Playing the devil's advocate: The causal effect of risk management on loan quality

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Abstract

Casual observation suggests that most banks do not try to align loan officer incentives with those of the bank (i.e. to grant positive NPV loans). Instead, they deliberately assign opposing incentives to loan officers (loan volume) and risk management (risk). Decisions are then driven by competition of loan officers and risk management trying to defend their particular causes. Using 75,000 retail mortgage applications at a major European bank from 2008-2011, I analyze the effect of risk management involvement on loan default rates. In the period under study, the bank requires risk management approval for loans that are considered risky based on hard information, using a sharp threshold that changes during the sample period. Using a difference-in-difference estimator and a regression discontinuity design, I am able to show that risk management involvement reduces loan default rates by more than 50%. These results add to the understanding of agency conflicts within banks and point to the crucial importance of risk management in resolving internal agency conflicts.

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1. Introduction

A fundamental function of banks is to screen potential borrowers — granting loans to “good” borrowers who will pay them back and rejecting loans from “bad” borrowers who won’t.[1] Banks hire agents to perform the screening and recent research has pointed out to the crucial role of loan officer incentives for the quality of a banks' screening decisions.[2] While prior research has focused on incentives of a single agent, the loan officer, most banks hire two agents: One is the loan officer, whose primary incentive is to focus on loan volume. The second agent is the risk manager, whose job is to focus on risk. Their different incentives introduces some tension into the loan-making process, but does it result in better outcomes? Surprisingly, the role of risk management in mitigating internal agency problems has caught little attention so far.

This study fills this gap by looking at the impact on loan default rates when risk managers are involved in screening decisions. As is the case with many banks, loan officers at the one I looked at (a major European lending institution) are able to approve certain loan applications on their own. But applications that exceed specified risk thresholds need to be evaluated by the risk department. The risk thresholds the bank has in place includes a hard-information rating (a single “score” factoring in data like credit history and income level) and a loan-to-value (LTV) percentage. I compare loan default rates just below and just above the thresholds using a regression discontinuity design. My findings — I analyze 75,000 retail mortgage applications between February 2008 and September 2011

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[1] For a theoretical motivation for this function, see Ramakrishnan and Thakor (1984), Diamond (1984), Allen (1990).

[2] Empirical studies include Agarwal and Ben-David (2013), Berg, Puri, and Rocholl (2013), Cole, Kanz, and Klapper (2013).

— show that the involvement of risk managers in the loan origination process reduces default rates by more than 50 percent.

I address concerns of a manipulation of the rating or LTV – which could invalidate the regression discontinuity design – by tracking loan officer inputs (loan amount, loan and customer characteristics) into the system. Doing so allows me to identify any loan applications where the initial rating-LTV combination would have required risk management involvement, but where the loan officer subsequently changed input parameters in order to avoid that. More formally, I instrument treatment status with the initial input parameters to control for any possible endogenous sorting around the threshold. Estimates from this instrumental variable regression are qualitatively similar and still highly significant.

For purposes of identifying causality, it also helps that the bank, in May of 2009, implemented changes to its threshold for involving the risk management department. Using a difference-in-difference estimator confirms the results from the regression discontinuity design. I also show that the change in default rates is concentrated around May 2009, ruling out any confounding factors that may gradually and differentially affect default rates between those rating-LTV combinations that became subject to a risk management assessment after the threshold change, and those that didn't.

The theoretical literature offers a variety of predictions about the effect of risk management involvement. One theory – which I call the Efficient Advocacy Hypothesis – says that splitting the responsibility for several tasks among two agents (as opposed to mandating one agent for several tasks) can result in superior decision-making (Holmstrom and Milgrom (1990, 1991), Dewatripont and Tirole (1999)). According to Dewatripont and Tirole, decision-making within organizations can be enhanced by assigning two agents to opposing objectives and allowing them, in effect, to compete. Among the more familiar examples of how this creates efficiency is the judicial system, in which defense attorneys and prosecutors make the strongest possible cases for whomever they're representing. An older example of advocacy is how decisions have been made in Christianity (usually in Catholicism) about who gets elevated to the level of a saint. On one side of the canonization process is the "devil's advocate"; on the other is someone who acts as "God's advocate." A second school of thought is much more skeptical about the value of using monitoring agents. Falk and Kosfeld (2006) conducted experiments that suggest that monitoring agents can add hidden costs, in the sense of other agents reducing their performance if they perceive the monitoring to be a control mechanism. This "Hidden Costs of Control Hypothesis" suggests that risk management, if itself viewed by loan officers as a control device, can have a negative effect on loan performance by reducing loan-officer effort. Finally, empirical evidence has lend support to the notion that people are subject to systematic biases, and make predictions that are generally inferior to predictions made purely on the basis of statistics (Meehl (1954), Tversky and Kahnemann (1974), Dawes, Faust and Meehl (1989)). This "Models are Superior to Experts Hypothesis" therefore suggests that relying on risk managers' judgment, instead of sticking to the results of statistical default models, leads to inferior screening decisions.

My findings show that the involvement of risk managers in the loan origination process reduces default rates by more than 50 percent, and thus lend strong support to the efficient advocacy hypothesis. Furthermore, I do not find any evidence that differences in experience are driving the results (the effect of risk management involvement is independent of loan officer experience). Nor do I find evidence that entrenchment plays a role (the effect of risk management involvement is similar for relationship and non-relationship customers). These results thus point to the crucial importance of risk management in resolving internal agency conflicts.

This study adds to the growing literature on agency problems within banks and the optimal organization design of banks to foster information production (Udell (1989), Stein (2002), Berger et al. (2005), Liberti and Mian (2009), Agarwal (2010), Puri, Rocholl, and Steffen (2011, 2013), Agarwal and Ben-David (2013), Berg, Puri, and Rocholl (2013)). Prior research has stressed the need to provide incentive-compatible contracts to employees in general (Baker, Jensen, and Murphy (1988)) and to loan officers in particular (Baker (2000), Heider and Inderst (2012)). In a one-principal-one-agent framework, high-powered incentives lead to greater screening effort, although the incentives' power is muted by deferred compensation and by the limited liability of loan officers (Cole, Kanz, and Clapper (2013)). In practice, the standard approach followed by most banks is to engage a monitor (the risk manager) to control the actions of the agent (the loan officer). It is exactly this risk management involvement that I analyze in this paper. While the role of monitoring other agents is well established in the theoretical literature on contract theory (Alchiam and Demsetz (1972), Holmstrom (1982), Rahman (2012)), there is surprisingly little empirical literature on the agency role of risk management in monitoring loan officers. Hertzberg, Liberti, and Paravisini (2010) provide evidence that loan-officer rotation helps to alleviate moral hazard in monitoring borrowers. Moral hazard stems from the fact that loan officers who have covered a borrower in previous years are reluctant to report bad news, as it would reflect poorly on their decision-making ability. In this paper, I look at loan-granting decisions so that any incentive conflicts do not stem from past decisions, but are a direct consequence of the opposing incentives provided to loan officers and risk managers by banks. In a related paper, Brown et. al. (2013) show that loan officers inflate soft information in reaction to internal risk management controls and thus points to possible hidden costs of control. My paper offers a complementary view by providing causal evidence that risk management can significantly reduce default rates.

This paper also relates to the growing literature on risk management in banks. Stulz (2008) provides a typology of risk management failures while Acharya et al. (2009) call for stronger risk-control management as a response to the recent financial crisis. This is supported by Ellul and Yerramilli (2011) and Aebi, Sabato, and Schmid (2012) who found that certain risk management-related corporate governance mechanisms were associated with a better bank performance during the financial crisis of 2007/2008. While these papers provide a macro view on the link between risk governance and bank performance, this paper aims to causally identify the impact on risk management involvement in the loan-granting process and it is, to the best of my knowledge, the first paper to provide such a micro foundation of risk management within banks.

The rest of the paper is organized as follows. Section 2 describes the loan origination process. Section 3 provides descriptive statistics of the data, Section 4 explains my empirical strategy, and Section 5 presents the empirical results. Section 6 concludes.

2. Loan origination process

I start by describing the loan origination process and the incentives of the parties involved in it. A high-level overview about the loan origination process is provides in Figure 1 and Figure 2.

[Figure 1 and 2 here]

The process proceeds along three steps:

1. Step 1 (Information collection): The loan officer collects information from the loan applicants and inputs it into the bank's systems. Data collected

includes information about the loan characteristics, the collateral and information about the loan applicant. For example, the desired amount and maturity of the loan are inputted into the systems, along with the collateral type (house or apartment), the collateral value as well as income, costs, and existing liabilities of the applicant.

2. Step 2 (Hard information filter): Using the data inputted by the loan officer, the bank's systems determine a hard-information rating, ranging from 1 (best rating) to 12 (worst rating), and the loan-to-value ratio (LTV). Loan applications are then classified using the so-called "traffic light approach": Loan applications with good ratings and/or low LTVs can be granted by the loan officer without risk management approval ("green applications"), while loan applications with a poor rating and/or high LTV require risk management approval ("yellow applications"). Loan applications with a very poor rating (less than 1% of all loan applications) are directly rejected ("red applications"). Figure 3 depicts rating-LTV combinations that require risk management approval: During subperiod 1 (February 2008 – April 2009) only loan applications with an LTV > 100% had to be approved by risk management.[3] During subperiod 2 (May 2009 – September 2011) the bank tightened its lending standards and additionally required loan applications with ratings 6-8 (90% < LTVs ≤ 100%) and rating 8 (72% < LTV ≤ 90%) to be approved by risk management. Loan applications with a rating of 9 or worse cannot be accepted.

[3] Loans can have an LTV above 100% if the bank finances taxes (~5% of the value of the house or aparment) and broker fees (3-7% of the value of the house or aparment) in addition to the purchase price of the house/aparment.

[Figure 3 here]

3. Step 3 (Risk management decision): For loan applications that require risk management approval according to step 2, a risk manager reviews the loan application and makes the final accept/reject decision. All risk managers are located in one single city and risk managers do not talk directly to potential borrowers. The risk manager receives an electronic version of all documents (for example, the income statement and the appraisal of the house/apartment) and communication with the loan officer takes place via email and telephone calls. Risk managers are assigned to specific branches of the bank, meaning that a loan officer always communicates with the same risk manager for all loan applications that s/he handles. Thus, while hard information can be easily transmitted and verified, soft-information can be incorporated to the extent that the risk manager trusts a specific loan officer from truly reporting soft information. The risk manager then communicates his/her final decision (accept/reject) to the loan officer, usually within one or two days after the first contact. The decision of the loan officer does not affect the rating, but just the accept/reject decision itself.

Table 2 provides four examples of risk management decisions. In the first example, the risk manager rejects a loan application. The house that the loan applicants want to purchase is old and clearly needs refurbishment. Refurbishment costs have not been considered, nor is it visible that the applicants would be willing or able to do the refurbishment on their own, nor is the income of the applicants sufficient to support any additional costs. The purchase of the house does not seem to be a well thought-out plan. While the loan officer has incentives to "overlook" the costs of refurbishment, the risk manager clearly has incentives to reject this loan application.

[Table 2 here]

If the loan applicant accepts the bank's loan offer, a contract is signed and the loan is disbursed on the loan start date (usually a couple of weeks after the loan is signed). The bank at hand does not securitize its mortgage loans, so all loans remain on the balance sheet of the bank. Our main variable of interest, the default dummy, is a variable equal to 1 if the loan defaults within the first 24 months after the loan start date. A loan is coded as being in default if it is 90 days past due or unlikely to pay and neither the loan officer nor the risk manager has any responsibility in monitoring the borrower after loan origination.

Loan officers are volume-incentivized while risk managers receive a fixed salary. Beyond these monetary incentives, risk management is viewed as being responsible for containing the level of loan defaults. Ex post, excessive defaults are thus not blamed on loan officers, but on a "failure of risk management". Therefore, loan officers and risk managers face detrimental incentives in the spirit of Dewatripont and Tirole (1999): While loan officers tend to stress arguments in favor of granting a loan, risk managers will usually focus on arguments against granting a (risky) loan. Excessive rejections by risk managers are contained by an implicit commitment to accept a certain fraction of loan applications. During our sample period, risk management accepted approximately 80% of all loan applications that required risk management was involved in.

3. Data and descriptive statistics

The data set contains 76,372 retail mortgage loan applications from a major European bank, spanning the time from February 2008 to September 2011. All loan applications in the data set are first lien loans for owner-occupied houses or apartments by either one or two (e.g., husband and wife) applicants. All loans are fixed rate loans with a scheduled amortization scheme.[4] I drop loan applications with a rating of 9 or worse (less than 1% of observations) as these are directly rejected without further consideration.

[Table 3 here]

Table 3 provides descriptive statistics of the sample. In total, the sample contains 76,372 loan applications of which 67,860 (89%) loan applications do not require risk management ("green applications") approval while 8,512 (11%) can only be approved after risk management involvement ("yellow applications"). Loan applications that do not need risk management approval are on average smaller (EUR 116,000 versus 139,000), have a higher expected recovery rate (77% versus 69%), are more frequently collateralized by a house (77% versus 67%). Loan applications from these "green" applications are on average older (44 years versus 38 years), they are more frequently from two applicants (average number of applicants of 1.67 versus 1.43), from relationship applicants (63% versus 41%) and applicants have a higher interest coverage ratio (31% versus 21%), measured as the ratio of (Net income per year – Cost of living per year) to

[4] The bank does not offer variable-rate interest schemes, negative amortization loans or teaser rate loans.

(Loan amount + Preexisting liabilities[5]). These differences are also reflected in the rating and LTV: The mean rating and LTV for "green" loan applications (rating = 3.75, LTV = 70.69%) is lower than the mean for loan applications with risk management involvement (rating = 5.78, LTV = 102.06%).

While 43% of all "green" loan applications result in a loan being granted (implying that 2 out of 5 loan applicants accept the bank's offer or loan applicants apply at 2.5 banks on average), only 28% of "yellow" loan applications result in a loan being granted. This is not surprising giving that risk management will reject loans it considers to be too risky. The default rate for "green" loans is 2.81% and therefore lower than the default rate for "yellow" loans (3.18%).

These differences in loan and customer characteristics between the "green" and the "yellow" sample provide the main challenge in identifying a causal effect of risk management on loan defaults. The key question is: Is the "yellow" default rate of 3.18% high or low relative to the 2.81% default rate for "green" loans *once the differences in loan and customer characteristics have been taken into account*? I will more formally describe the identification strategy in the next section, but provide same basic reference points in the following paragraphs.

Figure 4 plots default rates by rating grade and status (with/without risk management involvement). In each rating class, "green" loans default more frequently than "yellow" loans.

[Figure 4 here]

Table 4 provides default rates by subperiod (February 2008-April 2009) and rating-LTV combination. There is a decisive drop in default rates along three

[5] All loans are first lien mortgages, but preexisting liabilities, such as consumer loans, overdrafts, or student loans can exist.

dimensions: First, for each rating grade, default rates drop significantly when moving from "green" to "yellow" LTV-classes. For example, for rating classes 3 and 4 in subperiod 1, default rates drop from 5.26% to 1.77% when moving from an LTV below to LTVs above 100%. Second, for each LTV-class default rates drop when moving from "green" to "yellow" rating grades. For example, for LTVs between 90% and 100% in subperiod 2, default rates drop from 4.36% to 2.54% when moving from a rating of 5 to a rating of 6. Both observations suggest that loans that are close to the threshold, but narrowly "green", have higher default rates than loans that are narrowly "yellow". These observations are consistent with a dampening effect of risk management involvement on loan defaults.

[Table 4 here]

Third, I compare differences in default rates between subperiod 1 and subperiod 2 for rating/LTV-combinations that were affected by the change in the threshold (ratings 6-8 for LTVs between 90% and 100% and rating 8 for LTVs between 72% and 90%) versus rating/LTV-combinations that were not affected by the change in the threshold. Figure 5 plots the development of default rates for affected (upper-hand picture) and non-affected rating/LTV-combinations (lower-hand picture). It shows a significant downward jump in default rates for rating/LTV-combinations that were not subject to risk management approval before May 2009, but started to be subject to risk management approval after May 2009. There is no similar downward jump in default rates for rating/LTV-combinations that were not affected by the change in the threshold.

[Figure 5 here]

4. Empirical strategy

4.1 Difference-in-Difference

I define the difference-in-difference estimator as

$$Default(0/1) = f\left(\beta_1 \cdot Affected + \beta_2 \cdot Post + \beta_{12} \cdot Post \times Affected + \gamma \cdot X\right) \qquad (1)$$

where *Default(0/1)* is a dummy equal to one if a borrower defaults within 24 months after the loan start date, *f()* is a function such as the identity function (resulting in a linear model) or the logistic function (resulting in a logit model), *Post* is a dummy equal to one for loan applications in or after May 2009, *Affected* is a dummy equal to one for rating/LTV-combinations that were not subject to risk management approval before May 2009, but were subject to risk management approval after May 2009 (ratings 6-8 for LTVs between 90% and 100%, rating 8 for LTVs between 72% and 90%). *Controls* is a set of loan and customer characteristics. As loan characteristics, I control for the size of the loan (measured by the logarithm of the loan amount in EUR), the loan maturity (measured by the logarithm of the maturity in months), a dummy equal to 1 if the loan is collateralized by a house (the dummy is equal to zero if the collateral is an apartment), the age of the customer (measured by the logarithm of the age in years), the number of borrowers (equal to one for loan applications by a single borrower, equal to two by loan applications from two borrowers, e.g. husband and wife), a relationship dummy (equal to one if the customer has a checking account or current loan with the bank), and the interest coverage ratio (measured as the ratio of (Net income per year – Cost of living per year) to (Loan amount + Preexisting liabilities).

The underlying assumption behind a difference-in-difference estimator is that unobservable characteristics that affect the default rate are comparable between affected and non-affected rating/LTV-combinations. A possible violation for this comparability assumption would be if the improvement of the economy has a different impact on default rates of affected and non-affected rating-LTV-combinations. While it is impossible to *prove* that affected and non-affected rating-LTV-combinations are similar with respect to unobservables, I provide two types of analysis to support the claim that the drop in default rates is indeed a causal effect of risk management involvement. First, I test whether affected and non-affected rating/LTV-combinations follow a similar trend in the pre-event period ("parallel trend assumption"). This reduces a possible bias via unobservables to variables that have a different impact on default rates on affected/non-affected rating-LTV-combinations *from or after May 2009 on only*. Second, I apply econometric techniques to show that there is a downward jump – as opposed to a smooth downward trend – in the default rate in May 2009 for the affected rating-LTV combinations. This limits alternative explanations to unobservable factors that a) have a different impact on affected versus non-affected rating-LTV combinations, *and* b) suddenly changed at the same time when rules for risk management involvement were also changed.

4.2 Regression discontinuity design

A regression discontinuity design is a standard technique for causal inference in situations where treatment is determined by a threshold, with observations on one side of the threshold receiving treatment and observations on the other side of the threshold acting as a control group (Thistlewaite and

Campbell (1960), Imbens and Lemieux (2008), Roberts and Whited (2011)). I define the regression discontinuity estimator as

$$\begin{aligned} Default(0/1) = f\,[\beta_1 \cdot RMI(0/1) + g_1(DifferenceToCutOff) \\ + g_2(DifferenceToCutOff) \cdot RMI(0/1) + \gamma \cdot X\,] \end{aligned} \qquad (2)$$

where RMI(0/1) is a dummy ("Risk Management Involvement") equal to one risk management approval is required, g_1 and g_2 are polynomials fitted to the right and the left-hand side of the cutoff for risk management involvement. As above, f denotes a link function such as the identity (linear regression) or the logistic function (logistic regression) and X is the same set of loan and customer controls as used in the difference-in-difference estimator. The regression is estimated for a subset of observations than contains a discontinuity, e.g. for all loan applications with an LTV between 90% and 100% in subperiod 2 to estimate the change in default rates at the threshold rating of 5 (see Figure 3 and Table 4).

The regression discontinuity design relies on two key assumptions: First, the assumption that there are not "contaminating" thresholds. If loans with a rating directly above the threshold for risk management involvement perform significantly different than loans directly below the threshold, we can conclude that *something* happens at the threshold. However, if loans below and above the threshold are treated differently in any other respect apart from risk management involvement (i.e. bonus system, pricing, ex-post monitoring, etc.), there is no way to differentiate between these alternative explanations. I thus elaborated at great length with the staff of the bank to ensure that these thresholds are only used to determine risk management involvement and are not used for pricing purposes or in other process designs.

Second, the regression discontinuity design relies on the assumption that loan applications just below and just above the threshold are comparable.

Comparability follows, and does not have to be assumed by the researcher, if the running variable (rating, LTV) cannot be manipulated by the loan officer. There is some evidence in the literature that even hard information is subject to manipulation by delegated monitors (Berg, Puri, and Rocholl (2013)). As a stylized example of the effect of manipulation on causal inference, please consider the following example: If loan officers manipulate the rating or LTV for high-risk loans (because s/he fears rejection by risk management) but not for low-risk loans, then a higher default rate for loans directly above the threshold is a consequence of loan officer behavior, but not a causal effect of risk management involvement. The advantage of the data set at hand is that I am fully able to control for the extent of such manipulation. The data set allows me to track inputs by loan officers from initial inputs to the final inputs used to determine risk management involvement, and I am thus able to directly compare the performance of manipulated and non-manipulated loan applications. More formally, I am able to explicitly take into account a possible manipulation of the running variable by instrumenting treatment status with the initial input parameters inputted into the system by the loan officer.

4.3 Specifying the link function

Throughout the paper, I will mostly rely on a logistic link function f for economic reasons: I expect effects to be multiplicative and not additive. For example, economic conditions improve over time during the sample period. If two rating classes have a default rate of e.g. 10% and 1%, an improvement in the economy is likely to decrease default rates by the same portion (i.e. from 10% to 9% and 1% to 0.9%) as opposed to the same percentage points (i.e. from 10% to 9% and 1% to 0%). Similar arguments apply to risk management involvement, the main inference variable, and other loan and customer controls.

I therefore mainly use a logistic regression and report odds ratios (exponentiated coefficients) together with z-statistics. An odds ratio below one indicates that the variable of interest has a decreasing effect on default rates and vice versa. More formally odds ratios represent the term:

$$\frac{\frac{p(x+dx)}{1-p(x+dx)}}{\frac{p(x)}{1-p(x)}} \approx \frac{p(x+dx)}{p(x)} \quad \textit{for small } p(x) \qquad (3)$$

The approximation on the right-hand side follows from the fact that default rates are usually small, i.e. 2% or 5% and not 50% or 70%. We can therefore interpret the odds ratios for the covariate *x* as the factor by which default rates decrease/increase if *x* changes by 1 unit. To ensure the robustness of the results, I have also determined marginal effects (using the methodology of Ai and Norton (2003) for interaction terms) and used a linear regression instead of a logistic regression, with very similar results.

5. Empirical results

5.1 Difference-in-Difference analysis

Testing the parallel trend assumption

I start by testing the parallel trend assumption before May 2009. Looking at Figure 5, I observe that default rates are approximately flat before May 2009 for both the affected rating-LTV combinations as well as for the control group of non-affected rating-LTV combinations. I test the parallel trend assumption more formally using a logistic regression. Results are reported in Table 5. Column (1) reports results for the whole sample period before the threshold change (5 quarters from February 2008 to April 2009) and column (2) to (5) subsequently eliminate one quarter to see whether any difference in trends emerges close to May 2009. I find that the time trend is not significantly different from 1 (in terms of odds ratios), and also the treatment group does not show a time trend that deviates from the overall sample.

[Table 5 here]

Difference-in-Difference: Baseline specification

Table 6 provides the results for the baseline difference-in-difference specification. Column (1) provides results for a model that just contains the *Affected, After,* and *Affected* x *After* dummy variables. In line with the univariate results from Figure 5, I find that after the change of the threshold for risk management involvement, default rates decrease significantly for the affected loan applications, i.e. for rating-LTV combinations where no risk management involvement was required in subperiod 1, but risk management involvement was required in subperiod 2. The coefficient is not only statistically highly significant, but also economically: The odds ratio is 0.414, suggesting that the odds of defaulting versus not defaulting decreased by almost 60%. The other coefficients are also in line with the descriptive statistics: Affected loans default significantly more frequently than non-affected loans, and default rates decrease significantly after May 2009. Controlling for rating and LTV-classes (column (2)), as well as customer (column (3)) and loan controls (column (4)) and region fixed effects (column (5)) results in very similar coefficients on the interaction term, ranging from an odds ratio of 0.392 (column (3)) to 0.414 (column (1)).

[Table 6 here]

Difference-in-Difference: Establishing a jump in default rates in May 2009

The difference-in-difference estimator relies on a comparison of average default rates of affected and non-affected rating-LTV combinations pre and post the threshold change. Such a specification is vulnerable to different trends between affected and non-affected groups, for example caused by a different sensitivity to an improvement in economic conditions. While there is no evidence for differences in trends pre May 2009 (i.e. before the threshold is changed), there are clearly differences in the default rate *levels* between affected and non-affected rating-LTV classes. I thus provide further robustness tests with the aim of demonstrating that the change in default rates is concentrated around May 2009, i.e. at the onset of treatment. Table 7 reports the results. Column (1) reports results for a subsample restricted to +/- 4 quarters around the change in the threshold for risk management involvement (May 2008 to April 2010). Column (2) introduces separate time trends for the affected and non-affected groups to control for any smooth trend in default rates. Column (3) allows for different time trends pre and post May 2009 for both the affected and the non-affected rating-LTV combinations. Finally, borrowing from the regression discontinuity literature, column (4) fits 3^{rd} order polynomials on either side of May 2009 for both the affected and unaffected rating-LTV combinations. In all these specifications, results are very similar to the results from the standard difference-in-difference estimator used in Table 6.

[Table 7 here]

5.2 Regression discontinuity

While addressing several concerns, the difference-in-difference specification above still allows for an alternative explanation: Any contaminating event in May 2009 (when risk management thresholds were changed) that differentially impacts default rates between affected and non-affected rating-LTV combinations could potentially explain the pattern of default rates. To address this concern, I provide results for a regression discontinuity design. There are several subsamples for which regression discontinuity techniques can be applied (see Table 4):

1. Subsample 1: Subperiod 1, discontinuity at an LTV ratio of 100%.
2. Subsample 2: Subperiod 2, discontinuity at an LTV ratio of 100% for rating grades 1-5.
3. Subsample 3: Subperiod 2, discontinuity at a rating of 7.5 for LTVs between 72% and 90%.
4. Subsample 4: Subperiod 2, discontinuity at a rating of 5.5 for LTVs between 90% and 100%.

In the following I report results for the latter sample.[6] This choice is motivated by three considerations: First, loan applications just below and just above the 100% LTV threshold (the cutoff that the first two subsamples rely on) are likely not comparable: A 100% LTV is a psychological threshold with customers requesting loans above 100% LTV likely being different from customers requesting a 100% LTV loan. Second, LTV can easily be manipulated by (slightly) changing the requested loan amount. Third, the subsample No. 4 is the largest subsample with 14,659 loan applications (of which 6,212 loans were granted), of which 10,936 are above the threshold (rating 1-5) and 3,723 loan

[6] Results for the other samples are very similar, apart from the third subsample where the number of observations is too low to establish statistical significance.

applications are below the threshold (rating 6-8).[7] Thus, this sample contains almost half of all loan applications with risk management involvement (8,512, see Table 3).

Regression discontinuity: Baseline specification

Figure 6 provides a graphical presentation of the regression discontinuity design. The right-hand graphs provides results for subperiod 2, where the threshold for risk management involvement in the 90% < LTV ≤100% bracket was a rating of 5.5. The left-hand graphs provide results for subperiod 1, where no such threshold existed, for comparison. There is a clear drop in default rates between a rating of 5 and a rating of 6 in subperiod 2, a drop which is absent in subperiod 1 (see Panel A). Panel B shows that there is no drop in any of the control variables, i.e loan and customer characteristics cannot explain the drop in default rates.

[Figure 6 here]

Table 8 reports results of the formal regression, using a logistic regression around a bandwidth of +/-2 notches above and below the threshold rating of 5.5 and a linear trend on either side of the threshold. The bandwidth was determined using the optimal bandwidth selector suggested by McCrary (2008). Results using a linear regression (instead of the logistic regression), using half- or twice the optimal bandwidth and using higher order polynomials (instead of a linear function) are reported in the robustness section.

[7] As a comparision, the LTV class between 72% and 90% includes just 14,474 loan applications in subperiod 2 (5,681 loans granted) with only 686 loan applications being below the rating threshold of 7.5.

Column (1) reports the baseline specification using only the risk management involvement dummy – which is equal to one for loan applications with a rating of 5.5 or worse – and the linear trends on either side of the threshold. Risk management involvement significantly reduces default rates, with the odds ratio being 0.34 (66 percent reduction in the odds ratio). Using the average default rate of 4.36% for a rating of 5 just above the threshold, this means that risk management involvement reduces default rates by 2.8 percentage points. Results are very similar after introducing control variables (column (2) and (3)) as well as using a linear regression model (column (4)).

[Table 8 here]

Regression discontinuity: Instrumenting treatment status

In column (5), I instrument risk management involvement using the rating-LTV combination from the initial scoring trial. More formally, I use the input parameters from the initial scoring trial to determine an initial rating and LTV. This initial rating-LTV combination is then mapped to treatment status (risk management involvement = yes/no). Given the usual problems of IV estimator in non-linear models, I apply a linear regression model in the first as well as in the second stage. Consistent with loan officer manipulation, the IV-estimator results in slighly lower estimates of the effect of risk management involvement (-2.9% versus -3.3%) after controlling for endogenous sorting around the threshold. The coefficient is, however, still significant, both economically and statistically.

Regression discontinuity: Robustness tests

Table 9 provides further robustness tests using a different bandwidth choice around the threshold for risk management involvement and using higher order polynomials. Column (1) provides results for odds ratios from a logistic regression, column (2) provides marginal effects and column (3) provides results for a linear regression specification. Finally, column (4) uses a loss variable, defined as DefaultDummy(0/1) x (1 - Expected recovery rate) to see whether results still hold after taking into account expected receipts from the sale of collateral. All specifications confirm the previous results of an economically and statistically highly significant reduction in default rates or losses due to risk management involvement.

[Table 9 here]

Economic impact

A reduction of defaults is not an end in itself, rather the banks' aim is not to grant loans with a negative expected NPV. A back-of-the-envelope estimate of the net present value impact of risk management is as follows: A conservative estimate from the results above is a reduction in default rates by 50% due to risk management involvement. On the other hand, the ratio of loans-granted to loan applications is approximately 1/3 lower for loan applications with risk management involvement (28.42%) compared to loan applications without risk management involvement (43.01%, see Table 3, row labelled "loan granted"). If the mean default rate of loans subject to risk management approval is denoted by p, then these numbers suggest that accepted loans have a default rate of p/2 while rejected loans have a default rate of 2p.[8] For the main LTV-class of loans with 90% < LTV ≤ 100% the mean default rate at the threshold for risk management involvement is roughly 5% (see Table 4, Panel B). This implies a default rate of

[8] Please note that $p/2 \cdot 2/3 + 2p \cdot 1/3 = p$.

2.5% for loans granted with risk management approval and a default rate of 15% for loans that are rejected by risk management. Keeping in mind that these are 2-year cumulative default rates, these numbers suggest a projected annual default rate of 7.5% for loan applications that were rejected by risk management, implying that rejected loans would have been very likely negative NPV given average margins of roughly 100bps. These back-of-the-envelope calculations suggest that involving risk management did help in rejected negative NPV loans and thus improved the overall loan granting decision within the bank.

5.3 Ruling out alternative hypothesis

The prior analysis has shown that risk management involvement significantly reduces default rates. While I have stressed the importance of differential incentives, two alternative explanations need to be considered: First, the average risk manager might have more experience than the average loan officer, and thus differences in experience could drive the results. Second, entrenchment could drive the results if loan officers, in the absence of resistance from risk managers, would tend to overlook the risks of their long-term customers in an attempt to keep them happy.

To analyze these alternative explanations, I separately analyze the effect of risk management involvement for experienced and unexperienced loan officers as well as for relationship customers and non relationship customers. I measure experience by the number of loan applications processed over the past 12 months and split the sample at the median into "experienced" and "unexperienced" loan officers.[9] If experience plays a major role, then the effect of risk management

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[9] Results are very similar when using the number of loans instead of the number of loan applications or other time windows (3 months, 6 months, 2 years).

involvement should be larger for less experienced loan officers. Table 10 reports the results.

[Table 10 here]

I do not find any evidence for the experience channel; the effect of risk management involvement is independent of loan officer experience both in a difference-in-difference analysis (column (1)) as well as in the regression discontinuity design (column (3)).

To analyze a potential entrenchment effect, I analyze whether risk management involvement has a differential effect for non relationship customers – where entrenchment should not play a role – and relationship customers, where entrechment might affect the loan granting decision of the loan officer. I do not find any evidence for an entrenchment effect. Coefficents on *Affected x After x Relationship* in the differen-in-difference analysis and on *RiskMgmtInvolvement(0/1) x Relationship* in the regression discontinuity design are larger than one (suggesting the effect of risk management is *smaller* for relationship customers) and statistically insignificant.

6. Conclusion

Volume-incentivized loan officers are unlikely to make arguments against granting a loan, nevertheless, volume-based incentives dominate industry practice in the banking industry. Advocates in court are rarely found to make arguments for a conviction, yet the judicial system works because the other side of the argument is being made by prosecutors. In banks, risk management is responsible to make "the other side of the argument". Does hiring two agents, one responsible for loan volume (loan officers) and one responsible for risk (risk management), help to facilitate efficient screening decisions? In this study, I examine the impact of risk management involvement in the loan granting process on subsequent loan default rates. I thereby use a setting at a major European bank that requires retail mortgage applications to be approved by risk management if the hard-information rating and the loan-to-value (LTV) ratio cross certain thresholds.

Using a regression discontinuity design and a difference-in-difference estimator, I find that risk management involvement reduces default rates by more than 50%. I further show that loans rejected by risk management would likely have been negative NPV loans, suggesting that risk management involvement added value to the bank.

Prior literature has discussed the adverse effect of the widely used volume-based incentives for loan officers. While one solution is to provide loan officers with high-powered incentives based on ex-post default rates, this paper suggests that alternative routes are possible for containing risk. By deliberately assigning opposing incentives to loan officers (loan volume) and risk management (risk), both arguments in favor of granting a loan as well as arguments against it are considered in the loan granting process, leading to better decision making and lower loan default rates.

References

Acharya, V., T. Philippon, M. Richardson, and N. Roubini (2009): "The financial crisis of 2007-2009: Causes and remedies," *Financial Markets, Institutions & Instruments*, *18*(2), 89-137.

Aebi, V., G. Sabato, and M. Schmid (2012): "Risk management, corporate governance, and bank performance in the financial crisis," *Journal of Banking & Finance*, *36*(12), 3213-3226.

Agarwal, S. and I. Ben-David (2012): “Do Loan Officers’ Incentives Lead to Lax Lending Standards?,” Working Paper.

Agarwal, S. and Hauswald, R. (2010): “Authority and Information,” Working Paper.

Ai, C., E.C. Norton (2003): "Interaction terms in logit and probit models," *Economics letters*, *80*(1), 123-129.

Alchian, A. A., and H. Demsetz (1972): "Production, information costs, and economic organization." *The American Economic Review*, *62*(5), 777-795.

Allen, F. (1990): "The market for information and the origin of financial intermediation," *Journal of financial intermediation*, *1*(1), 3-30.

Baker, G. (2000). The use of performance measures in incentive contracting, "*The American Economic Review*," *90*(2), 415-420.

Baker, G. P., Jensen, M. C., and Murphy, K. J. (1988): "Compensation and incentives: Practice vs. theory," *The Journal of Finance*, *43*(3), 593-616.

Berg, T., Puri, M., and Rocholl, J. (2013): "Loan officer incentives and the limits of hard information," NBER Working Paper No. 19051.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein (2005): "Does Function Follow Organizational Form? Evidence from Lending Practices of Large and Small Banks," Journal of Financial Economics, 76, 237-269.

Brown, M., M. Schaller, S. Westerfeld, and M. Heusler (2013), "The Hidden Cost of Control – Evidence from Small Business Lending", Working Paper

Cole, S., M. Kanz and L. Klapper (2012): "Incentivizing Calculated Risk Taking: Evidence from a Series of Experiments with Commercial Bank Loan Officers," Harvard Working Paper.

Dawes, R. M., D. Faust, D., and P.E. Meehl (1989): "Clinical versus actuarial judgment," *Science*, *243*(4899), 1668-1674.

Dewatripont, M., and Tirole, J. (1999): "Advocates," *Journal of Political Economy*, *107*(1), 1-39.

Diamond, D. W. (1984): "Financial intermediation and delegated monitoring," *The Review of Economic Studies*, *51*(3), 393-414.

Ellul, A., and V. Yerramilli (2013): "Stronger risk controls, lower risk: Evidence from US bank holding companies," *The Journal of Finance, 68(5), 1757-1803.*

Falk, A. and Michael Kosfeld (2006): "The hidden costs of control," *American Economic Review*, 96(5), 1611-1630.

Heider, F. and Inderst, R. (2012): "Loan Prospecting," *Review of Financial Studies*, 25(8), 2381-2415.

Hertzberg, A., J. M. Liberti, and D. Paravisini (2010): "Information and Incentives Inside a Firm: Evidence from Loan Officer Rotation," Journal of Finance, 65(3), 795-828.

Holmstrom, B. (1982): "Moral hazard in teams," *The Bell Journal of Economics*, 324-340.

Holmström, B. and P. Milgrom, P. (1990): "Regulating trade among agents," *Journal of Institutional and Theoretical*, 146, 85-105.

Holmstrom, B. and P. Milgrom (1991). Multitask principal-agent analyses: Incentive contracts, asset ownership, and job design. *Journal of Law, Economics, and Organization*, *7*, 24-52.

Imbens, G.W. and T. Lemieux (2008): "Regression discontinuity designs," Journal of Econometrics, 142, 615-635.

Liberti, J. M., and A. R. Mian (2009): “Estimating the Effect of Hierarchies on Information Use," Review of Financial Studies, 22(10), 4057-4090.

McCrary, J. (2008): "Manipulation of the running variable in the regression discontinuity design: A density test," *Journal of Econometrics*, *142*(2), 698-714.

Meehl, P. E. (1954): "Clinical versus statistical prediction: A theoretical analysis and a review of the evidence," University of Minnesota Press.

Puri, M., J. Rocholl, and S. Steffen (2011): "Rules versus Discretion in Bank Lending Decisions," Working Paper.

Puri, M., J. Rocholl, and S. Steffen (2013): "What kinds of bank-client relationships matter in reducing loan defaults and why?," Working Paper.

Rahman, D. (2012): "But who will monitor the monitor?," *The American Economic Review*, *102*(6), 2767-2797.

Ramakrishnan, R. T., and Thakor, A. V. (1984): "Information reliability and a theory of financial intermediation," *The Review of Economic Studies*, *51*(3), 415-432.

Roberts, M.R. and T.M. Whited (2011): “Endogeneity in Empirical Corporate Finance,“ Working Paper.

Stein, J. C. (2002): “Information Production and Capital Allocation: Decentralized versus Hierarchical Firms," Journal of Finance, 57(5), 1891-1922.

Stulz, R. M. (2008): "Risk management failures: What are they and when do they happen?" *Journal of Applied Corporate Finance*, *20*(4), 39-48

Udell, G. F. (1989): “Loan Quality, Commercial Loan Review and Loan Officer Contracting," Journal of Banking & Finance, 13, 367-382.

Thistlewaite, D., and D. Campbell, (1960): “Regression-discontinuity analysis: an alternative to the ex-post facto experiment,” Journal of Educational Psychology, 51, 309-31.

Tversky, A. and Kahneman, D. (1974): "Judgment under uncertainty: Heuristics and biases," *Science*, *185*(4157), 1124-1131.

Figure 1: Loan granting without (Setup 1) and with risk management (Setup 2)

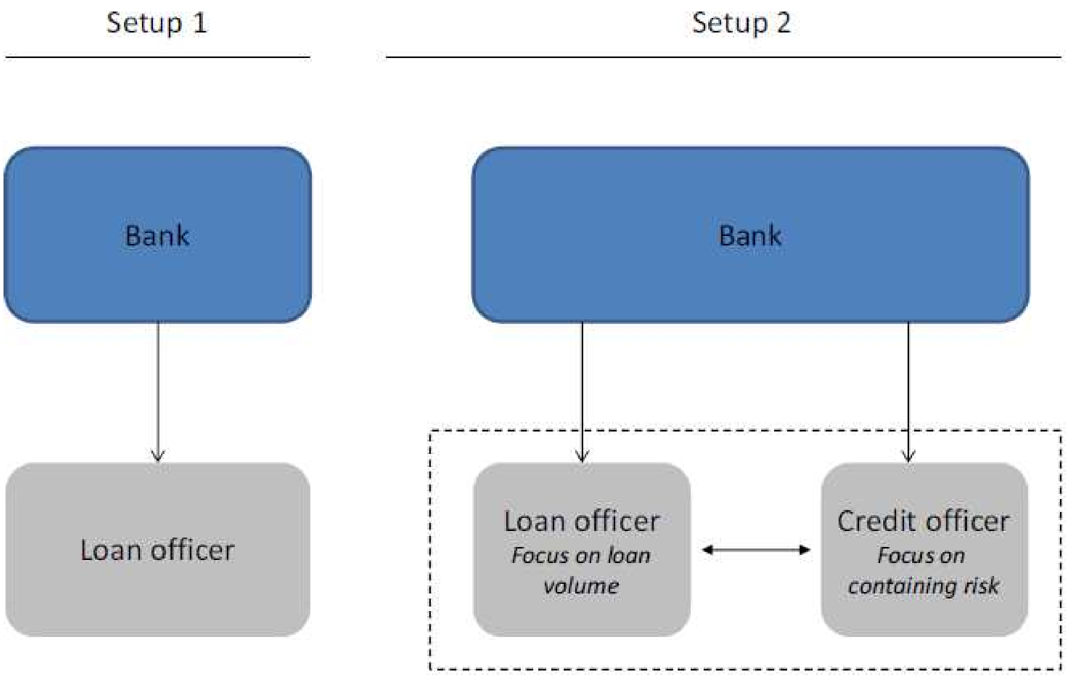
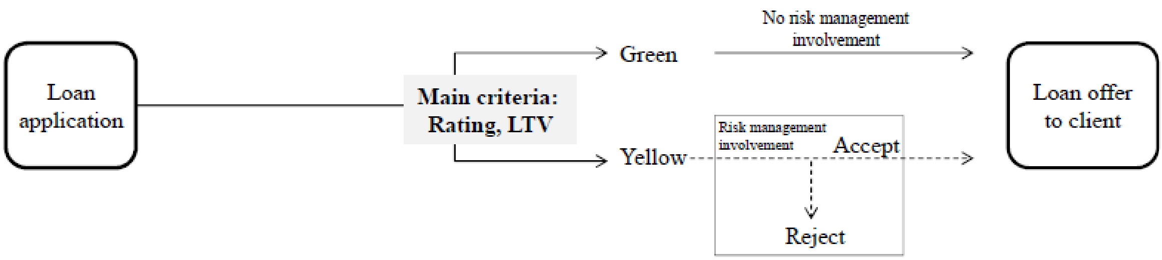


Figure 2: Loan origination process



	Step 1: Information collection	Step 2: Hard information filter	Step 3: Risk management involvement
Tasks	• Client contact • Input application into system	• Sort applications into green (no risk management involvement) and yellow (risk management approval necessary)	• Accept/reject loan application
Responsible	Loan officer	Loan officer (data) Risk mgmt (criteria)	Risk management

Figure 3: Criteria for risk management involvement

This figure depicts the criteria for risk management involvement for both subperiods. The green area, labelled "No risk management involvement", provides the LTV-Rating-combinations where loans can be granted without risk management approval. The yellow area, labelled "Risk management involvement", depicts the LTV-Rating-combinations where risk management approval is necessary to make a loan officer to the loan applicant. Rating denotes the customer's internal rating of the bank, with 1 being the best rating category.

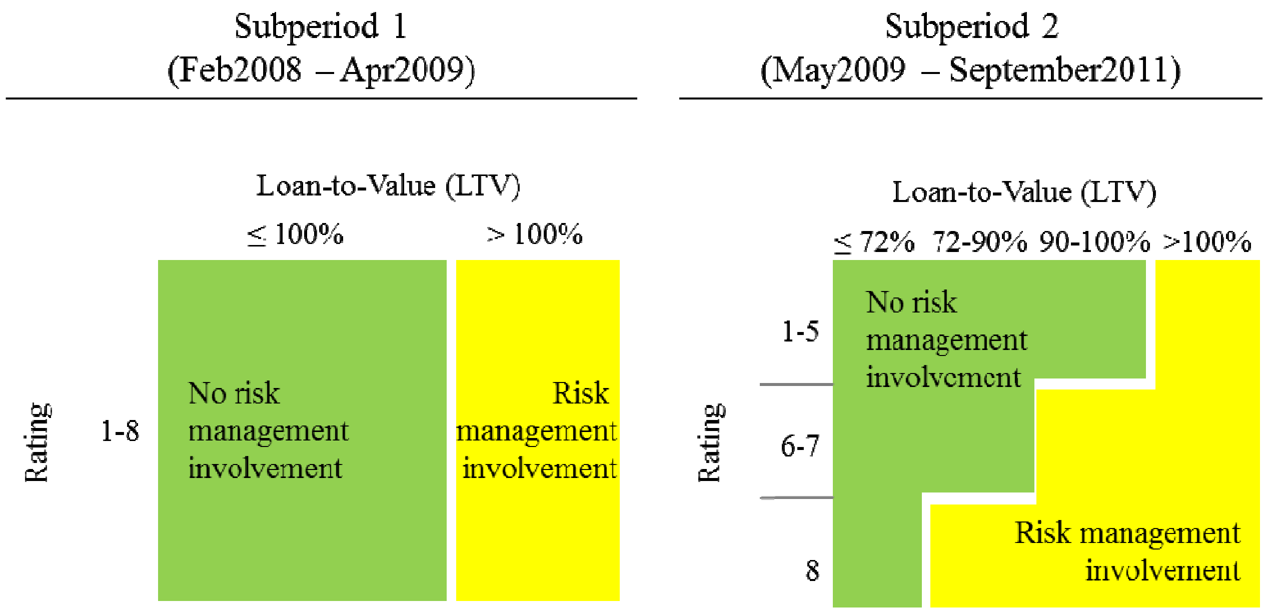


Figure 4: Default rates by process type (with/without risk management involvement)

This figure depicts the default rate over the first 24 months after the loan start date by process type. The dashed green line depicts default rates for loans approved without risk management involvement. The yellow solid line depicts default rates for loans approved with risk management involvement. The grey area depicts one standard error bands around the mean.

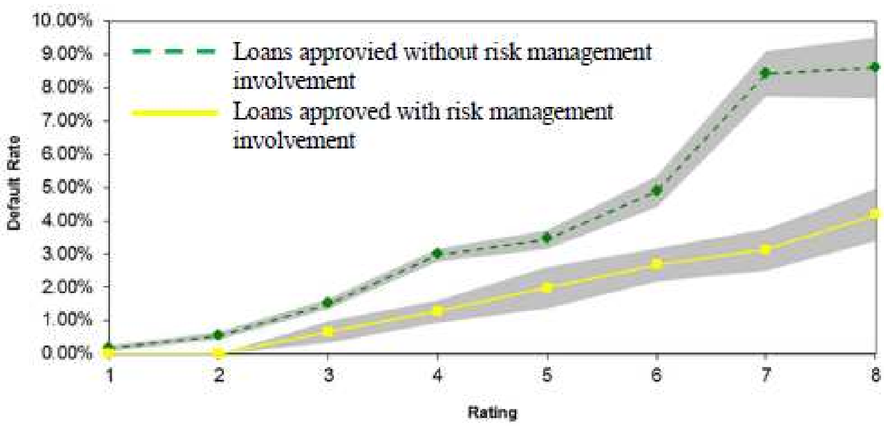
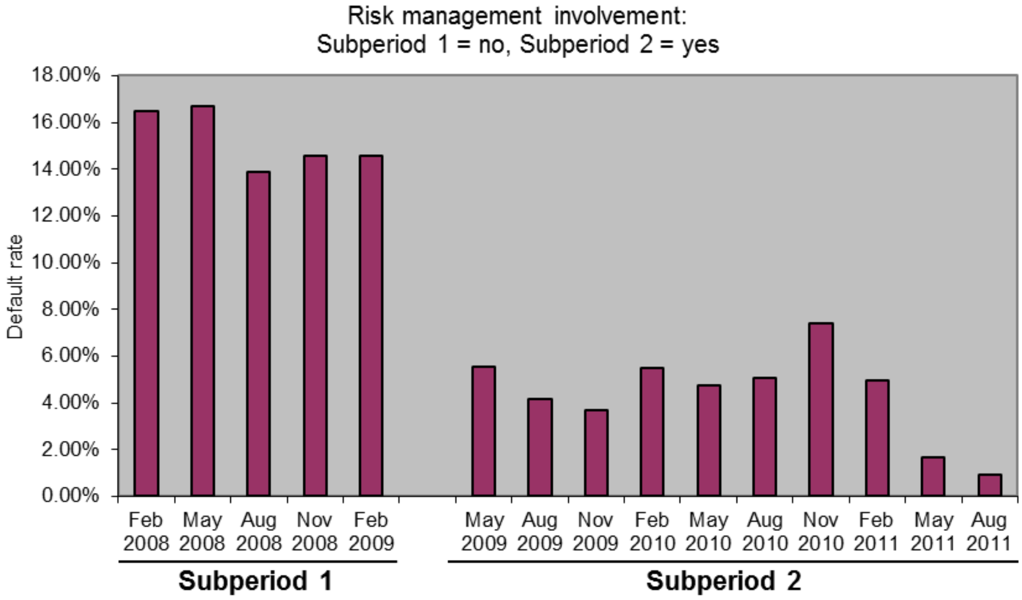


Figure 5: Time series of default rates

This figure depicts default rates over the first 24 months after the loan start date for different subsets of loans. The upper-hand figure presents default rates for rating-LTV combinations where no risk management approval was necessary during the first subperiod (February 2008 – April 2009) and risk management approval was necessary during the second subperiod (May 2009 – September 2011). The lower-hand figure presents default rates for rating-LTV combinations where either no risk management approval was necessary in both subperiods or risk management involvement was necessary in none of the subperiods.



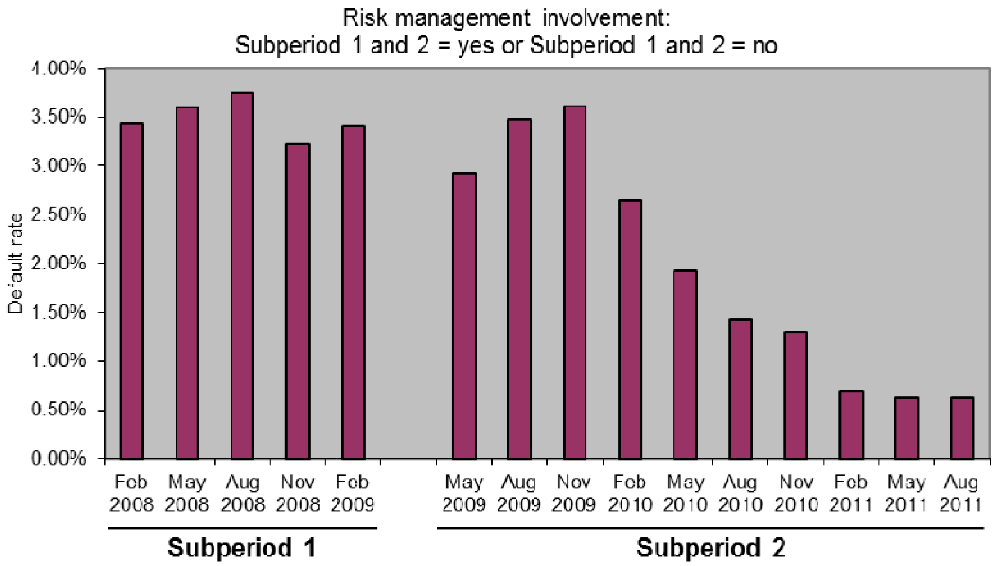
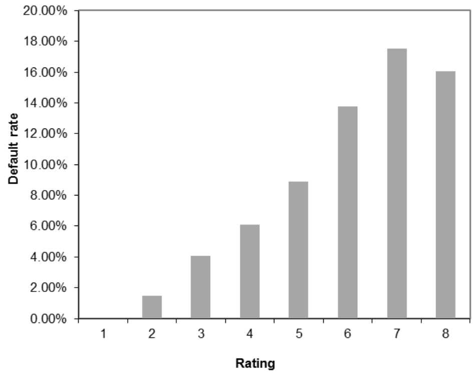


Figure 6: Regression discontinuity – Graphical presentation

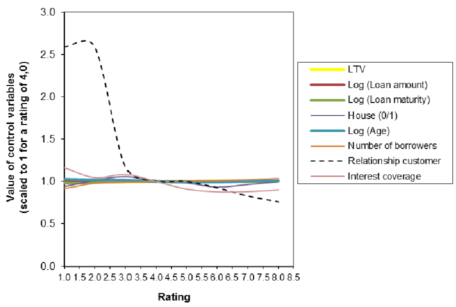
This figure depicts standard regression discontinuity graphs for all loan applications with an LTV between 90% and 100%. The left-hand panel provides graphs for subperiod 1 (February 2008 – April 2009) and the right-hand panel provides graphs for subperiod 2 (May 2009 to September 2011). Panel A provides default rates over the first 24 months after the loan start date by rating grade, with a rating of 5.5 being the threshold for risk management involvement in subperiod 2. Panel B provides mean values of the control variables scaled to a value of 1.0 for a rating of 4.0. Panel C provides a distribution of loan applications by rating grade.

Subperiod 1

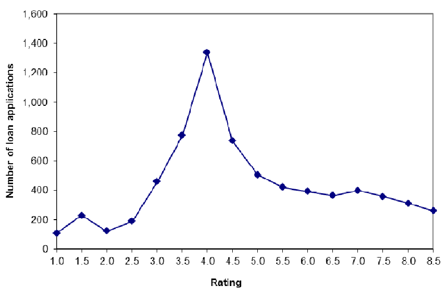
Panel A: Default rates



Panel B: Covariates

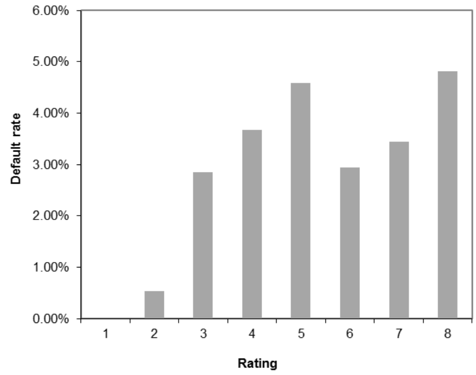


Panel C: Distribution of loan applications

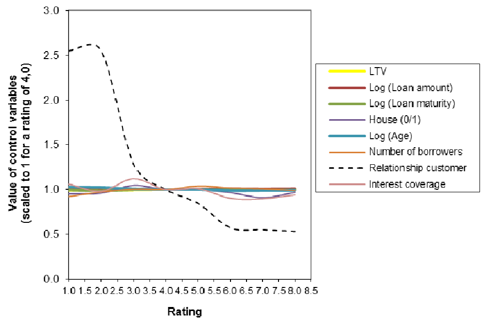


Subperiod 2

Panel A: Default rates



Panel B: Covariates



Panel C: Distribution of loan applications

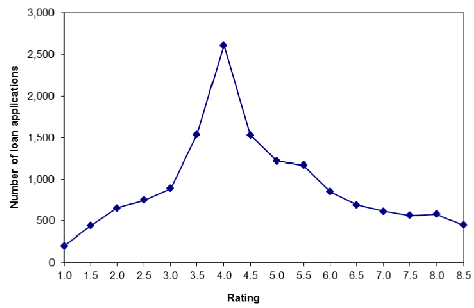


Table 1: Explanation of variables

Name	Description
Key variables	
Risk management involvement (0/1)	Dummy variable equal to one if a loan application has to be approved by risk management
Affected (0/1)	Dummy variable equal to one for all Rating-LTV combinations where no Risk Management Involvement is necessary to approve a loan in Subperiod 1 Risk Management Involvement is necessary in Subperiod 2. These Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%.
Rating	Internal rating ranging from 1 (best) to 12 (worst).
LTV	Loan-to-Value, determined by dividing the loan amount by the value of the collateral (i.e. the value of the house or apartment)
Loan granted (0/1)	Dummy variable equal to 1 if a loan is granted to the customer. Loans can only be granted to the customer if the loan officer and, if risk management involvement is necessary, a risk manager has approved the loan.
Default (0/1)	Dummy variable equal to 1 if a borrower has defaulted during the first 24 months after the loan start date.
Time and dates	
Subperiod 1	Time period from February 2008 to April 2009
Subperiod 2	Time period from May 2009 to September 2011
After (0/1)	Dummy variable equal to one if the date of the date of the loan application is in Subperiod 2, i.e. during or after May 2009
Date of loan application	Initial day of the loan application. It is the first day where all information is available that is necessary to determine whether risk management needs to be involved or not (in particular: Rating, LTV).
Time	Year fraction between the date of the loan application and May 1st 2009, for example, months is equal to -1/12 for loan applications in April, 1st, 2009 and it is equal to -3/12 for loan applications on July, 1st, 2009.
Loan start date	Date when loan is disbursed. If loan is disbursed in several tranches, the date where the first tranche is disbursed.
Loan characteristics	
Loan amount	Loan amount in EUR
Loan maturity	Loan maturity in months
Bank's expected recovery rate	Bank's expected recovery rate of the bank at the time of origination. The expected recovery rate is based on an internal model taking into account the location and type of the collateral.
House (0/1)	Dummy equal to one if the collateral is a house, and equal to zero if the collateral is an apartment.
Customer characteristics	
Age	Age of customer. If a loan application has several customers, e.g., husband and wife, the average age is used.
Number of borrowers	Number of customers per loan. The number of customers is equal to one is a single person is liable for the loan, it is equal to two if two persons (for example, husband and wife) are liable for the loan.
Relationship customer	Dummy variable equal to 1 if the customer had a checking account or a current loan with the bank before the loan application.
Interest coverage ratio	(Income – Costs) / (Loan Amount + Preexisting liabilities), where income is the yearly net income of the customer in EUR, costs are the non-discretionary costs of living of the customer in EUR, loan amount is the loan amount in EUR and preexisting liabilities are liabilities that exist at the time of loan origination, such as student loans, credit card debt or consumer loans.
Loan officer characteristics	
High experience (0/1)	Dummy equal to one if a loan officer has handled more loan applications over the past 12 months than the median loan officer.

Table 2: Examples

This table provides examples of decisions by risk management.

No.	Applicaion	Decision	Rationale
1	Couple, both 45 years old, apply for a mortgage to buy an old house that needs refurbishment. Two expensive car loans outstanding, no equity.	Reject	• Small amount of equity at this age and car loans outstanding suggest poor savings behaviour in the past. • No consideration of costs needed to refurbish house, likely to require additional financial resources. Implies that purchase of house not a well thought-out plan.
2	Loan applicant owns another one bedroom apparment. Income from this apartment entered twice (rent income and other income), and with the gross amount (includes utilities and heating) instead of the net amount that constitutes income to the owner.	Reject	• Ability to service the mortgage not safe enough after adjusting misspecified rent income.
3	33-year old Indian woman, lives in Europe since 1.5 years and works as an IT specialist, applies for a 15-year EUR 300,000 mortgage loan with payments from the mortgage loan summing up to 60% of net income. EUR 100,000 equity available.	Accept	• Permanent visa not tied to specific employer, IT specialists in high demand in the city she lives in, so job risk seems to be low. • Given her age, significant amount of savings available, account shows regular savings behavior. • Relatively short maturity of loan and young age means that mortgage payments can be reduced by extending the maturity of the loan.
4	Young couple, 30 years old, both working on a fixed-term contract, apply for a EUR 500,000 mortgage. Current income sufficient, but not with a big margin of error, to cover mortgage rates, no equity.	Accept	• CV requested. CV shows that both have studied at top universities abroad with top grades and several internships at renowned firms. This implies that current income is likely to be achieved in the future when fixed-term contract expires.

Table 3: Descriptive statistics

This table presents summary statistics for the sample of all loan applications between February 2008 and September 2011. Column (1) provides summary statistics for loan applications without risk management involvement, column (2) provides summary statistics for loan applications that have to be approved by risk management. For variable definitions see Table 1.

		(1) Without risk management involvement				(2) With risk management involvement			
		N	Mean	Median	Std.Dev.	N	Mean	Median	Std.Dev.
Key variables									
Rating	Number (1=Best, 8=Worst)	67,860	3.75	4.00	1.69	8,512	5.78	6.00	1.94
LTV		67,860	70.69%	75.41%	24.24%	8,512	102.06%	100.00%	9.35%
Loan granted	Dummy (0/1)	67,860	43.01%	0.00%	49.51%	8,512	28.42%	0.00%	45.11%
Default rate		29,184	2.81%	0.00%	16.52%	2,419	3.18%	0.00%	17.56%
Other loan characteristics									
Loan amount	EUR	67,860	116,039	100,000	78,008	8,512	139,422	122,000	82,865
Loan maturity	Months	67,860	120.00	120.00	43.00	8,512	124.00	120.00	39.00
Bank's expected recovery rate		67,860	77.15%	77.38%	12.36%	8,512	69.32%	70.85%	8.50%
House (0/1)	Dummy (0/1)	67,860	77.13%	100.00%	42.00%	8,512	66.91%	100.00%	47.06%
Other customer characteristics									
Age	Years	67,860	43.50	43.00	10.40	8,512	38.44	38.00	8.95
Number of borrowers	All	67,860	1.67	2.00	0.51	8,512	1.43	1.00	0.53
Relationship customer	Dummy (0/1)	67,860	0.63	1.00	0.48	8,512	0.41	0.00	0.49
Interest coverage		67,860	31.30%	21.79%	62.81%	8,512	20.95%	17.37%	16.75%

Table 4: Default rates by rating and LTV

This table provides default rates over the first 24 months after the loan start date by rating and LTV. Cells shaded in green indicate Rating-LTV combinations without risk management involvement, cells shaded in yellow indicate Rating-LTV combinations where risk management approval is necessary to grant a loan. Panel A presents default rates for Subperiod 1 (February 2008 – April 2009), Panel B presents default rates for Subperiod 2 (May 2009 – September 2011).

Panel A: Subperiod 1 (February 2008 – April 2009)

	LTV					
Rating	< 72%	72%-90%	90%-100%	> 100%	Total	Number of loans
1,2	0.53%	1.83%	0.65%	0.00%	0.83%	1,445
3,4	1.89%	2.59%	5.26%	1.77%	3.25%	5,050
5	3.13%	4.15%	9.36%	5.26%	6.27%	1,149
6	4.67%	4.30%	14.15%	6.25%	9.39%	863
7	5.88%	7.00%	17.44%	7.14%	11.95%	862
8	4.09%	11.35%	15.97%	6.25%	11.54%	641
Total	2.22%	3.75%	8.71%	2.97%	5.05%	10,010
Number of loans	3,558	2,213	3,802	437	10,010	

Panel B: Subperiod 2 (May 2009 – September 2011)

	LTV					
Rating	< 72%	72%-90%	90%-100%	> 100%	Total	Number of loans
1,2	0.17%	0.51%	0.38%	0.00%	0.28%	5,024
3,4	0.73%	1.40%	3.42%	0.58%	1.76%	9,588
5	0.81%	1.72%	4.36%	3.53%	2.48%	3,059
6	1.66%	2.54%	2.54%	4.04%	2.37%	1,860
7	2.17%	6.84%	3.46%	5.08%	4.59%	1,241
8	2.48%	3.77%	4.84%	4.00%	3.65%	821
Total	0.73%	1.97%	3.20%	1.79%	1.81%	21,593
Number of loans	8,919	5,681	6,212	781	21,593	

Table 5: Effect of risk management involvement on default rates – Parallel trend assumption

This table provides results of a test for parallel trends in default rates between rating-LTV combinations affected by the change in risk management threshold and the control group (rating-LTV combinations not affected by the change of the risk management threshold). The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression. *Time* is a variable that measures the time between the date of the loan application and May 1st, 2009 and it is measured as a year-fraction (e.g. *Time* is equal to -0.5 for a loan application from Nov. 1st, 2009). *Affected* is a dummy variable equal to one for all rating-LTV combinations where no risk management involvement is necessary to approve a loan in subperiod 1 but risk management involvement is necessary in subperiod 2 (these Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%). For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)		(5)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit		Logit	
Sample	5 quarters before May 2009		4 quarters before May 2009		3 quarters before May 2009		2 quarters before May 2009		1 quarters before May 2009	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat
TIME TREND										
Time	0.993	(-0.44)	0.988	(-0.67)	0.974	(-0.72)	0.962	(-0.63)	1.027	(0.17)
Time x Affected	0.996	(-0.16)	1.004	(0.12)	1.047	(0.70)	1.106	(1.10)	1.254	(0.61)
CONSTANTS										
Constant	0.035***	(-21.59)	0.034***	(-20.68)	0.032***	(-17.29)	0.031***	(-15.18)	0.036***	(-16.62)
Affected	4.864***	(10.50)	4.977***	(9.45)	5.665***	(6.78)	6.578***	(7.27)	6.358***	(4.58)
Diagnostics										
Adj. R^2	0.06		0.06		0.05		0.06		0.05	
N	10,010		8,076		5,614		3,600		1,689	

Table 6: Effect of risk management involvement on default rates – Difference in difference approach

This table estimates the effect of risk management involvement on default rates using a difference-in-difference approach. The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression. *Affected* is a dummy variable equal to one for all rating-LTV combinations where no risk management involvement is necessary to approve a loan in subperiod 1 but risk management involvement is necessary in subperiod 2 (these Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%). For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)		(5)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit		Logit	
Sample	Total		Total		Total		Total		Total	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat
INFERENCE										
Affected x After	0.414***	(-4.54)	0.400***	(-4.66)	0.409***	(-4.57)	0.392***	(-4.75)	0.407***	(-4.57)
Affected	5.010***	(13.96)	1.144	(0.83)	1.134	(0.76)	1.277	(1.46)	1.231	(1.24)
After	0.478***	(-6.91)	0.507***	(-6.16)	0.482***	(-6.32)	0.458***	(-6.65)	0.463***	(-6.69)
RATING (Reference: Rating =1)										
Rating = 2			3.896**	(2.32)	4.138**	(2.42)	4.369**	(2.52)	4.325**	(2.51)
Rating = 3			8.083***	(3.38)	8.884***	(3.53)	7.335***	(3.22)	7.047***	(3.15)
Rating = 4			13.768***	(4.35)	15.088***	(4.50)	12.524***	(4.23)	11.892***	(4.13)
Rating = 5			17.423***	(4.73)	18.952***	(4.86)	15.932***	(4.59)	15.293***	(4.50)
Rating = 6			24.593***	(5.23)	26.041***	(5.33)	19.490***	(4.81)	18.912***	(4.73)
Rating = 7			37.624***	(5.89)	39.388***	(5.95)	28.984***	(5.42)	28.189***	(5.35)
Rating = 8			35.800***	(5.74)	38.209***	(5.84)	28.126***	(5.28)	27.773***	(5.23)
LTV (Reference: LTV>100%)										
LTV ≤ 72%			0.673	(-1.52)	0.902	(-0.43)	1.311	(1.10)	1.340	(1.21)
72% ≤ LTV <= 90%			1.191	(0.79)	1.411*	(1.68)	1.964***	(3.22)	2.078***	(3.63)
90% ≤ LTV <= 100%			2.362***	(3.50)	2.480***	(3.73)	3.021***	(4.68)	3.096***	(4.85)
Other customer controls	No		No		Yes		Yes		Yes	
Other loan controls	No		No		No		Yes		Yes	
Region fixed effects	No		No		No		No		Yes	
Diagnostics										
Adj. R^2	0.06		0.11		0.13		0.16		0.16	
N	31,603		31,603		31,603		31,603		14,748	

Table 7: Difference in difference approach – Establishing that the change in default rates is concentrated around May 2009

This table provides results of various regressions that aim to ensure that the change in default rates for the affected rating-LTV combinations is concentrated around May 2009, i.e. the time where the thresholds for risk management involvement were changed. The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression. Column (1) provides results for a narrow time period (+/- 4 quarters) around May 2009, column (2) adds separate time trends for the affected and the non-affected groups. Column (3) allows these time trends to differ pre and post May 2009 and column (4) estimates a flexible 3rd order polynomial for affected and non-affected groups both before and after May 2009. *Affected* is a dummy variable equal to one for all rating-LTV combinations where no risk management involvement is necessary to approve a loan in subperiod 1 but risk management involvement is necessary in subperiod 2 (these Rating-LTV combinations are: Ratings 6, 7, and 8 for 90% < LTVs ≤ 100%, rating 8 for 72% < LTVs ≤ 90%). For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit	
Sample	+/- 4 quarters around event		+/- 4 quarters around event		+/- 4 quarters around event		Total	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat
INFERENCE								
Affected x After	0.371***	(-3.13)	0.361**	(-2.50)	0.203**	(-2.21)	0.299**	(-1.97)
Affected	1.292	(1.28)	1.310	(0.91)	1.265	(0.74)	1.694	(1.18)
After	0.787*	(-1.75)	1.027	(0.11)	1.018	(0.07)	0.747	(-1.24)
TIME TRENDS								
Time trend affected			0.981	(-0.68)				
Time trend non-affected			0.980	(-1.36)				
TIME TRENDS PRE								
Time trend pre affected					0.972	(-1.06)	Yes, 3rd order polynomial	
Time trend pre non-affected					0.976	(-1.22)	Yes, 3rd order polynomial	
TIME TRENDS POST								
Time trend post affected					1.077	(0.84)	Yes, 3rd order polynomial	
Time trend post non-affected					0.984	(-0.83)	Yes, 3rd order polynomial	
Rating controls	Yes		Yes		Yes		Yes	
LTV controls	Yes		Yes		Yes		Yes	
Other customer controls	Yes		No		Yes		Yes	
Other loan controls	Yes		No		Yes		Yes	
Region fixed effects	Yes		No		No		Yes	
Diagnostics								
Adj. R^2	0.16		0.16		0.16		0.18	
N	14,748		14,748		14,748		31,603	

Table 8: Effect of risk management involvement on default rates – Regression discontinuity approach

This table estimates the effect of risk management involvement on default rates using a regression discontinuity approach. The sample is based on all loans during subperiod 2 with an LTV between 90% and 100%. The dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. The model is estimated using a logistic regression (columns (1)-(3)) and a linear regression (columns (4) and (5)). *Risk Management Involvement (0/1)* is a dummy variable equal to one if risk management involvement is necessary to approve a loan (rating 6-8). For variable definitions see Table 1. Z-values (t-value for column (4) and (5)) based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)		(5)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Linear		IV	
Sample	Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%	
Methodology	Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff		Local regression +/- 2 notches around RMI cutoff	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Coeff.	t-stat	Coeff.	t-stat
INFERENCE										
Risk mgmt involvement (0/1)	0.343**	(-2.50)	0.313***	(-2.62)	0.315***	(-2.65)	-0.033***	(-2.90)	-0.029*	(-1.73)
RATING										
(Rating-CutOff) x Affected	1.104	(0.58)	1.168	(0.92)	1.166	(0.94)	0.006	(0.91)	0.007	(1.48)
(Rating-CutOff) x (1-Affected)	1.893**	(2.18)	1.762*	(1.87)	1.743*	(1.83)	0.015	(1.61)	0.005	(0.55)
Other customer controls	No		Yes		Yes		Yes		Yes	
Other loan controls	No		Yes		Yes		Yes		Yes	
Region fixed effects	No		No		Yes		Yes		Yes	
Diagnostics										
Pseudo. R^2 / Adj. R^2	0.01		0.08		0.09		0.03		0.03	
N	4,013		4,013		4,013		4,013		4,013	
FIRST-STAGE REGRESSION										
Initial Rating > RMI cutoff									0.897***	(69.49)
Other customer controls									Yes	
Other loan controls									Yes	
Region fixed effects									Yes	
Adj. R^2									0.86	
N									4,013	

Table 9: Robustness tests - Regression discontinuity

This table provides robustness test for the regression discontinuity approach. The sample is based on all loans during subperiod 2 with an LTV between 90% and 100%. In column (1) to (3), the dependent variable is a default dummy equal to one if a loan defaults over the first 24 months after the loan start date. In column (4), the dependent variable is a loss variable that is constructed by multiplying the default dummy by (1-Expected recovery rate). The models are estimated using a logistic regression (columns (1)-(2)) and a linear regression (columns (3)-(4)). Only coefficients on the main variable of interest, the risk management involvement dummy, are reported. For variable definitions see Table 1. Z-values (t-value for column (3) and (4)) based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Loss	
Model	Logit, Odds Ratios		Logit, Marginal Effects		Linear		Linear	
Sample	Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%		Subperiod 2, LTV 90-100%	
Parameter	Odds Ratio	z-stat	Average marginal effects	z-stat	Coeff.	t-stat	Coeff.	t-stat
METHODOLOGY								
LOCAL REGRESSION								
Optimal bandwidth (+/- 2 notches around RMI cutoff)	0.315***	(-2.65)	-0.040***	(-2.63)	-0.033***	(-2.90)	-0.010***	(-3.02)
1/2 x Optimal bandwidth (+/- 1 notch around RMI cutoff)	0.227**	(-2.49)	-0.051**	(-2.57)	-0.040***	(-2.91)	-0.015***	(-3.41)
2 x Optimal bandwidth (+/- 4 notches around RMI cutoff)	0.328***	(-3.30)	-0.035***	(-3.26)	-0.033***	(-3.43)	-0.010***	(-3.76)
HIGHER-ORDER POLYNOMIAL								
2^{nd} order	0.246**	(-2.20)	-0.042**	(-2.30)	-0.041***	(-3.19)	-0.013***	(-3.41)
3^{rd} order	0.230**	(-2.24)	-0.044**	(-2.35)	-0.032**	(-2.16)	-0.012***	(-2.78)
4^{th} order	0.218**	(-2.39)	-0.045**	(-2.50)	-0.042**	(-2.39)	-0.016***	(-3.10)

Table 10: Alternative explanations: Experience, Entrenchment

This table provides tests for alternative explanations. Column (1) and (3) provide differential effects of risk management involvement for experienced versus unexperienced loan officers. Experience is measured as the number of loan applications handled over the past 12 months, with the dummy *High Experience* being equal to one if experience exceeds the median of all loan officers. Column (2) and (4) provide differential effects of risk management involvement for relationship customers versus non relationship customers. While column (1) and (2) provide results for a difference-in-difference estimator, column (3) and (4) provide results for a regression discontinuity design. The sample and regression specification is based on column (5) of Table 6 for the difference-in-difference estimator and on column (3) in Table 8 for the regression discontinuity design. For variable definitions see Table 1. Z-values based on standard errors clustered at the branch level are reported in parentheses. ***, **, * denote significance at the 1, 5 and 10 % level, respectively.

	(1)		(2)		(3)		(4)	
Dependent	Default (0/1)		Default (0/1)		Default (0/1)		Default (0/1)	
Model	Logit		Logit		Logit		Logit	
Identification	Difference-in-Difference		Difference-in-Difference		RDD		RDD	
Alternative explanation	Experience		Collusion		Experience		Collusion	
Parameter	Odds Ratio	z-stat	Odds Ratio	z-stat	Odds Ratio	z-stat	Coeff.	t-stat
KEY INFERENCE VARIABLES								
Affected x After	0.395***	(-2.81)	0.323***	(-4.25)				
Affected x After x High Experience	1.046	(0.11)						
Affected x After x Relationship			1.197	(0.27)				
Risk mgmt involvement (0/1)					0.335**	(-2.55)	0.341**	(-2.44)
Risk mgmt involvement x High Experience					1.047	(0.10)		
Risk mgmt involvement x Relationship							1.192	(0.19)
TWO-WAY AND NON-INTERACTED								
Affected x High Experience	0.938	(-0.28)						
After x High Experience	0.952	(-0.26)						
Affected x Relationship			1.477***	(2.62)				
After x Relationship			0.764	(-1.24)				
After	0.475***	(-5.57)	0.536***	(-3.21)				
Affected	1.282	(1.10)	1.357	(1.44)				
High Experience Dummy	0.971	(-0.22)			0.931	(-0.34)		
Relationship Dummy			0.666***	(-3.23)			0.543**	(-2.07)
Linear function on both sides of cut-off	NA		NA		Yes		Yes	
Rating and LTV controls	Yes		Yes		No		No	
Other customer controls	Yes		Yes		Yes		Yes	
Other loan controls	Yes		Yes		Yes		Yes	
Region fixed effects	Yes		No		Yes		Yes	
Diagnostics								
Pseudo. R^2 / Adj. R^2	0.16		0.15		0.09		0.09	
N	31,603		31,603		4,013		4,013	