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Dutch mortgages: Impact of the crisis on probability of default

Jan Kroot[a], Evangelos Giouvris[b,*]

[a] ING Bank
[b] School of Management, Royal Holloway, University of London, Egham, TW20 0EX, United Kingdom

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ABSTRACT

This paper analyzes the impact of the financial crisis on the probability of default (PD) for a large Dutch mortgage portfolio covering a period from 2001 until 2012. A statistical model has been developed, which determines the likelihood that a healthy mortgage customer defaults within 12 months. The PD model is based on risk drivers which are related to the characteristics of the customers and their products (internal risk drivers) and to market factors such as stock market illiquidity, GDP, unemployment and house price index (external risk drivers). Data shows that the financial crisis did not seem to have had the expected worsening impact on the observed customer defaults. However, this is the result of simultaneous debt collection improvements. This paper shows how the internal drivers of the model are able to pick up the effect of the collection process improvements (decrease in PD), whereas the external drivers add significant value to the model to also address the crisis effect (increase in PD).

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1. Introduction

Banks are required to hold sufficient capital to protect them against unexpected losses. In the Basel II framework, the amount of capital that a bank should hold is calculated on the basis of risk-weighted assets formulas. One of the major components in the derivation of these risk-weighted assets is the probability of default (PD). The PD is a quantitative measure which expresses the likelihood that a financially performing borrower defaults within 12 months. PD models are typically determined separately for different customer segments, such as large corporates, small and medium enterprises, and private individuals.

Extensive literature exists on PD modelling. Typically, loans to businesses require expert modelling, because the number of observed defaults is too low for statistical analysis. Therefore, banks often make use of external ratings from e.g. credit rating agencies (CRAs) such as Standard and Poor's and Moody's. Large datasets, suitable for statistical analyses, are available in case either a lot of defaults occur, or when the loan portfolios are large. The latter is the case for retail lending, such as mortgage loans. Literature on statistical models used for PD modelling is also extensive, especially as a result of the upcoming capital regulations in the last couple of decennia. This literature discusses the representativeness and the completeness of the used data, the types of statistical models and the corresponding parameters, and the relevance of application in different regimes of the economic cycle. However, literature about the application of PD models to mortgage portfolios is limited, especially with the inclusion of the data of the recent credit crisis. This paper aims to fill the gap in literature to assess how the crisis has impacted the PD of mortgages. The underlying dataset from March 2001 until October 2012 covers a full

* Corresponding author. Tel.: +441784276115+.
E-mail addresses: j.m.b.kroot@gmail.com (J. Kroot), evangelos.giouvris@rhul.ac.uk (E. Giouvris).

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economic cycle in the Netherlands and specifically includes the crisis years. Note that this paper is not aiming to introduce a new statistical model, or to prove the completeness of the dataset, because this can already be derived from the fact that the model, for it to be Basel II compliant, has been validated and approved by the relevant regulatory institutions. Additionally, whereas regulatory models typically only include customer and contract information internally available in a bank, the model presented in this paper also incorporates external market information.

This paper investigates the impact of the financial crisis on the PD model for Dutch mortgages, based on data of one of the largest Dutch mortgage providers[1]. There are several reasons to expect that the impact is large. Customers are likely to default due to worsening market factors such as increasing unemployment, declining house prices and tightening borrowing practices. As part of the impact analysis of the crisis, a number of related sub-questions need to be answered, such as: (i) What are the main specificities of the Dutch mortgage market that affects the model? (ii) Can a statistical model be constructed in such a way that it picks up the changes in the market and in customer behaviour to come up with an accurate PD estimate on portfolio level? iii) To what extent do changes in collection processes have an effect on the model outcome? In order to answer these questions, the first step is to design a statistical model that can predict the probability of default (PD) accurately. The statistical method that will be applied is the logistic regression method. It searches for relevant risk drivers that can predict the PD level per customer and a calibration level that is conceptually sound. The resulting statistical model can then be used to analyze the impact of the crisis on the PD scores.

This study may serve as a much awaited update on older papers (see e.g. Medema et al., 2009). It also closes a gap in the literature since the financial crisis is incorporated in the analysis and proprietary data is used. In addition, this paper incorporates external macroeconomic factors into its modelling such as stock market liquidity, a variable the authors have not come across in any other relevant study and other qualitative variables such as changes (intensification) in instalment collection processes which lower probability of default (PD). Overall, the authors believe that risk managers, policy makers, academics, bankers, and even macro-economists have a lot to learn from the Dutch experience. Existing models should be enriched to include more external market risk drivers such as macroeconomic variables but also qualitative variables such as changes in internal policies (in this case intensification of collection processes). To summarize, this study adds to the existing body of knowledge by providing a validation methodology for an extended sample that incorporates the financial crisis while at the same time considers external drivers that previous studies have not considered in their modelling and shows that those new variables can actually make a difference.

The remainder of this paper is organised as follows. Section 2 explains the regulatory framework of capital requirements to which the PD model has to comply. Section 3 summarizes the existing literature on PD modelling approaches and their applications to Dutch mortgages specifically. Section 4 provides relevant background information on the Dutch housing market, macro-economic factors and market liquidity. These external factors play an important role in the enhancement of the PD model during the economic downturn. Section 5 presents the set-up of the model, including data collection, the list of possible default risk drivers, the univariate analysis, multivariate analysis, model calibration and the testing and validation of the resulting model. In Section 6, the results are presented. Section 7 summarizes the conclusions of this paper and provides some recommendations for further research.

2. Regulatory requirements

Regulatory capital is the amount of capital a bank has to hold, as required by its financial regulator. Requirements are put in place to ensure that a bank does not expose itself to high risks through its lending and investment practices. The greater the risk to which the bank is exposed, the greater the amount of capital the bank needs to hold to safeguard its solvency and overall economic stability.

The main international effort to establish rules around capital requirements has been through the Basel Accords, published by the Basel Committee on Banking Supervision (BCBS), housed at the Bank for International Settlements (BIS). This sets a framework on how banks must calculate their capital. In 1988, the committee decided to introduce a capital measurement system commonly referred to as Basel I; see e.g. BCBS (1998). This framework has been replaced in 2005 by a significantly more complex capital adequacy framework commonly known as Basel II; see e.g. BCBS (2005) and BCBS (2006).

Banks that have implemented the so-called advanced internal rating-based (AIRB) approach may rely on their own internal estimates of risk components in determining the capital requirement for a given exposure. Derivation of the risk-weighted assets depends on the estimates of the following risk components: probability of default (PD), loss given default (LGD) and exposure at default (EAD) and, in some cases, effective maturity (EM). The PD model predicts the likelihood that a default occurs within the next 12 months. The EAD model predicts the level of exposure at the moment of default in relation to the current exposure. The LGD component expresses the percentage of loss to be expected from that EAD in case of a default. The EM formula determines the time-weighted average of the cash flow schedule of a contract or portfolio. For residential mortgages, Basel II does not require explicit maturity adjustment for retail risk-weight functions; see BCBS (2006, §327).

[1] The authors are very grateful to ING Netherlands for making the data available for the research in this paper. The results presented in this paper are not meant to provide any specificities of the ING mortgage portfolio, but serve to prove the thesis of this paper that the impact of the crisis on the PD model for Dutch mortgages is observed via the external market risk drivers.

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