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ENDOGENOUS/EXOGENOUS SEGMENTATION IN THE A-IRB FRAMEWORK AND THE PRO-CYCLICALITY OF CAPITAL: AN APPLICATION TO MORTGAGE PORTFOLIOS

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Endogenous/Exogenous Segmentation in the A-IRB Framework and the Pro-cyclicality of Capital: An Application to Mortgage Portfolios

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Abstract

This paper investigates the pro-cyclicality of capital in the advanced internal ratings-based (A-IRB) Basel approach for retail portfolios and identifies the fundamental assumptions required for stable A-IRB risk weights over the economic cycle. Specifically, it distinguishes between endogenous and exogenous segmentation risk drivers and, through application to a portfolio of first mortgages, shows that risk weights remain stable over the economic cycle when the segmentation scheme is derived using exogenous risk drivers, while segmentation schemes that include endogenous risk drivers are highly pro-cyclical. Also analyzed is the sensitivity of the A-IRB framework to model risk resulting from the selection, at the quantification stage, of a data sample period that does not include a period of significant economic downturn. The analysis illustrates important limitations and sensitivities of the A-IRB framework and sheds light on the implicit restrictions embedded in recent regulatory guidance that underscore the importance of rating systems that remain stable over time and throughout business cycles.

JEL classification: G20, G32, G33

Keywords: Basel Accord, credit risk, regulatory capital, mortgages

[1] This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia or the Federal Reserve System. I have benefited from comments by Carlos Gutierrez-Mangas (Federal Reserve Bank of Chicago) and participants at the Interagency Risk Quantification Forum (Office of the Comptroller of the Currency, Washington, D.C., December 2016) and RiskMinds Americas (Chicago, September 2016). Any errors or omissions are the responsibility of the author. Corresponding author: José J. Canals-Cerdá, Federal Reserve Bank of Philadelphia, 10 Independence Mall, Philadelphia, PA 19106. Phone: (215) 574-4127, Fax: (215) 574-4146, e-mail: Jose.Canals-Cerda@phil.frb.org. This paper is available free of charge at www.philadelphiafed.org/research-and-data/publications/working-papers.

1. Introduction

This paper investigates the potential sources of pro-cyclicality in the advanced internal ratings-based (A-IRB) Basel framework and identifies the fundamental assumptions required by a quantification credit risk framework that is, on the one hand, compliant with the A-IRB requirements and, on the other hand, stable over the economic cycle. This analysis is illustrated through an empirical application of the internal ratings-based (IRB) framework to a mortgage portfolio over a long time period comprising a full economic cycle.

The computation of risk-weighted assets (RWAs) is an essential step in the assessment of a bank's regulatory capital adequacy. A recent study by the Basel Committee on Banking Supervision (BCBS) across more than 100 major banks around the world indicates that "[c]redit risk is the primary component of RWAs and the dominant source of overall RWA variations at the bank level, accounting for 77% of the dispersion" (BCBS 2013, 7). In a 2016 consultative document, the BCBS issued new guidance on the A-IRB framework. A key objective of this guidance is to "address excessive variability in the capital requirements for credit risk" (BCBS 2016, p. 1). This guidance highlights principle-based requirements of a sound regulatory capital framework but does not specify how these requirements should be implemented in practice. More specifically, the guidance indicates that "[r]ating systems should be designed in such a way that assignments to rating categories generally remain stable over time and throughout business cycles. Migration from one category to another should generally be due to idiosyncratic or industry-specific changes rather than due to business cycles" (BCBS 2016, p. 7). A clear understanding of the fundamental restrictions implied by these principle-based requirements may simplify and accelerate the design of rating systems with the desired properties and can facilitate discussions around regulatory compliance. Otherwise, both banking organizations and regulators may find themselves trying to attain multiple, principle-based, regulatory objectives that in some cases may be in conflict with each other. Specifically, contemporaneous regulatory guidance emphasizes the importance of homogeneity of the segmentation framework and rank order accuracy, which may have to be considered in conjunction with the potentially binding goal of creating risk-ranking systems that remain stable over the business cycle.[2]

[2] Supervision and Regulation (SR) letter 11-7, "Guidance on Model Risk Management," available at https://www.federalreserve.gov/bankinforeg/srletters/sr1107.htm, emphasizes the importance of accuracy and discriminatory power, among other things.

The BCBS has established a framework for the calculation of regulatory capital that considers two possible alternatives: the A-IRB approach, which allows banks to use their own internal models, subject to regulatory approval; and the standardized approach, which relies primarily on supervisory guidance.[3] For the case of credit risk in retail portfolios, the A-IRB approach consists of four steps. The first step considers the categorization of a bank's exposures into different asset classes. The second step considers the segmentation of retail exposures into homogeneous segments according to risk characteristics. In the third and fourth steps, the bank quantifies risk and calculates the RWAs at the segment and portfolio levels. The standardized approach assigns pre-determined risk weights to different segments of a mortgage portfolio specifically defined by regulation and is presented as a complement and/or alternative to the A-IRB approach.

The primary objective of this paper is to analyze what fundamental restrictions to the A-IRB are implicit in the guidance statements highlighted at the beginning of this paper. It is argued that reducing pro-cyclicality in RWAs for retail portfolios implies restrictions on the set of risk drivers employed at the portfolio segmentation stage, which is a critical part of the credit risk A-IRB framework. Specifically, differentiation is made between two types of risk drivers: those that are not fundamentally affected by the business cycle, which we call exogenous; and those that are susceptible to business cycle variability, which we call endogenous. The argument is that a segmentation structure that generates stable risk weights over the economic cycle should be derived from a set of exogenous risk drivers. Furthermore, it is illustrated how the segmentation framework defined in the standardized approach can be viewed as a particular example of exogenous segmentation. Analysis of the potential trade-off between reducing pro-cyclicality and achieving short-run predictive accuracy is also provided. Finally, the sensitivity of the A-IRB framework to judgments related to data availability and sample coverage is analyzed. This analysis is informed with data from a mortgages portfolio, but the concepts put forward in this paper are more broadly applicable to retail portfolios in general (i.e., credit cards, auto loans, and others). How the Basel II framework performs under the restrictions implicit in the new guidance is evaluated by examining how it would have fared during the Great Recession.

Section 2 presents an overview of the regulatory capital treatment of mortgage portfolios, and Section 3 presents an analysis of the sources of pro-cyclicality in the A-IRB framework. Section 4 describes the data used in the empirical application, analyzes different examples of A-IRB

[3] The international IRB framework is described in the "International Convergence of Capital Measurement and Capital Standards" (BCBS 2006). The U.S. implementation of the IRB framework is described in "Risk-Based Capital Standards: Advanced Capital Adequacy Framework—Basel II; Final Rule" (72 Fed. Reg. (December 7, 2007).

segmentation frameworks using endogenous and exogenous risk drivers, and provides an analysis of over-the-cycle segment migration across segmentation strategies. Section 5 investigates the pro-cyclicality of the A-IRB framework under different endogenous and exogenous segmentation strategies as well as presents analysis on the sensitivity of the A-IRB framework to model risk. Section 6 concludes. Tables and figures are presented at the end of the paper.

2. The Capital Treatment of Mortgage Portfolios

The BCBS Basel II framework "International Convergence of Capital Measurement and Capital Standards" (BCBS 2006) presents two approaches for calculating regulatory capital: the standardized approach and the A-IRB approach. The standardized approach relies primarily on regulatory guidance, while the A-IRB approach allows banks to use their own internal risk models to quantify the risk in their portfolios, subject to regulatory approval. Both approaches have been updated in recent years in light of lessons learned during the most recent banking crisis. In this section, key aspects of these approaches specific to credit risk in retail portfolios are reviewed, with an emphasis on mortgage portfolios.

2.1. The Standardized Approach

The original BCBS Basel II 2006 standard proposed to assign a risk weight of 35% to "lending fully secured by mortgages on residential property that is or will be occupied by the borrower" but allowed some level of supervisory discretion to "evaluate whether the risk weights … are considered to be too low based on the default experience for these types of exposures in their jurisdictions" (BCBS 2006, 24). Formally, a 35% risk weight indicates that the contribution to overall RWAs of this asset class will be 0.35 of the bank's exposure.

In 2015, the BCBS released "Revisions to the Standardised Approach for Credit Risk" (BCBS 2015a and 2015b). This document "forms part of the Committee's broader work on reducing variability in [RWAs]" (BCBS 2015a, 1). When issuing this document, some specific objectives of the committee included "increasing risk sensitivity; reducing national discretions; strengthening the link between the standardised approach and the [A-IRB] approach; and enhancing comparability of capital requirements across banks" (BCBS 2015a, 1). The revision to the standardized approach proposes a significant increase in the risk weight assigned to mortgages secured by residential real estate. Furthermore, the revision proposes different risk weights across prescribed loan-to-value (LTV) segments in order to increase the risk sensitivity of the approach. In the standardized approach, the LTV of a loan is defined as the ratio of the loan amount at the current time over the loan's appraisal value at the time of loan origination. Thus, in general the LTV concept employed by the standardized approach should not be impacted by cyclical fluctuations in home prices after loan origination. At the same time, this way of defining the LTV ratio has significant implications for the risk-ranking ability of the proposed segmentation scheme, as will be shown in the empirical part of the paper.

Table 1 describes the proposed risk weights for residential exposures in the standardized approach, with the first part of the table showing the risk weight-scheme adopted in the international proposal and the second part showing the risk weight-scheme proposed in the United States. In the U.S. standardized approach, "category 1 residential mortgage exposures would generally include traditional, first-lien, prudently underwritten mortgage loans. The proposed definition of category 2 residential mortgage exposures would generally include junior-liens and non-traditional mortgage products" ("Regulatory Capital Rules: Standardized Approach for Risk-Weighted Assets" 2012, 195–196).[4] Because the data consists of loans in the United States, in the empirical part of the paper the risk weights stated in the United States version of the standardized approach are employed, which generally assigns higher risk weights to segments that are similar but not equal to those prescribed in the international version. Note that the proposed standardized approach was not adopted in the United States; instead the final rule assigns exposures secured by one-to-four family residential properties to either the 50 percent risk-weight category, for exposures secured by a first-lien, or the 100 percent risk-weight category in other cases.[5]

2.2. The A-IRB Approach

The alternative A-IRB approach gives banks more flexibility when assigning risk weights to different portfolio segments by allowing them to use their own models to determine a proper portfolio segmentation scheme and to develop their own estimates of relevant risk parameters, subject to regulatory approval. The A-IRB approach consists of four steps. The first step considers the categorization of a bank's exposures into different asset classes. The empirical example focuses on mortgage portfolios that are included in the category of residential mortgage exposures, one of three possible categories applicable to retail exposures. The second step considers the segmentation of retail exposures into homogeneous segments according to risk characteristics. In

[4] In the international standardized case, category 2 broadly refers to when repayment materially depends on the cash flow generated by the property securing the loan. If certain conditions are not satisfied, then the assigned risk weight will be 150%. See BCBS 2015a and 2015b for additional information.
[5] "Regulatory Capital Rules: Regulatory Capital, Implementation of Basel III, Capital Adequacy, Transition Provisions, Prompt Corrective Action, Standardized Approach for Risk-weighted Assets, Market Discipline and Disclosure Requirements, Advanced Approaches Risk-Based Capital Rule, and Market Risk Capital Rule." 78 Fed. Reg. 62018 (October 11, 2013).

this step, the bank uses its own internal models to divide a retail portfolio (mortgages in this paper's example) into segments of loans that are broadly homogeneous with respect to a set of risk parameters considered in the next step. In the third step, the bank quantifies and assigns risk parameters to each segment, specifically the probability of default (PD), loss given default (LGD), and exposure at default (EAD) are estimated at the segment level. In the final step, the bank calculates the RWAs of the portfolio by applying a prescribed A-IRB formula for retail exposures, (mortgages in this case) to determine each segment's regulatory capital, or K:

$$K = \left\lfloor LGD * N\left(\frac{N^{-1}(PD)+\sqrt{R}*N^{-1}(0.999)}{\sqrt{1-R}}\right) - LGD * PD \right\rfloor,$$

where N(.) represents the normal distribution, and R = 0.15,[6] for residential mortgage exposures, represents a prescribed measure of default correlation within the portfolio. The value K represents a measure of unexpected loss rate defined as a percentage of the EAD. The value K is computed as the difference of two components, with the first component, LGD*PD, representing a measure of loss rate for a given long-run PD and the second component representing a measure of loss rate under a stress PD derived from a structural model, as described in the next subsection. The associated RWAs are computed as 12.5 x K x EAD, with 12.5 representing the inverse of the traditional 8% capital ratio, and EAD representing the EAD measured in dollars.

2.3. The Model Foundation of the A-IRB Formula

Many papers have already described in detail the structural foundation of the A-IRB capital formula.[7] Thus, we only provide a basic description here and focus our attention on its implications for cyclicality.

The A-IRB formula is formally derived from a so-called asymptotic single risk factor (ASRF) model (Gordy 2003; Kupiec 2006; Vasicek 2002). This model assumes that the default probability for any particular exposure in a homogeneous retail portfolio can be derived from a latent unobserved factor model that can be decomposed into a common risk factor Z and an idiosyncratic factor E_i, in additive form:

$$v_i = \sqrt{R} \cdot Z + \sqrt{1-R} \cdot E_i.$$

[6] Calem and Follain (2003) conduct an analysis of the correlation parameter for mortgages.
[7] In particular, Gordy (2003) shows how to derive the IRB formula from a Merton (1974) model with a single common risk-factor, and BCBS (2005) provides an explanatory note on the IRB function.

Both factors are assumed to be uncorrelated and to have a standard normal distribution. In this framework, it can be shown that the portfolio default rate at the 99.9th percentile level of the default distribution is:

$$\emptyset(PD) = N\left(\frac{N^{-1}(PD)+\sqrt{R}*N^{-1}(0.999)}{\sqrt{1-R}}\right),$$

where PD is defined in the Basel II accord as "[t]he empirically based best estimate of the long-run average of one-year default rates … over a mix of economic conditions (including economic downturn conditions) sufficient to provide a reasonable estimate of the average one-year default rate over the economic cycle for the segment."[8] Thus, by definition PD should remain constant over the economic cycle. Similarly, $\emptyset(PD)$ should also be independent of the economic cycle. Of course, in practice the estimated value of PD may change over time if there is uncertainty around the default distribution, which will be the case if the initial estimation was not performed over a full economic cycle; this issue will be addressed in the empirical section.

The model accepts a simple graphical representation illustrated in Figure 1A. Specifically, for a certain loan portfolio the expected loss (EL) component represents the average level of credit losses that can reasonably be expected under normal economic conditions. In addition, the unexpected loss (UL) component represents loss beyond the EL that may arise under stress economic conditions. The EL is part of the cost of doing business under normal economic conditions. In principle, unexpected losses can bring the total loss up to 100% of the value of the portfolio. In the Basel framework, the level of UL losses is specified at the 99.9% level, or a level of loss to be experienced in a "once in a thousand years" event. Of course, it is not feasible in practice to estimate a "once in a thousand years" event with any level of accuracy. Thus, this threshold can be better interpreted as a conceptual artifact of the structural modeling framework rather than an arithmetic certainty. In the Basel framework, EL will be computed as PD*LGD*EAD, while UL will be equal to K*EAD. Figure 1B depicts examples of RWA curves across PD values for two different LGD rates (25% and 45%); Figure 1B also depicts the relationship between PD and "stress PD" or $\emptyset(PD)$.

3. The A-IRB Approach and the Pro-cyclicality of Regulatory Capital

A study by the BCBS in 2016 across more than 100 major banks around the world indicates that credit is the dominant source of overall RWA variation. In order to reduce this variability, the

[8] 72 Fed. Reg. 69308 (December 7, 2007).

BCBS proposal recommends providing “greater specification of parameter estimation practices to reduce variability in [RWAs]” (BCBS 2016, 1). One of the recommendations for reducing the variation in RWAs proposes that “[r]ating systems should be designed in such a way that assignments to rating categories generally remain stable over time and throughout business cycles. Migration from one category to another should generally be due to idiosyncratic or industry-specific changes rather than due to business cycles” (BCBS 2016, 7). In this section, the potential sources of pro-cyclicality for retail portfolios in the A-IRB framework are analyzed and the fundamental restrictions implied by the BCBS recommendation of designing stable rating systems are identified.

Of the four steps of the A-IRB framework described in the previous section, the two intermediate steps of the process (i.e., the homogeneous portfolio segmentation and the assignment of risk parameters to each homogeneous segment) should be the focus in the analysis of potential sources of pro-cyclicality.

3.1. The A-IRB Parameters as a Potential Source of Pro-cyclicality

First, I argue that the assignment of risk parameters to homogeneous segments is not a source of pro-cyclicality because of how these parameters are defined in the rule. A necessary assumption in this argument is that the data is sufficiently representative of a complete business cycle including a significant period of economic downturn, as prescribed in the rule. On the other hand, if this assumption is violated, then pro-cyclicality in parameters may arise as a result of model risk and parameter uncertainty; this case will be reviewed in the empirical section of the paper.

The rule defines PD as “the bank’s empirically based best estimate of the long-run average of one-year default rates for the exposures in the segment, capturing the average default experience for exposures in the segment over a mix of economic conditions (including economic downturn conditions) sufficient to provide a reasonable estimate of the average one-year default rate over the economic cycle for the segment.”[9] Thus, because PD is measured as an average of the through-the-cycle (TTC) default rate, it should not be prone to pro-cyclicality. The other parameter in the A-IRB capital formula, LGD, is defined in the rule as “an estimate of the economic loss that would be incurred on an exposure, relative to the exposure’s EAD … during economic downturn conditions.”[10] Thus, the estimate of LGD, at any stage of the business cycle, should reflect

[9] 72 Fed. Reg. 69308 (December 7, 2007).
[10] 72 Fed. Reg. 69309 (December 7, 2007).

economic downturn conditions, and for this reason it should not be prone to pro-cyclicality. Finally, in the case of first mortgages, the EAD is basically the bank's carrying value of the exposure, which is for the most part a deterministic function of time from the origination of the mortgage, and should not be sensitive to pro-cyclicality.[11]

Thus, by reduction we are left with segmentation as the primary driver of pro-cyclicality (along with cyclical changes in portfolio composition broadly unrelated to the A-IRB framework itself). The segmentation step is addressed next.

3.2. The A-IRB Segmentation as a Potential Source of Pro-cyclicality

I have argued that the risk parameters in the A-IRB framework are insulated from pro-cyclicality by design. Thus, segmentation must represent the central source of pro-cyclicality in the A-IRB credit risk framework.

It is straightforward to illustrate how segmentation can be a significant source of pro-cyclicality in a portfolio if segment composition changes endogenously with the business cycle. For example, it has been shown empirically that credit risk in mortgage portfolios is sensitive to cyclical changes in home prices (Deng, Quigley, and Van Order, 2000). Thus, a segmentation approach that exhibits dependence on cyclical changes in home prices will be sensitive to pro-cyclicality. In particular, this will be the case if the updated loan-to-value (ULTV) ratio is a risk driver in the segmentation scheme.[12] Segments with high ULTV will be associated with a higher PD and a higher LGD, and therefore a higher credit risk and a higher K. In this scenario, when home prices decline, loans will migrate to the segments of the portfolio associated with higher ULTV, due to a decline in home values, and the K of the overall portfolio will increase as a result. Similarly, a segmentation approach that relies on updated behavioral variables, such as current delinquency status, will also be subject to pro-cyclicality since the proportion of delinquent accounts is likely to increase during a downturn; as a result, the portfolio will experience migration to segments associated with a higher delinquency status and a higher K.

Risk drivers can be broadly categorized into three groups from a time-dimension perspective: risk drivers identified at the time of loan origination, such as loan amount and credit score at origination; risk drivers identified at the present time, such as updated credit score, ULTV, present

[11] In general, for other retail asset classes, like credit cards, the estimated EAD would reflect what would be expected during a period of economic downturn conditions.
[12] ULTV is defined as the ratio of the loan balance to the current market value of the home; if home prices decrease the market value of the home decreases and ULTV increases.

delinquency status and realized delinquency history, or loan age; and other drivers of risk projected at a future time, such as forecasted macroeconomic conditions and credit supply. I argue that in order to be immune to pro-cyclicality a segmentation framework, or ratings system, must be constructed based on risk drivers that are either fixed at origination, deterministic after origination, like for example loan age, or exogenous to business cycle fluctuations or to the common risk factor, using language from the ASRF framework. Formally, if I interpret the common risk factor Z as a proxy for economic fluctuations and denote by X the vector of risk drivers employed in the segmentation step, then I define a vector of risk drivers as exogenous to Z if $F(X|Z,X_0) = F(X| X_0)$, where F(.) represents the distribution of relevant risk drivers X and X_0 represents the value of the risk drivers at the time of loan origination, which are a function of credit policy and may in principle be influenced by the economic cycle. If this condition is not satisfied then, a change in economic conditions, or a change in Z, will impact the vector of risk drivers and ultimately the segmentation structure; in this case, the vector of risk drivers is defined as endogenous.

3.3. Mitigating Pro-cyclicality

Going now back to the original example, the ULTV ratio as a risk driver is clearly sensitive to economic fluctuations that affect home prices; therefore, if focusing on exogenous risk drivers in the segmentation stage, ULTV should not be used as a risk driver. Instead, the LTV ratio proposed in the standardized approach (i.e., the ratio of the loan amount at the time of calculation over the loan's appraisal value at the time of loan origination, which should be largely exogenous to economic fluctuations) could be used. Thus, interestingly the standardized approach represents a particular example of segmentation scheme build on exogenous risk drivers.[13]

Table 2 defines a set of variables that should be available in most standard mortgage panel datasets. The table is divided into variables that can be categorized as exogenous (and thus are candidates to be included in an exogenous segmentation framework) and as endogenous (and thus should be excluded from a segmentation framework designed to be robust to pro-cyclicality).[14] These variables will be employed in the empirical example in the next section in order to define

[13] Stress test models employed in the Comprehensive Capital Analysis and Review (CCAR) and Dodd–Frank Annual Stress Testing (DFAST) exercises are subject to SR letter 11-7, which highlights the importance of model fit over other considerations. Thus, it is to be expected that most institutions subject to CCAR and DFAST will be developing models that employ endogenous risk drivers to improve model fit. In general, models employed in stress test exercises are likely to be exposed also to the pro-cyclicality induced by endogenous risk drivers.

[14] The mortgage panel dataset employed in this paper consists of 25 static variables and 17 dynamic variables, but not all these variables are useful risk drivers.

endogenous and exogenous segmentation schemes and analyze the performance of these alternative options over the business cycle.

As will be seen in the empirical example, there is a trade-off between exogeneity to business cycles and point-in-time accuracy. Depending on the analyst's willingness to insulate the segmentation framework from business cycle fluctuations, it may be reasonable to focus on risk drivers that are uncorrelated or weakly correlated with the business cycle.

4. An Application to Mortgage Portfolios

4.1. The Data

In the empirical analysis, I employ a publicly available mortgage panel dataset of loans originated between 1999 and 2015, including their historical performance information. This dataset is available from Freddie Mac, which is making available loan-level credit performance data on a portion of fully amortizing fixed-rate mortgages that the company purchased or guaranteed as part of a larger effort to increase transparency.[15] The dataset covers approximately 22.5 million fixed-rate mortgages originated between January 1, 1999, and September 30, 2015. I use a smaller sample comprised of 50,000 loans per origination-year that is also available for download. Monthly loan performance data, including credit performance information up to and including property disposition, are being disclosed. Specific credit performance information in the dataset includes voluntary prepayments and loans that were foreclosure alternatives and real estate owned. Specific actual loss data in the dataset include net sales proceeds, mortgage insurance (MI) recoveries, non-MI recoveries, expenses, current deferred unpaid principal balance, and due date of last paid installment.

Figure 2 depicts the distribution of risk drivers across origination years at the time of loan origination, while Figure 3 depicts the distribution of risk drivers across different cohorts (e.g., for loans active at the time of observation). Figure 2 shows stable underwriting standards until 2008 and a tightening in underwriting standards after that. In particular, the average origination credit score remained stable at around 720 until 2008 and increased to 765 during the period from 2008 to 2012. Similarly, combined LTV remained relatively stable at around 0.74 until 2008 and decreased to 0.69 during the period from 2009 to 2011. The same tendency toward more

[15] Comprehensive information about the dataset described in this section, including access to the overall dataset, is available from http://www.freddiemac.com/news/finance/sf_loanlevel_dataset.html. Much of the data description in this section is extracted directly from the information provided at this website.

conservative underwriting is also observed in Figure 2 for the origination debt-to-income after 2008. Figure 3 shows an improvement in origination risk drivers across cohorts during the downturn years. This is the result of two complementary effects: the tightening of underwriting standards during periods of economic stress; and the selection effect generated by the increase in defaults primarily among the most risky accounts, resulting in an improvement in the origination characteristics of the pool of non-defaulted accounts. Figure 3 also depicts relevant cyclical variables. Specifically, a significant downward shift in the equity ratio distribution as well as a significant increase in delinquencies is observed during the period from 2008 to 2012. A significant increase in the state unemployment rate as well as a downward shift in the county home price index is also observed during the same period.

4.2. Forecasting and Risk-Ranking Ability Across Models

In order to analyze the importance of endogenous segmentation on the pro-cyclicality of capital, I create exogenous and endogenous segmentation schemes employing standard multivariate models to rank accounts according to their projected one-year PD and their projected LGD. The LGD models are estimated over a period of economic downturn.[16] The PD models are estimated during the period from 2001 to 2012, which includes a full economic cycle. We consider three different model specifications. The most basic specification employs only the exogenous risk drivers listed in Table 1 and is used to rank mortgages in the exogenous segmentation scheme. A second model specification expands on the previous one by including also the first set of endogenous risk drivers listed in Table 1, while the third model specification considers in addition the macroeconomic risk drivers listed in Table 1. These endogenous specifications will be denoted “endogenous A” and “endogenous B” respectively.[17]

Figure 4A presents model fit during the period from 2001 to 2014 for the three model specifications considered with respect to the realized one-year default probability. Perhaps not surprisingly, the model that relies on exogenous risk drivers performs poorly during the downturn period; the models that also include endogenous variables in its specification perform significantly better

[16] For LGD segmentation, I consider accounts defaulted between 2007 and 2009.
[17] This paper presents model fit results; actual model parameter estimates are not included in the journal version of the paper but are available in an Appendix not for publication but included in the working paper version of the paper.

during the same period. In particular, the model that includes also controls for macro drivers provides the best fit of the data.[18]

The Basel II framework requires the segmentation of a portfolio into homogeneous segments and the assignment of risk parameters to each segment. Consistent with this framework, I use the three risk-ranking models described in the previous paragraph to segment the portfolio and assign to each segment the long-run average PD for that segment. Figure 4B analyzes the performance of the different exogenous and endogenous segmentation schemes and, in addition, also considers the risk-tracking ability of the segmentation implied by the standardized approach.[19] There are not significant differences in model fit with respect to Figure 4A. Perhaps the only relevant finding from this figure is the poor risk-ranking ability of the standardized segmentation approach. In fact, the implied default probability from the standardized segmentation approach projects lower default rates during the downturn. Taking into account that the standardized approach relies on the loan's appraisal value at the time of loan origination, its poor performance during the downturn is a reflection of the observed improvement in the distribution of origination risk drivers in downturn cohorts due to tightening in underwriting standards after 2007 (Figure 2) as well as the selection effect resulting from the economic downturn (as discussed in Section 4.1).

A common measure of the rank order ability of a segmentation scheme is the analysis of the area under the receiver operating characteristic (ROC), which measures the fraction of default cases that are correctly classified (sensitivity) against the fraction of non-default cases that are incorrectly classified (1 - Specificity). A larger value of ROC indicates higher rank order ability on the part of the segmentation scheme, with an ROC value of 1, indicating perfect rank order ability. Figure 5 shows that the endogenous segmentation approach generates the highest ROC of 0.93 with a slight improvement in endogenous segmentation B vs. A. In contrast, the exogenous segmentation approach generates a ROC of 0.79, while the prescribed segmentation in the standardized approach generates a ROC of 0.61. Not surprisingly, the endogenous segmentation strategy performs best in terms of rank order ability, while the prescribed standardized approach performs worse.

4.3. Segment Migration During Downturn Economic Conditions

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[18] It is not surprising that a model that includes risk drivers and is built with data that includes the downturn period will fit the data well. However, we have also estimated a similar model with data up to 2006 (excluding the downturn) and found a similar result; this finding is consistent with Gerardi et al., 2008.

[19] I use a simple scheme that employs the risk-ranking models to segment the portfolio into 18 segments with minimal differences in measured PD within segments.

Figure 6 analyzes segment migration across PD and LGD segments for three different segmentation schemes by comparing the distribution across segments in 2004, prior to the economic downturn, and 2010 toward the end of the Great Recession. Segments are sorted according to their average PD and LGD ranking. Not surprisingly, the endogenous segmentation is much more sensitive to the economic cycle than either the exogenous or the standardized segmentation. In the case of the endogenous segmentation, an economic downturn results in a significant shift in distribution toward higher severity segments. In contrast, both the exogenous and standardized segmentations are for the most part stable over downturn periods. For the exogenous segmentation, a small shift toward higher severity PD segments is observed as well as a shift toward lower severity LGD segments. This is not surprising since changes in LGD during the downturn are driven primarily by over-the-cycle changes in home prices, which will not be captured by the exogenous segmentation scheme. Instead, a segmentation based only on exogenous risk drivers will be more impacted by the tightening in underwriting standards after 2007 (Figure 2) as well as the selection effect generated by the increase in defaults primarily among the most risky accounts, resulting in an improvement in the origination characteristics of the pool of non-defaulted accounts. In the next section, the pro-cyclicality of regulatory capital under different segmentation strategies is analyzed.

5. Exogenous vs. Endogenous Segmentation in the A-IRB Framework

In section 3 we identified segmentation as the primary source of pro-cyclicality in the A-IRB framework, and in section 4 we argued that pro-cyclicality is primarily a phenomenon that is likely to arise when the segmentation framework incorporates endogenous risk drivers, while a segmentation framework based on exogenous risk drivers only should be robust to pro-cyclicality. In this section we consider the pro-cyclicality of the A-IRB framework under endogenous and exogenous segmentation schemes, as well as the standardized framework. As we show, the results broadly confirm our claims.

5.1. The Pro-Cyclicality of Capital

Figure 7A.1 considers the evolution of portfolio risk weights over time. The standardized segmentation produces the most conservative risk weights at the aggregate portfolio level uniformly across cohorts, although risk weights decrease during the downturn because of the higher origination standards and selection effects already discussed. Risk weights from exogenous segmentation remained stable over time, at around 40%, with a small increase in risk weights during the downturn. In contrast, risk weights from endogenous segmentation B, with macro risk drivers, experienced significant cyclicality; risk weights fluctuate between 10% in the 2005 to 2006 period and 40% at the height of the downturn. Endogenous segmentation A also experienced significant, although less pronounced, cyclicality. We also analyze the evolution of risk weights for the 75th and 95th percentile of the risk distribution across segments, as measured by the associated default probability to default. Figure 7B.1, for the 75th risk percentile, shows a significant increase in risk weights across segmentation schemes, while the standardized approach continues to deliver the most conservative values and the endogenous segmentation strategies exhibit significant cyclicality. Figure 7C.1, for the 95th risk percentile, shows a significant increase in risk weights across segmentation schemes. In this case, the standardized approach produces significantly lower risk weights than the exogenous segmentation strategy, while the endogenous segmentation strategies continue to experience significant cyclicality. Furthermore, at the peak of the crisis both endogenous segmentation strategies produce risk weights that are about 35% higher than those from the exogenous segmentation and about twice as large as those from the standardized approach. Overall, pro-cyclicality of the endogenous segmentation is more pronounced for the more risky segments.

Figures 7.A.2, 7.B.2, and 7.C.2 describe the evolution over time of the model-predicted loss at the 99.9th percentile level for the overall portfolio as well as the 75th and 95th percentile risk segments. For comparison purposes, I also include the realized one-year defaults loss rate as well as an imputed loss rate associated with the standardized approach. I start by discussing how I computed loss in the standardized framework. The standardized approach prescribes risk weights for specific segments but, unlike the A-IRB approach, does not provide a formula for computing overall estimated losses at the 99.9th percentile. For this reason, I use the risk weights of Table 1 to derive the corresponding UL component and use the endogenous segmentation framework to impute the EL component, because it provides the most accurate point in time prediction. I use the sum of these EL and UL components as a proxy for the overall loss in the standardized framework.

Figure 7A.2 describes the evolution over time of the predicted portfolio loss at the 99.9th percentile over a one-year default horizon. I observe that the standardized segmentation produces the largest estimated loss rate at the aggregate portfolio level at around 5%. The estimated loss under the exogenous segmentation approach remains relatively stable over time, at around 3.5%, with a small increase during the downturn. In contrast, the predicted loss rate under the endogenous segmentation approach experiences significant cyclicality, with the predicted loss rate fluctuating from 1% in good economic times to 4% at the peak of the downturn. Figure 7A.2 also reports the realized one-year default portfolio loss over time, which was around 0.1% during good economic conditions and increased to just above 1% at the peak of the economic downturn.

Figures 7.B.2 and 7.C.2 demonstrate the evolution of model-predicted loss rates at the 99.9th percentile for the 75th and 95th percentile of the risk distribution. At the 75th percentile, both standardized and exogenous segmentations continue to produce higher loss rates and much lower cyclicality than the endogenous segmentation. In contrast, at the 95th percentile, the exogenous segmentation predicts higher loss rates than the standardized segmentation, while the endogenous segmentation exhibits significant cyclicality and exhibits the largest loss rates at the peak of the downturn, with predicted loss rates of 16%, which are significantly higher than the 12% loss rates predicted by the exogenous segmentation approach. In contrast, the realized loss rate associated with the one-year PD peaks at around 3% at the height of the last downturn.

5.2. Accounting for Model Risk

The A-IRB framework employs internal models to define portfolio segmentation and parameters as inputs in the supervisory formula. These intermediate models are open to several forms of model error identified in the supervisory guidance on model risk.[20] The A-IRB framework requires a strong validation subject for supervisory review, which minimizes the likelihood of many forms of model error. For this reason, I focus here on the potential impact of model error associated with the selection of data period coverage in the A-IRB framework. The selected data period is subject to data availability and a certain level of expert judgment, and it may be limited by a lack of coverage of a full economic cycle or a sufficiently severe downturn period in the available data.

Figure 8 presents results from an empirical exercise in which the sample is constrained to defaults occurring prior to 2007. Specifically, I restrict the PD sample to the period from 2001 to 2006. Thus, the sample includes five years of data, which represent a minimum requirement in the A-IRB framework. Furthermore, because the data does not include a significant downturn, instead of using the concept of downturn LGD I use the expected loss given default (ELGD) risk parameter, which I compute as the average LGD in the restricted sample, in combination with the supervisory mapping function defined as LGD = 0.08 + 0.92*ELGD. This formula was proposed by the

[20] SR letter 11-7, "Guidance on Model Risk Management," available at https://www.federalreserve.gov/bankinforeg/srletters/sr1107.htm.

regulatory agencies in the United States as an alternative to the downturn LGD for banks that were not able to estimate reliably the downturn LGD risk parameter.[21]

Figure 8A compares average portfolio risk weights over time from the TTC quantification with results from the restricted sample. The risk weights estimated with the restricted sample are about three times lower than the risk weights estimated under the exogenous segmentation framework in our TTC quantification, although they are consistent with those observed using the endogenous segmentation framework in the TTC analysis for periods of good economic conditions.

Figure 8B compares the projected portfolio loss rate at the 99.9th risk percentile using the A-IRB formula for the TTC and restricted samples, along with the exogenous segmentation. Figure 8B also includes realized loss rates for one-, two-, and three-years forward defaults. Interestingly, the projected loss at the 99.9th percentile level using the restricted sample results in a stable loss rate of 1% over time, which is similar to the highest one-year loss rate observed at the pick of the latest downturn. In contrast, the projected loss rate at the 99.9% level with the TTC sample is around 4%, which is similar to the highest three-year loss rate observed at the peak of the latest downturn.

The Basel II rule requires certain parameters in the A-IRB framework to be estimated over a period of downturn economic conditions and requires the PD parameter to represent a long-run average of a one-year-average estimate of default. The empirical exercise conducted here illustrates the high sensitivity of the A-IRB framework to judgments over sample coverage to be employed in the quantification stage.

6. Conclusion

The BCBS in a recent consultative document issued new guidance on the A-IRB framework to "address excessive variability in the capital requirements for credit risk" (BCBS 2016, 1). This paper shows that the pro-cyclicality of capital is not a necessary feature of the A-IRB framework for retail portfolios; pro-cyclicality can be largely avoided following simple design strategies highlighted in the paper. Specifically, I show that pro-cyclicality in the A-IRB framework arises primarily at the portfolio segmentation level when the segmentation is endogenous to the economic cycle. An endogenous segmentation framework generates significant portfolio migration across segments over the business cycle, and, as a result, it also produces significant cyclicality in portfolio risk weights. A segmentation scheme based on risk drivers that are exogenous to the

[21] The supervisory mapping function was proposed in the U.S. Basel II notice of proposed rulemaking (71 Fed. Reg. 55830, September 25, 2006) but was eliminated from the final rule in response to objections from many comments to the proposal.

economic cycle is robust to this type of portfolio migration and cyclicality of risk weights. However, perhaps not surprisingly, we also show that there is a trade-off between point-in-time predictive ability and exogeneity of the segmentation framework. This conflict between point-in-time accuracy and robustness to pro-cyclicality makes our principle-based analysis even more relevant as it highlights the restrictions required to build an A-IRB framework that portfolio risk weights that are stable over the cycle. I also analyze the standardized Basel framework and show that it is consistent with the analysis of a stable segmentation but is restricted in its risk-ranking ability by its constrained segmentation structure.

In the final part of the paper, I also analyze the sensitivity of the A-IRB framework to the selection of data period coverage. Specifically, I show that if the A-IRB quantification framework lacks sufficient coverage of downturn economic conditions this results in capital levels that are significantly lower than those of an A-IRB framework that includes a mix of economic conditions comprising a full economic cycle, a requirement of the rule. This empirical exercise illustrates the high sensitivity of the A-IRB framework to judgments related to data availability and sample coverage.

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8. Tables and Figures

Table 1: Standardized Approach – Risk Weights Across Segments

International Standardized Approach

LTV ratio (in percent)	*Category 1 loans*	*Category 2 loans*
Less than 40%	25%	70%
Greater or equal to 40% and less than 60%	30%	70%
Greater or equal to 60% and less than 80%	35%	90%
Greater or equal to 80% and less than 90%	45%	120%
Greater or equal to 90% and less than 100%	55%	120%
Greater or equal to 100%	75%	120%

U.S. Standardized Approach

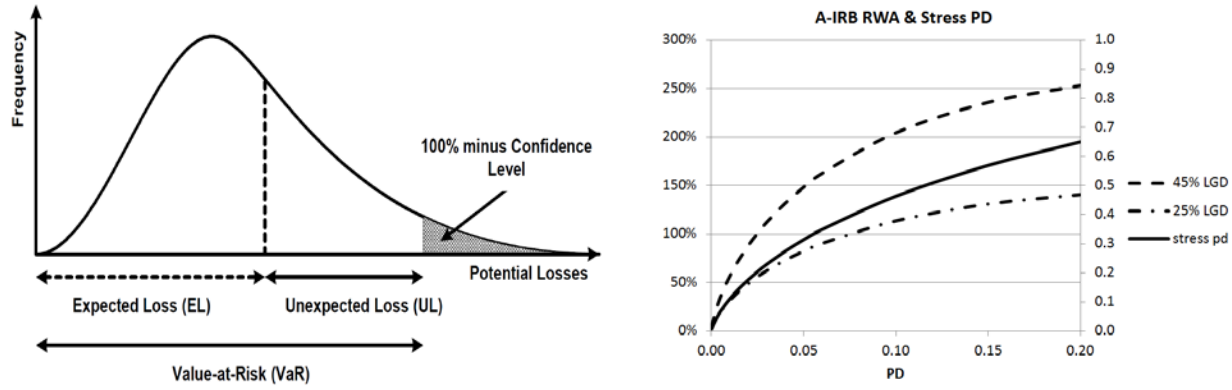
LTV ratio (in percent)	*Category 1 loans*	*Category 2 loans*
Less than or equal to 60%	35%	100%
Greater than 60% and less than or equal to 80%	50%	100%
Greater than 80% and less than or equal to 90%	75%	150%
Greater than 90%	100%	200%

Note: For additional information about the international version, see BCBS 2015b. For information about the United States' proposed standardized approach, see Table 5 of "Regulatory Capital Rules: Standardized Approach for Risk-Weighted Assets; Market Discipline and Disclosure Requirements" (2012). Note that the proposed standardized approach was not finally adopted in the United States; instead the final rule assigns exposures secured by one-to-four family residential properties to either the 50% risk-weight category, for exposures secured by a first-lien, or the 100% risk-weight category.

Table 2: Relevant Variable Definitions

	Exogenous variables
Account age	Categorical controls for account age in years
FICO score	Categorical controls for credit score range at origination for the following ranges: up to 580, 580–620, 620–650, 650–680, 680–720, 720–760, 760–900
Debt-to-income	Categorical controls for debt-to-income at origination for the following ranges: less than 20, 20–30, 30–35, 35–40, 40–45, more than 45
LTV	Categorical controls for LTV at origination for the following ranges: less than 75%, 75–80%, 80–85%, 85–90%, 90–95%, 95–100%, 100–105%, 105–110%, more than 110%
Interest rate spread	Interest rate spread at origination, measured with respect to the 10-year Treasury note ratio
Borrowers	Categorical control for number of borrowers
Purpose	Categorical control for loan purpose
Loan balance	Categorical controls for loan balance range at origination for the following ranges: less than 75K, 75–100K, 100–150K, 150–250K, 250–325K, more than 325K
Occupancy type	Categorical control for occupancy type
First-time buyer	First-time buyer dummy.
Judiciary	Dummy for judiciary state
	Endogenous variables – updated account information
Delinquency history	Specific risk drivers derived from delinquency history
Highest del. in the past 12 months	Highest delinquency history over the past 12 months
Delinquency status	Updated delinquency status at observation time
Equity ratio	Categorical controls for updated equity ratio using appraisal at origination combined with a price index updated history and the updated loan amount
	Endogenous variables – macroeconomic risk drivers
Interest rate spread	Updated interest rate spread, measured with respect to the 10-year treasury Note
House price index change	Updated 12-month home price index change
Unemployment	Updated unemployment rate
Unemployment change	Updated change in unemployment rate

Figure 1: A-IRB framework.

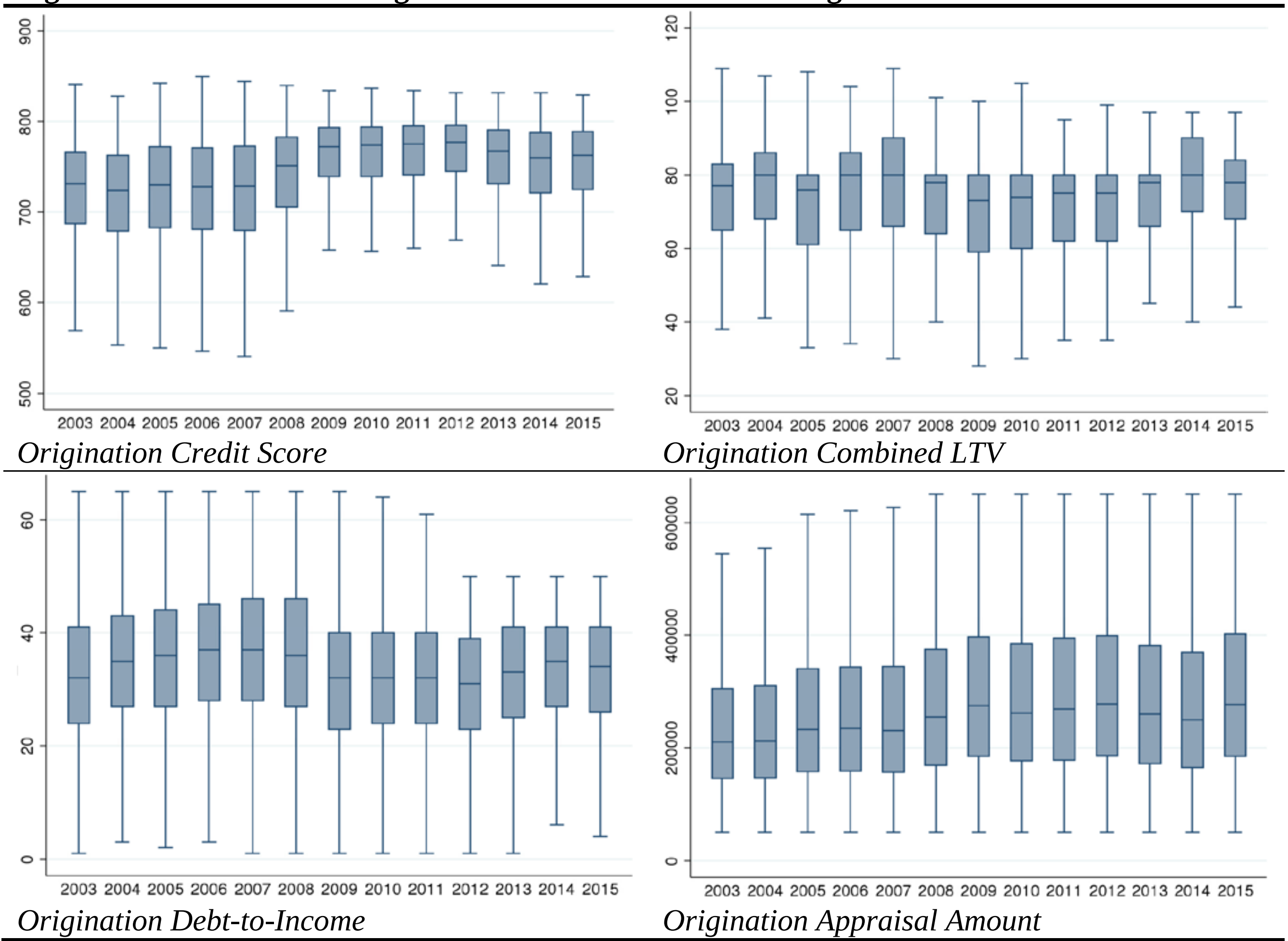


A. Value-at-risk for the A-IRB framework

B. A-IRB RWA and stress PD as a function of long-run PD

Note: Figure 1.A is from BCBS 2005.

Figure 2: Distribution of Origination Risk Drivers Across Origination Years



Origination Credit Score

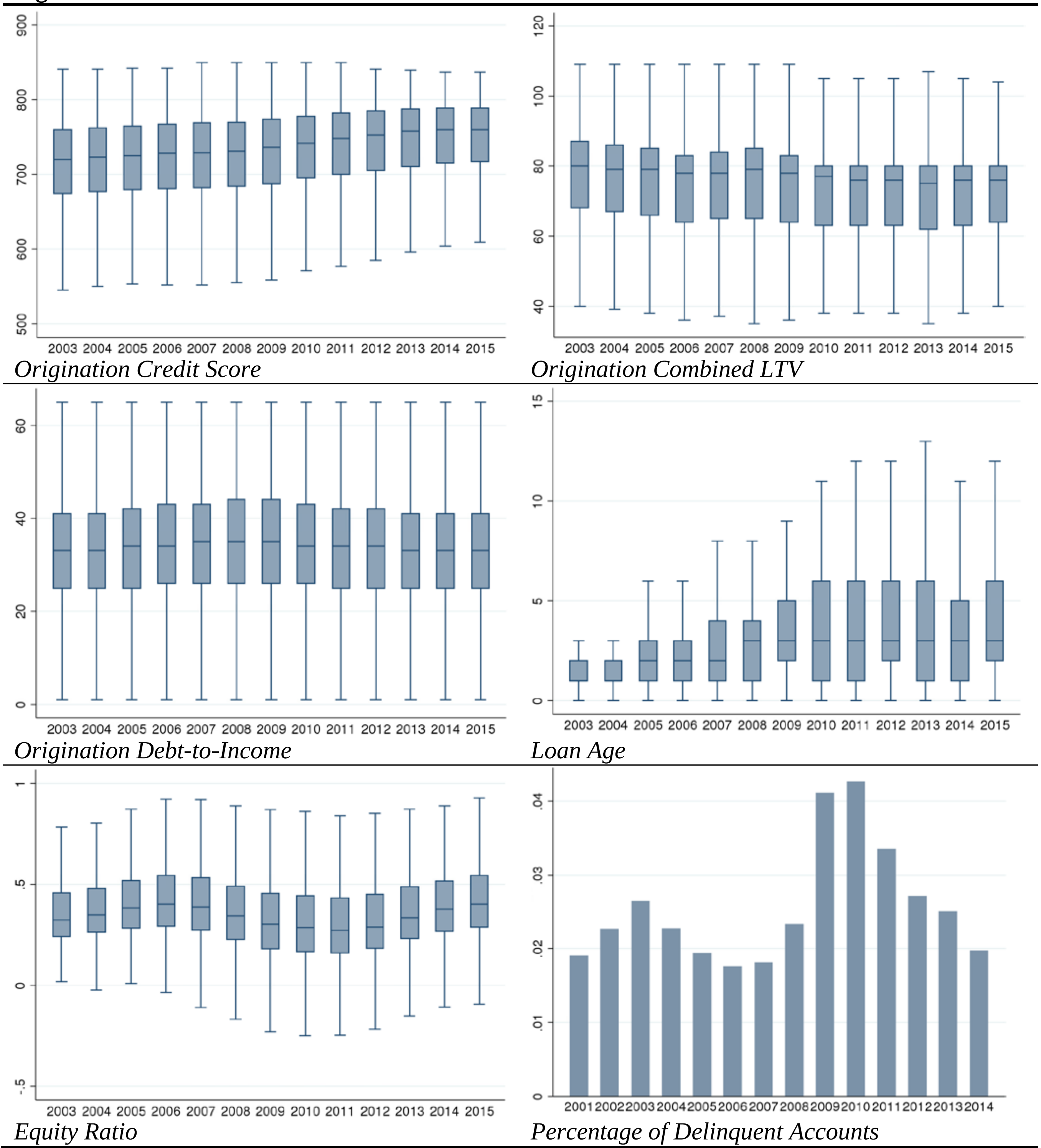
Origination Combined LTV

Origination Debt-to-Income

Origination Appraisal Amount

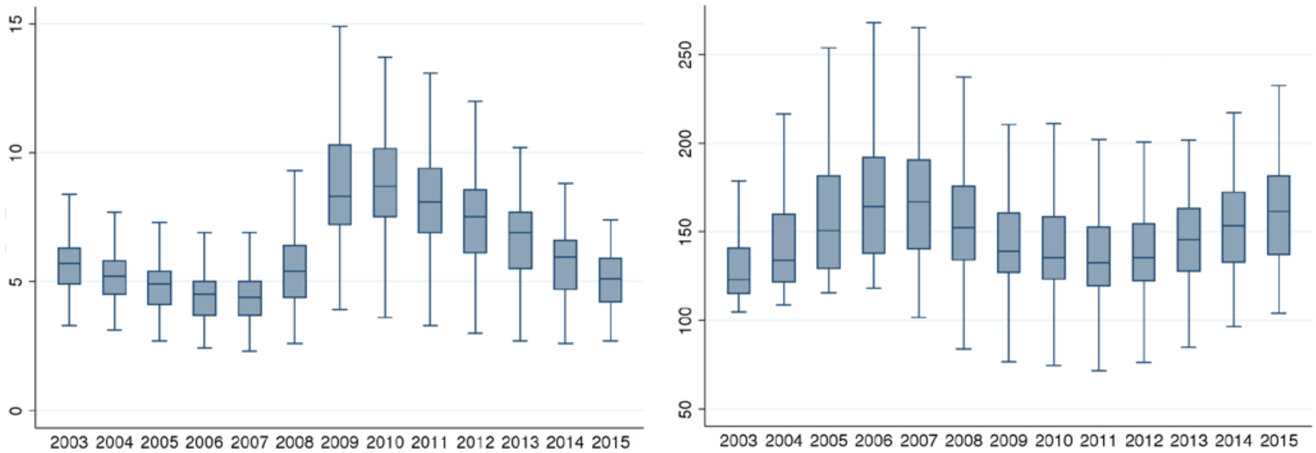
Note: For each origination year, the table presents loan characteristics at origination for that particular year.

Figure 3: Distribution of Risk Drivers Across Different Cohort Years at Observation Time



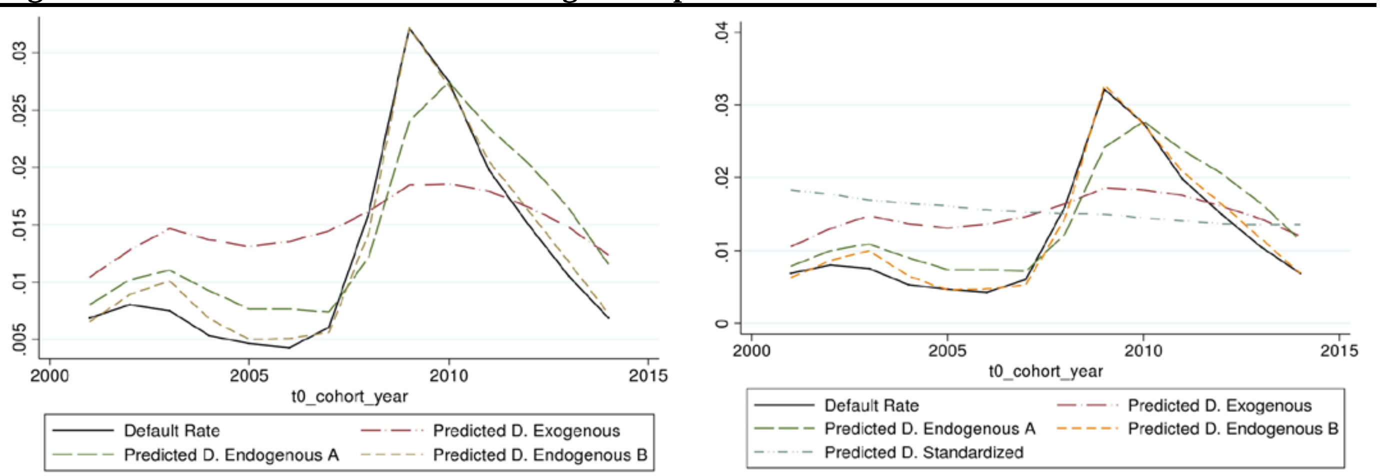
Note: Each cohort represents the sample of active loans in that particular year.

Figure 3 (cont.)



State Unemployment Rate *County Home Price Index*

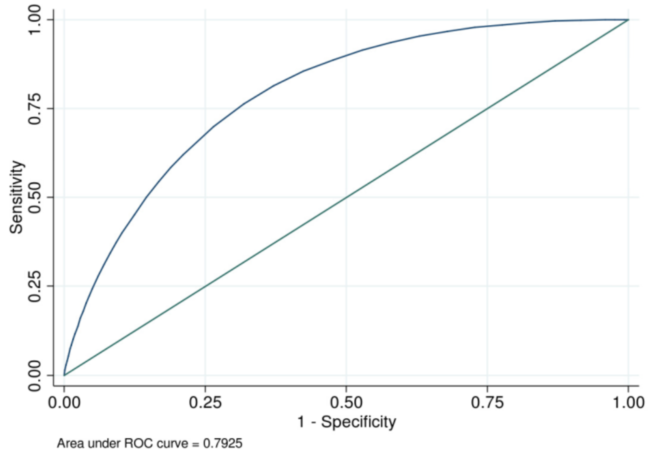
Figure 4: Model Fit Across Model and Segment Specifications



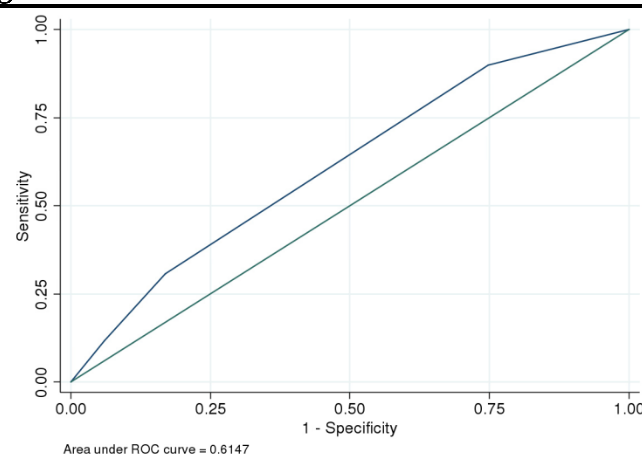
A. Realized PD vs. exogenous and endogenous model specifications.

B. Realized PD vs. predicted PD in the exogenous, endogenous, and standardized segmentation schemes.

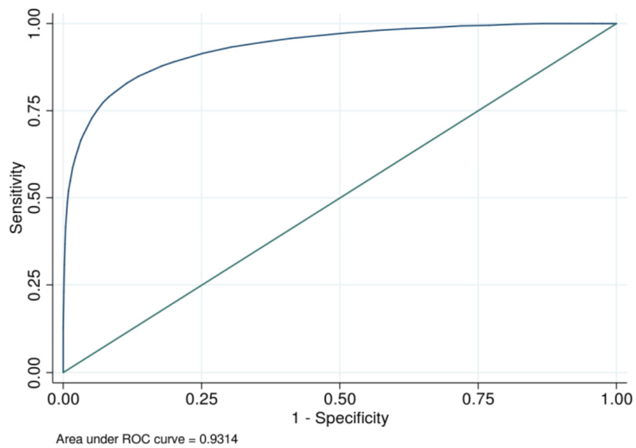
Figure 5: Area Under ROC Curve Across PD Segmentation Schemes



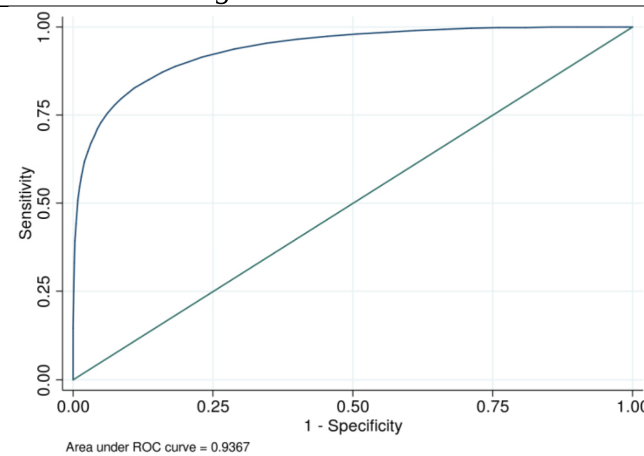
Exogenous Segmentation



Standardized Segmentation



Endogenous Segmentation A



Endogenous Segmentation B

Figure 6: Segment Migration Across Different PD and LGD Segmentation Schemes

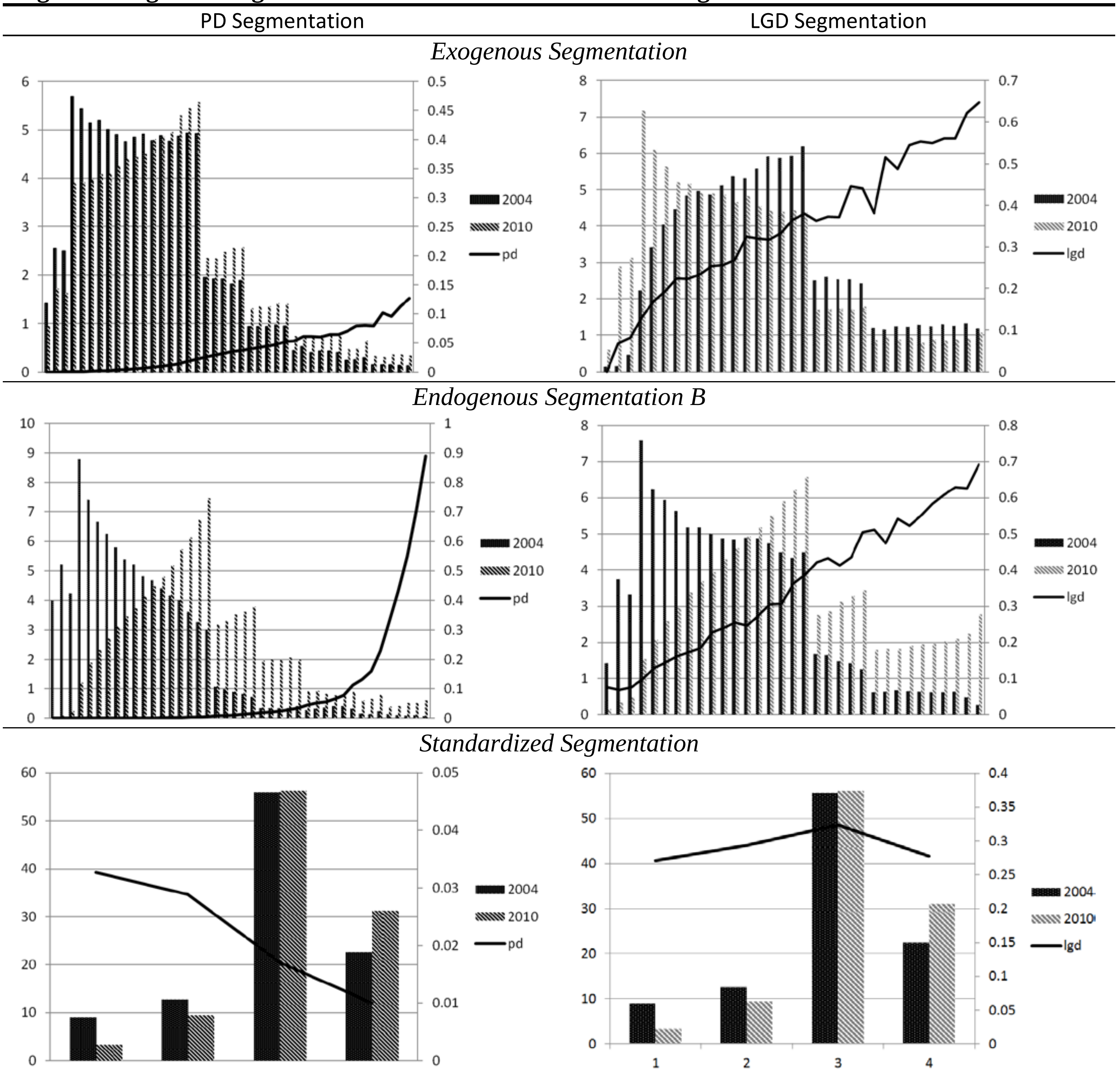
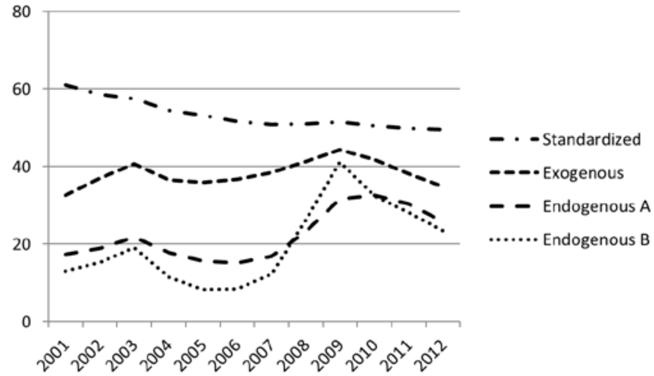
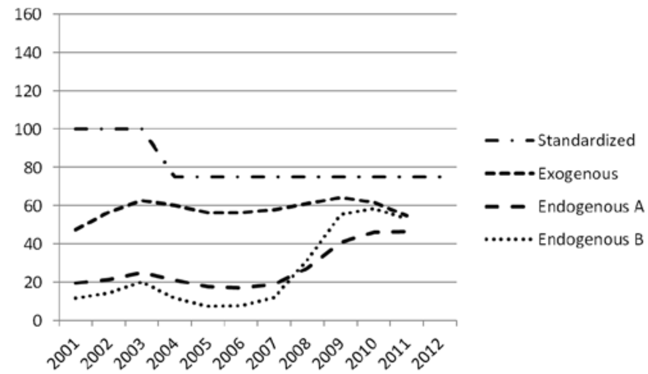


Figure 7: Pro-Cyclicality of Capital

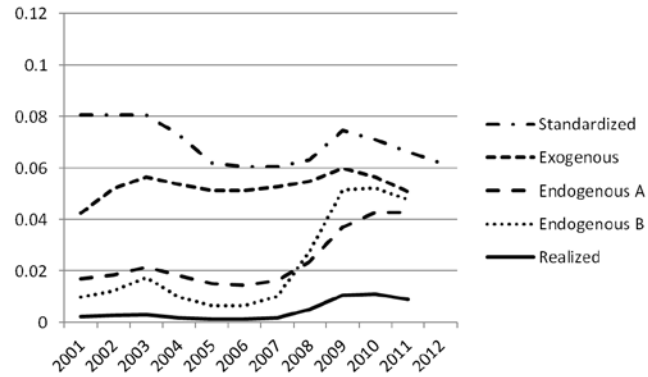


A.1 Portfolio Risk Weights

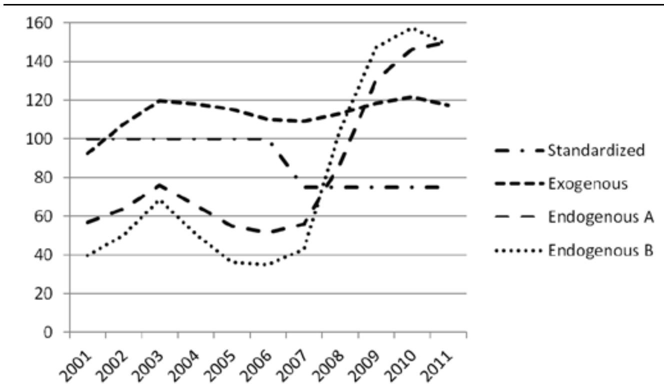
A.2 Portfolio Projected Loss Rate at the 99.9th Percentile vs. Realized Overall Portfolio Loss Rate



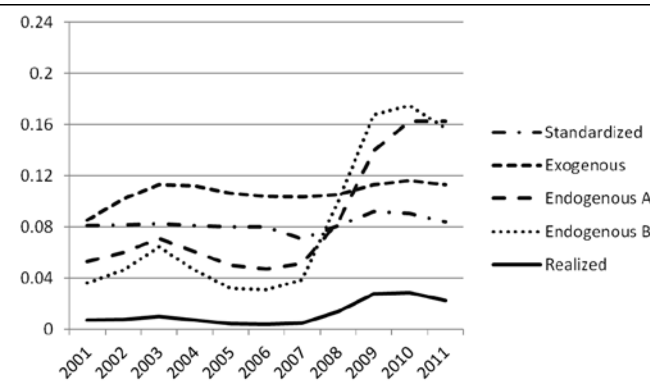
B.1 Portfolio Risk Weights at the 75th Risk Percentile



B.2 Portfolio Projected Loss Rate at the 99.9th Percentile vs. Realized Overall Portfolio Loss Rate at the 75th Risk Percentile

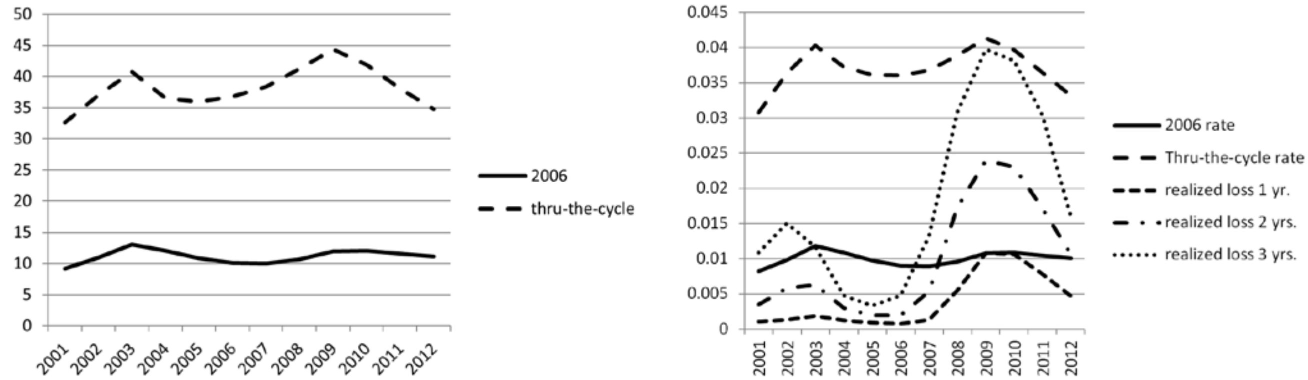


C.1 Portfolio Risk Weights at the 95th Risk Percentile



C.2 Portfolio Projected Loss Rate at the 95th Risk Percentile

Figure 8: Model Error from Lack of a Downturn in the A-IRB Quantification Framework



A. Portfolio Risk Weights Exogenous Segmentation with Data From Years 2001-2006 and TTC (2001-2012).

B. Projected Portfolio Loss Rate at the 99.9th Percentile vs. Realized Overall Portfolio Loss Rate over 1, 2, and 3 years.

Note: Projected portfolio risk weights and loss rates have been computed using data from the 2001–2006 sample of defaults or using data from the 2001–2012 sample, which is defined as the TTC sample.

9. Appendix (not for publication): Model Parameter Estimates

Table A1: One-year PD Logit Model Parameters for the Exogenous Model

Variable	Coef.	T-val	Variable	Coef.	T-val
Orig. Credit Score			Orig. Interest Rate Spread	1.60	50.87
up to 580	control var.		Multiple Borrowers	0.50	-58.87
580–620	0.93	-1.55	*Purpose*		
620–650	0.73	-7.27	Purchase	control var.	
650–680	0.55	-13.73	Cash-out Ref.	2.18	46.04
680–720	0.39	-21.88	No-cash-out Ref.	1.56	25.21
720–760	0.25	-32.1	*Mortgage Balance at Orig.*		
760+	0.14	-43.98	Up to 75K	control var.	
Orig. Debt-to-Income			75K–100K	1.06	2.9
up to 20	control var.		100K–150K	1.19	9
20–30	1.18	5.58	150K–250K	1.65	25.78
30–35	1.44	12.03	250K–325K	2.42	36.34
35–40	1.69	17.62	325K+	5.19	43.26
40–45	1.86	20.78	*Occupancy Status*		
45+	2.29	29.19	Owner Occupied	control var.	
Orig. LTV			Investment Property	1.36	8.45
up to 75	control var.		Second Home	1.52	16.8
75–80	1.47	20	*First-time Buyer*		
80–85	1.81	37.05	No	control var.	
85–90	2.19	29.95	Yes	1.00	0.15
90–95	2.40	40.85	Na	0.63	-25.97
95–100	2.63	40.54	Non-Judicial State	1.00	-0.03
100+	6.30	45.15	Constant	0.01	-50.69
Age in years dummies	yes			yes	
N. obs.	2,058,101				
LLF	-147557.69		Pseudo R2	0.1108	

Note: The table displays estimation results from a logistic regression of one-year default for the exogenous model specification.

Table A2: One-year PD Logit Model Parameters for the "Endogenous A" Model

Sample:	Current		Del 30–59		Del 60–89		Del 90+	
Variable	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**
Orig. Credit Score								
up to 580	control var.		control var.		control var.		control var.	
580–620	1.06	0.65	1.00	0.04	0.98	-0.15	1.37	1.64
620–650	0.94	-0.76	1.10	0.96	1.06	0.56	1.25	1.19
650–680	0.87	-1.60	1.18	1.75	1.11	1.12	1.56	2.37
680–720	0.72	-3.78	1.26	2.35	1.49	4.12	2.16	4.03
720–760	0.54	-7.21	1.34	2.92	1.53	4.15	2.16	3.81
760+	0.33	-12.70	1.30	2.48	1.73	4.85	2.30	3.74
Orig. Debt-to-Income								
up to 20	control var.		control var.		control var.		control var.	
20–30	1.15	2.95	1.01	0.12	0.79	-2.77	1.32	1.57
30–35	1.37	6.55	1.02	0.24	0.93	-0.84	0.96	-0.26
35–40	1.59	9.88	1.11	1.40	0.91	-1.09	1.19	1.04
40–45	1.66	10.77	1.18	2.15	0.88	-1.56	1.02	0.10
45+	1.86	13.83	1.24	2.93	0.91	-1.14	1.00	0.02
Orig. LTV								
up to 75	control var.		control var.		control var.		control var.	
75–80	1.12	3.69	1.04	0.86	0.98	-0.32	0.88	-1.18
80–85	1.18	6.20	1.16	3.37	0.98	-0.34	1.00	0.01
85–90	1.11	2.45	1.03	0.48	0.94	-0.76	0.82	-1.32
90–95	1.05	1.33	0.83	-3.07	0.80	-3.48	0.93	-0.59
95–100	0.99	-0.20	0.86	-2.38	0.68	-5.64	0.79	-1.69
100+	1.33	4.26	1.00	0.00	1.18	1.22	1.43	1.30
Orig. Interest Rate Spread	1.33	18.94	1.09	3.81	1.06	2.23	1.02	0.29
Multiple Borrowers	0.57	-29.20	0.71	-10.80	0.77	-7.78	0.83	-2.63
Purpose								
Purchase	control var.		control var.		control var.		control var.	
Cash-out Ref.	1.70	19.66	1.32	6.13	1.11	2.11	1.21	1.85
No-cash-out Ref.	1.54	15.42	1.22	4.34	1.18	3.23	1.27	2.26
Mortgage Balance Orig.								
Up to 75K	control var.		control var.		control var.		control var.	
75K–100K	0.97	-0.78	0.97	-0.57	1.04	0.59	1.04	0.31
100K–150K	0.94	-2.13	1.02	0.37	1.04	0.80	0.94	-0.60
150K–250K	1.13	3.92	1.20	3.66	1.16	2.69	1.16	1.31
250K–325K	1.45	9.39	1.43	5.39	1.33	4.02	1.22	1.37
325K+	2.38	14.54	2.19	7.07	1.81	4.48	1.53	1.65

Table 2A (cont.)

Sample:	current		Del 30–59		Del 60–89		Del 90+	
Variable	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**
Occupancy Status								
Owner Occupied	control var.		control var.		control var.		control var.	
Investment Property	1.10	1.72	1.10	0.92	1.48	3.23	2.73	2.97
Second Home	1.52	10.95	1.50	5.92	1.84	7.28	1.86	3.02
First-time Buyer								
No	control var.		control var.		control var.		control var.	
Yes	1.00	0.03	1.00	-0.02	1.21	3.03	0.94	-0.48
Na	0.76	-9.65	0.90	-2.35	0.96	-0.86	0.79	-2.42
Non-Judicial State	0.92	-4.65	0.96	-1.51	0.87	-4.35	0.81	-3.23
Highest Del. Past 12m. (Obs. Time)								
Current (0–29 dpd)	control var.		control var.		control var.		control var.	
30–59 dpd	3.60	50.28	0.36	-8.03				
60–89 dpd	7.53	45.85	0.48	-5.60	0.69	-3.43		
90–119 dpd	5.97	23.67	0.60	-3.60	1.39	2.98		
120+ dpd	6.13	20.87	0.73	-2.00	0.82	-1.50	0.48	-10.71
Equity ratio								
30%+	control var.		control var.		control var.		control var.	
20%–30%	1.94	22.63	1.58	10.66	1.37	6.86	1.24	2.32
10%–20%	3.45	40.68	2.04	15.09	1.73	10.75	1.74	5.21
5%–10%	5.57	42.89	2.83	15.45	2.20	10.22	1.68	3.47
0%–5%	7.37	45.66	3.75	17.56	2.09	8.35	1.63	2.86
from -10%– 0%	9.84	57.60	4.30	20.13	2.93	13.19	2.31	5.13
from -10%–0%	12.59	54.07	4.93	18.07	2.86	10.88	1.93	3.58
less than -20%	19.24	74.89	7.00	24.52	3.71	14.83	3.05	6.87
constant	0.00	-34.59	0.12	-7.69	0.44	-3.25	2.72	2.06
Age in years dummies	yes		yes		yes		yes	
N. obs.	1992774		41355		16803		7169	
LLF	-65045		-15456		-10796		-3002	
Pseudo R2	0.16		0.07		0.07		0.06	

Note: This table displays estimation results from a logistic regression of one-year default for the “endogenous A” model specification. I estimate four different models for a sample segmented by the severity of the delinquency rate at observation time.

Table 3A: One-year PD Logit Model Parameters for the "Endogenous B" Model

Sample:	current		Del 30-59		Del 60-89		Del 90+	
Variable	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**
Orig. Credit Score								
up to 580	control var.		control var.		control var.		control var.	
580–620	1.03	0.37	0.97	-0.27	0.96	-0.39	1.29	1.28
620–650	0.92	-0.92	1.07	0.69	1.01	0.12	1.17	0.81
650–680	0.86	-1.72	1.15	1.40	1.06	0.55	1.44	1.89
680–720	0.71	-3.88	1.21	1.90	1.41	3.49	2.00	3.57
720–760	0.54	-7.14	1.28	2.42	1.43	3.43	2.01	3.40
760+	0.32	-12.83	1.23	1.89	1.60	4.10	2.11	3.30
Orig. Debt-to-Income								
up to 20	control var.		control var.		control var.		control var.	
20–30	1.16	3.07	1.00	-0.04	0.78	-2.96	1.27	1.37
30–35	1.37	6.49	1.00	0.04	0.90	-1.18	0.93	-0.43
35–40	1.59	9.85	1.10	1.16	0.90	-1.28	1.17	0.89
40–45	1.65	10.57	1.15	1.76	0.85	-1.84	0.98	-0.13
45+	1.81	13.18	1.19	2.29	0.87	-1.70	0.93	-0.41
Orig. LTV	control var.		control var.		control var.		control var.	
up to 75								
75–80	1.36	9.56	1.24	4.04	1.10	1.72	1.04	0.33
80–85	1.52	14.74	1.43	7.86	1.14	2.67	1.21	1.84
85–90	1.66	11.13	1.45	5.21	1.18	2.13	1.08	0.49
90–95	1.68	13.36	1.24	3.42	1.05	0.76	1.29	1.84
95–100	1.76	12.95	1.41	4.90	0.96	-0.54	1.19	1.16
100+	2.31	12.15	1.63	4.01	1.59	3.28	2.13	2.61
Orig. Interest Rate Spread	1.43	22.27	1.13	4.80	1.12	4.05	1.05	0.87
Multiple Borrowers	0.59	-27.44	0.73	-10.02	0.77	-7.52	0.84	-2.47
Purpose								
Purchase	control var.		control var.		control var.		control var.	
Cash-out Ref.	1.60	17.41	1.25	4.85	1.05	0.91	1.16	1.42
No-cash-out Ref.	1.57	16.00	1.24	4.58	1.19	3.36	1.26	2.15
Mortgage Balance Orig.								
Up to 75K.	control var.		control var.		control var.		control var.	
75K–100K	0.97	-0.97	0.95	-0.95	1.01	0.19	1.00	0.00
100K–150K	0.92	-2.82	0.98	-0.45	0.99	-0.12	0.85	-1.44
150K–250K	1.08	2.28	1.13	2.40	1.09	1.52	1.05	0.39
250K–325K	1.33	7.21	1.26	3.48	1.19	2.42	1.01	0.09
325K+	2.10	12.40	1.82	5.37	1.50	3.02	1.21	0.73

Table 3A (cont.)

Sample:	current		Del 30–59		Del 60–89		Del 90+	
Variable	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**
Occupancy Status								
Owner Occupied	control var.		control var.		control var.		control var.	
Investment Property	0.98	-0.45	1.01	0.05	1.37	2.51	2.30	2.45
Second Home	1.40	8.61	1.42	5.05	1.74	6.47	1.67	2.50
First-time Buyer								
No	control var.		control var.		control var.		control var.	
Yes	0.97	-0.90	0.97	-0.55	1.16	2.40	0.89	-0.92
Na	0.81	-7.41	0.97	-0.76	1.00	-0.01	0.85	-1.64
Non-Judicial State	0.88	-7.07	0.93	-2.54	0.84	-5.05	0.77	-3.81
Highest Del. Past 12m.								
Current (0–29 dpd)	control var.		control var.		control var.		control var.	
30–59 dpd	3.77	51.63	0.32	-8.94				
60–89 dpd	8.16	47.51	0.45	-6.12	0.65	-3.86		
90–119 dpd	6.70	25.22	0.55	-4.10	1.31	2.40		
120+ dpd	7.24	22.87	0.70	-2.24	0.81	-1.55	0.47	-10.89
Equity ratio								
30%+	control var.		control var.		control var.		control var.	
20%–30%	1.55	14.90	1.32	6.30	1.21	3.95	1.07	0.73
10%–20%	2.10	22.77	1.39	6.45	1.33	5.14	1.34	2.54
5%–10%	2.76	23.40	1.61	6.54	1.48	4.75	1.12	0.72
0%–5%	3.22	24.29	1.96	8.16	1.32	2.93	0.98	-0.13
from -10% –0%	3.75	28.82	2.00	8.50	1.68	5.68	1.29	1.43
from -10%–0%	4.51	28.15	2.17	7.88	1.56	4.18	1.04	0.18
less than -20%	6.39	37.96	2.93	11.64	1.96	6.67	1.55	2.33
Macro variables								
Interest Rate Spread	1.08	14.29	1.04	4.93	1.06	5.78	1.04	1.70
House Price Index (HPI) chg. 12m %	0.01	-37.13	0.01	-17.26	0.03	-11.00	0.03	-5.67
Unemployment Rate (UR) level	1.04	8.56	1.03	3.41	1.03	3.10	1.05	2.51
UR change 12 m	1.04	6.13	1.06	5.16	1.06	5.16	1.06	2.33
Constant	0.00	-39.92	0.06	-9.69	0.22	-5.58	1.33	0.55
Age in years dummies	yes		yes		yes		yes	
N. obs.	1,991,290		41,306		16,782		7,162	
LLF	-63400		-15048		-10545		-2934	
Pseudo R2	0.18		0.09		0.09		0.08	

Note: This table displays estimation results from a logistic regression of one-year default for the "endogenous B" model specification. I estimate four different models for a sample segmented by the severity of the delinquency rate at observation time.

Table A4: LGD Tobit Model Parameters for Three Different Model Specifications

Variable Selection:	Exogenous		Endogenous A		Endogenous B	
Variable	**Coef.**	**T-val**	**Coef.**	**T-val**	**Coef.**	**T-val**
Orig. Credit Score						
up to 580						
580—620	0.04	1.05	0.03	0.91	0.03	0.85
620—650	0.06	1.86	0.05	1.54	0.05	1.45
650—680	0.10	2.85	0.07	2.13	0.07	1.98
680—720	0.12	3.58	0.09	2.69	0.08	2.46
720—760	0.11	3.21	0.07	1.96	0.06	1.81
760+	0.13	3.51	0.07	2.00	0.06	1.84
Orig. Debt-to-Income						
up to 20						
20—30	-0.03	-1.28	-0.03	-1.62	-0.03	-1.31
30—35	-0.06	-2.58	-0.06	-3.02	-0.05	-2.62
35—40	-0.04	-1.80	-0.04	-2.19	-0.04	-1.89
40—45	-0.06	-2.90	-0.07	-3.25	-0.06	-2.85
45+	-0.07	-3.38	-0.08	-4.10	-0.07	-3.71
Orig. LTV						
up to 75						
75—80	0.16	11.96	0.11	8.43	0.14	10.48
80—85	0.18	16.15	0.11	10.19	0.15	13.04
85—90	0.11	5.73	0.01	0.72	0.07	3.67
90—95	0.06	4.02	-0.04	-2.52	0.03	1.55
95—100	0.05	3.09	-0.07	-4.20	0.00	-0.07
100+	0.04	1.62	-0.13	-5.05	-0.02	-0.88
Orig. Interest Rate Spread	0.01	1.27	0.00	0.47	0.00	0.44
Multiple Borrowers	-0.06	-6.56	-0.06	-7.13	-0.06	-6.76
Purpose						
Purchase						
Cash-out Ref.	0.12	9.54	0.10	8.82	0.10	8.72
No-cash-out Ref.	0.08	6.54	0.09	7.59	0.10	8.02
Mortgage Balance at Orig.						
Up to 75K.						
75K—100K	-0.12	-7.70	-0.13	-8.62	-0.14	-9.29
100K—150K	-0.20	-13.90	-0.23	-17.02	-0.25	-18.17
150K—250K	-0.27	-18.41	-0.33	-23.12	-0.35	-24.50
250K—325K	-0.33	-19.10	-0.40	-23.41	-0.43	-25.05
325K+	-0.32	-12.72	-0.39	-16.18	-0.42	-17.21
Occupancy Status						
Owner Occupied						
Investment Property	0.16	6.76	0.11	4.72	0.10	4.35

Second Home	0.20	11.37	0.18	10.65	0.18	10.80

Table A4 (cont.)

	Coef.	T-val	Coef.	T-val	Coef.	T-val
First-time Buyer						
No						
Yes	0.04	2.84	0.04	2.32	0.03	2.13
Na	-0.01	-1.00	-0.01	-0.51	0.00	-0.28
Non-Judicial State	0.00	0.41	-0.03	-3.24	-0.04	-4.80
Behavioral Variables						
Highest Del. Past 12m.						
Current (0–29 dpd)						
30–59 dpd			-0.07	-6.88	-0.07	-6.11
60–89 dpd			-0.11	-8.74	-0.09	-7.84
90–119 dpd			-0.08	-5.66	-0.07	-4.93
120–149 dpd			-0.07	-5.21	-0.06	-4.15
150+ dpd			-0.06	-4.08	-0.05	-3.19
Equity Ratio						
30%+						
20%–30%			0.10	8.68	0.10	8.21
10%–20%			0.16	12.20	0.13	9.37
5%–10%			0.21	12.08	0.15	8.26
0%–5%			0.24	13.12	0.17	8.58
from -10%–0%			0.30	18.47	0.20	10.81
from -20%–-10%			0.33	16.73	0.20	8.80
less than -20%			0.41	22.79	0.24	10.93
Macro variables						
HPI chg. 12m %					-0.80	-12.38
UR level					0.02	5.32
UR change 12 m					-0.03	-6.09
Constant	-0.29	-2.26	-0.09	-0.74	-0.23	-1.88
Age in years dummies	yes		yes		yes	
N. obs.	13,150		13,150		13,150	
LLF	-8813.83		-8390.52		-8302.87	
Pseudo R2	0.081		0.1251		0.1336	

Note: This table displays estimation results from a tobit regression of LGD under three different model specifications: exogenous risk drivers, "endogenous A" risk drivers, and "endogenous B" risk drivers.