Modelling mortgage default resolution times

Trevor Fitzpatrick*and Christophe Mues

Abstract

This research explores the drivers of resolution times for defaulted mortgages. Recoveries on mortgage loans are typically work-out with cash-flows coming from sale of the property collateral. In a distressed mortgage market, resolution duration may be longer and loss severities could be higher. A longer time to recovery for a mortgage may mean increased uncertainty as to the timing of cash-flows from collateral realisation and the value received at the sale date. Using survival analysis, the paper investigates what the important factors are for explaining post-default resolution times for mortgages in Ireland. Given the setting of a distressed mortgage market, the paper whether any of the explanatory factors have a non-linear effect on resolution time and the sensitivity of model choice to the estimated resolution time.

Keywords— survival analysis, resolution time, mortgages, non-performing loans

1 Summary

This research explores the drivers of resolution times for defaulted mortgages. Recoveries on mortgage loans are typically work-out with cash-flows coming from sale of the property collateral. In a distressed mortgage market, resolution duration may be longer and loss severities could be higher. A longer time to recovery for a mortgage may mean increased uncertainty as to the timing of cash-flows from collateral realisation and the value received at the sale date. This is a particular problem in a distressed property market.

Because recoveries can be incomplete, this research draws on two strands of the LGD modelling literature. LGD samples can be relatively short, while time to recovery can be

*School of Management, University of Southampton; e-mail: T 'dot' Fitzpatrick 'at' soton 'dot' ac 'dot' uk. The views expressed in the paper are those of the author and do not represent the views of the Central Bank of Ireland, the Single Supervisory Mechanism/European Central Bank.

relatively long. As a result, recoveries are often right censored due to the LGD sample-end date. The censored recoveries may have different characteristics from those of non-censored or closed recoveries. Work in this part of the literature adapts survival analysis to investigating work-out LGD (Dermine and de Carvalho, 2006; Chen, 2018), estimates of recovery time (Rapisarda and Echeverry, 2013), or the factors and specifications that can affect recovery time (Betz et al., 2016, 2017). Using survival analysis enables the inclusion of incomplete workouts.

The second strand deals with various drivers of LGD (Loterman et al., 2011; Gurtler and Hibbeln, 2013; Tong et al., 2014; Krüger and Rösch, 2017). A model of LGD depends on several groups of factors such obligors characteristics, collateral types, product features, the macro- economic environment since origination. These have been investigated in (Qi and Yang, 2009; Zhang and Thomas, 2014; Bellotti and Crook, 2013; Tobback et al., 2014; Dendramis et al., 2018).

Most of this research is based on a period since the Global Financial Crisis (GFC). As a result of the GFC in several countries, a significant amount of loan restructuring occurred to return borrowers to performing status. In some countries, because of public policy changes during the crisis period, recourse to collateral was restricted (Dendramis et al., 2018). In others, rather than engage in lengthy repossession proceedings due to a large number of distressed borrowers, some banks engaged in a voluntary sale/surrender deals with borrowers (Kelly and McCann, 2016). In addition, the volatile economic environment in post crisis countries also may affect estimation of resolution times. Overall, this suggests that models should be potentially adaptable to changing conditions during the observation period.

This context leads to the main questions addressed by this research. First, what are the important factors for explaining post-default resolution times for mortgages and the relative importance of different explanatory factors?. Second, given the setting of a distressed mortgage market, we investigate whether any of the explanatory factors have a non-linear effect on resolution time. This may be particularly important for Loan to Value (LTV) at default. This could be the case because mortgage distress typically follows a housing boom, and many borrowers in the subsequent downturn could experience negative equity at the point of default. Third, the implications of various modelling approaches for estimation of resolution time are explored.

The proposed research contributes in three main ways. It examines whether the type of resolution systematically affects recovery time. Better understanding of resolution times for Non Performing Loans is particularly important post-crisis as Non-Performing Loans (NPLs) remain a financial stability and prudential supervision risk. Second, for practitioners and regulators, time to resolution is an important in parameter collective provisioning models as they determine the period over which discounting of collateral cash-flows occurs. For IFRS 9 purposes, estimation of life-time losses for collective impairment calculations requires appropriate estimation of this parameter. Finally, a significant amount of the emerging literature on resolution time focuses on Small and Medium-sized Enterprises (SME) and corporate credit. Mortgages are a substantial asset class for European and US banks and are therefore the subject of this paper.

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