



Risk-based capital requirements for mortgage loans

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Abstract

We contribute to the debate over the reform of the Basel Accord by developing risk-based capital requirements for mortgage loans held in portfolio by financial intermediaries. Our approach employs simulation of both economic variables that affect default incidence and conditional loss probability distributions. Results indicate that appropriate capital charges for credit risk vary substantially with loan characteristics and portfolio geographic diversification. Hence, rules that offer little risk differentiation, including the current Basel I regime and “standardized” approach proposed in Basel II result in significant divergence between regulatory and economic capital. These results highlight the incentive problems inherent in simplified methods of capital regulation.

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1. Introduction

Banks play a central role in the economy through their liquidity- and credit-creation functions but their asset–liability structure makes them fragile. Assets include risky loans while liabilities are not contingent claims but relatively short-term

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deposits, susceptible to runs. The public costs of widespread financial distress in the banking sector can be substantial, as the savings and loan debacle of the late 1980s and early 1990s demonstrated. In the United States, deposit insurance plays a role in promoting public confidence in bank liabilities while ongoing supervision and regulatory capital requirements are intended to mitigate insolvency risk.

Assuming that capital regulation is an appropriate intervention in the case of banks, what standards should regulatory agencies apply to depository institutions under their supervision? This question is central to the Basel Committee for Banking Supervision, which is in the process of revising current capital standards (hereafter Basel I) to align regulatory requirements with actual credit risk. Similarly, capital levels are of concern to the Office of Housing Enterprise Oversight, which supervises the huge government-sponsored enterprises (Fannie Mae and Freddie Mac, hereafter called the GSEs) that form the foundation of the secondary mortgage market. In addition, effective internal risk management processes require appropriate capital allocation.

In this paper, we contribute to the debate over capital reform by determining the economic capital necessary to cover credit risk on a portfolio of 30-year, fixed-rate, residential mortgages. While the precise capital levels we generate are conditional on the data and methods used, both our estimates and our technique may provide helpful guidelines for others grappling with the same problem.

Our results highlight some limitations of Basel I and reform proposals (hereafter Basel II). We find that the economic capital required for mortgage portfolios varies widely in relation to underwriting variables (the loan-to-value ratio and the credit rating of the borrower). For example, for prime loans in a geographically diversified portfolio, a loan with a loan-to-value ratio (LTV) of 95% requires three times as much capital as a loan with an LTV of 80%. Hence, rules that offer little risk differentiation, including Basel I, and the “standardized approach” contained in Basel II, result in significant divergence of regulatory from economic capital.

We also find that economic capital depends importantly on the degree of geographic diversification of the mortgage portfolio. Our simulation results for a benchmark, geographically diversified portfolio and a benchmark, regionally concentrated portfolio indicate that the latter requires at least twice the amount of economic capital as the former. Yet neither Basel I nor Basel II directly address portfolio geographic concentration.¹

To assess capital for mortgage portfolio credit risk we need the shape of the credit loss distribution. Economic capital is then allocated in proportion to the distance between a specified, far-tail loss rate of the distribution and the expected loss rate (a measure termed “value-at-risk”). Simulation techniques to generate loss probability distributions have become standard in evaluating economic capital for corporate-debt credit risk.² Economic capital for residential mortgages, and consumer assets in general, has received far less attention.

¹ Under the current and proposed standards, geographic concentration is to be addressed at the supervisory level.

² See, for instance, Crouhy et al. (2000) and Gordy (2000a) for description and comparative analysis of these models.

In our simulation, we follow Carey's (1998) non-parametric re-sampling method to derive probability distributions over future paths of house prices and interest rates; that is, we generate scenarios for these risk factors by Monte-Carlo re-sampling from historical data. These economic factors (house prices and interest rates) determine the probability of mortgage termination, whether by default (potentially producing credit loss) or by prepayment, via conditional survival probabilities calibrated to empirical data. For these conditional survival estimates, we rely on the transition matrices contained in the commercially available LoanPerformance Risk Model, a performance prediction model for residential mortgages developed by a private firm with access to an extraordinarily large set of mortgage market data.³

Our approach is related to that used by The Office of Federal Housing Enterprise Oversight (OFHEO), which regulates the GSEs. OFHEO recently proposed a risk-based capital rule based on a stress test (OFHEO, 2001) that asks whether the GSEs would be adequately capitalized in the event that a particular worst-case scenario occurred. Under this stress test, house price depreciation that occurred in a few states during the early to mid-1980s is assumed to occur nationwide; hence, geographic diversification provides no benefit. Our procedure, on the other hand, employs a probabilistic approach, quantifying the likelihood of stress scenarios that involve substantial house price declines in several regions of the country simultaneously.⁴

The plan for the balance of the paper is as follows. In Section 2, we briefly discuss recent developments in bank capital regulation. Section 3 describes the LoanPerformance Risk Model and other data and statistical estimates used to calibrate the simulation procedure. In Section 4 we describe the simulation procedure in detail and in Section 5 report results. Section 6 provides concluding comments and potential extensions.

2. Policy background

The Basel Committee on Banking Supervision began work on a revised capital Accord, what has come to be known as Basel II, in 1999. For a discussion of Basel I, as adopted in 1988, see Avery and Berger (1991). The Basel II proposal has been revamped once, and banks await a second revision, due out in early 2003. A final rule is expected in October 2003 with implementation scheduled for 2006. The Basel Committee's proposed rule has three principal components. The first centers on actual capital requirements; the second on how supervisors view a bank's risk management systems; and the third improves market discipline through expanded transparency.

³ The Risk Model is a product of LoanPerformance, a company based in San Francisco, and is estimated on its proprietary database of tens of millions of mortgage loan histories.

⁴ We are aware of one prior study in the academic literature that addresses credit risk and economic capital for mortgage portfolios. Quigley and Van Order (1991) analyze economic capital for savings institutions using estimates of mean and variance of loss rates by region and covariance across regions.

Basel I was a simplified approach, establishing specific capital levels for broad categories of assets. A basic 4% standard for *tier one* (equity) capital in relation to “risk-weighted” assets was established, together with a set of four risk “buckets” corresponding to *tier one* capital of 0%, 0.8%, 2.0%, and 4.0% (Greenspan, 1998). Corporate loans, for example, receive a risk weighting of 100% (a minimum of 4% equity capital required), while treasury securities are assigned a 0 risk weighting (implying no capital charge.) The risk weighting was intended to reflect differences in credit risk across these broad asset categories.

Most residential mortgages receive a risk weighting of 50% (a minimum of 2% equity capital), since the 50% weight is assigned to any performing loan that has been “prudently underwritten”. In practice, the 50% weight has been applied to loans backed by private mortgage insurance, and to loans without insurance provided the loan-to-value ratio does not exceed 90% and the borrower is not of subprime credit quality. Residential mortgages not meeting these criteria fall into the 100% risk weight (4% capital) category.⁵

The “one size fits all” approach across wide segments of a bank’s portfolio has been criticized as leading to misallocations of capital within and across institutions. Moreover, the current regulatory approach also promotes securitization and other financial innovations that often enable institutions to reduce regulatory capital requirements with little or no corresponding reduction in overall economic risk (Avery and Berger, 1991; Jones, 2000). This process has come to be called “regulatory capital arbitrage” and has received little academic attention due, in part, to the difficulty of measuring risk transfer under complex asset-backed security structures. The proliferation of regulatory capital arbitrage has also made it difficult for supervisors to assess an institution’s true capital adequacy.

The way banks are capitalized is expected to change significantly as a result of Basel II, which is intended to more closely align regulatory risk weights with economic capital for credit risk. Under the proposed new rules, global banks would qualify for an “internal ratings-based” standard if they could convince regulators that their risk management systems and loan rating models were sufficiently sophisticated. Institutions opting and qualifying for this approach would assign an internal risk rating to each of their exposures and would quantify the credit risk associated with each rating within each product line by assigning to it an average probability of default, percent exposure-at-default, and loss severity. The proposed rule specifies a quantitative mapping of the risk parameters and the asset’s maturity into a loan-level capital requirement. This regulatory mapping is derived from an industry model that is widely used to quantify corporate-debt credit risk (Wilde, 2001). As of this writing, aspects of the mapping are quite preliminary, particularly for retail products (including mortgages).

⁵ In early 2001, the federal bank regulatory agencies issued a supervisory letter directing supervisory authorities to pay particular attention to subprime lending programs and assess additional capital to such loans as appropriate.

Institutions unable to do such complex analyses, presumably smaller institutions, would be governed by the “standardized” approach under Basel II, which is a simplified approach in which specific capital levels are set by asset class. The “standardized” approach would be similar to the old rule, but would allow for increased differentiation of credit risk. In particular, for large corporate exposures, risk weights will be based on external ratings of the borrowers. Retail risk weights for the proposed standardized approach are likely to be revised as well, although as of this writing these have not been calibrated.

Incentives to engage in regulatory capital arbitrage may persist under the “standardized” approach, due to its limited differentiation of credit risk across individual exposures, particularly for residential mortgages, as we argue below. The “internal ratings-based approach” allows for differentiation of credit risk consistent with an institution’s own internal risk-measurement processes, and thus has the potential to significantly reduce incentives to engage in regulatory capital arbitrage. But even the “internal ratings-based” approach may perpetuate regulatory capital arbitrage for asset classes with inappropriate regulatory risk mappings. Moreover, neither approach under Basel II accounts for the impact of geographic diversification on portfolio credit risk, which, we demonstrate below, is a significant omission in the case of mortgages.⁶

The issue of appropriate capital for residential mortgage credit risk is important because of both the size of the market and the level of bank investment. Residential mortgages are a major component of the loan portfolio at large banking institutions. As shown in Table 1, as of year-end 1999, the 25 largest banking organizations in the US held 436.8 billion dollars worth of residential mortgages, representing the second largest category of loans on the balance sheet, after commercial and industrial loans.⁷ In addition, mortgage-backed securities (MBS) represent the largest category of debt securities on the balance sheet of these organizations, as shown in Table 2, although they generally bear only residual credit risk on these assets.^{8,9} Moreover, since some non-banks are major players in the mortgage market, the issue of a level playing field across firm types is of concern.¹⁰

⁶ In fact, the underlying conceptual framework for the “internal ratings-based” standard is a single risk factor model, where it is assumed that all loans in the portfolio are subject to the same set of market conditions. The portfolio capital requirement is then obtained by simple adding up of capital calculated at the loan level, without consideration of portfolio geographic composition (Gordy, 2000b; Wilde, 2001).

⁷ Large corporate, middle-market, and small business loans are grouped together within the commercial-and-industrial category.

⁸ The Federal Housing Association (FHA) bears all of the credit risk on GNMA issued securities. Otherwise, MBS issuers generally take a first-loss position.

⁹ Also, loans sold by banks into MBS with recourse result in off-balance sheet risk, since recourse involves an obligation by the issuer to absorb future credit losses up to a specified amount. Total recourse exposure on mortgages at the 25 largest banking organizations was 9.8 billion dollars as of year-end 1999, equal to about 20% of the outstanding balances of the sold mortgages. This exposure amounted to about one-third of the total recourse exposure of these organizations on all sold loans.

¹⁰ Among the top non-bank mortgage lenders in the US are subsidiaries of General Motors and Cendant Corporation (parent of Avis Rent-A-Car), for example.

Table 1

Composition of the aggregate domestic loan portfolio of the 25 largest banking organizations in the US (as of December 31, 1999)

Loan category ^a	\$ Amount (billions)	Percent
Residential mortgages	436.38	26.0
Multifamily mortgages	21.83	1.2
Farm mortgages	6.38	0.4
Construction	58.68	3.2
Commercial mortgages	164.08	9.0
Commercial and industrial	524.14	28.9
Consumer	278.88	15.4
Lease financing	129.44	7.1
Other	203.12	9.8
Total	1814.37	100.0

Source: Consolidated reports of condition and income (FR-Y9C).

^a Residential mortgage category consists of loans secured by 1–4 family properties; multifamily consists of loans secured by properties with five or more units; farm consists of loans secured by farmland.

Table 2

Composition of the aggregate debt security investment portfolio of the 25 largest banking organizations in the US (as of December 31, 1999)

Debt security category ^a	\$ Amount (billions)	Percent
US treasury and agency	73.74	12.0
GSE pass-through MBS	136.88	22.8
GNMA pass-through MBS	47.20	7.7
Other GSE and GNMA MBS	56.78	9.2
Other US MBS	28.74	4.7
US state and local government issues	43.38	7.1
Other domestic issues	164.36	26.8
Foreign issues	63.23	10.3
Total	614.30	100.0

Source: Consolidated reports of condition and income (FR-Y9C).

^a GSE denotes government-sponsored enterprises (Fannie Mae and Freddie Mac); GNMA denotes Government National Mortgage Association (which issues securities backed by FHA-insured residential mortgages); MBS denotes mortgage-backed securities.

Both Basel I and Basel II explicitly focus on *credit risk* in assigning relative risk weights. Basel II discussions further have emphasized calibrating an institution's overall capital charge to obtain a reasonable degree of coverage for credit risk plus operating risk.¹¹ Interest rate risk is considered apart from credit risk in the regulatory capital context. Adjustments to regulatory capital in response to varying exposure to interest rate risk are made at the supervisory level or through rules associated with the 1995 "Market Risk Amendment" to the Basel Accord, which governs hedging and other activities conducted through the bank's trading account.

¹¹ Operating risk is defined as direct or indirect loss resulting from inadequate or failed internal processes, people and systems, or from external events.

Accordingly, the analysis that follows restricts attention to credit risk, except insofar as we jointly model prepayment and default. Mortgage portfolios are also subject to interest rate risk, including prepayment risk, typically managed through a well-established market in interest rate derivatives. While some might argue that we employ too narrow a definition of risk, our intent is constructive recommendations in the context of the existing regulatory framework.

3. Calibration of the simulation procedure

Our simulation procedure has two parts: calibration, the subject of the current section, and implementation, discussed in the following section. Calibration involves obtaining estimates of conditional probabilities for transitions to delinquency, prepayment, and foreclosure (including deed-in-lieu of foreclosure) or short sale¹² in relation to housing market and loan-level variables, and estimates of conditional expected loss given foreclosure in relation to these variables. In addition, loan-level characteristics, such as credit rating and geographic location, and the discount factor must be calibrated. Stage two is implementation. Using the calibrated conditional survival probabilities and loss-given-foreclosure relationships, a simulated probability distribution over discounted portfolio credit losses is generated by randomizing over risk factor realizations via Monte-Carlo re-sampling from historical data.

We restrict attention to 30-year single-family fixed-rate mortgages (FRMS), the most commonly used instrument to finance owner-occupied housing in the United States,¹³ further focusing on mortgages of conforming size.¹⁴ This seems the natural starting point for analysis of capital requirements for mortgages. While adjustable-rate mortgages (ARMS) are also widely held in institutional portfolios, modeling their termination risk is significantly more complex than FRMS.¹⁵ ARMS have some unique risk factors due to interest-rate dependent payment uncertainty, so we cannot claim that our results apply directly to them.¹⁶

¹² A “short sale” occurs when a lender agrees to the sale of collateral still owned by the borrower for less than the loan amount outstanding and to accept sale proceeds, sometimes accompanied by an unsecured note in the amount of any deficiency, in satisfaction of the debt.

¹³ The mortgage market is huge, now exceeding even the size of the government bond market. As of 2001, a total of \$6.0 trillion in mortgage debt was outstanding, with single-family mortgage debt of \$4.4 trillion representing the largest share. Commercial banks and savings institutions directly hold about 34% of total mortgage debt. An additional 47% has been securitized in agency and non-agency MBS. Other financial institutions, such as insurance companies, and individuals hold the balance.

¹⁴ Mortgages may be divided into conforming, i.e. eligible for purchase by the GSEs (Fannie Mae and Freddie Mac) and non-conforming. A primary criterion is loan size – larger loans (jumbos) are non-conforming. The current cut-off point is \$300,700 for single-family properties.

¹⁵ See, for example, Ambrose and LaCour-Little (2001) for discussion of the complexities associated with modeling adjustable rate mortgage performance.

¹⁶ For example, the spread between long- and short-term interest rates is an additional risk factor affecting prepayment of ARMS that would have to be incorporated into our simulation procedure.

3.1. Conditional transition probabilities

We assume that during any quarter subsequent to origination, conditional on surviving to that quarter, a loan is subject to the following possible transitions. If “current” (less than 90 days delinquent) in its payment status at the beginning of the quarter, the loan may transition to “default” (become 90 days or more delinquent); terminate via full repayment (prepay); or it may remain current. Conditional on being in default at the beginning of a quarter, it may remain in default; return to being current in its payments (cure); terminate via foreclosure or short sale; or be prepaid. Loans are assumed to generate losses if and only if they terminate in foreclosure or short sale.¹⁷

Formally, consider that a loan in state x will transition to state y in quarter n , conditional on its state in quarter $n - 1$. Thus, a loan that is current in quarter $n - 1$ may transition to default or prepayment in quarter n and a loan that is in default in quarter $n - 1$ may transition to current, to foreclosure, or to prepayment in quarter n . Let $P^{xy}(n)$ denote the probability that a loan transitions to state y by the end of the n th quarter after origination (if the loan is current) or n th quarter after default, conditional on it being in state x at the end of quarter $n - 1$. We assume that these probabilities depend on the age of the loan (equal to $n - 1$ if the loan is current), denoted AGE. We also assume that they depend on the current loan-to-value ratio, denoted CLTV; the spread between the current market interest rate and the contract rate on the mortgage, denoted SPREAD; and a vector of fixed loan characteristics \mathbf{Q} , specified below. Thus

$$P^{xy}(n) = f(n, \text{AGE}, \text{CLTV}, \text{SPREAD}, \mathbf{Q}). \quad (1)$$

When the transition relationships (1) are calibrated, and expected loss in the event of foreclosure or short sale also is calibrated, a loan’s expected loss over a given horizon conditional on a realized scenario for house prices and interest rates can be calculated. This is the essence of the simulation procedure developed in the following section.

We obtain estimates of the conditional survival probabilities $P^{xy}(n)$ from a private vendor model, the LoanPerformance Risk Model, as described below. In an earlier phase of this research (Calem and LaCour-Little, 2001), we directly estimated conditional survival probabilities using a large proprietary data set from an individual lender and generated qualitatively similar results. We do not report those here in the interest of brevity.

3.2. Applying the LoanPerformance Risk Model

The LoanPerformance Risk Model is a performance prediction tool for residential mortgage portfolios that calculates delinquency, foreclosure, short sale, and prepayment probabilities at the loan level under either user-specified or model-

¹⁷ In practice, lenders may incur additional costs to manage delinquent accounts regardless of ultimate outcome, but these can be considered operating costs rather than credit losses.

generated scenarios for local market house price levels (a market price index) and market interest rates. The Risk Model uses empirical estimates from logit models of delinquency, foreclosure, and prepayment to assign conditional transition probabilities of the form (1) to each loan over a specified horizon.¹⁸

Defining features of each loan (elements of \mathbf{Q}), such as initial amount and loan-to-value ratio, contractual interest rate, and the borrower's initial FICO score are supplied as an input data set by the user. FICO scores are commercially available credit scores developed by Fair, Isaac and Company and have become the credit industry standard for evaluating consumer credit risk. FICO scores range from 200–900 with higher values representing better credit or less risk.¹⁹

For FRMS, these fixed characteristics along with the two time-varying risk factors CLTV and SPREAD determine quarterly conditional transition probabilities in the Risk Model. CLTV is calculated by multiplying the original loan-to-value ratio times the ratio of the initial to current value of the market price index.

Calibration of the transition relationships (1) for our simulation procedure involved two steps. First, we used the Risk Model to calculate quarterly conditional transition probabilities for a large set of loans that were assigned to various metropolitan areas and time periods and calibrated with varying contract interest rates and characteristics \mathbf{Q} consisting of original loan amount, original loan-to-value ratio, and FICO score. The OFHEO repeat sales price index for each location and period and the historical series for the Freddie Mac average contract rate were replicated via the Risk Model's scenario-generating function and used to generate time paths for CLTV and SPREAD for this calculation.²⁰ Second, the resulting conditional transition probabilities were approximated using parametric survival function representations of (1) that in turn were used to calibrate our simulation procedure.²¹

3.3. Calibrating loss given foreclosure or short sale

When a loan terminates in foreclosure or short sale, proceeds from sale of the property offset some or all of the unpaid principal balance (UPB). We define

$$\text{Net recovery} = \text{Gross sale proceeds} - \text{UPB}. \quad (2)$$

¹⁸ The empirical models underlying the Risk Model were estimated from the company's enormous mortgage performance database, which tracks the performance of tens of millions of individual mortgages. The data were drawn from a variety of sources, including many of the nation's leading mortgage-servicing institutions, with coverage beginning in 1990 for some participating institutions and later for others.

¹⁹ The national median score for all households (with or without mortgages) is 725. A decline of 20 points in the score doubles the estimated odds of default.

²⁰ These historical data are available from www.ofheo.gov and www.freddiemac.com, respectively.

²¹ It was impractical to calculate economic capital for a simulated portfolio by inputting scenarios generated by each of our simulation runs directly into the Risk Model, because that would have required individually inputting thousands of sets of scenarios. Therefore, we used the Risk Model essentially as a tool to calibrate our own capital calculator. In the case of transitions from current to default or prepayment, we represented (1) using exponential survival functions with polynomial terms in CLTV, SPREAD, and the elements of \mathbf{Q} . In the case of transitions from default, we used simpler logit models. Proprietary considerations preclude us from reporting further details.

The loss to the lender in the event of foreclosure or short sale (denoted LGF) is then the sum of interest carrying charge and property and foreclosure transaction costs, minus the net recovery (typically a negative quantity), and minus mortgage insurance reimbursement if any. We calculate loss given short sale or foreclosure identically, except that for short sales we reduce the final tally by 5% of UPB, consistent with empirical findings in De Franco (2001).

Interest carrying charge represents the cost of funding a non-performing mortgage during the holding period between the last payment date and the date of collateral liquidation, with interest accruing at current market rates. The simulation procedure calculates interest carrying charge as interest accrued from the quarter prior to the date of default (since the loan is already 3 months delinquent as of the date of default) through the date of collateral liquidation, based on the 6-month, jumbo certificate-of-deposit rate. The UPB on which interest accrues is calculated by amortizing the original loan amount to the quarter prior to default.

Property disposition costs include real-estate commissions, property taxes, hazard insurance, utilities, repairs, and maintenance, and foreclosure transaction costs include attorneys' fees and other costs. Foreclosure and property disposition costs (assessed at the date of foreclosure) are estimated at 5% and 10% of total unpaid balance, consistent with industry sources: OFHEO (2001) and Wilson (1995).

Net recovery is a particularly important component of loss-given-foreclosure from the perspective of analyzing economic capital, since it links LGF to change in house prices. OFHEO kindly permitted us to estimate a regression equation relating net recovery on a foreclosure sale to loan characteristics and housing market conditions using the agency's proprietary data. The estimated regression equation is used in the simulation procedure to impute the net recovery component of LGF.²²

The OFHEO sample contained about 120,000 observations of 15- and 30-year first-lien, FRMS financing 1–4 family owner-occupied properties located in metropolitan statistical areas (MSAs). The loans were originated between 1989 and 1997 and terminated in foreclosure prior to year-end 1999. The data were collected from the GSEs, so that the sample included only conforming-size loans (maximum of \$250,000). The data included dollar amounts from the sale of the foreclosed properties and UPB, from which net recovery was calculated using (2). The dependent variable for the regression was percentage net recovery (the ratio of net recovery to UPB, multiplied by 100).

The data also included the original loan-to-value ratio and loan amount; dates of loan origination and foreclosure; and geographic identifiers (state, MSA, and ZIP code) for location of the property. These data were supplemented with the OFHEO repeat sales price index for each MSA. In addition, the relative median income of each ZIP code, defined as median income in the ZIP code relative to median income

²² We assume that a foreclosed property is liquidated 2 months after the foreclosure date, and then discount the imputed net recovery to ensure that all the components of loss are calculated as of the foreclosure date. Similarly, we discount that part of the interest carrying charge accruing after the foreclosure date. The discount factor used is discussed below in the text.

of the MSA in which it is located, from the 1990 US Census, was merged into the data. The following regression equation then was estimated:

$$\begin{aligned} \% \text{ Net recovery} = & a_0 + a_1\text{CLTV} + a_2\text{CLTV}^2 + a_3\text{LTV} + a_4\text{LTV}^2 \\ & + a_5\text{SIZE} + a_6\text{SIZE}^2 + a_7\text{RELINC} \\ & + a_8\text{RELINC}^2 + a_9\text{LOAN_AGE} + \varepsilon. \end{aligned} \quad (3)$$

The impact of housing market conditions was captured by inclusion of estimated current loan-to-value ratio (CLTV) as of the foreclosure date (calculated as above). The model's explanatory variables also included the original loan amount in constant dollars (SIZE), the relative median income in the property zip code (RELINC), the original loan-to-value ratio (LTV), and the age of the loan as of the foreclosure date (LOAN_AGE), each of which correspond to inputs into the simulation procedure. The regression allowed for non-linear relationships via spline terms for CLTV and LTV (slope changes at 90% for CLTV and 80% for LTV), represented by CLTV2 and LTV2, and via quadratic terms for SIZE and RELINC. The equation was estimated with ordinary least squares.

Table 3 shows coefficient estimates and *t*-statistics. All explanatory variables are statistically significant at the 1% level and the regression R^2 was 25%. Consistent with

Table 3
Regression analysis results

INTERCEPT	-3.81*
	(2.74)
CLTV	-1.141*
	(96.6)
CLTV2	0.263*
	(16.6)
SIZE	3.1E-4*
	(52.9)
SIZESQ	-9.6E-10*
	(43.3)
RELINC	0.690*
	(58.0)
RELINCSQ	-2.3E-3*
	(42.6)
LTV	0.300*
	(28.1)
LTV2	0.142*
	(3.7)
LOAN_AGE	-0.206*
	(22.0)
Number of observations	120,289
Estimated standard error of ε	21.15
R^2	0.25

Dependent variable: % net recovery on defaulted loans (OFHEO data) (*t*-statistics in parenthesis).

* Statistically significant at the 1% level.

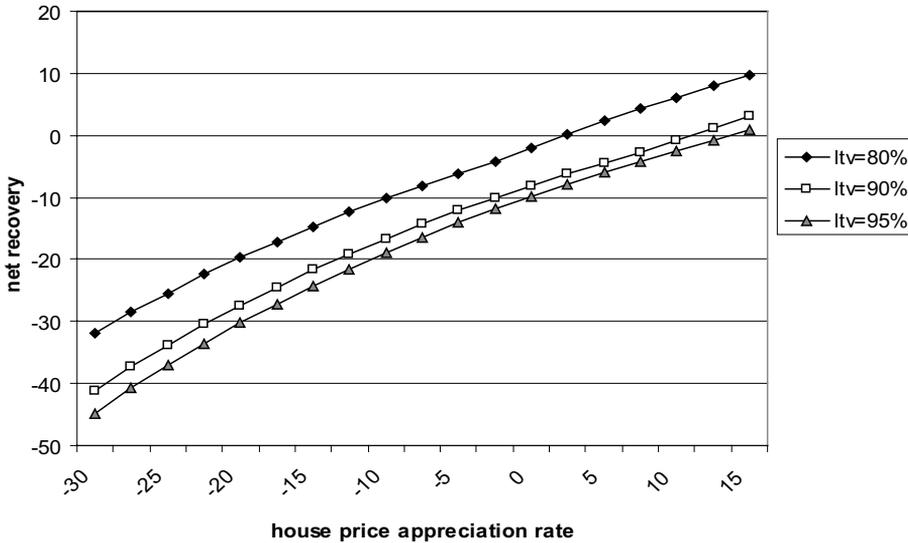


Fig. 1. Estimated relationship between house price appreciation and net recovery.

economic intuition, the results indicate an inverse relation between percentage net recovery and CLTV, consistent with larger recoveries when the loan has proportionately more collateral. Fig. 1 plots the predicted value of percentage net recovery relative to housing appreciation (the percentage change in the market price index between date of origination and date of property liquidation), with LTV set equal to 80%, 90%, and 95% and with other variables set equal to their sample means. The pattern suggests housing market cycles have a significant effect on recovery rates. For example, given LTV = 80, a 25% decline in house prices (a plausible scenario, implying CLTV = 106.67 and CLTV2 = 16.67) yields a percentage net recovery of -25%, and zero appreciation yields a percentage net recovery of -2%.

Moreover, holding CLTV constant, LTV is positively associated and LOAN_AGE inversely associated with net recovery. These findings suggest that the lower the original loan-to-value ratio or the older the loan, the more likely the calculated CLTV provides an underestimate of the actual ratio of loan amount to liquidation value for loans that terminate in foreclosure.

The remaining component of LGF to be calibrated is reimbursement from private mortgage insurance (MI), if any.²³ The presence of MI matters for calculating economic capital to the extent that it reduces the depository institution’s exposure to losses from foreclosure or short sale. The typical MI contract reimburses most losses

²³ It is customary for prime, conventional mortgages with original loan-to-value ratios above 80% to have MI; although depository institutions sometimes “self-insure” the high-LTV loans they retain by explicitly pricing the marginal credit risk. Sometimes, this is done by originating a first mortgage with a loan-to-value ratio of 80% and a second mortgage at a higher interest rate for the remaining portion of the total loan amount.

up to a specified percentage of the “claim amount”, which consists of UPB plus a share of funding and transactions costs and typically equals about 115% of UPB, according to industry sources. These ceilings are typically 25% for loans with LTV of 90% or less, and 30% for loans with LTV greater than 95%. In some simulations, we allow MI on high-LTV loans, adopting these coverage levels for the calibration.

Note that the random term ε in (3) represents the sole source of idiosyncratic variation in the calibrated LGF. For loans without MI, this random variation across loans will average out to zero and is, therefore, of little consequence. For loans with MI, however, the idiosyncratic variation becomes important because it contributes to whether a loss will exceed the insurer’s first-loss position. For calculating LGF in the presence of MI, we assume that ε is normally distributed with a standard deviation equal to the estimated standard error of the regression equation (3). Further, note that the LGF calculation assumes that the MI contract itself is without risk, which may be a reasonable approximation because MI companies are highly capitalized and have high investment grade credit ratings.

3.4. *Discount factor*

The simulation procedure generates a probability distribution over cumulative discounted losses for a simulated loan portfolio, from which economic capital is inferred. We discount losses from the date of foreclosure to the initial date using quarterly 6-month CD rates, which approximate a bank’s cost of funds. The interpretation is that a bank finances losses by money market borrowing.

3.5. *Loan characteristics*

As described in detail in the following section, we conduct a series of economic capital calculations, each involving sets of loans that are homogeneous with respect to initial loan-to-value ratio (LTV) and borrower credit score (FICO) but contain a mix of loan sizes and geographic locations. Calculations are performed with LTV fixed at 80%, 90%, and 95%, respectively, and with FICO score fixed at 620, 660, 700 and 740, respectively. These scores are roughly representative of subprime, A-, prime, and super-prime levels of credit. For each LTV level, we perform calculations with the four alternative calibrations of FICO.

Since original loan amount (SIZE) and neighborhood relative income (RELINC) are covariates in the LGF function, we need to calibrate these for the simulation. We do so by assigning sizes and neighborhood relative incomes to a set of loans in a fashion that approximates the joint empirical distribution of these characteristics in the aggregate portfolio of the 100 largest depository institutions as reported in Home Mortgage Disclosure Act (HMDA) data during 1997–1999.²⁴ Table 4

²⁴ Loans originated or purchased during the fourth quarters are excluded due to potential underreporting of sales of these loans (sales that occur in the next calendar are not recorded in the data). All institutions that were subsidiaries of these organizations as of year-end 1999, including institutions acquired during 1997–1999, are included in the calculations.

Table 4

Aggregate distribution of conforming-size residential mortgages retained by the 25 largest portfolio lenders, by neighborhood income and size

Tract relative income category ^a	Percent of total number of loans	Loan size category	Percent of total number of loans
<80%	10.0	<\$25,000	18.2
80–100%	9.7	\$25,000–50,000	20.5
100–120%	17.5	\$50,000–75,000	14.3
120–140%	26.8	\$75,000–100,000	12.2
140–160%	22.7	\$100,000–125,000	9.5
>160%	13.3	\$125,000–150,000	7.8
–	–	\$150,000–175,000	5.4
–	–	\$175,000–200,000	4.5
–	–	>\$200,000	7.6

Aggregate distribution by tract relative income and loan size, based on 1997–1999 HMDA data (fourth quarters excluded), size < \$250,000 originated or purchased and retained in the portfolio.

^a Ranges are based on tract median income relative to the median income of the metropolitan area (or, for non-MSA tracts, the median income of all non-metropolitan counties in the state) where the tract is located.

summarizes the empirical marginal distributions of these variables. We assign the midpoints of these ranges to a simulated set of loans so that the frequency distribution of the assigned values approximates the observed joint frequency distribution across the corresponding ranges. For example, about 5 percent of the loans are assigned a size of 62,500 together with a relative median income of 110 percent, reflecting the empirical joint frequency of the ranges for which these are midpoints.

3.6. Regional concentration

Since house price changes are regionally correlated, we expect a critical determinant of mortgage portfolio credit risk to be geographic concentration. We calibrate the degree of regional concentration for the simulation procedure by specifying the degree to which loans are dispersed across different cities and regions. A regionally concentrated portfolio will have a large fraction of its loans in a small number of regions. We define a region as one of the nine US Census Divisions, each of which is a collection of states and, therefore, contains multiple metropolitan areas. For example, the New England and Mid-Atlantic regions would include the Boston, Hartford, New York, and Philadelphia, metropolitan areas, among others.

Empirically, large depository institutions hold portfolios that span multiple metropolitan areas but are at least moderately regionally concentrated. Table 5 summarizes geographic concentration for the 100 largest mortgage lenders among depository institutions, based on the same HMDA database mentioned above. The proportion of the portfolio contained within a single Census division, and within two Census divisions, defines regional concentration. At most institutions, more than half of the total dollar amount of the portfolio is confined to a single Census division. Ten portfolios are concentrated entirely in a single region.

Table 5

Degree of regional concentration of mortgage portfolios of large depository institutions (based on 100 largest mortgage-lending institutions)

Degree of regional concentration	Number of institutions
More than 99% of loan volume in a single Census division	10
Less than 99% but more than 75% in one Census division	25
Less than 75% but more than 50% in one Census division	25
Less than 75% in any one but more than 50% in two Census divisions	31
Less than 50% in any two Census divisions	9

Source: 1997–1999 Home Mortgage Disclosure Act data.

For the sake of brevity, the simulation analysis focuses on two polar cases of geographic diversification. The first benchmark case is a highly regionally concentrated portfolio, defined as loans spread across 12 MSAs but confined to a single Census division, with two thirds of the portfolio in three cities. The second is a highly diversified portfolio based on the least geographically concentrated institutions among those represented in Table 5. Here loans are dispersed across all nine Census divisions and across 30 MSAs, and the two Census divisions with the largest concentration contain 40%, and the three cities with the largest concentration contain 20% of the aggregate portfolio. We refer to the first case as the benchmark concentrated portfolio and the second as the benchmark diversified portfolio. From Table 5, we can infer that the concentrated case would apply to roughly 10% of large institutions whereas the diversified case would apply to fewer than 10%. Hence, the majority of institutions have portfolios with a moderate degree of diversification, somewhere between these two polar cases.

4. Simulation model

The simulation procedure involves randomly drawing scenarios for changes in local house prices and interest rates from historical data. In a single iteration of the procedure, the selected paths for these risk factors together with each loan's risk characteristics determine each loan's transition probabilities and loss in the event of foreclosure for each quarter over a specified horizon. We focus on the conditional expected loss rate for a small set of representative loans. Thus, in each trial, it suffices to calculate the expected loss rate for these loans conditional on the risk factor outcomes, rather than simulate the individual performance of each loan in an entire large portfolio.²⁵ Note that for loans with MI, this conditional expected loss rate

²⁵ The model applies to portfolios with a high degree of granularity such that idiosyncratic risk can be ignored. A portfolio's conditional loss rate is equal to the sum of the conditional expected losses for each loan, divided by total loan volume. For a technical discussion justifying the use of conditional expected loss rates to obtain a portfolio loss distribution (see Gordy, 2000b).

depends on the frequency with which losses in the event of foreclosure or short sale would exceed the insurer's first loss position.²⁶

We cannot restrict attention to a single representative loan because we must represent the effects of varying geographic location across the loans in a bank's portfolio. Accordingly, we employ sets of 500 loans, to which we assign the same LTV, FICO, and loan age to each loan and assign distributions of loan sizes and location as described previously. For example, a simulated set of 500 loans with prime quality risk characteristics might have originated in, say, 1989. Over a 10-year time horizon, all loans will experience the path of interest rates that prevailed over the period 1989–1999, but house prices would evolve in accordance with metropolitan area averages. For those loans assigned, say, house price scenarios from cities in the Northeast, house prices would be apt to initially decline in value, then recover, while for loans assigned Midwestern scenarios, house price growth generally would be slow but consistently positive.

A single iteration of the simulation procedure yields the expected loss over the specified horizon, conditional on the drawn scenarios and specified loan characteristics. A large number of trials yield a probability distribution over loss rates for the simulated set of loans.

4.1. Selecting risk factor scenarios via re-sampling

Risk factor scenarios are generated by Monte-Carlo re-sampling, with replacement, from historical data from the 76-quarter period 1982 through 2000. As emphasized in Carey (1998), a significant advantage of the re-sampling methodology is that it avoids parametric assumptions relating to spatial and, in our context, temporal correlation of risk factors. Of course, sampling from historical data limits the set of possible combinations to those that can be constructed from past history. Because of limitations on the house price series prior to 1982; in particular, a sharp decline in the number of metropolitan areas covered, it is not feasible to go back farther for sampling. Concern over the limited historical coverage is ameliorated, however, by the fact that the 1980s and 1990s were periods of greater house price volatility and, hence, greater mortgage credit risk, than the 1970s. Moreover, high inflation rates, which produced rapidly increasing house prices between 1975 and 1982, mitigated mortgage credit risk during this period.

We begin each trial by randomly selecting a year and quarter from the beginning of 1982 through the end of 1991 (the “designated quarter”) to represent the starting point for loan performance tracking. The draws are restricted to no later than the last quarter of 1991 to permit calculation over horizons as long as ten years. As in Carey (1998), selection of a designated quarter may be interpreted as a draw from

²⁶ Let μ denote the mean of conditional expected loss given foreclosure; that is, its value when ε in (3) is 0. Given our calibration of the distribution of ε , conditional expected loss given foreclosure depends only on μ and the insurer's first loss position. We facilitate the simulation procedure by using piecewise quadratic functions of μ and μ^2 to construct almost exact approximations to conditional expected loss given foreclosure.

the best information about macroeconomic environments affecting risk-factor evolution. Market interest rate scenarios are drawn directly from Freddie Mac's quarterly mortgage interest rate series beginning with the designated quarter through the end of the horizon. The note rate on the loan is set at the initial rate in the series for the quarter drawn, and the path of the quarterly series provides the subsequent market rates.

The next step is to draw market-level scenarios for local house prices. Prior to the first trial, we assign each loan in the portfolio to a region (defined as a Census division) and to an MSA in accordance with our assumed degree of regional concentration. For expository purposes, we refer to the MSA and region to which the loan has been assigned as the loan's "home market" and "home region", respectively. During each trial, we then draw market-level scenarios for local house prices by randomly pairing the home region with one of the nine Census divisions (the "designated region") and randomly pairing the home market with an MSA within the designated region (the "designated MSA"). Loans originally assigned to New York could have the Houston experience, for example, while loans originally assigned to Philadelphia could have the Dallas experience or the Houston experience, but both must draw from the same set of regional scenarios. The evolution of house prices in the home market is then the OFHEO house price index series in the designated MSA beginning with the quarter drawn and through the end of the specified horizon.²⁷

All loans sharing the same home MSA will share the same designated MSA, and all loans sharing the same home region will share the same designated region. Together, the random selection of a designated quarter, region, and market may be interpreted as a draw from the best available information about local economic environments affecting risk-factor evolution. Implicitly, this assumes that no region is more or less prone to economic stress than any other.

4.2. Calculating transition probabilities and expected loss rates

Given a realized path for house prices and interest rates and the implied quarterly, conditional transition probabilities, the expected loss for each loan is computed recursively. For now, we let H denote any horizon of interest, in quarters. Let δ_t denote the discount factor in quarter t . Let TRAN_FCL_{ij} denote the probability that a loan transitions to foreclosure in quarter j conditional on default in quarter $i < j$, and let TRAN_REPAY_{ij} denote the probability that a loan transitions to full repayment in quarter j conditional on default in quarter $i < j$, and let LGF denote the loss given foreclosure or short sale. Given any H we can recursively compute the expected loss in quarter j given default in quarter i , denoted $\text{ELGD}_i(j)$, for $j = i + 1, \dots, H$, via:

²⁷ Obviously, designated MSAs are drawn from the set of MSAs for which a continuous OFHEO house price series exists for 1982–1998, subject to imputation of isolated missing values and the following stipulation. If an OFHEO series exists only from 1985 on, we extrapolate back to the first quarter of 1982 using the state house price index. We remove extreme values for quarterly changes in house prices by placing a cap of 25% on the absolute value of quarterly percentage change. The final sample incorporated 186 MSAs, with no fewer than 12 in any one region.

$$\begin{aligned}
 \text{ELGD}_i(j) &= (\text{TRAN_FCL}_{ij})(\text{LGF}), \quad j = H, \\
 \text{ELGD}_i(j-1) &= (\text{TRAN_FCL}_{ij})(\text{LGF}) \\
 &\quad + \delta_{j-1}(1 - \text{TRAN_FCL}_{ij} - \text{TRAN_REPAY}_{ij})(\text{ELGD}_i(j)), \quad j < H.
 \end{aligned}
 \tag{4}$$

These are simply present value formulas for cumulative expected loss within the specified horizon, and are easily modified to allow some probability of short sales. Similarly, let TRAN_DEF_i denote the probability that a current loan transitions to default in quarter i and let TRAN_PREPAY_i denote the probability that the loan transitions to prepayment in quarter i . We recursively compute the expected loss in quarter i , denoted $\text{EL}(i)$, for $i = 1, \dots, H$, via:

$$\begin{aligned}
 \text{EL}(H) &= 0, \\
 \text{EL}(i) &= \delta_i(\text{TRAN_DEF}_i)(\text{ELGD}_i(i+1)) \\
 &\quad + \delta_i(1 - \text{TRAN_DEF}_i - \text{TRAN_PREPAY}_i)(\text{EL}(i+1)), \quad i < H.
 \end{aligned}
 \tag{5}$$

A loan's expected loss as of the starting date of performance tracking, given the drawn scenarios, is $\text{EL}(1)$. Summing these expected losses for the simulated set of loans and then dividing by the total loan amount yields the expected loss rate associated with a particular iteration of the simulation process.

4.3. Calculating economic capital

A single iteration of the simulation yields a conditional expected loss rate over a specified horizon for the simulated set of loans, and a large number of trials yield a simulated probability distribution over loss rates. We employ 15,000 trials.²⁸ Standard practice is then to equate economic capital with the difference between a selected far-tail loss rate and the mean of the simulated probability distribution – a quantity termed value-at-risk.²⁹ There are two remaining issues. First, which far-tail percentile should be used; that is, what is the appropriate “solvency” standard? Second, what is the appropriate horizon for calculating conditional expected losses?

Basel II proposes tying the solvency standard to a desired equivalent bond rating. Table 6, in columns 1–3, shows historical cumulative default frequencies for bonds in Standard & Poor's (S&P) A, BBB+, and BBB– rating categories, for horizons ranging from 5 to 10 years. Basel II proposes a solvency standard for the “internal ratings-based approach” corresponding to a BBB+ rating; for instance, an 8-year

²⁸ Experimentation with differing numbers of trials indicated that 15,000 trials were sufficient to eliminate idiosyncratic variation from estimates of the tail percentiles of interest.

²⁹ See, for instance, Crouhy et al. (2000). The usual assumption is that losses up to the mean of the distribution are covered by reserves (allowances) for loan losses and margin income. There is some debate, however, over whether regulatory capital should also cover at least part of the expected loss over the life of a loan. The argument opposing a pure value-at-risk calculation is that banks may have difficulty maintaining margin income or loss reserves at adequate levels during stress periods.

Table 6
Performance horizon comparisons

Horizon (years)	A cumulative default rate (%) ^a	BBB+ cumulative default rate (%) ^a	BBB– cumulative default rate (%) ^a	Economic capital for a concentrated portfolio: 740 FICO, 80 LTV (%)	Economic capital for a diversified portfolio: 620 FICO, 90 LTV (%)
5	0.38	1.1	3.0	0.51	1.95
6	0.54	1.6	4.0	0.79	2.49
7	0.65	1.83	4.8	0.82	2.40
8	0.83	2.00	5.56	0.84	2.38
9	1.05	2.07	6.04	0.85	2.36
10	1.30	2.17	6.33	0.86	2.35

Historic default rates on BBB+, BBB–, and A rated bonds, and selected economic capital calculations (BBB+ standard).

^a Source: Standard & Poor's (February 2000).

solvency probability of 98%.³⁰ Since this standard would apply to all asset classes, we adopt it as our baseline.

Once a solvency standard has been specified, the far-tail percentile for computing economic capital is determined by the stipulation that the bank must hold the minimum amount of capital sufficient for the asset to qualify for this rating based on the probability of exhausting capital (“insolvency”) over a specified horizon. For any given loan, we use the horizon that produces the largest requirement. This criterion generates a horizon much shorter than time-to-maturity of the loan, for several reasons. First, because the solvency standard is defined in terms of a bond rating equivalent, lengthening the horizon lowers the target solvency probability (since a longer horizon corresponds to a higher cumulative default frequency for a given bond rating). Thus, lengthening the horizon enables the solvency standard to be met with higher cumulative discounted losses. Second, toward the end of a long horizon, there tend to be relatively few additional defaults and losses. Third, due to discounting, losses that occur in later years have a relatively small impact on the discounted cumulative loss distribution.

The indicated horizons range from 6 to 10 years, and tend to be shorter for loans with higher LTV or lower FICO scores, and for seasoned loans. This is illustrated in Table 6, columns 4 and 5, which show simulation results for two newly originated loans under a BBB+ standard, where we vary the horizon between 5 and 10 years. For an 80% LTV loan with a FICO score of 740 in a regionally concentrated

³⁰ See Basel Committee on Banking Supervision (November 2001). The Basel Committee's rationale for adopting this standard is that a regulatory standard tends to function as a minimum requirement. In order to limit the likelihood of violating the standard, or in response to bond market expectations, or in some cases as a result of supervisory directives in response to perceived weaknesses, institutions generally will capitalize beyond the regulatory requirement. Hence, a BBB+ standard is being viewed as sufficiently conservative by the regulatory authorities.

portfolio (column 4), a 10-year horizon is indicated, and for a 90 LTV loan with a FICO score of 620 in a regionally diversified portfolio (column 5), a 6-year horizon is indicated.

We also calculate economic capital under A and BBB– standards. Comparisons presented below characterize the sensitivity of capital requirements to the target bond-rating equivalent standards.

4.4. Additional comments

Although we mostly confine our attention to newly originated loans, the simulation procedure is applicable to new or to seasoned loans. Seasoning is addressed by treating the selection of an initial year and quarter as the selection of a begin-date for tracking loan performance, rather than as the loan origination date. Loan seasoning directly affects transition probabilities, which are conditioned on loan age. Also, the accelerated amortization for seasoned loans affects CLTV and UPB, but the simulation is otherwise unchanged.

Our model averages over the business cycle to calculate economic capital, inasmuch as risk factor draws are not conditional on current economic information or weighted using forecasted house price movements. This is consistent with the Basel II framework, where the capital allocated to a particular risk class would be invariant to the business cycle, and with the internal economic capital systems of banks that employ a “through-the-cycle” capital concept. In principal, the model can be adapted to weight risk factor draws based on current economic or housing market conditions.

5. Simulation results

Table 6 presented selected economic capital results in comparison to historic default rates for selected bond rating categories, over differing horizon periods, to illustrate the effect of horizon choice. Turning to Table 7, we examine how expected

Table 7

Ten-year expected cumulative foreclosure and short-sale rate and expected discounted loss rates for newly originated loans with various risk characteristics

LTV\FICO	620 (subprime)	660 (A-)	700 (prime)	740 (super-prime)
A. Ten-year expected cumulative foreclosure and short-sale rate (%)				
80	3.79	2.30	1.51	1.09
90	7.27	4.56	3.07	2.25
95	9.86	6.31	4.30	3.17
B. Ten-year discounted expected loss rate, without MI (%)				
80	0.68	0.42	0.28	0.20
90	1.63	1.04	0.71	0.52
95	2.35	1.53	1.06	0.79
C. Ten-year discounted expected loss rate, with MI (%)				
90	0.71	0.46	0.32	0.24
95	0.83	0.56	0.40	0.30

cumulative foreclosure and loss rates vary with a loan’s initial risk characteristics, fixing the horizon at 10 years, for convenience. Table 7 summarizes results from simulations with 15,000 random trials and 500 loans, assumed to be newly originated, under alternative calibrations of LTV, FICO, and MI coverage, for two benchmark risk measures: the 10-year expected cumulative foreclosure plus short-sale rate and 10-year expected discounted loss rate. Panel A shows cumulative foreclosure plus short-sale rates arrayed by LTV and FICO; Panels B and C, respectively, show cumulative expected loss rates for loans with and without MI, by LTV and FICO. The results indicate substantial increases in credit risk with higher LTV and lower FICO.

Table 8 summarizes economic capital results from simulations with 15,000 random trials and sets of 500 loans, newly originated without MI, under alternative calibrations of LTV, FICO, and regional concentration. No MI would be typical in the subprime market segment, for example. Panels A, B, and C, respectively, report

Table 8
Economic capital for newly originated loans without MI

LTV\FICO	620 (subprime)	660 (A-)	700 (prime)	740 (super-prime)
A. Regionally diversified portfolio: BBB+ solvency standard (%)				
80	1.20	0.86	0.61	0.46
90	2.49	1.91	1.51	1.22
95	3.27	2.61	2.14	1.78
B. Regionally diversified portfolio: BBB– solvency standard (%)				
80	0.79	0.53	0.37	0.27
90	1.72	1.25	0.94	0.74
95	2.34	1.78	1.39	1.10
C. Regionally diversified portfolio: A solvency standard (%)				
80	1.65	1.15	0.84	0.63
90	3.30	2.62	2.01	1.64
95	4.21	3.48	2.88	2.38
D. Regionally concentrated portfolio: BBB+ solvency standard (%)				
80	2.60	1.70	1.17	0.86
90	5.82	4.15	3.01	2.33
95	8.09	5.93	4.50	3.54
E. Regionally concentrated portfolio: BBB– solvency standard (%)				
80	1.63	1.00	0.66	0.47
90	3.95	2.56	1.74	1.26
95	5.73	3.84	2.66	1.97
F. Regionally concentrated portfolio: A solvency standard (%)				
80	4.31	3.03	2.16	1.64
90	9.18	7.02	5.42	4.40
95	11.86	9.41	7.89	6.54

Simulated capital charges for newly originated loans by LTV and credit score. The horizon for calculating economic capital varies with LTV, FICO score, degree of regional concentration, and solvency standard and is the horizon that yields maximal capital in each case.

simulated capital charges for a geographically diversified portfolio under a BBB+, BBB–, and A solvency standard. Panels D through F present corresponding results for a regionally concentrated portfolio.

The results in Table 8 highlight some limitations of both Basel I and proposed Basel II reforms, and provide benchmarks for calibration of a risk-sensitive capital standard for fixed-rate, conforming-size residential mortgages. The results show that appropriate capital requirements vary widely across LTV and FICO categories and show a substantial effect of geographic diversification. Table 8 also shows considerable variation depending on the solvency standard applied. These results contrast with Basel I and the proposed “standardized” approach in Basel II, both of which incorporate little risk differentiation within the residential mortgage category and thereby perpetuate the regulatory capital arbitrage incentive. Furthermore, neither the simplified approaches nor the proposed, more sophisticated, “internal ratings-based” approach directly address geographic concentration. One consequence may be implicit subsidization of institutions with regional concentrations.

For instance, focusing on the BBB+ insolvency standard that is currently favored by the Basel Committee, within a regionally diversified portfolio, a loan with a 95% LTV and 620 FICO score requires seven times the amount of capital as a loan with an 80% LTV and 740 FICO score; while in a regionally concentrated portfolio, the former requires about nine times the amount of capital as the latter. Economic capital for loans with 95 LTV is three to four times that for loans with 80% LTV, and capital allocations for the regionally concentrated portfolio are two to two-and-one-half times larger than those of the diversified portfolio.³¹

For a regionally diversified portfolio, the calculated economic capital allocations are below current regulatory minimum requirements for loans without MI (4% for 95 LTV or subprime, 2% otherwise). On the other hand, economic capital allocations for the regionally concentrated portfolio mostly exceed current regulatory minimum standards in the 90 and 95 LTV categories. The latter result suggests that the current standard may not provide adequate coverage for mortgage credit risk for institutions with highly concentrated portfolios.

5.1. *Stress test*

Our approach is similar to traditional stress test methodology, but it employs a more probabilistic approach to generating loss scenarios. In particular, we select sce-

³¹ Additional simulation experiments suggested that marginal increases in concentration relative to our benchmark, diversified portfolio have a smaller impact than marginal decreases relative to our benchmark, concentrated portfolio. For example, in the case of a portfolio spanning 12 cities and two regions, where 75% of loans are in one region and half are concentrated in three cities, capital under a BBB+ standard for a 90 LTV, 620 FICO loan was 4.59. This represents a 20% reduction relative to the benchmark concentrated portfolio. For a portfolio spanning 30 cities and most regions with 60% of the portfolio concentrated in the two largest regions and 30% in the three largest cities, capital under a BBB+ standard for a 90 LTV, 620 FICO loan was 2.67. This represents only a 7% increase relative to the benchmark, diversified portfolio.

Table 9
Stress test capital for newly originated loans without MI

LTV\FICO	620 (subprime)	660 (A-)	700 (prime)	740 (super-prime)
80	2.67	1.71	1.15	0.83
90	6.14	4.33	3.09	2.31
95	8.43	6.30	4.67	3.59

Implied capital from “OFHEO-type” stress test (%). Calculated by averaging over scenarios for interest rates and house prices drawn from origination quarters in 1983–1984 and MSAs in Alabama, Arkansas, Mississippi, and Oklahoma, with a 10-year performance horizon.

narios corresponding to a target bond-rating solvency probability. Thus tail loss rates are generated by draws of origination quarters and regions or cities linked to major housing market declines. Informally, a “bad draw” means being in the wrong place at the wrong time. The West South Central division with origination quarters in 1983 and 1984 plays the most prominent role in generating tail scenarios. For instance, in the case of a regionally concentrated portfolio, two thirds of tail loss rates exceeding the BBB+ solvency standard are associated with this region and these origination quarters. The Mountain division with origination quarters in 1983 also plays a prominent role; in particular, these are associated with most of the remaining BBB+ tail scenarios in the case of a regionally concentrated portfolio.

In contrast, a pure stress test would be based on selection of a single scenario for house prices and interest rates applied to the entire portfolio. Table 9 presents results from application of an “OFHEO-type” stress test, which is based on the average experience from origination quarters in 1983 and 1984 and MSAs in Alabama, Arkansas, Mississippi, and Oklahoma, and provides a useful benchmark for judging the relative stringency of the proposed BBB+ standard.³² We again employ a set of 500 loans, newly originated, without MI, under alternative calibrations of LTV and FICO. We calculate cumulative discounted loss over a 10-year horizon, averaging over scenarios drawn from this period and these states. Our results indicate that the “OFHEO-type” stress test is comparable to the BBB+ solvency standard in the case of a regionally concentrated portfolio, but is substantially more stringent than even the A solvency standard in the case of a regionally diversified portfolio.

5.2. Mortgage insurance

Typically, prime high-LTV loans are originated with private mortgage insurance (MI); indeed, they must be if intended for sale to the GSEs. We have also conducted

³² These are the time period and states used to generate the house price scenario for the actual OFHEO stress test. However, the interest rate scenario for that test is specified separately, in contrast to what we do here. Our sample contained 10 MSAs in these four states. Note that two of these states (Arkansas and Oklahoma) are in the West Central Division, which, as noted above, along with origination quarters in 1983 and 1984 played a prominent role in generating tail scenarios in the simulation model.

Table 10
Economic capital for newly originated loans with MI

LTV\FICO	620 (subprime)	660 (A-)	700 (prime)	740 (super-prime)
A. Regionally diversified portfolio: BBB+ solvency standard (%)				
90	1.57	1.25	0.97	0.79
95	1.88	1.52	1.27	1.05
B. Regionally diversified portfolio: BBB– solvency standard (%)				
90	1.05	0.78	0.59	0.47
95	1.29	1.01	0.78	0.64
C. Regionally diversified portfolio: A solvency standard (%)				
90	2.12	1.68	1.31	1.08
95	2.46	2.08	1.69	1.43
D. Regionally concentrated portfolio: BBB+ solvency standard (%)				
90	3.58	2.51	1.81	1.39
95	4.43	3.30	2.47	1.93
E. Regionally concentrated portfolio: BBB– solvency standard (%)				
90	2.03	1.34	0.91	0.68
95	2.55	1.75	1.24	0.93
F. Regionally concentrated portfolio: A solvency standard (%)				
90	5.79	4.50	3.48	2.80
95	6.93	5.54	4.58	3.77

Simulated capital charges for newly originated loans by LTV and credit score. The horizon for calculating economic capital varies with LTV, FICO score, degree of regional concentration, and solvency standard and is the horizon that yields maximal capital in each case.

simulations allowing for full reimbursement of losses up to the typical contract maximums noted earlier.

Table 10 summarizes economic capital allocations from simulations with 15,000 random trials and a set of 500 loans, assumed to be newly originated with MI, under alternative calibrations of LTV (90% or 95%), FICO, and regional concentration. We continue to observe substantial differences by LTV and FICO score and between regionally diversified and concentrated portfolios. In the case of the regionally diversified portfolio, economic capital allocations under a BBB+ solvency standard generally are well below the current, 2% regulatory standard for loans with MI, while for the regionally concentrated portfolio, they substantially exceed the current regulatory standard in half of the risk categories.

5.3. Seasoned loans

Extension of the procedure to moderately seasoned loans produces small increases in economic capital. For instance, we find that capital requirements are about 10% larger for loans that are 3 years old compared to new loans. Thus, for an aging portfolio, modest increases in capital appear to be appropriate. This is because losses are relatively unlikely to occur early on in a loan's life and, hence, present value losses over any horizon are lower on newly originated loans. One implication here is that

regulators might reasonably require a capital infusion as a condition for approving acquisition of institutions with seasoned portfolios.

6. Conclusions

We have developed and implemented a method for calculating risk-based capital requirements for mortgage loans held in portfolio by financial intermediaries. Our method uses a non-parametric simulation procedure following Carey (1998) together with traditional hazard models of mortgage loan performance. The values reported are essentially credit value-at-risk measures, i.e. the excess of far-tail loss probabilities over expected values.

Our results are quite intuitive and demonstrate the benefits of geographic diversification, together with the increased credit risk associated with high LTV and/or sub-prime lending. Results highlight limitations of Basel I and the reform proposals in Basel II that provide little risk differentiation and/or do not directly address geographic concentration. In addition, results provide preliminary benchmarks for calibration of a risk-sensitive capital standard for fixed-rate, conforming-size residential mortgages. Precise results are, of course, conditional on the data and econometric model used to calibrate the simulation procedure.

Our results also suggest that current regulatory capital standards generally are too high for banks with regionally diversified portfolios. Tying regulatory capital requirements more closely to economic risks for mortgage assets would likely reduce incentives for such institutions to engage in regulatory capital arbitrage. Economic capital allocations for a regionally concentrated portfolio generally are about double those for a diversified portfolio, and frequently exceed the current regulatory minimum standards.

We recognize that the fixed-rate conforming-size loan category examined here is only one of several major mortgage product categories and hope to extend the analysis to adjustable-rate and jumbo non-conforming loans in future research. We also recognize that the non-parametric, re-sampling approach employed here has certain limitations, since it restricts possible scenario combinations to those that can be constructed from past history. We believe that both parametric and non-parametric approaches should be investigated and hope also to develop a simulation procedure based on parametric modeling of risk factor evolution in future research.

We cannot claim to have established definitive risk-based capital requirements ready for implementation by regulatory agencies, since our results depend on the particular simulation methodology and calibration employed, although we do believe our results represent a significant improvement over Basel I standards. Moreover, we believe our approach is sufficiently general that it can be adapted to alternative calibrations based on application of survival analysis techniques to mortgage loan performance databases. We recommend our method and its results as a guideline for both regulatory agencies and to individual lenders. The latter group may find our approach helpful for preparing for Basel II requirements later in this decade or improving their overall risk management processes today.

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