This PDF is a selection from a published volume from the National Bureau of Economic Research

Volume Title: The Risks of Financial Institutions

Volume Author/Editor: Mark Carey and René M. Stulz, editors

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-09285-2

Volume URL: http://www.nber.org/books/care06-1

Conference Date: October 22-23, 2004

Publication Date: January 2007

Title: Bank Trading Risk and Systemic Risk

Author: Philippe Jorion

URL: http://www.nber.org/chapters/c9605

1

Bank Trading Risk and Systemic Risk

Philippe Jorion

1.1 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-

1. See Bikhchandani, Hirshleifer, and Welch (1992), Banerjee (1992), or more recently Morris and Shin (1998). Bikhchandani, Hirshleifer, and Welch (1998) provide a useful survey of contagion models based on information asymmetries.
2. See Kodres and Pritsker (2002).

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.

In practice, the VaR-induced herding effect depends on commonalities in the positions in financial institutions. As Morris and Shin (1999, p. 141) 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, and 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, this paper also evaluates the profitability of bank trading revenues, thus contributing to the literature on diversification in banking.[3]

This paper is structured as follows. Section 1.2 provides a review of VaR and herding theories. Section 1.3 presents the empirical analysis, and section 1.4 concludes.

1.2 VaR and Systemic Risk

In recent years, 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 for capital requirements.

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

1.2.1 The VaR Capital Charge

The use of internal VaR models was officially sanctioned by the BCBS, which amended the 1988 Basel Accord to include a charge for market risk (BCBS 1995, 1996). 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. Because in practice the internal-model approach leads to lower capital charges than the standardized model, this has led to the generalized use of VaR methods.

To use the internal-model approach, a bank must first satisfy various qualitative requirements. 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: (1) a horizon of ten trading days, or two calendar weeks, (2) a 99 percent confidence interval, and (3) 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 ten-day VaR by scaling up their one-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 (SRC). The latter 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 sixty business days, times a multiplicative factor k:

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

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 profit and loss (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 the minimum amount of

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 ten or more exceptions.

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.

1.2.2 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 widespread use of VaR could actually increase systemic risk. The novel 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 of 1998 triggered turbulences in financial markets that eventually led to the collapse of the hedge fund Long-term Capital Management (LTCM). In the search for culprits, fingers have 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, p. 20) 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* (June 10; pp. 65–66) 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 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 1.1. The troubling conclusion is that VaR tools increase volatility and are inherently dangerous.[8]

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, that is, after VaR limits have been breached, which could cause higher volatility in financial markets. On the other hand, Cuoco and Liu (2006) 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.

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

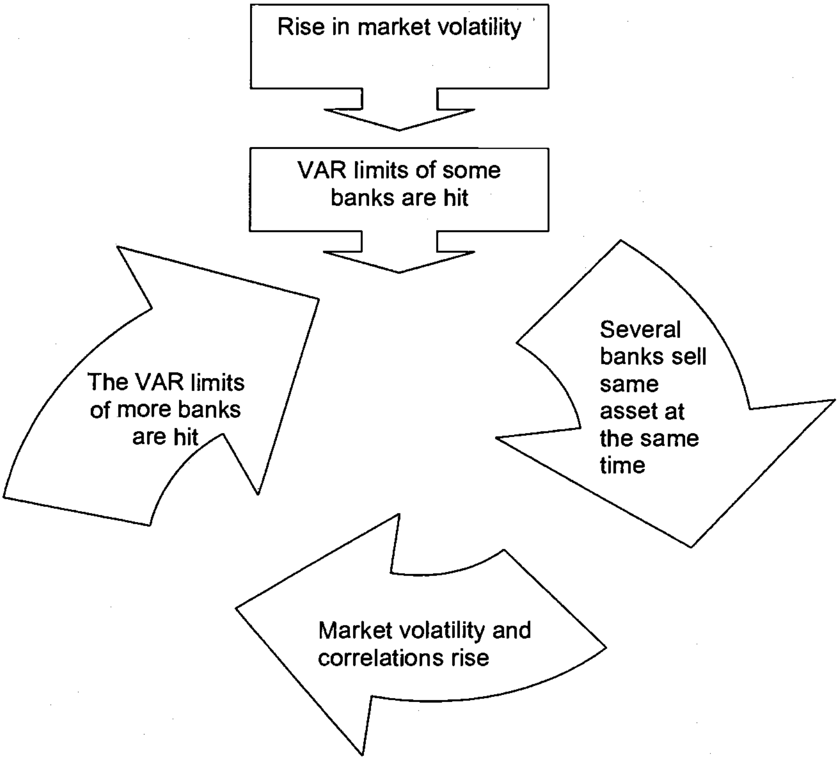

Fig. 1.1 The VaR vicious circle hypothesis
Source: Persaud (2000).

This line of argument should be a serious source of concern given the generalized trend toward risk-sensitive capital adequacy requirements. The current revisions 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 an important issue facing bank 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 in fact 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

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 creates similar trading patterns.

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.

1.2.3 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 $S(i, t-1)$. The position is assumed unchanged until 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 dollar returns can arise because of correlations in the risk factors (R). Or, correlations could occur because positions change together (n). This could reflect herding.

It is axiomatic that every trade has a buyer and seller. Herding therefore must refer to a subset of participants; for example, 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

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

which should be reflected in positive correlations. 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:

$$\Delta n(i, t) = f[I(i, t-1) \ldots]. \tag{3a}$$

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

$$\Delta n(i, t) = f[R(i, t-1) \ldots]. \tag{3b}$$

As an example, momentum investors will tend to buy an asset that just went up in value. This creates positive correlations across momentum investors, which 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. Arbitrageurs will buy the cheap asset at the same time, creating positive correlations across their positions that have nothing to do with herding:

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

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; for example, momentum strategies or stock-index arbitrage for broker-dealers, as explained previously.

Alternatively, constraint-based herding theories can be tested by examining correlations among trading returns directly (or xR). The VaR vicious circle hypothesis postulates that banks 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.

1.2.4 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 examinations. To preserve the confidential nature of the data, the numbers are scaled, which makes it impossible to conduct cross-sectional tests.

Instead, the authors perform time-series tests of unconditional and conditional coverage. Their main conclusion is that, relative to their actual P&L, banks report VaR measures that are conservative, or too large. For four out of six banks, the average VaR is 1.6 to 3 times the actual 99th percentile of the P&L distribution. 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, from August to October 1998. These results are surprising because they imply that the banks' VaR, and hence their market risk charge, is too high. Banks therefore allocate too much regulatory capital to their trading activities.

Berkowitz and O'Brien (2002) give two explanations for this observation. First, P&L include not only changes in mark-to-market positions, but also income from market-making activities, such as fees and spread, as well as net interest income. This increases the P&L, reducing the number of violations.[9] In theory, VaR should be measured against hypothetical income, taken as the change in the market value of a frozen portfolio, ignoring other effects. This is in fact the procedure in place in Germany. Jaschke, Stahl, and Stehle (2003) also compare the VaRs for thirteen German banks to the 99th percentile. They find that these VaR measures are, on average, less conservative than with U.S. data.[10]

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.[11] We would also expect VaR models to improve over time.

Yet another 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 so as to avoid the possibility of regulatory intrusion. This is possible because the market risk capital represents a small fraction—about only two percent—of total regulatory capital.[12] Still, these practices impoverish the informational content of VaR numbers.

9. On the other hand, intraday 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. Berkowitz and O'Brien (2002) find that 83 percent of their banks reported higher values of VaRs, which exceeded the 99th percentile by an average of 70 percent. In contrast, Jaschke, Stahl, and Stehle (2003) find that 67 percent of their banks had higher values of VaRs, which were on average actually less than the 99th percentile by 4 percent. So, VaR measures are less biased when using hypothetical P&L measures.

11. 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.

12. Hirtle (2003) reports a median ratio of MRC to total capital requirement of approximately 1.9 percent for large U.S. banks.

Berkowitz and O'Brien (2002) also find that a simple generalized autoregressive conditional heteroskedastic (GARCH) model appears to capture risk much better than the banks' structural models. This is not astonishing, however, because the one-year observation period requirement imposed by the Basel rules disallows fast-moving GARCH models and leads to slowly changing capital requirements.[13]

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.[14] 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. Finally, daily data are provided for total trading revenues and are not disaggregated at the level of business lines.

Instead, Jorion (2002b) 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 directly on the market risk charge, as described in equation (1). Hirtle (2003) finds that market risk charges (MRCs) provide useful information about future trading risks. The MRC, however, differs from end-of-period VaR because of the averaging process, changes in the multiplier, and in the specific risk charge.

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 (2002), 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 five-day horizon. This is why it is useful to examine a quarterly horizon, a longer sample period, and different types of trading activities.

13. See Jorion (2002a) for a description of the movements in the market risk charge. The standard RiskMetrics model, for instance, based on exponentially weighted moving average volatility forecast, is not Basel compliant because it places too much weight on recent data.

14. This conclusion is based on daily forecasts, which tend to lose forecasting power after more than fifteen days. Andersen et al. (chapter 11, this volume), however, show that realized volatility, based on intraday data, is highly persistent up to sixty days.

1.3 Empirical Evidence

1.3.1 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 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 dataset 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 confidence level and in their 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.[15] 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 forty BHCs that have nonzero entries in the MRC data 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 eleven BHCs with complete histories over the 1998–2003 period. This is the most important group, anyway. It accounts for 95 percent of the value of the aggregate market risk charge in March 1998 and 92 percent 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,

15. In practice, the MRC is reported as a market risk equivalent asset figure, which is the MRC divided by 8 percent. The rationale for this is that the market risk charge is added to the credit risk charge, which is taken as 8 percent of (credit) risk-weighted assets. Thus, adding the market risk equivalent asset figure to the (credit) risk-weighted assets gives a single number, which after multiplication by 8 percent gives the total minimum capital requirement. For our purposes, the numbers we report are the reported market risk equivalent assets (item 1651) multiplied by 8 percent and translated into millions of dollars.

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.[16] This procedure is conservative, however, for the purpose of measuring the information content of VaR.

1.3.2 Summary Statistics

Table 1.1 displays the eleven BHCs with a complete time-series history over the twenty-three quarters.[17] Over this five-year period, nearly all banks have increased in size. Total assets have grown by 34 percent, equity by 56 percent, and derivatives notional amounts by 118 percent. The major exception is Deutsche Bankers Trust (DBT), whose operations were wound down after its acquisition by Deutsche Bank.

Table 1.2 displays trading position data for the bank sample. It shows the size of trading assets, trading liabilities, and of the MRC. Comparing the two tables, we see that trading assets account for approximately 14 percent of total assets as of 2002. Three banks, JP Morgan Chase, Bank of America, and DBT, have large trading operations in terms of relative size of trading assets. Overall, trading liabilities amount to approximately half of trading assets. These numbers, however, like derivatives notional amounts, are not very informative, because they fail to capture the risk and correlations of positions, which is better measured by the MRC.

1.3.3 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 eleven banks as of 2002. In relation to total assets or equity, however, this is a small number. The MRC averages about 1.4 percent of total trading assets, or 2.4 percent of total book 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 percent and 4.6 percent, respectively. At the other extreme, Keycorp's MRC is only 0.2 percent of equity.

The aggregate MRC hardly changed over this five-year period, increasing from \$6.5 to only \$6.7 billion. This number, however, is mainly driven by large banks, and is partly offset by a large drop in the MRC for DBT. Figure 1.2 displays the MRC for all eleven banks. Apart from DBT, MRCs steadily increase over time. 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

16. Strictly speaking, the VaR of a portfolio can only be less than the sum of the individual VaRs for elliptical distributions. Artzner et al. (2001) show pathological cases where this so-called coherence property is not satisfied.

17. This sample includes all eight banks analyzed by Jorion (2002b), of which two disappeared due to mergers (JP Morgan and NationsBank).

Table 1.1 **Summary information for bank holding companies (BHCs; in millions of dollars)**

	Total assets		Equity		Derivatives notional		
Bank holding company	March 1998	Dec. 2002	March 1998	Dec. 2002	March 1998	Dec. 2002	Mergers
Deutsche Bank Trust	157,537	58,083	5,812	4,545	2,005,662	48,276	
Bank of NY	59,611	77,564	4,812	6,684	242,253	413,133	
J P Morgan Chase	637,254	758,800	33,638	42,306	13,980,827	28,201,736	Chase & JPM to Sept. 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	231,666	277,383	18,472	22,440	1,116,818	1,049,397	Banc One & First Chi. to Sept. 1998
Mellon Financial	47,543	36,306	4,086	3,395	52,399	81,566	
Wachovia	237,090	341,839	17,586	32,078	127,431	1,794,589	Wachovia & First Union to June 2001
Bank of America	579,939	660,458	45,104	50,319	3,505,507	12,100,962	Bank Am. & NationsBank to June 1998
State Street	39,010	85,794	2,077	4,788	111,079	232,264	
Wells Fargo	190,913	349,259	19,909	30,358	3,406	198,837	Wells Fargo & Norwest to Sept. 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 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 1.2 **Trading positions for bank holding companies (in millions of dollars)**

	Trading assets		Trading liabilities		Market risk charge		Ratios, Dec. 2002 (%)			
Bank holding company	March 1998	Dec. 2002	March 1998	Dec. 2002	March 1998	Dec. 2002	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 percent. The ratios are for trading assets over total assets (A), trading liabilities over trading assets, MRC to TrA, and MRC over equity (Eq). 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.

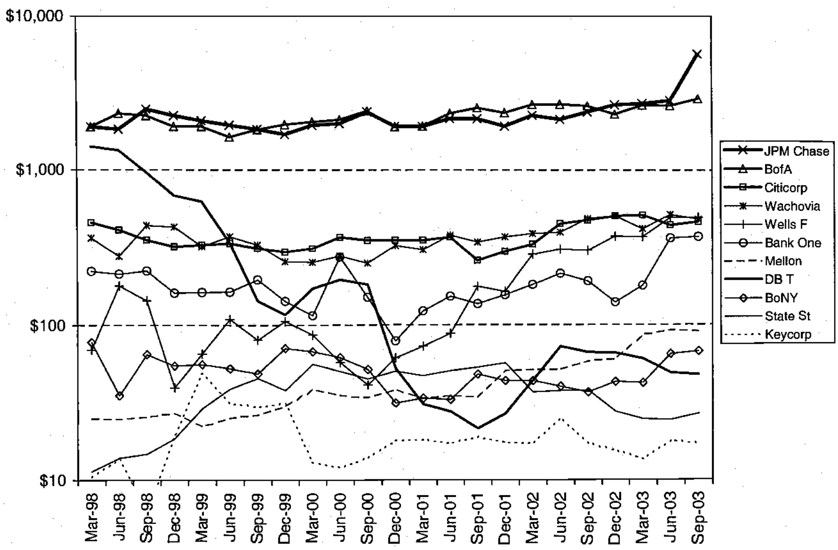

Fig. 1.2 Market risk charge (millions of dollars)

of the quarterly rate of growth for various series across banks. Figure 1.3 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.[18]

We now examine the time-series behavior of the MRC, an ex ante measure of risk. Table 1.3 displays the quarterly *relative* change in the MRC, along with the value-weighted and equally weighted averages across banks. The bottom of the first panel displays the mean and standard deviation of each time series. Note that the mean is systematically smaller than the standard deviation. For JP Morgan Chase, for instance, the mean is 7.0 percent, and the standard deviation 23.9 percent. As a result, tests have little statistical power. The t-statistics do not allow us to reject the hypothesis of zero mean change in the MRC.[19]

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 percent, which is within the range of typical fluctuations in VaR. There is no evidence that the market risk charge went up

18. This could be explained by an increase in general market risk, as measured by VaR, or in specific risk. Casual observation from annual reports, however, indicates that these banks have increased their VaR over this period. See the *Financial Times* (March 25, 2004), "The balancing act that is Value at Risk."

19. The only exception is Mellon Bank, for which the t-statistic is 2.1.

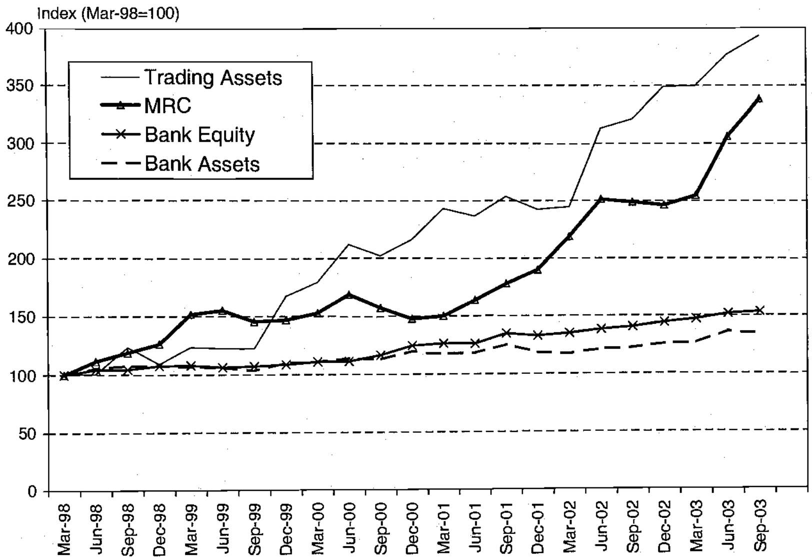

Fig. 1.3 Relative growth in trading (equally weighted)

sharply during this period. Perhaps market volatility went up and positions were cut, however.

Finally, the bottom of table 1.3 displays the correlation matrix between changes in VaR. The average correlation is –0.033, which is close to zero.[20] Only one correlation among the fifty-five entries is significantly different from zero. This highest correlation is 0.625, between Citicorp and DBT. The correlation between the two biggest trading operations, JP Morgan (JPM) Chase and Bank of America (BofA), is 0.302, which is still small. Thus, a single high correlation is not evidence of general VaR-induced herding.

To assess the economic implication of diversification effects, we can compare volatility measures under different assumptions. Define x_i as the variable of interest, say the relative change in the MRC. The volatility of the average (equally weighted) is derived from:

$$\sigma^2\left[(1/N)\sum x_i\right] = (1/N)^2\left[\sum_i \sigma_i^2 + 2\sum_i \sum_{i \neq j} \sigma_i \sigma_j \rho_{ij}\right] \tag{5}$$

The volatility of the average, which is shown in the last column, is only 7.8 percent.

We can then compare this volatility with what we would obtain under

20. The pairwise correlation coefficients are not independent because the correlation matrix must obey positive-definiteness conditions. We also report the average of positive entries and the average of negative entries. These must obviously be greater than the grand average, and reflect the average correlation between banks that have positive or negative correlations.

Table 1.3 **Properties of relative changes in market risk charges (%)**

	Bank												
	DBT	BoNY	JPM Chase	Citicorp	Keycorp	Bank One	Mellon	Wachovia	BofA	State St	Wells F	VW total	EW average
June 1998	–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
Sept. 1998	–28.3	89.9	35.0	–13.7	–55.4	4.9	3.4	58.1	–2.9	5.8	–19.4	4.5	6.5
Dec. 1998	–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
March 1999	–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
June 1999	–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
Sept. 1999	–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. 1999	–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
March 2000	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
June 2000	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
Sept. 2000	–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. 2000	–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
March 2001	–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
June 2001	–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
Sept. 2001	–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. 2001	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
March 2002	63.4	–0.3	17.5	11.3	–1.2	16.6	1.4	5.1	13.2	–35.2	79.9	15.5	15.1
June 2002	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
Sept. 2002	–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. 2002	–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
March 2003	–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
June 2003	–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
Sept. 2003	–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
Average of SD													29.9

Correlation matrix

DBT	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	
Average												–0.033
Average, 20 positive values												0.196
Average, 35 negative values												–0.170

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 (SD), and the correlation matrix for these entries. Asymptotic standard error of correlation is 0.229.

**Significant at the 5 percent level

different correlation scenarios. With perfect correlations, equation (5) simplifies to a volatility measured as $(1/N)[\Sigma_i \sigma_i]$, which is the average of volatilities across banks. This is 29.9 percent in our sample, which is much greater than what we observe. On the other hand, with zero correlations, the volatility of the average should be $(1/N)[\Sigma_i \sigma_i^2]^{1/2}$, which is 10.2 percent in our sample. The fact that the actual volatility of 7.8 percent is even lower than this last 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.

1.3.4 Trading Revenues

Next, table 1.4 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 percent. Two banks, however, return more than 10 percent. These banks, Mellon Financial and State Street, have relatively small values for 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 the bank has a large trading operation relative to its other activities.

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 the economic risk capital required to support the trading activity. The ratios are all very high, reaching 1,069 percent per annum for State Street. The ratio for the total is 184 percent. Even after deduction of expenses, these ratios seem high.

Assume for instance that costs account for 80 percent of revenues, which is a high but conservative number.[21] This gives a net return before taxes to the MRC of 184 percent $\times$ (1 – 80 percent) = 37 percent, which is still very

21. Goldman Sachs, for example, reports segment information for proprietary trading. Over the last three years, operating expenses for this segment ranged from 66 percent to 76 percent of net revenues.

Table 1.4 **Annual trading revenues for bank holding companies (June 1998 to September 2003)**

	Average total trading revenue				Trading revenue by category ($)			
Bank holding company	TrR ($)	TrR/TrA (%)	TrR/Eq (%)	TrR/MRC (%)	Fixed income	Currency	Equity	Commodity
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 1998 to September 2003 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), book equity (Eq), and the market risk charge (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 entry" refers to the arithmetic average of entries for all 11 banks.

high. For Citicorp, for instance, the table implies a net return on MRC of 852 percent × (1 – 80 percent) = 170 percent. This is much higher than its total return to equity of about 30 percent over recent years. For this sample, seven out of eleven banks show a ratio of trading revenue to MRC above 184 percent. 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 1.4 decomposes trading revenues into its four categories. Based on total dollar revenues, fixed-income trading accounts for 35 percent of the total; currency trading accounts for 45 percent, equity trading for 16 percent, and commodity trading for 4 percent. Smaller banks tend to specialize in currency and fixed-income trading and are thus less diversified.

Next we turn to a correlation analysis of trading revenues. To increase the sample size, the analysis starts in March 1995, for a total of thirty-five quarters instead of twenty-three as in the previous sample. Trading revenues are deflated by trading assets at the beginning of each quarter to produce a rate of return. Table 1.5 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 for the eleven banks.

The table shows that correlations are generally low. The average correlation is only 0.163, which does not support a generalized theory of herding. 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, on average. Even the average of positive values is still relatively low, at 0.275; the average of negative entries is –0.167, which is also low. The main exception is for the two largest trading operations, JPM Chase and BofA, which have a high correlation coefficient of 0.709. These banks account for 52 percent and 17 percent, respectively, of total trading assets for this sample. So the two largest banks in the sample have commonalities in trading revenues. This might be a source of concern but still does not create systemic risk, as market risk represents only a small fraction of the risks incurred by U.S. commercial banks.

Figure 1.4 plots the quarterly scaled trading revenue for the industry as a whole. 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 value 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

Table 1.5 **Volatility and correlation of trading revenues (scaled by trading assets; March 1995 to September 2003)**

	Bank												
	DBT	BoNY	JPM Chase	Citicorp	Keycorp	Bank One	Mellon	Wachovia	BofA	State St	Wells F	VW total	EW 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							
DBT	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
Average, 41 positive values													0.275
Average, 14 negative values													–0.167
						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 September 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 nondiagonal 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.

**Significant at the 5 percent level.

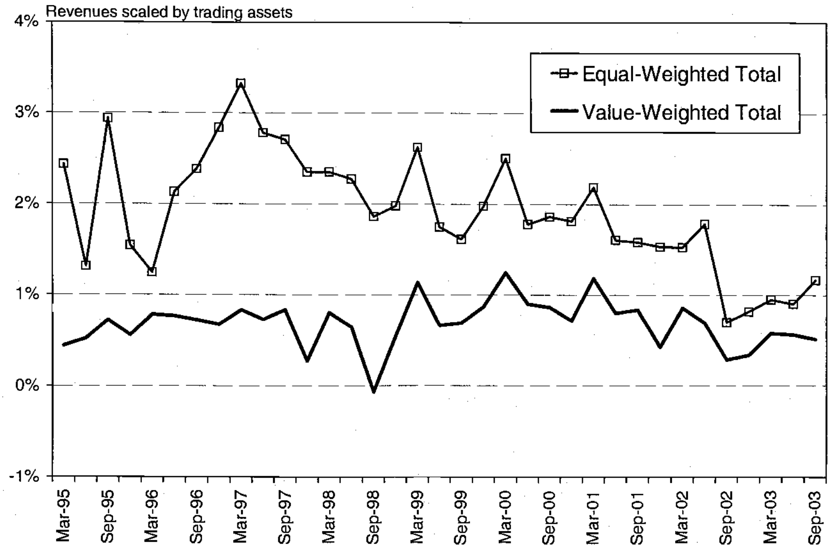

Fig. 1.4 Aggregate trading revenues

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

Perhaps these results mask high correlations for some categories of trading. To check this, table 1.6 provides a more detailed analysis by trading category. The bottom of the table describes the distribution of correlation coefficients for fixed-income, currency, equity, and commodity trading.[22] 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.[23] Equity trading portfolios have the highest correlation, which averages 0.149, still a low number.

Table 1.6 also shows diversification effects across categories for each

22. Not all banks engage in trading activities across all categories. All banks were active in fixed-income and currencies, but only eight banks report equity trading, and nine banks report commodity trading.

23. Notably, JPM 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 alone. Note that because correlations are not linear operators the correlation for the sum may be greater than the correlations for the four business lines.

Table 1.6 **Risk analysis and correlation of trading revenues by category (March 1995 to September 2003)**

	Bank												
	DBT	BoNY	JPM Chase	Citicorp	Keycorp	Bank One	Mellon	Wachovia	BofA	State St	Wells F	VW 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)												
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
Diversification	–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	SD	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 September 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.

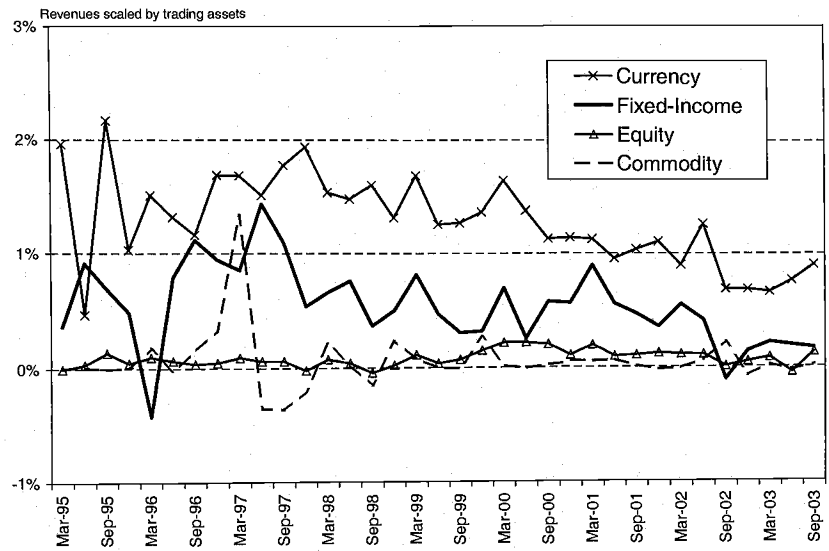

Fig. 1.5 Components of average trading revenues

bank. The risk decomposition panel lists volatilities scaled as a percentage of each bank's total trading risk. The first four categories correspond to the individual risk of each trading line. For JPM Chase, for instance, the trading risk is 62.6 percent of the total for fixed-income, 29.6 percent for currencies, 34.5 percent for equities, and 30.0 percent for commodities. These numbers are representative of the industry as a whole, with more trading risk coming from fixed-income products. These numbers sum to an undiversified risk of 156.7 percent of the actual risk. The difference, or 56.7 percent, is a diversification effect. The table shows substantial diversification effects across trading categories. The average diversification effect across banks is 74 percent. This effect is visually confirmed by figure 1.5, which shows that the four components of the equally-weighted bank index behave relatively independently of each other. Thus, these banks are fairly diversified across risk categories.

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 1.7 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 portfolios has increased over time.

Table 1.7 **Tests of stability in volatility of trading revenues**

	Bank												
Volatility	DBT	BoNY	JPM Chase	Citicorp	Keycorp	Bank One	Mellon	Wachovia	BofA	State St	Wells F	VW total	EW 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
1998–2003	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 in parentheses. "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. One-tailed significance at the 5 percent level indicated by $*^{-}$ for decreases and $*^{+}$ for increases.

Finally, table 1.8 revisits the trading performance of this bank sample, now adjusting for risk. The cross-sectional average of mean scaled trading revenues was 7.68 percent and the average volatility was 2.27 percent. The last columns show that these correspond to very high Sharpe ratios. The average Sharpe ratio based on dollars trading revenues is 3.54 for this sample (from the cross-sectional average of the average trading revenue divided by its volatility). Using trading revenues scaled 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, Krail, and Liew (2001), although they do not take costs into account.[24]

Perhaps these results are due to the shape of distribution of trading revenues. Table 1.8 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 are similar to those for hedge funds. Even so, risk adjustments based on volatility alone should be viewed with caution, as they ignore tail risks.

These results are in line with those of Kwan (1997). He finds that trading is more profitable, but riskier, than banking activities.[25] Interestingly, he also reports that trading by primary dealer subsidiaries, which overlap with the large banks in our sample, has a negative correlation with banking activities, providing diversification benefits to bank holding companies. No doubt this explains the increased focus on proprietary trading.

1.4 Conclusions

VaR systems and the discipline of risk-sensitive capital charges have focused the attention of financial institutions on improving risk management practices. No doubt this helps explain the resilience of the banking system in the face of the recent recession and ever-bigger corporate and sovereign defaults. A nagging concern, however, 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. In addition, the relatively short sample periods do not allow investigating correlations in the tails, which may be different from the average correlations used here.

24. 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.

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

Table 1.8 **Risk-adjusted performance of trading activities (March 1995 to September 2003; annualized)**

	Average trading revenue		Volatility		Skewness	Excess 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 1995 to September 2003 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 total reports the annualized average, volatility, and Sharpe ratio, or ratio of average to volatility. "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 entry" 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.

**Significant at the 5 percent level.

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 Roger Ferguson (2002) said in a recent speech, these concerns seem "overestimated."

References

Artzner, Philippe, Freddy Delbaen, Jean-Marc Eber, and David Heath. 1999. Coherent measures of risk. *Mathematical Finance* 9 (July): 203–28.

Asness, Clifford, Robert Krail, and John Liew. 2001. Do hedge funds hedge? *Journal of Portfolio Management* 28 (Fall): 6–19.

Banerjee, A. V. 1992. A simple model of herd behavior. *Quarterly Journal of Economics* 93 (3): 797–817.

Basak, Suleyman, and Alex Shapiro. 2001. Value-at-Risk based risk management: Optimal policies and asset prices. *Review of Financial Studies* 14 (Summer): 371–405.

Basel Committee on Banking Supervision. 1995. *An internal model-based approach to market risk capital requirements.* Basel, Switzerland: Bank for International Settlements.

———. 1996. *Amendment to the Basel Capital Accord to Incorporate Market Risk.* Basel, Switzerland: Bank for International Settlements.

Berkowitz, Jeremy, and James O'Brien. 2002. How accurate are Value-at-Risk models at commercial banks? *Journal of Finance* 57 (June): 1093–1111.

Bikhchandani, Sushil, David Hirshleifer, and Ivo Welch. 1992. A theory of fads, fashion, custom, and cultural change in informational cascades. *Journal of Political Economy* 100 (October): 992–1026.

———. 1998. Learning from the behavior of others: Conformity, fads, and informational cascades. *Journal of Economic Perspectives* 12 (Summer): 151–70.

Christoffersen, Peter, and Francis Diebold. 2000. How relevant is volatility forecasting for financial risk management? *Review of Economics and Statistics* 82 (February): 12–22.

Cuoco, Domenico, and Hong Liu. 2006. Forthcoming. An analysis of VaR-based capital requirements. *Journal of Financial Intermediation.*

Dunbar, Nicholas. 2000. *Inventing money.* New York: Wiley.

Ewerhart, Christian. 2002. Banks, internal models, and the problem of adverse selection. Mimeograph, University of Bonn, Germany.

Ferguson, Roger. 2002. Financial engineering and financial stability. Speech presented at the Annual Conference on the Securities Industry. Washington, DC: Board of Governors of the Federal Reserve System, November.

Hirtle, Beverly J. 2003. What market risk capital reporting tells us about bank risk. *Federal Reserve Bank of New York Economic Policy Review* 9 (September): 37–54.

Jaschke, Stefan, Gerhard Stahl, and Richard Stehle. 2003. Evaluating VaR forecasts under stress. The German experience. Working paper. Center for Financial Studies, Frankfurt, Germany.

Jorion, Philippe. 2002a. Fallacies about the effects of market risk management systems. *Journal of Risk* 5 (Fall): 75–96.
———. 2002b. How informative are Value-at-Risk disclosures? *Accounting Review* 77 (October): 911–31.
Ju, Xiongwi, and Neil Pearson. 1999. Using value at risk to control risk taking: How wrong can you be? *Journal of Risk* 1 (Winter): 5–36.
Kodres, Laura, and Matthew Pritsker. 1996. Directionally similar position taking and herding by large futures market participants. In *Risk measurement and systemic risk: Proceedings of a joint central bank research conference,* pp. 271–72. Washington, DC: Board of Governors of the Federal Reserve Systems.
———. 2002. A rational expectations model of financial contagion. *Journal of Finance* 57 (April): 769–99.
Kwan, Simon. 1997. Securities activities by commercial banking firms' Section 20 subsidiaries: Risk, return, and diversification benefits. Federal Reserve Bank of San Francisco Working Paper.
Morris, Stephen, and Hyun Song Shin. 1999. Risk management with interdependent choice. *Financial Stability Review* 7 (November): 141–50.
———. 1998. Unique equilibrium in a model of self-fulfilling currency attacks. *American Economic Review* 88 (June): 587–97.
Persaud, Avinash. 2000. Sending the herd off the cliff edge: The disturbing interaction between herding and market-sensitive risk management practices. *Journal of Risk Finance* 2:59–65.
Schinasi, Garry, and R. Todd Smith. 2000. Portfolio diversification, leverage, and financial contagion. *International Monetary Fund Staff Papers* 47 (December): 159–76.
Scholes, Myron. 2000. Crisis and risk management. *American Economic Review* 90 (May): 17–21.
Stiroh, Kevin. 2004. Diversification in banking: Is noninterest income the answer? *Journal of Money, Credit, and Banking* 36 (October): 853–82.