The Informational Advantage of Specialized Monitors: The Case of Bank Examiners

Robert DeYoung
Federal Reserve Bank of Chicago

Mark J. Flannery
University of Florida

William W. Lang
Office of the Comptroller of the Currency

Sorin M. Sorescu
University of Houston

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Please direct all comments to Robert DeYoung, Federal Reserve Bank of Chicago, Economic Research – 11th Floor, 230 South LaSalle Street, Chicago, IL 60604, or robert.deyoung@chi.frb.org.

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Abstract: Large commercial banking firms are monitored by specialized private-sector monitors *and* by specialized government examiners. Previous research suggests that bank exams produce little useful information that is not already reflected in market prices. In this article, we apply a new research methodology to a unique data set, and find that government exams of large national banks produce significant new information which financial markets do not fully internalize for several additional months. Our results indicate that specialized government monitors can identify value-relevant information about private firms, even if those firms are already actively followed by investors and their private-sector agents.

The asymmetry of information between firm insiders and outside investors constitutes an important problem in corporate finance. A firm will incur relatively high costs of raising external capital when it is costly for individual investors to obtain detailed information about the firm's activities. Without this information, a firm's outside claimants may also have trouble monitoring and disciplining the firm's managers, who otherwise may shirk or divert the firm's resources to their own private purposes. Specialized monitoring institutions (e.g., bond rating agencies, underwriters, auditors, bank lenders) can reduce the asymmetry between inside and outside information by devoting specialized resources to these monitoring and information problems. Previous studies have established that specialized outside monitors can obtain information that is not known to individual investors, which suggests that these outside monitors are able to observe a more accurate signal of firm quality than individual market participants find it optimal to obtain. "Outside" members of the board of directors provide a similar service for the firm's investors by monitoring and disciplining the firm's managers.

While most U.S. corporations are subject to the scrutiny of some form of private-sector monitor, many industries face the *additional* scrutiny of government inspectors.[1] Government inspections gather specialized information about firm operations, and are generally empowered to take corrective action when they observe unfavorable signals. While specialized monitors in the private sector are generally believed to provide valuable services (otherwise, it is argued, they would fail and exit the industry), government inspectors operate under different incentives and economic pressures. It is therefore interesting to determine whether specialized government monitors can also obtain information which is unknown to market participants.

This paper investigates this general question in the context of the U.S. commercial banking sector, which is prominently supervised by both government and market agents. Approximately once every 12 to 18 months, federal or state supervisors examine each U.S. commercial bank to assess its safety and soundness. At the close of each exam, the supervisor

[1] Examples include the banking, transportation, health, and nuclear power sectors.

assigns a CAMELS rating, which summarizes the bank's Capital adequacy, Asset quality, Management, Earnings, Liquidity, and (beginning January 1997) the bank's Sensitivity to market risk.[2] These ratings are derived from a combination of publicly available information (such as recent financial statements) and private information produced by bank examiners during their investigation (such as the quality of individual loans). Supervisors report these ratings only to a few top officials at the bank, who may not reveal them to employees, customers, or financial market participants. Even though these ratings are kept secret, banks prefer to have a good CAMEL rating because it can affect how much capital a bank must hold, what activities it may undertake, how much it pays for deposit insurance, and how frequent and rigorous future exams will be.

In comparing CAMEL ratings against various market assessments of bank condition, most previous researchers have concluded that bank exams reveal little useful information that is not already reflected in market prices. This paper applies a new research methodology to a unique data set, and concludes that bank exam ratings contain useful private information about bank safety and soundness which is *not* already known by financial markets. Using a three-step approach, we evaluate the private supervisory information contained in the CAMEL ratings of national bank subsidiaries of holding companies that have traded debentures outstanding. First, we regress each bank's CAMEL rating on publicly available financial data that were available at the time of the bank's most recent examination. The residuals from this (ordered logit) regression proxy for the private information known only to bank supervisors. Next, we compute an option-adjusted risk premium on the subordinated debt of the holding companies that own our sample banks. Finally, we test whether, when, and to what degree the market incorporates the private supervisory information into the risk premium paid on holding company debentures.

[2] CAMELS ratings range in whole numbers from 1 (strong performance and practices, posing the least supervisory concern) to 5 (critically deficient performance, posing the most supervisory concern). For more details, see OCC Bulletin 97-1, "Uniform Financial Institutions Rating System and Disclosure of Component Ratings," Office of the Comptroller of the Currency, January 3, 1997. Prior to 1997, bank regulators did not assign a market sensitivity (S) rating. Because our investigation uses pre-1997 data, we will refer to CAMEL ratings, rather than CAMELS ratings, for the remainder of the paper.

Our empirical results clearly indicate that bank exams produce private information that financial markets find useful, and that the market learns some of this information only a few months subsequent to the exam. These results demonstrate that specialized government monitors can successfully identify value-relevant information about private firms, even when those firms are followed and analyzed by a large number of investors and their private-sector agents. We conjecture that government examinations of small banking firms (which are scrutinized by fewer private sector monitors) will produce greater amounts of new information than identified here for subsidiaries of the largest U.S. banking companies.

1. Literature Review

Previous studies have examined the informational advantage of specialized monitors over the marginal stock or bond investor (whose opinion is reflected in security prices). Some test directly whether private monitors gather information that is unknown to individual investors. Others treat the announcement of a monitoring relationship as an event, and test whether the stock market reaction reflects a perceived enhancement in firm value. Finally, a number of studies have investigated whether government assessments of banking firms' condition are more accurate or timely than those of market analysts (investors).

Hand, Holthausen and Leftwich [1992] examine the impact of bond rating changes on a firm's excess bond and stock returns. They use an expectation model to classify rating changes as either expected or unexpected. While expected announcements produce no reaction in either the bond or stock markets, unexpected *downgrade* announcements cause significantly negative bond and stock returns. By contrast, they find little evidence of a positive bond price reaction to unexpected *upgrade* announcements. This asymmetry suggests that managers are more willing to release "good" news than "bad" news, and that bond credit analysts specialize in obtaining accurate signals of deteriorating asset quality. Our empirical analysis allows for this same type of asymmetry, which we find to be quite important for bank examiners.

Empirical studies have also documented the impact of other private monitors on firm value.[3] For example, underwriter quality has been shown to influence the extent of IPO underpricing (Beatty and Ritter [1986], Carter and Manaster [1990]), as has the identity of an IPO firm's auditors (Beatty [1989]). A long literature documents the positive effect of bank loan announcements on a firm's stock price (e.g., Mikkelson and Partch [1986], James [1987], Lummer and McConnell [1989]), including the finding that announced loans from higher-quality lenders are associated with more positive borrower abnormal returns (Billett, Flannery, and Garfinkel [1995]). Finally, Brennan and Subramanyam [1995] report that the equity of firms which are followed by a larger number of investment analysts trade with smaller bid-ask spreads, reflecting lower informational asymmetries across traders in the market.

Another stream of relevant research has focused on the informational content of bank CAMEL ratings. Hirschhorn [1987] used a multi-factor market model to predict quarterly stock returns for the 15 largest U.S. banks between 1979 and 1987. He included both contemporaneous CAMEL ratings and lagged quarter-to-quarter changes in CAMEL ratings as explanatory variables. Although the lagged CAMEL values were not useful for predicting stock returns, Hirschhorn found that contemporaneous CAMEL ratings were significantly related to stock returns. These results suggest that exam ratings contain useful information, but that most of this information is not private -- market participants have either independently inferred this information at the time of the exam, or this information has been leaked shortly after the exam was completed.

Cargill [1989] studied the effect of CAMEL ratings on the interest rates paid on large certificates of deposits (CDs) at 58 U.S. banks during 1984-986. Presumably, CAMEL ratings should be more closely related to deposit risk premia than to equity returns, since depositors and examiners both care most about down-side risk, while equity holders care about both upside and downside risk. Nevertheless, Cargill found that CAMEL ratings contributed little or no

[3] Chemmanur and Fulghieri [1994] provide some theoretical support for these studies, in the form of a model in which security underwriters' reputational capital leads them to function faithfully as specialized monitors in a repeated game.

explanatory power when added to regressions of large CD rates on market risk measures.

Berger and Davies [1994] evaluate the impact of CAMEL rating changes on the parent holding company's stock price. They separate stock price changes into two components: a ‘private information’ effect (which identifies the public's awareness of new information discovered by examiners), and a ‘regulatory discipline’ effect (which values the regulators' presumed ability to force a bank to change its behavior). Berger and Davies' empirical results provide only weak evidence of a regulatory discipline effect, but they find a strong private information effect. However, the information effect applies only to CAMEL downgrades, which tend to precede stock price declines. Consistent with the findings of Hand, Holthausen and Leftwich [1992], Berger and Davies find no movement in stock prices following a CAMEL upgrade.

Berger, Davies, and Flannery [1998] apply Granger causality analysis to the leading and lagging relationships between exam ratings and the actions of bank stakeholders in financial markets for 184 bank holding companies between 1989 and 1992. They find that lagged movements in BOPEC ratings (the safety and soundness ratings for bank holding companies) explain 1.6 percent of the ‘additional’ variation in shareholder market variables (i.e., stock returns, changes in insider and institutional shareholdings), but explain 4.1 percent of the ‘additional’ variation in bond ratings.[4] This is not surprising, since the objectives of bank supervisors are more closely aligned with those of bank creditors.

Previous research also suggests that the information in supervisory (CAMEL) assessments will deteriorate over time. Cole and Gunther [1998] found that new (less than 6 months old) CAMEL ratings more accurately predict bank financial distress than financial ratios can, but that financial ratios are better predictors than older (more than 6 months old) CAMEL ratings. O’Keefe and Dahl [1996] conclude that this result may be asymmetric: they found that CAMEL ratings became less reliable over time for banks with deteriorating finances, but not for banks with improving financial condition.

[4] Berger, Davies and Flannery [1998] define ‘additional’ variation as the variation not already accounted for by lagged values of the market variables themselves.

We study the ability of government monitors to extract new, value-relevant information about banking firms, using an unusual data set which combines public and private assessments of bank condition over a relatively turbulent macroeconomic period (1989-1995). Because bond investors and government examiners share a primary concern about a bank's probability of failure, we expect that examiners' private information is more likely to be relevant to bond investors than to stock investors. Our empirical specifications reflect two key features of the existing literature: the asymmetric ability of monitors to identify new "bad" information and the plausible notion that the value of examiners' assessments declines with the passage of time. At the same time, our methodology adds two important features to previous studies. First, we differentiate between a "raw" CAMEL rating and the component of the rating which reflects examiners' *private* information. Second, we explicitly compare current examiner assessments with subsequent market assessments, to determine whether the market ultimately ratifies examiner opinions.

2. Methodology

We seek to determine whether bank exams produce unique information that is not already known to financial market participants. Our tests require two primary pieces of data: a measure of the market's information about the examined bank, and a proxy for the information produced during a bank exam. We measure the market's assessment of bank condition by the option-adjusted risk premium (called *SPREAD*) on subordinated debt issued by the bank's parent holding company. Previous research has concluded that these spreads accurately reflect holding company risk exposures, at least after regulators had withdrawn conjectural guarantees of debentures after about 1989 (Flannery and Sorescu [1996]). We use subordinated debt rather than an equity-related measure of bank condition because the safety and soundness objectives of bank supervisors are more closely related to the concerns of bank debtholders: the primary concern of both bank supervisors and bank debtholders is the down-side risk that a bank will default.

We measure the "private" information produced during a bank exam by estimating an ordered logit model of the CAMEL ratings for each of the banks in our sample.[5] Regressing each bank's CAMEL ratings on its most recent public financial information (from the quarterly condition reports) isolates the private information known only by the bank examiner in the regression residuals. We aggregate this estimate of examiners' private information across all banks in the same holding company, and use it to explain subsequent changes in the holding company's debenture *SPREAD*. A finding that the CAMEL residuals significantly explain subsequent changes in *SPREAD* would indicate that examiners learn relevant information before it becomes known to public investors.

2.1 *"Private" Examiner Information about Bank Condition*

Examiners form assessments of bank condition on the basis of both public and private information. Using available financial statements to represent publicly available information, we can decompose examiners' total information using a regression of the form:

$$(1) \qquad Y_{i,t} = \mathrm{f}(\ [\textit{bank financial ratios}]_{t-1}\ ) + \varepsilon_{i,t}$$

where $Y_{i,t}$ is examiners' total information about bank i at time t, the $\textit{bank financial ratios}_{t-1}$ are assumed to reflect the most recently available public information about bank i,[6] and the residual term $\varepsilon_{i,t}$ measures the examiners' private information about bank i at time t.

We cannot observe Y directly, but we can observe bank CAMEL ratings. CAMEL ratings sort banks into five discrete safety and soundness categories. It is generally accepted that the

[5] We use bank CAMEL ratings to measure private examiner information, rather than the BOPEC rating of the parent company that issued the subordinated debt, for two reasons. First, most holding companies hold primarily bank assets. Hall, Meyer, and Vaughan [1997] find a 0.93 correlation between bank holding company BOPEC ratings and the "B," or "bank," component of this rating. Second, CAMEL information is likely to be more timely than BOPEC information for our purposes, since the "B" component of BOPEC is basically an asset-weighted average of the CAMEL ratings previously assigned to subsidiary banks. (Berger, Davies and Flannery [1998] explain the relation between BOPEC and CAMEL ratings.)

[6] In alternative regression specifications, we augmented the vector of bank financial ratios to include both the bond rating and the market-to-book ratio of the parent holding company. Adding these two variables had very little effect on the regression results, which we do not report because missing values reduced our number of observations by about 25%.

difference in safety and soundness across these five categories is not linear: the difference between 1-rated and 2-rated banks is not necessarily equal to the difference between 2-rated and 3-rated banks, between 3-rated and 4-rated banks, etc. Thus, after replacing the unobservable cardinal variable *Y* with the observable ordinal variable *CAMEL*, we use an ordered logit model to estimate the following equation:

$$(2) \qquad CAMEL_{i,t} = \mathrm{f}(\ [\mathit{bank\ financial\ ratios}]_{t-1}\ ) + \varepsilon_{i,t}$$

where $CAMEL_{i,t}$ is the rating produced by an examination of bank *i* at time *t*.[7] The vector of $\mathit{bank\ financial\ ratios}_{t-1}$ contains publicly known financial information about bank *i* at the quarter-end date that most recently precedes the exam date *t*. Banks are typically examined only once every 12 to 18 months, so even though we observe each bank multiple times during our sample period, the majority of banks will be unexamined in any given quarter. Once (2) is estimated, we can construct the private information residual term ε as follows:

$$(3) \qquad \hat{\varepsilon}_{i,t} = CAMEL_{i,t} - \sum_{\rho=1}^{5} \rho * Prob_{\rho,t}(CAMEL = \rho)$$

where each of the five probabilities $Prob_{i,t}(CAMEL=D)$ are generated from the estimated parameters of the ordered logit model (2). Multiplying each of these estimated probabilities by its corresponding ρ value (ρ = 1,2,3,4,5) and summing generates the *expected* CAMEL rating for bank *i* based on publicly available financial information at time *t*. If variables on the right-hand-side in (2) reasonably approximate the publicly available information about the bank's financial condition, then the estimated residuals $\hat{e}_{i,t}$ will measure private information about the bank known only to the bank supervisor. A positive (negative) residual suggests that examiners have bad

[7] See Greene [1997, p. 926] for further details on the ordered logit model.

(good) private news about the bank.[8]

Our ultimate objective is to test whether examiners' private information about banks (ε) can predict the market-determined risk premia on bank holding company subordinated debt (*SPREAD*). Before running such a test we must first combine the private examiner information about the banks in each holding company. This task is complicated by the fact that banks are examined on an irregular schedule that is not coordinated across the various banks in a holding company. We address these timing and aggregation issues by constructing a private information variable for each holding company *j* at the end of each quarter *t*:

$$(4) \qquad PRIVINFO_{j,t} = \left(\frac{\sum_{i=1}^{m} assets_i}{total\ \ assets_j} \right) * \sum_{i=1}^{m} \left(\frac{assets_i}{\sum_{i=1}^{m} assets_i} \right) * \hat{e}_{i,t}$$

$PRIVINFO_{j,t}$ is an asset-weighted average of the *most recent* private information ($\hat{e}_{i,t}$) for each bank *i* in holding company *j* at the end of each quarter *t*. Our data set includes CAMEL ratings only for national banks, so we can estimate ε only for the national banks in each holding company. To ensure that the asset weights (the second bracketed term) sum to unity, the denominator includes only the assets held by the *m* (i=1,m) national bank affiliates in holding company *j*. However, since most bank holding companies also hold the assets of state chartered banks and/or non-bank operating subsidiaries, we scale $PRIVINFO_{j,t}$ by the proportion of holding company *j*'s assets that come from national banks (first bracketed term). This construction effectively places less weight on the holding companies for which national banks comprise a smaller percentage of total assets.[9] As with the estimated residual $\hat{e}_{i,t}$, a positive (negative) value for $PRIVINFO_{j,t}$ implies that examiners have bad (good) private news about the bank holding company on average.

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[8] Berger and Davies [1994] use the simple change in CAMEL ratings to measure examiners' potential private information. Our approach in (3) provides a less discrete measure of examiner information and separates out the component in the CAMEL rating that was already known to public market investors.

[9] As we report below, our test results are largely unaffected when we exclude holding companies for which national banks constitute less than 75% or less than 90% of total assets.

Previous literature has determined that managers voluntarily release "good" news more readily than they release "bad" news (Hand, Holthausen, and Leftwich [1992]). In order to test whether this phenomenon affects the quality of the information examiners typically acquire, we disaggregate $PRIVINFO_{j,t}$ into good and bad private information. Our "bad" private information variable is:

$$(5) \qquad BADNEWS_{j,t} = \left(\frac{\sum_{i=1}^{m} assets_i}{total\ \ assets_j} \right) * \sum_{i=1}^{B} \left(\frac{assets_i}{\sum_{i=1}^{m} assets_i} \right) * \hat{e}_{i,t}$$

where the summation from i=1 to i=B includes only banks for which examiners have bad information, i.e., banks for which $\hat{e}_{i,t}$ >0. *BADNEWS* equals zero if $\hat{e}_{i,t}$ #0 for all of the national bank affiliates in holding company *j*. Our "good" private information variable is:

$$(6) \qquad GOODNEWS_{j,t} = \left(\frac{\sum_{i=1}^{m} assets_i}{total\ \ assets_j} \right) * \sum_{i=1}^{G} \left(\frac{assets_i}{\sum_{i=1}^{m} assets_i} \right) * \hat{e}_{i,t}$$

where the summation from i=1 to i=G includes only banks for which examiners have good information, i.e., banks for which $\hat{e}_{i,t}$ <0. *GOODNEWS* equals zero if $\hat{e}_{i,t}$ $ 0 for all of the national bank affiliates in holding company *j*.

2.2 *The Market's Assessment of Bank Condition*

Normally we would expect the risk premium on a corporation's debentures to change when the public gains new information about the firm's condition, in particular upon the release of new financial statements. We might model this relationship as follows:

$$(7) \qquad \Delta SPREAD_{j,t} \;=\; \gamma * \Delta HC_{j,t} \;+\; \eta_{j,t}$$

where $SPREAD_{j,t}$ is the option-adjusted risk premium on the subordinated debt of holding company j at time t, computed as in Flannery and Sorescu [1996]; $\Delta SPREAD_{j,t}$ is the one-quarter change in *SPREAD* between the end of quarters t-1 and t; $\Delta HC_{j,t}$ is the one-quarter change in a vector of public information about holding company j between the end of quarters t-1 and t; and $\eta_{j,t}$ is a normally distributed random disturbance term.[10] Specifying both the dependent variable *SPREAD* and the holding company variables *HC* as changes rather than levels cancels-out the effects of fixed company-specific variables omitted from the specification and obviates the need for an intercept term.

The market often learns about changes in a firm's financial condition before these changes are reflected in financial statements. In equation (7), any change in the risk premium ($\Delta SPREAD$) based on information not yet reflected in financial statements (ΔHC) will remain in the residual term (η). Adding our measure of private examiner information (*PRIVINFO*) to the right-hand-side of (7) allows us to test whether bank examinations uncover some of this "not-yet-public" information about bank safety and soundness; that is, to test whether the private information in CAMEL ratings is *relevant* to financial markets. We augment (7) as follows, which we will estimate using nonlinear least squares:

$$(8) \qquad \begin{aligned} \Delta SPREAD_{j,t} \;=\; & \alpha * PRIVINFO_{j,t} * e^{\beta * AGE_{j,t}} \;+\; \gamma * \Delta HC_{j,t} \;+\; \delta * SPREAD_{j,t\text{-}1} \\ & + \lambda * Q_t \;+\; \eta_{j,t} \end{aligned}$$

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[10] Specifying both the dependent variable *SPREAD* and the holding company variables *HC* as changes rather than levels washes out the effects of any omitted company-specific variables and obviates the need for an intercept term.

where $PRIVINFO_{j,t}$ is defined above; $AGE_{j,t}$ is the asset-weighted average (across the holding company's national bank subsidiaries) of the number of days elapsed between each subsidiary bank's most recent exam and the end of quarter *t*; $SPREAD_{j,t-1}$ is the lagged risk premium; and Q_t is a vector of quarter dummies.

The interactive specification of *AGE* and *PRIVINFO* in (8) in essence "weights" the value of private examiner information by its vintage. If examiners' assessments become less informative as time passes (either because the holding company's true situation becomes public or because its financial condition changes), then the effect of those assessments on *SPREAD* should diminish with *AGE*. That is, β should be negative.[11] Figure 1 illustrates, for two reasonable values of β, the effect of using AGE to weight our private information variable. A smaller value for β implies that exam information remains relevant for a longer period of time. Rather than imposing a shape on the decay of private information, we permit the data to determine the best value for β. We include the lagged risk premium ($SPREAD_{j,t-1}$) in (8) to allow for mean reversion in the dependent variable, and the quarter dummies Q_t to capture systematic changes in economic and regulatory conditions.

A significant effect of *PRIVINFO* on SPREAD within the same calendar quarter in equation (8) would indicate that the bond market learns and incorporates at least some of the information produced by bank examiners during the quarter in which the exam occurred.[12] Equation (8), however, is not useful for revealing whether *PRIVINFO* systematically *predates* *SPREAD*. If private examiner information predates the market's assessments of bank holding company condition, and if this private information becomes public only slowly, we should be able to predict future changes in *SPREAD* from estimates of current *PRIVINFO*. We test the predictive power of *PRIVINFO* as follows:

[11] Cole and Gunther [1998] report that CAMEL ratings can predict failure more accurately than financial ratios can, but only if the ratings are less than 6 months old.

[12] The bond market might learn this information independent of the bank examination, or via a leak of exam information from the supervised bank. An econometrician cannot discriminate between these two hypotheses.

$$(9) \qquad \Delta SPREAD_{j,t+k} = a * PRIVINFO_{j,t} * e^{b*AGE_{j,t}} + d * SPREAD_{j,t} + l * Q_t + h_{j,t}$$

where $\Delta SPREAD_{j,t+k}$ measures the (future) change in *SPREAD* between the end of quarter *t* and the end of quarter *t+k*, and $SPREAD_{j,t}$ is assumed to capture all public information about holding company *j* at time *t*.[13] Statistically significant effects of *PRIVINFO* and *AGE* in (9) would be consistent with the hypothesis that bank examinations produce at least some value-relevant information that is not immediately impounded in debenture prices.

We modify equations (8) and (9) to allow for the possibility that "good" private examiner information may affect *SPREAD* differently than does "bad" private examiner information, perhaps because banks prefer to announce good information promptly but tend to obscure bad information. We therefore estimate a "non-symmetric" version of (8):

$$(10) \qquad \begin{aligned} \Delta SPREAD_{j,t} = {} & a_G * GOODNEWS_{j,t} * e^{b_G * AGE^G_{j,t}} + a_B * BADNEWS_{j,t} * e^{b_B * AGE^B_{j,t}} \\ & + g * \Delta HC_{j,t} + d * SPREAD_{j,t-1} + \sum l_t * Q_t + h_{j,t} \end{aligned}$$

where AGE^B and AGE^G are, respectively, the asset-weighted average ages of *BADNEWS* and *GOODNEWS* (see equations (5) and (6) above). We also estimate a similar non-symmetric version of (9):

$$(11) \qquad \begin{aligned} \Delta SPREAD_{j,t+k} = {} & a_G * GOODNEWS_{j,t} * e^{b_G * AGE^G_{j,t}} + a_B * BADNEWS_{j,t} * e^{b_B * AGE^B_{j,t}} \\ & + d * SPREAD_{j,t} + \sum l_t * Q_t + h_{j,t} \end{aligned}$$

2.3 *Market Responses to Exam Information*

Knowing whether examiner assessments of bank condition routinely predate the market's assessments of bank condition is crucial for regulatory design. If examiner information does not predate market information, then the government monitor is redundant to specialized private sector monitors. In this case, bank supervisors should reallocate their examination resources to small and moderate-sized banks that are not actively evaluated by private market monitors.

If examiner information does predate market information, then the government monitor is not redundant. The actions of the bank supervisor will be based on its informational advantage, and these actions will likely influence the market's assessment of bank condition. Suppose examiners uncover "bad" private information about the bank's financial condition. This information will eventually become public as examiners require that it be recorded in financial statements (e.g., bad loans) and as specialized private sector monitors uncover bad information with a lag. As the examiner's private information becomes public, the bank's *SPREAD* will increase to reflect greater risk. Call this the "information effect." The supervisor might also impose restrictions or issue warnings designed to reduce risk and halt the bank's deteriorating financial condition. These supervisory actions will eventually become public knowledge, and if the market believes that the actions were appropriate then the bank's *SPREAD* will decrease to reflect reduced risk -- call this the "regulatory discipline effect."[14] Note that both the information effect and the regulatory discipline effect are symmetric. As "good" private examiner information becomes public, the information effect predicts a reduction in *SPREAD* as the market reduces its assessment of risk, and the regulatory discipline effect predicts an increase in *SPREAD* as the market expects less rigorous regulatory oversight.

The information effect and the regulatory discipline effect are not mutually exclusive, so the *net* impact of *PRIVINFO* on *SPREAD* is theoretically ambiguous. We summarize the possible net impacts in Table 1. Consider the first row in Table 1, in which *PRIVINFO* and Δ*SPREAD* are

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[13] We relax this assumption in alternative versions of (9) by adding either $\Delta HC_{j,t}$ or $HC_{j,t}$ as right-hand-side variables (results not reported). This modification had little effect on the signs or the (joint) significance of estimated α or β.

[14] Explicit regulatory action is not the only explanation for a negative sign on $\partial\Delta SPREAD/\partial PRIVINFO$. If an examination produces "bad" information that the bank itself did not previously know or fully appreciate, the bank may take unilateral action to reduce risk to a level it finds more acceptable.

contemporaneously positively correlated (i.e., $\partial\Delta SPREAD_t$ / $\partial PRIVINFO_t$ in equation (8) is positive). This implies that examiners and market investors have learned at least some of the same information by the end of the quarter, but does not indicate whether examiners have an informational advantage over the market at quarter-end.[15] If examiners do have an informational advantage, market participants should discover some of that private information only in subsequent quarters (i.e., $\partial\Delta SPREAD_{t+k}$ / ∂ $PRIVINFO_t$ in equation (9) is not equal to zero). Cell "1" implies that examiners have an informational advantage over market participants that lasts for at least a quarter. Cell "2" implies that examiners have no informational advantage, or that the advantage erodes quickly as market participants learn the examiner's private information before the quarter-end. Cell "3" implies that that examiners have an informational advantage over market participants, but that the "regulatory discipline" effect dominates the "information" effect when market participants learn the private information and incorporate it into market prices.

The second row of Table 1 considers scenarios in which *PRIVINFO* and Δ*SPREAD* are not contemporaneously correlated. Cell "4" provides the strongest possible indication of examiner informational advantage: the market is currently unaware of examiner *PRIVINFO*, but upon learning it in subsequent quarters finds it valuable and impounds it into *SPREAD*. By contrast, cell "5" implies that market prices never reflect examiners' private assessments. This could occur if the market believes that examiner opinions are irrelevant, or if market investors never understand the typical bank's true condition. Cell "6" implies that the market is initially unaware of examiner *PRIVINFO*, but upon learning it in subsequent quarters impounds the regulator's response to this information (rather than the information itself) into *SPREAD*.

Finally, the third row of Table 1 considers scenarios in which *PRIVINFO* and Δ*SPREAD* are contemporaneously negatively correlated (i.e., $\partial\Delta SPREAD_t/\partial PRIVINFO$ in equation (8) is negative). We have no appealing explanation for the possible outcome in cell "7." Cell "8" implies that market participants learn *PRIVINFO* within the quarter, assume from this information

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[15] We also do not know which party learned its information first, or whether the parties learned their information through the same or different channels.

that the supervisor has taken (or soon will take) countervailing measures, and impound the effects of these regulatory actions in *SPREAD*. This same process occurs more slowly in cell "9."

3. Data and Variables

We estimate equation (2) using a panel of quarterly data for 1,079 national banks from the third quarter of 1986 (1986:2) through the first quarter of 1995 (1995:1). We estimate equations (8), (9), (10), and (11) separately using the results from equation (2) and a panel of quarterly data for the 61 parent holding companies from 1989:1 to 1995:1. The shorter 1989-1995 holding company panel corresponds roughly to the post-"too-big-to-fail" period, during which the bond market has been shown to price subordinated bank debt efficiently (Flannery and Sorescu [1996]). The longer 1986-1995 bank panel allows us to generate estimates of *PRIVINFO* for banks in 1989 whose most recent exam rating was up to three years old. Both data panels are unbalanced. Mergers and acquisitions that occurred mid-way through our sample period caused some holding companies to drop out of the data set, while other holding companies only began to issue subordinated debt mid-way through the sample period. Similarly, the commercial bank affiliates associated with these holding companies changed during the sample period due to new bank charters, acquisitions, or failure.

Summary statistics for the variables used in equation (2) are displayed in Table 2. All of these variables are observed at the end of each quarter in which the bank was examined.[16] *CAMEL* is the safety and soundness rating that was assigned at the bank's most recent exam. *lnASSETS* is the natural log of bank assets in 1995 dollars. *ROA* is return on assets, defined as net income over total bank assets. *LIAB/EQ* equals total liabilities divided by total book equity, and measures a bank's leverage. Asset quality is measured by three variables: *NAL*, the ratio of

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[16] We assign bank exams to calendar quarters based on the 'exam approval' date, which is the day the OCC officially closes the exam. This differs from the 'exam end' date, which is the day examiners leave the bank. These dates are generally less than a month apart. The 'exam end' date would be the first date on which complete exam information might unintentionally leak out to the public, while the 'exam approval' date would be the first date that on which supervisors could intentionally release (if they changed current policy and chose to do so) official CAMEL ratings to the public. These distinctions are a moot point for this study, however, because the 'exam end' dates were not available for a substantial portion of the data early in the sample period.

nonaccruing loans to total bank assets; *PD90*, the ratio of loans past due 90 days or more to total bank assets; and *OREO*, the ratio of other real estate owned to bank assets. *GAP* is the absolute value of the bank's one year maturity gap (earning assets repriceable within one year less liabilities repriceable within one year) as a proportion of the bank's equity market value, and is included to measure interest rate risk.[17]

Table 3 reports summary statistics for the bank holding company variables used in estimating equations (8), (9), (10) and (11). All of these variables are observed at the end of every quarter for which the holding company existed, not just in the quarters during which its subsidiary banks were examined. The dependent variable *SPREAD* is the average option-adjusted risk premium on the subordinated debt issues of the holding company.[18] *PRIVINFO* is computed as in equation (4). *AVGAGE* is the weighted average number of days since the affiliate national banks in the holding company have been examined, using the same asset weighting scheme used to construct *PRIVINFO*. The variables *ROA*, *LIAB/EQ*, *NAL*, and *GAP*, *RATING*, and *RELMKTBK* correspond to their bank-level counterparts, and are computed for the consolidated holding company.[19] *RATING* is a weighted average of the Moody's and S&P bond ratings for all of the bonds outstanding at the end of the quarter, and ranges from 1 (equivalent to Moody's Aaa+ rating or S&P AAA+ rating) to 23 (equivalent to Moody's or S&P's D rating).[20]

[17] Several of the variables in Table 2 have extreme outlying values. The outlying values for *LIAB/EQ* and *GAP* are for banks with very small absolute values of equity in the denominator. The outlying values for *ROA* occur because the numerator of this variable is constructed by annualizing (i.e., multiplying by 4) quarterly net income, which exacerbates the volatility of an already volatile number. The 1st and 99th percentiles of the distributions for each of these variables have economically reasonable magnitudes.

[18] *SPREAD* is calculated as follows. For each bond issue, we calculated the difference between the yield to maturity and the maturity-matched rate on Treasury securities, less an option adjustment computed as in Flannery and Sorescu [1996]. *SPREAD* equals the weighted average of these option adjusted risk premia, using the outstanding principal of each bond as weights. *SPREAD* takes on extreme maximum values in Table 3 for some holding companies just prior to defaulting on their debt.

[19] The definition of *GAP* for bank holding companies is the same as in Flannery and Sorescu [1996]. The definition of *GAP* for banks is somewhat different, however, due to changes in bank call reports over the sample period. Details are available from the authors.

[20] Most holding companies have several bond issues outstanding at any given date, and we used all of these bonds (callable and noncallable bonds, floating and nonfloating rates) to construct *RATING*. We began by converting the Moody's and S&P ratings for each bond into numbers from 1 to 23. We then averaged these two numerical ratings together for each bond issue, and computed a weighted average (using each bonds' outstanding principal value) of the mean bond ratings. This method of aggregation is consistent with the one used to construct *SPREAD*. In about 2 percent

RELMKTBK is the ratio of the parent company's market-to-book ratio to the mean market-to-book ratio for all sample companies in the same quarter.

These data were taken from a variety of sources. Debenture data (including call conditions, yield, and *RATING* were taken from the Warga-Lehman Brothers Fixed Income Database (see Warga [1995]). The stock prices and the number of shares outstanding were taken from the CRSP tapes. The bank-level level values of *ASSETS*, *ROA*, *LIAB/EQ*, *NAL*, *PD90*, *OREO*, and *GAP* came from the Reports of Condition and Income ("call reports"), while the holding company values of these variables were constructed from the FRY-9C reports. *CAMEL* ratings and *AGE* were taken from confidential OCC examination records. National bank assets comprised at least 75 percent of total holding company assets for 60.11 percent of these observations, and comprised at least 90 percent of total holding company assets for 38.09 percent of these observations.[21]

4. Results

Table 4 presents the estimation results for the ordered logit (*CAMEL*) equation (2). All of the estimated coefficients are significantly different from zero and have appropriate signs. The negative coefficients on *ROA* and *lnASSETS* indicate that high values of these variables associated "good" (numerically low) CAMEL ratings. Conversely, the positive estimated coefficients on *LIAB/EQ*, *NAL*, *PD90*, *OREO*, and *GAP* indicate that high values for these variables are associated with "bad" (numerically high) CAMEL ratings. The predicted CAMEL rating (i.e., the CAMEL rating to which the model assigned the highest probability) matched the actual CAMEL rating for 79 percent of the observations, so that the model correctly "explained" the CAMEL ratings for about 4 out of 5 banks. Panel 4B shows that the "private information" residuals ε constructed using equation (3) averaged near zero, with a standard deviation of about one-half of a CAMEL rank.

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of our quarterly bank observations, we had data only for the Moody's rating *or* the Standard & Poor's ratings, but not both. Since we could not average across ratings services in those instances, we simply used a single service's rating. When both ratings were available, the correlation between Moody's ratings and Standard & Poor's ratings was 0.93.

[21] We report results using these 75% and 90% subsamples in subsequent footnotes.

4.1 *Contemporaneous DSPREAD Regressions*

Table 5 contains the results of the contemporaneous)*SPREAD* regressions. Consider first the symmetric specification (8), which does not differentiate between "good" and "bad" examiner information. We first note that the two public information variables carry appropriate signs. The coefficient on *PRIVINFO* (which equals the partial derivative M)$SPREAD_t$ / M$PRIVINFO_t$ evaluated at *AGE*=0) is positive, while *AGE* carries a negative coefficient, indicating that the informativeness of private examiner information diminishes as time since the exam passes. Although neither the *PRIVINFO* nor the *AGE* coefficient differs significantly from zero, the calculations at the bottom of the Table indicate that the combined effect of these two variables on)*SPREAD* is significantly positive when private examiner information is neither brand new nor quite old.[22] Specifically, when the exam occurred between 60 and 270 days (*AGE*) before the quarter's end, the effect of *PRIVINFO* on)*SPREAD* is statistically significant and positive, implying that the private information contained in CAMEL ratings is value-relevant for bond investors. The magnitude of this partial derivative declines with *AGE* (because $ is negative), which is consistent with the "shelf-life" results of Cole and Gunther [1998].

The non-symmetric specification (10) fits the data slightly better, but more importantly shows that examiners' BADNEWS is driving the results of the symmetric specification:)*SPREAD* responds significantly to contemporaneous *BADNEWS* but not to contemporaneous *GOODNEWS*. Good information identified during an on-site examination is either irrelevant to market valuations or is already known to market investors. We conjecture that managers disseminate good news promptly to the market, but try to delay the announcement of bad information. Examiners uncover at least some of this bad information, and the significantly positive coefficient on *BADNEWS* indicates that the public knows at least some of this bad

[22] We use a Wald test to determine whether the derivative M∆SPREAD/ MPRIVINFO is statistically different from zero. The value of this estimated derivative and the estimated asymptotic standard error associated with it are functions of AGE. Our point estimates indicate this derivative declines monotonically with AGE, and the estimated standard error increases (and the associated confidence intervals get wider) as AGE moves further from the means of the data. Thus, it is relatively difficult to reject the null hypothesis that M∆SPREAD/ MPRIVINFO = 0 for very small and very large values of AGE.

information within the quarter. We cannot determine whether the public learned this information before or after examiners did. However, the fact that even 270-day-old exam information affects Δ*SPREAD* indicates that at least some examiner *PRIVINFO* becomes known to market investors with only a considerable lag. The magnitude of these estimated effect is quite substantial: the estimated coefficient on *BADNEWS* (about 1.05) indicates that a one standard deviation increase in *BADNEWS* (0.267) increases *SPREAD* by about 28 basis points, which is equivalent to a 13% increase in the risk premium for the average bank holding company in our sample.[23]

4.2 *The Predictive Power of PRIVINFO*

Table 6 displays the relationship between current *PRIVINFO* and *future* Δ*SPREAD*, based on the symmetric specification of private examiner information in equation (9). We estimate this equation twelve separate times, testing whether *PRIVINFO* at time *t* is useful for predicting Δ*SPREAD* one month ahead (*t*+1), two months ahead (*t*+2), etc. As in Table 5, the coefficients on *PRIVINFO* are positive, and the coefficients on *AGE* are negative. Although neither of these coefficients tends to be statistically significantly by itself, their combined effect indicates that exam information that is between 0 and 60 days old is useful for predicting future Δ*SPREAD* up to 9 months into the future. Note that the coefficient on $SPREAD_t$ eventually becomes negative and significant, indicating regression to the mean in the risk premium.

Table 7 shows the results of equation (11), which specifies "good" and "bad" examiner news asymmetrically and hence does not obscure the differential effects of this information on future Δ*SPREAD*. The predominance of *BADNEWS* is readily apparent. *BADNEWS* that is between 0 and 120 days old is useful for predicting future Δ*SPREAD* up to nine months into the future, but current *GOODNEWS* is never a significant barometer of future risk premia.[24]

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[23] We re-estimated equations (8) and (10) for subsamples of holding companies with at least 75% or 90% of their assets in national banks. In all cases, the partial derivatives ∂Δ*SPREAD*/∂*PRIVINFO*, ∂Δ*SPREAD*/∂*GOODNEWS*, and ∂Δ*SPREAD*/∂*BADNEWS* retained the same signs and significance levels as in Table 5, and in some instances the coefficient magnitudes were larger.

[24] We re-estimated equations (9) and (11) for subsamples of holding companies with at least 75% or 90% of their assets in national banks. In virtually all cases, the partial derivatives with respect to private examiner information retained the same signs and significance levels as in Tables 6 and 7, but with slightly larger magnitudes. The only exception was that ∂Δ*SPREAD*/∂*GOODNEWS* was negative and significant in equation (11) for the 2-month prediction of Δ*SPREAD* for

Cole and Gunther [1998] find that the information content of CAMEL ratings diminishes substantially once it is 6 months old. With this result in mind, we estimated alternative versions of equations (10) and (11) that identified two kinds of private exam information: more than 6 months old and less than 6 months old (results not shown). On the right-hand-side of these equations we interacted dichotomous age variables with the asymmetric private examiner information variables ($GOODNEWS*NEW^G$, $GOODNEWS*OLD^G$, $BADNEWS*NEW^B$, and $BADNEWS*OLD^B$), where the dichotomous variable NEW^G=1 for exams bearing good news that are less than 180 days old, OLD^G=1 for exams bearing good news that are more than 180 days old, etc. Consistent with the Table 5 results, both "new" (less than 180 days old) and "old" (more than 180 days old) *BADNEWS* was significantly and positively related to contemporaneous $\Delta SPREAD$, while "new" and "old" *GOODNEWS* were not. Consistent with the Table 7 results, "new" *BADNEWS* was significantly and positively related to future *SPREAD*, while "old" *BADNEWS*, "new" *GOODNEWS,* and "old" *GOODNEWS* were not.

4.3 *Interpretation of Regression Results*

We return to Table 1 to interpret the empirical results presented in Tables 5, 6, and 7. The distinctly different effects of good examiner information and bad examiner information means that we cannot summarize our results in terms of a single cell in Table 1. "Good" examiner information is unrelated to both contemporaneous $\Delta SPREAD$ (Table 5) and future $\Delta SPREAD$ (Table 7). Thus, good news is fully reflected in debenture risk premia within one calendar quarter of the exam. This corresponds to Cell 5 in Table 1: *GOODNEWS* has no marginal impact on *SPREAD*, beyond the information that already lies in the public domain.

By contrast, "bad" examiner information is positively related to both contemporaneous $\Delta SPREAD$ (Table 5) and future $\Delta SPREAD$ (Table 7). This corresponds to Cell 1: a portion of *BADNEWS* is publicly known by the end of the exam quarter, but it is not fully known to the public for at least nine months after the examination is formally completed. The absence of any

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holding companies that held at least 90% of their assets in national banks. This is the only result that corresponds with the "regulatory discipline" effect, and it offers weak evidence that, upon learning good news about a bank, the market significant negative effects of *PRIVINFO* on Δ*SPREAD* in either Tables 5, 6, or 7 implies either the absence of a "regulatory discipline" effect, or that the average exam's "information effect" tends to dominates any "regulatory discipline" effects.[25]

5. Conclusions

Government supervisors operate under non-market incentive and compensation schemes. This has led some observers to conclude that the efforts of government supervisors to gather information and apply prudential discipline will be inferior to those of private analysts and investors operating under more “normal” market incentives. Contrary to these suspicions, our empirical results strongly indicate that bank examiners routinely uncover value-relevant information about the safety and soundness of banks several months before this information is impounded in debenture prices. Thus, bank supervisors act like effective monitors of large banking firms. Furthermore, we find that examiners are more likely to uncover “bad” private information than “good” private information, which is consistent with managers' incentives to obscure bad information but promptly convey good information to the market. In this regard, government bank examiners closely resemble private bond monitors, who also seem particularly adept at uncovering negative new information.

Our results naturally raise two public policy questions. First, does the current combination of government sector and private sector monitors produce more information about bank condition than the purely private arrangements that would evolve in the absence of regular government exams? Other than noting some similarity between the motives of bank supervisors and bond rating agencies, we have little to say about this important regulatory design issue. Our conclusion that government supervisors produce information more quickly than does the market are themselves conditional on the existence of the current "dual" system of monitoring.

Second, would public dissemination of bank examiners' private information improve managerial discipline in the banking sector? Over the past decade, a number of commentators

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might expect less rigorous regulatory oversight.

[25] The sole exception to this is discussed in the previous footnote.

have proposed that bank regulators should publicly disclose exam ratings (e.g., Kane [1991], Scott, Jens, and Spudeck [1991b], Horvitz [1996]). A common argument for disclosing CAMEL ratings is that nondisclosure wastes scarce information which, if released, would improve the market's ability to control and discipline individual banks. Our findings strongly support the notion that information in CAMEL ratings significantly adds to what the market already knows about the safety and soundness of large, publicly traded banking firms. We conjecture further: the value of specialized government monitors is even greater for the small banking firms (excluded from our study) which do not issue traded debentures and are not followed by as many private sector investors and analysts.

Although bank supervisors may feel encouraged by our empirical results, they have plausible reasons to oppose public disclosure of exam ratings (Scott, Jens, and Spudeck [1991a, 1991b], Horvitz [1996]). First, publicly disclosing a poor CAMEL rating might weaken public confidence in the bank at a time when the bank can least afford it. Second, publicizing exam ratings might make the interaction of bankers and examiners more adversarial, thus changing the nature of the exam process and reducing the informativeness of ratings it produces. Maximizing the social value of specialized government monitors may well depend on balancing the efficiency improvements from reduced information asymmetries in public markets with preserving the efficacy of the monitoring process.

References

Beatty, Randolph P. "Auditor Reputation And The Pricing Of Initial Public Offerings," *The Accounting Review*, 1989, v64(4), 693-709.

Beatty, Randolph P., and Jay R. Ritter, 1986, Investment Banking, Reputation, and the Underpricing of Initial Public Offerings, *Journal of Financial Economics* 15, 213-232.

Berger, Allen N., and Sally M. Davies, "The Information Content of Bank Exams," *Bank Structure and Competition*, Federal Reserve Bank of Chicago, May 1994.

Berger, Allen N., Sally M. Davies, and Mark J. Flannery, "Comparing Market and Regulatory Assessments of Bank Performance: Who Knows What When?" Federal Reserve Board of Governors FEDS working paper 1998.

Billett, Matthew T., Mark J. Flannery and Jon A. Garfinkel. "The Effect Of Lender Identity On A Borrowing Firm's Equity Return," *Journal of Finance*, 1995, v50(2), 699-718.

Brennan, Michael J. and Avanidhar Subramanyam. "Investment Analysis And Price Formation In Securities Markets," *Journal of Financial Economics*, 1995, v38(3), 361-381.

Cargill, Thomas, "CAMEL Ratings and the CD Market," *Journal of Financial Services Research*, 3: 347-358 [1989].

Carter, Richard and Steven Manaster. "Initial Public Offerings And Underwriter Reputation," *Journal of Finance*, 1990, v45(4), 1045-1067.

Chemmanur, Thomas J. and Paolo Fulghieri. "Investment Bank Reputation, Information Production, And Financial Intermediation," *Journal of Finance*, 1994, v49(1), 57-79.

Cole, Rebel A., and Jeffery W. Gunther, “Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems”, *Journal of Financial Services Research*, forthcoming 1998.

Flannery, Mark J. and Sorin M. Sorescu, "Evidence of Bank Market Discipline in Subordinated Debenture Yields: 1983-1991," *Journal of Finance* 51: 1347-1377, 1996.

Greene, William H., *Econometric Analysis*, third edition, Upper Saddle River, New Jersey: Prentice Hall, 1997.

Hall, John R., Andrew P. Meyer, and Mark D. Vaughan, “Do Markets and Regulators View Bank Risk Similarly? An Empirical Investigation of Market-Based Risk Measures and Regulators’ BOPEC Scores for Bank Holding Companies,” working paper, February 1997.

Hand, John R.M., Robert W. Holthausen, and Richard W. Leftwich, 1992, "The effect of bond rating agency announcements on bond and stock prices," *Journal of Finance* 47, 733-752.

Hirschhorn, Eric, "The Informational Content of Bank Examination Ratings," Federal Deposit Insurance Corporation, *Banking and Economic Review*, July/August: 6-11 [1987].

Horvitz, Paul M., "Financial Disclosure: Is More Always Better?" *Journal of Retail Banking Services*, Winter 1996.

James, Christopher. "Some Evidence On The Uniqueness Of Bank Loans," Journal of Financial Economics, 1987, v19(2), 217-236.

Kane, Edward J., "Dissecting Current Legislative Proposals for Deposit Insurance Reform," *Bank Structure and Competition*, Federal Reserve Bank of Chicago, May 1991.

Lummer, Scott L. and John J. McConnell. "Further Evidence On The Bank Lending Process And The Capital-Market Response To Bank Loan Agreements," Journal of Financial Economics, 1989, v25(1), 99-122.

Mikkelson, Wayne H. and M. Megan Partch. "Valuation Effects Of Security Offerings And The Issuance Process," Journal of Financial Economics, 1986, v15(1/2), 31-60.

Office of the Comptroller of the Currency, "Uniform Financial Institutions Rating System and Disclosure of Component Ratings," OCC Bulletin 97-1, January 3, 1997.

O'Keefe, John, and Drew Dahl, "The Scheduling and Reliability of Bank Examinations: The Effect of FDICIA," paper presented to the Financial Management Association, October 1996.

Scott, Jr., David F., William G. Jens, Jr., and Raymond E. Spudeck, "The Secrecy of CAMELs," *The Bankers Magazine*, September/October 1991a.

Scott, Jr., David F., William G. Jens, Jr., and Raymond E. Spudeck, "Give Public Access to Taxpayer-Funded Secret Bank Ratings System," *Challenge*, November/December 1991b.

Warga, A., 1995, A fixed income database, Fixed incomre research program, University of Houston.

Table 1

Possible effect of private exam information (***PRIVINFO***) on contemporaneous and future changes in bond risk premia (Δ*SPREAD*).

		PRIVINFO* correlated with subsequent D*SPREAD		
		positive	**zero**	**negative**
PRIVINFO* correlated with contemporaneous D*SPREAD	**positive**	1	2	3
	zero	4	5	6
	negative	7	8	9

1 = Exam information is partially known within the quarter, and the bond market learns the rest of this information over time.
2 = Exam information is known completely. Bond market fully incorporates this information into prices immediately.
3 = Bad *PRIVINFO* was partly known to the public; examiners' discovery leads to corrective regulatory discipline.

4 = Exam information is private. Bond market learns this information over time, and gradually incorporates it into prices.
5 = The information generated by bank exams does not affect *SPREAD*.
6 = Exam information is private. Bond market learns this information over time, and expects regulators and/or banks will take action to correct any problems.

7 = No apparent rationale.
8 = Exam information is known completely. Bond market anticipates that regulators and/or banks will take action to correct any problems.
9 = Exam information is partially known. Bond market learns the rest of this information over time, and expects regulators and/or banks will take action to correct any problems.

Table 2

Summary Statistics for Banks used in CAMEL Regressions.
3,992 Observations of 1,079 different National Banks from 1986:2 through 1995:1.

	Mean	Std. Dev.	Minimum	Median	Maximum
CAMEL	2.041	0.815	1.000	2.000	5.000
ASSETS (thousand $)	3,500,645	12,314,020	342	309,844	210,490,000
lnASSETS	13.150	2.032	6.095	12.767	19.181
ROA	0.008	0.038	-0.889	0.010	1.443
LIAB/EQ	13.460	55.516	-33,441	13.829	630.500
NAL	0.010	0.015	0.000	0.006	0.261
PD90	0.003	0.005	0.000	0.001	0.074
OREO	0.004	0.010	0.000	0.001	0.201
GAP	5.530	24.863	0.000	4.702	1,531

CAMEL = bank exam rating.
ASSETS = bank assets (thousands of 195 dollars).
ROA = bank net income divided by bank assets.
LIAB/EQ = bank liabilities divided by book equity.
NAL = nonaccruing loans divided by bank assets.
PD90 = loans past due 90 days or more divided by bank assets.
OREO = ›other real estate owned' divided by bank assets.
GAP = absolute value of the one year maturity gap (earning assets minus current liabilities that reprice within a year) divided by book value of equity.

Table 3

Summary Statistics for Bank Holding Companies used in *SPREAD* Regressions
1,064 Quarterly Observations of 61 Bank Holding Companies from 1989:1 through 1995:1

	Mean	Std. Dev.	Minimum	Median	Maximum
ΔSPREAD	0.044	1.878	-25.905	0.014	21.747
SPREAD	2.211	3.211	0.164	1.374	49.450
PRIVINFO	0.056	0.354	-0.865	0.009	1.499
BADNEWS	0.162	0.267	0.000	0.053	1.499
GOODNEWS	-0.107	0.170	-0.865	-0.020	0.000
AGE	126	114	0	99	661
lnASSETS	17.021	1.089	14.237	17.103	19.425
ROA	0.004	0.006	-0.041	0.004	0.020
LIAB/EQ	14.741	6.025	-98.980	14.041	89.280
NAL	0.016	0.014	0.001	0.011	0.130
RATING	8.680	2.904	2.924	8.000	19.500
GAP	3.248	1.830	0.000	3.184	11.336
RELMKTBK	0.985	0.345	-0.323	0.981	2.537

SPREAD = weighted average of the option-adjusted risk premium for holding company's outstanding debt issues.
PRIVINFO = weighted average for the holding company of examiners' private information about the national bank affiliates.
GOODNEWS = weighted average for the holding company of examiners' private information about the national bank affiliates for which the examiners have net "good" news.
BADNEWS = weighted average for the holding company of examiners' private information about the national bank affiliates for which the examiners have net "bad" news.
AGE = weighted average for the holding company of the number of days since the closing date of each affiliate nationally-chartered banks' most recent exam.
lnASSETS = natural log of holding company assets (millions of 1995 dollars).
ROA = holding company net income divided by holding company assets.
LIAB/EQ = holding company liabilities divided by market value equity.
NAL = nonaccruing loans divided by holding company assets.
GAP = absolute value of the one year maturity gap (earning assets minus current liabilities that reprice within a year) divided by book value of equity.
RATING = weighted average of Moody's and S&P bond ratings (converted to numerical values from 1 (lowest risk) to 23 (highest risk)) for holding company's outstanding debt issues.
RELMKTBK = holding company market-to-book ratio, divided by sample average market-to-book ratio.

Table 4

4A: Ordered Logit Regression Results. Dependent Variable is CAMEL.

3,992 Observations of 1,079 different National Banks.
Based on safety and soundness exams finished from 1986:2 through 1995:1.

	parameter estimate	standard error	Wald Chi-Square	p-value
Intercept 1	*		0.52	0.4717
Intercept 2	*		225.02	0.0001
Intercept 3	*		581.22	0.0001
Intercept 4	*		690.91	0.0001
lnASSETS	-0.0459	0.0174	6.99	0.0082
ROA	-15.5259	1.6778	85.63	0.0001
LIAB/EQ	0.0425	0.0033	161.84	0.0001
NAL	90.7166	3.9810	519.27	0.0001
PD90	40.4218	7.8182	26.73	0.0001
OREO	78.2306	5.4694	204.58	0.0001
GAP	0.0988	0.0078	159.82	0.0001
-2 Log Likelihood	6,583.9860		2,285.93	0.0001

* These intercept terms have been suppressed to preserve confidentiality of the CAMEL ratings.

4B: Expected and Residual CAMEL Values

	Mean	std. dev.	minimum	median	maximum
CAMEL (actual)	2.0408	0.8146	1.0000	2.0000	5.0000
CAMEL (fitted value)	2.0409	0.5906	1.0000	1.8651	5.0000
ε (constructed residual)	-0.0001	0.5696	-2.9877	0.0917	3.0808

Table 5: Contemporaneous D*SPREAD*, Symmetric (8) and Non-Symmetric (10) Specifications

$$\Delta SPREAD_{j,t} = a * PRIVINFO_{j,t} * e^{b * AGE_{j,t}} + g * \Delta HC_{j,t} + d * SPREAD_{j,t-1} + l * Q_t + h_{j,t} \qquad (8)$$

$$\Delta SPREAD_{j,t} = a_G * GOODNEWS_{j,t} * e^{b_G * AGE^G_{j,t}} + a_B * BADNEWS_{j,t} * e^{b_B * AGE^B_{j,t}} + g * \Delta HC_{j,t} + d * SPREAD_{j,t-1} + \sum l_t * Q_t + h_{j,t} \qquad (10)$$

Dependent variable is the *current* change: *SPREAD*(t) - *SPREAD*(t-1). Independent variables are defined in Table 3. Estimated coefficients on the quarter dummies are not shown. Test statistics are based on asymptotically efficient (White=s) estimate of the covariance matrix. ***, **, * indicate a significant difference from zero at the 1, 5, and 10 percent levels, respectively.

	Symmetric *PRIVINFO* (8)		**Non-symmetric *PRIVINFO* (10)**	
	Estimate	P-value	Estimate	P-value
PRIVINFO	0.6707	0.196	--	--
AGE	-7.74E-5	0.850	--	--
BADNEWS	--	--	1.073*	0.092
AGE^B	--	--	-7.49E-5	0.981
GOODNEWS	--	--	-0.424	0.464
AGE^G	--	--	-3.58E-3	0.668
ΔlnASSETS	-2.2745***	0.001	-2.1079***	0.002
ΔROA	-18.0411	0.657	-13.935	0.733
) LIAB/EQ	0.0322***	0.000	0.0327***	0.000
) NAL	72.3562	0.108	77.6656*	0.086
) RATING	1.0025***	0.006	0.9780***	0.006
) GAP	0.0084	0.914	0.0145	0.855
) RELMKTBK	-1.7809***	0.004	-1.7732***	0.005
LAGGED *SPREAD*	-0.2016*	0.097	-0.2126*	0.081
R-squared	0.2735		0.2794	
Adj. R-sq	0.2503		0.2548	
N	1064		1064	

(continued)

Table 5 (continued)

	Symmetric *PRIVINFO* (8)		Non-symmetric *PRIVINFO* (10)	
	Estimate	P-value	Estimate	P-value
M) $SPREAD_t$/M$PRIVINFO_t$:				
AGE_t = 0 days	0.6707	0.196		
AGE_t = 30 days	0.6554	0.137		
AGE_t = 60 days	0.6403*	0.084		
AGE_t = 90 days	0.6256**	0.044		
AGE_t = 120 days	0.6113**	0.021		
AGE_t = 150 days	0.5972**	0.013		
AGE_t = 180 days	0.5835**	0.014		
AGE_t = 210 days	0.5701**	0.024		
AGE_t = 240 days	0.5570**	0.050		
AGE_t = 270 days	0.5442*	0.090		
AGE_t = 300 days	0.5318	0.147		
AGE_t = 330 days	0.5195	0.207		
AGE_t = 360 days	0.5076	0.267		
M) $SPREAD_t$/M$BADNEWS_t$:				
AGE_t = 0 days			1.0731*	0.092
AGE_t = 30 days			1.0707*	0.055
AGE_t = 60 days			1.0683**	0.029
AGE_t = 90 days			1.0659**	0.015
AGE_t = 120 days			1.0635***	0.009
AGE_t = 150 days			1.0611***	0.008
AGE_t = 180 days			1.0587**	0.013
AGE_t = 210 days			1.0564**	0.024
AGE_t = 240 days			1.0540**	0.047
AGE_t = 270 days			1.0516*	0.081
AGE_t = 300 days			1.0493	0.125
AGE_t = 330 days			1.0469	0.173
AGE_t = 360 days			1.0446	0.223
M) $SPREAD_t$/M$GOODNEWS_t$:				
AGE_t = 0 days			-0.4235	0.464
AGE_t = 30 days			-0.3803	0.400
AGE_t = 60 days			-0.3416	0.336
AGE_t = 90 days			-0.3067	0.286
AGE_t = 120 days			-0.2754	0.263
AGE_t = 150 days			-0.2474	0.278
AGE_t = 180 days			-0.2221	0.323
AGE_t = 210 days			-0.1995	0.385
AGE_t = 240 days			-0.1791	0.450
AGE_t = 270 days			-0.1609	0.511
AGE_t = 300 days			-0.1445	0.563
AGE_t = 330 days			-0.1297	0.608
AGE_t = 360 days			-0.1165	0.646

Table 6: Predicted Δ*SPREAD*, Symmetric (9) Specification

$$\Delta SPREAD_{j,t+k} = a * PRIVINFO_{j,t} * e^{b * AGE_{j,t}} + d * SPREAD_{j,t} + l * Q_t + h_{j,t}$$

Dependent variable is the *predicted* change: *SPREAD*(t+k) - *SPREAD*(t). Independent variables are defined in Table 3. Estimated coefficients on the quarter dummies are not shown. Test statistics are based on asymptotically efficient (White's) estimate of the covariance matrix. ***, **, * indicate a significant difference from zero at the 1, 5, and 10 percent levels, respectively.

Dependent Variable:	$\Delta SPREAD_{t+1}$		$\Delta SPREAD_{t+2}$		$\Delta SPREAD_{t+3}$		$\Delta SPREAD_{t+4}$		$\Delta SPREAD_{t+5}$		$\Delta SPREAD_{t+6}$	
	Est.	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**
PRIVINFO	1.2593	0.223	0.9651*	0.088	1.6425	0.175	2.4486	0.187	3.6163	0.161	1.6993	0.265
AGE	-0.0219	0.313	-0.0105	0.312	-0.0145	0.284	-0.0182	0.225	-0.0209*	0.082	-0.0112	0.413
$SPREAD_t$	-0.0553	0.503	-0.0401	0.822	-0.1344	0.300	-0.2316	0.054	-0.2288	0.152	-0.2366*	0.071
R-squared	0.1009		0.0691		0.1363		0.1764		0.1348		0.1684	
Adj. R-sq	0.0811		0.0484		0.1169		0.1581		0.1154		0.1495	
N	1158		1152		1140		1101		1095		1083	
$\partial \Delta SPREAD_{t+k} / \partial PRIVINFO_t$:												
AGE_t = 0 days	1.259	0.223	0.965*	0.088	1.643	0.175	2.449	0.187	3.616	0.161	1.699	0.265
AGE_t = 30 days	0.653*	0.081	0.704**	0.026	1.063**	0.040	1.418**	0.039	1.928*	0.055	1.212*	0.088
AGE_t = 60 days	0.339	0.274	0.514**	0.047	0.688**	0.049	0.821*	0.069	1.028*	0.067	0.866**	0.034
AGE_t = 90 days	0.176	0.499	0.375	0.157	0.446	0.202	0.476	0.255	0.548	0.193	0.618	0.133
AGE_t = 120 days	0.091	0.633	0.273	0.302	0.288	0.379	0.276	0.436	0.292	0.349	0.441	0.317
AGE_t = 150 days	0.047	0.714	0.199	0.426	0.187	0.511	0.159	0.559	0.156	0.474	0.315	0.467
AGE_t = 180 days	0.024	0.767	0.146	0.519	0.121	0.601	0.092	0.642	0.083	0.566	0.225	0.572

(continued)

Table 6: Predicted Δ*SPREAD*, Symmetric (9) Specification (continued)

Dependent Variable:	$\Delta SPREAD_{t+7}$		$\Delta SPREAD_{t+8}$		$\Delta SPREAD_{t+9}$		$\Delta SPREAD_{t+10}$		$\Delta SPREAD_{t+11}$		$\Delta SPREAD_{t+12}$	
	Est.	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**
PRIVINFO	2.3567	0.262	0.9792	0.139	1.7035	0.202	1.4007	0.326	2.0682	0.135	7.0125	0.346
AGE	-0.016	0.248	-0.0012	0.835	-0.0104	0.536	-0.0129	0.615	-0.0076	0.556	-0.0417	0.202
$SPREAD_t$	-0.355***	0.004	-0.362**	0.050	-0.452***	0.001	-0.4686***	0.001	-0.5002***	0.001	-0.5406***	0.001
R-squared	0.2073		0.1480		0.2302		0.2257		.1978		0.2877	
Adj. R-sq	0.1891		0.1287		0.2125		0.2079		.1793		0.2710	
N	1042		1036		1024		982		824		963	
$\partial \Delta SPREAD_{t+k} / \partial PRIVINFO_t$:												
AGE_t = 0 days	2.357	0.262	0.979	0.139	1.704	0.202	1.4007	0.326	2.0682	0.135	7.0125	0.346
AGE_t = 30 days	1.446	0.109	0.945**	0.084	1.247*	0.079	0.9499	0.139	1.6462	0.197	2.0145	0.228
AGE_t = 60 days	0.887*	0.088	0.911**	0.056	0.912	0.175	0.6443	0.333	1.3103	0.272	0.5787	0.435
AGE_t = 90 days	0.544	0.216	0.879	0.055	0.668	0.375	0.4369	0.555	1.0439	0.325	0.1662	0.647
AGE_t = 120 days	0.334	0.384	0.848	0.081	0.489	0.528	0.3864	0.679	0.8301	0.459	0.0477	0.749
AGE_t = 150 days	0.205	0.514	0.818	0.134	0.358	0.628	0.2009	0.752	0.6607	0.559	0.0137	0.807
AGE_t = 180 days	0.126	0.605	0.789	0.206	0.262	0.695	0.1363	0.799	0.5259	0.631	0.0039	0.843

Table 7: Predicted Δ*SPREAD*, Non-Symmetric (11) Specification

$$\Delta SPREAD_{j,t+k} = a_G * GOODNEWS_{j,t} * e^{b_G * AGE^G_{j,t}} + a_B * BADNEWS_{j,t} * e^{b_B * AGE^B_{j,t}} + d * SPREAD_{j,t} + \sum l_t * Q_t + h_{j,t}$$

Dependent variable is the *predicted* change: *SPREAD*(t+k) - *SPREAD*(t). Independent variables are defined in Table 3. Estimated coefficients on the quarter dummies are not shown. Test statistics are based on asymptotically efficient (White's) estimate of the covariance matrix. ***, **, * indicate a significant difference from zero at the 1, 5, and 10 percent levels, respectively.

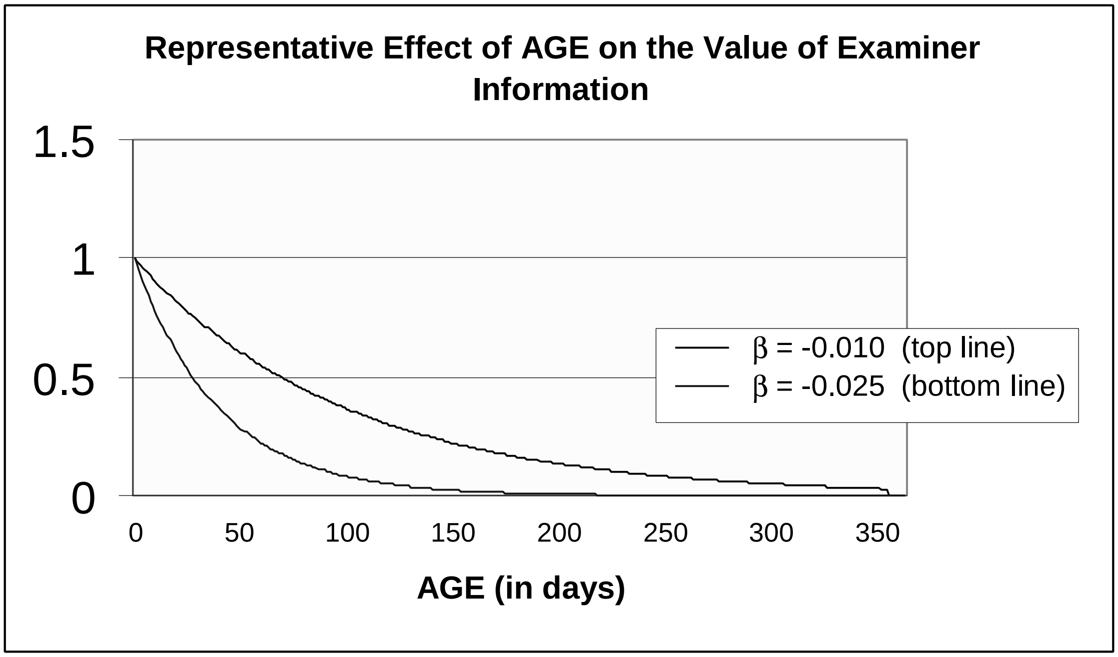
Dependent Variable:	**Δ$SPREAD_{t+1}$**		**Δ$SPREAD_{t+2}$**		**Δ$SPREAD_{t+3}$**		**Δ$SPREAD_{t+4}$**		**Δ$SPREAD_{t+5}$**		**Δ$SPREAD_{t+6}$**	
	Est.	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**
BADNEWS	1.4638	0.152	1.2037*	0.060	1.8211	0.120	2.4495	0.154	3.6669	0.156	1.7850	0.201
AGE^B	-0.0148	0.362	-0.0085	0.358	-0.0106	0.326	-0.0141	0.256	-0.0180	0.112	-0.0067	0.541
GOODNEWS	-0.6644	0.252	-0.2383	0.464	-0.2810	0.454	-0.4686	0.777	2.1585	0.469	-1.1187	0.516
AGE^G	-0.0078	0.471	-0.0001	0.986	-0.0008	0.861	0.0047	0.503	-0.3794	0.815	-0.0272	0.509
$SPREAD_t$	-0.0601	0.467	-0.0443	0.806	-0.1400	0.283	-0.2359	0.051	-0.2331	0.147	-0.2458*	0.057
R-squared	0.1071		0.0719		0.1394		0.1769		0.1353		0.1712	
Adj. R-sq	0.0857		0.0496		0.1185		0.1569		0.1143		0.1508	
N	1158		1152		1140		1101		1095		1083	
$\partial \Delta SPREAD_{t+k} / \partial BADNEWS_t$:												
AGE_t = 0 days	1.464	0.152	1.204*	0.060	1.821	0.120	2.450	0.154	3.667	0.156	1.785	0.201
AGE_t = 30 days	0.939*	0.028	0.934**	0.022	1.323**	0.028	1.603**	0.043	2.135*	0.054	1.458*	0.067
AGE_t = 60 days	0.602	0.113	0.725**	0.045	0.962**	0.029	1.049*	0.057	1.243*	0.067	1.191**	0.028
AGE_t = 90 days	0.387	0.332	0.562	0.140	0.699	0.126	0.687	0.191	0.725	0.163	0.973*	0.084
AGE_t = 120 days	0.248	0.501	0.436	0.270	0.508	0.279	0.449	0.356	0.421	0.313	0.795	0.225
AGE_t = 150 days	0.159	0.609	0.339	0.388	0.369	0.413	0.294	0.484	0.245	0.441	0.649	0.371
AGE_t = 180 days	0.102	0.681	0.263	0.480	0.268	0.514	0.192	0.575	0.143	0.537	0.530	0.483
$\partial \Delta SPREAD_{t+k} / \partial GOODNEWS_t$:												
AGE_t = 0 days	-0.664	0.252	-0.238	0.464	-0.281	0.454	-0.469	0.777	2.159	0.469	-1.119	0.516
AGE_t = 30 days	-0.525	0.151	-0.238	0.420	-0.274	0.413	-0.054	0.763	0.000	0.983	-0.494	0.328
AGE_t = 60 days	-0.416	0.124	-0.237	0.373	-0.268	0.369	-0.062	0.748	0.000	0.992	-0.218	0.549
AGE_t = 90 days	-0.329	0.185	-0.236	0.322	-0.261	0.325	-0.071	0.731	0.000	0.994	-0.096	0.716
AGE_t = 120 days	-0.259	0.299	-0.236	0.269	-0.255	0.280	-0.082	0.713	0.000	0.996	-0.073	0.799
AGE_t = 150 days	-0.205	0.515	-0.235	0.217	-0.249	0.239	-0.094	0.691	0.000	0.997	-0.019	0.846
AGE_t = 180 days	-0.163	0.508	-0.235	0.172	-0.243	0.205	-0.109	0.666	0.000	0.997	-0.008	0.875

(continued)

Table 7: Predicted $\Delta SPREAD$, Non-Symmetric (10) Specification (continued)

Dependent Variable:	$\Delta SPREAD_{t+7}$		$\Delta SPREAD_{t+8}$		$\Delta SPREAD_{t+9}$		$\Delta SPREAD_{t+10}$		$\Delta SPREAD_{t+11}$		$\Delta SPREAD_{t+12}$	
	Est.	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**	**Est.**	**P-value**
BADNEWS	2.4497	0.240	1.2714*	0.068	1.9294	0.133	1.5875	0.222	2.4701	0.196	6.6159	0.307
AGE^B	-0.0131	0.296	-0.0002	0.957	-0.0080	0.539	-0.0099	0.593	-0.0057	0.541	-0.0332	0.195
GOODNEWS	-0.7553	0.690	-0.4209	0.787	-1.6933	0.436	-2.7606	0.429	-2.2613	0.483	-2.2879	0.493
AGE^G	-0.0357	0.705	-0.0166	0.843	-0.0268	0.496	-0.0325	0.439	-0.0342	0.469	-0.0314	0.468
$SPREAD_t$	-0.361***	0.004	-0.373***	0.040	-0.460***	0.001	-0.4764***	0.001	-0.5141***	0.001	-0.5493***	0.001
R-squared	0.2081		0.1508		0.2320		0.2274		.2009		.2898	
Adj. R-sq	0.1886		0.1298		0.2128		0.2079		.1807		.2716	
N	1042		1036		1024		982		976		837	
$\partial \Delta SPREAD_{t+k} / \partial BADNEWS_t$:												
AGE_t = 0 days	2.450	0.240	1.271*	0.068	1.959	0.133	1.5875	0.222	2.4701	0.196	6.6159	0.307
AGE_t = 30 days	1.654	0.107	1.264*	0.057	1.516*	0.079	1.1776	0.133	2.0833	0.195	2.4405	0.209
AGE_t = 60 days	1.117*	0.091	1.257*	0.058	1.191	0.163	0.8735	0.275	1.7570	0.267	0.9002	0.318
AGE_t = 90 days	0.754	0.179	1.249*	0.069	0.936	0.320	0.6479	0.164	1.4818	0.377	0.3321	0.551
AGE_t = 120 days	0.509	0.331	1.242*	0.091	0.736	0.459	0.4807	0.294	1.2498	0.485	0.1225	0.678
AGE_t = 150 days	0.344	0.462	1.235	0.123	0.578	0.559	0.3565	0.677	1.0541	0.574	0.0452	0.752
AGE_t = 180 days	0.232	0.558	1.228	0.163	0.454	0.632	0.2645	0.734	0.8890	0.646	0.0167	0.799
$\partial \Delta SPREAD_{t+k} / \partial GOODNEWS_t$:												
AGE_t = 0 days	-0.755	0.690	-0.421	0.787	-1.693	0.436	-2.7606	0.429	-2.2613	0.483	-2.2879	0.496
AGE_t = 30 days	-0.259	0.673	-0.256	0.671	-0.757	0.319	-1.0399	0.272	-0.8092	0.703	-0.8928	0.356
AGE_t = 60 days	-0.089	0.827	-0.156	0.750	-0.338	0.574	-0.3917	0.578	-0.2895	0.748	-0.3484	0.549
AGE_t = 90 days	-0.030	0.889	-0.095	0.846	-0.151	0.726	-0.1475	0.736	-0.1036	0.784	-0.1359	0.726
AGE_t = 120 days	-0.010	0.920	-0.057	0.894	-0.068	0.802	-0.0556	0.811	-0.0371	0.814	-0.0531	0.808
AGE_t = 150 days	-0.004	0.938	-0.035	0.919	-0.030	0.846	-0.0209	0.854	-0.0133	0.839	-0.0307	0.853
AGE_t = 180 days	-0.001	0.949	-0.021	0.936	-0.013	0.874	-0.0079	0.881	-0.0047	0.861	-0.0081	0.881

Figure 1


Representative Effect of AGE on the Value of Examiner Information
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AGE (in days)
β = -0.010 (top line)
β = -0.025 (bottom line)