Stress-testing the return on lending under real extreme adverse circumstances

Maria Rocha Sousa[a,*], João Gama[a,b], Elísio Brandão[a]

[a]School of Economics and Management, University of Porto
[b]LIAAD-INESC TEC

Abstract

This paper presents renewed empirical credit risk measures using the Freddie Mac's single family mortgage loan-level dataset, released in 2013. In the aftermath of the last global crisis, lenders consistently decline the subprime loans, below score 620. We found that much of the disturbances in the return on lending occur when the Loss Given Default (LGD) is sufficiently high. Below LGD=25%, empirical simulations show that lending to borrowers with lower scores produces positive returns in the long-run. If sufficiently mature, these loans can boost portfolios' compositions, because they are less exposed to anticipated payments. So, rather than strictly prohibiting these loans, regulators and lenders should ascertain the LGD boundaries under which the bank operates, to drive lending policies in retail banking.

Keywords: Stress-testing; Return on risk-adjusted; Freddie Mac; Mortgage loans; FICO score; Probability of Default (PD); Loss Given Default (LGD); Capital Requirements; Risk-Weighted Assets (RWA); Basel II; Basel III.

1. Introduction

The subprime mortgage lending crisis in the U.S. came to public's attention when home foreclosures begun to rise in 2006 and moved out of control in 2007. A large decline in home prices prompted a devaluation housing-related securities and an unprecedented rise in mortgage delinquencies. Worldwide, banks' liquidity has plummeted with a significant disruption of the financing of businesses and consumers. This brought dramatic changes to financial regulation and banking supervision, including in the area of mortgages and consumer credit. Simultaneously, consumer financial protection regulation has been strengthened and expanded, and consumer financial behaviour has been changing so far. Our study develops an empirical risk measure that relies heavily on the historical experience of delinquencies in this evolving landscape. In so doing, we contribute to enhanced knowledge in the area of credit risk assessment that is relevant for setting regulatory and lending policies. We address the problem of the disturbances that affect the return on lending in real-world environments. The research question is if lending to the borrowers with the lower scores at the time of the loan application always produces negative returns.

Since 21 March 2013, Freddie Mac is making available loan-level credit performance data on a portion of fully amortized 30-year fixed-rate mortgages that the company purchased or guaranteed since 1999. The data is

[*] Corresponding author
Email addresses: 100427011@fep.up.pt (Maria Rocha Sousa), jgama@fep.up.pt (João Gama), ebrandao@fep.up.pt (Elísio Brandão)

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provided in a “living” dataset (Freddie Mac, 2013) and by June 2014, the database covered over 16.7 million of fully amortized, 30-year fixed-rate mortgages in the U.S., originated between 1999 and the first quarter of 2013. These loans represent a total amount granted of over 3,020 US B$. Based on the historical realized delinquencies, we employ stress-testing as an attempt to project the returns under realistic extreme adverse economic scenarios. Returns are modelled under the current Basel Capital Requirements, and so, the impact analysis is made considering two settings – applying the risk-weights as defined by the Basel Committee, and considering the parameters of the Final Rule under the Basel III for the US banking organizations. We stand on some basic ideas of Saunders and Allen (2010) and on the model of Ruthenberg and Landskroner (2008), adapting the formulation of the model to our problem. We formulate the Basel Capital Requirements based on the work of Antão and Lacerda (2011), and in the Basel Committee regulation for Basel II and Basel III (BCBS, 2006, Committee, 2010).

Under the Basel Capital Requirements, banks tailor their strategies to suitably remunerate their shareholders. In tailoring their activity strategies, commercial banks have two important decisions: selecting the borrowers’ desired risk profile, and position the pricing strategy, subjected to the market competitors and to regulatory boundaries.

When selecting the borrower’s desired risk profile, lenders determine if the risk of lending to a borrower is acceptable under certain parameters of credit risk, borrower’s credit capacity and collateral evaluation. In retail lending, a great proportion of the loan applications are automatically evaluated. In this setting, credit score is the central, if not unique, indicator of the borrowers’ credit risk, either when the credit decision assessment is fully automatic or when it is an input for human decision. A person without a credit score or with a low score (meaning high risk) is unlikely to have credit, whilst an application of a person with a high score has good chances to be accepted. An analysis on the causes and effects of the mortgage meltdown states that in 2007, 40% of all subprime loans have been generated by automatic underwritings in the U.S. This has been associated to lax controls in the underwriting processes (Bianco, 2008). Automated processes meant fasters decision, but less documentation scrutiny.

In positioning their pricing strategies, banks increasingly use risk-based pricing models to price loans, which are also moving towards credit score’s over-dependence. In the U.S., since its introduction 20 years ago, FICO score is calculated from the information available in the individuals’ credit bureau reports, and has become an industry standard. It is claimed to be used in 90% of lending decisions, to determine how much money each individual can borrow, and how much interest he will pay. As a result of the industry standards, the performance of credit loans depends on the credit scoring models accuracy, both in the short-term as in the long-run predictions. In 2007 and 2008, the delinquency rate in the mortgage loans in the US rose sharply, both in borrowers in the lower scores as in the highest scores bands, showing that the actual risk of these borrowers has been underestimated.

Anderson, Scott, and Janet Jozwik (2014) proposed a framework for developing a credit model based on the Freddie Mac’s dataset. For a 180-days delinquent target event, the authors conclude that much of the variation in credit performance across loans and over different stages of the economic cycle is explained by loan-level variables. Unsurprisingly, by adding factors to capture broader macroeconomic effects and the quality of underwriting, they significantly improve the model. Goodman, Landy, Ashworth and Yang (2014) present an exploratory paper providing a first look through the data, to find potential implications for guarantee pricing. The authors show the vintage composition as a percentage of the initial balance in a cross-analysis of the original borrowers’ FICO score by the original loan to value (LTV). They follow the cumulative default in three groups in the score ranges 300 to 700, 700 to 750 and 750 to 850 crossed by the original LTV in selected buckets. They conclude that default rates are dramatically higher on higher LTV/lower scores, and so, they suggest that investors should look not only at the average LTV and FICO scores, but also at the FICO/LTV loans’ distribution. The authors conjecture that pricing these portfolios by looking at averages is likely to lead to under-priced default risk, but they do not present evidence. Sousa, Gama and Brandão (2015) investigate the same database and find evidence that the first year cumulative default of the borrowers in the highest scores has tripled in first years of the last Global Crisis, suggesting that credit risk may has been under-priced in these cases. They show that default rates increased sharply during the crisis, but it did not increase uniformly along the range of borrowers' credit scores. They also show that, two years after the crash, lending decision threshold moved markedly to borrowers with scores higher than 620, which led to an increase in concentration of lending in those individuals. Although this is a reasonable prudential measure, excessive lending bias and concentration towards the highest scores require more precise default estimation to correctly price credit risk.

Discussion is being pushed towards risk-based pricing reliability. Previous studies (Anderson and Jozwik, 2014, Goodman et al., 2014, Sousa et al., 2015) suggest that risk-based pricing models will remain dependent on credit scores. Complementing the previous works, we focus on the performance of returns in different arrangements of borrowers' credit risks, through contrasting phases of the cycle, including the years of exacerbated financial distress of the last global crisis.

This paper follows in section 2 with a description of the return on risk-adjusted model that is used in our study. We describe the regulatory environment, under the current Basel Capital Requirements, and the base concepts that rule the model. In section 3, we describe the conditions of our empirical study. First, we make an overview of the database used in our experiments. Then, we provide a descriptive analysis regarding the interest rates setting, and about the lending evolution over the analysed period. Finally, we describe the main assumptions of the stress-testing exercise of this research. Section 4 provides the results for nine tested scenarios. A pessimistic scenario that has been drawn from the real historical default rates of the global crisis is depicted. Conclusions are presented in section 5.

2. Return on risk-adjusted model

Our model assumes a commercial bank that operates in the primary market, raising deposits from the clients and extending credit to the public. It also operates in the secondary market, where it transacts with other commercial banks, with central bank, and in the financial markets. The bank holds regulatory capital as defined under the internal ratings-based (IRB) in Basel II as a cushion against unexpected losses. We assume that the bank uses a risk-based pricing (RBP) model to price loans. The objective function is to maximize the expected profits as a function of credit risk, based on the decision variable, customer score, s, which represents the probability of the customer entering in default in the loan after the credit has been granted.

2.1. Regulatory environment and base concepts

2.1.1. Regulatory capital for credit risk

The Basel II Accord, established in 2004 and revised in 2006, attempted to implement more risk-sensitive credit exposure measures into capital requirements (BCBS, 2006). Banks[†] were allowed to choose the way of determining the requirements of mimimum capital, by selecting the methodology of calculating the risk-weighted assets: the Standardized approach or the Internal Rating Based (IRB) approach. The Standardized approach is based on external credit risk assessments, while in the IRB, financial institutions use their internal credit risk models' system to determine the credit risk of each activity, such as commercial or consumer lending.

There has been a great deal of talk about Basel II leading to greater risk-based pricing in loan markets, because the new rules for the risk-weighted assets amplified the difference between capital required for risky and safe lending categories and borrowers. Lenders using the IRB, the Advanced banks, have a much lower cost of funding when lending safer types of debt or to safer borrowers. This should have pushed lending away from riskier types of debt, and shorten the prices to safer categories such as low LTV mortgages.

The impact of the new rules on borrowers is hard to discern, because it is not certain that banks had the right incentives to affect the prices by the differences in the cost of capital according to the type of debt or risk of the borrower. In fact, many lenders were already using risk-based pricing, especially for higher risk lending such as subprime mortgages and consumer loans, to compensate the exposure's expected losses. In the one extreme, banks may not be motivated to reduce prices where the cost of funding got lower, in particular to safer borrowers, because their return on equity goes higher. In the other extreme, banks may have not been able to reflect the higher cost of funding to higher risks loans. The first reason is because many jurisdictions have issued consumers' protection laws that impose a maximum cap in the loans' rate. The second reason is because, wordwide, Advanced banks are playing in markets were there are competitors using the Standardized approach, which use a lower risk-weights constant parameter in the highest risk borrowers.

In the aftermath of the global crisis, the Basel III capital framework that was agreed upon internationally in December 2010, and revised in June 2011, established the new minimum risk-based capital ratios to be adopted worldwide (Committee, 2010). The international package includes a new 4.5% common equity Tier I capital requirement, a 6% Tier I capital requirement, and retained the general requirement for banks to hold a minimum total capital, or regulatory capital, of 8% of their total risk-weighted assets (RWA), i.e.:

$$\frac{\text{Eligible regulatory capital}}{\text{Total RWA}} \geq 8\% \,. \tag{1}$$

In addition to the minimum capital ratios, banks are required to maintain a capital conservation buffer of 2.5% of risk-weighted assets to avoid restrictions on their ability to distribute capital and to pay some discretionary bonus payments to executive officers. Hence, the minimum capital ratios effectively increased to 7%, 8.5%, and 10.5%, respectively. Banks falling within the buffer will be required to limit dividends, share repurchases or redemptions, and discretionary bonuses. For banks using the IRB, the capital buffer may be increased during periods of extensive credit growth by an incremental countercyclical capital buffer of up to 2.5% of the risk-weighted assets.

[†] Throughout this paper the term "bank" is used to mean bank, banking group or other entity (e.g. holding company) whose capital is measured under the Basel Accord.

Currently, for the exposures not in default, financial institutions using the IRB compute the total RWA by multiplying the capital requirements for market risk, CR_M, and operational risk, CR_O, by 12.5 (i.e. the reciprocal of the minimum capital ratio of 8%) and adding the resulting figures to the sum of risk-weighted assets for credit risk. Then a scaling factor of 1.06 is applied to the risk weighted assets for credit risk aiming to broadly maintain the aggregate level of minimum capital requirements.

$$\text{Total RWA} = 12.5(1.06 * K * EAD + CR_M + CR_O) \qquad (2)$$

where K is the capital requirement for the credit risk asset amounts, whose formula is disclosed within the Basel II regulation (BCBS, 2006), and EAD is the exposure at default. According to a recent report of the European Banking Authority (EBA, 26 Feb 2013) the RWA component related to credit risk for the aggregate of the European banks operating under the IRB represents about 77% of the total RWA.

The derivation of risk-weighted assets depends on the estimates of the PD, LGD, EAD and, in some cases, effective maturity (M), for a given exposure. The PD is a measure of the borrower's risk, the loss given default, LGD, is the expected proportion of the exposure that the financial institution will recover conditional to the borrower entering in default. The formulas for computing the K parameter vary according to the risk category of the assets, whether the exposure at risk belongs to one of the macro-segments: corporate, sovereign, banks and retail. Corporate segment includes the exposures of all enterprises, excepting the non-financial enterprises of small and medium size, SME, with exposures bellow 1 million Euros. Enterprises excluded from the corporate segment are considered in retail. In the retail segment, the risk weights are differentiated by the type of credit, whether it is in the category of residential exposure, a qualifying revolving credit line, or other retail exposure.

2.1.2. Exposure at default

Our model considers a loan with the original conditions, at the time of the application: amount A, annual interest rate R, term of n years and regular monthly payments. This assumptions determine the number of payments, $N = 12n$, the monthly interest rate, $r = R/12$, and installment amount:

$$M = \frac{rA}{1-(1+r)^{-N}} \qquad (3)$$

A basic assumption is that the monthly installment consists of the sum of two parts. One part corresponds to the interests' amount to be paid in the month and the other is to repay the initial amount granted, such that in the month i, i=1.. N, these two parts are computed as follows:

- Interests' amount to be paid (I_i):

$$I_i = M - P_i = rC_{i-1} \qquad (4)$$

- Repayment of amount granted (P_i):

$$P_i = (M - rA)(1+r)^{i-1} \qquad (5)$$

where C_{i-1} is the exposure at default in the end of the month $i-1$ and in the beginning of the month i, i.e. the amount after amortization, which is computed based on the following:

$$C_{i-1} = A - (M - rA)\sum_{k=1}^{i-1}(1+r)^{k-1} \text{ and } C_0 = A. \qquad (6)$$

Equivalent to

$$C_{i-1} = A - (M - rA)\left(\frac{1-(1+r)^{i-1}}{r}\right) \text{ and } C_0 = A. \tag{7}$$

Here we assume that until the default event, the borrower entirely pays the instalments according to the debt service plan. For simplicity, the current setting of model does not distinguish the early repayments, which have an effect on the expected returns. Therefore, the exposure at default in the month i, i=1..N, for a borrower that did not reach the default event is:

$$EAD_i = C_{i-1}. \tag{8}$$

2.1.3. Cost of funding

An asset of amount A is funded by equity, E, and debt, D, such that:

$$A = E + D. \tag{9}$$

The equity needed to fund the asset, related to credit risk, can be assumed as:

$$\mathrm{E} = sr.rw.\mathrm{A}, \tag{10}$$

where rw is the risk-weight factor for credit risk, and sr is the solvability ratio targeted by the bank, which needs to be at least 8%. The rw parameter is defined by the Basel Committee, both for the Advanced or for the Standardized approach, and may be adjusted by local bank regulatory agencies, as it happens in the US and in the EU. Examples of local conventions include the Final Rule issued by the US bank regulatory agencies that set comprehensive regulatory capital framework for the US banking organizations under the Basel III and implements the capital-related provisions of the Dodd-Frank Act. In the EU, Basel Accords have been introduced via the Capital Requirements Directive (CRD). This Directive provides a common framework for implementation, but allows for national discretions. One example of a national discretion is the LTV limit for qualifying residential mortgages with the preferential risk weighting of 35%. In the UK, for example, this limit has been set at 80% by the Financial Services Authority (FSA). For a bank using the IRB approach without any changes rw is $12.5 * 1.06 * \mathrm{K}$.

Equation (9) can be rewritten as:

$$A = sr.rwA + (1 - sr.rw)A \tag{11}$$

The cost of equity, C_E, can be evaluated according to the return required by the shareholders, for which we assume the profitability measure return on equity, r_E.

$$C_E = r_E E. \tag{12}$$

Equity is the most costly way of financing. So, financial institutions using the IRB benefit from lower costs of funding when lending to entities of better risks, i.e. lower PD and lower LGD. In the other extreme their cost of funding is higher when lending to entities of worst risks, i.e. higher PD and higher LGD. This can easily be realized from the monotonic behaviour of the *rw* factor when varying these two parameters, which we illustrate with an example in Fig. 1.

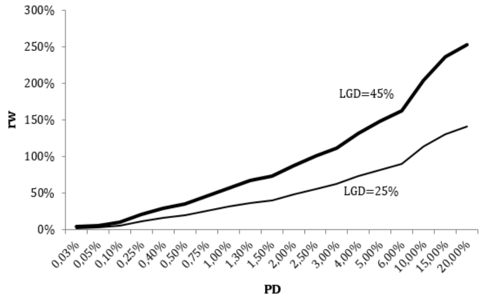


Fig. 1: Illustrative IRB risk-weights for residential retail, considering LGD 25% and LGD 45%; source (BCBS, 2006) Annex 5, pg. 279.

On the other side, the cost of debt, C_D, is

$$C_D = r_D D, \tag{13}$$

where r_D is the price of debt, considering the structure of financing and price that the bank can get in wholesale funding (central banks and markets) and from clients deposits.

2.1.4. Expected loss

Our model assumes that when a borrower enters in default then from that point onwards he will not leave the default status. If the PD_i, i=1.. N, is the probability of the borrower entering in default in the month i and the LGD is the loss given default conditioned on the default event, then the expected loss for that borrower in that month, EL_i, is

$$EL_i = PD_i.LGD.EAD_i \tag{14}$$

The cumulative default until the end of the loan is equal to the sum of the probabilities of default in each year, as illustrated in Fig. 2.

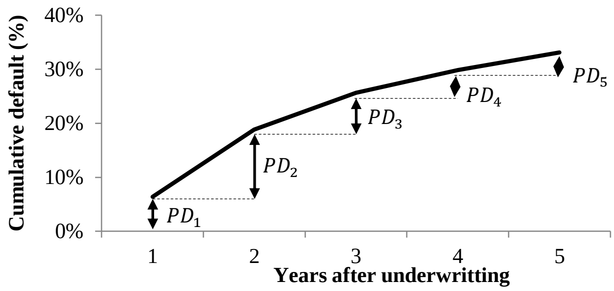


Fig. 2: Illustrative example of a cumulative default curve of loan with a 5-years maturity, and the probability of default in each year of the life of the asset.

In the remainder of the paper, we will assume that both the PD and the LGD parameters are known for each borrower at the time of the origination.

2.2. Return on risk-adjusted model

The starting point for the deduction of the return expected for the loan is the equality:

$$\text{Profits} = \text{Costs} \tag{15}$$

For the costs associated with the loan, we consider the cost of funding and the losses associated with credit default events, the expected loss (EL). Other costs, like general and administrative costs, are not considered in this model, despite of being relevant for the banks' activity based costing.

$$\text{Costs}=C_E + C_D + EL \tag{16}$$

The profits include the fees and the interests charged on the loan. We assume that the interest rate consists of a market reference rate, $\mathrm{r_r}$, plus a spread, sp. The spread component is intended to cover a profit margin and the risks that are associated with the loan, such as credit risk, liquidity risk, market risk, operational risk, and other risks as may be identified by the bank from time to time. Traditionally, fees, f, can be either *ad valorem* or bullet. The former is equivalent to using a spread. The later can be converted into a spread prior to the calculation of profits, based on the maturity of the loan and the frequency of payments.

$$\text{Profits}=(r_r + sp)A + f \tag{17}$$

Considering the equalities in 16 and 17, equation 15 is rewritten as:

$$(r_r + sp)A + f = C_E + C_D + EL \tag{18}$$

equivalent to:

$$(r_r + sp)A + f \ = \ r_E E + r_D D + EL \tag{19}$$

Isolating the components of spread intended to cover the credit and liquidity risks, applied to the total amount to be financed, it is rewritten as:

$$(r_r + sp_c + sp_l + sp_o)A + f \ = \ r_E E + r_D D + EL \tag{20}$$

where, sp_c is the credit risk spread, sp_l is the liquidity spread, and sp_o is the spread that covers the profit margin and remaining risks, like operational or country risk.

2.2.1. Credit risk spread

Equation 20 can be rewritten as:

$$sp_c A = \ r_E E + r_D(A - E) + EL - (r_r + sp_l + sp_o)A - f \tag{21}$$

Rearranging the arguments, and isolating the credit risk spread, this is equivalent to:

$$sp_c = \ \frac{E}{A}(r_E - r_D) + (r_D - r_r - sp_l - sp_o) + \frac{EL - f}{A} \tag{22}$$

Considering the equality in 10, then the credit spread that allows an adequate return on equity[‡] is:

[‡] Here we consider the return before taxes.

$$sp_c = rs.rw.(r_E - r_D) + (r_D - r_r - sp_l - sp_o) + \frac{EL - f}{A} \tag{23}$$

If the bank funds the debt by the market reference rate, i.e. $r_D = r_r$, then the credit risk spread is:

$$sp_c = rs.rw.(r_E - r_r) - (sp_l + sp_o) + \frac{EL - f}{A} \tag{24}$$

2.2.2. Return on equity of a loan

Rearranging the arguments in equation 20, and isolating r_E, then the return on equity rate needed to fund the loan is given by:

$$r_E = \tfrac{1}{E}(sp_c A - EL) - \tfrac{A}{E}(r_D - r_r - sp_l - sp_o) + r_D + f. \tag{25}$$

Or, stated equivalently:

$$r_E = \frac{1}{rs.rw}\left[(sp_c - r_D + r_r + sp_l + sp_o) - \tfrac{EL}{A}\right] + r_D + f. \tag{26}$$

Likewise, if the bank funds the debt by the market reference rate, i.e. $r_D = r_r$, then the return needed to fund a loan is

$$r_E = \frac{1}{rs.rw}\left[(sp_c + sp_l + sp_o) - \tfrac{EL}{A}\right] + r_r + f. \tag{27}$$

3. Empirical study

3.1. Data

The simulation summarized here was conducted in the Freddie Mac’s single family mortgage loan-level dataset, first published in March 2013. We follow the performance of 16.7 million of fully amortized 30-year fixed-rate mortgages loans in the U.S., originated between January 1, 1999 and March 31, 2013, and representing a total amount granted of over 3,020 US B$. The loans performance[§] is outlined in a monthly basis and, at the time of this research, data for performing loans and those that were up to 180 days delinquent were available through September 30, 2013. Disseminating these data follows the direction of the regulator, the Federal Housing Finance Agency (FHFA), as a part of a larger effort to increase transparency and promote risk

[§] Loan performance information includes the monthly loan balance, delinquency status and information regarding termination events: Voluntary prepayments in full; 180 days delinquency (“D180”); Repurchases prior to D180; Third-party sales prior to D180; Short sales prior to D180; Deeds-in-lieu of foreclosure prior to D180; Real estate owned (REO) acquisition prior to D180. Specific credit performance information in the dataset includes voluntary prepayments and loans that were short sales, deeds-in-lieu of foreclosure, third party sales, and REOs.

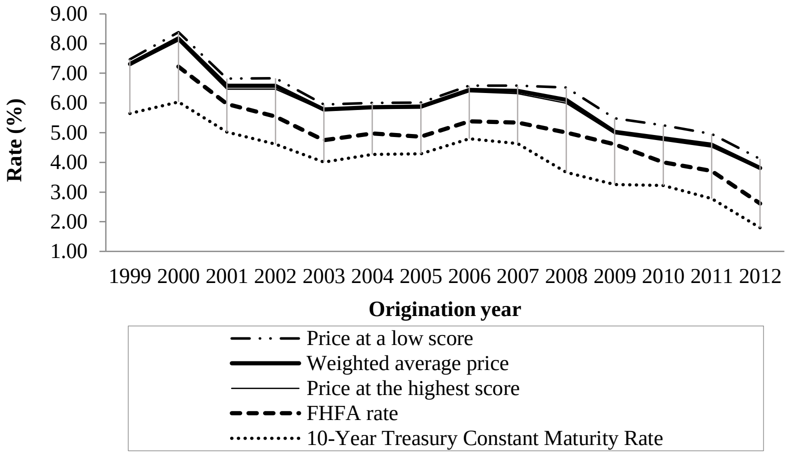
sharing. The primary goal of turning this data available was to help investors build more accurate credit performance models in support of the risk sharing initiatives highlighted by the FHFA in the 2013 conservatorship scorecard (FHFA, 2013). The dataset is a living dataset updated over time, typically at the end of each quarter. The release changes are recorded online (Freddie Mac, June 2014a) as well as a general user guide describing the file layout and data dictionary (Freddie Mac, December 2013). Freddie Mac's information regarding the key loan attributes and performance metrics can be linked to this research in the aggregated summary statistics (Freddie Mac, June 2014b).

Data of the original datasets were aggregated by the origination year. Scores may vary in the range 300-850, or be unknown. Situations where the score is unknown are described by Freddie Mac (Freddie Mac, December 2013)[**]. We divided the range of possible scores into equidistant intervals of 25, except for the lower and upper bounds. To have dimension, these bounds were aggregated in the buckets [300, 550[and [800, 850[, respectively.

3.2. Descriptive analysis

3.2.1. Interest rates setting

Mortgage interest rates are affected by many factors. In the United States they are heavily influenced by the monetary policies of the Federal Reserve board's Federal Open Market Committee (FOMC). Trends in interest rates on longer financial instruments, such as mortgages, typically follow the fluctuation of the 10-year Treasury note yield. Fig. 3 shows the evolution of the 10-year Treasury constant maturity rate over the period 2005 through 2012, and the 10-year constant maturity advance rates authorized by the Federal Housing Finance Agency (FHFA) for the advance pricing.



[**] A possible reason is when the seller requires a reduced level of verification.

Fig. 3: Rates evolution in the period 1999-2012. Sources: Freddie Mac's single-family loan level dataset, FHFA historical advance rates and FED 10-year Treasury note yield.

These rates serve as a reference for the 30-year fixed-rate mortgage loans, which are also exhibited in Fig. 3, together with the average rate, the prime rate and the subprime rate. Borrowers' scores are used to differentiate the interest rates of the mortgages, with the subprime rates being superior to the prime rates. For the entire period, the average rates are near the prime rates, because lending is more shifted to the borrowers with the higher scores. The gap between the subprime and the prime rates slightly increased in the aftermath of the Crisis, between 2008 and 2011, as illustrated in Fig. 4.

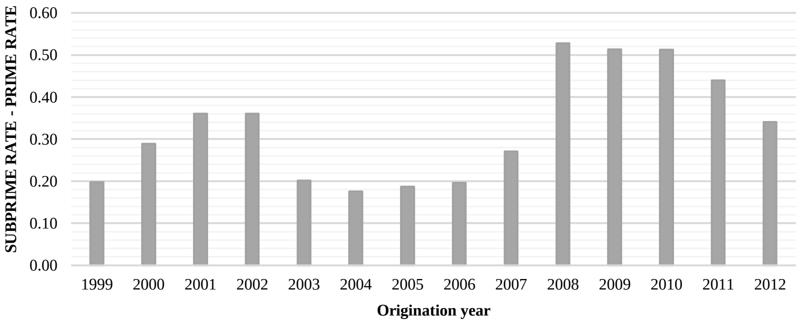


Fig. 4: Gap between the subprime and the prime rate in the period 1999 to 2012. Source: Freddie Mac single-family loan level dataset.

Between 2004 and 2007, spreads placed around 170 bps for the prime loans and average portfolio, and around 190 bps for the subprime loans. Spreads increased in the aftermath of the crisis, and reached a peak in 2008 (Fig. 5). Spreads decreased in 2009 and 2010 and started increasing since 2010. A recent report of the Federal Housing Finance Agency says that a 170 bps spread is expected for the future period from 2015 through 2017 (Schultz, August 2014) to cover liquidity and credit risks.

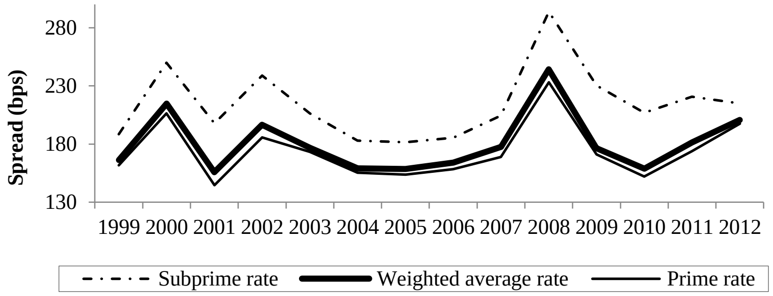


Fig. 5: 30-year mortgage spreads in the period 1999-2012.

3.2.2. Lending through 1999 to 2013(Q1)

The evolution of new loans over the analysed period illustrates the U.S. housing bubble between 2001 and 2005. Higher peaks occur between 2001 and 2003, where the numbers of new loans continuously rose from nearly 800 thousand new loans in 2000 to 1,930 thousands in 2003 (Table 1, 1st row). This massive increase in the volumes was one of the sources of the raise in the real state property values that reached a peak by 2005.

Table 1: Main indicators for mortgage loans originated between 1st January 1999 and the 1st quarter of 2013. Source: Freddie Mac.

Indicator	Origination year														
	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013 (Q1)
Total loans (thousands)	1.095	787	1.757	1.685	1.930	1.131	1.324	1.083	1.069	986	1.513	788	556	787	247
Total original amount (billion US $)	138	104	260	262	311	188	240	202	202	210	345	177	131	192	58
Avg original loan amount ('000 US $)	126	132	148	156	161	167	181	187	189	213	228	224	236	244	237
Scores concentration index††	13%	13%	13%	13%	14%	13%	13%	12%	12%	14%	20%	19%	20%	21%	20%
Scores stability index‡‡		0,02	0,01	0,00	0,03	0,02	0,03	0,00	0,00	0,10	0,28	0,00	0,00	0,01	0,00
Average interest rate (%)§§	7,31	8,18	6,58	6,58	5,78	5,86	5,88	6,44	6,41	6,10	5,02	4,81	4,59	3,81	3,64

In the entire period, the analysis confirms that the scores are used to differentiate the interest rates of the loans. As shown in Table 2, there is a decreasing trend of the average interest rate from the lower to the higher score buckets. It can be said that a risk-based pricing based in scores is being applied. By the crisis, the default of the borrowers in the highest scores' borrowers has tripled in relation to the previous years. This suggests that credit risk is these borrowers may has been under-priced.

Table 2: Average original rate of the loan by score. Loans originated in the period 1999-2013(Q1). Unit: %. Source: Freddie Mac.

Score bucket	Credit risk assessment	Origination year													
		1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Unknown	Unpublished	7,49	8,28	6,74	6,74	5,91	5,98	5,92	6,30	6,28	6,40	5,31	5,10	5,14	3,97
[300;550[	Highest risk	7,50	8,29	6,88	6,88	5,97	6,04	6,09	6,75	6,92	6,77	5,48	5,46	0,00	3,71
[550;575[	↑	7,50	8,35	6,93	6,94	6,02	6,10	6,14	6,72	6,81	6,75	5,62	5,44	5,38	4,00
[575;600[		7,53	8,53	7,00	7,00	6,07	6,10	6,11	6,65	6,67	6,60	5,56	5,29	4,99	3,95
[600;625[		7,46	8,38	6,83	6,83	5,95	6,00	6,01	6,58	6,59	6,52	5,48	5,25	4,96	4,12
[625;650[		7,40	8,29	6,73	6,73	5,89	5,95	5,97	6,53	6,53	6,48	5,44	5,22	4,97	4,12
[650;675[		7,36	8,23	6,65	6,65	5,84	5,90	5,93	6,50	6,48	6,36	5,34	5,14	4,90	4,07
[675;700[		7,33	8,20	6,59	6,60	5,81	5,88	5,90	6,46	6,44	6,20	5,22	5,01	4,80	3,96
[700;725[		7,30	8,16	6,56	6,56	5,78	5,86	5,88	6,44	6,41	6,13	5,11	4,89	4,69	3,87
[725;750[		7,27	8,13	6,53	6,53	5,75	5,84	5,86	6,43	6,38	6,06	5,04	4,82	4,62	3,81
[750;775[		7,25	8,10	6,50	6,50	5,73	5,81	5,83	6,40	6,35	6,02	5,00	4,78	4,57	3,79
[775;800[		7,26	8,08	6,47	6,47	5,72	5,81	5,81	6,37	6,31	5,98	4,97	4,76	4,54	3,77
[800; 850[	Lowest risk	7,27	8,09	6,47	6,47	5,74	5,82	5,83	6,39	6,32	5,99	4,97	4,74	4,52	3,78
Weighed average rate		7,31	8,18	6,58	6,58	5,78	5,86	5,88	6,44	6,41	6,10	5,02	4,81	4,59	3,81

†† We used Herfindahl-Hirschman Index (HHI), for which values below 20% are commonly considered acceptable.
‡‡ We used population stability index, for which values bellow 0,25 are commonly considered normal.
§§ Calculated as the weighted average of rates by score buckets.

Adjustments to the risk premium were made by 2009. Single-family mortgage loans' average rate was maintained through 2001 and 2002, in the aggregate and in score buckets' level (Table 2). This effect may be linked to the crash of the dot-com bubble in 2000 which has been associated to the beginning of the decline in real long-term interest rates (Bianco, 2008). The mortgage interest rates continued to decline until 2005 (Table 2). As the mortgage rates are typically set in relation to 10-year Treasury bond yields, this was an outcome of very low Fed funds' rates in the period. By that period lenders were self-reliant that they were taking little risk because the value of the collateral was rising too fast.

3.3. Stress testing scenarios

3.3.1. Expect margin and expected losses assumptions

We analyse the performance of the returns in each year after the loan has been underwritten. We empirically estimate these losses based on the past realized default rates in each score bucket. Rather than just using the average default, as traditional approaches normally do, we focus on the two possible extreme circumstances – an optimistic scenario and a pessimistic scenario. The optimistic scenario considers the cumulative default rates by vintage of an origination year with a lower 1-year default rate (1999). The pessimistic scenario is based in the cumulative default rates by vintage of the origination year with the highest 1-year default rate (2008). We also analyse an average scenario, based on the weighted average annual default rates in the period between 1999 and 2008. The default rates measured after 2008 were not considered in this analysis because the vintage curves could not be calculated from the fifth year onwards (e.g. for the loans underwritten in 2009, only a 4-years vintage can be measured until 2013, and for the loans underwritten in 2012, only a 1-year vintage can be measured until 2013). A borrower is considered to enter in default after completing 90 consecutive days in delinquency. The vintage curves presented in a previous study of Landy, Ashworth and Yang (2014) suggest that the cumulative default rates reach a plateau in the fifth year. Hence, for this analysis we assume the measures of default rates in the first five years of the loan will reveal most of the expected default of the portfolio. The real default rates were measured from the single-family mortgages loan level dataset in each year between 1999 and 2008.

For the three scenarios of default evolution under hypothesis - the average, the optimistic and the pessimistic - we study the performance of the returns along time based on three representations of the expected losses. Hence, we analyse the performance of the returns under nine potential circumstances, thoroughly illustrated in Fig. 6. For simplicity, only the cumulative default curves in the average portfolio and in two distant score buckets are represented – the low score is in the range [600; 625[, and high score is in the range [800; 850[. The three representations of the expected losses are:

- *Conjectural model*: assumes that the proportion of new defaults in each year remains constant over time during the expected life of the asset. In other words, if p is the probability of default one year after the loan has been granted then the probability of new defaults in the year i is $(1-p)^{i-1}p$.
- *Semi-conjectural model*: The evolution of new defaults is given by the conjectural model until the fifth year, and from that point onwards the model assumes that there are no new defaults.
- *Observed model*: assumes the real proportion of new default measured until the fifth year of the loan and that from that point onwards there are no new defaults.

We measure the expect returns along time, after the loan has been originated, using the methodology described in section 2. For the expected loss calculation we assumed the PD implied in each of the nine scenarios under hypothesis (Fig. 6) and retaining the two LDG values behind the Basel Committee's illustrative IRB risk weights***, 25% and 45% (BCBS, 2006). To calculate the expected margin we considered the average advance rates in the origination year, which are published online by the Federal Home Loan Bank (FHLB, 2014).

3.3.2. Risk-weights parameter assumptions

Under the Basel III capital requirements, countries may define specific rules for the risk-weight parameters.

Many banks using the IRB in the European Union (EU) calculate the risk weights for mortgage loans based on the formula provided by the Basel Committee for the residential retail risk category. And so, the risk weight attached to these mortgages largely depends on the lender's historical default losses experience, subject to cyclical phases' (e.g. downturn) assumptions, which drives the internal risk models. For realistic values of PD and LDG this can give rise to risk weights on this risk category well below 35%.

In the United States (US) the Final Rule approved on July 2, 2013, by the Board of Governors of the Federal Reserve System brought the US banks into compliance with the Basel III capital framework agreed in December 2010. For the banks subject to the advanced approaches in computing risk-based regulatory capital, the final rule took effect in January 1, 2014. For the majority of the US banks operating under the standardized approach, the Final Rule took effect on January 1, 2015. The Final Rule establishes the standardized approach and the advanced approach to calculate risk-weighted assets in the US. However, for Advanced Banks, the standardized approach is considered to establish the minimum generally applicable capital floor requirements for purposes of the section 171 of Dodd-Frank - the Collins Amendment. The Final Rule retained the 50% risk-weight for the residential mortgage loans secured by a first lien on a one-to-four family residential owner-occupied or rented property. This does not apply to the loans imprudently underwritten, that are 90 days or more past due or in accrual status, or modified or restructured loans, other than pursuant to the Home Affordable Modification Program.

In this research we aimed at representing the most relevant risk-weights parameters. Hence, to assess the expect returns, we considered two risk-weighting approaches:

- A fixed 50% risk-weight, as used within the US banks for the residential mortgage loans secured by a first lien on a one-to-four family residential owner-occupied or rented property.
- The risk-weights parameters computed with the Basel Committee formula for the residential retail risk category, $12.5 * 1.06 * \mathrm{K}$, used within many Advanced banks in the European Union (EU).

*** Annex 5, page 279.

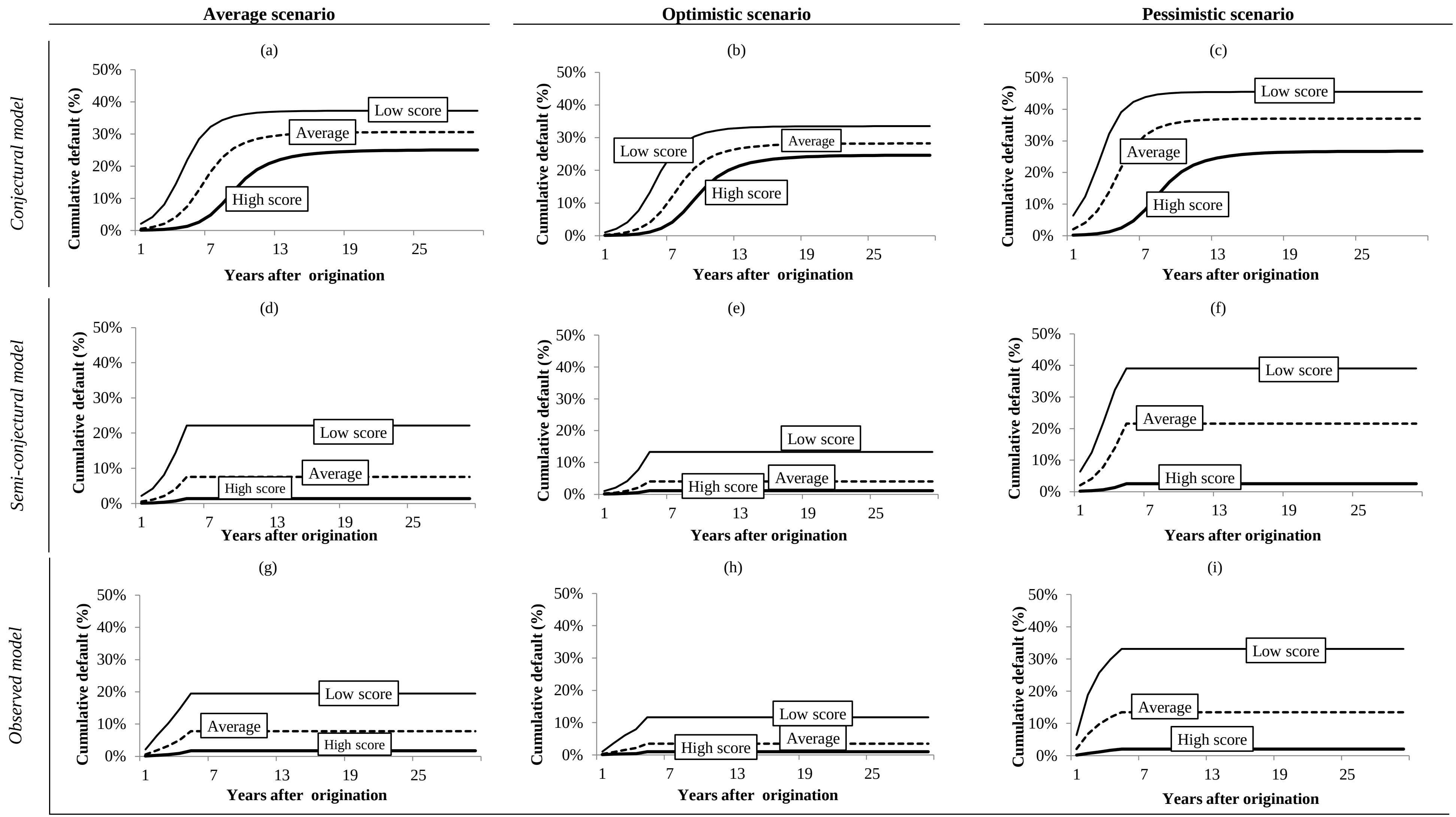


Fig. 6. Cumulative default rates behind the calculation of the expected losses in each scenario - average, optimistic and pessimistic – and using three models to represent the cumulative default rate evolution – conjectural, semi-conjectural and observed. The low score is in the range [600; 625[, and high score is in the range [800; 850[. The average is the weighted average cumulative default rate of the portfolio.

4. Results

Results are shown for each hypothesized scenario and applying the risk-based model described in section 2. Throughout this section we exhibit a set of figures presenting the returns along the life of the assets, since the loan has been originated until maturity. In each graph, the bottom curves represent the returns in the lower score buckets, beginning in the score 300. Return curves move progressively along score buckets in the direction of the upper curve that represents the returns in the higher scores bucket [800; 850[. The returns of the aggregate portfolio of loans originated in the same year are represented in the bold line in each graph – the average return. Any random pooling of loans of the aggregate portfolio, which have been originated in the same year, should produce the average return. Any portfolio of loans, originated in the same year, in selected ranges of scores should produce a weighted average return of those score ranges. Some combinations of loans with different origination years may produce negative returns if the resulting portfolio has a significant proportion of loans that did not reached the break-even point or if it has a significant proportion of loans in specific score ranges that coexist with negative returns in a given point in time.

Our study shows the extent to which return on equity to finance loans largely depends on the rule for calculating the risk-weighted assets. When banks use a constant risk-weight factor, like in the US, returns are upper-bounded. If the bank is using the risk-weights as defined by the Basel Committee and operate in markets where the competitors use the standard approach, they may have little incentive to decrease prices to customers with the highest scores, by placing their prices in the market prices. If this happens, they certainly reach huge returns in lending to these segments.

It is now clear that the credit losses arising from credit defaults were far superior than anticipated during the subprime crisis. This was an outcome of an unprecedented decline in home prices that led to a devaluation housing-related securities and rise in foreclosures, together with a sudden escalation of the delinquency rates. This was translated into an abrupt increase in the loss given default. The estimation of the LGD parameter depends mostly on the banks' ability to recover the assets granted on a loan if the borrowers enter in default. Banks in the advanced economies have their own estimates for the loss given default. Banks may use assessment methods ranging from simple estimations of the LGD at an aggregate level to more sophisticated models, as under the IRB. This information is usually reserved, and so this study analyse the returns under two standard reference values of the Basel Committee for the LDG - 25% and 45%. To the extent of our knowledge, for the residential retail exposures, the LGD should be closer to the 25% reference value in average conditions. But this value is expected to rise in times of recession, when banks are swamped with defaulted loans and high provisions. Hence, the 45% LGD reference should better allow replicating the conditions of a catastrophic situation.

For values of LGD up to 25%, most of the credit score buckets produce positive returns along the entire life of the asset, either in average conditions or in adverse circumstances. Few exceptions are remarked in the very lowest scores ranges, the subprime loans, between score 300 and score 625, where the returns turn negative somewhere between the second and the fourth year after the loan has been originated, if the loan is originated under the most adverse scenario. These findings are confirmed in the graphs of the pessimist scenario in Fig. 8 and Fig. 9, and more markedly in the observed default model (graphs (i)). Yet, returns turn positive from the fifth year onwards either if we assume that the cumulative defaults reach a plateau by the fifth year (Fig. 8(f), Fig. 8(i), Fig. 9(f) and Fig. 9(i)) or if we consider that the new default evolve constantly over time until loan maturity (Fig. 8(c) and Fig. 9(c)). A portfolio of loans randomly selected from the aggregate portfolio, originated in the same year, generates positive returns along the entire life of the assets (see the bold curve is the graphs of all scenarios in Fig. 8 and Fig. 9).

Placing the LGD in 45% suggests a discussion from a very different perspective. A higher LGD amplifies the disturbances stimulated by the default rate increases, and so, under this setting a significant number of loan pooling can generate negative returns. This is valid throughout the cycle, in average conditions, but is more applicable to adverse circumstances, because an LGD of 45% is more likely to occur during times of serious financial distress. Hence, we centre our discussion in the results for the pessimistic scenario. In this setting, a portfolio of loans randomly selected, originated in the same year, should produce a weighted average return, represented in the bold curve in Fig. 10 and Fig. 11, which even under the pessimistic scenario produce positive returns during most of time of the life of the assets. However, in the years of sharp rise in new defaults rates, returns are negative, which may occur somewhere between the third (Fig.10(i) and Fig.11(i)) and the fifth year (Fig. 10(c), Fig. 10 (f), Fig. 11(c) and Fig. 11(f)). When isolating the returns in each score bucket, a wide range of scores has negative returns in the first years of the loan. In particular, up to the score 675, returns are below the average. In the score range [300; 575[returns are negative from the origination point until the fifth year. In the score range [575; 675[returns go negative between the first and sixth year, depending in the scenario of default evolution (conjectural, semi-conjectural or observed). When the new default evolves as defined under the conjectural default model, i.e. assuming that the new defaults evolve constantly over time, then the best scored loans also reach negative returns is some point in time, until the tenth year of the loans (Fig. 10(c) and Fig. 11(c)). This is more pronounced when using the risk-weights calculated with the Basel Committee formula (Fig. 11(c)). Under this setting, the loans with the highest scores may produce highly negative returns around the tenth year.

Following the subprime crisis, lenders are firmly declining the subprime loans, below the score 620, as described in a paper of Keys et al. (2008), and demonstrated in the study of Sousa et al. using the Freddie Mac's single family mortgage loan-level dataset (2015). In fact, the risk of these loans is higher than in other scores, as previously stated. However, when these loans go older, mostly after the fifth year, the expected returns increase.

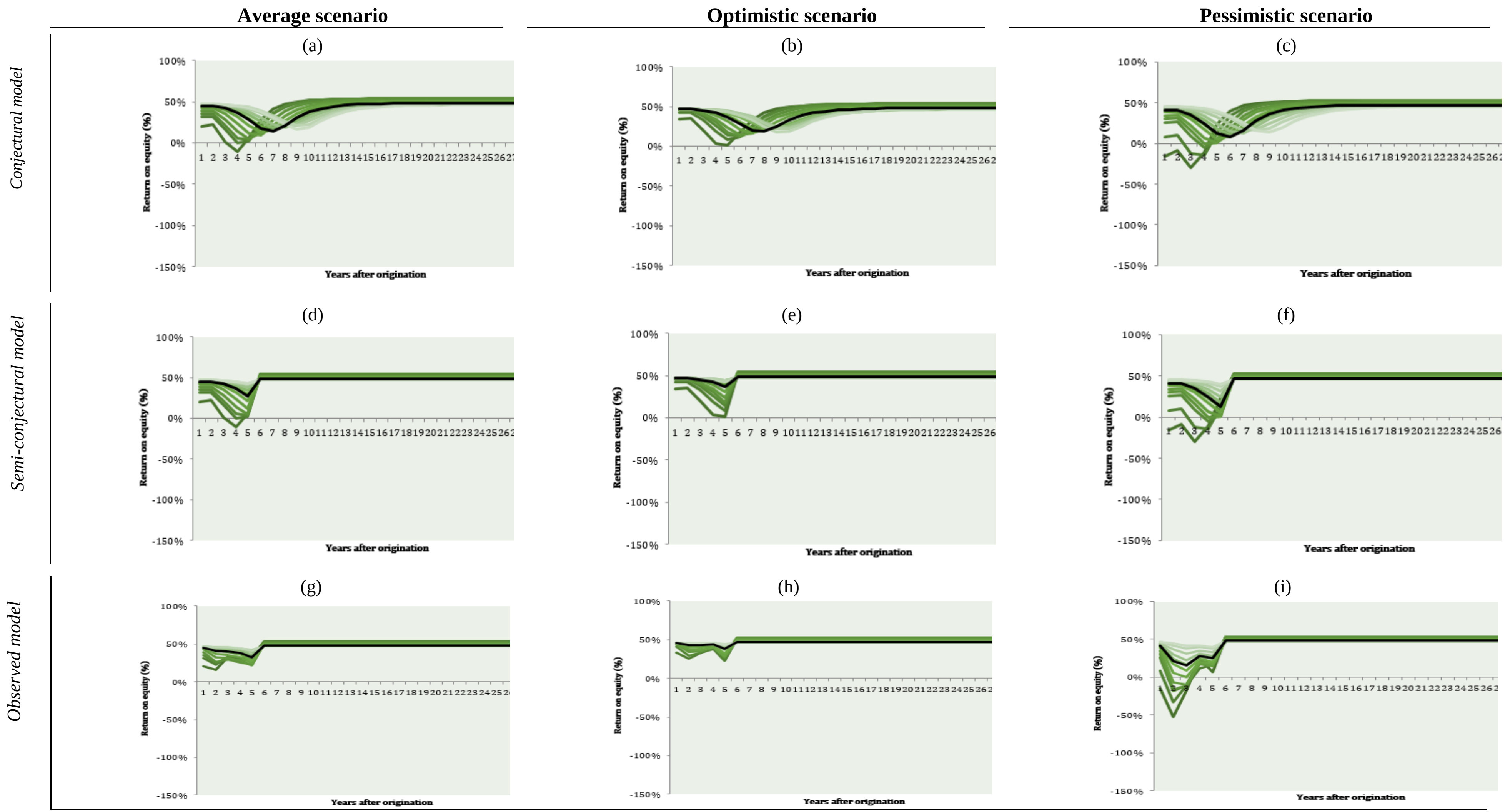


Fig. 7. Expected returns in each scenario, assuming a 50% risk-weight and LGD=25%. From down to the top of the image, lines represent the expected returns in the score buckets [300; 550[, [550; 575[,[575; 600[, [600; 625[,[625; 650[, [650; 675[,[675; 700[, [700; 725[, [725; 750[, [750; 775[,[775; 800[, [800; 850[, respectively.

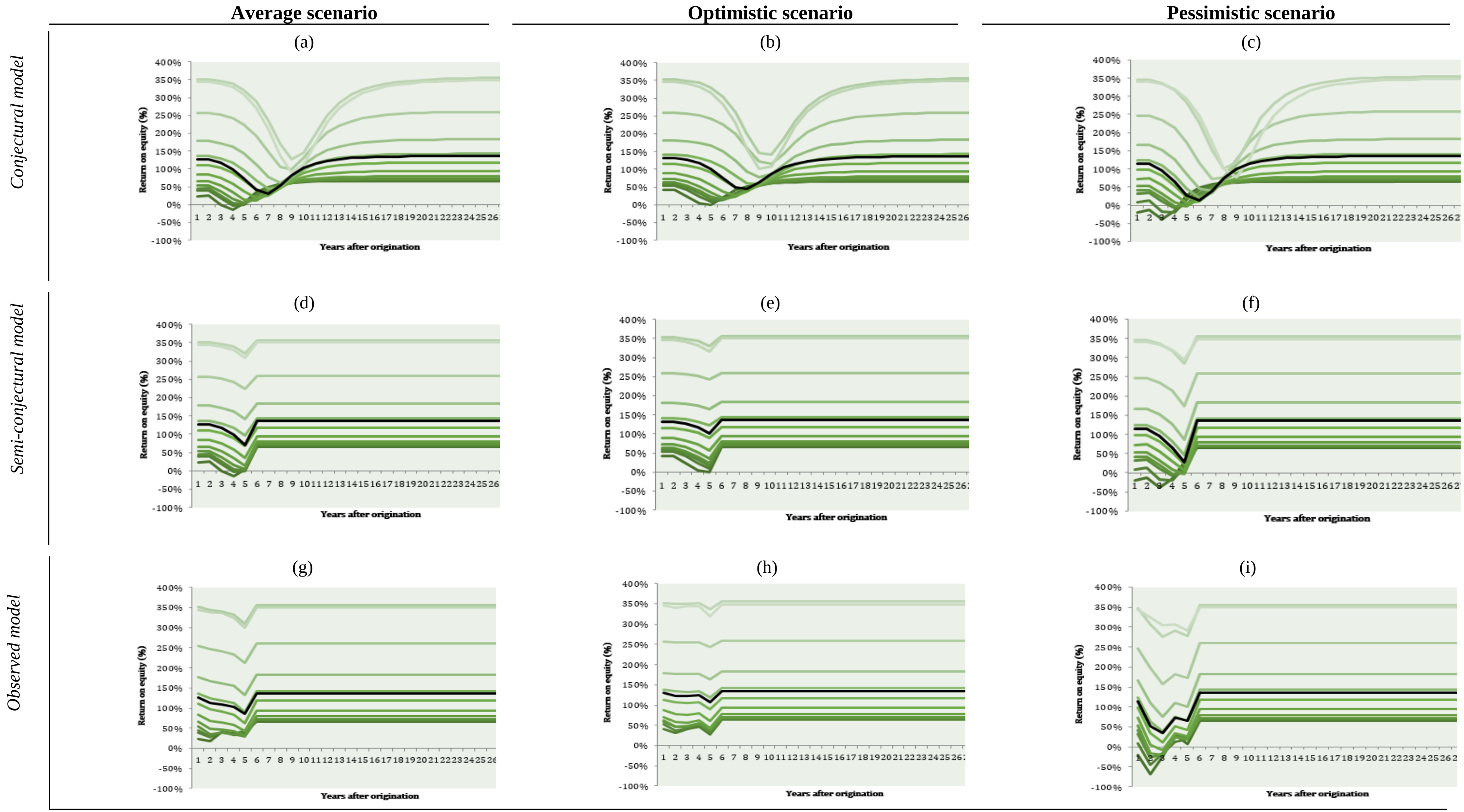


Fig. 8. Expected returns in each default scenario assuming a risk-weight equal to 12.5*1.06*K and LGD=25%. From down to the top of the image, lines represent the expected returns in the score buckets [300; 550[, [550; 575[,[575; 600[, [600; 625[,[625; 650[, [650; 675[,[675; 700[, [700; 725[, [725; 750[, [750; 775[,[775; 800[, [800; 850[, respectively.

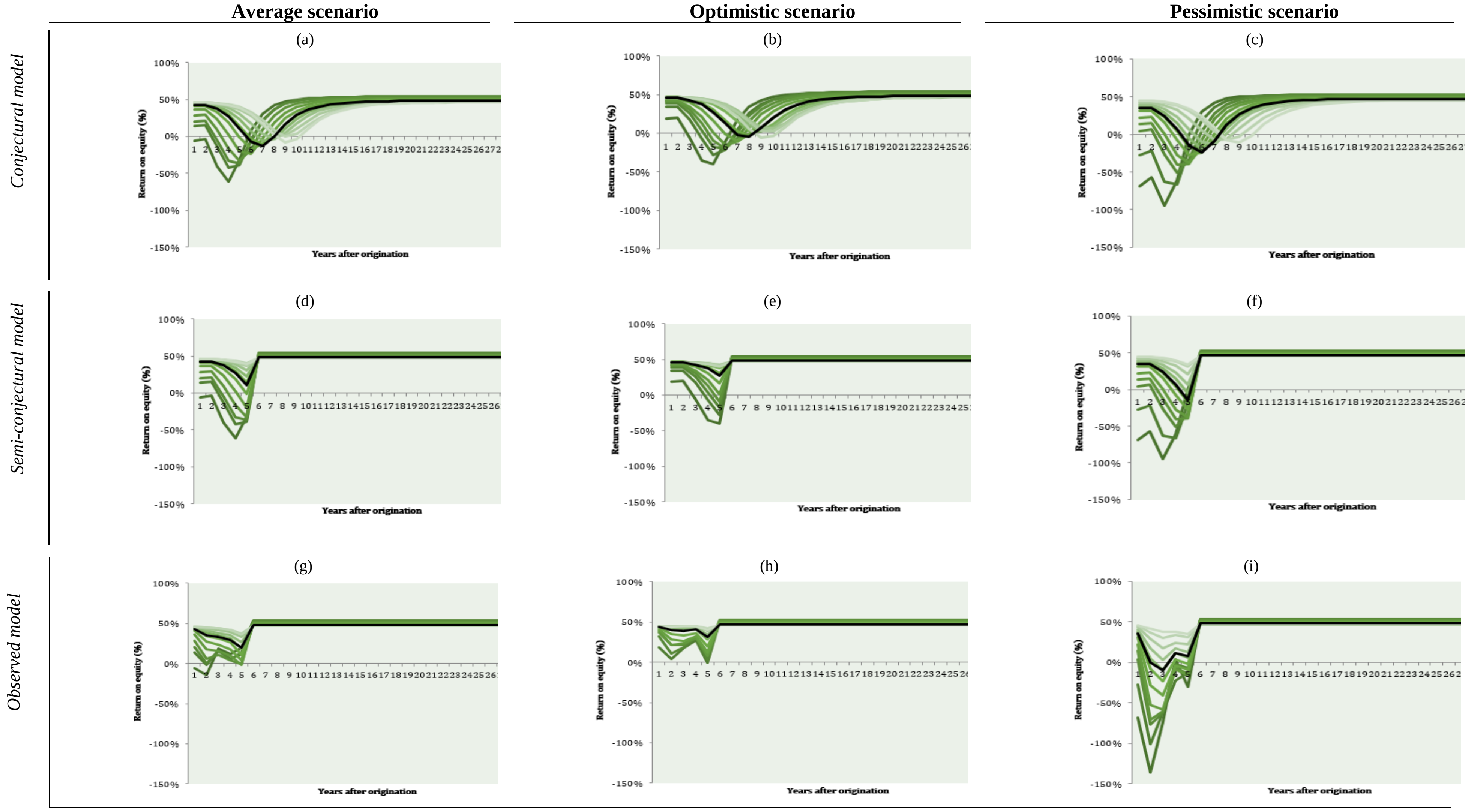


Fig. 9. Expected returns in each default scenario assuming a 50% risk-weight and LGD=45%. From down to the top of the image, lines represent the expected returns in the score buckets [300; 550[, [550; 575[,[575; 600[, [600; 625[,[625; 650[, [650; 675[,[675; 700[, [700; 725[, [725; 750[, [750; 775[,[775; 800[, [800; 850[, respectively.

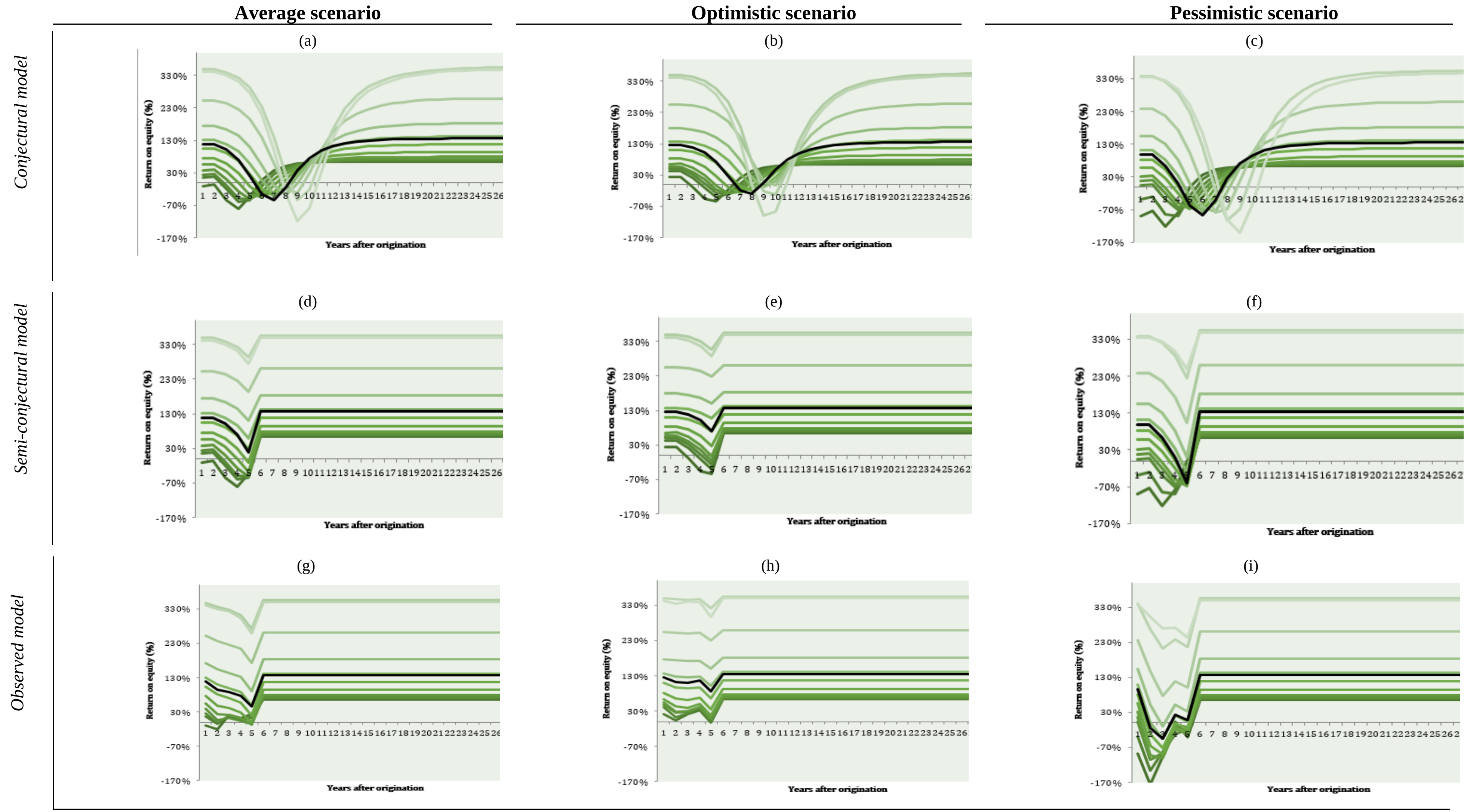


Fig. 10. Expected returns in each default scenario assuming a risk-weight equal to 12.5*1.06*K and LGD=45%. From down to the top of the image, lines represent the expected returns in the score buckets [300; 550[, [550; 575[,[575; 600[, [600; 625[,[625; 650[, [650; 675[,[675; 700[, [700; 725[, [725; 750[, [750; 775[,[775; 800[, [800; 850[, respectively.

5. Conclusions

Regulators, academics and the financial industry increasingly recognize the importance of stressing their reference models under extreme circumstances. Stress-testing often rely on theoretical assumptions or heavily depend in projections (e.g. GDP growth, unemployment or the business in the following period), which in turn are based in several other conjectures. This approach may be of little value if the premises are inaccurate or if the projections remain valid during a short-term period. The former may lead to misleading conclusions; the latter may turn outdated fairly quickly. If, on the one hand, the practical value of these exercises may be debatable, on the other, understanding how real systems evolve in normal conditions and during exacerbated circumstances is of a great use.

We present a stress-testing exercise based in a real-world dataset of 16.7 million loans that were at the epicentre of the global crisis, the Freddie Mac's single family mortgage loan-level dataset, first published in March 2013. We did not attempt to draw a set of baseline assumptions for the future macroeconomic or business conditions. Instead, we simulated the most extreme circumstances of the past, which impacted severely in credit risk and in returns. The measure of risk uses the FICO score, which is an industry standard in the US, currently used in 90% of the lending decisions to determine how much money each individual can borrow and to set the interest rate for each loan. Hence, since its introduction 20 years ago, the latest financial crisis might have been the most severe disruption affecting the borrower's ability to repay their debt.

We analysed the performance of the returns over time considering nine potential scenarios of default rate evolution, each was replicated for an LGD of 25% and LGD of 45%, for a constant 50% risk-weight and applying the risk-weight formula of the Basel Committee for the IRB approach. With very few exceptions, for an LGD up to 25%, most of the credit score buckets produce positive returns along the entire life of the asset, either in average conditions or in adverse circumstances. Within this setting, a portfolio of loans randomly selected from the aggregate portfolio, originated in the same year, should generate positive returns. Higher LGD amplifies the disturbances caused by default rate increases. For a 45% LGD, a significant number of loan pooling arrangements can generate negative returns, either through the cycle, but more noticeably under extreme adverse circumstances. Under this setting, for a wide range of scores, up to 675, returns are below the average in the first years of the loans. If the new default rates evolve constantly over time, then the best scored loans may also reach negative returns is some point in time, in the first 10 years of the loans.

Following the subprime crisis, lenders are firmly declining the subprime loans, below the score 620, and restricting credit to the adjacent lower score borrowers. Although the risk of these loans is higher than in other scores, more consideration should be promoted around the expected return of these loans, including the subprime. When these loans go older, mostly after the fifth year, the expected returns increase, meaning that in the long run, the loans in the lowest scores can positively contribute to the overall return of the portfolios. Although we did not analyse the effect of anticipated payments, intuition and practical knowledge also suggest that these loans will probably not be paid in advance, and so they are valuable for the portfolios' compositions. So, current regulation would be improved if specific rules were developed for accurately pricing loans to the low scores borrowers, rather than strictly prohibiting. This could be complemented by imposing boundaries in the proportion of these loans in the composition of the portfolios, bearing in mind that the risk significantly reduces when these loans go older, in contradiction to the highest score loans that may reach peaks of negative returns around the tenth year. In so doing, the target market, which now is concentrated in the prime scores borrowers, would expand, which is crucial in retail banking. This is one area where more sophistication is needed and more effort should be put to promote renewed principles in retail banking.

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