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Evidence of predictability in the cross-section of bank stock returns

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Abstract

In this paper, we examine the predictability of the cross-section of bank stock returns by taking advantage of the unique set of industry characteristics that prevail in the financial services sector. We examine predictability in the cross-section of bank stock returns using information contained in individual bank fundamental variables such as income from derivative usage, previous loan commitments, loan-loss reserves, earnings, and leverage. We find that variables related to non-interest income, loan-loss reserves, earnings, leverage, and standby letters of credit are all univariately important in forecasting the cross-section of bank stock returns. Surprisingly, neither book-to-market nor firm size is important in our sample. We examine whether this cross-sectional predictability is due to increased risk, or another explanation, such as investor under or overreaction. Our results suggest that this predictability is not due to increased risk, but rather is consistent with investor underreaction to changes in banks' fundamental variables. Furthermore, out-of-sample testing demonstrates this underreaction appears to be exploitable using simple cross-sectional trading strategies.

JEL classification: C14; G12; G14; G21
Keywords: Asset-pricing; Bank stock returns; Market efficiency; Trading strategies

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1. Introduction

1.1. Background

Cross-sectional asset-pricing studies typically exclude financial institutions because of their high leverage and the high level of industry regulations. This suggests that financial firms may be suspected to be outliers in any study spanning industries with differences in capitalization and regulation. [1] However, because of the "special nature" of financial institutions, or banks (Diamond 1984, 1991), there 'may exist important links between bank-specific fundamental variables and the cross-section of banking institutions' expected stock returns. In this paper, we examine the predictability of the cross-section of bank stock returns by taking advantage of this special nature of banks as compared to regular industrial firms. Thus, we make use of the banking industry's relative homogeneity and examine the ability of bank-specific accounting ratios to price the cross-section of monthly bank stock returns. This paper contributes to the asset-pricing literature by providing an evaluation of the importance of bank-specific fundamental variables in explaining the cross-section of expected bank stock returns.

1.2. Summary of results and contribution

We employ fundamental variables from traditional and non-traditional financial intermediation activities that capture the dramatic changes recently experienced by the banking industry that may affect the fundamental riskiness of banks. [2] Specifically, we examine predictability in the cross-section of bank stock returns using information contained in individual bank stock fundamental variables such as income from derivative usage, previous loan commitments, interest rate swap activity, loan-loss reserves, earnings, and leverage.

Using one-way sorts and cross-sectional regressions (Fama and MacBeth, 1973), we find that variables related to percentage changes in non-interest income to net income, loan-loss reserves to total loans, earnings per share, the book value of equity of total assets, and standby letters of credit to total loans, are all univariately important in forecasting the cross-section of bank stock returns. Surprisingly, neither book-to-market nor firm size is important in our sample of banks. [3] In a multivariate framework, percentage changes in bank earnings, non-interest income, and book

[1] For example, Fama and French (1992) exclude financial firms because "the high leverage that is normal for these firms probably does not have the same meaning as for non-financial firms, where high leverage more likely indicates distress". In their study of industries and momentum, Moskowitz and Grinblatt (1999) include a financial grouping that comprises depository and non-depository institutions.

[2] See for example Thakor (1987), Grammatikos and Saunders (1990), Avery and Berger (1991), Boot and Thakor (1991), Madura and Zarruk (1992), Kim and Santomero (1993), Docking et al. (1997), Shockley and Thakor (1997), Carter and Sinkey (1998), and Rogers and Sinkey (1999) among others.

[3] In related work, Barber and Lyon (1997) show that financial firms' book-to-market ratios are priced in the cross-section of financial firms' expected returns from 1973 to 1994. In this study, our sample of banks, collected from the Federal Reserve Call Reports, spans 1986–1999.

value of equity to total assets emerge as dominant factors; increases in back earnings, decreases in non-interest income, and increases in book value of equity to total assets have a positive relation with the cross-section of bank stocks returns.

After documenting the apparent predictability of bank stock returns, we examine if this predictability is due to increased risk, microstructure effects, or some type of irrational pricing behavior, such as under or overreaction. [4] To address risk and potential microstructure problems in the portfolios formed by the one-way sorts, we examine the portfolios' Sharpe ratios, intercepts from a four-factor model (Carhart, 1997), average price, and average market capitalization. The results of the first two measures suggest that the dispersion in expected bank stock returns is *not* the result of increased risk. Also, the average firm capitalization and price per share is not unusually low for the more profitable one-way sort deciles, suggesting that large bid–ask spreads and price-pressure effects would most likely not be a concern in implementing these strategies. These results strongly suggest that the evidence of predictability in the cross-section of bank stock returns is not attributable simply to increased risk or increased transaction costs.

Next, we employ a two-way sort methodology, similar in spirit to Chan et al. (1996), [5] to further disentangle the potential sources of predictability found in the one-way cross-sectional sorts. Specifically, using the dispersion in expected returns created by the one-way sorts, we define "good" news and "bad" news states of the fundamental bank variables to be the deciles that result in portfolios with high and low monthly returns, respectively. These definitions of good and bad news states are then employed in two-way sorts of lagged returns and fundamental variables to form the basis of a test to determine if the dispersion of returns from the one-way sorts is consistent with a contrarian or a momentum type effect. For example, if overreaction is the return generating process creating dispersion in expected returns, then we should observe that negative (positive) lagged return securities should have systematically larger *reversals* as we condition on increasingly bad (good) news during the portfolio formation period. Conversely, if underreaction is the return generating process, then we should observe greater return *continuations* in portfolios formed from negative (positive) lagged return securities as we condition on increasingly bad (good) news.

The results from the two-way sorts are consistent with investor underreaction to firm specific good and bad news. Specifically, positive shocks to (or good news about) fundamental variables result in increased subsequent monthly returns.

[4] Fama and French (1992) argue that evidence of predictability from book-to-market and other "value" strategies is attributable to risk because investors in value stocks, such as high book-to-market stocks, tend to bear some sort of greater risk, and that the higher expected returns are simply compensation for bearing this risk. In contrast, Lakonishok et al. (1994) examine a broad range of value strategies and conclude that these investment styles are not fundamentally riskier and that they represent a contrarian style of investment, in which "investors should sell stocks with high past growth ... and buy stocks with low past growth."

[5] Chan et al. (1996) employ two-way sorts on lagged returns and earning information to show that lagged returns-based momentum strategies can be explained by investor underreaction to earnings news.

Negative shocks to (or bad news about) fundamental variables result in decreased subsequent monthly returns. This effect is even stronger for stocks in which the news shock is more of a surprise. For example, bad (good) news shocks this period for securities that are past winners (losers) result in larger relative decreases (increases) in subsequent monthly returns. To further explore this issue, we also examine long-horizon event-time cumulative returns to our sample of stocks after they have incurred a large or small quarterly shock to one of the bank fundamental variables. We find cumulative profits tend to rise for a period of time after large shocks, and then gradually decrease, consistent with a behavioral based explanation (see Daniel et al., 1998) for returns predictability.

Finally, we show that these bank-specific fundamental variables would have been useful to a "real-time" investor. Specifically, we implement an out-of-sample experiment to determine if a real-time investor, operating without the benefit of hindsight concerning which variables provide the most predictability, can use some combination of the variables, selected in an ex ante manner, to beat a buy-and-hold strategy. The out-of-sample experiment suggests that a real-time investor who pursues the bank fundamental variable strategy with relatively low transaction costs will strongly outperform an investor who follows a buy-and-hold strategy.

Overall, changes in firm specific fundamental variables appear to be important predictors of US banks' returns. Our results suggest that investors underreact to changes in bank stocks' fundamental variables and that this underreaction is exploitable in cross-sectional trading strategies. In addition, our results may have implications for bank managers seeking to maximize shareholder wealth. To the extent that managers have control over the growth in book value of equity relative to assets, off-balance sheet activity, and earnings, our results provide some important general guidelines for managers to follow in order to optimize firm value.

Our results contain a combination of obvious and subtle conclusions regarding the stock returns associated with specific bank operations and bank manager's decisions. For example, larger earnings increases for commercial banks are associated with larger stock returns. This is nothing unique to banks, however, as others have found predictability from earning shocks on all firms (Bernard and Thomas, 1990). On the other hand, we also find that increases in our book value of equity to total assets variable is associated with larger stock returns. This suggests that the market rewarded those banks that increased their capital ratios, relative to other banks, over our sample period. This may be because the market recognized the value of operational flexibility. It is also unlikely that banks with low capital ratios will be granted permission by bank regulators to engage in non-traditional banking activities, such as securities or insurance underwriting. Our results also shed some light on the controversial issue of the value of non-traditional or off-balance sheet activities of commercial banks. Specifically, we find that larger relative decreases in non-interest income as a percentage of net income have a positive relation with the cross-section of bank stock returns. These changes may also reflect that on average, the market rewarded those banks that increased their reliance on traditional sources of income, such as interest income. This result suggests that bank managers may need to reassess the value to their bank of non-traditional activities. And, considering that our results are risk adjusted, this also suggests that bank managers are paying too much for the benefits of diversifying their income streams.

The remainder of this paper is organized as follows: Section 2 provides a background on our bank-specific fundamental variables, explains the construction of our variables, and details the portfolio methodology employed to measure the relationship between the cross-section of fundamental variables and expected returns. In Section 3 we examine the relationships between the bank-specific fundamental variables and the cross-section of future returns. In Section 4, we analyze whether the documented predictability from Section 3 is due to increased risk or some sort of market inefficiency. In Section 5 we perform an out-of-sample experiment in an attempt to control for data snooping. Section 6 provides some concluding remarks.

2. Banks, fundamental variables, and expected returns

This study evaluates the role of specific fundamental variables in explaining the cross-section of expected bank stock returns. Subsequently, we employ variables that have been shown to be important in determining the fundamental riskiness of banks or reflect recent changes in business practices that may affect bank risk.

Traditional banking practices have received considerable attention from academic studies. For example, Thakor (1987), Grammatikos and Saunders (1990), Madura and Zarruk (1992), Kim and Santomero (1993), and Docking et al. (1997) discuss links between information about loan portfolio quality and the market's valuation of the fundamental soundness and performance of banks. Yet, the difficulty of investors to value and accurately measure the risk of bank loans may be compounded by the considerable flexibility that bank managers have in reporting changes in loan portfolio risk. For example, Slovin et al. (1992) discuss how reported information on loan-loss reserves represent managerial judgment about future loan-losses and are subject to discretionary adjustment. These characteristics of the information structure of the bank's traditional operations may limit the market's access to information needed to evaluate individual bank value and risk.

The 1980s witnessed US banks becoming less profitable as non-depository firms became increasingly competitive in traditional banking activities. Commercial banks responded to these competitive pressures by rebalancing their portfolios with a greater weight given to off-balance sheet activity in such areas as loan commitments, standby letters of credit, and interest rate swaps. Academic research is beginning to focus more attention on these non-traditional activities and how they affect bank risk. An early study by Kane and Unal (1990) examines the relationship between the market value of banking firms and their off-balance sheet items from 1975 to 1985. They find that the market perceived off-balance sheet items to be a drain on capital value prior to 1980, but these non-traditional activities appeared to have no effect upon bank valuation in the latter half of the study. Importantly, this early study of off-balance sheet activities occurs about the time US banks began to expand greatly the scope and depth of non-traditional activities. Given the informational nature of traditional banking practices, the investment community may have even greater difficulty in assessing how these non-traditional activities affect the fundamental risks of banks.

The above research studies and banking practices suggest that fundamental variables associated with a bank's traditional and off-balance sheet activities may contain important information for the cross-section of financial institution's expected returns. Thus, we create several measures to attempt to characterize a bank's risk and then analyze how these measures affect future returns.

2.1. Fundamental variable construction

We construct eight bank-specific variables that contain fundamental information. The variables are measures representing quarterly changes, [6] in: (1) earnings per share, (2) loans as a percent of total assets, (3) loan-loss reserves as a percent of total loans, (4) non-interest income as a percent of net income, (5) unused loan commitments as a percent of total loans, (6) interest rate swaps as a percent of total assets, (7) standby letters of credit as a percent of total loans, and (8) the book value of equity as a percent of total assets. To minimize dramatic swings in the values of the quarterly changes, we construct the measures as quarterly percentage changes relative to the mean of the last four quarters. [7] In the following subsections, we describe the construction of the information variables and the portfolio methodology employed to measure their relationship with expected returns.

2.1.1. Percent change in quarterly earnings per share

Quarterly earnings per share data, though historical accounting information, are closely followed by investors who use the information to monitor changes in a firm's performance. Previous studies link changes in quarterly earnings to future stock returns of all firms (not just financial firms). Beginning with the research of Rendleman et al. (1982) and evolving into the work of Bernard and Thomas (1990), the post-earnings announcement drift phenomenon has been well documented. The quarterly percentage change measure for earnings is constructed using quarterly earnings per share before extraordinary items and discontinued operations. Although earnings information, unlike the other measures we examine, is not unique to banks, we include it in our study since fluctuations in bank's earnings tend to be less severe over time (because of the ability of banks to insulate earnings with adjustments from loan-loss

[6] Our approach differs from earlier papers such as Fama and French (1992), and Lakonishok et al. (1994) that examine the relation of expected returns to levels of fundamental variables. By constructing our fundamental variables as changes, we are able to impose "good" and "bad" news shock connotations to the variables. Categorizing shocks allows us in subsequent sections of the paper to employ various tests using two-way sort methods (see Chan et al., 1996) and a long-horizon-event study approach in an attempt to disentangle whether the dispersion in expected returns created from one-way sorts is due to investor under or overreaction.

[7] All of the quarterly percentage change measures are constructed for a given accounting ratio in time t as: $(\text{ratio}_t - \text{average}(\text{ratio}_{(t-1)\text{ to }(t-4)})/\text{average}(\text{ratio}_{(t-1)\text{ to }(t-4)})) \times 100$.

reserves) than non-financial firms, and thus shocks to this variable may have an important impact on future returns. [8]

2.1.2. Percent change in quarterly loans-to-total assets

Loans typically represent the major portion of a bank's investment portfolio, thus relative changes in total loans may indicate changes in the future health of the financial institution. Diamond (1984, 1991), Ramakrishnan and Thakor (1984), Fama (1985), and Boyd and Prescott (1986) develop models in which banks initially collect and process private information about loan customers and continue to acquire private information through the monitoring of borrower activities. Yet the confidentiality of the bank-borrower relationship and limited disclosure about lending agreements amplifies the difficulty of marking bank loans to market (O'Hara, 1993). In such an environment, bank claims held by shareholders are unlikely to fully reflect information impounded in the bank's loan portfolio. Slovin et al. (1992) suggest that this may be related to the limited nature of borrower disclosure about private lending agreements. [9] This private information forms the foundation for the loan portfolio and increases the difficulty in valuing loans (Santomero, 1983), thus changes in the loan/asset mix may be difficult to interpret by outside investors. Our quarterly percentage change measure for loans is constructed using a ratio of total loans to total assets.

2.1.3. Percent change in quarterly loan-loss reserves to total loans

Changes in loan-loss reserves may indicate changes in the health of a bank's loan portfolio and, suggests Thakor (1987), may signal changes in the future performance of the institution. Other studies substantiate the importance the market places on this variable, but find that the reason for the adjustment affects the market's response. Madura and Zarruk (1992) observe a contagion effect, with negative share price responses, when increases in loan-loss reserves are related to bad real estate loans. Grammatikos and Saunders (1990) find a weak effect on bank stock return portfolios while the effect on individual bank returns was related to the size of a bank's less developed country (LDC) debt exposure. Lancaster et al. (1993) observe that increases in loan-loss reserves that are above the expected annual reserve provision produce negative effects on shareholder wealth. Similarly, Docking et al. (1997) show that there is a negative loan-loss reserve announcement day effect on shareholder worth and that this effect is more negative for announcements accompanied by profit decreases and dividend reductions. Wahlen (1994) examines the information content in non-performing loans, loan-loss provisions and loan charge-offs [10] and finds that all three components are important for explaining returns and future cash flows.

[8] For example, Docking et al. (1997), employing event study methodology, find that shareholder wealth is more negatively affected for loan-loss reserve announcements that coincide with earning decreases.

[9] Only publicly traded firms with loan agreements in excess of 10% of corporate assets are required to file with the SEC, and these filings typically do not include the name of the lending bank.

[10] Loan-loss reserves (time t) = loan-loss reserves $(t-1)$ + loan-loss provisions (t) − loan charge-offs (t).

Emphasizing the value within this information, Kim and Santomero (1993) discuss the importance of developing unbiased estimates of a bank's loan-loss reserves. Though an institution's management has significant discretion on the timing and size of the reserve's change, increases (decreases) in loan-loss reserves may provide new information on the deterioration (improvement) of a bank's loan portfolio. Thus, Musumeci and Sinkey (1990) and Strong and Meyer (1987) suggest that investors use information on loan-loss provisions to revise their expectations of a bank's future performance. Our quarterly percentage measure, which captures the change in loss provisions as a percent of a bank's total loans, is constructed using the ratio of loan loss reserves to total loans.

2.1.4. Percent change in non-interest income to net income

Commercial banks in the US are rapidly expanding their range of business activities to maintain growth in revenues and to diversify their sources of income. The broadening of the scope of business occurs while there is steady erosion in their traditional business of financing loans. Thus, activities generating non-interest income are becoming increasingly important to the financial health of banks. An early study of foreign currency trading and investment activities by Grammatikos et al. (1986) finds that US banks may reduce risk by carefully engaging in off-balance sheet activities that generate non-interest income. Recent trends show that banks are focusing upon non-traditional financing activities that generate fees, e.g., mortgage servicing or sales of mutual funds. Rogers and Sinkey (1999) observe that non-interest income has risen relative to income from traditional activities. Their study suggests that banks emphasizing new sources of income tend to be larger and exhibit less risk since they have more diverse sources of revenue and greater access to financial market. Our quarterly percentage change measure for this variable is constructed using the ratio of non-interest income to net income. This variable should capture the changing nature of revenue streams from business activities that may affect the riskiness of financial institutions.

2.1.5. Percent change in total unused loan commitments to total loans

While loans represent a significant portion of a bank's portfolio that readily affects bank risk, loan commitments prior to origination may also impact risk. [11] Financial studies provide mixed results over the interaction between loan commitment activity and bank risk. Avery and Berger (1991) argue that loan commitments increase a bank's risk by obligating and bank to issue future loans under terms that may no longer be acceptable. [12] Conversely, Boot and Thakor (1991) suggest that loan commitments act as incentives to constrain the risk-taking behaviour of bank management. Shockley and Thakor (1997) assert that banks can include escape clauses in financial contracts or buy/sell commitments to reduce risk exposure.

[11] Shockley and Thakor (1997) note that approximately 80% of commercial lending to corporations in the US is done via loan commitments.

[12] Chaudhry et al. (2000) focus specifically on foreign currency commitments and find they contribute mildly to bank risk.

Our unused loan commitment variable represents the sum of commercial and residential loans, credit card lines, securities underwriting, and miscellaneous unused commitments. The quarterly percentage change measure is constructed using a ratio of total unused loan commitments to total loans.

2.1.6. Percent change in total standby letters of credit to total loans

An increasing trend in US banking has been the making of contingent financial commitments, yet this specific business practice has received little attention in the academic literature. Standby letters of credit (LC) represent this growing area of off-balance sheet activity that accounted for almost 5% of total bank assets in 1997 (Federal Reserve Bulletin, 1998). Brewer and Koppenhaver (1992) observe that issuances of LCs affect the systematic and total risk of bank stock returns, though less significantly than traditional balance sheet lending. Our quarterly percentage change measure for this variable is constructed using the ratio of standby letters of credit to total loans.

2.1.7. Percent change in interest rate swaps to total assets

The use of interest rate derivatives by commercial banks is a growing area of off-balance sheet activity. The Federal Deposit Insurance Corporation Improvement Act of 1991 requires that banks set aside capital to cover interest rate risk, and identifies interest rate swaps as an important component in measuring this form of risk. [13] Carter and Sinkey (1998) examine mid-sized commercial banks that are end-users of interest rate swaps and find a mild, positive relationship between the use of interest rate derivatives and interest rate risk. Brewer et al. (1996a) examine the relationship between risk taking and derivative usage among savings and loans. They find that savings and loans used derivatives to decrease their interest rate risk exposure. [14] For this variable, our quarterly percentage change measure is constructed using the ratio of (the notional value of) interest rate swaps to total assets.

2.1.8. Book value of equity to total assets

A different leverage structure is one reason why financial institutions have been largely ignored in earlier studies of return behaviour. We include a leverage variable to determine if changes in leverage contain important information for bank-specific stock prices. Leverage has been demonstrated to be important in explaining the stock market performance of financial institutions. For example, in Brewer et al. (1996a) and Brewer et al. (1996b), financial leverage was found to be an important variable in explaining financial institutions' risk and return. More specifically, Cantor and Johnson (1992) find a strong positive relationship between improving capital ratios and stock market returns for bank holding companies. They also demonstrate that

[13] Small banks lose their exemption from allocating capital for interest rate risk when off-balance sheet interest rate swaps exceed 10% of total assets or exceed other specified measures.

[14] We also examine a variation of this variable that excludes money center banks and the largest regional banks from our sample so that end-users are emphasized. Similarly, we examine a sample that includes only money center banks and the largest regional banks, inasmuch as these banks are the institutions most likely to hold a trading portfolio of swaps.

of the various methods used to increase capital ratios, increases in earnings were associated with the largest stock price increases. Our quarterly percentage change in leverage measure is constructed using the ratio of book equity to total assets.

2.2. The data

We employ quarterly US bank holding company (BHC) data from the Federal Reserve System (Fed) and stock return data from the CRSP tapes from June 1986 through December 1999. These data are unique in that they reflect all information gathered from the quarterly reports of condition (Y-9s) that bank holding companies must submit to the Fed. This data source provides a detailed set of variables that captures the non-traditional banking activities that have not been available in other financial data sources. We construct a large sample formed by the intersection of the Fed BHC data and CRSP tapes. From the universe of over 10,000 BHCs that submitted quarterly reports during this period, we form a sample of the 213 publicly traded BHCs that are found on CRSP. These 213 firms are listed in the appendix. Our list demonstrates that we have included most of the major bank holding companies in our sample. These bank holding companies collectively account for the majority of banking industry assets in the US.

To be more specific about our sample construction, we obtain the bank accounting data from the Fed's quarterly consolidated financial statements for bank holding companies. [15] Using the Fed's data items, we construct the eight bank variables as spelled out in Section 2.1. From CRSP, we obtain monthly returns, including dividends. There is no requirement that a firm continually exist over the entire sample. The Federal Reserve System data contains quarterly dates corresponding to each firm's quarterly data. To ensure that the accounting data is actually public information, we make the conservative assumption that the information is not actually known until two months after the date on the Fed data. The quarterly accounting variables are then merged with monthly return information from CRSP. The accounting variables are matched with a CRSP monthly return only if the most recent Fed data is known prior to the start of a return formation period. This is done to ensure that the accounting variables are known before the returns they are used to explain. For example, a Fed quarterly report date of March 31 would be assumed, using our previously stated policy of waiting two months after the Fed date, to be publicly known at the end of May. Thus, this data would be used as lagged accounting data for June returns. Additionally, this data would be matched with return data for July and August. Once new quarterly data is known, that data is used to match accounting data with returns data for September, October, and so on.

Given the importance of individual firm book-to-market and firm capitalization in previous studies of cross-sectional predictability on non-financial firms (Fama and French, 1992) and on financial firms (Barber and Lyon, 1997), we include these two measures. Specifically, we form the book-to-market ratio of equity (B/M) by di-

[15] The data files are located at the Federal Reserve Bank of Chicago's web site, http://www.chicagofed.org.

viding the book value of a bank's equity each quarter from the Fed's quarterly consolidated financial statements by the market value of CRSP. [16] The CRSP market value of equity used in the book-to-market ratio is taken at the same month as the quarterly date in the Fed data. The book-to-market ratio is then lined up with CRSP monthly returns in the same manner as described above for the other eight variables. Market capitalization, when used as an independent variable, (i.e., not in the construction of book-to-market), is simply the lagged one-month value of CRSP market value of equity.

Finally, in the construction of the eight bank fundamental variables and book-to-market, and similar to Fama and French (1992) and Lakonishok et al. (1994), we consider only observations with positive values of the accounting items for use in the construction of the percentage growth ratios. Specifically, we delete observations with negative or zero values of earnings, non-interest income, book value of equity, unused commitments, interest rate swaps, and standby letters of credit. [17] This is done to insure a consistent definition of increases or decreases in the quarterly percentage change measures and to allow a more direct comparison with other papers, especially the book-to-market results in Barber and Lyon (1997). Note that we do not throw out negative or zero values of the percentage change measures, just negative and zero values of the component accounting items used to construct the measures.

As background, Table 1 presents summary statistics of the 213 banks' stock returns and the firm specific information variables. Most of the Fed-based variables have approximately the same number of firm months, ranging from approximately 16,000–18,000, with the exception of interest rate swaps to total assets (ΔIRS), with 9996 firm-month observations. The average unconditional monthly return to the sample over the 1986–1999 period is 1.39%. The average firm capitalization is just under \$2.2 Billion. From examining the means of the quarterly change variables, it appears that all bank fundamental variables experience, on average, positive

[16] The book value of equity is defined as total shareholder's equity minus the book value of preferred stock (which includes surplus related to preferred stock).

[17] In most cases, screening out zero and negative values results in relatively few observations being moved from the data. For example, eliminating firms with negative and zero values for earnings results in a loss of 6.2% of the earnings observations; 6.2% of the non-interest income to net income; 1.2% of the unused loan commitments to total loans; 1.8% dollar value of standby letters of credit to total loans; 0.52% of the book value divided by total assets; and 42.1% of the interest rate swaps to total assets. All of the removed interest rate swap data have values of zero, and are exclusively non-money center banks. Since removing zero values of interest rate swap results in a relatively large reduction in observations, we run a one-way sort on ΔIRS without throwing out zero values. This sort results in statistically insignificant return dispersion across decile portfolios. Finally, there are no negative or zero values of loans to total assets or loan-loss reserves to total loans. Note that removing negative or zero values of these variables does not result in a bias towards falsely rejecting the null hypothesis of no predictability in our study. As long as the strategies are implementable, that is, as long as the variables are known at or before portfolio formation, then any estimated differences in returns arising from the sorts should be viewed as a property of this particular subset of firms.

Table 1
Characteristics of sample banks, 1986–1999[a]

	Firm months	Mean (%) (Std.)	Q25	Median	Q75	Q95
Monthly returns	24 301	1.39 (10.19)	−3.33	0.94	5.93	15.64
ΔEPS	16 737	290.15 (600.17)	−49.56	−2.08	45.10	107.75
ΔLTA	17 903	0.19 (5.73)	−2.45	0.36	2.88	7.8
ΔLLR	17 903	2.72 (20.98)	−5.8	−0.72	5.52	34.55
ΔNINT	16 746	75.08 (372.21)	−10.64	−1.42	6.71	50.65
ΔUNCM	16 828	96.45 (595.18)	−6.92	1.61	10.98	99.48
ΔIRS	9996	33.60 (489.74)	−10.83	3.72	27.43	110.71
ΔLOC	17 556	1.81 (53.63)	−11.00	−1.15	8.14	35.04
ΔLV1	17 735	0.55 (9.92)	−2.84	1.09	4.53	12.14
B/M	19 778	0.742[b] (2.103)	0.531	0.695	0.902	1.586
CAP	22 029	$2.19B[c] (6.22 B)	0.155 B	0.496 B	1.67 B	9.37 B

[a] This table provides average, median, Q25, Q75, and Q95 values for the 213 bank firms' monthly returns and fundamental variables. The bank-specific variables are constructed as quarterly percentage changes relative to the mean of the last four quarters. The variables are percentage changes in earnings per share (ΔEPS), loans-to-total assets (ΔLTA), loan-loss reserves to total loans (ΔLLR), non-interest income to net income (ΔNINT), unused loan commitments to total loans (ΔUNCM), interest rate swaps to total assets (ΔIRS), dollar value of standby letters of credit to total loans (ΔLOC), and book value o f equity to total assets (ΔLV1). We also report characteristics of quarterly book-to-market (B/M) and market capitalization of equity (CAP) distributions. The number of firm months is the total number of observations for a given variable across firms and months.

[b] The B/M ratio is expressed in fractional form, not percent.

[c] The firm capitalization is expressed in billions of dollars, not percent.

growth. However, most of these distributions' means appear to be heavily weighted by large positive values in the right hand tails of the distributions. For example, our quarterly growth in non-interest income to net income (ΔNINT) variable has a mean of 75% but a median of negative 1.42%. Obviously, large positive outliers are influencing the mean. However, this does not create any biases in our tests. This is because all of our basic sorts and cross-sectional regressions are based on non-parametric methods. For example, outliers do not influence the one-way and two-way sorts. This is also true when we perform cross-sectional regressions; to control for possible non-linearities and the effects of outliers, similar to Chan et al. (1996), we express each independent variable in terms of its percentile rank for any given month and scale it to lie between 0 and 1.

3. Empirical results

3.1. The cross-section of expected bank stock returns: One-way sorts

In this section, as a first cut for relating the fundamental variables to the cross-section of expected bank stocks returns, we perform one-way decile sorts. Specifically, at the beginning of every month, stocks are allocated to deciles based on their most recently available lagged values of the fundamental variables. To be included in a given sort, for a given month's portfolio, a stock need only have data available for the most recent ranking period for that variable. For example, each month, lagged monthly percentage changes in loan-loss reserves-to-total loans (ΔLLR) are sorted into decile groupings, based on breakpoints calculated across all firms with non-missing values of the sort variable, and then equally weighted portfolios are formed of all stocks having non-missing values of ΔLLR.

Table 2 documents the average monthly returns for portfolios formed on one-way sorts of the lagged variables. The profit figures reported are for a positive investment; hence, portfolio returns that increase (decrease) in the trade month will appear as positive (negative) returns. The one-way sort results for the fundamental variables suggest that a subset of the firm specific variables is important in predicting future bank firm stock returns. Across the eight bank variables, we observe statistically significant differences, as judged by a chi-square test, in monthly returns across the portfolios formed from lagged percent change in earnings per share (ΔEPS), lagged percent change in non-interest income-to-net income (ΔNINT), and lagged percent change in book value of equity to total assets (ΔLV1). [18] Consistent with the literature on earnings for non-financial firms, we observe a pattern of increasing portfolio returns as we move from negative earning shocks (ΔEPS) in decile 1 to large positive earning shocks in decile 10. For example, the portfolio formed from the smallest decile of ΔEPS averages 1.235% per month, and increases approximately monotonically to 2.476% per month for the largest decile portfolio. Thus, investors appear to view favorably large increases in earnings.

[18] We use a χ^2_1-statistic to test the null hypothesis of equality of monthly returns across the sort decile portfolios. Specifically, we use GMM with the following moment conditions to form the χ^2-statistic:

$$\left\{\begin{array}{l} \varepsilon_1 = R_{p1} - \mu^* 1 \\ \varepsilon_2 = R_{p2} - \mu^* 1 \\ \vdots \\ \varepsilon_{10} = R_{p10} - \mu^* 1 \end{array}\right\},$$

where R_{pn} is a $t \times 1$ time series of trades from the portfolio formed from the equally weighted average of stocks in decile n, 1 is a column vector of ones, and μ is the mean return parameter to be estimated. The system of moment conditions is overidentified, with 10 moment conditions and only one parameter to estimate. Thus, the resulting χ^2_9-statistic tests the null hypothesis of $\bar{R}_{p1} = \bar{R}_{p2} = \cdots = \bar{R}_{p10}$, where $\bar{R}_{pn}$ is the mean return to sort decile n for a given one-way sort. The statistics are robust to heteroskedasticity and autocorrelation (Gallant, 1987). For examples of similar tests on portfolio returns using this framework (see Conrad and Kaul, 1998; Cooper, 1999).

Table 2
Average monthly returns for portfolios formed on one-way sorts[a]

Ranked by	1 (small)	2	3	4	5	6	7	8	9	10 (large)	χ^2 test
ΔEPS	1.235	1.336	1.403	1.290	1.710	1.538	1.676	2.015	2.124	2.476	24.35***
ΔLTA	1.689	1.632	1.348	1.679	1.428	1.617	1.784	1.715	1.466	1.620	4.52
ΔLLR	1.621	1.861	1.729	1.801	1.591	1.657	1.727	1.634	1.589	0.695	8.26
ΔNINT	2.306	1.983	2.084	2.015	1.981	1.520	1.344	1.316	1.266	0.933	30.76***
ΔUNCM	1.106	1.466	1.520	1.174	1.138	1.588	1.358	1.283	1.733	1.213	8.89
ΔIRS	1.367	2.075	1.523	1.612	1.760	1.938	1.589	1.742	1.896	1.584	5.86
ΔLOC	1.337	1.313	1.492	1.571	1.654	1.640	1.802	1.756	1.870	1.447	6.88
ΔLV1	0.641	1.170	1.568	1.756	1.470	1.731	1.917	1.779	1.857	2.019	16.31*
B/M	1.528	1.086	1.173	1.236	1.327	1.354	1.454	1.745	1.302	1.360	10.52
LCAP	1.122	1.505	1.187	1.536	1.413	1.693	1.399	1.505	1.571	1.423	11.08

*, *** The null hypothesis of equality of average monthly portfolio returns across decile sorts for a given sort is rejected at the 10% and 1% levels, respectively.

[a] Average monthly percentage returns for portfolios formed on decile ranks of lagged bank fundamental variables. Each variable is sorted monthly into deciles using all banks with non-missing values of the sort variable from June 1986 to September 1999. Equally weighted portfolios are formed and returns are calculated for the following month. In the last column, we use a χ^2_9-statistic to test the null hypothesis of equality of monthly returns across the sort decile portfolios. The χ^2_9-statistics are robust to heteroskedasticity and autocorrelation (Gallant, 1987). The lagged variables are quarterly percentage changes relative to the mean of the last four quarters for: earnings per share (ΔEPS), loans to total assets (ΔLTA), loan-loss reserves to total loans (ΔLLR), non-interest income to net income (ΔNINT), unused loan commitments to total loans (ΔUNCM), interest rate swaps to total assets (ΔIRS), dollar value of standby letters of credit to total loans (ΔLOC), and book value equity divided by total assets (ΔLV1). We also examine lagged quarterly book-to-market (LB/M) and lagged monthly firm capitalization of equity (LCAP).

Similarly, ΔNINT earns 2.3% per month for the smallest decile, and decreases to 0.99% per month for the largest decile. Thus, investors view large increases in non-interest income as a percentage of net income less favorably than decreases in the relative impact that non-interest income has upon net income. These findings provide some support for Rogers and Sinkey (1999) who suggest that relative increases in non-interest income stems from more diverse sources of revenue, which reduces risk. However, Brewer et al. (1996a) find that increases in non-traditional revenue producing activities sometimes lead to increases in market risk. Nonetheless, the results in Table 2 are not risk adjusted, and suggest that investors would expect lower future returns from banks that reduce risk through diversification into non-traditional revenue activities.

For ΔLV1, the smallest decile averages 0.641% per month and increases to over 2% for decile 10. Thus, investors seem to view decreases in leverage as a positive sign and large increases as negative for future firm stock return performance. This is consistent with the findings of Cantor and Johnson (1992).

There is some hint of return dispersion created by the loan-loss reserve (ΔLLR) and standby letters of credit to total loans (ΔLOC) variables. For example, large increases in loan-loss-reserves appear to be negatively related to future returns, consistent with Lancaster et al. (1993). Also, large increases in standby letters of credit result in greater future returns than do decreases in this variable. However, the spread in expected returns created by ΔLLR and ΔLOC are not significant as judged by their chi-square tests. The other three bank variables, loans-to-total assets (ΔLTA), unused loan commitments to total loans (ΔUNCM), and interest rate swaps to total assets (ΔIRS) do not create any sort of recognizable dispersion across the sort deciles. This suggests that, at least for this sample, simple percentage changes in these three variables do not offer investors a source of predictability concerning future bank stock returns. [19,20] This result in not surprising given the complex nature of these variables. For example, an increase in our interest rate swaps to total assets variable (ΔIRS) may suggest a bank is using more interest rate swaps to reduce risk by hedging interest rate risk. Or, it may suggest a bank is using more interest rate swaps to increase risk by speculating on future directions of interest changes. And, of course, with either strategy, a bank's ability to use interest rate swaps profitably will be a function of its managerial talent. Because of these dependencies, it is not surprising that simple percentage changes in our interest rate swap variable do not offer investors a source of predictability (see Brewer et al., in press).

We also examine lagged quarterly book-to-market (LB/M) and lagged monthly firm capitalization of equity (LCAP) to see what, if any effect, these two variables have on the expected returns of our sample. Barber and Lyon (1997) show that the book-to-market and firm capitalization is important for the cross-section of financial firms. [21] Surprisingly, neither variable, as judged by a lack of monotonicity across the sort deciles and by insignificant chi-square test statistics, has a significant relation with the cross-section of expected returns. [22]

[19] In a later section of the paper, we implement an out-of-sample experiment to determine if a real-time investor, operating without the benefit of hindsight concerning which variables provide the most predictability, can use some combination of the variables, selected in an ex ante manner, to beat a buy-and-hold strategy.

[20] Because of the different types of uses and volume of activity for interest rate swaps across banks, we examine one-way sorts of the interest rate swaps to total assets variable (ΔIRS) that excludes money center institutions and one-way sorts that only include money center banks. Neither sort results in a statistically significant return dispersion across decile portfolios. Also, following Brewer et al. (2000), we examined two other measures of loan growth in addition to the loans-to-total assets measure (ΔLTA). These two measures are constructed as change in loans this quarter minus loans last quarter, divided by total assets last quarter, and change in loans this quarter minus loans last quarter, divided by loans last quarter. Neither of these variants results in statistically significant returns dispersion across decile portfolios.

[21] Our sample of bank firms differs from Barber and Lyons in two important aspects. First, the time period differs; their study covers 1973 through 1994, ours covers 1986 through 1999. Second, the sample of firms is different; theirs includes all financial firms in the SIC code range of 6000–6999, ours includes only firms with quarterly consolidated financial statements for bank holding companies on the Fed database that are also listed on CRSP.

[22] The lack of significance of book-to-market and firm size to price the cross-section of bank stock returns is to some extent consistent with the observed time variation in these premiums over this period. For example, over our sample period, from 1986 to 1999, Fama and French's (1993, 1995, 1996) proposed factors, SMB (SMB is a zero-investment portfolio that is long on small capitalization stocks and short on big cap stocks) and HML (HML stands for a zero-investment portfolio that is long on high book-to-market (B/M) stocks and short on low B/M stocks) exhibit large variability. In fact, from 1986 to 1999, the means of SMB and HML, with both series formed using all stocks excluding financial firms, are negative; SMB's mean monthly premium is −0.504% and HML's mean monthly premium is −0.162% (we obtained this data from Kenneth French's web site hosted at http://web.mit.edu/kfrench/www/index.html).

Overall, the one-way sorts on earnings, non-interest income-to-interest income and book equity-to-total assets suggest that these variables contain important information in predicting the cross-section of expected bank stock returns. These fundamental variables give rise to large spreads in portfolio returns, in many cases over 1% per month, suggesting that the market does not instantaneously incorporate the information contained in shocks to these variables. In Section 3.2, we use cross-sectional regressions to explore these relations in more detail.

3.2. Cross-sectional regressions

We employ cross-sectional regressions similar to Fama and MacBeth (1973) to determine which variables are significant in a multiple regression framework. Table 3 presents the results of regressions of monthly returns on combinations of the eight bank-fundamental variables, as well as book-to-market and firm capitalization. We employ a cross-sectional methodology in which returns are regressed on lagged factors for each set of monthly observations. Next, we calculate the time series averages of the slope coefficients. To control for possible non-linearities and the effects of outliers, similar to Chan et al. (1996), we express each independent variable in terms of its percentile rank for any given month and scale it to lie between 0 and 1. This has the benefit of allowing us to directly compare the point estimates of the explanatory variables.

The results from the univariate regressions (models 1 through 10) are presented first in Table 3. These results confirm the findings of the one-way sorts; ΔEPS, ΔNINT, and ΔLV1 are highly significant, while ΔLLR and ΔLOC are, to a lesser extent, also significant. Also, as we found in the one-way sorts, book-to-market and capitalization are not significant. In models 11–13, we examine which variables are most important in a multivariate framework. In model 11, we examine the five significant univariate variables, ΔEPS, ΔNINT, ΔLV1, ΔLLR and ΔLOC. In this model, the earnings per share, non-interest income and leverage variables emerge as the significant three, subsuming the loan-loss and standby letters of credit variables. In addition, as can be seen in model 12, ΔEPS, ΔNINT, and ΔLV1 remain significant once we control for LB/M and LCAP. Finally, in model 13, we include all eight bank variables, as well as LB/M and LCAP. Now, only ΔEPS and ΔLV1 remain strongly significant, while ΔNINT drops in significance ($p = 0.13$). The drop in significance of the non-interest income variable is not that surprising, since in the full model we are including other variables which may also serve as proxies for non-traditional activities for US banks. Thus, in model 13, the inclusion of unused commitments to total loans (ΔUNCM), interest rate swaps to total assets (ΔIRS), and dollar value of standby letters of credit to total loans (ΔLOC), which are all related to non-traditional activity, likely contribute to the weakening of ΔNINT.

We also examine the subperiod stability of the cross-sectional regressions coefficients by splitting our sample into two equal subperiods. Over our sample period from 1986 to 1999, the competitive nature and financial performance of the banking industry changed dramatically. For instance, the last half of this period was charac-

Table 3
Monthly cross-sectional regressions[a]

Model	LCAP	LB/M	ΔEPS	ΔLTA	ΔLLR	ΔNINT	ΔUNCM	ΔIRS	ΔLOC	ΔLV1
1	0.045									
	(0.639)									
2		0.046								
		(0.631)								
3			0.254							
			(0.000)							
4				−0.001						
				(0.98)						
5					−0.126					
					(0.056)					
6						−0.272				
						(0.000)				
7							0.035			
							(0.53)			
8								0.013		
								(0.808)		
9									0.092	
									(0.045)	
10										0.225
										(0.000)
11			0.144		0.013	−0.163			0.025	0.136
			(0.002)		(0.801)	(0.000)			(0.543)	(0.003)
12	−0.006	0.058	0.154		0.025	− 0.150			0.005	0.120
	(0.954)	(0.467)	(0.001)		(0.604)	(0.004)			(0.901)	(0.009)
13	−0.162	−0.013	0.117	−0.012	0.033	−0.111	0.039	−0.056	−0.011	0.132
	(0.192)	(0.893)	(0.007)	(0.831)	(0.547)	(0.131)	(0.523)	(0.254)	(0.834)	(0.030)

[a] Mean and *p*-values (in parentheses) of estimated coefficients from monthly cross-sectional regressions of monthly returns regressed on the fundamental variables from June 1986 to September 1999. In the regressions, each explanatory variable is expressed in terms of its percentile rank and is scaled to lie between 0 and 1. The reported point estimates are the means of the times series of coefficients from monthly cross-sectional regressions. All point estimates are expressed in percentage terms. The lagged variables are: firm capitalization of equity (LCAP), quarterly book-to-market (LB/M), and eight bank-specific variables. The bank-specific variables are constructed as quarterly percentage changes relative to the mean of the last four quarters. The variables are: earnings per share (ΔEPS), loans-to-total assets (ΔLTA), loan-loss reserves to total loans (ΔLLR), non-interest income to net income (ΔNINT), unused loan commitments to total loans (ΔUNCM), interest rate swaps to total assets (ΔIRS), dollar value of standby letters of credit to total loans (ΔLOC), and book value of equity to total assets (ΔLV1).

terized by increased competition as a result of deregulation and record earnings (and profits) as a result of a strong economy coupled with improved industry efficiencies. As a result of these differences, we would expect a larger percentage of banks in the second half of our sample period to report increased earnings and to diversify into non-traditional banking services. Therefore, we would expect the predictive power of our earnings and earnings diversification variables to lessen in the later half of our sample period. The pattern that emerges from our subperiod analysis is consistent with our expectations. For example, we observe a decrease in the point estimates of the earnings variable (ΔEPS) and the non-interest income variable (ΔNINT), but little change in the leverage (ΔLV1) in the second half of our sample period. Specifically, we estimate model 12 using subperiods (not reported in the table), and find that the coefficients for ΔEPS drops from 0.20 to 0.11 (t-statistic = 1.90), ΔNINT changes from −0.20 to −0.10 (t-statistic = 1.70), and ΔLV1 increases from 0.11 to 0.126 (t-statistic = 2.17), from the first to the second half of the sample, respectively.

Overall, the results form the cross-sectional regressions support the non-parametric results of the one-way sort portfolios. Taken together, the one-way sorts and the cross-sectional regressions provide reasonably strong evidence for the existence of bank-industry-wide cross-sectional predictability arising from changes in earnings, non-interest income and leverage. In the remaining sections of the paper, we examine possible sources of this predictability.

4. Decomposing the sources of predictability

Fama (1991) suggests that predictability, in and of itself, does not imply market inefficiency. Lakonishok et al. (1994), Haugen and Baker (1996), and Daniel and Titman (1997) have argued that predictability may arise from irrational investor behavior. Others have argued that apparent "profits" could arise from either data snooping, as discussed in Lo and MacKinlay (1990), Black (1993), Foster et al. (1997), or from risk differences as presented in Fama and French (1993, 1995, 1996). Thus, we explore each of these explanations in an attempt to explain the previous section's results.

4.1. Alternative explanations of predictability: Adjusting for risk

It has become common place in the literature to use the Fama–French three factor model (1996) as the derigueur method of risk adjustment. We follow this practice, and also include the "up-minus-down" UMD momentum factor from Carhart (1997). We report in Table 4 the results of regressing combined portfolios from the one-way sorts of Table 2 on these four factors. Combined portfolios for each of the eight bank variables, and for book-to-market and capitalization, are formed from subtracting the returns each month of decile 10 from decile 1. For each variable, the combined portfolio is then regressed on the monthly return of the CRSP value-weighted index less the risk free rate (EXMKT), the monthly premium of the book-to-market factor (HML), the monthly premium of the size factor (SMB), and the monthly premium of winners minus losers (UMD). A significant intercept indicates "excess returns" above and beyond that suggested by the four-factor model of Carhart.

The results from Table 4 show that the earnings per share (ΔEPS), loan-loss reserves to total loans (ΔLLR), non-interest income to net income (ΔNINT), and book value of equity divided by total assets (ΔLV1) all have significant intercepts. Each of these variables has a t-statistic above 2 for the intercept, with average excess monthly returns (the point estimate of the intercept) around 1% or slightly greater in absolute magnitude. In general, the significant-alpha combined portfolios do not load signif-

Table 4
Time series regressions of combined portfolio profits on a four-factor model[a]

Regression	ΔEPS	ΔLTA	ΔLLR	ΔNINT	ΔUNCM	ΔIRS	ΔLOC	ΔLV1	LB/M	LCAP
α	0.0121	0.0018	−0.0116	−0.0124	0.0029	0.0024	−0.001	0.0124	0.002	−0.0019
	(2.96)	(0.52)	(−2.17)	(−2.57)	(1.14)	(0.66)	(−0.24)	(2.55)	(0.35)	(−0.42)
β_{mkt}	0.071	−0.337	0.044	0.055	−0.03	0.007	0.097	−0.137	0.082	0.372
	(0.69)	(−3.21)	(0.24)	(0.37)	(−0.36)	(0.07)	(1.00)	(−1.10)	(0.55)	(2.76)
β_{HML}	−0.120	−0.156	0.330	0.201	−0.372	−0.073	0.045	−0.50	1.031	−0.150
	(−0.72)	(−1.05)	(1.40)	(1.24)	(−2.64)	(−0.31)	(0.40)	(−2.30)	(4.32)	(−0.65)
β_{SMB}	−0.220	0.124	0.194	0.096	−0.194	−0.298	−0.045	−0.528	1.165	−0.951
	(−1.41)	(0.98)	(1.22)	(0.65)	(−1.77)	(−2.33)	(−0.52)	(−2.94)	(4.86)	(−5.37)
β_{UMD}	−0.063	0.095	0.197	−0.102	−0.152	−0.056	0.070	0.189	−0.192	0.062
	(−0.42)	(0.72)	(1.29)	(−0.72)	(−1.40)	(−0.36)	(0.76)	(1.19)	(−1.00)	(0.35)

$\text{Combined}_t = \alpha_t + \beta_{MKT}\text{EXMKT}_t + \beta_{HML}\text{HML}_t + \beta_{SMB}\text{SMB}_t + \beta_{UMD}\text{UMD}_t + \varepsilon_t$.

[a] Combined portfolios for each of the eight bank variables, and for book-to-market and capitalization, are formed from subtracting the returns each month of decile 10 from decile 1. For each variable, the combined portfolio is then regressed on the monthly return of the CRSP value-weighted index less the risk free rate (EXMKT), monthly premium of the book-to-market factor (HML) the monthly premium of the size factor (SMB), and the monthly premium on winners minus losers (UMD) from Fama and French (1996) and Carhart (1997). The bank-specific variables are constructed as a quarterly percentage changes relative to the mean of the last four quarters. The variables are: earnings per share (ΔEPS), loans-to-total assets (ΔLTA), loan-loss reserves to total loans (ΔLLR), non-interest income to net income (ΔNINT), unused commitments to total loans (ΔUNCM), interest rate swaps to total assets (ΔIRS), dollar value of standby letters of credit to total loans (ΔLOC), and book value of equity to total assets (ΔLV1). The intercept α from the regression is reported in decimal form, i.e., 0.01 equals 1%. The t-statistics, in parenthesis, are robust to heteroskedasticity and autocorrelation (Gallant, 1987). Sample period: June 1986 to September 1999.

icantly on the factors, with the exception of ΔLV1's loadings on HML and SMB. Those loadings are negative for ΔLV1, suggesting that the combined portfolio performs better when HML and SMB premiums are low, thus providing a hedge against down periods of value and size styles of investing.

We also examine, but do not report in the tables, the average Sharpe ratio, price, and capitalization of the one-way sort portfolios of Table 2. From a simple mean–variance standpoint, if the higher return portfolios are more risky, we should see a decreased Sharpe ratio for these portfolios. For the significant variables from the sorts and the cross-sectional regressions, the general pattern is of increasing Sharpe ratios as we sweep across the deciles. For example, for quarterly shocks to earnings per share (ΔEPS), the monthly Sharpe ratio for decile 1 is 0.15, increasing fairly monotonically up to 0.36 for decile 10. The same pattern of increasing Sharpe ratios as we sweep across the deciles is observed for ΔNINT and ΔLV1. Thus, the pattern of Sharpe ratios across the sort deciles suggests that the higher performing deciles are less risky from a mean–variance standpoint.

Finally, we also examine the average values of price per share and capitalization for each decile of the one-way sorts. If microstructure problems such as large bid-ask spreads or price-pressure effects are likely to be impediments to implementing the portfolios formed by the one-way sorts, we would expect to see smaller average size and price firms in the more profitable portfolios. [23] However, that is not what we observe. For earning shocks (ΔEPS) there is a relatively flat dispersion in size across the 10 deciles, with slightly larger (smaller) capitalization and price firms in the more (less) profitable deciles. For example, decile 10 (1) of earning shocks has an average capitalization of $3.53 B ($2.92 B) and average price of $33.52 ($30.62). For ΔNINT, the relationship across deciles is flat for both price and capitalization, and for ΔLV1, we observe a higher price and capitalization for the higher Sharpe ratio portfolios. Thus, the average firm capitalization and price per share for the more profitable one-way sort deciles is not unusually low, suggesting that large bid-ask spreads and price-pressure effects would not likely be a concern in implementing these strategies.

Overall, the evidence from the four-factor regressions, the Sharpe ratios, and the average cap and price strongly suggest that the evidence of predictability in the cross-section of bank stock returns is not attributable simply to increased risk or increased transaction costs.

4.2. Behavioral explanations

In this section we attempt to address the question of whether the expected return dispersions from the one-way sorts are in part attributable to investors' under or overreaction to the quarterly fundamental variable shocks. To address this issue, we perform two types of tests. First, we employ a two-way sort methodology, similar in spirit to Chan et al. (1996), sorting both lagged returns and the quarterly percentage change variables. Second, similar to Jegadeesh and Titman (2001) we examine in event-time up to 36 month-out returns following large and small changes in the fundamental variables to see if there are patterns consistent with over or underreaction.

4.2.1. Two-way sort portfolios

Using the dispersion in expected returns created by the one-way sorts, we define "good" news and "bad" news states of the fundamental bank variables to be the deciles that result in portfolios with high and low monthly returns, respectively. Reviewing the results of the one-way sorts from Table 2, we observe that investors view negative (positive) changes in quarterly earnings for banks as bad (good) news for future returns. For changes in non-interest income to net income (ΔNINT), we observe increasing monthly returns from decile 10 (the largest) to decile 1 (the smallest). Thus, investors view relative increases in non-interest income as bad news and view relative decreases in non-interest income as good news. For our book equity-to-total assets (ΔLV1) variable, investors appear to view relative negative (positive) changes in book equity for banks as bad (good) news for future returns. This finding suggests that investors view increased use of equity financing as a positive signal for a bank's future performance.

[23] For example, Keim and Madhavan (1997) estimate the trading costs for 21 institutions from January 1991 to March 1993 and find that trading costs increase as both the price and capitalization of a firm decreases.

Thus, for each fundamental variable, we have a range of the variable's cross-sectional distribution that corresponds to good or bad news. These definitions of good and bad news states will be employed in two-way sorts of monthly lagged returns combined with the fundamental variables to form the basis of a test to determine if the dispersion of returns from the one-way sorts is due to a contrarian or a momentum type effect. By using empirical proxies for good and bad news (e.g. the cross-sectional distribution values of loan-loss reserves, loans-to-total assets, and earnings that result in higher and lower returns) together with good and bad news states of lagged returns, we can employ the two-way sorts as a double-confirmation method to determine the likely investor behavior generating return dispersion in the one-way sorts. Specifically, if "overreaction is the return generating process creating dispersion in expected returns", we would expect to observe systematically larger *reversals* by portfolios formed from negative (positive) lagged return securities as we condition on increasingly bad (good) news in the portfolio formation period. Conversely, if underreaction is the return generating process, then we should observe greater return *continuations* in portfolios formed from negative (positive) lagged return securities as we condition on increasingly bad (good) news in the portfolio formation period.

In Table 5, panels A, B, and C, we report the results for two-way sorts for quarterly changes to earnings per share (ΔEPS), non-interest income to net income (ΔNINT), and book value of equity divided by total assets (ΔLV1), respectively. Each month, we perform two-way sorts by first sorting lagged monthly returns into terciles and then independently sorting values of the lagged fundamental variables into terciles. For each of the three two-way sorts, we form nine portfolios. All securities are equally weighted within a given portfolio.

When we examine the return dispersion created by the two-way sorts in Table 5, it appears that the results are generally consistent with investor underreaction to changes in the firms' earnings, non-interest-to-net income, or book equity-to-total assets. Specifically, we observe increased (decreased) monthly returns when conditioning on good (bad) states of the fundamental variables for formation period winners (losers); this is consistent with underreaction. For example, in panel A, stocks that are both losers (prior monthly return tercile = 1) and experience bad news in quarterly changes in earnings (ΔEPS = 1) have lower returns, at 2.069%, than do loser stocks with large positive shocks to earnings (ΔEPS = 3), at 2.937%. For formation period winner stocks (prior monthly return tercile = 3), those with smaller earning changes (ΔEPS = 1) again have lower returns than do those stocks with larger earning changes (ΔEPS = 3); 0.524% versus 1.221%, respectively. The same basic pattern is observed for non-interest income to net income (ΔNINT) and book value of equity divided by total assets (ΔLV1). In addition, all of the two-way sorts create a meaningful dispersion in returns, as judged by the significant chi-square statistics, across the nine portfolios in each two-way sort. We also examine in Table 6 three cross-sectional regression models using two-way combinations of lagged monthly returns and the three quarterly change variables that are employed in the two-way sorts. The results of the regressions confirm the patterns from the two-way sorts; the lagged returns point estimate is always negative and significant; the ΔEPS point

Table 5
Average monthly returns for portfolios formed on two-way independent sorts[a]

Panel A: Lagged percent change in earnings per share (ΔEPS)									
Prior monthly return	1 (loser)	1	1	2	2	2	3	3	3 (winner)
ΔEPS	1 (low)	2	3	1	2	3	1	2	3 (high)
Monthly return	2.069	2.267	2.937	1.200	1.733	2.421	0.524	0.781	1.221
χ^2 test: 44.59***									
Panel B: Lagged percent change in non-interest income to net income (ΔNINT)									
Prior monthly return	1 (loser)	1	1	2	2	2	3	3	3 (winner)
ΔNINT	1 (low)	2	3	1	2	3	1	2	3 (high)
Monthly return	2.770	2.735	1.738	2.341	1.697	1.341	1.277	0.803	0.404
χ^2 test: 46.32***									
Panel C: Lagged percent change in book value divided by total assets (ΔLV1)									
Prior monthly return	1 (loser)	1	1	2	2	2	3	3	3 (winner)
ΔLV1	1 (low)	2	3	1	2	3	1	2	3 (high)
Monthly return	1.669	2.578	2.619	1.203	1.774	2.047	0.386	0.914	1.030
χ^2 test: 40.52***									

*,**,*** The null hypothesis of equality of average monthly portfolio returns across the nine portfolios is rejected at the 10%, 5%, and 1% levels, respectively.

[a] In Panels A–C, at the beginning of every month, all stocks are ranked by their prior monthly return and grouped into one of three equal-sized portfolios. All stocks are also independently ranked into one of three equal-sized portfolios each month by a lagged quarterly percent change bank-fundamental variable. The intersections of the sort by prior return and the sort of the fundamental variable give nine portfolios each. All stocks are equally weighted within a portfolio. The bank fundamental variable, constructed as a quarterly percentage changes relative to the mean of the last four quarters, are earnings per share (ΔEPS), non-interest income to net income (ΔNINT), and book value of equity to total assets (ΔLV1). Reported monthly returns are in percent. We report a χ^2_1-statistic to test the null hypothesis of equality of monthly returns across the nine portfolios. The χ^2_1-statistics are robust to heteroskedasticity and autocorrelation (Gallant, 1987).

estimate is positive and significant; the ΔNINT point estimate is negative and significant; and the ΔLV1 point estimate is positive and significant.

It is interesting to note that we observe the greatest (least) levels of profits in the two-way sorts for positive (negative) shocks to the fundamental variables during loser (winner) lagged return states. For example, non-interest income to net income (ΔNINT), (in Table 5, Panel B) has the greatest (least) levels of profits, 2.770%, (0.404%) in the two-way sorts for positive (negative) shocks to the fundamental variables during loser (winner) lagged return states. This pattern is consistent for ΔEPS and ΔLV1. These return patterns also appear to be consistent with investor underreaction, suggesting that investors may underreact to a greater degree for stocks in which the news shock is more of a surprise. The patterns of return behavior observed in the two-way sorts do not appear to be consistent with investor overreaction to news shocks during the portfolio formation period. If investors were overreacting, we would expect greater reversals for losers (winners) conditioning on bad (good) news shocks. However, we do not observe this behavior. In the next section, seeking

Table 6
Monthly cross-sectional regressions for the two-way sorts[a]

Model	LR	ΔEPS	ΔNINT	ΔLV1
1	−0.508 (0.000)	0.283 (0.000)		
3	−0.515 (0.000)		−0.303 (0.000)	
2	−0.461 (0.000)			0.257 (0.000)

[a] Mean and *p*-values (in parentheses) of estimated coefficients from monthly cross-sectional regressions of monthly returns regressed on lagged monthly returns (LR) and either quarterly percent changes in earnings per share (ΔEPS), non-interest income to net income (ΔNINT), or book value of equity to total assets (ΔLV1). In the regressions, each explanatory variable is expressed in terms of its percentile rank and is scaled to lie between 0 and 1. The reported point estimates are the means of the times series of coefficients from monthly cross-sectional regressions. All point estimates are expressed in percentage terms. Sample period: June 1986 to September 1999.

to further explore the sources of the documented profits, we examine long-horizon return implications arising from quarterly shocks to the bank variables.

4.2.2. Long-horizon event-time cumulative returns

Another useful method to explore whether the previous sections' documented predictability emanates from over or underreaction as opposed to a risk based explanation is to examine longer horizon returns to our sample of stocks after they have incurred a large or small quarterly shock to one of the bank fundamental variables. Recent empirical and theoretical papers in the lagged returns literature such as, Barberis et al. (1998), Daniel et al. (1998), and Conrad and Kaul (1998), suggest that behavioral based explanations and risk based explanation for returns momentum will have different implications for long-horizon return patterns.

For example, Barberis et al. (1998) examine how a "conservatism bias" might lead investors to underreact to information. In their model, investors underweight new information in updating their priors. Their model implies that prices will slowly adjust to new information, but once this information is impounded in prices there is no more predictability in stock returns. Thus, in the context of Barberis, Shleifer and Vishny, after large information shocks, we should see increasing return spreads between portfolios formed from large good news and bad news shocks and we should observe no subsequent reversion in prices in the long run.

In contrast, Daniel et al. (1998) present a behavioral explanation of predictable security price behavior based on investor overconfidence in their private signal and variations in confidence arising from biased self-attribution. In their model, investors are overconfident about their private signals and the level of investor overconfidence is increased by the arrival of public signals that confirms the validity of their individual actions. They use the behavioral notion of attribution bias, to suggest that investors react asymmetrically to new information: individuals attribute confirming public signals to their own ability (hence, increasing overconfidence) but ascribe disconfirming signals to external noise. When a public signal is contrary to his private signal, the investor attributes it to external factors, causing his confidence to fall only moderately, if at all. On the other hand, if the public signal confirms the private signal, the investor attributes this to his own ability and, thus, increases his confidence. This increase in confidence leads to further price change in the same direction. Hence, the outcome-based adjustment in investor confidence produces positive price momentum in the short term. In the long run, this momentum is reversed as public information dissipates gradually across the investing public to push the price towards fundamentals. Thus, in the context of Daniel, Hirshleifer, and Subrahmanyam, after large information shocks, we should see increasing return spreads between portfolios formed from large good news and bad news shocks. These spreads should be eventually reversed, as prices trend back to their fundamentals.

Finally, Conrad and Kaul (1998) show that a substantial portion of momentum profits come from cross-sectional variation in mean security returns suggesting a simple explanation for momentum profits. Essentially, they claim that momentum strategies may, on average, involve long positions in high mean return securities (winners) and short positions in low mean securities (losers), suggesting that differences in the mean returns are due to differences in risk. Thus, in the context of Conrad and Kaul, we should see constant return spreads between portfolios formed from large good news and bad news shocks. These spreads should stay constant and not change over time.

In Fig. 1, we plot event-time cumulative returns to combined portfolios for earnings per share (ΔEPS), non-interest income to net income (ΔNINT) and book value of equity divided by total assets (ΔLV1). Event-time zero represents the first announcement of a quarterly shock that places a stock in the top or bottom decile. We then plot the cumulative returns to the combined portfolios (constructed as decile 10 minus decile 1 for ΔEPS and ΔLV1, and decile 1 minus decile 10 for ΔNINT) for the next 36 months. The variations in the combined portfolios' profits over the 36-month event window are not consistent with a risk based explanation, and tend to be most consistent with the Daniel et al. (1998) explanation. For all three variables, in the first few months after portfolio formation, we see increasing cumulative

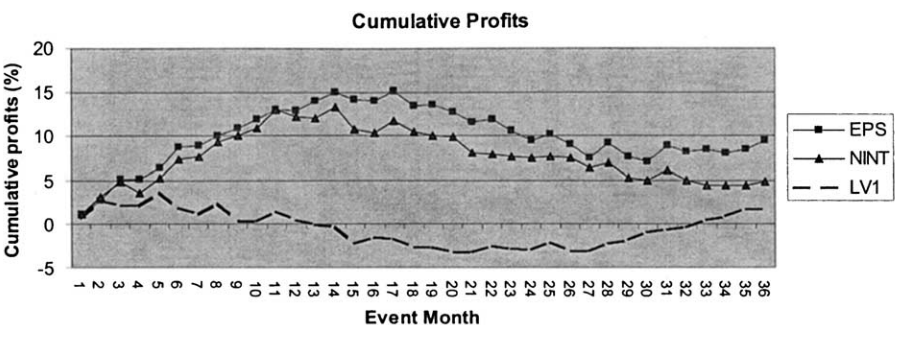

Fig. 1. Cumulative profits to combined portfolios. This figure presents event-time cumulative returns to combined portfolios for earnings per share (ΔEPS), non-interest income to net income (ΔNINT), and book value divided by total assets (ΔLV1). Event-time zero represents the first announcement of a quarterly shock to one of the three-fundamental variables that places a stock in the top or bottom decile. We then plot the cumulative returns to the combined portfolios (constructed as decile 10 minus decile 1 for ΔEPS and ΔLV1, and decile 1 minus decile 10 for ΔNINT) for the next 36 months.

profits. For ΔEPS and ΔNINT, the profits continue until approximately months 14–18. We then observe reversals in the profits, as the cumulative profits gradually decrease. For ΔLV1, the "correction" in profits occurs much more rapidly than for the other two variables, with reversals in profits occurring after month five. The results in Fig. 1 are consistent with models such as Daniel et al. (1998), which predict that underreaction induced momentum profits will eventually be reversed and that these profits arise from investor's behavioral biases.

5. Controlling for data-snooping: A real-time simulation

All of the one-way and two-way sorts in the previous sections are ex ante trading rules. However, the knowledge of which bank variables are "best" is obtained ex post. For example, Bossaerts and Hillion (1999) illustrate the pitfalls of relying on ex post evidence of predictability. They document large degrees of in-sample predictability on international stock returns, but find that the evidence of predictability vanishes out-of-sample. Thus, in this section, we examine if an investor, equipped only with information from prior periods to form expectations on which variables best forecast the cross-section of expected bank stock returns, is capable of finding predictability. We adopt a recursive forecasting methodology similar in spirit to approaches used previously in Pesaran and Timmermann (1995), Bossaerts and Hillion (1999), and Cooper (1999). We follow these papers' philosophy that allowing for alternative, competing variables is the crucial element of proper ex ante out-of-sample testing. To this end, we perform an out-of-sample forecasting experiment that simulates an investor's portfolio decisions in "real time". Real-time forecasts arise because of the algorithm's method of endogenously determining within in-sample periods the best variables and how to best use these variables. The important point is that our simulation uses information before time *t* (prior to out-of-sample periods) to determine the portfolio formation rules used in out-of-sample periods (after time *t*).

We use the 1986–99 period for the simulation. We allow our hypothetical real-time investor to consider combinations of *all* the variables considered in the paper, not just the variables that are significant in previous sections of the paper. We follow these steps, similar to those of Allen and Karjalainen (1996), Pesaran and Timmermann (1995), and Cooper (1999) to obtain out-of-sample forecasts:

(1) The investor's first decision period is December 31, 1990. The first in-sample period is defined as January 1986 through December 1990. At the beginning of each month in the in-sample period, all bank stocks are sorted into terciles based on the eleven variables separately. [24] Equally weighted returns to all corner portfolios of the 55 combinations of two-way sorts are calculated for each month of the five-year,

[24] The eleven variables are firm capitalization of equity (LCAP), Quarterly book-to-market (LB/M), monthly lagged returns, and eight bank-specific variables. The bank-specific variables are quarterly percentage changes relative to the mean of the last four quarters for earnings per share (ΔEPS), loans-to-total assets (ΔLTA), loan-loss reserves to total loans (ΔLLR), non-interest income to net income (ΔNINT), unused commitments to total loans (ΔUNCM), interest rate swaps to total assets (ΔIRS), dollar value of standby letters of credit to total loans (ΔLOC), and book value of equity divided by total assets (ΔLV1).

in-sample period, resulting in 220 rules. The rules in the highest (lowest) decile of Sharpe ratio over both the first half and second half of the in-sample period are identified as the optimal LONG (SHORT) rules.

(2) The first out-of-sample period is from January 1991 to December 1991. Using the optimal in-sample rule set, an equally weighted long and short portfolio is formed. The rules select stocks by using Boolean logical functions of "AND" and "OR". Securities are selected from each optimal two-way rule using an "AND" operator across the two variables. The rules are then combined across two-way sorts using an "OR" operator to create LONG and SHORT portfolios. If no securities meet the criteria to form a LONG or SHORT portfolio, then the respective portfolio invests in a risk-free asset. [25] We form a combined portfolio by subtracting the return of the SHORT portfolio from the LONG portfolio. If no LONG (SHORT) portfolio exists in a given month, then the combined portfolio invests only in the SHORT (LONG) portfolio.

(3) The five-year in-sample window is then rolled forward one year, and the process is repeated for each of the remaining eight out-of-sample years (January 1992 through September 1999). The investor's decision period rolls forward to December 31 of the next year (1991 for the second time through the steps). We repeat these steps until we reach the end of the sample, resulting in a total of nine non-overlapping out-of-sample forecasts spanning January 1991 through September 1999.

We test the optimal rules out-of-sample, and judge their performance in comparison to a buy-and-hold strategy, Jensen's alpha, and Carhart (1997) four-factor model alpha.

Table 7 reports the profitability of the out-of-sample forecasts. The active long strategy earns an average of 2.69% per month over the 1991–1999 period while the benchmark portfolio, EW Market (a "buy-and-hold" portfolio formed from buying all the available bank stocks each year), earns an average monthly return of 2.21%. The short strategy "earns" 0.88% per month, resulting in a spread between the long and short portfolio, as reflected in the combined portfolio's profit, of 1.79% per month. The profit figures reported for the LONG and SHORT portfolios are for a positive investment. Hence, the short portfolio's return of 0.88% represents a loss to an independent short selling strategy. Obviously, the main advantage of the short portfolio is the large spread it creates relative to the benchmark and the LONG portfolio and its application in combined portfolio strategies.

From a risk-adjusted standpoint, all three active portfolios appear to outperform the benchmark. The Jensen's alphas (constructed using the EW market portfolio) are all relatively large and significant. Using the four-factor model, we also observe significant risk-adjusted returns. For example, the long out-of-sample portfolio's four-factor-model intercept is 84 basis points per month, beating the EW Market benchmark, which earns a risk-adjusted 49 basis points per month. The combined

[25] Because the two-way sorts are independent sorts, the situation could arise in which a long or short portfolio is not formed in a given out-of-sample month. For the out-of-sample period from January 1991 through September 1999, there are four (five) months for which the LONG (SHORT) portfolio does not trade.

Table 7
Out-of-sample performance[a]

	Mean monthly return (%) (Std. dev)	Jensen's alpha (%)	Terminal wealth	Four-factor model intercept (%)	MKT	HML	SMB	UMD
EW Market	2.21 (4.55)	–	$9.56	0.49*	1.19***	0.91***	0.21**	−0.13
LONG	2.69 (5.40)	0.60**	$15.10	0.84*	1.18***	0.94***	− 0.03	0.002
SHORT	0.88 (5.26)	−1.17***	–	−0.98**	1.22***	0.75***	−0.09	−0.03
COMBINED	1.79 (4.01)	1.76***	–	1.80***	−0.045	0.19	0.05	0.04

*,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[a] Using all 11 variables from the one-way and two-way sorts of Tables 2 and 5, a time series of monthly out-of-sample returns is generated from January 1991 through September 1999. Consider the first in-sample period, which extends from January 1986 to December 1990. At the beginning of each month from 1986 to 1990, all bank stocks are sorted into terciles based on the 11 variables separately. Equally weighted returns to all corner portfolios of the 55 combinations of two-way sorts are calculated for each month of the five-year in-sample period, resulting in 220 rules. The rules in the highest (lowest) decile of Sharpe ratio over both the first half and second half of the in-sample period identify the stocks selected for the out-of-sample LONG (SHORT) portfolio in the first out-of-sample period from January 1991 to December 1991. Monthly returns are calculated for the LONG (SHORT) portfolio over the out-of-sample period. The five-year in-sample window is then rolled forward one year, and the process is repeated for each of the nine out-of-sample years (January 1991 through September 1999). If no securities meet the criteria to form a LONG or SHORT portfolio, then the respective portfolio invests in a risk-free asset. The out-of-sample COMBINED portfolio is defined by subtracting the return of the SHORT portfolio from the LONG portfolio. If no LONG (SHORT) portfolio exists in a given month, then the COMBINED portfolio invests only in the SHORT (LONG) portfolio. The mean equally weighted monthly returns (standard deviation of monthly returns) to the LONG, SHORT, COMBINED and equally-weighted (EW Market) market index of all bank stocks in the sample are reported below. The parameters from the Carhart (1997) four-factor model are reported for the LONG, SHORT, COMBINED, and EW portfolios. The Jensen's alpha is reported for the LONG, SHORT, and COMBINED. In estimating the Jensen's alpha, we use the EW Market index of all bank stocks as the "market." For the EW Market and LONG portfolios, we also report the terminal wealth, defined as the value at the end of September 1999 from investing $1 in either portfolio at the beginning of the out-of-sample period. "–" indicates that the measure is not applicable.

portfolio has an intercept of 1.80% per month, with insignificant loadings on the MKT, HML, SMB, and UMD factors. There is an increase in performance in the second half of the out-of-sample 1991–1999 period, with the combined portfolio experiencing a four-factor alpha of 2.76% per month in the second half versus 0.98% in the first half of the sample. To the extent that a market model and the four-factor model correctly adjust for risk, the performance measures suggest there is genuine out-of-sample predictability and that this predictability is not an effect that market participants are reducing over time.

Table 7 also reports the terminal wealth of the EW Market and long portfolio. With no transaction costs, the terminal wealth (defined as the final value in 1999 of investing $1 in 1991) of the long and benchmark portfolios are $15.10 and $9.56, respectively. We do not report a terminal wealth for the combined portfolio since it can obviously be arbitrarily scaled up or down. We estimate the break-even round-trip transaction costs (the one-way trading costs to equate the terminal wealth of the long to the EW Market) to be approximately 90 basis points. Clearly, the profitability of the out-of-sample strategies is very dependent on transaction costs. [26] Also, to the extent that one attempts to "fine-tune" the optimal rebalancing horizon by taking advantage of the long-horizon drifts in Fig. 1, then one could perhaps significantly reduce the effects of transaction costs. We merely offer this as a suggestion, as a complete exploration of this is beyond the scope of this paper.

The individual rules selected to form portfolios in the out-of-sample periods are in general consistent with the previous results from the paper. For example, ΔEPS, lagged returns, ΔNINT, and ΔLV1 are the most often selected variables, while ΔIRS, LCAP, LB/M, and ΔUNCM are the least often chosen. Also, the average tercile of the selected rules for the four most chosen variables is consistent with the previous results. For example, for the long rules, the average tercile for ΔEPS, lagged returns, ΔNINT, and ΔLV1 is 2.53, 1, 1, and 2.68, respectively. Therefore, the optimal rules that emerge from the out-of-sample simulation are similar to the in-sample results presented in Tables 2 and 3.

Although the optimal in-sample rules appear to be sufficiently stationary to generate significant out-of-sample risk-adjusted profits, there is a non-trivial decrease in profits between the rules' in-sample and out-of-sample returns. For example, the average return across all long (short) in-sample optimal rules (not reported in the tables), is 2.87% (0.504%). In contrast, the out-of-sample long and short portfolios earn 2.69% and 0.88%, respectively. Thus, the out-of-sample profits are approximately 10–40% less than the returns of the in-sample rules used to generate them. The degradation in performance between the in-sample and out-of-sample periods might imply that the significance of some of the in-sample optimal rules are partly based on spurious relations, or that some of the optimal in-sample rules are not sufficiently stationary over the out-of-sample periods. Nevertheless, the decrease in profits highlights the importance of running real-time simulations to validate returns predictability.

Overall, the out-of-sample findings support the in-sample conclusions that the use of the bank fundamental variables results in meaningful cross-sectional predictability for bank stock returns.

6. Conclusion

This paper documents predictability in the cross-section of bank stock returns using variables that have been shown in previous banking studies to be related to risk and shareholder value. Studies such as Madura and Zarruk (1992), Grammatikos and Saunders (1990), Musumeci and Sinkey (1990), and Docking et al. (1997) have

[26] Although transaction costs have undoubtedly varied across the sample, Keim and Madhavan (1997) report round-trip total execution costs ranging from 0.32% to 0.72% (price impact, bid–ask spreads, and commission costs), depending on the size of the trade, calculated from actual trades placed by 21 institutional investors on the largest quintile (similar in size to our sample) of NYSE securities over the 1991–1993 period.

typically employed an event study methodology to document shareholder wealth effects around announcement date windows of changes in bank loan quality and/or quantity. However, in this paper, we show that fundamental variables related to information about a bank's earnings, non-interest income, and leverage, can reliably price the cross-section of future bank stock returns.

The results also suggest that the documented dispersion in expected returns from sorting on deciles of quarterly shocks to bank's earnings, loan-loss reserves and loans-to-total assets is not an expected-return phenomenon. Various measures designed to measure risk of our portfolios, such as the four-factor model (Carhart, 1997), imply that the predictability is not due to increased risk. Rather, the results appear due to investor underreaction to new bank information. This underreaction persists for approximately 6–18 months, and is then gradually reversed, consistent with behavioral-based models such as Daniel et al. (1998).

For future research, this paper may serve as a starting point in developing a banking industry specific asset-pricing model to aid in risk adjustment, performance evaluation, and cost of capital applications for financial firms.

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Appendix A

Sample of firms[a]

Firm name	Firm name
Acadiana Bancshares, Inc.	Bankamerica Corporation
Affiliated Bankshares of Colorado, Inc.	Bankers Trust Corporation
Ameritrust Corporation	Banks of Iowa, Inc.
Amoskeag Bank Shares, Inc.	Bar Harbor Bankshares
Amsouth Bancorporation	Barnett Banks, Inc.
Associated Banc-Corp.	Baybanks, Inc.
Atico Financial Corporation	Boatmen's Bankshares, Inc.
Bancfirst Ohio Corp.	Bostonfed Bancorp., Inc.
Bancoklahoma Corp.	Brenton Banks, Inc.
Bancorpsouth, Inc.	Bridge View Bancorp.
Bancserve Group, Inc.	C & S/Sovran Corporation
Bank of New England Corporation	CCNB Corporation
Bank of New York Company, Inc., The	CFX Corporation
Bank One Corporation	Camden National Corporation
Bank One Arizona Corporation	Centerre Bancorporation
Bank South Corporation	Central Banking System, Inc.
Bankeast Corporation	Central Fidelity Banks, Inc.

Firm name	Firm name
Central Pacific Corporation	First Interstate of Iowa, Inc.
Centura Banks, Inc.	First Midwest Bancorp, Inc.
Chase Manhattan Corporation	First NH Banks Inc.
Chittenden Corporation	First Ohio Bancshares, Inc.
CITICORP	First Pennsylvania Corporation
Citizens and Southern Corporation	First Philson Financial Corporation
Citizens Bancorp.	First Security Corporation
Citizens Financial Group, Inc.	First Security Corporation of Kentucky
Citizens First Bancorp., Inc.	First Source Corporation
Citizens Holding Company	First Tennessee National Corporation
City National Corporation	First Union Corporation
City Trust Bancorp., Inc.	First Union Corporation of Virgina
Cobanco, Inc.	First United Bancshares, Inc.
Colonial Bank Group, Inc., The	First Virgina Banks, Inc.
Colorado National Bankshares, Inc.	First West Virginia Bancorp, Inc.
Comerica Incorporated	First Wyoming Bancorporation
Commerce Bancorp, Inc.	Firstbank of Illinois Co.
Commerce Bancshares, Inc.	Firstier Financial, Inc.
Commercial Bancshares, Inc.	Flagler Bank Corporation
Community Bankshares, Inc.	Fleetboston Financial Corporation B*B
Community Bank system, Inc.	Florida National Banks of Florida, Inc.
Community Banks, Inc.	Fourth Financial Corporation
Community Capital Corporation	Great American Corporation
Community Independent Bank, Inc.	Greenpoint Financial Corp.
Comsouth Bankshares, Inc.	Hawkeye Bancorporation
Conifer Group Inc.	Hibernia Corporation
Continental Bank Corporation	Huntington Bancshares incorporated
Corestates Financial Corp.	Imperial Bancorp
Cornerstone Bancorp, Inc.	Independent Bankshares, Inc.
Corpus Christi Bancshares, Inc.	Interchange Financial Services Corporation
Crestar Financial Corporation	Interfirst Corporation
Cullen/Frost Bankers, Inc.	James Madison Limited
Duphin Deposit Corporation	Jefferson Bancorp, Inc.
Deposit Guaranty Corp.	J.P. Morgan & Co. Incorporated
Dime Financial Corporation	Keycorp
Eldorado Bancorp	Keystone Financial Inc.
Equimark Corporation	Keystone Heritage Group, Inc.
Equitable Bancorporation	LSB Bancshares Inc.
F & M National Corporation	Lamar Capital Corporation
Falmouth Bancorp, Inc.	Landmark Bancorp
Fidelcor, Inc.	Landmark Bancshares Corporation
Fifth Third Bancorp	Lincolin Financial Corporation
First Amarillo Bancorporation, Inc.	M & T Bank Corporation
First American Corporation	MBNA Corporation
First of America Bank Corporation	MCB Financial Corporation
First Chicago Corporation	MNC Financial, Inc.
First Citizens Bancstock, Inc.	Magna Group, Inc.
First Commercial Corporation	Manufacturers Hanover Corporation
First Commonwealth Financial Corporation	Manufacturers National Corporation
First Illinois Corporation	Mark Twain Banshares, Inc.
First Interstate Bancorp	Marshall & Ilsley Corporation

Firm name	Firm name
Mellon Financial Corporation	Riggs National Corporation
Mercantile Bancorporation Inc.	Seacoast Banking Corporation of Florida
Mercantile Banshares Corporation	Security Bancorp, Inc.
Merchants National Corporation	Security Pacific Corporation
Meridian Bancorp, Inc.	Shawmut National Corporation
Michigan National Corporation	Signet Banking Corporation
Mid-America Bancorp	South Carolina National Corporation
Midlantic Corporation	Southeast Banking Corporation
Midsouth Bancorp, Inc.	Southtrust Corporation
Multibank Financial Corp.	Southwest Georgia Financial Corporation
Napa Valley Bancorp	State Bancorp, Inc.
National Bancshares Corporation of Texas	State Street Corporation
National City Bancorporation	Sterling Bancorp
National City Corporation	Suntrust Banks, Inc.
National Commerce Bancorporation	Surety Capital Corporation
National Penn Bancshares, Inc.	Susquehanna Bancshares inc.
Nationsbank Texas Bancorporation, Inc.	Sussex Bancorp
Neworld Bancorp, Inc.	Synovus Financial Corp.
North Fork Bancorporation, Inc.	Texas American Bancshares Inc.
Northeast Bancorp, Inc.	Tompkins Trustco, Inc.
Northern Trust Corporation	Trustco Bank Corp. NY
Old Kent Financial Corporation	Trustmark Corporation
One Valley Bancorp, Inc.	UMB Financial Corporation
PAB Bankshares, Inc.	Union Planters Corporation
PNC Bank Corp.	Unionbancal Corporation
Pacific Inland Bancorp	United Banks of Colorado, Inc.
Pacific Western Bancshares, Inc.	United Carolina Bancshares Corporation
Pacwest Bancorp	United Financial Banking Companies Inc.
Park National Corporation	US Bancorp
Peoples Holding Company, The	US Trust Corporation
Premier Bancorp, Inc.	Valley Bancorporation
Premier Bancorp, Incorporated	Wachovia Corporation
Professional Bancorp, Inc.	Wells Fargo & Company
Puget Sound Bancorp	West One Bancorp
Redwood Empire Bancorp	Westamerica Bancorporation
Regions Financial Corporation	Wilmington Trust Corporation
Republic New York Corporation	Worthen Banking Corporation
Republic Security Financial Corporation	Zions Bancorporation
Resource Bankshares Corporation	

[a] This exhibit provides a list of the 213 firms in our sample. To be in our sample, a firm must be listed in the Federal Reserve Board's quarterly consolidated financial statements for bank holding companies and be listed on CRSP. The period is 1986–1999.

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