Macroprudential mortgage restrictions and the risk profile of new lending

Fergal McCann and Ellen Ryan[1]

Financial Stability Division

Central Bank of Ireland

Abstract

The Irish experience provides a textbook example of the interaction between credit dynamics, leverage and real estate prices and the consequences for both the financial system and real economy. With the lessons from the financial crisis period fresh in the minds of policy makers, the Central Bank of Ireland introduced a package of borrower-based measures consisting of both limits on loan to value (LTV) and loan to income (LTI) ratios for new mortgage loans in February of 2015. The aim of this paper is to provide an early assessment of developments in the resilience of bank lending since the introduction of these borrower-based measures. We focus on the evolution over time of two key components of "expected loss" for a bank's loan portfolio, namely probability of default and loss given default. The availability of granular loan-level data allows for a detailed examination of these key measures of resilience, including their drivers and their variation both within and across loan portfolios.

(1) **Introduction**

Since the financial crisis the use of macroprudential instruments, aiming to mitigate the build-up of systemic risk and increase the financial system's resilience, has expanded across Europe (see ESRB (2017)). Given the interaction between credit dynamics, leverage and real estate prices, many of these instruments directly target the real estate sector. The Irish experience is a textbook example of these dynamics. House prices in Ireland underwent growth of 60% between 2003 and their peak in 2007, before falling by over 50% to their trough in 2013. Related to this decline in house prices and associated collapse in economic activity, was a surge in mortgage arrears cases which contributed to a solvency crisis in the domestic banking system, leading to injections of government capital in the 2011 Prudential Capital Assessment Review (PCAR).

With the lessons from the financial crisis period fresh in the minds of policy makers, the Central Bank of Ireland introduced a package of borrower-based measures consisting of both limits on loan to value (LTV) and loan to income (LTI) ratios for new mortgage loans in February of 2015.[2] These measures have two primary aims;

1. to enhance the resilience of borrowers and lenders and;
2. to prevent the development of future price-credit feedback loops in the housing market.

The aim of this paper is to provide an early assessment of developments in the resilience of bank lending since the introduction of the borrower-based measures. We focus on the evolution over time of two key components of "expected loss" for a bank's loan portfolio. Expected loss for any given loan (or at an aggregate level loan portfolio) can be calculated as follows

Expected Loss = (Probability of Default)(Exposure at Default)*(Loss Given Default)*

[1] The views presented in this paper are those of the authors alone and do not represent the official views of the Central Bank of Ireland or the European System of Central Banks.

[2] Further information on the Central Bank of Ireland' macroprudential mortgage measures can be found on the Central Bank's website here.

This paper first uses a Probability of Default (PD) model developed at the Central Bank of Ireland to provide model-based estimates of the financial resilience of pools of mortgages in terms of the likelihood_of loan default. As the implications of any given level of PD for bank resilience will be determined by the magnitude of loss given default (LGD), we then examine changes in hypothetical LGD over time under a range of house price shock scenarios. Both approaches focus on the originating characteristics of cohorts of mortgages originated between 2003 and 2016, as this allows a fair comparison of the risk profile of loans *as they were issued* across the thirteen-year time horizon. Our analysis provides a PD and LGD profile of lending before and after the introduction of the borrower-based measures; it should not however be interpreted as providing evidence of the *causal effect* of the measures on balance sheet resilience of borrowers or lenders.

(2) Data

We utilise data on every mortgage outstanding in five Irish banks' mortgage books at end-2014, and all loans issued in 2015 and the first half of 2016. The banks submitting the mortgage data are Allied Irish Banks (including all loans originally issued by EBS before these institutions merged), Bank of Ireland, Permanent TSB, KBC Ireland and Ulster Bank Ireland Limited. The data come from two separate sources. Firstly, for all loans issued up to the end of 2014, we take information on the originating characteristics of these loans from the Central Bank's Loan Level Data (LLD), which captures information on all loans outstanding at participating banks on a six-monthly basis. From the LLD, the originating profile of all mortgages issued between 2003 and 2014 (and still outstanding at 2014) is compiled. This is combined with information on all new loans issued in 2015 and 2016 in a “Monitoring Template"” (MT) database which is submitted by all mortgage lenders to the Central Bank to allow monitoring of compliance with the regulations.

Differentiating between loans that are and are not subject to the borrower-based measures (the regulations), allows us to compare the risk profile of mortgage loans originated under the regulations to cohorts of loans issued earlier. In the MT data, loans can be classified as "in-scope", meaning that they are subject to the regulations, or "out-of-scope", meaning that the loan was originated in 2015 but is not subject to the restrictions set out in the regulations. Loans can be out-of-scope because they were originated before the regulations' introduction date of 9/2/2015, or because they were drawn down after the regulations' introduction but approved beforehand, as well as for other reasons.

(3) Probability of Default

For all loans in the data, we aim to calculate a “year one PD” in order to measure the risk profile of mortgages as they appeared at the time they were originated. These default probabilities are calculated over a one-year horizon, using an internal stress testing model for the Irish mortgage market. An early version of the residential Irish mortgage PD model is available in Kelly and O’Malley (2016), while the broader LLF framework of the Central Bank of Ireland is discussed in detail in Gaffney, Kelly and McCann (2013).

The model utilised is a Multi-State Model (MSM), first introduced by Jackson (2011) whereby coefficients are estimated on a set of covariates affecting both the transition into and out of default. The model's statistically significant coefficient estimates confirm that the longer loans spend in default, the less likely they are to return to performing status (“cure”). Loans with a higher Originating Debt Service Ratio are shown to have a higher PD. Loans with a higher Current Loan to Value are shown to have both a higher PD and a lower probability of cure. The same is true of loans in regions with higher unemployment and loans with higher interest rates. Standard Variable Rate (those where the lender has discretion over how the interest rate varies throughout the loan’s lifetime) and Tracker mortgages (those whose interest rate varies mechanically with variations in the ECB policy rate with a fixed margin) are shown to have higher PDs than fixed rate loans. Loans attached to multi-loan facilities are also shown to have higher PDs. The effect of loan age is shown to be non-linear: as loans age from their first year through to their eighth, the PD continues to rise, and falls thereafter. Finally, Buy To Let loans are shown to have both higher PD and lower probability of cure than primary dwelling loans.

To allow for a comparison of the risk profile of new lending over time, we transform all mortgages in the data to appear as they did when the loan was issued. We then use the coefficients from the aforementioned PD model to calculate an at-origination PD for each loan issued from 2003 to 2016. In all cases, the statistic calculated, PD_{it} is the probability that a performing loan i issued in year t will transition into default over a one-year horizon.

(3.1) Probability of Default findings

In Figure 1, we calculate the balance-weighted portfolio PD, PD_{pt} , across all loans issued in each year t

$$PD_{pt} = \frac{\sum_{i=1}^{n} OB_{it} * PD_{it}}{\sum_{i=1}^{n} OB_{it}}$$

Where OB_{it} is the drawn balance at origination of each loan i issued in year t, which is summed across all loans issued in year t. As would be expected, loans issued in the 2006 to 2008 period had the highest-risk profile at origination according to the model parameters. The chart illustrates that the loans issued within the scope of the regulations (both 2015_Reg and 2016) are low-risk in an aggregate historical perspective, with PD_{pt} being at its lowest level since 2011.

Figure 1: ***Percentage of total drawn balance predicted to enter default over a one year horizon as per originating characteristics of mortgages***

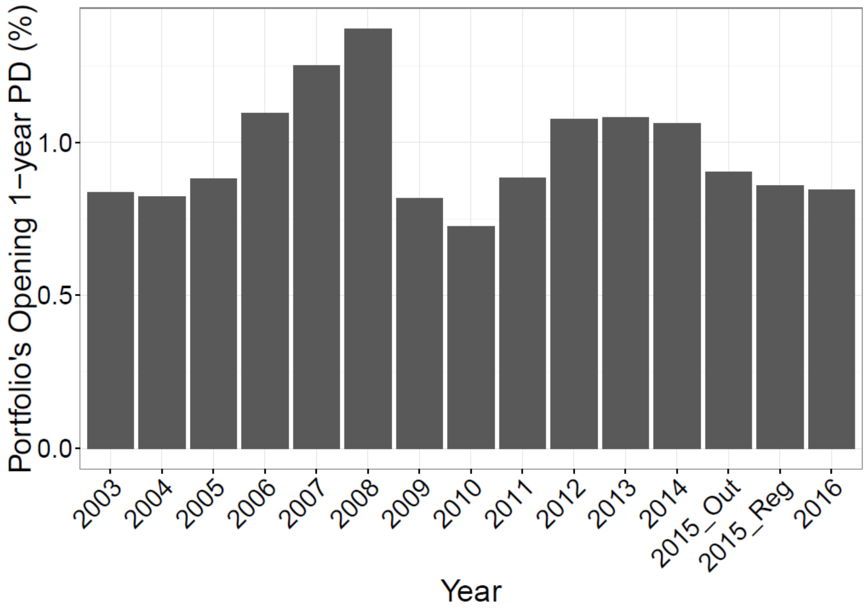
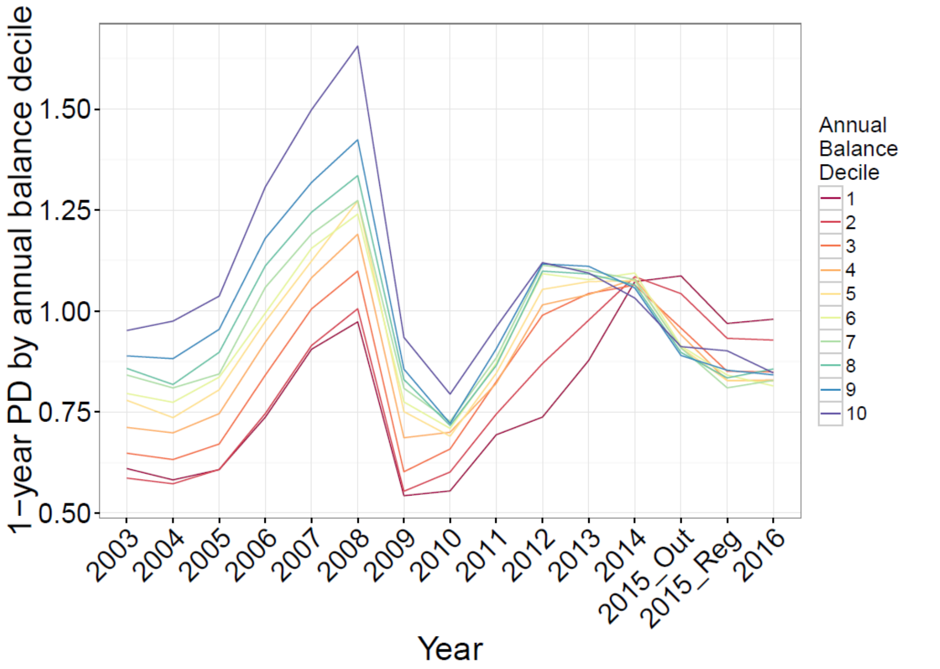


Figure 2 splits each year's originating loan size distribution into deciles and calculates the average PD within each year-decile. The average PDs from 2003 to 2008 follow the pattern that one would expect given the property price boom experienced in Ireland during the period, with PDs rising within each decile in each year. During that period there is also a clear relationship between loan size and risk: PDs increase as we move up the loan size distribution. By 2008, the average originating PD in the top decile of loan size was close to double that in the bottom decile. The post-2008 period however brought about compression in the spread of loan risk across the loan size distribution. In the years up to 2013, larger loans continued to have higher PDs, but differentials across loan size deciles were smaller. The 2014-2016 period has seen this relationship overturned, with the largest loans having lower PDs on average.

Figure 2: ***Average PD per decile of each year's originating loan balance distribution***



A breakdown in the relationship between loan size and loan risk has obvious benefits from a financial stability perspective, in that overall portfolio Expected Losses will always be lower, all other things equal, in cases where loans with larger balances are lower-risk. While there has been a change in the correlation between loan size and OLTV, as will be shown in the next section, this is only part of the explanation for the lowering of PDs on large loans in recent years. On top of this change in the LTV distribution, more high-balance loans are now being issued with fixed mortgage interest rates (and commensurately lower interest rates due to banks' pricing policies), and more low-balance loans are now being issued to BTL borrowers. Given that the model assigns a higher PD to loans with higher interest rate, SVR loans and Tracker loans (relative to fixed-rate loans), and BTL loans, the aforementioned changing patterns in lending across the loan size distribution are all contributing to changes in aggregate cohort PDs through time.

(4. Loss Given Default

While the likelihood of a lender's loans defaulting is obviously central to any analysis of its resilience, the size of loss incurred in the event of default is also of great importance as this has the potential to limit or amplify the effect of any given level of PD on portfolio Expected Loss. Our analysis focuses on losses that would be experienced by a lender in the event of a default, abstracting from both the probability of default (PD) and its drivers. Prior to undertaking our analysis, a number of assumptions are made regarding sale costs in the event of liquidation and realisation of collateral:

- Legal and administrative costs of repossession amount to 5% of the price of a house at the time of its sale and;
- A “liquidation haircut” or “fire sale discount” of 20% is also applied to acknowledge that properties in repossession may be subject to additional price cuts that result from reduced demand for repossessed properties, potential for value reduction due to lack of investment in property upkeep during the foreclosure and externalities arising from the sale of many properties of a similar nature in a downturn.

Hypothetical loss magnitude is then calculated for each loan under negative house price shocks ranging from 0 to 20%. Loss occurs when the recovery value of collateral (the property) is less than the originating value of the corresponding loan. Given cost assumptions, recovery value can be calculated as

$$Recovery\ Value = (Original\ Property\ Value) * (1 - \ Price\ Shock) * (1 - Legal\ and\ Admin\ Costs) * (1 - Liquidation\ Haircut)$$

Hypothetical loss size can then be calculated as the difference between loan size and recovery value.

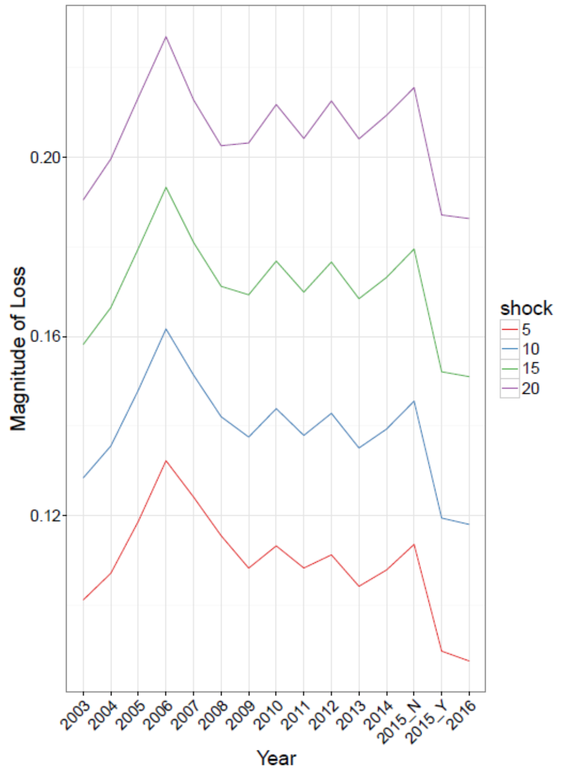
$$Loss = Originating\ Loan\ Size - Recovery\ Value$$

To examine the implications of lending behaviour for bank resilience we compare the magnitude of hypothetical losses likely to be experienced under various house price scenarios across years of origination. We construct an aggregate yearly measure of bank loss by aggregating potential losses among all loans issued within a given year. We express this measure as a ratio to total new mortgage lending in the same year and refer to it as the magnitude of loss.

$$Magnitude\ of\ Loss = \frac{Sum\ of\ losses}{Total\ lending}$$

In the above calculation, in cases where the recovery value is greater than the outstanding loan amount, a loss value of zero is applied. In Figure 3 we see that, relative to the total size of loans issued in a year, the magnitude of possible losses under each house price scenario rose steadily from 2003 to 2006. There has been a downward trend or stabilisation between 2007 and 2013, depending on the house price shock chosen. Following "2015-N" (loans issued in 2015 but outside the scope of regulation) there is a substantial drop in loss severity implying that since the regulations, in the event of default, these loans will pose a lesser threat to bank stability through portfolio level Expected Loss.

Figure 3: Aggregate loss measures under varying shocks to house prices

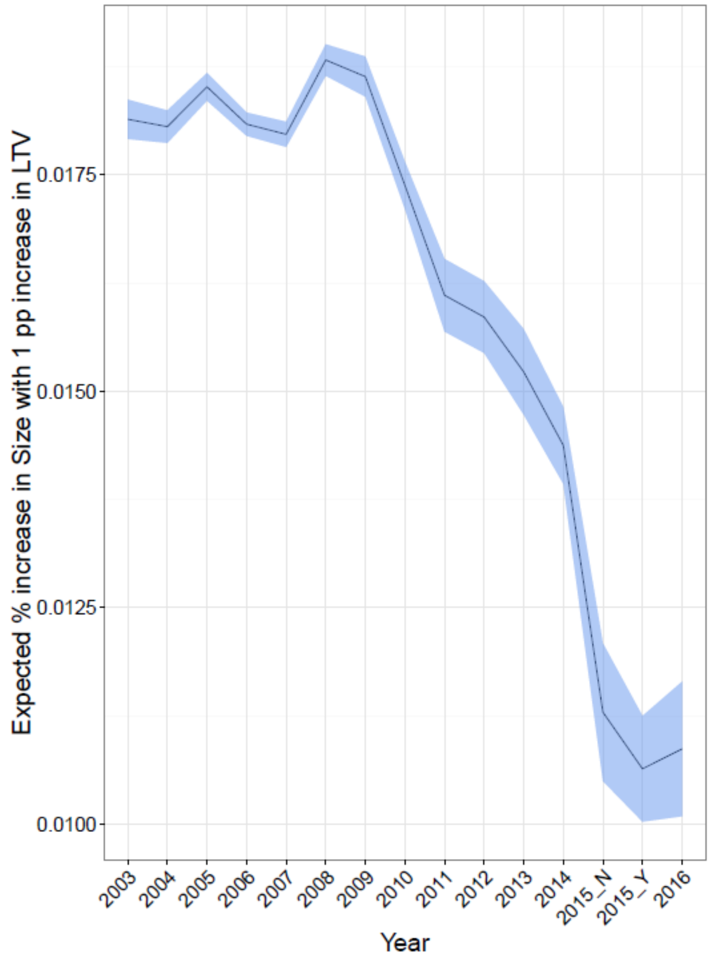


(4.1) OLTV and Loan Size

Figure 3 has shown that total losses among those loans experiencing a loss was increasing prior to the crisis and that this result holds across a number of house price shocks. This suggests that bigger proportionate losses were made on bigger loans, implying an increasingly positive relationship between originating loan size (EAD) and originating LTV (LGL). To test this formally, we run a set of simple linear regressions of the log of originating loan size on originating LTV for each year. Figure 4 shows the slope coefficients from this regression along with their 95% confidence intervals.

In line with the relationship between loan size and PD observed in Figure 2, a positive relationship is found across all years in Figure 4. In the years 2003 to 2006, a one percentage point increase in OLTV was associated with a 1.75% increase in originating loan size. This coefficient of correlation has steadily decreased in every year from 2008 to 2015, to the point where a one percentage point increase in OLTV is associated with a 1.1% increase in originating loan size in the 2015 and 2016 cohorts. A lowering in this correlation is seen as favourable from a financial stability and prudential perspective, as it lowers the correlation between exposure at default and loss given default.

Figure 4: Cohort-specific correlation between OLTV and originating loan size



Each point on the graph is the coefficient from a cohort-specific linear regression of originating LTV on the natural log of originating drawn loan balance. 95% confidence intervals are represented by the shaded area.

(4.2) Sensitivity to house price change

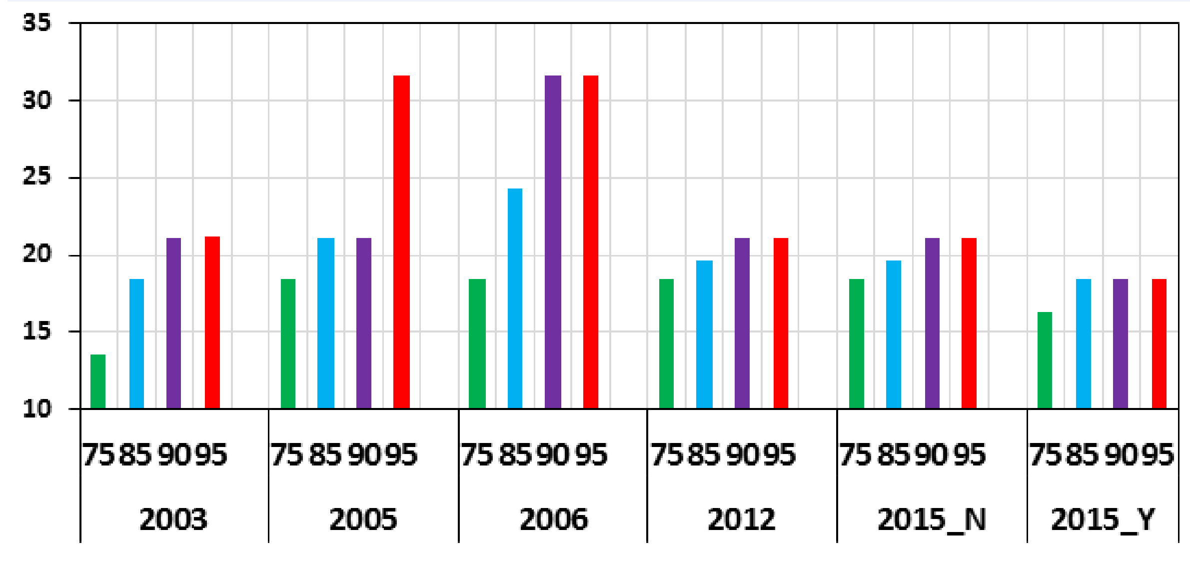
We measure the sensitivity of loan resilience to house price movements by calculating the house price change at which the lender breaks even on a loan. We impose the same assumptions regarding sale costs as laid out in Section 4.1 and calculate the measure as follows:

$$Breakeven = 100 * \left(\left(\frac{Outstanding\ Balance}{Original\ Property\ Value * (1 - Legal\ Costs) * (1 - LiqHaircut)}\right) - 1\right)$$

Figure 5 provides the 75th, 85th, 90th and 95th percentile breakeven values for a selection of loan cohorts (i.e. breakeven points for the riskiest loans issued). In 2003 a 21% house price increase was required for banks not to make a loss on the top ten per cent of their loans, should they default. The corresponding required growth was 32% in 2006, 21% in 2015 for loans not covered by the regulations and 18% for loans, which were covered by the regulations.

While breakeven values at the right tail of the OLTV distribution have clearly reduced significantly since the financial crisis, it is interesting to note that the 75th percentile value increases prior to the crisis but does not fall afterward. This suggests that, while the extremely high-leverage loans that characterised the most excessive risk-taking of the pre-crisis period have been absent from Irish mortgage lending since 2008, for the less risky three quarters of the mortgage book there has been very little change over the 2005 to 2016 period.

Figure 5: Right tail break-even house price growth levels across cohorts (Percentile values)



Breakeven values are calculated for every loan in the data as the house price growth rate below which a bank will make a loss on a loan, given the originating LTV and a set of assumptions on repossession costs and fire sale discounts. Higher percentile values indicate loans for which more favourable house price growth is required for a bank to avoid making a loss, i.e. loans originated with higher LTVs.

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