Internal Loan Ratings, Supervision, and Procyclical Leverage*

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ABSTRACT

We build a Markov model of banks' internal loan ratings to illustrate the relationship between ratings inflation and systematic ratings drift. 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, suggesting that screening and pricing information is not being fully incorporated into ratings. We use 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. We employ our model to investigate various counterfactual capital ratios and provide new insights about the relationship between 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 an 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 reconcile the revelation that their ex ante risk assessments were overstated in addition to recognizing 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 procyclicality of leverage, which, together with our findings on the effects of supervision, suggest that loan-level supervision may mitigate the severity of shocks to bank capital during a crisis.

Our structural model of loan ratings dynamics assumes that ratings are upgraded and downgraded following a Markov process with five states corresponding to the five regulatory ratings, i.e., pass, special mention, substandard, doubtful, and loss. 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 (e.g,, 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, 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 are 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 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 the 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.[1] 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 based on industry performance or growth may be experiencing changes in credit quality, so we would expect banks to change the ratings of these loans even before the exam

[1]Throughout this paper, we refer to the agent bank as "bank" because we do not consider other banks in the loan syndicate.

starts. We take these hypotheses into account by evaluating the causal effect of examinations on loan ratings using the difference in ratings between the post-exam rating and the bank's pre-exam submission. We find evidence that examinations increase the timeliness of internal loan ratings by 41.8% 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 SNC 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 SNC 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.

Procyclical leverage refers to the positive co-movement between bank leverage and the business cycle (Adrian and Shin, 2010, 2013; Beccali, Boitani, and Di Giuliantonio, 2015; Laux and Rauter, 2017).[2] 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 (Laux and Rauter, 2017). 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 notion of procyclicality as the positive co-movement between economic and financial variables and economic activity contrasts with the notion of procyclicality used by prudential policymakers. According to this notion, 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. Consistent with this broader view, changes in bank leverage lead to changes in lending and credit availability that amplify swings in the business cycle.

We explore the implications of ratings inflation for loan loss provisioning and the procyclicality of 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 an economic downturn when ratings *should* be downgraded. We explore these hypotheses in two ways. First, we employ 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

[2] Several of these studies follow Adrian and Shin (2010, 2013) 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.

supervisory exam program is expanded. In these settings, banks increase loan loss provisions in all years, but especially so in the run up to the 2007-09 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 differences in internal loan ratings of the same loans across banks, and emphasized disagreement stemming from differences in the level of bank capital (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

For our empirical analysis, we use data from several sources. We employ data provided by the 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 commercial credits that exceed $20 million and are held by three or more unaffiliated supervised institutions. In January 2018, the eligibility threshold increased from $20 million to $100 million. Banks are required to submit their internal ratings in advance of the exams to allow the SNC Program office to process and sample the eligible loans. Ratings submissions are followed by supervisory examinations, which are intended to validate the banks' ratings submissions. Examinations may result in rating updates for loans that are reviewed by SNC Program examiners. In our data set, we use data on both banks' submitted ratings and the final ratings following SNC exams. We incorporate the full sample period (1994:Q2-2021:Q1) in estimations that do not require detailed information about the SNC exams. In tests that require detailed information about SNC exams, we restrict the sample to the 2007:Q2-2015:Q2 period because the SNC exams changed in structure and design in 2016.

The SNC database provides ratings information, in order of increasing riskiness, on pass, special mention, substandard, doubtful, or loss categories of loans. For our primary regressions, the main variable of interest that we construct is an ordinal variable with values 1 to 5. Each value represents a SNC rating category, where 1 represents the pass rating and each remaining value represents riskier ratings in increasing order, where the value 5 represents the loss rating category. We classify a loan in the riskiest rating category for which a loan has a loan share greater than zero. Banks may assign loans to multiple risk classifications. We follow the SNC Program by assigning loans with split risk classifications to the riskiest classification. This is relevant for about 1.5 percent of the loans in our sample.

From the SNC database, we calculate measures of banks' exposure for individual loans. These measures include the size of the loan or loan commitment, the utilization rate of a loan commitment, and the amount of the loan retained by the agent bank relative to the agent bank's SNC portfolio. 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 also use information from the SNC database on loan origination dates, maturity dates, and rating dates to calculate measures of loan age and remaining maturity length. Loan age is calculated as the difference in years between a loan's origination and a SNC exam year. The remaining maturity length of a loan is the difference, measured in years, between the maturity date and the SNC exam date.

We obtain additional data on SNC loan terms from the Loan Pricing Corporation's DealScan database, where the primary variable of interest is a loan's interest-rate spread at origination. DealScan only provides information regarding syndicated loans at origination. The information dates for DealScan differ from the SNC database in that DealScan does not track loan terms, or performance, after a loan's origination date. In addition, the DealScan database also differs from the SNC database in that the Dealscan database contains much more comprehensive information on loan terms at origination. However, the DealScan database does not contain information on loan terms that change over time, when a loan is renegotiated or restructured.

Loan data in the DealScan database are organized by deal and facility for a loan deal, and span the same sample period as our SNC data. In DealScan, a loan deal is a contract between a borrower and one or more lenders at a particular date and a single loan deal may consist of multiple loan facilities. In DealScan, about 75 percent of the deals contain one facility, and 20 percent of the loans contain two facilities. Because there may be differences in loan terms across facilities, we gather data on loan interest-rate spreads for individual loan facilities. The loan spreads from the DealScan database are 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 floating-rate markups over varying base interest rates. 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, particularly in later years, when 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 remaining loan contract term data from DealScan to merge DealScan loan facility interest-rate spread data to the SNC database. We use the loan contract terms data from DealScan to merge loan facilities from the two databases. Since a loan facility has multiple observations for each year the loan is outstanding and covered by the SNC program, individual loan facility observations from DealScan merge with multiple loan-year observations in the SNC database. Given this merged data structure, loan spread observations from DealScan will be constant over the observed life of the loan in the SNC database.

We also calculate multiple measures of an obligor's observable risk factors from commonly used data sources, which include stock price data from the Center for Research in Security Prices (CRSP) and financial statement data from Standard and Poor's Compustat Annual database. Using the CRSP database, we calculate estimates of borrowers' 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 then annualize it, by multiplying by $\sqrt{52}$. The remaining variables that we calculate from Compustat data are standard in the literature.[3] This set of variables includes 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 of equity); and the ratio of EBITDA to assets (earnings before interest, taxes and depreciation divided by total assets).

We use FFIEC 031 and 041 regulatory filings (Call Reports) to calculate several bank-level

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

variables derived from banks' balance sheets and income statements. We calculate quarter-over-quarter asset growth (log change in year end RCFD2170), loan growth (log change in year-end RCFD 2122), commercial and industrial loan growth (log change in year-end sum of 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 obtain additional income and balance sheet variables directly from the Call Reports, including loan loss provisions (RIAD4230), net income (RIAD4340), and Tier 1 capital (RCFD8274 prior to 2015 and RCFA8274 afterwards).

Table I provides summary statistics of the key variables we use in our analysis. Table II presents a ratings transition matrix. The table reports the probability of moving from one rating at time t-1 to another rating at time t. Figure 1 shows the number of classified (substandard, doubtful, loss) and special mention ratings as a share of total ratings over time. The figure shows that the share of loans rated in the classified or special mention categories changes significantly over the business cycle. Though the fractions of loans rated in these categories have declined considerably since peaking in early 2010, they have increased recently due to the negative impact of the COVID-19 pandemic on economic conditions.

III. Ratings inflation

A. Ratings inflation model

This section presents the ratings inflation model underlying our main regression models that are used to characterize SNC ratings inflation. 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 full set of SNC rating categories. The state-space values 1 through 5 stand for the pass, special mention, substandard, doubtful, and loss rating categories, respectively. We denote the one-period

Markov transition probability matrix as:

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

where $\mathbf{P}$ is the Markov transition matrix and p_{jk} is the probability that the Markov chain transitions 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 transition matrix assumes that the probability of transition to a current state k only depends on the previous state j and is independent of the rating history. Since the transition probabilities do not depend on the time parameter t, the Markov chain is time-homogeneous.

For the transition matrix, the steady-state probability distribution of ratings is represented by a 5×1 column vector of probabilities, with $\boldsymbol{\pi}' = (\pi_1, \pi_2, \pi_3, \pi_4, \pi_5)$, 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 satisfy $\boldsymbol{\pi}' = \boldsymbol{\pi}' P$ and are functions of the underlying transition probabilities.

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

In terms of our model, we see that the change in the average rating in the steady-state distribution is equal to zero, since $E[R_{t+1}] - E[R_t] = \pi' \mathbf{P} N' - \boldsymbol{\pi}' \boldsymbol{P} N' = 0$. 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 in 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 interpret this as ratings inflation, and if it is less than zero, we interpret it as ratings deflation.

In an empirical setting, if the rating for a loan, i, at time $t+1$, is regressed on a constant, $R_{i,t+1} = \alpha_{i,t+1} + \epsilon_{i,t+1}$, the estimated constant $\alpha_{i,t+1}$ would be an estimate of the average rating at time $t+1$, where $\epsilon_{i,t+1}$ is an error term. We assume that the difference in average ratings from time t to $t+1$ would equal zero in the long-run steady-state. Therefore, in a regression of the unconditional change in ratings $R_{i,t+1} - R_{i,t}$ on a constant, the average ratings change would be predicted to be equal to zero,

$$\begin{aligned} R_{i,t+1} - R_{i,t} &= \alpha_{i,t+1} - \alpha_{i,t} + \epsilon_{t+1} - \epsilon_t && (2) \\ \Delta R_{i,t+1} &= \Delta\alpha_{i,t+1} + \Delta\epsilon_{t+1} && (3) \\ E[\Delta R_{i,t+1}] &= \alpha - \alpha + E[\epsilon_{i,t+1}] - E[\epsilon_{i,t}] = 0, && (4) \end{aligned}$$

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

However, if we estimate equation (3) and find the estimated $\Delta\alpha_{i,t+1} \neq 0$, i.e., the rating change is positive, or negative, on average, this would imply average ratings systematically deviate from the long-run steady-state. Importantly, if the average difference in ratings is greater than zero, then there is ratings inflation relative to the long-run steady-state ratings distribution.

B. Predicting ratings changes and relation to the steady state

This section describes whether ratings inflation would be predictable conditional on observable loan and financial information correlated with ratings in the long-run steady state. We show that, because the correlation dies out over time, lagged information would have a correlation with ratings inflation that is the inverse of the correlation of the information with steady state ratings. We explain how a correlation between measures of greater borrower risk and greater ratings inflation indicates that risk measures can predict ratings inflation. This predictive power implies that this information is not fully incorporated into SNC ratings.

What is relevant for our purposes, is that, if the information in any risk factor or variable with information about borrower risk is not initially fully incorporated in ratings when the information is first known, the correlation between these variables and ratings would increase over time if the correlation between the information in initial spreads and ratings increases, as the information is later incorporated into the ratings. This information could be imputed into ratings as banks incorporate it into ratings through forward-looking risk assessment changes, or also if the lagged information becomes more correlated with future ratings due to an increase in realized risk reflected in ratings at future dates that happens to be correlated with the lagged variables.

To describe our emprical analyses, we assume that there is information that has predictive content for obligor risk ratings, and that this information is observed prior to a rating at t. The information is contained in a variable labeled x_0, which can take two values, labeled H or L for states High and Low, respectively. For the sake of illustration, we assume that this variable indicates whether the initial loan spread is either high or low, where a higher loan spread indicates greater borrower risk. We would expect that if the information in loan spreads is not imputed in SNC ratings when it is known, that loan spreads would have a positive correlation with changes in future ratings.

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

$$R_{i,t+1} - R_{i,t} \quad = \quad \gamma + \beta_{x_0} x_0 + \epsilon_{t+1}. \tag{5}$$

Our main empirical prediction is that if the information in x_0 is not imputed into ratings when it is known, then the coefficient β_{x_0} would be different from zero and have the sign of the relation between x_0 and the level of of SNC ratings.

We also note that if lagged information is fully incorporated into ratings, then the lagged information would not forecast future ratings in auto-regressive regression models for ratings at consecutive future dates. Because our focus in this paper is on ratings inflation and drift toward the long-run unconditional ratings distribution, we rely on forecast models for ratings changes, rather than auto-regressive time series models. However, to provide further evidence as to whether lagged information is efficiently incorporated into ratings when the information could be known, we also estimate forecast models for differences where we control for lagged ratings. In these models with lagged ratings, we would expect that lagged information would contain no forecast power for future ratings changes if the information in the variable x_0 if fully imputed into ratings. These tests would also confirm the empirical relation between the x_0 variables and the level of SNC ratings. In these auto-regressive regression models, the sign of the relation between x_0 and future ratings should match the sign of β_{x_0} in equation (5).

C. Baseline ratings inflation results

Table III reports estimation results for a fixed effects regression that decomposes variation in ratings drift and reports F-tests and adjusted R^2s. In obtaining these results, 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.[4] Columns (2) to (7) report the F-statistics for tests of the joint significance of the different sets of fixed effects. Our inferences from these regression models focus on F-tests and adjusted R^2, which provide information on whether each set of dummy variables better explains the variation in ratings drift. If a set of dummy variables, or fixed effects, explains

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

ratings drift, then the average ratings drift varies with the dimensions specified by that set of fixed effects.[5]

Overall, Table III shows that the average ratings drift is about .069 per year, or 6.9 percent of a rating grade per year. The results 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. This suggests that there is significant heterogeneity in average ratings drift along each of the fixed-effects dimensions used to stratify the data 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

Here, we examine whether loan ratings and ratings inflation vary with loan age. For this analysis, we regress loan ratings and the change in loan ratings on loan age. Results for these models are included in Figure 3.[6] The panel on the left, which plots the relation between loan ratings and loan age, shows that the level of loan ratings tends to worsen and become downgraded over the life of a loan. Additionally, the panel on the right, which plots the relation between ratings changes and loan age, shows that ratings inflation tends to decrease over the life of a loan. Taken together, these results suggest that loans are downgraded early in the life of a loan and that loan ratings inflation decreases over time.

E. Ratings inflation and banks' loan exposures

Here, we examine whether and the extent to which ratings inflation varies with banks' loan exposure. Overall, we 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 in order to

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

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

minimize the consequences of weaker ratings, such as higher loan loss provisions, lower net income, and lower equity capital. In this scenario, we expect a positive relation between ratings inflation and bank's loan exposure. Another scenario is the case where banks would have more incentive to monitor larger loans, which might lead to more timely downgrades for these loans. For this case, we would expect a negative relation between ratings inflation and a bank's loan exposure.

To examine this issue, we regress loan rating changes on measures of agent banks' loan exposures, including utilized percentage of the loan commitment *(Utilized % of Loan Commitment)* and the logarithm of the loan's utilized amount *(Log(Utilized Exposure))*. The results presented in Table IV illustrate that loans with a greater utilization rate have greater ratings inflation and that loans that represent a greater fraction of banks' exposures have lower ratings inflation. Ratings inflation would be given by the sum of the constant and the coefficient on banks' loan exposure. The results suggest that bank's loan exposure is positively related to ratings' inflation. Column (1) shows that average ratings inflation would start out small (i.e., 0.015) for loans with zero utilization and increase significantly above the average estimates of around .07, presented earlier. Results in column (3) and (4) indicate that even after controlling for past rating, the positive relation between ratings inflation and a bank's loan exposure is still significant.

Taken together, the results presented in Table IV are consistent with banks inflating the ratings of loans that are more fully utilized, possibly to alter the perceptions of the risk-return trade-offs of these loans, or to avoid the consequences of worse risk ratings. These results suggest that banks either gather more negative information on, or are pressured to downgrade, large loans in their portfolios sooner.

F. Borrower risk information available to banks and ratings inflation

In this section, we examine whether observable information on borrower risk can predict ratings inflation. We assume that banks have access to information about borrowers' financial statements, stock market valuations, and loan contract terms at origination. Banks can obtain 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 of the terms that are negotiated and incorporated into loan contracts.

For these empirical tests, we regress loan rating changes on borrower characteristics derived from public financial statements and stock market information at the time of loan origination as well as loan contract terms. As stated earlier in Section III.B, if the lagged information sets we use as our predictors are fully incorporated into ratings when the information is observed, the Markov property means that lagged information would not predict the change in future ratings.

The results for these regressions are presented in Tables V and VI. Columns (1)-(5) in Table V show that each of the financial statement and stock market variables predicts future ratings drift when included individually in the regressions. Column (6) shows that when all of the financial statement and stock market variables are included as independent variables, all variables retain significant explanatory power, except for the cash-to-assets ratio at loan origination. Column (7) shows that the results hold when including lagged ratings as an explanatory variable.

In Table VI, columns (1)-(2) show that origination loan spreads predict ratings drift, and columns (3)-(4) show that loan spreads predict ratings drift controlling for the lagged rating. In columns (2) and (4), we report results for ratings inflation across quintiles of the interest rate spread. The results suggest that higher interest rate spreads are more highly correlated with higher ratings inflation, as the magnitudes of the coefficient estimates generally increase as the quintiles increase. These results suggest that banks are compensated for long-run loan risk that is greater than previous results would suggest. Moreover, this result would also be consistent with the notion that banks have a higher perceived risk-return trade-off earlier in the life of a loan.

IV. Loan-level supervisory exams and ratings inflation

A. Direct effects of exams on ratings inflation

In this section, we examine whether bank supervision has an effect on loan ratings inflation through SNC examinations. We hypothesize that, if banks downgrade loan ratings too slowly, then supervisory scrutiny of banks' internal loan 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 over time would lead to less overall observable ratings drift.

In our empirical analysis, we identify the causal effect of supervision on ratings inflation using random variation in the assignment of SNC loans for review. We assume, conditional on randomized supervision, that the effect of supervision will be independent of potential outcomes and that we could identify an estimate of the average causal effect. In particular, we examine the effect of supervision at date t on 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 empirical analysis, we attempt to identify a more conceptually sound causal effect by exploiting the details of the SNC ratings assignment process. In the SNC examination process, if a SNC loan 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 a 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 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 final rating assigned at the conclusion of the year's exam cycle would be the rating assigned by the bank.

We suggest that, one interpretation of banks' submitted ratings at the beginning of the exam cycle, is that the ratings proxy for the counterfactual rating that a loan would have received in the absence of supervision. 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 an 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, would be denoted as $E[R_{i,t}|S_{i,t,s=1} = 1] - E[R_{i,t}|S_{i,t,s=1} = 0]$.[7] This calculation provides 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, $E[R_{i,t}|S_{i,t,s=1} = 1] - E[R_{i,t}|S_{i,t,s=1} = 0]$, equals 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 a regression model for testing the effect of SNC supervision with the following two regression equations

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

$$R^e_{i,t} - R^a_{i,t} = \alpha^a + \beta^a d^a_{i,t} + \epsilon_t. \quad (7)$$

We hypothesize that both of these equations could provide causal estimates of the effect of supervision on ratings inflation and drift. In these equations, we interpret the coefficients, β^e and β^a, for the terms, $d^e_{i,t}$ and $d^a_{i,t}$ as the treatment effects of SNC supervision on ratings drift. The subscript e in equation (6) refers to examination ratings and regressions where we estimate effect of SNC supervision on changes in examination ratings, and the subscript a in equation (7) refers to agent-bank submitted ratings and regressions where we estimate the causal effect of supervision on changes between agent-bank submitted ratings and final exam updated ratings. We note here

[7] 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.

that we use these subscripts to refer to these ratings and causal effects in regression models for the remainder of the text. We interpret the coefficient estimates on the supervision dummy variable from equation (6) as a measure of the average treatment effect. In equation (7), we 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 the 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 of supervision on supervised loans.

Another complication that 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 a 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 in order to interpret the coefficient on the SNC supervision dummy variable as the causal effect of supervision on ratings drift.

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

The results presented in Table VII suggest that supervision may cause a significant increase in ratings drift from lower- to higher-risk loan rating categories. The results show the significant effect of supervision on the difference between the current and previous examination ratings. To the extent that the rating submitted by the agent bank proxies for the counterfactual rating assigned to read loans, this result could be interpreted as the causal effect of supervision on ratings drift.

Next, 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 unrelated to the difference in ratings between agent banks' newly submitted ratings and the exam ratings from the previous year. These results are presented in Table VIII. 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 SNC loans, i.e., the mandatory-read loans, are a function of past ratings changes, we 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 do not expect the read dummy variable to be associated with lagged ratings changes. The results in columns (1) through (3) show that the read variable, conditional on the mandatory-read dummy variable, has no association with the 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. Columns (4)-(6) suggest that ratings drift towards higher risk categories is higher for read and mandatory loans.

B. Indirect spillover effects of exams on ratings inflation

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 loan ratings inflation.

We predict that examiners' activities could result in spillovers in exam-related ratings changes, if examiners learn new information about risks related to a broader set of obligors by reviewing and becoming informed about the risks of other 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 of other obligors in the same 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 within banks.

Another possible channel 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 conduct their examinations, then we could see spillovers in supervisory ratings changes.

To capture and examine the effect of SNC exam spillovers on ratings inflation, we adopt the econometric approach of Berg et al. (2021). Their regression 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 regression analysis, we could use the fraction of loans that is treated by being read by SNC examiners as the relevant group to measure spillovers. In terms of our notation, we 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 its loan at as the relevant group where spillovers would occur. Given the fraction of treated loan observations at a supervised bank, we specify our spillover models as:

$$
\begin{aligned}
R^e_{i,t} - R^e_{i,t-1} &= \alpha^e + \beta^e d^e_{i,t} + \beta^e_T d^e_{i,t} \bar{d}^e_{g,t} + \beta^e_C \bar{d}^e_{g,t} \left(1 - d^e_{i,t}\right) + \epsilon_t && (8) \\
R^e_{i,t} - R^a_{i,t} &= \alpha^a + \beta^a d^a_{i,t} + \beta^a_T d^a_{i,t} \bar{d}^a_{g,t} + \beta^a_C \bar{d}^a_{g,t} \left(1 - d^a_{i,t}\right) + \epsilon_t. && (9)
\end{aligned}
$$

The regression 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) provide a 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 loans rating inflation, and β_C captures spillovers of group treatment on non-read loans rating inflation. The total effect of group supervision on ratings drift equals:

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

$$E\left[R^e_{i,t} - R^a_{i,t}\right] \; = \; \alpha^a + \beta^a + (\beta^a_T + \beta^a_C)\bar{d}^e_{g,t}. \tag{11}$$

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 affect 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 SNC 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 particular prediction regarding the effect of banks' knowledge spillovers on read-loan 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 their loan ratings subsequent to the exams.

The results from estimating equations (8) and (9) are presented in Table IX. The first two columns show estimates of the effect of supervisors' knowledge spillovers on other supervised ratings, and the last four columns show estimates of the effect of banks' knowledge spillovers on their future submitted ratings. The results reported in the first two columns are consistent with the prediction that there are spillovers in examination knowledge between loans that are read by examiners that results in greater downward drift in SNC ratings. The results reported in the last four columns show that knowledge spillovers lead to banks downgrading loans that were not read during the previous exam cycle, which results in greater downward drift in SNC ratings between the examination cycle, where spillovers were generated, and the loan ratings submissions for the subsequent exam cycle.

Overall, these results show that spillover effects have a meaningful impact on ratings downgrades and ratings 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' credit risk is valuable, and that the ability of examiners to acquire relevant knowledge from the SNC exams is important for supervision.

C. Ratings inflation, loan loss provisions, and bank capital

An expected benefit of reducing ratings inflation is that banks could make more timely, forward-looking loan loss provisions (LLPs). This would result in more informative reported accounting earnings and capital ratios, as banks could make loan loss provisions upon loan origination based on long-run ratings' expectations. In this section, we present the results of loan loss provisions simulations, based on the information available in our data, of the effect of removing loan ratings inflation.

To calculate the provision for each loan, we simplify the calculation by assuming that banks make provisions for 20 percent of substandard rated loans, 50 percent of doubtful rated loans, and 100 percent of loss rated loans. We also assume that banks follow this provisioning scheme in making provisions for loans when they are downgraded to substandard, doubtful, and loss rating categories. These assumptions follow Ivanov and Wang (2022), though they do not necessarily reflect the accounting and reserving practices of banks over time. In this analysis, our goal is not to model bank provisioning policy directly, but rather to fix provisioning across banks so that our counterfactual analysis focuses only on the effects of different ratings inflation regimes.

We provide results for a scenario where we assume banks could apply uniform provisions for all loans based on the long-run SNC ratings steady-state 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 sample.

In Figure 4, we plot the ratio of loan loss provisions to total committed amounts for loans in the SNC portfolios of banks in our sample. The dashed line represents the provisions on SNC loans that would occur under the provisioning scheme, presented above, based on the observed distribution of loan ratings. The solid line represents the provisions that would occur under the provisioning scheme if banks had perfect foresight about the default rate of SNC obligors. The difference between the solid line and the dashed line represents the increase in the rate of provisions that we would expect to observe if banks eliminated ratings inflation.

In Figure 5, we consider the effect of eliminating ratings inflation on leverage. To do so, we calculate the counterfactual and realized rate of provisions within the SNC portfolio and apply this rate to the total loan portfolio of the bank. In other words, we assume that banks have a similar provisioning policy in their SNC portfolios as they do with their other loans. This figure illustrates the percentage increase in book equity we would expect to observe if banks eliminated ratings inflation from their reporting practices.

In both Figures 4 and 5, we present evidence that provisions would be higher before and lower during the financial crisis of 2007-09. Because provisions directly reduce earnings and, therefore, book equity, this counterfactual evidence suggests that ratings inflation contributes to leverage procyclicality. In particular, eliminating ratings inflation would have increased provisions, such that, book equity would have been nearly 30% lower in 2007, and almost 10% higher in 2009.

Next, we analyze the extent to which ratings inflation is related to performance measures in bank-level regressions. In these regressions, we consider a hypothetical case in which ratings inflation among the banks' commercial and industrial loans that are eligible for SNC exams is representative of ratings inflation in other parts of the banks' loan portfolio. Given the counterfactual analysis discussed earlier, we should expect ratings inflation to be associated with lower future equity-to-assets and, through the imposition of more binding capital regulation, lower asset growth. Indeed, the results presented in Table X show that ratings inflation negatively impacts the equity-to-asset ratio and asset and loan growth. 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 economic downturns.

V. Conclusion

We build a Markov model of banks' internal loan ratings to illustrate the relationship between ratings inflation and systematic ratings drift. The model implies that systematic downward drift in banks' internal loan ratings reflect initial ratings inflation. We take the model to administrative data from the SNC Program, which contains internal loan ratings for eligible syndicated loans submitted by reporting banks. We find evidence of systematic downward drift in ratings, consistent with initial ratings inflation. We also find evidence that the drift is predictable based on pre-issuance borrower characteristics, suggesting that screening and pricing information is not being fully incorporated into ratings at loan origination.

To analyze the role of loan-level bank supervision, we employ the conditional random assignment of supervisory examinations in the SNC Program. This experimental setting allows us to study the causal impact of loan-level supervision on loan ratings. Our evidence suggests that supervision significantly increases the timeliness and accuracy of banks' internal loan ratings. We also find evidence of information spillovers within banks' loan portfolios, consistent with banks applying information gained from a supervisory exam to the loan ratings of related obligors.

Finally, we employ our model to investigate counterfactual capital ratios based on scenarios in which banks have different levels of foresight about the evolution of obligors' ratings. Our findings provide new insights into the debate on the role of bank supervision in bank capital cyclicality.

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Figure 1. Ratings distribution over time

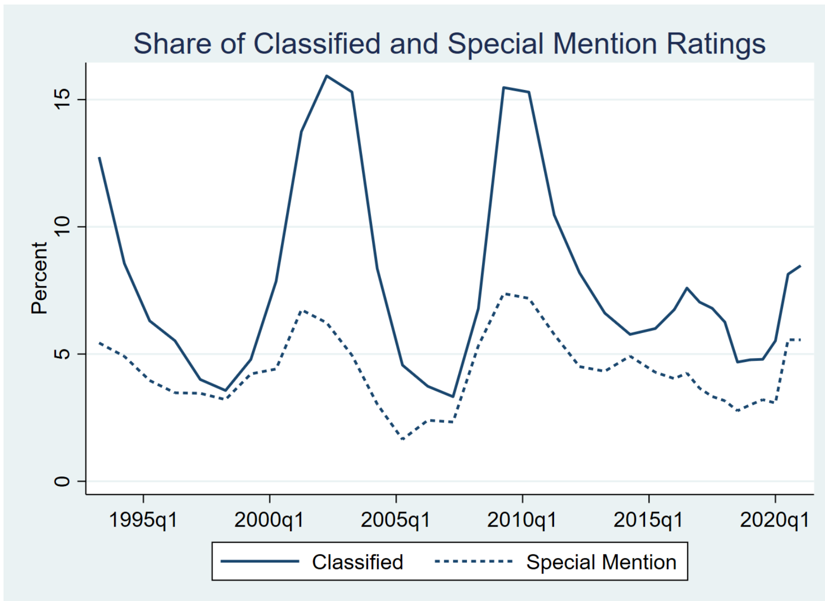

Figure 2. Ratings inflation over time

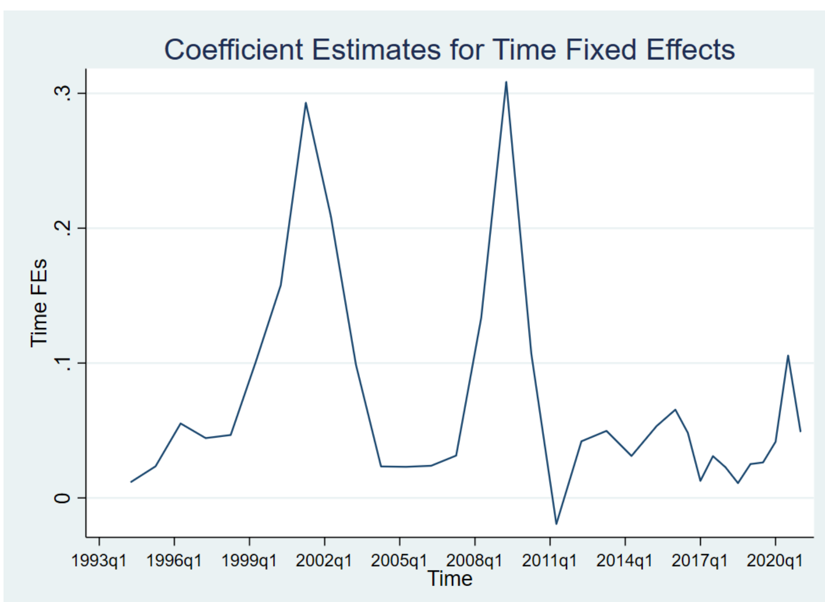

Figure 3. Ratings inflation over the age of the loan

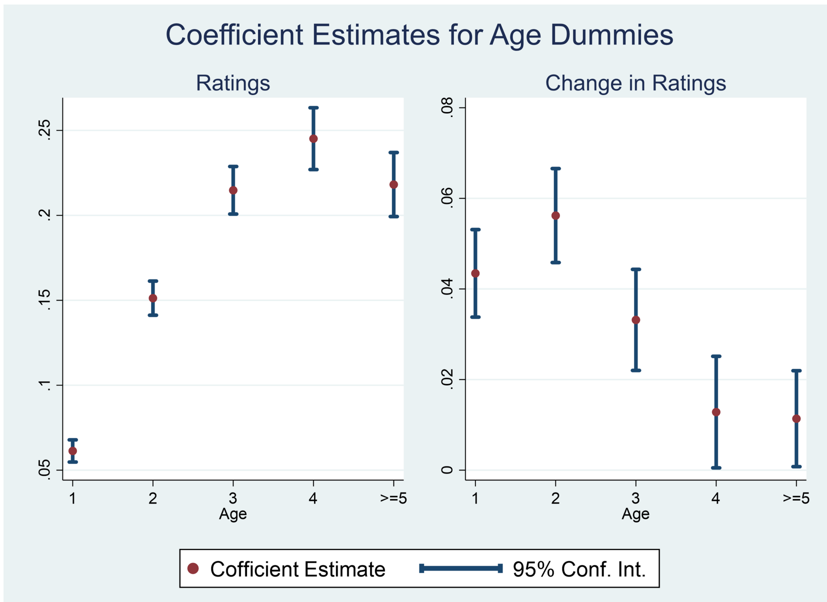

Figure 4. Provisions as a share of Total Commitment Amount

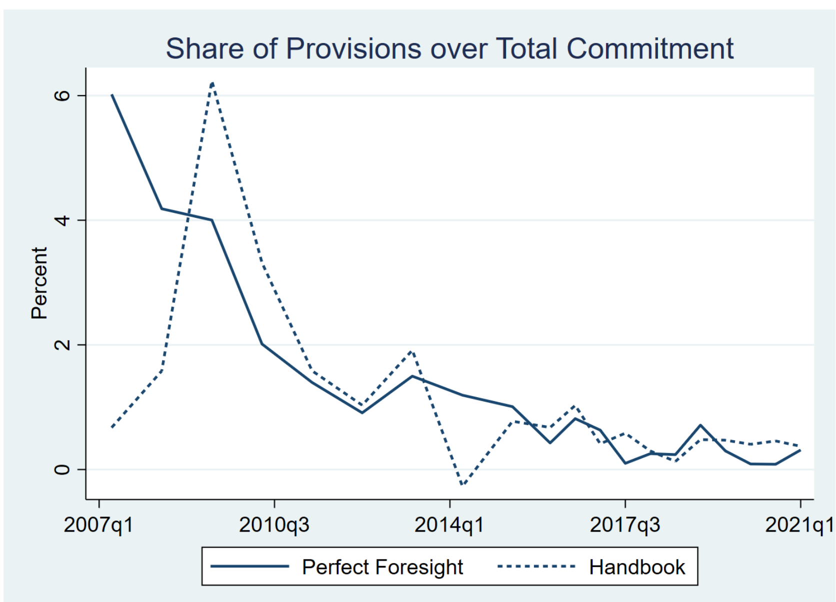

Figure 5. Provisions as a share of Total Lagged Equity

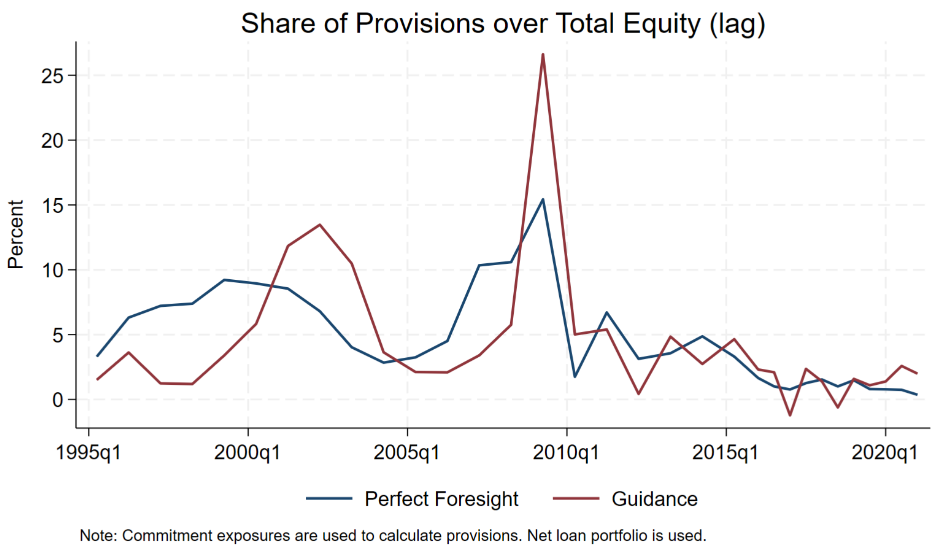

Figure 6. Additional Provisions as a share of Total Lagged Equity

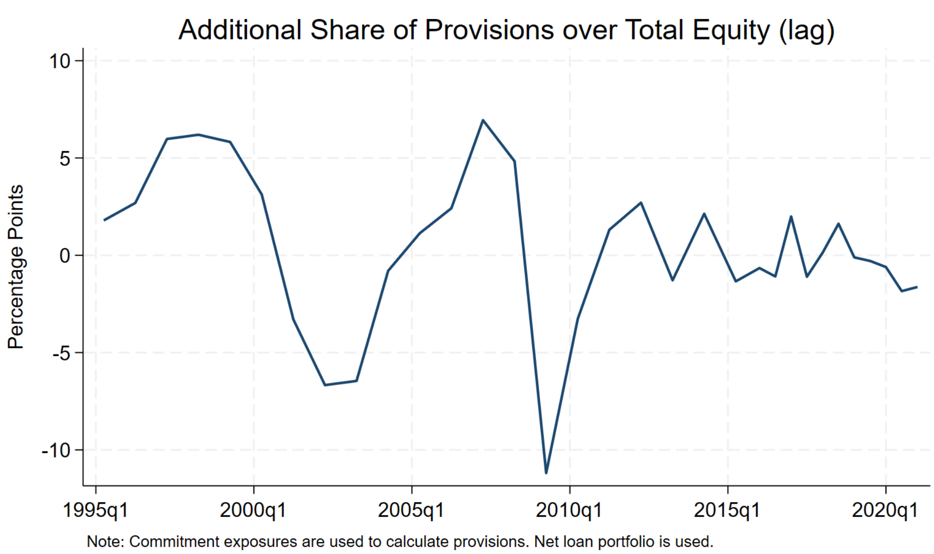

Figure 7. Provisions as a share of Total Lagged Equity

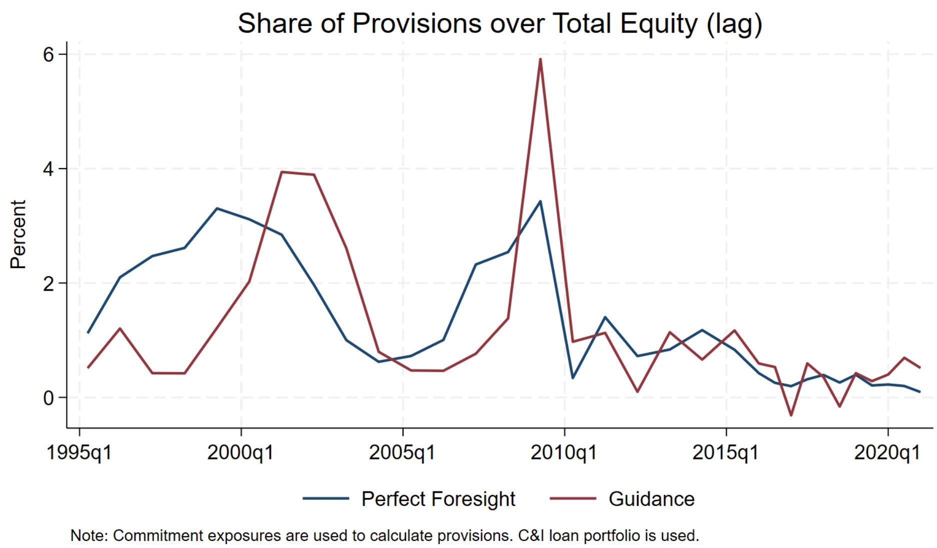

Figure 8. Additional Provisions as a share of Total Lagged Equity

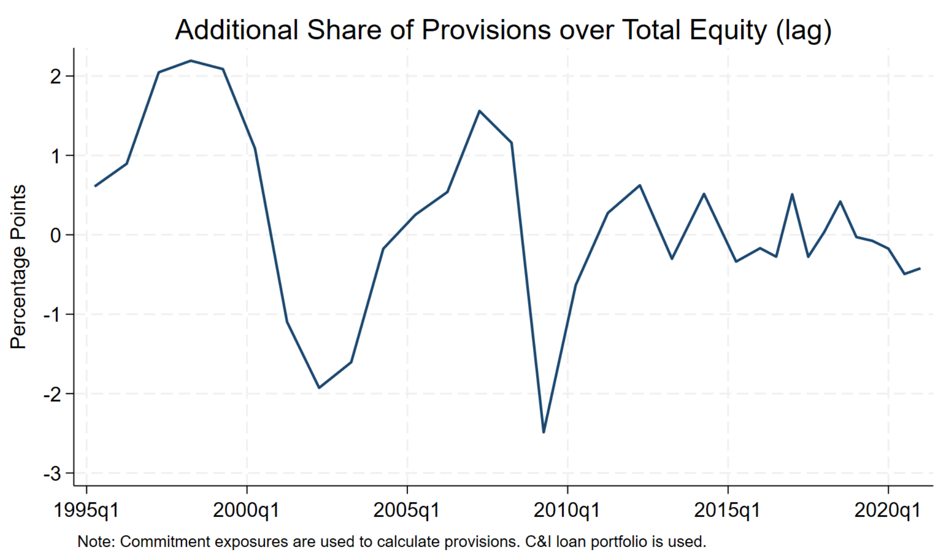

Table I. Summary Statistics

	p10	p50	Mean	p90	St. Dev.	N
Credit:						
Rating	1.00	1.00	1.25	2.00	0.72	203,389
Δ Rating	0.00	0.00	0.07	0.00	0.47	203,389
Read	0.00	0.00	0.30	1.00	0.46	34,113
Mandatory	0.00	0.00	0.14	1.00	0.34	34,113
Downgrade	0.00	0.00	0.03	0.00	0.16	21,078
Utilized % of Loan Commitment	0.00	0.65	0.56	1.00	0.42	203,283
Log(Utilized Exposure)	15.89	18.07	17.94	19.93	1.74	160,850
All-In-Drawn Spread	45.00	175.00	212.41	425.00	167.14	25,371
Borrower:						
Initial Log(Assets)	5.89	7.87	7.95	10.13	1.62	39,027
Initial Cash/Assets	0.00	0.04	0.07	0.19	0.10	39,023
Initial Market Leverage	0.19	0.43	0.45	0.73	0.20	31,399
Initial EBITDA/Assets	0.06	0.12	0.13	0.22	0.07	36,789
Initial Stock Ret. Vol.	0.09	0.14	0.16	0.25	0.07	34,553
Bank:						
$\text{Equity}_{t+1}/\text{Assets}_t$	0.07	0.10	0.11	0.15	0.05	999
Asset Growth_{t+1}	-0.03	0.01	0.02	0.08	0.06	999
Loan growth_{t+1}	-0.03	0.01	0.02	0.06	0.07	999
C&I Loan Growth_{t+1}	-0.07	0.01	0.02	0.08	0.11	999

This table summarizes the characteristics of credits, borrowers, and banks in the sample. *Rating* is the regulatory rating of the loan, Δ Rating is the change in rating from time t to $t+1$. *Read* dummy is equal to one if the loan is read, *Mandatory* dummy is equal to one if the loan is a mandatory read, and *Downgrade* dummy is equal to one if the loan is downgraded. *Utilized % of Loan Commitment* is the utilized percentage of the loan commitment, and *Log(Utilized Exposure)* is the the logarithm of the loan's utilized amount. *Log(All-In-Drawn Spread)* is the all-in-drawn spread of the loan at initiation. *Initial Log(Assets)* is the logarithm of borrower's total assets at origination, *Initial Cash/Assets* is borrower's cash over total assets at origination, *Initial Market Leverage* is borrower's total liabilities over market value at origination, *Initial EBITDA/Assets* is borrower's EBITDA over total assets at origination, *Initial Stock Ret. Vol.* is borrower's stock return volatility at origination. For the banks, $\textit{Equity}_{t+1}/\textit{Assets}_t$ is one-quarter ahead equity over total assets at time t, *Asset* $\textit{Growth}_{t+1}$ is one-quarter ahead quarter-on-quarter asset growth, *Loan* $\textit{growth}_{t+1}$ is one-quarter ahead quarter-on-quarter loan growth, and *C&I Loan* $\textit{Growth}_{t+1}$ is one-quarter ahead quarter-on-quarter commercial and industrial loan growth.

Table II. Ratings Transition Matrix

	Rating$_t$					
Rating$_{t-1}$	1	2	3	4	5	Total
1	95.04	2.56	2.01	0.22	0.16	100.00
2	25.13	47.13	23.20	2.68	1.85	100.00
3	10.32	5.70	69.55	7.08	7.33	100.00
4	3.05	1.49	17.75	46.07	31.64	100.00
5	2.69	0.70	23.73	14.16	58.72	100.00
Total	86.90	4.51	6.43	1.06	1.10	100.00

This table reports the probability of going from one rating at time $t-1$ to another rating at time t.

Table III. Ratings Inflation

		F-Tests on Fixed Effects For: F-stat, p-value, no of constraints							
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)
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		

This table reports the results for fixed effects panel regressions. The dependent variable is the change in the SNC rating and the fixed effects include the following: 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 IV. Ratings inflation and loan exposures

	(1)	(2)	(3)	(4)
Utilized % of Loan Commitment	0.096***		0.120***	
	(0.000)		(0.000)	
Log(Utilized Exposure)		0.003***		0.003***
		(0.000)		(0.000)
Lag(Reg. Rating)			-0.107***	-0.096***
			(0.000)	(0.000)
Constant	0.015***	0.030**	0.128***	0.147***
	(0.000)	(0.026)	(0.000)	(0.000)
No of Obs.	203,283	160,850	203,283	160,850
R^2	0.0455	0.0448	0.0623	0.0582
FE	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time
Cluster	Obligor	Obligor	Obligor	Obligor

This table reports results of regressions of the change in SNC ratings on measures of agent banks' loan exposures. *Utilized % of Loan Commitment* is the utilized percentage of the loan commitment, *Log(Utilized exposure)* is the the logarithm of the loan's utilized amount. 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. Ratings inflation and obligor characteristics at loan issuance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial Log(Assets)	-0.013***					-0.011***	-0.013***
	(0.000)					(0.000)	(0.000)
Initial Cash/Assets		-0.079***				-0.026	-0.025
		(0.001)				(0.344)	(0.405)
Initial Market Leverage			0.111***			0.082***	0.127***
			(0.000)			(0.001)	(0.000)
Initial EBITDA/Assets				-0.218***		-0.124**	-0.137**
				(0.000)		(0.044)	(0.036)
Initial Stock Ret. Vol.					0.580***	0.385***	0.524***
					(0.000)	(0.000)	(0.000)
Lag(Reg. Rating)							-0.136***
							(0.000)
Constant	0.142***	0.047***	-0.010	0.071***	-0.048***	0.049*	0.171***
	(0.000)	(0.000)	(0.123)	(0.000)	(0.000)	(0.088)	(0.000)
No of Obs.	39,027	39,023	31,390	36,785	34,590	28,211	28,211
R^2	0.0509	0.0491	0.0533	0.0471	0.0574	0.0639	0.0856
FE	Agent	Agent	Agent	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time	Time	Time	Time
Cluster	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor	Obligor

This table reports results for regressions of the change in SNC ratings 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 VI. Ratings inflation and loan characteristics

	(1)	(2)	(3)	(4)
Log(All-in-Drawn Spread)	0.032***		0.042***	
	(0.000)		(0.000)	
Quintile: 2		0.036***		0.040***
		(0.000)		(0.000)
Quintile: 3		0.043***		0.051***
		(0.000)		(0.000)
Quintile: 4		0.056***		0.072***
		(0.000)		(0.000)
Quintile: 5		0.085***		0.108***
		(0.000)		(0.000)
Lag(Reg. Rating)			-0.110***	-0.110***
			(0.000)	(0.000)
Constant	-0.108***	0.013**	-0.033	0.128***
	(0.000)	(0.017)	(0.129)	(0.000)
No of Obs.	25,371	25,371	25,371	25,371
R^2	0.0533	0.0535	0.0682	0.0684
FE	Agent	Agent	Agent	Agent
FE	Time	Time	Time	Time
Cluster	Obligor	Obligor	Obligor	Obligor

This table reports results for regressions of the change in SNC ratings on origination loan spreads. Columns (1) and (3) include the level of the all-in-drawn spread, columns (2) and (3) include the deciles of all-in-drawn spread. Columns (3) and (4) also include lagged regulatory rating. 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 VII. Effect of supervision on loan ratings

	Current Exam Rating – Previous Exam Rating		
	(1)	(2)	(3)
Read	0.046***		0.054***
	(0.001)		(0.000)
Mandatory		-0.088**	-0.098**
		(0.030)	(0.016)
Constant	0.110***	0.136***	0.121***
	(0.000)	(0.000)	(0.000)
No of Obs.	34,113	34,113	34,113
R^2	0.431	0.431	0.432
FE	Agent-Bucket-Time	Agent-Bucket-Time	Agent-Bucket-Time
Cluster	Obligor	Obligor	Obligor

This table reports results for regressions of 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. 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. Effect of supervision on loan ratings

	Agent Rating - Previous Exam Rating			Current Exam Rating - Agent Rating		
	(1)	(2)	(3)	(4)	(5)	(6)
Read	-0.001		0.010	0.047***		0.043***
	(0.952)		(0.385)	(0.000)		(0.000)
Mandatory		-0.150***	-0.152***		0.063***	0.054***
		(0.000)	(0.000)		(0.001)	(0.006)
Constant	0.110***	0.131***	0.128***	0.000	0.006*	-0.006**
	(0.000)	(0.000)	(0.000)	(0.989)	(0.067)	(0.040)
No of Obs.	34,113	34,113	34,113	34,113	34,113	34,113
R^2	0.438	0.440	0.440	0.274	0.273	0.275
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

This table reports results of regressions of 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)-(3) and the difference between the current exam rating and agent bank rating in columns (4)-(6). 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. Supervision spillovers

	Contemporaneous Spillovers		Future Spillovers			
	(1)	(2)	(3)	(4)	(5)	(6)
Read	0.047***	0.038***	0.007	0.011		
	(0.000)	(0.000)	(0.673)	(0.534)		
Read * Read %		0.341**		0.076		
		(0.022)		(0.664)		
(1-Read) * Read %		-0.091		0.661**		
		(0.218)		(0.024)		
Down					-0.329***	-0.335***
					(0.000)	(0.000)
Down * Down %						0.281
						(0.421)
(1-Down) * Down %						-0.192
						(0.831)
Constant	0.000	-0.002	0.055***	0.050***	0.066***	0.066***
	(0.989)	(0.514)	(0.000)	(0.000)	(0.000)	(0.000)
No of Obs.	34,113	34,113	21,078	21,078	21,078	21,078
R^2	0.274	0.275	0.244	0.244	0.251	0.251
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 the dependent variable 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 X. Ratings inflation at the bank level

	Equity$_{t+1}$/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 reports results of regressions of 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.