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Loss severities on residential real estate debt during the Great Recession

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ABSTRACT

This study develops estimates of expected loss severities on mortgage exposures using data from Florida during the Great Recession. This paper marks the first attempt at addressing sample selectivity in the context of loss models. We also construct measures of home equity that are more accurate than those employed in previous studies. We find that failing to address sample selection and the use of noisy equity measures in loss models can bias loss estimates significantly. We also find significantly higher loss severities and a greater sensitivity of loss severity to equity than what previous studies report.

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1. Introduction

The ability to accurately predict loss severities is important not only to promote more efficient lending policies and debt allocation across consumers, but also to ensure the stability of the financial system.[1] The bursting of the housing bubble and the associated destruction of nearly $8 trillion of household wealth resulted in enormous credit losses that brought the U.S. banking system to its knees.[2] These credit losses came about not only as a result of soaring mortgage default rates, but also as a result of significantly higher loss severities on defaulted mortgage exposures. Conceptually, minimum regulatory capital under the Basel II accord is supposed to safeguard against unexpected credit losses that occur no more frequently than one in a thousand times (see Basel Committee, 2007). Under the Advanced Internal Ratings Based (A-IRB) approach, estimates of default rates in the 99.9th percentile are obtained from distributional assumptions relating the estimated long-run default rate (PD) to stressed default rates. As long as the distributional assumptions embedded in the capital formula are valid, estimates of stressed default rates can be obtained from reference data over any mix of economic conditions that results in an unbiased long-run estimate. In contrast, loss given default (LGD) estimates over a one-year horizon are not derived from any distributional assumptions, but are instead based on observed losses during downturn economic conditions. Hence, estimates of the expected loss severities when default-related losses are in the 99.9th percentile would, in principle, necessitate the observation of such conditions in reference data. Given the comparatively mild and oftentimes localized housing market downturns predating the 2008 financial crisis, it is not surprising that previous studies of mortgage LGD based upon older data produced estimates that fell short of actual loss severities observed during the recent housing market collapse.

In this paper we provide loss severity estimates on first lien mortgages that have been obtained using data that are arguably conceptually closer to what may be considered a one in-a-thousand event: the losses associated with defaults on first lien mortgages for single-family units in Florida between the first quarter of 2008 and the third quarter of 2011. Over this time

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[1] There is extensive literature showing how asymmetric information about the riskiness of borrowers may contribute to an inefficient allocation of credit and credit rationing (e.g., Jaffee and Russell, 1976; Stiglitz and Weiss, 1981).

[2] Greenlaw et al. (2008) estimated that the total credit losses on residential mortgages between 2006 and 2013 would be approximately $400 billion.

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period, the precipitous decline in housing prices left more than half of homeowners in the state with negative equity and resulted in default rates soaring to over 10%.

Beyond developing estimates of loss severities during very adverse economic conditions, an important contribution of this paper is methodological in nature. The reference data used to estimate LGD models are characterized by inherent sample selection: exposures do not default at random, and many of the same unobservables that influence default are likely to also have an impact on loss severities. Furthermore, loss severities are only observed on defaults for which the workout process has been completed, and evidence strongly suggests a systematic relationship between recovery rates and resolution periods, with more lengthy workout periods associated with greater losses. Both of these selection channels could possibly contaminate loss estimates, an issue that has not yet been addressed in the LGD literature. In this paper, to guard against selection bias, we derive a regression model from a simple economic model of the evolution of property prices in case of default, where observability is governed by a bivariate Probit model that incorporates both of the aforementioned selection mechanisms. The maximum likelihood estimator we develop can naturally be applied in other settings beyond the estimation of LGD.

Another major contribution is the use of measures of equity, identified both through our model and previous literature as the key driver of loss severities, which are more accurate than the equity measures used in existing studies. Previous empirical work on LGD estimation has generally relied upon equity measures constructed by updating the property's most recent sales price or the property value assessment of appraisers, in case of a re-finance loan, using publicly available house price indexes (HPI) such as those provided by Case-Shiller, FHFA, and CoreLogic. Although such indexes can be used to capture general, region-wide trends in home prices, the indexes are arguably of limited usefulness for constructing equity measures for LGD quantification, for several reasons. First, it is widely accepted that housing markets are highly localized; consequently, the variation in the value of a specific home will generally not be well captured by HPIs constructed using coarse geographies such as the metropolitan area, particularly when a long time has lapsed since a sale was last recorded on the property. This measurement error is particularly problematic for loss estimation because of the selective nature of reference data: mortgage defaults, which determine the observability of loss severities, can be expected to be systematically correlated with idiosyncratic home price movements and with any potential errors in appraisals. Second, the equity relevant for LGD purposes is in most cases the value of the property based upon a distressed sale, whereas many HPIs are explicitly designed to capture the dynamics of non-distressed properties. Third, concerns over appraisal inflation, particularly during the housing bubble, suggest that the valuations used to make underwriting decisions may not always be reflective of real property values.[3] The aforementioned limitations to popular approaches to property valuation likely introduced a substantial amount of measurement error into the loan-to-value (LTV) measures used in the empirical models of previous studies, reducing their explanatory power. We improve upon the strictly HPI-based approach to calculating LTV by leveraging annual estimates of market values provided by county property assessors that are updated annually, audited for accuracy and performed independently from the mortgage loan underwriting process.

The results from our empirical analysis show that accounting for sample selectivity and using more accurate measures of equity when estimating loss severities significantly improve the explanatory power of our model and its ability to differentiate the loss severity risk among borrowers. The broader implication of this finding is that the current state of loss severity modeling in the industry may unnecessarily contribute to credit rationing and an inefficient allocation of credit across consumers. There are important implications related also to the magnitude of the estimated loss severities in this study. Our estimates suggest that were a homeowner to default during the kind of adverse economic conditions experienced in Florida during the Great Recession, the expected discounted economic loss on the borrower's fully collateralized first lien mortgage would be in excess of 75% of the defaulted loan balance. Not only does the magnitude of loss undermines the risk-mitigating effects of collateralization, but it also begs the question whether banks' estimates of minimum capital on mortgage portfolios, based on LGDs that are typically much lower than we report here, are sufficiently conservative to safeguard against the intended one-in-a-thousand credit loss event.

The remainder of the paper is organized as follows. Section 2 reviews the existing literature on loss severity estimation. The various databases used to estimate our empirical model are described in Section 3, and our empirical model is outlined in Section 4. We present our results in Section 5. Section 6 concludes.

2. Literature review

The literature on the estimation of LGD of residential mortgage exposures is still quite sparse,[4] and as of this writing, no study has yet documented residential mortgage loss severity or investigated the performance of LGD models estimated on samples representative of the full spectrum of credit quality – including both prime and non-prime borrowers – using data from the most recent housing crash. Furthermore, despite the widespread acceptance that LTV ratios are one of the most important predictors of loss severity, no study has investigated how the performance of LGD models varies across different LTV estimation methodologies.

Of the small number of existing LGD studies of mortgage default, most have been based on data from the 1990s. The earliest of such studies is by Pennington-Cross (2003), who used data on conforming mortgages securitized by the government-sponsored enterprises (GSE) from 1995 through 1999. As expected, he found that recovery rates are sensitive to a loan's LTV ratio, which in this study was calculated by updating property values using the HPI constructed by the Office of Federal Housing Enterprise Oversight (OFHEO).[5] The average LGD in Pennington-Cross (2003) sample was an astonishingly low 2%, and his regression models were generally able to explain over 95% of the variation in recovery rates; both of these figures are likely explained by the relative calm in regional housing markets over this time period. Because of the absence of any severe housing price volatility in Pennington-Cross' (2003) data, it is unlikely that results from this study would generalize to downturn periods. Like Pennington-Cross (2003), Calem and LaCour-Little (2004) also used GSE data to estimate recovery rate models via ordinary least squares (OLS). Although Calem and LaCour-Little (2004) found that loans with higher LTVs – which were also calculated using the OFHEO index – suffered higher relative losses, their results differ from those of Pennington-Cross (2003) in that Calem and LaCour-Little's (2004) models have much lower explanatory power (of roughly 25%) and lower recoveries.

More recently, Qi and Yang (2009) estimated LGD models using data on high-LTV loans from private mortgage insurers. The

[3] Cho and Megbolugbe (1996), Agarwal et al. (2012), and LaCour-Little and Malpezzi (2003) represent studies that empirically document evidence of appraisal inflation.

[4] For a general overview of LGD estimation methods see Qi and Zhao (2011).

[5] During the financial crisis, OFHEO was merged with the Federal Housing Finance Board to form the Federal Housing Finance Agency (FHFA). FHFA continues to produce this house price index series.