Empirical Evidence on Bank Trading Risk and Systemic Risk

Philippe Jorion

University of California at Irvine

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Correspondence can be addressed to:

Philippe Jorion
Graduate School of Management
University of California at Irvine,
Irvine, CA 92697-3125
Phone: (949) 824-5245, E-mail: pjorion@uci.edu

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ABSTRACT

This paper provides an empirical analysis of the risk of trading revenues of U.S. commercial banks. We collect quarterly data on trading revenues, broken down by business line, as well as the Value at Risk-based market risk charge. The overall picture from these preliminary results is that there is a fair amount of diversification across banks and within banks across business lines. These low correlations do not corroborate systemic risk concerns. Neither is there evidence that the post-1998 period has witnessed an increase in volatility of trading revenues.

JEL Classifications:

Keywords: Trading; systemic risk; market risk disclosures; value at risk; Basel Committee

I. INTRODUCTION

The last decade has witnessed a revolution in financial risk management. Quantitative techniques such as option pricing, portfolio insurance, and Value at Risk (VAR) have become essential tools of portfolio management. The generalized use of these techniques, however, has raised concerns that they could induce similar trading patterns, or "herding," across banks using VAR systems to limit their risks. As the argument goes, some exogenous shock to volatility could push VAR above the limit, forcing banks to liquidate their positions, further depressing falling prices.

If so, the generalized use of risk management systems could cause higher volatility in times of stress, perversely making financial markets less safe than before. This could raise the prospect of systemic risk, which arises when a shock threatens to create multiple simultaneous failures in financial institutions.

Various theories have been advanced to explain herding behavior. A necessary precondition for herding is that investors within a group tend to buy (or sell) when similar participants buy (or sell). This could reflect the belief that other investors have superior information, as in informational cascade theories.[1] Alternatively, another class of contagion theories emphasizes the effect of liquidity shocks, which force some market participants to liquidate their holdings to obtain cash, perhaps due to a call for additional collateral.[2] This applies to participants with high leverage, such as bank proprietary trading desks or hedge funds. The herding effect due to VAR is closest to this latter explanation. We can classify these herding theories into "information-based" and "constraint-based" theories.

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[1] See Bikhchandani et al. (1992), Banerjee (1992), or more recently Morris and Shin (1998). Bikhchandani et al. (1998) provide a useful survey of contagion models based on information asymmetries.

[2] See Kodres and Pritsker (2002).

In practice, the VAR-induced herding effect depends on commonalities in the positions in financial institutions. As Morris and Shin (1999) have stated, "One theme which has emerged in the subsequent debate on the performance of the risk management systems has been the criticism that many financial entities entered the period of turbulence with very similar trading positions."

Thus, VAR herding requires similar positions across VAR-constrained institutions. This study tests this hypothesis by investigating the ex-ante and ex-post trading risk profile of U.S. commercial banks based on quarterly banking reports over the period 1995 to 2003. These reports contain information on quarterly trading revenues broken down by risk factor category as well as the overall VAR-based market risk charge. Using segment information, broken down into fixed-income, currencies, equities, commodities categories, should prove useful to detect commonalities in positions. To my knowledge, this is the first paper to do so.

Similar positions should be revealed by high correlations between banks' trading revenues, as well as between banks' VAR measures. We also examine correlation patterns across risk categories to assess diversification effects. Finally, we examine the variance of aggregate trading returns from banks in the sample and break it down into different components to examine diversification effects across the industry. As a by-product of the analysis, we evaluate the profitability of bank trading revenues. This research also contributes to the literature on diversification in banking.[3]

This paper is structured as follows. Section II provides a review of VAR and herding theories. Section III presents the empirical analysis and Section IV concludes.

[3] Stiroh (2004) provides a review of this literature. He shows that non-interest income has increased in importance for U.S. banks and is much more volatile than traditional interest income, based on accounting data.

II. VAR AND SYSTEMIC RISK

In recent year, VAR has become a universally-accepted benchmark for measuring market risk. The Basel Committee on Banking Supervision (BCBS), for example, provides annual descriptions of market risk disclosures by banks and securities houses. In 1993, only 5 percent of the sample reported VAR information. By 2001, this proportion had gone up to 98 percent. In addition to its role as a ubiquitous *passive* risk measure, VAR has become a tool for the *active* management of risk, including setting risk limits and capital charges. Much of this development was spurred by regulatory standards.

The VAR Capital Charge

The use of internal VAR models was officially sanctioned by the Basel Committee on Banking Supervision (BCBS), which amended the 1988 Basel Accord to include a charge for market risk (BCBS 1995, 1996a). Since January 1998, banks have had 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. This has led to a widespread movement toward VAR because in practice, the internal model approach leads to lower capital charges than the standardized model.

To use the internal model approach, a bank must satisfy various qualitative requirements first. The bank must demonstrate that it has a sound risk management system, which must be integrated into management decisions. Notably, the bank has to use the regulatory VAR forecast directly for management decisions. This point is important, as it forces commercial banks to use the same parameters as dictated by the Basel rules.

When the qualitative requirements are satisfied, the market risk charge is based on the following quantitative parameters for VAR: (i) a horizon of 10 trading days, or two calendar weeks, (ii) a 99 percent confidence interval, (iii) an observation period based on at least a year of historical data and updated at least once a quarter.[4] In practice, banks are allowed to compute their 10-day VAR by scaling up their 1-day VAR by the square root of 10.

The Market Risk Charge (MRC) is then computed as the sum of a general market risk charge and a specific risk charge. The later represents the risk of individual issues that is not reflected in the general market risk measure. The general market risk charge is taken as the higher of the previous day's VAR, or the average VAR over the last 60 business days, times a "multiplicative" factor k:

$$\mathrm{MRC}_t = \mathrm{Max}(k \frac{1}{60} \sum_{i=1}^{60} \mathrm{VAR}_{t-i}, \mathrm{VAR}_{t-1}) + \mathrm{SRC}_t \qquad (1)$$

where k is to be determined by local regulators, subject to an absolute floor of three.[5] In practice, the first term in the parentheses is binding because it is multiplied by a factor of at least three. Banks are also subject to a backtest that compares the daily VAR to the subsequent P&L. Banks that fail the backtest can be subject to an increase in k from three to four.[6]

In this application, VAR is used to determine a minimum amount of equity capital that the bank must carry as protection against market risk. It can be viewed as a measure of "economic capital" to support the trading activities.

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[4] More precisely, the average "duration" of historical observations must be at least six months.

[5] The specific risk charge is explained in more detail in the Basel Amendment (1996).

[6] The backtesting procedure consists of matching daily VAR with the subsequent P&L. If a loss exceeds the VAR, an exception is said to have occurred. Banks can have up to four exceptions over the previous year. Beyond four exceptions, k is increased progressively, subject to the regulator's evaluation of the cause for the exception, and reaches four for 10 or more exceptions.

The VAR Vicious Circle Hypothesis

Some recent literature has emphasized the limitations of VAR. VAR is a single summary measure of downside loss. Because VAR only represents one quantile of the P&L distribution, it gives no indication about the tail loss, beyond the quantile. In theory, traders could willfully attempt to "game" their VAR limit by altering the distribution of P&L to satisfy a fixed VAR at the expense of a small probability of large losses.[7]

Other authors argue that wide-spread use of VAR could actually increase systemic risk. The new aspect of the Basel market risk charge is that, for the first time, it creates capital requirements that are risk-sensitive. The internal model approach was put into operation in January 1998. It so happened that 1998 was a tumultuous year.

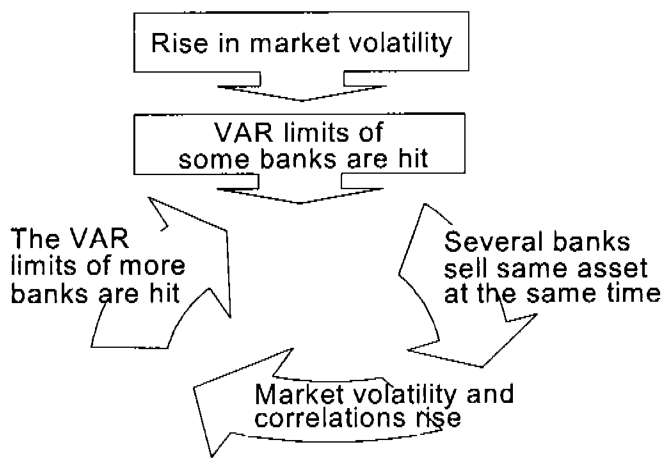
The Russian default triggered turbulences in financial markets that led to the collapse of the hedge fund LTCM. In the search for culprits, fingers have been pointed to the generalized use of risk measures, such as VAR. Some observers claimed that the application of strict VAR limits led to position-cutting by traders, which put additional downward pressures on prices. These claims have been advanced by Dunbar (2000) in his book on LTCM, by Persaud (2000), and have also been echoed in the press. Likewise, Scholes (2000) states that "banks and financial entities… add to the volatility in financial crises."

The argument is that some shock in volatility, say due to the Russian default, increases the VAR of outstanding positions. In 1999, the Economist has argued that, as VAR goes up, a "bank is then faced with two choices: put in extra capital or reduce its positions, whatever and

[7] See for instance Ju and Pearson (1999) for an analysis at the trader's level. Basak and Shapiro (2001) examine the effect of this gaming at the level of the institution on financial markets. They show that strict VAR limits could induce banks to take on more risk in bad states of the world, i.e. after VAR limits have been breached, which could cause higher volatility in financial markets. On the other hand, Cuoco and Liu (2002) argue that the VAR limit should be implemented on a dynamic basis. They find that capital requirements advocated by the Basel Committee can be very effective in curbing the risk of trading portfolio and inducing truthful revelation of this risk.

wherever they may be. This is what happened last autumn." As the argument goes, several banks could sell the same asset at the same time, creating higher volatility and correlations, which exacerbates the initial effect, forcing additional sales. This VAR "vicious circle" hypothesis is described in Figure 1. The troubling conclusion is that VAR tools increase volatility and are inherently dangerous.[8]

FIGURE 1. The VAR Vicious Circle Hypothesis



This line of argument should be a serious source of concern given the generalized trend toward risk-sensitive capital adequacy requirements. The current revision of the Basel credit risk charges, dubbed "Basel II", also go in the direction of more sensitive risk charges. The worry is that the design of such capital adequacy requirements might destabilize the financial system, by inducing banks to tighten credit as credit risk increases, precisely at the wrong time in a recession. This prospect of "procyclicality" is perhaps the most important issue facing bank

[8] Even so, many other reasons can also contribute to a practice of selling in a falling market. Typical examples are positive feedback technical trading rules or stop-loss rules. Margin calls can also lead to liquidation sales after prices have fallen. Schinasi and Smith (2000) also argue that the practice of rebalancing to fixed weights with leverage also creates similar trading patterns.

regulation today. While it is beyond the scope of this paper to discuss procyclicality of credit risk rules, the question is whether this "vicious circle" argument does apply to the market risk charges.

This argument requires most VAR-constrained traders to start from similar positions. Otherwise, they could simply cross their trades with little effect on prices. Ultimately, positions cannot be directly compared as these data are proprietary and jealously guarded. Instead, we can examine correlations in trading revenues.

Correlations in Positions and Returns

This section reviews empirical approaches to theories of herding. Realized returns reflect positions and innovations in risk factors. Consider a daily horizon indexed by t. Call $x(i,t-1)$ the dollar position on asset i at the end of day $t-1$. This is the number of units $n(i,t-1)$ times the unit value $S(i,t-1)$. For now, the position is assumed unchanged over the next day. Define $R(i,t-1)=[S(i,t)-S(i,t-1)]/S(i,t-1)$ as the rate of return on the asset, which is unitless. The dollar return on the position is then

$$x(i,t-1)\, R(i,t) = n(i,t-1)\, S(i,t-1)\, R(i,t)$$

Contemporaneous correlations across portfolios can arise for a number of reasons. With fixed positions, correlations in returns can arise because of correlations in the risk factors. Or, correlations could occur because positions change together. This could reflect herding.

It is axiomatic that every trade has a buyer and seller. Herding therefore must refer to a subset of participants, e.g. financial institutions. It is often thought that institutions are more likely to herd because their information set may be more homogeneous. "Information-based" herding implies that movements in the positions depend on actions of other investors k

$$\Delta n(i,t) = f[\Delta n^k(i,t) \ldots] \quad (2)$$

where correlations must be positive. Herding implies buying or selling an asset when others are doing the same. One class of herding models emphasizes information asymmetries as the source of herding. Investors may imitate the transactions of others whom they think have a special information advantage.

Tests of herding usually focus on portfolio positions for a subgroup of investors. Unfortunately, these tests are contaminated by other effects. Portfolio positions could change together because of common new information I:

$$\Delta n(i,t) = f[\, I(i,t-1) \ldots] \quad (3a)$$

For instance, a positive shock to interest rates may make stocks less attractive, leading to simultaneous sales by many investors. Alternatively, correlations in portfolio adjustments could be due to similar trading patterns. Technical trading rules, for instance, are defined as movements in the positions that depend on previous movements in the risk factor

$$\Delta n(i,t) = f[\, R(i,t-1) \ldots] \quad (3b)$$

As an example, momentum investors will tend to buy an asset that just went up in value. This creates positive correlations across momentum investors that has nothing to do with herding. Alternatively, arbitrage trading can take place if the current basis, or difference between the cash and forward prices S and F, is out of line with the cash-and-carry relationship.

$$\Delta n(i,t) = f[\, S(i,t-1), F(i,t-1) \ldots] \quad (3c)$$

Again, arbitrageurs will buy at the same time the cheap asset, creating positive correlations across positions that have nothing to do with herding.

Empirical tests are bedeviled by this contamination effect. Among others, Kodres and Pritsker (1996) examine the behavior of institutional investors with large positions on major U.S.

futures contracts. They compute correlations between changes in daily positions within each group (broker-dealers, pension funds, commercial banks, foreign banks, and hedge funds). For a fixed contract i and two investors k and l within the same group, this is measured as

$$\rho[\Delta n^k(i,t),\ \Delta n^l(i,t)] \tag{4}$$

They report that average correlations within each group are close to zero, with a range of –0.30 to +0.34. This provides no evidence of herding. Even with positive correlations, however, these results would have been difficult to interpret because common movements could be due to similar trading strategies, e.g. momentum strategies or stock-index arbitrage for broker-dealers.

Alternatively, "constraint-based" herding theories can be tested by examining correlations among trading returns directly. The VAR vicious circle hypothesis postulates that bank traders start from similar positions, because they are forced to sell similar positions after the VAR limits are hit. If so, correlations among ex post trading revenues and ex-ante risk measures based on VAR forecasts should be high. But first, the issue is whether large-scale VAR models successfully predict the risk of trading portfolios.

Empirical Evidence on VAR and Trading Revenues

Berkowitz and O'Brien (2002) provide the first empirical study of the accuracy of banks' internal VAR models. Their paper uses daily VAR and trading revenue data for six U.S. commercial banks over the period January 1998 to March 2000, or approximately 500 trading days. The data are confidential because they are provided in the course of the bank's regulatory examination. Because of the confidential nature of the data, cross-sectional tests are not provided.

Instead, the authors perform unconditional and conditional coverage time-series tests. Their main result is that, relative to their actual P&L, banks report VAR measures that are conservative. In other words, the reported VAR numbers are much too large. For four out of six banks, the average VAR is 1.6 to 3 times the actual 99^{th} percentile P&L. Put differently, the number of exceptions is too low. Only one bank had more than three exceptions over this period, when the expected number was five. Furthermore, most of these exceptions occurred during a short period, August to October 1998. These results are surprising because they imply that the VAR, and hence the market risk charge is too high. Banks therefore allocate too much regulatory capital to their trading activities.

Berkowitz and O'Brien give two explanations for this observation. First, P&L include fee income, but VAR forecasts do not. This increases the P&L, reducing the number of violations.[9] Second, they report that some VAR models are obtained by aggregating different sectors without taking correlations into account. By neglecting diversification effects, this practice overestimates VAR. These drawbacks, however, are straightforward to correct by the internal risk measurement system. By doing so, the banks would be releasing additional risk capital, or alternatively could be taking on more trading risk with the same amount of capital.[10]

Yet another, and simpler, explanation is that capital requirements are currently not binding. The amount of economic capital U.S. banks currently hold is in excess of their regulatory capital. As a result, banks prefer to report high VAR numbers to avoid the possibility of regulatory intrusion. This is possible because the market risk capital represents a small

[9] On the other hand, intra-day trading will typically increase the portfolio risk relative to close-to-close positions because trading positions are typically cut down toward the close of the day.
[10] Ewerhart (2002) advances another explanation attributed to adverse selection. Assuming all banks are well capitalized, banks can be separated into prudent and less prudent ones. Because the regulator cannot differentiate among banks, more prudent ones have an incentive to report conservative capital requirements.

fraction, about 2 percent only, of total regulatory capital.[11] Still, these practices impoverish the informational content of VAR numbers.

Berkowitz and O'Brien also find that a simple GARCH model appears to capture risk much better than the banks' structural models. This is not astonishing, however, because the 1-year observation period requirement imposed by the Basel rules disallows fast-moving GARCH models and lead to slowly-changing capital requirements.[12]

This analysis, however, is limited in time and ignores cross-sectional information. Using daily data also has drawbacks. GARCH processes decay relatively fast. Christoffersen and Diebold (2000) show that there is scant evidence of volatility predictability at horizons longer than ten days. Thus, there is little point in forecasting time variation in volatility over longer horizons. In addition, daily marking-to-market introduces pricing errors for illiquid positions and positions across time zones that tend to disappear over longer horizons.

Instead, Jorion (2002a) analyzes the informativeness of quarterly VAR numbers disclosed in financial reports. These are the only numbers available to the public. VAR measures appear to be useful forecasts of trading risks, especially in cross-sections. Time-series results for individual banks are less strong. VAR forecasts are significant only for four out of the eight banks in the sample.

Yet another approach is to focus on directly on the market risk charge, as described in Equation (1). Hirtle (2003) finds that market risk charges provide useful information about future trading risks. The MRC, however, could differ from end-of-period VAR because of the averaging process, the multiplier, and the specific risk charge.

[11] Hirtle (2003) reports a median ration of MRC to total capital requirement of approximately 1.9 percent.
[12] See Jorion (2002b) for a description of the movements in the market risk charge. RiskMetrics is not Basel-compliant because it has too much weight on recent data.

The current paper also focuses on movements in market risk charges. Commonalities in positions should be reflected in high correlations in changes in MRCs across banks. The paper will also examine correlations across trading revenues. Apparently, the only other paper that deals with this issue is that by Berkowitz and O'Brien, who report an average correlation of 0.17 only over the period January 1998 to March 2000. They also indicate that these correlations double over a 5-day horizon. This is why it is useful to examine a quarterly horizon, a longer sample period, and different types of trading activities.

III. EMPIRICAL EVIDENCE

Data Sample

This study uses trading income and risk data reported by large U.S. bank holding companies (BHC) to the Federal Reserve. All BHCs file quarterly balance sheet and income statement reports on forms Y-9C. Trading income is reported on Schedule HI, consolidated income statement, and the market risk charge (MRC) is reported on Schedule HC-R, regulatory capital. These are large, internationally-active banks that are most likely to raise systemic risk concerns.

An advantage of this data is that the MRC data are measured consistently across institutions, using the same parameters, and are reported as quarter-end figures. Banks also report VAR data in their quarterly and annual reports filed with the SEC. These financial reports often have more detail by risk categories, but are less consistent across banks and across time. Banks differ in their choice of the confidence level and in the reporting of quarter-average or quarter-end figures. In addition, the BHC database is more comprehensive as it covers institutions that do not file SEC reports.

The database reports quarterly MRC data starting in March 1998 and ending in September 2003.[13] In addition, we collect total assets, equity, trading assets and liabilities, derivatives notional, and total trading revenues. Trading revenues are broken down into fixed-income, currency, equity, and commodity categories. The detailed trading revenue series start in March 1995.

There is a total of 40 BHCs that have non-zero entries in the MRC field over the 1998-2003 sample period. For the correlation analysis, this study requires a continuous sample over the same period. Hence, the sample is restricted to the 11 BHCs with complete histories over the 1998-2003 period. This is the most important group anyway. It accounts for 95% of the value of the aggregate market risk charge in March 1998 and 92% at the end of the period.

Mergers and acquisitions, however, are frequent occurrences that require special treatment. We reconstructed the time series of the merged entity by adding up the series for the separate institutions. For instance, total assets for JP Morgan Chase before September 2000 are taken as the sum of assets for the two banks before the merger. This is only an approximation because it ignores transactions between the two banks. This procedure also overestimates the VAR of the merged entity, which is likely to be less than the sum of the separate VARs due to diversification effects.[14] This procedure is conservative, however.

[13] In practice, the MRC is reported as a "market risk equivalent asset" figure, which is the MRC divided by 8 percent. This figure is then added to the credit risk-weighted assets. The total capital requirement is a minimum of 8 percent of the total. Therefore, the numbers we report are the reported market risk equivalent assets (item 1651) multiplied by 8 percent and translated into millions of dollars.

[14] Strictly speaking, the VAR of a portfolio can only be less than the sum of the individual VARs for elliptical distributions. Atrzner et al. (2001) show pathological cases where this so-called "coherence" property is not satisfied.

Summary Statistics

Table I displays the 11 BHCs with a complete time-series history over the 23 quarters.[15] Over this five-year period, nearly all banks have increased in size. Total assets have grown by 34%, equity by 56%, and derivatives notional by 118%. The major exception is Deutsche Bankers Trust (DBT), whose operations were wound down after its acquisition by Deutsche Bank. At the start of the sample period, however, it had one of the biggest trading operations.

Table II displays trading position data for the bank sample. It shows the size of trading assets, trading liabilities, and of the Market Risk Charge. Comparing the two tables, we see that trading assets account for approximately 14% of total assets as of 2002. Three banks, JPM Morgan Chase, Bank of America, and DBT, have relatively large trading operations in terms of relative size of trading assets. Trading liabilities amount to approximately 50% of trading assets. Like derivatives, however, these are traditional accounting numbers. Notional amounts are not very informative because they fail to capture the risk and correlations of positions, which is better measured by the MRC.

The Market Risk Charge

We now turn to the description of the market risk charge. This amounted to $6.7 billion in total for these 11 banks as of 2002. In relation to total assets or equity, however, this is a small number. The MRC averages about 1.4% of total dollar assets, or 2.4% of total dollar equity. This masks differences across banks, however. As of December 2002, JP Morgan Chase and Bank of America had the biggest trading operations, with an MRC/equity ratio of 6.3% and 4.6%, respectively. At the other extreme, Keycorp's MRC is only 0.2% of equity.

[15] This sample includes all 8 banks analyzed by Jorion (2002a), of which 2 disappeared due to mergers (JP Morgan and NationsBank).

The aggregate MRC has hardly changed over this 5-year period, increasing from $6.5 to $6.7 billion only. This number, however, is mainly driven by large banks and is partly offset by a large drop in the MRC for DBT. Figure 2 displays the MRC for all 11 banks. Apart from DBT, the MRC experiences steady increases. Some banks with low initial MRC, such as Mellon Bank, State Street, and Wells Fargo, do increase their market risk substantially in relative terms. To abstract from size, we compound the average of the quarterly rate of growth for various series across banks. Figure 3 compares the growth of the MRC, trading assets, bank equity, and bank assets. For the average bank, trading has become more important over the last five years.

We now examine the time-series behavior of the MRC, an ex ante measure of risk. Table III displays the quarterly *relative* change in the MRC, along with summary statistics. Note that the average rate of change is systematically much smaller than the standard deviation. As a result, t-statistics do not allow us to reject the hypothesis of zero mean change in the MRC. The only exception is Mellon Bank, for which the t-statistic is 2.1.

Since some observers have blamed VAR for the volatility experienced in the third quarter of 1998, we would expect to see a sharp increase in the aggregate VAR from June to September 1998. Instead, the relative change in total VAR is only 4.5%, which is within the range of typical fluctuations in VAR. There is no evidence that the market risk charge went up sharply during this period. Perhaps market volatility went up and positions were cut, however.

Finally, the bottom of Table III displays the correlation matrix between changes in VAR. The average correlation is -0.03, which is close to zero. Only one correlation among is the 55 entries is significantly different from zero. The correlation between the two biggest trading operations, JP Morgan Chase and BofA, is 0.30, which is still small.

To measure diversification effects, we can focus on the volatility of the average (equally-weighted) value of x_i:

$$\sigma^2[(1/N)\Sigma x_i] = (1/N)^2 [\Sigma_i \sigma^2_i + \Sigma_i \Sigma_{i \neq i} \sigma_i \sigma_j \rho_{ij}] \quad (5)$$

The average volatility is $(1/N) [\Sigma_i \sigma_i] = 29.9\%$. This would be the volatility of the average with perfect correlations. On the other hand, if the series were uncorrelated, the volatility of the average should be $(1/N) [\Sigma_i \sigma^2_i]^{1/2} = 10.2\%$. Instead, the volatility of the average, which is shown in the last column, is 7.8% only. This low number reflects the many negative correlations across series. In other words, there seems to be substantial idiosyncratic movement in the market risk charge. Thus, there is no support for the hypothesis that VAR measures move strongly together.

Trading Revenues

Next, Table IV reports measures of trading revenues. The first column reports the average annual trading revenue in dollars. This is annualized by multiplying the quarterly average by four. The numbers are all positive but are hard to compare to each other because the scale of the operations are so different. Instead, the second column reports the average of the quarterly trading revenue deflated by beginning-of-quarter trading assets, which is similar to a "return-on-assets" measure (rather, revenue-on-assets since expenses are not taken into account). The range of values is striking. Many banks return less than 5%. Two banks, however, return more than 10%. These banks, Mellon and State Street, have relatively small trading assets.

The next column deflates trading revenues by book equity instead, giving a metric similar to "return-on-equity". This is also an incomplete measure because equity supports not only market risk but also other risks. Here also, there is a wide dispersion in ratios. The ordering of banks is generally similar to that in the previous column, except for JP Morgan Chase which now ranks with the highest ratio, because it has relatively less equity devoted to other activities than trading.

We verify whether these results still hold when using the market risk charge as the denominator instead of trading assets. The next column reports the average of trading revenue deflated by the beginning-of-quarter MRC, which can be interpreted as economic risk capital required to support the trading activity. The ratios are all very high, reaching 1,069% per annum for State Street. The ratio for the total is 184%. Even after deduction of expenses, these ratios seem high.

Assume for instance that costs account for 80% of revenues, which is a high but conservative number.[16] This gives a net return before taxes to the MRC of $184\%\times(1-80\%) = 37\%$, which is still very high. For Citicorp, for instance, the table implies a net return on MRC of $852\%\times0.20=170\%$. This is much higher than its total return to equity of about 30% over recent years. For this sample, 7 banks out of 11 show a ratio of trading revenue to MRC above 184%. Either proprietary trading has been very profitable over these years, or the MRC is too low as a measure of economic capital.

The right side of Table IV then decomposes trading revenues into its four categories. Based on total dollar revenues, fixed-income trading accounts for 35% of the total; currency trading for 45%, equity trading for 16% and commodity trading for 4%. Smaller banks tend to specialize in currency and fixed-income trading and are thus less diversified.

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[16] Citicorp, for instance, experienced an overall ratio between 60 and 65% over the last three years. This is measured as operating expenses divided by net interest income plus other revenues.

We then turn to a correlation analysis of trading revenues. To increase the sample size, the analysis starts in March 1995, for a total of 35 quarters instead of 23 in the previous sample. Trading revenues are deflated by trading assets at the beginning of each quarter to produce a rate of return. Table V presents the volatility of scaled trading revenues and their correlations. The next-to-last column is the total, aggregate number. This is a value-weighted aggregate obtained by scaling the total dollar trading revenues by total dollar trading assets. The last column represents the arithmetic, or equally-weighted average of the rate of return for the 11 banks.

The table shows that correlations are generally low. The average correlation is 0.163 only. Note that there is substantial imprecision in these numbers. Under the null of zero correlation, for example, the standard error is 0.177. Thus, there is no evidence that trading activities for these banks are highly correlated. The mark-to-market values of the positions are relatively uncorrelated. The main exception is for the two largest trading operations, JP Morgan Chase and BofA, which have a high correlation coefficient of 0.709. These banks account for 52% and 17% of total trading assets for this sample, respectively.

Figure 4 plots the quarterly trading revenue for the industry as a whole, scaled by total trading assets. The top line represents the equal-weighted average, the bottom line the value-weighted average. The equal-weighted average is higher, reflecting the higher profitability of smaller banks when scaling by trading assets. The value-weighted index drops to a slightly negative only once, during the third quarter of 1998. This reflects the losses suffered by the larger banks during the LTCM crisis. The equal-weighted index, however, only registers a small drop during this quarter.

As before, we can measure the diversification effect by comparing the average volatility and the volatility of the equally-weighted average. The average volatility, which assumes no diversification effects, is 1.13%. If the series were totally uncorrelated, the volatility of an equally-weighted portfolio should be 0.46%. Instead, the volatility of the average, which is shown in the last column, is 0.64% only. This number is slightly higher than the uncorrelated volatility but still much lower than the undiversified volatility of 1.13%, confirming that the trading risk of the commercial banking system is rather diversified.

Perhaps these results mask high correlations for some categories of trading. To check this, Table VI provides a more detailed analysis by trading category. The table describes the distribution of correlation coefficients for fixed-income, currency, equity, and commodity trading.[17] The averages are all low, ranging from -0.039 to 0.149, indicating little commonality in trading positions within each category. Even the fixed-income positions, often thought to be similar to those assumed by LTCM, have low correlations.[18] Equity trading portfolios have the highest correlation, which averages 0.149, still a low number.

The table also shows diversification effects across categories for each bank. The risk decomposition panel lists volatilities scaled as a percentage of each bank's trading risk. The first four categories correspond to the individual risk of each trading line. For JP Morgan Chase, for instance, the trading risk is 62.6% of the total for fixed-income, 29.6% for currencies, 34.5% for equities, and 30.2% for commodities. These numbers are representative of the industry as a whole, with more trading risk coming from fixed-income products. These entries sum to an "undiversified" risk of 156.7% of the actual risk. The difference, or 56.7%, is a diversification effect. The table shows substantial diversification effects across trading categories. The average

[17] Not all banks engage in trading activities across all categories. All banks were active in fixed-income and currencies, but only 8 banks report equity trading, and 9 banks commodity trading.

[18] Notably, JP Morgan Chase and BofA have a correlation of 0.512, 0.157, 0.680, and 0.322, for fixed-income, currency, equity, and commodity risk, respectively. So, the high correlation of 0.709 for their total trading is not driven by fixed-income positions.

diversification effect is 74%. This effect is visually confirmed by Figure 5, which shows the four components of the equally-weighted index of the 11 banks in the sample. Thus, these banks are fairly diversified across risk categories.

To provide more insight into correlations, Table VII investigates commonalities in trading revenues. Quarterly trading returns are regressed on factors often selected as significant in each market. This approach is similar to the style analysis of hedge funds performed by Fung and Hsieh (1997) and uses similar factors. For the fixed-income market, these are the JP Morgan U.S. and non-U.S. government bond indices, the 3-month Eurodollar rate, and the change in the Baa to 10-year Treasury spread.[19] For the currency markets, these are the changes in the yen, pound, and mark (or euro). For the equity market, these are the changes in the MSCI U.S., MSCI non-U.S., IFC emerging market, and Russell 2000 small-stock indices. For the commodity market, these are the changes in the price of gold, oil, and the Goldman Sachs Commodity Index.

Fund and Hsieh (1997) report that hedge funds have low R-squares with these risk factors, unlike mutual funds. While more than half the mutual funds have R-squares above 75%, half of the hedge funds have R-squares below 25%. This is because hedge funds pursue dynamic trading strategies and often take non-directional bets and.[20] We would expect that bank trading revenues have similar characteristics.

Table VII reports the cross-sectional average of the betas, R-square as well as the number of positive and negative betas. The table does not reveal systematic patterns. The average R-square is rather low, as for hedge funds. As in Table VI, the highest R-square, 0.215, is obtained

[19] This variable was found by Jorion (2000) to be highly correlated with monthly returns experienced by LTCM.
[20] Agarwal and Naik (2004) go one step further and also regress U.S. equity-based hedge fund returns on stock index options. They find that strategies such as event arbitrage, event-driven, and relative value arbitrage are equivalent to short positions in out-of-the-money puts.

for the equity trading portfolios. Most of the betas on US large stocks are positive and two are significant. The next highest R-square of 0.179 is obtained for the fixed-income market. There is no systematic exposure on these risk factors, however, across banks. Overall, this confirms that bank trading revenues have low commonalities.

Next, we provide a direct test of the hypothesis that the risk of trading portfolio has increased since the internal models approach, based on VAR, was put in place in 1998. Table VIII compares the volatility of scaled trading revenues before and after 1998. The evidence is inconclusive. Six banks had increased risk, five had lower risk, a few significantly so in either direction. Based on the value-weighted data, trading risk seems to have increased. Based on an equal-weighted portfolio, however, volatility went down post-1998. Similarly, the average of individual volatilities dropped from 0.0128 to 0.0084 in the post-1998 period. This does not suggest the average volatility of trading bank portfolio has increased over time.

Finally, Table IX revisits the trading performance of this bank sample, now adjusting for risk. This sample returned an average ratio of trading revenues to trading assets of 7.68%, with a volatility of 2.27%. The last columns show that these correspond to very high Sharpe ratios. The average ratio based on dollars trading revenues is 3.54 for this sample. Deflating trading revenues by trading assets gives a similar ratio of 3.42. These numbers are much higher than the Sharpe ratio of 1.30 for an aggregate hedge fund index reported by Asness et al. (2001).[21]

Perhaps these results are due to the shape of distribution of trading revenues. Table IX also reports skewness and excess kurtosis. The average skewness is close to zero; none is significant. Excess kurtosis is generally positive, with four significant entries. These numbers

[21] The data are over a similar period, January 1994 to September 2000. The Sharpe ratio for the S&P index is 1.39, also expressed in raw rather than excess returns.

are similar to those for hedge funds. Still, risk adjustments based on volatility alone should be viewed with caution.

These results are in line with those of Kwan (1997). He finds that trading is more profitable, but riskier, than banking activities.[22] Interestingly, he also reports that trading by primary dealer subsidiaries, which overlap with the large banks in our sample, has negative correlation with banking activities, providing diversification benefits to bank holding companies. No doubt this explains the increased focus on proprietary trading.

[22] Over the period 1990.II to 1997.II. Kwan (1997) reports average trading revenues over trading assets for primary dealers of 6.0%, with a volatility of 2.3%, using annual data.

IV. CONCLUSIONS

VAR systems and the discipline of risk-sensitive capital charges have focused the attention of financial institutions on improving risk management practices. The issue is whether the generalized use of these techniques could increase volatility in financial markets.

This study provides a first attempt at addressing this issue. In the absence of position data, it relies on the time-series behavior of market risk charges and trading revenues broken down by line of activity. This analysis must be qualified, however, by the use of quarterly returns that could mask the risk of proprietary trading portfolios, which follow dynamic trading strategies with even higher turnover than hedge funds.

Nevertheless, the overall picture from these preliminary results is that there is a fair amount of diversification across banks and within banks across business lines. There is also no evidence that the post-1998 period has witnessed an increase in volatility. Thus, arguments that bank trading and VAR systems contribute to volatility due to similar positions has no empirical support. As Fed Vice-Chairman Ferguson (2002) said in a recent speech, these concerns seem "overestimated."

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Table I
Summary Information for Bank Holding Companies
(Millions of Dollars)

	Total Assets		Equity		Derivatives Notional		Mergers
Bank Holding Company	Mar-98	Dec-02	Mar-98	Dec-02	Mar-98	Dec-02	
Deutsche Bank Trust Corp.	157,537	58,083	5,812	4,545	2,005,662	48,276	
Bank of NY Co.	59,611	77,564	4,812	6,684	242,253	413,133	
J P Morgan Chase & Co.	637,254	758,800	33,638	42,306	13,980,827	28,201,736	Chase&JPM to Sep-2000
Citicorp	330,414	727,337	21,471	73,540	2,768,682	8,043,202	
Keycorp	73,269	84,710	5,338	6,835	31,159	64,368	
Bank One Corp.	231,666	277,383	18,472	22,440	1,116,818	1,049,397	Banc One&First Chi. to Sep-1998
Mellon Financial Corp.	47,543	36,306	4,086	3,395	52,399	81,566	
Wachovia Corp.	237,090	341,839	17,586	32,078	127,431	1,794,589	Wachovia&First Union to Jun-2001
Bank of America Corp.	579,939	660,458	45,104	50,319	3,505,507	12,100,962	BankAm.&NationsBank to Jun-1998
State Street Corp.	39,010	85,794	2,077	4,788	111,079	232,264	
Wells Fargo & Co.	190,913	349,259	19,909	30,358	3,406	198,837	Wells Fargo&Norwest to Sep-1998
Total:	2,584,247	3,457,533	178,303	277,288	23,945,223	52,228,331	
Growth in Total:		34%		56%		118%	

Notes: Sample of 11 Bank Holding Companies (BHCs) with continuous market risk data from March 1998 to September 2003.
Data for merged banks are obtained by adding up data for separate entities.

Table II
Trading Positions for Bank Holding Companies
(Millions of Dollars)

	Trading Assets		Trading Liabilities		Market Risk Charge		Ratios, Dec-02			
Bank Holding Company	Mar-98	Dec-02	Mar-98	Dec-02	Mar-98	Dec-02	TrA/A	TrL/TrA	MRC/TrA	MRC/Eq
Deutsche Bank Trust	$60,363	$10,529	$29,118	$2,876	$1,419	$66	18.1%	27.3%	0.6%	1.4%
Bank of NY	$2,225	$7,309	$1,591	$2,800	$78	$43	9.4%	38.3%	0.6%	0.6%
J P Morgan Chase	$194,570	$248,301	$120,063	$133,091	$1,903	$2,663	32.7%	53.6%	1.1%	6.3%
Citicorp	$39,740	$49,042	$31,291	$26,371	$456	$505	6.7%	53.8%	1.0%	0.7%
Keycorp	$640	$2,561	$705	$2,088	$11	$15	3.0%	81.5%	0.6%	0.2%
Bank One	$9,321	$11,000	$6,442	$4,921	$222	$140	4.0%	44.7%	1.3%	0.6%
Mellon Financial	$650	$1,911	$524	$1,240	$25	$60	5.3%	64.9%	3.1%	1.8%
Wachovia	$7,879	$33,155	$6,597	$22,903	$362	$505	9.7%	69.1%	1.5%	1.6%
Bank of America	$54,425	$95,829	$31,004	$48,459	$1,905	$2,313	14.5%	50.6%	2.4%	4.6%
State Street	$1,118	$3,435	$1,078	$2,373	$11	$27	4.0%	69.1%	0.8%	0.6%
Wells Fargo	$2,223	$10,167	$124	$4,774	$69	$374	2.9%	47.0%	3.7%	1.2%
Total:	$373,153	$473,240	$228,538	$251,897	$6,461	$6,710	13.7%	53.2%	1.4%	2.4%
Average of ratios:							*10.0%*	*54.5%*	*1.5%*	*1.8%*

Notes: The table reports trading assets (TrA), trading liabilities (TrL), and the market risk charge (MRC) at two points in time.
The MRC is obtained by multiplying the reported market risk equivalent assets by 8%.
The ratios are for trading assets over total assets, trading assets over trading liabilities, MRC to TrA, and MRC over equity.
For the ratios, "Total" refers to the ratio of the dollar sum of trading assets over the sum of assets, for example.
"Average" refers to the arithmetic average of entries (ratios) for all 11 banks.

Table III
Properties of Relative Changes in Market Risk Charges

	Bank											VW	EW
	DB T	BoNY	JPM Cha	Citicorp	Keycorp	Bank On	Mellon	Wachovi	BofA	State St	Wells F	Total	Average
Jun-98	-5.5%	-54.7%	-3.5%	-10.5%	30.1%	-4.2%	-0.6%	-23.6%	21.9%	22.1%	157.1%	3.1%	11.7%
Sep-98	-28.3%	83.9%	35.0%	-13.7%	-55.4%	4.9%	3.4%	58.1%	-2.9%	5.8%	-19.4%	4.5%	6.5%
Dec-98	-29.1%	-15.5%	-9.0%	-9.1%	217.4%	-27.7%	5.8%	-2.2%	-14.9%	25.9%	-72.4%	-14.9%	6.3%
Mar-99	-8.4%	2.2%	-7.2%	2.5%	152.3%	0.9%	-17.8%	-25.1%	-0.1%	56.3%	65.1%	-4.3%	20.1%
Jun-99	-45.8%	-6.0%	-6.5%	2.4%	-35.9%	0.8%	12.7%	16.0%	-14.6%	34.1%	67.3%	-10.7%	2.2%
Sep-99	-57.6%	-7.3%	-5.9%	-7.1%	-5.6%	19.6%	5.0%	-11.5%	11.8%	17.1%	-26.6%	-3.5%	-6.2%
Dec-99	-18.2%	45.8%	-7.5%	-5.1%	5.6%	-27.0%	14.1%	-21.7%	7.7%	-16.6%	32.1%	-2.4%	0.8%
Mar-00	46.6%	-4.8%	14.8%	5.4%	-58.7%	-19.1%	28.2%	-1.2%	4.3%	47.5%	-18.4%	7.6%	4.0%
Jun-00	14.2%	-8.4%	2.4%	17.9%	-7.1%	137.1%	-8.6%	9.8%	3.2%	-10.1%	-33.8%	6.5%	10.6%
Sep-00	-7.2%	-16.5%	18.9%	-4.3%	15.8%	-44.9%	-3.3%	-10.2%	13.9%	-10.8%	-28.4%	8.4%	-7.0%
Dec-00	-71.3%	-39.4%	-19.2%	0.0%	29.4%	-47.8%	12.0%	30.3%	-20.8%	12.0%	49.1%	-18.1%	-6.0%
Mar-01	-41.4%	7.4%	-0.4%	0.0%	0.6%	56.1%	-12.4%	-6.1%	0.6%	-6.7%	18.7%	0.3%	1.5%
Jun-01	-10.4%	-2.2%	12.7%	4.5%	-5.2%	24.4%	4.2%	23.8%	20.9%	7.7%	20.9%	16.1%	9.2%
Sep-01	-22.1%	45.4%	-0.3%	-29.1%	10.0%	-10.7%	-2.2%	-9.7%	8.7%	4.9%	101.6%	2.4%	8.8%
Dec-01	24.3%	-9.4%	-10.5%	14.4%	-7.9%	14.3%	47.9%	8.0%	-7.0%	6.6%	-7.2%	-5.4%	6.7%
Mar-02	63.4%	-0.3%	17.5%	11.3%	-1.2%	16.6%	1.4%	5.1%	13.2%	-35.2%	73.9%	15.5%	15.1%
Jun-02	66.2%	-8.1%	-5.4%	35.5%	45.1%	17.6%	0.2%	2.2%	0.8%	1.9%	7.7%	1.8%	14.9%
Sep-02	-8.5%	-8.3%	11.5%	5.5%	-31.4%	-10.6%	13.1%	22.3%	-2.6%	0.7%	-1.6%	4.0%	-0.9%
Dec-02	-0.8%	16.8%	11.4%	6.3%	-10.3%	-26.9%	3.2%	4.1%	-11.6%	-27.1%	23.4%	0.5%	-1.1%
Mar-03	-8.4%	-1.8%	1.9%	1.7%	-11.7%	28.1%	42.9%	-17.5%	14.2%	-10.4%	-0.9%	5.2%	3.5%
Jun-03	-19.0%	54.3%	4.6%	-14.0%	31.7%	102.4%	8.0%	23.6%	-0.6%	-1.2%	33.0%	6.6%	20.3%
Sep-03	-2.6%	4.2%	98.7%	5.1%	-4.6%	2.1%	-1.6%	-6.8%	10.9%	9.8%	0.4%	41.0%	10.5%
Mean	-7.7%	3.5%	7.0%	0.9%	13.8%	9.4%	7.1%	3.1%	2.6%	6.1%	20.1%	2.9%	6.0%
SD	34.8%	30.6%	23.9%	13.1%	62.0%	43.8%	15.8%	20.2%	11.6%	22.1%	51.2%	12.0%	7.8%

Correlation Matrix

	DB T	BoNY	JPM Cha	Citicorp	Keycorp	Bank On	Mellon	Wachovi	BofA	State St	Wells F
DB T	1.000										
BoNY	-0.073	1.000									
JPM Chase	0.182	0.238	1.000								
Citicorp	**0.625**	-0.386	0.013	1.000							
Keycorp	-0.104	-0.225	-0.296	-0.093	1.000						
Bank One	0.141	0.188	-0.008	0.203	-0.130	1.000					
Mellon	0.128	-0.066	-0.162	0.115	-0.321	-0.145	1.000				
Wachovia	-0.134	0.334	0.119	0.034	-0.343	0.145	0.094	1.000			
BofA	0.293	-0.038	0.302	-0.103	-0.222	0.169	-0.122	-0.432	1.000		
State St	-0.197	-0.238	-0.123	-0.135	0.318	-0.193	-0.012	-0.107	-0.178	1.000	
Wells F	-0.026	-0.105	-0.175	-0.252	-0.057	-0.107	-0.209	-0.228	0.227	0.057	1.000

Notes: The top part of the table reports the quarterly rate of change in the banks' market risk charge (MRC), as well as that of the total for the 11 banks.
"VW Total" refers to the sum of the dollar MRCs.
"EW Average" refers to the arithmetic average of entries for all 11 banks.
The table also reports the mean value, the standard deviation, and the correlation matrix for these entries.
Asymptotic standard error of correlation is 0.229. Entry in bold is significant at the 5% level.

Table IV
Annual Trading Revenues for Bank Holding Companies
(June 1998 to Sept. 2003)

	Average Total Trading Revenue				Trading Revenue by Category			
Bank Holding Company	TrR	TrR/TrA	TrR/Eq	TrR/MRC	Fixed Inc.	Currency	Equity	Commod.
Deutsche Bank Trust	$2	0.4%	0.4%	149.9%	-$43	$70	-$36	$11
Bank of NY	$253	5.4%	4.3%	552.1%	$77	$175	$2	
J P Morgan Chase	$4,590	2.3%	12.0%	219.0%	$2,154	$1,081	$1,041	$315
Citicorp	$3,058	7.8%	8.0%	851.5%	$786	$1,965	$285	$22
Keycorp	$133	9.5%	2.1%	820.5%	$91	$33		$9
Bank One	$183	1.9%	0.9%	110.1%	$60	$98	$4	$20
Mellon Financial	$178	19.4%	4.7%	503.5%	$11	$157	$10	$0
Wachovia	$274	1.7%	1.2%	83.4%	$172	$86	$16	$0
Bank of America	$1,116	1.8%	2.4%	54.1%	$191	$490	$380	$56
State Street	$321	15.3%	10.5%	1068.7%	-$16	$337		
Wells Fargo	$287	8.2%	1.1%	267.0%	$168	$119		-$1
Total:	$10,396	2.78%	4.73%	183.77%	$3,651	$4,612	$1,701	$432
Average entry:	*$945*	*6.69%*	*4.31%*	*425.43%*	*$332*	*$419*	*$213*	*$48*

Notes: The table reports trading revenue (TrR) data averaged over the June 98 to Sept. 03 period and expressed in annual terms.
Trading revenue data are measured in millions of dollars and as a fraction of beginning-of-quarter trading assets, book equity, and the MRC.
"Total" refers to the aggregated series, which is the ratio of the sum of trading revenues over the sum of trading assets, equity, or MRC.
"Average" refers to the arithmetic average of entries for all 11 banks.

Table V
Volatility and Correlation of Trading Revenues
(Scaled by Trading Assets, March 1995 to Sept. 2003)

	Bank											VW	EW
	DB T	BoNY	JPM Cha	Citicorp	Keycorp	Bank On	Mellon	Wachovi	BofA	State St	Wells F	Total	Total
Volatility	0.0041	0.0078	0.0026	0.0062	0.0233	0.0036	0.0176	0.0046	0.0038	0.0162	0.0350	0.0026	0.0064
										Average=	*0.0113*		

Correlation Matrix

	DB T	BoNY	JPM Cha	Citicorp	Keycorp	Bank On	Mellon	Wachovi	BofA	State St	Wells F
DB T	1.000										
BoNY	0.064	1.000									
JPM Chase	**0.421**	0.198	1.000								
Citicorp	0.233	**-0.364**	0.245	1.000							
Keycorp	**0.442**	0.308	**0.456**	-0.127	1.000						
Bank One	-0.098	-0.297	-0.019	**0.464**	-0.245	1.000					
Mellon	0.109	0.217	0.143	0.102	0.335	-0.109	1.000				
Wachovia	0.249	**0.387**	**0.422**	-0.183	**0.432**	-0.163	0.124	1.000			
BofA	**0.442**	-0.028	**0.709**	0.343	0.330	0.187	0.244	**0.435**	1.000		
State St	0.197	0.344	0.051	-0.228	**0.375**	-0.214	**0.714**	0.261	0.083	1.000	
Wells F	0.204	0.174	0.041	-0.180	0.225	-0.081	0.031	0.102	0.156	0.282	1.000
										Average=	*0.163*

Memo: Trading Assets (millions of $)												
Mean	$32,438	$4,925	$184,231	$38,739	$1,203	$11,181	$898	$16,527	$60,259	$1,878	$3,313	$355,591
Fraction	9.1%	1.4%	51.8%	10.9%	0.3%	3.1%	0.3%	4.6%	16.9%	0.5%	0.9%	100.0%

Notes: The table describes the quarterly trading revenue scaled by beginning-of-quarter trading assets over the period March 1995 to Sept. 2003.
The table reports the quarterly volatility and the correlation matrix.
"VW Total" refers to the value-weighted series, obtained as the ratio of the sum of trading revenues over the sum of trading assets.
"EW Total" refers to the equal-weighted series, obtained as the average of ratios of trading revenues over trading assets.
"Average" refers to the cross-sectional average of entries for all 11 banks; for the correlation matrix, this is the average of non-diagonal entries..
Mean of trading assets gives the time-series average for each bank and its fraction of the total.
Asymptotic standard error of correlation is 0.177. Entry in bold is significant at the 5% level.

Table VI
Risk Analysis and Correlation of Trading Revenues by Category
(March 1995 to Sept. 2003)

	Bank											VW	
	DB T	BoNY	JPM Cha	Citicorp	Keycorp	Bank On	Mellon	Wachovi	BofA	State St	Wells F	Total	Average
Volatility	0.0041	0.0078	0.0026	0.0062	0.0233	0.0036	0.0176	0.0046	0.0038	0.0162	0.0350	0.0026	*0.0113*

Risk Decomposition (Percent of Total Volatility)

	DB T	BoNY	JPM Cha	Citicorp	Keycorp	Bank On	Mellon	Wachovi	BofA	State St	Wells F	VW Total	Average
Fixed-income	72.8%	52.0%	62.6%	65.0%	81.0%	68.3%	13.0%	92.3%	96.6%	115.5%	94.9%	61.9%	*74.0%*
Currency	33.3%	91.7%	29.6%	58.0%	35.8%	31.0%	97.1%	21.2%	35.0%	159.6%	26.7%	25.8%	*56.3%*
Equity	50.2%	5.9%	34.5%	29.9%		15.1%	13.0%	41.2%	33.6%			33.0%	*27.9%*
Commodity	8.6%		30.0%	30.2%	91.0%	82.0%	1.9%	2.1%	9.8%		5.0%	17.2%	*28.9%*
Sum	164.9%	149.6%	156.7%	183.1%	207.8%	196.3%	125.0%	156.7%	175.1%	275.1%	126.6%	137.9%	*174.3%*
Diversificatior	-64.9%	-49.6%	-56.7%	-83.1%	-107.8%	-96.3%	-25.0%	-56.7%	-75.1%	-175.1%	-26.6%	-37.9%	*-74.3%*
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	*100.0%*

Correlation statistics:

	Average	Median	Std.Dev.	Max	Min
All	0.163	0.197	0.245	0.714	-0.364
Fixed-income	0.069	0.049	0.180	0.512	-0.513
Currency	0.073	0.133	0.317	0.649	-0.672
Equity	0.149	0.131	0.321	0.680	-0.597
Commodity	-0.039	0.019	0.306	0.560	-0.735

Notes: The table describes the quarterly trading revenue scaled by beginning-of-quarter trading assets over the period March 1995 to Sept. 2003 for each of the subcategories, fixed-income instruments, currencies, equities, and commodities.
"VW Total" refers to the series constructed as the ratio of the sum of trading revenues over the sum of trading assets, using dollar amounts.
"Average" refers to the arithmetic average of entries for all 11 banks.
The top line reports the volatility over the sample period.
The middle panel provides a risk decomposition of volatility by category, as a percentage of volatility of total revenues.
The bottom panel describes the distribution of correlation coefficients within each trading category and the total.

Table VII
Tests of Stability in Volatility of Trading Revenues

	Bank											VW	EW
Volatility	DB T	BoNY	JPM Cha	Citicorp	Keycorp	Bank On	Mellon	Wachovi	BofA	State St	Wells F	Total	Total
1995-97	0.0029	0.0061	0.0022	0.0033	0.0259	0.0018	0.0194	0.0048	0.0017	0.0197	0.0534	0.0017	0.0067
1998-03	0.0044	0.0082	0.0028	0.0059	0.0149	0.0041	0.0171	0.0042	0.0045	0.0132	0.0133	0.0030	0.0053
F-test	0.428	0.557	0.589	0.327	3.017^{*-}	0.191	1.284	1.302	0.140^{*+}	2.211^{*-}	16.234^{*-}	0.337	1.602
(p-value)	(0.936)	(0.853)	(0.829)	(0.976)	(0.011)	(0.998)	(0.292)	(0.282)	(0.999)	(0.049)	(0.000)	(0.973)	(0.160)

Notes: The table describes tests of equality of variance across two subperiods for the quarterly trading revenue scaled by beginning-of-quarter trading assets.
The significance level for the F test is between parentheses. One-tailed significance at the 5 percent level indicated by $^{*-}$ for decreases and $^{*+}$ for increases.
"VW Total" refers to the series constructed as the ratio of the sum of trading revenues over the sum of trading assets, using dollar amounts.
"EW Total" refers to the series constructed from the arithmetic average of scaled trading revenues for all 11 banks.

Table VIII
Commonalities in Trading Revenues

Factors:	Fixed-Income				
Factors:	3mo Rate	US Gov Bonds	Non-US Gov	Baa-10y Spread	R-square
Average	-0.36	-0.01	0.06	0.41	0.179
Number positive	5	3	7	6	
Number negative	6	8	4	5	
	Currency				
Factors:	$/JPY	$/GBP	$/DEM		R-square
Average	-0.02	0.02	-0.01		0.094
Number positive	4	7	4		
Number negative	7	4	7		
	Equity				
Factors:	US Large	Non-US	Emerging	US Small	R-square
Average	0.41	0.06	-0.01	-0.59	0.215
Number positive	7	5	3	2	
Number negative	1	3	5	6	
	Commodity				
Factors:	Gold	Oil	GSCI		R-square
Average	0.37	-0.64	-0.03		0.062
Number positive	4	4	3		
Number negative	3	3	4		

Notes: The table summarizes regressions of trading returns on risk factors in each category, using quarterly data from March 1995 to Sept. 2003.
Risk factors for the fixed-income markets are the 3-month Eurodollar rate, the return on the JPM U.S. and non-U.S. government bond indices, and in the Baa to 10-year Treasury spread.
Risk factors for the currency markets are the changes in the dollar/yen rate (JPY), British pound rate (GBP), and German mark (or euro) rate (DEM).
Risk factors for the equity markets are the MSCI U.S. and non-U.S. indices, the IFC emerging market index, and the Russell 2000 small-stock index.
Risk factors for the commodity markets are the changes in the prices of gold, oil, and Goldman Sachs Commodity Index (GSCI).
"Average" line reports average betas and R-square.
"Number positive" or "negative" reports the number of betas that are positive or negative.

Table IX
Risk-Adjusted Performance of Trading Activities
(March 1995 to Sept. 2003, Annualized)

	Average Trading Revenue		Volatility		Skewness	Exc. Kurtosis	Sharpe Ratio	
Bank Holding Company	TrR	TrR/TrA	TrR	TrR/TrA	TrR/TrA	TrR/TrA	TrR	TrR/TrA
Deutsche Bank Trust	$281	0.8%	$355	0.8%	-1.17	1.92	0.79	0.98
Bank of NY	$193	6.0%	$51	1.6%	0.53	-0.93	3.81	3.88
J P Morgan Chase	$4,149	2.4%	$960	0.5%	-0.46	0.06	4.32	4.60
Citicorp	$2,542	6.7%	$508	1.2%	0.45	-0.61	5.00	5.40
Keycorp	$98	13.5%	$40	4.7%	1.25	**4.42**	2.48	2.90
Bank One	$170	1.6%	$65	0.7%	1.61	**4.34**	2.62	2.26
Mellon Financial	$149	19.8%	$23	3.5%	-0.04	-0.70	6.56	5.61
Wachovia	$226	2.2%	$109	0.9%	0.27	0.23	2.08	2.37
Bank of America	$1,057	2.0%	$403	0.8%	-1.39	**5.85**	2.62	2.62
State Street	$270	17.2%	$46	3.2%	0.79	0.21	5.90	5.28
Wells Fargo	$218	12.3%	$79	7.0%	1.13	**5.61**	2.75	1.76
Total:	$9,355	2.74%	$1,846	0.52%	-0.40	1.44	5.07	5.29
Average entry:	*$850*	*7.68%*	*$240*	*2.27%*	*0.27*	*1.85*	*3.54*	*3.42*

Notes: The table reports trading revenue (TrR) data averaged over the March 95 to Sept. 03 period and expressed in annual terms.
Trading revenue data are measured in millions of dollars and as a fraction of beginning-of-quarter trading assets (TrA).
The table reports the annualized average, volatility, and Sharpe ratio, or ratio of average to volatility.
"VW Total" refers to the series constructed as the ratio of the sum of trading revenues over the sum of trading assets, using dollar amounts.
"Average" refers to the arithmetic average of entries for all 11 banks.
Asymptotic standard error of skewness and excess kurtosis is 2.42 and 1.21, respectively. Entries in **bold** are significant at the 5% level.

Fig. 2. Market Risk Charge (Millions of Dollars)

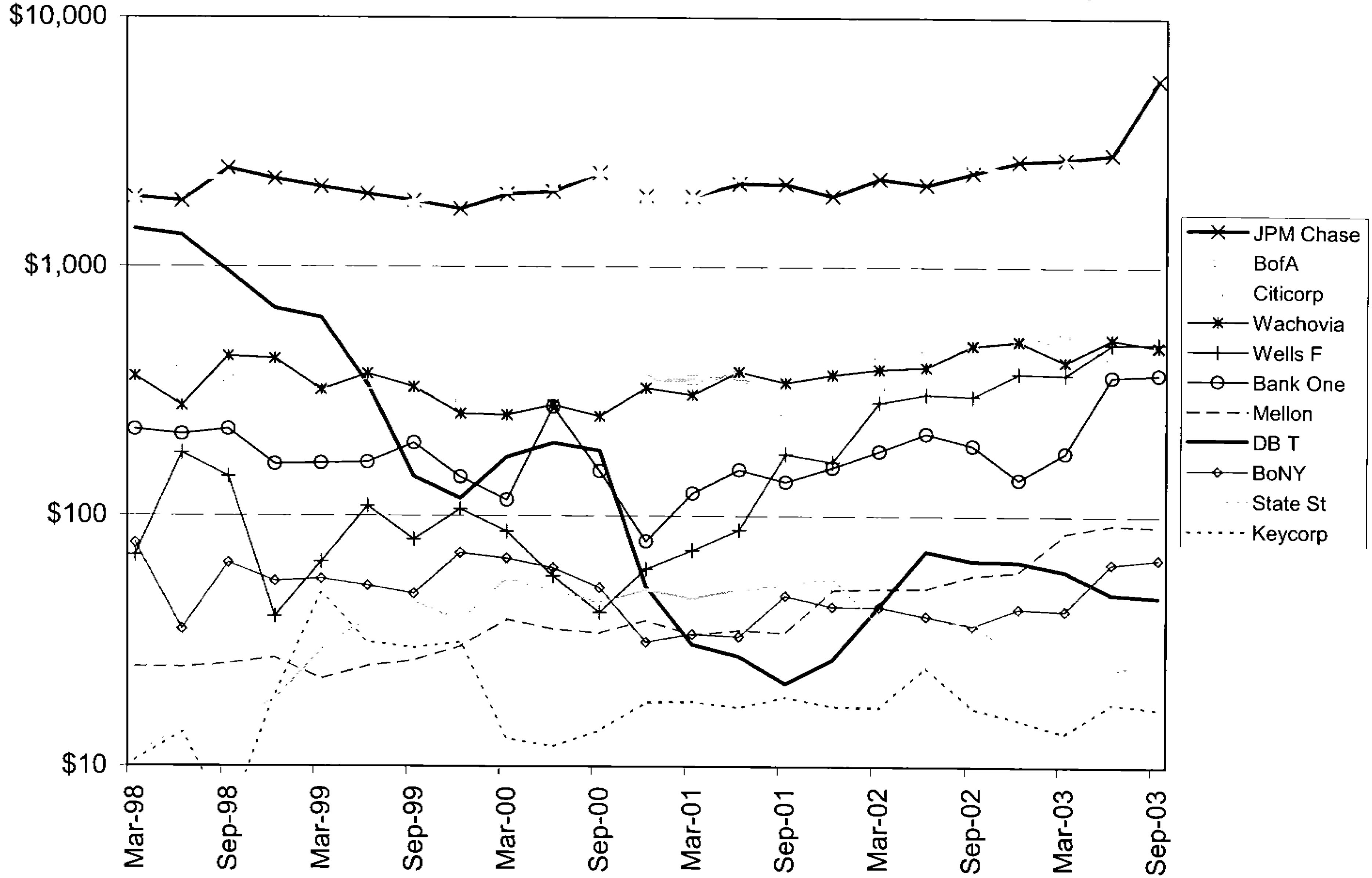

Fig. 3. Relative Growth in Trading (Equally-Weighted)

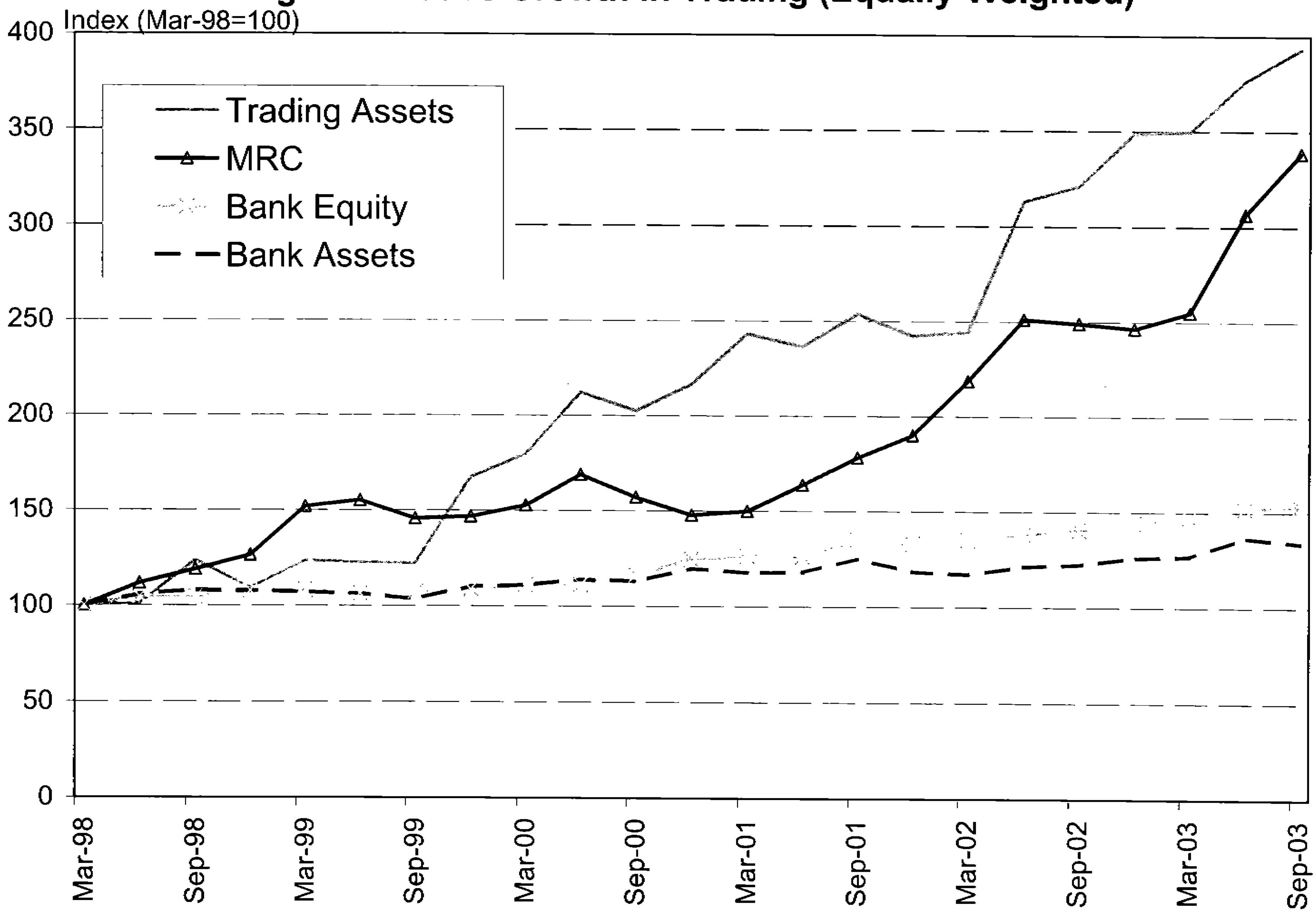

Fig. 4. Aggregate Trading Revenues (Scaled by Trading Assets)

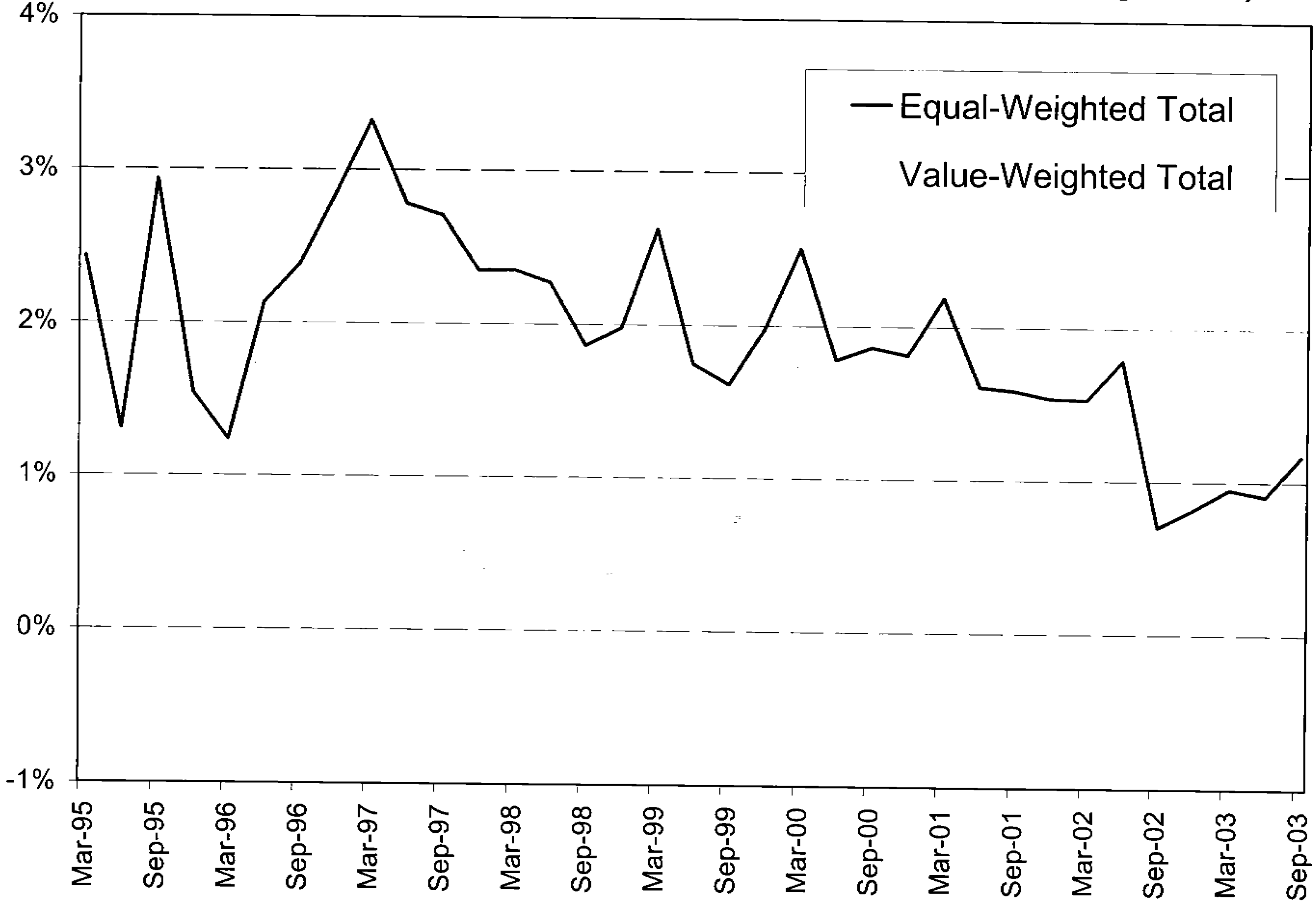

Fig. 5. Components of Average Trading Revenues