Subjective Assessment of Managerial Performance and Decisionmaking in Banking

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We examine subjective supervisory assessments of managerial performance in the banking industry. Results of empirical tests show that better assessments are (i) positively associated with decisions made by examiners to upgrade relatively objective bank performance ratings; (ii) negatively associated with decisions made by examiners to downgrade relatively objective bank performance ratings; and (iii) positively associated with decisions made by bank holding company managers to distribute resources among subsidiary banks. These results are consistent with the finding that soft information generated in the supervisory process is validated by subsequent decisionmaking both internally (by bankers) and externally (by examiners). (JEL G28, G21, L14)

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1 INTRODUCTION

Subjective assessments of managerial performance have been widely hypothesized to play an important role in contracting within firms and other organizations. Empirical support for this hypothesis, however, is limited by overlaps with objective metrics on which performance also depends.

We approach this issue from the perspective of information identified by bank examiners during their evaluations of managers of commercial banks. Examiners are well placed to observe the subtleties of managerial behavior (Baker, Gibbons, and Murphy, 1994) and are therefore able to assess contributions to firm value that are not objectively measurable. Their assessments rely on soft information that requires effort to obtain, judgment to assess, and knowledge that becomes less useful when separated from the environment in which it was collected (Eisenbach, Luca, and Townsend, 2016, and Liberti and Petersen, 2019).

Performance ratings are prominent in this process. These ratings are assigned by examiners following on-site inspections to measure capital (C), asset quality (A), earnings (E), management (M), liquidity (L), and market sensitivity (S). They range numerically from 1, for the best banks, to 5, for the worst. They collectively are rolled up into a composite (CAMELS) rating. All are non-public.

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The management rating, the M component, encompasses a broad range of factors that are subjective in nature. They include community service, the nature and degree of working relationships, and the level and quality of oversight (Federal Deposit Insurance Corporation [FDIC], 2022; Board of Governors of the Federal Reserve System [BOG], 2021). They have been said to include those that are so intuitive as to reflect "a particular banker's temperament" (Effinger, 2017).

Critics contend that the management rating is excessively subjective. They advocate an overhaul that emphasizes "clear, cogent and objective measures of financial condition over vague, arbitrary and subjective ones" (Baer and Newell, 2017). Supervisors appear sympathetic: The BOG, the Federal Financial Institutions Examination Council, and the FDIC are exploring how to ensure that the different agencies and different examiners within each agency are applying ratings consistently and uniformly (McWilliams, 2019a,b).

We contribute to this debate by determining whether soft information about a bank—embodied in its management rating—can be linked to decisionmaking. We use a proxy variable for soft information, derived from CAMELS components, that is statistically independent of information that is more quantitative in nature. Separate analyses consider decisions that are made externally, by examiners in establishing subsequent CAMELS component ratings, and internally, by bank holding company managers in allocating resources among affiliated banks.

With respect to decisions of examiners, results of tests using a sample of 27,484 commercial banks over the 2011 to 2017 period show that subjective assessments indicating better managerial performance are positively related to improvement and negatively related to deterioration in subsequent CAMELS component ratings. Base-case scenarios are confirmed in robustness tests that account for potential endogeneity in how examiners are assigned to specific banks.

With respect to decisions of bank managers, results of tests based on 21,259 observations on subsidiaries in multi-bank holding companies over the 1999 to 2017 period show that subjective assessments indicating better performance are positively related to the likelihood that a bank subsidiary receives more resources from its parent holding company. Base-case scenarios are confirmed in robustness tests that account for potential endogeneity in how examiners, or managers, are assigned to specific banks.

Results across the two analyses are consistent with a production of soft information whose usefulness is validated in decisions about banks that are made both internally (by bankers) and externally (by examiners). The former has theoretical roots in prior empirical analyses of qualitative factors in corporate decisionmaking (Jian and Lee, 2011; Duchin and Sosyura, 2013; McNeil and Smythe, 2009; Glaser, Lopez-De-Silanes, and Zautner, 2013; and Gaspar and Massa, 2011), while the latter can be understood in the context of earlier studies showing that CAMELS ratings predict regulatory outcomes (Cole and Gunther, 1998; Hirtle and Lopez, 1999; Berger and Davies, 1998; DeYoung et al., 2001; and Gopalan, 2018). Both are part of a larger theoretical literature on how information is used in contracting within organizations (Rajan and Reichelstein, 2006; Baker, Gibbons, and Murphy 1994; and MacLeod, 2003).

2 SOFT INFORMATION AND CAMELS RATINGS

The role of M as a measure of soft information may be attenuated by correlations with other CAMELS components. We address this issue with an approach used by Calomiris and Carlson

(2018) to extract soft information generated by bank examiners in the nineteenth century. They found that this information was useful in forecasting performance outcomes.

Our methodology uses the residual of a regression of the M rating on C, A, E, L, and S ratings as a proxy for soft information:

$$(1)\quad \mathrm{M}_{i,(t-1)} = b_0 + b_1\mathrm{C}_{i,(t-1)} + b_2\mathrm{A}_{i,(t-1)} + b_3\mathrm{E}_{i,(t-1)} + b_{4i,(t-1)} + b_5\mathrm{S}_{i,(t-1)} + e_{i,(t-1)},\ i = 1,\ldots.n,$$

where n denotes the number of banks for which ratings are observed. The residual, $e_{i,(t-1)}$, will be designated as $\mathrm{SOFT}_{i,(t-1)}$ in both studies. It is orthogonal to the more objectively assessed elements of performance embodied in $\mathrm{C}_{i,(t-1)}$, $\mathrm{A}_{i,(t-1)}$, $\mathrm{E}_{i,(t-1)}$, $\mathrm{L}_{i,(t-1)}$, and $\mathrm{S}_{i,(t-1)}$. More positive values of $\mathrm{SOFT}_{i,(t-1)}$ indicate that actual M ratings were worse (larger numerically) than what would be expected based on the more objective C, A, E, L, and S ratings; conversely, negative values are associated with actual M values that were better (lower numerically) than expected based on the objective assessments.[1]

3 THE FIRST ANALYSIS: SOFT INFORMATION AND CHANGES IN RATINGS

We use a sample of 27,484 observations on commercial banks over the 2011 to 2017 period to determine whether soft information that reveals better (worse) managerial performance is positively (negatively) related to improvement or negatively (positively) related to deterioration in subsequent performance ratings.[2] We derive $\mathrm{SOFT}_{i,(t-1)}$ at the point of bank i's initial examination at $t-1$ in the 2011 to 2015 period.[3] The time to the next examination at time t could vary from one quarter to eight quarters, at which point we truncate our analysis.[4] The fourth quarter of 2017, therefore, is the last quarter in which the succeeding (second) examination could have occurred.

3.1 The Model

Over the interval from $t-1$ to t, any given bank i could exhibit an upgrade, no change, or downgrade in rating for C, A, E, L, or S.[5] Conditional on our assessed measure of soft information, we fit a multinomial (generalized) logit model for response variable y to assess the impact of $\mathrm{SOFT}_{i,(t-1)}$ on the likelihood of an upgrade in rating ($y = 1$) or downgrade in rating ($y = 3$) relative to the reference category of no change in rating ($y = 2$). For each of the relatively objective ratings C, A, E, L, and S, separately, we define $P_j(t \mid \mathrm{SOFT}_{i,(t-1)})$ as the probability that $y = j$ for observed value $\mathrm{SOFT}_{i,(t-1)}$ at subsequent examination time t:

$$(2)\qquad \log_e\left(\frac{P_j(i,t)}{P_2(i,t)}\right) = a_j + b_j\,\mathrm{SOFT}_{i(t-1)} \text{ for } j = 1,3 \quad \text{and } i = 1,\ldots..n$$

and thus e^{b_j} provides the multiplicative change in the odds of an upgrade ($j = 1$) or downgrade ($j = 3$) relative to no change in rating per unit change in $\mathrm{SOFT}_{i,(t-1)}$.

We hypothesize a negative coefficient on $\mathrm{SOFT}_{i,(t-1)}$ in determining the odds of an upgrade (i.e., $b_1 < 0$) and a positive coefficient for the odds of a downgrade (i.e., $b_3 > 0$). Specifically, when $b_1 < 0$ and observed M is better than what would be expected based on objective assessments C, A, E, L, and S, in which case $\mathrm{SOFT}_{i,(t-1)} < 0$, then our model predicts a (multiplicative) increase in the odds of an upgrade ($j - 1$). The opposite holds if $b_3 > 0$ and $\mathrm{SOFT}_{i,(t-1)} > 0$, as this results in increased odds of a downgrade.

The distributions of ratings, upgrades, and downgrades are presented in Table 1. Mean ratings were highest (worst) for earnings and lowest (best) for liquidity. Variation in ratings was highest for capital and lowest for market sensitivity.

Table 1

Descriptive Statistics, CAMELS Components

	$M_{(t-1)}$	$C_{(t-1)}$	$A_{(t-1)}$	$E_{(t-1)}$	$L_{(t-1)}$	$S_{(t-1)}$
Mean	2.41	2.24	2.47	2.54	1.89	2.13
Standard deviation	1.03	1.13	1.21	1.22	0.92	0.87
Coefficient of variation	42.9	50.6	49.0	47.9	48.8	40.6
Upgrades	3,755	2,981	5,022	3,989	2,385	2,537
Downgrades	1,814	1,150	1,535	1,756	1,499	1,429

Upgrades were more common than downgrades for every CAMELS component, which is unsurprising insofar as our sample period coincides with economic expansion. The number of upgrades was highest for asset quality and lowest for liquidity. Downgrades were most common for management.

3.2 The Derivation of $\mathrm{SOFT}_{(t-1)}$

Results for equation (1) deriving $\mathrm{SOFT}_{(t-1)}$ are presented in Table 2. All of the independent variables have positive and statistically significant coefficients. The coefficients are largest for asset quality and lowest for liquidity.

Table 2

Regression Results for Derivation of $\mathrm{SOFT}_{(t-1)}$

Dependent variable: $M_{i(t-1)}$

INT	$C_{(t-1)}$	$A_{(t-1)}$	$E_{(t-1)}$	$L_{(t-1)}$	$S_{(t-1)}$
0.265*** (6.10)	0.162*** (0.006)	0.253*** (0.005)	0.158*** (0.004)	0.135*** (0.006)	0.232*** (0.006)
N = 27,484					

NOTE: INT is intercept. *** indicates the coefficient is statistically significantly different from 0 at an α level of 0.01. Standard errors are in parentheses.

3.3 Multinomial Results

Our base-case assessments using equation (2) are presented in Table 3. Each column has results for upgrade, no change, or downgrade in $C_{(t)}$, $A_{(t)}$, $E_{(t)}$, $L_{(t)}$, and $S_{(t)}$. We designate b_3 in equation

(2) as $\text{DOWNSOFT}_{(t)}$ and b_1 in equation (2) as $\text{UPSOFT}_{(t)h}$, $\text{UPINT}_{(t)}$, and $\text{DOWNINT}_{(t)}$ are intercept coefficients a_1 and a_3, respectively.

Because the multinomial logit model in equation (2) computes standard errors for estimated coefficients based on the expected value of the second derivative of the conditional log-likelihood, and thus may underestimate unexplained variation and hence standard errors, we obtained robust parameter estimates and standard errors using 1,000 bootstrap samples taken with replacement from the original data for each C, A, E, L, and S. Means and standard deviations for $\text{UPSOFT}_{(t-1)}$ and $\text{DOWNSOFT}_{(t-1)}$ are shown in the lower panel of Table 3. The bootstrap standard deviations are consistent with the standard errors from the fit of equation (2) to the original dataset. We conclude that the multinomial logit model has adequately assessed the significance of coefficients.

Table 3

Multinomial Logit Results for Likelihood of Change in Rating

	$C_{(t)}$	$A_{(t)}$	$E_{(t)}$	$L_{(t)}$	$S_{(t)}$
$\text{DOWNINT}_{(t-1)}$	–3.022*** (0.030)	–2.623*** (0.026)	–2.541*** (0.024)	–2.762*** (0.026)	–2.817*** (0.027)
$\text{DOWNSOFT}_{(t-1)}$	0.318*** (0.061)	0.272*** (0.053)	0.447*** (0.049)	0.223*** (0.054)	0.375*** (0.054)
$\text{UPINT}_{(t-1)}$	–2.059*** (0.019)	–1.438*** (0.015)	–1.708*** (0.017)	–2.291*** (0.021)	–2.237*** (0.024)
$\text{UPSOFT}_{(t-1)}$	–0.096** (0.041)	–0.384*** (0.035)	–0.376*** (0.038)	–0.208*** (0.046)	–0.319*** (0.054)
–2 Log *L*	28,117	37,175	35,063	27,536	27,766
Upgrades	2,981	5,022	3,989	2,385	2,537
Downgrades	1,150	1,535	1,756	1,499	1,429
No change	23,335	20,927	21,739	23,600	23,518
Bootstrap averages					
Mean $\text{DOWNSOFT}_{(t-1)}$	–0.098	–0.384	–0.376	–0.207	–0.319
STD $\text{DOWNSOFT}_{(t-1)}$	0.043	0.035	0.038	0.046	0.044
Mean $\text{UPSOFT}_{(t-1)}$	0.317	0.270	0.447	0.223	0.377
STD $\text{UPSOFT}_{(t-1)}$	0.060	0.053	0.050	0.052	0.052

NOTE: **, *** indicate the coefficient is statistically significantly different from 0 at an α level of 0.05 and 0.01, respectively. Standard errors are in parentheses. $\text{DOWNSOFT}_{(t)}$ is b_3 in equation (2) and $\text{UPSOFT}_{(t)}$ is b_1. $\text{UPINT}_{(t)}$ and $\text{DOWNINT}_{(t)}$ are intercept coefficients a_1 and a_3, respectively. Bootstrap averages were obtained from random samples of the original dataset. STD is standard deviation.

The coefficients on $\text{DOWNSOFT}_{(t-1)}$ are positive and statistically significant at the 1 percent level in all cases. This finding indicates that banks with more positive values for $\text{SOFT}_{(t-1)}$, which represent worse performance than expected based on objective measures, are more likely to experience downgrades in subsequent performance evaluations. The coefficients on $\text{UPSOFT}_{(t-1)}$ are negative and statistically significant at the 1 percent level for each regression of $A_{(t)}$, $E_{(t)}$, $L_{(t)}$, and $S_{(t)}$, and at the 5 percent level for $C_{(t)}$. These findings indicate that banks with more positive values for $\text{SOFT}_{(t-1)}$, which represent worse performance than expected, are less likely to experience upgrades in objective performance outcomes.

Our results confirm the finding of Gilbert, Meyer, and Vaughn (2002) that supervisory decisions to downgrade CAMELS ratings are more likely when a bank's management rating (M) is worse than its composite rating (CAMELS)—and extend that research by considering decisions to upgrade as well. Our results contrast with Gaul and Jones (2021, p. 5), who found that management ratings "have little or no predictive power" for bank failures after controlling for CAMELS composite ratings. Interpretations of both studies are limited by large overlaps between management ratings and composite ratings (Gaul and Jones, 2021) that our methodology is intended to limit.

The focus of previous research on downgrades, including Gilbert, Meyer, and Vaughn (2002), is understandable from the perspective of assessing risks to financial system stability. But our inclusion of upgrades is important to the extent that subjective assessments of soft information by examiners are found to be symmetric—that is, examiner opinions are not limited by consideration of characteristics that only are useful in the prediction of underperformance. From this perspective, they are not necessarily arbitrary in terms of this aspect of potential bias (Baer and Newell, 2017).

3.4 Robustness

Examination intervals can vary in response to bank condition. This variation raises an issue of endogeneity that we address with supplemental tests that isolate banks in different ratings categories. It is a useful decomposition of our sample because the vast majority of banks within a given rating category are examined at fixed, scheduled intervals (BOG, 2021).

In Table 4, we present this analysis for $E_{(t)}$ only (separate analyses for $C_{(t)}$, $A_{(t)}$, $L_{(t)}$, and $S_{(t)}$ generated comparable results but are not shown, to conserve space). In these models, we employ a binary logit, rather than a multinomial logit, as movement from some categories to others are possible in one direction only.

Table 4

Logit Model Results at Varying Initial Levels of M

Panel A: Odds of downgrade in rating for $E_{(t)}$				
	M = 1	M = 2	M = 3	M = 4
INT	–1.844*** (0.177)	–2.364*** (0.206)	–2.617*** (0.376)	–3.399*** (0.740)
$SOFT_{(t-1)}$	0.237*** (0.087)	0.6160*** (0.092)	0.645*** (0.118)	0.650*** (0.156)
Downgrades	773	576	265	142
Panel B: Odds of upgrade in rating for $E_{(t)}$				
	M = 2	M = 3	M = 4	M = 5
INT	–2.261*** (0.172)	–0.853*** (0.183)	–1.538*** (0.349)	–2.082*** (0.476)
$SOFT_{(t-1)}$	–0.317*** (0.076)	–0.567*** (0.065)	–0.336*** (0.076)	–0.059 (0.112)
Upgrades	1,163	1,581	880	365

NOTE: INT is intercept. *** indicates the coefficient is statistically significantly different from 0 at an α level of 0.01. Standard errors are in parentheses. $SOFT_{(t-1)}$ is the residual of a regression of the $M_{(t-1)}$ rating on $C_{(t-1)}$, $A_{(t-1)}$, $E_{(t-1)}$, $L_{(t-1)}$, and $S_{(t-1)}$.

Coefficients on $\mathrm{SOFT}_{(t-1)}$ are positive and statistically significant in the determination of downgrades in each of the four possible initial management ratings (1, 2, 3, and 4). Coefficients on $\mathrm{SOFT}_{(t-1)}$ are negative in the determination of upgrades in each of the four possible initial management ratings (2, 3, 4, and 5) and statistically significant for all ratings except 5. These results are similar to those previously reported. We conclude that our findings in Table 3 are robust to varying levels of initial rating levels.

Another concern is that the error term in equation (2) may incorporate criteria that are not captured by the independent variables and intercept terms. Practical impacts of our parsimonious approach are limited, however, insofar as CAMELS ratings are assessed in a "comprehensive and uniform manner" (FDIC, 2022). We note, however, that alternative versions of equation (1) that include bank-specific and economic variables generated comparable results to those reported. The sign and significance of the coefficients on $\mathrm{SOFT}_{(t-1)}$ were unaffected in all equations.

Another potential criticism of our empirical approach concerns the possibility that the personal attributes or incentives of examiners in overseeing CAMELS ratings may not be randomly distributed across banks. For example, it is possible that an individual examiner may justify a high (low) subjective assessment with subsequent ratings upgrades (downgrades). To address this issue, we exploit the alternating examination program whereby most state-chartered banks are assigned to rotations between state and federal regulators. Specifically, we use alternate regressions to isolate banks that switched examination status (state to federal and federal to state). The results are comparable to those reported.

4 SECOND ANALYSIS: SOFT INFORMATION AND THE ALLOCATION OF INTERNAL CAPITAL

Bank holding companies are organizations with controlling interest in one or more subsidiary banks that operate as separate reporting entities for regulatory purposes. Managers at the holding company level typically do not run the day-to-day operations of these banks but rather exercise control over management and policies. They distribute resources on which the growth and sustainability of their subsidiaries depend.

We measure resource flows in terms of allocations of equity capital by holding companies to their subsidiary banks.[6,7] Our sample consists of 21,259 bank observations for the 1999 to 2017 period. Of these banks, 2,390 received allocations.

4.1 The Model

The likelihood of receiving capital allocation is modeled using a binary logit methodology to determine the probability of a bank experiencing, or not experiencing, a capital allocation during year *t* (see Dahl and Shrieves, 1990). Defining $P_{i,(t)}$ to be the probability of a capital allocation to subsidiary bank *i* during year *t*, our logit equation to be tested is

$$\log_e\left(P_{i,(t)}/\left(1 - P_{i,(t)}\right)\right)=b_0 + b_1\,\mathrm{SOFT}_{i,(t-1)} + b_2\,\mathrm{ECAP}_{i,(t-1)} + b_3\,\mathrm{CASH}_{i,(t-1)} + b_4\,\mathrm{GROW}_{i,(t-1)} + b_5\,\mathrm{BNKSIZE}_{i,(t-1)}. \tag{3}$$

Among the independent variables is $\mathrm{ECAP}_{(t-1)}$, the ratio of equity capital to assets, which controls for incentives for holding companies to allocate capital to undercapitalized subsidiary banks. $\mathrm{BNKSIZE}_{(t-1)}$ is the log of beginning-of-period bank assets. $\mathrm{CASH}_{(t-1)}$ is the sum of net income plus provisions for loan losses and is expressed relative to assets. To the extent that internally generated funds substitute for capital allocation, the sign of the coefficient for this variable will be negative. If, on the other hand, capital is allocated to banks in which cash flows are higher, the coefficient will be positive. $\mathrm{GROW}_{(t-1)}$ is the median growth rate of loans for all banks in the market in which a given bank operates.[8] Expected growth, all else equal, would require additional capital.

The key variable is $\mathrm{SOFT}_{(t-1)}$. Since a positive value for $\mathrm{SOFT}_{(t-1)}$ corresponds to an observed M that is higher numerically (worse) than what would be anticipated on the basis of $C_{(t-1)}$, $A_{(t-1)}$, $E_{(t-1)}$, $L_{(t-1)}$, and $S_{(t-1)}$, and a negative value corresponds to an observed $M_{(t-1)}$ that is lower numerically (better) than what would be anticipated, we hypothesize that $\mathrm{SOFT}_{(t-1)}$ will have a negative coefficient, meaning that the odds of decisions by bank holding company managers to allocate capital to a subsidiary are lower when soft information is worse (higher numerically).[9]

4.2 Derivation of $\mathrm{SOFT}_{(t-1)}$

Table 5 presents results of equation (1) for deriving $\mathrm{SOFT}_{(t-1)}$. (Note that the sample of banks used in this regression differs from that used in the previous analysis.) All independent variables, once again, have positive and statistically significant coefficients.

Table 5

Logit Regression Results for $\mathrm{SOFT}_{(t-1)}$

Dependent variable: $M_{(t-1)}$

INT	$C_{(t-1)}$	$A_{(t-1)}$	$E_{(t-1)}$	$L_{(t-1)}$	$S_{(t-1)}$
0.300***	0.155***	0.301***	0.148***	0.094***	0.184***
(0.027)	(0.014)	(0.010)	(0.009)	(0.011)	(0.010)

NOTE: INT is intercept. *** indicates the coefficient is statistically significantly different from 0 at an α level of 0.01. Standard errors are in parentheses.

Descriptive statistics on the overall sample are presented in Table 6.[10] Panel A is for banks that received capital allocations, and Panel B is for banks that did not receive capital allocations. Comparisons between the panels indicate that banks receiving capital allocations had lower cash flow, less capital, and higher market growth potential. The mean $\mathrm{SOFT}_{i,(t-1)}$ is –0.013 in Panel A and –0.003 in Panel B. These findings indicate that the derived measure of soft information is, on average, lower numerically (better) for banks obtaining capital allocations versus those that do not.

Table 6

Descriptive Statistics

Panel A: Banks receiving capital allocations (N = 2,390)				
	Mean	STD	Minimum	Maximum
$ECAP_{(t-1)}$	0.096	0.055	0.040	0.826
$CASH_{(t-1)}$	0.011	0.009	–0.009	0.097
$GROW_{(t-1)}$	0.118	0.105	–0.099	0.494
$BNKSIZE_{(t-1)}$	12.426	1.697	6.784	21.36
$SOFT_{(t-1)}$	–0.013	0.436	–1.208	1.967
Panel B: Banks not receiving capital allocations (N = 18,869)				
$ECAP_{(t-1)}$	0.109	0.064	0.027	0.898
$CASH_{(t-1)}$	0.014	0.08	–0.009	0.099
$GROW_{(t-1)}$	0.076	0.078	–0.099	0.497
$BNKSIZE_{(t-1)}$	11.801	1.412	6.429	21.21
$SOFT_{(t-1)}$	–0.003	0.433	–1.280	2.699

NOTE: STD is standard deviation. $ECAP_{(t-1)}$ is equity/assets; $CASH_{(t-1)}$ is net income plus provisions for loan losses/assets; $GROW_{(t-1)}$ is the median market loan growth; $BANKSIZE_{(t-1)}$ is the log of bank assets; and $SOFT_{(t-1)}$ is the residual of a regression of the $M_{(t-1)}$ rating on $C_{(t-1)}$, $A_{(t-1)}$, $E_{(t-1)}$, $L_{(t-1)}$, and $S_{(t-1)}$.

4.3 Results

Results using the logit model in equation (3) are presented for each of the four levels of M in Table 7.

In all columns of Table 7, the coefficients on $GROW_{(t-1)}$ are positive and statistically significant for all rating categories except 4 (lowest); banks in markets with greater growth in loans are more likely to obtain capital allocations. The coefficients on $BANKSIZE_{(t-1)}$ are positive and statistically significant. The coefficients on $ECAP_{(t-1)}$ are negative, as hypothesized, but are not always statistically significant. The coefficients on $CASH_{(t-1)}$ are negative, indicating that internally generated funds substitute for capital allocation, but, once again, have varying levels of statistical significance.

Our key findings concern the coefficients on $SOFT_{(t-1)}$. In the first column, for the highest rated banks, the coefficient is –2.190 and statistically significant. The negative coefficient means that when the assessment of soft information is worse (higher numerically), or better (lower numerically), the odds of an allocation, respectively, decrease (increase). The effect is economically significant; for the subsample of M = 1, an increase of one-quarter of a point in $SOFT_{(t-1)}$ (slightly more than one standard deviation) implies a multiplicative decrease in the odds of an allocation of 42 percent ($\exp[-2.190 * 0.25] = 0.58$).

The coefficients on $SOFT_{(t-1)}$ remain negative and statistically significant, albeit at smaller magnitudes: –1.029, –1.058, and –0.775 in the second through fourth columns, respectively. Supplemental inferential tests among M levels indicate that these coefficients are statistically different at the 5 percent level only for M = 1 and not for M = 2, M = 3, or M = 4. We note that the odds of an allocation when M = 1 starts lower overall, before considering the effects of all predictors in equation (3), as is evident from its more negative intercept. Thus, a more negative coefficient for $SOFT_{(t-1)}$

Table 7

Logit Model Results, All Bank Sample

	M = 1	M = 2	M = 3	M = 4
INT	–8.532***	–4.456***	–4.780***	–4.031
	(0.886)	(0.543)	(1.181)	(2.232)
$SOFT_{(t-1)}$	–2.190***	–1.029***	–1.058***	–0.775*
	(0.244)	(0.123)	(0.215)	(0.420)
$ECAP_{(t-1)}$	0.174	–10.599***	–7.406	–18.163**
	(1.848)	(2.585)	(2.672)	(8.628)
$CASH_{(t-1)}$	–40.815***	–61.864***	–21.034	–11.069
	(14.89)	(11.85)	(13.32)	(14.37)
$GROW_{(t-1)}$	5.047***	6.125***	6.319***	5.537*
	(0.574)	(0.396)	(0.952)	(2.580)
$BNKSIZE_{(t-1)}$	0.258***	0.273***	0.301***	0.431**
	(0.034)	(0.028)	(0.059)	(0.193)
N	8,548	11,316	1,203	192

NOTE: INT is intercept. *, **, *** indicate the coefficient is statistically significantly different from 0 at an α level of 0.10, 0.05, and 0.01, respectively. Standard errors are in parentheses. The dependent variable indicates capital allocation (1 for allocation, zero otherwise). All estimated regression coefficients are on the logit scale. $ECAP_{(t-1)}$ is equity/assets; $CASH_{(t-1)}$ is net income plus provisions for loan losses/assets; $GROW_{(t-1)}$ is the median market loan growth; $BANKSIZE_{(t-1)}$ is the log of bank assets; and $SOFT_{(t-1)}$ is the residual of a regression of the $M_{(t-1)}$ rating on $C_{(t-1)}$, $A_{(t-1)}$, $E_{(t-1)}$, $L_{(t-1)}$, and $S_{(t-1)}$

when M = 1 adjusts the lower starting odds of allocation by increasing the odds more for the same improvement in subjective performance in comparison to the 2, 3, and 4 M levels.

4.4 Robustness

In addition to the previous base case, we also create two subsamples for further tests of equation (3). The first subsample consists of banks that experience a change in M rating from year $t-2$ to year $t-1$. This subsample mitigates concerns with a potentially endogenous assignment of managers in which subjective performance may be easier to achieve—or easier for examiners to identify—in certain banks or markets (which are now held constant as performance changes).

A second subsample exploits the alternating examination programs between state and federal regulators as previously described. This subsample allows us to identify a sample of banks that change "examiners-in-charge" from year $t-2$ to year $t-1$.

Results of these tests are reported in Tables 8 and 9. The coefficients on $SOFT_{(t-1)}$ remain negative and statistically significant.

Table 8

Logit Model Results, Banks that Change Management Rating

	M = 1	M = 2	M = 3	M = 4
INT	–4.580***	–4.278***	–4.017***	–3.057
	(1.101)	(0.684)	(1.038)	(2.420)
$SOFT_{(t-1)}$	–1.464***	–0.691***	–1.165***	–1.074**
	(0.544)	(0.206)	(0.232)	(0.474)
$ECAP_{(t-1)}$	–1.718	–10.588***	–16.469***	–12.609
	(3.612)	(2.874)	(5.741)	(9.518)
$CASH_{(t-1)}$	–84.900***	–73.161***	–11.309	–19.677
	(25.94)	(17.62)	(16.76)	(20.27)
$GROW_{(t-1)}$	5.972***	5.141***	7.985***	3.771
	(0.574)	(0.713)	(1.288)	(2.431)
$BNKSIZE_{(t-1)}$	0.258***	0.337***	0.369***	0.339*
	(1.019)	(0.051)	(0.075)	(0.201)
N	1,243	1,957	670	124

NOTE: INT is intercept. *, **, *** indicate the coefficient is statistically significantly different from 0 at an α level of 0.10, 0.05, and 0.01, respectively. Standard errors are in parentheses. The dependent variable indicates capital allocation (1 for allocation, zero otherwise). All estimated regression coefficients are on the logit scale. $ECAP_{(t-1)}$ is equity/assets; $CASH_{(t-1)}$ is net income plus provisions for loan losses/assets; $GROW_{(t-1)}$ is the median market loan growth; $BANKSIZE_{(t-1)}$ is the log of bank assets; and $SOFT_{(t-1)}$ is the residual of a regression of the $M_{(t-1)}$ rating on $C_{(t-1)}$, $A_{(t-1)}$, $E_{(t-1)}$, $L_{(t-1)}$, and $S_{(t-1)}$

Table 9

Logit Model Results, Banks that Change Examiner-in-Charge

	M = 1	M = 2	M = 3	M = 4
INT	–6.710***	–5.103***	–4.459***	–3.340
	(0.857)	(0.598)	(1.344)	(3.432)
$SOFT_{(t-1)}$	–2.854***	–1.019***	–0.966***	–1.083*
	(0.349)	(0.152)	(0.280)	(0.628)
$ECAP_{(t-1)}$	–11.050**	–14.350***	–6.828	–36.617**
	(1.848)	(2.675)	(5.468)	(16.871)
$CASH_{(t-1)}$	–42.490***	–83.213***	–27.355	69.677**
	(16.46)	(12.30)	(22.02)	(28.72)
$GROW_{(t-1)}$	6.808***	5.380***	7.582***	1.248
	(0.769)	(0.501)	(1.241)	(3.113)
$BNKSIZE_{(t-1)}$	0.323***	0.447***	0.344***	0.513**
	(0.052)	(0.043)	(0.103)	(0.272)
N	4,548	5,452	662	71

NOTE: INT is intercept. *, **, *** indicate the coefficient is statistically significantly different from 0 at an α level of 0.10, 0.05, and 0.01, respectively. Standard errors are in parentheses. The dependent variable indicates capital allocation (1 for allocation, zero otherwise). All estimated regression coefficients are on the logit scale. $ECAP_{(t-1)}$ is equity/assets; $CASH_{(t-1)}$ is net income plus provisions for loan losses/assets; $GROW_{(t-1)}$ is the median market loan growth; $BANKSIZE_{(t-1)}$ is the log of bank assets; and $SOFT_{(t-1)}$ is the residual of a regression of the $M_{(t-1)}$ rating on $C_{(t-1)}$, $A_{(t-1)}$, $E_{(t-1)}$, $L_{(t-1)}$, and $S_{(t-1)}$

4.5 Section Summary

Our results show that soft information revealed by examiners creates informational value given that it is validated by the decisions of bank holding company managers to allocate capital among their subsidiary banks: Subsidiaries with better subjective assessments of managerial ability are more likely to obtain capital infusions. This finding is consistent with an accumulation of soft information on personal attributes including experience, expertise, and competence (Hattori, Shintani, and Uchida, 2015). It also is consistent with an expansion of credit by banks in markets in which they have better local information or better relationships with local borrowers (Gilje, Loutskina, and Strahan, 2016).

Our results are relevant, more generally, to prior studies of subjective managerial characteristics and corporate decisionmaking. Jian and Lee (2011) study decisions within corporations that are motivated by reputations of divisional managers as imputed from performance outcomes. Duchin and Sosyura (2013) evaluate the "influence" of divisional managers as evident in factors such as manager salaries. The power of divisional managers in McNeil and Smythe (2009) and in Glaser, Lopez-De-Silanes, and Zautner (2013) is based, in part, on the number of years managers have worked at a firm. Gaspar and Massa (2011) consider a trust between CEOs and managers based on shared educational institutions, non-profit organizations, and other connections.

We extend these studies by showing that decisions based on soft information regarding managerial attributes are not necessarily limited to those correlated with data-dependent metrics or those that happen to coincide with the activities and backgrounds of CEOs. They are, rather, assessed subjectively by bank examiners that are independent of the bank and its management. Our research extends the "growing literatures on the role of manager-specific characteristics" (Gaspar and Massa, 2011, p. 845) on corporate decisionmaking.

5 CONCLUSIONS

Results of empirical tests show that soft information revealing better managerial performance is positively related to improvement and negatively related to deterioration in subsequent performance ratings that are relatively objective. Other test results show that subsidiaries in multi-bank holding companies with soft information that reveals better managerial performance are more likely to obtain resources that are allocated at the holding company level. Both serve as a counterpoint to criticisms that qualitative aspects of performance ratings are excessively arbitrary.

Our results also can be viewed, more generally, from the perspective of intra-organizational performance assessment. Our finding that soft information generated in the supervisory process is validated in subsequent decisionmaking by bankers and examiners provides evidence that subjectivity in performance evaluation, despite being difficult to specify or verify for contracting purposes (Rajan and Reichelstein, 2006), can serve as a useful complement to objective measures (Baker, Gibbons, and Murphy, 1994, and MacLeod, 2003). ■

NOTES

[1] The variables are expressed as lags to accommodate easier interpretation in later analyses.

[2] Data are obtained from call reports published by the Federal Financial Institutions Examination Council.

[3] Multiple observations on the same bank are possible.

[4] Examination intervals longer than two years are extremely rare, less than 0.001, and may reflect aberrational circumstances.

[5] Time points $t-1$ and t vary for each bank based on its individual examination schedule.

[6] To focus on allocations that are relatively infrequent and comparatively large, we consider only those that constitute 5 percent or more of beginning equity capital. Supplementary tests considered thresholds of 1 percent and 10 percent of equity. The results are comparable to those reported.

[7] We excluded from the sample banks with capital allocations greater than zero but less than 5 percent of equity, banks that changed holding company ownership in the year of allocation, and banks with other allocations in the previous three years.

[8] A market is defined as a standard metropolitan statistical area (SMSA), if applicable, or a county. Some markets include only one bank. In these situations, market loan growth and bank loan growth are the same.

[9] We used repeated measures to capture bank-to-bank variation in the form of a single variance term and fixed effects for years. Attempts to include the large number of fixed effects for banks created a highly collinear collection of bank and year effects with a non-positive definite variance-covariance matrix and unstable parameter estimation (see Belsley, Kuh, and Welsch, 1980). Fixed effects for years were excluded in some categories for the same reasons.

[10] We excluded observations on banks exceeding the upper 1 percent level for $\mathrm{CASH}_{(t-1)}$, $\mathrm{GROW}_{(t-1)}$, and $\mathrm{ECAP}_{(t-1)}$. Inclusion of these outlying observations in alternate tests did not affect the coefficients on $\mathrm{SOFT}_{(t-1)}$ but did reduce the statistical significance of some other independent variables.

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