Testing for East-West Contagion in the European Banking Sector during the Financial Crisis*

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October 2010

Abstract

With the significant increase in foreign presence in Eastern Europe, linkages across European banking systems have grown markedly. This paper aims at identifyng potential risk of cross-border contagion using a sample of large Western and Eastern European banks. We assume that contagion risk is associated with extreme co-movements in a market-based measure of bank soundness, controlling for underlying common factors. We find evidence that contagion risk across European banks heightened significantly during the recent crisis. Contagion among Western European banks with the highest market share in Eastern Europe and from this group to Eastern European banks shows the largest increase in our sample. We find also evidence of contagion spreading from Eastern European banks, but this effect seems to reflect a broader phenomenon of contagion from emerging markets to banks in advanced countries exposed to these markets.

JEL classification: G21, G15, C12.

Keywords: Banking contagion, Distance to default, Testing hypothesis, Logit model.

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*We thank Mardi Dungey, Massimo Sbracia, Demosthenes Tambakis and Melvyn Weeks for helpful comments. Part of the work was carried out while one of the author was visiting University of Cambridge. The views expressed in this paper are those of the authors and do not necessarily reflect those of the Bank of Italy.

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1 Introduction

Contagion is widely perceived to be an important element of banking crises and systemic risk. With the significant increase in foreign presence in Eastern Europe (EE),[1] interlinkages among Western and Eastern European banking systems have grown markedly. Large and growing international financial linkages have raised susceptibility to contagion for the host countries, as well as the home countries of the foreign banks active in many EE countries. This paper is intended to contribute to a better understanding of the degree to which European banking systems have become interconnected and how banking problems could spread across borders. In particular, its aim is to identify potential risk of cross-border contagion among the banking sectors of Western and Eastern European countries, using information captured in banks' stock prices and financial statements.

We use the *distance to default* as a comprehensive measure of a bank's default risk. Being a market-based measure of distress, the distance to default has the advantage of including the expectations of market participants and therefore it is forward looking. Moreover, information from security prices helps to deal with data limitations and imperfect knowledge about indirect exposures across financial institutions, connected, for example, to the use of similar investment strategies.

We assume that *contagion risk* is associated with extreme co-movements in banks soundness and we focus on the behavior of the left tail of the distribution of the change in the distance to default. More specifically, we estimate the probability of one bank experiencing a large negative shock following large negative shocks in other banks in the sample, after controlling for common (country specific and global) factors.

We use a dataset of daily distance to default of 33 European listed banks. Our data sample comprises most of the largest banks operating in Eastern Europe, the Western European banking groups which, through their branches and subsidiaries, own the highest market share in the EE banking systems and the remaining largest, and globally systemic, European banking groups.

The approach applied in this paper builds on a recent body of literature which uses a similar methodology to estimate cross-border contagion (Chan-Lau, Mitra and Ong, 2007, Čihák and Ong, 2007, Gropp, Lo Duca, Vesala, 2010). We extend previous research on the transmission of shocks among banks and banking systems in the following directions:

1) We test for contagion risk among banks in EE and the largest Western European banking groups, some of which operate in Eastern Europe. To our knowledge, this is the first comprehensive attempt to measure contagion

[1] In the paper with EE we refer to the new EU member states of Central and Eastern Europe (excluding Slovenia), along with Croatia, Russia, Serbia and Ukraine.

among banking systems in the two regions.

2) We provide new evidence of how contagion risks in European banking systems evolved in the recent global financial crisis (i.e. after the summer of 2007).[2]

3) We introduce a test to evaluate whether changes in contagion effects across time and regions are significant.

4) To control for broader contagion from emerging markets, we carry out a counterfactual experiment, comparing our model's results to those obtained substituting a sample of Latin American banks to the Eastern European one.

The remainder of the paper is organized as follows. The next Section describes various potential sources of contagion between Western and Eastern European banking systems. Sections 3 and 4 discuss the methodology and the input data. Section 5 shows estimation results and discusses a few issues related to the robustness of our findings. Finally, Section 6 concludes the paper.

2 Potential Sources of Contagion between Western and Eastern European Banking Systems

In this paper the term contagion is taken to mean the transmission of an idiosyncratic shock affecting one bank to other banks or banking sectors. Defined in this way, contagion is included in the broader concept of a systemic crisis, which may be the result of either contagion or common shocks affecting all banks symmetrically and simultaneously. There exist several avenues through which a bank failure may spread to other banks, as contagion may result from direct linkages connecting banks or informational externalities (for a survey of the theoretical literature see Moheeput, 2008, and Allen, Babus and Carletti, 2009).[3]

Direct linkages may take the form of contractual arrangements, such as the cross-holding of deposits or loans in the interbank market. Interbank exposures may create problems if aggregate liquidity provision is insufficient and banks try to avoid liquidation of their long-term assets liquidating their claims on other banks (possibly in other regions). A financial crisis in one region could then spread by contagion to other regions and thereby introduce liquidity problems in the latter. Without interlinkages between banks operating in different regions, the financial crisis would not spread between regions (Allen and Gale, 2000). Direct linkages may also take less explicit

[2] Lucey and Ševic (2009) carry out a similar analysis but only up to October 2008.

[3] Empirical research in this field largely focuses on testing for the existence of contagion and to a lesser extent on estimating the different channels through which shocks propagate. Dungey et al. (2005) provide a review of alternative methods to test for the presence of contagion.

forms, such as those arising from payments and settlements infrastructures, asset prices or common investors.

Informational spillovers through market expectations represent a second potential channel for contagion. For example, if banks' fundamentals are believed to be correlated, bad news on one bank may lead investors in another bank to change their perception of its soundness. This may be the case of banks sharing similar business and geographic strategies or operating in the same region. In Archarya and Yorulmazer (2008) the return to bank loans has two components, a systematic component and an idiosyncratic component, and depositors can only observe the overall realisation of bank loan returns, but not the actual decomposition. Hence, a banks' poor performance spills over into other banks' borrowing costs.

Since the beginning of the decade banking systems in EE have been closely integrating with the rest of Europe. Currently, most EE economies are highly dependent on Western European banks, either directly, via cross-border credit extended by headquarters to bank and non-bank residents in the region, or through the activity of local branches and subsidiaries. According to BIS data, at end-2008 outstanding consolidated foreign claims (cross-border claims and local claims of foreign affiliates) on non-banks were equivalent, on average, to about 42 per cent of total cross-border and domestic credit to non-banks in EE, even though the magnitude of the exposure varied significantly across countries. Austria, Germany, and Italy accounted for the largest share of foreign claims on the region as a whole, with the notable exception of the Baltics, where claims were mainly held by Swedish banks. A few EE economies had relatively more diversified sources of funds (Table 1).

The high exposure of EE banking systems reflects the strong presence of foreign intermediaries in domestic markets, as the share of foreign owned banks account for the bulk of the banking system assets in many countries. Moreover, given the high degree of foreign ownership, and the relatively undeveloped state of domestic capital markets, banks in EE have been increasingly relying on external funding sources (mostly syndicated loans or parent support) to finance their operations. On average, cross-border claims on banks in EE were equivalent to 17 per cent of total banking liabilities at the end of 2008, but for some countries foreign funding played a bigger role, in particular in the Baltics, in Romania and, to a lesser extent, in Bulgaria, Croatia, Hungary and Slovakia.

For EE subsidiaries the importance of funding in wholesale international interbank markets is generally small if compared to parent bank financing and syndicated lending, since the latter source of funding is more expensive for the subsidiary, given the risk premia and counterparty risks. Therefore, the wholesale interbank market does not seem to be a major channel of cross-border contagion in the case of EE banks, even though it may be not negligible in some banking systems, for instance in Russia (Árvai, Driessen and Öcker-Robe, 2009).

Banking systems that are heavily dependent on foreign funding may face a shortfall of (or more costly access to) funds in case of a sudden reassessment of exposure to the host country due to concerns about vulnerabilities in that country or in the region. Moreover, while reputational risks and long-term business strategy may make it unlikely for parent banks to withhold support of their affiliates, the degree of their support depends on funding conditions in home markets, and may be limited if these conditions have become strained.

Problems in a host country may also result in liquidity or solvency pressures for the home country banking system, provided that the exposure to the former is substantial. The magnitude of foreign exposure of Western European bank to withhold is on average contained. The share of claims on EE was about 4 per cent of total banking assets in home countries at end-2008. This share was higher for Austria, Sweden and Belgium, while the other countries were less exposed. However, aggregate country-level data may blur relevant linkages across individual banks. In fact, a relatively small set of Western European banking groups have been taking advantage of the high growth potential offered by EE markets, developing a multiple-country presence in the region and acquiring a significant market shares in a number of countries (Table 2). For some of these groups, operations in EE account for a substantial share of their profits as well as of their assets, implying that they could be negatively affected by adverse developments in this region (Figure 1). As these groups have in some cases a systemic relevance in Western European markets and, at the same time, are exposed to several EE countries, a shock affecting one EE country may spread in many directions through these institutions. Indeed, the concentration of the business among few large and niche players may have an ambivalent effect on financial stability, as the failure of a particular market participant may affect others more severely and with a greater probability. It does not only impose losses on other institutions, but it can also create doubts about the health of other institutions. In order to analyse these potential sources of contagion, our research relies on a bank-to-bank approach, differently from other empirical papers (e.g. Van Rijckeghem and Weder, 2001).

3 Methodology

3.1 Measure of default risk

We use the *distance to default* as a comprehensive measure of a bank's default risk. The distance to default is the number of standard deviations that separates the bank's asset value from the book value of its liabilities (Crosbie and Bohn, 2003). A greater distance to default is associated with a lower probability of distress. Gropp, Vasala and Vulpes (2006) argue that the distance to default is a complete and unbiased (from a supervisory perspective) indicator of bank fragility, because it combines information about market value of assets, earnings expectations, leverage and volatility of assets, thus encompassing the most important determinants of bank default risk, and is not affected by the potential incentives of the stock holders to prefer increased risk taking (unlike e.g. in the case of unadjusted equity returns) or by the presence of explicit or implicit safety nets (unlike e.g. subordinated debt spreads). They show that the distance to default is a good predictor of banks' rating downgrades in developed countries, even though its predictive performance is poorer when closer to default[4].

Alternatively, probabilities of default derived from Credit Default Swap (CDS) spreads might as well be used as a measure of bank's distress risk (Goodhart and Segoviano, 2009). However, CDS are not available for most of the Eastern banks included in our sample. In fact, banks in Eastern Europe do not generally issue bonds, so contracts protecting against the default of these obligors are scarcely required.

The derivation of the distance to default (DD) is described in detail in Gropp, Lo Duca and Vasala (2006) and in Chan Lau, Mitra and Ong (2007). Here, we recall it shortly. The distance-to-default (DD) measure is based on the structural valuation model of Black and Scholes (1973) and Merton (1974). As equity holders are residual claimants in the firm since they only get paid after creditors, equity can be expressed as a call option with strike price equal to the face value of debt D and maturity T. At expiration, the value of equity, E_T, is given by:

$$E_T = \max(A_T - D_T, 0)$$

where A_T is the asset value of the firm at expiration.

Given the standard assumptions underlying the derivation of the Black-Scholes option pricing formula, the DD in period t for the horizon of T years is given by the following formula:

$$DD_t = \frac{\ln(\frac{A_t}{D_t}) + \left(r - \frac{\sigma_A^2}{2}\right) T}{\sigma_A \sqrt{T}}$$

where r is the risk-free rate and σ_A is the asset volatility. Default occurs when the value of the firm's assets is less than the strike price, that is, when the ratio of the value of assets to debt is less than one. The DD is essentially

[4] Chan-Lau, Jobert and Kong (2004) find analogous evidence in emerging market countries. The distance to default has become part of the set of analytical tools in financial stability reports, such as the IMF's Global Financial Stability Report and ECB's Financial Stability Review.

the number of standard deviations that the firm value is from the default point.

Calculating DD requires knowing both the asset value and the asset volatility. The required values, however, correspond to the economic values rather than the accounting figures. In practice assets value and volatility are not observable and must be estimated solving a system of simultaneous equations,[5] using the observable market value of equity capital and the equity price return volatility.[6]

To measure contagion, we concentrate on extreme co-movements, rather than examining statistical interdependence for the entire distribution,[7] as the transmission process of shocks across banks may be nonlinear and looking at interdependencies in the tails of the distribution allows the examination of these nonlinearities, as well as a relaxation of the assumption of multivariate normality, which in the case of fat-tailed financial market data tend to be violated (De Bandt and Hartmann, 2001; Straetmans, 2000). Gropp and Moerman (2004) show that not only that the distribution of distances to default of individual banks exhibits fat tails, but also that the correlation among banks' distances to default is substantially higher for larger shocks. Bae, Karolyi, and Stulz (2003) do the same for emerging-market stock returns. Both papers suggest that it is necessary to examine the tails of the distribution of returns or the distance to default separately from the overall distribution.

For these reasons, in the paper we focus on the tail of the distribution of percentage changes in distance to default, in the spirit of "extreme value theory". In particular, we consider the probability that one bank is in the negative tail of the distribution, given that other banks are in the negative tail as well.

[5] To get daily time series of DD for each bank, we have to solve a non-linear system, which also implies the computation of the cumulative normal distribution. We approximated the normal distribution with a high-order polynomial, following Gapen et al (2008), and we implemented a routine in MATLAB to solve the nonlinear equations.

[6] The value of equity capital corresponds to the market capitalization of the firm, equity volatility corresponds to historical equity volatility. In our case, we drew from Datastream and Bloomberg daily market value for each bank starting from 1 January 2002 and we computed 1-year historical equity volatility as $\sigma_E = \sqrt{252*}\sigma_d$,where σ_d is the standard deviation of daily returns in the previous year, to reduce noise. The last parameter, the value of liabilities, D, is assumed equal to the face value of total liabilities and the time horizon T is fixed at one year. We calculate D from yearly balance-sheet data; then we interpolate them linearly in order to get a daily estimate. In alternative, in the literature D is sometimes assumed equal to the face value of short-term liabilities plus half the face value of long-term liabilities.

[7] Interdependencies of financial returns have been traditionally modelled based on correlation analysis (De Bandt and Hartmann, 2001). However, correlation is a measure of dependence in the centre of the distribution, which gives little weight to tail events (i.e., extreme events) when evaluated empirically. Since distress is characterized as a tail event, correlation may not be an appropriate measure of distress dependence when marginal distributions of financial assets are non-normal (Goodhart and Segoviano, 2009).

We calculate the weekly (5 trading-day) changes in the DD (ΔDD), on a daily basis, as we assume that extreme events are more significant if they are prolonged, while events that last for only a day are of little concern. In addition, the use of weekly changes reduces "noise" in the data.[8] We identify extreme values or large shocks as the 15^{th} percentile left tail of the common distribution of the ΔDDs across all banks in each sub-period.[9]

The large negative shock (*exceedance*) for each bank at time t is thus modelled as a binary variable, y, such that:

$$y = \left\{ \begin{array}{c} 1\ if\ \Delta DD \succeq T15 \\ 0 \text{ otherwise} \end{array} \right\}$$

where T15 is the 15^{th} percentile threshold in the left tail of the distribution.

In order to derive a feasible distribution of exceedances, we use the empirical distribution of percentage changes in DD (ΔDD) of all banks in our sample.

3.2 Empirical Model

In order to identify contagion effects and the direction of contagion from one bank to others, we employ a binomial logit, following Chan-Lau, Mitra and Ong (2007).

More specifically, we estimate the conditional probability that bank y will be in distress at time t conditional on other banks $x_i (x \neq y)$ being in distress at time $t-1$, after controlling for other country-specific and global factors z_j. For each bank, we run the following regression:

$$\Pr(y_t = 1 \mid x\beta) = \frac{\exp(\alpha_t + \sum_{s=1}^{5} \beta_s y_{t-s} + \sum_i \pi_i x_{it-1} + \sum_{j=1}^{4} \gamma_j z_{jt})}{1 + \exp(\alpha_t + \sum_{s=1}^{5} \beta_s y_{t-s} + \sum_i \pi_i x_{it-1} + \sum_{j=1}^{4} \gamma_j z_{jt})}$$

The parameters β represents the sensitivity of bank y to extreme shocks (exceedances) experienced by the same bank in the previous periods (up to 5

[8] Daily data also contain a lot of bid-ask bounce and non-synchronous trading effects (e.g. see Karolyi and Stulz, 1996).

[9] The same threshold is used in Duggar and Mitra (2007). Ideally, a 10^{th} or even 5^{th} percentile left tail would capture the very extreme events; however, either cut-off would have resulted in much too few observations for estimations in the second part of this paper, when we consider a shorter time span to study the effect of crisis on contagion mechanism. We have checked that our estimates are robust to the choice of a lower threshold; Tables 12 and 13 show that considering only the 10^{th} percentile left tail differences from the baseline are in general not statistically significant, with the notable exception of contagion among EE banks.

lags[10]); π represents the sensitivity of bank y to extreme shocks experienced by the rest of the banks in the sample during the previous period ($x_i \neq y$) or in other words, the *co-exceedance* of shocks to bank y with shocks to other banks in the sample;[11] γ represents the sensitivity of bank y to "common shocks" z_i, i.e. financial developments in its own country as well as in global markets. All control variables are also transformed in binomial 1/0 variables (following a similar procedure used for the DDs) so that only extreme common shocks are identified (see, for instance, Boyson et al., 2010). Control variables are considered exogenous and therefore included at time t.[12]

3.3 Mapping risk and testing for cross-border contagion

The focus of our analysis is not on the specific nature of linkages between individual banks *per se.* Rather, we are interested in the risk that an individual bank failure turn into a chain of failures and, potentially, in a systemic crisis. Therefore, starting from a bank-to-bank perspective, we try to map these risks across European banking systems. For this reason, we prefer a time series approach to a panel one. A panel analysis, carried out in few papers (Van Rijckeghem and Weder, 2000, Baur and Fry, 2006 and 2009) has the notable advantage of better accounting for common factors underlying shock transmissions, but on the other hand, it only provides evidence of the average contagion within the sample. Instead, we are interested in measuring differences in the intensity and direction of contagion, depending on the source of shocks and the banks affected.

We carry out separate logistic regressions for each single bank in the sample and for each period. Then, we summarize our results to measure contagion among different subsets of banks, collecting the significant (positive) coefficients in individual regressions and grouping them by each subset.[13]

As the maximum number of significant coefficients depends on the number of banks in each subset, we measure contagion as the percentage of

[10] We include five lags of the dependent variable in order to control for any autocorrelation in the residuals that may be induced by the use of overlapping weekly changes in the DD.

[11] As only one lag *co-exedancees* are included, we may miss those cases of contagion taking place within one day that would occur if financial markets are efficient and incorporate information very quickly (Gropp, Lo Duca, Vesala, 2006). On the other hand, potential simultaneity biases arising from the presence of endogenous variables suggest the use of lagged variables. As shown in Pesaran and Pick (2007), using contemporaneous regressors in this kind of models is likely to bias upward the measure of contagion.

[12] Details on data and sources can be found in section 4.

[13] This is basically a meta-analysis' approach, which aims at measuring the effect of a variable on another within a specific model/relationship by collecting results from different studies (in our case estimates) and testing for the significance of their overall effect, generally comparing the mean of an experimental group to that of control group. See for instance Rosenthal, R. (1991), *Meta-Analytic Procedures for Social Research.*

positive and significant coefficients π_i^+ out of all coefficients (regressors) π_i in the subset, that is, positive significant *contagion* effects are expressed as percentage of all possible bank *contagion* effects, where possible cases are computed as the sum of all bank-to-bank coefficients in each set of regressions:

$$\frac{\sum_i \pi_i^+}{\#(\pi_i \; coefficients)}$$

Finally, in order to compare differences in contagion effects both across subsets and over time, we carry out a specific test for these percentages. The significance of a variable in a regression can be considered a dichotomous Bernoulli random variable (yes/no). The number (sum) of significant effects or their proportion, assuming that each variable is independent and identically distributed, is then a binomial distribution.[14] Assuming independence between two random variables, a commonly used statistic for testing the difference of proportions is given by $Z = \frac{p_1 - p_2}{V(p_1 - p_2)}$, where $V(p_1 - p_2)$ is the estimated variance of the difference $V(p_1 - p_2) = p_1(1- \; p_1)/n_1 + p_2(1- p_2)/n_2$.

Although this distribution is no longer binomial, we can reasonably use the normal approximation, which is acceptable for n large enough and p far from zero.[15] Equipped with this simple tool, we can test the significance of contagion among groups of banks and evaluate the differences over time, before and during the crisis.[16]

We also carried out McNemar's test, a testing procedure used when the two proportions p_1 and p_2 are correlated (Sheskin, 2007). As expected, all our results are confirmed with a higher probability.[17]

[14] Let x_1 be the number of significant *co-exceedances* and n_1 the number of regressors in a first group of banks. Then $p_1 = \frac{x_1}{n_1}$, the proportion of significant *co-exceedances,* has a binomial distribution with mean p_1 and variance $p_1(1- \; p_1)$. Similarly, the proportion of the significant *co-excedances* in a second group of regressions has a binomial distribution with mean p_2 and variance $p_2(1- \; p_2)$.

[15] A simple rule of thumb is np and n(1-p) > 5, a condition met in our case. See for instance Sheskin, 2007.

[16] We are assuming that significant coefficients are mutually independent from each other. This cannot be the case, however, because coefficients come from regressions which have common regressors. This hypothesis is not restrictive, though, as the test in case of dependent samples would be more powerful at detecting a significant difference in the samples (alternative hypothesis). Hence, our approach can be seen as conservative towards the null hypothesis of no difference in the samples.

[17] This test is feasible when the two samples are made up of the same units and so we applied it to differences over time. It cannot be used for cross-group comparisons.

4 Data and descriptive statistics

Our sample is composed of 33 listed European banks. The number of banks included in the sample is the result of a selection based on the need to keep the time span sufficiently long and, at the same time, to pick up most of the largest banks operating in EE.[18] The data sample is divided in three subsets. The first one (EEB) is composed of the largest Eastern European banks listed in a stock exchange and with available stock prices data from January 2003 to March 2009 (Table 3). According to these criteria, we have left out all banks in Serbia and Ukraine (as stock prices data are available only since 2006), Estonia (as there are no listed banks) and Latvia (as these banks were in the lower end of the size ranking). The sub-sample of EE banks is composed of 15 banks, including the two largest independent groups in the region (Sberbank and OTP) and 10 subsidiaries of banking groups with headquarters in advanced economies, 5 of which are included in our sample of Western European groups. The other two sub-samples (Table 4) are made up of the 9 Western European banking groups with the highest market shares in the EE banking system (SWG), provided they are listed in a stock exchange over the entire period under analysis, and the 9 remaining largest European banking groups (OWG).

In order to control for shocks affecting the local economy and global markets, we use four variables, drawing on the existing literature on financial crisis and contagion. We include the local stock market weekly returns to control for country-specific market shocks, the MSCI world price index weekly returns to control for global market shocks, the weekly percentage changes in the implied volatility index (VIX), reported by the Chicago Board Options Exchange, as a proxy of shocks to investors' risk appetite, and the weekly percentage changes in spreads between the three-month U.S. Treasury Bill interest rate and the three-month LIBOR (TED spread), as a proxy for shocks to global funding conditions. In the regressions, control variables are considered exogenous and are included at time t, except for the VIX, which is lagged by one period, to take into account the difference in trading hours between the US and Europe.

After computing banks' DD, we derive the percentage changes in DD and identify extreme negative values in the ΔDDs of individual banks across the sample in two periods, defined as January 1, 2003-July 31, 2007 (*calm period*) and as August 1, 2007-March 31, 2009, the latter starting with the global liquidity squeeze associated with the pressure in the U.S subprime market and dubbed the *crisis period*.[19]

[18] As highlighted by Chan Lau et al. (2007), including smaller-non systemic banks could have the effect of overestimating the impact of certain banking systems on others.

[19] The end of March 2009 is generally considered the turning point of the crisis in financial markets. In particular financial markets in emerging market countries bounced back quite quickly from the lowest levels after that time.

Figure 2 presents the distribution of ΔDDs (we have 39,435 observations in the first period and 14,355 in the second period) and the 15th percentile left tail. As expected, the distribution is not normal, with fat tails which include few extreme values. Moreover, in the *crisis period* there is a shift of the distribution to the left.

Figure 3 shows the number of banks experiencing an extreme negative shock at time t, that is the number of *exceedances* at each date. Looking at the histograms, it is quite evident that tail events in the first sub-period are more evenly spread, while in the *crisis period* they are mostly concentrated in three episodes, and in particular after the collapse of Lehman Brother in September 2008.

By construction, *exceedances* occur in 15% of all observations in each sub-period. For each sub-set of banks, however, the frequency of *exceedances* may differ. In the first period, *exceedances* are relatively more frequent among EE banks than among SWGs and OWGs (respectively, 18%, 13% and 12% of all observations in each group). This pattern reversed during the crisis, with a prevalence of *exceedances* among SWGs and OWGs compared to EE banks (20%, 18% and 10%, respectively).

These figures are useful to shed some light on how the frequencies of *exceedances* evolve, given the occurrence of at least one shock (i.e. an *exceedance)* in our sample in the previous period. In particular, if there were not contagion, these frequencies should not be affected by the presence of shocks occurred in the previous period. The ij^{th} entry of Table 5b shows the (conditional) probability of observing at least one shock to a bank in group j in column at time t, given that at least a shock has occurred in a bank in group i in row at time $t-1$.[20] In both periods, conditional probabilities are much higher than unconditional ones, indicating that shocks tend to spread across banks and regional boundaries. Moreover, shocks seem to be persistent: the probability of a shock continuing much higher than the probability of observing shocks on two consecutive periods if these were independent. For example, in the calm period the empirical probability that a shock in SWG continues is 23%, which is more than 10 times as large as the probability of two consecutive shocks in the same group (0.13*0.13=1.69%). Finally, conditional probabilities in the crisis period are higher and in some case more than double compared to the calm period, with the notable exception of shocks to EEB, which remain broadly unchanged in the two periods.[21]

The fact that the probability of a shock tends to increase following a previous shock in another bank indicates that shocks disseminate and may

[20] This kind of analysis goes back to Kaminsky and Reinhart (2000). See Markwat, Kole van Dijk (2009) for details.

[21] Symmetrically, we construct the transition matrix of shocks at time t under the circumstance of absence of shocks at time $t-1$ (Table 5a). As expected, in both sub-periods shock probabilities are much lower than in the presence of shocks in the previous period, and in most cases are lower than unconditional probabilities.

bring about more severe effects over time. However, this preliminary analysis may overestimate contagion, as exceedances could be the result of common shocks affecting several banks at once (such as deteriorating liquidity conditions, shifts in investors' risk aversion, etc.) and for which we do not control for. In addition, probabilities are conditioned on a group of banks at a time, thus assuming independence from the third group of banks left out. Finally, for each group of banks, exceedances are summed over time and across banks, neglecting the fact that they are linked over time by their coming from different time series, one for each bank. We take into account all these aspects by modelling probability of contagion in a logit model.

5 Estimation Results

As stated above, we run 33 regressions in each period. From each equation we collect the significant (positive) coefficients, out of all 1,056 coefficients, and we tabulate them by sub-sample of banks and sub-period in Table 6 (*baseline model*).[22][23]

In the *calm period* (left-hand side of Tables 6), there is some evidence of contagion among all the three groups of banks.[24] This matches with the preliminary evidence we have drawn from the analysis of the transition matrix, where the transmission of extreme negative shocks across banks is not negligible even in the calm period. Moreover, considering the sample as a whole, no subset of banks stands out as a source of contagion, as shown by the percentages in the last column (All banks).

Looking at evidence of contagion for SWGs, it does not appear to be a specific source of contagion from both EEB and SWG groups, respectively, due to linkages between the two groups or similar geographic investment strategies. This result seems to be at odds with the strong presence in EE of the specialized banking groups in our sample. A possible explanation is that, at the beginning of the time span considered in our analysis, the weight of EE in SWGs' strategies was fairly modest. More importantly, the calm period was largely characterized by a very strong economic growth in EE countries, and banks operating there made sizable profits without carrying any relevant risk.

[22] As only positive coefficients are considered, we use one-side t-test at 5% significance level. Standard errors are Huber/White robust. Regressions are available upon request.

[23] Table 7 summarizes the results on the statistical significance of control variables (percentage of significant coefficients). Local market shocks show the highest proportion of significant coefficients for both EEB and SWG groups. The significance of global funding conditions strongly increased in the crisis period, especially for OWGs. However, as global banks' performance and strategies influence global financial conditions, the increase of significant common factors may reflect an endogeneity problem (Pesaran and Pick, 2007).

[24] Percentages of co-exceedances are all different from zero at conventional levels (results available upon request).

By contrast the other sub-sample of large European banks (OWG) shows a relatively high level of contagion coming from banks within the same subset.

EEBs look relatively prone to contagion only from the same group.

Summing up, before the crisis contagion risk appears to be concentrated mainly among the largest Western European banking groups.[25] In the period of eased financial conditions and solid economic growth up to the summer of 2007, spillovers across banking systems in Western and Eastern Europe were contained. In particular, groups investing in EE were less affected by risks in their operation in the region, possibly as, owing to the stable and high returns realized in these banking markets, the market reaction to negative news was more subdued.

This pattern, however, changed following the outburst of the international financial crisis.

Our results for the *crisis period* are summarized in the right-hand side of Tables 6. In addition, in Table 8 we show the results of a test of significance of the differences in contagion risks between the crisis and the calm periods.

The main results are summed up below.

Overall, there is a more than twofold increase in contagion risk in our sample compared to the calm period (from 9.8 to 20.9% of significant *co-exceendances* on average). Contagion effects rise for all bank groups, *within* each subset and *between* each pair of subsets. The only exception is the risk of contagion *within* OWG, which is lower in the crisis period compared with the calm period, even though the difference is not statistically significant.[26]

During the crisis, contagion among SWGs, and from them to EEB, tripled. Also contagion among EEBs and from EEBs to SWGs increased notably. Therefore, after global financial conditions changed in 2007, uncertainties about the risk of operations in EE and their adverse impact on banks' soundness seem to have contributed to a deeper stress in SWGs. At the same time, SWGs coming under increasing pressure from the global financial turmoil have heightened market participants' concerns about regional banks' shock-absorption capacities.

Our findings offer only mixed evidence on the existence of a direct ownership channel. In the *crisis period*, the percentage of significant coefficients

[25] Our findings are broadly consistent with those of Čihák and Ong (2007), who analyse contagion in a sample of 33 (mostly Western) European major banks between May 2000 and April 2007. The authors find significant spillovers in about 11 per cent of all possible links among the banks in their sample.

[26] This result may reflect the fact that the crisis started primarily as a leap in systemic risk in the banking systems of advanced economies, and among the largest banking groups idiosyncratic shocks were blurred by the markets' perception of an overall deterioration of banking system conditions, over and above direct and bilateral links, as shown also by the increased significance of global funding conditions as explanatory variable (Table 7, column 2). The same reasoning may be applied to the low increase in cross-contagion among SWGs and OWGs.

relative to subsidiaries in parent banks' regressions is 25% and it is not statistically different from the overall average for SWGs. On the other hand, about 40% of all coefficients relative to parent banks in subsidiaries' regressions are significant, a percentage much higher than the average for EEBs and this result seems to suggest that the banking group linkages may have played a role in the transmissions of contagion to Eastern European banking systems during the recent financial crisis. However, the weight of this channel should not be overstated, as significant coefficients relative to parent-subsidiaries linkages represent no more than 9% of all significant coefficients representing the subset of contagion effects from SWGs to EEBs. Most importantly, the result that contagion from SWGs to EEB increased during the recent crisis is not statistically affected by the presence of parent subsidiaries linkages, and would stand up even not considering significant coefficients related to this effect.

Finally, the increase of co-excedances within EEB shows evidence of regional contagion. This effect and contagion coming from SWGs may support a common lender explanation.[27]

Our results come with some caveats. As we use lagged bank's idiosyncratic shocks in order to avoid a likely positive simultaneity bias, we may miss those cases of contagion taking place within one day. Some banks in our sample may play a significant role in interbank markets or in global or local stock markets, suggesting that some common shock variables, such as conditional volatility, may in fact pick up effects that are related to contagion. Our approach is rather conservative, as regards the testing procedure as well as the definition of *co-exceedances*, based on filtered data, which may reduce the power of regressions to pick up contagion.[28]

5.1 Testing for emerging market contagion

In order to gain further insight into the transmission of shocks among Eastern and Western European banking systems we perform in this section a counterfactual experiment, replacing the sample of EEBs by an equal number of emerging market banks, all from South America, taken as a control group. Our goal is to test the hypothesis that, with respect to contagion from and to EEBs, our results reflect specific effects, associated to existing linkages with Western European banks, and do not reflect a broader contagion to and from emerging markets. In order to run our experiment, we select 15 large Latin American banks (LAB), 4 of which belong to two European banking groups included in our sample (Table 9).

[27] The role of specialisation also emerges by comparing contagion to EEBs from the two subset of Western European banks. Contagion to EEBs from OWGs is significantly lower than contagion from SWGs (the difference between the two effects is of 9 percentage points, significant at a 10% level).

[28] See Dungey et al. (2005b).

Results are displayed in Table 10, while in Table 11 we carry out a test for significance of the differences in contagion risks between the baseline model and the model with Latin American banks. Two results are worth noticing. In the crisis period contagion from SWGs to EEBs is significantly higher than contagion to LABs. This, together with the circumstance that estimates of contagion among SWGs are not statistically different from the baseline, can be seen as evidence of robustness of our results regarding specialized Western groups. By contrast, contagion from EEBs to SWGs is higher than contagion from LABs to SWGs, but not significantly different.

Overall, these two latter results suggest that while during the crisis regional specialisation of some European banks resulted in a higher level of contagion to Eastern European banking systems, there is much weaker evidence that contagion from Eastern Europe banks to Western European groups was any different than contagion from other emerging market.[29]

6 Conclusions

In this paper we use a stock market-based indicator, the distance to default, to highlight contagion risks in Western and Eastern European banking sectors. In the spirit of "extreme value theory", we identify wide variations in this measure as depicting major shocks in banks' financial conditions. Contagion occurs when the incidence of such tail events is associated to similar shocks hitting other banks in the previous period, after controlling for common factors. We distinguish between the period before and after the crisis, as, due to information problems, contagion risk may have heightened significantly in the latter period. Improving on the literature, we introduce a testing procedure to measure changes in contagion effects across different groups of banks and over time.

We find that before the recent financial crisis, contagion was generally contained to the largest Western European banking groups, while contagion from Western to Eastern Europe, and the reverse, was relatively less likely. The crisis has not only heightened the risks of cross-border contagion but also modified their patterns. Contagion among Western European banks with the highest market share in the EE and from these group to Eastern European banks shows the largest increase in our sample. We also find evidence of contagion spreading from Eastern European banks to their Western European counterparts, but this result is much weaker, possibly reflecting the presence of a broader phenomenon of contagion from emerging markets sources.

[29] A high level of contagion between two areas apparently with limited economic and financial linkages can occur through cross-market rebalancing: global investors respond to a shock to a market by readjusting their portfolio in another market. Due to asymmetric information problems, this effect is more intense during crises (see Krodes and Pritsker, 2002).

Our findings suggests that after global financial conditions changed in 2007, uncertainty about the risk stemming from operation in EE has swollen market participants' concerns about banks' shock-absorption capacities and have contributed to a deeper stress in the Western European banks with a strong market presence in EE as well as to Eastern European banks. This is not surprising, as since the onset of the crisis financial analysts have singled out EE as one of the riskiest regions among emerging market economies, less able to stand a sudden deterioration of global financial conditions.

In this paper, we do not explore the exact nature of the underlying transmission channels of contagion. Rather, our approach captures contagion as perceived by banks' equity holders, and its main advantage is to encompass all possible channels of transmissions, without relying on accurately measuring any particular one. Nevertheless, according to our results some channels were more likely than others during the crisis. For example, "runs" by equity holders have likely represented an important channel of propagation of contagion, as shocks seem to have propagated due to asymmetric information, with negative news about one bank triggering widespread sell-offs in stocks of other banks sharing similar business strategies.[30]

[30] An example is offered by the events following the release by the rating agency Moody's, in mid-February 2009, of a report titled "*Western European ownership of East European banks during financial and macroeconomic stress*", warning that it might downgrade banks active in Eastern Europe owing to their heavy exposure to the region and the region's rapidly deteriorating macroeconomic environment. The report shocked investor confidence, leading to a sharp drop in banks' equity prices and a steep increase in parent banks' CDS premia.

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Tables and Figures

Table 1 Foreign claims on Eastern European countries

	Foreign claims on non-banks	Cross-border claims on banks	Claims of Western European banks on EE countries (3)						
	(1)	(2)	Austria	Belgium	France	Germany	Italy	Netherlands	Sweden
Bulgaria	64.5	25.8	10.2	3.8	7.1	5.3	14.9	1.3	0.0
Croatia	81.4	28.8	33.7	0.7	8.5	24.5	42.9	0.3	0.0
Czech Republic	96.8	11.1	24.7	22.8	13.6	5.2	5.9	3.1	0.0
Estonia	86.8	51.8	0.8	0.4	0.5	3.4	1.3	0.0	93.2
Hungary	72.9	27.9	20.7	10.0	5.9	18.9	16.5	2.7	0.2
Latvia	76.3	40.0	0.9	0.0	0.6	9.6	2.1	0.0	51.6
Lithuania	70.9	41.1	0.7	0.2	1.2	8.7	1.9	0.3	73.8
Poland	67.9	15.5	4.2	6.6	5.1	14.5	11.2	9.4	2.1
Romania	94.6	37.7	35.8	1.0	13.4	3.6	11.0	8.8	0.1
Russia	20.4	9.5	2.4	1.1	2.8	4.4	2.5	2.2	1.1
Serbia	69.0	18.1	21.4	0.2	7.5	11.1	16.6	0.1	0.0
Slovakia	99.0	17.3	40.8	13.4	6.1	4.2	23.4	3.8	0.7
Ukraine	29.0	21.3	9.1	0.7	7.7	3.6	3.2	2.6	4.6
Eastern Europe	41.9	17.1	11.1	5.2	5.6	8.0	8.2	3.7	4.5
Memorandum item									
Exposure of reporting countries (4)	-	-	17.1	6.7	1.2	1.7	3.7	2.7	8.3

Source: BIS, ECB, IMF and national authorities.

(1) Cross-border claims and local claims of foreign affiliates as percent of total cross-border and domestic credit to non-banks.

(2) Cross border claims on banks as percent of total banking liabilities in host country.

(3) As percent of total banking assets in host country.

(4) As percent of total banking assets in the home country.

Table 2 Market share of key Western European banking groups (1)

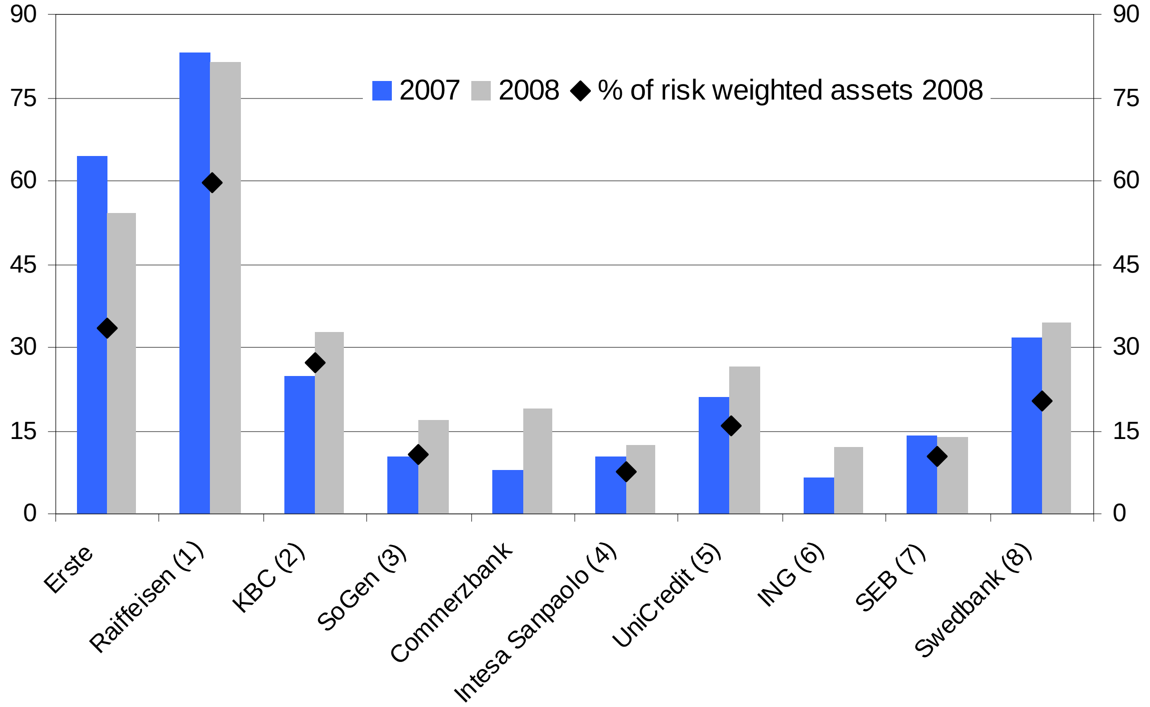
	UniCredit (Italy)	Erste (Austria)	Raiffeisen (Austria)	KBC Group (Belgium)	SocGen (France)	Intesa Sanpaolo (Italy)	Commerzbank (Germany)	ING (Netherland)	Swedbank (Sweden)	SEB (Sweden)
Bulgaria	15.8	0.0	9.9	2.7	3.6	0.0	0.0	0.7	0.0	0.0
Croatia	24.3	12.1	11.2	0.0	7.3	18.2	0.0	0.0	0.0	0.0
Czech Republic	6.9	20.4	6.5	24.7	16.8	0.0	2.2	3.2	0.0	0.0
Estonia	0.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	48.9	21.1
Hungary	6.2	8.5	8.7	10.3	0.0	9.9	0.9	0.0	0.0	0.0
Latvia	3.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	22.7	13.0
Lithuania	1.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	22.2	28.8
Poland	12.8	0.0	2.8	3.7	0.4	0.0	8.4	6.7	0.0	0.0
Romania	5.2	20.5	5.7	0.0	15.1	1.0	0.0	0.0	0.0	0.0
Russia	2.0	0.0	2.0	0.6	2.8	0.3	0.3	0.6	0.2	0.0
Serbia	5.0	2.8	9.1	0.9	4.0	14.1	0.0	0.0	0.0	0.0
Slovakia	7.1	19.0	16.1	12.4	0.5	16.7	0.3	2.9	0.0	0.0
Ukraine	6.5	1.2	7.1	0.0	0.0	0.8	2.2	1.0	2.3	0.0
Eastern Europe	6.1	4.8	4.5	4.5	3.9	2.3	1.8	1.8	1.7	1.0

Source: company data and national authorities

(1) As percent of total banking assets in host country.

Note: data as of end-2008, representing ownership structure as of December 2009. Only participations of 50% or more of share capital are considered.

Figure 1 Western Bank Groups' Exposure to Emerging Europe
(% of operating income in 2008 and 2009 and of risk weighted assets in 2008)



Source: company data.

Notes:

(1) Central Europe, South-Eastern Europe, Russia and other CIS. Net interest income instead of operating income.

(2) Banking RWA in CEER business line as percentage of total risk-weighted banking assets.

(3) RWA of subsidiaries in Czech Republic, Bulgaria, Croatia, Romania, Russia and Serbia. On-balance sheet commitments in Eastern Europe for 2007.

(4) International subsidiaries bank division. Loans to customer instead of RWA.

(5) Poland and CEE Divisions.

(6) Underlying income for retail banking operations in Central Europe to total underlyng income in retail banking.

(7) Baltic countries. On and off balance sheet credit exposure instead of RWA.

(8) Baltic and international banking operations.Total assets instead of RWA. External income instead of operating income.

Table 3 Sample of Eastern European banks

Bank	Country	Western European Parent Group	Total Assets in 2008 (eur million)
		Eastern European banks (EEB)	
SBERBANK	Russia		164,753
Bank Pekao	Poland	UniCredit	32,010
OTP Bank	Hungary		35,866
Komercni Banka	Czech Republic	Société Générale	25,964
BRE Bank	Poland	Commerzbank	20,041
ING Bank Slaski	Poland	ING Group	16,888
Zagrebacka Banka	Croatia	UniCredit	14,501
Bank Handlowy Warszawie	Poland	Citigroup	10,323
Privredna Banka Zagreb	Croatia	Intesa Sanpaolo	9,927
Bank Millennium	Poland	Millenium BCP	11,428
Vseobecna Uverova Banka	Slovakia	Intesa Sanpaolo	11,370
AB DnB NORD Bankas	Lithuania	DnB NOR	4,092
Bankas Snoras	Lithuania		2,478
Central Cooperative Bank	Bulgaria		862
BRD	Romania	Société Générale	12,910

Source: Bankscope

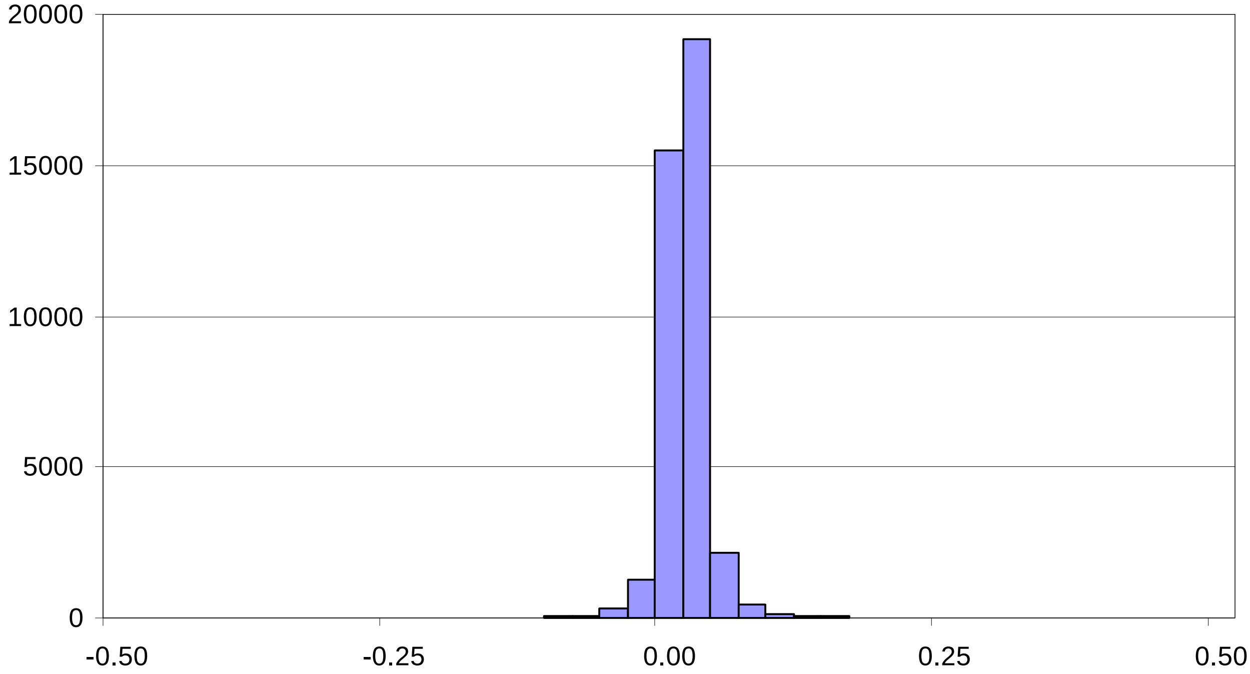
Table 4 Sample of Western European groups

Bank	Country	Total Assets in 2008 (eur million)
Specialised Western European groups (SWG)		
ING Group	Netherland	1,034,689
KBC Group	Belgium	318,550
Société Générale	France	1,130,003
UniCredit	Italy	1,045,612
Intesa Sanpaolo	Italy	636,133
Commerzbank	Germany	625,196
Erste Group Bank	Austria	201,441
Swedbank	Sweden	166,670
Skandinaviska Enskilda Banken	Sweden	230,976
Other Western European groups (OWG)		
BNP Paribas	France	2,075,551
Credit Agricole	France	857,471
Deutsche Bank	Germany	2,202,423
Barclays	United Kingdom	2,150,537
Royal Bank of Scotland	United Kingdom	1,967,122
Banco Santander	Spain	1,049,632
BBV Argentaria	Spain	542,650
Lloyds Banking Group	United Kingdom	456,742
HSBC	United Kingdom	968,127

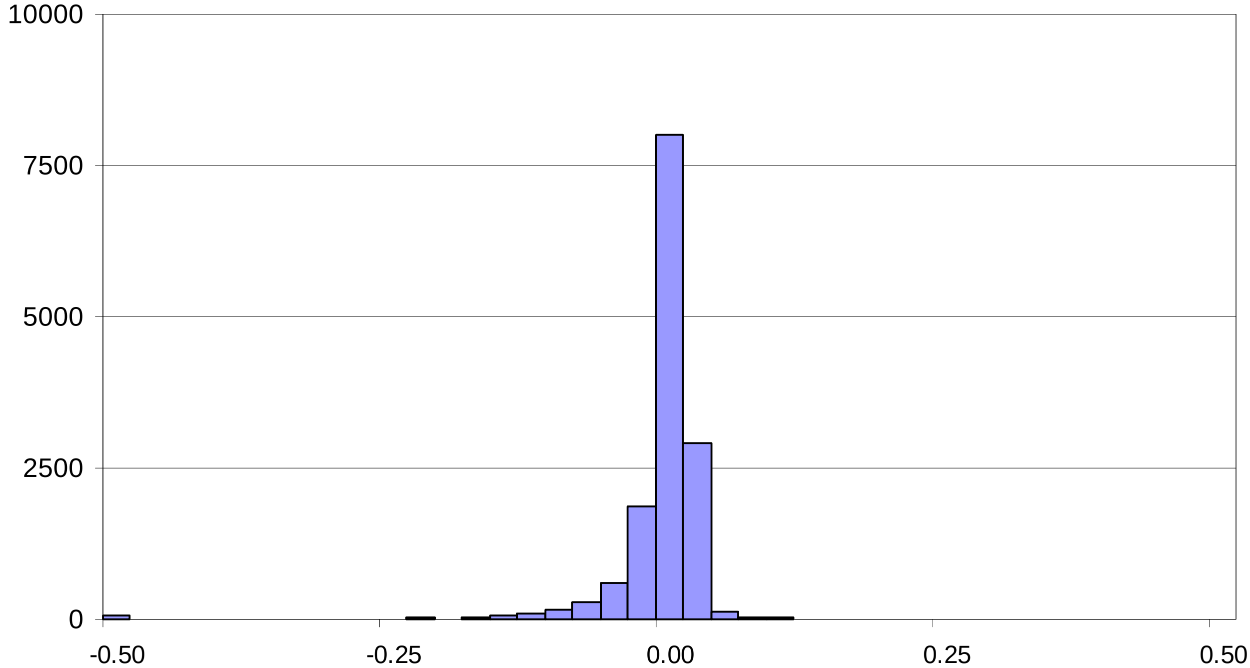
Source: Bankscope

Figure 2 Distribution of changes in distance to default

1 January, 2003 to 31 July, 2007



1 August, 2007 to 31 March, 2009



Source: authors' calculations.

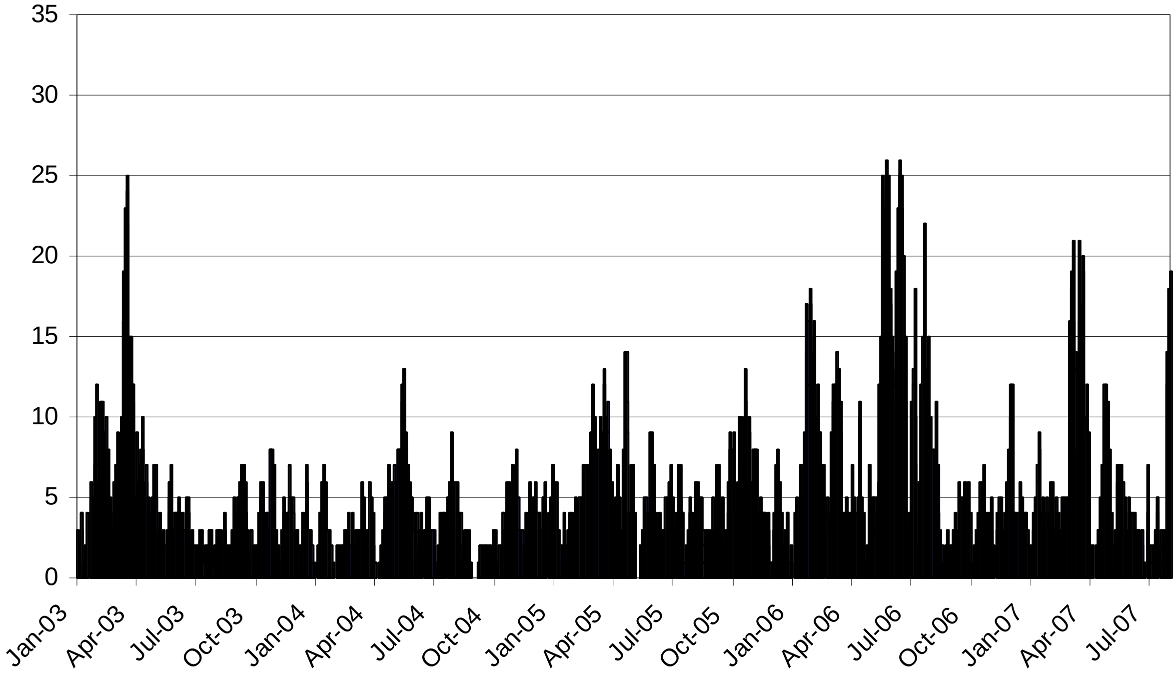
Notes:

Distribution of stacked data on 33 banks' changes in the distance to default.

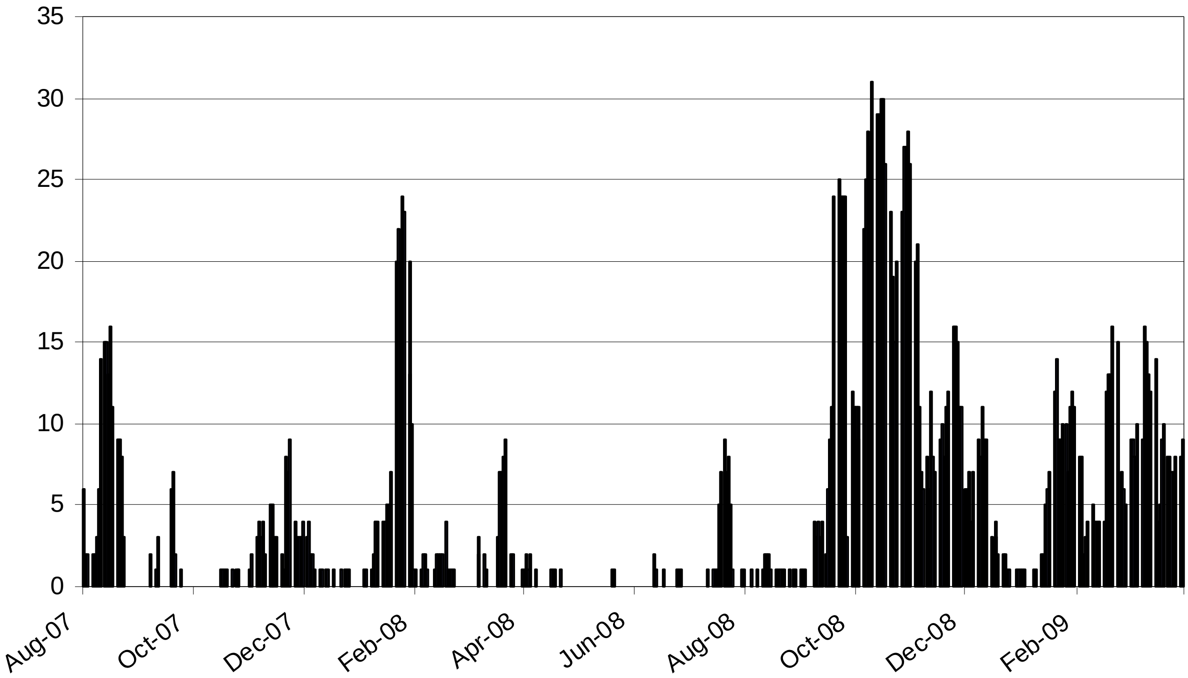
Observations are 39,435 in the first period and 14,355 in the second period. 15^{th} percentile left tail is -0.009 in the period January 2003 to July 2007 and -0.036 in the period August 2007 to March 2009

Figure 3 Exceedances
(number of banks out of 33 in the negative tail)

1 January, 2003 to 31 July, 2007



1 August, 2007 to 31 March, 2009



Source: authors' calculations.

Table 5a Shock transition probabilities in the absence of shock in $t-1$
(As percent of all possible outcomes)

	(January 2003 - July 2007)				*(August 2007 - March 2009)*			
	SWG	OWG	EEB	All banks	SWG	OWG	EEB	All banks
SWG	2.8	4.6	17.5	10.0	1.3	4.1	3.5	3.0
OWG	5.6	1.6	16.7	9.6	15.5	13.7	7.9	11.5
EEB	8.1	6.4	3.9	5.7	5.4	8.9	1.2	4.5

Note: cell ij in the table shows the probability of observing at least one shock to a bank in group j at time t, given that no shock occurred in the bank group i at time t-1.

Table 5b Shock transition probabilities given a shock in $t-1$
(As percent of all possible outcomes)

	(January 2003-July 2007)				*(August 2007-March 2009)*			
	SWG	OWG	EEB	All banks	SWG	OWG	EEB	All banks
SWG	23.1	19.6	18.8	20.2	39.5	39.8	18.9	30.2
OWG	23.3	26.7	20.1	22.7	29.9	30.6	14.6	23.2
EEB	13.4	12.6	19.6	16.0	29.9	30.0	18.6	24.8

Note: cell ij in the table shows the probability of observing at least one shock to a bank in group j at time t, given that at least a shock occurred in the bank group i at time t-1.

Table 6 Significant co-exceedances, baseline model
(As percent of all possible links)

	(January 2003-July 2007)				*(August 2007-March 2009)*			
	Contagion to:				*Contagion to:*			
	SWG	OWG	EEB	All banks	SWG	OWG	EEB	All banks
Initial shock to:								
SWG	6.9	14.8	8.9	10.1	26.4	23.5	26.7	25.7
OWG	8.6	20.8	6.7	10.8	17.3	11.4	17.9	16.1
EEB	5.9	10.4	10.0	9.0	20.5	19.1	22.5	21.0
All banks	6.9	14.2	8.8	9.8	21.1	18.4	22.4	20.9

Note: only positive significant coefficients (up to 5% in a one-side t-test) are included. Standard errors are Huber/White robust.

Table 7 Control variables
(Percent of significant coefficients)

	(January 2003 - July 2007)				*(August 2007 - March 2009)*			
	SWG	OWG	EEB	All banks	SWG	OWG	EEB	All banks
Variable								
Global market shocks	11.1	22.2	13.3	15.2	11.1	12.5	27.3	17.9
Local market shocks	66.7	11.1	46.7	42.4	33.3	33.3	46.2	38.7
Investor risk appetite	0.0	44.4	6.7	15.2	0.0	44.4	0.0	12.5
Global funding conditions	0.0	0.0	13.3	6.1	11.1	75.0	7.1	25.8

Note: significant coefficients up to 10% are included.

Table 8 Change in significant co-exceedances
(August 2007 - March 2009 to January 2003 - July 2007)
(Percentage points)

	Contagion to:			
	SWG	OWG	EEB	All banks
Initial shock to:				
SWG	19.4***	8.6	17.8***	15.6***
	(6.0)	(6.1)	(4.6)	(3.1)
OWG	8.6*	-9.4	12.7***	6.1*
	(5.1)	(6.1)	(3.9)	(2.8)
EEB	14.5***	8.7**	12.5***	12.0***
	(4.1)	(4.3)	(3.6)	(2.3)
All banks	14.1***	4.2	13.6***	11.2***
	(2.8)	(3.1)	(2.3)	(1.6)

Note: standard errors in parentheses; *, **,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 9 Sample of Latin American banks

Bank	Country	Western European Parent Group	Total Assets in 2008 (eur million)
Latin America banks (LAB)			
Itau Unibanco Holdings	Brazil		183,675
Banco do Brasil	Brazil		160,329
Banco Santander Chile	Chile	Banco Santander	24,142
Banco de Chile	Chile		20,706
Banco de Credito e Inversiones	Chile		15,404
Banco de Credito del Peru	Peru		12,701
Banco Inbursa	Mexico		11,127
Mercantil Banco Universal	Venezuela		10,112
Banco Provincial	Venezuela	BBVA	9,498
BBVA Banco Continental	Peru	BBVA	7,654
BBVA Banco Frances	Argentina	BBVA	5,405
Banco Santander Rio	Argentina	Banco Santander	5,141
Banco de Galicia y Buenos Aires	Argentina		5,115
Banco Macro	Argentina		4,694
Banco Mercantil do Brasil	Brazil		2,081

Source: Bankscope

Table 10 Significant co-exceedances: Latin American banks
(As percent of all possible links)

	(January 2003-July 2007)			*(August 2007-March 2009)*		
	Contagion to:			*Contagion to:*		
	SWG	OWG	LAB	SWG	OWG	LAB
Initial shock to:						
SWG	15.3	16.0	4.4	22.2	14.8	14.7
OWG	12.3	19.4	7.4	9.9	12.5	20.5
LAB	5.9	3.0	10.0	14.5	13.0	32.4

Note: only positive significant coefficients (up to 5% in a one-side t-test) are included. Standard errors are Huber/White robust.

Table 11 Change in significant co-exceedances
(Baseline to Latin American banks)
(Percentage points)

	(January 2003-July 2007)			*(August 2007-March 2009)*		
	Contagion to:			*Contagion to:*		
	SWG	OWG	EEB to LAB	SWG	OWG	EEB to LAB
Initial shock to:						
SWG	-8.3	-1.2	4.4	4.2	8.6	12.1**
	(5.2)	(5.7)	(3.0)	(7.1)	(6.1)	(5.1)
OWG	-3.7	1.4	-0.7	7.4	-1.1	-2.6
	(4.8)	(6.7)	(3.1)	(5.4)	(5.4)	(5.1)
EEB to LAB	0.0	7.4**	0.0	5.9	6.1	-9.9*
	(2.9)	(3.0)	(2.9)	(4.8)	(4.7)	(5.4)

Note: standard errors in parentheses; *, **,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 12 Significant co-exceedances: large negative shock as the 10^{th} percentile
(As percent of all possible links)

	(January 2003-July 2007)				*(August 2007-March 2009)*			
	Contagion to:				*Contagion to:*			
	SWG	OWG	EEB	All banks	SWG	OWG	EEB	All banks
Initial shock to:								
SWG	15.3	19.8	9.7	13.9	22.2	14.8	29.4	23.3
OWG	18.5	20.8	7.4	10.8	20.0	21.7	25.2	22.9
EEB	9.7	11.1	10.0	10.2	21.4	23.1	35.7	27.9
All banks	13.6	16.0	9.2	12.2	21.2	20.2	30.8	25.2

Note: only positive significant coefficients (up to 5% in a one-side t-test) are included. Standard errors are Huber/White robust.

Table 13 Change in significant co-exceedances
(Baseline to large negative shock as the 10^{th} percentile)
(Percentage points)

	(January 2003-July 2007)			*(August 2007- March 2009)*		
	Contagion to:			*Contagion to:*		
	SWG	OWG	EEB	SWG	OWG	EEB
Initial shock to:						
SWG	-8.3	-4.9	-0.8	4.2	8.6	-2.6
	(5.2)	(5.9)	(3.5)	(7.1)	(6.1)	(5.5)
OWG	-9.9*	0.0	-0.7	-2.7	-10.3*	-7.3
	(5.3)	(6.8)	(3.1)	(6.1)	(6.3)	(5.1)
EEB	-3.8	0.7	0.0	-0.9	-4.0	-13.2***
	(3.3)	(3.8)	(2.9)	(5.0)	(5.2)	(4.6)

Note: standard errors in parentheses; *, **,*** denote statistical significance at the 10%, 5% and 1% levels, respectively.