to negative equity, as rational investors will discount future earnings (rent) and capital appreciation (house price expectations) against current cost (loan outstanding). Results show the BTL segment of the book is also convex in LTV with the same increase in LTV from 150 to 165 yielding a 22 per cent increase in 3 year default probabilities.

In the debate comparing the improvement of the loan book due to house price recovery versus labour market recovery, the coefficient on 90-360DPD to 60-90DPD is more than three times greater for unemployment compared to LTV. For example, taking a loan with an LTV of 87 (average LTV across all loans as of December 2011), a balance reduction of 45 per cent(€7.5 billion or 6.75 of total mortgage book value) of loans in 90+DPD is required to have the same effect on cure rates from 90+DPD to performing as a labour market recovery to an unemployment rate of 7 per cent[11]. These results suggest policies aimed at stimulating domestic demand and hence lowering unemployment levels could be more cost effective than loan modifications such as debt forgiveness aimed at lowering current LTV levels.

A key advantage of modelling the macro drivers of mortgage delinquency and default rates is to accurately provide predictions of changes to economic conditions. For example, if

[11] It is important to note, LTV exhibits a non-linear relationship with default probability and therefore this scenario is dependent on LTV starting point. Further, this scenario only considers simple first round effects and ignores the relationship between labour market recovery and house prices.

house prices were to remain depressed in the medium term but the domestic economy experiences a recovery, the lower unemployment rates would result in a significant improvement in the delinquency rates. Out-of sample forecasts allow one to test the predictive ability of the model. Transition intensities are estimated over the sub-sample of December 2009 to December 2010 and are used to forecast arrears pools through 2011. Figure 7 presents the actual and forecast of the changes in the default (360+DPD) pool, with 95 per cent confidence intervals generated from boot-strapping with 100,000 replications. The forecast provides an accurate estimate of the arrears trends through 2011 with only a small level of forecast error, always remaining within the 95 per cent confidence bands.

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 then applied to the loan books of the four guaranteed banks.[12] Expected loss estimates are generated for the mortgages books over the three year horizon, 2011 to 2013 under differing scenarios for the housing market and unemployment outlook.

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

- *The probability of a mortgage defaulting, a unique value based on the loan vintage, current LTV and local labour market conditions.*
- *A mortgage is considered to default upon entering state 5, i.e. greater than 360 days in arrears.*
- *The loss given default (LDG) is calculated as negative equity proportion of the mortgage and a further 20 per cent of the current balance.*

Negative equity for the LDG is calculated as the difference between current house price and the mortgage balance outstanding. As outlined in Section 4.2, current house prices are calculated as the property valuation at origination brought forward using the change

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

in median regional house prices, from more recently issued loans. The additional 20 per cent 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.[13] Two different sets of estimates are provided based on forecasts of economic conditions between 2011 and 2013. The forecast of the housing market conditions and unemployment rates are based upon the baseline and the stressed cases as outlined in the macro scenarios for capital assessment published by the Central Bank of Ireland.[14]

All owner occupier loans from the covered institutions, with a total balance of €74.5billion are used in the expected loss calculations. Lending into the UK (approximately €20.4billion) is not analysed but the underlying framework could be extended to include foreign lending. The baseline scenario involves house prices falls (unemployment rates) of 13.4 (13.4) and 14.4 (12.7) per cent in 2011 and 2012 and a small recovery of 0.5 (11.5) per cent in 2013, while, under the stress scenario, the economic conditions are more severe with house prices falling (unemployment rates) of 17.4 (14.9) and 18.8 (15.8) per cent in 2011 and 2012 and a small recovery of 0.5 (15.6) per cent in 2013.

If the stock of 360+day arrears at December 2010 (2 per cent of outstanding balance) is evenly realised over the 3 year period and future loans entering into the default state are immediately realised, the expected loss in the baseline scenario is 4.6 per cent of the book. A higher loss of 6 per cent of the mortgage book occurs under the stressed scenario. The timing of when the banks realise the losses has a significant impact on the size, as the main driver of losses is negative equity and therefore reflect future house price paths. The difference in the average LGD (43 and 52 per cent) under the scenarios above shows the potential effect of losses occurring at different points in the house price cycle.

Direct comparison of these losses with those outlined under the FMP 2011 is difficult as these losses are only for owner occupier mortgages, which, as shown in Section 4.1, have a significantly lower risk profile. Further, the FMP estimates are conservative by design and take 69 per cent of BlackRock Solutions lifetime (30 year) stressed losses (after the impact

[13] The 20 per cent fixed cost matches the assumptions outlined under PCAR 2011.

[14] See www.centralbank.ie

of deleveraging) into the 2011-2013 loss calculations.[15]

6 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/IMF and ECB. 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 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 modelled in a migration framework, where loans are classified into one of five 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.

In comparison to a Logit/Probit framework, the estimation of the entire system and not just the single transition from performing to 90 day arrears provides a richer framework for calculation of expected loss estimates for mortgage books. The default probabilities are calculated at the loan level and reflect the baseline and the stressed cases outlined in the macro scenarios for capital assessment published by the Central Bank of Ireland.[16] The baseline scenario generates losses of 4.6 per cent of the book, while a higher loss of 6 per cent of the mortgage book occurs under the stressed scenario. The stressed scenario involves larger house price drops and unemployment levels which remain in the region of 15.5 per cent.

Crucially in this framework, the transition probabilities are a function of macro factors such as house prices and unemployment. In terms of these variables, the rates of transitions are found to be significantly more sensitive to unemployment compared to house price

[15]See www.centralbank.ie

[16]See www.centralbank.ie

movements. For a recourse mortgage market such as Ireland, this shows the ability-to-pay effect dominates the negative equity behavioural hypothesis. This suggests policies aimed at stimulating the domestic economy, and hence lowering unemployment will yield more efficient outcome than policy aimed a debt reduction (lowering current LTV).

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Figure 1
Possible Transition Paths for Loans

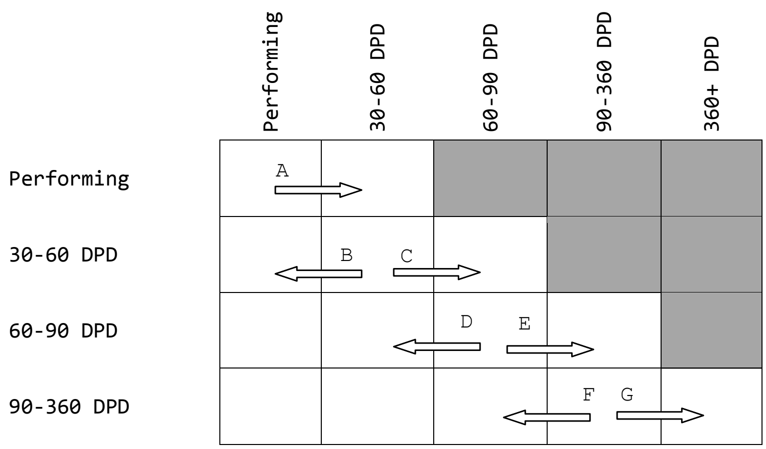


Table 1: One Year Unconditional Transition Probabilities

	PDH					BTL				
	P	30-60DPD	60-90DPD	90-360DPD	360+DPD	P	30-60DPD	60-90DPD	90-360DPD	360+DPD
P	95.14%	1.98%	0.88%	1.66%	0.34%	92.34%	2.20%	1.22%	3.28%	0.96%
30-60DPD	57.12%	3.32%	3.83%	25.82%	9.91%	45.77%	1.78%	2.56%	31.41%	18.48%
60-90DPD	15.07%	2.28%	4.51%	51.60%	26.54%	6.54%	0.66%	2.35%	50.88%	39.56%
90-360DPD	1.85%	1.00%	3.36%	55.28%	38.52%	0.61%	0.28%	1.75%	48.35%	49.01%
360+DPD	0%	0%	0%	0%	100.00%	0%	0%	0%	0%	100.00%

Table 2: Goodness-of-Fit Tests

	PDH	LTV
Lag Specification		
UN	1.189	4.274
UN_3	1.188	4.268
UN_6	1.184	4.249
UN_9	1.178	4.204
UN_{12}	1.157*	4.108*
UN_{24}	1.198	4.279

Notes: This table shows the sum of the errors (in percentage terms) between the observed number of loans in the default state and the number predicted from the fitted model, with unemployment entered at various lag lengths. The estimated model takes the form of the proportional hazard model,

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

where λ is the transition intensity between states A and B (e.g. P to 30-60DPD), z^T is a covariate vector containing $Vint_{t,i}$, $Vint^2_{t,i}$, $LTV_{t,i}$ and $UN_{t,i}$ - the number of months since origination, number of months since origination squared, current loan-to-value ratio and regional unemployment at the loan level.* denotes the specification with superior fit

Table 3: Coefficient Estimates for Macro Effects on Transition Intensities

	PDH		BTL	
	LTV	UN	LTV	UN
Deteriorating Transitions				
P to 30-60DPD	0.0063*	0.012*	0.007*	0.028*
	(0.0062,0.0066)	*(0.010,0.013)*	*(0.006,0.008)*	*(0.024,0.031)*
30-60DPD to 60-90DPD	0.0017*	-0.001	0.0036*	0.00449*
	(0.0014,0.0020)	*(-0.0036,0.0005)*	*(0.0031,0.0041)*	*(0.0001,0.009)*
60-90DPD to 90-360DPD	0.0002	-0.001*	0.0019*	0.0028
	(-0.0001,0.0005)	*(-0.004,0.0004)*	*(0.0013,0.0024)*	*(-0.0022,0.0078)*
90-360DPD to 360+DPD	0.0001	0.0033*	0.0013*	0.0119*
	(-0.0001,0.0002)	*(-0.0004,0.044)*	*(0.0004,0.00023)*	*(0.003,0.020)*
Improving Transitions				
30-60DPD to P	-0.0033*	-0.009*	-0.004*	0.002
	(-0.0035,-0.0031)	*(-0.01,-0.007)*	*(-0.005,-0.003)*	*(-0.002,0.006)*
60-90DPD to 30-60DPD	-0.0041*	-0.007*	-0.0046*	-0.0075*
	(-0.0045,-0.0037)	*(-0.0102,-0.0037)*	*(-0.0056,-0.0037)*	*(-0.008,-0.006)*
90-360DPD to 60-90DPD	-0.0062*	-0.019*	-0.007*	-0.012*
	(-0.0067,-0.0056)	*(-0.0234,-0.015)*	*(-0.008,-0.006)*	*(-0.022,-0.001)*

Notes: P = performing and DPD = days past due.
This table shows the LTV and UN coefficients for each transition intensity in the proportional hazard model,

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

where λ is the transition intensity between states A and B (e.g. P to 30-60DPD), z^T is a covariate vector containing $Vint_{t,i}$, $Vint^2_{t,i}$, $LTV_{t,i}$ and $UN_{12,t,i}$ - the number of months since origination, number of months since origination squared, current loan-to-value ratio and regional unemployment at the loan level. The 95 percent confidence intervals for coefficients are given in parenthesis. * denotes significance with 95 per cent confidence. Other possible transition paths (i.e. 60-90DPD to P, 90-360DPD to 30-60DPD and 90-360DPD to P) are not estimated due to the limited number of transitions on these paths - less that 0.5 per cent of all transitions. Any loan moving from 90-360DPD to P is assumed to travel through 30-60DPD and 60-90DPD.

Figure 2
Proportion of Mortgage Book in Arrears (Outstanding Balance)

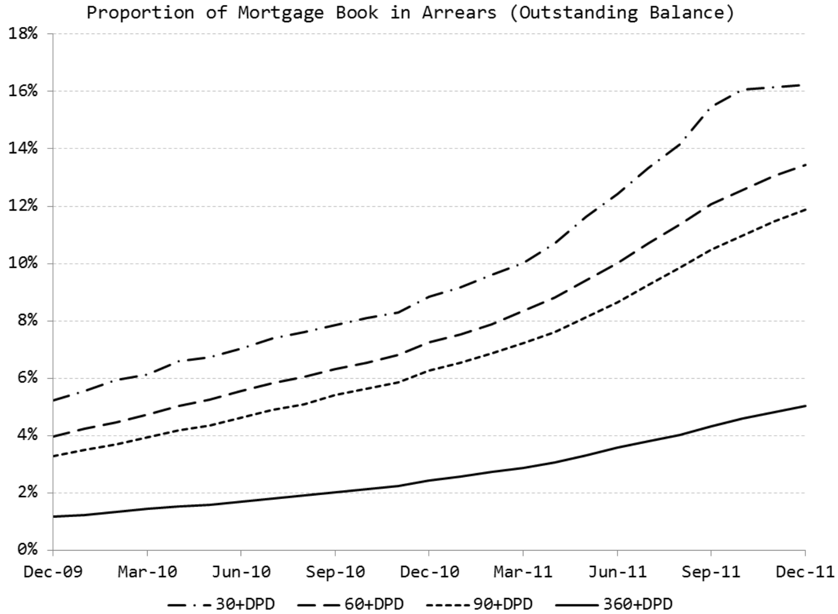
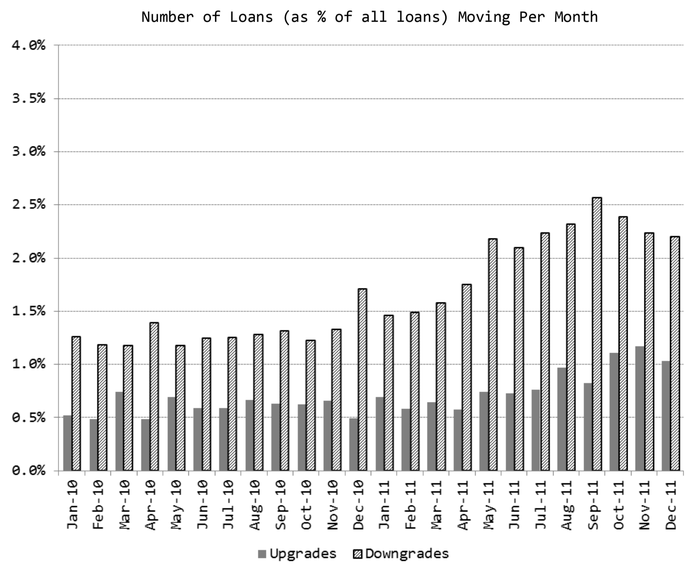


Figure 3
Monthly Upgrades and Downgrades between States (Dec2009 – Dec2011)



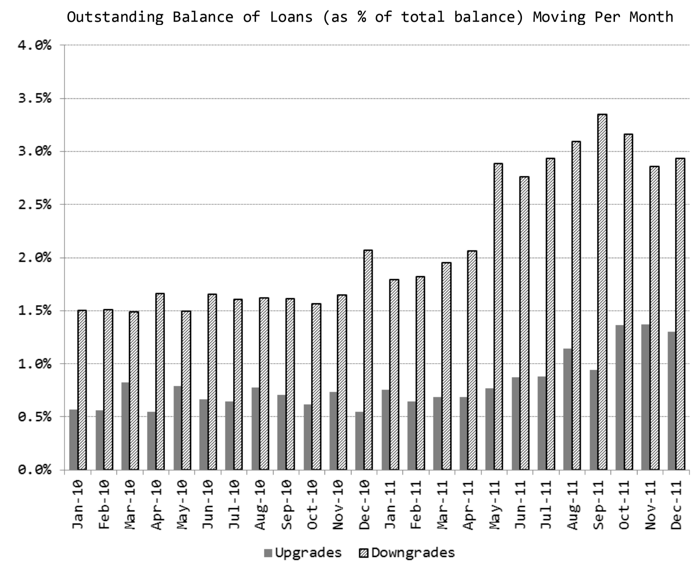
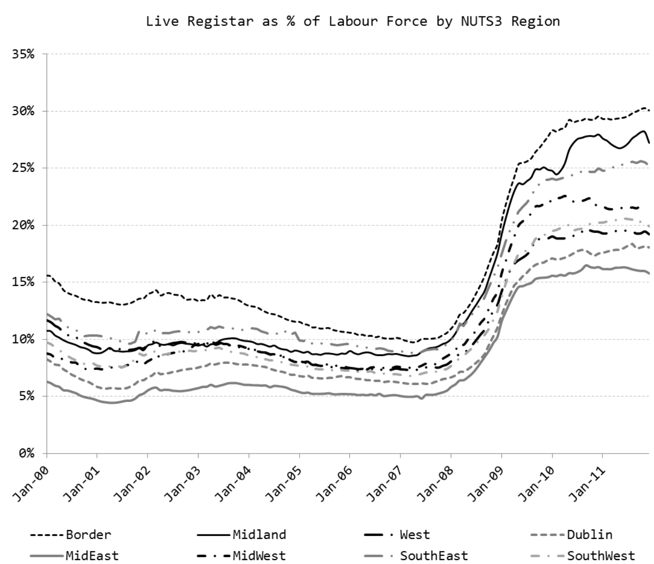


Figure 4
Time Series of Macro Factors



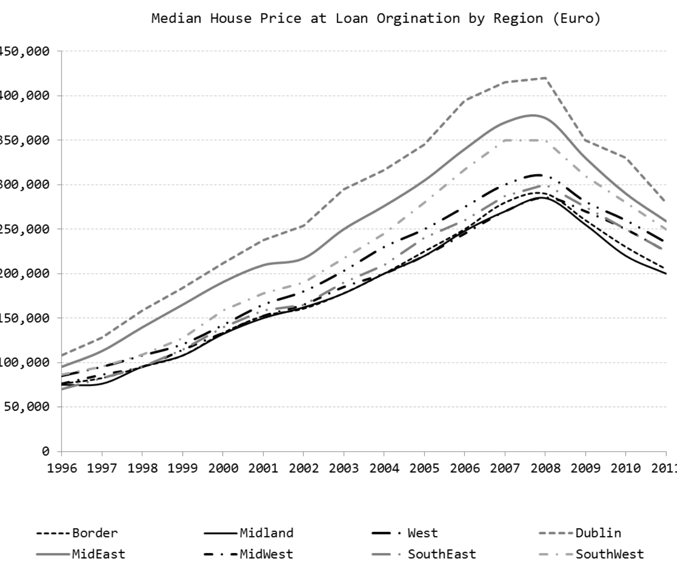


Figure 5
3Yr Default Probability for Performing Mortgages by Loan Type

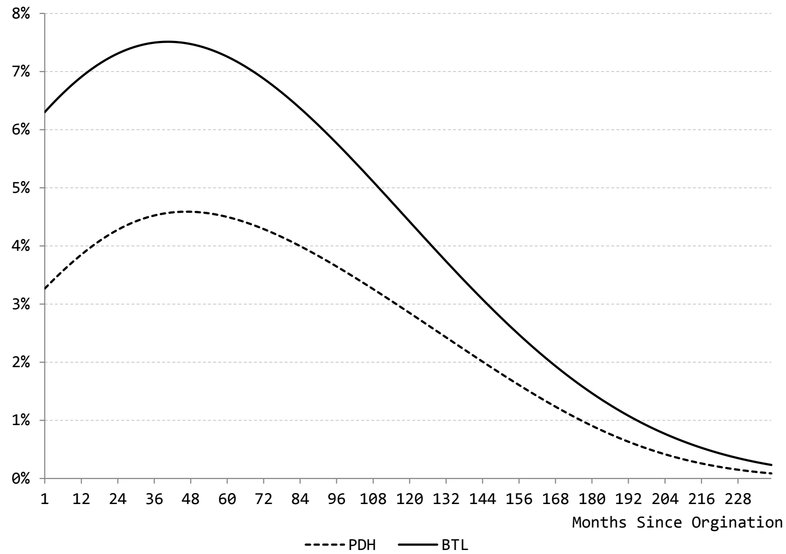
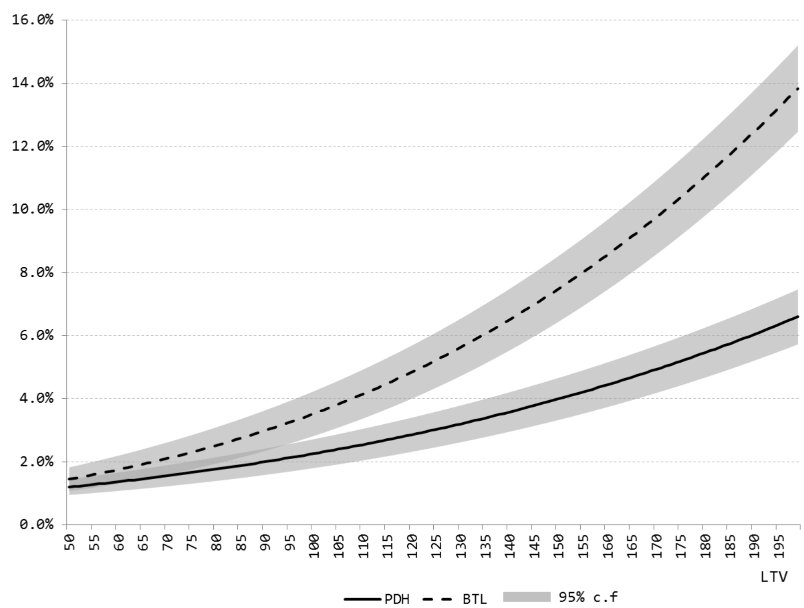


Figure 6
Relationship between Default Probabilities and LTV



Note: To illustrate the relationship between default probabilities and current LTV, vintage is fixed to loan issued in 2006 and unemployment is fixed at the current national rate (14.1% as of December 2011).

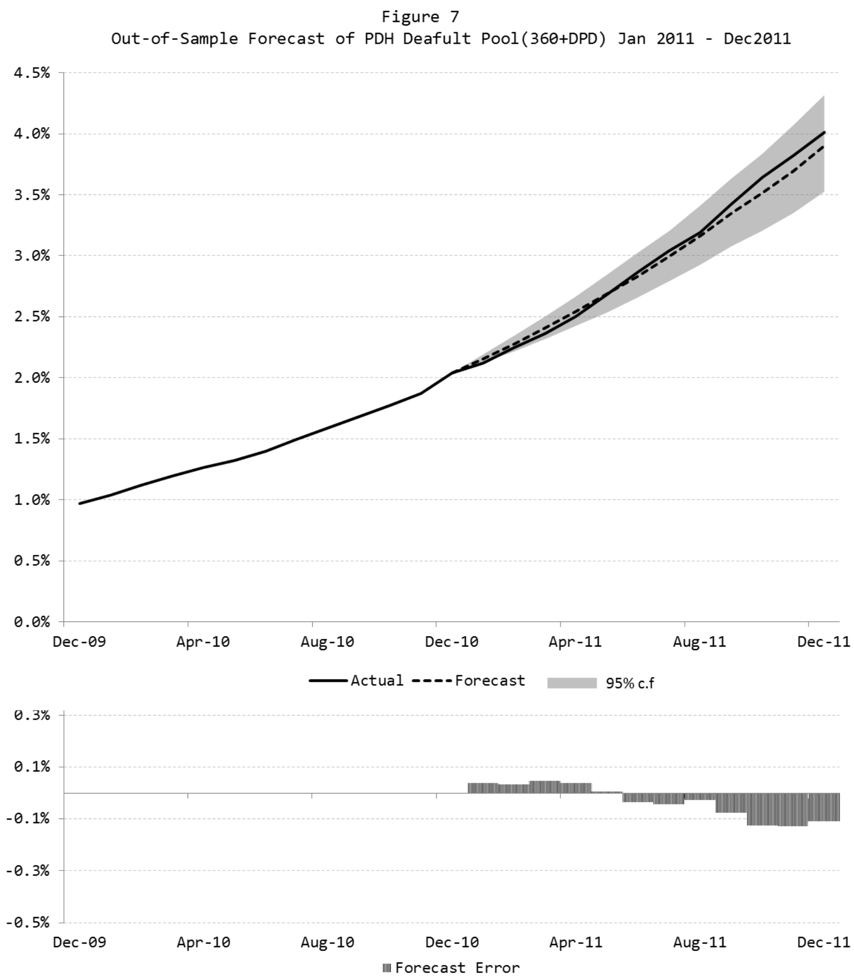


Figure 7
Out-of-Sample Forecast of PDH Deafult Pool(360+DPD) Jan 2011 - Dec2011
4.5%
4.0%
3.5%
3.0%
2.5%
2.0%
1.5%
1.0%
0.5%
0.0%
Dec-09
Apr-10
Aug-10
Dec-10
Apr-11
Aug-11
Dec-11
Actual
Forecast
95% c.f
0.3%
0.1%
-0.1%
-0.3%
-0.5%
Dec-09
Apr-10
Aug-10
Dec-10
Apr-11
Aug-11
Dec-11
Forecast Error