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Author: James M. O'Brien, Jeremy Berkowitz

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Estimating Bank Trading Risk
A Factor Model Approach

James O'Brien and Jeremy Berkowitz

2.1 Introduction

Bank dealers play a central role in securities and derivatives markets and are active traders in their own right. Their trading risks and risk management are important to the banks' soundness and the functioning of securities and derivatives markets. In this paper, we use proprietary daily trading revenues of six large bank dealers to study their market risks using a market factor model approach. We estimate the bank dealers' exposures to exchange rate, interest rate, equity, and credit market factors.

Traditionally, the safety and soundness of the banking system has been the principal focus of interest in bank dealer risk. Important for this purpose is the level of market risk taken by bank dealers and the level of commonality in their risk exposures. In recent literature, the focus has been extended to the effects of bank dealers' and other trading institutions' risk-management policies on market stability. In using risk measures based on market volatility, and in particular value at risk (VaR), it has been argued that institutions' demands for risky assets will move simultaneously, which will lead to exaggerated price movements and market instability. When market volatility is low, institutions will increase demands to hold risky assets, putting upward pressure on prices and, when market volatility becomes high, institutions will attempt to reduce their positions in risky assets, putting downward pressure on prices. This behavior is said to have

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exaggerated market instability in the late summer and fall of 1998, following the Russian ruble devaluation and debt moratorium and the near failure of Long-term Capital Management (LTCM).[1]

Despite the strong interest, there has been little study of bank dealer risks and risk management, and there appears to be little formal evidence on the size, variation, or commonality in dealer risks. In significant measure, this owes to limited public information on dealer positions and income, which limits the study of dealer risks and risk management. Individual banks report on trading positions and revenues only quarterly, and reporting is limited to securities and derivatives in broad market categories. While there is weekly reporting, it includes security positions and transactions—but only limited information on derivatives, and data is reported only for aggregated primary (bank and nonbank) dealers.[2]

Bank VaRs, which forecast the maximum loss on the trading portfolio with a given confidence, provide a direct measure of market risk. However, VaRs do not reveal the dealers' underlying market exposures or their size. Berkowitz and O'Brien (2002) also found the risk forecast performance of the daily VaRs for the banks examined in this study to be weak. Further, there was no common pattern in the correlation of VaRs across banks.

Here we apply a factor model to the daily trading revenues of six large bank dealers to estimate their market risk exposures. Factor models have long been used to study portfolio and firm market risks (e.g., Chen, Roll, and Ross 1986, Flannery and James 1984). Closer to our objectives is their application to mutual fund and hedge fund returns to characterize the market risks in the funds' portfolios (e.g., Sharpe 1992, Fung and Hsieh 1997).

With daily trading revenues, we can study the effects of daily market price moves on the banks' trading portfolios. Also, the sample sizes are large, about 1,200 daily observations per bank. However, the trading revenue data is subject to significant limitations as well. Risk exposures can be inferred only through effects on trading revenues. Trading revenues include fee and spread income and net interest income, as well as market gains and losses on positions. Further, while used by the banks internally and required for VaR model testing, the daily trading revenues lack the accounting scrutiny accorded to quarterly reports.

1. For dynamic analyses of market effects of a VaR constraint, see Basak and Shapiro (2001), Danielsson, Shin, and Zigrand (2002), Persaud (2000), and Morris and Shin (1999). For different analyses of the risk-taking incentives and portfolio choice effects of a VaR constraint, see Basak and Shapiro (2001), Cuoco and Liu (2003), and Alexander and Baptista (2004).

2. Jorion (2005) analyzes bank dealer trading risks and VaRs and implications for systemic market risk using quarterly reported trading revenues and VaR-based market risk capital requirements. Adrian and Fleming (2005) provide a description of data collected and reported for primary securities dealers and present some evidence on dealer risk taking based on dealer financing data.

In the standard factor model, factor coefficients represent estimates of fixed portfolio exposures. For bank dealers, exposures are variable, as dealers actively trade their positions and are not buy-and-hold investors. Thus, the standard factor model approach may not apply here. This leads us to first consider a factor model framework and estimation issues when positions are variable. The framework is used in implementing two empirical modeling approaches where trading positions are variable.

One approach is a random coefficient model, where the factor coefficients represent randomly varying market factor exposures. Using the random coefficient framework of Hildreth and Houck (1968), the dealers' mean exposures to different market factors and the variances of exposures are estimated. Estimates of average daily market risk exposures are small relative to average trading revenues and cannot account for much of the trading revenue variation. The signs of the exposures also differ across the banks, indicating heterogeneity in average exposures. A notable exception is the interest rate factor, where all banks but one exhibit small net long exposures to interest rate risk.

Even with small average exposures risk taking could still be large, since dealers could vary positions between large long exposures and large short exposures. Our estimates indicate significant variation in market exposures that include both long and short positions. Nonetheless, the ranges of potential variation in trading revenues due to variation in market exposures do not appear large relative to the total variation in trading revenues.

The random coefficient model is based on highly simplifying assumptions about the variability in exposures. Especially important is the assumption that exposures are independent of the market factors, which conflicts with portfolio strategies that are related to market prices. This issue has also been important in hedge fund studies, some of whom have tailored the functional form of the factor model to certain types of portfolio strategies. It is subsequently argued that specifying an appropriate functional form requires a good deal of specificity on the portfolio strategy. However, our information on bank dealer strategies is too sparse to formulate a specific portfolio strategy or unambiguously interpret results from alternative functional forms that might be used.

A more limited approach to considering market price-dependent trading strategies is taken here. For each bank, a linear factor model with a 150-day rolling sample is estimated. Using historical plots, the six banks' rolling regression factor coefficients are compared to the respective factors' contemporaneous 150-day rolling means. The latter will reflect periods of rising and declining market prices. Of interest is whether the rolling coefficients move systematically with the factors. This would indicate that the dealers' market exposures vary with the market factors and, hence, a possible price-dependent trading strategy.

For all factors but interest rates, the six banks' rolling factor coefficients show no common movement with the factors' rolling means. For the interest rate factor, the banks' rolling factor coefficients tend to vary inversely with the level of the interest rate. This would be consistent with the interest rate durations for their trading portfolios becoming larger (smaller) when rates are declining (rising).

The samples for the factor regressions include many days when factor changes are small. However, the conclusions are basically the same if we restrict the analysis to days of large price movements. The banks' trading revenues do not show a common systematic relation with large price changes for the noninterest rate factors, but trading revenues tend to be abnormally low on days of relatively large interest rate increases.

In sum, our principal findings are: significant heterogeneity across dealers in their market exposures, relatively small exposures on average, and a limited range of long or short exposures. Commonality in dealer exposures is limited to interest rate risk, with exposure levels inversely related to the level of rates. The implications of these results for aggregate bank dealer risk and market stability are discussed in the concluding section of the paper.

The remaining sections are as follows. In the next section, the bank data and the distribution of trading revenues are described. The factor model framework and empirical model specifications are developed in section 2.3. The estimation and results for the random coefficient model are presented in section 2.4, the rolling regressions in section 2.5, and the relation between trading revenues and large market price changes in section 2.6.

2.2 Bank Trading Revenues

The Basel Market Risk Amendment (MRA) sets capital requirements for the market risk of bank holding companies with large trading operations. The capital requirements are based on the banks' internal 99th percentile VaR forecasts with a one-day horizon. Banks are required to maintain records of daily trading revenue for testing their VaR models. The daily trading revenue for six large trading banks is used in this study.[3]

All of the banks in the study meet the Basel MRA "large trader" criterion and are subject to market risk capital requirements. Four of the six banks are among the largest derivatives dealers worldwide, and the other two are among the largest in the United States. The six trading banks and the sample periods for each bank were selected so as to exclude banks or periods for which there was a major merger, which could substantially change the size and mix of trading. So as not to reveal dollar magnitudes, trading revenues are divided by the sample standard deviations of the respective banks' trading revenues.

3. The six banks were studied in Berkowitz and O'Brien (2002), using a shorter sample period.

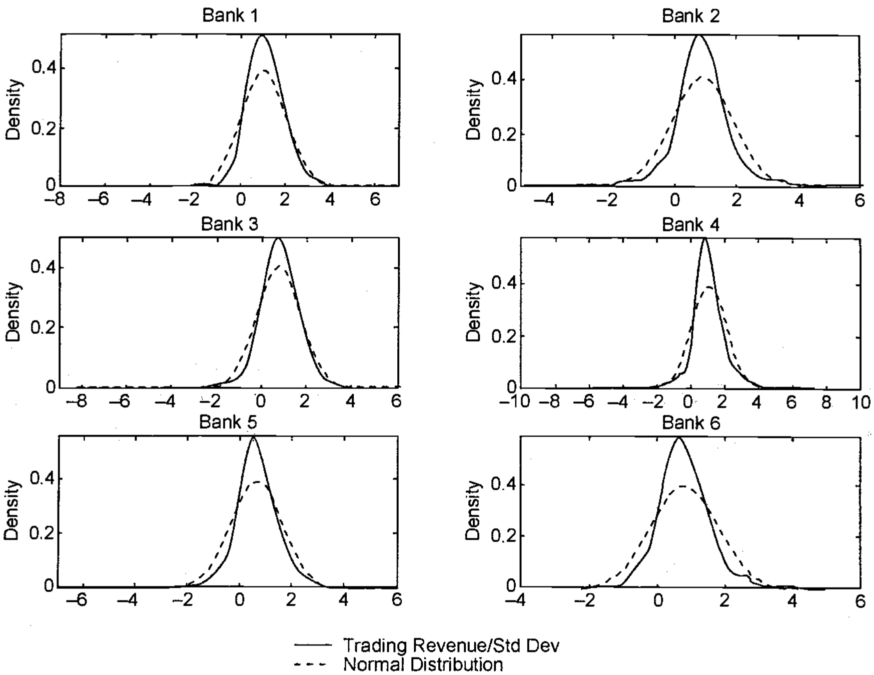

Fig. 2.1 Densities for bank trading revenues

Trading revenues are for the consolidated bank holding company and include gains and losses on trading positions, fee and spread income from customer transactions, and net interest income. Trading positions are required to be marked-to-market daily. Some smoothing of daily valuations is possible, although this would conflict with mark-to-market accounting rules. In this study, pricing inaccuracies are necessarily treated as a residual item. An attempt is made to represent the effects of fee and spread income and net interest income on trading revenues using proxy variables.

In figure 2.1, kernel densities for the banks' trading revenues (divided by trading revenue standard deviations) are presented. A normal distribution having the same means and standard deviations as the banks' distributions is provided for reference. Descriptive statistics are presented in table 2.1. As figure 2.1 and table 2.1 show, trading revenues are typically positive. For the median bank, mean daily trading revenues equal .78 trading revenue standard deviations. As shown in the bottom of table 2.1, losses occurred on less than 20 percent of trading days for any bank. The typically positive trading revenues likely reflect the importance of fee and spread income and net interest income.

The trading revenue distributions also have high peaks and heavy tails, as revealed in figure 2.1 and by the excess kurtosis statistics in table 2.1. The

Table 2.1 **Daily trading revenue descriptive statistics**

Bank	Dates	No. of obs.	Mean	Excess kurtosis	Skewness
1	Jan. 1998–Dec. 2000	762	1.05	10.75	–0.60
2	Jan. 1998–Sept. 2000	711	0.79	4.82	0.16
3	Jan. 1998–Sept. 2001	1524	0.77	13.13	1.49
4	Jan. 1998–Dec. 2003	1544	0.90	4.17	0.46
5	Jan. 1998–Dec. 2003	1551	0.62	6.46	–0.62
6	Jan. 1998–June 2002	1166	0.72	79.64	–3.98

		Quantiles					
	Loss rate	0.005	0.01	0.05	0.95	0.99	0.995
1	0.074	–2.29	–1.83	–0.22	2.72	3.77	4.15
2	0.132	–3.05	–1.98	–0.63	2.39	3.93	5.15
3	0.146	–2.99	–2.18	–0.60	2.24	3.11	3.89
4	0.111	–1.83	–1.63	–0.54	2.71	4.08	4.57
5	0.188	–3.41	–2.45	–0.84	2.15	3.40	4.15
6	0.147	–1.87	–1.40	–0.55	2.16	3.49	3.90

Notes: Trading revenues in both panels are divided by bank's sample standard deviations. Loss rate is the fraction of days when reported trading revenues were negative.

5 percent and 95 percent quantiles for the banks' trading revenues in the bottom panel of table 2.1 lie inside 5 percent and 95 percent quantiles, which would be consistent with a normal distribution. The 1 percent and 99 percent and the 0.05 percent and 99.5 percent quantiles lie outside quantiles consistent with a normal distribution. There also is no indication of any common skewness in the banks' trading revenue distributions.

To provide more information on the heavy tails, the lowest and highest 10 percent returns for each bank are plotted by historical dates in figure 2.2. The plotted values are expressed as deviations from trading revenue means and are divided by sample standard deviations. With some exceptions for bank 1, the lowest 10 percent returns are all losses. Several features of figure 2.2 are notable.

One is that, while there is temporal clustering in both high and low returns, the clustering tends to be greater for low returns. This asymmetry in temporal clustering may be due to periodic large fees earned by dealers from customer transactions that are more evenly dispersed through time. In contrast, low returns are likely to reflect mostly portfolio losses from adverse market moves and persistency in market volatility (operational costs are not included in trading revenues).

A second and related feature of figure 2.2 is that all of the banks encountered loss clustering, with some also experiencing positive spikes, during the market turmoil in the late summer and fall of 1998. The market in-

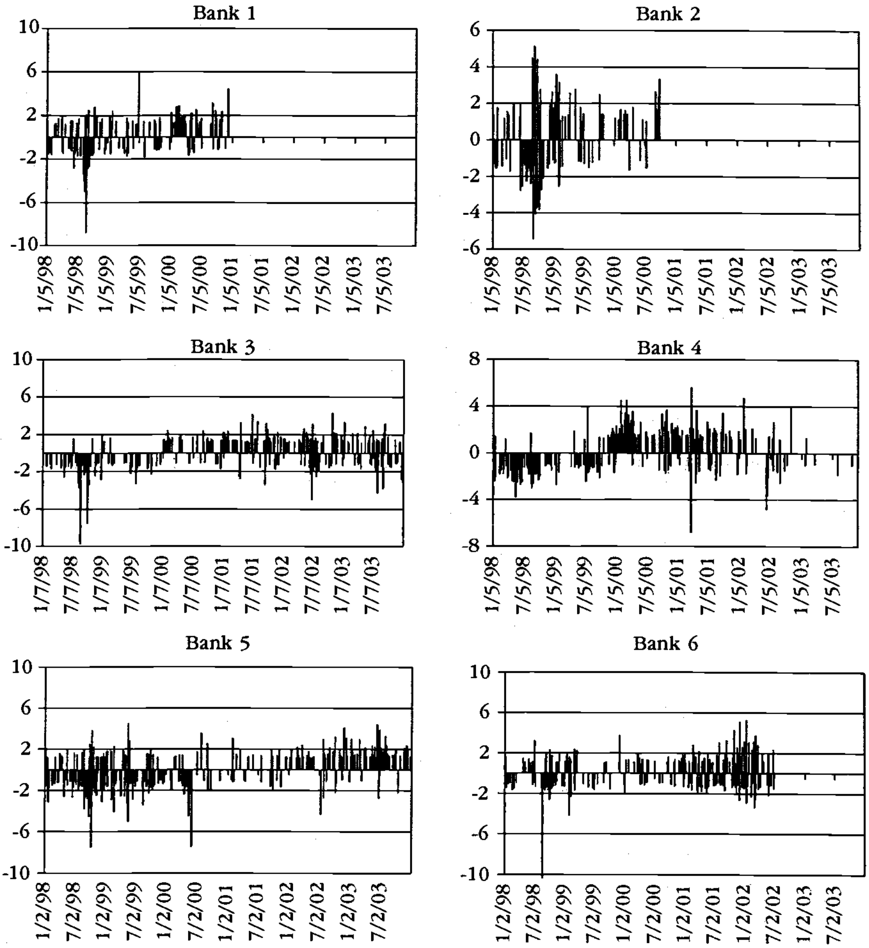

Fig. 2.2 Trading revenues: 10 percent lowest and highest values

Notes: Values are expressed as deviations from the banks' sample means and in terms of the sample standard deviations. The large negative spike for bank 6 exceeds 10 standard deviations.

stability during this period had important common effects on the banks' trading revenues. For all six banks, daily averages of trading revenues for the second half of 1998 were low and this period had a large effect on the full sample trading revenue kurtosis for banks 1, 2, 3, and especially 6.[4]

It should be noted that variation in dealer positions is also a potentially

4. For the second half of 1998, daily averages of trading revenues for banks 1 to 6 were respectively 0.55, 0.39, 0.22, 0.15, 0.15, and 0.39. If the second half of 1998 is excluded from the sample, the excess kurtosis for banks 1 through 6 are respectively 4.30, 2.63, 2.84, 4.42, 6.07, and 4.64. See table 2.1 for comparable statistics for the full-period samples.

Table 2.2 **Cross-bank trading revenue correlations and VAR (trading revenue above the diagonal and VAR below the diagonal)**

	Bank					
Bank	1	2	3	4	5	6
1		0.415	0.210	0.182	0.028	0.145
2	–0.027		0.112	0.070	0.158	0.147
3	0.99	–0.151		0.243	0.169	0.145
4	0.060	–0.812	0.130		0.048	0.146
5	–0.119	0.684	0.097	–0.503		0.094
6	–0.314	–0.300	–0.271	0.627	–0.330	

important determinant of the trading return distribution. The dependency of the trading return distribution on the dynamic management of positions under a VaR constraint is a major feature in Basak and Shapiro (2001).

Table 2.2 presents cross-bank correlations for daily trading revenues above the diagonal and, for comparison, cross-bank daily VaR correlations below the diagonal. The trading revenue correlations are all positive and significant using a standard t-test. The potential contribution of exposures to market factors on the trading revenue correlations is considered in the following. In contrast, the bank VaR correlations show no common pattern, as correlations are both positive and negative and vary widely.

2.3 Factor Model with Varying Positions

A factor model framework when positions are variable is developed here and is used to guide the empirical specifications. Consider a portfolio with positions in K risky securities and a risk-free asset. Positions in securities and the risk-free asset may be long or short and include those held indirectly through derivatives. For measuring the portfolio's sensitivity to market factors, bid-ask spreads are abstracted from and the values of short or long positions are measured at a single price, for example, the midmarket price. The portfolio can be adjusted continuously, but returns are observed only for discrete time units.

Let t denote time measured in discrete units. At the start of t, the bank holds an amount x^0_{kt} in risky security categories $k = 1, \{. . .\}, K$ and x^0_{0t} in the risk-free asset, which are referred to as the bank's positions. Positions may be carried over from $t - 1$ or new positions may be set at the start of t prior to any price changes since $t - 1$. Positions and prices measured at the end of period t are denoted by $x_k(t)$, $x_0(t)$, and $p_k(t)$. The price of the risk-free asset is fixed at 1. Using this notation, the values of the portfolio at the start of t and at the end of t are respectively

(1a) $$W_t^0 \equiv \sum_{k=1}^{K} \mathrm{x}_{kt}^0 p_k(\mathrm{t} - 1) + x_{0t}^0$$

(1b) $$W(t) \equiv \sum_{k=1}^{K} x_k(t) p_k(t-1)\left(\frac{p_k(t)}{p_k(t-1)}\right) + x_0(t).$$

For the factor model, we want to express the 1-period change in the portfolio value as a function of 1-period changes in market prices $r_k(t) \equiv [p_k(t) - p_k(t-1)]/p_k(t-1)$. If positions are fixed, the change in the portfolio value will be determined by the 1-period market price changes. However, if positions are variable, the change in the portfolio value can be affected by intraperiod price movements not revealed in the 1-period price changes. Thus, the suitability of a factor model when portfolio values are observed only discretely requires restrictions on intraperiod position and/or possibly price changes. A highly simplifying assumption made here is that intraperiod changes in security positions and prices are uniform over the period. This assumption becomes accurate for very short periods and it may be a reasonable approximation for one-day returns. It implies that the intraperiod position and price changes can be measured from the full period changes.

A second assumption is made to avoid complications from outside cash infusions or withdrawals: there are no exogenous intraperiod capital flows to the portfolio, and intraperiod cash payments and accrued interest on positions are accumulated in a separate account. Under this assumption, changes in positions at any time τ within period t, $dx_{kt}(\tau)$, made at prices $p_{kt}(\tau)$, will satisfy a self-financing constraint: $\Sigma_{k=1}^{K} dx_{kt}(\tau)p_{kt}(\tau) + dx_{0t}(\tau) = 0$.

Using the self-financing constraint and (1), the change in the portfolio value over the period, $w(t) \equiv W(t) - W^0(t)$, is

(2) $$w(t) = \sum_{k=1}^{K}\left[x_{kt}^0 p_k(t-1) + \frac{1}{2}\Delta x_k(t) p_k(t-1)\right] r_k(t),$$

where $\Delta x_k(t)$ is the change in the position over period t (see appendix). Note that $x_{kt}^0 p_k(t-1) + [1/2\Delta x_k(t) p_k(t-1)]$ is the average position in the period valued at the price of k at the end of $t-1$.

The change in the portfolio value can be expressed using a factor model form:

(3) $$w(t) = \sum_{k=1}^{K} V_k(t) r_k(t)$$

where $V_k(t) \equiv [x_k^0(t) + 1/2\Delta x_k(t)] p_k(t-1)$. $V_k(t)$ is the value of the portfolio position in factor k and measures the portfolio's exposure to factor shock $r_k(t)$. Unlike the standard factor model assumption, the factor exposures are not constant. With daily data, they would reflect time-varying daily average positions. Two specifications of equation (3) will be considered.

For the first specification, $V_k(t)$ is assumed to be a random draw from a stationary process with mean $\overline{V}_k$. Further, the positions' values, $V_k(t)$, are assumed to be independent of market factor changes and mutually independent. Under these conditions, the portfolio return in equation (3) satisfies the random coefficient models developed in Hildreth and Houck (1968).

With $\overline{V}_k$ as the mean position value in factor k and $v_k(t) \equiv V_k(t) - \overline{V}_k$ as the random change in the position value, the details of the factor model can be expressed by

$$\text{(4a)} \qquad w(t) = \sum_{k=1}^{K} r_k(t)\overline{V}_k + u(t)$$

$$\text{(4b)} \qquad u(t) \equiv \sum_{k=1}^{K} r_k(t)v_k(t)$$

$$\text{(4c)} \qquad E[w(t)] = \sum_{k=1}^{K} \mu_k(t)\overline{V}_k$$

$$\text{(4d)} \qquad \sigma_{ww} = \sum_{k=1}^{K}\sum_{l=1}^{K} \overline{V}_k\overline{V}_l\omega_{kl} + \sum_{k=1}^{K} \sigma_{v_k v_k}\omega_{kk},$$

where $\mu_k \equiv E[r_k(t)]$ is the expected change in the market price represented by factor k, $\sigma_{v_k v_k}$ is the variance for factor position k; σ_{ww} is the unconditional variance of changes in the value of the portfolio, and ω_{kl} is the covariance (variance) for individual factors $r_k(t)$ and $r_l(t)$. For the following analysis, it is assumed that $\mu_k = 0$.

Equation (4a) expresses the change in the value of the portfolio as the sum of change in value conditioned on average positions and the change in value conditioned on the positions' realized random components, the latter being defined in equation (4b). Equations (4c) and (4d) are the portfolio's unconditional mean change and variance. The unconditional variance is the sum of the variances for $\Sigma_{k=1}^{K} r_k(t)\overline{V}_k$ and $u(t)$. The variance is the sum of the factor variances and covariances weighted by the mean positions plus the sum of the products of the factor variances and position variances. Thus, with variable positions, the volatility of positions interacts with the volatility of the factors in determining the dispersion of portfolio returns.

The factor model in equations (4a)–(4d) also provides for the correlation between the changes in banks' i and j portfolio values that come from market factor shocks. This correlation represents a measure of cross-bank commonality in market risks. Using subscripts for banks i and j, we have (see appendix)

$$\text{(5)} \qquad \rho_{w_i w_j} = \rho_{\hat{w}_i \hat{w}_j}\sqrt{RS_i}\sqrt{RS_j} + \rho_{u_i u_j}\sqrt{1 - RS_i}\sqrt{1 - RS_j},$$

where $w_i(t) = \hat{w}_i(t) + u_i(t)$, $\hat{w}_i(t) \equiv r(t)\overline{V}_i$ and $u_i(t)$ is the residual for bank i in equation (4b).

Equation (5) describes two sources of commonality in banks' market risks. $\rho_{\hat{w}_i\hat{w}_j}$ is the correlation between changes in i and j's portfolio values when factor exposures are conditioned on the mean positions. One source of commonality is similar mean positions, which would make $\rho_{\hat{w}_i\hat{w}_j}$ positive. $\rho_{u_iu_j}$ is the correlation associated with the variation in positions, as reflected in $u_i(t)$ and $u_j(t)$. A second source is common variation in positions. RS_i and RS_j determine the relative importance of these two sources of correlated returns. RS_i is the (population) R-square from a regression of i's portfolio value changes on market factors with factor coefficients set at their means ($RS_i \equiv \sigma_{\hat{w}_i\hat{w}_j}/\sigma_{w_iw_j}$).

Using the random coefficient model and with observations on trading portfolio value changes and market factors, it is possible to estimate the bank dealers' average factor positions and their variances and some components of the cross-bank correlations.

The assumptions, of course, are restrictive and limit the generality of results. The assumption that position changes are mutually independent is one of notational convenience but potentially important for empirical tractability if there are many factors. Dropping this assumption would require recognizing all the covariances between position changes in equation (4d).

Assuming that market exposures are independent of factor changes is particularly limiting because portfolio management may be related to market price movements. As discussed earlier, such policies have been said to adversely affect market stability. Dropping the assumption of independence has important effects on the factor model formulation and, specifically, can make portfolio returns nonlinear in the factor changes, $r_k(t)$.

An illustration of this is when the portfolio is managed such that returns resemble a call or put option on, say, security k. The optionlike portfolio implies a position in the security and a cash position. Changes in the security price have both first-order and higher-order effects on the portfolio return. The higher-order effects imply changes in the security and cash positions that are related to the factor price change. For security k, $\Delta x_k(t)$ in equation (2) is positive and depends on the price change, $r_k(t)$. A second-degree polynomial provides a second-order approximation to the effect of the market factor on the portfolio value.

$$w(t) = a_k^0(t)r_k(t) + b_k^0(t)[r_k(t)]^2 \tag{6}$$

The coefficient for the linear component in equation (6) is analogous to the option's delta and that for the quadratic component to the option's gamma.

Nonlinear portfolio return equations such as (6) and returns expressed as functions of traded option values have been used in hedge fund studies to capture positions that vary with market returns.[5] However, a particular

5. Chan et al. (2005) use higher-order polynomials in market factors to capture nonlinearity in hedge fund returns. Agarwal and Naik (2004) use returns to call and put options as the

portfolio strategy, including the strategy horizon, is needed to specify or interpret a particular functional form. For example, the strategy specified in the preceding illustration implies that the squared market factor in equation (6) reflects the nonlinear sensitivity of the portfolio to the market factor, that is, the option's "gamma." Without this specification, the interpretation of the squared factor would be ambiguous (e.g., it might represent the sensitivity of the portfolio value to market volatility). Further, the coefficients $a_k^0(t)$ and $b_k^0(t)$ expressed in equation (6) are for period t. They depend on the security value at the start of the period and also the portfolio management horizon (option's time to expiration). Treating the two coefficients as constants implies that the portfolio is being rebalanced to a constant composition and horizon at the start of each sample observation, for example, each month if observations are monthly.

We have little specific information on bank dealers' portfolio strategies and we are not testing a specific strategy. This lack of specificity includes the time dimension of the dealer's strategy as it relates to our daily observation period.

A less formal approach to price-dependent strategies is taken here. For each bank, we estimate a linear regression of trading revenues on market factor changes (and nonmarket factor variables) with 150-day daily rolling samples. For the six banks, the estimated rolling coefficients are plotted along with coincidental 150-day rolling means for the respective factors (factor price levels, not changes). The 150-day rolling means will reflect periods of rising or declining market prices. Of interest is whether the rolling factor coefficients move systematically with the factors. This would indicate dealers' market exposures vary with the market factors and, hence, a possible price-dependent strategy. The significance of any comovement will be judged according to whether it is common among the six banks.

While observed comovement between the factor coefficients and the factors would indicate that the dealers' market exposures are related to the market factors, this may still not uniquely identify the price-dependent portfolio strategy. We consider this issue in evaluating the rolling regression results.

Before presenting the empirical factor models, the treatment of other components of trading revenues needs to be mentioned. (1) Portfolio revenues include accrued and explicit interest payments and payments for risk-bearing. (2) Trading revenues also includes fee and spread income from market-making. We do not have direct measures of these additional components. Proxy variables are used to capture the effects of trading volume and net interest income on dealer trading revenues. (3) Portfolio revenues also are affected by (interperiod) changes in the portfolio's capital.

factors in hedge fund factor regressions to capture the nonlinearity between the hedge fund's returns and the underlying market factors that arise from option-type trading strategies. Mitchel and Pulvino (2001) apply a piecewise linear factor model in returns to risk arbitrage strategies.

Changes in the capital of the portfolio are not explicitly accounted for other than what can be represented by a trend variable.

2.4 Random Coefficient Model

We first describe the explanatory variables used in the empirical analysis.

2.4.1 Explanatory Variables

In selecting market factors, four broad market categories are represented: exchange rates, interest rates, equity, and credit spreads. For exchange rates, equities, and credit spreads multiple factors are used for each category. A ten-year U.S. Treasury rate is used to capture interest rate risk in the trading portfolio. In an earlier version, a ten-year rate and a three-month rate were used, with qualitatively similar coefficients estimated for both factors. There are a total of eleven market factors, which are identified in panel A of table 2.3 with descriptive statistics.

For exchange rate factors, regional exchange rate indices were constructed. They are weighted averages of log changes in individual country exchange rates. The exception is Russia, the only Eastern Europe country for which we had historical data. The weights are shown in panel B of table 2.3. They were constructed from worldwide dealer foreign exchange (FX) spot and derivatives turnover reported in Bank of International Settlements (BIS) Central Bank Surveys in 1998 and 2001.

Exchange rate and equity factors are measured as log differences; interest rate and credit spread factors are first differences. For the exchange rate and equity market factors, positive differences indicate increases in asset values and, for the interest rate and credit spreads, positive differences indicate decreases in asset values.

In addition to the market factors, a proxy variable is used to represent trading volume that generates fee and spread income. We do not have direct information on dealers' daily transactions and use detrended daily volume on the New York Stock Exchange (NYSE) plus NASDAQ to represent a market volume influence on trading revenue. Also, we do not have data on net interest income from trading positions. To proxy for net interest income, we use a monthly lagged moving average of the ten-year U.S. Treasury rate. This is intended to represent the gradual realization in the portfolio of upward and downward movements in interest rate levels.

A trend variable is used to capture any trend in the level of the bank's activity. Lagged trading revenue is also included. If dealers smooth position revaluations, this could produce serially correlated returns.

2.4.2 Market Risk Estimates

We use the generalized least squares (GLS) random coefficient estimators developed by Hildreth and Houck (1968) to estimate the banks' mean exposures to the market factors, $\overline{V}_k$, shown in equation (4a), and the exposure

Table 2.3 Market factors

A. Market factors: Daily changes, 1998–2003[a]

Exchange rates	Mean	Equity	Mean	Interest rates	Mean	Credit spreads[b]	Mean
Western Europe	0.00009	NYSE	0.00012	10-yr U.S. Treasury rate	–0.00084	10-yr Baa	0.00050
	(0.00558)		(0.01156)		(0.06302)		(0.03497)
Russia	–0.00107	NASDAQ	0.00015			5-yr high yield	0.00049
	(0.02274)		(0.02222)				(0.09338)
Asian Pacific	0.00012					10-yr swap	–0.00007
	(0.00603)						(0.03185)
South America	–0.00037					EMBI+	–0.00060
	(0.00611)						(0.24070)

B. Exchange rates with U.S. dollar: Construction of regional indices[c]

Western Europe (1998)		Western Europe (1999–2002)		Asian Pacific		South America	
Country	Weight	Country	Weight	Country	Weight	Country	Weight
Germany	0.54	Europe	0.633	Japan	0.727	Mexico	0.658
United Kingdom	0.198	United Kingdom	0.222	Australia	0.136	Brazil	0.342
France	0.092	Switzerland	0.102	Hong Kong	0.075		
Switzerland	0.127	Sweden	0.043	Singapore	0.035		
Sweden	0.043			Korea	0.027		

[a]Standard deviations are in parentheses. Units for factor means and standard deviations: Exchange rates and equity means are daily log differences of levels; interest rates and credit spreads are daily first differences of levels expressed as percentage points.

[b]Credit spreads are spreads from treasury rates with the same maturity. EMBI+ is JP Morgan's Emerging Markets Bond Spread Index Plus.

[c]Regional exchange rates are weighted log differences. Weights are based on worldwide dealer FX spot and derivatives turnover volume reported for different currencies. Turnover volume is taken mostly from the 2002 BIS Central Bank Survey. The survey date is June April 2001. June 1998 turnover volume from the 1999 Central bank Survey is used to determine weights for Western Europe currencies for pre-Euro 1998 (country coverage in the 1998 survey is limited).

Table 2.4 **Summary statistics for factor model and coefficient variances regressions**

	Bank					
	1	2	3	4	5	6
	Factor model regressions[a]					
Regression R^2	0.18	0.15	0.22	0.32	0.15	0.07
Regression F-values	10.09	7.64	27.44	45.36	17.93	5.33
Market factor F-values	1.84	1.05	2.36	7.93	0.97	1.88
Sample size (n)	728	681	1,484	1,485	1,483	1,109
	Coefficient variance regressions[b]					
Regression R^2	0.06	0.18	0.08	0.03	0.04	0.02
Regression F-values	3.82	13.73	11.07	4.16	5.59	1.98
Sample size (n)	728	681	1,484	1,485	1,483	1,109

[a] .05 critical F-values: for regression $F(16,n-16) = 1.65$; for market factors $F(11,n-16) = 1.80$.
[b] .05 critical F-values: $F(12,n-12) = 1.76$.

variances, $\sigma_{v_k v_k}$, shown in equations (4d) and (4e).[6] For the estimation we are assuming that $v_k(t)$ is i.i.d. independent of the market factors, and that $v_k(t)$ and $v_l(t)$ are independent for $k \neq l$. The residual in the trading revenue equation will include the residual that arises from random position changes, that is, $u(t)$ in equation (4b), as well as any independent sources of trading revenue not accounted for in the model. Under these assumptions, Hildreth and Houck provide unbiased and consistent estimators of the mean coefficients and coefficient variances. Here, we allow only the eleven market factors to have variable coefficients.

Appendix tables 2A.1 and 2A.2 contain the detailed regression results. Reported coefficients are estimated using trading revenues divided by sample standard deviations and thus measure trading revenue effects in terms of trading revenue standard deviations. The estimates are discussed here using several summary tables. In the top part of table 2.4, summary statistics for the regressions estimating mean exposures to the market factors and including other regressors are presented. As shown, the full set of regressors has significant explanatory power based on F-values and regression R-squares. However, the F-values measuring the joint explanatory power for the eleven market factors are not very high and do not exceed the 0.05 critical value for two banks. Thus the market factors do not have a lot of explanatory power (excluding these factors from the regressions, causes the R-squares to drop by about four basis points). Since the factor coefficients reflect the estimated mean factor exposures, this implies

6. Specifically, we use (14), p. 587, to estimate the coefficient variances and $\tilde{\beta}$ estimator in (25), p. 589, to estimate the mean market factor positions.

that average market exposures cannot account for much of the variability of trading revenues.

In contrast, equity volume, used as a proxy for market transactions volume, is positive for all banks and highly significant for all but one bank (appendix table 2A.1). Trading revenues also have a significant positive trend. The estimated coefficients for the moving-average interest rate (to proxy interest income) and lagged trading revenue have mixed signs and significance across the banks.

The bottom part of table 2.4 presents summary statistics for the regressions estimating the variances of the market factor coefficients. While R-squares are low, the F-values are highly significant, implying significant variability in the market factor coefficients. The estimator used for the variances of the market factor coefficients is unbiased under the model assumptions. While Hildreth and Houck suggest constraining the coefficient estimates to nonnegative values (pp. 587–89), this constraint was not imposed here. A little more than a third of the estimated coefficients are negative, although only two are significant at a 0.05 level and one at a 0.01 level (appendix table 2A.2). We regard the negative coefficients as reflecting sampling error and exclude them in evaluating the variability of the dealers' market exposures. We have no reason to believe that this biases our interpretation of the results.

In table 2.5, two measures of the dealers' potential exposures to large market factor shocks are constructed using appendix tables 2A.1 and 2A.2. The top number in each cell is equal to the respective factor's coefficient from table 2A.1—the estimate of the bank's mean exposure to the factor—multiplied by a 2 standard deviation shock to the factor. Recall that the coefficient estimates measure trading revenue effects in terms of trading revenue standard deviations. Hence, the top number in the cell measures trading revenue effects in terms of trading revenue standard deviations from a 2 standard deviation factor shock.

The two numbers underneath are the 2.5 percent and 97.5 percent estimated quantiles for factor exposures, that is, 95 percent intervals. The quantile estimates use the estimated mean coefficients (table 2A.1) and coefficient variances (table 2A.2), and assume the coefficients are normally distributed. The quantile estimates also are multiplied by 2 standard deviation factor shocks. The italic numbers indicate where coefficient variance estimates are negative (a zero interval is reported but is not used in the following analysis).

Consider first the estimated mean factor exposures (the top number in each cell). The estimates are small compared to the mean trading revenues shown in table 2.1. For all factors, a 2 standard deviation market factor shock produces less than a 0.3 standard deviation change in a bank's trading revenue and less than a 0.1 standard deviation change in trading revenue for two-thirds of the factors. For the median bank, mean trading revenues

Table 2.5 **Scaled factor coefficients with 2.5 percent and 97.5 percent quantiles[a] (estimated coefficient quantiles)**

	Bank											
Factors[b]	1		2		3		4		5		6	
fx w eur	0.062		0.063		0.051		0.076		–0.082		0.062	
	0.062	*0.062*	–0.066	0.192	–0.732	0.833	*0.076*	*0.076*	–0.813	0.648	*0.062*	*0.062*
fx russia	0.041		0.082		0.228		–0.004		0.028		–0.047	
	–0.087	0.169	–0.410	0.575	–0.586	1.042	–0.004	–0.004	–0.461	0.516	–0.047	–0.047
fx asia pac	–0.216		–0.103		–0.024		0.046		0.034		0.007	
	–1.413	0.982	–1.422	1.215	–0.909	0.861	*0.046*	*0.046*	–1.261	1.329	*0.007*	*0.007*
fx so amer	–0.049		–0.071		–0.006		0.057		–0.080		0.164	
	–0.049	*–0.049*	*–0.071*	*–0.071*	–0.688	0.676	–0.932	1.046	*–0.080*	*–0.080*	*0.164*	*0.164*
nyse	–0.126		–0.118		0.052		0.237		–0.149		–0.045	
	–1.295	1.043	–1.087	0.850	*0.052*	*0.052*	–0.414	0.887	*–0.149*	*–0.149*	–1.334	1.243
nasdaq	0.082		0.108		0.007		–0.072		0.044		–0.063	
	–0.650	0.815	*0.108*	*0.108*	–0.081	0.094	–1.083	0.939	*0.044*	*0.044*	*–0.063*	*–0.063*
10-yr treas	–0.276		0.101		–0.190		–0.204		–0.071		–0.088	
	–1.356	0.803	*0.101*	*0.101*	–1.970	1.590	*–0.204*	*–0.204*	–1.979	1.836	–1.063	0.888
Baa sprd	–0.041		0.165		–0.083		0.022		–0.021		0.162	
	–0.041	*–0.041*	–0.938	1.268	*–0.083*	*–0.083*	*0.022*	*0.022*	*–0.021*	*–0.021*	*0.162*	*0.162*
hi yld sprd	–0.081		0.011		–0.168		–0.189		–0.037		–0.227	
	–0.081	–0.081	–1.406	1.428	–1.219	0.883	–1.085	0.708	*–0.037*	*–0.037*	–0.910	0.455
10-yr swap sprd	–0.017		–0.015		0.075		0.012		0.025		–0.037	
	–1.193	1.159	–0.266	0.236	–0.554	0.705	*0.012*	*0.012*	*0.025*	*0.025*	*–0.037*	*–0.037*
embi+ sprd	0.006		0.081		–0.134		–0.347		–0.032		0.047	
	–1.954	1.966	–1.879	2.041	–2.094	1.826	–2.307	1.613	–1.992	1.928	–1.913	2.007

[a]Scaled coefficients equal the change in trading revenue measured in terms of trading revenue standard deviations due to 2 standard deviation factor shocks. Italic numbers indicate the estimated variance was negative.

[b]Factors expressed as log changes for exchange rates and equity and first differences for interest rate and credit spreads.

equal 0.78 standard deviations. Thus, 2 standard deviation shocks to individual factors and even to multiple factors would still leave a positive expected trading revenue.

Among individual market categories, the estimated mean exposures for the interest rate factor are negative for five of six banks. The negative exposures would imply bank dealers have (small) net long exposures to interest rate changes on average; that is, the portfolio duration is positive. For the three other broad market categories, however, there does not appear to be a clear pattern of directional mean exposures to these market categories, although coefficients are mostly positive for the Western Europe exchange index. Generally, the coefficients vary in sign across broad market categories for a given bank and for the most part across banks for a given factor.

Now consider the estimated 95-percentile intervals for the market factor exposures reported under the mean exposure estimates in table 2.5. The interval estimates cover both positive and negative values, indicating that factor exposures can vary between long and short positions. Also, for the factor variances with nonnegative estimates, the 95 percent coefficient bounds are large relative to the estimated mean coefficients. However, the bounds do not appear to be particularly large when measured against the trading revenue quantiles shown in the bottom panel of table 2.1.

Specifically, the 95 percent bounds in table 2.5 measure potential trading revenue variation from 2 standard deviation market factor shocks. Conditioned on a 2 standard deviation factor shock, they represent 95 percent bounds on portfolio gains and losses. The trading revenue quantiles in table 2.1 measure trading revenue variation due to market factor shocks *and* variation from other influences, such as market-making revenues. The bounds in table 2.5 tend to be within the 1 percent and 99 percent quantiles for trading revenues shown in table 2.1. Also, the bounds in table 2.5 are for 2 standard deviation market factor shocks. Thus, trading revenues conditioned on estimates of relatively large factor exposures and factor shocks do not produce extreme outliers relative to the unconditional variability of the trading revenues.

Overall, the results from the random coefficient model do not indicate that bank dealers take large market risks relative to the size of average trading revenues and trading revenue volatility, and there is significant cross-dealer heterogeneity in exposures. However, at times dealers may still have large exposures to particular factors, creating the potential for significant losses on days of extreme market conditions.

2.4.3 Cross-Bank Trading Revenue Correlations

As described earlier in section 2.2, cross-bank trading revenues show small but consistently positive correlations (table 2.2). As shown in equation (5), cross-bank trading return correlation due to market risk exposures can come from dealers either having common average exposures to market factors or common variation in exposures. Based on the random coefficient regression results, average factor exposures seem unlikely to be an important source of cross-bank trading revenue correlation. This can be determined by applying the mean and variance estimates of the random coefficients for the market factors to estimate $\rho_{\hat{w}_i\hat{w}_j}\sqrt{RS_i}\sqrt{RS_j}$ in equation (5) for banks' i and j.[7] The cross-bank correlation component reflecting positions at their mean values was calculated for each pair of banks. For all but one bank this component is less than 0.02 (for banks 2 and 4, it is –0.04).

If market exposures account for most of the observed trading revenue correlations, it must be mainly due to common changes in banks' exposures; that is, the component $\rho_{u_iu_j}\sqrt{1 - RS_i}\sqrt{1 - RS_j}$ in equation (5). To determine this component requires estimates of the variable exposure component $u_i(t)$ in each bank's residual revenue (equation [4b]). The best that can be done is to use the factor model regression residuals for $u_i(t)$ to calculate $\rho_{u_iu_j}\sqrt{1 - RS_i}\sqrt{1 - RS_j}$ for each combination of banks. Unfortunately, the regression residuals will include both $u_i(t)$ and other unspecified components of trading revenues.

Nonetheless, correlations reported in the bottom panel of table 2.6 were obtained by calculating $\rho_{u_iu_j}\sqrt{1 - RS_i}\sqrt{1 - RS_j}$ using the regression equation residuals (correlations above the diagonal are the trading revenue correlations displayed in table 2.2). The correlations below the diagonal typically are slightly more than half the trading revenue correlations above the diagonal. Whether the former represent a small commonality in trading revenue due to common market exposures or due to other common influences on trading revenues not controlled for in the regressions is difficult to say. Employing different approaches, further consideration is given to dealer commonality in market exposures in the next two sections.

2.5 Rolling Regressions

In this section, we present estimates of market factor coefficients for daily rolling regressions. Using ordinary least squares (OLS), each bank's trading revenue is regressed on the market factors and other explanatory variables, including our proxy variables for trading volume and net interest payment effects on trading revenues. The rolling window is 150 days. The first 150-day regression ends on August 11, 1998 (August 14, 1998, for bank 1). The regression equations are reestimated daily, dropping the last day and adding a new day using each bank's available sample period.

In figures 2.3–2.6, plots of rolling coefficients that are representative of

7. $\rho_{\hat{w}_i\hat{w}_j}$ is generated by historically simulating $\hat{w}_i$ for each bank, using the estimated factor coefficients and historical factor data. For $RS_i = \sigma_{\hat{w}_i\hat{w}_i}/\sigma_{w_iw_i}$, $\sigma_{\hat{w}_i\hat{w}_j}$ is similarly obtained. $\sigma_{w_iw_i}$ can be generated from equation (4.e) in the text, using the estimated factor coefficients for $\overline{V}_k$, the sample factor variances for ω_{kk}, and the estimated factor coefficient variances used for $\sigma_{v_kv_k}$.

Table 2.6 Cross-bank trading revenue correlation due to market factors (unconditional trading revenue correlations above diagonal; correlations due to market factors below diagonal)

	Bank					
Bank	1	2	3	4	5	6
1		0.415	0.21	0.182	0.028	0.145
2	0.301		0.112	0.070	0.158	0.147
3	0.139	0.064		0.243	0.169	0.145
4	–0.011	–0.028	0.138		0.048	0.146
5	0.029	0.121	0.042	0.017		0.094
6	0.123	0.107	0.056	0.063	0.045	

Notes: The cross-bank correlations due to market factors were calculated using equation (5). For details of the calculations, see the explanation in text.

the results for the different broad market categories are presented along with 150-day coincidental moving averages of the respective factors. The coefficients for each factor are in the same units as the random coefficient model estimates in appendix table 2A.1 (average values of the rolling coefficients are of the same order of magnitude as those in the random coefficient model in table 2A.1). The rolling means of factors are expressed as factor levels (not differences). They show large ranges of variation over the sample period, which includes a business cycle peak in March 2000 and a trough in November 2001. The interest rate, equity, and credit spread factors (Baa and high yield) show evidence of business cycle influences.

Our interest is in whether the rolling coefficients vary systematically with the factors, which would indicate that the dealers' market exposures are related to market prices.

Consider first the coefficients for the interest rate factor plotted in figure 2.3. The coefficients for all but bank 4 show a rising and declining pattern that roughly tracks the rising and declining interest rate pattern. The pattern implies a tendency for the portfolio's interest rate exposure to move inversely with interest rates to the point where exposures may go from long to short or short to long.

This pattern would be consistent with dealers' reducing net long positions in longer-term securities when interest rates are rising, even to the point of taking short positions. When interest rates decline, dealers increase their net long positions so that, in low interest rate environments, they tend to have relatively large interest rate exposures.

A more passive strategy also might be consistent with the results in figure 2.3. As shown in equation (3), the factor coefficients measure factor exposures in terms of position values. Rather than actively alter positions, dealers might have simply held their same positions and allowed position values to deteriorate, even becoming negative, as rates increased (prices de-

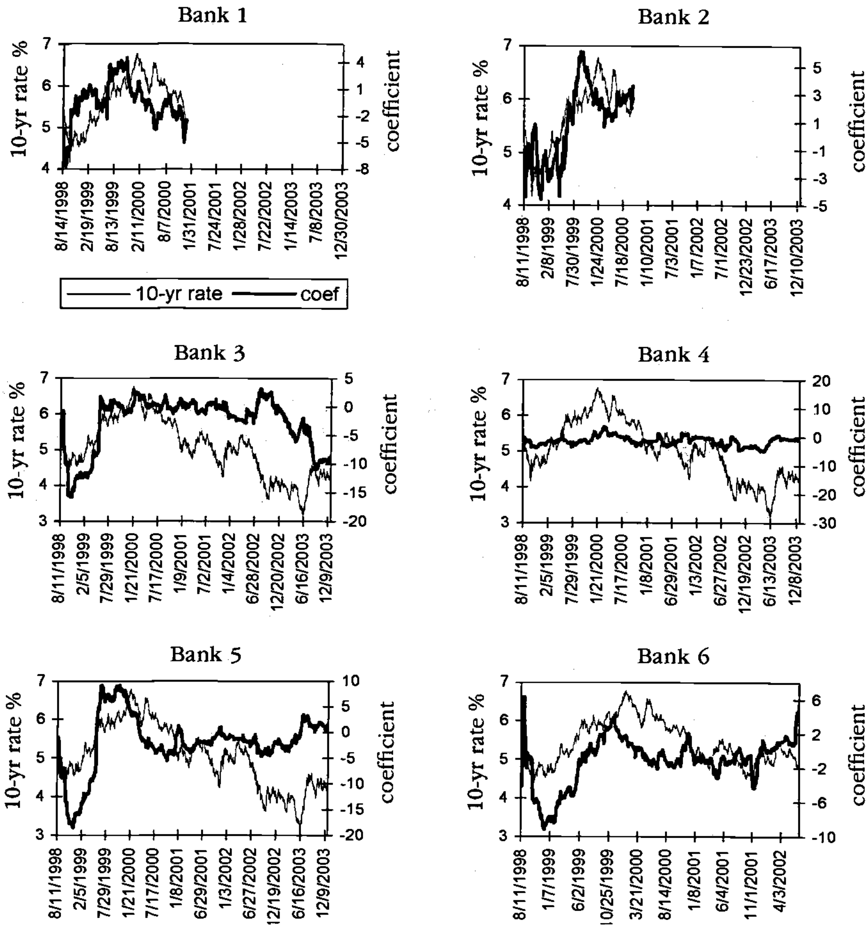

Fig. 2.3 Interest rate regression coefficients and moving-average interest rate

clined) and then increase as rates subsequently declined. Against this explanation, however, market analysts suggested that dealers were increasing their long-term positions as interest rates declined to low levels in the early 2000s.[8]

Aside from the explanation for the rolling interest rate coefficients, it is shown in table 2.7 that cross-bank correlations for the coefficients are all positive. This reinforces the impression from figure 2.3 of common variation in the dealers' interest rate exposures.

For the most part, the rolling coefficients for the other factors do not

8. See *Financial Times* article by Jenny Wiggins, March 11, 2004. Also see Adrian and Fleming (2005), p. 4.

Table 2.7 Cross-bank correlations for rolling regression coefficients

	xwe	xru	xap	xsa	nyse	nasdaq	r10yr	Baa	hy yld	swap	embi
Median correlation	0.09	0.03	0.18	0.28	0.18	0.20	0.74	0.16	0.59	0.25	0.13
Percent positive correlation	53	53	53	67	73	60	100	60	80	67	67

Note: There are 15 cross-bank correlations for each market factor.

show any clear patterns of comovement with their respective factors that are common to all or most banks. In figures 2.4 and 2.5, plots are presented for the rolling coefficients and factors for the NYSE and high yield spreads. These results are representative of results for the other factors as well, excluding the Russian ruble (see the following). For some individual banks, comovement is observed between the coefficients and factors—for example, the NYSE rolling coefficients and NYSE factor for bank 2. Whether this represents an underlying relationship for a particular bank or just a chance realization of the data can't be determined. Nonetheless, for the non-interest rate factors, the results do not indicate any covariation between the factor exposures and the factors that is common among the dealers.

Something of an exception to these results is the behavior of the Russian ruble coefficients shown in figure 2.6. For all six banks, the coefficients move toward zero in late August and early September 1998 as the ruble declined precipitously. The estimated coefficients remain close to zero until mid-1999 (several months after the August–October 1998 period passed out of the rolling samples). This behavior would be consistent for the banks becoming insulated against the ruble.[9]

2.6 Dealer Trading Revenues on Days of Large Market Moves

The results from the two-factor model approaches suggest that, in the aggregate, bank dealers are not consistently on one side of the market, except possibly for (default-free) interest rate exposures. However, as described in section 2.2, all six banks had abnormally low, though still mostly positive, trading revenues in the latter part of 1998. This was a period that included both high market volatility and sharp declines in credit and other risky asset prices and increases in U.S. Treasury security prices. In a final exercise, we look to see whether dealer trading revenues might be commonly related to price movements on days of large price changes. This may

9. While difficult to see in the figure, prior to convergence to zero, the rolling coefficients across the six banks were quite different and included both positive and negative coefficient values, implying long and short exposures in the ruble. Note also that the volatility of the ruble (measured as absolute daily log changes) remained above pre-August 1998 levels over the rest of the year and into the first half of 1999.

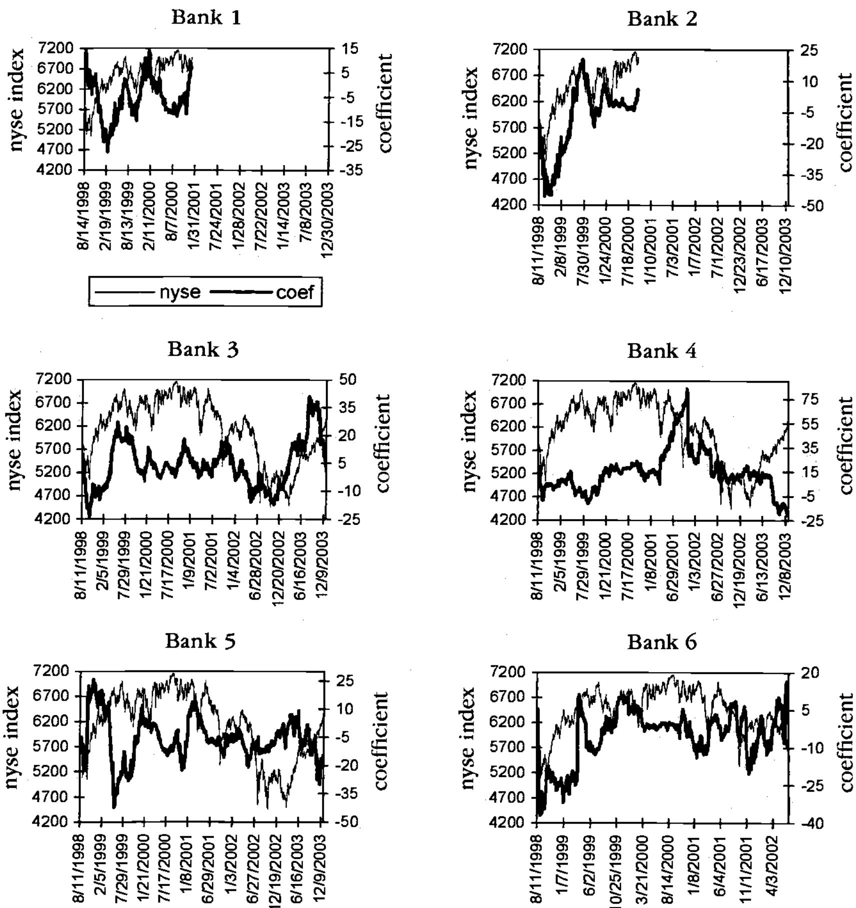

Fig. 2.4 NYSE regression coefficients and moving-average NYSE index

not be evident in the factor model regressions based on the full samples where, on many days, price changes are small.

For simplicity, days of relatively large price increases and, separately, price declines are identified only for the broad market categories—exchange rate, equity, interest rate, and credit. For each market factor, days where factor shocks fall into the first quintile and the fifth quintile are separately sorted. For a market category, a large market decline day (or a large market increase day) is defined as a day when at least one factor in the category is in the first (the fifth) quintile and none is in the fifth (the first) quintile. For example, a day when the change in the NYSE index is in the first quintile and the NASDAQ index is not in the fifth quintile is a large equity market decline day. Typically, when one factor in a market category expe-

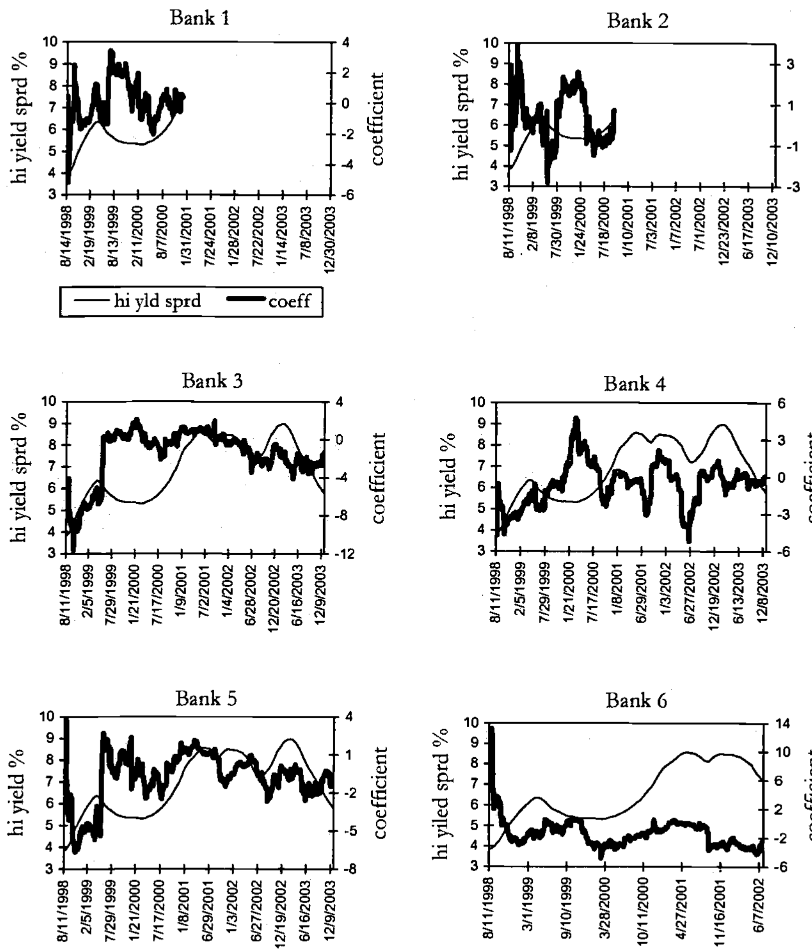

Fig. 2.5 High-yield regression coefficients and moving-average high-yield spread

riences a large change, other factor(s) in that category change in the same direction, although this is less true for exchange rates (further description of the large factor changes is provided in table 2.8). Large market move days span the entire six-year sample period, but with a higher frequency in the second half of 1998.

Mean and median bank trading revenues for low and high market return days for each of the four market categories are reported in table 2.8. Except for the interest rate category, mean and median trading revenues for the six banks on low return days in each of the other market categories are not uniformly lower, or higher, than on high return days. For these market categories, this comparison does not indicate that dealers' market exposures bear a common systematic relation to market prices. For the interest rate

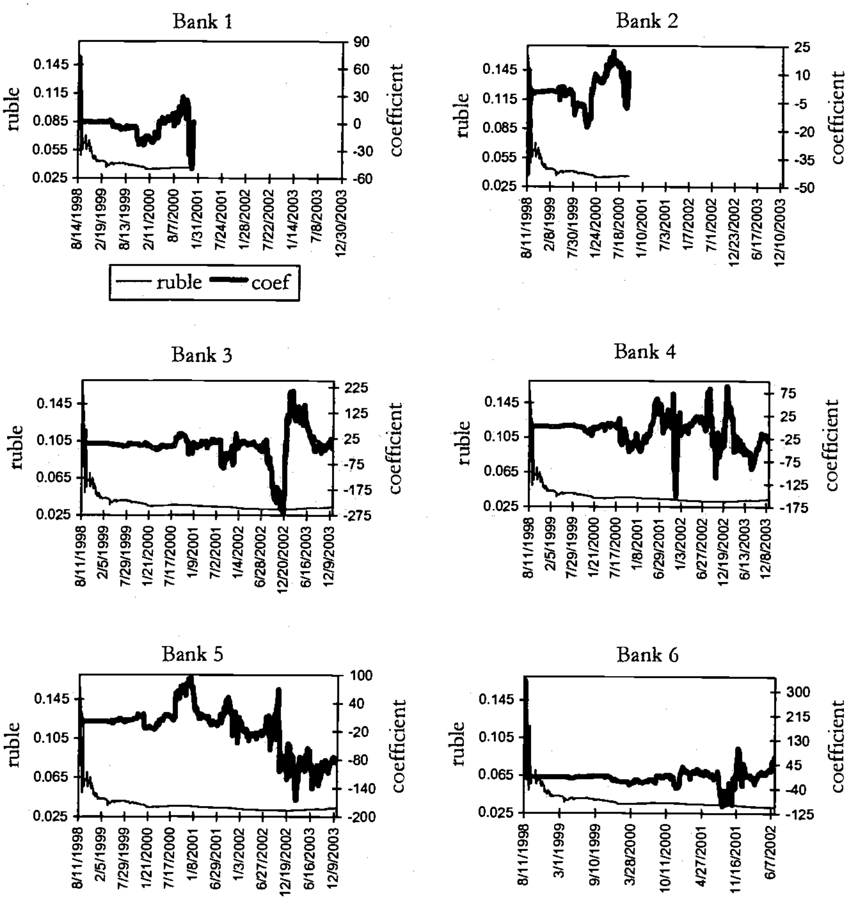

Fig. 2.6 Russian ruble regression coefficients and moving-average exchange rate

category, on days of large rate increases, trading revenues are uniformly lower across the six banks than on days of large rate declines, suggesting long (positive duration) interest rate exposures are typical. These results are consistent with the results from the factor models.

While heterogeneity in exposures will reduce the likelihood of large aggregate dealer losses, the chance realization of losses (or abnormally high returns) for a group of dealers is still more likely during a period when volatility is high across markets. The summer and autumn of 1998 was such a period, and the higher volatility in the banks' trading revenues is apparent from figure 2.2.[10] Nonetheless, with cross-bank heterogeneity in expo-

10. We also looked at absolute trading revenues on days of high and low absolute changes in market factors, where absolute values are used to measure the size of daily fluctuations or volatility. Days of high and low volatility were defined at the market category level using an analogous procedure to that followed in determining days of large market declines and large

Table 2.8 Bank trading revenues conditioned on large one-day market moves

	Exchange rate change				Interest rate change			
	Trading revenue: Mean		Trading revenue: Median		Trading revenue: Mean		Trading revenue: Median	
Bank	Decline	Increase	Decline	Increase	Decline	Increase	Decline	Increase
1	1.14	1.04	1.07	0.97	1.29**	1.00	1.22**	0.90
2	0.87	0.85	0.82	0.78	0.93	0.85	0.82	0.80
3	0.70	0.81	0.70	0.75	0.86**	0.71	0.90*	0.72
4	0.85	0.98**	0.81	0.81	0.95	0.93	0.87	0.78
5	0.60	0.61	0.55	0.59	0.69**	0.57	0.70**	0.55
6	0.63	0.69	0.63	0.68	0.87**	0.63	0.81**	0.64
	Equity price change				Credit spread changes			
	Trading revenue: Mean		Trading revenue: Median		Trading revenue: Mean		Trading revenue: Median	
	Decline	Increase	Decline	Increase	Decline	Increase	Decline	Increase
1	1.17	1.06	1.06	0.89	1.00	1.13	0.93	1.13
2	0.93	0.77	0.86	0.78	0.72**	0.92	0.64**	0.84
3	0.74	0.86	0.78	0.85	0.84	0.73	0.76	0.78
4	0.83	1.20**	0.80	0.93**	1.01	0.91	0.85	0.83
5	0.60	0.51	0.59	0.45	0.68	0.63	0.64	0.61
6	0.82	0.72	0.75	0.75	0.73	0.73	0.66	0.77

Notes: Bank trading revenue is normalized by full sample bank trading revenue standard deviations. Sample sizes for each of the "Decline" and "Increase" categories range from 167 to 606, with a median of 323. For individual factors (e.g., NYSE for equity category), their mean values for the "Decline" quintile is 1 to 2 standard deviations below the mean values for the "Increase" quintile. Means test is a standard difference of two means. Medians test uses the Mann-Whitney-Wilcoxon rank sum test for large samples.

**Significant at .05 for the difference between "Decline" and "Increase" day trading revenue mean (median) values.

sures, losses are likely to come from positions in different markets. For the 1998 third and fourth quarters, major U.S. bank dealers reported quarterly losses or low revenues in different market categories—interest rate (including credit), equity, and commodities.[11] For the six banks studied here, it was also the case that different banks reported quarterly losses or low returns in different markets.

increases (table 2.8), except in terms of the size of absolute factor changes. For each of the six banks, mean and median absolute one-day trading revenues are consistently higher on high market volatility days than on low market volatility days for all four market categories, with significance at the 0.05 level for almost 75 percent of the mean and median calculations.

11. For large bank dealers, see "Bank Derivatives Report, Fourth Quarter 2001," Office of the Comptroller of the Currency, p. 13. Note that the quarterly revenue reports include fee and spread income as well as changes in position market values.

2.7 Conclusions

To recap the main results, bank dealers do not consistently maintain exposures on one side of the market, with the exception of small average long exposures to interest rate risk. They vary their exposures in size and direction but, except for interest rate exposures, the variation is heterogeneous across the dealers. Interest rate exposures tend to vary inversely with the level of interest rates. Variation in trading revenues from market exposures also does not seem large relative to the variation in total trading revenues, which also include fee, spread, and net interest income.

These results are subject to important limitations imposed by limitations of the trading revenue data that were used, inherent factor model limitations, and to a small sample of bank dealers. Also, the two-factor modeling approaches employ different underlying assumptions whose consequences have not been examined. If these limitations are put aside, a number of points can be made about the relation between dealer market risks, VaR, and market prices based on the results.

Heterogeneity in dealers' market exposures reduces the likelihood that dealers as a group will incur large losses in periods of market stress or that their aggregate risk-taking behavior contributes significantly to a herding phenomenon. The heterogeneity in exposures also applies to arguments that dealers' common use of VaR for risk management leads to herding behavior. Shifts in market volatility could produce common changes in dealers' VaRs and desired risk exposures but without leading to common directional shifts in risky asset demands because dealers have both short and long positions. A potential exception is commonality in adjustments to interest rate risk exposures.

While heterogeneity in dealers' market exposures reduces the likelihood of large aggregate dealer losses, the chance occurrence of common losses (or abnormally high returns) among banks is still more likely in a period of generally high market volatility. The summer and autumn of 1998 was such a period, when volatility was high across markets and dealers' losses or low returns occurred in different markets.

Especially during periods of extreme market conditions, there are areas of dealer activity other than securities trading that may be more important to financial market stability and bank risk. This would include dealers' market-making role under extreme market conditions. For example, see Routledge and Zinn (2004), with some empirical evidence on the summer and autumn of 1998 in Furfine and Remolona (2002). Also potentially important is dealer (including parent bank), credit exposures to hedge funds, and other important market players. The issue of bank credit exposures to hedge funds and large market players is taken up in Kho, Lee, and Stulz (2000), Furfine and Remolona (2002), and Chan, Getmansky, Hass, and Lo (2005).

Appendix

Factor Model Derivations

Factor Model Portfolio Value (equation [2])

Here the 1-period change in the value of the portfolio shown in equation (2) is derived. Two assumptions are used. One is a self-financing constraint within the period, $\Sigma_{k=1}^{K} dx_{kt}(\tau)p_{kt}(\tau) + dx_{0t}(\tau) = 0$. The second is that price and position changes within the period are uniform: $dp_{kt}(\tau) = \Delta p_k(t)d\tau$ and $dx_{kt}(\tau) = \Delta x_k(t)d\tau$ for $t-1 < \tau < t$. The starting position for security k is x_{kt}^0. The derivation uses continuous price and position changes within the period. The change in the value of the portfolio is $w(t) \equiv W(t) - W_t^0$.

Using the above assumptions and notation:

$$\text{(A.1)}\quad w(t) = \int_{t-1}^{t}\left[\sum_{k=1}^{K} x_k(\tau)dp_k(\tau) + p_k(\tau)dx_k(\tau) + dx_0(\tau)\right]d\tau$$

$$= \sum_{k=1}^{K}\int_{t-1}^{t} x_k(\tau)dp_k(\tau) \qquad \text{(using the self-financing constraint)}$$

$$= \sum_{k=1}^{K}\int_{t-1}^{t}\left[x_{kt}^0 + \int_{t-1}^{\tau} dx_k(\varsigma)d\varsigma\right]dp_k(\tau)d\tau$$

$$= \sum_{k=1}^{K}\left[x_{kt}^0 + \frac{1}{2}\Delta x(t)\right]\Delta p(t) \qquad \text{(using uniform price and position changes)}$$

$$= \sum_{k=1}^{K}\left[x_{kt}^0 p_k(t-1) + \frac{1}{2}\Delta x(t)p_k(t-1)\right]r_k(t)$$

where $r_k(t) \equiv \Delta p_k(t)/p_k(t-1)$.

Cross-Bank Portfolio Value Correlation Due to Market Factors (equation [5])

The correlation in portfolio value changes between bank i and j due to market factor shocks is derived under the assumptions used for the random coefficient model presented in equations (4a)–(4d). The following vector notation is used here: $r(t)$, $V_i(t)$, $\overline{V}_i$ and $v_i(t)$ are $K \times 1$ vectors of the market factors, factor coefficients, mean coefficients and random coefficient components, respectively. The factor shocks $r(t)$ are assumed to have a zero expected value.

Using equation (4a) in the text, $w(t) = \Sigma_{k=1}^{K} r_k(t)\overline{V}_k + u(t)$ and equation (4b), $u(t) \equiv \Sigma_{k=1}^{K} r_k(t)v_k(t)$, the expected cross-product of returns for banks i and j, conditioned on $r(t)$, is:

(A.2) $E(w_i(t)w_j(t) \mid r(t)] = E_{v_i,v_j}\{[\overline{V}_i' r(t) + v_i'(t)r(t)][\overline{V}_j' r(t) + v_j'(t)r(t)] \mid r(t)\},$

where $E_{v_i v_j}[g(v_i, v_j) \mid r(t)] \equiv \int_{v_{i1}} \ldots \int_{v_{jK}} g[v_{i1} \ldots, v_{jK}, r(t)] f[v_{i1} \ldots, v_{jK} \mid r(t)] dv_{i1} \ldots, dv_{jK}$. Using $E[v_i(t)] = 0$ and independence between $v_i(t)$ and $r(t)$, $E_{v_j}[\overline{V}_i' r(t)r'(t)v_j(t) \mid r(t)] = E_{v_i}[v_j'(t)r(t)r'(t)\overline{V}_j \mid r(t) = 0$. Using this orthogonality, (A.2) becomes

$$\text{(A.3)} \quad E(w_i(t)w_j(t) \mid r(t)] = \overline{V}_i' r(t)r'(t)\overline{V}_j + E_{v_i,v_j}[v_i'(t)r(t)r'(t)v_j(t) \mid r(t)]$$
$$= \overline{V}_i' r(t)r'(t)\overline{V}_j + \sum_{k=1}^{K}\sum_{l=1}^{K} \sigma_{v_{ik}v_{jl}} r_k(t)r_l(t).$$

Since the factor shocks are zero mean, the (unconditional) covariance between portfolio returns to i and j is $\sigma_{w_i w_j} \equiv E[w_i w_j] = E_r\{E[w_i(t)w_j(t) \mid r(t)]\}$. Applying $E_r\{E[w_i(t)w_j(t) \mid r(t)]\}$ to (A.3) yields

$$\text{(A.4)} \quad \sigma_{w_i w_j} = E_r[\overline{V}_i' r(t)r'(t)\overline{V}_j] + E_r\left[\sum_{k=1}^{K}\sum_{l=1}^{K} \sigma_{v_{ik}v_{jl}} r_k(t)r_l(t)\right]$$
$$= \overline{V}_i' \Omega \overline{V}_j + \sum_{k=1}^{K}\sum_{l=1}^{K} \sigma_{v_{ik}v_{jl}} \omega_{kl},$$

where $\Omega \equiv E[r(t)r'(t)]$ is the covariance matrix for $r(t)$ and $\omega_{kl} \equiv E[r_k(t)r_l(t)]$ the covariance for $r_k(t)$ and $r_l(t)$. $\overline{V}_i' \Omega \overline{V}_j$ is the covariance between changes in bank i and bank j's portfolio values conditioned on market exposures set at their mean values. $\Sigma_{k=1}^{K} \Sigma_{l=1}^{K} \sigma_{v_{ik}v_{jl}} \omega_{kl}$ is the covariance between changes in i and j's portfolio values due to the interaction between the random shifts in the coefficients and the market factors. Note the sign for $\sigma_{v_{ik}v_{jk}} \omega_{kk}$ is the same as that for $\sigma_{v_{ik}v_{jk}}$.

To obtain the correlation coefficient for $w_i(t)$ and $w_j(t)$, define $\sigma_{\hat{w}_i \hat{w}_j} \equiv \overline{V}_i' \Omega \overline{V}_j$ and $\sigma_{u_i u_j} \equiv \Sigma_{k=1}^{K} \Sigma_{l=1}^{K} \sigma_{v_{ik}v_{jl}} \omega_{kl}$. Define $\rho_{w_i w_j}$ as the correlation between $w_i(t)$ and $w_j(t)$. Using this notation, we can express the various correlations and covariances between changes in i and j's portfolio values as follows:

$$\text{(A.5a)} \quad \rho_{w_i w_j} \equiv \sigma_{w_i w_j} / \sqrt{\sigma_{w_i w_i}}\sqrt{\sigma_{w_j w_j}}$$

$$\text{(A.5b)} \quad \sigma_{\hat{w}_i \hat{w}_j} \equiv \rho_{\hat{w}_i \hat{w}_j} \sqrt{\sigma_{\hat{w}_i \hat{w}_i}}\sqrt{\sigma_{\hat{w}_j \hat{w}_j}}$$

$$\text{(A.5c)} \quad \sigma_{u_i u_j} \equiv \rho_{u_i u_j} \sqrt{\sigma_{\hat{w}_i \hat{w}_i}}\sqrt{\sigma_{\hat{w}_j \hat{w}_j}}$$

Also, from equation (A.4), we have $\sigma_{w_i w_j} = \sigma_{\hat{w}_i \hat{w}_i} + \sigma_{u_i u_i}$. Using this result with the definitions in equations (A.5a)–(A.5c) gives the unconditional correlation between changes in i and j's portfolio values, shown in equation (5) in the text:

$$\text{(A.6)} \quad \rho_{w_i w_j} = \rho_{\hat{w}_i \hat{w}_j} \sqrt{\frac{\sigma_{\hat{w}_i \hat{w}_i}}{\sigma_{w_i w_i}}} \sqrt{\frac{\sigma_{\hat{w}_j \hat{w}_j}}{\sigma_{w_j w_j}}} + \rho_{u_i u_j} \sqrt{\frac{1 - \sigma_{\hat{w}_i \hat{w}_i}}{\sigma_{w_i w_i}}} \sqrt{\frac{1 - \sigma_{\hat{w}_j \hat{w}_j}}{\sigma_{w_j w_j}}}$$

$$= \rho_{\hat{w}_i \hat{w}_i} \sqrt{RS_i} \sqrt{RS_j} + \rho_{u_i u_j} \sqrt{1 - RS_i} \sqrt{1 - RS_j}.$$

Table 2A.1 Market factor model for bank trading revenue

Variable	Bank 1	2	3	4	5	6
constant						
β_0	–0.105	1.152	–0.575	–2.632	1.397	0.422
t-value	–0.26	2.81	–2.54	–11.24	5.51	1.44
fx we						
β_1	5.568	5.652	4.528	6.771	–7.380	5.575
t-value	0.92	0.94	1.02	1.64	–1.52	1.13
fx russia						
β_2	0.901	1.814	5.011	–0.088	0.605	–1.038
t-value	0.56	0.97	2.57	–0.08	0.35	–0.72
fx asia pac						
β_3	–17.873	–8.553	–2.006	3.794	2.843	0.550
t-value	–3.02	–1.45	–0.47	1.01	0.58	0.13
fx s amer						
β_4	–3.993	–5.830	–0.506	4.637	–6.527	13.453
t-value	–0.60	–0.91	–0.12	1.03	–1.43	2.43
nyse						
β_5	–5.437	–5.112	2.241	10.230	–6.432	–1.959
t-value	–1.19	–1.14	0.79	3.50	–2.06	–0.53
nasdaq						
β_6	1.855	2.440	0.148	–1.621	0.985	–1.410
t-value	0.92	1.19	0.10	–1.07	0.62	–0.89
10-yr treas						
β_7	–2.192	0.804	–1.507	–1.618	–0.566	–0.696
t-value	–2.23	0.78	–2.38	–2.89	–0.85	–0.99
Baa sprd						
β_8	–0.593	2.355	–1.184	0.314	–0.305	2.312
t-value	–0.41	1.58	–1.30	0.36	–0.31	2.12
hi yld sprd						
β_9	–0.434	0.059	–0.901	–1.011	–0.200	–1.218
t-value	–0.62	0.07	–2.06	–2.46	–0.48	–2.48
swap sprd						
β_{10}	–0.268	–0.234	1.181	0.191	0.397	–0.582
t-value	–0.21	–0.21	1.53	0.28	0.51	–0.64
embi+ sprd						
β_{11}	0.013	0.168	–0.279	–0.722	–0.066	0.097
t-value	0.07	0.86	–2.12	–5.55	–0.44	0.52
equity vol						
β_{12}	0.353	0.418	0.223	0.363	0.083	0.236
t-value	3.78	4.21	4.97	8.07	1.71	4.00

Table 2A.1 (continued)

	Bank					
Variable	1	2	3	4	5	6
10-yr treas move ave						
β_{13}	0.143	–0.124	0.150	0.529	–0.206	0.024
t-value	1.91	–1.60	4.07	13.42	–5.03	0.47
PL_{t-1}						
β_{14}	0.142	0.181	0.203	0.227	–0.081	–0.028
t-value	4.03	5.09	8.30	9.65	–3.17	–1.07
trend						
β_{15}	0.001	0.001	0.001	0.001	0.001	0.000
t-value	3.59	3.45	9.05	12.08	6.71	4.37
F-Stat2	9.236	6.081	22.368	44.293	14.593	4.576
R^2	0.172	0.128	0.196	0.325	0.137	0.063
N	728	681	1,484	1,485	1,483	1,109

Notes: Trading revenues are divided by the banks' sample standard deviations. Equity volume has been scaled by 1 million. Coefficients are estimated for equation (4.a) in the text with additional explanatory variables described in the text. A GLS estimator is used, which is described in Hildreth and Houck (1968). See their description for β, second equation in (25), p. 589.

Table 2A.2 **Estimates of coefficient variances for market factors**

	Bank					
Variable	1	2	3	4	5	6
constant						
α_0	0.48	0.40	0.44	0.57	0.56	0.90
t-value	3.25	3.89	5.86	8.21	5.76	2.41
fx w eur						
α_1	–528.20	34.75	1281.02	–87.84	1114.55	–2052.03
t-value	–0.26	0.02	1.19	–0.09	0.80	–0.39
fx russia						
α_2	2.05	30.54	83.44	–19.82	30.01	–108.13
t-value	0.10	2.18	5.85	–1.51	1.62	–1.75
fx asia pac						
α_3	2567.56	3111.68	1401.34	–240.30	3002.21	–449.13
t-value	3.00	5.26	2.43	–0.45	4.00	–0.18
fx s amer						
α_4	–1526.15	–333.83	810.87	1705.42	–862.05	–2801.47
t-value	–1.71	–0.54	1.57	3.58	–1.28	–1.13
nyse						
α_5	665.46	456.79	–301.12	206.31	–35.02	808.70
t-value	1.28	1.19	–1.22	0.90	–0.11	0.56

continued

Table 2A.2 (continued)

	Bank					
Variable	1	2	3	4	5	6
nasdaq						
α_6	70.81	–80.79	1.01	134.72	–38.89	–154.61
t-value	0.56	–0.70	0.02	2.23	–0.46	–0.51
10-yr treas						
α_7	19.11	–4.55	51.94	–8.02	59.64	15.60
t-value	0.74	–0.25	5.87	–0.98	5.10	0.31
Baa sprd						
α_8	–58.85	64.78	–78.46	–29.95	–16.59	–69.86
t-value	–0.86	1.44	–3.07	–1.27	–0.50	–0.55
hi yld sprd						
α_9	–0.15	15.00	8.25	6.00	–0.55	3.48
t-value	–0.02	1.52	3.24	2.56	–0.17	0.28
swap sprd						
α_{10}	88.76	4.04	25.43	–15.60	–15.92	–24.42
t-value	2.49	0.16	1.42	–0.95	–0.68	–0.25
embi+ sprd						
α_{11}	1.39	1.68	0.19	0.37	0.56	4.73
t-value	3.11	5.73	0.78	1.68	1.79	4.44
F-Stat	3.82	13.73	11.07	4.16	5.59	1.98
R^2	0.06	0.18	0.08	0.03	0.04	0.02
N	728	681	1,484	1,485	1,483	1,109

Note: The coefficients (variances) and their standard errors use an unbiased least-squares estimator developed in Hildreth and Houck (1968), equation (14), p. 587.

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Comment on Chapters 1 and 2

Kenneth C. Abbott

First of all, I want to thank the NBER for inviting me to this conference. Among the attendees are professors from my student days, academics whose works I've admired for years, and regulators whose role I have come to respect more and more. I also thank the authors of the two papers for their work in this important field.

For years, value-at-risk (VaR) has had both its supporters and its detractors in the academic and regulatory communities. The detractors have been quick to point out that VaR fails to capture extreme market movements and does not react quickly enough to changes in market conditions. Supporters, on the other hand, simply look to its simplicity of purpose (to gain some crude measure of likely trading loss) and, more importantly, to the degree of uniformity it has imposed on the risk measurement processes used at banks and brokerages. I agree that it's far from perfect, but it does serve a very useful purpose.

As a practitioner, my concern has always been (and continues to be) that those studying the numbers emanating from banks' risk processes view

These comments reflect the opinion of the author alone and do not represent the views of Morgan Stanley.

those numbers as being similar to the random variables coming from some natural, or at least stationary, statistical process. While it is certainly not my intention to throw mud at the risk processes that financial institutions have spent so much time, effort, and money to put in place, I feel the need to make clear to everyone some of the problems inherent in those processes.

First, there is a considerable lack of consistency in the measurement of VaR across financial institutions. The Market Risk Amendment of 1996 standardized some aspects of VaR calculation, including the confidence level, the time frame of the loss estimate, the minimum amount of historical data required, and the minimum number of yield curve points necessary, to name but a few. It did not, however, say which methodology should be used (variance/covariance, Monte Carlo simulation, or Historical Simulation), nor did it specify exactly how much data should be used in the process.

I recently conducted an informal poll of fifteen major financial institutions and found that Historical Simulation is used by about 80 percent of them. One institution still used variance/covariance, while the rest did Monte Carlo simulations. What surprised me, however, was that the amount of data used ranged from one year to five years, with the mode of the distribution being two years. What this suggests is that banks' risk measurements will show varying degrees of sensitivity to short-term (and possibly short-lived) changes in market volatility. Most institutions update their datasets quarterly. The addition of one quarter to a rolling four-quarter dataset will be significantly greater than that to a twenty-quarter dataset.

Equally important, the Market Risk Amendment did not clearly define the standards for profit and loss (P&L) calculation for use in VaR backtests. While the recently released Consultative Paper makes some reference to the standardization of P&L, it has remained unclear. Regulators have been known to differ on the definition of the "clean" P&L required for backtests.

A major issue I see with studying VaR in conjunction with trading P&L in a time series framework (e.g., autoregressive integrated moving average [ARIMA], generalized autoregressive conditional heteroskedastic [GARCH], etc.) regards the stationarity of the measures themselves. VaR is clearly a function of the underlying trading position in a given trading book. Some books are very stable or change slowly over time. Certain proprietary books, for example, will hold on to sets of positions for extended periods of time. Other books, however, will show very high degrees of turnover. I have seen certain trading books used for intraday positioning that have shown no end-of-day positions. As a result, they would have no VaR attributed to them. (As a practical matter, for days when the book was flat, I assigned a certain *de minimus* VaR to them based on the average level of risk taking over a period of time.)

This is especially important in the context of very liquid derivatives markets. These portfolios are often very large and frequently represent the plurality of the risk taking going on within a financial institution. These positions can go from hugely long to hugely short in the course of minutes. As a result, these desks are often the risk "steering wheels" for banks' trading portfolios.

Another area where the changing composition of trading books is important to note involves books used to contain large syndication or block trading positions. Here, the book might go from levels of risk near zero to ones of tens of millions of dollars of VaR in an afternoon. Their risk might be reduced quickly, or it might be worked off gradually over time. Either way, the risk of these types of books is anything but stationary.

A third area of concern involves changing risk appetites within firms. Certain trading books may be cut back, often drastically, by senior management. This may take place during market crises, or it may reflect management's lack of confidence in a strategy or a trader. It would be difficult to account or correct for this in any time series analysis of VaR.

A fourth consideration involves the tendency of banks to err on the side of conservatism in their VaR measures. Given a choice between a highly accurate measure that might occasionally understate the VaR and a more conservative metric, all banks are likely to choose the conservative measure. This is because there is a severe penalty for an excess number of outliers (i.e., more than 1 percent at the 99 percent confidence level) in the regulatory capital calculation. In fact, it is not uncommon for books to show no outliers over extended periods of time. This is pointed out in earlier work (2002) by Berkowitz and O'Brien.

A final consideration regarding methodology involves changes in the methodology itself. Firms are constantly upgrading the techniques used to estimate their risk. Notably, these are not uniformly to reduce VaR. In fact, a casual examination of changes in bank's methodologies are likely to reveal as many VaR-increasing changes as decreasing ones. Usually, one does not go back to restate earlier trading days' VaR to reflect the new methodology unless the change took place near the beginning of a quarter. These changes are likely to manifest themselves as jumps in the VaR that have nothing to do with true trading risk.

The measurement of P&L presents still more issues relevant in this context. Some recent work has suggested that time series analysis of actual trading P&L be used as a measure of VaR. While this would certainly reflect market volatility better, it presents a number of difficulties.

First, one has to define trading P&L. While Financial Accounting Standard 133 has helped to define what should be marked-to-market, the actual definition of marked-to-market varies from book to book. In most cases it is fairly easy. Cash equity books have prices that are posted daily. These prices are used (among other things) to set margin levels, so they can probably be counted on to be reasonable.

Second, other trading books have less transparent pricing. Consider the U.S. corporate bond market, for example. Pricing is available every day for most bonds, but much of that is matrix pricing and does not necessarily represent where a bond would trade in the market. Even if the price were "real" it might be a bid for an odd lot and not for size.

Third, firms are likely to use trader marks for positions, checking them periodically with outside sources for veracity. Many of these books have positions within them that have poor price discovery. Many high-yield bonds, for example, are only repriced weekly. Other trading books have positions which are clearly "trading" positions, inasmuch as they are there to capture short-term gains, but for which there is no pricing available at all. It is not uncommon for banks to have distressed debt positions for which one will observe no price changes for weeks or even months at a time. As a result, all measures of P&L on these portfolios must be viewed as approximations of changes in value.

Fourth, the timing of certain P&L events may be subjective. For example, one may observe that a bond spread has widened 10 basis points between day 1 and day 10. Is it safe to assume that the widening took place gradually, suggesting that the loss be recognized on a straight-line basis? Or is it more appropriate to take the loss all at once, perhaps when there was another trade on the market to justify the new price?

The subjectivity of P&L events is exaggerated in the mark-to-model framework, which may affect many derivative transactions. Model changes for derivative books may result in P&L events in dealer portfolios. While some of these events may be covered by reserves set aside for such purposes, other losses may not. This may be due to models behind large positions that are based primarily upon variables that cannot be observed directly.

I think that one possible way of addressing all of these issues is to make bank regulators much more aware of all of the issues involved in the calculation of P&L and the estimation of VaR. I think it would be enormously instructive for bank examiners to study P&L time series to come to an understanding of which pieces of it are purely objective (i.e., based upon prices and/or model input parameters clearly observed in the market) and which pieces less so.

On the VaR side, regulators need to remember that VaR is simply an order statistic—a (sometimes) crude heuristic used to estimate the shape of a loss distribution.

While I'm sure that many firms would be hesitant to release detailed P&L and risk data freely into the academic community, there are probably ways to normalize the data and obfuscate the exact source (i.e., which desk produced the results) that would pass banks' data security rules. This might help all involved gain more insight into how it can be used more effectively.

Comment on Chapters 1 and 2 Paul Kupiec

Let me begin by thanking the NBER for the opportunity to participate in the Woodstock financial regulatory conference. I would also like to thank the authors, Philippe Jorion, James O'Brien, and Jeremy Berkowitz for the opportunity to discuss their papers.

Both of the papers I have been asked to discuss are motivated by the conjecture that the widespread adoption of value-at-risk (VaR) measurement and risk management techniques leads to increased market volatility. The mechanism causing excess volatility is herding behavior among market participants who identically measure and manage risk. Groupthink in risk measurement and management practices, it is alleged, leads investors to construct similar exposures and display a uniform reaction to unanticipated market developments. Presumably this leads to overreactions in market clearing prices, as liquidity providers are ill-prepared to absorb the sales demand of the stampeding VaR-driven investors. The corollary to this conjecture is that unless there is diversity among investor risk measurement and management practices, the buy side of the capital markets are in danger of evaporating when unanticipated market events create sell signals for VaR-focused investors.

In considering the merits of this conjecture, it is unclear to me what special role VaR has to do with creating herdlike behavior. Value at risk is not a trading strategy—it is a specific way of measuring risk. VaR has no direct link with expected return and so it cannot play a defining role in the construction of profitable trading strategies. There is no theoretical or empirical literature of which I am aware that suggests that there is a market price for bearing VaR exposure.[1] VaR limits can be used to control trading losses, but the use of VaR limits does not create positive feedback trading demands that are, for example, required by portfolio insurance dynamic hedges.

VaR is a useful way of measuring and monitoring the exposure of agents that trade risk on behalf of a financial institution. It may, moreover, also be convenient for an institution to use VaR to set limits on these agents' capacity to assume risk. But VaR is not unique in this regard. Risk measures and limits based on durations, convexity, and fixed shocks to the yield curve have long been used to monitor and place limits on the interest rate risks taken by fixed-income traders. Similarly, before the popularization of VaR, options traders' positions were monitored and limited according to rules that used the aggregate delta and vega values of their portfolios. What

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1. Yet many investors have used VaR measures in the denominator of pseudo-Sharpe measures of ex post trading performance.

is unclear to me is why the use of VaR should be unique in its power to cause herding and excess volatility. If risk management encourages herding, then any measure of risk that facilitates monitoring and control of trading activity could give rise to the excess volatility concerns that have been voiced regarding the use of VaR.

It is possible that VaR could be a stronger stimulant for herding behavior than would be the case for other risk and control measures. Unlike duration-based or other methods for limiting risk, VaR estimates are a direct determinant of a bank's minimum regulatory capital requirement. The Basel Market Risk Amendment sets a bank's capital requirement for market risks using the bank's VaR estimates in a formula for minimum regulatory capital (MRC; this formula is well described in Jorion's paper). It is possible that unanticipated changes in asset prices, correlations, or volatilities could result in pressure on regulatory capital capacities in a manner that encourages banks to initiate portfolio adjustments. No other widely used risk monitoring measure has a direct link to minimum regulatory capital needs. The problem with this line of reasoning is that, to date, no U.S. bank has been at risk of becoming less than adequately capitalized due to an unanticipated increase in MRC for market risk.

Quantitative requirements surrounding the construction of banks' MRCs ensure that a bank's daily VaR estimate reacts sluggishly to increases in market volatility.[2] As a consequence, it is highly improbable that unanticipated increases in market factor volatilities can increase daily VaR to a point that it dominates the sixty-day moving average component of the MRC formula, given the attached multiplier of three.[3] Thus, spikes in market volatilities alone are unlikely to cause large daily trading rebalancing demands. For daily VaR to dominate in the MRC calculation, a bank must increase its exposures to market factors by a substantial amount. Absent large changes in bank positions, MRC requirements move only sluggishly from day to day. Moreover, even when banks change positions substantially, the sixty trading-day moving average component of the MRC formula ensures that minimum regulatory capital can only decline gradually. This feature limits the effectiveness of stop-loss trading and wholesale position liquidations as a capital minimization feature.

Even if banks exhibit herdlike reactions to changes in market conditions,

2. The Basel Committee on Banking Supervision (1996a, p. 46) specifies quantitative standards for the implicit calculation of market factor volatilities and correlations in regulatory VaR calculations: "The choice of *historical observation period* (sample period) for calculating value-at-risk will be constrained to a minimum length of one year. For banks that use a weighting scheme or other methods for the historical observation period, the "effective" observation period must be at least one year (that is, the weighted average time lag of the individual observations cannot be less than 6 months)."

3. A 3 multiplier on the sixty-day moving average VaR component applies to a bank with satisfactory backtest results. The multiplier can be increased should a bank's VaR perform poorly in backtests (see the Basel Committee on Banking Supervision 1996a).

bank MRC requirements provide only a weak signal of banks' position adjustments. The signal will be further diminished if banks reallocate the proceeds of their liquidated positions to other positions in the trading book. Bank trading desks may, moreover, also rebalance away from troubled markets but attempt to maintain internal VaR utilization targets.[4] All of these issues make MRC a less-than-ideal medium for studying bank herding behavior. It is perhaps not surprising that Jorion finds very little evidence of a strong positive correlation in bank's market risk minimum capital requirements. While the evidence that Jorion presents is consistent with diversity among bank trading positions and strategies, given MRC construction, the lack of strong positive correlation among bank MRCs is not strong evidence against the possibility of herding behavior in at least some trading markets.

Since unanticipated increases in market volatility are unlikely to increase a bank's market risk capital requirement in a manner that would cause significant shedding of risky positions, the regulatory risk to a bank would seem to be driven by the bank's performance on VaR backtests. For backtesting, daily VaR estimates must be compared against daily trading book profits and losses (Basel Committee on Banking Supervision 1996b). If losses exceed a bank's daily VaR estimate, an exception is recorded. An excessive number of exceptions within a 250-day window is cause for an increase in the bank's regulatory multiplier.

In their 2002 paper, Berkowitz and O'Brien document that daily VaR exceptions are rare events. In a sample that includes six large U.S. banks over the period January 1998 through March 2000, only sixteen exceptions were recorded. Of these, fourteen occurred during the period August 1989–October 1998. Only one bank in their sample experienced enough exceptions during this interval to qualify it for an elevated regulatory capital multiplier.[5] To date, it appears that banks have experienced few, if any, situations where an unanticipated movement in markets has caused losses that put banks at risk of insufficient or higher regulatory capital requirements for market risk. Still, if VaR-based capital regulations are a cause of herding, one would expect capital regulations to have caused risk control sales during the August 1998–October 1998 period. In an earlier draft of their paper, Berkowitz and O'Brien focused on bank daily trade revenue data from this period. While they found some commonalities among bank trading revenues during this episode, they did not find strong evidence of trading behavior consistent with VaR-driven herding behavior.

Market risk capital regulations alone seem unlikely to make VaR a spe-

4. In my experience, many banks set VaR limits for trading activities and monitor desks according to their utilization of a given VaR limit.

5. Some individual bank exceptions documented in the Berkowitz and O'Brien study appear to be large enough so that the bank's daily loss exceeded the bank's MRC, but these losses were still small relative to the bank's overall capital position.

cial attractor that encourages herding among institutional investors. Institutional investors may, however, still exhibit herding tendencies, yet these tendencies may not be very apparent when examining banks' quarterly MRCs and trading revenues (as in Jorion), or even when examining bank daily trading revenues (as in Berkowitz and O'Brien).

If investors follow similar trading strategies and have stop-loss control measures in place, unanticipated market movements could periodically trigger sympathetic rebalancing behavior that is unrelated to regulatory capital constraints. Again, this has nothing to do with VaR, even though VaR measures may be used by banks to measure and monitor risk exposure. If institutions exhibit such behavior, positive fee and interest income components recorded in trading operations revenues and the revenue diversification benefits gained from multiple trading activities (equity, FX, fixed income, etc.) may make it difficult to detect, in quarterly data, the commonality of trading patterns generated by herding. If herding is a feature of these markets, one might anticipate finding stronger evidence of its existence in the daily profit and loss (P&L) trading account data analyzed by Berkowitz and O'Brien. In the remainder of this discussion, we consider issues associated with the analysis of daily trading revenues.

Berkowitz and O'Brien (2005) analyze the daily trading P&Ls for a sample of six large U.S. banks from January 1998 to March 2003. They analyze these data by interpreting the estimates from both a random coefficient linear-factor model and a 150-day rolling window linear-factor model that generates time-varying factor loadings. The authors discuss a number of limiting issues associated with the interpretation of the random coefficient factor-model estimates, and, for me at least, the exercise only confirms that bank positions (factor loadings) vary daily, and sometimes by substantial magnitudes. The random coefficients approach turns out to be less than ideal for drawing inferences about bank herding behavior, and Berkowitz and O'Brien focus on estimates from a rolling factor model regression approach. They argue that time series comovements between factor loading estimates and the level of the risk factors is evidence that banks rebalance as factors move. After analyzing the relationship between rolling regression-factor loading estimates and the level of market risk factors, Berkowitz and O'Brien find only fragmentary evidence of commonalities in banks' factor-loading movements. They conclude that there is no strong evidence that supports the VaR-herding hypothesis in their sample data. Even here, however, the interpretation of the rolling-regression model estimates presented by Berkowitz and O'Brien is difficult, and it is unclear what their results imply regarding the herding hypothesis.

Berkowitz and O'Brien estimate a model where trading revenue is a linear function of percentage changes in some market risk factors (exchange rate and equity market factors) and changes in the levels of other market factors (the ten-year Treasury rate, and four credit spread measures). In a typical linear factor model for equity positions, asset returns are modeled as linear functions of the returns on common market factors. Ignoring dividend income, a linear factor model with a single factor, $\tilde{F}_t$, for equity returns is typically written

$$\frac{\Delta P_t}{P_{t-1}} = \alpha_0 + \beta\frac{\Delta F_t}{F_{t-1}} + \tilde{e}_t. \tag{1}$$

If expression (1) holds, trading revenue in a mark-to-market book that is not rebalanced is given by

$$\Delta\tilde{P}_t = \alpha_0 + (\beta P_{t-1})\frac{\Delta F_t}{F_{t-1}} + \tilde{e}_t P_{t-1}. \tag{2}$$

If the return-factor model beta coefficient is positive, we would expect the estimated factor loadings in the 150-day rolling Berkowitz and O'Brien trading revenue model to be positively related to the level of the factor. When the market risk factor increases over time, the estimated rolling regression coefficient should also increase if the linear-factor *return* model correctly describes asset price dynamics.

In the fixed income setting, relationships between daily trading revenues and interest rate changes are harder to predict, even if bank fixed-income positions are not rebalanced. If a bank's positions are not rebalanced and are exclusively floating rate (for simplicity, assume rates are continuously reset), accrued interest will decline in proportion with rates, and the mark-to-market change in the floating rate position's value will be zero. A bank with such exposures should exhibit a constant negative coefficient in a linear regression of fixed-income trading revenue on the change in the level of interest rates. Alternatively, at the other end of the spectrum, should a bank's fixed income instruments be exclusively long-term discount instruments, the Berkowitz and O'Brien factor model specification should produce factor loading estimates that are larger (in absolute value) the lower are ten-year Treasury rates, owing to the convexity of long-dated discount instruments.

These issues complicate the interpretation of the time-series relationship between the market risk factors (measured in levels) and the factor loading estimates from the 150-day rolling regressions in the Berkowitz and O'Brien paper. A strong correlation between movements in the rolling-window trading revenue-factor model loading estimates and the level of market risk factors does not necessarily imply that a bank has altered its trading book positions in response to a change in the market factor. Information on changes in daily trading revenues and market risk factors by themselves may not be sufficient to identify bank rebalancing activities.

To summarize my discussion let me reiterate that I do not stay up nights worrying about whether the widespread adoption of VaR techniques has increased the potential for herding behavior. Based on my professional experience—which is clearly limited, but includes studying, working in, and examining financial institutions—I think that capital market participants may at times demonstrate what appears to be fadlike behavior in their investment strategies. In my view, apparent commonalities in bank trading activities have nothing to do with the institutions' use of VaR measurement. Value at risk is just one of many risk management and control tools available, and its widespread adoption will not increase the tendency for risk-takers to herd. I think it is fair to say that the authors of both papers share my views regarding the use of VaR. While both authors claim to find little systematic evidence in their respective datasets that links the use of VaR to herdlike behavior among dealer banks, it is also clear that the available data may not be adequate to produce powerful tests of the herding hypothesis.

References

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Discussion Summary

A single general discussion of these two related papers was conducted. Part of the discussion centered on whether herding by banks, especially in crisis situations, is a material concern, and on how the authors might better present evidence about it. In their responses, both *Jorion* and *O'Brien* agreed that the extent of herding is an interesting and important question but noted that it is largely beyond the scope of their papers, which are focused on whether the use of VaR measures is likely to cause herding. They interpreted the remarks as being consistent with their own conclusions—that it does not. They agreed that their data and methods are not ideal for addressing the broader questions.

Andrew Lo suggested some additional measures would be informative. Noting that outliers matter more to systemic risk than average correlations, he suggested looking at averages of absolute value of correlations. He also suggested a greater focus on the experience of individual banks, since a systemic event need involve a failure of only one or two major banks.

Richard Evans suggested that the VaR data used by all of the authors, while different in the details of sources and construction, may suffer from a lack of comparability across institutions. The assets that are included in the portfolios for which VaR measures are disclosed differ cross-sectionally and over time at a given financial institution. Profit-and-loss results are badly distorted, especially at a daily frequency, for a number of reasons, such as the impact of accounting reserves. Some institutions that appear in the samples are relatively small; the behavior of their VaR measures may be different and of less interest than at the major dealer banks. Overall, although he believes that better data would reveal higher correlations of VaR and returns than the authors find, use of VaR measures does not itself cause herding by the dealer banks.