Estimating Systemic Risk in the International Financial System

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Abstract

Using a unique and comprehensive dataset, this paper develops and uses three distinct methods to quantify the risk of a systemic failure in the global banking system. We examine a sample of 334 banks (representing 80% of global bank equity) in 28 countries around 6 global financial crises (such as the Asian and Russian crises and September 11, 2001), and show that these crises did not create large probabilities of global financial system failure. First, we show that cumulative negative abnormal returns for the subset of banks not directly exposed to a negative shock (unexposed banks) rarely exceed a few percent. Second, we use structural models to obtain more precise point estimates of the likelihood of systemic failure. These estimates suggest that systemic risk is limited even during major financial crises. For example, maximum likelihood estimation of bank failure probabilities implied by equity prices suggests the Asian crisis induced less than a 1% increase in the probability of systemic failure. Third, we also obtain estimates of systemic risk implied by equity option prices of U.S. and European banks. The largest values are obtained for the Russian crisis and September 11 and these show increases in estimated average default probabilities of only around 1-2%. Taken together our results suggest statistically significant, but economically small, increases in systemic risk around even the worst financial crises of the last 10 years. Although policy responses are endogenous, the low estimated probabilities suggest that the distress of central bankers, regulators and politicians about the events we study may be overstated, and that current policy responses to financial crises and the existing institutional framework may be adequate to handle major macroeconomic events.

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Keywords: Systemic risk, default risk, credit risk, banks, exposure, emerging markets, 9/11
JEL Classification: G3, F4, F3

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"In practice, the policy choice of how much, if any, extreme market risk should be absorbed by government authorities is fraught with many complexities. Yet we central bankers make this decision every day, either explicitly, or implicitly through inadvertence. Moreover, we can never know for sure whether the decisions we make are appropriate. The question is not whether our actions are seen to have been necessary in retrospect; the absence of a fire does not mean that we should not have paid for fire insurance. Rather, the question is whether, ex ante, the probability of a systemic collapse was sufficient to warrant intervention. Often, we cannot wait to see whether, in hindsight, the problem will be judged to have been an isolated event and largely benign."

International Financial Risk Management, Remarks by Chairman Alan Greenspan before the Council on Foreign Relations, Washington, D.C. November 19, 2002

1 Introduction

Systemic risk in the banking system has rightly attracted the attention of financial researchers (as well as regulators and policymakers) since the genesis of the discipline; bank failure and either simultaneous or subsequent macroeconomic collapse represents a financial dislocation with large and far-reaching consequences. Indeed the recent debate on the necessity for reforms to the global financial architecture depends critically upon the ability of the global payments system to weather massive, albeit localized, economic shocks. As Rogoff (1999) notes, "More immediately, developing country financial instability poses a potential threat to industrialized country banks."[1]

Despite its importance, we know little about the absolute magnitude of such a systemic failure. Recent structural changes to the global financial system have led to competing theories about whether this probability has increased or decreased. On one hand, industry consolidation, dramatic increases in capital mobility, relaxations in international lending restrictions, and changes in capital allocation rules have raised the specter that, for example, a credit crisis in emerging markets might bleed into developed credit markets

[1] Much of this discussion centers on policies to constrain volatility of short-term capital flows to developing countries, which is clearly related to the probability of systemic banking failure via banking bailouts and the need for lenders of last resort to both countries and distressed banks to ensure continued access to credit in the aftermath of crises. See for instance Fischer (1999), Rogoff (1999), and Summers (2000).

via disruptions in local lending channels.[2] In contrast, others (see especially, Darby 1994) have argued that recent financial innovations (e.g., the burgeoning credit derivatives market) and the increased activity of non-banking financial intermediaries (e.g., re-insurance companies) may have lessened the risk that systemic shocks are transmitted throughout the global banking system. Indeed, much of the acrimonious argument over Basel II credit allocation rules has focused upon the ability of large financial institutions to internally measure and manage the risk of credit crises without transmitting such shocks to other banks, and whether such measures will be adequate to forestall insolvencies in the wake of a major macroeconomic dislocation.[3]

Using unique data on exposure measures, this paper directly tests the strength of the transmission mechanism between banks under the assumption of capital (equity) market efficiency for a large sample of international banks. Specifically, we use three separate approaches to infer the increased risk of systemic banking failure by examining a sample of banks around significant financial crises (Mexican devaluation in 1994, Asian crisis in 1997-1998, Russian default and LTCM in 1998, Brazilian devaluation in 1999, and the terrorist attacks of September 11, 2001). First, we show that there are generally small abnormal returns to banks without exposure to the crises, whereas exposed banks tend to have large abnormal returns over the same periods. Second, using a version of the Merton structural model of the firm, we extract default probabilities and show that there are small "flow-through" effects of the crisis on an unexposed bank's probability of failure. Third, we derive estimates of bankruptcy probabilities using daily options market data and show that these crises events are associated with only modest increases in default probabilities for banks unexposed to the crises. In short, we find little evidence of substantial systemic transmission of financial shocks through developed economies even prior to the imposition of Basel II capital rules. However, the

[2] For example, see DeNicolo and Kwast (2001) for an analysis and discussion of the effect on systemic risk of banking industry consolidation, and Kaminsky and Reinhart (1999) on the linkages between banking and currency crises.

[3] See also Acharya (2001) and cites therein for recent theoretical work on systemic risk.

interpretation of our results depends somewhat on the subjective assessment of what constitutes a "large change" in the probability of a systemic failure.

1.1 Existing Literature

Financial economists in academia, central banks, and international organizations alike have intensely studied various facets of the recent financial crises in Latin America, Asia, and Russia. While theoretical models (e.g. by Freixas, Parigi and Rochet (2000), Allen and Gale (1998), and Rochet and Triole (1996)) analyze systemic risk in interbank lending relationships, most empirical work focuses not on systemic risk *per se*, but on contagion effects in order to identify the mechanics and channels through which these crises spread across markets and countries.[4] To illustrate, Kho, Lee and Stulz (2000) study the effect of currency crises and the LTCM crisis on a sample of 78 U.S. banks and document that banks with exposures to a crisis country are adversely affected by crisis events and positively affected by IMF bailout announcements. Similarly, Kho and Stulz (2000) examine the impact of the Asian crisis on bank indices in four developed and six Asian countries. Bae, Karolyi and Stulz (2003) study the probability of joint occurrences of extreme returns across countries (co-exceedances) and find that contagion depends on interest rates, exchange rate changes, and conditional volatility, and that the United States is not immune from contagion from Latin America, but is insulated from Asian contagion. Linkages between economies in crisis periods and potential spillover effects from one country to another may, for instance, exist in the form of trade (Glick and Rose (1999); Van Rijckeghem and Weder (2001)) or through financial linkages (Baig and Goldfajn (1999); Goldfajn and Valdés (1998)). In contrast, the analysis in this paper pertains directly to the phenomenon of systemic risk among banks and attempts to provide an empirical assessment of the

[4] Karolyi (2003) gives an excellent analysis and critique of different approaches to define and measure contagion. De Bandt and Hartmann (2000) offer a broad review of the theoretical and empirical literature on contagion and its systemic implications.

likelihood of a failure of the global banking system. It thus addresses the important issue of *quantifying* the consequences of contagious effects, rather than explaining their existence.

Conceptually, a systemic failure in the global banking system could be defined as a failure (seizing) of the global inter-bank payment system or a loss of confidence in banks which results in a global 'bank-run'. For example, payment failures could mean that banks not receiving payments on loans (explicit or implicit) would become technically insolvent. Cascading bank insolvencies and bank-runs could cause additional financial and economic spillovers such as rapid credit reduction, and ultimately, macroeconomic contraction (see, for example, Bernanke (1983)). Prior research has discussed how different types of shocks might cause systemic risk. For example, Kaufman (2000) describes systemic risks that can arise from a "big shock" (e.g., failure of a major bank), "spillovers" (e.g., East Asian contagion), and "common shock" (e.g., 9/11). Other researchers have distinguished between credit and operational risks. Since there does not exist an easy or accepted way of classifying shocks by type (and we examine only 5 events), we do not attempt to draw conclusions about how different types of shocks affect changes in systemic risk probabilities.

Our first method for estimating this risk of a systemic failure relies on measuring the impact of global financial shocks on the stock price of a subset of banks that are not directly exposed to the shock. Specifically, the abnormal performance of these stocks should reflect primarily the probability of systemic failure in the banking system. In efficient capital markets, negative information such as devaluations of emerging market currencies or the tragedy of 9/11 will affect bank stock prices only if banks are exposed to the particular events. In contrast, unexposed bank stock prices should be largely unaffected by these events. As a result, stock market reactions of unexposed banks to crisis events can be interpreted as a crude measure of systemic risk. This is because negative returns of these banks are not due to direct exposure to the crises *per se*, but they are the result of negative returns of exposed banks that affect unexposed banks through the financial system.[5]

Other researchers (including some of those noted above) have also used market prices of stocks and stock options to evaluate bank risks. For example, Pettway and Sinkey (1980) show that stock market returns can be used as an effective early-warning tool for identifying U.S. banks likely to fail. Bongini, Laeven, and Majnoni (2002) use a Merton model to estimate East Asian bank failure probabilities during the Asian crisis and find that these estimates respond more quickly to changing financial conditions than ratings of credit risk agencies (but did not outperform measures using only balance sheet data).[6] Swidler and Wilcox (2002) find that equity option implied volatilities of banks add timely information about bank risk beyond what is available from other measures and suggest that this information can be used to more accurately estimate bank failure probabilities. However, none of these papers attempt to measure systemic risk.

1.2 Overview of Methodology

Our analysis is based primarily on a sample of 334 banks in 28 countries representing about 80% of global bank equity. The first of our three approaches examines equity returns of unexposed banks during financial crises. Both raw returns and cumulative abnormal returns (CARs) for unexposed banks show relatively small declines (typically less than 4%) regardless of time horizon or exposure definition. The exception is immediately after 9/11 when CARs for unexposed banks are in the range of -4% to -6%.

Our second method provides more precise point estimates of the likelihood of systemic failure based on a structural credit risk model (i.e., Merton, 1974). We derive maximum likelihood estimates of

[5] Even in the absence of systemic failure, financial crises could on average have a negative effect on global economies and therefore on banks in general. If we measure this effect, it will bias our estimates of systemic risk upward.

[6] See also Krainer and Lopez (2001).

probabilities of and corresponding distances to default for the sample banks as a function of characteristics such as market value, face value of debt and demand deposits, and asset volatility. While the model relies on several simplifications, model misspecification may largely wash out in intertemporal comparisons of the recovered default probabilities. Consequently, we interpret the difference between average pre-crisis and post-crisis probabilities for banks that are not directly exposed to the crisis as a measure of systemic risk. Our results suggest very little chance of increased systemic failure during any of the crises, although there is a noticeable reaction to the LTCM credit crisis in the aftermath of the Russian shock. For example, the largest increase in average default probabilities for unexposed banks occurs during the Asian crisis when probabilities increase from 2.1% to 2.8%. Our estimates of increases in systemic failure are less than 1% across all crises, with much of the impact on unexposed banks generated by European banks.

Our third approach for assessing systemic risk in the banking system comes from estimating bank default probabilities implied by equity option prices. This method has the advantage of not relying on relatively infrequent (and stale) accounting data. In addition, the model can be estimated real-time using exclusively live market quotations thus making it a potentially valuable regulatory tool. Our analysis assumes a particular model for option prices that explicitly includes the probability of bankruptcy. Parameters of the model are estimated using a large set of publicly traded options on a subset of European and U.S. banks. The model makes the important assumption that over a finite horizon stocks follow a delta-geometric random walk (see Câmara (2004)) and thus have a finite chance of going bankrupt. The valuation equations can be inverted to yield the probability of bankruptcy. Because of data limitations, the sample is restricted to 14 European and 62 U.S. banks. Again, we study the difference in implied default probabilities between exposed and unexposed banks and find that none of the crises are associated with a substantial increase in systemic risk. The crises events with the largest impacts are the Russian/LTCM crisis and 9/11, but these events engender an average increase of only about 2% in the default probability for the unexposed banks.

1.3 Policy Implications and Paper Organization

The results in this paper have important policy implications. While *a priori* a justifiable and sensible concern, the findings of low probabilities of a meltdown of the international financial system suggest that the distress of central bankers, regulators and politicians about such events may be disproportionate. In essence, this would be empirical confirmation of the simulation evidence presented by Gould, Koury, and Naftilan (2004). Of course, the lack of systemic risk may also be a result of contemporaneous and judicious policy actions by central bankers and regulators. Thus, the findings could be interpreted as justifying the responses of these actors during the crises. Either way, given that chances of systemic failure appear low even during major financial crises, it seems that financial intermediaries on a global scale are more efficient and robust than often thought (or feared), and that current policy tools and responses may be more than sufficient.

The paper is organized as follows. Section 2 describes the data. Section 3 examines stock market reactions of portfolios of banks that are not exposed to a particular crisis event. Section 4 provides more precise point estimates of bank default probabilities and thus systemic risk based on structural models of failure. Section 5 derives probabilities of a systemic failure from equity option prices of banks. Section 6 summarizes the results and concludes.

2 Sample Construction and Data Sources

The key to all of the three approaches we use to estimate the risk of systemic failure is that the market price reaction for banks without direct exposure to a crisis event reflects the increased risk of failure in the system as a whole. Thus, we analyze the default probabilities of a global sample of banks during emerging market financial crises in Mexico (1994), Asia (1997), Russia and Long-term Capital Management (1998), and Brazil (1999) and for differing degrees of exposure to these events. Moreover, we include the terrorist attack on September 11, 2001 since New York is a critical world financial center and widely publicized disruptions in the payment system and financial markets occurred (i.e., Bank of New York's operations, closing of equity markets, and squeezes in the repo market). Although this crisis may be fundamentally different in origin from the other crises, its inclusion provides valuable evidence over the cross-section of crises "causes". Appendix A lists the dates we associate with each crisis as well as a brief description of each event.

To construct our sample, we select all banks that are in the list of the largest 100 banks in the world compiled by Euromoney for at least one of the years between 1997 and 2002. We exclude banks that are private/state-owned (e.g. Westdeutsche Landesbank). Subsequently, we manually identify the main issue/listing of these banks in their home market on Datastream and exclude those that have no stock return data. We then add all banks in the Datastream banking index. The final sample consists of 334 banks in 28 countries (Australia, Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Luxembourg, Netherlands, Norway, Portugal, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, Turkey, UK, and the United States; see Table 1). These banks represent roughly 80% of global bank equity capital (book values) during the sample period.

2.1 Accounting for Mergers

For all of these banks, we manually search the Global Access database in order to retrieve their annual reports for the crisis years. Due to the complex merger and takeover activities in the banking sector during the sample period, the different names for banks used on different databases, and the change of names, security identifiers and legal entities over time, the compilation of the dataset is complex. To illustrate, the bank listed as Yasuda Trust & Banking Co. Ltd. on Global Access became Mizuho Asset Trust & Banking Co. Ltd., the name used on Datastream, with the last filing of Yasuda at the 12/20/2001 and the first of Mizuho at 03/31/2002. Similarly, Credito Agrario Bresciano SPA CAB (the name of the entity on

Global Access) emerged as consolidation at a regional level through the acquisition and absorption of Banca Lombarda (the name on Datastream) in 1995.

In many cases, we account for multi-way mergers, acquisitions and takeovers. For example, we consider that Chemical Banking Corporation merged with Chase National Bank in 1996 to form Chase Manhattan Corporation, which merged with J.P. Morgan & Co. Inc. on December 2000 to form J.P. Morgan Chase & Co. By the same token, BOE Corporation of South Africa undertook a three-way merger with NBS Boland Group Limited and Orion Selections in August 1998 and was taken over by Nedcor Limited effective January 2003. Fortis (B) of Belgium was controlling the Belgium operations of Fortis and had equal voting powers in the holding entity overseeing itself and Fortis (NL), which controlled the Dutch operations. This two-tier structure was unwound and combined into one group, called Fortis Group, unifying the two separate legal entities under the Fortis brand in early 1998. In mid-1998, Fortis Group took over Generale Bank, which was fully integrated into its operations by mid-1999.

2.2 Exposure Classifications

The annual report information from Global Access is verified and complemented with annual reports from EDGAR, Global Reports and Perfect Information.[7] Subsequently, banks are classified into those with and without exposure based on information published in their annual reports as this can be assumed to be public information that is reflected in stock prices (Table 1). Only in a few cases are we not able to obtain an annual report for a particular bank and year and thus exclude the bank from the analysis of the respective crisis. Annual reports are used since no better sources of information about exposures are publicly available for a large sample of banks (Burnside, Eichenbaum and Rebelo, 2001; Kho and Stulz, 2000). For each bank, the annual report that is closest to the first event of the crisis is manually

[7] Global Reports is an online information provider of public companies in full-color, portable document format (PDF).

searched/read to identify information on exposure (typically loans) to the crisis country. In particular, U.S. banks report very explicitly about the country composition of their loan portfolio. Based on this information, banks are classified as exposed or unexposed. Three alternative measures of exposure are used: exposure to the crisis country ("country"); exposure to the crisis region ("region"); and a broad measure of exposure that refers to any relevant exposure of a bank to a particular crisis ("broad").

For example, Bank of America Corporation reports in their 1998 annual report loans of USD 1,501 million to Brazil and of USD 43 million to Russia, giving rise to exposure to the crises in these countries. The 1997 annual report of Abbey National indicates that it has some, though small, regional exposure to the Asian crisis, but it does not give a breakdown by country: "The financial crisis in Indonesia, South Korea, Thailand, the Philippines and Malaysia impacted on markets world-wide. However, Treasury sustained its profit growth through careful management of risks throughout the year. At the end of 1997, the Group's exposure to these troubled Asian economies totaled just over €500 million (0.3% of total Group assets) and consisted of bonds issued by banks guaranteed or supported by their national governments." For the LTCM crisis, we consider those banks that participated in the rescue of the fund exposed in the narrow sense since these banks were willing to put up their own funds to prevent the crisis from worsening. These are mostly the 10 LTCM commercial bank creditors and a few others directly invested, i.e. Citicorp, Bankers Trust, Chase, JP Morgan, UBS, Dresdner Bank AG, Credit Suisse First Boston, Sumitomo Bank, Republic National Bank, Deutsche Bank, Barclays, Credit Agricole, Banque Paribas, and Societé Generale. In the region (broad) definition of LTCM exposure, banks with country (region) exposure to the Russian crisis are added, respectively.

For the terrorist attack on the World Trade Center on 9/11, all banks in New York City are included in the narrowest exposure category, the regional classification adds all banks with headquarters in New York City, Boston, London and Frankfurt, and the broadest exposure category further includes all U.S. banks reflecting the fact that the potential threat in the post-crisis period was to Western money-center banks. Table 1 summarizes the exposure distribution of the banks by country, and Tables B-1 and B-2 in Appendix B report descriptive statistics by exposure category and the categorical correlation coefficients (phi) between all the exposure categories. Finally, we note that if annual reports do not completely disclose banks' exposures, this should bias our estimates of systemic risk upward.

3 Returns of Exposed and Unexposed Banks

Our first approach to estimating the risk of a systemic failure relies on observing the market reaction to global financial shocks for a subset of banks that are not directly exposed to the shock. In particular, we assume that the abnormal performance of these stocks reflects the probability of systemic failure in the banking system. In efficient capital markets, negative information such as devaluations of emerging market currencies or the tragedy of 9/11 will affect banks only if they are exposed to the particular events. In contrast, unexposed banks should be largely unaffected by these events. Results by Lee, Kho and Stulz (2000) document that market participants can indeed distinguish between exposed and unexposed banks. As a result, stock market reactions of unexposed banks to crisis events can be interpreted as a measure of systemic risk.

3.1 Results on Raw Returns

Table 2 provides simple (raw) holding period returns of value-weighted portfolios of banks with and without exposure and the corresponding market indices for the different crises and exposure concepts. Returns for the bank stocks as well as the respective market indices are based on logarithmic daily dollar returns. The crisis or event dates (t=0) are defined as December 19, 1994 (Mexico 1994), July 2, 1997 (Asia 1997), August 17, 1998 (Russia 1998), September 2, 1998 (LTCM), January 6, 1999 (Brazil 1999) and September 11, 2001. Here we examine the Russian default and the ensuing problems at LTCM separately since opinions differ on which event constituted a more important crisis. Holding periods are calculated for the precrisis period (calendar days -110 to –11), the crisis period (–10 to +50), and the post-crisis period (+51 to +120 (and +121 to +209 for the Asian crisis)). Nonparametric Wilcoxon tests are performed to test for differences in holding period returns between the bank portfolios and the corresponding market portfolios, as well as between exposed and unexposed banks.

For returns in U.S. dollars (Panel A), exposed banks tend to have larger negative holding period returns compared to unexposed banks. To illustrate, banks with exposure to the Mexico crisis had dollar holding period returns of –3.0%, while unexposed banks had zero returns during the crisis. Similarly, holding period returns of exposed banks are –5.4% and –24.9% during the Asian and Russian crises, respectively, while unexposed banks have returns of 6.4% and -7.3%. Similar effects are apparent during the LTCM crisis, with exposed banks returning -18.3% vs. 2.0% for unexposed banks. In contrast, exposed banks appear to have larger returns than unexposed banks for the Brazil crisis and 9/11. Results for returns in local currency are similar (Panel B). Nevertheless, the differences in holding period returns are not large enough to be significant in most cases which suggests the need for more powerful econometric methods. While this result could be interpreted as crisis shocks affecting exposed as well as unexposed banks in similar ways, the lack of significance is likely the result of noise in the tests and missing control variables.

3.2 Results on Cumulative Abnormal Returns

Because of the limitations associated with examining differences in returns, we turn to tests that assess the impact of the crisis events on unexposed banks in the presence of various control variables. In particular, we control for general market dynamics by including the return on the local market index or the Datastream world market index in the regressions. Similarly, we control for sensitivity to macroeconomic factors resulting from the characteristics of the banks' asset and liability composition by including exchange rate returns and interest rates in the regressions.

Depending on the controls we use, we define several measures of cumulative abnormal returns (CAR).[8] First, we examine just raw returns. Next, CAR1 is based on abnormal returns defined as the difference between raw returns of the value-weighted portfolio of unexposed banks and returns on a portfolio of corresponding market indices. CAR2 is based on abnormal returns defined as the difference between raw returns of the value-weighted portfolio of unexposed banks and returns on the Datastream world market index. CAR3 is based on abnormal returns defined as the difference between returns of the value-weighted portfolio of unexposed banks in excess of the Euro-currency interest rate and predicted excess returns from a regression during days –110 to –11 of returns on a portfolio of corresponding market indices, the Canadian Dollar, the German Mark, the French Franc, the British Pound, the Italian Lira, the Japanese Yen and the one-day return on a 7-day Euro-dollar deposit on the return of a value-weighted portfolio of unexposed banks. Bank and market index returns are in excess of the Euro-currency interest rate. Currency returns are calculated as the difference between the one-day Euro-currency rate of the foreign currency (compounded by the exchange rate) and the one-day Euro-currency rate of the U.S. dollar. CAR4 is similar to CAR3, but uses the world market index instead of the value-weighted portfolio of market indices corresponding to the composition of the bank portfolio.

Table 3 presents the cumulative abnormal returns of unexposed banks during the immediate post-crisis period covering the calendar days 0 to +50 (+210 for the Asian crisis), where the event date (t=0) is defined as before. For 3 of the crises (Mexico, Asia, and Brazil) the unexposed bank portfolios have positive CAR4s, and for the three other crises the CAR4s are slightly negative with only 9/11 being significantly negative across all measures. The fact that we see little if any negative reaction in the portfolios of unexposed banks in the wake of these significant impacts on the financial system, after controlling for the

[8] In order to account for the fact that U.S. equity markets were closed after September 11, 2001 for 4 days, we calculate one weekly return for all banks in the sample between September 10 and September 17.

usual systematic effects, is a weak indication that the implied probability of a failure of the financial system is relatively low.

Figure 1 offers a graphical representation of the CARs of value-weighted portfolios of exposed and unexposed banks (based on CAR4 as defined above) and provides a clear picture of exactly how the returns of unexposed banks react in the crises. For the Mexican, Asian, and Russian/LTCM crises (Panels A, B, C, and D) the unexposed banks show positive cumulative abnormal returns. During the Asian crisis, unexposed banks actually perform very well (in sharp contrast to the exposed banks). Banks unexposed to Brazil show slightly negative CARs whereas exposed banks show a surprisingly large positive CAR.s. This is probably due to the resolution of uncertainty regarding the Brazilian situation and the generally positive response to the government's handling of the devaluation (e.g., Brazilian stocks rallied). Only after 9/11 do unexposed banks show a significant negative cumulative abnormal return. Interestingly, while both exposed and unexposed banks drop in the immediate wake of the 9/11 event, exposed banks rapidly recover (possibly as a result of immediate policy responses by central banks) before falling back to the level of the unexposed banks. As expected, exposed banks tend to underperform unexposed banks. For the remainder of the paper we focus on just the September 2, 1998 event date for the Russian/LTCM crisis since Panels C and D are so similar, and there appears to be a somewhat bigger market reaction to the problems surrounding LTCM.

3.3 Robustness Tests For The Existence of Institutional Support

Because of the broadness and international composition of our bank sample, a confounding effect in our results could be the differing degrees of institutional support across our panel of banks.[9] That is, banks with exposure to the crisis but with a high probability of a governmental bailout will have less risk

[9] This measure would be highly correlated with, yet slightly broader than, the distinction of existence of either explicit or implicit deposit insurance, as in Demirguc-Kunt and Kane (2002).

than exposed banks who do not enjoy such support. To test the robustness of our results to this factor, we subdivide the exposure classifications into high and low institutional support categories and re-estimate the CAR results. Banks are classified as having high institutional support if their Fitch Public Support Rating as of the crisis date is 1, 2 or 3; ratings of 4, and 5 are associated with low support, and banks without ratings are dropped from the sample.[10] The Fitch Bank Support Rating is a measure of both the willingness and the ability of a potential supporter (either a sovereign nation or an institutional owner) to provide assistance when a bank liquidity or insolvency event occurs. The results for all crises are graphed Panels A-E of Figure 2.

Overall, our results are mostly unchanged (or strengthened, especially in the cases of the Mexican and Russian crises) when we incorporate the effects of institutional support. Of particular note is the lack of relationship between returns and level of support; if anything, banks with *low* degrees of institutional support tend to systematically outperform corresponding portfolios of banks with higher support within each exposure category (potentially indicating some degree of moral hazard or government intervention in lending policies). Banks with higher risk due to lower support tend to produce higher returns in the wake of financial crises. Particularly in the aftermath of the Mexican and Asian crises, this premium can be quite significant, but controlling for support does not seem to affect the key finding of low systemic risk.

Taken together, the results of this section suggest that the financial crises (and contagions) of the 1990s posed little threat to the global financial system though the terrorist attacks of 9/11 seem to have had a much larger effect. One limitation of the abnormal returns approach is the assumption that market portfolios are not significantly affected by systemic failure in the banking sector. One way to address this concern, and at the same time make potentially more precise point estimates of systemic risk, is to estimate firm-specific models of bankruptcy. Therefore, the remainder of the paper examines two such methods.

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[10] This also provides an additional robustness check in that it weights the portfolios towards larger, more liquid banks.

4 Estimating Default Probabilities from a Structural Credit Risk Model

In order to get more precise point estimates of systemic risk, we assess the default probabilities of banks during the crisis periods under a structural model of default estimated from an observed series of equity prices. The structural approach to estimating default revolves around the intuition developed by Merton (1974), that a firm's securities can be priced as contingent claims on the value process of the firm. Merton (1977) points out the applicability of the contingent claims approach to pricing deposit insurance in the banking context. The approach has been applied by Ronn and Verma (1986), Jones, Mason, and Rosenfeld (1984), and Duan (1994).[11] Using the estimation procedure in Duan (1994, 2000) and Duan et al. (2003), we use equity prices and balance sheet data from pre-crisis and post-crisis periods to infer the implied changes in default probabilities for exposed and unexposed banks by country. We then aggregate across regions to assess the increased probability of bank failure attributable to the crisis event. Using this methodology to assess the risk of systemic failure around the crisis events, we can find no evidence of an increase in systemic risk. Indeed, the estimated increase in the risk of systemic failure is less than 1%.

4.1 Methodology

Structural models define equity and risky debt values, and by extension the probability of bankruptcy, as a function of the firm's asset value, its payout, risk-free rates, its expected return and volatility, and the amount and maturity of its debt. We can thus invert the problem and use the equity value, accounting data on the debt structure, the risk-free rate, and the firm's expected return and volatility to solve for an implied probability of bankruptcy. If we further assume that the value of the firm follows a geometric diffusion, and that the equity value of the firm is some function of firm value (typically a call option on the firm assets), the problem simplifies to statistically estimating the mean and volatility of a diffusion from equity

[11] Work by Laeven (2002) and Kaplan-Appio (2002) has recently used variations of the Merton deposit insurance framework to assess moral hazard in national and international guarantors and to provide forward looking estimates of banking crises.

data. A maximum-likelihood approach to this problem is derived in Duan et al. (2003), where the likelihood function for the equity value of the firm is derived in a structural model framework. Maximizing this function yields estimates (and asymptotic distributions) for the expected return and asset volatility of the firm, which can be then (non-linearly) used to solve for implied default probabilities of the firm.

The only difficulty in estimating structural models of default results from the fact that two critical parameters, the asset drift and the asset volatility, are unobserved. Traditional approaches as in Ronn and Verma (1986) or Jones, Mason and Rosenfeld (1984) use transformations under the structural model to relate asset values and volatilities to equity values and volatilities respectively.[12] Equity volatility is approximated with either its historical estimator, or more recently, estimates obtained from options data. The estimate of equity volatility is then used with the equity value to solve for the asset value in the other equation and the process proceeds until some convergence criterion is reached. The estimates of the asset value and volatility, together with the balance sheet data items on bankruptcy threshold (debt face value), debt maturity, and (in the Leland and Toft (1996) model) cash payouts, are used to generate either the bond value or the default probability under the model.[13]

As Duan, Gauthier, Simonato, and Zaanoun (2003) and Ericsson and Reneby (2004) point out, this approach has several flaws: (1) The procedure is theoretically inconsistent since it estimates the asset volatility as a constant when it is clearly stochastic under the assumed model. The primary effect of this inconsistency is to invalidate inference under the procedure, since neither estimate will be consistent; (2) Results in Ericsson and Reneby (2004) show that the approach is practically biased as well as inefficient, producing standard errors that are several orders of magnitude higher than the maximum likelihood approach; and

[12] Crouhy, Galai and Mark (2000) describe a similar approach to estimating default probabilities in a commercial context by KMV, now owned by Moodys.

[13] Procedures similar in spirit to this are employed in recent work by Vassalou and Xing (2004) and Duffie and Wang (2004), but in these cases the goal is to generate covariates for a regression, and the inference on the actual estimates is not of direct interest.

(3) Estimates of asset volatility are most likely to be biased in cases where leverage is high and stock prices have moved significantly over the period.

A maximum likelihood estimation approach with the methods developed by Duan (1994) based on transformed data and applied to structural credit models by Ericsson and Reneby (2004) and Duan et al. (2003) addresses these issues. Simply, it derives the likelihood function of the data under the model as the product of the likelihood function of the implied asset values and the Jacobian of the (monotonic) equity price transformation evaluated at the implied asset values. The asset value and volatility estimates and asymptotic distributions are then straightforwardly obtained by maximizing the likelihood function and applying standard distributional arguments. In Appendix C, we briefly outline the methodology we use to generate our estimates.

4.2 Implementation of Structural Model Tests

In order to compute the default probabilities, we first need to fix values for "constant" balance sheet values, such as the face value and maturity of the debt, or equivalently the point at which the bank "fails". Duan et al. (2003) suggest (for manufacturing companies) using the full value of the short-term liabilities (which in our banking case are deposits and other short-term debt) plus ½ of the long-term liabilities as the face value of debt.[14] They set the maturity of debt at 1 year, for all times, reflecting either pure convenience or a periodic "auditing," which in our case can be interpreted as an annual bank examination. In our implementation, interest rates are assumed constant.[15] In our estimation, we use a constant 1 year maturity, and two separate definitions of the default barrier: the short-term and currently due portion of debt plus the immediately due demand deposits; or this definition plus half the long-term debt of the bank. For

[14] This follows at least from the disclosed version of the approximations made by Crosbie and Bohn (2001).

[15] Comparative static exercises show little effect from variations in the interest rate, reflecting the relatively short maturity of the option. Of course, stochastic rates and high (and varying) correlations between asset value and interest rates could materially affect the model, albeit substantially increasing both the complexity and required assumptions of the model.

most countries, and certainly in aggregate, the changes in estimates pre- and post-crisis are fairly robust to the various specifications. As is well known, accurately estimating the drift of even a perfectly observed diffusion process is difficult, and is particularly challenging in our case, where our pre-crisis and post-crisis periods are approximately 250 days. As a consequence, we set the drift of the process equal to the average of the German (later the Euro), Japanese, and US short-term interest rates over the crisis period.[16]

We estimate volatility of the asset process and the implied asset values using equity values for the year prior to the date of the crisis (these dates are given in Appendix A) and for the year after, excluding respectively the 2 days before and after the actual date. The annual frequency of the balance sheet items complicates the analysis since we need to have a default barrier for each data point. We linearly interpolate the values for all dates over the period, using end of year values for accounting items. The interpolation method has the advantage of producing a smooth implied asset value process, which is more consistent with the theory, and in particular avoids "jumps" in the implied default probabilities due to impounding the entire change in the barrier to one day at the end of each period.

Once we obtain estimates for the asset volatility of each bank (as reported in Table 4), we calculate the default probability for the pre-crisis period using the asset value implied 2 days prior to the crisis and for the post-crisis period using the asset value implied 2 days after. We then average these estimates across exposure levels and regions and report these means in Table 5. We also compute a measure of each bank's distance to default (DTD), which can be interpreted as the number of standard deviations between current asset value and the insolvency point. Averages of these measures are reported in Table 6. Daily default probabilities are calculated during the year pre-crisis and post-crisis using the estimated asset volatility cor-

[16] An earlier version of this paper attempted to estimate the drift as well as the volatility for both the Russian and Asian crises, and as expected, estimates of the drift were very unstable and had very large standard errors such that in only a few cases the drift was significantly different than zero. We have experimented with varying assumptions for the drift of the process, including setting it to zero, using the actual daily regional rate for each date, using the actual daily country rate for each date, and setting it to several (low) constant values. The estimates we report are not markedly different than our results for each of these alternative specifications.

responding to the period and the implied asset values for each date. The averages of these default probabilities across exposed and unexposed banks for each of the five crises are graphed in Figure 3.

4.3 Results From Structural Model Tests

We find little evidence that the financial crises we study created widespread systemic risk in the international banking system. All estimates of the change in default probabilities for unexposed banks are less than 1%, with the largest (.655%) occurring during the Asian crisis. The two earliest crises, Mexico and Asia, produce the largest increase in default probabilities for exposed banks (at 1.7% and 3.2%, respectively) whereas the later crises are marked by small decreases in default probabilities.[17] The Brazil crisis, the largest decrease in default probabilities for exposed banks, probably reflects the widely anticipated nature of the devaluation, and the run-up in stock prices (and subsequent growth in the economy) following the crisis. The most curious result is the drop in default probabilities for the banks unexposed to 9/11 that is attributable primarily to a drop in risk for European banks, perhaps indicative of a flight to safety away from money center banks and to smaller, regional European banks.

Regional effects show that at least with regard to the Asian crisis, European banks have the greatest jump in the default probabilities for unexposed banks, indicating that this is the region with the most transmission of systemic risk. Intuitively, European banks also show a significant increase in default risk during the Russian crisis, with unexposed banks' default probabilities nearly doubling from 1.3% to 2.6%. Asian banks seem to suffer increased risk of systemic failure in the Mexican crisis but show few effects in subsequent crises, perhaps reflecting the relative strengthening of the Japanese banking system in the late 1990s.

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[17] The reported standard errors are based on the variance of the asset volatility and are computed using the outer product of the gradient at the estimate. The small size of the default probability errors is a function of the fact that the only source of uncertainty is the asset volatility, which is very precisely measured.

Results on distance to default (in Table 6) show that as a group the unexposed banks are farther from default than the exposed banks. The primary result from this analysis is that there is very little change, either in exposed or unexposed groups, in the DTD metric from pre-crisis to post-crisis. If there was a significant increase in the probability of systemic failure in the banking system, it does not appear to have changed the individual risk of bank insolvency.

Rather than focusing on the exact point estimates of default probability or DTD, which depend on the implied asset value just before and just after the crisis, Figure 3 shows the entire time series of default probabilities for the whole pre-crisis and post-crisis periods. Panel A, depicting the Mexican crisis, is a classic example of an increase in default risk for exposed banks and a (smaller) jump for the unexposed portfolio. A similar dynamic is shown in Panel B, the Asian crisis, with an even more dramatic increase in exposed bank risk and only a small increase in the risk of systemic failure. Panel C, the Russian crisis, clearly shows that while there is little effect on exposed banks immediately post-crisis, there is a significant jump in risk later in September as the full impact of LTCM exposure becomes apparent. Again, there is a similar, but much muted, response in the unexposed banks, and eventually the exposed banks' default risk declines and the unexposed banks' increase until they meet nearly a year after the crisis. Panel D, the Brazil crisis, shows the widely anticipated nature of the crisis, as exposed banks have a very large jump in default risk prior to the crisis date (in October 1998) when the sovereign payments problems became critical and reserves outflows accelerated.[18]

Results for 9/11 (Panel E) are curious; while there is little change in exposed banks, this may be in part due to the relatively low default levels at which they enter the crisis. The unexposed banks' decline in default risk is anomalous and is related to a fall in the estimated asset volatility (possibly due to shifting of

[18] Given the date, and the jump in Russian exposure banks' default risk, this may be attributable to overlap in the exposure measures. In fact, the overlap between measures (given in Table A-2 of the appendix) shows a correlation of 0.65, which is significant, but probably not enough to fully account for the jump.

assets in a flight to safety). However, it also highlights a limitation to this type of estimation which requires use of accounting data which are available only infrequently and with a lag. For this reason and because it may provide a more effective policy tool, it would be nice to devise estimates of default probabilities that can be independently estimated using only real-time data. Consequently, in the next section we turn to one potentially powerful method for estimating daily default probabilities with options market data.

Overall from this section, we conclude that the evidence from structural models supports our hypothesis that banks not directly exposed to these major financial dislocations did not suffer significantly greater risk of failure due to increased systemic risk in the international financial system.

5 Estimating Default Probabilities from Equity Option Prices

Our third approach to assess the risk of systemic failure uses default probabilities of banks implied in their equity option prices. In a complete market, equity option prices reflect market estimates of the risk-neutral distribution of future stock prices (see, for example, Breeden and Litzenberger, 1978). Likewise, assuming a known asset price process or distributional form allows for the estimation of unobserved process parameters, such as implied volatility from a Black-Scholes (BS) model. In this section, we utilize an option pricing model by Câmara (2004), in which asset prices follow a geometric random walk but may jump to zero (bankruptcy) with a finite probability. We assume that the probability of unexposed banks' stock prices jumping to zero is analogous the probability of a systemic failure in the banking system. Using daily stock and option prices for 62 U.S.-listed banks and 14 major European banks, we solve for the implied value of this parameter.

5.1 Description of Options Data

Our options data for U.S.-listed banks are provided by a major options market maker and data for European banks are from the LIFFE and EUREX exchanges. Our sample includes all banks with listed options on these exchanges and cover many of the largest American, European and global banks.[19] The data are not available until 1996, so we examine all but the Mexican crisis. We use daily settlement put and call prices for near-the-money American options (strike price divided by underlying stock price between 0.7 and 1.3) for options with maturities between 15 and 195 days. This yields an average of 46.2 observations per bank per day or 1,100,484 unique option prices across all four crises we analyze.

5.2 Implementation of Option-Based Measures of Default

Câmara (2004) derives in closed-form the price of options given a delta-geometric random walk (δ-GRW) distribution for the underlying stock price. The pricing equation may be inverted to yield implied values for the volatility, σ, and the bankruptcy probability, δ_i. We estimate values for these parameters by minimizing the sum of squared percentage error for each bank on each day. We assume risk-free rates to be LIBOR equivalents and subtract the present value of dividends from the stock price.[20] The optimization restricts both parameters to non-negative values. If the optimization does not converge (e.g., as the result of data errors) we drop that bank-day. In 16.7% of cases the estimated value of delta is zero.[21] In 97.7% of cases with estimated delta greater than zero, the value is statistically greater than zero at the 5% confidence level. Estimates for the implied volatility parameter are always significantly greater than zero at the 5% confidence level. We average the estimated parameters for each day. This yields daily time series for each crisis which are plotted in Figures 4-7. For each figure, Panel A shows average values of the volatility parameter, σ, and Panel B plots the variable of interest, the average bankruptcy probability, δ_i. In each graph separate lines are plotted for exposed and unexposed banks (using the broad measure classifi-

[19] The LIFFE and EUREX banks are Abbey National, ABN Amro, Barclays, Bank of Scotland, BNP Paribas, Commerzbank, Credit Suisse Group, Deutsche Bank, Hypovereinsbank, Lloyds TSB, Royal Bank of Scotland, Standard Charterd Bank, and UBS Group.

[20] Our results are essentially unchanged if we limit the analysis to call options with no dividends paid before maturity.

[21] An estimated value of zero for delta is equivalent to a preference for the Black-Scholes model over the augmented δ-GRW model.

cation except for 9/11 which uses the regional classification). We also plot the implied volatility of the S&P 500 index (VIX) in Panel A to serve as a comparison.

5.3 Results on Options-Based Estimates of Systemic Risk

Results for the Asian crises are plotted in Figure 4 and show that there is little immediate reaction in the options markets to the depreciation of the Thai Baht after July 2, 1997. Implied volatilities, and to a lesser degree implied bankruptcy volatilities, drift up over the next two months. In fact, implied bankruptcy probabilities for both exposed and unexposed banks remain in a tight range around 1.0% until Monday October 27, 1997 when the implied bankruptcy probabilities for exposed banks more than double to about 2.6%. Interestingly, implied bankruptcy probabilities for unexposed banks are essentially unchanged. The sudden jump for exposed banks on October 27th is likely the fallout in global capital markets from the Taiwanese Dollar devaluation of the previous week which was considered particularly ominous because of Taiwan's large foreign currency reserves. On October 27th, Asian markets collapse, lead by the Hong Kong's Hang Seng index losing 5.80%. In New York, the Dow Jones Industrial Average posts its single-biggest point loss ever, falling 7.18%. The decline in the U.S. markets is so steep that it triggers the first ever (and only, to date) suspension of trading. Latin American markets also suffer panic selling with stock prices in Brazil, Argentina, and Mexico seeing their biggest single-day losses.[22] Arguably, this may be the single date during the Asian Crisis when market fear of systemic failure was greatest. Over the subsequent weeks implied bankruptcy probabilities increase slightly (to about 2%) for unexposed banks while values for exposed banks trend upward, eventually reaching almost 4%. We interpret these findings as consistent with the prior findings that markets did not price a significant risk of systemic failure during the Asian Crisis.

[22] Condensed from a detailed timeline of the Asian Crises by Nouriel Roubini at http://www.stern.nyu.edu/globalmacro/.

Results for the LTCM crisis are presented in Figure 5. Qualitatively the results are similar to those for the Asian Crisis. Around the event date, estimated default probabilities change little for unexposed banks. However, default probabilities for exposed banks increase significantly to over 4%. Starting in the second week of September default probabilities increase for all banks—to nearly 4% for unexposed banks and to about 8% for exposed banks. This run-up coincides with the first public rumors of Long-term Capital's (LTCM) demise and the associated potential failure of a major investment bank. Later in the Fall ($t>25$), the implied bankruptcy probabilities of all banks again increase though the values for unexposed banks only briefly reaches the generally higher levels measured for exposed banks. The evidence from this time period is less conclusive because we observe somewhat large absolute changes for unexposed banks.

Results for the Brazilian default are presented in Figure 6. Although implied volatilities for exposed banks appear to tick up about 5% around the event date, implied bankruptcy probabilities show a slight decline. This is consistent with the prior evidence which suggests any concerns about systemic failure during this period were negligible.

Results surrounding the terrorist attacks of September 11, 2001 are presented in Figure 7. Panel A shows that for the first four trading days of September, values for sigma are relatively constant around 30%, but starting September 7th the volatility estimates start increasing rapidly. In fact, the increases on Friday, September 7th and Monday September 10th for exposed banks are substantially larger than any prior daily increases in 2001. This is consistent with rumors of trading in the stocks and options of airlines and financial companies (both in the US and in Europe) by persons with advance knowledge of the terrorist attacks.[23] On September 11th, volatilities of European banks spike further to the highest level of the year as U.S. markets close in response to the attacks (not plottted). When U.S. markets re-open on September 17th, implied volatilities gap higher. Over the next few weeks bank volatilities remain high, reaching a

[23] See, for example, "Profits of Doom," by Grant Rigshaw, Sunday Telegraph (London, U.K.), September 23, 2001.

maximum on September 20th-21st. For the remainder of the year values trend downward and finish the year near the annual average value.

Panel B plots average implied bankruptcy probability, δ. Surprisingly, immediately after September 11th there is no significant change in the estimated probability of bankruptcy for either exposed or unexposed banks (though there is about a 1% increase for each in the prior week). However, in late September and early October, coinciding with the anthrax attacks on U.S. government and media offices, the implied bankruptcy probability starts to increase notably for both exposed and unexposed banks. Bankruptcy probabilities peak around October 20th and stay high for the remainder of the year. Interestingly, bankruptcy probabilities for both exposed and unexposed banks follow a very similar pattern over this time frame though exposed banks have consistently higher values.

It is difficult to interpret these patterns as suggesting the terrorist attacks caused a significant increase in the probability of systemic failure. Although the implied probability of bankruptcy of unexposed banks does increase after the terrorist attacks, it does so with a significant delay. This is not the result of any data or estimation issues since no corresponding delay is evident in the implied volatility estimates. In addition, there is no uncertainty regarding the time frame in which market participants and regulators were most concerned about dangers in the financial system (i.e., the two weeks immediately after the attacks). Examining just the European banks whose options continued to trade during the week of the attacks does not reveal any immediate increase in default probabilities (and reversal) over the very short-term. In sum, the graphical evidence does not support the hypothesis that the terrorist attacks led to a significant risk of systemic failure in the global financial system. The increase in bankruptcy probabilities with the onset of the anthrax attacks might be the result of a fear that terrorists might engage in sustained attacks against Western targets.

Table 7 quantifies changes in average estimated default probabilities of unexposed banks from the pre-crisis to post-crisis periods. Panel A compares the average delta from the 100 trading days prior to each crisis date with the average delta for the first 20 and 50 (or 200 in the case of Asia) trading days after the crisis date. Simple non-parametric estimates for *p*-values for the post-crisis averages are generated by comparing post-crisis averages with the distribution of deltas in the 100-day pre-crisis period. The Asian crisis and Brazilian devaluation show no significant increase in average delta. However, the Russian/LTCM and 9/11 events each show a significant increase in average delta of about 2%. It is important to recall from the plots in Figures 6 and 8 that the higher averages are not from immediately higher levels of delta but from generally higher levels over the ensuing month(s).

5.4 Statistical Tests of Option-Based Estimates of Systemic Failure

To get a more precise estimate of the change in default probability we estimate fixed-effect panel regressions with the daily estimate of each bank's delta as the dependent variable. To determine the effect of the crisis on estimated deltas, we include a dummy variable equal to 1 in the post-crisis period and 0 otherwise. A significant coefficient on this variable indicates a statistically significant increase in delta in the post-crisis period. Panel B of Table 7 reports the results of these regressions and indicates that the changes in estimated default probabilities in the post-crisis period are always significantly different from zero (though negative for the Brazilian devaluation). Nonetheless, the largest increase is still economically quite small (i.e., 2.17% after the Russia/LTCM event).

Inspection of Figures 5-8 suggests that average estimated deltas are autocorrelated. We are also concerned that model overfitting resulting from data errors could exaggerate estimates of the delta parameter on average (since it is constrained to be non-negative). Consequently, we expand the specification in Panel B to include as control variables (i) the one-period lagged value of estimated delta, and (ii) the model sum of squared errors for that bank-day. Results are presented in Panel C of Table 7 and show that these controls attenuate the coefficient estimates for the crisis dummy. In particular, the estimated coefficients remain statistically significant but none are greater than 1% in magnitude.

Overall, it appears that the specific events we consider are not associated with a substantial increase in estimated bankruptcy probabilities immediately after the event dates. However, the average increases are statistically significant, so this conclusion is not driven by our tests lacking power. The magnitude of the average changes for Russia/LTCM and 9/11 (about 1-2%) may or may not be economically significant based on one's own views. In absolute terms these do not seem like large changes, but they represent large changes relative to the average levels observed in the pre-crisis periods.

6 Conclusion

Systemic risk is a matter of great concern to central bankers, regulators and politicians around the world. The resilience of the global financial payments system is a key component of both domestic and international financial stability. Because a breakdown of the banking system is likely to occur in the context of an (international) financial crisis, the analysis of major financial disasters such as emerging market currency crises or the terrorist attack of 9/11 appears relevant. Interestingly, existing research has mostly focused on the mechanics and channels of the transmission of shocks from one country to another during crisis periods. In contrast, little is known about the magnitude of systemic risk *per se*, in the sense of the probability of bank default and a concomitant failure of the banking system.

This paper attempts to fill this gap by taking three different approaches to provide reasonable estimates of the risk of a systemic failure. Based on our large sample of global banks, we interpret the generally small increases in estimated default probabilities of unexposed banks as indicating that these crises generated little risk of a systemic failure in the global financial system. There are several possible explanations for these results. First the shocks may not be large enough. Second, effective policy responses may have limited the risks. Third, our methods may not be able to accurately measure the risks. Finally, the risk of systemic failure simply may not be as large as many observers believe.

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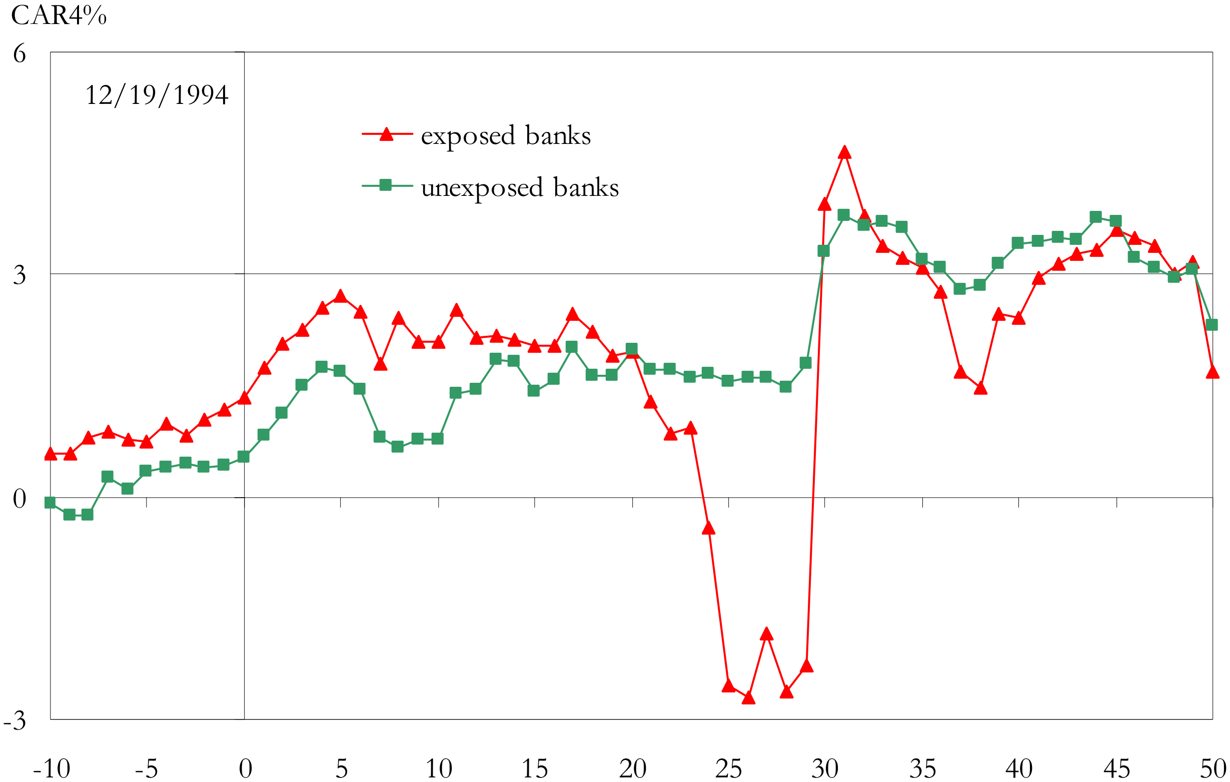
Figure 1: Cumulative Abnormal Returns of Exposed and Unexposed Banks

The figure shows cumulative abnormal returns (CARs) for value-weighted portfolios of exposed and unexposed banks for different crises. The crisis period covers the calendar days –10 to +50 (+210 for the Asian crisis), where the event date (t=0) is defined as 19Dec1994 (Mexico 1994), 2Jul1997 (Asia 1997), 17Aug1998 (Russia 1998), 2Sep1998 (LTCM 1998), 6Jan1999 (Brazil 1999) and 11Sep2001 (Sept. 11, 2001). The cumulative abnormal return CAR4 is based on abnormal returns defined as the difference between bank portfolio returns in excess of the Euro currency interest rate and predicted excess returns from a regression during –110 to –11 of returns on the world market index, the Canadian Dollar, the German Mark, the French Franc, the British Pound, the Italian Lira, the Japanese Yen and the one-day return on a 7-day Euro-dollar deposit on the return of a value-weighted portfolio of exposed/unexposed banks. Bank portfolio and world market index returns are in excess of the Euro-currency interest rate. Currency returns are calculated as the difference between the one-day Euro-currency rate of the foreign currency (compounded by the exchange rate) and the one-day Euro-currency rate of the U.S. dollar. Panel A refers to the Mexican crisis 1994, Panel B to the Asian crisis 1997, Panel C to the Russian crisis 1998, Panel D to the LTCM 1998 crisis, Panel E to the Brazilian crisis 1999, and Panel F to the terrorist attack on September 11, 2001.

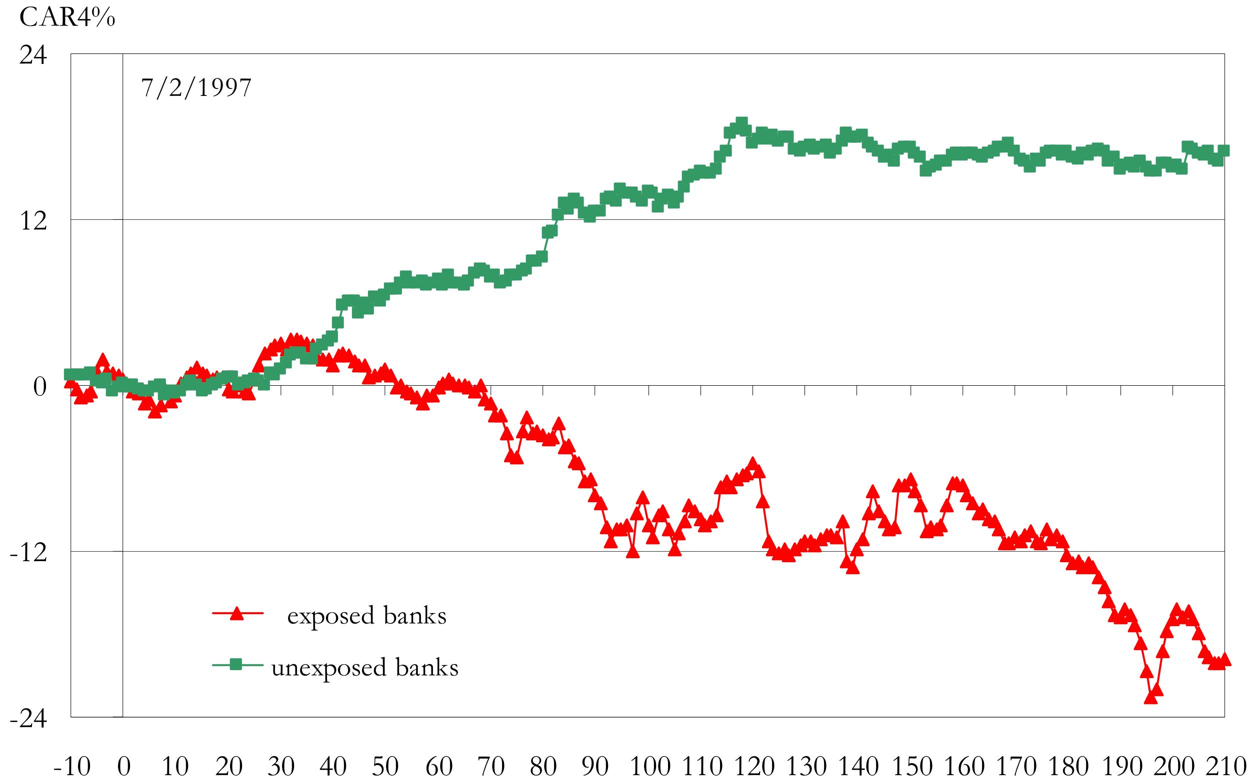
Panel A: Mexican Crisis 1994



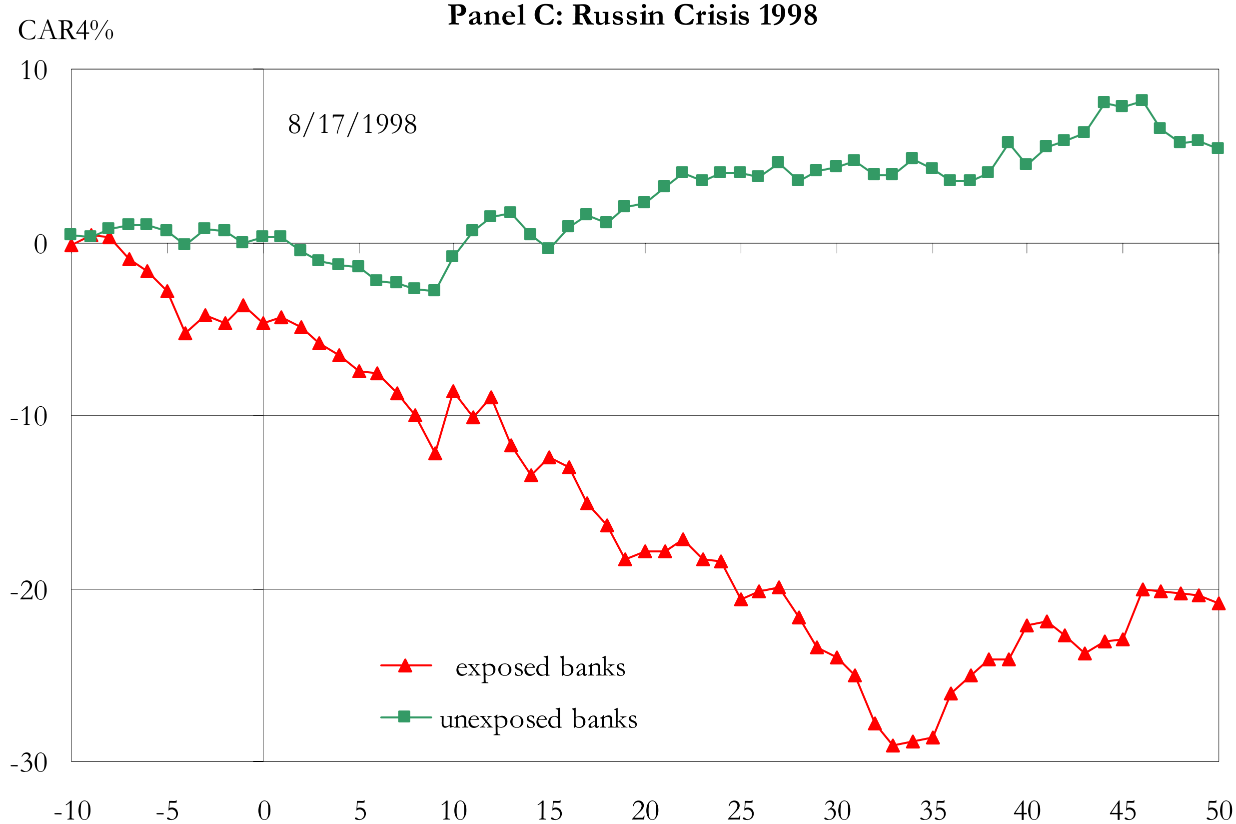
(continued)

Figure 1: Cumulative Abnormal Returns of Exposed and Unexposed Banks (continued)

Panel B: Asian Crisis 1997



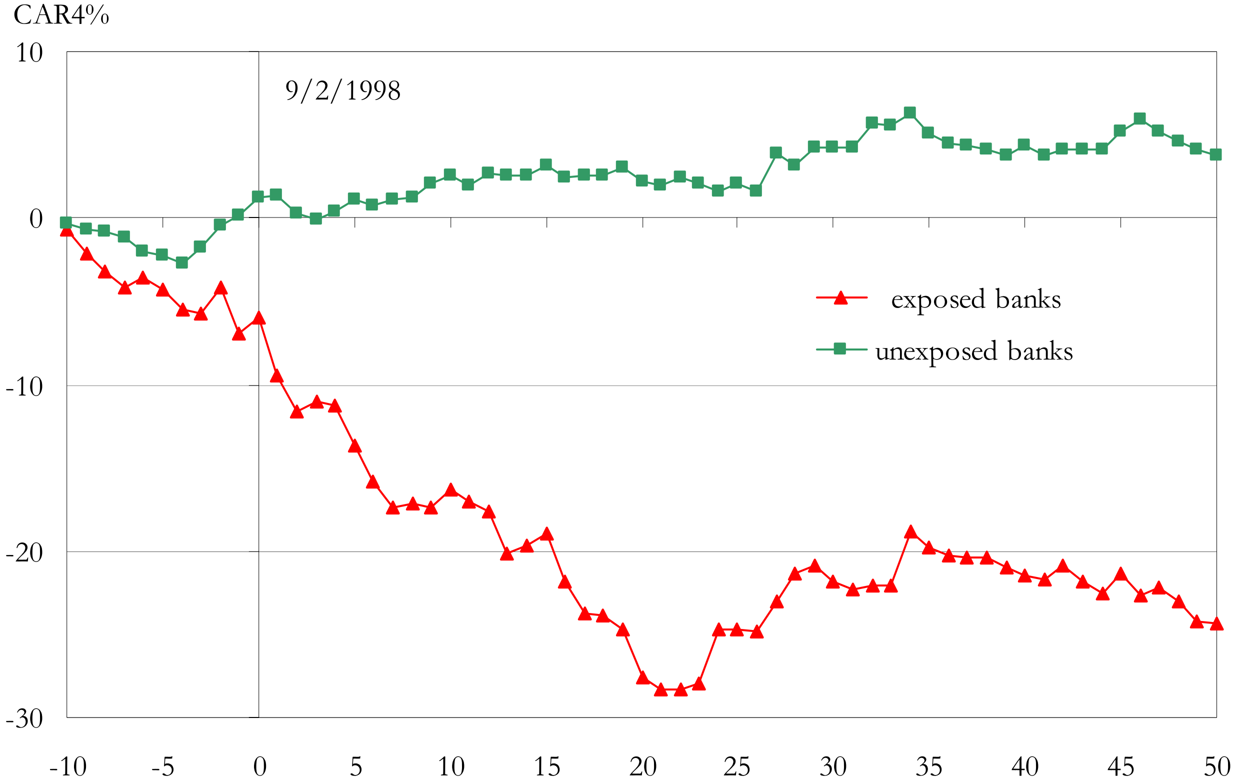
Panel C: Russin Crisis 1998



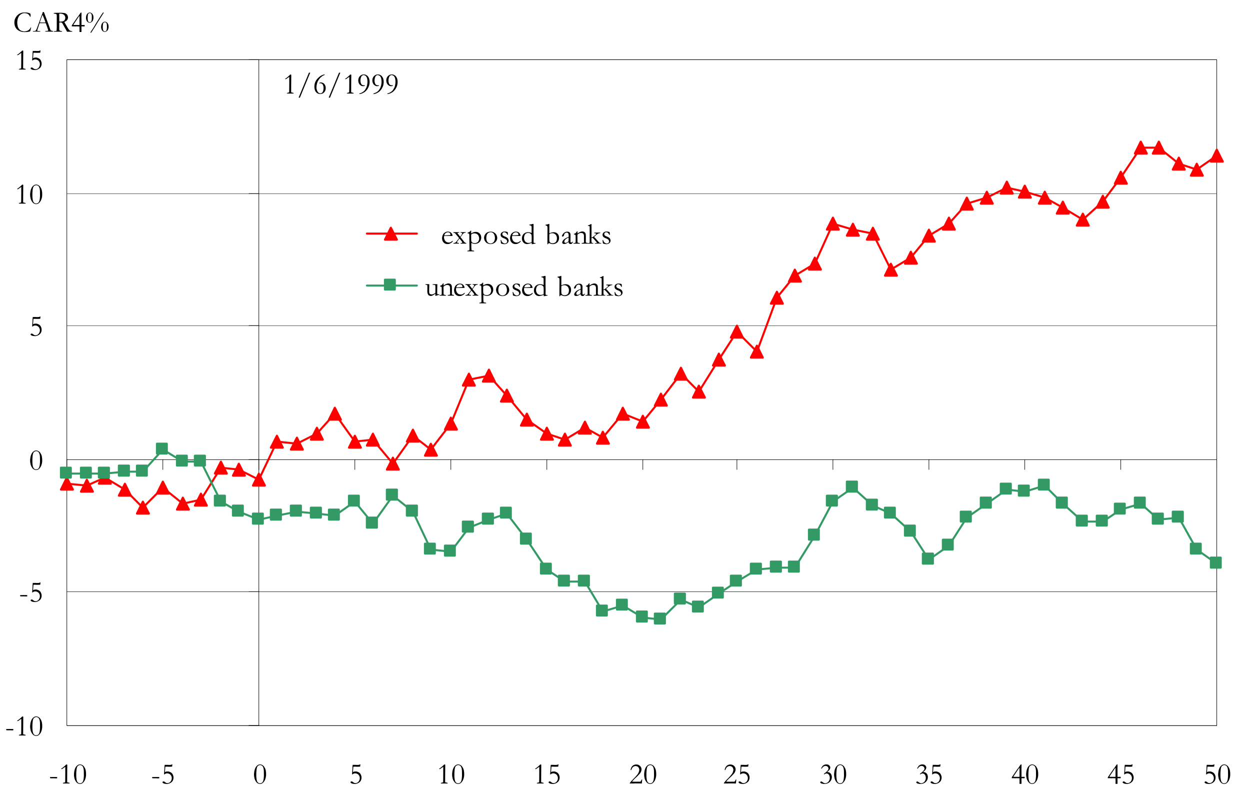
(continued)

Figure 1: Cumulative Abnormal Returns of Exposed and Unexposed Banks (continued)

Panel D: LTCM Crisis 1998



Panel E: Brazil 1999



(continued)

Figure 1: Cumulative Abnormal Returns of Exposed and Unexposed Banks (continued)

Panel F: September 11, 2001

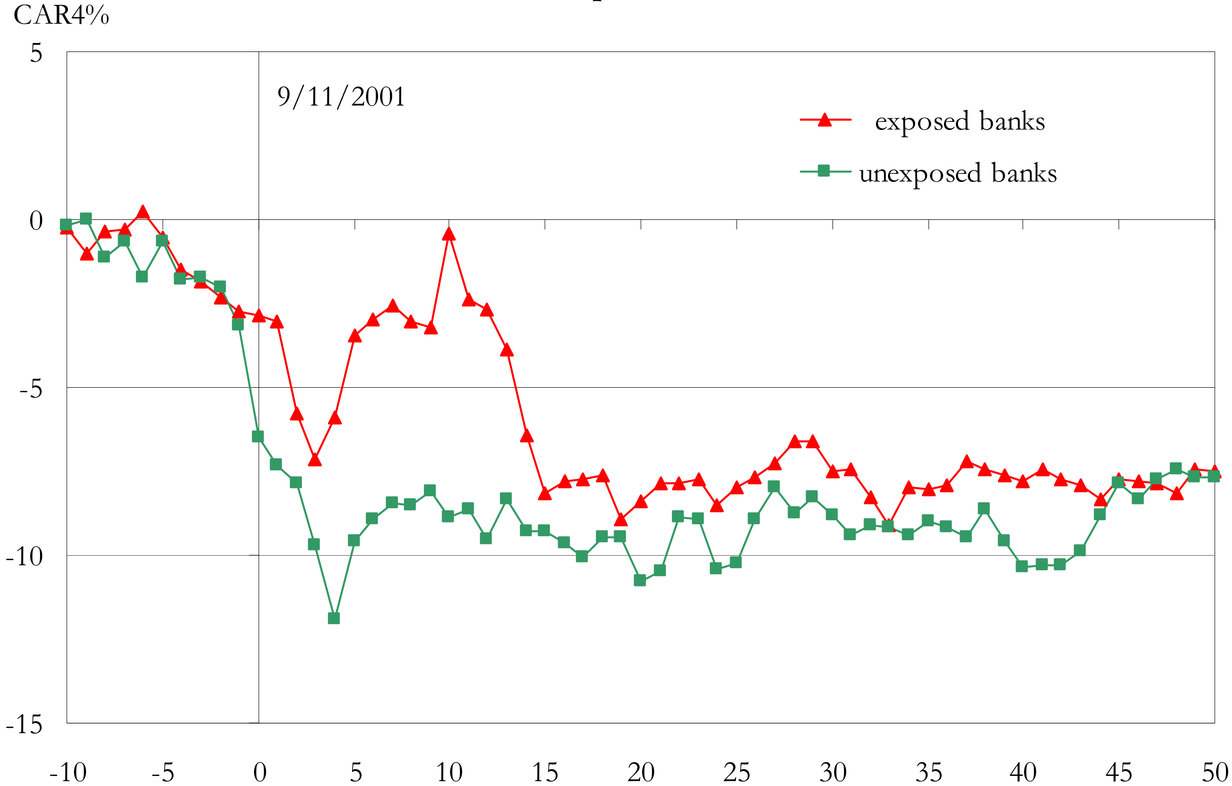
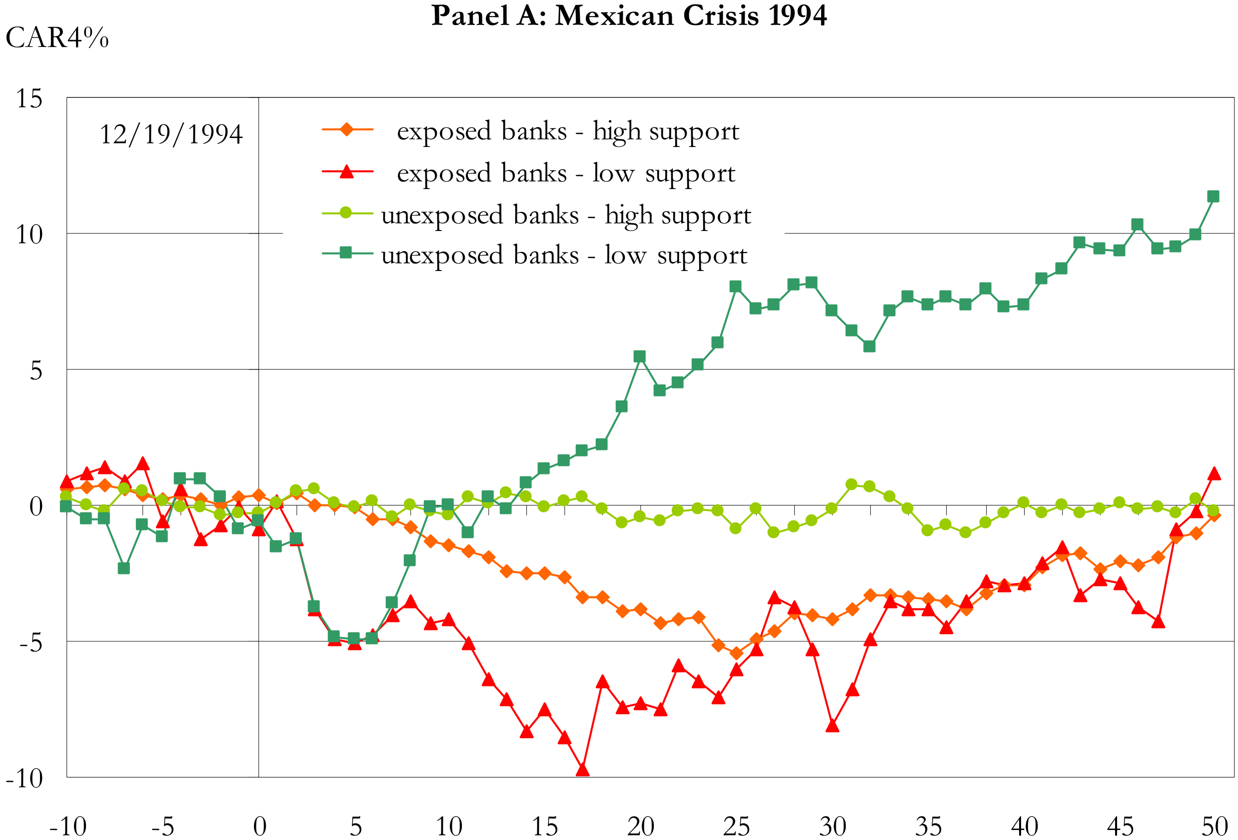


Figure 2: Public Support CARs for Exposed and Unexposed Banks

The figure shows cumulative abnormal returns (CARs) for value-weighted portfolios of exposed and unexposed banks with differing degrees of public support for different crises. High support is defined as a 1, 2 or 3 rating in the Fitch Public Support Rating and low support is defined as a 4 or 5 support rating. All ratings are measured for each bank at the crisis date. The crisis period covers the calendar days –10 to +50 (+210 for the Asian crisis), where the event date (t=0) is defined as 19Dec1994 (Mexico 1994), 2Jul1997 (Asia 1997), 17Aug1998 (Russia 1998), 2Sep1998 (LTCM 1998), 6Jan1999 (Brazil 1999) and 11Sep2001 (Sept. 11, 2001). The cumulative abnormal return CAR4 is based on abnormal returns defined as the difference between bank portfolio returns in excess of the Euro currency interest rate and predicted excess returns from a regression during –110 to –11 of returns on the world market index, the Canadian Dollar, the German Mark, the French Franc, the British Pound, the Italian Lira, the Japanese Yen and the one-day return on a 7-day Euro-dollar deposit on the return of a value-weighted portfolio of exposed/unexposed banks. Bank portfolio and world market index returns are in excess of the Euro-currency interest rate. Currency returns are calculated as the difference between the one-day Euro-currency rate of the foreign currency (compounded by the exchange rate) and the one-day Euro-currency rate of the U.S. dollar. Panel A refers to the Mexican crisis 1994, Panel B to the Asian crisis 1997, Panel C to the LTCM 1998 crisis, Panel D to the Brazilian crisis 1999, and Panel E to the terrorist attack on September 11, 2001.

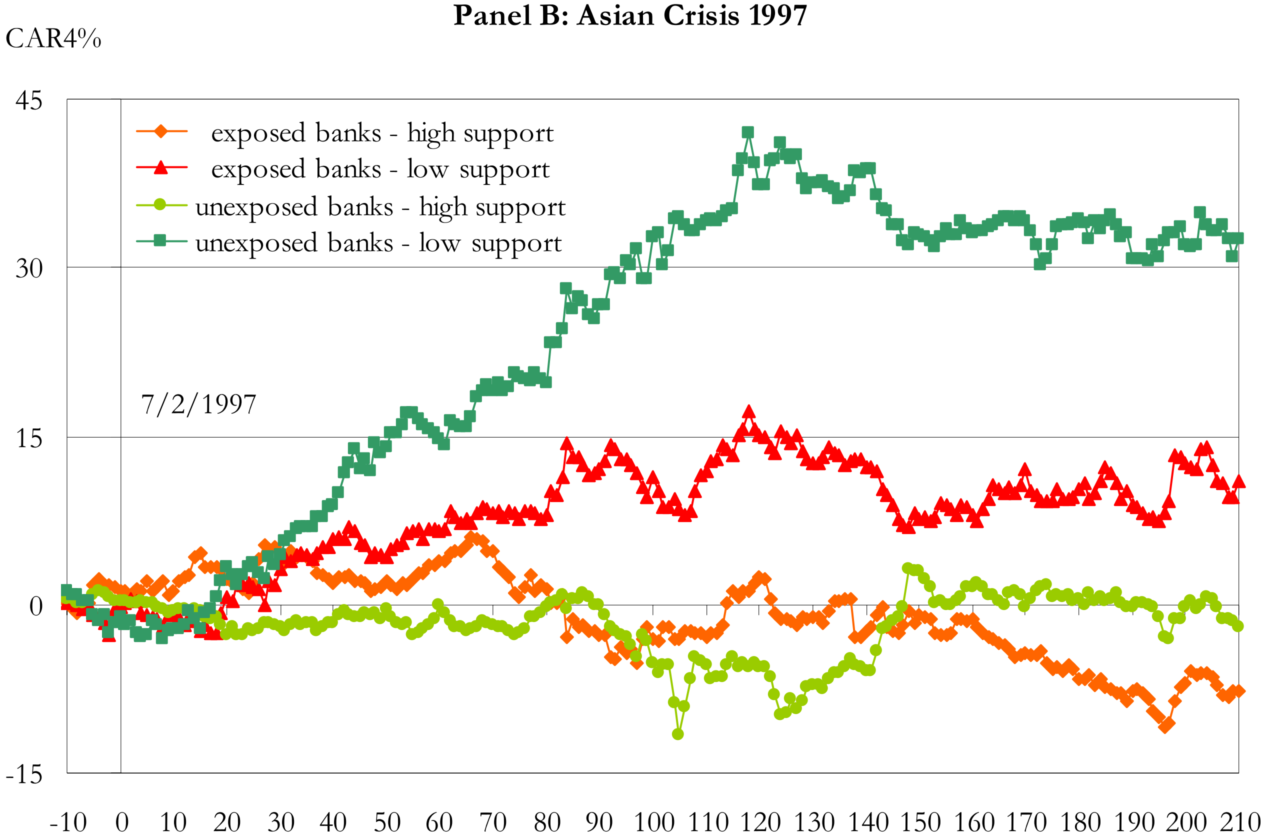
Panel A: Mexican Crisis 1994



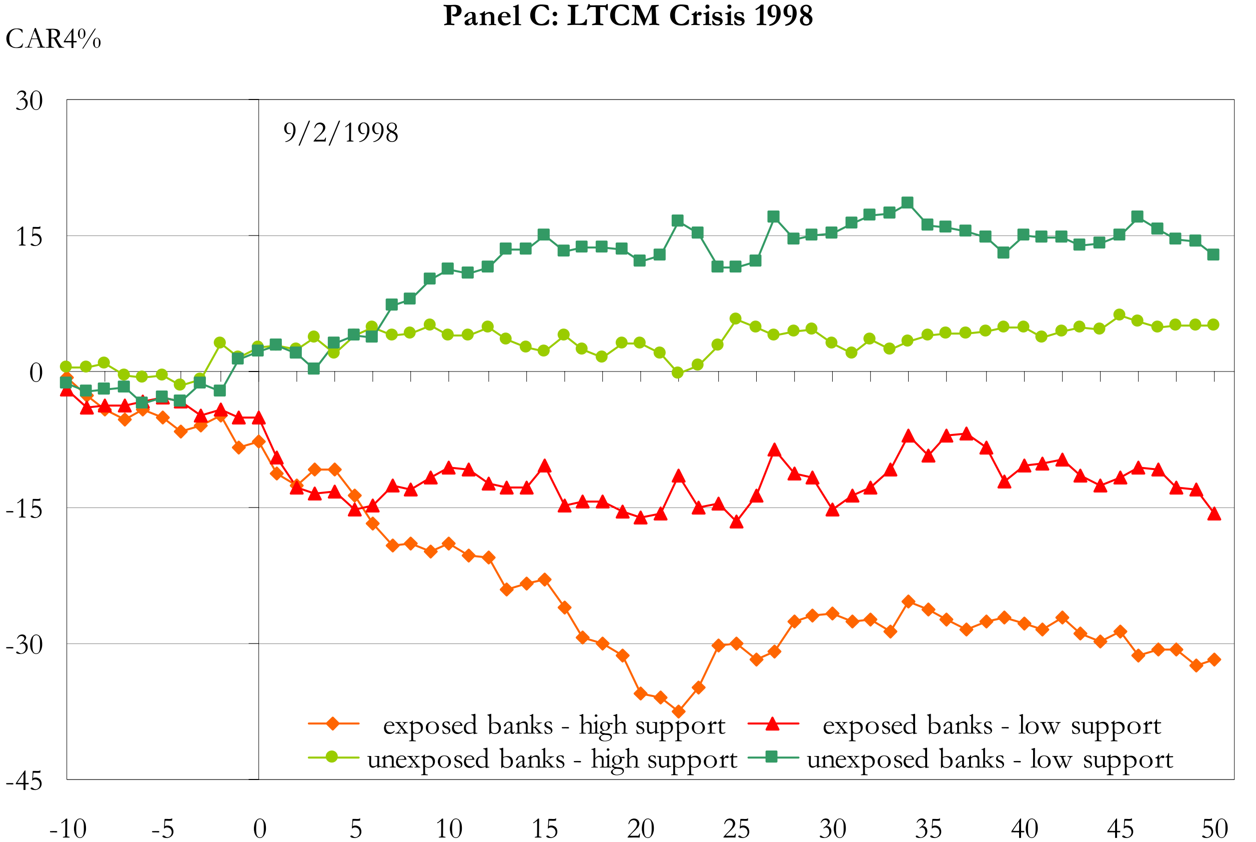
(continued)

Figure 2: Public Support CARs for Exposed and Unexposed Banks (continued)

Panel B: Asian Crisis 1997



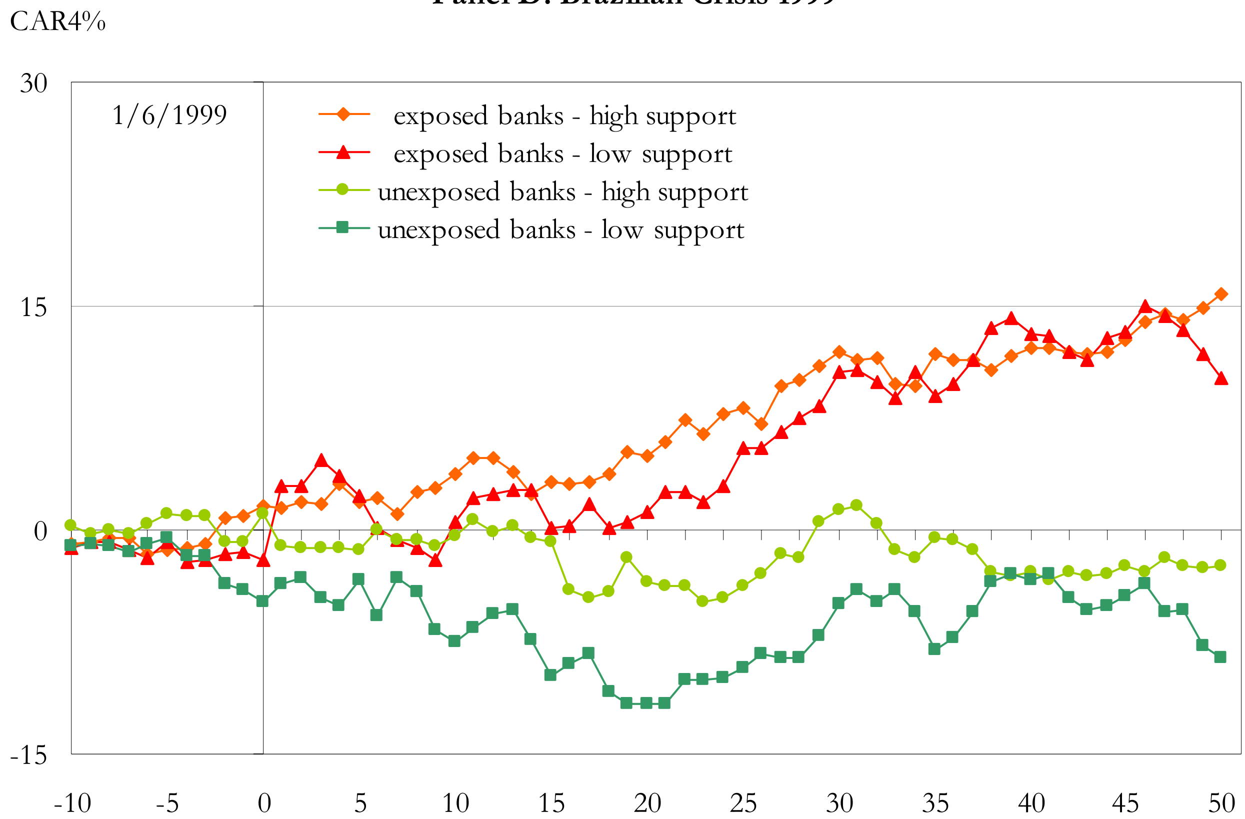
Panel C: LTCM Crisis 1998



(continued)

Figure 2: Public Support CARs for Exposed and Unexposed Banks (continued)

Panel D: Brazilian Crisis 1999



Panel E: September 11, 2001

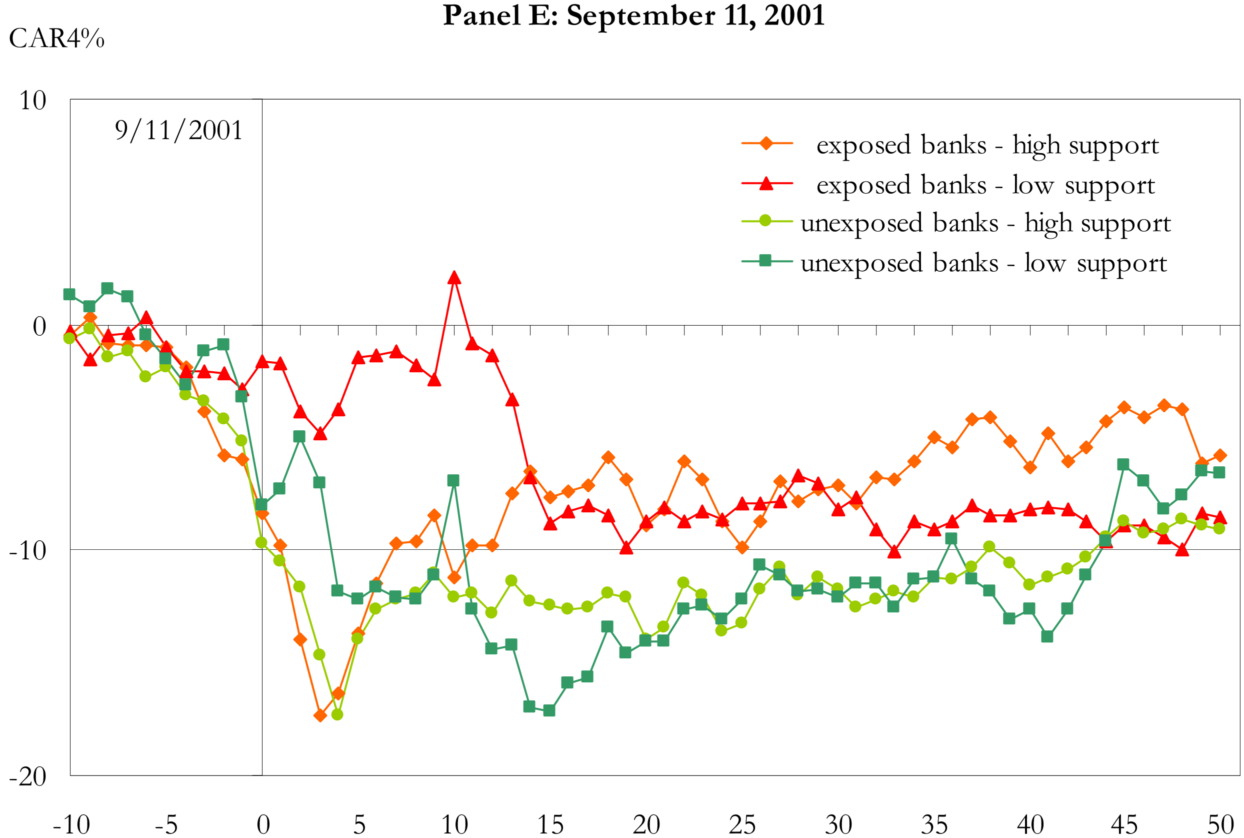
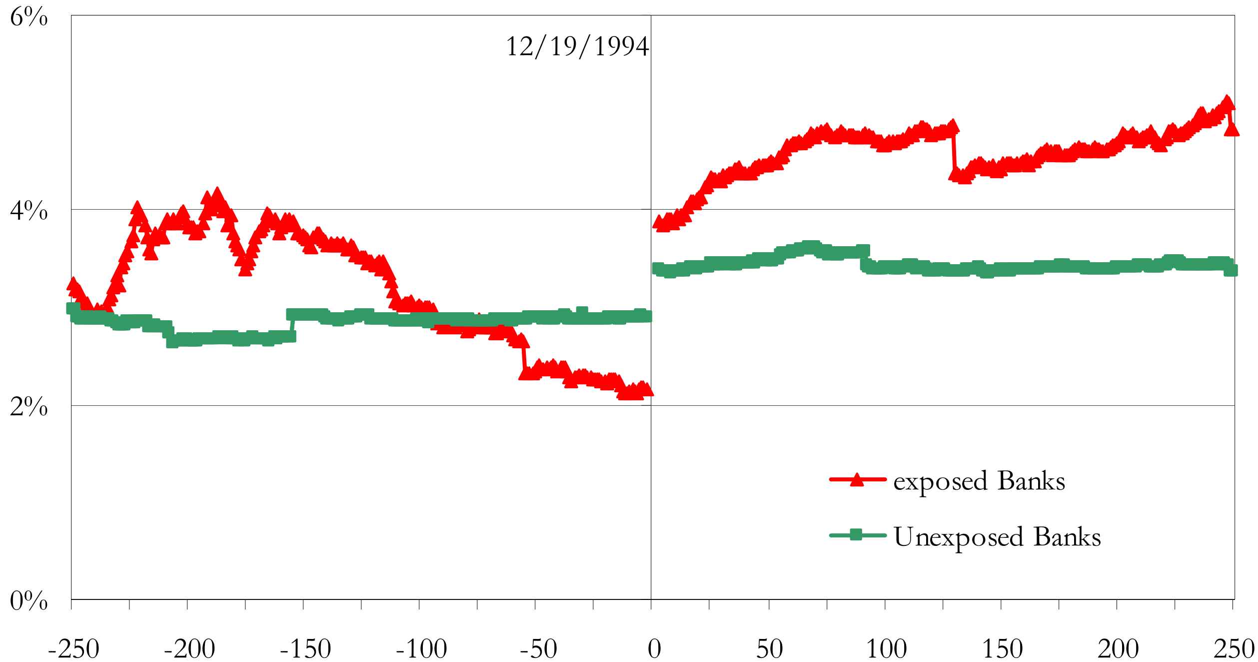


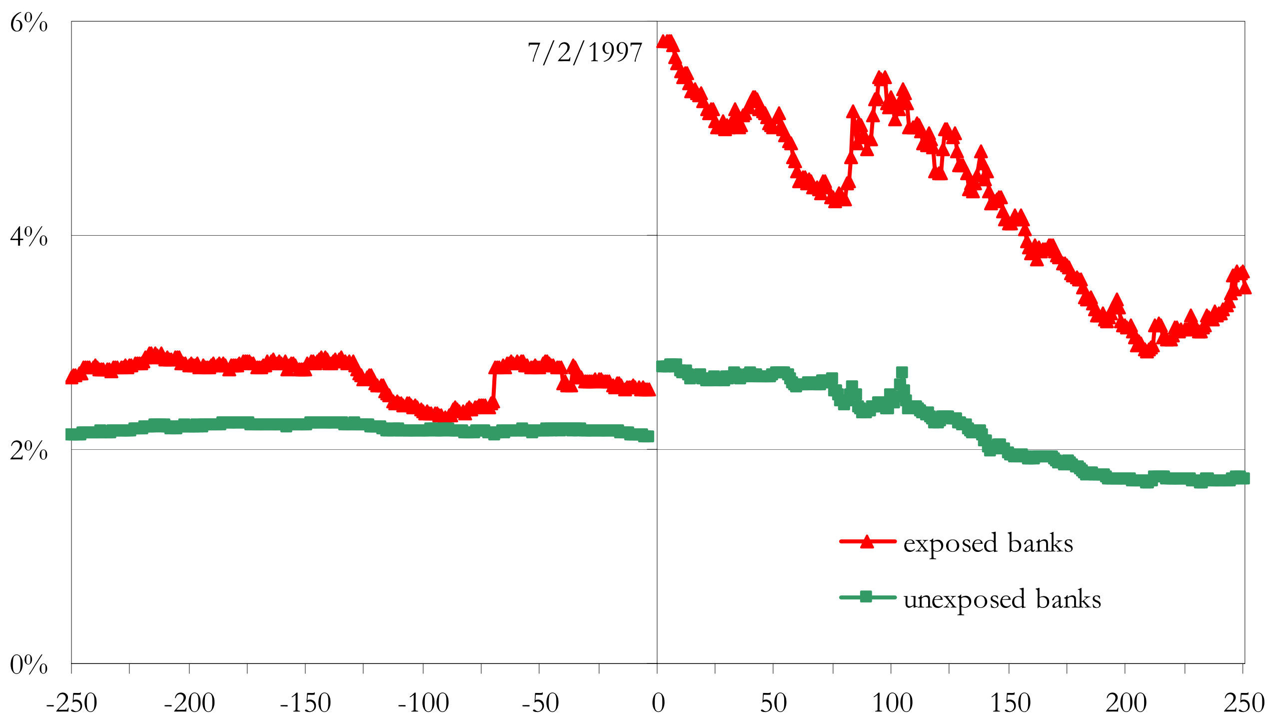
Figure 3: Smoothed Default Probability Estimates

This plot shows the default probabilities averaged across banks exposed and unexposed to each crisis event. The estimates are obtained from the estimated asset volatilities and implied asset values from the structural model. The assumed default horizon is 1 year, the default barrier is assumed to be demand deposits plus short-term debt, and the average of USD, Euro (German), and Japanese short-term government rates at the crisis date is used as the riskfree rate. Default probabilities for each bank are computed using maximum likelihood from data the year prior (PreCrisis) or the year after (PostCrisis) the crisis date, with a linearly interpolated default barrier.

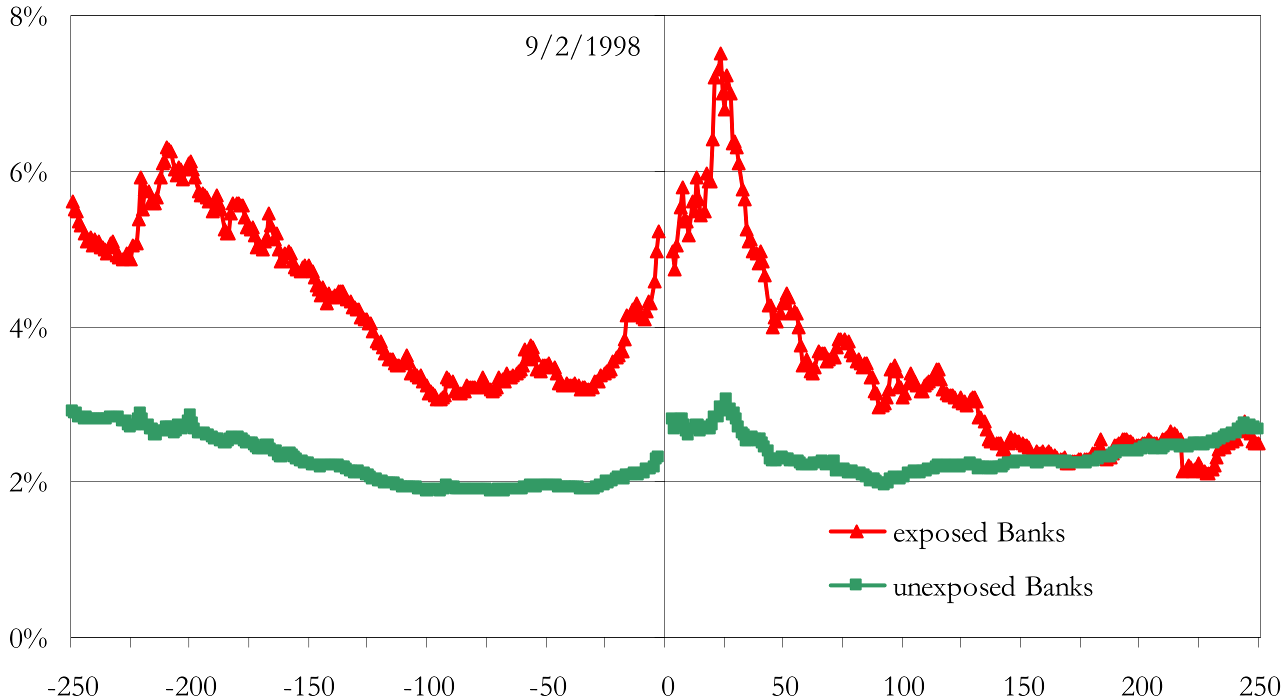
Panel A: Mexican Crisis 1994



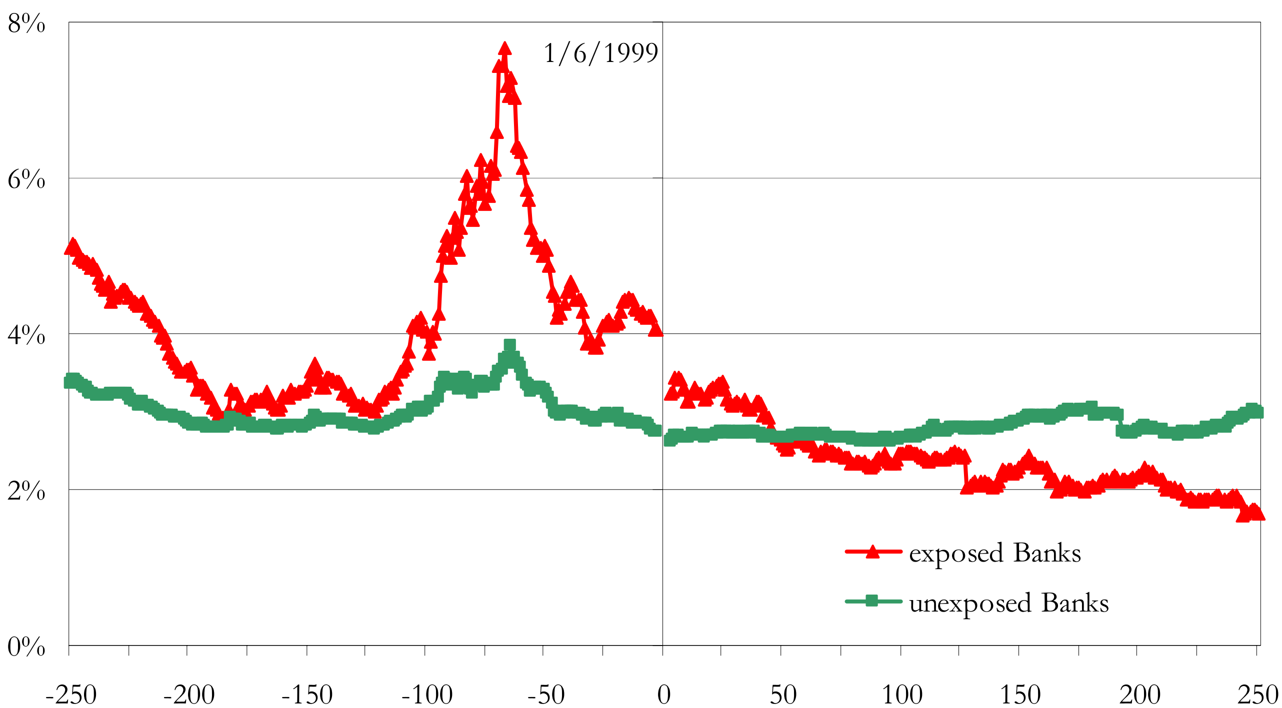
Panel B: Asian Crisis 1997



Panel C: LTCM Crisis 1998



Panel D: Brazilian Crisis 1999



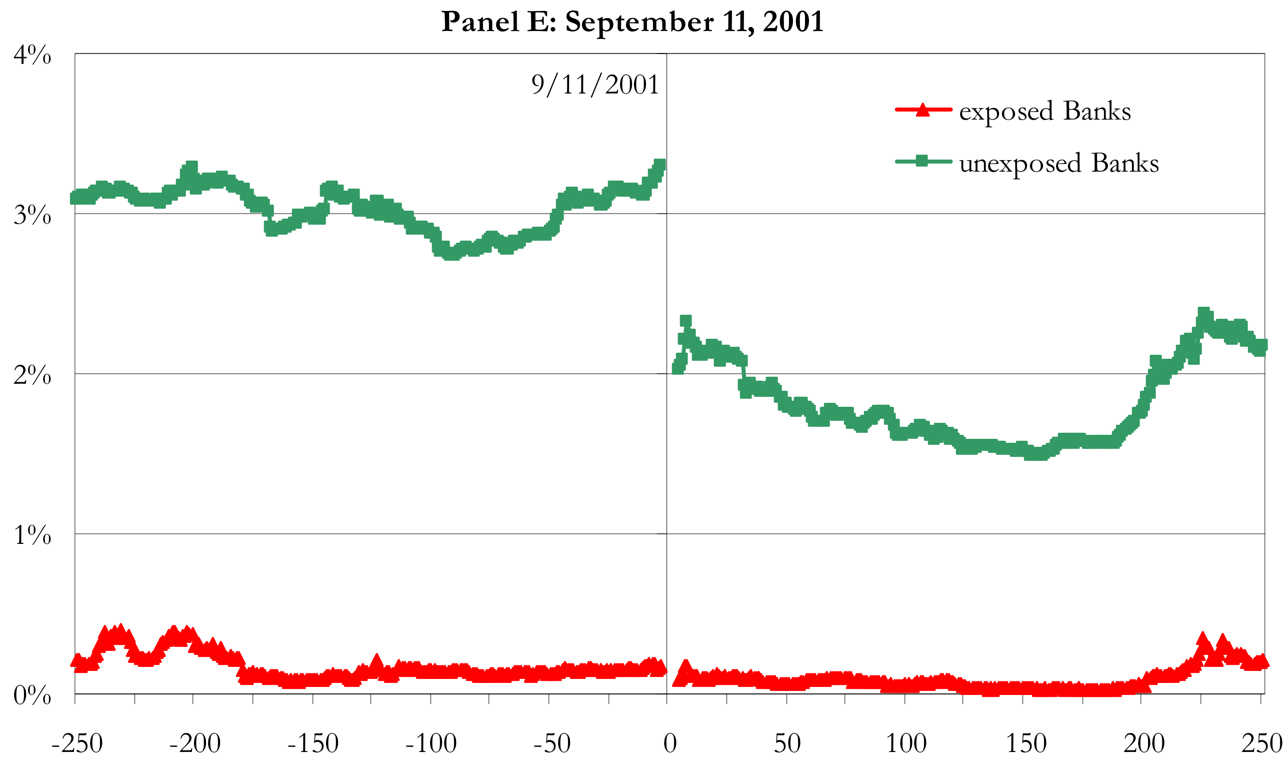
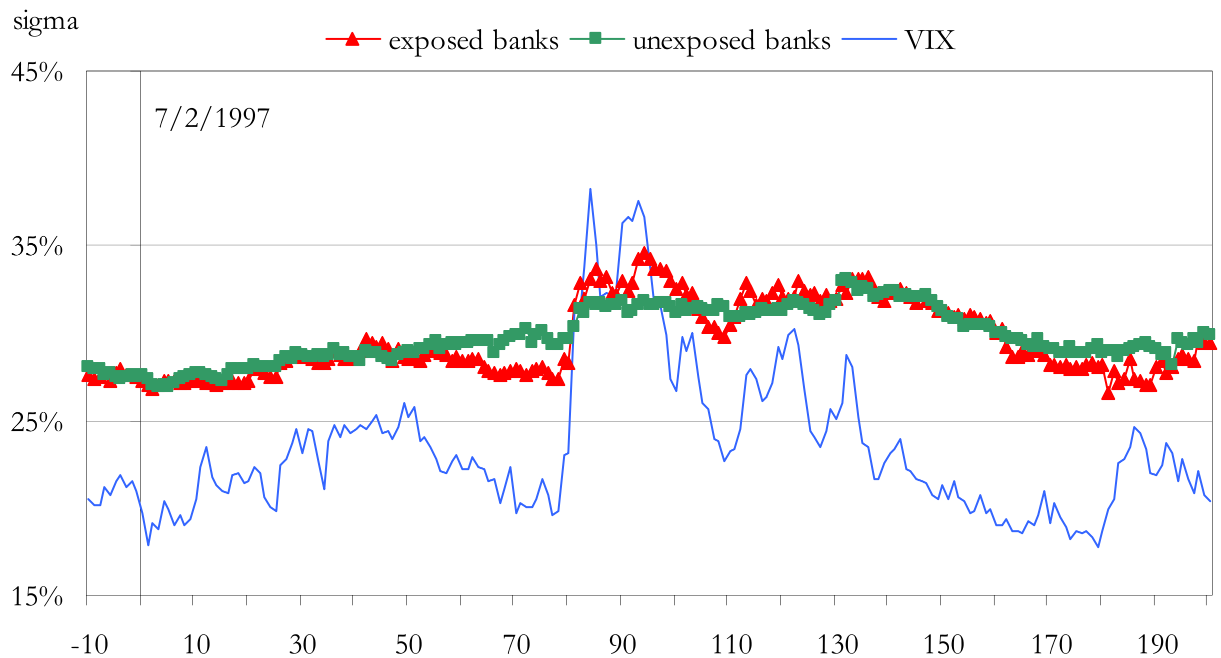

Panel E: September 11, 2001
9/11/2001
exposed Banks
unexposed Banks
4%
3%
2%
1%
0%
-250
-200
-150
-100
-50
0
50
100
150
200
250

Figure 4: Implied Bankruptcy Probabilities from Option Prices: Asian Crisis 1997

The graphs below plot the implied volatilities (Sigma, Panel A) and implied default probabilities (Delta, Panel B) from option prices of banks around the Asian crisis. Estimates are daily averages of the banks exposed and unexposed to the crisis event (Day 0) obtained via non-linear least squares estimation of the Câmara delta-geometric option pricing model. VIX is the S&P 500 implied volatility index.

Panel A: Average Implied Volatility



Panel B: Average Implied Default Probability

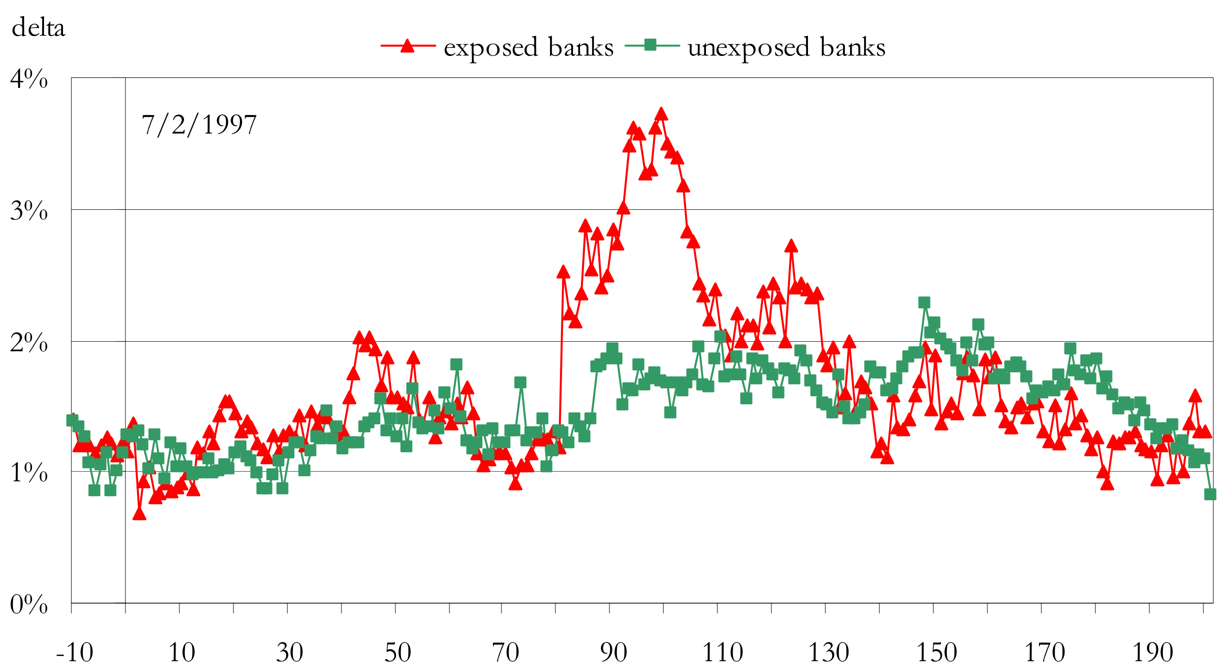
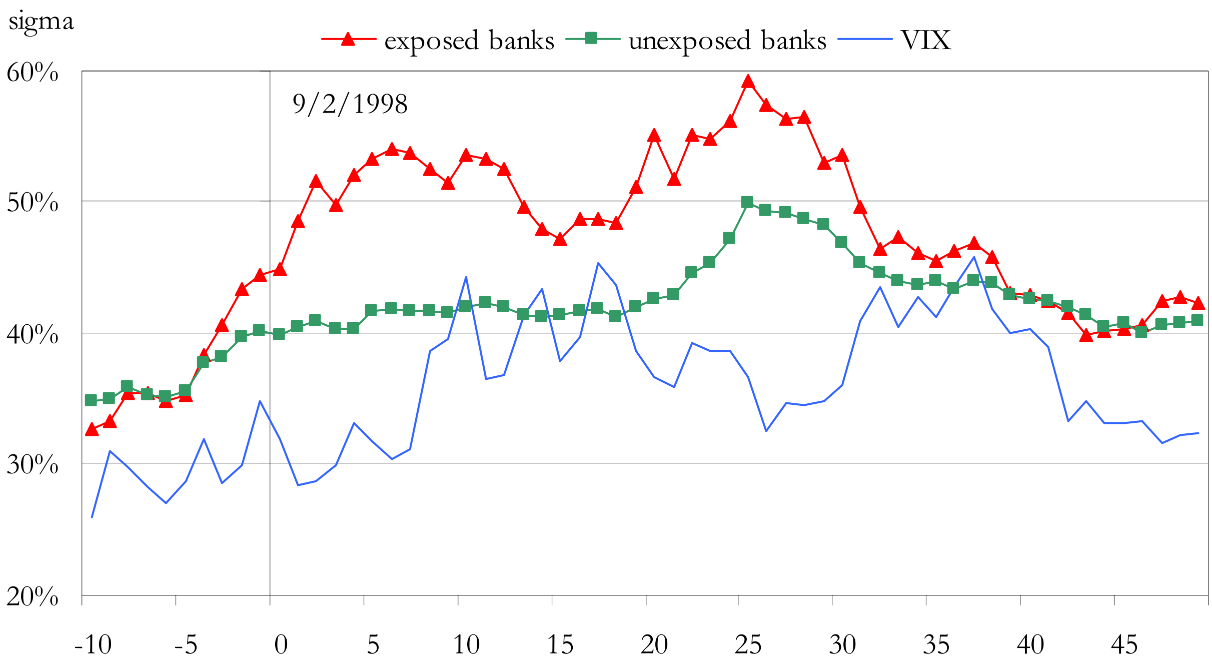


Figure 5: Implied Bankruptcy Probabilities from Option Prices: Russian/LTCM Crisis 1998

The graphs below plot the implied volatilities (Sigma, Panel A) and implied default probabilities (Delta, Panel B) from option prices of banks around the Russian crisis. Estimates are daily averages of the banks exposed and unexposed to the crisis event (Day 0) obtained via non-linear least squares estimation of the Câmara delta-geometric option pricing model. VIX is the S&P 500 implied volatility index.

Panel A: Average Implied Volatility



Panel B: Average Implied Default Probability

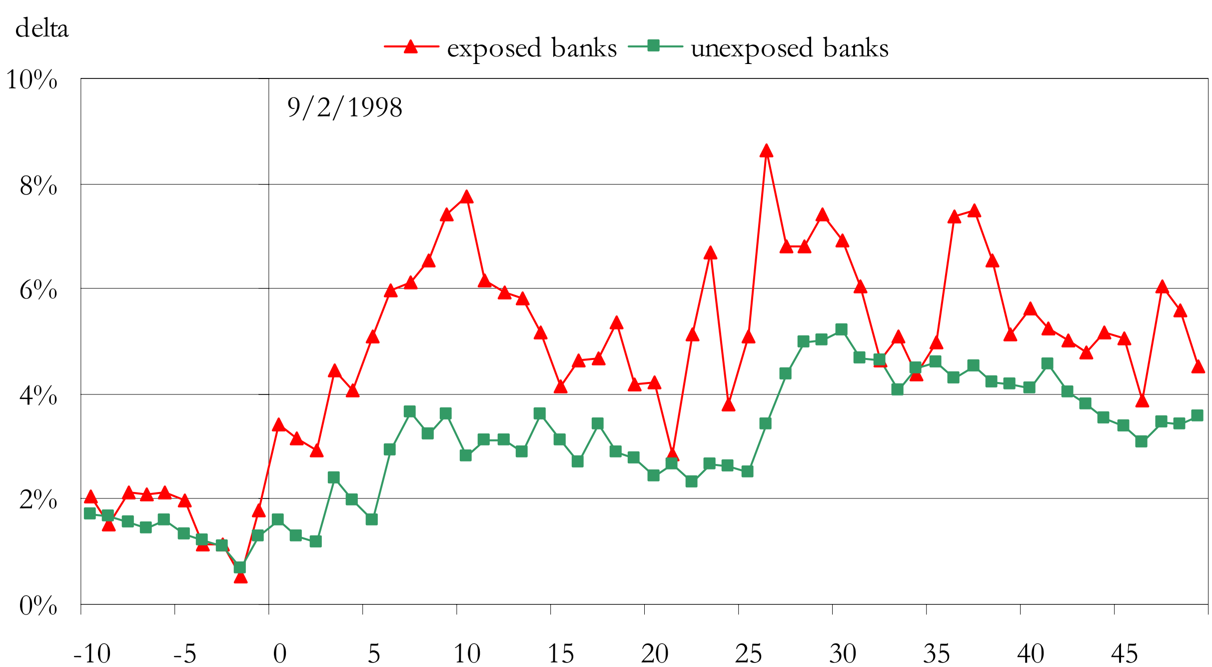
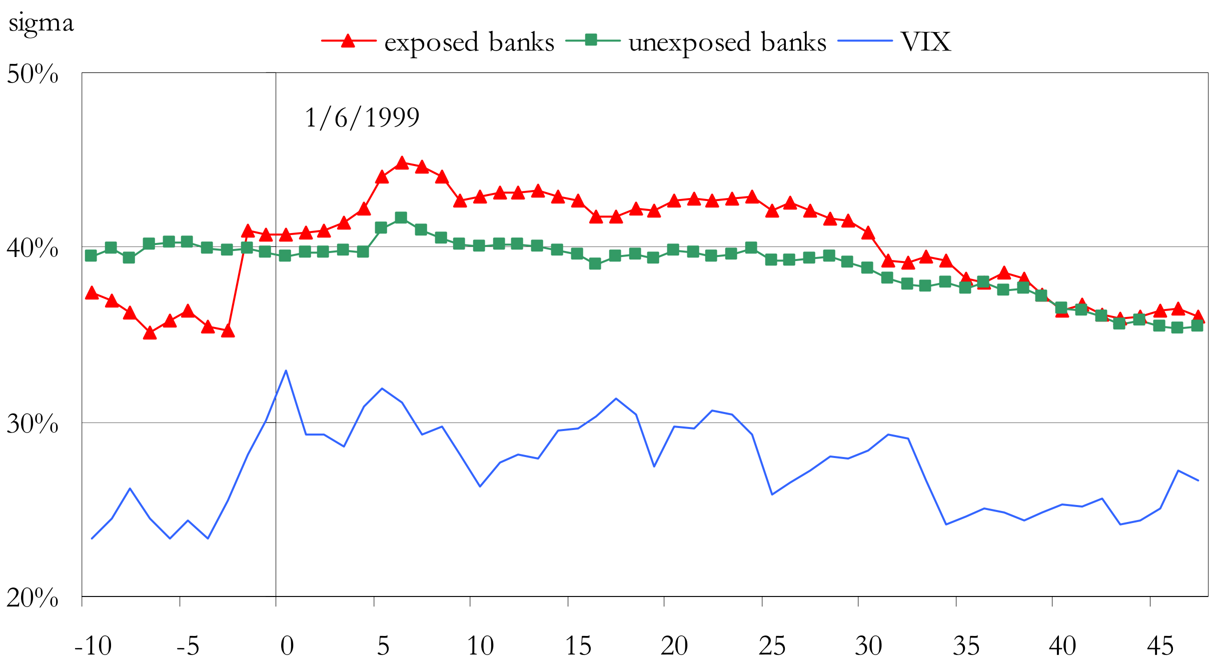


Figure 6: Implied Bankruptcy Probabilities from Option Prices: Brazilian Crisis 1999

The graphs below plot the implied volatilities (Sigma, Panel A) and implied default probabilities (Delta, Panel B) from option prices of banks around the Brazilian crisis. Estimates are daily averages of the banks exposed and unexposed to the crisis event (Day 0) obtained via non-linear least squares estimation of the Câmara delta-geometric option pricing model. VIX is the S&P 500 implied volatility index.

Panel A: Average Implied Volatility



Panel B: Average Implied Default Probability

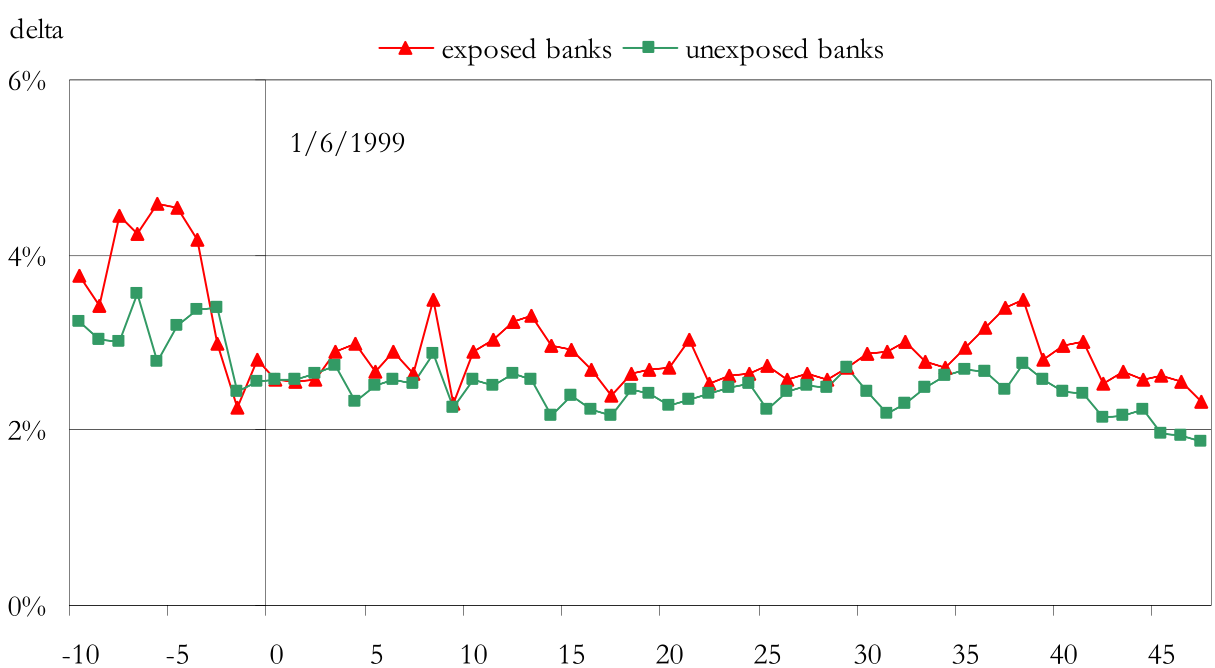
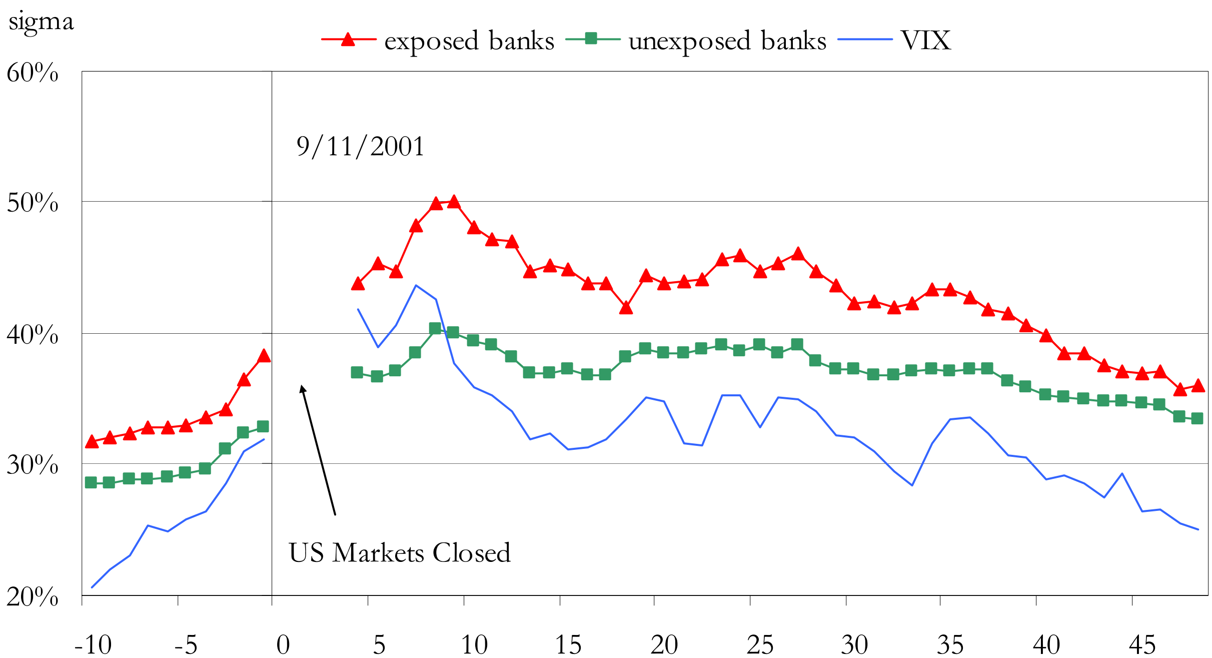


Figure 7: Implied Bankruptcy Probabilities from Option Prices: September 11, 2001

The graphs below plot the implied volatilities (Sigma, Panel A) and implied default probabilities (Delta, Panel B) from option prices of banks around the terrorist attacks. Estimates are daily averages of the banks exposed and unexposed to the crisis event (Day 0) obtained via non-linear least squares estimation of the Câmara delta-geometric option pricing model. VIX is the S&P 500 implied volatility index.

Panel A: Average Implied Volatility



Panel B: Average Implied Default Probability

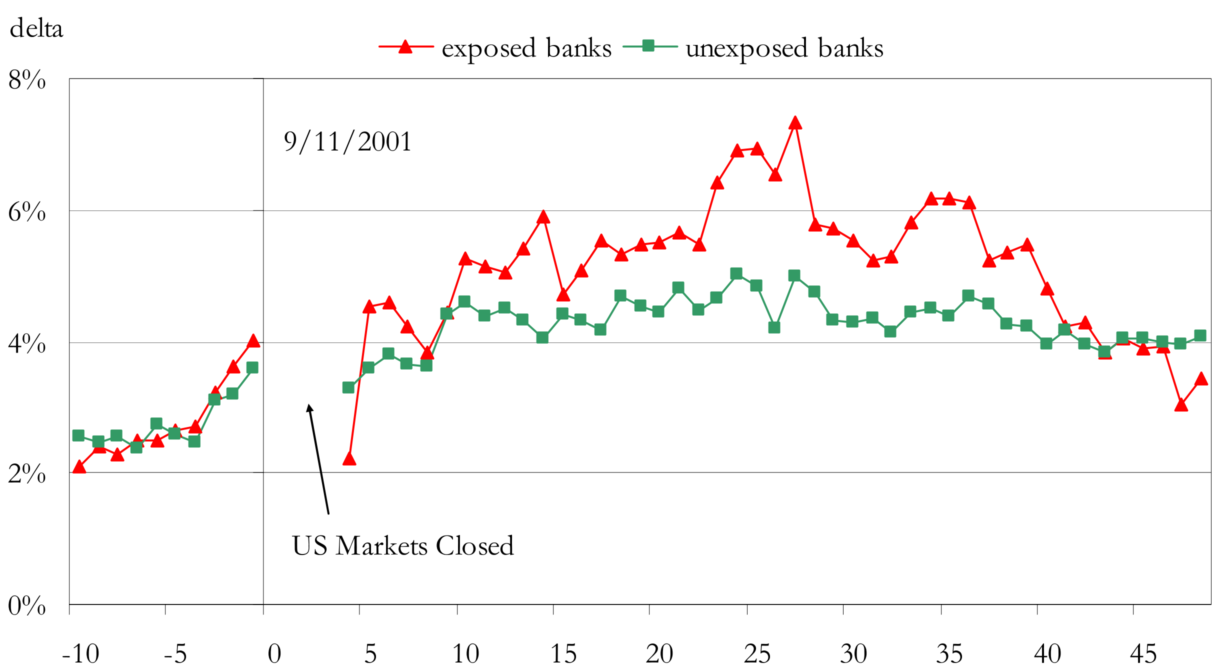


Table 1: Sample Statistics on Banks

The table shows the total number of banks in the sample as well as the number of banks that are exposed to different financial crises by country. Banks are classified as having exposure if the annual report at the time of the crisis contains evidence about a positive exposure to the respective country/region (e.g. through a loan). Broad exposure refers to any relevant exposure of a bank to a particular crisis, independent of its significance. The event dates (t=0) are defined as 19Dec1994 (Mexico 1994), 2Jul1997 (Asia 1997), 17Aug1998 (Russia 1998), 2Sep1998 (LTCM 1998), 6Jan1999 (Brazil 1999) and 11Sep2001 (Sept. 11, 2001).

		Number of exposed banks																	
	Total	Country exposure						Region exposure						Broad exposure					
	# of	Mexico	Asia	Russia	LTCM	Brazil	9\11	Mexico	Asia	Russia	LTCM	Brazil	9\11	Mexico	Asia	Russia	LTCM	Brazil	9\11
Country	banks	1994	1997	1998	1998	1999	2001	1994	1997	1998	1998	1999	2001	1994	1997	1998	1998	1999	2001
Australia	4		3	1		1		2	4	3	1	3		4	4	4	3	4	
Austria	6			3		2			1	3	3	3		2	1	3	3	3	
Belgium	5		2	1		2		1	4	2	1	3		1	4	2	2	3	
Brazil	3					3		3				3		3	3	3		3	
Canada	8	4	4	1		5		6	5	4	1	5		6	5	5	4	5	
Denmark	4							1	1					1	1				
Finland	1			1		1		1	1	1	1	1		1	1	1	1	1	
France	6	1	5	6	3	6		5	6	6	6	6		5	6	6	6	6	
Germany	16		4	10	2	2		3	10	10	10	6	7	3	10	10	10	8	7
Greece	8			1						1	1			7	7	8	1	8	
Hong Kong	1		1						1					1	1	1		1	
Ireland	4	1						1	1					1	1				
Italy	25	2	7	10		10		7	10	11	10	10		8	11	14	11	14	
Japan	99	7	10	4	1	6		9	17	5	4	10		13	20	17	5	17	
Luxembourg	1								1						1	1		1	
Netherlands	3	1	1	1				1	2	1	1	1		1	2	1	1	1	
Norway	2			1		1			1	1	1	1			1	1	1	1	
Portugal	7	3		4		4		3	3	4	4	5		3	3	5	4	5	
Singapore	4		3						4					3	4	4		4	
South Africa	2								1					2	2	2		2	
South Korea	1		1						1					1	1	1		1	
Spain	17	2		1		1		8	4	1	1	7		8	4	2	1	7	
Sweden	4		2	3		4			4	4	3	4			4	4	4	4	
Switzerland	15	1		2	2	2		4	8	4	2	7		5	8	4	4	7	
Taiwan	1		1						1					1	1	1		1	
Turkey	7		1	1					2	1	1			6	7	6	1	6	
UK	11	3	5	4	1	4		3	7	4	4	5	6	5	7	6	4	6	6
US	69	11	10	7	4	9	6	14	14	7	7	15	9	15	17	12	7	17	68
All	334	36	60	62	13	63	6	72	114	73	62	95	22	106	137	124	73	136	81

Table 2: Holding Period Returns (%) on Portfolios of Banks and Market Indices

The table shows raw returns of value-weighted portfolios of exposed and unexposed banks, and corresponding market indices, by crisis, exposure concept and period. Also reported are *p*-values (in brackets) of Wilcoxon tests of differences in returns between bank returns and market returns as well as between exposed and unexposed banks. The event dates (t=0) are defined as 19Dec1994 (Mexico 1994), 2Jul1997 (Asia 1997), 17Aug1998 (Russia 1998), 2Sep1998 (LTCM 1998), 6Jan1999 (Brazil 1999) and 11Sep2001 (Sept. 11, 2001). Panel A is based on U.S. dollar returns; Panel B shows local currency returns.

Panel A: U.S. Dollar Returns

			Exposed Banks			Unexposed Banks			
Crisis	Exposure	Period	Banks	Market	Banks vs Market	Banks	Market	Banks vs Market	Exp. vs Unexp.
Mexico 1994	country	-110 to -11	-9.3	-8.2	[0.46]	-6.1	-5.7	[0.50]	[0.36]
		-10 to 50	-3.0	-6.3	[0.46]	-0.6	-2.2	[0.41]	[0.22]
		51 to 120	14.7	11.0	[0.41]	13.9	10.4	[0.36]	[0.37]
	region	-110 to -11	-8.0	-7.5	[0.49]	-6.1	-5.7	[0.49]	[0.42]
		-10 to 50	-2.9	-5.5	[0.48]	-0.6	-2.2	[0.40]	[0.25]
		51 to 120	14.4	10.8	[0.42]	13.9	10.4	[0.36]	[0.35]
	broad	-110 to -11	-7.1	-7.0	[0.49]	-7.0	-6.0	[0.48]	[0.48]
		-10 to 50	-3.0	-5.4	[0.48]	0.0	-1.7	[0.50]	[0.27]
		51 to 120	14.5	10.8	[0.44]	13.1	10.1	[0.37]	[0.39]
Asia 1997	country	-110 to -11	22.3	15.5	[0.19]	14.0	15.1	[0.41]	[0.24]
		-10 to 50	2.5	-2.3	[0.49]	3.6	1.2	[0.33]	[0.24]
		51 to 120	-7.3	-5.2	[0.44]	6.0	1.0	[0.37]	[0.27]
		121 to 210	6.4	10.0	[0.37]	16.0	16.1	[0.43]	[0.28]
	region	-110 to -11	21.7	15.7	[0.20]	14.0	15.3	[0.42]	[0.27]
		-10 to 50	0.9	-1.8	[0.44]	3.6	1.3	[0.32]	[0.25]
		51 to 120	-4.7	-3.7	[0.41]	5.9	0.8	[0.38]	[0.30]
		121 to 210	10.0	12.0	[0.45]	15.3	15.7	[0.45]	[0.41]
	broad	-110 to -11	21.8	15.5	[0.19]	13.5	15.9	[0.45]	[0.23]
		-10 to 50	1.0	-1.7	[0.45]	3.6	0.8	[0.30]	[0.25]
		51 to 120	-5.4	-3.9	[0.43]	6.4	0.8	[0.37]	[0.30]
		121 to 210	10.3	12.1	[0.46]	14.4	15.3	[0.50]	[0.44]
Russia 1998	country	-110 to -11	15.1	7.9	[0.27]	-1.3	2.9	[0.40]	[0.09]
		-10 to 50	-29.9	-9.8	[0.19]	-9.0	-6.9	[0.43]	[0.22]
		51 to 120	13.0	13.3	[0.39]	10.4	15.5	[0.28]	[0.50]
	region	-110 to -11	13.2	7.1	[0.31]	-1.5	3.2	[0.41]	[0.13]
		-10 to 50	-28.5	-9.7	[0.22]	-9.3	-7.1	[0.45]	[0.22]
		51 to 120	13.6	13.6	[0.43]	11.4	15.2	[0.31]	[0.48]
	broad	-110 to -11	8.1	5.1	[0.44]	-0.9	4.2	[0.37]	[0.24]
		-10 to 50	-24.9	-9.1	[0.25]	-7.3	-6.2	[0.42]	[0.25]
		51 to 120	13.5	13.5	[0.44]	9.7	15.7	[0.27]	[0.40]
LTCM 1998	country	-110 to -11	4.3	1.7	[0.26]	-6.2	-2.2	[0.40]	[0.18]
		-10 to 50	-28.8	-1.8	[0.15]	-3.8	0.4	[0.49]	[0.20]
		51 to 120	16.2	6.1	[0.38]	5.8	7.7	[0.42]	[0.40]
	region	-110 to -11	3.3	1.0	[0.39]	-10.1	-3.6	[0.35]	[0.19]
		-10 to 50	-20.2	-2.4	[0.22]	2.4	1.6	[0.50]	[0.20]
		51 to 120	10.9	6.7	[0.43]	7.1	8.5	[0.37]	[0.46]
	broad	-110 to -11	1.8	0.3	[0.43]	-9.8	-3.3	[0.37]	[0.22]
		-10 to 50	-18.3	-1.9	[0.26]	2.0	1.3	[0.50]	[0.23]
		51 to 120	10.6	6.8	[0.44]	7.3	8.5	[0.37]	[0.45]
Brazil 1999	country	-110 to -11	-9.7	4.2	[0.33]	9.4	8.0	[0.41]	[0.32]
		-10 to 50	11.4	5.5	[0.34]	6.0	8.5	[0.33]	[0.36]
		51 to 120	-2.2	1.7	[0.36]	-0.9	3.8	[0.35]	[0.42]
	region	-110 to -11	-8.7	4.0	[0.37]	9.2	7.7	[0.45]	[0.35]
		-10 to 50	10.8	5.2	[0.34]	7.6	8.4	[0.39]	[0.37]
		51 to 120	-1.8	1.5	[0.40]	0.2	3.8	[0.41]	[0.38]
	broad	-110 to -11	-7.2	4.1	[0.38]	10.1	8.6	[0.41]	[0.38]
		-10 to 50	10.9	6.0	[0.35]	4.7	7.7	[0.31]	[0.24]
		51 to 120	-1.8	2.2	[0.36]	-0.8	2.9	[0.44]	[0.39]
Sept. 11	country	-110 to -11	7.2	4.6	[0.49]	4.1	-0.9	[0.28]	[0.39]
		-10 to 50	2.9	-1.6	[0.35]	-7.8	-5.0	[0.41]	[0.25]
		51 to 120	-7.7	0.4	[0.44]	0.7	-0.3	[0.43]	[0.49]
	region	-110 to -11	4.2	1.2	[0.48]	4.6	-0.8	[0.25]	[0.37]
		-10 to 50	-0.3	-3.2	[0.32]	-8.7	-5.1	[0.32]	[0.21]
		51 to 120	-4.2	0.6	[0.42]	1.1	-0.5	[0.40]	[0.42]
	broad	-110 to -11	6.5	2.9	[0.41]	2.4	-3.4	[0.29]	[0.45]
		-10 to 50	-2.1	-2.4	[0.44]	-11.0	-6.8	[0.36]	[0.25]
		51 to 120	1.3	0.5	[0.39]	-1.9	-0.9	[0.47]	[0.25]

(continued)

Table 2: Holding Period Returns (%) on Portfolios of Banks and Market Indices (continued)
Panel B: Local Currency Returns

			Exposed Banks			Unexposed Banks			
Crisis	Exposure	Period	Banks	Market	Banks vs Market	Banks	Market	Banks vs Market	Exp. vs Unexp.
Mexico 1994	country	-110 to -11	-7.4	-6.2	[0.49]	-4.7	-4.3	[0.47]	[0.47]
		-10 to 50	-6.0	-9.3	[0.42]	-3.4	-5.0	[0.40]	[0.16]
		51 to 120	4.9	1.1	[0.41]	6.9	3.3	[0.25]	[0.37]
	region	-110 to -11	-6.2	-5.7	[0.48]	-4.7	-4.3	[0.47]	[0.48]
		-10 to 50	-5.9	-8.5	[0.46]	-3.5	-5.1	[0.41]	[0.20]
		51 to 120	5.3	1.7	[0.45]	6.9	3.3	[0.25]	[0.32]
	broad	-110 to -11	-5.4	-5.3	[0.47]	-5.5	-4.5	[0.47]	[0.50]
		-10 to 50	-5.8	-8.2	[0.47]	-3.3	-4.9	[0.41]	[0.23]
		51 to 120	5.8	2.1	[0.44]	5.8	2.8	[0.26]	[0.40]
Asia 1997	country	-110 to -11	20.5	13.8	[0.11]	14.0	15.0	[0.41]	[0.24]
		-10 to 50	5.6	0.7	[0.48]	5.7	3.3	[0.36]	[0.32]
		51 to 120	-4.9	-2.8	[0.47]	7.1	2.0	[0.35]	[0.30]
		121 to 210	7.2	10.8	[0.33]	17.2	17.2	[0.44]	[0.22]
	region	-110 to -11	20.7	14.7	[0.12]	13.9	15.1	[0.40]	[0.20]
		-10 to 50	4.0	1.3	[0.39]	5.6	3.3	[0.34]	[0.28]
		51 to 120	-2.8	-1.8	[0.45]	7.1	1.9	[0.34]	[0.31]
		121 to 210	10.9	13.0	[0.41]	16.4	16.9	[0.43]	[0.32]
	broad	-110 to -11	21.0	14.7	[0.13]	12.8	15.2	[0.43]	[0.19]
		-10 to 50	4.2	1.4	[0.40]	5.4	2.6	[0.31]	[0.28]
		51 to 120	-3.2	-1.8	[0.46]	7.3	1.7	[0.36]	[0.32]
		121 to 210	11.5	13.2	[0.41]	15.0	15.9	[0.47]	[0.37]
Russia 1998	country	-110 to -11	15.6	8.4	[0.24]	1.0	5.2	[0.38]	[0.10]
		-10 to 50	-35.7	-15.6	[0.21]	-13.3	-11.2	[0.41]	[0.19]
		51 to 120	16.0	16.2	[0.39]	11.8	16.9	[0.28]	[0.44]
	region	-110 to -11	14.2	8.1	[0.30]	0.5	5.3	[0.36]	[0.13]
		-10 to 50	-34.0	-15.3	[0.23]	-13.8	-11.6	[0.43]	[0.19]
		51 to 120	16.3	16.2	[0.41]	13.0	16.8	[0.30]	[0.43]
	broad	-110 to -11	10.3	7.3	[0.39]	0.1	5.3	[0.36]	[0.22]
		-10 to 50	-31.1	-15.3	[0.26]	-11.4	-10.2	[0.40]	[0.21]
		51 to 120	15.9	15.8	[0.41]	10.9	16.8	[0.27]	[0.38]
LTCM 1998	country	-110 to -11	4.0	1.4	[0.27]	-4.8	-0.9	[0.39]	[0.21]
		-10 to 50	-34.1	-7.1	[0.18]	-8.4	-4.2	[0.46]	[0.22]
		51 to 120	17.9	7.8	[0.37]	7.0	8.8	[0.42]	[0.37]
	region	-110 to -11	3.2	0.9	[0.39]	-8.3	-1.9	[0.34]	[0.21]
		-10 to 50	-25.2	-7.4	[0.24]	-1.8	-2.6	[0.50]	[0.18]
		51 to 120	12.7	8.5	[0.43]	8.2	9.6	[0.37]	[0.39]
	broad	-110 to -11	2.3	0.8	[0.43]	-8.3	-1.8	[0.32]	[0.22]
		-10 to 50	-23.2	-6.8	[0.27]	-2.0	-2.7	[0.49]	[0.21]
		51 to 120	12.3	8.4	[0.46]	8.5	9.7	[0.35]	[0.41]
Brazil 1999	country	-110 to -11	-14.4	-0.4	[0.31]	5.8	4.4	[0.44]	[0.30]
		-10 to 50	14.1	8.1	[0.39]	7.5	10.0	[0.33]	[0.34]
		51 to 120	0.6	4.6	[0.38]	0.8	5.5	[0.37]	[0.45]
	region	-110 to -11	-14.1	-1.4	[0.34]	5.3	3.8	[0.47]	[0.30]
		-10 to 50	13.6	8.0	[0.43]	9.2	10.1	[0.37]	[0.38]
		51 to 120	1.2	4.6	[0.40]	2.0	5.6	[0.42]	[0.40]
	broad	-110 to -11	-12.4	-1.1	[0.36]	6.4	4.9	[0.39]	[0.33]
		-10 to 50	13.7	8.7	[0.43]	6.0	9.0	[0.27]	[0.22]
		51 to 120	1.1	5.1	[0.37]	0.9	4.5	[0.43]	[0.42]
Sept. 11	country	-110 to -11	7.2	4.6	[0.49]	3.4	-1.9	[0.33]	[0.44]
		-10 to 50	2.9	-1.6	[0.35]	-6.1	-3.0	[0.40]	[0.27]
		51 to 120	-7.7	0.4	[0.44]	1.5	0.8	[0.45]	[0.47]
	region	-110 to -11	4.2	1.3	[0.44]	3.7	-2.0	[0.30]	[0.42]
		-10 to 50	0.7	-2.0	[0.32]	-7.0	-3.1	[0.40]	[0.23]
		51 to 120	-4.3	0.5	[0.45]	2.1	0.9	[0.40]	[0.39]
	broad	-110 to -11	6.5	2.9	[0.43]	1.1	-5.2	[0.29]	[0.49]
		-10 to 50	-1.5	-1.8	[0.45]	-8.6	-3.9	[0.35]	[0.35]
		51 to 120	1.3	0.4	[0.38]	-0.5	1.1	[0.49]	[0.31]

Table 3: Tests of Returns of Unexposed Banks

The table shows the raw returns and cumulative abnormal returns (CARs) of unexposed banks for different crises, time intervals and exposure definitions. In particular, returns are calculated for alternatively 20 days after the event date (i.e. [0, 20]) or the entire period after the event (i.e. [0, 210] for the Asian crisis and [0, 50] for all other crises). For each crisis, exposure definition and time interval, the table reports the number of banks (N), the raw returns or cumulative abnormal returns (CAR) as well as the corresponding *p*-values (in brackets) of tests for returns being equal to zero. The event dates (t=0) are defined as 19Dec1994 (Mexico 1994), 2Jul1997 (Asia 1997), 17Aug1998 (Russia 1998), 2Sep1998 (LTCM 1998), 6Jan1999 (Brazil 1999) and 11Sep2001 (Sept. 11, 2001). CAR1 is based on abnormal returns defined as the difference between raw returns and returns on the local market index. CAR2 is based on abnormal returns defined as the difference between raw returns and returns on the Datastream world market index. CAR3 is based on abnormal returns defined as the difference between returns in excess of the Euro currency interest rate and predicted excess returns from a regression during days –110 to –11 of returns on the local market index, the Canadian Dollar, the German Mark, the French Franc, the British Pound, the Italian Lira, the Japanese Yen and the one-day return on a 7-day Euro-dollar deposit on the bank return. Bank and market index returns are in excess of the Euro-currency interest rate. Currency returns are calculated as the difference between the one-day Euro-currency rate of the foreign currency (compounded by the exchange rate) and the one-day Euro-currency rate of the U.S. dollar. CAR4 is similar to CAR3, but uses the world market index instead of the local market index. Panel A is based on U.S. dollar returns; Panel B shows local currency returns.

Panel A: U.S. Dollar Returns

Crisis	Exposure	Interval	N	Raw Return		CAR1		CAR2		CAR3		CAR4	
Mexico 1994	country	[0,20]	217	2.52	[0.00]	-0.04	[0.92]	1.22	[0.00]	1.06	[0.02]	1.34	[0.01]
		[0,50]	217	2.21	[0.00]	2.43	[0.00]	3.61	[0.00]	2.19	[0.01]	2.52	[0.01]
	region	[0,20]	216	2.54	[0.00]	-0.03	[0.94]	1.24	[0.00]	1.08	[0.01]	1.35	[0.00]
		[0,50]	216	2.20	[0.00]	2.43	[0.00]	3.60	[0.00]	2.21	[0.01]	2.51	[0.01]
	broad	[0,20]	190	3.06	[0.00]	-0.14	[0.68]	1.75	[0.00]	1.14	[0.01]	2.19	[0.00]
		[0,50]	190	2.69	[0.00]	2.78	[0.00]	4.09	[0.00]	2.83	[0.00]	4.12	[0.00]
Asia 1997	country	[0,20]	202	1.45	[0.05]	-0.13	[0.85]	-2.07	[0.00]	0.77	[0.27]	-0.10	[0.90]
		[0,210]	204	17.88	[0.00]	7.12	[0.00]	4.18	[0.12]	11.03	[0.00]	6.86	[0.02]
	region	[0,20]	198	1.37	[0.06]	-0.22	[0.75]	-2.15	[0.00]	0.74	[0.30]	-0.19	[0.80]
		[0,210]	200	17.46	[0.00]	7.04	[0.00]	3.76	[0.16]	11.50	[0.00]	6.50	[0.03]
	broad	[0,20]	180	0.94	[0.10]	-0.81	[0.05]	-2.58	[0.00]	0.57	[0.18]	-0.27	[0.57]
		[0,210]	182	15.63	[0.00]	7.45	[0.00]	1.94	[0.49]	15.64	[0.00]	7.92	[0.01]
Russia 1998	country	[0,20]	232	-3.99	[0.00]	0.68	[0.30]	-0.16	[0.85]	-0.62	[0.49]	-2.25	[0.02]
		[0,50]	232	-0.16	[0.92]	-0.71	[0.63]	-0.25	[0.88]	-1.55	[0.28]	-4.34	[0.01]
	region	[0,20]	227	-3.94	[0.00]	0.74	[0.27]	-0.11	[0.90]	-0.58	[0.52]	-2.18	[0.03]
		[0,50]	227	-0.21	[0.90]	-0.80	[0.60]	-0.30	[0.86]	-1.70	[0.25]	-4.40	[0.01]
	broad	[0,20]	191	-1.52	[0.05]	1.79	[0.00]	2.31	[0.00]	0.19	[0.80]	0.01	[0.99]
		[0,50]	191	2.64	[0.01]	0.92	[0.28]	2.55	[0.02]	-0.22	[0.85]	-1.40	[0.25]
LTCM 1998	country	[0,20]	312	-2.43	[0.00]	-0.62	[0.40]	-2.94	[0.00]	-0.41	[0.55]	-2.52	[0.00]
		[0,50]	312	8.36	[0.00]	-0.89	[0.47]	-2.42	[0.07]	1.65	[0.19]	-2.01	[0.17]
	region	[0,20]	231	-0.62	[0.50]	0.76	[0.38]	-1.13	[0.22]	0.65	[0.42]	-0.37	[0.70]
		[0,50]	231	8.87	[0.00]	-1.29	[0.42]	-1.98	[0.23]	1.24	[0.41]	-1.05	[0.55]
	broad	[0,20]	227	-0.57	[0.54]	0.78	[0.38]	-1.08	[0.25]	0.63	[0.44]	-0.31	[0.75]
		[0,50]	227	8.74	[0.00]	-1.45	[0.37]	-2.11	[0.21]	1.04	[0.50]	-1.16	[0.52]
Brazil 1999	country	[0,20]	208	-1.25	[0.03]	-1.57	[0.01]	-1.63	[0.01]	-1.08	[0.08]	0.83	[0.22]
		[0,50]	208	2.38	[0.02]	-2.52	[0.01]	-0.37	[0.71]	0.04	[0.96]	6.15	[0.00]
	region	[0,20]	206	-1.12	[0.05]	-1.42	[0.02]	-1.50	[0.01]	-0.95	[0.12]	0.97	[0.15]
		[0,50]	206	2.54	[0.01]	-2.36	[0.01]	-0.21	[0.83]	0.17	[0.87]	6.37	[0.00]
	broad	[0,20]	179	-1.89	[0.00]	-2.19	[0.00]	-2.26	[0.00]	-1.41	[0.02]	0.18	[0.77]
		[0,50]	179	-0.75	[0.35]	-4.64	[0.00]	-3.50	[0.00]	-1.09	[0.26]	3.34	[0.00]
Sept. 11	country	[0,20]	300	-5.81	[0.00]	-4.25	[0.00]	-4.78	[0.00]	-5.46	[0.00]	-6.10	[0.00]
		[0,50]	300	-2.02	[0.01]	-5.42	[0.00]	-6.82	[0.00]	-5.36	[0.00]	-3.22	[0.00]
	region	[0,20]	286	-5.82	[0.00]	-4.22	[0.00]	-4.79	[0.00]	-5.39	[0.00]	-6.09	[0.00]
		[0,50]	286	-2.20	[0.01]	-5.50	[0.00]	-7.00	[0.00]	-5.48	[0.00]	-3.28	[0.00]
	broad	[0,20]	231	-5.52	[0.00]	-3.57	[0.00]	-4.49	[0.00]	-4.30	[0.00]	-5.20	[0.00]
		[0,50]	231	-3.41	[0.00]	-6.08	[0.00]	-8.22	[0.00]	-5.23	[0.00]	-2.01	[0.05]

(continued)

Table 3: Tests of Returns of Unexposed Banks (continued)

Panel B: Local Currency Returns

Crisis	Exposure	Interval	N	Raw Return		CAR1		CAR2		CAR3		CAR4	
Mexico 1994	country	[0,20]	217	1.33	[0.00]	-0.04	[0.92]	1.32	[0.00]	1.07	[0.01]	2.10	[0.00]
		[0,50]	217	-0.05	[0.95]	2.44	[0.00]	3.91	[0.00]	2.56	[0.00]	3.73	[0.00]
	region	[0,20]	216	1.34	[0.00]	-0.03	[0.94]	1.34	[0.00]	1.10	[0.01]	2.12	[0.00]
		[0,50]	216	-0.07	[0.92]	2.43	[0.00]	3.91	[0.00]	2.60	[0.00]	3.75	[0.00]
	broad	[0,20]	190	1.64	[0.00]	-0.14	[0.68]	1.86	[0.00]	1.25	[0.00]	2.31	[0.00]
		[0,50]	190	0.06	[0.93]	2.79	[0.00]	4.44	[0.00]	2.86	[0.00]	4.15	[0.00]
Asia 1997	country	[0,20]	202	4.30	[0.00]	-0.13	[0.85]	-2.12	[0.00]	1.12	[0.11]	1.01	[0.16]
		[0,210]	204	24.99	[0.00]	7.12	[0.00]	4.64	[0.09]	8.76	[0.00]	5.88	[0.05]
	region	[0,20]	198	4.18	[0.00]	-0.22	[0.75]	-2.20	[0.00]	1.10	[0.12]	0.93	[0.20]
		[0,210]	200	24.61	[0.00]	7.04	[0.00]	4.22	[0.12]	9.16	[0.00]	5.51	[0.07]
	broad	[0,20]	180	3.64	[0.00]	-0.81	[0.05]	-2.60	[0.00]	0.97	[0.02]	0.83	[0.07]
		[0,210]	182	21.49	[0.00]	7.45	[0.00]	2.09	[0.46]	13.11	[0.00]	6.55	[0.02]
Russia 1998	country	[0,20]	232	-8.54	[0.00]	0.68	[0.30]	-0.11	[0.90]	-1.18	[0.19]	-4.46	[0.00]
		[0,50]	232	-9.67	[0.00]	-0.73	[0.63]	-0.23	[0.89]	-2.23	[0.12]	-7.11	[0.00]
	region	[0,20]	227	-8.51	[0.00]	0.74	[0.27]	-0.05	[0.95]	-1.17	[0.20]	-4.41	[0.00]
		[0,50]	227	-9.76	[0.00]	-0.81	[0.60]	-0.29	[0.86]	-2.42	[0.10]	-7.19	[0.00]
	broad	[0,20]	191	-6.54	[0.00]	1.79	[0.00]	2.32	[0.00]	-0.60	[0.42]	-2.28	[0.00]
		[0,50]	191	-7.63	[0.00]	0.91	[0.29]	2.56	[0.02]	-1.47	[0.20]	-4.25	[0.00]
LTCM 1998	country	[0,20]	312	-4.22	[0.00]	-0.62	[0.40]	-2.91	[0.00]	-0.57	[0.39]	-2.89	[0.00]
		[0,50]	312	3.40	[0.01]	-0.90	[0.47]	-2.47	[0.06]	1.81	[0.16]	-1.47	[0.32]
	region	[0,20]	231	-2.15	[0.02]	0.76	[0.38]	-1.10	[0.23]	0.44	[0.58]	-0.79	[0.39]
		[0,50]	231	3.85	[0.03]	-1.30	[0.41]	-2.04	[0.22]	1.40	[0.35]	-0.54	[0.76]
	broad	[0,20]	227	-2.10	[0.03]	0.78	[0.38]	-1.06	[0.26]	0.40	[0.62]	-0.73	[0.44]
		[0,50]	227	3.74	[0.03]	-1.46	[0.37]	-2.17	[0.20]	1.19	[0.43]	-0.64	[0.72]
Brazil 1999	country	[0,20]	208	0.29	[0.62]	-1.57	[0.01]	-1.62	[0.01]	-1.00	[0.10]	0.56	[0.40]
		[0,50]	208	6.99	[0.00]	-2.51	[0.01]	-0.37	[0.72]	0.92	[0.33]	6.36	[0.00]
	region	[0,20]	206	0.44	[0.45]	-1.41	[0.02]	-1.49	[0.01]	-0.86	[0.16]	0.69	[0.29]
		[0,50]	206	7.19	[0.00]	-2.36	[0.01]	-0.21	[0.84]	1.05	[0.27]	6.58	[0.00]
	broad	[0,20]	179	-0.59	[0.28]	-2.19	[0.00]	-2.26	[0.00]	-1.24	[0.05]	0.00	[1.00]
		[0,50]	179	3.49	[0.00]	-4.63	[0.00]	-3.50	[0.00]	0.12	[0.90]	3.75	[0.00]
Sept. 11	country	[0,20]	300	-5.85	[0.00]	-4.27	[0.00]	-4.80	[0.00]	-5.68	[0.00]	-5.87	[0.00]
		[0,50]	300	-0.19	[0.80]	-5.40	[0.00]	-6.80	[0.00]	-5.19	[0.00]	-3.10	[0.00]
	region	[0,20]	286	-5.85	[0.00]	-4.24	[0.00]	-4.81	[0.00]	-5.63	[0.00]	-5.84	[0.00]
		[0,50]	286	-0.39	[0.62]	-5.48	[0.00]	-6.98	[0.00]	-5.28	[0.00]	-3.12	[0.00]
	broad	[0,20]	231	-5.56	[0.00]	-3.60	[0.00]	-4.52	[0.00]	-4.59	[0.00]	-4.90	[0.00]
		[0,50]	231	-1.18	[0.20]	-6.05	[0.00]	-8.19	[0.00]	-4.99	[0.00]	-1.81	[0.06]

Table 4: Structural Model Asset Volatility Estimates

This table shows asset volatility estimates from the structural model for each of the crisis events, averaged across broad exposure classifications and regional locations. Standard errors are asymptotic standard errors for the portfolio obtained from the maximum likelihood estimates (outer product of the gradient). The assumed maturity is 1 year, the default barrier is assumed to be demand deposits plus short-term debt, and the average of USD, Euro (German), and Japanese short-term government rates at the crisis date is used as the riskfree rate. Asset volatilities for each bank are computed using maximum likelihood from data the year prior (PreCrisis) or the year after (PostCrisis) the crisis date, with a linearly interpolated default barrier.

	All Banks		Asian Banks		European Banks		Americas Banks	
	Exposed	**Unexposed**	**Exposed**	**Unexposed**	**Exposed**	**Unexposed**	**Exposed**	**Unexposed**
Mexico								
n	77	160	13	55	43	57	21	48
PreCrisis	10.230%	10.215%	10.113%	13.355%	8.724%	6.983%	13.384%	10.454%
std.error	*0.049%*	*0.037%*	*0.135%*	*0.076%*	*0.061%*	*0.045%*	*0.102%*	*0.071%*
PostCrisis	8.565%	10.338%	11.805%	15.337%	8.344%	5.125%	7.010%	10.801%
std.error	*0.047%*	*0.036%*	*0.140%*	*0.081%*	*0.059%*	*0.040%*	*0.087%*	*0.070%*
Δ(PrePost)	-1.665%	0.124%	1.692%	1.983%	-0.380%	-1.859%	-6.374%	0.347%
std.error	*0.008%*	*0.004%*	*0.054%*	*0.015%*	*0.013%*	*0.008%*	*0.029%*	*0.014%*
Asia								
n	89	117	14	47	57	40	18	30
PreCrisis	9.293%	10.988%	12.599%	14.289%	7.003%	6.183%	13.974%	12.224%
std.error	*0.044%*	*0.045%*	*0.146%*	*0.084%*	*0.046%*	*0.055%*	*0.121%*	*0.097%*
PostCrisis	15.038%	15.007%	17.919%	17.292%	13.887%	9.903%	16.444%	18.232%
std.error	*0.057%*	*0.053%*	*0.171%*	*0.092%*	*0.066%*	*0.071%*	*0.133%*	*0.118%*
Δ(PrePost)	5.745%	4.019%	5.320%	3.003%	6.884%	3.721%	2.470%	6.007%
std.error	*0.008%*	*0.006%*	*0.060%*	*0.018%*	*0.011%*	*0.014%*	*0.042%*	*0.028%*
Russia/LTCM								
n	83	173	16	64	55	53	12	56
PreCrisis	15.257%	14.916%	15.814%	15.359%	14.400%	10.816%	18.445%	18.292%
std.error	*0.057%*	*0.042%*	*0.147%*	*0.071%*	*0.066%*	*0.062%*	*0.168%*	*0.083%*
PostCrisis	13.286%	15.783%	14.509%	15.571%	13.146%	12.196%	12.294%	19.421%
std.error	*0.059%*	*0.046%*	*0.151%*	*0.077%*	*0.070%*	*0.069%*	*0.158%*	*0.091%*
Δ(PrePost)	-1.972%	0.867%	-1.304%	0.212%	-1.254%	1.381%	-6.150%	1.129%
std.error	*0.009%*	*0.005%*	*0.053%*	*0.013%*	*0.013%*	*0.013%*	*0.067%*	*0.016%*
Brazil								
n	93	166	16	64	59	51	18	51
PreCrisis	17.562%	16.342%	15.375%	15.098%	17.731%	12.774%	18.949%	21.471%
std.error	*0.061%*	*0.046%*	*0.149%*	*0.073%*	*0.074%*	*0.070%*	*0.151%*	*0.097%*
PostCrisis	13.256%	15.694%	16.449%	16.859%	12.935%	12.599%	11.471%	17.328%
std.error	*0.054%*	*0.044%*	*0.154%*	*0.077%*	*0.065%*	*0.065%*	*0.121%*	*0.087%*
Δ(PrePost)	-4.305%	-0.648%	1.074%	1.760%	-4.796%	-0.176%	-7.478%	-4.143%
std.error	*0.008%*	*0.005%*	*0.054%*	*0.013%*	*0.013%*	*0.013%*	*0.046%*	*0.018%*
Sept. 11								
n	70	199	0	87	12	102	58	10
PreCrisis	12.349%	12.092%	n/a	13.905%	6.130%	10.684%	13.636%	10.695%
std.error	*0.063%*	*0.035%*	*n/a*	*0.059%*	*0.104%*	*0.044%*	*0.074%*	*0.156%*
PostCrisis	10.931%	10.682%	n/a	13.443%	5.453%	8.434%	12.064%	9.594%
std.error	*0.059%*	*0.033%*	*n/a*	*0.057%*	*0.097%*	*0.040%*	*0.069%*	*0.144%*
Δ(PrePost)	-1.418%	-1.410%	n/a	-0.461%	-0.677%	-2.250%	-1.572%	-1.101%
std.error	*0.010%*	*0.003%*	*n/a*	*0.009%*	*0.041%*	*0.006%*	*0.013%*	*0.067%*

Table 5: Structural Model Default Probabilities Estimates

This table shows default probability estimates from the structural model for each of the crisis events, averaged across broad exposure classifications and regional locations. Standard errors are asymptotic standard errors for the portfolio obtained from the maximum likelihood estimates (outer product of the gradient). The assumed default horizon is 1 year, the default barrier is assumed to be demand deposits plus short-term debt, and the average of USD, Euro (German), and Japanese short-term government rates at the crisis date is used as the riskfree rate. Default probabilities for each bank are computed using maximum likelihood from data the year prior (PreCrisis) or the year after (PostCrisis) the crisis date, with a linearly interpolated default barrier, and the implied asset value 3 days before and after the crisis date, respectively.

	All Banks		**Asian Banks**		**European Banks**		**Americas Banks**	
	Exposed	**Unexposed**	**Exposed**	**Unexposed**	**Exposed**	**Unexposed**	**Exposed**	**Unexposed**
Mexico								
n	77	160	13	55	43	57	21	48
PreCrisis	2.143%	2.907%	0.001%	4.004%	1.558%	4.091%	4.668%	0.190%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
PostCrisis	3.862%	3.393%	0.011%	5.989%	5.180%	3.471%	3.548%	0.324%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Δ(PrePost)	1.719%	0.485%	0.010%	1.986%	3.622%	-0.620%	-1.120%	0.134%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Asia								
n	89	117	14	47	57	40	18	30
PreCrisis	2.553%	2.120%	0.007%	4.089%	1.993%	1.390%	6.307%	0.008%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
PostCrisis	5.805%	2.775%	2.292%	4.182%	6.606%	2.608%	6.002%	0.793%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Δ(PrePost)	3.252%	0.655%	2.285%	0.092%	4.612%	1.217%	-0.305%	0.785%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Russia/LTCM								
n	83	173	16	64	55	53	12	56
PreCrisis	5.264%	2.393%	6.619%	4.278%	4.370%	1.334%	7.555%	1.275%
std.error	*0.000%*	*0.000%*	*0.001%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
PostCrisis	5.229%	2.819%	5.822%	3.921%	5.567%	2.548%	2.917%	1.835%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Δ(PrePost)	-0.035%	0.425%	-0.797%	-0.358%	1.197%	1.214%	-4.638%	0.560%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Brazil								
n	93	166	16	64	59	51	18	51
PreCrisis	3.905%	2.735%	4.299%	3.632%	3.588%	3.394%	4.596%	0.968%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
PostCrisis	3.182%	2.639%	7.205%	2.976%	2.994%	4.335%	0.222%	0.527%
std.error	*0.000%*	*0.000%*	*0.001%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Δ(PrePost)	-0.723%	-0.096%	2.906%	-0.656%	-0.594%	0.941%	-4.374%	-0.441%
std.error	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Sept. 11								
n	70	199	0	87	12	102	58	10
PreCrisis	0.200%	3.410%	n/a	2.458%	0.534%	3.958%	0.131%	5.912%
std.error	*0.000%*	*0.000%*	*n/a*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
PostCrisis	0.087%	2.047%	n/a	1.705%	0.400%	1.965%	0.023%	5.726%
std.error	*0.000%*	*0.000%*	*n/a*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*
Δ(PrePost)	-0.113%	-1.362%	n/a	-0.753%	-0.134%	-1.993%	-0.108%	-0.187%
std.error	*0.000%*	*0.000%*	*n/a*	*0.000%*	*0.000%*	*0.000%*	*0.000%*	*0.000%*

Table 6: Structural Model Distance to Default Estimates

This table shows estimates of the distance to default metric using the asset volatilities and implied asset values from the structural model for each crisis event, averaged across broad exposure classifications and regional locations. For estimating the asset volatilities, the assumed maturity is 1 year, the default barrier is assumed to be demand deposits plus short-term debt, and the average of USD, Euro (German), and Japanese short-term government rates at the crisis date is used as the riskfree rate. Distances to default are computed using the pre- and post-crisis asset volatility estimates, and the implied asset value and linearly interpolated default barrier 3 days before and after the crisis date, respectively.

	All Banks		**Asian Banks**		**European Banks**		**Americas Banks**	
	Exposed	**Unexposed**	**Exposed**	**Unexposed**	**Exposed**	**Unexposed**	**Exposed**	**Unexposed**
Mexico								
n	77	160	13	55	43	57	21	48
PreCrisis	3.157	4.151	3.733	4.434	2.769	4.208	3.598	3.791
PostCrisis	3.113	4.054	3.590	4.415	2.749	3.977	3.548	3.750
ΔPost-Pre	-0.044	-0.097	-0.143	-0.019	-0.020	-0.231	-0.050	-0.041
Asia								
n	89	117	14	47	57	40	18	30
PreCrisis	3.535	4.479	3.508	4.231	3.510	4.944	3.639	4.260
PostCrisis	3.518	4.416	3.454	4.215	3.508	4.832	3.604	4.204
ΔPost-Pre	-0.016	-0.063	-0.054	-0.017	-0.002	-0.112	-0.034	-0.056
Russia/LTCM								
n	83	173	16	64	55	53	12	56
PreCrisis	2.165	3.144	2.028	3.930	2.208	2.942	2.160	2.475
PostCrisis	2.087	3.137	1.946	3.902	2.124	2.899	2.117	2.497
ΔPost-Pre	-0.078	-0.007	-0.082	-0.027	-0.084	-0.043	-0.043	0.022
Brazil								
n	93	166	16	64	59	51	18	51
PreCrisis	2.101	3.211	2.224	4.395	2.028	2.568	2.226	2.401
PostCrisis	2.057	3.204	2.130	4.361	1.958	2.530	2.328	2.425
ΔPost-Pre	-0.044	-0.008	-0.094	-0.034	-0.070	-0.038	0.102	0.024
Sept. 11								
n	70	199	0	87	12	102	58	10
PreCrisis	2.937	3.949	n/a	4.874	2.744	3.225	2.977	2.876
PostCrisis	2.826	3.935	n/a	4.840	2.323	3.203	2.930	2.888
ΔPost-Pre	-0.111	-0.014	n/a	-0.034	-0.421	-0.023	-0.047	0.012

Table 7: Implied Bankruptcy Probabilities from Option Prices of Unexposed Banks

This table reports statistics derived from implied default probabilities (Deltas) from option prices of unexposed banks around financial crisis. Delta estimates are obtained from non-linear least squares estimation of the Câmara (2004) delta-geometric option pricing model. Panel A reports time-series averages of daily cross-sectional averages for different periods before and after each crisis date. T=50 for all but the Asian crisis when T=200. The reported *p*-values are inverse ranks of the average post-crisis values compared with the 100 trading days preceding each crisis date. Panel B reports estimated coefficients and *p*-values from time-series panel regressions with bank fixed effects. The variable Crisis Dummy is equal to 0 for the pre-crisis period ($t<0$) and 1 for the post-crisis period ($t\geq0$). A value significantly greater than zero implies an increase in estimated default probabilities in the post-crisis period. Panel C repeats the regressions in Panel B but includes lagged estimated default probabilities and the model sum of squared errors as control variables. For the Asian crisis the estimation includes 200 trading days before and after each crisis date. For the other crises the estimation includes 50 trading days before and after the crisis date. All estimates use the "broad" exposure definitions except September 11th which uses the "region" definition.

Panel A: Average Estimated Deltas

	Asia	**Russia/LTCM**	**Brazil**	**Sept. 11**
Pre-Crisis (t=-100,..., -1)	1.34%	1.11%	3.08%	2.53%
Post-Crisis (t=0,...,20)	1.10%	2.68%	2.48%	4.28%
ΔPost-Pre	-0.24%	1.58%	-0.60%	1.75%
p-value	0.76	<0.01	0.77	<0.01
Post-Crisis (t=0,...,T)	1.48%	3.38%	2.43%	4.22%
ΔPost-Pre	0.15%	2.27%	-0.65%	1.69%
p-value	0.34	<0.01	0.77	<0.01

Panel B: Time-Series Panel Regression with Bank Fixed Effects

Dependent Variable: Delta(t)		**Asia**	**Russia/LTCM**	**Brazil**	**Sept. 11**
Crisis Dummy	*coef.*	0.17%	2.17%	-1.01%	1.81%
	p-value	<0.001	<0.001	<0.001	<0.001
R-Square		0.237	0.364	0.415	0.434
Number of Unexposed Banks		46	52	50	57
Time-Series Observations		401	101	101	101

Panel C: Time-Series Panel Regression with Bank Fixed Effects and Controls

Dependent Variable: Delta(t)		**Asia**	**Russia/LTCM**	**Brazil**	**Sept. 11**
Crisis Dummy	*coef.*	0.04%	0.88%	-0.23%	0.76%
	p-value	0.010	<0.001	<0.001	<0.001
Control Variables:					
Delta (t-1)	*coef.*	0.713	0.627	0.652	0.566
	p-value	<0.001	<0.001	<0.001	<0.001
SSE	*coef.*	0.0004	-0.0005	0.0044	0.0014
	p-value	<0.001	0.117	<0.001	<0.001
R-Square		0.628	0.622	0.674	0.619
Number of Unexposed Banks		46	52	50	57
Time-Series Observations		401	101	101	101

Appendix A: Crisis Dates and Descriptions

Mexican Crisis - December 19, 1994

On December 19, 1994, the Zedillo administration, in order to supposedly better manage the nation's foreign reserves, instructed the Banco de Mexico (Mexico's central bank) to widen the band for trading pesos with the U.S. dollar from 3.47 to 4.00--a rise of 15.3 percent. Contrary to expectations, this supposedly modest 15 percent devaluation triggered a massive speculative run against the peso as markets concluded that the announced peg could not be maintained. Despite the Central Bank's efforts to defend the peso, foreign financiers and domestic investors, fearing a repetition of the 1982 debt crisis, fled the country. In the ensuing stampede, Mexico lost over $5 billion in international reserves in less than two days. On December 22, the authorities allowed the peso to float freely against the dollar, provoking an immediate additional 15 percent depreciation of the peso. As the financial hemorrhage (now christened the Mexican peso crisis) deepened, it became evident that a contagion, the so-called tequila effect, was beginning to take its toll on neighboring countries and threatening to engulf the entire region. (Source: The Missed Lessons of the Mexican Peso Crisis, by Shalendra Sharma, *Challenge*, Jan, 2001)

Asian Crisis - July 2, 1997

On July 2, 1997, The Bank of Thailand announces a managed float of the baht and calls on the International Monetary Fund for "technical assistance." The announcement effectively devalues the baht by about 15-20 percent. It ends at a record low of 28.80 to the dollar. This is a trigger for the East Asian crisis. In the coming months, additional East Asian currencies come under attack and devalue one by one. (Source: http://www.stern.nyu.edu/ globalmacro/AsiaChrnology1.html)

Russian Crisis - August 17, 1998 and LTCM Crisis - September 2, 1998

On August 17, 1998, the Government of the Russian Federation and the Central Bank of Russia announced the gradual devaluation of the Ruble, the imposition of a repayment moratorium on certain loans to foreigners and the compulsory restructuring of approximately $40 billion of outstanding short term treasury securities. The announcements unsettled financial markets in Russia to a significant degree and led to a rapid decline in the value of the Ruble, a collapse in the value of traded equity stock in Russian companies and the virtual cessation of international fixed income securities offerings by both Russian sovereign and corporate issuers. This led President Yeltsin to remove the reform-minded Government led by Prime Minister Kiriyenko, which precipitated a further decline in confidence in the Russian financial system and further downward pressure on the value of the Ruble. Subsequent actions by the Central Bank and the acting representatives of the Russian Government did little to generate confidence among the investment community that Russia's financial problems could be addressed rapidly. The widening of interest rate differentials between developed and developing market debt caused difficulties for a major US hedge fund, Long Term Capital Management (LTCM). With largely borrowed funds LTCM had speculated extensively in a general narrowing of yield differentials. As markets started to assess the size of LTCM's holdings, rumors of an eminent collapse at a major global bank started to swirl. These rumors are widely believed to have started on September 2nd. Eventually, the Federal Reserve Bank of New York coordinated a bailout of the fund (announced September 23). This along with three cuts in the Federal Funds target rate (on September 29, October 15, and November 17) by the Federal Open Market Committee served to lessen worries of an impending global financial meltdown. (Sources include: Russian Financial Crisis, by Wayne P. J. McArdle, *Thomson FindLaw*)

Brazilian Crisis- January 6, 1999

On January 6, 1999, Itamar Franco, the governor of the influential province of Minas Gerais, announced a moratorium on his state's payments to the central government. Following on the heels of a critical defeat on fiscal deficit reduction, the payment suspension triggered a crisis of confidence in the ability of the Cardoso regime and led to a rapid acceleration in the capital outflows that had already halved the nation's reserves from a level of $70 billion in early 1998. The president of the central bank tendered his surprise resignation, and a week later, in reaction to capital outflows and a diving stock market, Brazil's government devalued the nation's currency, allowing it to fall more than 8%. This devaluation rekindled fears about the country's stability and set off turbulence in financial markets around the globe, primarily due to renewed fears that Brazil's financial difficulties could destabilize other Latin American nations, undermine the rescue efforts of the International Monetary Fund and lead to lower currency values in developing countries. On January 15, the Brazilian government, battered by an outflow of dollars from its foreign reserves, devalued further by lifting exchange-rate controls and allowing the currency to trade freely at market value. The announcement that the central bank would permit market forces to determine the value of its currency came 24 hours after the bank had ruled out such a move -- fearing it would send currency downward in value. However, investors were relieved that Brazil had apparently abandoned its policy of spending dollar reserves to defend its currency against unrestrained selling by speculators who were betting it would fall in value. Brazilian stocks rise by 33% on the news. (Source: Brazil Devalues Its Currency Sending Shock Waves Around The World, *Dollars & Sense*, January 1999, Vol. 4, No.1)

Terrorist Attacks on U.S.- September 11, 2001

Aside from the appalling loss of life and sizable loss of property, one of the most visible effects of the terrorist attacks of September 11, 2001, was the disruption to the workings of the financial system. The destruction of the World Trade Center towers in New York inflicted severe damage on banking and financial institutions in Lower Manhattan; markets closed, participants relocated to backup sites, communications links failed or were unreliable, settlement instructions were lost, payments were delayed, and the Federal Reserve at one point injected more than $100 billion in additional liquidity, an unprecedented sum. At the core of it all was the disruption of interbank payments. Several banks had difficulty processing payment instructions, and the resulting accumulation of large balances drove net balances in the remainder of the banking system negative, necessitating the Fed's huge injections. Problems continued to plague financial markets, in particular the security lending and repurchase market where settlement failures were widespread. Failures to settle various transactions left offsetting payment and security delivery obligations sitting on the balance sheets of market participants, along with the underlying cash or securities that were awaiting delivery, reducing bank capital ratios. In addition, many firms drew on bank lines of credit in response to operational difficulties rolling over commercial paper. On Friday September 14, federal banking regulators issued a Joint Interagency Statement noting that many banks may experience temporary balance sheet growth, and urging banks to contact their regulators should they anticipate a resulting decline in their regulatory capital ratio. The Federal Reserve later issued a Supervisory Letter allowing banks some flexibility in calculating capital ratios for the third quarter of 2001. Bank regulators also encouraged banks to lend to customers ("take prudent steps to make credit available to sound borrowers") affected by the events of September 11. (Source: Payment System Disruptions and the Federal Reserve Following September 11, 2001, by Jeffrey M. Lacker, *Federal Reserve Bank of Richmond working paper*).

Appendix B: Summary Statistics

Table B-1: Summary Statistics of Time Series

The table shows the mean, standard deviation, minimum and maximum of returns on value-weighted portfolios of banks with and without broad exposure and the corresponding market indices. Excess returns are calculated as logarithmic daily dollar returns in excess of the one-day return on the 7-day Eurodollar deposit.

Crisis	Exposure	Variables	Mean	Std Dev	Minimum	Maximum
Mexico 1994	no	Bank portfolio return	0.026	0.701	-2.480	2.410
		Market portfolio return	0.010	0.671	-2.501	2.087
		Bank portfolio excess return	0.011	0.701	-2.497	2.393
		Market portfolio excess return	-0.005	0.671	-2.516	2.071
	yes	Bank portfolio return	0.019	1.129	-3.962	7.078
		Market portfolio return	-0.007	0.779	-3.130	2.617
		Bank portfolio excess return	0.004	1.129	-3.978	7.062
		Market portfolio excess return	-0.022	0.779	-3.146	2.600
Asia 1997	no	Bank portfolio return	0.118	0.811	-4.149	2.718
		Market portfolio return	0.102	0.760	-4.609	3.033
		Bank portfolio excess return	0.103	0.811	-4.164	2.702
		Market portfolio excess return	0.087	0.760	-4.625	3.018
	yes	Bank portfolio return	0.087	1.311	-4.334	6.526
		Market portfolio return	0.068	0.802	-3.255	3.645
		Bank portfolio excess return	0.071	1.311	-4.349	6.510
		Market portfolio excess return	0.053	0.802	-3.270	3.629
Russia 1998	no	Bank portfolio return	0.006	1.364	-4.569	4.373
		Market portfolio return	0.060	1.059	-3.734	3.218
		Bank portfolio excess return	-0.008	1.364	-4.584	4.358
		Market portfolio excess return	0.045	1.059	-3.749	3.203
	yes	Bank portfolio return	-0.014	1.705	-5.818	5.004
		Market portfolio return	0.041	1.080	-3.693	2.942
		Bank portfolio excess return	-0.029	1.705	-5.832	4.989
		Market portfolio excess return	0.026	1.080	-3.709	2.927
LTCM 1998	no	Bank portfolio return	-0.002	1.354	-4.672	3.946
		Market portfolio return	0.028	1.056	-3.785	2.825
		Bank portfolio excess return	-0.017	1.354	-4.687	3.931
		Market portfolio excess return	0.013	1.056	-3.800	2.810
	yes	Bank portfolio return	-0.025	1.786	-5.837	4.869
		Market portfolio return	0.022	1.125	-3.785	3.055
		Bank portfolio excess return	-0.040	1.786	-5.852	4.854
		Market portfolio excess return	0.007	1.125	-3.801	3.040
Brazil 1999	no	Bank portfolio return	0.061	1.352	-4.110	4.897
		Market portfolio return	0.083	1.047	-3.959	3.264
		Bank portfolio excess return	0.047	1.352	-4.126	4.883
		Market portfolio excess return	0.069	1.047	-3.974	3.249
	yes	Bank portfolio return	0.008	1.614	-5.415	4.325
		Market portfolio return	0.053	1.012	-3.709	2.588
		Bank portfolio excess return	-0.006	1.615	-5.430	4.310
		Market portfolio excess return	0.039	1.012	-3.724	2.573
Sept. 11	no	Bank portfolio return	-0.045	1.016	-5.425	3.943
		Market portfolio return	-0.048	0.982	-5.293	3.129
		Bank portfolio excess return	-0.053	1.017	-5.475	3.936
		Market portfolio excess return	-0.057	0.983	-5.352	3.124
	yes	Bank portfolio return	0.025	1.198	-4.692	5.124
		Market portfolio return	0.004	1.096	-4.830	3.956
		Bank portfolio excess return	0.017	1.199	-4.745	5.116
		Market portfolio excess return	-0.004	1.097	-4.889	3.948

Table B-2: Pearson Correlation Coefficients of Exposures

The table shows the Pearson correlation coefficients between country exposures (Panel A), region exposures (Panel B) and broad exposures (Panel C) across different crises. A, b, and c refer to the 1%, 5%, and 10% significance level, respectively.

Panel A: Correlations of Country Exposures

	Mexico 1994	Asia 1997	Russia 1998	LTCM 1998	Brazil 1999
Asia 1997	42.5[a]				
Russia 1998	42.7[a]	60.2[a]			
LTCM 1998	38.1[a]	34.7[a]	41.7[a]		
Brazil 1999	57.0[a]	63.0[a]	81.0[a]	37.4[a]	
Sept 11	26.9[a]	19.0[a]	16.2[a]	43.9[a]	15.6[a]

Panel B: Correlations of Region Exposures

	Mexico 1994	Asia 1997	Russia 1998	LTCM 1998	Brazil 1999
Asia 1997	52.5[a]				
Russia 1998	48.5[a]	65.3[a]			
LTCM 1998	43.9[a]	60.1[a]	96.1[a]		
Brazil 1999	63.1[a]	63.7[a]	73.6[a]	70.4[a]	
Sept 11	20.1[a]	20.9[a]	20.0[a]	23.4[a]	16.8[a]

Panel C: Correlations of Broad Exposures

	Mexico 1994	Asia 1997	Russia 1998	LTCM 1998	Brazil 1999
Asia 1997	69.4[a]				
Russia 1998	61.4[a]	74.3[a]			
LTCM 1998	42.3[a]	58.8[a]	74.1[a]		
Brazil 1999	64.8[a]	74.4[a]	89.9[a]	65.1[a]	
Sept 11	-8.9	-11.2[b]	-16.3[a]	-8.3	-14.6[a]

Appendix C: Structural Model Estimation Methodology

Recall that under the Merton (1974) model, the firm's asset value V_t evolves according to the diffusion:

$$dV_t = \mu V_t dt + \sigma_V V_t dW_t \tag{1}$$

with expected return, μ, and volatility, σ_V, both unobserved. The equity value of the firm at time t is denoted by S_t, and the firm's (zero-coupon) debt has face value F, maturing at T, and with value $D_t(\sigma_V)$ at time t, where the functional dependence of the risky debt value is made explicit. The following accounting identity holds at all times:

$$V_t = S_t + D_t(\sigma_V). \tag{2}$$

Note that this directly implies that given a functional form under the model for the risky debt value D_t, S_t is an invertible function of V_t for any σ_V. Under the Merton model, the debt value is:

$$D_t(o_V) = Fe^{-r(T-t)}\left(\frac{V_t}{Fe^{-r(T-t)}}\Phi(-d_t) + \Phi\left(d_t - \sigma_V\sqrt{T-t}\right)\right) \tag{3}$$

$$d_t = \frac{\ln(V_t) - \ln(F) + \left(r + \frac{1}{2}\sigma_V^2\right)(T-t)}{\sigma_V\sqrt{T-t}} \tag{4}$$

And therefore the key functional relationship for the equity value is:

$$S_t = g(V_t; t, \sigma_V) = V_t\Phi(d_t) - Fe^{-r(T-t)}\Phi\left(d_t - \sigma_V\sqrt{T-t}\right), \tag{5}$$

which can be solved for any fixed t and asset volatility, σ_V, for the implied firm value, v^*. Finally, we note that the probability of default under the actual measure, is given by:

$$P_t = \Phi\left(\frac{\ln(F) - \ln(V_t) - \left(\mu - \frac{1}{2}\sigma_V^2\right)(T-t)}{\sigma_V\sqrt{T-t}}\right). \tag{6}$$

In order to derive the likelihood function, suppose that we observed the asset values, *v*, of a firm with a constant face value of debt over a sample period of size *N* with a time step of *h*.[24] That is, the hypothetical observed asset value sample up to *t* is denoted $\{v_0, v_h, v_{2h}, v_{3h}, \ldots, v_{Nh}\}$ with $t = Nh$. Since the conditional distribution of the observed asset values is log-normal, the log-likelihood function is

$$L\left(v_0, v_h, v_{2h}, \ldots, v_{Nh}; \mu, \sigma_V\right) = -\frac{N}{2}\ln\left(2\pi\right) - \frac{N}{2}\ln\left(\sigma_V^2\right)h - \sum_{k=1}^{N}\frac{w_{kh}^2}{2\sigma_V^2 h} - \sum_{k=1}^{N}\ln v_{kh}$$
$$w_{kh} = \ln\left(\frac{v_{kh}}{v_{(k-1)h}}\right) - \left(\mu - \frac{1}{2}\sigma_V\right)h \tag{7}$$

However, we observe only the equity values $\{s_0, s_h, s_{2h}, s_{3h}, \ldots, s_{Nh}\}$ with $t = Nh$. These values are related directly to the unobserved asset values by equation (5). Thus we can express the likelihood function of the sample equity values as the product of the asset value likelihood and the Jacobian of the transformation $S_t = g\left(V_t; t, \sigma_V\right)$. The log-likelihood is:

$$L\left(s_0, s_h, s_{2h}, \ldots, s_{Nh}; \mu, \sigma_V\right) = -\frac{N}{2}\ln\left(2\pi\right) - \frac{N}{2}\ln\left(\sigma_V^2\right)h - \sum_{k=1}^{N}\frac{w^{*2}_{kh}}{2\sigma_V^2 h} - \sum_{k=1}^{N}\ln v^*_{kh} - \sum_{k=1}^{N}\ln\Phi\left(d^*_{kh}\right)$$
$$w^*_{kh} = \ln\left(\frac{v^*_{kh}}{v^*_{(k-1)h}}\right) - \left(\mu - \frac{1}{2}\sigma_V\right)h$$
$$v^*_{kh} = g^{-1}\left(s_{kh}; kh, \sigma_V\right)$$
$$d^*_{kh} = \frac{\ln\left(v^*_{kh}\right) - \ln\left(F\right) + \left(r + \frac{1}{2}\sigma_V^2\right)\left(T - kh\right)}{\sigma_V\sqrt{T - kh}} \tag{8}$$

Given parameters for *F*, *r*, and *T* (obtained from balance sheet data and interest rate markets) and equity values, we maximize Equation 8 to obtain estimates of the unobserved asset drift and volatility. These estimates both pre- and post-crisis are then used to compute the change in default probabilities.

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[24] Typically, the value of *h* for daily data would be 1/250.