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Has the Global Banking System Become More Fragile over Time?

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Abstract

This paper examines time-series and cross-country variations in default risk co-dependence in the global banking system. The authors construct a default risk measure for all publicly traded banks using the Merton contingent claim model, and examine the evolution of the correlation structure of default risk for more than 1,800 banks in more than 60 countries. They find that there has been a significant increase in default risk co-dependence over the three-year period leading to the financial crisis. They also find that countries that are more integrated, and that have liberalized financial systems and weak banking supervision, have higher co-dependence in their banking sector. The results support an increase in scope for international supervisory co-operation, as well as capital charges for "too-connected-to-fail" institutions that can impose significant externalities.

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Has the Global Banking System Become More Fragile over Time?

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1. Introduction

The last decade has seen a tremendous transformation in the global financial sector. Globalization, innovations in communications technology and de-regulation have led to significant growth of financial institutions around the world. These trends had positive economic benefits and have led to increased productivity, increased capital flows, lower borrowing costs, and better price discovery and risk diversification. But the same trends have also led to greater linkages across financial institutions around the world as well as an increase in exposure of these institutions to common sources of risk. The recent financial crisis has demonstrated that financial institutions around the world are highly inter-connected and that vulnerabilities in one market can easily spread to other markets outside of national boundaries.

In this paper we examine whether the global trends described above have led to an increase in co-dependence in default risk of commercial banks around the world. The growing expansion of financial institutions beyond national boundaries over the past decade has resulted in these institutions competing in increasingly similar markets, exposing them to common sources of market and credit risk. During the same period, rapid development of new financial instruments has created new channels of inter-dependency across these institutions. Both increased interconnections and common exposure to risk makes the banking sector more vulnerable to economic, liquidity and information shocks. There is substantial theoretical literature that models the various channels through which such shocks can culminate in a systemic banking crisis (see for instance Bhattacharya and Gale 1987, Allen and Gale 2000, Diamond and Rajan 2005; and focusing on the recent crisis, Brunnermeier 2009, Danielsson, Shin, and Zigrand 2009, Battiston et al. 2009 among others.) To examine whether the global banking sector has become more interdependent and more fragile to shocks, we construct a default risk measure for all publicly traded banks using the Merton (1974) contingent claim model. We compute weekly time series of default probabilities for over 1,800 banks in over 60 countries and examine the evolution of the correlation structure of default risk over the 1998 – 2010 time period.

Our empirical findings show that there has been a substantial increase in co-dependence in default risk of publicly traded banks starting around the beginning of 2004 leading up to the global financial crisis starting in the summer of 2007. Although we observe an overall trend towards convergence in default risk globally, this trend has been much stronger for North American and European banks. We also find that increase in co-dependence has been higher for banks that are larger (with greater than 50 billion in assets). We also examine variation in co-dependence across countries. We find that countries that are more integrated, have liberalized financial systems and weak banking supervision have higher co-dependence in their banking sector.

Increased co-dependence in credit risk in the banking sector has important implications for capital regulations. In the aftermath of the sub-prime crisis of 2007/08, there has been renewed interest in macro-prudential regulation and supervision of the financial system. There has also been a growing consensus to adjust capital requirements to better reflect an individual bank's contribution to the risk of the financial system as a whole (Brunnermeier, Crockett, Goodhart, Persaud, and Shin 2009, Financial Stability Forum 2009a, 2009b). Recently a number of papers have tried to measure and quantify systemic risk inherent in the global banking sector. Adrian and Brunnermeier (2009), Huang, Zhou, and Zhou (2009), Chan-Lau and Gravelle (2005), Avesani et al. (2006), and Elsinger and Lehar (2008), use a portfolio credit risk approach to compute the contribution of an individual bank to the risk of a portfolio of banks. Our paper is related to this strand of literature, but our focus is not on quantifying systemic risk of large financial institutions but rather to examine time series trends for a large cross-section of banks. A number of papers have examined the correlation structure of equity returns of a subsample of banks. De Nicolo and Kwast (2002) find rising correlations between bank stock returns in the U.S. from 1988 and 1999. Schuler (2002) find similar results for Europe using a sample from 1980 to 2001. Hawkesby, Marsh and Stevens (2005) analyze co-movements in equity returns for a set of US and European large complex financial institutions using several statistical techniques and find a high degree of commonality. This paper is also related to the literature that studies contagion in financial markets (see among others Forbes and Rigobon 2002, Kee-Hong Bae and Stulz 2003) and also the literature that examines the impact of globalization on convergence of asset prices (Bekeart and Wang 2009, Longin and Solnik 1995, Bekaert and Harvey 2000, and Bekaert, Hodrick and Zhang 2009).

This paper differs from the existing literature in three respects. First, our empirical analyses cast a wider net than the existing literature which focuses only in a particular region or a country and covers a shorter time period. Second we examine time series trends in co-dependence and test for structural changes over time. Finally, we examine cross-country differences in co-dependence and link the differences to measures of financial and economic openness and regulatory frameworks in different countries.

Policymakers may be able to draw important implications from our analysis. Co-dependence in bank default risk has important consequences for systemic stability. We find increasing co-dependence in banks located in different national jurisdictions. Although we do find that strong banking supervision tends to reduce co-dependence in a given country, our results call for banking supervisory co-operation at a global level. This is especially true for larger banks which have grown more interconnected over the past decade.

The rest of the paper is organized as follows. Section 2 describes the data sources and describes the construction of the Merton (1974) default risk measure. Section 3 presents the empirical results, and finally Section 4 concludes.

2. Data Sources and Credit Risk Measure

The key variables for our analysis come from *BANKSCOPE* which provides bank-level balance sheet information, and *DATASTREAM* which provides information on stock prices, market capitalization and stock volume. We use weekly market data and annual accounting information in creating our credit risk measure. All data items are in US dollars to make comparisons across countries possible. We compute default probabilities implied from the structural credit risk model of Merton (1974). This approach treats the equity value of a company as a call option on the company's assets. The probability of default is computed using the "distance-to-default" measure, which is the difference between the asset value of the firm and the face value of its debt, scaled by the standard deviation of the firm's asset value. The Merton (1974) distance-to-default measure has been shown to be good predictor of defaults outperforming accounting-based models (Campbell, Hilscher and Szilagyi 2008; Hillegeist, Keating, Cram, and Lundstedt, 2004; Bharath and Shumway, 2008). Although the Merton distance-to-default measure is more commonly used in bankruptcy prediction in the corporate sector, Merton (1977) points out the applicability of the contingent claims approach to pricing deposit insurance in the banking context. Bongini, Laeven, and Majnoni (2002), Bartram, Brown and Hundt (2008) and others have used the Merton model to measure default probabilities of commercial banks.

We follow Campbell, Hilscher and Szilagyi (2008) and Hillegeist et al. (2004) to calculate Merton's distance-to-default. The market equity value of a company is modeled as a call option on the company's assets:

$$
\begin{aligned}
V_E &= V_A e^{-\P T} N(d_1) - X e^{-rT} N(d_2) + (1 - e^{-\P T}) V_A \\
d_1 &= \frac{\log(V_A / X) + (r - \P - (s_A^2 / 2))T}{s_A \sqrt{T}} \\
d_2 &= d_1 - s_A \sqrt{T}
\end{aligned}
\qquad (1)
$$

Above V_E is the market value of a bank. V_A is the value of bank's assets. X is the face value of debt maturing at time T. r is the risk-free rate and $\P$ is the dividend rate expressed in terms of V_A. s_A is the volatility of the value of assets, which is related to equity volatility through the following equation:

$$
s_E = \left(V_A e^{-\P T} N(d_1) s_A\right) / V_E \qquad (2)
$$

We simultaneously solve the above two equations to find the values of V_A and s_A.

We use the market value of equity for V_E and short-term plus one half long-term liabilities to proxy for the face value of debt X. We have found similar results using short term debt plus currently due portion of long term liabilities plus demand deposits as the default barrier. Since the accounting information is on an annual basis, 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 and avoids jumps in the implied default probabilities at year end. s_E is the standard deviation of weekly equity returns over the past 12 months. In calculating standard deviation, we require the company to have at least 36 non-zero and non-missing returns over the previous 12 months. *T* equals one year, and *r* is the one-year treasury bill rate, which we take to be the risk free rate. The dividend rate, *d*, is the sum of the prior year's common and preferred dividends divided by the market value of assets. We use the Newton method to simultaneously solve the two equations above. For starting values for the unknown variables we use, $V_A = V_E + X$, and $\sigma_A = \sigma_E V_E/(V_E + X)$. Once we determine asset values, V_A , we then compute asset returns as in Hillegeist et al. (2004): $\mu_t = \max\left(V_{A,t}/V_{A,t-1} - 1, r\right)$ As expected returns cannot be negative, if asset returns are below zero they are set to the risk-free rate.[1] Merton's distance-to-default is finally computed as:

$$MertonDD = -\frac{\log\left(V_A / X\right) + \left(\mu - d - \left(\sigma_A^2/2\right)\right)T}{\sigma_A\sqrt{T}} \tag{3}$$

The default probability is the normal transform of the distance-to-default measure, defined as: $PD = \mathrm{N}(MertonDD)$. The summary statistics for the distance-to-default measure are provided in Table 1. In the table we also report the number of banks covered by both *BANKSCOPE* and *DATASTREAM* as well as the number of banks that remain after we impose data filters described above. In all, we have 1,942 banks in 68 countries for which we are able to calculate Merton DD measure. Figure 1 plots the value weighted average distance-to-default measure over time. Table 2 provides annual average distance-to-default measure for different regions. In the analyses that follow we focus on log changes in default probability: $\Delta\log(PD)$.

In addition we use a number of country level variables to explain co-dependence in the banking sector across countries. These measures relate to financial development, financial structure, as well as to financial and economic integration. We also use measures of banking regulation and supervision as explanatory variables. The first table in the appendix, Table A1, provides an overview of the definitions and sources of these variables. Table A2 presents

[1] We obtain similar results if we use a 6% equity premium instead of asset returns as in CHS (2008).

summary statistics. In the next section we explain the various measures of co-dependence used in the analyses.

3. Co-dependence in the Banking Sector

3.1 Co-dependence Measures

There are a number of different approaches to measuring co-dependence. In this paper we use three complementary measures. The first is the variance ratio calculated as the ratio of the average variance of changes in log probability of default divided by the variance of the average changes in log default probability:

$$PR_t = \log\left(\frac{\mathrm{VAR}(\frac{1}{N}\sum_i \Delta\log\,(PD_{i,s}))}{(\frac{1}{N}\sum_i \mathrm{STD}(\Delta\log\,(PD_{i,s})))^2}\right) \text{ for } s \in \ [t-52, t] \tag{4}$$

The variance ratio increases as correlations in changes in default risk between banks increase. If the correlations are one, then the log variance ratio takes on a value of zero. The variance ratio has been previously used by Ferreira and Gama (2005) and Bakert and Wang (2010) in examining convergence of asset prices in international markets. Figure 2 plots variance ratio calculated on annual basis for all banks in our sample.

The second measure we use is derived from quantile regressions, which estimate the functional relationship among variables at different quantiles (Koenker and Hallock 2001). Quantile regression allows for a more accurate estimation of the credit risk co-dependence during stress periods by taking into account nonlinear relationships when there is a large negative shock. We model the changes in a default risk of a particular bank as a function of changes in default risk of all banks:

$$\hat{\beta}(\tau) \ = \ \mathrm{argmin}_{\beta\in\boldsymbol{R}^{\rho}} = \sum_{t=1}^{T} \rho_\tau \ \left(\Delta\log\,(PD)_{i,t} - \frac{1}{N}\sum_{i=1}^{N} \ \Delta\log\,(PD)_{i,t}\right)$$

5)

The estimation of a quantile regression relies on the minimization of the sum of residuals. The residuals are weighted asymmetrically depending on the quantile, ρ_τ, estimated (Koenker and Hallock 2001). Other financial studies using the quantile regression approach include Koenker and Bassett (1978), Engle and Manganelli (2004), and more recently Adrian and Brunnermeier (2009) and Boyson, Stahel and Stulz (2010). Figure 3 plots the betas calculated by estimating equation (5) for each year for all the banks in our sample using the 0.90 quantile.

In contrast to the second measure which focuses on large changes in default risk in the banking sector, our final measure focuses on collective behavior that may precede these very large changes. Asset correlations increase dramatically during crisis periods when there are large swings in asset prices (see for instance Ang and Chen 2002). In other words, correlations tend to increase when the magnitudes of changes in prices are large. Since we are interested in interdependence in the banking sector, we also want to analyze periods when co-dependence may be high even when the magnitude of changes in default risk is low. With the final measure, following Harmon et al. (2011), we focus on the fraction of banks whose default risk moves in the same direction. This measure can more accurately capture collective behavior and mimicry that may culminate in a crisis. We slightly modify the methodology used by Harmon et al. (2011) and measure the 52 week rolling standard deviation of the fraction of banks that have positive change in their default probability in a given week:

$$ST_\tau = \mathrm{STD}_{t\in[t,\tau]}\left(\frac{1}{N}\sum_{i=1}^{N}\mathbf{I}_{\,\Delta\log(PD)_{i,t}>0}\right)$$

6)

Above **I** is an indicator function. First we compute the fraction of banks with a positive increase in credit risk and then compute the time series standard deviation of this measure. If the changes in credit risk are random across banks then the standard deviation will be zero. As co-dependence increases so does our measure. Figure 4 plots this co-movement measure calculated on an annual basis using all banks in our sample.

3.2 Commonality in Default Risk

Before examining time-series variation in co-dependence for the three measures we have outlined above, we first explore commonality in changes in default for the whole sample period. We begin by examining correlation in changes in default risk between different regions. To compute these correlations, we first calculate value-weighted changes in log default probability, $\Delta \log(PD)$, for each region and then compute correlations over the sample period. Table 2 presents the matrix of pairwise correlations across regions. The correlations are fairly high across regions except for the Middle and North Africa region. The correlations range from -8% to over 90% with an average of 50%. Next, we conduct a standard principal components analysis on the covariance of weekly changes in default probabilities. The results are reported in Table 4. The first principal component explains more than 60 percent of the variation, while the first three principal components explain close to 90 percent. The principal component analyses results suggest that there is a significant amount of commonality in the variation of default risk changes. Furthermore, the first principal component consists of a roughly uniform weighting of default risk changes for countries in our sample. The first principal component, thus, resembles a global factor affecting the default risk changes of all banks. Consistent with this result we observe significant clustering of changes in bank default probabilities. Figure 5 shows the percentage of banks that had their worst change in default risk in the same week over a 12 month time period. If the changes in credit risk are independent we would expect to see an even distribution of worst changes in default risk for banks over time. In other words we would expect to see a flat line with no spikes. Instead, we see significant clustering. The extent of clustering during the recent financial crisis is especially dramatic.

To explore further the systematic variation in changes in bank default risk, we follow the methodology of Heston and Rouwenhorst (1994) and decompose changes in default risk into three components: global effect, country effects and asset size effects. The rationale for including asset size is the substantial increase in bank size and concentration over the sample period we study (Demirguc-Kunt and Huizianga 2010). The larger banks tend operate beyond national borders and compete in similar markets and activities. As larger banks tend to engage in risk-transfer with other banks of similar size, they share many linkages and are exposed to significant counter-party risk. For these reasons there maybe commonality in default risk in larger banks distinct from the rest of the banking sector. Following Demirguc-Kunt and Huizianga (2010), we classify banks into three size categories: banks with assets less than 10 billion, assets between 10 to 50 billion and assets greater than 50 billion. We model log changes in default probability as follows:

$$\Delta \log(\mathrm{PD})_{\mathrm{ijkt}} = \mathrm{a_t} + \sum_{j=1}^{J} \mathrm{I(I)_{ij}\, I_{jt}} + \sum_{k=1}^{K} \mathrm{I(C)_{ik}\, C_{kt}} + \epsilon_{\mathrm{ijkt}} \tag{7}$$

Above $I(I)_{ij}$ is a dummy variable equal to one, if bank i belongs to size group j, and zero otherwise. $I(C)_{ik}$ is a dummy variable equal to one, if bank i is headquartered in country k, and zero otherwise. In total we have three size groups ($J = 3$) and 47 countries ($K = 47$). Following Heston and Rouwenhorst (1994), we impose restrictions in order to avoid multi-collinearity when estimating the parameters of the model. In particular, we impose the country and size effects weighted by the number of banks to be zero: $\sum_{j=1}^{J} n(I)_j\, I_{jt} = 0$ and $\sum_{k=1}^{K} n(C)_k\, C_{kt} = 0$ with $n(I)_j$ and $n(C)_k$ equal to the number of banks in each size category *j* and country *k*, respectively. For each period *t*, we run a cross-sectional regression to estimate the coefficients, a_t, I_{jt}, and C_{kt}. For each individual bank belonging to country *k* and in size group *j*, the proportion of systematic variance explained by country effects is approximately given by: $\frac{\mathrm{var}(C_{kt})}{\mathrm{var}(a_t)+\mathrm{var}(I_{jt})+\mathrm{var}(C_{kt})}$. The proportion of systematic variance explained by size and global effects are computed in a similar fashion. Table 5 shows the results from this decomposition. We report averages by region to save space. On average the global effect accounts for 20% of the systematic variation in changes in default risk. Asset size accounts for modest portion of systematic variation, on average 7%. But for larger banks with assets greater than fifty billion dollars, size accounts for 26% of the systematic variation. These results indicate that that there is a significant global component to changes in default risk in the banking sectors across different countries.

3.3 Time Series Analyses

In this section, we examine time series variation of co-dependence in the banking sector. In particular we are interested in whether there have been structural shifts in co-dependence over the sample period from 1998 to 2010. Following Bakeart and Wang (2009) we use trend tests to detect potential changes in co-dependence. We compute the variance ratio (PR_t) for each region over 52 week rolling intervals.[2] We use the following empirical model:

$$\begin{aligned} PR_t = {} & \alpha_1 I_{\{t \in 1998.01-2003.12\}} + \beta_1 I_{\{t \in 1998.01-2003.12\}} \cdot t + \alpha_2 I_{\{t \in 2004.01-2007.06\}} \\ & + \beta_2 I_{\{t \in 2004.01-2007.06\}} \cdot t + \alpha_3 I_{\{t \in 2007.06-2009.12\}} + \beta_3 I_{\{t \in 2007.06-2009.12\}} \cdot t + \varepsilon_t \end{aligned} \tag{8}$$

Where $I_{\{t \in period\}}$ is a dummy variable that takes on a value of one over the specified time period, and *t* is the linear time trend. In estimating the coefficients, we correct for auto correlation. We split the sample into three intervals. Time period from June 2007 to December 2009 corresponds roughly to the global financial crises. Although it is difficult pin down the exact date, it was towards the end of June 2007 when the first significant signs of the crisis began to appear. Market uncertainty increased and spreads started to widen significantly as subprime mortgage backed securities were discovered in portfolios of banks and hedge funds around the world. Few weeks later, BNP ceased redemptions in three of its funds due to "complete evaporation of liquidity" in the markets.[3] January 2004 to June 2007 is the period leading up the subprime crisis. It was around the beginning of 2004 when there began a substantial increase in subprime lending, growth of so-called shadow banking (Gorton 2011), increase in leverage of major financial institutions and reliance in short-term borrowing (Adrian and Shin 2011, Morris and Shin 2009) as well as increase in global imbalances (Jagannathan, Kapoor and Schaumburg 2009) that culminated in a crisis starting the summer of 2007.

The results from the empirical model in equation (8) are reported in Table 6. There is an increase in co-dependence during the crises period (July 2007 to December 2009) for all regions.

[2] We obtain similar results using the co-movement measure or the quantile betas described in Section 3.1.

[3] http://invest.bnpparibas.com/cid3162415/bnp-paribas-investment-partners-temporaly-suspends-the-calculation-of-the-net-asset-value-of-the-following-funds-parvest-dynamic-abs-bnp-paribas-abs-euribor-and-bnp-paribas-abs-eonia.html?pid=769

In fact there is not a single country which did not see an increase in co-dependence during this period. However we do see variation in the magnitude of the increase across countries and to some extent regions. For the time period leading up to the crises (January 2004 to June 2007), we see much greater variation. There was an increase in co-dependence throughout most of the developed world. Banks in United States, Japan and especially European Union have seen a significant rise in co-dependence. Banks located in developing countries on the other hand have seen a decline in co-dependence over the same time period. As with the crisis period, we again see much variation across countries. It is these cross-sectional differences that we explore next.

3.4 Cross-country Analyses

In this section we examine the cross-country differences in default risk co-dependence. A number of papers have linked commonality in asset returns and asset liquidity to financial and trade liberalization.[4] We are interested in whether policies that lead to financial and economic openness and greater integration also increase co-dependence. We are also interested in the extent to which banking de-regulation and banking supervision has led to changes in co-dependence. The empirical model we use to test these relationships is the following:

$$PR_{i,t} = \alpha + C_i + \beta BankCrisis_{i,t} + \gamma X_{i,t} + \theta M_{i,t} + \varepsilon_{i,t} \quad (9)$$

Our dependent variable is the variance ratio, $PR_{i,t}$, calculated for each country *i* for each year *t*. We obtain similar results using the co-movement measure or the quantile betas described in Section 3.1. Since correlations increase during crises periods, we include a dummy variable, $BankCrisis$, that takes on a value of one if a country in our sample has experienced a banking crises in a given year. We use the banking crisis definition and the data provided in Leaven and Valencia (2010). $M_{i,t}$ is a vector of country level variables that measure economic/financial openness and banking regulation/supervision. $X_{i,t}$is a vector of country level controls. We use GDP per capita, GDP per capita growth to control for levels of economic and financial development. Previous literature has shown that more developed countries tend to have lower commonality in asset prices and liquidity (see for instance Karolyi, Lee and Van Dijk 2009). To

[4] See for instance Karolyi, Lee and Van Dijk (2009) and Bekaert and Wang (2009).

control for differences in financial structure, we use stock market capitalization over GDP and bank deposits over GDP (Beck, Demirgüç-Kunt, and Levine, 2000). We may expect to see differences in co-dependence in bank vs. market based systems. We also include liquid assets ratio and capital ratio to control for the funding liquidity of the domestic financial system (Beck and Demirgüç-Kunt 2004). Overall liquidity in the financial system may reduce or eliminate some channels of contagion which increase co-dependence. Finally we control for the log of the number of banks in the sample, since correlation may be mechanically linked to the number of cross-sectional observations (Morck 2000). We also exclude countries with less than 7 banks from the analyses. The regressions include country fixed effects (C_i) and we report robust standard errors clustered at the country level.

Cross-sectional regression results are reported in Table 7. As expected we find the coefficient on the bank-crises dummy to be significant and positive. That is co-dependence increases significantly during crises periods. As mentioned earlier, consistent with the prior literature we find gdp per capita growth to reduce co-dependence, although the level of GDP per capita is insignificant. We find stock market capitalization over GDP to increase co-dependence. One possible explanation is that more market based systems have more potential channels of contagion. Surprisingly, the coefficient on the liquid assets ratio is negative and significant. The capital assets ratio is insignificant.

As mentioned earlier we are particularly interested in the impact of financial and economic openness and integration on co-dependence. We are also interested in the extent to which banking de-regulation and banking supervision can explain cross-country differences in co-dependence. We use a number of different variables to measure integration and financial openness. The first measure is stock market turnover which has a positive statistically significant effect on co-dependence. Trade over GDP has been previously used in the literature to measure economic integration (Bekaert and Wang 2009). We do not find it to be significant after controls. The Chin-Ito measure quantifies capital control policies and other regulations and restrictions on capital flows (Chin and Ito 2008). It shows up positive and significant. We also consider the impact of social and political integration. We use the KOF political and social globalization index (Dreher et al. 2000).[5] Political integration variable shows up as significant and positive while the social integration variable is insignificant.

Next we examine the impact of deregulation and financial liberalization on co-dependence. We use the database created by Abiad Detragiatche and Tressel (2010) that quantifies financial reforms over a thirty year time period. Results under models 6 and 7 show that reforms that have led to international capital liberalization and stock market liberalization have increased co-dependence. Reforms that have led to stronger bank supervision, however, have decreased co-dependence (model 8). We also examine the impact of bank concentration as measured by assets of 3 largest banks as a share of assets of all commercial banks. As mentioned earlier, there has been a substantial increase in concentration in both developing and developed countries. As the recent crisis has demonstrated, large complex financial institutions can cause systemic disruptions affecting all other financial institutions. We find concentration to increase co-dependence. This is in contrast to Beck, Demirgüç-Kunt, and Levine (2006) who show that countries with a more concentrated banking system are less likely to suffer a systemic banking crisis. Finally, we examine the impact of moral hazard on co-dependence. If there is an implicit guarantee provided by the State to cover losses stemming from a systemic crisis, banks will have incentives to take on correlated risks (Acharya 2005). Guaranteed banks will not have incentives to diversify their operations, since the guarantee takes effect only if other banks fail as well. We use the deposit insurance coverage ratio (Beck and Demirgüç-Kunt 2004) as a proxy for moral hazard. We find a positive and significant relationship between moral hazard and co-dependence. Overall, our results suggest that countries which are more integrated, and which have liberalized financial systems and weak banking supervision also have higher co-dependence in their banking sector.

4. Conclusion

This paper examines time-series and cross-country variations in default risk co-dependence in the global banking sector. We compute weekly changes in default probabilities based on the Merton (1974) model for over 1,800 banks in over 70 countries. We show that systematic default risk has a significant global component in the banking sector accounting for 20% of the

[5] KOF means "Konjunkturforschungsstelle" - Swiss Economic Institute.

systematic variation. During the global financial crisis, there has been a uniform increase in co-dependence across all countries. However, we do find cross-sectional differences in the magnitude of the increase across different countries. We also find that there has been a significant increase in default risk co-dependence over the three year period leading up to the financial crisis. During this time period we find even greater cross-country variation, with banks located in the developed countries (and especially banks located in the US and the European Union) seeing an increase co-dependence while banks located in developing countries seeing a decrease. Examining the 1998-2010 time period, we find that countries which are more integrated, and which have liberalized financial systems and weak banking supervision and greater safety net coverage also have higher co-dependence in their banking sector. The results in this paper have important policy implications. Most importantly, our results support an increase in scope for international supervisory co-operation, as well as capital charges for too-connected-to-fail' institutions that can impose significant externalities.

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Figure 1. Global Distance-to-Default

This figure shows the weekly weighted-average distance-to-default of all banks satisfying the data requirements outlined in Section 2 of the paper. Market capitalizations of the banks are used as weights.

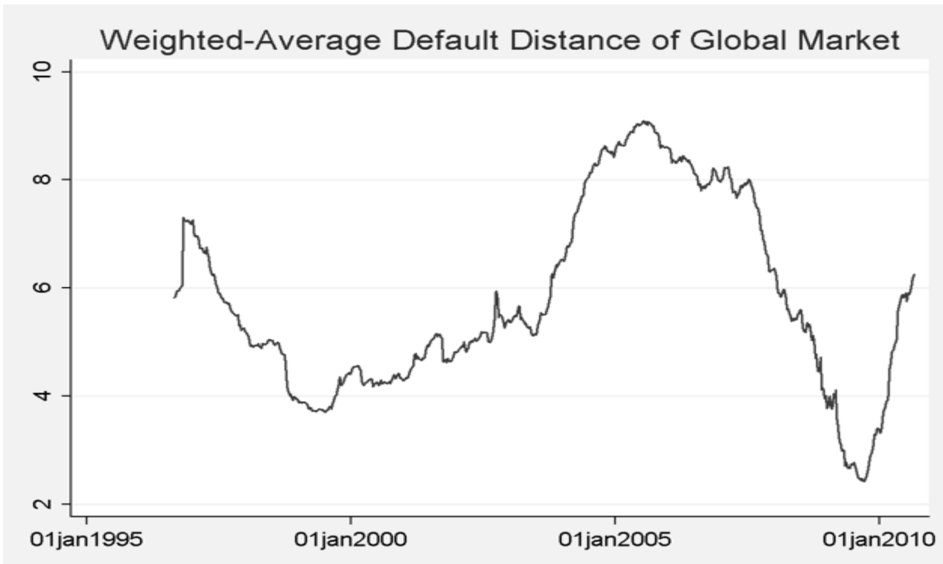

Figure 2. Variance Ratio

This figure shows the variance ratio calculated as the ratio of the average variance of changes in log probability of default divided by the variance of the average changes in log default probability (equation 4) for all banks in the dataset. Variance ratio is calculated each year using weekly data.

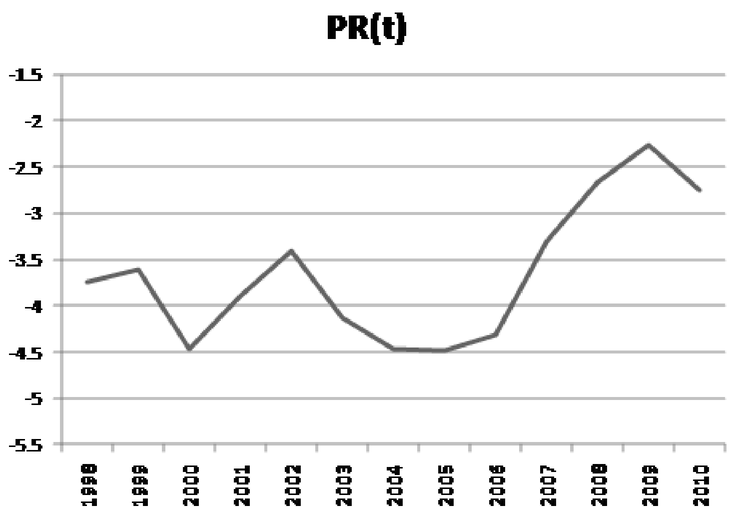

Figure 3. Quantile Regression Estimates

This figure shows the Beta coefficient estimates from the quantile regression specified in equation (5) of the paper. The coefficient is estimated each year using the 0.90^{th} quantile.

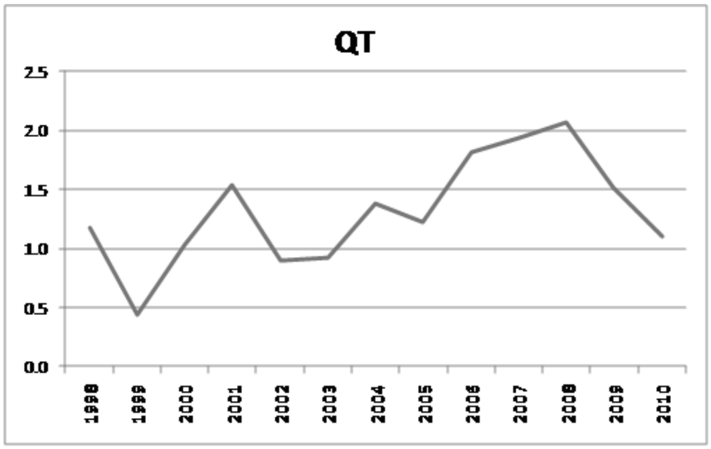

Figure 4. Co-movement Measure

This figure shows the co-movement measure (specified in equation (6) of the paper) calculated as the 52 week rolling standard deviation of the fraction of banks that have positive change in their default probability in a given week. The co-movement measure is computed each year using weekly data.

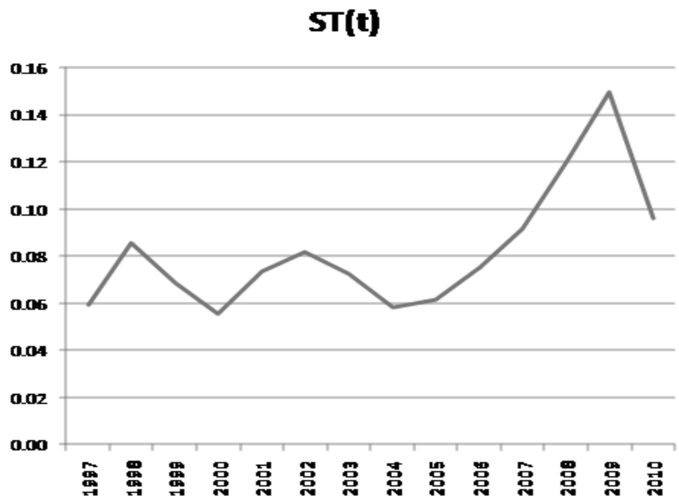

Figure 5. Clustering in Default Risk

This figure shows the percentage of banks in a given week that have simultaneous worst change in default risk over a 12 month time period. We compute log changes in default probability each week for each bank in our dataset. Each year, we then count the number of banks that had their worst change in log default probability in the same week. We then divide this count by the total number of banks in the dataset in that particular year.

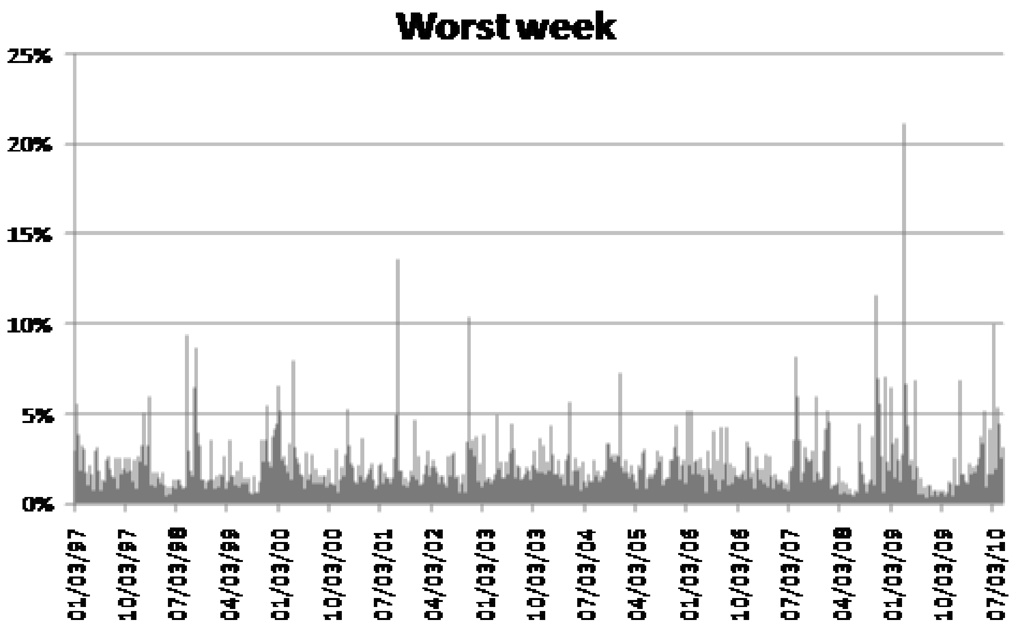

Table 1: Data Coverage and Summary Statistics of Distance-Default.

This table shows the summary statistics for the distance-to-default measure for countries for which we have at least one observation. Our original data from both BankScope and Datastream covers 2,294 publicly traded banks across 86 countries. Of these banks, 1,942 of them satisfy our requirement that 1) they have at least 36 weekly non-zero volume and non-missing returns over the previous 12 months, 2) they have non-missing liabilities and market capitalization, in order to compute distance-to-default.

Country	Number of Banks with BANKSCOPE and DATASTREAM Coverage	Number of Banks with Distance-to-Default Measure	Mean	Standard Deviation	p5	p50	p95
ARGENTINA	8	8	4.09	1.81	1.87	3.80	7.81
AUSTRIA	14	13	9.33	3.22	2.77	10.83	12.00
AUSTRALIA	20	19	6.47	1.95	3.05	6.56	9.73
BELGIUM	6	6	6.99	2.98	1.84	6.78	12.00
BAHRAIN	16	11	5.30	2.26	2.30	4.87	9.98
BERMUDA	17	13	4.02	2.24	1.46	3.53	8.84
BRAZIL	30	25	3.88	2.07	1.35	3.39	8.14
CANADA	20	18	6.60	2.63	2.71	6.28	12.00
SWITZERLAND	24	24	7.63	3.44	2.56	7.24	12.00
CHILE	9	8	6.00	2.41	2.40	5.76	11.70
CHINA-PEOPLE'S REP.	12	12	4.68	1.86	2.21	4.48	8.03
COLOMBIA	9	6	4.83	1.63	2.59	4.80	7.87
CZECH REPUBLIC	3	2	5.33	2.62	1.94	4.67	11.68
GERMANY	31	30	6.90	3.48	1.99	6.54	12.00
DENMARK	20	18	7.56	2.59	3.33	7.51	12.00
EGYPT	3	3	3.83	1.40	2.20	3.40	6.03
SPAIN	12	12	6.85	2.57	3.06	6.62	11.65
FINLAND	7	7	6.66	2.71	2.34	6.41	11.65
FRANCE	58	55	8.42	3.41	2.73	8.71	12.00
UNITED KINGDOM	53	50	5.78	2.75	1.87	5.32	11.30

GREECE	18	17	3.90	1.75	1.69	3.68	6.93
HONG KONG SAR, CHINA	17	16	4.72	2.45	1.55	4.24	9.70
HUNGARY	3	3	4.25	1.60	1.80	3.93	7.64
INDONESIA	20	15	2.47	1.04	0.91	2.39	4.11
IRELAND	6	5	6.02	2.53	1.29	5.79	10.32
ISRAEL	12	8	6.92	2.23	3.56	6.72	11.16
INDIA	29	26	4.14	1.86	1.73	3.84	7.45
ICELAND	7	6	4.22	1.35	1.87	4.29	6.58
ITALY	43	38	6.58	2.76	2.60	6.17	12.00
JORDAN	12	11	4.86	1.43	2.80	4.61	7.35
JAPAN	164	160	7.06	3.05	2.46	6.98	12.00
KENYA	9	7	4.57	3.03	1.97	3.34	12.00
KOREA REP. OF	16	13	4.35	2.25	1.47	4.00	9.76
KUWAIT	22	22	4.59	1.87	1.74	4.47	7.93
KAZAKHSTAN	9	1	2.73	0.35	2.28	2.61	3.40
LEBANON	6	1	6.95	2.07	4.25	7.25	10.21
LIECHTENSTEIN	2	2	6.76	2.16	3.50	6.76	12.00
SRI LANKA	13	8	5.04	1.94	2.30	4.91	8.39
LITHUANIA	5	3	4.01	1.38	1.67	4.18	6.07
LUXEMBOURG	7	6	7.37	3.04	3.19	6.70	12.00
MOROCCO	6	6	6.56	2.09	3.50	6.40	10.31
MAURITIUS	2	2	8.67	1.95	6.52	7.67	12.00
MEXICO	14	10	5.70	3.04	1.87	4.89	12.00
MALAYSIA	29	29	4.71	2.37	1.14	4.42	9.18
NETHERLANDS	12	12	6.21	3.07	2.44	5.37	12.00
NORWAY	22	22	9.18	3.02	3.35	10.18	12.00
NEW ZEALAND	1	1	8.12	2.22	5.11	7.79	11.68
OMAN	3	3	4.33	1.41	2.12	4.45	6.44
PERU	4	4	4.87	1.87	2.42	4.45	8.68

PHILIPPINES	17	16	4.18	1.97	1.67	3.85	8.19
PAKISTAN	17	14	4.05	1.73	1.68	3.77	7.61
POLAND	15	15	3.69	1.42	1.65	3.55	6.21
PORTUGAL	9	8	6.96	2.87	3.02	6.39	12.00
QATAR	6	6	3.49	0.94	2.09	3.38	5.41
ROMANIA	3	2	3.41	1.32	1.25	3.49	5.41
RUSSIAN FEDERATION	15	7	3.61	1.90	1.16	3.19	7.31
SAUDI ARABIA	10	10	4.06	1.64	2.19	3.59	7.39
SWEDEN	11	11	5.05	2.41	1.83	4.64	9.82
SINGAPORE	17	17	5.47	2.82	1.64	4.96	11.11
SLOVENIA	7	2	5.78	1.01	4.24	5.77	7.64
SLOVAKIA	4	3	7.78	3.24	2.53	8.00	12.00
THAILAND	29	28	3.55	1.66	1.04	3.37	6.50
TURKEY	24	22	2.56	0.84	1.34	2.55	3.90
TAIWAN, CHINA	36	34	4.59	2.00	1.97	4.19	8.57
UKRAINE	6	1	2.69	0.41	2.23	2.61	3.54
USA	1064	916	5.80	2.42	2.20	5.54	10.34
VENEZUELA	8	6	4.02	2.24	1.86	3.34	9.60
SOUTH AFRICA	32	27	3.77	1.62	1.53	3.63	6.48

Table 2: Distance-to-Default Regional Time Series

This table shows the weighted-average distance-to-default measure for 9 different regions computed each year. We calculate weighted-average distance-to-default by market capitalization each week for each region. We then compute arithmetic averages across 52 weeks in a given year.

regions	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Africa	3.49	1.92	3.42	4.17	3.83	4.81	4.87	5.02	4.72	4.27	4.04	2.62	4.39
Central Asia & Eastern Europe	2.29	2.07	2.80	3.12	3.77	4.50	4.20	4.34	3.74	4.08	3.64	1.65	2.73
East Asia and Pacific	4.44	3.64	4.65	4.98	4.75	6.07	6.23	7.65	7.49	6.11	4.36	3.13	4.59
Japan	4.37	3.68	4.17	5.60	5.39	5.39	4.70	6.51	5.35	6.31	5.16	4.81	7.30
Latin America & Caribbean	3.23	2.93	3.77	4.29	4.78	4.42	5.39	5.18	4.19	4.32	3.32	2.11	4.11
Middle East & North Africa	6.97	5.89	6.78	8.19	8.97	6.77	7.12	5.17	4.20	4.67	4.62	2.88	4.98
North America	4.87	3.89	3.46	3.89	5.19	5.65	8.05	8.79	8.92	8.47	4.47	1.68	3.88
South Asia	4.75	3.65	3.56	4.85	5.64	6.39	4.32	4.20	4.33	3.90	3.07	2.35	3.36
Western Europe	4.86	4.21	5.45	5.18	5.39	5.88	8.41	10.18	8.87	8.33	7.07	2.97	5.26

Table 3: Regional Distance-to-Default Correlations

This table reports the time-series correlations from 1998 to 2010 between different regions. First, we calculate weighted-average distance-to-default by market capitalization in each region per week. Then the pair wise Pearson correlation coefficients are calculated from weekly data.

	Africa	CAEE	EAP	Japan	LAC	MENA	NA	SA	WE
Africa	1								
Central Asia & Eastern Europe	0.7709	1							
East Asia and Pacific	0.7643	0.7709	1						
Japan	0.5986	0.5320	0.5142	1					
Latin America & Caribbean	0.7357	0.8035	0.7656	0.4834	1				
Middle East & North Africa	0.1221	0.2428	-0.0128	-0.0701	0.4400	1			
North America	0.6356	0.7283	0.8773	0.3969	0.7010	-0.0086	1		
South Asia	0.3013	0.4732	0.3883	0.1759	0.4986	0.6411	0.2996	1	
Western Europe	0.7297	0.7864	0.8776	0.4809	0.7166	-0.0844	0.9044	0.1371	1

Table 4: Principal Component Decomposition of Changes in Credit Risk

This table reports the first five components from a principle components analysis of default risk. First, we compute value-weighted average changes in log default probability for banks in our dataset. The market capitalizations are used as weights. We then perform a principal component decomposition. Eigenvalues, marginal and cumulative proportion variances are reported respectively.

Component	Eigenvalue	Proportion of Variance Explained	
		Marginal	Cumulative
Comp1	5.582	0.6202	0.6202
Comp2	1.809	0.2010	0.8213
Comp3	0.612	0.0679	0.8892
Comp4	0.404	0.0449	0.9341
Comp5	0.246	0.0274	0.9615

Table 5: Variance Decomposition of Default Risk

In this table, we report the systematic variance attributable to global, country and size effects. We use Heston & Rouwenhorst (1994)'s method to decompose the systematic variance of changes in log default probability ($\Delta\, log(PD)$). Each week we run a cross-sectional regression of$\Delta\, log(PD)$ onto a constant and 47 country dummy variables and 3 size dummy variables: $\Delta\, log(PD)_{ijkt} = a_t + \sum_{j=1}^{J} I(I)_{ij} I + \sum_{k=1}^{K} I(C)_{ik} C + \varepsilon_{ijkt}$. In the regression, $I(I)_{ij}$ is a dummy variable equal to one, if bank i belongs to size group j, and zero otherwise. $I(C)_{ik}$ is a dummy variable equal to one, if bank i is headquartered in country k, and zero otherwise. We impose restrictions in order to avoid multi-collinearity when estimating the parameters of the model. In particular, we impose the country and size effects weighted by the number of banks to be zero: $\sum_{j=1}^{J} n(I)_j\, I_{jt} = 0$ and $\sum_{k=1}^{K} n(C)_k\, C_{kt} = 0$ with $n(I)_j$ and $n(C)_k$ equal to the number of banks in each size category j and country k, respectively. For each period t, we run a cross-sectional regression to estimate the coefficients, a_t, I_{jt}, and C_{kt}. For each individual bank belonging to country k and in size group j, the proportion of systematic variance explained by country effects is approximately given by: $\frac{\mathrm{var}(C_{kt})}{\mathrm{var}(a_t)+\mathrm{var}(I_{jt})+\mathrm{var}(C_{kt})}$. The proportion of systematic variance explained by size and global effects are computed in a similar fashion.

Country	Number of Banks	Global Effect	Country Effect	Size Effect
Panel A: Regions				
Africa	34	28.30%	65.00%	6.71%
Central Asia & Eastern Europe	62	21.44%	68.23%	10.33%
East Asia and Pacific	201	11.84%	83.32%	4.85%
Japan	161	11.35%	81.20%	7.45%
Latin America & Caribbean	74	18.09%	75.12%	6.79%
Middle East & North Africa	65	14.71%	80.51%	4.78%
North America	964	44.19%	43.30%	12.52%
South Asia	47	15.19%	80.32%	4.50%
Western Europe	300	13.98%	77.93%	8.09%
Panel B: Asset Size ($ billions)				
Assets less than $10	1464	54.76%	36.70%	8.54%
Assets larger than $10 but less than $50	495	23.78%	61.28%	14.94%
Assets larger than $50	276	17.22%	56.85%	25.93%

Table 6: Time-series Analysis

This table shows the regression estimates from equation (8) in the paper. Following Bakeart and Wang (2009) we use trend tests to detect potential changes in co-dependence. First, the variance ratio (PR_t) is computed for each region each week over 52 week rolling intervals. We use log changes in default probability and include banks with at least 26 observations to compute the variance ratio. We then run the following regression: $PR_t = \alpha_1 I_{\{t\in 1998.01-2003.12\}} + \beta_1 I_{\{t\in 1998.01-2003.12\}} \cdot t + \alpha_2 I_{\{t\in 2004.01-2007.06\}} + \beta_2 I_{\{t\in 2004.01-2007.06\}} \cdot t + \alpha_3 I_{\{t\in 2007.06-2009.12\}} + \beta_3 I_{\{t\in 2007.06-2009.12\}} \cdot t + \varepsilon_t$. Where $I_{\{t\epsilon period\}}$ is a dummy variable that takes on a value of one over the specified time period, and *t* is the linear time trend. In estimating the coefficients, we correct for auto correlation using Newey-West with three lags.

	World	Developed	Developing	European Union	USA	Japan	Africa	Eeastern Europe & Central Asia	East Asia & Pacific	Latin America & Carribean	Middle East & N Africa	North America	South Asia	Western Europe
int 1998.01 - 2003.12	-3.424***	-3.434***	-2.273***	-3.044***	-3.378***	-2.078***	-1.414***	-1.800***	-2.032***	-2.237***	-0.724***	-3.393***	-1.446***	-3.057***
	(-26.291)	(-26.015)	(-29.887)	(-25.238)	(-29.785)	(-34.073)	(-13.769)	(-44.343)	(-19.055)	(-41.373)	(-7.450)	(-30.109)	(-17.253)	(-24.015)
slope 1998.01 - 2003.12	-0.002***	-0.001***	-0.003***	0.000	-0.001***	-0.000	-0.001***	-0.001***	-0.003***	-0.002***	-0.002***	-0.001***	-0.001***	0.000
	(-3.645)	(-2.839)	(-12.327)	(0.307)	(-3.670)	(-0.499)	(-3.259)	(-10.576)	(-6.981)	(-7.024)	(-7.254)	(-3.373)	(-4.581)	(0.699)
int 2004.01 - 2007.06	-6.588***	-6.413***	-2.421***	-7.111***	-5.451***	-2.529***	0.432*	-3.169***	-2.588***	-2.482***	-0.706	-5.336***	-2.640***	-7.941***
	(-21.959)	(-18.918)	(-4.665)	(-16.365)	(-22.876)	(-10.212)	(1.653)	(-22.073)	(-6.415)	(-12.651)	(-1.093)	(-20.613)	(-7.338)	(-17.706)
slope 2004.01 - 2007.06	0.004***	0.004***	-0.004***	0.008***	0.002***	0.002***	-0.005***	0.001***	-0.002**	-0.001***	-0.005***	0.002***	0.001	0.009***
	(6.608)	(5.897)	(-3.188)	(8.921)	(4.161)	(3.892)	(-8.789)	(4.608)	(-2.361)	(-3.482)	(-3.637)	(3.297)	(1.621)	(10.630)
int 2007.07 - 2009.12	-11.953***	-11.616***	-12.650***	-11.422***	-10.315***	-1.344***	-8.000***	-11.175***	-10.057***	-8.404***	-10.293***	-10.443***	-9.735***	-10.694***
	(-25.455)	(-24.897)	(-19.020)	(-24.689)	(-17.376)	(-6.614)	(-14.525)	(-10.538)	(-37.861)	(-32.621)	(-17.243)	(-17.570)	(-26.888)	(-26.209)
slope 2007.06 - 2009.12	0.015***	0.014***	0.015***	0.015***	0.012***	0.000	0.011***	0.014***	0.013***	0.010***	0.012***	0.012***	0.013***	0.014***
	(19.754)	(19.380)	(14.475)	(19.703)	(12.893)	(0.828)	(12.084)	(8.660)	(29.477)	(23.109)	(12.933)	(13.128)	(21.483)	(20.395)
N	662	662	662	662	662	662	662	662	662	662	662	662	662	662
lags	3	3	3	3	3	3	3	3	3	3	3	3	3	3

Table 7: Cross-country Regressions

This table shows the results from cross-country regressions from the following model: $PR_{i,t} = \alpha + C_i + \beta BankCrisis_{i,t} + \gamma X_{i,t} + \theta M_{i,t} + \varepsilon_{i,t}$. The dependent variable is the variance ratio, $PR_{i,t}$, calculated for each country *i* for each year *t*, using log changes in default probabilities. The dummy variable, $BankCrisis$, that takes on a value of one if a country in our sample has experienced a banking crises in a given year. We use the banking crisis definition and the data provided in Leaven and Valencia (2010). $X_{i,t}$is a vector of country level controls, includes GDP per capita, GDP per capita growth, stock market capitalization over GDP, bank deposits over GDP, liquid assets ratio, capital ratio and log of the number of banks. These variables are described in detail in the appendix. In the regressions, we exclude countries with less than 7 banks. The regressions include country fixed effects (C_i) and we report robust standard errors clustered at the country level.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Stock mkt Cap / GDP	0.127*	0.136*	0.152*	0.228**	0.257**	0.213*	0.246**	0.139*	0.104	0.279*
	(1.727)	(1.764)	(1.869)	(1.963)	(2.433)	(1.938)	(2.258)	(1.804)	(1.347)	(1.891)
Bank Deposits / GDP	-0.05	0	0.035	0.258	0.199	-0.027	-0.116	-0.043	-0.002	0.102
	(-0.187)	(0.001)	(0.118)	(0.891)	(0.627)	(-0.114)	(-0.511)	(-0.147)	(-0.007)	(0.43)
Bank Crisis Dummy	0.273***	0.299***	0.294***	0.264***	0.286***	0.202**	0.195*	0.302***	0.273***	0.327***
	(2.696)	(2.949)	(2.836)	(2.62)	(2.745)	(1.99)	(1.896)	(3.054)	(2.719)	(3.063)
Log # of Banks	-0.691***	-0.807***	-0.807***	-0.729***	-0.696***	-0.704***	-0.721***	-0.680***	-0.829***	-0.882***
	(-3.692)	(-3.951)	(-4.002)	(-3.849)	(-3.299)	(-8.008)	(-7.905)	(-3.440)	(-4.354)	(-2.771)
Bank Capital / Assets	0.039*	0.019	0.022	0.021	0.026	0.012	0.013	0.013	0.016	0.018
	(1.826)	(0.828)	(0.942)	(0.856)	(1.121)	(0.555)	(0.576)	(0.59)	(0.675)	(0.553)
Liquid Assets Ratio	0.029**	0.035**	0.034**	0.039***	0.036**	0.039***	0.036***	0.041***	0.036**	0.039***
	(2.259)	(2.483)	(2.36)	(2.685)	(2.561)	(3.002)	(2.782)	(2.965)	(2.529)	(2.688)
log GDP/cap	-0.007	0.025	0.02	-0.049	-0.169	-0.077	0.045	0.022	0.041	-0.062
	(-0.067)	(0.222)	(0.166)	(-0.337)	(-1.092)	(-0.242)	(0.155)	(0.191)	(0.409)	(-0.456)
GDP/cap growth	-0.033**	-0.039**	-0.040**	-0.049***	-0.039**	-0.058***	-0.059***	-0.048***	-0.037**	-0.048**
	(-2.283)	(-2.435)	(-2.095)	(-2.946)	(-2.543)	(-4.015)	(-4.028)	(-3.384)	(-2.306)	(-2.196)
Global integration and Financial Openness										
Stock mkt turnover	0.130***									
	(2.933)									
Chin-Ito Financial Openness		0.100**								
		(1.971)								
Trade / GDP			-0.001							
			(-0.707)							
KOF Social globalization				0.015						

				(1.301)						
KOF Political globalization					0.028**					
					(2.356)					
Regulation and Supervision										
Security market liberalization						0.241***				
						(3.998)				
International capital liberalization							0.643***			
							(7.537)			
Banking supervision								-0.129**		
								(-2.553)		
Bank concentration									0.445*	
									(1.867)	
Deposit Insurance Coverage										0.211***
										(3.178)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.287	0.253	0.256	0.276	0.277	0.285	0.303	0.284	0.265	0.305

Table A1. Country-Level Variables Used in the Empirical Analyses

This table describes the country-level variables used in the analyses in this paper. The data sources are provided under the ‘Source’ column.

Variable Name	Description	Source
Bank capital / assets	Bank capital to assets ratio %	World Development Indicator (World Bank)
Bank Concentration	Assets of three largest banks as a share of assets of all commercial banks.	Financial Structure Database (World Bank)
Bank Deposit / GDP	Demand, time and saving deposits in deposit money banks as a share of GDP, calculated using the following deflation method: {(0.5)*[Ft/P_et + Ft-1/P_et-1]}/[GDPt/P_at] where F is demand and time and saving deposits, P_e is end-of period CPI, and P_a is average annual CPI	Financial Structure Database (World Bank)
Bank liquid reserves / assets	Bank liquid reserves to bank assets ratio %	World Development Indicator (World Bank)
Banking supervision	Measure of prudential regulations and supervision of the banking sector	Abiad, Detragiache and Tressel 2009 (IMF)
Chinn-Ito Index of Financial Openness	A measure of the degree of financial openness of a country where higher value indicates greater de jure financial openness.	Chinn & Ito (September 2008)
Crisis Dummy	Dummy set to one if a country is experiencing a banking crisis	Laeven Banking Crisis Database
Financial Reform Index	Measure of financial reform. Normalized from 0 to 1. (1 stands for fully liberalized)	Abiad, Detragiache and Tressel 2009 (IMF)
GDP per capita growth	GDP per capita growth annual %	World Development Indicator (World Bank)
International capital liberalization	Measure of restrictions and regulations on international financial transactions	Abiad, Detragiache and Tressel 2009 (IMF)
Liquid Liabilities / GDP	Ratio of liquid liabilities to GDP, calculated using the following deflation method: {(0.5)*[Ft/P_et + Ft-1/P_et-1]}/[GDPt/P_at] where F is liquid liabilities, P_e is end-of period CPI, and P_a is average annual CPI	Financial Structure Database (World Bank)

Ln(number of banks)	The number of banks used in the analyses each year for each country	Datastream & BankScope
Political Globalization	Index of political globalization	KOF Index of Globalization
Security market liberalization	Government policies related to development of securities markets and restrictions on foreign investors	Abiad, Detragiache and Tressel 2009 (IMF)
Social Globalization	Index of social globalization	KOF Index of Globalization
Stock Market Capitalization / GDP	Value of listed shares to GDP, calculated using the following deflation method: {(0.5)*[Ft/P_et + Ft-1/P_et-1]}/[GDPt/P_at] where F is stock market capitalization, P_e is end-of period CPI, and P_a is average annual CPI	Financial Structure Database (World Bank)
Stock Market Turnover Ratio	Ratio of the value of total shares traded to average real market capitalization, the denominator is deflated using the following method: Tt/P_at/{(0.5)*[Mt/P_et + Mt-1/P_et-1] where T is total value traded, M is stock market capitalization, P_e is end-of period CPI P_a is average annual CPI	Financial Structure Database (World Bank)
Trade / GDP	Total exports plus total imports to current GDP	World Development Indicator (World Bank)

Table A2. Summary Statistics of Country Variables

This table shows the summary statistics of country-level variables used in this paper. The variables are described in detail in Table A1.

Variable name	Obs	Mean	Std. Dev.	Min	Max
Bank capital / assets	595	7.820	2.798	2.700	15.900
Bank Concentration	804	0.650	0.213	0.119	1.000
Bank Deposit / GDP	745	0.733	0.582	0.124	4.724
Bank liquid reserves / assets	738	6.611	7.988	-7.877	57.049
Banking supervision	728	1.739	0.829	0.000	3.000
Chinn-Ito Index of Financial Openness	754	1.318	1.405	-1.831	2.500
Crisis Dummy	814	0.127	0.333	0.000	1.000
Financial Reform Index	684	0.834	0.144	0.345	1.000
GDP per capita growth	782	2.797	3.163	-14.296	16.236
International capital liberalization	728	2.346	0.881	0.000	3.000
Ln(number of banks)	814	2.182	1.128	0.000	6.719
Political Globalization	782	81.436	17.584	3.496	98.431
Security market liberalization	728	2.190	0.837	0.000	3.000
Social Globalization	782	66.495	18.299	25.823	94.573
Stock Market Capitalization / GDP	786	0.905	0.869	0.036	7.425
Stock Market Turnover Ratio	797	0.791	0.829	0.001	6.224
Trade/GDP	774	90.946	70.076	15.841	438.092