Internal Loan Ratings, Supervision, and Procyclical Leverage*

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ABSTRACT

We build a first-order Markov model of banks' internal loan ratings to illustrate the relationship between ratings inflation and systematic drift in ratings. Using administrative data from the Shared National Credit (SNC) Program, we find evidence of systematic downward drift in ratings, consistent with initial ratings inflation. The drift is predictable based on pre-issuance borrower characteristics, which suggests that information used in screening and pricing the loan is not incorporated into ratings. We employ the conditional random assignment of loan examinations to study the causal impact of loan-level supervision on ratings, and find not only that supervision reduces ratings inflation but also that these effects spill over within a bank's loan portfolio, consistent with learning. The direct link between ratings and loan loss provisions allows us to use our model to construct counterfactual capital ratios for banks based on a variety of scenarios, including an expansion of bank supervision. Our findings provide new insights to the debate about the role of bank supervision in bank capital cyclicality.

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I. Introduction

The procyclicality of leverage in the banking sector has been proposed as a possible threat to financial stability (Adrian and Shin, 2010, 2013; Laux and Rauter, 2017), and prior work has highlighted a variety of possible drivers, including mark-to-market accounting (Adrian and Shin, 2010), bank business models (Beccalli, Boitani, and Di Giuliantonio, 2015) and procyclical capital regulation (Behn, Haselman, and Wachtel, 2016). Following Basel II, asset risk weights and provisions for loan losses, which reduce earnings and equity capital, may be determined by banks' internal risk ratings for loans. This provides bankers wishing to report higher profitability and regulatory capital ratios with incentive to systematically overstate or inflate internal loan ratings (Plosser and Santos, 2018; Gopalan, Gopalan, and Koharki, 2019). However, when loan performance deteriorates, banks with inflated ratings must not only reconcile the revelation that their ex ante risk assessments were lenient in addition to the decline in loan performance itself. In the past two decades, the microprudential supervision toolkit has expanded to include on-site examinations that target the accuracy of internal ratings. Two natural questions emerge from this supervisory landscape: do banks systematically inflate ratings and, if so, does microprudential supervision mitigate this behavior?

In this paper, we address these questions with U.S. regulatory data on banks' internal loan ratings and a supervisory experiment in which loan-level examinations are randomly assigned conditional on observable loan characteristics. Both the data and the experimental setting are available to us through the implementation of the Shared National Credit (SNC) program. We build a simple model of internal loan ratings and find evidence of systematic ratings inflation, predictable cross-sectional patterns that provide insight into the potential underlying mechanisms, and economically significant moderating effects of supervision. Moreover, we document a link between ratings inflation and the cyclicality of leverage, which, together with our findings on the effects of supervision, suggest that loan-level supervision may mitigate the severity of leverage shocks during a crisis.

Our simple structural model of loan ratings dynamics assumes that ratings are upgraded and downgraded following a Markov process with five states corresponding to regulatory ratings. Because transition probabilities are not time dependent, this model implies a steady state distribution of ratings. The core testable implication of this model is that any systematic deviation from the steady state distribution, or ratings drift, reflects ratings inflation or deflation in prior periods – i.e., at loan initiation. Moreover, ratings drift quantitatively corresponds to the degree of ratings inflation or deflation. We find statistically robust and economically significant evidence of ratings drift across time, lenders, and sectors, at a rate of -0.07 ratings per year. While a link between low ratings and loan loss provisions and, hence, book equity could provide banks with the incentive to inflate loan ratings, predictable drift may not necessarily reflect strategic motives.

To investigate potential strategic and informational determinants of ratings drift, we link loan and borrower characteristics known to the lender at the time of loan initiation to subsequent ratings drift. Just as our model implies that evidence of a systematic downward ratings drift reflects initial ratings inflation, any evidence of incremental drift across loan or borrower characteristics would suggest that information available to the bank at the time of loan initiation was not incorporated into loan ratings. The direction of incremental drift for specific characteristics of the loan or borrower – e.g., loan spread, utilization rate, credit quality – may shed light on potential explanations for the gap between information contained in ratings and information available to the bank at the time of loan initiation. Whether we measure credit quality with loan spreads or borrower financials, we find systematic evidence of stronger drift and, hence, stronger ratings inflation at initiation, for low credit quality loans. This result suggests that loan ratings do not incorporate information contained in loan spreads at the time of loan initiation, or that some information that is relevant for pricing a loan is not used to rate it. We also find systematically stronger downward ratings drift for loans with high utilization rates. Because downgrades for these loans would require larger loan loss provisions, banks may have an incentive to avoid downgrading them. These two pieces of evidence suggest that ratings inflation is stronger when the benefits that banks could obtain from avoiding ratings downgrades is larger.

Bank supervision in the form of loan-level examinations was designed to ensure that loan ratings and loan loss accounting accurately reflected credit assessments of the borrower and loan. We take advantage of the design of the Shared National Credit program between 2007 and 2015 to ask whether these exams mitigate or even eliminate ratings inflation. The design of the SNC program during the the 2007-2015 period is particularly useful in addressing this question. In each year, a subset of eligible loans are targeted for examination based on priorities of the SNC program office. The remainder are randomly sampled for examination at a rate that depends on their size, previous loan rating, and lender type. We exploit this conditional randomization to study the causal effect of examination on loan ratings by representative examiners from the Office of the Comptroller of the Currency, the Federal Deposit Insurance Corporation, and the Board of Governors of the Federal Reserve System.

Our baseline evidence on the systematic drift in loan ratings defines a dependent variable as the annual change in post-exam rating. A benefit of the SNC program is that we observe both the pre-exam loan rating submitted by the bank *and* the post-exam loan rating that incorporates the results of the examination if applicable. This feature allows us to both evaluate the internal validity of the experiment and to directly study the impact of examinations. Because banks submit pre-exam loan ratings before knowing whether the loan has been selected for examination, we do not expect examinations to explain the update between the previous exam rating and the banks' pre-exam rating submission. On the other hand, loans selected into examinations due to SNC program office priorities are likely to be experiencing downturns, so we would expect banks to downgrade these loans even before the exam starts. We verify both of these hypotheses in the data, and then proceed to evaluating the causal effect of examinations on loan ratings by analyzing the difference in ratings between the post-exam rating and the bank's pre-exam submission. We find evidence that examinations reverse ratings inflation by almost 70% through rating downgrades.

Whether or not they result in rating downgrades, examinations may reveal information to banks about the credit risk of their borrowers. Unless this information is specific to a particular loan or borrower, we might expect the bank to apply this knowledge and revise its internal ratings of *other* loans. To test this learning channel, we adapt the approach to estimating spillover effects of Berg, Reisinger, and Streitz (2021), and study the within-spillover effects of SNC loan-level supervision on *other* loans from the same sector in the lender's portfolio. Because borrower sector influences the organizational structure of banks' commercial loan groups, this methodology allows us to investigate whether a higher fraction of supervised loans affects the likelihood of the bank revising ratings for other supervised loans and non-supervised loans.

If supervisory exams generate sector-specific information about borrowers, banks may leverage that information and update their ratings. Furthermore, if information gleaned from supervisory exams across same-sector loans are complements, then we should expect larger effects from exams in sectors with a higher fraction of supervised loans. Importantly, the timing of these spillover effects should depend critically on whether the *other* loan is examined or not. This is because the ratings of loans that are not selected cannot be revised during the exam period. Hence, if banks learn from supervisory exams, we should expect positive contemporaneous spillover effects in the case of other examined loans and positive future spillover effects for non-examined loans. This is precisely what we find. However, it still may be the case that banks respond to exam-driven downgrades and not information gleaned from exams. To test this alternative mechanism, we estimate the same spillovers model replacing the fraction of same-sector examined loans with the fraction of same-sector downgraded loans. Here we find no evidence of spillover effects, consistent with the supervisory exam – and not the threat of downgrades – driving bank behavior.

It is useful at this point to define what is meant by procyclical leverage in our analysis. Procyclical leverage (assets-to-equity ratio) refers to the positive co-movement between bank leverage and the business cycle (Adrian and Shin, 2010, 2014; Kalemli-Ozcan, Sorensen, and Yesiltas, 2012; Damar, Meh, and Terajima 2013; Beccali, Boitani, and Di Giuliantonio, 2015; Laux and Rauter, 2017).[1] As noted by Laux and Rauter (2017), the literature on procyclical bank leverage is largely interested in the leverage that banks use to finance credit on their balance sheets, for which book leverage is appropriate, instead of market leverage. Book leverage is defined as total book assets divided by book equity, and we employ the same definition of leverage here. While the largest U.S. banks' leverage is procyclical, their capital-to-assets ratios are countercyclical; that is, they fall during economic upswings and increase during economic downturns (Elliott (2021)). The definition of procyclicality as the positive co-movement between economic and financial variables, such as leverage, and economic activity (Abel and Bernanke, 1995) contrasts with the notion of procyclicality as viewed by prudential policymakers. According to this view, procyclicality refers to the reinforcing interaction (positive feedback) between the functioning of the banking sector and the real economy, resulting in excessive economic growth during upturns and deeper recessions in downturns, leading to concerns with financial instability (Borio et al., 2001; Financial Stability Forum, 2009; BCBS, 2010, 2021). Consistent with this broader view, procyclical bank leverage leads to lending and credit availability that are procyclical and which amplify swings in the business cycle.

We explore the implications of ratings inflation for loan loss provisioning and the procyclicality of bank book leverage. Regulation dictates a direct translation of supervisory loan ratings to loan loss provisioning. This provides banks with an incentive to inflate ratings, but it also suggests that the effects of ratings inflation should be largest at the outset of a downturn when ratings *should* be downgraded. We explore these hypotheses in two ways. First, we leverage our structural model to estimate counterfactual loan loss provisions in each year across banks for a variety of scenarios. We consider experiments in which we eliminate ratings inflation, in which we require banks to use all available information used in pricing loans when rating them, and in which the supervisory exam program is expanded. In these settings, banks increase loan loss provisions in all years,

[1] Several of these studies follow Adrian and Shin (2010, 2014) and measure procyclical bank leverage as a positive association between changes in leverage and changes in total assets. However, the size of banks' balance sheets tends to increase during upswings and decrease during downturns in economic activity. Given this, a positive association between leverage changes and assets growth implies a positive association between changes in leverage and changes in economic activity.

but especially so in the run up to the 2007-2008 financial crisis, suggesting that ratings inflation contributed to the significant drop in capital ratios during that period. While these counterfactuals illustrate the channel through which ratings inflation affects bank leverage, we are restricted from drawing direct implications for leverage due to data limitations. Therefore, we also conduct a bank-level analysis that links future equity-to-assets ratios and asset growth to ratings inflation. In these regressions, we consider a hypothetical case in which ratings inflation among the bank's commercial and industrial loans that are eligible for SNC exams is representative of ratings inflation in other parts of the bank's loan portfolio. In this case, we should expect ratings inflation to be associated with lower future equity-to-assets and lower asset growth, and we find evidence consistent with this hypothesis. Together, these findings suggest that banks with the most inflated ratings experience larger drops in capital ratios and, if capital requirements are binding, lower subsequent loan growth during downturns.

Our work is related to three strands of literature on internal loan ratings, procyclical leverage, and the efficacy of supervision. Prior work on internal loan ratings has documented within-loan differences in internal loan ratings across banks, and emphasized disagreement stemming from differences in capitalization (Plosser and Santos, 2018). Others have suggested that internal loan ratings are uninformative about borrower distress, and linked this risk-insensitivity of internal loan ratings to discretionary reporting (Gopalan, Gopalan, and Koharki, 2019) and to banks' market power (Beyhaghi, Fracassi, and Weitzner, 2022;Müller, Juelsrud, and Andersen, 2019). To this literature, we contribute new evidence that initial internal loan ratings are inflated and systematically omit information used in screening and pricing the loan, and that microprudential loan-level supervision disciplines ratings inflation directly and indirectly through information spillovers within banks' loan portfolios.

II. Data Sample

For the empirical analysis, we obtain data from several sources. First, we employ the data provided by the Shared National Credit (SNC) Program administered by the Federal Deposit Insurance Corporation, the Federal Reserve Board, and the Office of the Comptroller of the Currency. The SNC Program collects detailed confidential information on all credits that exceed $20 million and are held by three or more unaffiliated supervised institutions. Typically, banks were required to send information on their internal ratings by December 31^{st} of each calendar year. Submission of data is followed by supervisory examination that are intended to validate the internal ratings provided by banks, and these examinations usually take place before May of the following calendar year. The examinations often result in banks updating their ratings for loans that are reviewed by SNC program examiners. In our data set, we use banks' December 31^{st} data submissions which contains loan risk assessments prior to bank examinations.

The SNC ratings database contains information on the percentages of loans rated, in order of increasing riskiness, as either pass, special mention, substandard, doubtful, or loss categories, as well as summary loan ratings that take on values from 1 to 5. For our primary analysis, our main variable of interest that we construct is an ordinal variable with values 1 to 5 where each value represents a SNC rating category where 1 represents the pass rating and each remaining value represents riskier ratings in order where the value 5 represents the loss rating category. We align with the SNC Program sampling assumptions by assigning loans with split risk classifications to the riskiest classification. Banks rarely split loans into multiple risk classifications, and therefore, in our estimation samples almost all ratings represent a loan's unique risk rating.

From the SNC database, we also calculate measures of the size of a loan or loan commitment, the utilization rate of a loan commitment, and the size of a loan relative to the agent bank's SNC portfolio. We use loan date information to number the years a loan has been outstanding and the maturity length of a loan. We use information on loan ownership structure to calculate the number of lenders in the loans' syndicate and the agent bank's share of loan ownership.

We obtain additional information on syndicated loans from the Loan Pricing Corporation DealScan database, which provides information about syndicated loans at origination in contrast to the SNC program which tracks loans over time. Data in the DealScan database are organized by deal and facility where a loan deal is the contract between a borrower and multiple lenders at a particular date and a single loan deal may consist of multiple loan facilities. In the DealScan database, about 75 percent of the deals contain one facility, and 20 percent of the loans contain two facilities. Because there may be differences in pricing across facilities, we gather data on loan spreads for individual loan facilities. The measure of loan spreads from the DealScan database is the All-In-Drawn spread, which is measured in basis points, and is typically provided as a fixed markup over LIBOR. Total interest rates paid by borrowers on syndicated loans are calculated floating rate markups over the base interest rate. The base interest rate has typically been the LIBOR rate for the vast majority of loans in the DealScan data history, but could have included other rates, in particular in later years in our data sample where LIBOR was in the process of being phased out as a baseline interest rate. In our analysis we have focused on interest rates that are a markup over LIBOR, but include analyses with other base rates. In DealScan, the All-In-Drawn spread is a measure of the overall cost of a loan and accounts for both one time and recurring fees.

We use the loan contract terms data from DealScan to merge origination loan spreads from the DealScan database to what we can identify as the identical loan facility from the SNC database. Since a loan facility has multiple observations for each year the loan is outstanding and covered by the SNC program, origination loan spreads from DealScan merge with multiple loan year observations in the SNC database and take a constant value across time for individual loans.

We supplement the syndicated loan data with borrowers' stock price data from Center for Research in Security Prices (CRSP) and financial statement data from Standard and Poor's Compustat Annual database. From the CRSP database we calculate estimates of firms' stock return volatility. To calculate a consistent stock price series, we first adjust daily stock price data with the cumulative adjustment factor from CRSP. We then calculate stock return volatility as the standard deviation of firms' daily stock returns for each calendar year, and we annualize by multiplying by multiplying by $\sqrt{52}$. We construct several standard control variables for borrower risk characteristics from the Compustat database which are standard in the literature.[2] Borrower-level risk risk characteristics include measures of borrower size (log of total assets), the ratio of cash to assets (cash divided by total assets), market leverage (total liabilities divided by market value), the ratio of EBITDA to assets (earnings before interest, taxes and depreciation divided by total assets).

We use FFIEC 031 and 041 regulatory fillings (Call Reports) to calculate several bank-level variables based on banks' balance sheets and income statements. We calculate quarter-over-quarter asset growth (RCFD2170), loan growth (RCFD 2122), commercial and industrial loan growth (RCFD1766 and RCFD1600). We also calculate a measure of a bank's balance sheet equity capital ratio which is total equity over one-quarter lagged total assets (RCFD3210/RCFD2170). We also get provisions (RIAD4230), net income (RIAD4340), Tier 1 capital (RCFD8274 prior to 2015 and RCFA8274 afterwards) variables.

III. Ratings inflation

A. Ratings inflation model

In this section we describe the reasoning behind our main regression models that describe and characterize the SNC ratings inflation. First, let the SNC rating of a loan at time t denoted by R_t be a discrete-time 5-state Markov Chain with the state space set $M = \{1, 2, 3, 4, 5\}$ to capture SNC rating categories. The values 1 through 5 stand for pass, special mention, substandard, doubtful,

[2]For more discussion of the control variables used in the literature, see Santos (2010), Santos and Winton (2019), and Strahan (1999).

and loss specifically. We denote the one-period Markov transition probability matrix as:

$$\mathbf{P} \quad = \quad \begin{pmatrix} p_{11} & p_{12} & p_{13} & p_{14} & p_{15} \\ p_{21} & p_{22} & p_{23} & p_{24} & p_{25} \\ p_{31} & p_{32} & p_{33} & p_{34} & p_{35} \\ p_{41} & p_{42} & p_{43} & p_{44} & p_{45} \\ p_{51} & p_{52} & p_{53} & p_{54} & p_{55} \end{pmatrix} \tag{1}$$

where $\mathbf{P}$ is the Markov transition matrix and p_{jk} is the probability that the Markov chain jumps from state j at time $t-1$ to state k at time t with $p_{jk} = P[R_t = k|R_{t-1} = j] \geq 0$ and $\sum_{k \in M} p_{jk} = 1$, $k \in S$. The Markov transition matrix implies that the probability of transition to a current state k only depends on the previous state j and is independent of the rating history. Furthermore, the transition probabilities do not depend on the time parameter t; the Markov chain is therefore "time-homogeneous" which implies that the rating transition probabilities are independent of time.

For the Markov transition matrix, the steady-state probability distribution of ratings would be represented by a 5×1 vector of probabilities, $\boldsymbol{\pi}' = (\pi_1, \pi_2, \pi_3, \pi_4, \pi_5)'$, where π_1 is the steady state-share of loans that are rated pass, π_2 is the steady state-share of loans that are rated special mention, and so on. The steady-state probabilities are defined as $\boldsymbol{\pi}' = \boldsymbol{\pi}' P$ and are complicated functions of the underlying transition probabilities, but can be interpreted as measures of the overall expected flow of ratings transitions into a given state divided by the overall flow of transitions into all states within the ratings system.

The expected rating in each period can be calculated from the transition probability matrix, $\mathbf{P}$, a vector of time t distribution of ratings given by $\pi_t' = (\pi_{t,1}, \pi_{t,2}, \pi_{t,3}, \pi_{t,4}, \pi_{t,5})'$, and a vector of rating states $N = (1, 2, 3, 4, 5)$ as $E[R_t] = \pi_t' \mathbf{P} N'$. If the ratings distribution at any time t coincides with the long-run unconditional steady-state probabilities, $\boldsymbol{\pi}$, then the average rating will remain equal to the long-run average rating and will not systematically increase or decrease over time toward the long-run. However, if the ratings distribution at any time t deviates from the long-run unconditional steady-state probabilities, then there would be systematic increases or decreases in the average rating toward the long-run average steady-state rating in future periods.

In terms of our model, we can see that the change in the average rating in the steady-state distribution would be equal to zero as $E[R_{t+1}]-E[R_t] = \pi'\mathbf{P}N' - \boldsymbol{\pi}'\boldsymbol{P}N' = 0$. However, if we observe a change in average ratings that is either greater than or less than zero, i.e. $E[R_{t+1}] - E[R_t] \neq 0$, this would imply that the ratings distribution is not at the steady-state and therefore $\pi_t \neq \boldsymbol{\pi}$ and $E[R_{t+1}] - E[R_t] = \pi'\mathbf{P}N' - \boldsymbol{\pi}'\boldsymbol{P}N' \neq 0$. If the change in average ratings is greater than zero, we can interpret this as ratings inflation, and if it is less than zero, we can interpret it as ratings deflation.

In an empirical setting, if we regress the rating for a loan, i, at time $t+1$ on a constant, $R_{i,t+1} = \alpha_{i,t+1} + \epsilon_{i,t+1}$, the estimate for the constant $\alpha_{i,t+1}$ would be an estimate of the average rating at time $t+1$, and $\epsilon_{i,t+1}$ is the residual. Based on the assertion that the difference in average ratings from time t to $t+1$ would equal zero in the long-run steady-state, in a regression of the change in ratings $R_{i,t+1} - R_{i,t}$ on a simple constant would be predicted to be equal to zero:

$$R_{i,t+1} - R_{i,t} = \alpha_{i,t+1} - \alpha_{i,t} + \epsilon_{t+1} - \epsilon_t \tag{2}$$

$$E[R_{i,t+1} - R_{i,t}] = \alpha - \alpha + E[\epsilon_{i,t+1}] - E[\epsilon_{i,t}] = 0, \tag{3}$$

where α refers to the long-run steady-state average rating.

However, if we estimate equation (6) and find $\alpha_{i,t+1} - \alpha_{i,t} \neq 0$, i.e., the rating change is positive or negative on average, this would imply average ratings systematically deviate from the long-run steady-state in the data. More importantly, if the average difference in ratings is greater than zero, then there is persistent ratings inflation relative to the long-run steady-state ratings distribution.

B. Predicting ratings changes and relation to the steady state

In this section we briefly describe why the difference in ratings generated by a Markov transition model would not be predictable by lagged outside information correlated with ratings. The main reason is that A property of a Markov transition model is that one period steady state ratings transition probabilities are always calculated the same computation each period. In the model, the transition probabilities between ratings at two dates, t and 0, is equal to $\pi_t = \pi_0 P^t = \pi_{t-1} P$ where $\pi_{t-1} P$ is the same steady state transition probabilities for each time period. Now assume that there is another piece of information that is informative about borrower risk ratings that is observed prior to the rating at $t + j$ labeled X_0 that takes on two values labeled H or L for states high and low. For example, this could indicate the initial spread on a loan as high or low. Assume that the probability of each rating 1 though 5 for for each value of x_0 is given by

$$\mathbf{Q} = \begin{pmatrix} q_{11} & q_{12} & q_{13} & q_{14} & q_{15} \\ q_{21} & q_{22} & q_{23} & q_{24} & q_{25} \end{pmatrix} \tag{4}$$

and that the probabilities of each state are $\pi_{x,H}$ and $\pi_{x,L}$. Therefore, the initial probability distribution for ratings as a function of the loan spread distribution, π_0 would equal

$$\pi_{x,0} = \begin{pmatrix} \pi_{x,H} \\ \pi_{x,L} \end{pmatrix}' \begin{pmatrix} q_{11} & q_{12} & q_{13} & q_{14} & q_{15} \\ q_{21} & q_{22} & q_{23} & q_{24} & q_{25} \end{pmatrix}. \tag{5}$$

Therefore, given the initial distribution from equation (5), the rating probabilities at date 1 is

$$\begin{aligned} \pi_1 &= \pi_x' Q \pi' \\ \pi_1 &= \pi, \end{aligned}$$

where the second equation above states that the inital probability at time 1 would equal the steady state ratings distribution. The ratings distribution at any future date would be given by

$$\pi_{t+1} = \pi_{x,0}' Q \pi'^{t+1}$$

$$
\begin{aligned}
&= \pi_1' P^{t+1} \\
&= \pi' P
\end{aligned}
$$

where the second equation is derived from the Markov property, and implies that the initial distribution would contain no information for ratings at any later date that is not contained contained in the ratings.

In our empirical analyses, to estimate whether observed factors such as initial loan spreads predict ratings drift, we estimate regressions models where we regress the change in ratings on a constant and an observable factor which we denote again as x_0. We denote these regressions and the model predictions as

$$
\begin{aligned}
R_{i,t+1} - R_{i,t} &= \alpha_{i,t+1} - \alpha_{i,t} + \beta_{x_0} x_0 + \epsilon_{t+1} - \epsilon_t \\
E[R_{i,t+1} - R_{i,t}] &= \alpha - \alpha + \beta_x X_0 + E[\epsilon_{i,t+1}] - E[\epsilon_{i,t}] = 0.
\end{aligned}
$$

The expected change in ratings is equal to zero if the ratings distribution is the steady state distribution. This is because in the steady state, $\beta_{x_0} = 0$ and $\beta_{x_0} = (\pi' PN - \pi' PN) - (\pi' PN - \pi' PN) = 0$.

C. Baseline ratings inflation results

Table I displays estimation results of equation (XX) and reports F-tests and adjusted R^2. Specifically, we regress the change in the SNC rating on a constant and different sets of fixed effects which vary across combinations of four different dimensions: agent bank, sector, obligor, and time. We report the coefficient estimate in the first column for each estimation.[3] Columns from (2) to (7) report on the F-statistics from tests of the joint significance of the different sets of fixed effects.

[3] For each estimation, we present the constant number presented by Stata's *reghdfe* command (Correia, 2014). Because the average of all of the fixed effect terms will be equal for for any combination of fixed effect models, the constant term presented by Stata will be identical for each set of fixed effect variables. Therefore, across regression specifications, the constant term and coefficients on fixed effects will not provide distinct inferences across specifications.

Our inferences from these regression models will focus on F-tests and adjusted R^2 which will provide information as to whether each set of dummy variables can better explain the variation in the ratings drift. If a set of fixed effects better explains the variation in ratings drift, this implies that the average drift varies along or with the dimensions specified by the set of fixed effects.[4]

Overall, Table I reports that the average ratings inflation is about .069 per year which is roughly 6.9 percent of a rating grade per year. The findings also show that the F-statistics are large and significant, especially for time fixed effects, and we reject the null hypothesis that the fixed effects are zero. Additionally, the adjusted R^2 increases with the granularity of the fixed effect dimension, which suggests that there is significant heterogeneity in the average ratings drift in the data set among each of the dimensions used to stratify fixed effects i.e., there is both significant cross-sectional and time-series variation in ratings drift over time.

D. Loan ratings and ratings inflation over time

Next, we examine whether loan ratings and ratings inflation varies with the loan age. In this analysis, we regress loan ratings and the change in loan ratings on loan age. Results for these models are included in Figure 2.[5] The panel on the left, where we examine the relation between loan ratings and loan age, show that the level of loan ratings tend to worsen and become downgraded over the life of a loan. Additionally, the panel on the right, where ratings changes is the dependent variable, suggests that ratings inflation tends to decrease over the life of loan. Taken together, these results suggest that loans are downgraded early in the life of a loan and that loan ratings inflation decreases as time passes.

[4] Sample sizes vary with the set of fixed effects because when sub-groups aligned with fixed effects have one single observation, the observation is dropped from the estimation sample.

[5] If a loan is aged five years or older, it is captured in the age 5 category.

E. Ratings inflation and banks' loan exposures

Next, we analyze whether and how ratings inflation varies with banks' loan exposure. Overall, we could expect banks' loan exposures to be either positively or negatively associated with ratings inflation. For example, a bank might prefer to delay downgrades on larger exposures to try and minimize consequences of weaker ratings such as higher loan loss provisioning, lower net income, and lower equity capital. In this scenario we would expect a positive link between ratings inflation and bank's loan exposure. Another scenario could be that banks have more incentive to monitor larger loans, which might lead to quicker downgrades for these loans, in which case we would see a negative link between ratings inflation and bank's loan exposure.

In these estimations, we regress loan rating changes on measures of agent banks' loan exposures: utilized percentage of the loan commitment *(Utilized % of Loan Commitment)*, the loan commitment as a percentage of agent bank's total commitment, *(Committed % of Bank's Total Commitment)*, the logarithm of the loan's utilized amount *(Log(Utilized Exposure))*, and the logarithm of the loan commitment *(Log(Loan Commitment))*.

Results in Table II illustrate that loans with a greater utilization rate have greater ratings inflation and loans that are a greater fraction of banks exposures have a lower ratings inflation. The total ratings inflation would be the sum of the constant and the relation with the banks' loan exposure. The results in the first and third columns suggest that the average ratings inflation would start our fairly small (0.015 or 0.030) for loans with zero utilization relative to our earlier estimates and increase significantly above our average estimates of around .07. The results in the second and forth columns suggest that ratings inflation decreases with the size of the exposure in the bank's loan portfolio and the size of the loan commitment, which could be driven by higher quality borrowers receiving larger loans and less likely to be downgraded.

Taken together, the results could be consistent with banks inflating the ratings of loans that are more fully utilized, possibly to increase perceptions of loans' risk-return trade-offs or avoid the consequences of worse risk ratings. We also speculate that these results could suggest that banks either gather more negative information on or are pressured to downgrade relatively large loans in their portfolios earlier.

F. Borrower risk information available to banks and ratings inflation

In this section, we analyze observable components of borrower risk can help forecast ratings inflation. We assume that banks have access to information about borrowers' financial statements, stock market valuations, and the terms of loan contract terms at origination. Banks can gather data on financial statements from public filings if borrowers do not already provide such information directly to the lenders themselves. Borrowers' stock market valuations are generally available through multiple sources at no cost. And, we expect that lenders' would have full information on all loan contract terms that are negotiated and incorporated into loan contracts.

In these empirical tests, we regress loan rating changes on borrower financial and stock market information reported at loan origination and the loan contract terms set at origination. As stated earlier in section 3.B, if the lagged information sets we use as our regressors are fully incorporated into ratings when the information is observed, the Markov property would predict that lagged information would not predict the change in future ratings.

Results for these regressions are included in Tables III, and IV. Columns (1)-(5) in table III indicate that each of the financial statement and stock market based variables predict future drift when included individually in the regression. Column (6) shows when all of the financial and stock market variables are included as independent variables, all variables retain significant explanatory power except for cash-to-assets ratio at loan origination.

Table IV shows that origination loan spreads predict ratings drift in columns (1)-(6) and that loan spreads predict drift controlling for the utilized percentage of the loan commitment in columns (4)-(6). In columns (2) and (5), we explore ratings inflation across the deciles of spread and in columns (3) and (6), we look at quintiles. Estimation results from both sets of groupings imply that higher spreads are more correlated with higher ratings inflation, as the magnitude of the coefficient estimates generally increase as deciles/quintiles increase. These result suggest that lenders are compensated for long-run loan risk that is greater than earlier ratings would suggest. Moreover, this result would also be consistent with the notion that banks have a higher than actual, perceived risk-return trade-off, earlier in the life of the loan, prior to later predictable rating downgrades.

IV. The effect of supervision and spillover effects of supervision

A. The effect of supervision on ratings inflation

In this section we analyze whether bank regulatory supervision has an effect on loan ratings inflation through the SNC examination process. Our hypothesis is that if bank's ratings behavior is too slow, then supervisory scrutiny of bank's internal ratings may decrease ratings inflation by shifting the initial ratings distributions closer to the long-run steady-state distribution. We predict that less overall movement to the long-run steady state distribution would result in less overall observable inflation.

In our analysis, we identify the causal effect of supervision on ratings inflation using random variation in the assignment of SNC loans for supervision. We assume, conditional on randomized supervision, that the effect of supervision will be independent of potential outcomes and that we could possibly identify an estimate of the average causal effect. In particular, we examine the effect of supervision at date t on the ratings inflation measured as the change in ratings between dates t and $t-1$, where the $t-1$ ratings reflect the final exam cycle ratings after all SNC examinations are completed.

In a second analysis we try to identify a potentially more conceptually sound causal effect by exploiting the details of the SNC ratings assignment process. In the SNC examination process, if a SNC credit is examined by SNC examiners, then the final SNC rating assigned to a given loan will be the final rating determined by the examination process. However, if a loan is not examined by the SNC program in a given year, then the final SNC rating equals the rating originally submitted by the bank for the given exam cycle. This means that following an exam cycle that concludes with ratings at time $t-1$, for the time t exam cycle, the bank initially submits an updated rating incorporating new information regarding the loan's risk between the between time $t-1$ exam cycle until the beginning of the time t exam cycle. However, if a loan is not examined in a given year's SNC exam cycle, the the final rating assigned at the conclusion of the year's exam cycle would be the original rating assigned by the bank.

Therefore, we suggest that one interpretation of banks' submitted ratings at the beginning of the exam cycle, is that the ratings could proxy for the counterfactual rating that a loan would have received in the absence of supervision. Therefore, if we denote the expected rating conditional on review under the SNC program as $E[R_{i,t}|S_{i,t,s=1} = 1]$ and the banks' submitted rating, which is typically unobserved treatment counterfactual, as $E[R_{i,t}|S_{i,t,s=1} = 0]$, then the treatment effect of supervision, at least on the supervised-treated loans, could be denoted as $E[R_{i,t}|S_{i,t,s=1} = 1] - E[R_{i,t}|S_{i,t,s=1} = 0]$.[6] This calculation could potentially provide an estimate of the average effect of the treatment on the treated. Furthermore, if the supervisory SNC review treatment is conditionally independent of the potential rating-outcome distribution of both supervised and unsupervised loans, that is both treated and untreated loans, then, $E[R_{i,t}|S_{i,t,s=1} = 1] - E[R_{i,t}|S_{i,t,s=1} = 0]$, could potentially equal the average treatment effect of SNC supervision denoted as $E[R_{i,t}|S_t = 1] - E[R_{i,t}|S_t = 0]$.

We can specify the regression equation for testing the effect of SNC supervision with the following two regression equations

$$R^e_{i,t} - R^e_{i,t-1} = \alpha^e + \beta^e d^e_{i,t} + \epsilon_t \tag{6}$$

$$R^e_{i,t} - R^s_{i,t} = \alpha^s + \beta^s d^s_{i,t} + \epsilon_t. \tag{7}$$

We hypothesize that both of these equations could provide causal estimates of the effect of super-

[6] In these expressions for the expectations, the subscript $s = 1$ in $S_{i,t,s=1}$ denotes loans that are supervised-treated by the SNC program.

vision on ratings drift. In these equations, we interpret the coefficients, β^e and β^s, for the terms, $d^e_{i,t}$ and $d^s_{i,t}$ as the treatment effects of SNC supervision on ratings drift. We would interpret the coefficient estimates on the supervision dummy variable from equation (6) as a measure of the average treatment effect. In equation (7), we would also interpret the coefficient on the supervision dummy variable as the average treatment effect if supervision is independent of the distribution of counterfactual ratings drift outcomes for both the supervised and unsupervised SNC loans. However, if the distribution of counterfactual ratings drifts is only independent of this distribution for supervised banks, then we could interpret the coefficient estimate as the effect of supervision as an estimate of the effect of treatment on the treated, or supervision on supervised loans.

Another complication we encounter in estimating the causal effect of supervision on SNC ratings inflation is that a fraction of SNC credits, referred to as mandatory reads, are sampled according to borrower and loan characteristics observed prior to the SNC examination. The complication that mandatory reads pose, is that mandatory reads are a function of the factors that would likely affect the distribution of SNC ratings and ratings transitions. Therefore, we need to control for mandatory reads to interpret the coefficient on the SNC supervision dummy variable as the causal effect of supervision on ratings drift. Unfortunately, we cannot disclose the factors that regulators use to classify SNC loans as mandatory reads because this information is confidential supervisory information.

To account for the effect of mandatory reads on our estimates of the effect of supervision on ratings drift in our analyses, we create dummy variables for each individual criteria for each SNC examination. Once we condition our estimates of the estimates of β on the mandatory read dummy variables in equations (6) and (7), we interpret our β estimates as the causal effect of supervision on ratings drift, conditional on the mandatory-read dummy variables.

The results for these models are included in Table VII. Before we consider the direct estimates of the effect of supervision, we discuss the results of a placebo test to assess whether the read variable, which we interpret as exogenous and independent of unobserved risk factors, is not related to the difference in ratings between agent banks newly submitted ratings and the exam ratings from the previous year. If *read loan* status is randomly assigned, then we expect that pre-sampling rating changes to not be predicted by future random read classifications. However, because a fraction of the read credits, the mandatory-read credits, are a function of past ratings changes, we would expect the component of the read dummy variable due to mandatory reads to be associated with lagged ratings changes. However, once we condition on the mandatory-read dummy variable, we would not expect that the read dummy variable would be associated with the lagged ratings changes. In the first panel of Table VII, in columns (1) trough (5), the results show that the mandatory-read variable, conditional on the mandatory-read dummy variable, has no association between the read dummy variable and lagged ratings changes. This result provides at least one piece of evidence in support of our claim that our analysis captures a random component of SNC exam sampling.

The remaining results in Table VII, which are the main focus this section, suggest that supervision may cause a significant increase in ratings drift to higher risk loan categories. In columns (11) through (15) where we analyze the effect of supervision between the current and previous examination ratings, we only find that loans that are both mandatory and read have greater drift to higher risk categories. To the extent that the rating submitted by the bank proxies for the counterfactual rating to read loans, this could imply a result that could be more convincingly interpreted as a causal effect of supervision on ratings drift.

Another result that we note is that between examination rating drift to higher risk categories is lower for mandatory loans that are not read. In addition, it seems possible that mandatory classified credits may actually have close to zero overall ratings inflation when the coefficient on the mandatory ratings variable is compared with the constant term. While we cannot explicitly tell why mandatory-read credits have less ratings inflation overall, we suggest a couple of possibly multiple explanations. Perhaps a near zero inflation on mandatory-read loans could imply that banks more pro-actively downgrade higher-risk loans that are classified as mandatory reads. Or, another possible reason could be that if the factors that determine whether a loan is classified as a mandatory read are persistent or predictable, then perhaps banks anticipate loan's mandatory-read classifications and more proactively downgrade these loans.

B. Exam knowledge spillovers

Recent research by Berg, Reisinger, and Streitz (2021), suggests that spillover effects can cause bias in estimates of treatment effects even if treatment assignment is random and uncorrelated with unobserved potential outcomes. Berg et al. (2021) suggest that estimates of causal effects could be biased in many corporate finance applications due to the violation of the stable unit treatment value assumption (SUTVA). In our context, the SUTVA would be the assumption that there are no interdependencies in the causal effects of supervision on ratings inflation.

There are multiple reasons that we expect could cause spillover effects in the effect of supervision on ratings inflation: both within a bank's portfolio and across different bank portfolios. We also predict that supervisory activities could create spillovers within and across ratings changes and observed ratings drift.

We predict that examiners activities could result in spillovers in exam related ratings changes if examiner learn new information about risks related to a broader set of related obligors by reviewing and becoming informed about the risks of another set of obligors. For example, an examiner could learn about the risks in a particular industry from a set of borrowers and conclude that they need to consider these same risks when reviewing loans from other obligors in the industry. Another related consequence of examiners gathering new information regarding risks of a set of borrowers could also be that these risks could inform the examiners about ratings downgrades necessary for other interrelated obligors such as the original set of obligors suppliers and customers. We expect that examiners could use their acquired knowledge across interrelated obligors to create interdependencies in ratings drift both within and across banks.

Another possible for supervision spillovers is that examiners could revise and reinterpret the information they acquire on obligors' credit risks. Existing theories of interpretation and acquisition of information suggest that individuals constantly reinterpret existing knowledge and synthesize existing and new knowledge together on a continuous basis. Therefore, if examiners revise and expand their knowledge regarding multiple obligors' credit risks as they proceed through their examinations, then we expect that we could see spillovers in supervisor-motivated ratings changes both within and across banks' portfolios.

Similarly, we expect that the same reasoning that could cause spillovers in the effect of supervision on ratings inflation, could also cause spillovers within and between banks in the effect of supervision on ratings changes and inflation. We reason that banks could possibly learn about relevant risks unknown to them with regard to individual banks due to inter-dependencies with other obligors now known to be higher risk. Also, we expect that banks could possibly learn about unknown risks related certain subsets of obligors, which for example, could include banks learning about previously unknown risks in particular industries.

To capture and analyze the effect of SNC supervisory spillovers on ratings inflation, we adopt the simple econometric specification provided by Berg et al., 2021. Their model assumes that spillovers can be captured by a measure of the fraction of units that are treated within a specific group where spillovers may occur. In our study, we could use fraction of a group that is treated by being read by SNC examiners as the relevant group to measure spillovers from. In terms of our notation, we would denote the fraction of treated loans as $\bar{d}^e_{g,t}$, where g denotes a group index. In our context, we treat the bank that an obligor has it's loan at as the relevant group where spillovers would occur. Given the fraction of treated loan observations at a supervised bank, we could write our spillover models as:

$$R_{i,t} - R_{i,t-1} = \alpha^e + \beta^e d^e_{i,t} + \beta^e_T d^e_{i,t} \bar{d}^e_{g,t} + \beta_C \bar{d}^e_{g,t} \left(1 - d^e_{i,t}\right) + \epsilon_t \tag{8}$$

$$R_{i,t} - R^s_{i,t} = \alpha^s + \beta^s d^s_{i,t} + \beta^s_T d^s_{i,t} \bar{d}^s_{g,t} + \beta^s_C \bar{d}^s_{g,t} \left(1 - d^s_{i,t}\right) + \epsilon_t. \tag{9}$$

The models in equations (8) and (9) are similar to the models in equations (6) and (7), with the addition of the terms for the treatment fraction, $\bar{d}^e_{g,t}$. While these variables and coefficients could be rearranged and estimated differently, the specifications in equation (8) and (9) facilitate simple and clear interpretation of the spillover effect estimates. In equations (8) and (9), β_T captures the spillover effects of the extent of group treatment on the treated obligors rating inflation, and β_C captures spillovers of group treatment on non-read obligors' rating inflation. The total effect of group supervision on oblifors' ratings drift equals:

$$E\left[R_{i,t} - R_{i,t-1}\right] = \; = \; \alpha^e + \beta^e + (\beta^e_T + \beta^e_C)\bar{d}^e_{g,t} \tag{10}$$

$$E\left[R_{i,t} - R^s_{i,t}\right] \; = \; \alpha^s + \beta^s + (\beta^s_T + \beta^s_C)\bar{d}^e_{g,t}. \tag{11}$$

In our analyses, we measure the fraction of group level treatment as either the fraction of a banks total loan commitments or the fraction of loan utilization that have their ratings scrutinized by regulators. Overall, we expect that supervisory knowledge spillovers would effect the ratings of loans that are read by supervisors, and impact the ratings changes and ratings inflation that occur between the submission of ratings by banks and the final ratings set following the same year's exam. This would be because the non-read ratings would not be eligible to be changed or adjusted in response to the examinations. We expect to observe spillovers on the ratings of non-read loans in post-exam ratings, as banks could adjust these ratings with information gleaned from supervisors regarding read loans during exams. We have no clear particular prediction regarding the effect of banks' knowledge spillovers on read ratings following the examinations. We could expect that spillovers from examiner knowledge could either be already fully incorporated in these ratings during the examinations which would result in no subsequent spillovers on these loans ratings. Or, we could also expect that banks could further consider the information acquired during the exam process and incorporate this information into the ratings subsequent to the exams.

These results are included in Tables **??** and VIII. The results in the first three columns represent estimates of the effect of supervisors knowledge spillovers on other supervised ratings, and the last three columns represent the effect of bank's knowledge spillovers on their future submitted ratings. These results in the first three columns of each table are consistent with the prediction that there are spillovers in examination knowledge between credits that are read by examiners that results in greater downward inflation in SNC ratings. The results in the last three columns indicate that knowledge spillovers result in banks downgrading credits that were not read during the previous exam cycle, which results in greater downward inflation in SNC ratings between the examination cycle where spillovers were generated and the ratings submissions for the subsequent exam cycle.

Overall, these results imply that spillover effects have a meaningful impact on ratings downgrades and inflation. This suggests that the impact of SNC supervision on the informativeness of SNC ratings is important beyond the SNC examination cycle as examiner knowledge spills over into bank's future ratings changes. In addition, these results suggest that the knowledge gained by examiners regarding banks' risk is valuable, and that the depth and ability of examiners to gain knowledge from the SNC exams could be important for supervision.

C. Effect of ratings inflation on borrower future performance

In this section we analyze whether the information in ratings inflation forecasts borrowers' future market-to-book ratios, interest coverage, and return on assets (ROA). In these analyses we condition future measures of the dependent variables on lagged ratings inflation and the past two years' ratings submitted by agent banks prior to SNC examinations. These results should capture the association between the conditional mean of the future dependent variables conditional on the control variables.

The results in table X show that rating downgrades and lower agent ratings are associated with significantly lower future market-to-book ratios and ROA. The results indicate that ratings downgrades or a one unit downgrade in ratings are associated with a roughly 10 to 20 percent lower future market-to-book ratios and ROA.

D. Simulation of eliminating ratings inflation on loan loss provisions and capital ratios

An expected benefit of reducing ratings inflation is that banks could make more forward looking loan loss provisions (LLPs) that could result in more informative reported accounting earnings and capital ratios as banks could make loan loss provisions immediately upon loan origination based on long-run ratings' expectations. In this section we present simple simulations, based on the information available in our data sets, of the effect of the approximately setting ratings inflation to zero on LLPs. We also try to ascertain how large counterfactual changes in LLPs from reducing ratings inflation could have been relative to the observed levels of capital, provisions, and earnings.

We provide results for a scenario where we assume banks could apply uniform provisions for all loans based on the long-run SNC ratings distribution. We use a simple estimate of the long-run distribution of our SNC ratings which is the percentage of each rating category that we have available for the last year of each loan in the data sample.

To calculate the provision for each loan, we simplify the calculation by using the recommended loan loss allowance for each loan cited in the Office of the Comptroller of the Currency's, Comptroller's Handbook for Allowance for Loan and Lease Losses, which recommends that banks make provisions for roughly 15 percent of substandard rated loans and 50 percent of doubtful rated loans. We also assume that banks would have actually made roughly these average provisions for loans once loan's were actually downgraded to substandard and doubtful. Therefore, to roughly adjust our counterfactual provision calculations for LLPs that banks could actually make, we subtract off provisions of either 15 or 50 percent for the first year in which loans become rated either substandard or doubtful. However, for loans' first transitions from substandard to doubtful rating status, we only remove a provision of 35 percent, which we assume to be roughly the increase in provisions following a downgrade from substandard to doubtful.

For this summary analysis, we present time series graphs of ratios based on our counterfactual LLP calculations as well as banks' actual observed aggregate-quarterly loan loss provisions. We present four figures that contain the time series plots.

The first one, figure 3, displays time series box-and-whisker plots of the bank-level distribution of the ratio of our counterfactual LLPs divided by banks' actual aggregate LLPs in addition to the counterfactual LLP calculations. We can see that there are minor fluctuations in the distributions of the ratio over time between roughly 20 percent and an arbitrarily small percentage. However, we emphasize that the plots indicate that the ratio is larger and more variable in periods with more benign macroeconomic conditions. These ratios suggest that in periods with better macroeconomic conditions that banks would recognize a greater fraction of LLPs from the SNC portfolio. This pattern is due to our assumption that banks immediately recognize LLPs following a loan origination, which mechanically boosts counterfactual loan loss provision calculations during periods of greater loan origination volumes. This plot suggests that the mechanical, immediate booking of LLPs at loan origination could be a potential avenue through which there could be a pro-cyclical increase in the recognition of LLPs, and that the increase in provisions could possibly be an economically large fraction of provisions for the banks that have ratios over 20 percent in a given time period.

The remaining figures, from 4 to 6, plot ratio of both reported loan loss provisions *(in red)* and counterfactual loan loss provisions plus reported provisions*in blue* to the level of balance sheet equity, Tier 1 regulatory equity capital, and pre-provision net revenue (PPNR). The three figures show that adding counterfactual provisions to reported provisions results in a qualitatively small upward shift in the time series plots, with no noticeable increase in the length of the box-and-whisker plots.

We also note that time-series plots of the distributions of counterfactual provisions from the SNC portfolio to the bank-level variables are small in magnitude, but suggest that banks would recognize provisions as a fraction of the bank-level variables in a more pro-cyclical manner. While the counterfactual SNC portfolio provisions are not large relative to the bank-level variables, we suggest that expanding the counterfactual-type LLP methodology to banks' entire loan portfolio might result in much more economically significant changes in the time series plots. That is, although the counterfactual provisions that we derive from the SNC portfolio do not appear to be an overwhelming fraction of banks' existing provisions, we suggest that a similar analyses of banks' other loan portfolios, such as residential mortgage or retail credit portfolios could be warranted.

References

Tobias Adrian and Hyun Song Shin. Liquidity and Leverage. *Journal of Financial Intermediation*, 19(3):418–437, 2010.

Tobias Adrian and Hyun Song Shin. Procyclical Leverage and Value-at-Risk. *The Review of Financial Studies*, 27(2):373–403, 2013.

Christian Laux and Thomas Rauter. Procyclicality of U.S. Bank Leverage. *Journal of Accounting Research*, 55(2):237–273, 2017.

Elena Beccalli, Andrea Boitani, and Sonia Di Giuliantonio. Leverage Procyclicality and Securitization in U.S. Banking. *Journal of Financial Intermediation*, 24(2):200–230, 2015.

Markus Behn, Rainer Haselman, and Paul Wachtel. Procyclical Capital Regulation and Lending. *The Journal of Finance*, 71(2):919–956, 2016.

Matthew C Plosser and João A. C. Santos. Banks' Incentives and Inconsistent Risk Models. *The Review of Financial Studies*, 31(6):2080–2112, 2018.

Radhakrishnan Gopalan, Yadav Gopalan, and Kevin Koharki. Assessing the Quality of Bank Loan Ratings. Available at SSRN, 2019. URL `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2803608`.

Tobias Berg, Markus Reisinger, and Daniel Streitz. Spillover Effects in Empirical Corporate Finance. *Journal of Financial Economics*, 142(3):1109–1127, 2021.

P.J. Elliott. How and Why Bank Capital Ratios Change Over the Business Cycle. Frb of philadelphia banking trends q1, 2021.

Mehdi Beyhaghi, Cesare Fracassi, and Gregory Weitzner. Bank Loan Markups and Adverse Selection. *Available at SSRN*, 2022. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3733932.

Carola Müller, Ragnar Juelsrud, and Henrik Andersen. Risk-Based Pricing in Competitive Lending Markets. *Available at SSRN*, 2019. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2803608.

João A. C. Santos. Bank Corporate Loan Pricing Following the Subprime Crisis. *The Review of Financial Studies*, 24(6):1916–1943, 2010.

João A. C. Santos and Andrew Winton. Bank Capital, Borrower Power, and Loan Rates. *The Review of Financial Studies*, 32(11):4501–4541, 2019.

Philip E. Strahan. Borrower Risk and the Price and Nonprice Terms of Bank Loans. *FRBNY Staff Report*, 90, 1999.

Sergio Correia. REGHDFE: Stata Module to Perform Linear or Instrumental-Variable Regression Absorbing any Number of High-Dimensional Fixed Effects, 2014. URL https://ideas.repec.org/c/boc/bocode/s457874.html.

Figure 1. Ratings inflation over time

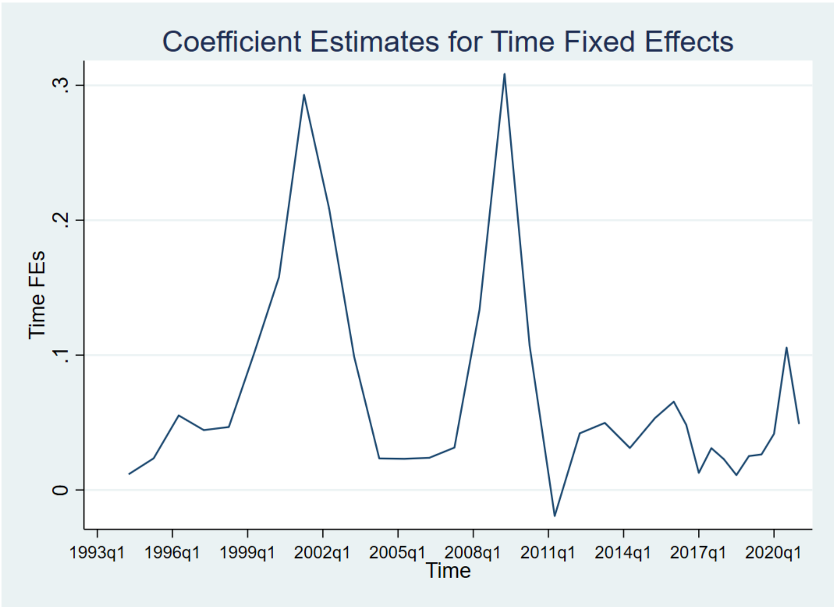

Figure 2. Ratings inflation over the age of the loan

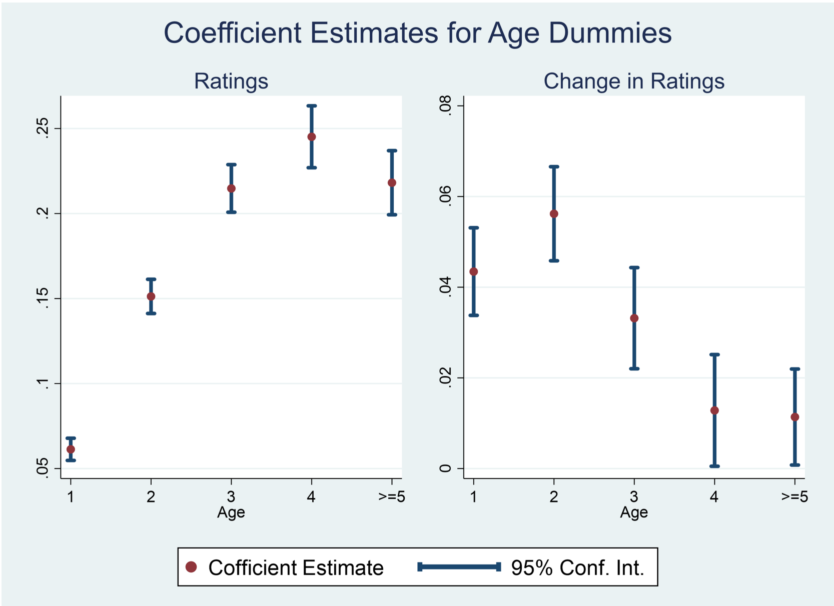

Figure 3. Counterfactual Provision Percentage

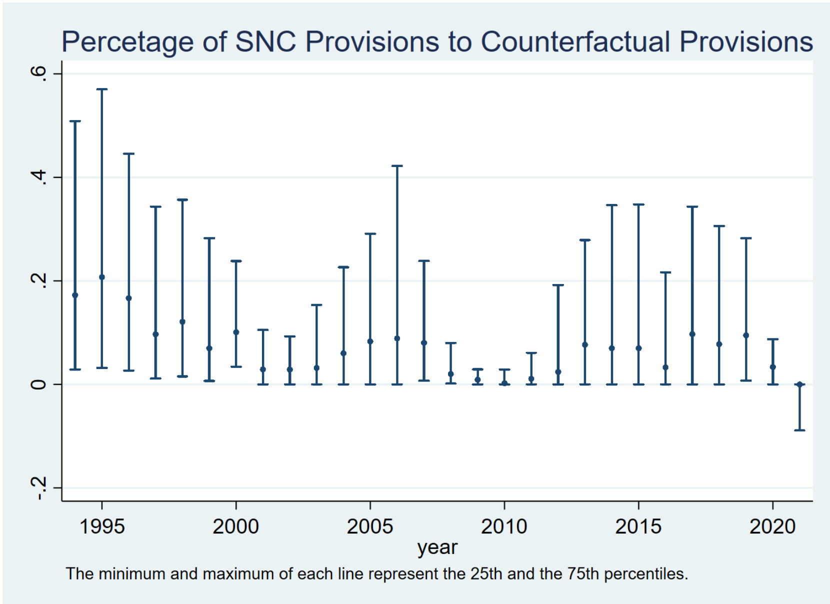

Figure 4. Counterfactual Provision as percentage of Equity

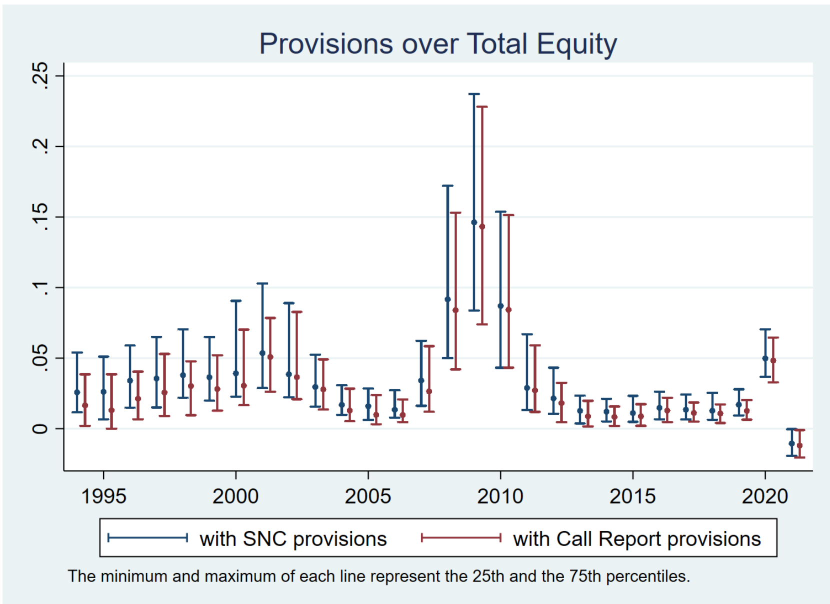

Figure 5. Counterfactual Provision as percentage of Tier 1 Equity Capital

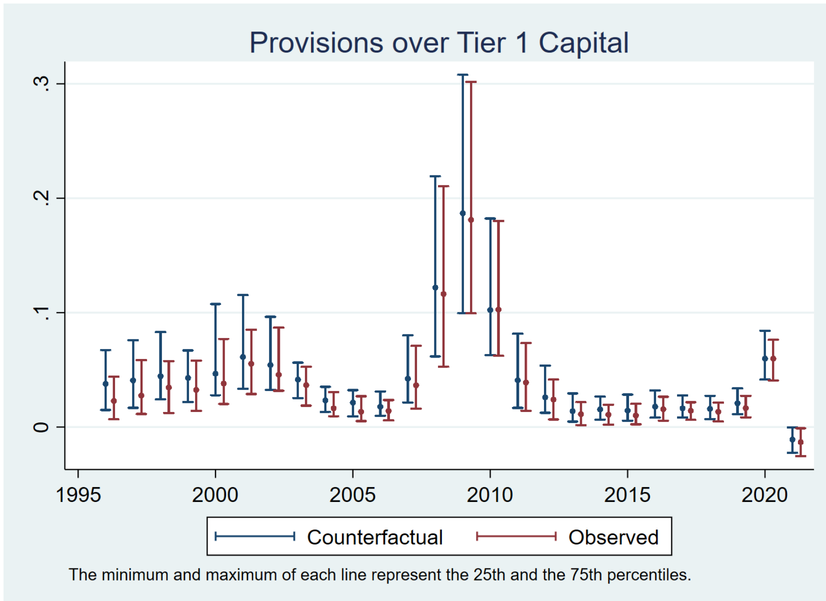

Figure 6. Counterfactual Provision as percentage of PPNR

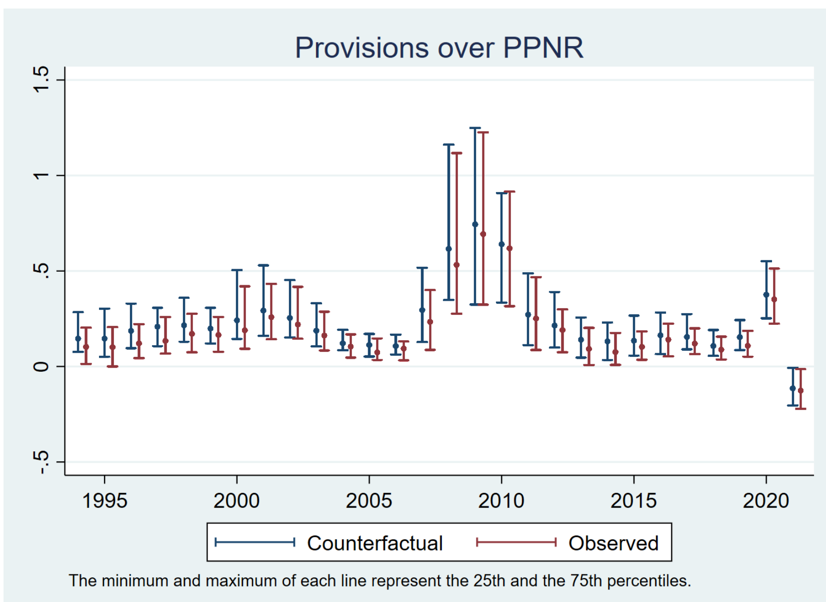

Table I. Ratings Inflation

Fixed Effects	Coef. (1)	Time (2)	Agent (3)	Sector (4)	Obligor (5)	Time-Agent (6)	Time-Agent-Sector (7)	N (8)	Adj. R^2 (9)
		F-Tests on Fixed Effects For: F-stat, p-value, no of constraints							
Time	0.069***	158.88						203,389	0.024
		0.000							
		32							
Time+Agent	0.069***	132.96	4.15					203,283	0.035
		0.000	0.000						
		32	718						
Time+Agent+Sector	0.069***	132.70	4.11	22.01				203,283	0.036
		0.000	0.000	0.000					
		32	718	7					
Time+Agent+Obligor	0.067***	70.45	1.82		2.55			198,989	0.176
		0.000	0.000		0.000				
		32	695		21,875				
Time-Agent+Obligor	0.067***				2.56	3.09		197,790	0.204
					0.000	0.000			
					21,704	4,378			
Time-Agent-Sector+Obligor	0.068***				2.62		2.91	193,744	0.257
					0.000		0.000		
					21,201		11,940		

Reported in the table are the results from fixed effects panel regressions. The dependent variable in the regressions is the change in SNC rating and the fixed effects included are row 1: time fixed effects; row 2: time and agent fixed effects; row 3: time, agent, and sector fixed effects; row 4: time, agent, and obligor fixed effects; row 5: row 3: time-agent and obligor fixed effects; row 6: time-agent-sector and obligor fixed effects.Reported are the F-tests for the joint significance of the time fixed effects (column 2), agent fixed effects (column 3), sector fixed effects (column 4), obligor fixed effects (column 5), time-agent fixed effects (column 6), and time-agent-sector fixed effects (column 7). For each F-test we report the value of the F-statistic, the p-value, and the number of constraints. Column 8 reports the number of observations, and column 9 the adjusted R^2s for each regression. *** indicates statistical significance at the 1% level.

Table II. Ratings inflation and loan exposures

	(1)	(2)	(3)	(4)
Utilized % of Loan Commitment	0.096***		0.077***	
	(0.000)		(0.000)	
Log(Utilized Exposure)		0.003***		0.008***
		(0.000)		(0.000)
Constant	0.015***	0.030**	-0.010	-0.077
	(0.000)	(0.026)	(0.746)	(0.121)
No of Obs.	203,283	160,850	28,211	19,759
R^2	0.0455	0.0448	0.0705	0.0794
Obligor controls	No	No	Yes	Yes
Sample	Full	Full	Merged	Merged
FE	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time
Cluster	Obligor	Obligor	Obligor	Obligor

This table regresses changes in SNC rating on measures of agent banks' loan exposures. *Utilized % of Loan Commitment* is the utilized percentage of the loan commitment, *Committed % of Bank's Total Commitment* is the loan commitment as a percentage of agent bank's total commitment, *Log(Utilized Exposure)* is the logarithm of the loan's utilized amount, *Log(Loan Commitment)* is the logarithm of the loan commitment. Obligor controls are obligor characteristics at the time of loan origination (log of total assets, cash/assets, market leverage, EBITDA/total assets, and stock return volatility). Full sample refers to the SNC sample, and merged sample refers to SNC sample merged with DealScan. All regressions include agent and time fixed effects. Standard errors are clustered at the obligor level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table III. Ratings inflation and obligor characteristics at loan issuance

	(1)	(2)	(3)	(4)	(5)	(6)
Initial Log(Assets)	-0.013***					-0.011***
	(0.000)					(0.000)
Initial Cash/Assets		-0.079***				-0.026
		(0.001)				(0.344)
Initial Market Leverage			0.111***			0.082***
			(0.000)			(0.001)
Initial EBITDA/Assets				-0.218***		-0.124**
				(0.000)		(0.044)
Initial Stock Ret. Vol.					0.580***	0.385***
					(0.000)	(0.000)
Constant	0.142***	0.047***	-0.010	0.071***	-0.048***	0.049*
	(0.000)	(0.000)	(0.123)	(0.000)	(0.000)	(0.088)
No of Obs.	39,027	39,023	31,390	36,785	34,590	28,211
R^2	0.0509	0.0491	0.0533	0.0471	0.0574	0.0639
FE	Agent	Agent	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time	Time	Time
Cluster	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor

This table regresses changes in SNC rating on measures of obligor characteristics at the time of loan origination. *Initial Log(Assets)* is the logarithm of total assets at origination, *Initial Cash/Assets* is cash over total assets at origination, *Initial Market Leverage* is total liabilities over market value at origination, *Initial EBITDA/Assets* is EBITDA over total assets at origination, *Initial Stock Ret. Vol.* is the stock return volatility at origination. All regressions include agent and time fixed effects. Standard errors are clustered at the obligor level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IV. Ratings inflation and loan characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Log(All-in-Drawn Spread)	0.032***		0.017***		-0.005	
	(0.000)		(0.000)		(0.493)	
Quintile: 2		0.036***		0.027***		0.006
		(0.000)		(0.000)		(0.482)
Quintile: 3		0.043***		0.023**		-0.008
		(0.000)		(0.015)		(0.516)
Quintile: 4		0.056***		0.036***		-0.010
		(0.000)		(0.000)		(0.545)
Quintile: 5		0.085***		0.052***		0.027
		(0.000)		(0.000)		(0.458)
Utilized % of Loan Commitment			0.104***	0.104***	0.098***	0.096***
			(0.000)	(0.000)	(0.000)	(0.000)
Initial Log(Assets)					0.001	0.002
					(0.678)	(0.529)
Initial Cash/Assets					0.020	0.018
					(0.390)	(0.436)
Initial Market Leverage					0.019	0.014
					(0.547)	(0.647)
Initial EBITDA/Assets					-0.105*	-0.104*
					(0.070)	(0.076)
Initial Stock Ret. Vol.					0.295***	0.275**
					(0.009)	(0.015)
Constant	-0.108***	0.013**	-0.077***	-0.018***	-0.026	-0.051
	(0.000)	(0.017)	(0.000)	(0.001)	(0.603)	(0.186)
No of Obs.	25,371	25,371	25,371	25,371	8,135	8135
R^2	0.0533	0.0535	0.0619	0.0623	0.0827	0.0834
FE	Agent	Agent	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time	Time	Time
Cluster	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor

This table regresses changes in SNC rating on origination loan spreads. Columns (1) and (4) include the level of the all-in-drawn spread, columns (2) and (4) include the deciles of all-in-drawn spread, and columns (3) and (6) include the quintiles of all-in-drawn spread. Columns (4)-(6) also include *Utilized % of Loan Commitment* which is the utilized percentage of the loan commitment. All regressions include agent and time fixed effects. Standard errors are clustered at the obligor level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table V. Effect of supervision on loan ratings

	Agent Rating - Previous Exam Rating				Current Exam Rating - Agent Rating			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Read	-0.001		0.010	0.020	0.047***		0.043***	0.021
	(0.952)		(0.385)	(0.186)	(0.000)		(0.000)	(0.153)
Mandatory		-0.150***	-0.152***	-0.182**		0.063***	0.054***	0.037
		(0.000)	(0.000)	(0.042)		(0.001)	(0.006)	(0.394)
L2.Log(Assets)				-0.004				0.005
				(0.242)				(0.190)
L2.(Cash/Assets)				-0.090***				-0.020
				(0.003)				(0.485)
L2.Market Leverage				-0.058**				0.044*
				(0.029)				(0.061)
L2.(EBITDA/Assets)				0.098				0.003
				(0.136)				(0.948)
L2.Stock Ret. Vol.				-0.452***				0.232***
				(0.000)				(0.004)
Constant	0.110***	0.131***	0.128***	0.183***	0.000	0.006*	-0.006**	-0.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.989)	(0.067)	(0.040)	(0.004)
No of Obs.	34113	34113	34113	6276	34113	34113	34113	6276
R^2	0.438	0.440	0.440	0.524	0.274	0.273	0.275	0.321
FE	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time
Cluster	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor

This table regresses various rating differences on *Read* and *Mandatory* dummies and borrower characteristics that were available at the time of the exam submission. *Read* dummy is equal to one if the loan is read and *Mandatory* dummy is equal to one if the loan is a mandatory read. The dependent variable is the difference between agent bank rating and the previous exam rating in columns (1)-(4) and the difference between the current exam rating and agent bank rating in columns (5)-(8). *L2.Log(Assets)* is the logarithm of total assets at the time of submission, *L2.(Cash/Assets)* is cash over total assets at the time of submission, *L2.Market Leverage* is total liabilities over market value at the time of submission, *L2.(EBITDA/Assets)* is EBITDA over total assets at the time of submission, *L2.Initial Stock Ret. Vol.* is the stock return volatility at the time of submission. All regressions include agent-bucket-time fixed effects. Standard errors are clustered at the obligor level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table VI. Effect of supervision on loan ratings

	Current Exam Rating - Previous Exam Rating			
	(1)	(2)	(3)	(4)
Read	0.046***		0.054***	0.042**
	(0.001)		(0.000)	(0.047)
Mandatory		-0.088**	-0.098**	-0.145
		(0.030)	(0.016)	(0.168)
L2.Log(Assets)				0.001
				(0.881)
L2.(Cash/Assets)				-0.109***
				(0.008)
L2.Market Leverage				-0.014
				(0.678)
L2.(Ebitda/Assets)				0.101
				(0.195)
L2.Stock Ret. Vol.				-0.220*
				(0.072)
Constant	0.110***	0.136***	0.121***	0.069
	(0.000)	(0.000)	(0.000)	(0.238)
No of Obs.	34113	34113	34113	6276
R^2	0.431	0.431	0.432	0.390
FE	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time
Cluster	Obligor	Obligor	Obligor	Obligor

This table regresses the difference between the current exam rating and the previous exam rating on *Read* and $Mandatory$ dummies and borrower characteristics that were available at the time of the exam submission. *Read* dummy is equal to one if the loan is read and $Mandatory$ dummy is equal to one if the loan is a mandatory read. *L2.Log(Assets)* is the logarithm of total assets at the time of submission, *L2.(Cash/Assets)* is cash over total assets at the time of submission, *L2.Market Leverage* is total liabilities over market value at the time of submission, *L2.(EBITDA/Assets)* is EBITDA over total assets at the time of submission, *L2.Initial Stock Ret. Vol.* is the stock return volatility at the time of submission. All regressions include agent-bucket-time fixed effects. Standard errors are clustered at the obligor level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table VII. Effect of supervision on loan ratings

	Agent Rating - Previous Exam Rating					Current Exam Rating - Agent Rating					Current Exam Rating - Previous Exam Rating				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Read	-0.001		0.010	-0.012	-0.009	0.047***		0.043***	0.044***	0.030**	0.046***		0.054***	0.032***	0.021
	(0.952)		(0.385)	(0.239)	(0.397)	(0.000)		(0.000)	(0.000)	(0.032)	(0.001)		(0.000)	(0.008)	(0.263)
Mandatory		-0.150***	-0.152***	-0.307***	-0.462***		0.063***	0.054***	0.062***	0.117*		-0.088**	-0.098**	-0.245***	-0.345**
		(0.000)	(0.000)	(0.000)	(0.000)		(0.001)	(0.006)	(0.000)	(0.082)		(0.030)	(0.016)	(0.000)	(0.012)
Read × Mandatory				0.191***	0.325***				-0.010	-0.092				0.181***	0.233*
				(0.004)	(0.005)				(0.625)	(0.214)				(0.008)	(0.076)
L2.Log(Assets)					-0.005					0.005					0.000
					(0.146)					(0.156)					(0.985)
L2.(Cash/Assets)					-0.084***					-0.021					-0.105***
					(0.004)					(0.449)					(0.009)
L2.Market Leverage					-0.056**					0.043*					-0.013
					(0.033)					(0.064)					(0.704)
L2.(EBITDA/Assets)					0.079					0.009					0.088
					(0.225)					(0.867)					(0.253)
L2.Stock Ret. Vol.					-0.458***					0.234***					-0.224*
					(0.000)					(0.004)					(0.066)
Constant	0.110***	0.131***	0.128***	0.133***	0.199***	0.000	0.006*	-0.006**	-0.006**	-0.119***	0.110***	0.136***	0.121***	0.126***	0.080
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.989)	(0.067)	(0.040)	(0.026)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.163)
No of Obs.	34,113	34,113	34,113	34,113	6,276	34,113	34,113	34,113	34,113	6,276	34,113	34,113	34,113	34,113	6,276
R^2	0.438	0.440	0.440	0.442	0.529	0.274	0.273	0.275	0.275	0.322	0.431	0.431	0.432	0.432	0.392
FE	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time
Cluster	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor

This table regresses various rating differences on *Read* and *Mandatory* dummies, their interaction *Read* × *Mandatory*, and borrower characteristics that were available at the time of the exam submission. *Read* dummy is equal to one if the loan is read, and *Mandatory* dummy is equal to one if the loan is a mandatory read. The dependent variable is the difference between agent bank rating and the previous exam rating in columns (1)-(5), the difference between the current exam rating and agent bank rating in columns (6)-(10), and the difference between the current exam rating and the previous exam rating in columns (11)-(15). *L2.Log(Assets)* is the logarithm of total assets at the time of submission, *L2.(Cash/Assets)* is cash over total assets at the time of submission, *L2.Market Leverage* is total liabilities over market value at the time of submission, *L2.(EBITDA/Assets)* is EBITDA over total assets at the time of submission, *L2.Initial Stock Ret. Vol.* is the stock return volatility at the time of submission. All regressions include agent-bucket-time fixed effects. Standard errors are clustered at the obligor level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table VIII. Supervision spillovers (year<2016)

	Contemporaneous Spillovers		Future Spillovers			
	(1)	(2)	(3)	(4)	(5)	(6)
Read	0.047***	0.027***	0.007	-0.005		
	(0.000)	(0.001)	(0.673)	(0.791)		
Read * Read %		0.400***		0.077		
		(0.006)		(0.669)		
(1-Read) * Read %		-0.069		0.337*		
		(0.422)		(0.063)		
Down					-0.347***	-0.351***
					(0.000)	(0.000)
Down * Down %						-0.493
						(0.553)
(1-Down) * Down %						0.838
						(0.231)
Constant	0.000	-0.000	0.055***	0.049***	0.078***	0.159***
	(0.989)	(0.998)	(0.000)	(0.000)	(0.000)	(0.000)
No of Obs.	34113	25273	21078	15634	35091	4704
R^2	0.274	0.283	0.244	0.249	0.215	0.394
FE	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time
Cluster	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor

The dependent variable in columns (1)-(2) is the change in the SNC rating from the agent bank submission to current exam rating and in columns (3)-(6) is the change in the SNC rating from current exam rating to next agent bank submission. *Read (Down)* is a dummy variable equal to one if the loan is read (downgraded). *Read% (Down %)* is the fraction of the agent bank's loan portfolio that is read (downgraded) in that SNC vintage, where the fraction is calculated based on commitment amount. All regressions include agent-bucket-time fixed effects. Standard errors are clustered at the obligor level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table IX. Ratings inflation at the bank level

	$\text{Equity}_{t+1}/\text{Assets}_t$	Asset Growth_{t+1}	Loan growth_{t+1}	C&I Loan Growth_{t+1}
	(1)	(2)	(3)	(4)
$\Delta R_{i,t}$	-0.017**	-0.048***	-0.063***	-0.062**
	(0.011)	(0.003)	(0.001)	(0.048)
Constant	0.109***	0.025***	0.022***	0.020***
	(0.000)	(0.000)	(0.000)	(0.000)
No of Obs.	942	942	942	942
No of banks	44	44	44	44
Adj R^2	0.444	0.062	0.059	0.071
FE	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time
Cluster	Agent	Agent	Agent	Agent

This table regresses various agent-bank level outcomes on changes in SNC ratings. $Equity_{t+1}/Assets_t$ is one-quarter ahead bank equity over total assets at time t, *Asset* $Growth_{t+1}$ is one-quarter ahead quarter-on-quarter asset growth, *Loan* $growth_{t+1}$ is one-quarter ahead quarter-on-quarter loan growth, and *C&I Loan* $Growth_{t+1}$ is one-quarter ahead quarter-on-quarter commercial and industrial loan growth. All regressions include agent bank and time fixed effects. Standard errors are clustered at the agent bank level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table X. Borrower future performance

	Market-to-Book$_{t+1}$		Int. Cov.$_{t+1}$		ROA$_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Rating$_t$	-0.527***		0.013		-0.016***	
	(0.000)		(0.679)		(0.000)	
Current Exam - Agent Bank		-0.414*		0.057		-0.014***
		(0.063)		(0.256)		(0.000)
Agent Bank - Previous Exam		-0.557***		0.000		-0.016***
		(0.000)		(0.994)		(0.000)
Constant	2.902***	2.906***	0.273***	0.273***	0.127***	0.126***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No of Obs.	31,846	31,779	34,567	32,864	33,369	31,649
R^2	0.044	0.044	0.030	0.030	0.066	0.063
FE	Agent	Agent	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time	Time	Time
Cluster	Agent	Agent	Agent	Agent	Agent	Agent

This table regresses various borrower performance variables on changes in SNC ratings. The dependent variable is the one-quarter ahead Market-to-Book ratio, *Market-to-Book*$_{t+1}$, in columns (1) and (2), is the one-quarter ahead Interest Coverage Ratio, *Int. Cov.*$_{t+1}$, in columns (3) and (4), and is Return on Assets, *ROA*$_{t+1}$ in columns (5) and (6). Δ *Rating*$_t$ is the change in rating from time $t-1$ to time t, *Current Exam - Agent Bank* is the change in the rating from agent-bank submission to current exam rating, and *Agent Bank - Previous Exam* is the change in the rating from previous exam to agent-bank submission. All regressions include agent bank and time fixed effects. Standard errors are clustered at the agent bank level. *p-values* are reported in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.