Review of Accounting Studies, 9, 265–294, 2004

How Banks' Value-at-Risk Disclosures Predict their Total and Priced Risk: Effects of Bank Technical Sophistication and Learning over Time

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Abstract. Using a sample of eight large commercial banks from 1994 to 2000, Jorion (2002) finds that banks' VaR disclosures for their trading portfolios predict trading income variability. We extend Jorion's findings using a larger sample of 17 banks from 1997 to 2002 reporting trading VaRs under FRR No. 48 (1997). We find that banks' trading VaRs have predictive power for trading income variability that increases with bank technical sophistication and over time. We find that banks' trading VaRs have predictive power for a bank-wide measure of total risk, return variability, and for two bank-wide measures of priced risk, beta and realized returns.

Keywords: value at risk, market risk, disclosures, banks, derivatives, basel committee

JEL Classification: G1, G21, M41

In response to a number of well-known financial disasters involving the use of derivatives in the early 1990s (e.g., Metallgesellschaft, Orange County, and Barings), bank and securities regulators, accounting standards setters, and various other interested parties worked aggressively to improve the risk management and financial reporting systems for derivatives. An important part of this response was the conception and development of value at risk (VaR) through a series of reports on good risk management practice beginning with the Group of Thirty (1993).[1] As a tool for risk measurement and disclosure, VaR's conceptually most appealing feature is its ability to aggregate risk across types of market risk (e.g., interest rate and exchange rate risk) and business activities (e.g., various trading positions and trading versus non-trading positions). This ability is particularly important when firms take positions with offsetting or otherwise cross-correlated risks, as is the case in hedging, asset-liability management, and most types of trading.[2]

In Financial Reporting Release (FRR) No. 48 (1997), the Securities and Exchange Commission (SEC) required US publicly traded corporations to report quantitative and qualitative information about market risk in their annual Form 10-K filings.

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VaR is one possible disclosure approach for the quantitative information under these requirements, one most commonly chosen by large commercial banks for their trading portfolios. In this regard, VaR's ability to aggregate risk across types of market risk for trading positions and across various trading positions has been widely applied in practice, while its ability to aggregate risk across trading versus non-trading activities generally has not.

For a sample of eight large US commercial banks from 1994 to 2000, Jorion (2002) finds that these banks' quarterly VaR disclosures for their trading portfolios (trading VaRs) predict the variability of next quarter's trading income. While Jorion's results imply that a few large banks have overcome the hurdles involved in estimating trading VaR sufficiently so that it predicts a measure of total (systematic plus unsystematic) risk that is tightly tied to those portfolios, his results also raise questions about whether and how these results generalize across banks and time and to the bank-wide and priced risk measures with which investors primarily are concerned.

We address these questions in this paper by extending the scope of Jorion's (2002) analysis in three ways. First, we investigate whether banks' trading VaRs have predictive power for the variability of trading income that varies across banks based on a measure of their technical sophistication and through time. The motivation for this extension is that VaR faces the following significant hurdles as a means for disclosing information about the risk of trading portfolios.

- While VaR's ability to aggregate risk is most appealing for large portfolios, such portfolios require very elaborate systems to model and implement VaR. For example, J. P. Morgan Chase discloses in its 2001 annual report that its trading VaR disclosure reflects over 500,000 positions and 220,000 market prices.

- The calculation of VaR requires a number of choices regarding its implementation that can have order-of-magnitude effects on the resulting VaR numbers.

- FRR No. 48 provides a variety of options for calculating and reporting VaR that render VaR disclosures imperfectly comparable across banks and time.

Reflecting our expectation that banks and also users of financial reports will overcome these hurdles over time and that technically sophisticated banks will do so more rapidly, we predict and find that banks' trading VaR disclosures have predictive power over next quarter's variability of trading income that is greater for more technically sophisticated banks and increases over time.

Second, we investigate whether banks' trading VaR disclosures predict a measure of their total (systematic plus unsystematic) bank-wide risk, return variability. The motivation for this extension is that market risk disclosures invariably are made on a piecemeal basis for defined market risks or business activities. These piecemeal disclosures place a significant burden on users of financial reports interested in assessing firm-wide risk. Trading VaR has advantages and disadvantages compared to other market risk disclosures in explaining firm risk. On the positive side, it is the only risk disclosure that aggregates risk across types of market risk. On the negative side, other risk disclosures, such as interest rate sensitivity, measure market risk either for a bank's non-trading exposures or the bank as a whole. Given these advantages and disadvantages, in our view it is a meaningful empirical question to ask whether banks' trading VaRs predict their total risk.

The predictive power of banks' trading VaR for their total risk depends on the extent to which banks' trading and non-trading exposures hedge or are otherwise cross-correlated with each other. Consistent with prior research that finds that banks only partially hedge their risks and our own findings that banks' trading and other exposures do not covary much, we predict and find that banks' trading VaRs have predictive power for the next quarter's variability of returns.

Third, we investigate whether banks' trading VaR predicts two measures of their priced (systematic) bank-wide risk: beta and realized returns. The motivation for this extension is that while VaR provides information about total market risk, investors care primarily about priced risk, since unsystematic risk can be diversified away. Consistent with prior empirical research that finds that interest rate risk and other market risks are priced, we predict and find that banks' trading VaR disclosures have predictive power for their next quarter's beta and realized returns.

Collectively, our three extensions of the scope of Jorion's (2002) analysis provide insights into the hurdles VaR faces as a risk disclosure device and the extent to which these hurdles have been overcome by different banks and over time by banks and users of financial reports. These insights should be useful to investors, financial reporting policymakers, and bank regulators.

We also construct a sample that is approximately 50% larger than the one in Jorion (2002), including 17 banks disclosing trading VaRs under FRR No. 48 from 1997 through the first quarter of 2002. While this sample remains relatively small, primarily because relatively few banks have trading operations, the increase in sample size allows us to refine Jorion's empirical methods and models in the following two ways. First, because our sample includes banks with a wider range of technical sophistication, it allows us to test for the effects of technical sophistication on the risk relevance of trading VaR. Second, it allows us to include a limited number of additional control variables in the empirical models—the notional amounts of derivatives (as in Jorion), repricing gap, lagged dependent variables, and market variables—so that our tests examine the incremental risk relevance of trading VaR disclosures beyond these variables. These tests better reflect the SEC's goal in FRR No. 48 to increase publicly available information about firms' market risk.

Despite our relatively small sample size, our results are stronger that those of a number of recent studies using FRR No. 48 disclosures and are robust to various specification tests. This is likely because our sample of banks is relatively homogeneous, because we are able capture some of the heterogeneity that does exist in our bank and time subgroups, and because the risks portrayed by banks' trading VaR disclosures are significant. Most other recent studies are hindered by sample heterogeneity induced by FRR No. 48's many options regarding the calculation and disclosure of market risk, and sometimes by samples of firms with low levels or heterogeneous types of market risk. Because of these uniquely desirable features of our banking sample, however, we emphasize that our results should not be interpreted as implying that trading VaR or any other market risk disclosures are risk relevant for other types of firms.

1. Value at Risk and Other Market Risk Disclosure Approaches under FRR No. 48

VaR measures the potential loss on a portfolio of exposures that occurs over a given period of time at a given confidence level under normal market conditions. For example, a bank might estimate the daily VaR of its trading portfolio to be \$1 million at the 99% confidence level, meaning that it expects a trading loss that exceeds \$1 million in only 1% of the trading days each year. In principle, VaR is an effective tool for modeling and disclosing the market risk of any portfolio (including an entire firm), because it incorporates the correlations of the exposures within the portfolio and uses a consistent time interval and confidence level.

In practice, however, the estimation of VaR involves various significant modeling and estimation issues. Most critically, it requires specifying the joint distribution of the returns to the various exposures in the portfolio. For tractability, banks typically aggregate or simplify their numerous exposures in some fashion.[3] Banks obtain information about this joint distribution from the empirical distributions over a specified prior period, and they incorporate this information into their VaR calculations using one of three general approaches: (1) by analytical methods assuming a multivariate normal distribution that reflects the variances and covariances of the empirical distributions, (2) by simulation directly from the empirical distributions, or (3) by Monte Carlo simulation from assumed parametric distributions chosen to balance the implications of the empirical distributions, other information, and theory. Prior research by Beder (1995) and others shows that both the prior period over which the empirical distribution is observed and the specific approach chosen can have order-of-magnitude effects on the calculation of VaR. While banks attempt to mitigate these problems by "stress testing" their VaR estimates to conceivable adverse realizations of the returns to their exposures not captured in the empirical or assumed distributions, banks' summary disclosures of these stress tests suggest that that these tests rarely lead to changes in reported VaR estimates.

Despite these practical issues, bank and securities regulators have supported the development and use of VaR. Most importantly, under the Basel Committee on Banking Supervision's (1995, 1996) internal-models approach, banks are required to hold regulatory capital for market risk in proportion to their trading VaR disclosures. In FRR No. 48 (1997), the SEC requires US publicly traded corporations to report quantitative and qualitative information about market risk in their annual Form 10-K filings.[4]

FRR No. 48 allows three disclosure approaches for the quantitative information:

1. *Tabular format*. This approach reports fair values and contractual terms sufficient to determine the amount and timing of cash flows over each of the next five years

and beyond five years for derivatives and other financial instruments grouped based on common characteristics.

2. *Sensitivity*. This approach reports the estimated loss of value, earnings, or cash flow that results from selected adverse market price movements chosen by management, subject to the constraint that these movements be at least 10% of the beginning market prices.

3. *VaR*. This approach reports the estimated loss of value, earnings, or cash flow over a selected period of time with a selected probability from adverse market price movements.

Notice that the sensitivity and VaR approaches focus only on the risk of loss, not gain, and they allow loss to be defined in terms of loss of value, earnings, or cash flow.

An important difference between VaR and the other risk disclosure approaches allowed under FRR No. 48 is that VaR does not indicate the direction of the market price movement that gives rise to losses. This renders VaR essentially useless for estimating the sensitivity of the firm to a potential or actual market price movement.

A company may choose any of these disclosure approaches for each exposure it holds and each market risk to which each exposure is subject. For example, trading-oriented banks often choose VaR for their trading portfolios and one of the other approaches for their other exposures. Because FRR No. 48 allows so many disclosure options (i.e., three approaches, three definitions of loss, and a large number of possible adverse price movements, time periods, and probabilities), and because different firms choose different permutations on these options for their various exposures, comparability of market risk disclosure across firms and even for a firm through time is highly limited. Sribunnak and Wong (2002) and other researchers emphasize that this makes it difficult to collect homogeneous samples of sufficient size using FRR No. 48 disclosures, and that this constitutes a significant roadblock to conducting well-controled and powerful empirical research using these disclosures. Like Jorion (2002), we focus on large commercial banks' trading portfolios, as this is the only context in which it is possible to amass a sample of any size with reasonably comparable VaR disclosures.

A sample trading VaR disclosure for Bank of America in 2000 is provided in Appendix A. Bank of America reports various statistics (average, high, and low) for trading VaR in the current and prior year. It also reports the contribution of each type of market risk (interest rate, foreign exchange rate, commodity price, equity price) or defined sub-portfolio (credit products and real estate/mortgage) to trading VaR, taking into account the covariances across types of risk and sub-portfolios. For example, the sum of the average daily trading VaRs across the various market risks and sub-portfolios for Bank of America in 2000 is $82.9 million, while the reported VaR is only half that at $41.5 million, implying a high degree of diversification across types of market risk and sub-portfolios.

In this paper, we examine whether banks' aggregate trading VaR disclosures are related to measures of the risk of their trading portfolios and the bank as a whole. As illustrated by the sample disclosure for Bank of America, banks' trading VaR disclosures include more disaggregated data about specific types of market risk than we use in this paper. In principle, we could use this disaggregated data by itself or in conjunction with other disclosures about each type of market risk for banks' non-trading exposures to assess each type of market risk either at the trading portfolio or bank level. While preferable to the analysis conducted in this paper in various ways, analysis of this disaggregated trading VaR data is infeasible in this study, due to our relatively small sample size and the fact that our banks disaggregate trading VaR in very different ways (some not at all). For these reasons, we do not have a sufficient number of trading VaR disclosures for each type of market risk to conduct meaningful empirical analysis.[5]

2. Prior Literature and Hypothesis Development

2.1. *Prior Literature*

Several papers investigate the association between firms' market risk disclosures prior to FRR No. 48 and the sensitivity of equity returns to specific market prices, with most of these papers finding significant associations in the predicted directions. McAnally (1996) finds that commercial banks' notional amounts of derivatives with market risk are negatively associated with beta. Schrand (1997) finds that savings and loan associations' regulatory disclosures of 0–1 year maturity gap[6] and the effect of derivatives on that gap are associated in the expected direction with interest rate sensitivity, while Collins and Venkatachalam (1996) and Ahmed et al. (1999) obtain similar results for commercial banks. Rajgopal (1999) finds that proxies for FRR No. 48 tabular format and sensitivity disclosures derived from SFAS Nos. 69 and 119 disclosures are associated in the expected direction with oil and gas producers' energy price sensitivity. Somewhat in contrast, Wong (2000) finds only weak evidence that disclosures of the notional amounts and fair values of manufacturing firms' foreign exchange derivatives required under SFAS No. 119 are associated with their foreign exchange rate sensitivity, likely because of the heterogeneous nature of foreign exchange risk.

Results from studies using FRR No. 48 disclosures depend on the research question being asked. One question is whether the act of providing this information increases the information available to investors, and there is evidence that this is the case. Linsmeier et al. (2002) find that non-financial firms' provision of FRR No. 48 market risk disclosures under any approach reduced investors' uncertainty and diversity of opinion about the effects of changes in interest rates, foreign exchange rates, and energy prices on these firms, as evidenced by a lower sensitivity of trading volume to changes in these market prices subsequent to the provision of disclosures. Sribunnak and Wong (2002) examine the association between non-financial firms' FRR No. 48 disclosures of foreign exchange sensitivity using any of the approaches and their future stock return variability. They find that firms that make market risk disclosures have lower foreign exchange rate sensitivity than those that do not.

A second question is whether there is an association between the magnitude of market risk indicated by FRR No. 48 disclosures and measures of firm risk, and evidence on this point is less consistent and generally weaker. Sribunnak and Wong (2002) find that non-financial firms' market risk measured under the (by far the most common) sensitivity approach is associated with their foreign exchange rate sensitivity, but that this is not the case for market risk measured under the tabular format and VaR approaches. Sribunnak and Wong's results suggest that it is critical to be able to develop a sample of sufficient observations that are comparable in their FRR No. 48 disclosures for the research design to have enough power to document an association. Hodder (2002) finds that commercial banks' FRR No. 48 interest rate sensitivity disclosures are not associated with future changes in income or fair value, conditioning on actual changes in market factors, but that their simpler regulatory repricing gap disclosures are so associated. Hodder interprets her results as suggesting that information about risk may be lost due to banks' modeling assumptions embedded in the estimation of FRR No. 48 sensitivity disclosures.

Using daily trading income data available only to bank regulators, Berkowitz and O'Brien (2002) provide a detailed analysis of the performance of trading VaR disclosures in describing the distribution of the trading income of six large US banks. They find that in most periods trading VaR estimates are conservatively high (i.e., fewer trading losses in excess of trading VaR occur than are predicted), but trading VaRs can be too low in abnormal periods such as the hedge fund crisis in 1998. They find that use of banks' trading VaR disclosures to predict the level and variability of their trading profits does not improve upon time-series models, a troubling result given the SEC's goal of improving market risk disclosures in FRR No. 48. Berkowitz and O'Brien (2002) interpret this result as attributable to VaR models' complexity reducing the predictive power of the information they generate, similar to Hodder's (2002) conclusion above.

Jorion (2002) is the only prior paper that focuses on banks' public trading VaR disclosures. Jorion (2002) models the theoretical relationship between these disclosures and the variability of unexpected trading income, and he finds that banks' trading VaR disclosures are associated with the variability of their next quarter's unexpected trading income. Jorion's modeling and results provide the starting point for the analysis in this paper.

In summary, while Jorion (2002) provides evidence that banks' trading VaRs provide information about the variability of future trading income, there is also evidence that VaR and other FRR No. 48 market risk disclosures are subject to modeling, estimation, and comparability problems that reduce the information they provide about firm risk.

2.2. Hypotheses

In this section, we develop hypotheses about the predictive power of trading VaRs for various measures of banks' risk. As depicted in Table 1, these risk measures differ along two dimensions. The first dimension distinguishes the risk of the trading

Table 1. Risk measures examined in paper.

	Total	Priced
Trading portfolio	Variability of trading income	
bank-wide	Variability of returns	Beta, realized returns

portfolio from bank-wide risk. The second dimension distinguishes total (systematic plus unsystematic) risk from priced (systematic) risk. The measure of the total risk of the trading portfolio in the upper left cell of Table 1, the variability of trading income, has the most direct conceptual tie to trading VaR. Jorion (2002) examines only this measure, and it is our primary measure. For this measure, we first propose a hypothesis consistent with Jorion's findings and then develop new hypotheses about the effect of bank technical sophistication and time.

Moving away from the upper left cell in Table 1 along each dimension makes the conceptual tie between trading VaR and risk less direct in a particular way. Moving from the total risk of the trading portfolio to the total risk of the bank, as measured by the variability of returns, introduces a potentially confounding variable, the covariance of trading and non-trading exposures. Moving from the total risk to the priced risk of the bank, as measured by beta and realized returns, raises the issue of whether trading VaR captures priced or unpriced risk. Our hypotheses and empirical tests for these risk measures provide evidence about whether and how moving along each dimension affects the risk-relevance of trading VaR.

We emphasize that we do not propose hypotheses (although we do provide descriptive findings) about the effects of either bank technical sophistication or time on the association between trading VaR and bank-wide measures of risk, for the following reasons. More technically sophisticated banks typically have larger trading portfolios and may manage their trading and non-trading exposures differently than other banks. Thus, any observed differences in these results across types of banks might be attributable to economic differences across bank types rather than to differences in the quality of their trading VaR disclosures. The covariance between banks' trading and non-trading exposures may have changed over time, or investors may have come to trust or learned to use trading VaR disclosures more over time. Thus, any observed differences in these results over time might be attributable to changes in economic factors or in investor behavior over time rather than to differences in the quality of trading VaR disclosures over time.

2.2.1. Trading Portfolio Risk

We first replicate Jorion's (2002) results on our sample by testing the following hypothesis.

H1: Banks' trading VaR disclosures are positively associated with the next quarter's variability of their unexpected trading income.

2.2.2. *Bank Technical Sophistication and Learning over Time*

As discussed in the introduction and Section 1, the calculation of VaR requires many complex modeling and data sampling choices that require technical sophistication to evaluate and implement. We expect the level of technical sophistication to vary across banks, with more technically sophisticated banks being better able to estimate trading VaR at any point in time.

H2: Trading VaR disclosures are more positively associated with the next quarter's variability of trading income for more technically sophisticated banks.

VaR is only a decade old as a concept and younger still as an actual risk management tool. Thus, we hypothesize that banks' ability to estimate trading VaR improves as they learn and refine their modeling and estimation techniques over time.

H3: Banks' trading VaR disclosures are more positively associated with the next quarter's variability of trading income over time.

2.2.3. *Bank-Wide Risk*

Prior research by Choi et al. (1992), Chamberlain et al. (1997), and others shows that banks' share returns are sensitive to market risk factors such as changes in interest rates and exchange rates. Assuming banks' trading VaRs are calculated sufficiently well, they should be associated with measures of bank-wide risk either if we can control for the risk of non-trading exposures or, in the absence of such control, if the risk of trading exposures is not canceled out or dominated by the risk of non-trading exposures.

Optimally, in our tests of bank-wide risk, we would control for the covariance of trading and non-trading exposures using one of two approaches: (1) estimate this covariance for each bank or (2) employ VaR measures that include both trading and non-trading exposures. Unfortunately, neither of these approaches is feasible in our view. As discussed in Section 3.2, the publicly available quarterly data on the fair value of banks' trading positions does not allow this covariance of trading and non-trading exposures to be estimated reliably at the bank level. None of the banks in our sample report VaR for (any portion of) their non-trading exposures.[7] Moreover, it is extremely difficult to construct an aggregate VaR measure from banks' various market risk disclosures, because banks' trading VaR disclosures are not comparable to their market risk disclosures for non-trading exposures in various critical ways.[8]

We do expect banks' trading exposures not to be canceled out or dominated by the risk of their non-trading exposures, however, for two reasons. First, while Venkatachalam (1996), Schrand (1997), Naik and Yadav (2000), and others find that banks and other financial institutions hedge their exposures using derivatives, the extent of the hedging documented is small in proportion to the magnitude of the exposures. For example, Venkatachalam's results suggest that banks hedge only 11% of the changes in the fair value of their non-derivative positions using derivatives. As discussed in Section 3.2, we provide evidence that banks' hedging of trading and non-trading exposures is even less than this level, likely reflecting the speculative nature of most trading. Because of this apparently low level of such hedging, we expect to find that higher trading VaRs imply higher bank-wide risk. Second, trading portfolios are risky and for the banks in our sample are of significant size relative to the banks' overall positions, and so their trading VaRs are likely to have an observable effect on the variability of their share returns.

Accordingly, we measure bank-wide total risk by the variability of next quarter's daily returns, and test the following hypothesis:

H4: Banks' trading VaR disclosures are positively associated with the next quarter's variability of their daily share returns.

All FRR No. 48 disclosures pertain to market risks, such as interest rate, foreign exchange, equity price, and commodity price risk. Each of these risks—especially interest rate risk, the main market risk faced by banks—has a macroeconomic component, and so is likely to be priced. In this regard, three of the five factors identified by Chen et al. (1986) as being priced in an arbitrage pricing theory (APT) framework pertain to credit riskless interest rates (expected inflation, unexpected inflation, and the slope of the yield curve), while a fourth pertains to credit risky rates (the default premium on corporate bonds). Hence, we expect trading VaR to be associated with measures of priced risk.

We examine two measures of bank-wide priced risk. Under the assumptions of the capital asset pricing model (CAPM), beta summarizes all priced risk, and so we hypothesize:

H5: Banks' trading VaR disclosures are positively associated with next quarter's beta.

A potential problem in interpreting our tests of hypothesis H5 is that research by Fama and French (1992) and others suggests that in practice beta is not an effective measure of priced risk. Accordingly, we also test whether trading VaRs are associated with future returns, hypothesizing:

H6: Banks' trading VaR disclosures are positively associated with next quarter's share returns.

An issue in interpreting our tests of hypothesis H6 is that realized returns include unexpected returns, which reflect the directional effects of the realization of information on firm value during the period. The inclusion of unexpected returns introduces noise in our tests of H6. Moreover, one of our control variables, repricing gap, should be associated with unexpected returns. In principle, it would be preferable to use a direct measure of expected returns as the dependent variable in H6. However, we obtained Brav et al. (2002) two measures of expected returns based on analyst earnings forecasts from First Call and Valueline, both of which they find to be strongly positively associated with beta for their broad sample of firms over a long time period. In contrast, we find these measures of expected returns to behave poorly for our small sample of banks and our relatively short time period. For example, the measure based on First Call forecasts is insignificantly correlated with beta and erratically correlated with realized returns across the subgroups. The measure based on Valueline forecasts is significantly negatively correlated with beta and weakly positively or negatively correlated with realized returns in the subgroups. We also lose about a quarter of our observations using these measures, because of missing or infrequent analyst earnings forecasts, which reduces the power of our tests. For these reasons, we use realized share returns as the dependent variable and omit repricing gap as a control variable in our tests of hypothesis H6.

3. Research Design

In this section, we first develop the regression equations used to test all the hypotheses. We then describe the subgroups for bank technical sophistication and time used to test hypotheses H2 and H3.

3.1. Regression Equation for the Variability of Unexpected Trading Income

Trading VaR is a measure of the expected trading loss that occurs with a given probability over a given interval. Jorion (2002) shows that if trading income is distributed symmetrically around zero, so that the probability of a trading loss of a given magnitude over a given period equals the probability of a trading gain of the same magnitude over the same period, then trading VaR is proportional to the dispersion of trading income. Jorion suggests that the assumption that trading income is distributed symmetrically is reasonable for large commercial banks whose trading portfolios typically include a wide range of instruments, though sufficiently large option-like or otherwise skewed trading exposures can render this assumption problematic. Berkowitz and O'Brien (2002) provide histograms and descriptive statistics showing that trading revenues are somewhat left-skewed, however, driven by a few large losses. Jorion (2002) also suggests that the assumption that expected trading income is zero (or dominated by unexpected trading income) is reasonable when trading income is measured over a sufficiently short time interval, since expected trading income typically accumulates gradually over time.

Specifically, Jorion (2002) shows that if trading income for a defined period length, *TI*, has a fixed and symmetrical conditional distribution around zero each period and trading VaR is measured without error over the same period length, then the expected absolute value of unexpected trading income is proportional to trading VaR:

$$E_t(|TI_{t+1}|) = \frac{k \times \mathrm{VaR}_t}{\alpha}. \tag{1}$$

Jorion (2002) shows that the constant k depends on the specific distribution for trading income, being approximately 0.8 for the normal distribution and 0.74 for the fatter-tailed t distribution. The constant α is the standard deviate for the distribution of trading income given the selected confidence level used in the calculation of trading VaR; for example, $\alpha = 2.33$ for the normal distribution and a confidence level of 99%.

As in Jorion (2002), we transform banks' reported trading VaR disclosures in two ways to make them comparable both to quarterly trading income and across banks. First, banks' reported trading VaR estimates reflect a one-day period, and so we rescale these estimates to match the duration of quarterly trading income; this rescaling does not affect our empirical analysis in any way except to yield more interpretable magnitudes of the coefficients on trading VaRs in our regression equation, consistent with equation (1). Assuming serially independent and identically distributed returns to the portfolio, trading VaR grows in proportion to the square root of time:

$$\mathrm{VaR}_t(\text{quarter}) = \mathrm{VaR}_t(\text{day})\sqrt{63}. \tag{2}$$

We assume that there are 63 trading days in each quarter, the average over our sample period. Second, since different banks use different confidence levels in calculating trading VaR, we use $s_t = \mathrm{VaR}_t(\text{quarter})/\alpha$, the forecasted variability of quarterly trading income implied by banks' reported trading VaRs in our regression equations.

Like Jorion (2002), we use quarterly data in the empirical analysis. Since this is a sufficiently long period for expected trading income to be a substantial amount, we remove an estimate of the mean of trading income in order to calculate the variability of trading income, which is measured as the absolute value of unexpected trading income. As in Jorion, we estimate expected quarterly trading income as its average over the previous four quarters:

$$E_t[TI_{t+1}] = \frac{1}{4}\sum_{i=0}^{3} TI_{t-i}. \tag{3}$$

The mean of unexpected trading income using this expectation is insignificantly different from zero in our sample.

Our regression equation relating the absolute value of unexpected trading income to our standardized measure of quarterly trading VaR, s_t, is based on equations (1) and (3) and related discussion above. As in some analyzes in Jorion (2002), we control in this and subsequent equations for the notional amounts of outstanding derivatives at the end of quarter t, NOT_t, an alternative measure of the market risk of the trading portfolio. As in all analyses in our paper, we control for the current quarter's value of the dependent variable, both to focus on how trading VaRs predict changes in market risk and to yield meaningful test statistics, because our small sample of banks necessitates pooling observations across time and our market risk measures variables are all serially correlated.

$$|TI_{t+1} - E_t[TI_{t+1}]| = a + bs_t + c\mathrm{NOT}_t + d|TI_t - E_{t-1}[TI_t]| + \varepsilon_{t+1}. \quad (4)$$

In estimating this equation, as in Jorion all variables are deflated by trading assets at the end of quarter t.

Based on prior research by Jorion (2002) and hypothesis H1, we expect the coefficient b in equation (4) to be significantly positive. Moreover, if trading income is normally distributed, s_t is measured without error, and the inclusion of the control variables does not affect the coefficient on s_t, then b should equal to 0.8, consistent with equation (1). Equation (4) is also used to test hypotheses H2 and H3, for which we expect the coefficient b to vary across bank subgroups.

3.2. Regression Equation for the Variability of Daily Returns

We assume that the market value of common stock equity for a bank in quarter t, MV_t, equals the sum of the market values of its net trading assets, TAMV_t, and net non-trading assets, NTAMV_t, in that quarter:

$$\mathrm{MV}_t = \mathrm{TAMV}_t + \mathrm{NTAMV}_t. \quad (5)$$

Equation (5) presumes no complementarity between trading and non-trading exposures, a reasonable assumption given these exposures are primarily financial in nature. Equation (5) implies that the variance of MV_t equals

$$\sigma^2_{\mathrm{MV}_t} = \sigma^2_{\mathrm{TAMV}_t} + \sigma^2_{\mathrm{NTAMV}_t} + 2\sigma_{\mathrm{TAMV}_t,\mathrm{NTAMV}_t}, \quad (6)$$

where variances are covariances are denoted in the usual fashion.

We derive our regression equation relating the variability of daily returns to trading VaRs from equation (6). As we focus on the prediction of risk, we replace $\sigma^2_{\mathrm{MV}t}$ by the variance of daily returns in quarter $t+1$, denoted σ^2_{Rt+1}. We replace $\sigma^2_{\mathrm{TAMV}t}$ by our standardized measure of quarterly trading VaR, s_t. We control for $\sigma^2_{\mathrm{NTAMV}t}$ by including 0–1 year repricing gap at the end of quarter t, denoted GAP_t.[9] This is a natural control for $\sigma^2_{\mathrm{NTAMV}t}$ because interest rate risk is the dominant market risk for most banks, and Hodder (2002) finds repricing gap to be far more related to banks' interest rate sensitivity than are FRR No. 48 interest rate sensitivity disclosures. We control for any systematic effects on the variance of returns by adding the variance of daily market returns during quarter $t+1$, denoted $\sigma^2_{\mathrm{Rm},t+1}$. As in all equations, we control for NOT_t and the lagged value of the dependent variable.

As discussed in Section 2.2.3, we have no effective control for $\sigma_{\mathrm{TAMV}t,\mathrm{NTAMV}t}$. We attempted to estimate this covariance for each bank using the reported fair value of trading exposures and the implied fair value non-trading exposures, measured as the market value of owners' equity minus the reported fair value of net trading assets, deflating the fair values of both exposures by the beginning book value of owners' equity. We did this both for the overall sample period (a maximum of 21 quarters per bank) and for the early and late subperiods. The estimated covariances are clearly unreliable, varying almost from plus one to minus one across banks, and the estimated covariances in the two subperiods are negatively correlated, implying that historical estimated covariances have no meaningfully interpretable predictive power for future estimated covariances. This unreliability likely is attributable to the limited time-series data, the volatility of the fair values of trading and non-trading exposures, and the covariance of the fair values of trading and non-trading exposures changing over time. Future researchers could attempt to control for this covariance by obtaining access to non-public regulatory data on the fair value of banks' daily trading positions, as in Berkowitz and O'Brien (2002).

To provide some indication of the seriousness of this omission of control for $\sigma_{\mathrm{TAMV}t,\mathrm{NTAMV}t}$, we conducted the following analysis similar to Venkatachalam's (1996) analysis of the extent that banks use derivatives to hedge their non-derivatives exposures. Using the quarterly data available on the regulatory Y-9C database from the first quarter of 1996 through the first quarter of 2002, we estimated a pooled regression of the quarterly change in the fair value of net trading assets on the implied quarterly change in the fair value of net non-trading assets, deflating both variables by the beginning book value of owners' equity. The R^2s in these regressions are 2% or less for the overall sample and for all subgroups, and the slope coefficients range from -0.05 to 0.01 across the samples, suggesting minimal cross-hedging of trading and non-trading exposures on average by the sample banks.

Thus, the equation explaining the variability of next quarter's returns is

$$\sigma^2_{R_{t+1}} = a + bs_t + c\mathrm{NOT}_t + d\mathrm{GAP}_t + f\sigma^2_{R_{m,t+1}} + g\sigma^2_{R_t} + \varepsilon_{t+1}. \tag{7}$$

Consistent with Ahmed et al. (1999) and Hodder (2002), we deflate the explanatory variables s_t, NOT_t, and GAP_t in this equation by the book value of owners' equity at the end of quarter t. The other variables in the equation are scaled by construction. Based on hypothesis H4, we expect the coefficient b to be significantly positive.

3.3. *Regression Equations for Beta and Realized Returns*

While prior research by Chen et al. (1986) and others suggests that banks' trading VaRs should be associated with priced risk, we do not have structural models of these relations. Accordingly, we estimate linear models such as those typically assumed in equilibrium pricing models. For example, under the CAPM (APT), expected returns are linearly related to β (a broad set of risk factors). The models we estimate are similar to equation (7) explaining the variability of daily returns, with adjustments being made to control appropriately for related market effects and the current values of the dependent variables.

Specifically, we regress next quarters' beta on s_t, NOT_t, GAP_t, and the current quarter's beta:

$$\beta_{t+1} = a + bs_t + c\text{NOT}_t + d\text{GAP}_t + f\beta_t + \varepsilon_{t+1}. \tag{8}$$

As in equation (7), we deflate the explanatory variables s_t, NOT_t, and GAP_t in equation (8) by the book value of owners' equity at the end of quarter t. The other variables in the equations are scaled by construction. Based on hypothesis H5, we expect the coefficient b in this equation to be significantly positive.

We regress next quarter's return on s_t, NOT_t, and beta in quarter t times next quarter's value-weighted market returns, $R_{m,t+1}$:

$$R_{t+1} = a + bs_t + c\text{NOT}_t + d(\beta_t \times R_{m,t+1}) + \varepsilon_{t+1}. \tag{9}$$

We interact beta and $R_{m,t+1}$ in order to capture both the predictive power of beta for expected returns and the association of bank returns with contemporaneous market returns in a parsimonious fashion that is consistent with the CAPM. We do not include the lagged dependent variable in equation (9) because it is insignificant.

Notice that, unlike in other equations, we do not include GAP_t as an explanatory variable in equation (9). As discussed in Section 2.2.3, the dependent variable in equation (9) includes unexpected returns, which reflect the directional effects of the realization of information on firm value during quarter $t+1$. This renders GAP_t problematic as an explanatory variable, because it is a directional predictor of unexpected returns conditional on interest rate movements. Banks with longer duration assets than liabilities gain when interest rates decrease, and vice-versa. Interest rates declined over the vast majority of the sample period and all the observations in our sample have positive gap, implying that GAP_t is positively associated with unexpected returns in our sample period. When we include GAP_t in equation (9), the coefficient on trading VaR becomes insignificant, reflecting repricing gap's advantage over trading VaR as a directional predictor of unexpected returns conditional on interest rate movements.

We deflate the explanatory variables s_t and NOT_t in equation (9) by the market value of owners' equity at the end of quarter t. This deflator differs from the book value of owners' equity used as a deflator in equations (7) and (8) and prior research; we chose this deflator for equation (9) because it conforms to the specification of the dependent variable. The other variables in this equation are scaled by construction. Based on hypothesis H6, we expect the coefficient b in this equation to be significantly positive.

3.4. Subgroups for Bank Technical Sophistication and Time

To evaluate the effects of bank technical sophistication, we divide the sample into two subgroups. The technically sophisticated subgroup includes the seven large, internationally active banks whose disclosure practices are surveyed in "Public Disclosures by Banks: Results of the 2000 Disclosure Survey" by the Basel

Committee on Banking Supervision (2002). The current names of these banks are: Bank of America, Bank of New York, Bank One, Citigroup, FleetBoston, J. P. Morgan Chase, and Wachovia. This subgroup overlaps considerably with the eight banks in Jorion's (2002) sample, with the differences being: two pairs of his banks merged (Bank of America with Nationsbank and Chase Manhattan with J. P. Morgan), Bankers Trust is dropped because it was acquired by a foreign bank (Deutsche Bank), and FleetBoston and Wachovia are added.

The other subgroup includes the remaining ten banks in our sample, whose current names are: Allfirst, BOK, Keycorp, Mellon, National City, Northern Trust, Pacific Century, PNC, Popular, and State Street. None of the banks in this subgroup is in Jorion's sample. Of course, we do not mean to suggest that these banks are technically unsophisticated, as they surely are more technically sophisticated than a representative bank, but only that on average they likely have less experience in modeling and estimating trading VaR than the banks in the first group.

We emphasize that our bank subgroups almost perfectly partition the banks based on the following measures of size: total assets, trading assets, and book value of equity. (The only exception is that Bank of New York, clearly a technically sophisticated bank, has slightly lower total assets and book value of equity than the largest banks in the other subgroup.) Hence, it is possible that our subgroups capture some size-related effect unrelated to technical sophistication, such as banks' ability to diversify trading assets. Given our small sample, it is not possible to distinguish the effects of technical sophistication from other effects of size.

To evaluate the effects of banks' learning over time about the modeling and calculation of trading VaR, we divided the sample into two subgroups of similar length: 1997–1999:1Q and 1999:2Q–2002:1Q. Notice that the first period includes the hedge fund crisis that began in August 1998 and was substantially resolved by the end of 1998; as discussed below, our results do not change if we omit this period. It is likely that the hedge fund crisis affected banks' understanding of VaR.

To test hypotheses H2 and H3 regarding the effect of banks' technical sophistication and time on the predictive power of trading VaR disclosures, we conduct t tests, denoted $t(b)$, on the difference of the coefficient b on s_t in equation (4) across each pair of groups.

4. Sample, Data, and Descriptive Statistics

4.1. Sample

We attempted to include any US registered commercial bank holding company (bank) in the sample if it disclosed trading VaR data under FRR No. 48 in its annual Form 10-K or quarterly Form 10-Q filings.[10] We collected these filings for the largest 200 banks based on total assets, presuming that smaller banks would be unlikely to have trading operations and thus to disclose trading VaR. The 17 banks in our sample are all among the nation's 60 largest banks suggesting this presumption is correct. Larger banks likely have more individually complex, collectively diverse, and trading-oriented exposures, and thus greater incentives to establish VaR-based risk management and disclosure systems. They also likely have greater resources and technical sophistication with which to develop such systems. The other banks whose market risk disclosures we assessed disclose their market risk under FRR No. 48 using some combination of the tabular format and sensitivity approaches.

Banks merged with or acquired each other (or, in the case of Citibank, with an insurance company) with considerable frequency over the sample period. We include only the dominant of the combining banks for the period before each business combination in the sample. The dominant bank invariably is apparent, though the (main portion of) the name that survives is sometimes that of the less dominant bank; e.g., for J. P. Morgan Chase, we include Chase Manhattan in the sample prior to its merger with J. P. Morgan. Though Travelers was dominant in its merger with Citibank, we include Citibank prior to the merger to avoid losing a bank. Appendix B summarizes the significant changes in the dominant banks' corporate names during the sample period.

Different banks began including trading VaR disclosures in their public financial reports at different times. We collected all the disclosures from the quarter in which the bank began to disclose trading VaR through the first quarter in 2002, details of which are reported in Tables 2 and 3. These tables indicate that while most banks calculate and disclose trading VaR fairly consistently over time, it is difficult to find two banks that calculate and disclose trading VaR in the exactly the same way. We standardized trading VaR for different confidence levels used by banks, as discussed in Section 3.1. It is not possible to standardize VaR when banks disclose using different frequency or format, however, as discussed in Section 4.2.

Table 2 reports the methods and confidence levels used in each bank's trading VaR disclosures to the extent that they were disclosed. Many banks either did not disclose the methods they used or provided only vague descriptions, which we briefly paraphrase in the table. This table also reports the first year and quarter that trading VaRs were reported in each bank's Form 10-K and 10-Q filings, respectively, including the years prior to the release of FRR No. 48 in 1997. FRR No. 48's requirements became effective for banks for fiscal years ending after June 15, 1997, so there is a big jump in the number of banks reporting trading VaRs in 1997. Table 3 reports which of average, ending, minimum, and maximum trading VaR statistics each bank reported in each year.

4.2. Choosing Disclosure Frequencies and Formats

Banks do not report their trading VaRs with the same frequency (i.e., annual versus quarterly) or formats (e.g., end-of-period versus average). It is not possible to standardize trading VaRs along these dimensions. Instead, we use the following sequence to determine quarterly trading VaR for each bank, selecting the first

Table 2. Summary of trading VaR estimation methods, confidence levels, and first disclosure dates by bank.

Bank	Description of Method	Confidence Level (%)	First Trading VaR Disclosure	
			10-K	10-Q
Technically Sophisticated Group:				
Bank of America	Sophisticated modeling	99	1998	1998:3Q
Bank of New York	Monte Carlo simulation	99	1998	1998:1Q
Bank One	Various statistical methods	99	1996	1998:Q4
Citigroup	Based on historical experience	97.5 before 1997, 99 after	1997	1998:Q1
Fleet Boston	Industry-standard risk measurement	99	1999	2000:Q1
J. P. Morgan Chase	Historical simulation	97.5 before 1997, 99 after	1994	1995:Q1
Wachovia	Variance/covariance	97.5	1997	1998:Q1
Other Group:				
Allfirst	Variance/covariance	99	1997	NA
BOK	Variance/covariance	99	1998	1998:Q1
Keycorp	Statistical methods	95	1997	1998:Q1
Mellon	Corporation's methodology	95	1996	1996:Q1
National City	Historical simulation	97.5	1997	NA
Northern Trust	Variance/covariance	95	1997	NA
Pacific Century	Variance/covariance	95	1997	1998:Q1
PNC	NA	NA	1997	1998:Q1
Popular	Assumptions and estimates	95	1999	NA
State Street	Simulation	99	1997	1998:Q1

disclosure available in the sequence for each bank, since such disclosures are closer to the conceptually correct trading VaR in equation (1).

1. End-of-quarter trading VaR.

2. Average trading VaR for the quarter.

3. Average trading VaR for the year.

4. End-of year trading VaR.

4.3. Other Variables

We collected trading income, trading assets, the notional amounts of derivatives, and 0–1 year repricing gap from regulatory Y-9C reports for bank holding companies available on the Federal Reserve Bank of Chicago's website.[11] This database covers

Table 3. Summary of trading VaR statistics reported each year by bank.

Bank	Trading VaR Statistics Reported
Technically Sophisticated Group:	
Bank of America	Average, min, max from 1998 on
Bank of New York	Average, end, min, max from 1997 on
Bank One	End in 1996; average, end, min, max from 1997 on
Citigroup	End in 1997; average, end, min, max from 1998 on
Fleet Boston	Average in 1998; average, end, min, max from 1999 on
J. P. Morgan Chase	Average in 1994–1996; average, end, min, max from 1997 on
Wachovia	End in 1997; average, end, min, max from 1998 on
Other Group:	
Allfirst	End from 1997 on
BOK	End, max from 1998 on
Keycorp	Average, end from 1997 on
Mellon	End in 1996–1997; average, end from 1998 on
National City	Max in 1997; average, min, max from 1998 on
Northern Trust	End in 1997; average, end, min, max from 1998 on
Pacific Century	End from 1997 on
PNC	End from 1997–1999; average, end from 2000 on
Popular	End from 1999 on
State Street	Average, min, max from 1997 on

all bank holding companies whether publicly traded or not. One of the banks in the sample, Allfirst, is a wholly owned subsidiary of Allied Irish Banks, and so Allfirst is not included in any analysis that requires security price data. As in Ahmed et al. (1999), reflecting the data available on the Y-9C reports, our measure of repricing gap treats demand deposits and money market accounts with indefinite term as repricing beyond one year.

Trading income includes realized and unrealized gains and losses from interest rate, foreign exchange, equity price, commodity, and other exposures, but excludes fee and interest income; this exclusion makes it more likely that the mean of trading income is close to zero, as assumed in equation (1). The notional amount of derivatives is the sum of the notional amounts of interest rate, foreign exchange, equity, and commodity derivatives.

We collected total assets, book value of equity, and market value of equity from Bank Compustat. We collected firm and value-weighted market returns from CRSP. Beta is estimated each quarter using that quarter's daily returns and the daily value-weighted market index return.

Panel A of Table 4 reports descriptive statistics on the variables in each of the equations estimated subsequently for the overall sample. The variables all appear to be well dispersed. Panel B of Table 4 reports descriptive statistics on the level and change in the standardized measure of quarterly trading VaR deflated by trading assets for the overall sample and the subgroups based on bank technical sophistication and size. Both the level and change of trading VaR have fairly similar distributions across the samples. Trading VaR appears fairly stable for most

Table 4. Means and quartiles of all equation variables for the overall sample (Panel A) and of the level and change in standardized measure of quarterly trading VaR for the overall sample and the subgroups (Panel B).

Panel A: All Equation Variables for the Overall Sample

Variable	Mean	Min.	25%	Med.	75%	Max.
Equation (4): 261 Observations						
$\lvert TI_{t+1} - E_t[TI_{t+1}]\rvert / TA_t$	0.0651	0.0002	0.0065	0.0172	0.0610	0.7695
s_t/TA_t	0.0221	0.0005	0.0021	0.0052	0.0144	0.3617
NOT_t/TA_t	0.0820	0.0000	0.3534	0.0668	0.0912	0.7186
Equations (7) and (8): 215 Observations						
$\sigma^2{}_{Rt+1}$	0.0230	0.0102	0.0176	0.0220	0.0272	0.0463
β_{t+1}	1.0558	0.0792	0.7669	1.0694	1.3336	2.106
s_t/BV_t	0.0023	0.0002	0.0007	0.0022	0.0035	0.0100
$\mathrm{NOT}_t/\mathrm{BV}_t$	0.2678	0.0000	0.0026	0.0082	0.0619	32.362
$\mathrm{GAP}_t/\mathrm{BV}_t$	3.494	0.0041	1.937	3.466	4.473	9.322
Equation (9): 201 Observations						
R_{t+1}	0.0244	−0.2527	−0.0652	0.0198	0.1002	0.4300
$s_t/\mathrm{MV}t$	0.0019	0.0000	0.0002	0.0007	0.0019	0.0108
$\mathrm{NOT}_t/\mathrm{MV}t$	0.0919	0.0000	0.0010	0.0035	0.0166	7.119
$\beta_{t^*}\ R_{m,t+1}$	0.0236	−0.2527	−0.0640	0.0198	0.0978	0.3682

Panel B: Level and Change in Standardized Measure of Quarterly Trading VaR Deflated by Trading Assets for Overall Sample and Subgroups

Variable and Sample	Mean	Min	25%	Med.	75%	Max	#obs
s_t/TA_t							
Overall	0.0221	0.0005	0.0021	0.0052	0.0144	0.3617	261
Technically sophisticated banks	0.0183	0.0005	0.0016	0.0028	0.0090	0.3299	126
Other banks	0.0250	0.0009	0.0038	0.0079	0.0187	0.3617	135
1997–1999:1Q	0.0294	0.0009	0.0027	0.0066	0.0138	0.3617	98
1999:2Q–2002:1Q	0.0174	0.0005	0.0020	0.0040	0.0148	0.3043	163
$\Delta s_t/TA_{t-1}$							
Overall	−0.0011	−0.2313	−0.0003	0.0000	0.0004	0.0938	261
Technically sophisticated banks	0.0010	−0.0475	−0.0004	0.0000	0.0004	0.0781	126
Other banks	−0.0032	−0.2313	0.0000	0.0000	0.0007	0.0937	135
1997–1999:1Q	−0.0003	−0.1576	−0.0002	0.0000	0.0001	0.0781	98
1999:2Q–2002:1Q	−0.0016	−0.2313	−0.0004	0.0000	0.0004	0.0938	163

Variable definitions: TI = trading income; TA = trading assets; s = standardized measure of quarterly trading VaR; NOT = notional amount of derivatives; σ_R^2 = variance of daily returns during quarter; β = beta; BV = book value of owners' equity; GAP = 0–1 year repricing gap. R = quarterly return; MV = market value of owners' equity; σ_{Rm}^2 = variance of daily value-weighted market returns during quarter.

Bank groups are defined in Appendix B.

Quarter t values of quarter $t+1$ dependent variables are omitted from the table, as they have approximately the same distributions as the quarter $t+1$ variables.

banks through time, but there are a few substantial changes (both increases and decreases).

5. Empirical Results

In this section, we report the OLS estimation of all regression equations both for the overall sample and for the bank and time subgroups, pooling data across the applicable time periods. We evaluate all regression equations using White's (1980) test and reject homoscedasticity, and so White's adjusted t-statistics are reported throughout. Observations with any variable in the extreme 1% of either tail of the pooled sample distribution of that variable are deleted. Unless stated otherwise, we say that a coefficient or difference of coefficients is significant if it exceeds the 95% confidence level in a one-tailed test.

5.1. Variability of Unexpected Trading Income

Table 5 reports the pooled OLS estimation of equation (4) for the overall sample and the bank and time subgroups. This equation regresses the absolute value of unexpected trading income in quarter $t + 1$ on the standardized measure of quarterly

Table 5. Pooled OLS estimation of regression of absolute value of next quarter's unexpected trading income on standardized trading VaR measure, the notional amount of derivatives, and absolute value of this quarter's unexpected trading income, for the overall sample and bank and time subgroups.

$$|TI_{t+1} - E_t[TI_{t+1}]| = a + bs_t + c\mathrm{NOT}_t + d|TI_t - E_{t-1}[TI_t]| + \varepsilon_{t+1}. \quad (4)$$

Sample	a	b	c	d	R^2	#obs	$t(b)$
Overall	0.016 (2.4)*	0.382 (2.3)*	0.068 (0.8)	0.668 (11.5)*	0.53	261	
Technically sophisticated banks	0.002 (0.2)	0.759 (3.9)*	0.042 (0.8)	0.257 (0.8)	0.56	126	
							3.2*
Other banks	0.041 (4.1)*	0.027 (0.2)	0.116 (1.2)	0.595 (9.4)*	0.47	135	
1997–1999:1Q	0.004 (0.4)	0.093 (0.7)	0.197 (1.2)	0.634 (5.4)*	0.68	98	
							1.7*
1999:2Q–2002:1Q	0.024 (2.5)*	0.839 (2.0)*	0.002 (0.0)	0.627 (7.6)*	0.46	163	

Variables are defined in Table 4. All variables are deflated by trading assets in quarter t.
Bank groups are defined in Appendix B.
t-statistics are in parentheses under coefficients. $t(b)$ in the right column denotes t-tests on the difference between the coefficient b on the standardized trading VaR measure across bank and time subgroups. Asterisks indicate t-statistics significant at the 5% level in a one-tailed test.

trading VaR in quarter t, s_t, the notional amount of derivatives in quarter t, NOT_t, and the value of the dependent variable in quarter t. For the overall sample, we find that the coefficient b on s_t is positive and significant ($t = 2.3$). Thus, consistent with Jorion's (2002) prior results and hypothesis H1, trading VaR has predictive power for the variability of future trading income incremental to that of the control variables. The coefficient b is significantly less than the value of 0.8 that is expected when the conditional distribution of unexpected trading income is normally distributed around a mean of zero ($t = -2.5$), however, suggesting either that this assumption does not hold or that the measure of trading VaR is noisy. The coefficient d on the lagged value of the dependent variable also is significant but the coefficient c on NOT_t is insignificant.

Consistent with hypothesis H2, we find that the coefficient b on s_t is significantly more positive for the technically sophisticated bank subgroup ($t(b) = 3.2$), suggesting that more technically sophisticated banks do a better job at estimating trading VaR. Moreover, for this subgroup we find that this coefficient is not significantly different from 0.8, suggesting that more technically sophisticated banks have worked out the significant modeling complexities and estimation difficulties involved in calculating trading VaR.

Consistent with hypothesis H3, we find that the coefficient b on s_t is significantly more positive for the last twelve quarters than for the prior portion of our sample period ($t(b) = 1.7$). Moreover, for the later period we find that this coefficient is not significantly different from 0.8, suggesting that the sample banks have worked out the issues involved in calculating trading VaR over time.

Table 6. Pooled OLS estimation of regression of variance of next quarter's daily share returns on standardized trading VaR measure, the notional amount of derivatives, 0–1 year repricing gap, variance of next quarter's daily value-weighted market index return, and variance of current quarter's daily share returns, for the overall sample.

$$\sigma^2_{R_{t+1}} = a + bs_t + c\text{NOT}_t + d\text{GAP}_t + f\sigma^2_{R_{m,t+1}} + g\sigma^2_{R_t} + \varepsilon_{t+1}. \tag{7}$$

Sample	a	b	c	d	f	g	R^2	#obs
Overall	0.008 (5.4)*	0.393 (2.2)*	0.000 (2.1)*	− 0.000 (−0.3)	1.186 (11.8)*	− 0.012 (−0.6)	0.37	215
Technically sophisticated banks	0.011 (3.5)*	0.739 (2.4)*	0.000 (2.6)*	− 0.000 (−0.8)	1.122 (7.4)*	− 0.081 (−1.2)	0.35	104
Other banks	0.008 (4.2)*	0.574 (1.3)	0.002 (1.0)	− 0.000 (−0.0)	1.184 (8.5)*	− 0.004 (−0.2)	0.39	111
1997–1999:1Q	0.005 (2.2)*	0.217 (1.2)	0.000 (3.1)*	− 0.000 (−0.1)	1.312 (10.2)*	0.070 (1.2)	0.49	103
1999:2Q–2002:1Q	0.010 (3.8)*	0.829 (2.4)*	0.002 (1.0)	− 0.000 (−0.3)	1.019 (6.7)*	− 0.030 (−1.0)	0.25	112

Variables, bank groups, and t-statistics are as in Table 5, except that s_t, NOT_t, and GAP_t are deflated by book value of equity in quarter t.

5.2. *Variability of Daily Returns*

Table 6 reports the pooled OLS estimation of equation (7) for the overall sample and the two pairs of subgroups. This equation regresses the variance of daily returns in quarter $t+1$ on s_t, NOT_t, 0–1 year repricing gap in quarter t, GAP_t, the variance of daily returns on the value-weighted market index in quarter $t+1$, $\sigma^2_{Rm,t+1}$, and the value of the dependent variable in quarter t. For the overall sample, we find that the coefficient b on s_t is positive and significant ($t = 2.2$), as are the coefficients c on NOT_t and f on $\sigma^2_{Rm,t+1}$. The coefficients on the other control variables are insignificant. Thus, consistent with hypothesis H4, banks' trading VaRs have predictive power for the variability of future daily returns incremental to that of the control variables. These results imply that banks' trading VaRs are useful for assessing bank-wide total risk despite reflecting only a portion of banks' exposures. This likely reflects banks' incomplete hedging of their trading and non-trading exposures and the substantial risk of their trading portfolios.

5.3. *Beta*

Table 7 reports the results of the pooled OLS estimation of equation (8) for the overall sample and the two pairs of subgroups. This equation regresses beta in quarter $t+1$ on s_t, NOT_t, GAP_t, and beta in quarter t. For the overall sample, we find that the coefficient b on s_t is positive and significant ($t = 2.7$), as are the coefficients c on NOT_t and f on the current quarter's beta. The coefficient d on GAP_t is insignificant. Thus, consistent with hypothesis H5, trading VaR has predictive

Table 7. Pooled OLS estimation of regression of next quarter's beta on standardized trading VaR measure, the notional amount of derivatives, 0–1 year repricing gap, and current quarter's beta, for the overall sample.

$$\beta_{t+1} = a + bs_t + c\mathrm{NOT}_t + d\mathrm{GAP}_t + f\beta_t + \varepsilon_{t+1}. \tag{8}$$

Sample	a	b	c	d	f	R^2	#obs
Overall	0.808 (9.4)*	39.966 (2.7)*	0.016 (5.1)*	0.007 (0.4)	0.133 (2.7)*	0.06	215
Technically sophisticated banks	0.838 (6.2)*	70.624 (3.4)*	0.015 (5.2)*	− 0.060 (− 2.1)	0.171 (2.4)*	0.19	104
Other banks	0.846 (7.8)*	− 15.597 (− 0.6)	− 0.026 (− 0.3)	0.045 (2.4)*	0.053 (0.8)	0.05	111
1997–1999:1Q	1.073 (9.0)*	13.767 (0.8)	0.012 (5.4)*	− 0.025 (− 1.4)	0.162 (1.9)*	0.06	103
1999:2Q–2002:1Q	0.633 (5.6)*	65.089 (3.2)*	0.030 (2.9)*	0.013 (0.6)	0.072 (1.3)	0.13	112

Variables, bank groups, and t-statistics are as in Table 6.

Table 8. Pooled OLS estimation of regression of next quarter's return on standardized trading VaR measure, the notional amount of derivatives, and next quarter's value-weighted market return times the current quarter's beta, for the overall sample.

$$R_{t+1} = a + bs_t + c\mathrm{NOT}_t + d(\beta_t \times R_{m,t+1}) + \varepsilon_{t+1}. \quad (9)$$

Sample	a	b	c	d	R^2	#obs
Overall	0.004 (1.0)	2.268 (1.9)*	−0.002 (−1.4)	0.814 (34.1)*	0.90	201
Technically sophisticated banks	−0.001 (−0.1)	2.908 (2.0)*	−0.002 (−1.0)	0.801 (22.3)*	0.88	93
Other banks	0.001 (0.2)	11.927 (1.0)	0.022 (0.4)	0.811 (22.6)*	0.90	108
1997–1999:1Q	0.001 (0.2)	1.373 (1.1)	−0.000 (−0.3)	0.748 (33.8)*	0.94	98
1999:2Q–2002:1Q	0.001 (0.2)	3.686 (2.1)*	−0.026 (−2.0)	0.915 (18.6)*	0.86	103

Variables, bank groups, and t-statistics are as in Table 5, except that s_t and NOT_t are deflated by market value of equity in quarter t.

power for beta incremental to that of the control variables. This implies that trading VaR, a measure of total market risk, has a priced component.

5.4. *Realized Returns*

Table 8 reports the results of the pooled OLS estimation of equation (9) for the overall sample and the two pairs of subgroups. This equation regresses return in quarter $t+1$ on s_t, NOT_t, and the value-weighted market return in quarter $t+1$ times beta in quarter t. For the overall sample, we find that the coefficient b on s_t is positive and significant ($t = 1.9$), as is the coefficient d on the value-weighted market return in quarter $t+1$ times beta in quarter t. The coefficient c on NOT_t is insignificant. Thus consistent with hypothesis H6, trading VaR has predictive power for next quarter's return incremental to that of the control variables. This again implies that trading VaR has a priced component.

5.5. *Specification Tests*

With the exception of GAP_t in equation (9) as discussed above, our results are robust to the inclusion and exclusion of control variables. We estimated all of the regression equations omitting the control variables individually and in groups. This does not qualitatively affect our results; our significance levels generally rise as control variables (especially the current value of the dependent variable in the regression equations where it is significant) are dropped. Our results for all equations are not qualitatively affected by the inclusion of the variability of net income and the ratio of trading assets to total assets as additional control variables, or by the use of alternative deflators. Our results for equation (9) are not affected by the inclusion of the change in various interest rates (the federal funds rate, US Treasury rates, and the prime rate), which are invariably insignificant.

We also performed contemporaneous association tests by estimating all the regression equations replacing next quarter's value of the dependent variable with the current quarter's value, and eliminating the current quarter's value as an explanatory variable. Not surprisingly, the results in these tests are stronger than in the prediction tests that we report.

We also conducted all analyses omitting the third and fourth quarters of 1998, during which the hedge fund crisis occurred. As discussed in Section 2, Berkowitz and O'Brien (2002) found that banks' trading VaR disclosures under-predicted losses during this period. Our results are not substantially affected by omitting this data.

6. Conclusion

Prior research examining FRR No. 48 market risk disclosures finds that these disclosures provide some information about firm risk. In particular, Jorion (2002) finds that quarterly trading VaR disclosures by banks predict the variability of the next quarter's trading income. However, prior research also finds that market risk disclosures are also subject to significant comparability and measurement issues. The latter is due in part to the fact that FRR No. 48 allows so many disclosure options, but also likely reflects the newness and ambitiousness of its disclosure requirements, especially those regarding VaR. FRR No. 48 disclosures have been required only since 1997, and VaR disclosures under this rule reflect a new, complex, and hard to implement concept. It is to be expected that the quality of VaR disclosures should improve over time as banks learn, and that more technically sophisticated banks should learn quicker than other banks.

In this paper, we provide evidence that this has been the case. For a sample of 17 large commercial banks from 1997 through the first quarter of 2002, we predict and find that banks' trading VaR disclosures predict their total and priced risk next quarter, both for the trading portfolio and the bank as a whole. We find that banks' trading VaR disclosures predict the variability of unexpected trading income better for technically sophisticated banks than for other banks, and that VaRs predict the variability of unexpected trading income better over time. These results hold out the promise that banks' market risk disclosures will continue to improve over time and that learning will diffuse across banks.

These results also suggest that research examining the usefulness of newly mandated complex and/or judgmental disclosures may not capture (the full extent of) that usefulness. For this reason, it may be worthwhile for researchers periodically to revisit studies examining such disclosures, especially when those studies use only the first few years of disclosures provided under a new requirement, as is commonly the case. Relatedly, it may be preferable for the FASB and SEC to wait for a period before deciding that a given disclosure is not sufficiently useful to continue to require it, as the FASB did in 1986 when FAS 89 eliminated FAS 33's required disclosures about the effects of changing prices that had been adopted in 1979.

This study has three limitations that represent opportunities for future research. First, we examine the relatively small number of banks that disclose trading VaR data under FRR No. 48. In our view, the use of such a restricted sample is appropriate because of the many disclosure options allowed under FRR No. 48; in particular, it yields a sample that is both sufficiently homogeneous and of sufficient size to conduct empirical tests with some power. However, the use of this sample also reduces the generalizability of our results, for example, to market risk disclosures under other approaches or by non-financial firms. This limitation could be overcome by accounting researchers conducting a series of similar studies using other samples and reconciling results across studies.

Second, we employ a measure of the technical sophistication of banks that is highly correlated with bank size, and so we cannot rule out the possibility that our measure captures some size-related effect unrelated to technical sophistication that makes it easier to estimate trading VaRs, such as banks' ability to diversify trading assets. A preferable measure of technical sophistication might be a measure of the historical accuracy of each bank's trading VaR in predicting the variability of its trading revenue. In our view, the quarterly public data on banks' trading VaRs and trading revenue is not sufficient to develop such a measure of accuracy. The limitation could be overcome by using non-public regulatory data on banks' daily trading positions as in Berkowitz and O'Brien (2002).

Third, we examine the relation between banks' trading VaR disclosures and bank-wide risk measures. In our view, this analysis is of interest because investors are most concerned with the assessment of firm-wide risk. However, the relationship between banks' trading VaR disclosures and bank-wide risk measures depends on the covariance of trading and non-trading exposures. While we would like to be able to control for the covariability of trading and non-trading exposures, we are unable to do so because of the limited frequency and time-series history of data on those exposures. This limitation could also be overcome by using non-public regulatory data on daily trading positions.

Due to the relative recency of market risk disclosures such as VaR, accounting research on these disclosures remains at an early stage, with many fundamental questions not addressed in this study being wide open to future research. Two important classes of questions that remain for further research on VaR disclosures are:

- What are the managerial implications of generating this data? Do managers respond to unusually high or low trading VaR assessments by making investment or other decisions that return firm risk to normal levels? Does the trading VaR data only capture the risk of existing positions held by the firm, or does it also indicate managers' tolerance for risk or their ability to manage risk? If so, what implications does a firm's trading VaR have for future investment or other decisions? Generalizing, trading VaR and other risk disclosures constitute fertile ground on which to link financial accounting research on disclosure and managerial accounting research on decision-making.

- To what extent do trading VaR and other risk disclosures reflect managers' discretionary choices based on their incentives? As discussed in Section 1, managers have many possible choices of disclosure approach under FRR No. 48. Do managers use this flexibility to make firms' risks more or less transparent or to bias investors or other outside parties' assessment of firm risk in some direction? Generalizing, it remains for future research to link market risk disclosures to the theoretical and empirical literature on discretionary disclosure.

Appendix A: Bank of America's 2000 Trading VaR Disclosure

Value at risk (VaR) is the key measure of market risk for the Corporation. VaR represents the maximum amount that the Corporation has placed at risk of loss, with a 99% degree of confidence, in the course of its risk taking activities. Its purpose is to describe the amount of capital required to absorb potential losses from adverse market movements.

In 2000, actual market risk-related revenue exceeded VaR measures one day out of 251 total trading days. Given the 99% confidence interval captured by VaR, this would be expected to occur approximately once every 100 trading days, or two to three times each year.

During 2000, the daily market risk-related revenue ranged from negative revenue of \$13 million to positive revenue of \$37 million. Over the same period, VaR ranged from \$25 million to \$53 million.

The following table summarizes the VaR in the Corporation's trading portfolios as of and for the years ended December 31, 2000 and 1999:

Trading activities market risk

	2000			1999		
(US Dollar Equivalents in Millions)	Average VaR[a]	High VaR[b]	Low VaR[b]	Average VaR[a]	High VaR[b]	Low VaR[b]
Interest rate	\$25.9	\$42.2	\$16.3	\$25.7	\$41.2	\$18.6
Foreign exchange	10.6	18.5	5.4	10.8	21.7	6.1
Commodities	2.1	5.2	0.5	1.6	5.8	0.6
Equities	26.7	41.5	5.5	13.1	26.8	2.6
Credit products[c]	10.1	17.4	3.2	n/a	n/a	n/a
Real estate/mortgage[c]	7.5	11.3	2.5	n/a	n/a	n/a
Total trading portfolio	41.5	53.0	25.1	31.7	42.6	23.5

Source: Bank of America 2000 Form 10-K filing.

[a] The average VAR for the total portfolio is less than the sum of the VARs of the individual portfolios due to risk offsets arising from the diversification of the portfolio.

[b] The high and low for the entire trading account may not equal the sum of the individual components as the highs or lows of the portfolio may have occurred on different trading days.

[c] Prior to 2000, the credit products and real estate/mortgage portfolios were reported as part of the interest rate portfolio.

Appendix B: Significant Changes in Dominant Banks' Names from 1997–2002:1Q

Current Names	Former Names
Technically Sophisticated Group:	
Bank of America	Nationsbank before 10/22/98, then BankAmerica until 5/11/99
Bank of New York	No change
Bank One	Banc One before 9/15/98
Citigroup	Citicorp before 7/22/98
FleetBoston	Fleet Financial before 9/30/99, then Fleet Boston until 3/28/00
J. P. Morgan Chase	Chase Manhattan until 11/21/00
Wachovia	First Union until 9/7/01
Other Group:	
Allfirst	First Maryland until 8/12/99
BOK	No change
Keycorp	No change
Mellon	No change
National City	No change
Northern Trust	No change
Pacific Century	Bancorp Hawaii until 2/3/97
PNC	No change
Popular	No change
State Street	State Street Boston until 3/11/97

Acknowledgments

We appreciate the comments of Bill Beaver, Maureen McNichols (the editor), two anonymous reviewers, Bin Ke (the discussant), and the participants in the 2003 *Review of Accounting Studies* conference. We appreciate Roby Lehavy providing us with expected return data. Chi-Chun Liu acknowledges the financial support of the National Science Council, Taiwan, Republic of China (NSC 90-2416-11-002-011).

Notes

1. See also reports by the US General Accounting Office in May 1994, the Bank for International Settlements (BIS), the International Organization of Securities Commissions (IOSCO) in July 1994, and the Derivatives Policy Group, the International Swaps and Derivatives Association (ISDA), Moody's, and Standard and Poor's subsequently.
2. Hull (1997) distinguishes three types of traders: hedgers, speculators, and arbitrageurs. Hedgers and arbitrageurs necessarily hold positions that largely offset, while speculators need not.
3. For example, Linsmeier and Pearson (2000) discuss the common practice of simplifying complex exposures into "standardized positions" in zero-coupon bonds and other similarly simple instruments.
4. See Linsmeier and Pearson (1997) for an extensive discussion of FRR No. 48.
5. With some heroic assumptions, it might be possible to amass a sample of observations with trading VaR data for interest rate risk, the main market risk for most banks. These assumptions would include assuming that banks that do not break down VaR by type of market risk are exposed only to interest rate risk, and that banks that break down VaR by sub-portfolios (e.g., Bank of America's "Credit

products" and "Real estate/mortgage" portfolios reported in Appendix A) rather than by types of market risk are exposed either only or not at all to interest rate risk on those sub-portfolios. Any such approach would ignore the covariance between interest rate risk and other types of market risk.

6. Maturity gap is the difference between the amounts of interest-earning assets and interest-paying liabilities maturing in an interval. In Schrand (1997) and most other research, the interval examined is the following year.
7. The only bank of which we are aware that has reported VaR for non-trading exposures is J. P. Morgan, which reported VaR for both trading and investing exposures in 1999 and perhaps other years. J.P. Morgan is not in our sample since it merged with Chase Manhattan and we deemed the latter the dominant bank.
8. Most importantly, banks' trading positions are measured at fair value on the balance sheet with changes in fair values recorded immediately in trading income as they occur. Thus, trading VaR reflects the variability of the fair values of banks' trading exposures even if the measure of loss underlying the calculation of trading VaR is chosen to be earnings, since earnings immediately include changes in the fair value of these exposures. In contrast, banks typically measure their other exposures at amortized cost on the balance sheet, with gains and losses on these exposures being recorded in income only when realized. Banks' market risk disclosures for these exposures usually reflect the variability of earnings measured on an amortized cost basis. For this reason, banks' market risk disclosures tend to understate the risk of their non-trading exposures relative to the more accurately portrayed risk of their trading portfolios.
9. Repricing gap (GAP) is the difference between the amounts of interest-earning assets and interest-paying liabilities repricing or maturing in an interval. It differs from maturity gap because an interest-bearing instrument may reprice without maturing. Our measure of GAP, which is described in Section 4.3, is positive for all the banks in our sample, and so GAP equals its absolute value, which is conceptually related to the variability of returns.
10. We did collect banks' VaR disclosures in pre-1997 Form 10-K and 10-Q filings; these disclosures were either made voluntarily or at the request of bank regulators. We did not include these observations in our sample because they are very few and raise a variety of selection bias issues.
11. www.chicagofed.org. Y-9C reports contain basic financial data from domestic bank holding companies on a consolidated basis. They include a balance sheet, an income statement, and detailed supporting schedules, including a schedule of off-balance-sheet items.

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