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Note rate modifications and subprime default rates

Camilo Sarmiento

Fannie Mae, 3900 Wisconsin Avenue, NW, Washington DC 20015, USA
E-mail: camilo_sarmiento@fanniemae.com

An important instrument to mitigate credit losses is modification of note rates of distressed borrowers. From a logistic model of early default, this article inferred the note rate impact on loan default probabilities, while controlling for loan characteristics (credit quality) and borrower location.

I. Introduction

During the US housing boom (period 2001 to 2006), the subprime sector multiplied fourfold. By 2006, subprime borrowers accounted for one in five new mortgages and 10% of all mortgage debt, partly due to the expansion of mortgage-backed securities (Bostic, 2002; Johnson, 2002; Chinloy and MacDonald, 2005). The end of the US housing boom in the second half of 2006, however, marked a large spike in default rates of subprime loans, and by the second half of 2007, the subprime market had collapsed (The Economist, 2007).[1] An important instrument to mitigate credit losses from subprime mortgages is modification of note rates of distressed borrowers. A lower note rate decreases the cost of the loan, which yields lower likelihood of default. This article estimates the impact of the note rate on the likelihood of default, while controlling for loan characteristics (credit quality) and borrower location. Estimation results show the importance of the note rate in mitigating subprime loan defaults.

II. Data and Estimation

The data source is subprime asset-backed securities (ABS) reported to LoanPerformance (LP), Inc. LP data is a public repository of subprime loans sold as ABS securities. The loan performance data set provides detailed information about individual loans. The data set includes many of the standard loan application variables such as loan-to-value (LTV) ratio, credit (FICO) score, loan amount and interest rate type (see Chomsisengphet and Pennington-Cross, 2006). To analyse the impact of monthly payments – as related to the note rate – on subprime defaults, the data contains information on whether the loan was in early default (90 + days delinquent in the first year of the loan). The data sample uses 1 006 098 observations originated in the year 2005.

In credit default models, the most common metric of credit risk is credit (FICO) score (Fabozzi, 2006), a credit quality index based on credit repayment history. Credit scores capture borrower ability to handle their financial constraints as well as borrower tendencies towards fulfilling their obligations. Another important risk metric is borrower equity, captured in the LTV ratio. Other risk components are loan amount, debt-to-income (DTI) ratio, occupancy status (e.g. investment property) and whether the borrower provided full income documentation.

A notice of default is sent to borrowers that are 90 days delinquent in their payments. Historically, only one out of five borrowers that default in their mortgage end up in foreclosure. Early default models capture relative probabilities of default. This article models the event of early default (90 + days delinquent in the first year of the loan) in terms of loan characteristics. Mathematically, denoting systematic factors as X_j (i.e. note rate, FICO score, LTV, loan amount,

[1] To stem subprime foreclosures, on December 2007, US Treasury Secretary announced a selective 5-year freeze on the rates of subprime adjustable-rate mortgages (ARMs).

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documentation, occupancy status, DTI$)_j$, the early default probability model is

$$Prob(Y_j = 1) = F(I_j)$$

where

$$I_j = G(X_j) \tag{1}$$

and, if $F(I_j)$ is a logistic distribution, then

$$Prob\left(Y_j = 1\right) = \frac{\exp\left(I_j\right)}{1 + \exp\left(I_j\right)}$$

The effect of location in Equation 1 is incorporated using a spatial index of the probability of default. This index is a spatial lagged dependent variable (e.g. see Sarmiento, 2008) in which the bandwidth length is set at the county level.[2] Under spatial correlation, Equation 1 is generalized as

$$I_j = G(X_j) + \gamma \frac{\sum_{k \neq j} I_k Y_k}{\sum_{k \neq j} I_k} \tag{2}$$

where

$I_k = 1$ if borrower k and j have loan originated in the same municipality (county), else $I_{kj} = 0$.

Equation 2 allows the municipality of the subprime borrowers to partly explain the default rates when controlling for other risk factors (Sarmiento, 2008). Estimation uses a nonlinear approximation of G(·) in Equation 2.

III. Estimation

Application of the maximum likelihood estimator with spatial correlation yields the partial correlation between loan characteristics and the probability of default in Equation 2. Table 1 summarizes the

Table 1. Coefficient estimates of subprime default equations

Variable	Category	Coefficient	χ^2	p-Value
Intercept		–1.0187	69.3	<0.0001
LTV – Indicator variables	LTV $\leq$ 60	–0.9459	1464.42	<0.0001
	60 $<$ LTV $\leq$ 70	–0.6776	1133.95	<0.0001
	70 $<$ LTV $\leq$ 80	–0.4542	1157.38	<0.0001
	80 $<$ LTV $\leq$ 90	–0.3903	945.94	<0.0001
	90 $<$ LTV $\leq$ 97	–0.2226	219.2	<0.0001
	97 $<$ LTV	0.0000		
FICO – Spline[a]	FICO $\leq$ 600	–0.0069	1385.55	<0.0001
	600 $<$ FICO $\leq$ 660	–0.0138	2768.39	<0.0001
	FICO $>$ 660	–0.0063	427.55	<0.0001
Investor		0.2756	298.79	<0.0001
Note rate		30.9834	6010.95	<0.0001
Origination amount		0.0009	778.65	<0.0001
Low income documentation		0.3216	1271.66	<0.0001
Debt to income – Spline*	DTI $\leq$ 0.36	0.179	3.29	0.0697
	DTI $>$ 0.36	1.4466	231.39	<0.0001
Spatial correlation		6.6387	793.87	<0.0001

Notes: [a]The spline captures additional coefficient contribution. That is,
If FICO $\leq$ 600, then the functional structure for FICO is –0.0069FICO.
If 600 $<$ FICO $\leq$ 660, then the functional structure for FICO is –4.14 – 0.0138(FICO – 600).
If FICO $>$ 660, then the functional structure for FICO is –4.97 – 0.0063(FICO – 660).
*If DTI $\leq$ 0.36, then the functional structure for DTI is –0.179DTI.
If DTI $>$ 0.36, then the functional structure for DTI is 0.06 + 1.45(DTI – 0.36).

[2] This parsimonious specification contrasts with the use of spatial effects that would involve modelling over 3400 municipalities (counties).

coefficient estimates. From the table, the default probability is positively correlated with the LTV ratio and inversely related to the FICO score. Moreover, loans with higher DTI ratio have higher default rates and the presence of low documentation increases the likelihood of default. Investors have larger probability of default than primary residences.

A very important component of default is borrower location (Calem *et al*., 2004). The spatial correlation component in Table 1 shows that default rates of subprime borrowers are strongly and positively correlated with borrowers that pertain to the same municipality. The importance of spatial correlation in risk evaluation is consistent with other applications (e.g. Sarmiento and Wilson, 2007; Sarmiento, 2008).

IV. Impact of the Note Rate on Default

The note rate is a main determinant for the cost of mortgage. A drop in the note rate can sharply increase housing affordability without an accompanying increase in income. Alternatively, an increase in the note rate may impose sufficient financial stress in the borrower increasing the probability of default. After controlling for borrower characteristics (e.g. FICO score, LTV ratio), Table 1 shows that the note rate has a significant impact on the borrower probability of default.

From the marginal note rate impact on default in Table 1, Fig. 1 shows the odds ratios (relative default probabilities) for various note rates. Specifically, Fig. 1 illustrates the probability of default (odds ratio) for different origination note rates relative to a 7.5% baseline (the average 2005 origination rate for subprime loans). The figure indicates that a 9% note rate yields 50% higher default rates than a 7.5% rate (i.e. odds ratio of 1.5), while controlling for borrower characteristics and location. A note rate of 5.5% (6.5%) yields 50% (33%) lower default rates than a 7.5% rate, all else equal. A note rate of 8% yields 60% higher default rates than a 6.5% rate, all else equal. Overall, results show the importance of the note rate in mitigating loan default in subprime.

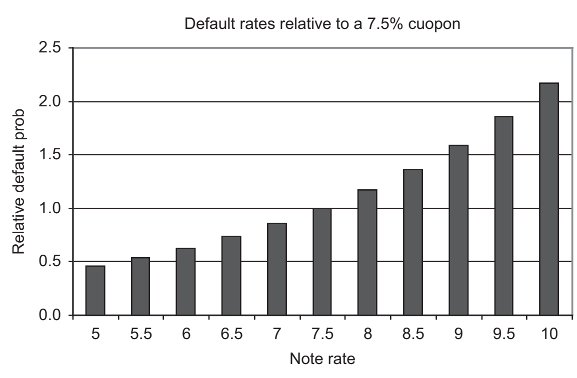

Fig. 1. Relative default rates by note rate level (all else equal)

Rate resets

The partial correlation between the note rate and the probability of default in Table 1 embeds the impact of increasing rates (e.g. rate reset) on default, keeping all else equal. For example, for a representative rate reset rate of 2.5% (for a subprime adjustable rate mortgage),[3] Fig. 1 shows that a note rate jump from 7.5% to 10% yields 2.2 times higher default risk. Therefore, freezing mortgage rates at lower origination rates is effective in preventing loan defaults. Monetary policy also has an impact on default rates for adjustable rate mortgages note (after the loan reset), as it affects the six-month London Inter-Bank Offered Rate (LIBOR).

V. Conclusion

An important instrument to mitigate credit losses is modification of note rates of distressed borrowers. From a logistic model of early default, this article inferred the note rate impact on loan default probabilities, while controlling for loan characteristics (credit quality) and borrower location.

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[3] The ARM rate reset is the difference between the fully index rate and the origination rate:

$$\text{Rate reset}_j = \text{fully indexed rate}_j - \text{origination rate}$$

where

$$\text{fully indexed rate}_j = \text{LIBOR rate}_j + \text{margin}_j$$

As the rate resets, the default rate will rise.

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