Rev Account Stud
DOI 10.1007/s11142-017-9430-2

Fundamental analysis of banks: the use of financial statement information to screen winners from losers

Partha Mohanram[1] · **Sasan Saiy**[2] · **Dushyantkumar Vyas**[1,3]

Abstract This study investigates the efficacy of a fundamental analysis-based approach to screen U.S. bank stocks. We construct an index (BSCORE) based on fourteen bank–specific valuation signals. We document a positive association between BSCORE and future profitability changes, as well as current and one-year-ahead stock returns, implying that BSCORE captures forward looking information that the markets are yet to impound. A hedge strategy based on BSCORE yields positive hedge returns for all but two years during our 1994–2014 sample period. Results are robust to partitions of size, analyst following, and exchange listing, and persist after adjusting for risk factors. We further document a positive relation between BSCORE and future analyst forecast surprises as well as earnings announcement period returns, and a negative relation between BSCORE and future performance-based delistings. Overall, our results show that a fundamental analysis-based approach can provide useful insights for analyzing banks.

Keywords Fundamental analysis · Bank stocks · Stock screening · Market efficiency · Financial statement analysis

JEL classifications G32 · M41

✉ Partha Mohanram
partha.mohanram@rotman.utoronto.ca

Sasan Saiy
ssaiy@uwaterloo.ca

Dushyantkumar Vyas
dushyantkumar.Vyas@rotman.utoronto.ca

1 Rotman School of Management, University of Toronto, Toronto, Canada

2 School of Accounting and Finance, University of Waterloo, Waterloo, Canada

3 Department of Management, University of Toronto, Mississauga, Canada

Published online: 21 November 2017

1 Introduction

This study examines the efficacy of a financial statement–driven fundamental analysis strategy for screening bank stocks. According to some estimates, the size of the U.S. banking sector as measured by total banking assets is as large as the annual GDP.[1] Despite the importance of the banking sector to the wider economy, most valuation research in accounting and finance excludes bank stocks. The exclusion of bank stocks may be partially justified, as the financial statement–based value drivers are substantially different for banks as compared to other industries. For example, while working capital accruals are important for firms in manufacturing and retail, specific accruals such as loan loss provisions are more important for banks.

The recent crisis has also brought to the fore criticisms concerning excessive fixation of bank managers and market participants on Return on Equity (ROE) as a key bank performance evaluation metric. Many observers (ECB 2010; Admati 2011; Admati et al. 2013; Moussu and Petit-Romec 2013) have suggested that ROE enhanced by risk and leverage may not reflect sustainable profits and may have contributed to value destruction during the recent financial crisis. Accordingly, we explore whether investors can improve upon a simple ROE-based investment strategy by incorporating additional fundamental signals.

We build upon prior studies in accounting that document the usefulness of signals constructed using historical financial statement data in predicting future accounting and stock return performance (e.g., Lev and Thiagarajan 1993; Bernard and Thomas 1989, 1990; Sloan 1996; among others). Our approach in this paper is similar to that of Piotroski (2000), who documents the efficacy of financial statement analysis in ex-ante identification of winners and losers among value stocks. Further, we are motivated by Mohanram (2005), who contextualizes fundamental analysis for growth stocks. In this paper, we attempt to contextualize fundamental analysis for bank stocks.

We combine fourteen bank-specific valuation signals to create a bank fundamentals index (BSCORE). We motivate our signals from the residual income valuation model developed in Ohlson (1995), Feltham and Ohlson (1995), and other papers. The value of a stock should depend on three factors—the ability to generate profitability in excess of the cost of equity (+), risk (−), and growth prospects (+). Our choice of specific signals is motivated by the guidance in Calomiris and Nissim (2007) and Koller et al. (2010), who analyze valuation of bank stocks.

We combine signals pertaining to: (i) overall measures of profitability (return on equity and return on assets), (ii) components of profitability (spread, operating expense ratio, non-interest income, earning assets, and loans-to-deposits ratio), (iii) prudent banking activities (loan loss provisions, non-performing loans, loan loss allowance adequacy, and tangible common equity ratio), and (iv) measures of growth (growth in revenues, total loans, and trading assets).

We first examine the mechanism through which BSCORE affects future returns. We conjecture that the fundamental signals included in BSCORE provide incremental predictive power for future profitability over current profitability. Multivariate

[1] http://www.helgilibrary.com/indicators/index/bank-assets-as-of-gdp

regression analyses provide evidence consistent with this expectation, as BSCORE is positively associated with the changes in one-year-ahead ROE and ROA. Second, we examine whether the stock market is able to incorporate the implications of current BSCORE signals for future profitability. We observe a positive relation between BSCORE and current stock returns after controlling for current profitability. This suggests that current-year stock returns reflect, at least to some extent, the implications of BSCORE fundamentals for future profitability. Lastly, we document a positive relation between BSCORE and one-year-ahead returns. Taken together, these results suggest that the stock market only partially incorporates the implications of BSCORE for future profitability.

The foregoing discussion hints at the possibility of a trading strategy based on the ability of BSCORE to improve investors' understanding of the sustainability of earnings. A strategy that is long (short) on the highest (lowest) BSCORE deciles yields an average annualized industry-adjusted return of 9.9% during our 1994–2014 sample period that is significant across size partitions and survives controls for commonly used risk factors. In addition, consistent with a mispricing-based explanation, we observe (1) a positive relation between BSCORE and analyst forecast surprises, as well as abnormal returns around subsequent earnings announcements, and (2) a negative relation between BSCORE and future performance-related delistings.

Our results have implications for the research on and the practice of fundamental analysis. They suggest that a simple yet systematic approach that augments summary measures of profitability with signals related to components of profitability, growth, and prudence can be used to screen bank stocks. The findings in our study contrast with the decline in returns to fundamentals-based trading strategies for non-financial firms. It is possible that returns to the BSCORE-based trading strategy used in this paper could also decline over time, once investors' attention is sufficiently focused on bank fundamentals. However, this was evidently not the case during the sample period used in this study—one of the interesting findings in our paper is that hedge returns are rarely negative and in fact peak around the financial crisis.

The rest of our paper is organized as follows. Section 2 discusses prior research in both banking and fundamental analysis in order to motivate our approach. Section 3 describes the individual components used in creating the BSCORE index, the sample selection process and descriptive statistics. Section 4 presents the empirical results, and Section 5 concludes.

2 Literature review

Our paper builds on research from two streams—banking and fundamental analysis. We briefly describe the relevant research in both of these areas, and use the insights from prior research to develop our approach towards fundamental analysis in banking.

2.1 Valuation of bank stocks

The valuation literature in accounting and finance typically deletes financial sector stocks. This may partly be due to the fact that banks have a business model that is very different from non-financial firms. We conjecture that bank stocks are in fact an ideal laboratory for fundamental analysis, due to reasons outlined below.

2.1.1 ROE fixation, leverage and the rationality of bank pricing

ROE is commonly used as a key bank performance measure by market participants and bank managers. The recent financial crisis, however, has highlighted the limitations of ROE as a measure of sustainable profitability. In particular, critics argue that improvement in ROE can stem not just from enhancing operating profitability, but also from increasing leverage and from undertaking increasingly risky credit and non-traditional banking activities (Admati 2011; Admati et al. 2013). Moussu and Petit-Romec (2013) demonstrate that ROE fixation creates incentives for excessive risk taking in banks. They document that increases in leverage, which enhanced ROE pre-crisis, contributed significantly to value destruction during the crisis.

The potentially destructive consequences of ROE fixation have attracted significant attention from bank regulators and economists. For example, according to a European Central Bank (ECB) report in 2010, banks with high levels of pre-crisis ROE exhibited particularly negative performance during the crisis.[2] The report highlights several key limitations of ROE: (a) it is not risk-sensitive, (b) it is short-term oriented and not forward-looking, and (c) it creates wrong incentives and provides opportunities for manipulation. Most relevant to our paper, the ECB report concludes that ROE should not be used as a stand-alone measure of profitability, but should be augmented to create a more comprehensive measure that mitigates these limitations. Our BSCORE metric not only includes changes in summary measures of profitability, but also fundamental signals pertaining to components of profitability, prudence, and growth.

The high leverage of bank stocks also makes their market valuation more susceptible to macroeconomic and market sentiment swings (Koller et al. 2010). This characteristic of bank stocks makes them ideal for fundamental analysis because, while the broader market may be concerned about macroeconomic and industry-wide factors, a fundamental-focused investor can potentially earn excess returns by screening bank stocks based on bank-specific value drivers.

The financial crisis period also exposed wild gyrations in the valuation of bank stocks. If this indeed was a period where valuations departed from fundamentals, it would also provide an interesting setting for testing a fundamentals-based investing strategy. Huizinga and Laeven (2012) show that during the financial crisis period banks overstated the value of their distressed (real estate-backed) assets. The authors attribute these findings to noncompliance with accounting rules and regulatory forbearance. In a similar vein, Vyas (2011) shows that financial institutions recorded losses in an untimely manner compared to the devaluations being implied by the underlying asset markets. Echoing these findings, Papa and Petres (2014) examine 51 large global banks before and after the crisis and document a lag between allowance for loan losses and market values. Calomiris and Nissim (2014), however, focus on the decline in banks' market-to-book ratios during the recent financial crisis, and show that the decline cannot be fully attributed to delayed recognition of losses on existing financial instruments.

[2] https://www.ecb.europa.eu/pub/pdf/other/beyondroehowtomeasurebankperformance201009en.pdf

2.1.2 Banks are "*different*"

Modern day banks are inherently different from other industries due to the inherent opacity or complexity of their balance sheet (Adams and Mehran 2003; Koller et al. 2010). Morgan (2002) calls banks "black holes of the universe." This opacity arises, among other things, from the limitations of the current accounting models in conveying information about the extent of credit losses, and from the pervasiveness of off–balance sheet exposures among large banks. Further complicating matters is the extent to which non-traditional banking activities (such as securitization and investment banking) drive bank value. Macey and O'Hara (2003) state that "not only are bank balance sheets notoriously opaque, but … rapid developments in technology and increased financial sophistication have challenged the ability of traditional regulation and supervision to foster a safe and sound banking system."

On the one hand, the inherent opacity in banks' financial statements suggests that a financial statement–based valuation approach might not be fruitful. On the other hand, investors often need a standardized yardstick to facilitate benchmarking between various firms, suggesting that a fundamentals index that is tailored to banking could be beneficial to investors. These two countervailing possibilities add some tension to our predictions and analyses.

Calomiris and Nissim (2007) conduct an activity-based valuation of bank holding companies in the U.S. They document that residuals from a regression of market-to-book on the activity-based value drivers predict future returns. However, these future returns are diminished considerably by trading costs. Our study differs in its focus on future profitability and returns. In addition, we successfully document a parsimonious and viable trading strategy that allows investors to incorporate the implications of a broader set of bank fundamentals instead of using traditional summary profitability metrics alone.

2.2 Fundamental analysis using financial statement analysis

While typically not focusing on bank stocks, an extensive prior literature has focused on the ability of financial signals to predict future stock returns. Ou and Penman (1989) show that certain financial ratios can help predict future changes in earnings. Lev and Thiagarajan (1993) analyze 12 financial signals purportedly used by financial analysts and show that these signals are correlated with contemporaneous returns and future earnings. Abarbanell and Bushee (1997) show that an investment strategy based on these signals earns significant abnormal returns.

Two studies most relevant to our paper are Piotroski (2000) and Mohanram (2005). Piotroski (2000) uses financial statement analysis to develop an investment strategy for high book-to-market (BM) or value firms. Motivated by the Dupont framework, he creates an index labeled FSCORE, which combines signals of overall profitability, asset turnover, profit margin, liquidity, and solvency. A strategy long in high FSCORE firms and short in low FSCORE firms generates significant excess returns. Mohanram (2005) follows a similar approach as Piotroski (2000) but focuses on low BM or growth stocks. He tailors the signals to better suit growth stocks. He combines eight binary signals into a single index called GSCORE and shows that the GSCORE strategy is successful in separating winners from losers among low BM firms. In this paper, we attempt to tailor fundamental analysis in the context of bank stocks.

3 Research framework, sample and descriptive statistics

3.1 Why traditional fundamental analysis might not be effective in bank stocks

The residual income valuation (RIV) model from Ohlson (1995) and Feltham and Ohlson (1995), among others, characterizes stock price as a function of book value and the present value of the stream of future expected abnormal earnings. The value of a stock increases with a firm's ability to generate abnormal profitability, and increases further with the persistence and growth in abnormal profitability. However, the value of a stock decreases with (systematic) risk, as future abnormal earnings are discounted further.[3] Prior research on fundamental analysis either explicitly or implicitly considers signals related to profitability, risk, and growth—e.g., the focus on profitability and risk in Piotroski (2000), and the additional focus on growth in Mohanram (2005).

Applying traditional ratio analysis in banks is problematic because many ratios use data that is either not meaningful or not provided for bank stocks. FSCORE incorporates signals related to asset turnover, profit margin, accruals, and the current ratio, which in turn require data on cost of goods sold, current assets, current liabilities, and working capital accruals. Similarly, GSCORE includes signals related to research and development, advertising, and capital expenditures. Hence, these papers either explicitly or implicitly (due to the data requirements) exclude bank stocks. While we cannot apply these approaches directly to bank stocks, we focus on bank-specific ratios related to the same drivers of value—i.e., the ability to generate abnormal profitability, risk, and growth.

3.2 Applying fundamental analysis to bank stocks: Construction of the BSCORE index

We look for signals associated with (abnormal) profitability, risk, and growth. We categorize these signals into four broad components: overall profitability, components of profitability, prudence in banking activities, and indicators of future growth.[4] Our choice of signals within each category is motivated by the guidance in the academic and practitioner literature (e.g., Calomiris and Nissim 2007; the McKinsey & Co. valuation book by Koller et al. 2010).

We construct the signals based on the relative ranks of annual changes in the individual BSCORE fundamental metrics within bank size groups (constructed as terciles of total assets within a given year). For each individual metric, we focus on changes rather than levels for two reasons. First, this approach mirrors Piotroski (2000), who uses a similar approach to identify firms with improving fundamentals. Second, this approach has the advantage of the firm serving as its own control. In addition, we focus on the relative rank of a signal within

[3] The use of residual income valuation by sell side analysts has been growing, as noted by Hand et al. (2015), especially for analysts associated with certain brokerage houses, such as Morgan Stanley and J.P. Morgan, that have embraced the RIV model. A search of research reports in the banking sector from the Investext database shows that bank stock analysts from these brokerages use RIV models to calculate price targets. These analysts routinely forecast ROE (or its variants such as return on economic equity) to arrive at their forecasts of net income / residual income.

[4] Note that the categorization of signals into these broad categories is not necessarily non-overlapping. For example, while the loans-to-deposits ratio indicates the ability of a bank to deploy a relatively stable source of funding into revenue-generating assets, reliance on deposits also has implications for financial leverage and liquidity risk.

size terciles. This allows for more meaningful comparisons of ratios across banks, as bank size is an important determinant of the business model mix, which tilts towards universal banking for large banks and towards traditional deposit and loan activities for smaller banks. Bank size is also likely to determine the extent of geographical and asset portfolio diversification, as well as the adoption of online banking and other technological innovations. The ranks are normalized such that each signal has a minimum value of 0 and a maximum value of 1. BSCORE is the sum of these fourteen individual signals and thus has a maximum (minimum) theoretical value of 14 (0).[5]

3.2.1 Overall profitability

We employ two metrics to measure a bank's overall profitability: *ROE* as a levered measure, and *ROA* as an unlevered measure.

1) *Return on equity (ROE)*: ROE is used very extensively in banking to evaluate performance. Accordingly, we use ROE as the first fundamental signal to screen bank stocks. A potential drawback to this approach is that if ROE is primarily driven by leverage, then its use as a signal of firm value could be questionable during economic downturns (when banks are more likely to deleverage and forgo true value creating activities). B1 is the normalized relative rank of ΔROE_t for a given bank-year within its size group.
2) *Return on assets (ROA)*: ROA is less immune to problems pertaining to leverage. Thus, it is a potentially useful measure of unlevered profitability. B2 is the normalized relative rank of ΔROA_t for a given bank-year within its size group.

3.2.2 Components of profitability

We employ five signals in this category. The first three signals (spread, operating expense ratio, and non-interest income) are analogous to profit margin, while the remaining two signals (earning assets and loans-to-deposits ratio) are measures of asset deployment efficiency.

3) *Spread*: We measure the spread on a bank's loan portfolio as the ratio of net interest income (interest income – interest expense) to total loans. Note that the sign of this signal is ambiguous, as higher spread could simply reflect higher risk on the loan portfolio. B3 is the normalized relative rank of $\Delta Spread_t$ for a given bank-year within its size group.
4) *Operating expense ratio*: We define operating expense ratio as non-interest expense divided by total revenue. This measures how large a proportion of revenues is spent on operating and administrative expenses. Revenue is defined as the sum of net interest

[5] In the previous version, we used a discrete version of BSCORE in which indicator variables are used to capture the direction of annual change for each of the metrics underlying the signals. The results are broadly similar. While the discrete approach is simple and is in line with mechanisms used by many retail investors in picking stocks, we use the continuous specification in the paper, as it better captures the extent of variation in the variables underlying BSCORE. Further, the discrete approach has a limitation in that a large proportion of signals can be classified as 1 or 0 depending upon the industry conditions during that year (e.g., all firms may have an increase or decrease in spread because of interest rate movements). Finally, with a discrete BSCORE measure, it is impossible to construct portfolios of exact sizes (like quintiles or deciles).

income (interest income – interest expense) and non-interest income. B4 is the normalized relative rank of $-\Delta$Expense_Ratio$_t$ for a given bank-year within its size group.

5) *Non-interest income*: We define non-interest income as the ratio of non-interest income to total revenue. This measure is particularly useful for larger universal banks that generate a significant portion of their income from non-lending/deposit activities. These revenues often arise from higher value-added services (such as investment banking and brokerage) that are potentially very profitable or are associated with no direct costs (such as service fees). B5 is the normalized relative rank of ΔNoninterest_Income$_t$ for a given bank-year within its size group.
6) *Earning assets*: Banks generate income from inter alia, loans and other investments that yield interest or dividend income—i.e., earning assets. We define the earning assets ratio as the ratio of earning assets to total assets. We expect that this measure of asset deployment efficiency should be positively related to future performance. B6 is the normalized relative rank of ΔEarning_Assets$_t$ for a given bank-year within its size group.
7) *Loans to deposits*: This signal is the ratio of loans to deposits, and measures the ability of a bank to efficiently deploy its primary source of funding (deposits) to grow its primary earning asset (loans). If the ratio is too low, it means that the bank has a lot of unused funds and accordingly implies increased inefficiency. Note that while this ratio is categorized as a component of profitability, it could also reflect liquidity risk if a large number of depositors withdraw their deposits simultaneously. B7 is the normalized relative rank of ΔLoans_Deposits$_t$ for a given bank-year within its size group.

3.2.3 Signals related to prudence: Lower credit risk and greater loss absorption capacity

We use non-performing loans and loan loss provisions as timely signals of future credit losses. Further, to measure the ability of banks to absorb credit losses and remain solvent, we include the allowance adequacy and tangible common equity measures that capture loss absorption capacity.

8) *Loan loss provisions (LLP)*: LLP is perhaps the most important accrual for banks, in terms of absolute magnitude as well as impact on overall profitability and capital adequacy (Beatty and Liao 2011; Liu and Ryan 2006). Accordingly, we define LLP as the ratio of annual loan loss provision to total loans. B8 is the normalized relative rank of $-\Delta$LLP$_t$ for a given bank-year within its size group.
9) *Non-performing loans (NPL)*: We employ NPL as a forward-looking credit risk metric measured as the ratio of non-performing loans to total loans. NPL, though noisy, may be one of the timeliest indicators of future loan losses. B9 is the normalized relative rank of $-\Delta$NPL$_t$ for a given bank-year within its size group.
10) *Allowance adequacy*: Banks with greater loan loss allowance adequacy are generally better able to absorb expected credit losses without impairing capital during periods of distress (e.g., Beatty and Liao 2011). Accordingly, we measure allowance adequacy as the ratio of loan loss allowance to non-performing loans. B10 is the normalized relative rank of ΔAllowance_Adequacy$_t$ for a given bank-year within its size group.
11) *TCE Ratio (TCE)*: Banks with greater TCE are generally better able to absorb unexpected losses and maintain solvency during periods of distress (e.g., Basel

Committee on Banking Supervision 2013). We measure TCE Ratio as the ratio of tangible common equity to total assets. B11 is the normalized relative rank of ΔTCE_Ratio$_t$ for a given bank-year within its size group.

3.2.4 Growth in revenues and assets

We employ three signals to measure growth: change in total revenue, change in loans, and change in trading assets. Change in total revenue measures growth in overall income, while changes in loans and trading assets measure the bank's growth in traditional activities and non-traditional activities, respectively.

12) *Revenue growth (SGR)*: Total revenue is defined as the sum of net interest income (interest income – interest expense) and non-interest income. We measure SGR as the percentage annual change in total revenue. B12 is the normalized relative rank of SGR$_t$ for a given bank-year within its size group. Note that this signal does not distinguish whether revenue growth arises from traditional banking activities or other non-banking activities. Our next two signals focus on such a decomposition.
13) *Loan growth (LGR)*: Regulators and market participants often evaluate banks on the basis of their ability to grow their total loan portfolio. On the one hand, increasing the loan base can result in increased revenue. On the other hand, it could also reflect increased credit risk. These concerns generally become acute during periods of financial distress, when banks are reluctant to extend credit due to economy-wide credit risk fears. LGR is defined as the percentage annual change in gross loans reported on the balance sheet. B13 is the normalized relative rank of LGR$_t$ for a given bank-year within its size group.
14) *Trading assets growth (TRADE)*: To reflect a bank's involvement in non-traditional banking activities, we measure TRADE as the change in the proportion of trading assets to total assets. Our last signal (B14) is the normalized relative rank of ΔTRADE$_t$ for a given bank-year within its size group.

As mentioned earlier, we define BSCORE to be the sum of the fourteen signals B1:B14. In addition, to understand the relative importance of signals from each category, we define PROFCOMP as the sum of the five signals B3:B7, PRUDENCE as the sum of the four signals B8:B11, and GROWTH as the sum of the three signals B12:B14.

3.3 Association of BSCORE with future accounting fundamentals and stock returns

BSCORE not only includes summary measures such as changes in ROE and ROA, but also twelve other fundamental signals. We conjecture that the inclusion of these additional signals will enable BSCORE to have incremental predictive power for future accounting profitability (over and above current profitability). Accordingly, we conduct multivariate regression analyses to test the relation between BSCORE and one-year-ahead changes in ROE and ROA.

If banks have strong (weak) fundamentals that investors have not completely impounded in stock price, then high (low) BSCORE firms should earn higher (lower) ex-post returns. We analyze future returns using a one-year horizon, with returns being compounded beginning four months after the fiscal year end. Our measure of annual returns is labeled RET_{t+1}, calculated as buy-and-hold annual returns with adjustments for delistings as in Shumway (1997). In addition, we also calculate industry-adjusted returns, $RETB_{t+1}$, as the difference between RET_{t+1} and the compounded equally weighted banking industry return over the same period.

3.4 Sample and descriptive statistics

We begin our sample construction using all banks on Bank COMPUSTAT between 1993 and 2014. Panel A of Table 1 presents our sample selection process. We restrict the sample to bank-years following 1993 due to limited data availability on Bank COMPUSTAT in prior years, providing us with 17,727 bank-year observations, corresponding to 2052 unique banks. Further filters pertaining to the need for lagged data as well as data availability of BSCORE components decrease the sample to 15,318 (1867) bank-year (bank-level) observations. We restrict our sample to December fiscal year end firms to ensure that the information availability and return compounding windows are aligned for all firms in a given year. As most banks have December fiscal year ends, this reduces our sample size marginally to 12,876 (1540) bank-year (bank-level) observations. Further conditioning on availability of returns on CRSP, along with elimination of outliers and firms below the size, stock price, and shares outstanding thresholds, results in our final sample of 10,472 (1269) bank-year (bank-level) observations.

Panel B of Table 1 presents descriptive statistics for the banks in our sample as well as for the variables underlying the fourteen signals used to construct BSCORE. As banks are typically asset intensive, the average (median) reported total assets are $29.5 billion ($1.2 billion). The distributions of assets, revenues, and market capitalization all show distinct right skewness, with means much larger than medians, reflecting the presence of large universal banks in the sample.

The mean (median) ROE is 8.7% (10.1%). In contrast, the mean (median) ROA is 0.8% (0.9%). The contrast in magnitudes of ROE and ROA is not surprising, as banks are generally highly levered. The mean (median) spread is 5.4% (5.1%) with a modest standard deviation of 1.6%, which reflects the competitive nature of the traditional banking industry, with limited scope for excessive interest margins. The mean (median) operating expense ratio is 82.5% (79.3%).

Mean (median) non-interest income of 21.7% (19.7%) shows that non-traditional banking activities drive a substantial part of total revenues. The mean (median) bank has 87.9% (89.8%) of its assets classified as earning assets—that mainly represent investments in loans and securities—as opposed to idle cash balances and other assets such as PP&E. Loans-to-deposits ratio exhibits a mean (median) of 88% (87.5%), suggesting that a substantially high proportion of funds raised through traditional deposit-raising activity are deployed into traditional banking assets—loans.

Mean (median) annual loan loss provision (LLP) is 0.55% (0.30%), while mean (median) non-performing loans are 1.68% (0.92%) of total year-end loans outstanding. Mean (median) allowance adequacy (loan loss allowance divided by non-performing loans) is 2.72 (1.26), implying that outstanding allowances were more than sufficient to cover expected loan losses. However, a closer examination (untabulated) reveals that allowance adequacy was severely stressed during the crisis years.

Table 1 Sample selection and descriptive statistics

Panel A: Sample selection

Criterion	**Bank-Years**	**Unique Banks**
Observations between 1993 and 2014 on Bank COMPUSTAT	17,727	2,052
Availability of information to compute the variables underlying B1:B14	16,010	1,895
Availability of lagged information to compute B1:B14 and BSCORE	15,318	1,867
December Fiscal Year End firms only	12,876	1,540
Availability of Future returns on CRSP	10,945	1,300
Stock Price > = $1, Shares Outstanding > = 1 million, Total Assets > = $100 million and Market Capitalization > = $10 million	10,472	1,269
FINAL SAMPLE	10,472	1,269

Panel B: Descriptive statistics (*N* = 10,472)

Variable	**Mean**	**Min**	**Q1**	**Median**	**Q3**	**Max**	**Stdev**
Total Assets	29,555	100	545	1200	3927	3,771,200	193,767
Revenues	1068	3	23	52	169	119,643	6,178
Market Capitalization	2732	10	59	151	584	283,431	13,906
ROE	8.74%	−58.87%	6.07%	10.12%	13.51%	26.25%	9.61%
ROA	0.80%	−3.80%	0.58%	0.90%	1.18%	2.45%	0.77%
ΔROE	−0.23%	−85.12%	−1.79%	0.05%	1.63%	85.12%	9.11%
Spread	5.38%	2.11%	4.29%	5.13%	6.11%	13.04%	1.65%
Expense_Ratio	82.5%	51.8%	74.0%	79.3%	85.7%	211.1%	18.8%
Non_Interest_Income	21.7%	−1.5%	12.8%	19.7%	28.1%	73.0%	13.9%
Earning_Assets	87.9%	54.1%	85.7%	89.8%	92.4%	97.3%	7.2%
Loans_Deposits	88.0%	35.6%	76.1%	87.5%	98.6%	151.1%	19.7%
LLP	0.55%	−0.35%	0.14%	0.30%	0.58%	5.25%	0.81%
NPL	1.68%	0.00%	0.44%	0.92%	1.96%	14.74%	2.21%
Allowance_Adequacy	2.72	0.00	0.64	1.26	2.52	38.54	5.30
SGR	13.2%	−34.7%	1.6%	8.8%	18.5%	125.7%	22.3%
LGR	14.1%	−22.9%	2.7%	9.7%	19.9%	107.3%	20.3%
TRADE	0.34%	0.00%	0.00%	0.00%	0.00%	16.70%	1.74%
TCE	8.26	1.26	6.32	7.84	9.53	24.00	3.22
BSCORE	7.10	1.13	5.53	7.15	8.68	12.13	1.57

Panel A presents the sample selection procedure. Panel B presents descriptive statistics. Please see Appendix for the definition of the variables.

The average bank-year exhibits robust mean (median) revenue growth (SGR) of 13.2% (8.8%) and mean (median) loan growth (LGR) of 14.1% (9.7%). Average trading assets (TRADE) as a percentage of total assets are quite low at 0.3% (0.0%), reflecting the limited number of banks with active trading desks. Finally, mean (median) tangible common equity ratio (TCE) is 8.26 (7.84), reflecting that the average bank is adequately capitalized. A low interquartile range for *TCE* indicates that banks are tightly clustered around the median regarding capital adequacy.

Finally, we include the descriptive statistics for BSCORE. As it is an index created from the average of fourteen signals that themselves range from 0 to 1 with an expected mean of 0.5, the mean of BSCORE is close to seven (7.10). The interquartile range is 3.15 (= 8.68–5.53), indicating considerable clustering around the median.

4 Empirical analyses

4.1 Relation between individual signals and future returns

To provide preliminary evidence on the efficacy of the individual signals, we examine the relation between each of the signals (B1:B14) and the average one-year-ahead bank industry-adjusted returns ($RETB_{t+1}$). In Table 2, we partition the sample based on above/below median values for each of the fourteen signals and compare the average $RETB_{t+1}$ for each group.

The first two rows of Table 2 document the return differential for the traditional profitability ratios, ΔROE_t and ΔROA_t, both of which are positive (2.99% and 2.43%, respectively) at the 1% level. The next set of rows presents the signals related to components of profitability. The return differences for $\Delta Spread_t$ (B3) and $-\Delta Expense\_Ratio_t$ (B4) are positive and significant as expected, whereas the return difference for $\Delta Noninterest\_Income_t$ (B5) is negative and significant, potentially reflecting greater reliance on non-traditional and risky banking activities. Further, the return differences for $\Delta Earning\_Assets_t$ (B6) and $\Delta Loans\_Deposits_t$ (B7) are positive but insignificant. The composite PROFCOMP measure shows a significant return spread of 2.23%. The next set of rows presents signals related to prudence. Return differences are positive for $-\Delta LLP_t$ (B8), $-\Delta NPL_t$ (B9), $\Delta Allowance\_Adequacy_t$ (B10), and ΔTCE_t (B11) and significant for all except B11.[6] The composite PRUDENCE measure shows a significant return spread of 4.27%. Finally, none of the growth signals show statistically significant return differences, though SGR (B12) is marginally significant. The composite GROWTH measure shows an insignificant return spread.

We include all signals in BSCORE, as cherry-picking only the signals that work would impose look-ahead bias. The last row of Table 2 reports a positive (3.11%) and significant return differential at the 1% level for BSCORE.[7,8]

[6] The insignificance of ΔTCE_t (B11) could be partially explained by the possibility that a larger equity cushion, while allowing banks to withstand unexpected credit losses, also reflects holding of costly equity capital that is viewed unfavorably by the stock market (Admati et al. 2013; Admati 2014).

[7] The $-\Delta NPL_t$ (B9) signal is the strongest univariate signal. If we combine this signal with ΔROE (quintiles of ΔROE further partitioned on the basis of ΔNPL), we find that hedge returns increase slightly compared to our overall BSCORE measure but are much more variable. Although the yearly average hedge return of 11.21% is higher than the 10.15% we report in Table 8, the Sharpe ratio is much lower at 0.73 with negative returns in four years.

[8] Another alternative is to use a holdout sample from an earlier period to test the signals and only use the signals that work in the succeeding period. We test the individual signals in the 1994–2003 period and find that only the following signals generate statistically significant return spreads: ΔROE (B1), −ΔExpense_Ratio (B4), ΔEarning_Assets (B6), ΔLoans_Deposits (B7), −ΔNPL (B9), ΔAllowance_Adequacy (B10), SGR (B12), and LGR (B13). We then recompute BSCORE using only these signals and find that the hedge returns for deciles of the adjusted BSCORE is 12.3%, almost identical to the 12.2% average that we report over the 2004–2014 period in Table 8. However, the returns are much more volatile, with four periods of negative returns as compared to two for our ex-ante method. Given that such an approach would leave us with a very short time series of eleven years, we prefer our ex-ante approach.

Table 2 Relation between individual signals and future returns

SIGNAL	Mean $RETB_{t+1}$ (Below Median)	Mean $RETB_{t+1}$ (Above Median)	Return Spread	*t*–statistic
Category 1: Traditional Profitability Ratios				
B1: ΔROE_t	−0.91%	2.07%	2.99%	5.26***
B2: ΔROA_t	−0.63%	1.80%	2.43%	4.28***
Category 2: Components of Profitability				
B3: $\Delta Spread_t$	0.00%	1.21%	1.21%	2.13**
B4: $-\Delta Expense\_Ratio_t$	−0.83%	2.01%	2.84%	5.01***
B5: $\Delta Noninterest\_Income_t$	1.48%	−0.39%	−1.86%	−3.28***
B6: $\Delta Earning\_Assets_t$	0.18%	1.01%	0.83%	1.46
B7: $\Delta Loans\_Deposits_t$	0.15%	1.03%	0.88%	1.55
PROFCOMP	−0.52%	1.71%	2.23%	3.94***
Category 3: Prudence				
B8: $-\Delta LLP_t$	−0.55%	1.74%	2.28%	4.03***
B9: $-\Delta NPL_t$	−1.80%	2.98%	4.77%	8.44***
B10: $\Delta Allowance\_Adequacy_t$	−0.60%	1.77%	2.37%	4.18***
B11: ΔTCE_t	0.30%	0.89%	0.59%	1.04
PRUDENCE	−1.53%	2.73%	4.27%	7.54***
Category 4: Growth				
B12: Revenue Growth (SGR)	0.12%	1.05%	0.93%	1.65*
B13: Loan Growth (LGR)	0.61%	0.58%	−0.03%	−0.06
B14: Trading Assets Growth (TAGR)	0.52%	1.54%	1.02%	0.78
GROWTH	0.50%	0.70%	0.20%	0.36
BSCORE	−0.96%	2.15%	3.11%	5.50***

This table presents the mean one-year industry adjusted returns ($RETB_{t+1}$) for the above and below median values of the individual fourteen BSCORE signals for the sample of banks. For variable definitions, please see the Appendix. t-statistic for difference in means is from a two-sample t-test. */**/*** represent statistical significance using 2-tailed tests at 10%/ 5%/ 1% levels.

4.2 Correlations between individual signals, BSCORE and future returns

Table 3 presents Pearson and Spearman correlations between ΔROE_t, ΔROA_t, BSCORE, its three components (PROFCOMP, PRUDENCE, and GROWTH), one-year-ahead change in ROE and ROA (ΔROE_{t+1} and ΔROA_{t+1}), and current and one-year-ahead industry-adjusted returns ($RETB_t$ and $RETB_{t+1}$). By construction, BSCORE is positively correlated with each of its subcomponents. The subcomponents are positively correlated among themselves, with the notable exception of a negative correlation between PRUDENCE and GROWTH, which suggests a tradeoff between prudence and growth. BSCORE and its components generally exhibit positive and significant pairwise correlations with contemporaneous and one-year-ahead industry-adjusted returns ($RETB_t$ and $RETB_{t+1}$), and contemporaneous changes in ROE and ROA (ΔROE_t and ΔROE_t). The exception is the insignificant negative correlation between GROWTH and $RETB_{t+1}$.

Table 3 Correlation matrix

	ΔROE_t	ΔROA_t	BSCORE	PROFCOMP	PRUDENCE	GROWTH	ΔROE_{t+1}	ΔROA_{t+1}	$RETB_t$	$RETB_{t+1}$
ΔROE_t		0.916^{***}	0.485^{***}	0.343^{***}	0.221^{***}	0.091^{***}	-0.185^{***}	-0.130^{***}	0.229^{***}	0.061^{***}
ΔROA_t	0.889^{***}		0.557^{***}	0.408^{***}	0.274^{***}	0.106^{***}	-0.146^{***}	-0.154^{***}	0.243^{***}	0.048^{***}
BSCORE	0.648^{***}	0.732^{***}		0.739^{***}	0.616^{***}	0.423^{***}	-0.054^{***}	-0.062^{***}	0.262^{***}	0.083^{***}
PROFCOMP	0.486^{***}	0.572^{***}	0.721^{***}		0.267^{***}	0.065^{***}	-0.041^{***}	-0.052^{***}	0.197^{***}	0.052^{***}
PRUDENCE	0.190^{***}	0.301^{***}	0.603^{***}	0.254^{***}		-0.105^{***}	0.039^{***}	0.043^{***}	0.178^{***}	0.093^{***}
GROWTH	0.133^{***}	0.115^{***}	0.392^{***}	0.058^{***}	-0.105^{***}		-0.047^{***}	-0.053^{***}	0.112^{***}	-0.004
ΔROE_{t+1}	-0.100^{***}	-0.091^{***}	-0.084^{***}	-0.069^{***}	0.017^{*}	-0.008		0.894^{***}	0.002	0.242^{***}
ΔROA_{t+1}	-0.081^{***}	-0.091^{***}	-0.078^{***}	-0.073^{***}	0.020^{*}	-0.001	0.891^{***}		0.011	0.269
$RETB_t$	0.248^{***}	0.253^{***}	0.308^{***}	0.215^{***}	0.184^{***}	0.109^{***}	0.032^{***}	0.042^{***}		0.020^{**}
$RETB_{t+1}$	0.053^{***}	0.051^{***}	0.078^{***}	0.045^{***}	0.098^{***}	-0.005	0.264^{***}	0.269^{***}	0.032^{***}	

This table presents correlations between the BSCORE index, its components, current changes in profitability (ΔROE_t and ΔROA_t), one-year-ahead changes in profitability (ΔROE_{t+1} and ΔROA_{t+1}), and current and one-year industry-adjusted returns ($RETB_t$ and $RETB_{t+1}$). For variable definitions, please see the Appendix. Coefficients above the diagonal are Pearson, and those below diagonal are Spearman rank-order correlations. */**/*** represent statistical significance at 10%/ 5%/ 1% levels.

We observe a significant negative Pearson (Spearman) correlation of −0.185 (−0.100) between ΔROE_t and ΔROE_{t+1}. This negative correlation is attenuated in the weaker negative Pearson (Spearman) correlation between BSCORE and ΔROE_{t+1} of −0.054 (−0.084), and a positive Pearson (Spearman) 0.039 (0.017) correlation between PRUDENCE and ΔROE_{t+1}. We also observe a significant negative Pearson (Spearman) correlation of −0.154 (−0.091) between ΔROA_t and ΔROA_{t+1}, but this negative relation is weaker between BSCORE and ΔROA_{t+1}, and in fact positive between PRUDENCE and ΔROA_{t+1}. Most importantly, the Pearson (Spearman) correlation between the BSCORE index and $RETB_{t+1}$ at 0.083 (0.078) is positive and significant at the 1% level. This is stronger than the correlation of 0.061 (0.053) between $RETB_{t+1}$ and ΔROE_t, and the correlation of 0.048 (0.051) between $RETB_{t+1}$ and ΔROA_t. Among the BSCORE components, PRUDENCE has the strongest correlation with future returns.

4.3 Relationship between BSCORE and future earnings growth

We next try to understand the mechanism through which BSCORE impacts future returns by testing the relation between BSCORE and one-year-ahead change in ROE and ROA.

The results are presented in Table 4. Panel A reports the results of the multivariate regression analyses for the relation between BSCORE and ΔROE_{t+1}. The first and third columns present the results for pooled regressions with year-fixed effects and two-way clustered t-statistics that control for time and firm clustering. The second and fourth columns report the results for Fama and Macbeth (1973) annual regressions. We observe a negative relation between ΔROE_t and ΔROE_{t+1} across all four specifications, with the relation being significant in the annual regressions. This negative relation between ΔROE_t and ΔROE_{t+1} is stronger for firms currently experiencing declines in ROE, as indicated by a consistent negative and significant coefficient on NEG*ΔROE_t. Pertinent to our study, the coefficient on BSCORE is positive and significant in the first (0.006) and second (0.005) columns at the 10% level. In terms of economic significance, it suggests that an increase of 1 unit of BSCORE is associated with a 0.5–0.6% increase in ROE.

The above regression suffers from potential multicollinearity, as ΔROE is both an independent variable as well as a component of BSCORE. As an alternate specification, we exclude overall profitability and include the other three components of BSCORE. An examination of BSCORE components in the third and last columns of Panel A indicates that the relationship between BSCORE and ΔROE_{t+1} is largely driven by PRUDENCE. Specifically, while the coefficients on PROFCOMP and GROWTH are positive but insignificant, the coefficient on PRUDENCE is positive and significant at the 5% level in both the pooled and annual regressions. In Panel B, we use ΔROA_{t+1} as the dependent variable to consider the impact of BSCORE on unlevered profitability. The results are broadly consistent with those observed in Panel A.

To summarize, our results show a significant relationship between BSCORE and future growth in profitability, largely driven by the PRUDENCE component. We next test whether this relationship is impounded into stock prices.

4.4 Relationship between BSCORE and current and future returns

Wahlen and Wieland (2011) show that using financial statement information to predict earnings increases can also predict future returns. Given that BSCORE is associated with

Table 4 Relationship between BSCORE and future earnings growth

Variable	Pooled	Annual	Pooled	Annual
Panel A: Dependent variable ΔROE_{t+1}				
Intercept	−0.0616**	−0.0528*	−0.0506**	−0.0419*
	(−2.38)	(−1.87)	(−2.44)	(−1.85)
NEG	−0.0004	−0.0042	−0.0052	−0.0074*
	(−0.09)	(−1.33)	(−1.50)	(−1.87)
ΔROE_t	−0.0225	−0.0954**	−0.0052	−0.08741*
	(−0.69)	(−2.27)	(−1.50)	(−1.87)
NEG*ΔROE_t	−0.6219***	−0.5562***	−0.6106***	−0.5592***
	(−7.23)	(−6.21)	(−6.90)	(−6.22)
BSCORE	0.0060*	0.0050*		
	(1.88)	(1.80)		
PROFCOMP			0.0049	0.0031
			(1.32)	(1.06)
PRUDENCE			0.0104**	0.0103**
			(1.96)	(1.96)
GROWTH			0.0015	0.0004
			(0.73)	(0.22)
Adj. R^2	21.7%	20.7%	21.7%	21.2%
Panel B: Dependent variable ΔROA_{t+1}				
Intercept	−0.0057**	−0.0046***	−0.0046***	−0.0037***
	(−3.10)	(−2.63)	(−3.10)	(−2.55)
NEG	0.0005	−0.0001	0.0002	−0.0003*
	(1.45)	(−0.42)	(0.69)	(−1.89)
ΔROA_t	−0.0444	−0.1551*	−0.0336	−0.1356*
	(−1.07)	(−1.82)	(−0.90)	(−1.79)
NEG*ΔROA_t	−0.5238***	−0.4734***	−0.5097***	−0.4728***
	(−5.00)	(−3.93)	(−4.82)	(−4.17)
BSCORE	0.0006***	0.0005***		
	(2.60)	(2.70)		
PROFCOMP			0.0005*	0.0003
			(1.85)	(1.43)
PRUDENCE			0.0010**	0.0009**
			(2.33)	(2.34)
GROWTH			0.0001	0.0001
			(0.45)	(0.39)
Adj. R^2	20.6%	16.9%	20.9%	17.8%

This table presents multivariate regression analyses for the relation between BSCORE (and its components) and future profitability. The dependent variable is the one-year-ahead change in return on equity (ΔROE_{t+1}) for Panel A, and one-year-ahead change in return on assets (ΔROA_{t+1}) for Panel B. NEG is a dummy variable that equals 1 when ΔROE_t or ΔROA_t is negative, and zero otherwise. Pooled regressions include year fixed effects and t-statistics that are two-way clustered by time and firm. Annual regressions are summarized using the Fama and Macbeth (1973) procedure. For variable definitions, please see the Appendix. t-statistic for difference in means is from a two-sample t-test. */**/*** represent statistical significance using 2-tailed tests at 10%/ 5%/ 1% levels.

future earnings changes, we now test whether BSCORE is also associated with future stock returns. We begin by first examining the association between BSCORE (and its components) with current bank-index adjusted stock returns ($RETB_t$). The results are presented in Panel A of Table 5.

The first two columns present a benchmark specification using ROE_t and ΔROE_t as the independent variables.[9] Both ROE_t and ΔROE_t are positively associated with $RETB_t$ in both specifications. In the next two columns, we augment the specification to include BSCORE. The coefficient on BSCORE is positive and significant in both specifications. The last two columns indicate that each BSCORE component is significantly positively related to current stock returns. Thus, the stock market considers the fundamental signals embedded in BSCORE to be incrementally value relevant to summary metrics of profitability. This does not address whether the market's contemporaneous assessment of BSCORE is complete.

Accordingly, in Panel B of Table 5, we test the relation between BSCORE (or its components) and *future* stock returns ($RETB_{t+1}$). Balachandran and Mohanram (2012) use a similar approach to examine the valuation of residual income growth. We first note that ROE_t does not exhibit a significant predictive power for future stock returns in all specifications. The coefficient on ΔROE_t is positive and significant in the first column but insignificant in all other specifications. However, the result of particular interest to us is the positive and significant association between BSCORE and $RETB_{t+1}$ in the third and fourth columns of Panel B. Together with the positive relation between BSCORE and current stock returns observed in Panel A, this suggests that while the stock market recognizes the incremental value relevance of BSCORE in current returns, the reaction is not complete, leading to a positive relation between BSCORE and future returns ($RETB_{t+1}$). In the pooled specification, BSCORE has a coefficient of 0.0119 (t-stat = 3.28). In terms of economic significance, this suggests that a unit increase in BSCORE is associated with a 1.19% increase in future annual returns.

The last two columns show that the PRUDENCE component of BSCORE dominates the PROFCOMP and GROWTH components. The coefficient on PRUDENCE is positive and significant at the 1% level in both specifications, whereas the coefficients on the other two components are insignificant (except for PROFCOMP, which is marginally significant in the annual regression). The strong performance of PRUDENCE is consistent with Uysal (2013), who finds a strong negative correlation between the change in non-performing loans and future stock returns.

In Panel C, we include controls for firm-level risk characteristics—size measured as log of market capitalization (SIZE), book-to-market ratio (BM), and momentum as measured by lagged returns ($RETB_t$). Among the newly added risk characteristics, only BM loads significantly (at the 5% level) in the three annual regressions. Importantly, the coefficient on BSCORE is positive and significant at the 1% level in both the pooled and annual specifications. Finally, breaking out BSCORE into its components shows a significantly positive association (significant at the 1% level) between PRUDENCE and $RETB_{t+1}$. GROWTH is insignificant in both specifications, while PROFCOMP is

[9] Easton and Harris (1991) regress returns on earnings and changes in earnings, where earnings is defined as earnings per share divided by lagged price per share. Given the focus on ROE in the banking sector, we redefine their approach and use ROE and ΔROE. We find very similar results if we use the exact specification in Easton and Harris (1991).

Table 5 Relationship between BSCORE and current and future returns

Variable	Pooled	Annual	Pooled	Annual	Pooled	Annual
Panel A: Dependent variable $RETB_t$						
Intercept	−0.0552***	−0.0384***	−0.3353***	−0.3280***	−0.3166***	−0.3027***
	(−6.26)	(−2.43)	(−12.00)	(−16.12)	(−10.97)	(−14.03)
ROE_t	0.5726***	0.5241***	0.5258***	0.4991***	0.5195***	0.4886***
	(5.55)	(5.25)	(5.40)	(5.12)	(5.27)	(4.92)
ΔROE_t	0.4919***	0.5915***	0.1574	0.1692	0.3002***	0.3548***
	(4.24)	(4.88)	(1.41)	(1.54)	(2.58)	(3.16)
BSCORE			0.0402***	0.0457***		
			(10.60)	(10.76)		
PROFCOMP					0.0448***	0.0432***
					(5.34)	(5.93)
PRUDENCE					0.0457***	0.0488***
					(6.02)	(5.56)
GROWTH					0.0409***	0.0381***
					(7.51)	(7.48)
N	10,472	10,472	10,472	10,472	10,472	10,472
Adj. R^2	10.02%	10.22%	13.76%	13.85%	13.10%	14.42%
Panel B: Dependent variable $RETB_{t+1}$						
Intercept	−0.0007	0.0047	−0.0831***	−0.078***	−0.0751**	−0.0628***
	(−0.05)	(0.35)	(−2.78)	(−3.60)	(−2.50)	(−2.88)
ROE_t	0.1463	0.0818	0.1328	0.0761	0.136	0.0733
	(1.12)	(0.60)	(1.01)	(0.56)	(1.04)	(0.54)
ΔROE_t	0.1362**	0.1473	0.067	0.0260	0.0659	0.0751
	(2.00)	(1.20)	(0.50)	(0.22)	(0.97)	(0.61)
BSCORE			0.0119***	0.0115***		
			(3.28)	(3.79)		
PROFCOMP					0.0077	0.010*
					(1.27)	(1.85)
PRUDENCE					0.0313***	0.0298***
					(4.89)	(4.15)
GROWTH					−0.0018	−0.0062
					(−0.21)	(−0.65)
N	10,472	10,472	10,472	10,472	10,472	10,472
Adj. R^2	1.72%	2.09%	2.02%	2.71%	2.37%	3.46%

Table 5 (continued)

Variable	Pooled	Annual	Pooled	Annual	Pooled	Annual
Panel C: Dependent variable $RETB_{t+1}$ with additional controls for risk factors						
Intercept	−0.007	−0.044	−0.1045	−0.1372	−0.0897	−0.1186
	(−0.17)	(−0.9)	(−1.99)	(−2.24)	(−1.66)	(−1.91)
ROE_t	0.2846***	0.2494***	0.2805***	0.2614***	v0.2816***	0.2439***
	(3.46)	(2.77)	(3.40)	(2.93)	(3.45)	(2.75)
ΔROE_t	0.0862	0.082	−0.0169	−0.0383	0.0162	0.0194
	(1.20)	(1.13)	(−0.23)	(−0.53)	(0.25)	(0.27)
BSCORE			0.0131***	0.0121***		
			(3.67)	(3.49)		
PROFCOMP					0.0098	0.0111**
					(1.38)	(2.08)
PRUDENCE					0.0318***	0.0290***
					(4.95)	(3.65)
GROWTH					−0.0013	−0.0012
					(−0.15)	(−0.14)
SIZE	−0.0054	−0.0029	−0.0049	−0.0027	−0.0054	−0.003
	(−0.73)	(−0.36)	(−0.67)	(−0.34)	(−0.74)	(−0.40)
BM	0.0364	0.068**	0.0393	0.0728***	0.0371	0.0658**
	(1.16)	(2.54)	(1.27)	(2.74)	(1.19)	(2.43)
$RETB_t$	0.0039	−0.0043	−0.0092	−0.0181	−0.0088	−0.0253
	(0.13)	(−0.09)	(−0.29)	(−0.35)	(−0.28)	(−0.48)
N	10,472	10,472	10,472	10,472	10,472	10,472
Adj. R^2	2.22%	8.31%	2.59%	8.82%	2.92%	9.42%

This table presents multivariate regression analyses for the relation between BSCORE (and its components) and current and future returns. The dependent variable in Panel A is the current industry-adjusted return ($RETB_t$), while the dependent variable in Panel B is the one-year-ahead industry-adjusted return ($RETB_{t+1}$). Panel C repeats the analysis in Panel B with additional controls for risk characteristics: SIZE (log of market capitalization), BM (book-to-market ratio) and momentum ($RETB_t$). Pooled regressions include year fixed effects and t-statistics that are two-way clustered by time and firm. Annual regressions are summarized using the Fama and Macbeth (1973) procedure. For variable definitions, please see the Appendix. t-statistic for difference in means is from a two-sample t-test. */**/*** represent statistical significance using 2-tailed tests at 10%/ 5%/ 1% levels.

positive and significant in the annual regression (at the 5% level). Panel C hence shows that risk is not driving the relation between BSCORE and future returns.

Taken as a whole, Table 5 documents significant explanatory power for BSCORE in explaining current and one-year-ahead stock returns, which suggests that the market does not immediately comprehend the implications of the fundamental signals underlying BSCORE.

4.5 Analysis of BSCORE-based hedge portfolios

We next analyze the hedge returns to a trading strategy based on BSCORE. The results are presented in Table 6. Panel A presents the results for deciles based on ΔROE as a benchmark. The means for both raw and industry-adjusted returns (RET_{t+1} and $RETB_{t+1}$) show generally monotonic increases as we move across ΔROE deciles. The spread in $RETB_{t+1}$ for a ΔROE-based trading strategy is 5.76% (= 3.37% + 2.39%) and is significant at the 1% level.

The next set of columns presents the returns for deciles based on BSCORE. The means for both RET_{t+1} and $RETB_{t+1}$ also generally increase monotonically across BSCORE deciles. The spread in $RETB_{t+1}$ for a BSCORE trading strategy is 9.90% (= 4.08% + 5.82%) and is significant at the 1% level. This is also significantly higher than the 5.76% return from a ΔROE-based trading strategy (difference = 4.14%, t-stat = 2.01).[10] Hence, a BSCORE-based hedge strategy that considers profitability, components of profitability, prudence, and growth performs significantly better than a ΔROE-based strategy that focuses on overall profitability. Also, note that a substantial portion of the hedge returns (4.08% out of 9.90% = 41%) stem from the long side. This is significant to note, as Beneish et al. (2015) argue that difficulties in shorting often affect the practical implementation of trading strategies.

Panel B presents returns for deciles based on the three other components of BSCORE. Consistent with our regression results in Table 5, we find the strongest results for PRUDENCE, weaker but significant results for PROFCOMP, and insignificant results for GROWTH.

4.6 Partition analysis

In this section, we partition the sample along several dimensions related to both information environment and implementability. We consider five partitions—firm size, analyst following, listing exchange, idiosyncratic risk, and trading turnover. The results are presented in Table 7. For parsimony, we present only $RETB_{t+1}$, and group all the middle portfolios together.

Panel A of Table 7 presents the returns by partitions of firm size (market capitalization). Consistent with prior research on fundamental analysis, the hedge returns are strongest in small firms, with mean hedge returns $RETB_{t+1}$ of 12.51%. For medium firms, the mean hedge returns $RETB_{t+1}$ are 9.49%, and for large firms the mean hedge returns $RETB_{t+1}$ are 7.13%. All the return differences are significant at the 1% level. The finding that results hold within the large bank stock partition may allay concerns related to the implementability of the BSCORE strategy.

The first set of columns of Panel B of Table 7 presents the returns by partitions of analyst following. The BSCORE strategy generates significantly positive hedge returns in both partitions. The returns are stronger for the subsample without analyst following (mean hedge $RETB_{t+1}$ = 12.66%) than for the subsample with analyst following (mean hedge $RETB_{t+1}$ = 8.07%). This suggests that analysts, at least to some extent, tend to go beyond the traditional summary profitability indicators (ΔROE_t and ΔROA_t) to assess the implications of fundamental signals similar to the ones that we use in BSCORE.

[10] To address concerns surrounding parametric tests in long-run returns settings, we conduct non-parametric bootstrap tests. Random pseudo-portfolios of sizes equal to the top and bottom groups are created from the sample with replacement. The difference in mean returns between these groups is calculated. This procedure is repeated a thousand times to create a distribution of return differences. The number of generated differences that are more than the actual difference in the data is presented, which provides a *p-value* for this test.

Table 6 Returns to an investment strategy based on BSCORE

Panel A: Mean returns by decile of ΔROE and BSCORE

	Deciles of ΔROE_t			Deciles of BSCORE		
Decile	**N**	RET_{t+1}	$RETB_{t+1}$	**N**	RET_{t+1}	$RETB_{t+1}$
1	1037	10.68%	-2.39%	1037	7.58%	-5.82%
2	1050	11.75%	-1.78%	1050	12.54%	-0.80%
3	1050	13.00%	-0.66%	1050	14.01%	0.27%
4	1047	13.06%	-0.77%	1047	14.28%	0.81%
5	1047	14.49%	0.87%	1047	15.13%	1.47%
6	1052	13.66%	0.15%	1052	14.72%	0.97%
7	1050	15.42%	2.04%	1050	15.06%	1.52%
8	1047	16.01%	2.37%	1047	14.50%	1.18%
9	1053	16.30%	2.75%	1052	15.82%	2.24%
10	1039	16.88%	3.37%	1040	17.55%	4.08%
10 – 1		6.20%	5.76%		9.98%	9.90%
t-stat		*3.28*	*3.93*		*5.44*	*6.87*
Bootstrap result		0/1000	0/1000		0/1000	0/1000
p-value		*0.000*	*0.000*		*0.000*	*0.000*

Panel B: Mean returns by decile of components of BSCORE

	Deciles of PROFCOMP			Deciles of PRUDENCE			Deciles of GROWTH		
Decile	**N**	RET_{t+1}	$RETB_{t+1}$	**N**	RET_{t+1}	$RETB_{t+1}$	**N**	RET_{t+1}	$RETB_{t+1}$
1	1037	9.22%	-4.01%	1037	7.78%	-5.81%	1037	14.62%	1.13%
2	1050	13.78%	0.10%	1050	12.54%	-0.98%	1051	14.61%	1.15%
3	1050	14.14%	0.48%	1050	11.16%	-2.35%	1049	13.18%	-0.30%
4	1045	14.83%	1.24%	1047	14.22%	0.71%	1047	14.59%	1.12%
5	1049	13.16%	-0.51%	1047	14.49%	0.72%	1047	13.23%	-0.62%
6	1052	14.75%	1.28%	1052	14.30%	0.73%	1052	13.90%	0.53%
7	1050	15.83%	2.18%	1050	15.26%	1.87%	1050	14.22%	0.75%
8	1048	14.69%	1.35%	1047	17.39%	3.85%	1047	14.23%	0.64%
9	1052	15.00%	1.44%	1054	16.72%	3.41%	1053	14.13%	0.62%
10	1039	15.82%	2.38%	1038	17.36%	3.77%	1039	14.53%	0.95%
10 – 1		6.60%	6.40%		9.59%	9.58%		-0.09%	-0.18%
t-stat		*3.75*	*4.75*		*5.66*	*7.47*		*-0.05*	*-0.12*
Bootstrap result		0/1000	0/1000		0/1000	0/1000		910/1000	988/1000
p-value		*0.000*	*0.000*		*0.000*	*0.000*		*0.910*	*0.988*

Panel A partitions the sample by ΔROE and by BSCORE deciles and presents mean values of one-year ahead $RET_{t+1}$and $RETB_{t+1}$. The last two rows present tests of differences in means between the top and bottom deciles. In Panel B, partitions are based on components of BSCORE. For variable definitions, please see the Appendix. t-statistic for difference in means is from a two-sample t-test. */**/*** represent statistical significance using 2-tailed tests at 10%/ 5%/ 1% levels

The next set of columns in Panel B reports the returns by exchange listing status. We partition the sample into two subsamples of firms listed on NYSE/AMEX or NASDAQ/Other exchanges. This partition is related to the implementability, as

Table 7 Returns to BSCORE strategy partitioned by size, analyst following, and exchange listing status

Decile	N	$RETB_{t+1}$	N	$RETB_{t+1}$	N	$RETB_{t+1}$	N	$RETB_{t+1}$
Panel A: Partitions based on market capitalization								
	Small Firms		**Medium Firms**		**Large Firms**			
1	387	−6.30%	335	−5.60%	315	−5.48%		
2 to 9	2708	2.40%	2825	0.61%	2862	−0.07%		
10	389	6.20%	336	3.89%	315	1.66%		
10–1		12.51%		9.49%		7.13%		
t–stat		*4.99****		*3.86****		*2.87****		
Bootstrap result		0/1000		0/1000		0/1000		
p-value		*0.000*		*0.000*		*0.000*		
Panel B: Partitions based on analyst following and exchange listing status								
	No Following		**Following**		**NYSE/Amex**		**NASDAQ**	
1	408	−8.27%	629	−4.24%	254	−6.95%	783	−5.46%
2 to 9	3391	0.67%	5004	1.16%	1957	1.25%	6438	0.87%
10	461	4.40%	579	3.83%	246	3.94%	794	4.12%
10–1		12.66%		8.07%		10.90%		9.58%
t–stat		*5.52****		*4.41****		*3.48****		*5.92****
Bootstrap result		1/1000		0/1000		1/1000		0/1000
p-value		*0.001*		*0.000*		*0.001*		*0.000*
Panel C: Partitions based on idiosyncratic risk and trading volume								
	Low Return Volatility		**High Return Volatility**		**Low Trading Turnover**		**High Trading Turnover**	
1	482	−4.77%	555	−6.74%	459	−5.38%	578	−6.17%
2 to 9	4317	0.78%	4078	1.15%	4333	0.77%	4062	1.16%
10	432	4.18%	608	4.01%	439	3.68%	601	4.37%
10–1		8.94%		10.75%		9.07%		10.54%
t–stat		*5.12****		*4.87****		*4.59****		*5.14****
Bootstrap result		0/1000		0/1000		0/1000		0/1000
p-value		*0.000*		*0.000*		*0.001*		*0.000*

The sample is divided into deciles based on the level of BSCORE, and is further partitioned into: three groups based on market capitalization at fiscal year-end (Compustat code: prcc_f*csho) in Panel A, two groups each based on analyst following and exchange listing in Panel B, and two groups each based on return volatility and trading volume in Panel C. Analyst following is based on I/B/E/S data in the current year. Return volatility is the standard deviation of daily returns (RET) from CRSP over the current calendar year. Trading turnover is the average of the monthly turnover using data from CRSP over the current calendar year (VOL/SHROUT). For variable definitions, please see the Appendix. t-statistic for difference in means is from a two-sample t-test. */**/*** represent statistical significance using 2-tailed tests at 10%/ 5%/ 1% levels.

shorting NYSE/AMEX stocks is generally easier and cheaper. The BSCORE strategy generates positive and statistically significant hedge returns in both partitions. For the NYSE/AMEX subsample, the mean hedge returns $RETB_{t+1}$ are 10.90%, while for the NASDAQ/Other subsample, the mean hedge returns $RETB_{t+1}$ are 9.58%.

Mashruwala et al. (2006) and Doukas et al. (2010) show that mispricing is more pronounced when arbitrage risk is high. In our next partition test, we divide our sample on the basis of return volatility, a commonly used measure of arbitrage risk. The results are presented in the first set of columns of Panel C of Table 7. While the hedge returns are marginally stronger in the subsample with high return volatility (mean hedge $RETB_{t+1}$ of 10.75%), they remain robust in the subsample with low return volatility (mean hedge $RETB_{t+1}$ of 8.94%). Finally, Lev and Nissim (2006) highlight the reluctance of large institutional investors to trade illiquid firms. Our last partition considers trading turnover as a measure of trading liquidity. The returns to the BSCORE strategy are strong both in the subsample with lower trading turnover (mean hedge $RETB_{t+1}$ of 9.07%) and in the subsample with high trading turnover (mean hedge $RETB_{t+1}$ of 10.54%).

4.7 Results across time

To ensure that the BSCORE results documented thus far are not attributable to extreme return patterns at some points in time or to time clustering of observations, we examine the performance of the BSCORE-based trading strategy for each year in our sample period (1994–2014). In particular, we create long and short portfolios based on the top and bottom deciles of BSCORE distribution each year. The results are presented in Table 8 and depicted in Fig. 1a.

Panel A of Table 8 and Fig. 1a show that a hedge strategy based on BSCORE deciles yields positive hedge returns ($HRET_{t+1}$) for all years in our 1994–2014 sample except 2011 and 2013. The mean $HRET_{t+1}$ across time is 10.15% (t-stat = 4.08). Interestingly, hedge returns peak during the 2007–2009 years, when the market was severely affected by the financial crisis. The consistent performance of the BSCORE strategy over time, including during the crisis period, seems to suggest that risk is unlikely to completely explain our results. In fact, the sample period includes sharp turns in the business cycle and materialization of tail risk events. Further, a Sharpe ratio of 0.89 suggests that mean performance relative to standard deviation remained strong during our sample period.[11] Excluding the crisis years (2007–2009), which generate the highest returns, reduces the mean hedge returns, although the results remain strong. The mean $HRET_{t+1}$ declines to 6.27%, while the Sharpe ratio rises to 1.03.

As a benchmark, we rerun the analysis using deciles of ΔROE. The results, depicted graphically in Fig. 1b, show that a strategy based on change in ROE alone is less fruitful and much more volatile, with a mean hedge return across time of 6.34% (t-stat = 2.63, Sharpe ratio = 0.57). This confirms our earlier pooled results that BSCORE performs much better, by focusing not just on ROE growth, but on how this ROE growth is obtained.[12]

[11] As a benchmark, the accruals-based strategy in Sloan (1996) generates an average return of 10.5% with a Sharpe ratio of 1.00 over the 1962–1991 period.

[12] Additionally, we attempt to compute FSCORE and GSCORE for the subset of bank stocks. FSCORE requires detailed information on components of the income statement and balance sheet, which are often unavailable or inapplicable for banks, as well as information on current assets and liabilities that is usually not broken out. Hence, it cannot be computed. Even after deleting inapplicable signals, FSCORE was computable for only 5070 observations out of the 10,472 observations in our sample, with no observations prior to 2004. The mean hedge return using FSCORE over this period was 7.9% (t-stat = 2.17), only marginally better than the 7.7% hedge return to ΔROE deciles and substantially below the 12.5% hedge return for BSCORE deciles in the same subsample. GSCORE does not require as many disaggregated items as FSCORE does. The only item that is always zero among GSCORE's signals is R&D. Consequently, GSCORE can be computed for 9172 observations with data available for each year. However, GSCORE is completely ineffective in bank stocks with mean hedge returns of 0.4% (t-stat = 0.19).

Table 8 Hedge returns across time

Panel A: Portfolios based on deciles of BSCORE

YEAR	N_{LONG}	N_{SHORT}	$LRET_{t+1}$	$SRET_{t+1}$	$HRET_{t+1}$	$LRETB_{t+1}$	$SRETB_{t+1}$	$HRETB_{t+1}$
1994	53	53	39.2%	29.9%	9.3%	−1.5%	−10.9%	9.4%
1995	52	52	38.9%	28.4%	10.4%	9.3%	−0.8%	10.1%
1996	52	52	70.9%	55.4%	15.6%	16.5%	1.5%	15.0%
1997	50	50	−10.5%	−10.8%	0.3%	5.7%	4.4%	1.4%
1998	47	47	-4.1%	−8.0%	3.9%	−0.1%	−3.1%	3.0%
1999	50	50	33.9%	22.4%	11.5%	8.4%	−5.9%	14.3%
2000	58	57	36.2%	30.8%	5.4%	3.7%	−1.2%	4.9%
2001	55	55	15.7%	3.7%	12.0%	1.7%	−10.6%	12.3%
2002	57	57	55.6%	47.9%	7.6%	6.1%	0.1%	6.0%
2003	57	57	8.0%	5.4%	2.5%	2.0%	−0.6%	2.6%
2004	56	56	20.0%	6.3%	13.8%	6.8%	−6.5%	13.3%
2005	56	55	−1.0%	−2.3%	1.3%	−3.2%	−4.7%	1.4%
2006	54	54	−25.0%	−25.4%	0.4%	−2.0%	−2.7%	0.6%
2007	52	51	−40.8%	−67.8%	27.0%	4.2%	−24.3%	28.5%
2008	46	46	30.9%	−8.5%	39.4%	7.4%	−29.8%	37.2%
2009	42	42	18.8%	−14.9%	33.7%	16.0%	−18.1%	34.1%
2010	41	41	8.4%	3.0%	5.3%	2.9%	−3.1%	6.0%
2011	40	40	20.0%	24.2%	-4.1%	−8.1%	−3.4%	-4.7%
2012	40	40	33.0%	17.6%	15.4%	8.6%	−5.9%	14.5%
2013	41	41	5.7%	8.6%	−3.0%	−3.8%	−0.5%	−3.2%
2014	41	41	9.6%	4.4%	5.2%	4.7%	−0.6%	5.3%
Analysis of Hedge Returns across time								
Mean Hedge Returns					10.15%			10.10%
Std. Dev of Hedge Returns					11.39%			11.30%
Sharpe Ratio					0.89			0.89
t-statistic					*4.08****			*4.10****
Min. Hedge Return					−4.1%			−4.7%
Max Hedge Returns					39.4%			37.2%
Years with negative returns					2/21			2/21

One concern might be that using deciles focuses on extreme ends of the distribution and results in small portfolios (between 40 and 57 firms in each extreme portfolio). Panel B of Table 8 repeats the analysis using quintiles. Given the larger portfolio sizes, the mean $HRET_{t+1}$ naturally declines, but remains strong at 6.68% (t-stat = 4.21), with a Sharpe ratio slightly higher at 0.92.

4.8 Controlling for identified risk factors

We next examine whether the returns to a BSCORE trading strategy persist after we control for commonly used risk factors in asset pricing tests. We create hedge portfolios long on the top group of BSCORE and short on the bottom group of BSCORE, where the groups are on

Table 8 (continued)

Panel B: Portfolios based on quintiles of BSCORE

YEAR	N_{LONG}	N_{SHORT}	$LRET_{t+1}$	$SRET_{t+1}$	$HRET_{t+1}$	$LRETB_{t+1}$	$SRETB_{t+1}$	$HRETB_{t+1}$
1994	106	106	43.3%	35.5%	7.8%	1.7%	−4.5%	6.3%
1995	105	105	36.5%	31.1%	5.4%	8.3%	2.4%	5.9%
1996	105	105	68.8%	59.2%	9.6%	13.8%	4.7%	9.1%
1997	101	101	−13.3%	−14.2%	0.9%	2.6%	1.4%	1.2%
1998	95	94	−5.8%	−9.5%	3.6%	−1.8%	−4.8%	3.0%
1999	100	100	32.2%	24.9%	7.3%	5.9%	−2.8%	8.7%
2000	116	115	33.2%	29.7%	3.5%	0.4%	−2.6%	3.1%
2001	110	110	14.8%	10.2%	4.5%	0.7%	−3.9%	4.6%
2002	115	114	54.5%	46.0%	8.5%	5.8%	−2.3%	8.0%
2003	115	115	7.6%	3.9%	3.6%	1.3%	−1.9%	3.2%
2004	112	112	16.6%	9.1%	7.4%	3.4%	−3.8%	7.1%
2005	112	111	2.8%	−0.1%	2.9%	0.6%	−2.4%	2.9%
2006	109	109	−23.6%	−20.2%	-3.4%	−0.8%	2.4%	−3.2%
2007	103	103	-41.6%	−63.6%	22.0%	3.5%	−18.7%	22.2%
2008	92	92	25.4%	7.6%	17.8%	2.1%	−14.7%	16.7%
2009	85	85	16.7%	−8.9%	25.7%	13.7%	−11.9%	25.6%
2010	83	82	4.9%	2.8%	2.0%	−0.6%	−3.5%	2.9%
2011	81	81	25.7%	23.7%	1.9%	−1.8%	−3.1%	1.3%
2012	81	81	31.3%	22.1%	9.2%	6.7%	−2.2%	8.8%
2013	83	83	8.2%	9.7%	−1.5%	−0.9%	1.0%	−2.0%
2014	83	83	6.5%	5.0%	1.5%	1.6%	0.1%	1.5%

Analysis of Hedge Returns across time	$HRET_{t+1}$	$HRETB_{t+1}$
Mean Hedge Returns	6.68%	6.54%
Std. Dev of Hedge Returns	7.28%	7.23%
Sharpe Ratio	0.92	0.90
t-statistic	*4.21****	*4.14****
Min. Hedge Return	−3.40%	−3.19%
Max Hedge Returns	25.68%	25.61%
Years with negative returns	2/21	2/21

The sample is divided into deciles (for Panel A) or quintiles (for Panel B), based on the level of BSCORE (see Appendix for details of BSCORE estimation). $LRET_{t+1}$ ($SRET_{t+1}$) is the equally weighted average raw return for the top (bottom) decile/quintile of BSCORE. $HRET_{t+1}$ is the difference between $LRET_{t+1}$ and $SRET_{t+1}$. $LRETB_{t+1}$ ($SRETB_{t+1}$) is the equally weighted average bank-industry adjusted return for the top (bottom) decile/quintile of BSCORE. $HRETB_{t+1}$ is the difference between $LRETB_{t+1}$ and $SRETB_{t+1}$. Sharpe ratio is the ratio of time series mean hedge return to standard deviation. t-statistic is the ratio of time series mean hedge return to standard error. *** represents statistical significance using 2-tailed tests at the 1% level.

the basis of deciles (Panel A) or quintiles (Panel B). We run calendar-time portfolio regressions using monthly returns for the 12 months after portfolio formation. The intercept (α) of the regression represents the monthly excess return for each hedge portfolio.

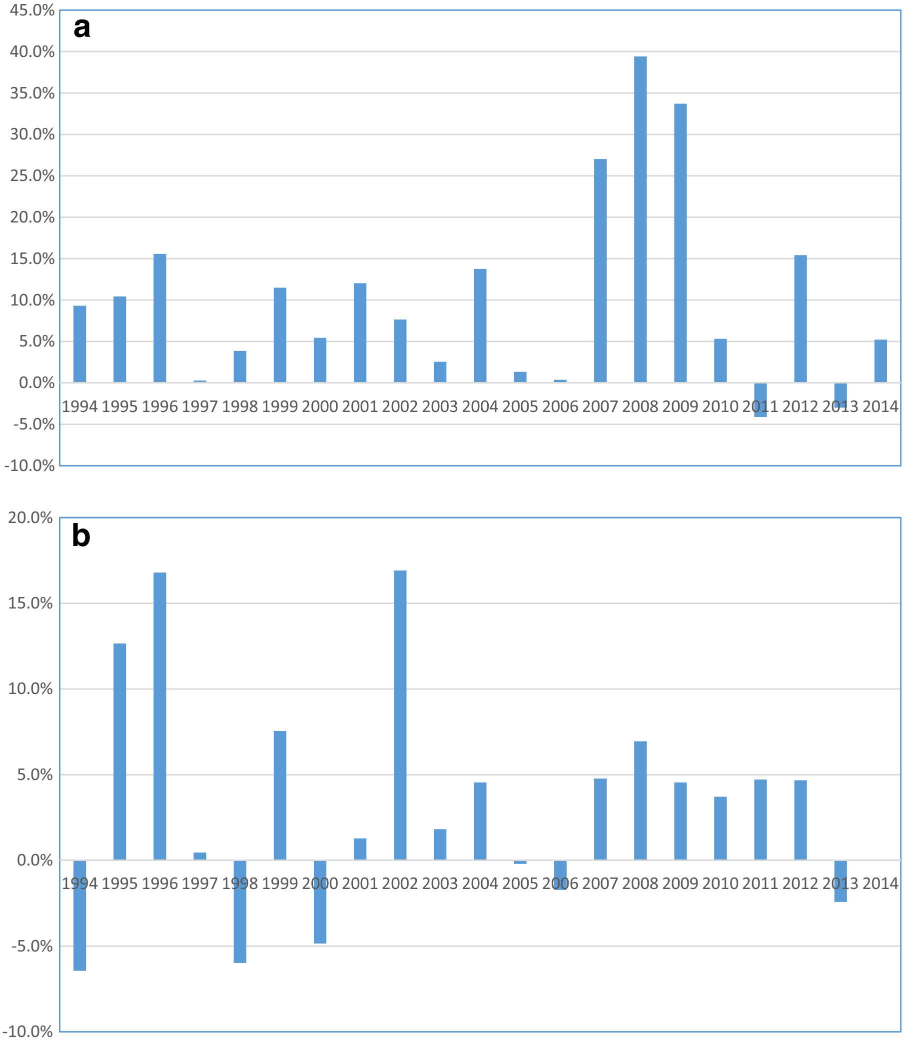

Fig. 1 Returns to BSCORE strategy across time. Figure 1a: Hedge returns ($HRET_{t+1}$) to a BSCORE strategy. Figure 1b: Hedge returns ($HRET_{t+1}$) to a ΔROE strategy

The first row of Panel A shows that using the Fama and French (1993) 3-factor model, the BSCORE decile strategy has a positive α of 0.921 (11.63% annualized), which is statically significant (t-stat = 3.70). The second row presents the results for the Carhart (1997) four-factor model. Momentum (UMD) loads positively (0.180) for the hedge strategy, leading to a decline in α to 0.780 (9.77% annualized), which is still statistically significant (t-stat = 3.18). The third row documents the results for the Fama and French (2015) five-factor model. Both the profitability (RMW) and investment (CMA) factors load significantly, consistent with BSCORE's focus on profitability and investment efficiency. The α is lower at 0.618 (7.67% annualized), but still statistically significant (t-stat = 2.40). Lastly, as banks are likely to be sensitive to macro-level interest rate and credit risk movements, we include the Fama and French (1993) bond factors (TERM and DEF), as well as an index of bank returns (BRET). Both TERM and DEF load marginally significantly, but the α remains positive at 0.619 (7.69% annualized), albeit at a lower level of significance (t-stat = 1.95).

Panel B repeats the analysis using quintiles instead of deciles. The alphas are expectedly lower, but remain statistically significant. For instance, using all the factors in our final specification, we find α of 0.422 (5.18% annualized). In summary, the results from Table 9 suggest that the efficacy of BSCORE strategy persists after we control for common risk factors.

4.9 Future earnings announcement returns, analyst surprises, and performance delistings

For the mispricing story to hold, market participants' reaction to future resolution of uncertainty must be positively correlated with BSCORE. Prior research in accounting has used such tests to support mispricing-based explanations (e.g., Sloan 1996; Piotroski 2000; Mohanram 2005). We examine analyst forecast errors, stock market reaction to future earnings announcements, and the extent of performance-related delisting. Table 10 documents the results.

In Panel A of Table 10, the third column presents the mean annual forecast surprise for the following fiscal year (SURP A1), using annual EPS forecasts obtained three months after prior fiscal year end, scaled by year-end stock price. Forecast surprises are more negative for Low BSCORE banks and less negative for High BSCORE banks, with a significant difference between top and bottom BSCORE deciles of 1.04% (t-stat = 5.29). Columns 5–8 repeat the analyses using quarterly forecasts obtained two months after prior quarter end and find similar results. The last column of Panel A presents the market reaction to future quarterly earnings announcements. Buy-and-hold banking industry–adjusted returns (EA_RET) are computed for a three-day window (−1 to +1) around earnings announcements and then summed across the four quarters. Quarterly announcement returns increase predictably and monotonically from Low BSCORE to High BSCORE deciles, and the return difference between the two extreme deciles is 1.11% and statistically significant (t-stat = 3.58). A high proportion (1.11/9.90 = 11%) of the annual hedge returns are realized during the 12 trading days surrounding quarterly earnings announcements, consistent with the stock market reacting to future earnings information predicted by BSCORE.

In Panel B of Table 10, we use the classification in Shumway (1997) to identify delistings associated with poor performance in the year after BSCORE computation. Performance delistings can be viewed as extreme negative return realization events.[13] We find that the proportion of bank stocks delisted due to performance reasons is significantly higher in the Low BSCORE portfolio (2.51%) than in the High BSCORE portfolio (0.29%).

Taken together, the results in Table 10 provide credence to our argument that BSCORE captures elements relevant to future performance that appear to predictably surprise the capital markets as information about future performance is revealed.

[13] In untabulated analyses, we repeat the Table 6 analysis after excluding banks that failed during the sample period (47 bank failures could be matched to our dataset) and find virtually identical results.

Table 9 Hedge returns after controlling for risk factors

Model	α	$R_m - R_f$	SMB	HML	UMD	RMW	CMA	BRET	DEF	TERM	Adj. R^2
Panel A: Hedge portfolios based on BSCORE deciles											
Fama French 3-Factor	0.921***	−0.115**	−0.033	−0.211***							7.82%
	(3.70)	(−2.03)	−0.43	(−2.62)							
Carhart Four-Factor	0.780***	−0.040	−0.061	−0.153*	0.180***						14.80%
	(3.18)	(−0.69)	(−0.81)	(−1.92)	(3.71)						
Fama French Five-Factor	0.618**	−0.001	0.106	−0.446***		0.464***	0.277*				12.31%
	(2.40)	(−0.01)	(1.22)	(−3.91)		(3.62)	(1.71)				
Default and Term Risk	0.619*	0.010	0.061	−0.362***	0.169***	0.399***	0.210	0.002	0.322*	0.147*	18.04%
	(1.95)	(0.14)	(0.70)	(−3.15)	(3.42)	(3.16)	(1.32)	(0.44)	(1.95)	(1.69)	
Panel B: Hedge portfolios based on BSCORE quintiles											
Fama French 3-Factor	0.588***	−0.084**	−0.051	−0.180***							8.44%
	(3.44)	(−2.15)	(−0.98)	(−3.25)							
Carhart Four-Factor	0.493***	−0.033	−0.070	−0.141***	0.122***						17.94%
	(2.93)	(−0.83)	(−1.37)	(−2.56)	(3.65)						
Fama French Five-Factor	0.409**	−0.016	0.026	−0.323***		0.266***	0.179				14.62%
	(2.30)	(−0.36)	(0.44)	(−4.10)		(3.00)	(1.60)				
Default and Term Risk	0.422**	−0.003	0.000	−0.266***	0.114***	0.223***	0.136	0.002	0.205**	0.131**	24.52%
	(1.84)	(−0.06)	(−0.01)	(−3.35)	(3.35)	(2.56)	(1.24)	(0.61)	(1.80)	(2.19)	

Calendar-time regressions are run for a hedge portfolio long on the highest BSCORE group and short on the lowest BSCORE group for the twelve months starting on the April of the year after fiscal year end. Groups are based on deciles (Panel A) or quintiles (Panel B). The regression has 236 observations from April 1995 until December 2014. The average monthly return for each decile portfolio is regressed on various combinations of these factors: Market ($R_m - R_f$), Size (SMB), Book-to-market factor (HML), Momentum (UMD), Profitability (RMW), Investment (CMA), Bank-index return (BRET), Default (DEF), and Term risk (TERM). Please see the Appendix for variable definitions. Figures in parentheses are t-statistics. */**/*** represent statistical significance using 2-tailed tests at 10%/ 5%/ 1% levels.

Table 10 Future forecast surprises, announcement period returns and delistings

The sample is partitioned each year into deciles based on BSCORE. Please see the Appendix for detailed definitions. We consider three portfolios—the top decile, the eight middle deciles, and the bottom decile. SURP A1 is the annual forecast surprise, measured as the difference between actual EPS and consensus mean annual EPS forecast issued three months after fiscal year end. SURP Q1–Q4 is the quarterly forecast surprise, measured as the difference between actual quarterly EPS and consensus quarterly EPS, measured two months after prior quarter end. All surprise variables are scaled by stock price at the end of the fiscal year. EA_RET is the average market-adjusted return around earnings announcements, using the 12 trading days around the earnings announcement dates (RDQ) in the following year, using the CRSP value-weighted index for market returns. For Panel B, we use the classification in Shumway (1997) to identify delistings

Panel A: Analyst forecast surprises and earnings announcement period returns

Decile	N	SURP A1	N	SURP Q1	SURP Q2	SURP Q3	SURP Q4	N	EA_RET
1	501	−1.02%	555	−0.33%	−0.57%	−0.41%	−0.57%	1002	−0.28%
2 to 9	4286	−0.47%	4756	−0.03%	−0.08%	−0.09%	−0.23%	8214	0.35%
10	498	0.02%	589	0.03%	−0.12%	−0.05%	−0.05%	1017	0.83%
10–1		1.04%		0.36%	0.45%	0.36%	0.52%		1.11%
t–stat		*5.29******		*3.17******	*3.28******	*2.95******	*4.32******		*3.58******

Panel B: Performance delistings

Decile	N	Proportion Delisted
1	1037	2.51%
2 to 9	8395	0.39%
10	1040	0.29%
10–1		−2.22%
t–stat		*−4.32******

5 Conclusion

The recent crisis has highlighted the limitations of fixating on ROE as banks' central performance measurement metric. In particular, critics argue that banks have tended to increase ROE by increasing financial leverage and undertaking risky lending and other non-traditional banking activities. Accordingly, we test whether investors can better screen bank stocks by employing fundamental analysis in addition to using traditional summary measures of profitability.

We ex-ante identify fourteen bank fundamental signals related to overall profitability, components of profitability, prudence in banking practices, and growth, to create an index of bank fundamental strength (BSCORE). We first document that BSCORE is positively associated with one-year-ahead change in profitability measures (ΔROE and ΔROA), over and above the current profitability changes. Further, the stock market only partially incorporates the information in BSCORE in current returns, leading to a positive association with future returns.

A long-short strategy based on deciles of BSCORE yields positive industry-adjusted hedge returns of 9.9% in the 1994–2014 period. The results are consistent across a variety of partitions related to information environment and implementability. Inconsistent with a risk-based explanation, positive hedge returns are obtained for all but two years during the sample period, and the hedge returns are especially strong during the financial crisis period. The hedge returns persist after controlling for a variety of potential risk factors in asset pricing tests. Lending credence to a mispricing-based explanation, we observe a positive relation between BSCORE and both future analyst forecast surprises and excess returns around subsequent earnings announcements, and a negative relation between BSCORE and future performance-related delistings.

It is interesting to observe that while returns to fundamentals-based trading strategies such as accruals seem to have diminished over time for non-financial firms, their importance for banks remains intact and, in fact, peaked during the recent financial crisis. This is consistent with the concept of adaptively efficient markets in Grossman and Stiglitz (1980)—i.e., markets may have blind spots, but they adapt and become efficient when these blind spots are pointed out. Green et al. (2011) and Mohanram (2014) show that accruals anomaly declines once investors and financial analysts, respectively, pay greater attention to accruals. Given that banks have not been systematically analyzed using an approach such as the one in this paper, it is not surprising to find continued strong returns to fundamental strategies in bank stocks.

Our results demonstrate that there are valuable signals related to profitability, risk, and growth embedded within past financial reports, and that these signals can serve as barometers of banks' health over and above commonly used summary indicators of profitability such as ROE. Thus, excessive focus on ROE often comes at the expense of ignoring fundamental performance signals that present a more nuanced picture of expected future performance.

Acknowledgements All errors are our own. We would like to thank the editor Richard Sloan, two anonymous referees, Zahn Bozanic, Patricia Dechow, Urooj Khan, Yaniv Konchitchki, Panos Patatoukas, Chandra Seethamraju, Christine Weidman, Xiao-Jun Zhang, and seminar participants at the University of California-Berkeley, Indian School of Business, London School of Economics, Chinese University of Hong Kong, and City University of Hong Kong for their comments. Partha Mohanram and Dushyant Vyas wish to acknowledge financial support from SSHRC-Canada.

Appendix: Variable definitions

Part 1: Definitions of the signals underlying BSCORE

Each signal equals the normalized rank of the underlying variable for a given bank-year within a size category, ranging from 0 for the lowest value and 1 for the highest value. BSCORE is the sum of the fourteen signals B1:B14.

Variable	Definition
Traditional profitability ratios	
ΔROE (B1)	Change in Return on equity (ROE), where ROE is calculated as net income divided by shareholders' equity [Compustat: ni/seq].
ΔROA (B2)	Change in Return on assets (ROA), where ROA is calculated as net income divided by total assets [Compustat: ni/at].
Components of profitability (PROFCOMP)	
ΔSpread (B3)	Change in the Spread on the bank's loan portfolio, which is measured as the ratio of net interest income earned during the year to total loans [Compustat: niint/lg].
-ΔExpense_Ratio (B4)	Negative of the change in the Operating Expense ratio, which is calculated as non-interest expense divided by total revenue [Compustat: (tnii + niint – ni)/(tnii + niint)].
ΔNoninterest_Income (B5)	Change in Non-interest Income, which is calculated as the ratio of non-interest income to total revenue [Compustat: tnii/(tnii + niint)].
ΔEarning_Assets (B6)	Change in Earning Assets, which is calculated as the ratio of earning assets to total assets [Compustat: (lg + tdst + ist)/at].
ΔLoans_Deposits (B7)	Change in Loans to Deposits, which is calculated as the ratio of total loans to total deposits [Compustat: lg/dptc].
Prudent business activities (PRUDENCE)	
-ΔLLP (B8)	Negative of the change in Loan Loss Provision ratio (LLP), which is calculated as the ratio of annual loan loss provision to total loans [Compustat: pll/lg].
-ΔNPL (B9)	Negative of the change in Non-performing Loans, which is calculated as the ratio of non-performing loans to total loans [Compustat: npat/lg].
ΔAllowance_Adequacy (B10)	Change in Allowance Adequacy, which is calculated as the ratio of loan loss allowance to non-performing loans [Compustat: rll/npat].
ΔTCE Ratio (B11)	Change in TCE ratio, which is calculated as the ratio of tangible common equity to total assets [Compustat: ceqt/at*100].
Growth in revenues and assets (GROWTH)	
SGR (B12)	Growth in total revenues, where revenue is calculated as the sum of net interest income (interest income – interest expense) and non-interest income [Compustat: tnii + niint].
LGR (B13)	Growth in total gross loans [Compustat: lg].
TAGR (B14)	Growth in trading assets [Compustat: tdst/at].

Part 2: Other variables

Variable	Definition
ΔROE	Change in Return on Equity (ΔROE), where ROE is calculated as net income divided by shareholders' equity [Compustat: ni/seq].
ΔROA	Change in Return on Assets (ΔROA), where ROA is calculated as net income divided by total assets [Compustat: ni/at].
RET	Buy-and-hold returns using a one-year horizon starting on April 1st after fiscal year end, adjusted for delisting returns consistent with Shumway (1997). RET_t refers to contemporaneous returns, while RET_{t+1} refers to one-year-ahead returns.
RETB	Banking industry adjusted buy-and-hold returns, calculated as the difference between RET and the compounded equally-weighted banking industry return over the same period (using data obtained from Ken French's data library). $RETB_t$ refers to contemporaneous returns, while $RETB_{t+1}$ refers to one-year-ahead returns.

Part 3: Risk factors used in asset pricing tests

See Fama and French (1993) and Fama and French (2015) for details. Data obtained from Ken French's data library.

Variable	Definition
$R_m - R_f$	Monthly Excess return of the market.
SMB	Monthly return for the size factor (Small minus Big).
HML	Monthly return for the book-to-market factor (High minus Low).
UMD	Monthly return for the momentum factor (Up minus Down).
RMW	Monthly return for the profitability factor (Robust minus Weak).
CMA	Monthly return for the investment factor (Conservative minus Aggressive).
BRET	Equally weighted monthly return for all bank stocks.
DEF	Monthly return for the default factor (the difference between returns on a market portfolio of long-term corporate bonds and the long-term government bond return)
TERM	Monthly return for the term factor (the difference between the monthly long-term government bond return and the one-month Treasury bill rate).

References

Abarbanell, J., & Bushee, B. (1997). Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research, 35*, 1–24.

Adams, R., & Mehran, H. (2003). Is corporate governance different for bank holding companies? *Economic Policy Review, 9*, 123–142.

Admati, A. (2011). Rethinking how banks create value. *Institute of Chartered Accountants in England and Wales (ICAEW).*

Admati, A. (2014). The compelling case for stronger and more effective leverage regulation in banking. *The Journal of Legal Studies, 43*, S35–S61.

Admati, A., Demarzo, P., & Hellwig, M. (2013). Fallacies, irrelevant facts, and myths in the discussion of capital regulation: why bank equity is not expensive. Stanford: Working Paper No. 2065, Graduate School of Business, Stanford University.
Balachandran, S., & Mohanram, P. (2012). Using residual income to refine the relationship between earnings growth and stock returns. *Review of Accounting Studies, 17*, 134–165.
Basel Committee of Banking Supervision. (2009). Consultative Document: Strengthening the resilience of the banking sector. Bank for International Settlements, December 2009.
Beatty, A., & Liao, S. (2011). Do delays in expected loss recognition affect banks' willingness to lend? *Journal of Accounting and Economics, 52*, 1–20.
Beneish, M., Lee, C., & Nichols, D. (2015). In short supply: short-sellers and stock returns. *Journal of Accounting and Economics, 60*, 33–57.
Bernard, V., & Thomas, J. (1989). Post-earnings-announcement drift: delayed price response or risk premium? *Journal of Accounting Research, 27*, 1–36.
Bernard, V., & Thomas, J. (1990). Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics, 13*, 305–340.
Calomiris, C., & Nissim, D. (2007). *Activity-based valuation of bank holding companies*. NBER: Working Paper.
Calomiris, C., & Nissim, D. (2014). Crisis-related shifts in the market valuation of banking activities. *Journal of Financial Intermediation, 23*, 400–435.
Carhart, M. (1997). On persistence in mutual fund performance. *The Journal of Finance, 52*, 57–82.
Doukas, J., Kim, C., & Pantzalis, C. (2010). Arbitrage risk and stock mispricing. *Journal of Financial and Quantitative Analysis, 45*, 907–934.
Easton, P., & Harris, T. (1991). Earnings as an explanatory variable for returns. *Journal of Accounting Research, 29*, 19–36.
European Central Bank (ECB). (2010). Beyond ROE – how to measure bank performance. *Appendix to Report on EU Banking Structures* (September 2010).
Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3–56.
Fama, E., & French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*, 1–22.
Fama, E., & Macbeth, J. (1973). Risk, return, and equilibrium: empirical testing. *Journal of Political Economy, 81*, 607–636.
Feltham, G., & Ohlson, J. (1995). Valuation and clean surplus accounting for operating and financial activities. *Contemporary Accounting Research, 11*, 689–731.
Green, J., Hand, J., & Laeven, L. (2011). Going, going, gone? The death of the U.S. accruals anomaly. *Management Science, 57*, 797–816.
Grossman, S., & Stiglitz, J. (1980). On the impossibility of informationally efficient markets. *American Economic Review, 70*, 393–408.
Hand, J., Coyne, J., Green, J., & Zhang, F. (2015). *The dual use of RI and DCF valuation models by U.S, sell-side equity analysts*. Working Paper: University of North Carolina.
Huizinga, H., & Laeven, L. (2012). Bank valuation and accounting discretion during a financial crisis. *Journal of Financial Economics, 106*, 614–634.
Koller, T., Goedhart, M., & Wessels, D. (2010). Valuation: measuring and managing the value of companies. McKinsey & Company, (Fifth Edition).
Lev, B., & Nissim, D. (2006). The persistence of the accruals anomaly. *Contemporary Accounting Research, 23*, 193–226.
Lev, B., & Thiagarajan, R. (1993). Fundamental information analysis. *Journal of Accounting Research, 31*, 190–215.
Liu, C., & Ryan, S. (2006). Income smoothing over the business cycle: changes in banks' coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom. *The Accounting Review, 8*, 421–441.
Macey, J., & O'Hara, M. (2003). The corporate governance of banks. *Economic Policy Review, 9*, 91–107.
Mashruwala, C., Rajgopal, S., & Shevlin, T. (2006). Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. *Journal of Accounting and Economics, 42*, 3–33.
Mohanram, P. (2005). Separating winners from losers among low book-to-market stocks using financial statement analysis. *Review of Accounting Studies, 10*, 133–170.
Mohanram, P. (2014). Analysts' cash flow forecasts and the decline of the accruals anomaly. *Contemporary Accounting Research, 31*, 1143–1170.
Morgan, D. (2002). Rating banks: risk and uncertainty in an opaque industry. *American Economic Review, 92*, 874–888.

Moussu, C., & Petit-Romec, A. (2013). *ROE in banks: myth and reality*. ESCP Europe: Working Paper.
Ohlson, J. (1995). Earnings, book values, and dividends in equity valuation. *Contemporary Accounting Research, 11*, 661–687.
Ou, J., & Penman, S. (1989). Accounting measurement, price-earnings ratio, and the information content of security prices. *Journal of Accounting Research, 27*, 111–144.
Papa, V., & Petres, S. (2014). Financial crisis insights on bank performance reporting (Part II): relationship between disclosed loan fair values, impairments, and the risk profile of banks. CFA Institute.
Piotroski, J. (2000). Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research, 38*, 1–41.
Shumway, T. (1997). The delisting bias in CRSP data. *The Journal of Finance, 52*, 327–340.
Sloan, R. (1996). Do stock prices fully reflect information in accruals and cash flows about future earnings? *The Accounting Review, 71*, 289–315.
Uysal, A. (2013). *A forward looking approach for assessing the loan portfolio quality of commercial banks*. Working Paper: University of California at Berkeley.
Vyas, D. (2011). The timeliness of accounting write-downs by U.S. financial institutions during the financial crisis of 2007-2008. *Journal of Accounting Research, 49*, 823–860.
Wahlen, J., & Wieland, M. (2011). Can financial statement analysis beat consensus analysts' recommendations? *Review of Accounting Studies, 16*, 89–115.