

How Informative are Value-at-Risk Disclosures?

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ABSTRACT

Value at Risk (VAR), a measure of the dollar amount of potential loss from adverse market moves, has become a standard benchmark for measuring financial risk. Spurred by regulators and competitive pressures, more institutions are reporting VAR numbers in annual and quarterly financial reports. To provide preliminary evidence on the informativeness of these new disclosures, I investigate the relation between the trading VAR disclosed by a small sample of U.S. commercial banks and the subsequent variability of their trading revenues. The empirical results suggest that VAR disclosures are informative in that they predict the variability of trading revenues. Thus, analysts and investors can use VAR disclosures to compare the risk profiles of trading portfolios.

Keywords: Derivatives; disclosure regulation; market risk disclosures; value at risk; Basel Committee; SEC.

Data availability: The data used in this study can be obtained from public sources.

I. Introduction

Value at Risk (VAR) has become a standard benchmark for measuring financial risk. The Group of Thirty (1993) report on derivatives stated that “market risk is best measured as value at risk.” Specifically, VAR provides a summary statistic of the order of magnitude of potential losses due to market risk. VAR is the maximum loss over a target horizon such that there is a low, prespecified probability that the actual loss will be larger. A company disclosing, for instance, that its daily VAR is \$30 million at the 95 percent level, means that there is only a 5 percent chance the firm will incur more than a \$30 million loss over the next day.

VAR summarizes the effects of leverage, diversification, and probabilities of adverse price movements in a single dollar amount that is easy to communicate. VAR disclosure also improves the governance of derivatives as it forces the firm to develop a systematic process of risk measurement.

This paper investigates the relation between publicly disclosed VAR measures and the volatility of trading revenues for a group of eight major U.S. commercial banks. I collected close to six years of historical data on VAR measures and associated trading revenues from quarterly and annual financial reports. Because only a few banks began disclosing VAR in 1995, only 8 banks with adequate disclosure history were available for study. I matched these banks’ quarterly trading revenues with VAR measures they reported on an annual or quarterly basis. My results suggest that VAR disclosures are informative measures of risks in that they can be used to predict the variability of banks’ trading revenues.

Before the advent of VAR, shareholders could not assess the total trading risks financial institutions assumed. Banks reported notional amounts of their derivatives positions, but these are not meaningful if positions hedge each other.

Few banks disclosed VAR before 1995. Since then, bank regulators, in particular the Basel Committee on Banking Supervision (BCBS), have prodded the industry to disclose more information. This started with the market risk amendment to the

Basel Accord (BCBS 1995), and continues with the latest revision of the Basel Accord (BCBS 2001), which “strongly recommends” that banks disclose their VAR.¹ By 1999, 66 of the 71 financial institutions the Basel Committee surveyed disclosed VAR numbers in their publicly-available financial reports (BCBS 1999). Most major financial institutions have implemented risk management systems and now publish their VARs on an annual or quarterly basis.

This study investigates whether the VAR numbers banks publicly disclose in their financial statements are related, cross-sectionally and over time, to subsequent fluctuations in banks’ trading revenues. Such evidence is relevant beyond the financial institution context. The Securities and Exchange Commission (SEC) now requires *all* large U.S. publicly traded corporations to report *quantitative* information about their market risk in financial reports filed with the SEC.² Registrants choose among three methods: (1) a tabular presentation describing fair value and contract terms, (2) a sensitivity analysis describing potential changes in fair values under market fluctuations, and (3) VAR numbers. The SEC’s market risk disclosure rule FFR-48, reviewed in Linsmeier and Pearson (1997), became effective in June 1998.

The SEC intended its market risk disclosure requirements to address the security analysts’ and accountants’ general concern that “users are confused.”³ Prior reporting guidelines provided insufficient detail on the scope of firms’ involvement in financial instruments and the potential effect of derivatives activity on corporate profits. The SEC reviewed U.S. public corporations’ *qualitative* disclosure statements, and found that management discussion was typically uninformative. Nearly all companies explain that they use derivatives to “hedge.” Few admit to outright speculation, even though the losses some corporations incurred are *prima facie* evidence to the contrary.⁴

Because the line between selective hedging and speculation is thin, such general qualitative statements shed little light on the extent and effectiveness of corporate derivatives activities. This explains why the SEC mandated quantitative disclosures

of market risk. Some observers, however, question whether such disclosures can be informative. For instance, Logan and Montgomery (1997, 3), representing the Treasury Management Association, testified that the SEC rules “are unlikely to enable investors to better understand a public company’s use of these (derivatives) instruments and its aggregate risk exposure.”⁵

No previous work investigates the informativeness of firms’ publicly-available VAR disclosures for the firms’ risk profiles. Most prior research on the informativeness of derivatives-related disclosure focuses on the extent to which these disclosures are informative about the firm’s exposure, or the linear sensitivity of share prices, to changes in a particular financial risk factor.⁶ Exposure is a component of financial risk but focuses on one risk factor only. Thus, most prior research focuses on industries that are exposed to one major source of financial risk. For instance, Schrand (1997) examines whether derivatives disclosures provide useful information for assessing the interest rate exposure of a sample of savings and loan associations. She reports that derivatives activities lower savings and loans’ interest rate exposure, measured by the sensitivity of stock prices to movements in interest rates. Similarly, Rajgopal (1999) finds that information about derivatives presented in a tabular and sensitivity analysis format is related to the share price exposure of oil and gas firms to oil and gas prices. Wong (2000) examines the foreign exchange rate exposure for a sample of U.S. manufacturing firms and finds that derivatives notionals partially explain exposure.

In contrast, a variety of risk factors affect large banks’ trading portfolios. VAR disclosures summarize the bank’s maximum potential losses after allowing for diversification across these different risk factors. This paper provides the first evaluation of the informativeness of publicly disclosed VAR measures for the risk of trading portfolios.

In a concurrent and independently developed working paper, Berkowitz and O’Brien (2001) investigate the association between daily VAR data that banks report *privately* to regulators, and subsequent daily trading revenues, for a sample of

six large dealer banks over a two-year period. They provide a detailed analysis of the forecasting performance of VAR models. Their results, however, do not address the informativeness of public financial reports, because daily VAR and trading revenue data are available only to bank regulators (e.g. the Federal Reserve Board), and not to the public. While we would expect short-horizon, daily VAR data to provide useful forecasts of daily volatility of trading revenues, this relation may not necessarily hold with quarterly or annual data. This study fills this void by analyzing the informativeness of VAR disclosures at quarterly frequencies.

The rest of the paper proceeds as follows. Section II presents the testing framework. Section III describes the data and descriptive statistics. Section IV presents results, and Section V contains some concluding observations.

II. Testing the Predictive Power of VAR

Denote the *daily* trading revenue a bank earned during day $t + 1$ as r_{t+1} and its associated VAR as VAR_t , measured as of the close of day t . VAR is the cutoff loss level where the probability that the bank incurs a loss beyond VAR equals 1 minus the confidence level (e.g. 1 percent for the typical confidence level of $c = 99$ percent):⁷

$$P[r_{t+1} - E(r_{t+1}) < -VAR_t] = 1 - c. \quad (1)$$

To investigate whether the VAR number adequately estimates future losses, one could match the realized distribution of daily trading revenues with the daily VAR forecast by counting the number of “exceptions,” or realizations of losses beyond VAR. This is in fact the “backtesting” framework bank regulators use.⁸ Bank daily trading data, unfortunately, are proprietary. As such, they are unavailable to financial analysts and investors, who only have access to the bank’s quarterly or annual VAR numbers and the bank’s quarterly trading revenues.

I therefore use an alternative approach that transforms the VAR number into a

measure of dispersion. Tests based on dispersion measures are more powerful than tests based on the number of exceptions because dispersion measures incorporate data from the whole distribution. The dispersion measure is based on the assumption that the distribution of trading revenues is symmetric. My approach accommodates the fat tails commonly observed in financial data.

This approach, however, is less appropriate when the distribution is highly skewed; for instance, for a trader dealing with short-term options, which are non-linear instruments with skewed payoffs.⁹ This is a lesser concern for a large commercial bank, whose trading portfolio typically includes a range of instruments exposed to a wide variety of risk factors.¹⁰

As an illustration, assume that r_{t+1} has a conditional normal distribution with mean $\mu = 0$ and forecasted volatility of s_t , $r_{t+1} \sim N(0, s_t^2)$. This trading revenue r_{t+1} is the effect of fixed positions w_t combined with movements in normally distributed market risk factors x_{t+1} over day $t + 1$. The portfolio variance is then $s_t^2 = w_t' \Sigma_t w_t$, where Σ_t is the forecasted covariance matrix for the market risk factors as of the close of day t . The VAR measure is the forecasted volatility s_t multiplied by the standard normal deviate α for the selected confidence level (e.g., $\alpha = 2.33$ for a one-tailed confidence level of 99 percent). Hence, we have

$$VAR_t = \alpha s_t. \quad (2)$$

With normally distributed market risk factors, the expectation of the absolute value $|r_{t+1}|$ is

$$E(|r_{t+1}|) = \sqrt{\frac{2}{\pi}} \times s_t = 0.80 \times s_t. \quad (3)$$

Thus, the expected absolute value of the trading revenue is linearly increasing in the forecasted volatility of trading revenues, s_t , which is proportional to VAR.

This setup is valid for a wide class of distributions including the normal distribution. As long as the conditional distribution of trading revenues is fixed and symmetrical, the expected absolute value of trading revenues increases linearly with

the VAR-based volatility. With distributions other than the normal, the coefficient will in general differ from $\sqrt{2/\pi}$, but the VAR measures should still be linearly related to the expected absolute value of trading revenues. For instance, when the conditional distribution is a Student-t with 6 degrees of freedom, which is typical of daily financial series such as exchange rates, the coefficient is 0.74 instead of 0.80.

Thus, I test the predictive power of banks' *quarterly* VAR disclosures by estimating the following equation:

$$|R_{t+1}| = a + b\sigma_t + \epsilon_{t+1}, \quad (4)$$

where R_{t+1} is the trading revenue for *quarter* $t+1$, and σ_t is the forecasted volatility of *quarterly* trading revenue inferred from the bank's public disclosure of its trading VAR as of the end of quarter t .

I extrapolate the banks' reported daily VAR numbers to a quarterly horizon. Banks publicly disclose VAR numbers every quarter, but these disclosed VAR numbers correspond to a horizon of one day, which must be extended to match the quarterly horizon of banks' reported trading revenues. Banks also publicly disclose R_{t+1} , the sum of daily revenues for each day of the quarter, $R_{t+1} = \sum_{i=1}^N r_i$, where N is the number of trading days in a quarter, taken as $N = 63$ (assuming 21 trading days in a month). I estimate the volatility in quarterly trading revenues from the daily volatility using the square root of time rule

$$\sigma_t = s_t \sqrt{N}. \quad (5)$$

VAR is informative about the risks of future trading revenues if b estimated in Equation (4) is significantly positive. The value of b will equal its theoretical value of 0.80 only if several assumptions are met.

The first assumption is that σ_t is measured without error. Measurement error in σ_t will downward bias the slope coefficient due to the errors-in-variables problem. One source of error in σ_t is the extrapolation of the bank's reported daily VAR, s_t , to a quarterly horizon, σ_t . This transformation assumes that the variance in the

bank's trading revenues is constant throughout the quarter. This assumption may be reasonable if VAR moves slowly over the quarter. Figure 1 displays the time variation in the daily VAR for J.P. Morgan for the years 1997-1998. The graph shows some variation within the quarter, but major changes occur over longer horizons. Other sources of error in σ_t include that the forecasted volatility in trading revenues is only an estimate, subject to sampling variability. Furthermore, banks must make simplifying assumptions in estimating VAR, such as limiting the number of risk factors considered.¹¹

A second assumption is that trading revenues, R_{t+1} , are measured without error. However, trading revenues are based on real portfolios with changing positions in which traders adapt their portfolios to market conditions, whereas VAR assumes that positions w_t are fixed over the horizon (i.e., fixed over the quarter, in this study's case).

The third assumption is that R_{t+1} has mean zero and is normally distributed. Thus, R_{t+1} must be the *unexpected* component of trading revenues. Unfortunately, trading revenues include other items such as fees and interest income, which banks exclude from the construction of VAR. In addition, we would expect trading revenues to generate sufficient profits to compensate for the immobilized capital and the operating expenses. This expected component of trading revenues may grow over time due to the increase in trading activities or change systematically as banks alter their risk profile. To correct for the expected component of the trading revenue, I measure the unexpected component as the difference between the quarterly trading revenue and its moving average over the previous four quarters. (I use the previous four quarters as the benchmark because trading revenues are not seasonal.) The "unexpected" trading revenue is then defined as

$$R_{t+1} - E[R_{t+1}] = R_{t+1} - (1/4) \sum_{i=1}^4 R_{t+1-i}. \quad (6)$$

This transformation implies that $|R_{t+1} - E[R_{t+1}]|$ should have an expected value

of zero.¹² These estimates of unexpected revenues are statistically indistinguishable from zero for my sample of banks. Also, as expected, forecasts of expected trading revenues were positive for every bank in every single quarter.

I then implement Equation (4) as

$$|R_{t+1} - E[R_{t+1}]| = a + b\sigma_t + \epsilon_{t+1}, \quad (7)$$

where the trading revenue has been replaced by its unexpected component. If the banks' VAR disclosures are informative about the risk of next quarter's trading revenues, then $b > 0$. Ideally, the regression R^2 should be high, implying that σ_t captures much of the variation in $|R_{t+1} - E[R_{t+1}]|$. The regression will be meaningful only if σ_t varies substantially across quarters. If a bank maintains a roughly constant risk profile throughout the six-year period, a simple time-series regression will yield an insignificant estimate for b , with the constant capturing the average value of $|R_{t+1} - E[R_{t+1}]|$ instead.

III. Data and Descriptive Statistics

The Bank Sample

The key criterion for including banks in this sample is the availability of publicly disclosed VAR data. I initially focused on the U.S. commercial banks with the largest derivatives positions, as reported by the Office of the Comptroller of the Currency over the period 1995 to 1999. Twelve banks appeared in the top 10 ranking at some point over the 1995-1999 period. These banks have large proprietary trading operations and are more likely to have established, centralized risk-management systems that enable them to report VAR numbers. Banks with large trading operations are exposed to a variety of risks, including interest rate, currency, equity, and commodity risk. This makes it necessary for them to measure risk on an aggregate basis.

Of these 12 banks, the 8 in the final sample issued VAR disclosures on a quarterly or annual basis beginning in December 1994.¹³ To avoid survivorship bias, I keep

NationsBank, which merged into BankAmerica during the sample period. Panel A of Table 1 provides more details on the type and frequency of the banks' VAR disclosures, including the method the bank used to compute VAR, and the confidence level.¹⁴

Figure 2 shows an example of Chase Manhattan Bank's VAR disclosure. Chase measures VAR at the 99 percent level of confidence over one day. The bank also gives general information about how it estimates VAR. Chase states that it is exposed to interest rate, foreign exchange, equity, and commodity market risk in its trading portfolio. The breakdown by type of risk indicates that this is a diversified portfolio. Chase reports the average, high, low, and end-of-period VAR across categories of market risk and for the portfolio as a whole. This is one of the more extensive VAR disclosures. Other banks' disclosures are typically less informative, although the quality of information has improved over time.

Panel B in Table 1 reports the book value of total assets and equity, which can be compared to the banks' trading risk, at the beginning and end of the sample period. The banks' positions in off-balance-sheet derivatives provide an indication of their potential trading risk. The table shows that the banks' derivatives notional positions grew by about 112 percent on average, which is triple the 40 percent growth in assets and equity. Most of these banks' notional positions exceed \$1 trillion, which is far larger than book equity, which is on the order of tens of billions of dollars. Notional amounts, however, do not reveal the risks banks actually face. Market risk could be minimal if the banks hedged all positions back-to-back. If unhedged, however, these banks could be assuming large trading risks. The VAR measure is designed to account for hedging and diversification effects.¹⁵

Trading Revenues

I collected quarterly trading revenues from banks' quarterly reports (10-Q) and annual reports (10-K), along with the banks' VAR disclosures. Because banks begin disclosing VAR data in 1994, I collect trading revenue data from 1994 to the third

quarter of 2000.

Most banks report “total trading-related revenues,” which includes (1) direct trading revenues, (2) fees, and (3) interest revenues on trading assets net of the costs to fund trading positions. Fees and net interest earned on assets and liabilities are more stable over time than are trading revenues. As explained earlier, I therefore abstract from the expected component of trading revenues to construct a measure of unexpected trading revenues.

Panel C in Table 1 reports the average and standard deviation of quarterly trading-related revenues, measured in millions of dollars, as well as statistics on the measure of unexpected trading revenues. Average trading revenues differ widely across banks, ranging from a low of \$35 million for Bank of New York to \$718 million for J.P. Morgan. The third column reports the banks’ total revenues, one component of which is trading revenues. For some banks, trading revenues are an insignificant proportion of total revenues. For Bank of New York, for instance, the ratio is 2.3 percent only. For other banks, the ratio is much higher, reaching 16.5 percent of revenues for J.P. Morgan.

Figure 3 shows an upward trend in the banks’ quarterly trading-related revenues. Volatility is also high, with some banks losing money during the third quarter of 1998. This was a period of turmoil in financial markets, beginning with the Russian default and leading to the débâcle of the hedge fund Long-Term Capital Management (LTCM). Financial markets were severely disrupted when it appeared that LTCM might collapse, due to the sheer size of LTCM’s positions.

Panel C in Table 1 shows that average unexpected trading revenues are much closer to zero than are raw trading revenues. Consistent with the assumption underlying my computation of unexpected trading revenues, I am unable to reject the hypothesis that the banks’ mean unexpected trading revenues equal zero, except for Bank of New York. Also, unexpected trading revenues have no detectable first-order autocorrelation.

Value at Risk

Firms normally measure VAR over a one-day horizon, assuming the current positions are fixed over the daily horizon. In practice, of course, traders change positions actively during the trading horizon. Moreover, the actual risk may be less than indicated by VAR if management takes corrective actions when losses begin to develop. Using a quarterly horizon exacerbates the noise created by assuming positions are fixed throughout the entire horizon. As a result, I cannot identify rapid changes in banks' risk profiles. Rather, my goal is to identify slow changes in risk profiles across time, as well as to compare the magnitude of risk profiles across banks.

Ideally, I would match end-of-quarter VAR data with subsequent unexpected trading revenue. I collected VAR data for trading activities from the banks' annual (10-K) and quarterly (10-Q) reports. Banks began disclosing annual VAR numbers in 10-K forms in 1994. Because the SEC's market risk disclosure rule FFR-48 was not effective until January 1, 1998, quarterly VAR disclosures are unavailable for some banks until 1998, as Panel A of Table 1 indicates. In some cases, I recovered quarterly VAR from daily VAR graphs published in annual reports. In addition, many banks report VAR only as an average or an end-of-period value, but not both. As a result, I use the following decision rule in collecting VAR measures:

- 1) End-of-quarter VAR data for the previous quarter when available.
- 2) Average VAR for the previous quarter.

If quarterly data are not available, I resort to annual data.

- 3) VAR reported at the end of the previous year.
- 4) Average VAR for the previous year.

This approach selects the VAR number that is the closest to the beginning of the subsequent quarter over which I measure trading revenue. Using annual VAR data instead of quarterly data, however, should reduce the accuracy of the risk forecast because in the regressions (Equation 7) four quarterly trading revenue observations correspond to the same value of the VAR-based independent variable.

Banks report VAR data in different formats, with different reporting horizons and different confidence levels. I converted these into a quarterly standard deviation assuming normal distributions and identically and independently distributed returns using Equations (2) and (5). (As stated previously, the relation between the absolute value of trading revenues and the measure of dispersion holds for a large class of distributions, not just the normal distribution.)

The two rightmost columns in Panel C of Table 1 describe average risk measures (i.e., the VAR-based forecasted volatility of trading revenues) and the standard deviations of these measures over the sample period. Risk profiles differ widely across banks. The average quarterly measure of VAR-based volatility ranges from a low of \$16 million for Bank of New York to a high of \$129 million for J.P. Morgan.

Figure 4 compares the risk measures for the banks in the sample over 1995 to 2000. The figure shows substantial variation across banks and, for some banks, over time. The VAR-based risk measures of J.P. Morgan and Bank of America have tripled over the period. In contrast, Chase's VAR-based risk measure has only increased from \$80 million to \$100 million, although its notional derivatives position has doubled. For some banks, there is limited time-series variation in the VAR measure, which will decrease the power of time-series regressions for these individual banks.

IV. Results

I test the informativeness of VAR measures by estimating the relation between the VAR-based quarterly volatility and the absolute value of the unexpected trading revenue in the subsequent quarter. I first estimate the regression in Equation (7) individually for each bank i .

Table 2 reports the results of the 8 bank-specific time-series regressions of unexpected trading revenue on VAR-based quarterly volatility. The table shows results based on univariate Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) regressions. The SUR method leads to slightly lower standard errors, but

can be applied to 7 banks only. I excluded NationsBank from the SUR analysis because it requires the same sample period for all series used to compute the covariance matrix.

The individual bank-specific regressions reveal some evidence that forecasts of volatility in unexpected trading revenues derived from VAR disclosures are positively associated with the magnitude of the next quarter's unexpected trading revenues. The relation is significant for the two banks with the greatest time-series variation in VAR-based volatility: Bank of America, and J.P. Morgan. The relation is also significant for First Chicago, which was one of the earliest disclosers of quarterly VAR data. In contrast, Figure 4 shows that other banks, such as Bank of New York and Citicorp, have little time-series variation in VAR-based volatility, which makes it difficult to identify a reliable relation.

The bottom of Table 2 reports the result of a joint test of significance of all seven banks' SUR slope coefficients. The null hypothesis of zero slope coefficients is strongly rejected, at $p < 0.001$. As a whole, I find that VAR-based volatility is positively associated with the variation in future unexpected trading revenues.

Figure 5 displays the pooled sample, which is similar to an analyst comparing risk profiles across firms. Higher VAR-based volatility is associated with greater variation in unexpected trading revenues.

Table 3 reports the results of a cross-sectional estimation of Equation (7). Panel A first reports the results of a "pooled sample-OLS" regression with 175 observations (seven banks with 23 quarters of data plus NationsBank with 14 quarters). The slope coefficient on the VAR-based volatility is 1.80, which is significant at $p < 0.001$. The regression R-square is 26 percent.

To correct for heteroskedasticity (evident from the increasing variance as the VAR-based volatility increases in Figure 5) and cross-sectional correlations (e.g., Figure 3 shows that many banks suffered drops in trading revenues during the third quarter of 1998), I use a two-step GLS approach.¹⁶ First, I estimate the covariance matrix of the

error terms from the individual regressions. Call this covariance matrix $\hat{\Sigma}$. I construct the Cholesky factorization as $\hat{\Sigma}^{-1} = P'P$, where P is a lower triangular matrix. Next, I transform the observations by pre-multiplying Equation (7) by P so that the error term has unit variance. This approach corrects for estimated correlations and also puts greater relative weight on banks with lower variability in trading revenues. I run the regression on the transformed variables, and report the GLS results on the second line in Table 3. The estimated coefficient on the VAR-based volatility is 0.57, highly significant, and in line with the slope of 0.80 expected from Equation (3), allowing for measurement errors in the variables. The regression R-square in the transformed space is 38 percent.

I also implemented a two-step time-series approach as in Fama and MacBeth (1973), which is more intuitive and does not require estimating the covariance matrix. I first estimate a cross-sectional regression every quarter, and then aggregate the coefficients \hat{b}_t over time. This approach corrects for correlations across banks. Table 3 reports an estimated coefficient on the VAR-based volatility of 1.67, similar to the OLS value and still highly significant. Overall, the results indicate that VAR-based volatility is significantly positively associated with the magnitude of future unexpected trading revenues.

Next, Panels B and C in Table 3 show that the inferences are not attributable to extreme observations in the third quarter of 1998. Panel B shows that dropping the quarter entirely from the sample decreases the estimated coefficients on the VAR-based volatility forecast, but they remain significant at $p < 0.001$. Panel C shows that dropping the third quarter of 1998 to the first quarter of 1999 does not affect the inferences.

The strongest results arise in the cross-sectional analysis. This raises the question of whether the results could be due to a scale effect, i.e., simply due to the fact that both VAR-based volatility and the volatility of trading revenues are measured in dollars. Moreover, market participants and researchers should be interested in whether

quantitative VAR disclosures contain useful information for predicting the volatility of unexpected trading revenues, above and beyond the information in traditional notional amounts. To address these questions, I estimate the following regression

$$|R_{i,t+1} - E[R_{i,t+1}]| = a + b\sigma_{i,t} + cNOT_{i,t} + \epsilon_{i,t+1}, \quad (8)$$

where $NOT_{i,t}$ is the outstanding notional value of bank i 's derivatives contracts at the end of the previous quarter.¹⁷ If VAR provides incremental information for predicting the volatility of unexpected trading revenues, then we would expect the coefficient b to remain significantly positive.

Table 4 reports the results from pooled cross-sectional regressions on the notional positions alone, as well as combined with the VAR-based volatility forecast. Panel A shows that the magnitude of the banks' derivatives positions is significantly positively related to the volatility in unexpected trading revenues. More interestingly, however, Panel B shows that notional amounts have little explanatory power beyond the information contained in the VAR-based volatility forecast. The R-squares are not much higher than those in Panel A in Table 3. In contrast, VAR-based volatility forecasts provide incremental new information about the volatility in unexpected trading revenues, after controlling for derivatives notional amounts.

As a further control for scale effects, Panels C and D report the results of estimating the regressions after scaling all variables by the previous quarter's assets. Panel C in Table 4 confirms that, even after scaling, there is a significantly positive relation between the magnitude of quarter $t + 1$ unexpected trading revenues and the VAR-based measure of volatility in quarter t . Panel D indicates that the estimated coefficient on VAR-based volatility is still significant after controlling for the banks' notional amounts. Thus this relation is not simply a scale effect.

V. Conclusions

This study investigates the relation between Value at Risk (VAR) measures for trading activities commercial banks disclose in their financial reports and the subsequent variability of their unexpected trading revenues. The informativeness of VAR disclosures in firms' financial reports is of considerable interest, given the SEC's recent requirement that corporations must disclose quantitative measures of their market risks.

After conducting informal surveys, the SEC (1998) concluded that these disclosures provide investors and analysts with "new and useful information." Until now, however, there has been no formal attempt to assess whether VAR measures banks disclose in their financial reports can predict future volatility in their unexpected trading revenues.

In addressing this question, I find that VAR-based volatility forecasts based on banks' publicly available VAR disclosures are significantly related to future market risk, especially in cross-sections. This suggests that analysts can meaningfully compare the risk profiles of different banks using their disclosed VARs.

Banks with low VAR measures appear to be exposed to limited downside risk, whether they report large or small notional derivatives positions. Banks with large VAR measures experience much greater fluctuations in unexpected trading revenues. Thus VAR measures published in banks' financial reports offer a useful predictor of the market risk of the banks' trading activities. Shareholders need to assess whether average trading revenues compensate for these risks.

However, even if I had found that VAR disclosures are not informative, the imposition of such disclosures could still improve the governance of derivatives. Calculation and public reporting of VAR numbers imposes a discipline on derivatives trading. It can also reassure investors that the bank has in place a process to measure and manage risk.

The quality of VAR disclosures should improve over time as methodologies become

more consistent. Thus, we would expect VAR-based volatility forecasts to become increasingly accurate indicators of the variability of banks' future trading revenues. In the meantime, the most reassuring aspect of VAR reporting is that banks, finally forced to reveal the full extent of their market risk, now must consider the delicate trade-off between risk and return.

References

- Bank of England. 1995. *Report of the Board of Banking Supervision Inquiry into the Circumstances of the Collapse of Barings*. London: HMSO Publications.
- Basel Committee on Banking Supervision (BCBS). 1995. *An Internal Model-Based Approach to Market Risk Capital Requirements*. Basel, Switzerland: BIS.
- . 1996a. *Amendment to the Basel Capital Accord to Incorporate Market Risk*. Basel, Switzerland: BIS.
- . 1996b. *Supervisory Framework for the Use of ‘Backtesting’ in Conjunction with the Internal Models Approach to Market Risk Capital Requirements*. Basel, Switzerland: BIS.
- . 1999. *Trading and Derivatives Disclosure of Banks and Securities Firms*. Basel, Switzerland: BIS.
- . 2001. *Consultative Document: Pillar 3 (Market Discipline)*. Basel, Switzerland: BIS.
- , and J. O’Brien. 2001. How accurate are the value at risk models at commercial banks? Working Paper. Board of Governors of the Federal Reserve System.
- Christofferson, P., Hahn, J. and A. Inoue. 2001. Testing, comparing, and combining value at risk measures. *Journal of Empirical Finance* 8 (July): 325–342.
- Fama, E. and J. MacBeth. 1973. Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81 (May): 607–636.
- Group of Thirty. 1993. *Derivatives: Practices and Principles*. New York: Group of Thirty.
- Jorion, P. 2000. *Value at Risk: The New Benchmark for Managing Financial Risk*. New York: McGraw-Hill.

- Ju, X. and N. Pearson. 1999. Using value at risk to control risk taking: How wrong can you be? *Journal of Risk* 1 (Winter): 5–36.
- Linsmeier, T., and N. Pearson. 1997. Quantitative disclosures of market risk in the SEC release. *Accounting Horizons* 11 (March): 107–35.
- , and ———. 2000. Value at risk. *Financial Analysts Journal* 56 (March): 47–67.
- , D. Thornton, M. Venkatachalam, and M. Welker. 2002. The effect of mandated market risk disclosure on trading volume sensitivity to interest rate, exchange rate, and commodity price movements. forthcoming, *Accounting Review* (April).
- Logan, D. and P. Montgomery. 1997. *Testimony on behalf of the Treasury Management Association concerning Disclosures of Accounting Policies for Derivatives and Disclosures of Quantitative and Qualitative Information about Market Risk Inherent in Market Sensitive Instruments before the Subcommittee on Securities Committee on Banking, Housing, and Urban Affairs*. 105th Congress, 1st session, March 4.
- Marshall, C. and M. Siegel. 1997. Value at risk: Implementing a risk measurement standard. *Journal of Derivatives* 4 (Spring): 91–110 .
- Rajgopal, S. 1999. Early evidence on the informativeness of the SEC's market risk disclosures: The case of commodity price risk exposure of oil and gas products. *Accounting Review* 74 (July): 251–280.
- Schrand, C. 1997. The association between stock-price interest rate sensitivity and disclosures about derivatives instruments. *Accounting Review* 72 (January): 87–109.
- Securities and Exchange Commission. 1997. *Disclosure of Accounting Policies for Derivative Financial Instruments and Derivative Commodity Instruments and*

Disclosure of Quantitative and Qualitative Information about Market Risk Inherent in Derivative Financial Instruments, Other Financial Instruments, and Derivative Commodity Instruments. Release 33-7386, FFR-48, Washington, DC: SEC.

———. 1998. *Review of the First Phase of Filings of Disclosures of Quantitative and Qualitative Information about Market Risk Inherent in Derivative Financial Instruments and Other Financial Instruments.* Washington, DC: SEC.

Venkatachalam, M. 1996. Value-relevance of banks' derivatives disclosures. *Journal of Accounting and Economics* 22 (August): 327–355.

Wong, F. 2000. The association between SFAS No. 119 derivatives disclosures and the foreign exchange risk exposure of manufacturing firms. *Journal of Accounting Research* 38 (Autumn): 387–417.

Footnotes

¹ The Basel Accord, established in 1988 to set minimum capital requirements for commercial banks against credit risks, was amended in 1996 to include a charge for market risk (BCBS 1995, 1996a). Banks now have a choice between using a “standardized” method, using predefined rules, or their own internal VAR measure as the basis for their capital charge for market risk. In practice, using internal VAR numbers leads to lower capital charges than the standardized model. This likely explains the industry-wide move to VAR measurement.

² The requirements cover derivatives and other financial instruments. The SEC also encourages, but does not require, inclusion of market risk due to nonfinancial assets, liabilities, or transactions, such as inventories or sales commitments to provide a more complete picture of market risk, although nonfinancial items may be more difficult to measure (Linsmeier and Pearson 1997).

³ This phrase is ascribed to the AICPA (SEC 1997).

⁴ As an example, Nick Leeson told his superiors at Barings that his positions on Japanese stock index futures hedged each other. However, he was taking large speculative positions that led to a loss of \$1.3 billion (Bank of England 1995).

⁵ The compliance costs these requirements impose on registrants are not clear. However, corporations that trade derivatives likely invest in risk management systems, and the SEC (1998, 2) reports that the market risk disclosures are “not terribly costly,” with a range of \$10,000 to \$50,000.

⁶ Other accounting literature has studied the informativeness of derivatives disclosures for explaining the level of market values, as opposed to risk exposures. Venkat-achalam (1996), for instance, finds that fair values for derivatives help explain the cross-sectional variation in bank share prices better than notional amounts. More recently, Linsmeier et al. (2002) conclude that increased market risk disclosures reduce

investors' diversity of opinion about the effect of market risk on firm value.

⁷ Another definition would exclude the expectation term. The definition given here, however, is consistent with deriving VAR from a multiple of the standard deviation. Some banks, like J.P. Morgan, explicitly define their "earnings at risk" as the deviation from the mean. In most applications with daily data, the expectation term is immaterial because it is dominated by the daily volatility. With the quarterly horizons used in this paper, however, the expectation term is more important. As a result, I include the expectation term to abstract from other items (e.g. fees, interest income, and expected profits) that do not represent unexpected trading revenues.

⁸ See the BCBS (1996b). Christoffersen et al. (2001) have developed other frameworks for evaluating risk forecasts.

⁹ The mere presence of options does not imply strongly asymmetric distributions if the risk horizon is short relative to the maturity of the option, however. The distribution of changes in values of long-term options, for instance, over the next day, is typically indistinguishable from a normal approximation. Consider an option on an asset worth $S = \$100$ with 10 percent annual volatility and zero dividend; interest rates are at 3 percent. Assuming 250 trading days in a year, the daily volatility is $0.10/\sqrt{250}$. For a six-month option, the Black-Scholes model gives a delta of 0.60 and gamma of 0.055. As a first approximation, I compute the 95 percent VAR from the delta of the option and the 95th percentile of the underlying asset, for which the associated standard normal deviate is $\alpha = 1.64$. This gives a linear $VAR = \Delta(\alpha\sigma S) = 0.60(1.64(0.10/\sqrt{250})\$100) = \$0.62$. For more precision, one could add a quadratic correction, which is $0.5\Gamma(\alpha\sigma S)^2 = \0.03 . Because this is a small fraction of the linear VAR for this option, the option distribution is close to a normal distribution over this 1-day risk horizon. As the risk horizon extends, however, the non-linearity in options induces skewness in the distribution of option returns. Using the same option over a one-month risk horizon, the linear VAR is \$2.84 and

the quadratic correction is \$0.62. Because the correction is a greater fraction of the linear VAR, the distribution is more asymmetrical.

¹⁰ That is, unless the bank “games” the VAR number by altering the distribution of profits and losses to satisfy a fixed VAR at the expense of a small probability of large losses. Ju and Pearson (1999) have analyzed such strategies, which are more likely to occur at the level of traders’ desks than at the aggregate level of large institutions such as the commercial banks in the sample.

¹¹ Banks must make additional simplifications in mapping financial instruments on the selected risk factors. These approximations introduce additional errors, or “model risk”. Marshall and Siegel (1997) find that, as financial instruments become more complicated, there is less agreement in VAR numbers produced by 10 different VAR software packages.

¹² One minor drawback of this approach is that the four-quarter moving average measure of expected trading revenues induces a slight negative autocorrelation in the unexpected trading revenues ($\rho = -0.05$). A quarter with, say, a large negative shock pulls down the estimate of $E[R_{t+1}]$ for the next three quarters, which is more likely to generate positive values for UR_{t+1} to UR_{t+3} .

The results are robust to an alternative moving average based on all previous data (not just the last four quarters), and to a measure of unexpected trading revenues defined as the deviation from a time trend fitted over the whole period.

¹³ For an overview of different VAR methods, see, e.g., Linsmeier and Pearson (2000) or Jorion (2000).

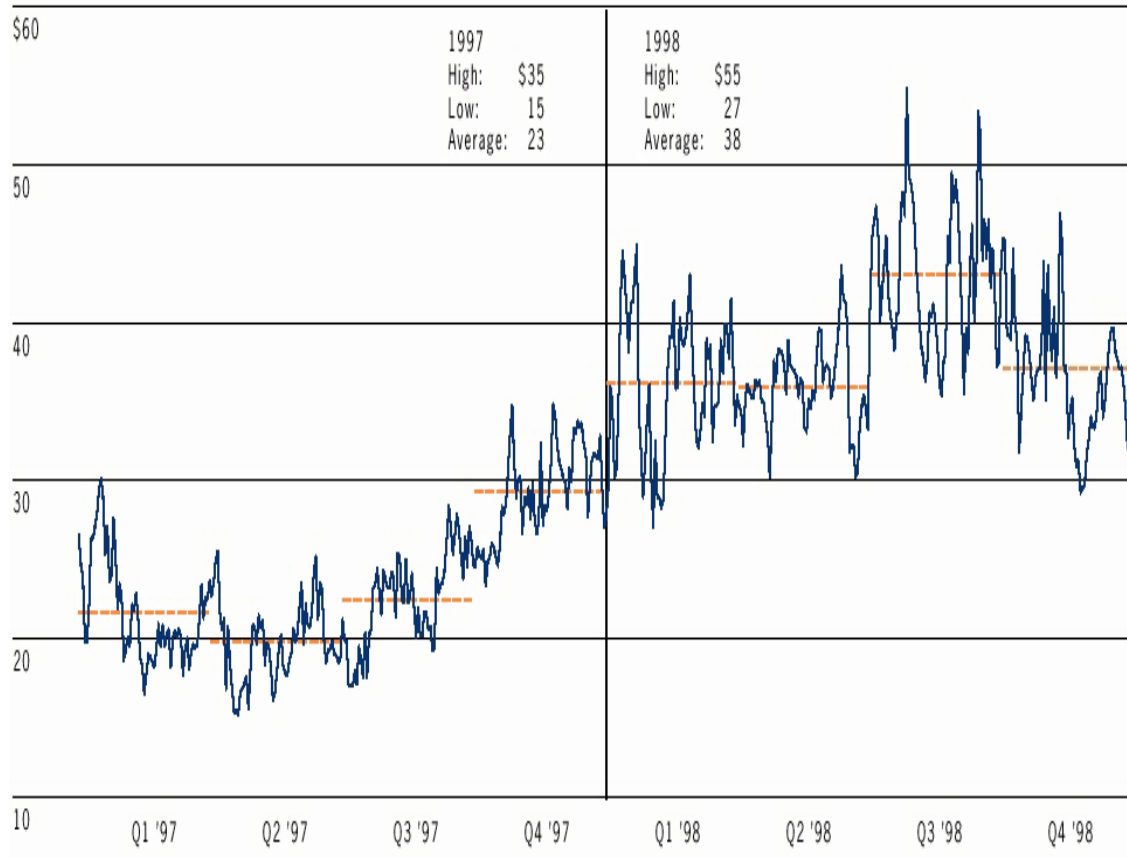
¹⁴ Smaller banks reported less information, if any, about VAR. Regional banks are mainly exposed to U.S. interest rate risk and instead report a sensitivity analysis to shocks in interest rates. FleetBoston and First Union did not begin providing VAR disclosures until 1996 and 1997, respectively. Neither Republic nor Wells Fargo report VAR.

¹⁵ To some extent, one could assess a bank's market risk profile from the historical volatility of its reported trading revenues. However, historical volatility is a backward measure of risk because exposures can change over time. Banks can change their derivatives strategies, exiting some markets or entering new ones. Thus, VAR is designed to provide a forward-looking gauge of market risk.

¹⁶ Including in the regression total assets or trading assets rather than the notional amounts led to similar inferences, except that the estimated coefficients on assets were even weaker than those obtained for notional amounts.

FIGURE 1

JP Morgan's Daily VAR



— Daily value at risk in millions of dollars - - - - Average quarterly value at risk

FIGURE 2
Excerpts from the Annual Report of
Chase Manhattan Bank, 1999
Dealing with Value at Risk

Value-at-Risk

VAR is a measure of the dollar amount of potential loss from adverse market moves in an everyday market environment. The VAR looks forward one trading day and is the loss expected to be exceeded with a 1 in 100 chance.

The VAR methodology used at Chase is historical simulation, which assumes that actual observed historical changes in market indices, such as interest rates, foreign exchange rates, and equity and commodity prices, reflect future possible changes. In its daily VAR calculations, Chase uses the most recent one-year historical changes in market prices and rates. Chase's historical simulation is applied to end-of-day positions, and it is shown by individual position and by aggregated positions by business, geography, currency and type of risk.

Trading Activities

Chase is exposed to interest rate, foreign exchange, equity and commodity market risk in its trading portfolios. No single risk statistic can reflect all aspects of market risk; in addition, market risk exposures change continuously through daily trading activities. Nonetheless, the tables that follow provide a meaningful overview of Chase's market risk exposure arising from its trading activities.

The table that follows represents Chase's average and period-end VARs for its total trading portfolio and for each of the major components constituting that portfolio.

	Year Ended December 31, 1999			At	At
	Average	Minimum	Maximum	Dec. 31,	Dec. 31,
(in millions)	VAR	VAR	VAR	1999	1998
Interest Rate	\$20.2	\$10.7	\$36.5	\$20.0	\$20.1
Foreign Exchange	7.0	2.3	21.3	3.0	2.3
Equities	6.3	3.4	10.1	7.2	4.6
Commodities	3.5	1.9	9.0	3.4	2.6
Hedge Fund Investments	4.1	3.1	4.6	3.3	NA
Less: Portfolio Diversification	(17.0)	NM	NM	(13.7)	(8.9)
Total VAR	\$24.1	\$12.3	\$41.8	\$23.2	\$20.7

NA - Not available. Chase started reporting in 1999 its market risk exposure to hedge fund investments as a separate VAR category. Prior to that, the market risk of hedge funds was in other categories.

TABLE 1

Panel A: Description of VAR Disclosures for the 8 U.S. Commercial Banks with the Largest Derivatives Positions and That Report VAR Beginning in 1994

Bank	Description of method as of Dec. 1999	Reporting details as of Dec. 1999	First VAR disclosure	Reported Average VAR since 1998-Q3	Reported End-quarter VAR since 1997-Q4	Confidence level
Bank of America	"Sophisticated techniques"	Average, min, max	Dec-94	1998-Q3	NA	95%, 97.5%, 99% since Sept. 98
Bank of New York	Monte Carlo simulations	Average, end, min, max	Dec-94	1996-Q4	1997-Q4	95%, 99% since Mar-98
Bankers Trust	"Proprietary simulations"	Average, end, min, max	Dec-94	1998-Q3	1998-Q3	99%
Chase Manhattan	Historical simulation	Average, end, min, max	Dec-94	1994-Q4	1997-Q4	95%, 97.5%, 99% since Dec-97
Citicorp	Covariance matrix	Average, end, min, max	Dec-94	1997-Q4	1997-Q4	97.7%, 99% since Dec-97
First Chicago	Not described	Average, end, min, max	Dec-94	1994-Q1	1997-Q4	99.87%, 99% since Dec-97
J.P. Morgan	Historical simulation	Average, end, min, max	Dec-94	1995-Q1	1997-Q4	95%
NationsBank	Scenario simulation	End	Dec-94	NA	1996-Q1	99%

Panel B: Banks' Book Value of Assets and Equity, and Derivatives Notional in 1994 and 1999 (\$ Billions)

Bank	Book Value of Assets			Book Value of Equity			Derivatives Notional		
	1994	1999	Growth	1994	1999	Growth	1994	1999	Growth
Bank of America	\$170	\$633	272%	\$11.0	\$44.4	304%	\$1,333	\$5,672	326%
Bank of New York	\$49	\$75	53%	\$4.3	\$5.1	19%	\$80	\$318	298%
Bankers Trust	\$97	\$68	-30%	\$4.9	\$4.3	-12%	\$1,982	\$323	-84%
Chase Manhattan	\$285	\$406	42%	\$18.9	\$23.6	25%	\$4,566	\$12,720	179%
Citicorp	\$250	\$389	56%	\$17.8	\$26.0	46%	\$2,265	\$3,712	64%
First Chicago/BankOne	\$113	\$269	138%	\$7.8	\$20.1	158%	\$622	\$1,034	66%
J.P. Morgan	\$155	\$261	68%	\$9.6	\$11.4	19%	\$2,489	\$8,839	255%
NationsBank	\$158	\$308	95%	\$11.0	\$26.7	143%	\$485	\$2,355	386%
Total	\$1,277	\$1,776	39%	\$85	\$117	37%	\$13,822	\$29,301	112%

Panel C: Banks' Quarterly Trading Revenues (\$ Millions) and VAR-Based Quarterly Volatility from 1995 to 2000 (\$ Millions)

Bank	Trading-Related Revenue		Total Revenue		Unexpected Trading Revenue			VAR-Based Quarterly Volatility	
	Average	Standard Deviation	Average	Percent Trading	Average	Standard Deviation	Rho(1)	Average	Standard Deviation
Bank of America	\$253	\$219	\$8,695	2.9%	\$38	\$226	0.15	\$94	\$45
Bank of New York	\$35	\$19	\$1,524	2.3%	\$6	\$8	0.10	\$16	\$7
Bankers Trust	\$188	\$235	\$2,265	8.3%	-\$18	\$229	-0.03	\$70	\$30
Chase Manhattan	\$564	\$218	\$7,703	7.3%	\$54	\$186	-0.19	\$74	\$13
Citicorp	\$591	\$150	\$9,456	6.3%	\$44	\$125	-0.27	\$67	\$16
First Chicago/BankOne	\$64	\$29	\$3,847	1.7%	\$4	\$31	-0.10	\$45	\$7
J.P. Morgan	\$718	\$297	\$4,348	16.5%	\$75	\$258	-0.04	\$129	\$36
NationsBank	\$75	\$23	\$4,959	1.5%	\$4	\$27	-0.17	\$67	\$15

Notes: In Panel B, values in 1994 and 1999 are taken from annual reports as of December. "Growth" refers to the total growth rate of these items over the period. Deutsche Bank acquired Bankers Trust and made Bankers Trust a wholly-owned subsidiary in June 1999. Chase Manhattan merged with Chemical Bank on March 31, 1996; prior data are restated for the merged entity. First Chicago NBD merged with BancOne on October 2, 1998 to become Bank One; data prior to the merger is that of First Chicago NBD, which had relatively large derivatives positions. NationsBank merged with Bank of America in September 1998 so it disappeared from the sample after June 1998. The "total" line excludes NationsBank in 1999 because another bank in the sample (Bank of America) absorbed its assets. Panel C presents averages and standard deviations from the first quarter of 1995 to the third quarter of 2000, except for NationsBank, for which data end in June 1998. "Unexpected trading revenues" is defined as the difference between the latest trading revenue and the average over the previous year. Rho(1) is the first-order autocorrelation in the unexpected trading revenues, for which the standard error is 0.21.

FIGURE 3

Banks' Quarterly Trading Revenues, 1994-2000

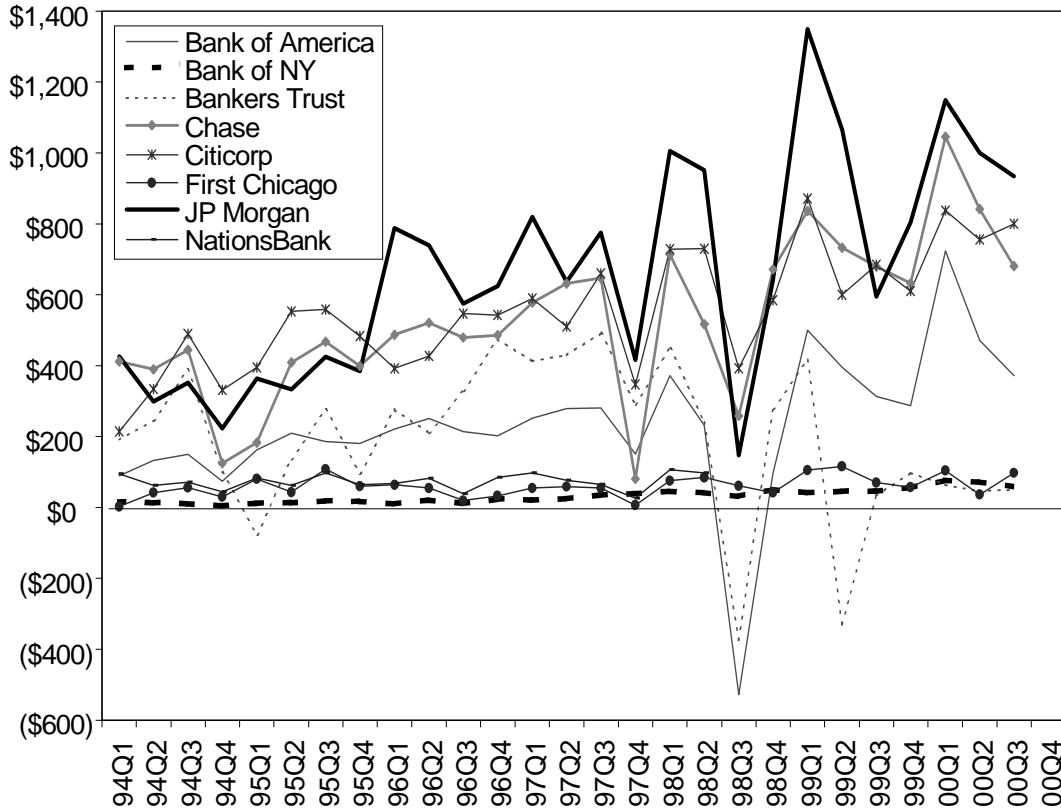


FIGURE 4

VAR-Based Quarterly Volatility in Banks' Trading Revenues, 1994-2000

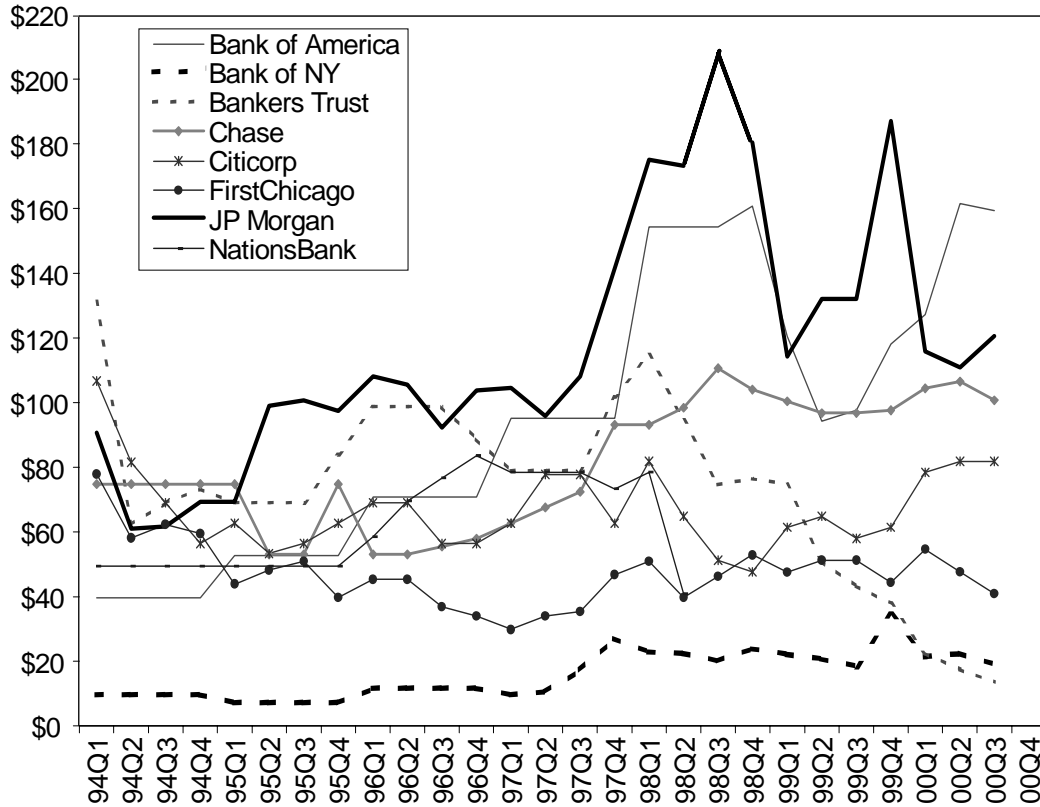


TABLE 2

**Individual Regressions of Absolute Value of Quarter $t + 1$ Unexpected
Trading Revenues on Quarter t VAR-Based Volatility**

$$|R_{i,t+1} - E[R_{i,t+1}]| = a_i + b_i\sigma_{i,t} + \epsilon_{i,t+1}$$

Bank	Period (Number of observations)	OLS			SUR	
		Constant (t-statistic)	Slope	R-square	Constant (t-statistic)	Slope
Bank of America	1995,Q1-2000,Q3 (23)	-73.48 (-0.94)	2.24* (2.86)	28.0%	13.48 (0.24)	1.29* (2.71)
Bank of New York	1995,Q1-2000,Q3 (23)	4.16 (1.21)	0.25 (1.24)	6.9%	4.00 (1.26)	0.26 (1.43)
Bankers Trust	1995,Q1-2000,Q3 (23)	47.59 (0.46)	1.38 (1.03)	4.9%	56.15 (0.74)	1.26 (1.38)
Chase	1995,Q1-2000,Q3 (23)	-80.29 (0.58)	3.12* (1.70)	12.1%	-34.68 (-0.31)	2.51* (1.67)
Citicorp	1995,Q1-2000,Q3 (23)	118.84 (1.74)	-0.12 (-0.12)	0.0%	66.22 (1.41)	0.67 (1.00)
First Chicago/ Bank One	1995,Q1-2000,Q3 (23)	-17.68 (-0.89)	0.97* (2.25)	19.5%	-22.17 (-1.31)	1.07* (2.91)
J.P. Morgan	1995,Q1-2000,Q3 (23)	-65.15 (-0.48)	1.99* (1.95)	15.1%	20.02 (1.32)	1.32* (2.08)
NationsBank	1995,Q1-1998,Q2 (14)	-2.44 (-0.12)	0.36 (1.20)	10.7%	-	-
Joint test of zero slopes						24.26* prob=0.001

Notes: $R_{i,t+1}$ is the quarterly trading revenue, $E[R_{i,t+1}]$ is the expected trading revenue in quarter $t + 1$ based on a moving average of the last four quarters, and $\sigma_{i,t}$ is the VAR-based volatility in unexpected trading revenue for bank i in quarter t . The table reports OLS and Seemingly Unrelated Regressions (SUR) regressions for each bank; NationsBank is not included in the SUR regressions due to its shorter sample period. The joint test of zero slope coefficients is distributed asymptotically as chi-square with 7 degrees of freedom. One-tailed significance at the 5 percent level denoted by *.

FIGURE 5

Absolute Value of Banks' Unexpected Trading Revenues in Quarter $t + 1$ and VAR-Based Volatility in Quarter t : Pooled Sample

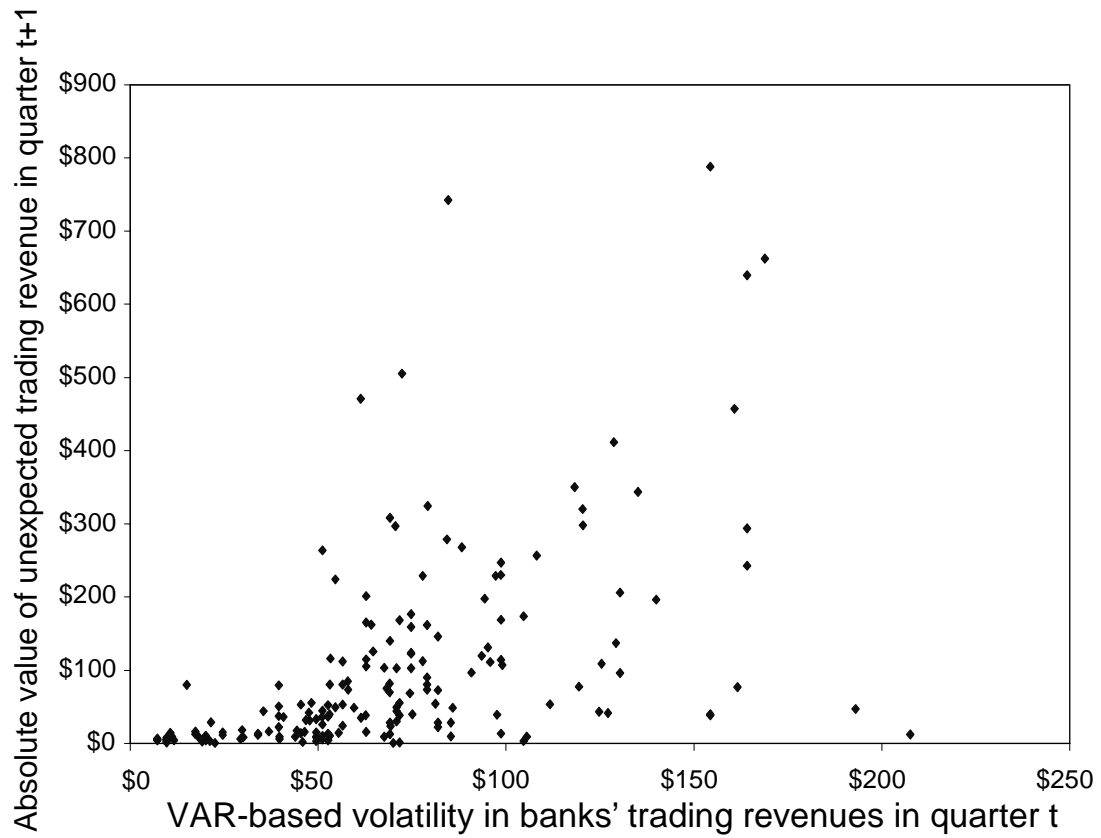


TABLE 3

**Pooled Regressions of Absolute Value of Quarter $t + 1$ Unexpected
Trading Revenues on Quarter t VAR-Based Volatility**

$$|R_{i,t+1} - E[R_{i,t+1}]| = a + b\sigma_{i,t} + \epsilon_{i,t+1}$$

Sample	Period (Number of observations)	Constant (t-statistic)	Slope (t-statistic)	R-square
Panel A: Total Sample				
Pooled Sample-OLS (8 banks)	1995,Q1-2000,Q3 (175)	-23.97 (-1.31)	1.80* (7.89)	26.4%
Pooled Sample-GLS (7 banks)	1995,Q1-2000,Q3 (161)	-1.88 (-0.90)	0.57* (6.24)	37.7%
Time-Series (Fama-MacBeth)	1995,Q1-2000,Q3 (19)		1.67* (4.92)	
Panel B: Sample without 1998,Q3				
Pooled Sample-OLS (8 banks)	1995,Q1-2000,Q3 (168)	-4.56 (-0.29)	1.32* (6.72)	21.4%
Pooled Sample-GLS (7 banks)	1995,Q1-2000,Q3 (154)	1.82 (0.08)	0.50* (6.79)	43.0%
Time-Series (Fama-MacBeth)	1995,Q1-2000,Q3 (18)		1.44* (5.32)	
Panel C: Sample without 1998,Q3 and 1999,Q1				
Pooled Sample-OLS (8 banks)	1995,Q1-2000,Q3 (154)	-3.11 (-0.19)	1.31* (6.08)	19.5%
Pooled Sample-GLS (7 banks)	1995,Q1-2000,Q3 (140)	-0.09 (0.56)	0.57* (7.35)	36.0%
Time-Series (Fama-MacBeth)	1995,Q1-2000,Q3 (16)		1.45* (5.64)	

Notes: $R_{i,t+1}$ is the quarterly trading revenue, $E[R_{i,t+1}]$ is the expected trading revenue in quarter $t + 1$ based on a moving average of the last four quarters, and $\sigma_{i,t}$ is the VAR-based volatility in unexpected trading revenue for bank i in quarter t . The OLS regression is a simple pooled time series and cross-sectional regression. The pooled GLS regression transforms the variables by the estimated covariance matrix; it accounts for heteroskedasticity and correlation in the series. The Fama-MacBeth approach consists of running cross-sectional regressions for each quarter and then taking the time-series average of estimated coefficients.

Panel A uses the total sample. Panel B drops the third quarter of 1998 from the sample. Panel C drops the third quarter of 1998 and the first quarter of 1999 from the sample.

One-tailed significance at the 5 percent level denoted by *.

TABLE 4

**Pooled Regressions of Absolute Value of Quarter $t + 1$ Unexpected
Trading Revenues on Quarter t VAR-Based Volatility and Notionals**

Sample	Period (Number of observations)	Constant	$\sigma_{i,t}$ Slope (t-statistic)	Notional Slope	R-square
Panel A: $ R_{i,t+1} - E[R_{i,t+1}] = a + cNOT_{i,t} + \epsilon_{i,t+1}$					
Pooled Sample-OLS (N=8)	1995,Q1-2000,Q3 (175)	46.63 (3.34)		0.0176* (5.51)	14.9%
Pooled Sample-GLS (N=7)	1995,Q1-2000,Q3 (161)	4.26 (3.59)		0.0187* (7.51)	40.5%
Time Series (Fama-MacBeth)	1995,Q1-2000,Q3 (19)			0.0210* (4.62)	
Panel B: $ R_{i,t+1} - E[R_{i,t+1}] = a + b\sigma_{i,t} + cNOT_{i,t} + \epsilon_{i,t+1}$					
Pooled Sample-OLS (N=8)	1995,Q1-2000,Q3 (175)	-23.48 (-1.29)	1.54* (5.43)	0.0055 (1.49)	27.4%
Pooled Sample-GLS (N=7)	1995,Q1-2000,Q3 (161)	-1.17 (-0.54)	0.36* (3.42)	0.0117* (3.94)	43.0%
Time Series (Fama-MacBeth)	1995,Q1-2000,Q3 (19)		1.09* (2.38)	0.0110* (1.93)	
Panel C: $ R_{i,t+1} - E[R_{i,t+1}] /A_{i,t} = a + b(\sigma_{i,t}/A_{i,t}) + \epsilon_{i,t+1}$					
Pooled Sample-OLS (N=8)	1995,Q1-2000,Q3 (175)	3.25 (0.31)	1.32* (5.29)		13.9%
Pooled Sample-GLS (N=7)	1995,Q1-2000,Q3 (161)	3.21 (0.87)	0.44* (3.45)		41.0%
Time Series (Fama-MacBeth)	1995,Q1-2000,Q3 (19)		1.52* (2.94)		
Panel D: $ R_{i,t+1} - E[R_{i,t+1}] /A_{i,t} = a + b(\sigma_{i,t}/A_{i,t}) + c(NOT_{i,t}/A_{i,t}) + \epsilon_{i,t+1}$					
Pooled Sample-OLS (N=8)	1995,Q1-2000,Q3 (175)	-13.68 (-1.22)	1.09* (4.31)	0.0192* (3.39)	19.3%
Pooled Sample-GLS (N=7)	1995,Q1-2000,Q3 (161)	4.46 (1.18)	0.32* (2.30)	0.0213* (5.10)	41.6%
Time Series (Fama-MacBeth)	1995,Q1-2000,Q3 (19)		1.35* (2.59)	0.0140* (2.31)	

Notes: $R_{i,t+1}$ is the quarterly trading revenue, $E[R_{i,t+1}]$ is the expected trading revenue in quarter $t + 1$ based on a moving average of the last four quarters, $\sigma_{i,t}$ is the VAR-based volatility in unexpected trading revenue for bank i in quarter t , and $NOT_{i,t}$ is the notional derivatives amount for bank i in quarter t . In Panels C and D, the variables are scaled by the previous quarter's assets $A_{i,t}$. See Table 3 for explanations of pooled OLS, GLS and time-series regressions.

One-tailed significance at the 5 percent level denoted by *.