Estimating Bank Trading Risk: A Factor Model Approach

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Abstract

Risk in bank trading portfolios and its management are potentially important to the banks' soundness and to the functioning of securities and derivatives markets. In this paper, proprietary daily trading revenues of 6 large dealer banks are used to study the bank dealers' market risks using a market factor model approach. Dealers' exposures to exchange rate, interest rate, equity, and credit market factors are estimated. A factor model framework for variable exposures is presented and two modeling approaches are used: a random coefficient model and rolling factor regressions. The study looks at average exposures to the market factors and the variances of the exposures, relations between exposures and the market factors, and commonality in factor exposures across the banks.

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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 6 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 commonality in their risk exposures. In recent literature, the focus has been extended to the effects of bank dealer 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 together, 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 exaggerated market instability in the late summer and fall of 1998 following the Russian ruble devaluation and debt moratorium and the near failure of 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. Individual banks report on trading positions and revenues only quarterly and reporting is limited to broad market risk and securities categories. While there is weekly reporting, it is limited to security positions and transactions for aggregated

[1] For dynamic analyses of market effects of a VaR constraint, see Basak and Shapiro (2001), Danielsson, Shin, and Zigrand (2002), Persaud (2002), 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).

primary (bank and non-bank) dealers. This limits the measurement of bank trading risks and determination of portfolio management policies.[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 the banks.

Here we apply a factor model to the daily trading revenues of 6 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 1200 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.

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

[2] However, 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.

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 for 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 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 argued below 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 price-dependent exposures is taken here. For each bank, a linear factor model with a 150-day rolling sample is estimated for each bank. Using historical plots, the 6 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. The rolling regression coefficients would be expected to covary with the respective factor rolling means if the bank's exposures systematically vary with market prices. For all factors but interest rates, the 6 banks show no common variation between their rolling factor coefficients and 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 non-interest rate factors but trading revenues tend to be abnormally low on days of relatively large interest rate increases.

Our principal findings then are significant heterogeneity across dealers in their market risk exposures, relatively small exposures on average and 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 to 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 3. The estimation and results for the random coefficient model are presented in section 4; the rolling regressions in section 5; and the relation between trading revenues and large market price changes in section 6.

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 1-day horizon. Banks are required to maintain records of daily trading revenue for testing their VaR models. The daily trading revenue for 6 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 6 banks are among the largest derivatives dealers world wide and the other two are among the largest in the U.S. The 6 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 the trading. So as not to reveal dollar magnitudes, trading revenues are divided by the sample standard deviations of the respective banks' 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

[3] The 6 banks were studied in Berkowitiz and O'Brien (2002) using a shorter sample period.

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. A limited attempt is made to represent the effects of fee and spread income and net interest income on trading revenues using proxy variables.

In Figure 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 1. As Figure 1 and Table 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 1, the daily loss rate is less than 20 percent for all banks. 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 1 and by the excess kurtosis statistics in Table 1. The 5% and 95% quantiles for the banks' trading revenues in the bottom panel of Table 1 lie inside 5% and 95% quantiles that would be consistent with a normal distribution. The 1% and 99% and the .05% and 99.5% quantiles lie outside quantiles consistent with a normal distribution.

To provide more information on the heavy tails in the trading revenue distributions, the lowest and highest 10 percent returns for each bank are plotted by historical dates in Figure 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 are notable.

One concerns differences between low and high returns. Both low returns and high returns tend to cluster but the clustering tends to be greater for low returns. Also, low returns tend to be more variable than high returns. A potential explanation for these asymmetries between low and high trading returns is that high returns include periodic large fees earned by dealers from customer transactions and these large payments are likely to be more evenly dispersed. In contrast, low returns are more likely to reflect portfolio losses from adverse market moves and the low returns may tend to cluster due to persistency in market volatility (operational costs are not included in trading revenues).

A second and related feature of Figure 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 instability during this period had important common effects on the banks' trading revenues. For all 6 banks, daily averages of trading revenues for the second half of 1998 were low and this period had a very 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 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 presents cross-bank correlations for daily trading revenues in the top panel and, for comparison, cross-bank daily VaR correlations in the bottom panel. 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 below. In contrast, there is no common pattern in the bank VaR correlations, as correlations are both positive and negative and vary widely.

3. Factor Model with Varying Positions

A factor model framework when positions are variable is developed here and 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, e.g., the mid-market 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_{kt}^0 in risky security categories $k = 1, \cdots, K$ and x_{0t}^0 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

[4] For the second half of 1998, daily averages of trading revenues for banks 1 to 6 were respectively .55, .39, -.22, .15, .15, .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 1 for comparable statistics for the full-period samples.

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 $p_k(t)$. $p_k(t-1)$ is the price at the end of t-1. The price of the risk-free asset is fixed at 1. Using this notation, the value of the portfolio at the start of t and the at the end of t are respectively

(1)

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

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

For the factor model, we want to expresses the 1-period change in the portfolio value as a function of 1-period changes in market prices $r_k(t) \equiv \left(p_k(t) - p_k(t-1) \right) / p_k(t-1)$. 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 intra-period 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 intra-period position, and/or possibly price changes. A highly simplifying assumption made here is that intra-period 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 1-day returns. It implies that the intra-period 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 intra-period capital flows to the portfolio and intra-period 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: $\sum_{k=1}^{K} dx_{kt}(\tau) p_{kt}(\tau) + dx_{0t}(\tau) = 0.$

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 $x_{kt}^0 p_k(t-1) + \frac{1}{2}\Delta x_k(t) p_k(t-1)$ is the average position in the period valued at the price of *k* at the end of *t-1*.

For empirical specification, express the change in the portfolio value using a factor model form

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

where $V_k(t) \equiv \left(x_k^0(t) + 1/2\Delta x_k(t) \right) p_k(t-1)$. $V_k(t)$ is the portfolio exposure for factor *k*. Unlike the standard factor model, the factor exposures are not constant. With daily data, they would reflect time-varying daily average positions. Two specifications of (3) will be considered.

For the first specification, $V_k(t)$ is assumed to be a random draw from a stationary process with mean $\bar{V}_k$. Further, the positions are assumed to be independent of the market factors and mutually independent. Thus there is no covariation between positions and factors or among the positions. Under these conditions, the portfolio return in (3) satisfies the random coefficient models developed in Hildreth and Houck (1968).

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

(4)

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

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

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

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

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 portfolio value the portfolio, and ω_{kl} is the covariance (variance) for individual factors $r_k(t)$ and $r_l(t)$. For the analysis below, 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 (4.b). (4.c) and (4d) are the portfolio's unconditional mean change and variance. The unconditional variance is the sum of the variances for $\sum_{k=1}^{K} r_k(t)\bar{V}_k$ and $u(t)$. The variance is the sum the factor variances and covariances weighted by the mean positions and 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 (4) 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)

$$\rho_{w_i w_j} = \rho_{\hat{w}_i \hat{w}_j} RS_i^{.5} RS_j^{.5} + \rho_{u_i u_j} (1 - RS_i)^{.5} (1 - RS_j)^{.5} \tag{5}$$

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

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. $\rho_{u_i u_j}$ 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 $(RS_i \equiv \sigma_{\hat{w}_i \hat{w}_i} / \sigma_{w_i w_i})$.

Under the random coefficient model assumptions and given observations on trading portfolio value changes (measured over a small time unit) 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 (4.d).

The assumption that positions are independent of the factors is particularly limiting because portfolio management may be related to market price movements as described earlier. As discussed, such polices have been said to adversely affect market stability. Dropping the assumption of independence has important effects on the factor model formulation. This potential dependency is considered in a second specification.

To first illustrate the effects and modeling complications when positions are related to market prices consider a portfolio that is managed such that its payoff resembles a Black-Scholes call or put option on security *k*. This option-like portfolio implies a position in the security and a cash position. Changes in the security price produce changes in the portfolio's positions. Let $x_k^0(t)p_k(t-1)$ in (2) represent the initial security position valued at the initial (end of previous period) security price. $x_k^0(t)p_k(t-1)$ is analogous to the option's delta. Let $\Delta x_k(t)p_k(t-1)$ in (2) represent the change in the security position due to a change in the security price also valued at the initial price. Set $\Delta x_k(t) = \Gamma_k^0(t)p_k(t-1)r_k(t)$, where $\Gamma_k^0(t) \equiv (\partial x_k / \partial p_k)$ evaluated at $x_k^0(t)$. $\Gamma_k^0(t)$ is analogous to the option's gamma. Equation (2) can now be rewritten as

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

where $a_k^0(t) \equiv x_k^0(t)p_k(t-1)$ and $b_k^0(t) \equiv (1/2)\Gamma_k^0(t)(p_k(t-1))^2$. Thus, a second-degree polynomial function provides a second-order approximation to the effect of the market factor on the portfolio's value.

Non-linear 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 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 the squared market factor in (6) reflects the non-linear sensitivity of the portfolio to the market factor, i.e., 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 (6) are for period *t*. They depend on the security position at the start of the period and, for $\Gamma_k^0(t)$, 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 at the start of each sample observation, e.g., each month if observations are monthly.

For bank dealers, we have little specific information on their portfolio strategies and 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 non-market factor variables) with 150-day daily rolling samples. For the 6 banks, the estimated rolling coefficients are plotted along with coincidental 150-day rolling means for the respective factors (factor levels, not changes). The 150-day rolling means will reflect periods of rising or declining market prices. For portfolio strategies where exposures move systematically with market prices, the 150-day factor regression coefficients would be expected to covary with the respective factors' rolling means. We use the plots to detect such covariation and thus indicate price-dependent strategies. Observed covariation between the rolling -coefficients for a factor and the factor's rolling means is judged to be significant when the pattern is common among the 6 banks.

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

[5] Chan et al (2004) use higher-order polynomials in market factors to capture non-linearity in hedge fund returns. Agarwal and Naik (2004) use returns to call and put options as the factors in hedge fund factor regressions to capture the non-linearity between the hedge fund's returns and the underlying market factors that arises from option-type trading strategies. Mitchel and Pulvino (2001) apply a piecewise linear factor model in returns to risk arbitrage strategies

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 for a measure of trading volume and net interest income. (3) Portfolio revenues also are affected by (inter-period) changes in the portfolio's capital. Changes in the capital of the portfolio are not explicitly accounted for other than what can be represented by a trend variable.

4. Random Coefficient Model

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

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 10-year U.S. Treasury rate is used to capture interest rate risk in the trading portfolio. In an earlier version, a 10-year rate and a 3-month rate were used, with qualitatively similar coefficients estimated for both factors. There are a total of 11 market factors, which are identified in the top panel of Table 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 the bottom panel of Table 3. They were constructed from world-wide dealer FX spot and derivatives turnover reported in 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 have do not have direct information on dealers' daily transactions and use de-trended daily volume on the 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 10-year U.S. Treasury rate.

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.

4.2. Market Risk Estimates

We use the GLS random coefficient estimators developed by Hildreth and Houck (1968) to estimate the banks' mean exposures to the market factors, $\bar{V}_k$ shown in (4.a), and the exposure variances, $\sigma_{v_k v_k}$ shown in (4.d) and (4.e).[6] For the estimation we are assuming that that $v_k(t)$ is iid, independent of the market factors and that $v_k(t)$ and $v_l(t)$ are independent for $k \neq l$. In addition, the residual in the trading revenue equation is assumed to consist of the residual that arises from random position changes, i.e. $u(t)$ in (4.b), and may also include an independent error consisting of revenue changes 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 11 market factors to have variable coefficients.

Appendix Tables A.1 and A.2 contain the detailed regression results. The estimates will be discussed here with several summary tables. In the top part of Table 4, summary regression statistics for the factor model estimating the mean exposures to the market factors and other regressors are presented. As shown, the full set of regressors including market factors and other variables have significant explanatory power based on F-values and regression R-squares. For the 11 market factors taken as a whole, however, the F-values are not very high and do not exceed the .05 critical value for 2 banks. The market factors do not have a lot of explanatory power (excluding the market factors from the regressions, causes the R-squares to drop by about 4 basis points). Since the factor coefficients reflect the estimated mean factor exposures, this implies that average market exposures cannot account for much of the variability of trading revenues.

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[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.

In contrast, equity volume, which is used as a proxy for market transactions volume is positive for all banks and highly significant for all but one bank (Appendix Table A.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 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. This implies that there is significant variability in the market factor exposures. 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 non-negative values (pp. 587-589), this constraint was not imposed here. A little more than a third of the estimated coefficients are negative, although only 2 are significant at a .05 level and 1 at a .01 level (Appendix Table A.2). We regard these negative coefficients as reflecting sampling error and in the subsequent analysis do not include them in evaluating the variability of the dealers' market exposures. We have no reason to believe that this biases our interpretation of the results

Table 5 provides information on the size of the estimated factor exposures and their variability based on Appendix Tables A.1 and A.2. The top number in each cell is the estimate of the factor's mean exposure and the two numbers underneath are the 2.5% and 97.5% estimated quantiles for factor exposures. The quantile estimates use the estimated mean exposures and exposure variances, and assume the coefficients are normally distributed. The shaded cells indicate where coefficient variance estimates are negative (a zero interval is reported but does not figure into our analysis).

The estimated mean exposures and quantiles in Table 5 are reported in units that allow comparison with the banks' average trading revenues and trading revenue quantiles shown in Table 1. As indicated earlier, daily trading revenues are divided by the trading revenue sample standard deviations. The estimated mean market factor exposures and exposure quantiles in Table 5 also are in terms of trading revenue standard deviations and are calibrated for a 2 standard deviation (i.e., relatively large) market factor shock.

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 1. For all estimates, a 2 standard deviation market factor shock produces less than a .3 standard deviation change in a bank's trading revenue and less than a .1 standard deviation change in trading revenue for two-thirds of the factors. For the median bank, mean trading revenues equal .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 5 of 6 banks. The negative exposures would imply bank dealers have (small) net long exposures to interest rate changes on average, i.e., 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 W. 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 5. The interval estimates cover both positive and negative values, indicating factor exposures can vary between long and short positions. Also, for the factor variances with non-negative estimates, the 95% 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 1.

The 95% bounds in Table 5 measure potential trading revenue variation due to 2 standard deviation market factor shocks. Conditioned on a 2-standard deviation factor shock, they represent 95% bounds on portfolio gains and losses. The trading revenue quantiles in Table 1 measure trading revenue variation due to market factor shocks *and* variation from other influences, such as market-making revenues. The bounds in Table 5 tend to be within the 1% and 99% quantiles for trading revenues shown in Table 1. Also, the bounds in Table 5 are for 2 standard deviation market factor shocks. Thus, estimated trading revenue volatility conditioned on relatively large exposures coupled with large market factor shocks do not produce extreme outlier trading revenues. Thus, relative to the total variability in the trading revenue, the variability that comes from market risks does not appear to be particularly large.

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

4.3. Cross-Bank Trading Revenue Correlations

As described earlier in section B, cross-bank trading revenues show small but consistently positive correlations (Table 2). Using equation (5) above, it was shown that cross-bank trading return correlation due to market risk exposures can come from either dealers having common average exposures to market factors or common variation in exposures. Based on the random coefficient regression results discussed above, average factor exposures seem unlikely to be an important source of cross-bank trading revenue correlation. This in fact can be determined by applying the mean and variance estimates of the random coefficients for the market factors to equation (5), i.e., to estimate $\rho_{\hat{w}_i\hat{w}_j} RS_i^{.5} RS_j^{.5}$ in (5) for banks' *i* and *j*.[7] The cross-bank correlation component reflecting positions at their mean values, $\rho_{\hat{w}_i\hat{w}_j} RS_i^{.5} RS_j^{.5}$, was calculated for each pair of banks. For all but one bank this component is less than .02 (for banks 2 and 4, it is -.04).

If market exposures account for the most of the observed trading revenue correlations, it must be mainly due to changes in banks' exposures, i.e., the component $\rho_{u_iu_j}(1-RS_i)^{.5}(1-RS_j)^{.5}$ in (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 $\rho_{u_iu_j}(1-RS_i)^{.5}(1-RS_j)^{.5}$ for each combination of banks. Unfortunately, the regression residuals will include both $u_i(t)$ and other unspecified components of trading revenues.

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[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 $RS_i = \sigma_{\hat{w}_i\hat{w}_i} / \sigma_{w_iw_i}$, $\sigma_{\hat{w}_i\hat{w}_i}$ 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 $\sigma_{v_kv_k}$.

Nonetheless, correlations reported in the bottom panel of Table 6 were obtained by calculating $\rho_{u_i u_j}(1-RS_i)^{.5}(1-RS_j)^{.5}$ using the regression equation residuals (correlations above the diagonal are the trading revenue correlations displayed in Table 2). The correlations below the diagonal typically are slightly more than half as large as 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. In the next two sections, further consideration is given to commonality in trading revenues on days of large market changes employing different approaches.

5. Rolling Regressions

In this section, we present estimates of market factor coefficients for daily rolling regressions. Using OLS, each bank's trading revenue is regressed on the market factors and other explanatory variables. 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 re-estimated daily dropping the last day and adding a new day using each bank's available sample period.

The time series of estimated rolling regression coefficients for factors representative of the four broad market categories were plotted with 150-day rolling means for the respective market factors. In Figures 3a – 3d, plots of rolling coefficients that are representative of 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 A.1 (average values of the rolling coefficients are of the same order of magnitude as those in the random coefficient model in Table A.1). The rolling means of factors are expressed as factor levels (not differences). They show large ranges of variation over the sample period that 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.

As described in section 3, our interest is in whether the coefficients appear to move systematically with the factors, which would indicate that market exposures are related to the market prices. The assessment is judgmental but we limit the assessment to the presence of a systematic relation that is common to all or most of the banks.

Consider first the coefficients for the interest rate factor plotted in Figure 3a. The coefficients for all but bank 4 show a rising and declining pattern that roughly tracks the rising and declining interest rate pattern. Since negative coefficients imply long positions, this suggests a tendency for the portfolio's duration to become positive and longer as interest rates decline, with the opposite tendency when rates are rising. Further, cross-bank correlations for the rolling interest rate coefficients are all positive (see Table 7), re-enforcing the impression from Figure 3a of common variation in the dealers' interest rate exposures.

For the most part, the rolling coefficients for the other factors do not show any clear patterns of co-movement with their respective factors that are common to all or most banks. In Figures 3b – 3d, rolling coefficient plots are presented for the NYSE, high yield, and Russian exchange rate factors. For some individual banks, co-movement is observed between the coefficients and factors—e.g., the NYSE rolling coefficients show a positive co-variation with the level of the NYSE for bank 2. This may represent a dependency of positions on market factors for individual banks or it may simply be a chance pattern for a particular bank.

Something of an exception to these results is behavior of the Russian ruble coefficients in Figure 3d. For all 6 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).[8] This behavior would be consistent the banks becoming insulated against the ruble.

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, all 6 banks had abnormally low,

[8] While difficult to see in the Figure, between mid-August and the end of September 1998, estimated rolling coefficients across the 6 banks were quite different, ranging between positive and negative values, but all converged toward 0 as the Russian rubble fell sharply. While most of the ruble's decline occurred by the end of September, the volatility of the ruble (measured in log changes) remained historically high over the rest of the year and was higher in the first half of 1999 than in pre-August 1998.

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, on days of large market price changes, dealer trading revenues are systematically related to price movements. This may 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 20th quintile and the 80th quintile are separately sorted. For a market category, a large market decline day (a large market increase day) is defined as a day where at least one factor in the category is in the 20th (the 80th) quintile and none is in the 80th (the 20th) quintile. For example, a large equity market decline day is when the change in the NYSE index is in the 20th quintile and the NASDAQ index is not in the 80th quintile. Typically, when one factor in a market category experiences 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 8). Large market move days span the entire 5-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 8. Except for the interest rate category, mean and median trading revenues for the 6 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 have common market exposures that are systematically related to market prices. However, for the interest rate category, on days of large rate increases, trading revenues are uniformly lower across the 6 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.

Heterogeneity in exposures will reduce the likelihood of large aggregate dealer losses. However, the chance realization of portfolio losses (or abnormally high returns) among a group of dealers is still more likely during a period of high volatility across markets, since dealers all will experience larger variability in their position values. The summer and autumn of 1998 was such a period and the higher volatility in the banks' trading revenues is apparent from Figure 2.[9] Nonetheless, with heterogeneity in exposures across the banks, losses are likely to be attributable to positions in different markets. In the third and fourth quarters of 1998, major U.S. bank dealers reported losses or abnormally low revenues in different market categories—interest rate (including credit), equity, and commodities.[10] At least for the 6 banks' studied here, it is also the case that there were differences among the banks in which market categories they reported losses or abnormally low revenues.

7. Conclusions

Based on our results, the bank dealers do not consistently maintain large exposures on one side of the market, although they tended to have small long average exposures to interest rate risk. While the size and direction of their exposures can vary significantly, the variation in trading revenues from market risk does not seem large in relation to the variation in total trading revenue. There also is significant heterogeneity across the dealers in their market risk exposures, with the exception that interest rate risk exposures tend to vary inversely with rate levels.

These results are subject to important limitations imposed by limitations of the trading revenue data that was 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

[9] 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. Similar to the procedure followed in determining that days of large market declines and large increases for Table 8, days of high (low) market volatility were defined at the market category level based on the size of changes in the factors belonging to a particular category. In contrast to the results in Table 8, for each of the 6 banks, mean and median absolute 1-day trading revenues are consistently higher on high market volatility days than on low market volatility days for all 4 market categories, with significance at the .05 level for almost 75 percent of the calculations.

[10] 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.

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 might be commonality in their adjustments to exposures in interest rate risk.

Heterogeneity in dealers' market exposures reduces the likelihood of aggregate dealer losses but the chance realization of this (or abnormally high returns) 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.

Dimensions of bank dealer activity other than portfolio management not considered here may be more important to financial market stability and bank risk. This would include dealers' market-making role. Routledge and Zinn (2004), for example, focus on dealers' optimizing behavior in extreme market conditions and how it can lead to increased bid-ask spreads, thereby reducing market liquidity. Furfine and Remolona (2002), using high frequency price quotes and trades in the inter-dealer market for U.S. government securities, find evidence of larger price impact of trades on stressful days in the last half of 1998, consistent with reduced market liquidity. Another dimension is the dealer and the parent banks' credit exposures to large market players. Furfine and Remolona (1998) and Kho, Lee, and Stulz (2000) consider potential adverse consequences for bank dealers and parent banks through counterparty exposures during a crisis period, such as to LTCM in 1998, which might affect the dealers' ability to continue their market-making role.[11]

[11] For counter-party risk between hedge funds and dealers, also see Chan, Getmansky, Hass, and Lo (2005).

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APPENDIX

1. 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, $\sum_{k=1}^{K} dx_{kt}(\tau) p_{kt}(\tau) + dx_{0t}(\tau) = 0.$ 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:

$$
\begin{aligned}
w(t) &= \int_{t-1}^{t} \left(\sum_{k=1}^{K} x_k(\tau) dp_k(\tau) + p_k(\tau) dx_k(\tau) + dx_0(\tau) \right) d\tau \\
&= \sum_{k=1}^{K} \int_{t-1}^{t} x_k(\tau) dp_k(\tau) \qquad \text{(using the self-financing constraint)} \\
&= \sum_{k=1}^{K} \int_{t-1}^{t} \left(x_{kt}^0 + \int_{t-1}^{\tau} dx_k(\varsigma) d\varsigma \right) dp_k(\tau) d\tau \qquad \text{(A.1)} \\
&= \sum_{k=1}^{K} \left(x_{kt}^0 + \frac{1}{2} \Delta x(t) \right) \Delta p(t) \qquad \text{(using uniform price and position changes)} \\
&= \sum_{k=1}^{K} \left(x_{kt}^0 p_k(t-1) + \frac{1}{2} \Delta x(t) p_k(t-1) \right) r_k(t)
\end{aligned}
$$

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

3. 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 (4). 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 (4.a) in the text, $w(t)=\sum_{k=1}^{K} r_k(t)\bar{V}_k + u(t)$ and (4b), $u(t)\equiv\sum_{k=1}^{K} r_k(t)v_k(t)$, the expected cross-product of returns for banks *i* and *j*, conditioned on $r(t)$, is:

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

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

(A.3) $$\begin{aligned} E[w_i(t)w_j(t)\,|\,r(t)] &= \bar{V}_i'r(t)r'(t)\bar{V}_j + E_{v_i,v_j}[v_i'(t)r(t)r'(t)v_j(t)\,|\,r(t)] \\ &= \bar{V}_i'r(t)r'(t)\bar{V}_j + \sum_{k=1}^{K}\sum_{l=1}^{K}\sigma_{v_{ik}v_{jl}} r_k(t)r_l(t) \end{aligned}$$

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

(A.4) $$\begin{aligned} \sigma_{w_iw_j} &= E_r[\bar{V}_i'r(t)r'(t)\bar{V}_j] + E_r[\sum_{k=1}^{K}\sum_{l=1}^{K}\sigma_{v_{ik}v_{jl}} r_k(t)r_l(t)] \\ &= \bar{V}_i'\Omega\bar{V}_j + \sum_{k=1}^{K}\sum_{l=1}^{K}\sigma_{v_{ik}v_{jl}}\omega_{kl} \end{aligned}$$

where $\Omega\equiv E[r(t)r'(t)]$ is the covariance matrix for $r(t)$ and $\omega_{ij}\equiv E[r_k(t)r_l(t)]$ the covariance for $r_k(t)$ and $r_l(t)$. $\bar{V}_i'\Omega\bar{V}_j$ is the covariance between changes in bank *i* and bank *j*'s portfolio values conditioned on market exposures set at their mean values. $\sum_{k=1}^{K}\sum_{l=1}^{K}\sigma_{v_{ik}v_{jl}}\omega_{kl}$ 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 $\sigma_{u_iu_j} \equiv \sum_{k=1}^{K}\sum_{l=1}^{K}\sigma_{v_{ik}v_{jl}}\omega_{kl}$. Define $\rho_{w_iw_j}$ as the correlation between $w_i(t)$ and $w_j(t)$. Using this notation, we can express the various correlations and covariances between between changes in *i* and *j*'s portfolio values as follows:

(A.5)

(A.5.a) $\rho_{w_iw_j} \equiv \sigma_{w_iw_j} / \sigma_{w_iw_i}^{.5}\sigma_{w_jw_j}^{.5}$

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

(A.5.c) $\sigma_{u_iu_j} \equiv \rho_{u_iu_j}\sigma_{u_iu_i}^{.5}\sigma_{u_ju_j}^{.5}$

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

(A.6)

$$\rho_{w_iw_j} = \rho_{\hat{w}_i\hat{w}_j}\left(\frac{\sigma_{\hat{w}_i\hat{w}_i}}{\sigma_{w_iw_i}}\right)^{.5}\left(\frac{\sigma_{\hat{w}_j\hat{w}_j}}{\sigma_{w_jw_j}}\right)^{.5} + \rho_{u_iu_j}\left(\frac{1-\sigma_{\hat{w}_i\hat{w}_i}}{\sigma_{w_iw_i}}\right)^{.5}\left(\frac{1-\sigma_{\hat{w}_j\hat{w}_j}}{\sigma_{w_jw_j}}\right)^{.5}$$
$$= \rho_{\hat{w}_i\hat{w}_j} RS_i^{.5} RS_j^{.5} + \rho_{u_iu_j}(1-RS_i^{.5})(1-RS_j^{.5})$$

Table 1. Daily Trading Revenue Descriptive Statistics[1]

Bank	Dates	Obs	Mean	Excess Kurtosis	Skewness
1	1/98 - 12/00	762	1.05	10.75	-0.60
2	1/98 - 9/00	711	0.79	4.82	0.16
3	1/98 - 9/01	1524	0.77	13.13	1.49
4	1/98 - 12/03	1544	0.90	4.17	0.46
5	1/98 - 12/03	1551	0.62	6.46	-0.62
6	1/98 - 6/02	1166	0.72	79.64	-3.98

Bank	Loss Rate[2]	Quantiles					
		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

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

Table 2. Cross-Bank Trading Revenue Correlations and VaR
(trading revenue above the diagonal and VaR below the diagonal)

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Bank 1		0.415	0.210	0.182	0.028	0.145
Bank 2	-0.027		0.112	0.070	0.158	0.147
Bank 3	0.099	-0.151		0.243	0.169	0.145
Bank 4	0.060	-0.812	0.130		0.048	0.146
Bank 5	-0.119	0.684	0.097	-0.503		0.094
Bank 6	-0.314	-0.300	-0.271	0.627	-0.330	

Table 3. Market Factors

3a. Market Factors: Daily Changes 1998 - 2003[1]

Exchange Rates	mean (std dev)	Equity	mean (std dev)	Interest Rates	mean (std dev)	Credit Spreads[2]	mean (std dev)
W Europe	0.00009	nyse	0.00012	10-yr treas	-0.00084	10-yr Baa	0.00050
(xwe)	(0.00558)		(0.01156)	(r10yr)	(0.06302)	(Baa)	(0.03497)
Russia	-0.00107	nasdaq	0.00015			5-yr hi yield	0.00049
(xru)	(0.02274)		(0.02222)			(hi yld)	(0.09338)
Asian Paci	0.00012					10-yr swap	-0.00007
(xap)	(0.00603)					(swap)	(0.03185)
S America	-0.00037					emerg mkt	-0.00060
(xsa)	(0.00611)					(embi+)	(0.24070)

3b. Exchange Rates with U.S. Dollar: Construction of Regional Indices[3]

W Europe (1998)		W Europe (1999 – 02)		Asian Pacific		South America	
country	weight	country	weight	country	weight	country	weight
Germany	0.54	Euro	0.633	Japan	0.727	Mexico	0.658
UK	0.198	UK	0.222	Austral	0.136	Brazil	0.342
France	0.092	Switzer	0.102	HK	0.075		
Switzer	0.127	Sweden	0.043	Sing	0.035		
Sweden	0.043			Korea	0.027		

1. 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.
2. Credit spreads are spreads from treasury rates with the same maturity. Embi+ is JP Morgan's Emerging Markets Bond Spread Index Plus.
3. Regional exchange rates are weighted log differences. Weights are based on world-wide 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 4. Summary Statistics for Factor Model and Coefficient Variances Regressions

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6
Factor Model Regressions[1]						
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[2]						
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

1. .05 critical F-values: for regression F(16,n - 16) = 1.65; for market factors F(11, n - 16) = 1.80.
2. .05 critical F-values: F(12,n - 12) = 1.76.

Table 5. Scaled Factor Coefficients with 2.5% and 97.5% Quantiles[1]

est coef
quantiles

	Bank 1		Bank 2		Bank 3		Bank 4		Bank 5		Bank 6	
xwe	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
xru	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
xap	-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
xsa	-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
r10yr	-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	-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	-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
swap	-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+	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

1. Scaled coefficients equal the change in trading revenue measured in terms of trading revenue standard deviations due to 2 standard deviation factor shocks. Shaded cells indicate the estimated variance was negative.

6. Cross-Bank Trading Revenue Correlation due to Market Factors[1]
(unconditional trading revenue correlations above diagonal; correlations due to market factors below diagonal)

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

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

Table 7. Cross-Bank Correlations for Rolling Regression Coefficients[1]

	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 pos correlation	53	53	53	67	73	60	100	60	80	67	67

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

Table 8. Bank Trading Revenues Conditioned on Large One-Day Market Moves

	Exchange Rate Change			
	Decline	Increase	Decline	Increase
Bank	Trading Rev: Mean		Trading Rev: Median	
1	1.14	1.04	1.07	0.97
2	0.87	0.85	0.82	0.78
3	0.70	0.81	0.70	0.75
4	0.85	0.98*	0.81	0.81
5	0.60	0.61	0.55	0.59
6	0.63	0.69	0.63	0.68

	Interest Rate Change			
	Decline	Increase	Decline	Increase
Bank	Trading Rev: Mean		Trading Rev: Median	
1	1.29*	1.00	1.22*	0.90
2	0.93	0.85	0.82	0.80
3	0.86*	0.71	0.90*	0.72
4	0.95	0.93	0.87	0.78
5	0.69*	0.57	0.70*	0.55
6	0.87*	0.63	0.81*	0.64

	Equity Price Change			
	Decline	Increase	Decline	Increase
Bank	Trading Rev: Mean		Trading Rev: Median	
1	1.17	1.06	1.06	0.89
2	0.93	0.77	0.86	0.78
3	0.74	0.86	0.78	0.85
4	0.83	1.20*	0.80	0.93*
5	0.60	0.51	0.59	0.45
6	0.82	0.72	0.75	0.75

	Credit Spread Changes			
	Decline	Increase	Decline	Increase
Bank	Trading Rev: Mean		Trading Rev: Median	
1	1.00	1.13	0.93	1.13
2	0.72*	0.92	0.64*	0.84
3	0.84	0.73	0.76	0.78
4	1.01	0.91	0.85	0.83
5	0.68	0.63	0.64	0.61
6	0.73	0.73	0.66	0.77

1. 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, depending on the bank. and the category. Sample sizes for each of the "Decline" and "Increase" categories range from 167 to 606, with a median of 323. For each factor in its designated market category (e.g., nyse for equity category), its mean value for the "Decline" quintile is 1 to 2 standard deviations below its mean value for the "Increase."
*Significant at .05 for difference between "Decline" and "Increase" day trading revenue mean (median) value. Means test is a standard difference of two means. Medians test uses the Mann-Whitney-Wilcoxon rank sum test for large samples.

Appendix Tables

Table A.1. Market Factor Model for Bank Trading Revenue[1]

		Bank					
Variable		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
xwe	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
xru	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
xap	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
xsa	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
r10yr	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	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	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	β_{10}	-0.268	-0.235	1.181	0.191	0.397	-0.582
	t-value	-0.21	-0.21	1.53	0.28	0.51	-0.64
embi+	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
aver10yr	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	1484	1485	1483	1109

1. 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

Table A.2. Estimates of Coefficient Variances for Market Factors[1]

		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
xwe	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
xru	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
xap	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
xsa	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
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
r10yr	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	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	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	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+	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	F-Stat	3.82	13.73	11.07	4.16	5.59	1.98
R^2	R^2	0.06	0.18	0.08	0.03	0.04	0.02
N	N	728	681	1484	1485	1483	1109

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

Figure 1. Densities for Bank Trading Revenues

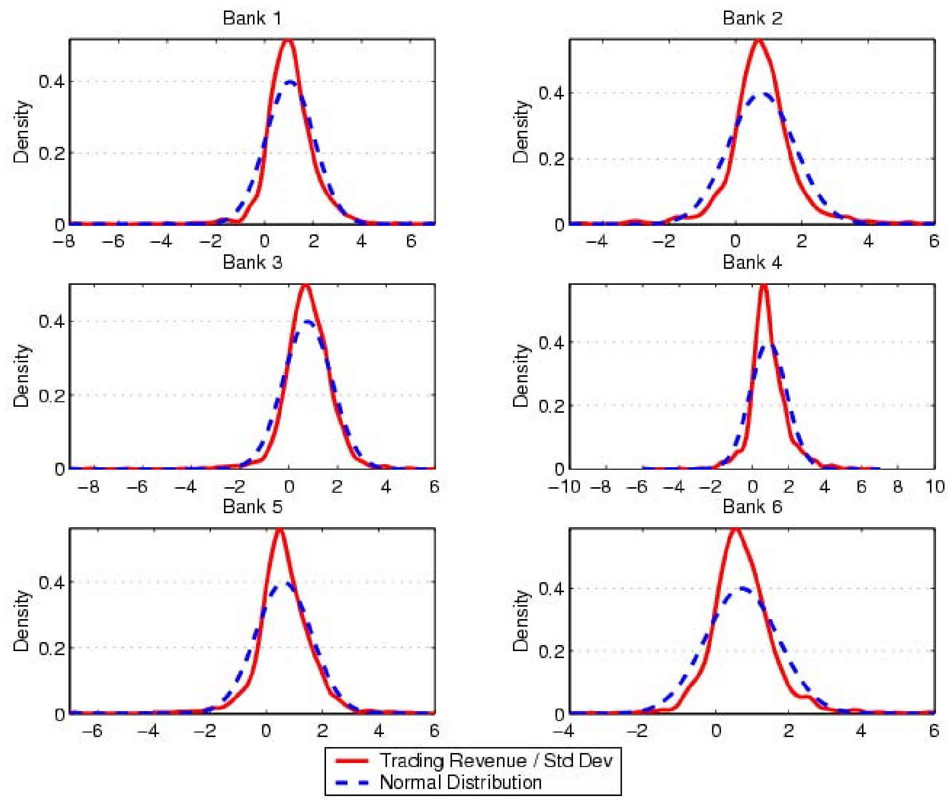
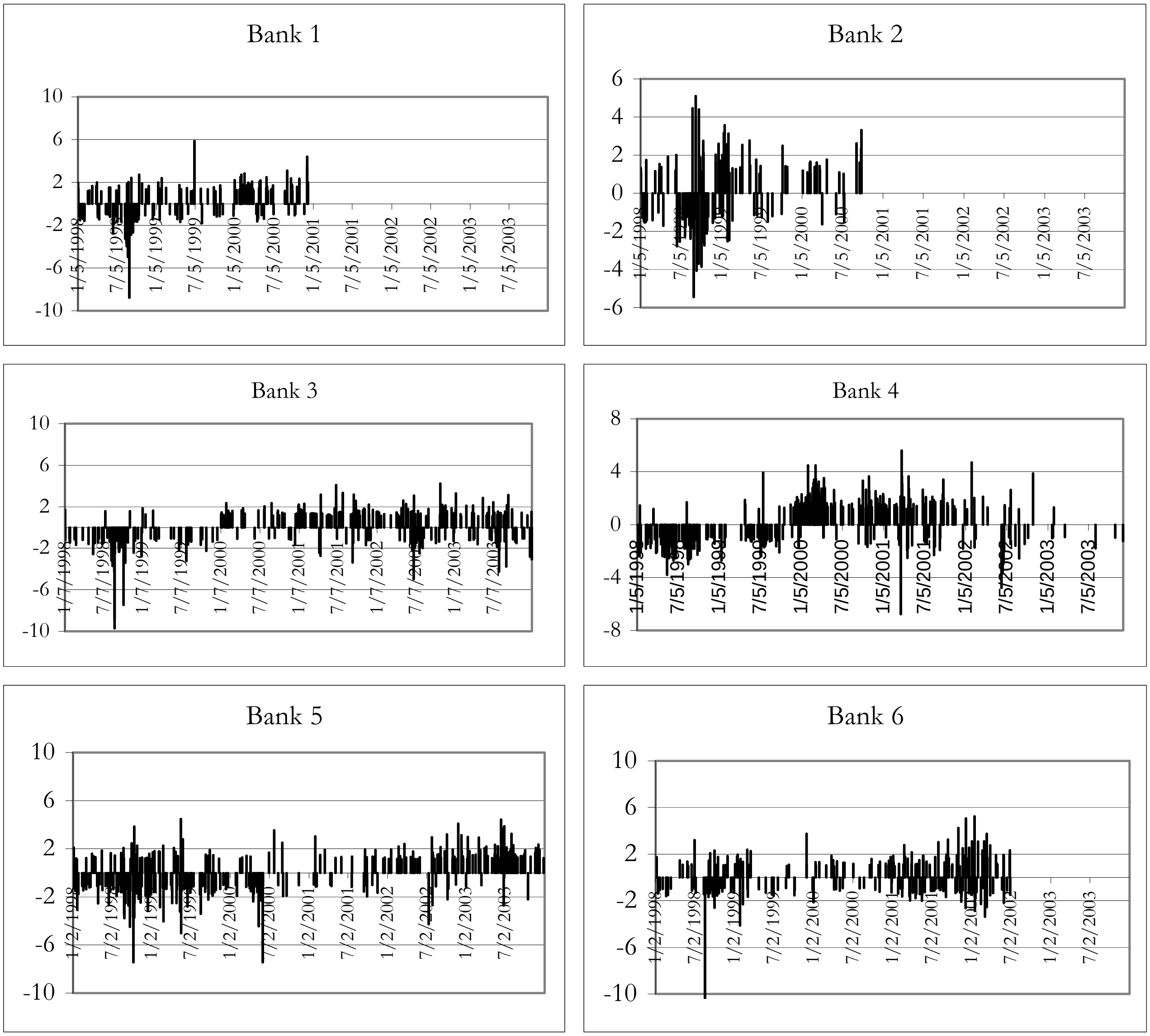


Figure 2. Trading Revenues: 10 Percent Lowest and Highest Values[12]



12 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.

Figure 3a. Interest Rate Regression Coefficients and Moving-Average Interest Rate

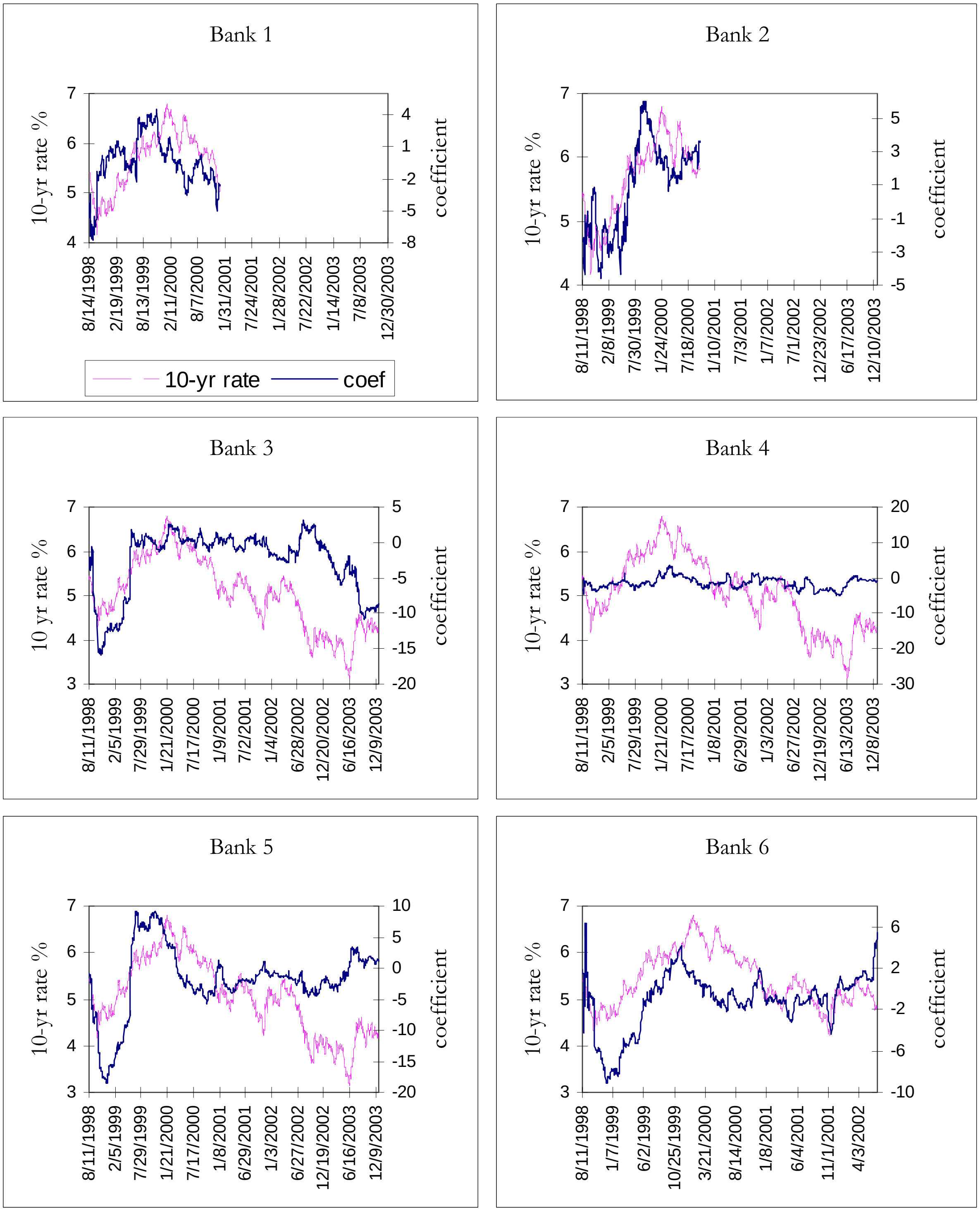


Figure 3b. NYSE Regression Coefficients and Moving-Average NYSE Index

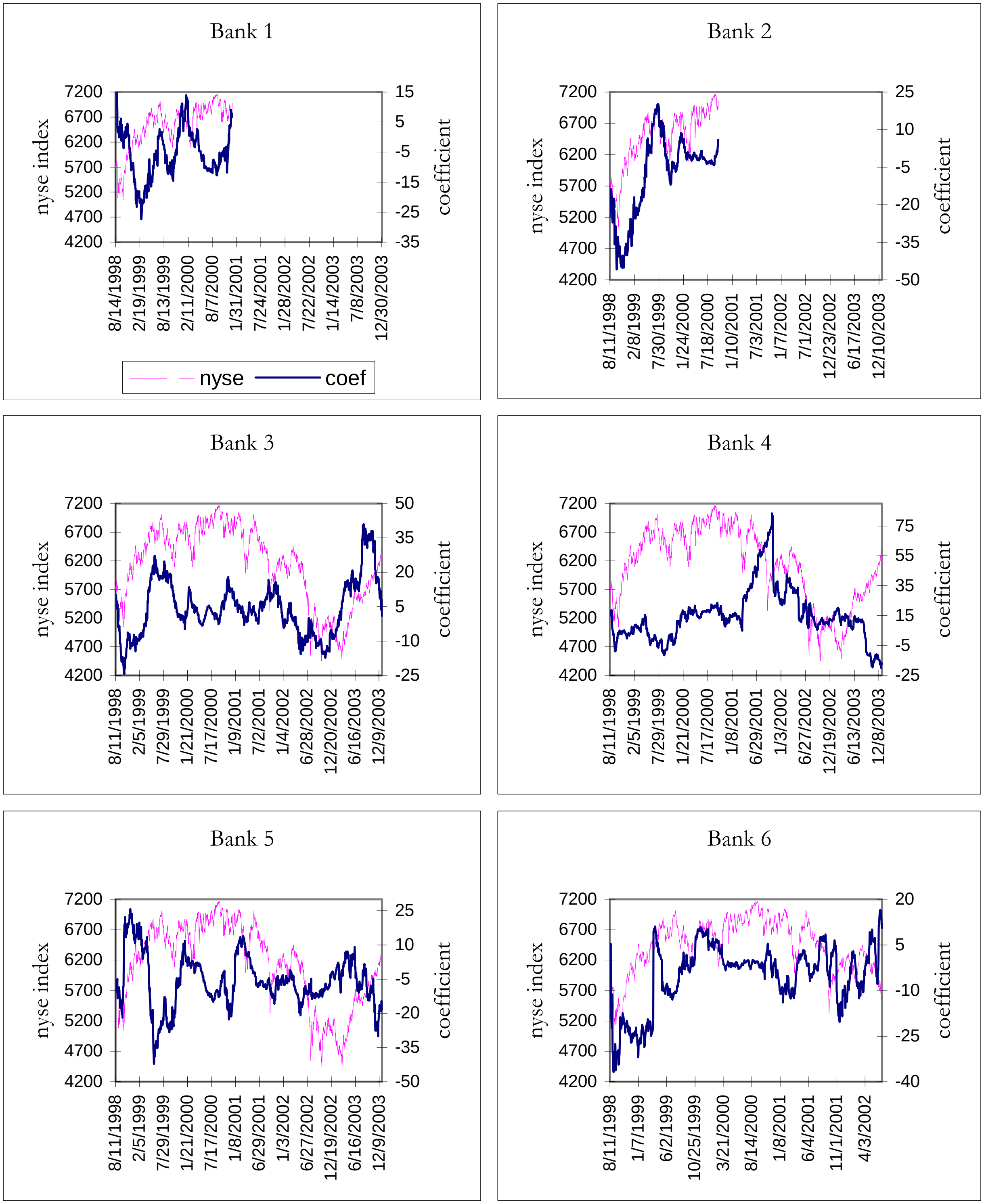


Figure 3c. High Yield Regression Coefficients and Moving-Average High Yield Spread

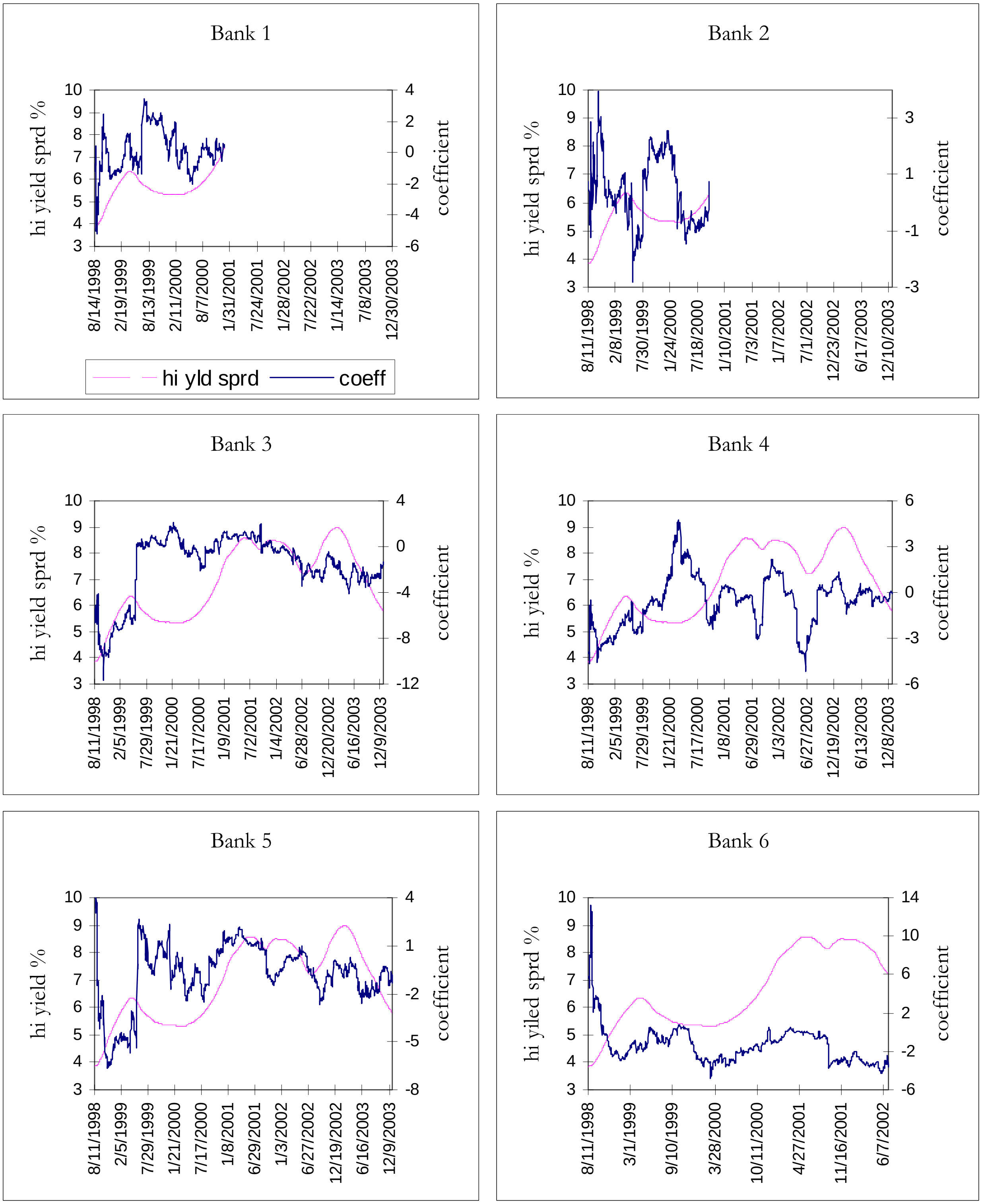


Figure 3d. Russian Ruble Regression Coefficients and Moving-Average Exchange Rate