Identifying Contagion Risk in the International Banking System: 
An Extreme Value Theory Approach

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Abstract

In this paper, we use the extreme value theory (EVT) framework to analyze contagion risk across the international banking system. We test for the likelihood that an extreme shock affecting a major, systemic global bank would also affect another large local or foreign counterpart, and vice-versa. Our results reveal several key trends among major global banks: contagion risk among banks exhibits “home bias”; individual banks are affected differently by idiosyncratic shocks to their major counterparts; and banks are affected differently by common shocks to the real economy or financial markets. In general, bank soundness appears more susceptible to common (macro and market) shocks when the global environment is turbulent; this may have important implications for global financial stability especially during stressful periods. Not surprisingly, our findings also suggest that bank contagion risk has risen over time, which emphasizes the need for continuing collaboration on cross-border supervision and crisis management.
I. INTRODUCTION

The international banking system has expanded rapidly since the late-1990s. In addition to the overall size of banking assets, the international positions of banks from many of the major banking systems have grown significantly, by several multiples, during this period (Figure 1). Thus, the banking sector, which continues to be of key importance for global financial stability, represents a potentially important channel for contagion risk through the international financial system.

Shocks to a major global bank, originating from their operations in the home country or in a host country could potentially impact the international banking system. The contagion could be channeled through its linkages with other major banks or through its operations in global financial centers. There are numerous specific ways in which this could occur. Notably, external linkages could stem from direct and indirect equity exposures of local banks to overseas banks or, conversely, shareholdings of local banks by foreign banks; direct exposures through loan books; deposit and funding sources from overseas and/or from foreign banks operating in a particular country; payments and settlement systems; holdings of credit risk transfer instruments written on assets held by local and/or overseas institutions. Contagion could also occur without any explicit links between banks when a negative shock in one bank is misinterpreted by investors as a signal of diminished soundness in other banks, either in the same country or in a different country.

Several other studies have looked at different transmission channels for spreading contagion risk within banks: Liquidity shocks affecting one bank causing deposit runs at other solvent banks (Freixas, Parigi and Rochet, 2000); shocks via the interbank market when banks withdraw their deposits at other banks (Allen and Gale, 2000; Freixas, Parigi and Rochet, 2000); or in the absence of explicit links, difficulties in one market are perceived as a signal of possible difficulties in others due to asymmetric information (Morgan 2002).

Key to the financial stability debate is that banks have also become increasingly inter-twined with other segments of the financial sector, both locally and across countries. For instance, banks provide insurers with liquidity facilities to pay current claims, and letters of credit as evidence of their ability to pay future claims. The formation of bancassurance groups through the merger of banks with insurers is another example of cross-sector linkages. Banks are also

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4 Schoenmaker and van Laecke (2006) examine the internationalization of cross-border banking, the public policy issues and the appropriate supervisory response.

5 We define contagion risk as the transmission of an idiosyncratic shock from one banking group to another. In other words, by adopting this definition, we are allowing for normal linkages among banks to be a possible channel of contagion, and not restricting our analysis to only cover changing cross-market linkages following a shock (referred to as “shift contagion” by Forbes and Rigobon, 2001).
increasingly providing services to investors such as hedge funds, mutual funds and pension funds, in the form of devising, intermediating and making markets for financial instruments. Cross-border lending activities have also increased strongly in recent years, especially with the sharp growth in private equity deals.

Figure 1. International Positions by Nationality of Ownership of BIS Reporting Banks

(a) Assets
(In billions of U.S. dollars)

(b) Liabilities
(In billions of U.S. dollars)

Sources: Table 8A of International Banking Statistics; and Bank for International Settlements.

This paper focuses on determining the channels of contagion risk among the world’s largest, systemic banks, using the extreme value theory (EVT) framework. Gropp, Lo Duca, and Vesala (2005) and Gropp and Moerman (2004) apply EVT in testing for contagion risk in the EU banking sector. It should be noted that the exact nature of the links between the financial institutions is not explored in this paper. Rather, the results are intended to represent “maps” that could guide the allocation of limited surveillance and supervisory resources, so that more detailed links may then be identified as necessary. In addition to highlighting the relationships among the major global banks, it could also focus cross-border collaboration among supervisors in these countries.6

Our aim is to identify potential risk concentrations among the world’s systemically important banks. Arguably, even if a crisis cannot ultimately be averted, early detection of vulnerabilities in the financial system could provide country authorities extra time to prepare contingency plans, and focus attention on likely stress points. To this end, understanding the interdependencies between individual banks with potential systemic impact and their exposure to economic and financial risks is crucial (Bank of England, 2006).

6 For example, Duggar and Mitra (2006) demonstrate that the major Irish banks are also vulnerable to shocks emanating from the Netherlands and the United States, contrary to the focus of the Irish supervisory authorities largely on the United Kingdom.
We attempt to answer the following questions on the global banking system. Firstly, given the increasing internationalization of financial services, are all banks similarly affected by common shocks to the global economy or financial system? Alternatively, is “home bias” the most dominant factor, notwithstanding the effects of globalization? In other words, are banks predominantly influenced by domestic shocks, either because of their domestic focus or the local regulatory environment, despite being largely integrated into the global financial system? Or, are different banks—irrespective of domicile—affected differently by shocks, due to their increasingly different business and geographic mixes?

Our results reveal several key trends among major global banks. Notably, “home bias” is an important factor in terms of contagion risk. Banks are also generally affected by common shocks to the real economy or financial markets, although the global banking system as a whole tends to be more exposed to these shocks during more turbulent periods, compared to the more benign periods. Further, contagion risk across the major global banks has risen in recent years. Several important relationships are also highlighted at a more specific, bank-by-bank level. Shocks to U.S. banks—especially to Morgan Stanley and Citigroup—appear to have become increasingly more important for foreign banks over time, while some of the major U.S. banks appear largely insulated from foreign banks’ idiosyncratic shocks. Among European banks, Societe Generale (France) represents an increasing risk for other regional counterparts. In contrast, shocks to Japan’s major banks have limited impact on their counterparts, and vice-versa.

This paper is organized as follows. Section II describes the method and data used in our paper. The empirical analysis of contagion risk across major banks is presented in Section III. Section IV concludes.

II. EMPIRICAL METHOD

The EVT approach to contagion better captures the information that large, extreme shocks are transmitted across financial systems differently than small shocks⁷. Multivariate EVT techniques are used to quantify the joint behavior of external realizations (or “co-exceedances”) of financial prices or returns across different markets. The body of literature on EVT has grown in recent years. Recent empirical work using EVT to model contagion in financial markets, including bond, equity, and currency markets, are Bae, Karolyi, and Stulz (2003); Chan-Lau, Mathieson, and Yao (2004); Forbes and Rigobon (2001); Hartmann, Straetmans, and de Vries (2004); Longin and Solnik (2001); Poon, Rockinger, and Tawn

⁷ For example, Granger-causality tests may not accurately depict the common occurrence of extreme events between banks, since relationships between banks are likely to be very different across tranquil and turbulent periods. High correlations in bank soundness during normal times provide little information on the likelihood of contagion. On the other hand, contagion—as we define it—during extreme events could well arise from inter-linkages that also exist during tranquil times.
(2004); Quintos (2001); and Starica (1999). Gropp and Moerman (2004) subsequently apply this approach to changes in the distances-to-default of 67 individual EU banks. They use non-parametric tests of banks’ changes in distances-to-default to test for contagion between two banks, after adjusting for bank size. Separately, Gropp, Lo Duca, and Vesala (2005) use a multinomial LOGIT model to the changes in the distances-to-default of European banks to determine cross-border contagion within the region.

Within this framework, we test for co-exceedances, that is, the likelihood that an extreme shock affecting a major, systemic global bank would also affect another large local or foreign counterpart. We assume that contagion risk is associated with extreme negative co-movements in bank soundness. In other words, we try to determine if extreme, but plausible, negative shocks to a particular bank’s stability could be associated with stresses experienced by other major banks in the international banking system. In our tests, we are able to identify the co-exceedances, or evidence of contagion, attributable to idiosyncratic shocks in the banking sector, since we factor out the impact of domestic and global shocks.

Our analysis differs from existing studies in several important ways:

- We test for contagion risk among individual, systemically important banks, rather than aggregating the effects for a particular country. Gropp, Lo Duca, and Vesala (2005) and Gropp and Moerman (2004) incorporate most listed banks in the EU, in their respective papers, including smaller banks that are likely non-systemic. This could have the effect of overestimating the impact of certain banking systems on others. Indeed, Gropp and Moerman (2004) observe that “an unreasonable number of very small banks” appear to have systemic importance in their results.

- We select the 24 biggest banking groups in the world, by total assets, on the basis that these banks could individually pose systemic risk to the domestic or foreign banking systems. In particular, we include institutions from two of the biggest banking systems in the world—that is, Japan and the United States—which contribute significantly to international banking activity. The influence of big banks from Japan and the United States, which represent 9 out of the 24 biggest banks, is likely to be very important, especially given the sharp increase in international banking activity in recent years. The focus on major banks is very pertinent given that the financial authorities in our sample countries are looking to improve cross-border collaboration on supervision issues and are thus highly concerned about the impact of systemically important banks.

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8 The DD is an indicator of default risk based on Merton (1974). Generally, empirical studies have shown that the DD is a good predictor of corporate defaults (Moody’s KMV), and is able to predict banks’ downgrades in developed and emerging market countries (Gropp, Vesala and Vulpes, 2004; and Chan-Lau, Jobert, and Kong, 2004).
• We incorporate local and global market and real economy factors into our model. Given the global nature of our dataset, we utilize a world stock market index to include shocks that are global in nature, in addition to using individual local stock market indices and domestic interest rate yield spreads to reflect domestic developments.

A. Model

Distance-to-Default

First, we calculate distances-to-default (DDs) as a comprehensive measure of a bank’s default/solvency risk. The DD measure is based on the structural valuation model of Black and Scholes (1973) and Merton (1974). The metric represents the number of standard deviations away from the point where the book value of a bank’s liabilities is equal to the market value of its assets, that is, the default threshold. The DD is an attractive measure in that it measures the solvency risk of a bank by combining information from stock returns with information from leverage and volatility in asset values—key determinants of default risk. It does not require specification of a particular channel through which the transmission of shocks occurs. An increase in the DD implies greater stability/soundness, or a lower risk of default.9

Black and Scholes (1973) and Merton (1974) first drew attention to the concept that corporate securities are contingent claims on the asset value of the issuing firm. This insight is clearly illustrated in the simple case of a firm issuing one unit of equity and one unit of a zero-coupon bond with face value $D$ and maturity $T$. At expiration, the value of debt, $B_T$, and equity, $E_T$, are given by:

\begin{align*}
B_T &= \min(V_T, D) = D - \max(D - V_T, 0), \\
E_T &= \max(V_T - D, 0),
\end{align*}

where $V_T$ is the asset value of the firm at expiration. The interpretation of equations (1) and (2) is straightforward. Bondholders only get paid fully if the firm’s assets exceed the face value of debt, otherwise the firm is liquidated and assets are used to partially compensate bondholders. Equity holders, thus, are residual claimants in the firm since they only get paid after bondholders.

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9 It should be noted that DDs are risk-neutral, that is, they do not take into account that risk preferences may be different between volatile and benign periods.
Note that equations (1) and (2) correspond to the payoff of standard European options. The first equation states that the bond value is equivalent to a long position on a risk-free bond and a short position on a put option with strike price equal to the face value of debt. The second equation states that equity value is equivalent to a long position on a call option with strike price equal to the face value of debt. Given the standard assumptions underlying the derivation of the Black-Scholes option pricing formula, the default probability in period $t$ for a horizon of $T$ years is given by the following formula:

$$p_t = N\left[\frac{\ln \frac{V_t}{D} + \left(\frac{r - \sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}}\right],$$

where $N$ is the cumulative normal distribution, $V_t$ is the value of assets in period $t$, $r$ is the risk-free rate, and $\sigma_A$ is the asset volatility.

The numerator in equation (3) is the DD. An examination of equation (3) indicates that estimating default probabilities requires knowing both the asset value and asset volatility of the firm. The required values, however, correspond to the economic values rather than the accounting figures. It is thus not appropriate to use balance-sheet data for estimating these two parameters. Instead, the asset value and volatility can be estimated. It is possible to solve the following equations (4) and (5) for the asset value and volatility:

$$E_t = V_t N(d_1) - e^{-rT} DN(d_2),$$

and

$$\sigma_E = \frac{V_t}{E_t} N(d_1),$$

if $E_t$, the value of equity; $\sigma_E$, the equity price return volatility; and $D$, the face value of liabilities, are known; and $d_1$ and $d_2$ are given by equations (6) and (7):

$$d_1 = \frac{\ln \frac{V_t}{D} + \left(\frac{r - \sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}},$$

and

$$d_2 = d_1 - \sigma_A \sqrt{T}.$$
• The time horizon \( T \) is fixed at one year.

• The value of equity, \( E_t \), corresponds to the market value of the firm. The data are obtained from Bloomberg by multiplying the number of shares outstanding for a firm by the closing share price on a particular day.

• The equity volatility, \( \sigma_E \), corresponds either to historical equity volatility or implied volatility from equity options. This is calculated from the standard deviation of daily share price returns over a one year period (which we define as 260 days).

• The face value of liabilities, \( D \), is usually assumed equal to the face value of short-term liabilities plus half of the face value of long-term liabilities.\(^{10}\) This number represents the “default barrier”. The liability data are obtained from Bankscope. The item “Deposits and Short-Term Funding” is used to represent short-term liabilities, while the long-term liabilities are derived by deducting the short-term liabilities from the “Total Liabilities” item. To obtain daily liability data from annual balance sheets, the data is intrapolated between two year-end balances.

• The risk-free rate, \( r \), is the one-year government bond yield, in the same currency as those of the market and balance sheet data.

Once the asset value and volatility are estimated, the default probability of the firm, and thus the DD, could be derived from equation (3).

**The Binomial LOGIT Model**

We employ a binomial LOGIT model to determine the likelihood that a large shock to one major bank would cause stress to a large counterpart. Specifically, we apply a model similar to that used by Gropp, Lo Duca, and Vesala (2005) to estimate the probability that the (percentage) change in the DD of one bank falls in a pre-specified percentile in the negative tail, following large negative shocks to the DDs in the rest of the banks in the sample, and after controlling for country-specific and global factors.

**Defining the “Extreme Values”**

First, we calculate the percentage change in the DD (which we denote “\( \Delta DD \)” from the generated series of DDs. The \( \Delta DD \) is calculated over 5 trading days for the following reasons: (i) extreme events are more significant if they are prolonged; events that last for

\(^{10}\) This is based on work done by Moody’s KMV (see Crobie and Bohn, 2003).
only a day are of little concern; (ii) the use of weekly changes reduces “noise” in the data.\(^{11}\) Corresponding ΔDDs between banks reflect interdependencies which incorporate all potential channels of contagion, thus precluding the need to define explicit links between banks or to specify a particular channel of contagion. We define large shocks (or “extreme values”) as the 10\(^{th}\) percentile left tail of the common distribution of the ΔDDs across all banks (Figure 2).\(^{12}\) We calculate the ΔDD, on a daily basis, as follows:

\[
\Delta DD_{it} = \frac{DD_{it} - DD_{it-5}}{|DD_{it-5}|}.
\]

Figure 2. Distribution of Changes in Distance-to-Default, 18-Bank Sample 1/

![Distribution of Changes in Distance-to-Default, 18-Bank Sample 1/](image)

Source: Authors’ calculations.

1/ The 10\(^{th}\) percentile left tail threshold for the stacked DD data of 18 banks is –0.018.

We then stack all \(\Delta DD_{it}\) observations from equation (8) and calculate the threshold, \(T_{10}\), for the bottom 10 percent tail. For estimation purposes, we initially omit six banks—the three Japanese banks, Credit Agricole (France), Credit Swiss (Switzerland) and HBOS (United Kingdom)—due to the shorter periods for which their respective data are available. From the remaining 18 banks over the sample period May 30, 2000 through August 2, 2006, the

\(^{11}\) For instance, stock price returns exhibit day-of-the-week effects (Chang, Pinegar, and Ravichandran, 1993; French, 1980; Jaffe and Westerfield, 1985; Keim and Stambaugh, 1984; and Lakonishok and Smidt, 1988), while non-synchronous trading effects related to the overnight or weekend non-trading periods impact the calculation of daily close-to-close returns (Rogalski, 1984), effects of which could be “smoothed” using weekly data.

\(^{12}\) Ideally, a first or even fifth percentile left tail would capture the very extreme events; however, either cut-off would have resulted in much too few observations for this period of data.
threshold for the 10th percentile left tail is calculated at –0.018. Observations that fall below this threshold, that is, in the bottom 10 percent tail, are the “extreme values”.

**Applying the Econometric Model**

A co-exceedance is defined as the probability that a particular bank will experience a large negative shock as a result of shock to another bank in the sample, after controlling for common shocks. That is, the observation of one extreme value as a result of another. The co-exceedances for each bank $i$ at time $t$ are defined as binary variables, $y_{it}$, such that:

$$
(9) \quad y_{it} = 1 \text{ if } \Delta DD_{it} < T_{10}, \text{ and } 0 \text{ otherwise},
$$

where $T_{10}$ is the 10th percentile threshold in the left tail of the distribution.

We estimate the conditional probability that bank $i$ will be in distress at time $t$ conditional on bank $j$ $(j \neq i)$ being in distress, after controlling for other country-specific and global factors, as:

$$
(10) \quad \Pr(y_{it} = 1 | x, \beta) = \frac{e^{\alpha F_{it} + \sum_{s=1}^{5} \rho_s C_{it-s} + \gamma_j \sum_{j=1}^{B} C_{jt-1}}}{1 + e^{\alpha F_{it} + \sum_{s=1}^{5} \rho_s C_{it-s} + \gamma_j \sum_{j=1}^{B} C_{jt-1}}},
$$

which is based on the cumulative distribution function for the logistic distribution, $x$ represents the explanatory variables $F$ and $C$, and $\beta$ the slope coefficients $\alpha$, $\rho$, $\gamma$. The parameter $\alpha$ represents the sensitivity of bank $i$ to real and financial developments in its own country and in the global market, $F_{it}$; $\rho$ represents the sensitivity of bank $i$ to extreme shocks it has experienced itself in the previous periods of up to $s$ lags, $C_{it-s}$; and $\gamma$ represents the sensitivity of bank $i$ to extreme shocks experienced by the rest of the banks in the sample during the previous period, $C_{jt-1}$ (where $j \neq i$), or in other words, the co-exceedance of bank $i$ with other banks. All the $C$ variables are lagged by one period to capture the impact on bank $i$ from developments at the other banks, taking into account the differences in trading hours across the different time zones. The other explanatory variables are defined in the next sub-section.$^{14}$

$^{13}$ This operation adjusts for any serial correlation in the residuals, which may be induced by our use of overlapping weekly $\Delta DD$s.

$^{14}$ The results are not significantly different when we apply the GOMPIT distribution, instead of the logistic distribution.
The goodness of fit in LOGIT (and other binary) models is given by the McFadden $R^2$. This statistic is the likelihood ratio index, computed as:

\begin{equation}
R^2 = \frac{(1 - l(\tilde{\beta}))}{l(\beta)},
\end{equation}

where $l(\tilde{\beta})$ is the restricted log likelihood—this is the maximized log likelihood value when all slope coefficients are restricted to zero, and is equivalent to estimating the unconditional mean probability of an observation being in the tail.

**Step 3: Incorporating Non-Bank Explanatory Variables**

**Country-Specific Market Shocks**

We use the local stock market return volatility to control for country-specific market shocks. We calculate the weekly (5 trading-day) returns on each country-specific benchmark stock index by taking the weekly log-difference of the stock index in the local currency. The volatility of returns is proxied by the conditional variance estimated from a GARCH(1,1) model of the weekly returns, such that,

\begin{align}
X_t &= c + \varepsilon_t, \text{ and} \\
\sigma^2_t &= w + \alpha \varepsilon^2_{t-1} + \beta \sigma^2_{t-1},
\end{align}

where $X_t$ is the weekly local currency return in the country’s stock price index and $\sigma^2_t$ is the GARCH volatility, at time $t$. The ARCH effect is captured by the lagged square residual, $\varepsilon^2_{t-1}$. We predict this period’s variance by forming the weighted average of a long term mean (the constant, $w$), the forecast variance from the previous period ($\sigma^2_{t-1}$), and information about volatility observed in the last period ($\varepsilon^2_{t-1}$). This model is consistent with the volatility clustering associated with financial returns data, where large changes in returns are likely to be followed by further large changes. Lagrange multiplier tests show significant ARCH(1) effects for all the stock market returns used in this paper.

\footnote{This method was introduced by Ding and Engle (1994), and subsequently applied by De Santis and Gerard (1997, 1998), Ledoit, Santa-Clara and Wolf (2003) and Bae, Karolyi and Stulz (2003).}
Developments in the Real Economy

We use (5 trading-day) changes in term structure spreads to represent expectations of changes in the business cycle in a bank’s home country. Put another way, the changes in the spreads reflect the broader real economy developments in that country. The term structure spread is calculated as the difference between a long-term interest rate (the 10-year government bond yield) and a short term rate (the 1-year government bond yield) in any one country. Thus, the change in yield curve slope—our explanatory variable—is defined as follows:

\[
\Delta yc_t = \frac{yc_t - yc_{t-5}}{|yc_{t-5}|},
\]

where \( yc_t \) is the term structure spread at time \( t \).

Global Market Shocks

We apply a global stock market return volatility variable to control for common shocks affecting global markets. This index is published in U.S. dollars, but is converted to the currency of the country in which the bank associated with the dependent variable is located. We use the same method as that for the local stock markets, and estimate the GARCH(1,1) volatility for the global stock market index.

B. Data

Our dataset includes the world’s top 24 largest exchange-listed banking groups by total assets, as at end-2005, according to Bankscope.\(^{16}\) These comprise institutions from other major banking systems such as France, Germany, Japan, the Netherlands, Switzerland, the United Kingdom and the United States; a Spanish banking group, a Belgian, and an Italian banking group also make up the top-24, although banking activity in these three countries are much smaller by comparison. All these banks have a presence in the major financial centers of the world. Balance sheet data for the individual banks, used in the DD calculations, are obtained from Bankscope, while the requisite market data are available from Bloomberg LP.

We use three separate control variables to account for common factors affecting local financial markets, the local real economy and global market developments. Specifically, we incorporate the price return volatility of the local stock market index returns to capture local

\(^{16}\) We originally selected the top 35 largest banks in the world, but subsequently refined the sample to the 24 largest exchange-listed banks for which good quality and sufficient data are available. The list of banks in our dataset and their corresponding data availability are presented in Appendix 1, Table A.1.
market influences; changes in the slope of the local term structure (between one- and ten-year
government bonds) to represent developments in the domestic real economy;\(^{17}\) and the price
return volatility in the Morgan Stanley Capital International (MSCI) All-Country World
Index (ACWI) returns to account for global market factors. These variables are constructed
using data from Bloomberg LP.\(^ {18}\)

The sample period, determined by data availability, is May 30, 2000 to August 2, 2006.
However, data for six banks—Credit Agricole (France), Credit Suisse (Switzerland), HBOS
(United Kingdom), Mitsubishi UFJ (Japan), Mizuho (Japan), and Sumitomo Mitsui
(Japan)—are only available from later dates. Thus, only 18 banks (the “main sample”) are
tested for the full sample period; the other banks are subsequently added to the main sample
as their data become available, and we rerun the tests for each expanded sample (see below).

Several caveats apply to our data. Firstly, some of the banking groups in our sample
represent important constituents in their respective country’s stock market indices, and may
also be represented represented in the MSCI ACWI. This means that some of the stock
market volatility effects captured in the results could be partly driven by the volatility in the
individual bank stocks. This suggests that the impact of idiosyncratic shocks on inter-bank
contagion represent “conservative” estimates.\(^ {19}\) Secondly, the balance sheet data on banks’
long- and short-term liabilities are only available on an annual basis from Bankscope. Thus,
our calculation of daily DDs require extrapolation between two data points. In this case, we
assume that the liabilities change proportionally each day between the two reporting dates.
Finally, the DD risk measure does not factor in default risk arising from off-balance sheet
exposures, which could be substantial especially for major international banks engaged in
proprietary trading activities.\(^ {20}\)

\(^{17}\) See, for example, Bernard and Gerlach (1998), Estrella (2005), and Estrella and Hardouvelis (1991).

\(^{18}\) Details and sources of the market data are presented in Appendix 1, Table A.2.

\(^{19}\) We test for robustness by omitting the local stock market variable and rerunning the binomial LOGIT model.
Our results show that the contagion effects remain largely the same; some of the local market effects are
captured by the global market variable. However, the McFadden \(R^2\) is slightly stronger for the existing model.

\(^{20}\) Notwithstanding this limitation, empirical studies have shown that the DD is still a good indicator of default
III. DEFAULT RISK AND CONTAGION RESULTS

A. Analysis

An examination of banks’ DD suggests that bank soundness broadly deteriorated across countries during the mid-2000 to mid-2003 period.\textsuperscript{21} The collective decline in DDs has coincided with the period following the bursting of the global information technology bubble; the slowdown in global economic growth; the economic and financial difficulties experienced in some Latin American countries, such as Argentina and Brazil, where some of the major banks have direct business interests. The U.K. and U.S. banks appear to have been less affected by the general turbulence, relative to banks from other countries, as their DDs remained relatively stable during this time.

The stresses on the global banking system during the first-half of the sample period are also evident from the number of negative extreme values, or left-tail events, across banks.\textsuperscript{22} The health of the global banking system then improved vastly over the mid-2003 to end-2005 period. The DDs of all banks in our sample rose strongly during this period; correspondingly, the overall number of left-tail events fell substantially. However, the global banking system came under some pressure in 2006. The number of left-tail events increased across many banks in our sample during this period. While the exact causes of the observed stress are unclear, it has coincided with the oil and commodity price shocks experienced in early-2006, as well as with the sharp corrections in global asset prices observed in the second quarter of 2006.

In the world’s biggest banking market, we find that U.S. banks are vulnerable to contagion risk from banks from their own country as well as from overseas. Table 1 suggests that some of these banks are also susceptible to shocks affecting European banks; however, no European bank represents a consistently common contagion factor. Among U.S. banks, Goldman Sachs appears to be largely insulated from external shocks, while shocks to U.S. banks have had some impact on their European counterparts. There appears to be little interaction between several U.S. banks with domestic stock market and interest rate shocks. This suggests that stresses to U.S. banks during this period have not necessarily been tied to developments in the local market or economy. Rather, bank soundness appears to be more closely related to volatilities in global markets, potentially reflecting the global nature of U.S. banking businesses.

\textsuperscript{21} See Appendix 2, Figure A.1.

\textsuperscript{22} See Appendix 2, Figure A.2.
Table 1. Contagion Risk among the World's Largest Banking Groups (18-Bank Sample), May 30, 2000–August 2, 2006
(In percent level of significance)

<table>
<thead>
<tr>
<th>Country</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>Netherlands</th>
<th>Spain</th>
<th>Switzerland</th>
<th>United Kingdom</th>
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<td>BNP Paribas</td>
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<td>Deutsche Bank</td>
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<td>Santander</td>
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<tr>
<td>McNelton R^2</td>
<td>0.45</td>
<td>0.47</td>
<td>0.45</td>
<td>0.45</td>
<td>0.57</td>
<td>0.49</td>
<td>0.50</td>
<td>0.47</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Sources: Bankscope, Bloomberg LP and authors' calculations.

Notes: Columns represent dependent variables; rows represent explanatory variables.
Blank cells represent non-significance at any level below 5 percent.
■ represents significance at the 5 percent level or lower.
□ represents significance at the 1 percent level or lower.
☑ represents significance (negative sign) at the 5 percent level or lower.
● represents coefficients on own-lags, of up to 5 lags.
☐ represents the grouping of major banks in any one country, where 3 or more banks are represented in the sample.
Contagion risk appears quite significant among European banks. Shocks to ABN Amro (Netherlands) appear to impact banks across several countries, including those in the United Kingdom and the United States, while Societe Generale (France), Deutsche Bank (Germany) and ING (Netherlands) are among those most vulnerable to contagion risk from other major international banks. With the exception of Barclays, U.K. banks appear mostly insulated from contagion risk from foreign banks. Contagion among same-country banks is difficult to determine, given the limited number of major global banks from each country. Among U.K. banks, for which we have a larger sample, contagion risk is significant. Both HSBC and RBS are exposed to contagion risk from Barclays; in turn, Barclays appears to be exposed to shocks from both of these banks as well.

Interestingly, our results thus far show some common threads with those of Gropp and Moerman (2004), notwithstanding the differences in time periods, model and bank samples. Like us, the authors identify ABN Amro (Netherlands) and HSBC (United Kingdom) to be among the more systemically important banks for those outside their own country. They also find close links among banks within countries.

**B. Robustness Tests with Sub-Samples**

Next, we split the sample period into two sub-samples, to determine the robustness of our initial findings. A natural structural break would be around mid-2003, which separates the more turbulent period in global economic and market conditions from the benign period that followed. Thus, we define the first sub-sample as May 30, 2000–May 30, 2003, and the second as June 1, 2003–August 2, 2006.

Our results reveal several broad trends among the major international banks. We find evidence of a contagion “home bias (Table 2). For example, contagion from U.K. banks to local counterparts are more prevalent than to foreign banks. Similarly, shocks to U.S. banks also have a proportionately greater impact on their local counterparts. That said, individual banks are affected differently by idiosyncratic shocks to their major counterparts, possibly due to their different business and geographic mixes. Banks are also not similarly affected by common shocks to the domestic real economy or to financial markets, although the global banking system as a whole tends to be more exposed to these shocks during more turbulent periods, compared to the more benign times.

Importantly, contagion risk across the major global banks has risen in recent years (Table 3). The exposure of U.S. banks to each other appears to have intensified; the impact of shocks U.S. banks on foreign banks has also increased, as has contagion from U.K. to continental European banks. Individually, shocks to Societe Generale (France), HSBC (United Kingdom) and Morgan Stanley (United States) have had increasingly greater impact on
foreign banks. Within Europe, contagion risk from the French banks appears to have increased over time.\(^{23}\)

**Table 2. Significant Co-exceedances, 2000–2006**  
(In percent of total possible bank transmission channels)

<table>
<thead>
<tr>
<th>Contagion to banks in:</th>
<th>Continental Europe</th>
<th>United Kingdom</th>
<th>United States</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial shock to banks in:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Continental Europe</td>
<td>17</td>
<td>4</td>
<td>9</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>6</td>
<td>67</td>
<td>6</td>
</tr>
<tr>
<td>United States</td>
<td>6</td>
<td>6</td>
<td>23</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations.

**Table 3. Change in the Number of Significant Co-exceedances, 2000–03 to 2003–06**  
(In percent)

<table>
<thead>
<tr>
<th>Contagion to banks in:</th>
<th>Continental Europe</th>
<th>United Kingdom</th>
<th>United States</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial shock to banks in:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Continental Europe</td>
<td>20</td>
<td>0</td>
<td>-25</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>400</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>United States</td>
<td>300</td>
<td>*</td>
<td>40</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations.  
* The number increased from zero to 1.

We subsequently add the remaining six banks to the sample of 18 banks as their data become available, and we rerun the tests for each expanded sample.\(^{24}\) The banks are added in the following order: Mitsubishi UFJ (Japan), HBOS (United Kingdom), Credit Agricole (France), Credit Suisse (Switzerland), Sumitomo Mitsui (Japan), and Mizuho (Japan).\(^{25}\) Our analysis of each of the six sets of results reveals several notable trends:

- Among U.S. banks, Morgan Stanley, and Goldman Sachs are largely insulated from contagion. Morgan Stanley consistently represents the biggest contagion risk for other foreign banks; Citigroup has also become increasingly important in recent years.

- In continental Europe, shocks to Societe Generale has had the widest impact over time, while banks such as Fortis (Belgium) and Santander (Spain) have become more exposed to shocks from elsewhere. In the United Kingdom, Barclays is the consistent risk factor for its local counterparts, while HSBC remains the most important U.K. contagion risk factor for foreign banks.

- Contagion risk for major Japanese banks has been limited. Japanese banks appear to pose little contagion risk to the other major international banks, despite the size of the banking system, which is the fourth largest in the world. Similarly, these banks are largely insulated from shocks to foreign banks.

\(^{23}\) The detailed results are available on request.

\(^{24}\) The 10\(^{th}\) percentile left tail for each sample, expanded by one bank at a time, remains at −0.018.

\(^{25}\) See Appendix 3, Table A.3 for the 24-bank results. Detailed results for the 19–23 bank samples are available on request.
IV. CONCLUSION

This paper uses market-based indicators to highlight potential inter-relationships among the world’s biggest banking groups and their exposure to contagion risk from their counterparts. Specifically, the main objective is to identify the direction of contagion among those banks through the international banking system. In doing so, our results also provide some information on areas where risks may be concentrated, thus highlighting relationships which may require closer supervision and surveillance and a more detailed understanding of linkages by the local authorities. Our findings could also help country authorities focus their collaborative supervisory efforts on specific areas, given their limited resources.

Using an EVT framework, our results yield several clear trends in the inter-relationships among the world’s biggest banks from three regions. Overall, the risk of contagion among local banks is important (“home bias”). Banks are also affected by common shocks to the real economy or financial markets, although they tend to be more vulnerable to these shocks during more turbulent periods, compared to the more benign times. Meanwhile, contagion risk among the major global banks appears to have increased over time.

In light of these findings, ensuring sound risk management practices continues to be a key challenge, both for supervisors and banks. Encouragingly, risk management by banks has become increasingly more professional, ahead of the introduction of new bank capital standards under Basel II. However, given the continuing growth and increased complexity of banks’ businesses, risk management techniques need to be continually enhanced and improved. In many countries, supervisors are also promoting greater use of stress-testing as a key risk management tool.

Appropriately, greater emphasis is being placed on improving cooperation in cross-border financial crisis prevention and management. European regulators and supervisors and the European Commission support more efficient, risk-based cross-border collaboration among supervisors. Internationally, the existing tripartite of Switzerland, the United Kingdom, and the United States is considered one of the most fully-developed examples of home/host collaboration in supervision. In other collaborative efforts, the U.K. Financial Supervisory Authority and the New York Federal Reserve have worked closely and continuously with major participants in the credit risk transfer market to resolve the issue of backlogs in trade confirmations and assignments, and continue to emphasize the need for “borderless” solutions in the oversight of the credit derivatives market (Geithner, McCarthy and Nazareth, 2006). EU authorities have also signed the Memorandum of Understanding for crisis management, which includes performing crisis simulation exercises at the EU level. Nonetheless, country authorities largely acknowledge that there is a need for further work on cross-border co-ordination and information sharing between national authorities in promoting financial stability (Gieve, 2006).
### Appendix 1. Data Details

#### Table A.1. List of Exchange-Listed Banks

<table>
<thead>
<tr>
<th>Rank</th>
<th>Total Assets as at End-2005</th>
<th>Banking Group</th>
<th>Nationality</th>
<th>Bloomberg Ticker</th>
<th>Date from which DD Data are Available</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td></td>
<td>Barclays PLC*</td>
<td>United Kingdom</td>
<td>BARC LN</td>
<td>May 17, 2000</td>
</tr>
<tr>
<td>2.</td>
<td></td>
<td>UBS AG*</td>
<td>Switzerland</td>
<td>UBSN VX</td>
<td>May 30, 2000</td>
</tr>
<tr>
<td>4.</td>
<td></td>
<td>HSBC Holdings PLC*</td>
<td>United Kingdom</td>
<td>HSBA LN</td>
<td>May 17, 2000</td>
</tr>
<tr>
<td>6.</td>
<td></td>
<td>BNP Paribas*</td>
<td>France</td>
<td>BNP FP</td>
<td>May 30, 2000</td>
</tr>
<tr>
<td>7.</td>
<td></td>
<td>ING Groep NV</td>
<td>Netherlands</td>
<td>INGA NA</td>
<td>May 30, 2000</td>
</tr>
<tr>
<td>8.</td>
<td></td>
<td>Royal Bank of Scotland Group PLC*</td>
<td>United Kingdom</td>
<td>RBS LN</td>
<td>May 17, 2000</td>
</tr>
<tr>
<td>10.</td>
<td></td>
<td>Crédit Agricole SA</td>
<td>France</td>
<td>ACA FP</td>
<td>December 16, 2002</td>
</tr>
<tr>
<td>15.</td>
<td></td>
<td>Credit Suisse Group*</td>
<td>Switzerland</td>
<td>CSGN VX</td>
<td>January 1, 2003</td>
</tr>
<tr>
<td>17.</td>
<td></td>
<td>Banco Santander Central Hispano SA</td>
<td>Spain</td>
<td>SAN SM</td>
<td>May 30, 2000</td>
</tr>
<tr>
<td>18.</td>
<td></td>
<td>HBOS PLC*</td>
<td>United Kingdom</td>
<td>HBOS LN</td>
<td>September 11, 2002</td>
</tr>
<tr>
<td>19.</td>
<td></td>
<td>UniCredito Italiano SpA</td>
<td>Italy</td>
<td>UC IM</td>
<td>May 30, 2000</td>
</tr>
<tr>
<td>22.</td>
<td></td>
<td>Fortis</td>
<td>Belgium</td>
<td>FORBB BB</td>
<td>May 30, 2000</td>
</tr>
</tbody>
</table>

Sources: Bankscope and Bloomberg LP.

*Identified by the Bank of England (BoE, 2006) as large, complex financial institutions (LCFIs), which carry out a diverse and complex range of activities in major financial centers.
Table A.2. Stock Market Indices and Government Bond Yields

<table>
<thead>
<tr>
<th>Country</th>
<th>Stock Market</th>
<th>Bloomberg Ticker</th>
<th>Maturity</th>
<th>Bond</th>
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</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>BEL20</td>
<td>BEL 20</td>
<td>EUR Belgium sovereign zero coupon yield, 1-year I90001Y</td>
<td>EUR Belgium sovereign zero coupon yield, 10-year I90010Y</td>
</tr>
<tr>
<td>France</td>
<td>CAC</td>
<td>CAC40</td>
<td>EUR France sovereign zero coupon yield, 1-year I01401Y</td>
<td>EUR France sovereign zero coupon yield, 10-year I01410Y</td>
</tr>
<tr>
<td>Germany</td>
<td>DAX</td>
<td>DAX30</td>
<td>EUR Germany sovereign zero coupon yield, 1-year F91001Y</td>
<td>EUR Germany sovereign zero coupon yield, 10-year F91010Y</td>
</tr>
<tr>
<td>Italy</td>
<td>S&amp;P MIB</td>
<td>SPMIB</td>
<td>EUR Italy sovereign zero coupon yield, 1-year F90501Y</td>
<td>EUR Italy sovereign zero coupon yield, 10-year F90510Y</td>
</tr>
<tr>
<td>Japan</td>
<td>Nikkei 225</td>
<td>NKY</td>
<td>JPY Japan sovereign 10-30 year zero coupon yield, 1-year F10501Y</td>
<td>JPY Japan sovereign 10-30 year zero coupon yield, 10-year F10510Y</td>
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<tr>
<td>Netherlands</td>
<td>AEX</td>
<td>AEX</td>
<td>EUR Netherlands sovereign zero coupon yield, 1-year F92001Y</td>
<td>EUR Netherlands sovereign zero coupon yield, 10-year F92010Y</td>
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<td>Spain</td>
<td>IBEX35</td>
<td>IBEX</td>
<td>EUR Spain sovereign zero coupon yield, 1-year F90201Y</td>
<td>EUR Spain sovereign zero coupon yield, 10-year F90210Y</td>
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<td>Switzerland</td>
<td>SMI</td>
<td>SMI</td>
<td>CHF Switzerland sovereign zero coupon yield, 1-year F25601Y</td>
<td>CHF Switzerland sovereign zero coupon yield, 10-year F25610Y</td>
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<td>U.K.</td>
<td>FTSE100</td>
<td>UKX</td>
<td>GBP United Kingdom zero coupon yield, 1-year I02201Y</td>
<td>GBP United Kingdom zero coupon yield, 1-year I02210Y</td>
</tr>
<tr>
<td>U.S.</td>
<td>S&amp;P 500</td>
<td>SPX</td>
<td>USD Treasury actives zero coupon yield, 1-year I02501Y</td>
<td>USD Treasury actives zero coupon yield, 10-year I02510Y</td>
</tr>
<tr>
<td>World</td>
<td>MSCI All-Country World</td>
<td>MXWD</td>
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</tr>
</tbody>
</table>

Sources: Bloomberg LP, individual country stock exchanges and Morgan Stanley Capital International.
Appendix 2. Data Details

Figure A.1. Distances-to-Default of Individual Banks

Sources: Bankscope; Bloomberg L.P; and authors’ calculations.
Figure A.2. Binomial LOGIT Representations of the 10th Percentile Left Tail (“Extreme Values” or “Exceedances”) of Individual Banks

Sources: Bankscope; Bloomberg LP; and authors’ calculations.
### Appendix 3. Binomial LOGIT Results for 24-Bank Sample

Table A.3. Contagion Risk among the World’s Largest Banking Groups (24-Bank Sample), March 12, 2004 – August 2, 2006
(In percent level of significance)

<table>
<thead>
<tr>
<th>Country</th>
<th>Belgium</th>
<th>France</th>
<th>Germany</th>
<th>Italy</th>
<th>Japan</th>
<th>Netherlands</th>
<th>Spain</th>
<th>Switzerland</th>
<th>U.K.</th>
<th>U.S.</th>
<th>Other factors</th>
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<tbody>
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<td>Bank</td>
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<td>U.K.</td>
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<tr>
<td>U.S.</td>
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</tbody>
</table>

Sources: Bankscope; Bloomberg LP; and authors’ calculations.

Notes: Columns represent dependent variables; rows represent explanatory variables.
- Blank cells represent non-significance at any level below 5 percent.
- □ represents significance at the 5 percent level or lower.
- ▪ represents significance at the 1 percent level or lower.
- ◯ represents significance (negative sign) at the 5 percent level or lower.
- ◆ represents coefficients on own-lags, of up to 5 lags.
- ■ represents the grouping of major banks in any one country, where 3 or more banks are represented in the sample.

Given the short sample period, a few banks with very few co-exceedances with other banks have to be dropped for the estimation processes to converge.
References


Crosbie, Peter and Jeffrey R. Bohn, 2003, “Modeling Default Risk,” Moody's KMV.


