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Economic Integration and Financial Stability: A European Perspective

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Economic Integration and Financial Stability: A European Perspective

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Abstract

This paper assesses changes in synchronization of real activity and financial market integration in Western Europe and evaluates their implications for financial stability. We find increased synchronization of real activity since the early 1980s and increased equity markets integration since the early 1990s. We also find that measures of systemic risk at large European financial institutions have not declined during the period 1990-2004 and that bank systemic risk profiles have converged. At the same time, the sensitivity of bank and insurance systemic risk measures to common real and financial shocks has increased in most countries. Overall, these results suggest that the integration process does not necessarily entail an unambiguously positive effect on financial stability.

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I. Introduction

Research on synchronization of real activity and financial integration in Europe has intensified in the past few years. Nevertheless, the implications of integration for financial stability remain largely unexplored. This paper aims at contributing to fill in this gap.

Structural changes in the environment in which financial firms operate, such as increased real synchronization and advances in financial integration, may affect individual and system-wide risk profiles of financial intermediaries differentially (see De Nicolò and Kwast, 2002, and De Nicolò and others, 2004e). On the one hand, enhanced synchronization in real activity may *reduce* the benefits of cross-country diversification. If either the shocks hitting a set of economies (and the relevant borrowers) become more similar, or the transmission mechanism of country-specific shocks becomes stronger, or both, then the pool of diversifiable (credit and market) risks available to intermediaries may shrink. On the other hand, financial integration may enhance diversification opportunities for *individual* intermediaries, which can rely on enlarged investment opportunities across activities and borders to enhance expected returns for the same amount of risk. Yet, a *set* of intermediaries may become less diversified as a whole if their exposures to the same risks increase, either by choice or because the sources of "aggregate" risk have become more similar. Moreover, increased linkages among intermediaries through enhanced common exposures to financial markets may make their exposure to contagion more likely.

Disentangling these possibly countervailing effects on financial stability is the main task of this paper. Accomplishing this task requires first assessing whether increases in real synchronization and advances in financial integration have indeed occurred, since the existing literature does not offer unequivocal answers. Second, it requires constructing measures of systemic risk, and relating them to outcomes of changes in real synchronization and financial integration.

With regard to real synchronization, several studies have attempted to identify a "European business cycle," but research on the existence of such an object is still ongoing; as a result, few studies have focused on *changes* in real synchronization.[2] Moreover, this literature has dealt almost exclusively with fluctuations of GDP and/or industrial production growth rates. As our focus is on the impact of changes in real synchronization on the risk profiles of financial institutions through their portfolio choices, synchronization of *volatility* of growth rates of real activity may be as important, if not more important, than synchronization in levels.

[2] For recent reviews of the literature, see Stock and Watson (2005) and Kose, Otrok, and Whiteman (2005). Persistence in business cycles heterogeneity within Europe is stressed by Artis (2003).

With regard to financial integration, recent studies have documented increased convergence in prices of money and bond markets, while noting the slower pace of price convergence in retail bank credit markets (Barros and others, 2005; Baele and others, 2004; and Adam and others, 2002). However, the literature exhibits mixed results concerning the integration of equity markets. As stressed by Adjaouté and Danthine (2004), a difficulty in assessing integration lies in disentangling pricing effects from changes in fundamentals. Yet, we view an assessment of advances in equity market integration as a robust gauge of advances in financial integration more generally, since equity markets are ones in which claims on a large variety of countries' investment opportunities are traded, and integration in such markets does not necessarily follow mechanically from cross-country convergence of interest rates.

We proceed in three steps. First, we assess cross-country convergence of the first *and* second moments of output growth. The consideration of second moments is novel, and turns out to be informative on the changing nature of common versus country-specific driving forces of the dynamics of real activity. Second, we test whether cross-country convergence of estimates of a discount factor used to price "idiosyncratic" risks in equity markets has occurred, employing a version of the methodology introduced by Flood and Rose (2005).

Finally, we document the dynamics of proxy measures of systemic risk based on data for a set of large European banks and insurance companies in the past 15 years. We test convergence in both levels and volatility of these dynamics, and assess whether the risk profiles of these financial institutions have become more sensitive to common real and financial shocks. In doing so, we view the sensitivity of financial institutions' risk profiles to common real and financial shocks as a useful metric to gauge the implications of increased synchronization in real activity and advances of financial integration through the overall exposure of intermediaries to "common" market and credit risks.

Our investigation yields three main sets of results. First, we find evidence of increased synchronization in the dynamics of real activity since the early 1980s, in the form of declining trends in the cross-country dispersion in the mean *and* volatility of industrial production monthly growth rates. These declining trends are found after controlling for common shocks, whose magnitude has become smaller, and are mainly driven by business cycle synchronization. Second, we find evidence of increased equity markets integration since the early 1990s, in the form of a declining trend in the cross-country dispersion of expected discount factors estimated in each of the European equity markets considered.

Third, we find lack of evidence of a decline in risk profiles for European banks and insurance companies during the period 1990-2004. Importantly, we find that these risk profiles have converged, and that the sensitivity of bank risk profiles to both common real and financial shocks has significantly increased. An interpretation of these findings is that increased synchronization in real activity and advances in financial integration may have reduced the benefits of cross-country diversification.

The remainder of the paper consists of three sections. Section II assesses synchronization in real activity, while Section III considers integration of equity markets. Section IV constructs indicators of system-wide financial risk for a set of systemically important banks and insurance companies in a large set of European countries, and relates the dynamics of these measures to the outcomes of increased real synchronization and advanced financial integration. Section V concludes.

II. Synchronization of Real Activity

We gauge changes in synchronization of real activity by the evolution of the cross-country dispersion in the first *and* second conditional moments of seasonally adjusted monthly industrial production growth (IPG) for the 10 European countries for which we have complete data for the period 1961:01-2004:12.[3] Subject to an important qualification detailed below, a downward trend in the dynamics of the *cross-country variance* of IPG *and* its country-specific volatility may capture increased synchronization in real activity, as this indicates increased correlation of the IPG series in the sample.[4] A statistical model for such dynamics is obtained as follows.

Let X_{it} denote IPG in country i at date t. X_{it} turns out well described by the following E(xponential)GARCH(1,1) model:

$$X_{it} = \alpha_{it} + \beta_i F_t + \gamma X_{it-1} + h_{it}\varepsilon_{it} \tag{1}$$

$$Ln(h_{it}^2) = a_{it} + b\varepsilon_{it-1}^2 + cLn(h_{it-1}^2) \tag{2}$$

The term F_t in the mean Equation (1) is a risk factor common to all countries. The variance Equation (2) describes the evolution of country-specific volatility. As customary, the innovations ε_{it} are assumed to be i.i.d. and normally distributed with zero mean and unit variance.

We take a weighted average of IPG rates as a proxy measure of the *common component* of IPG rates. Thus, we set $F_t = \sum_i w_{it} X_{it} / N$. This common component is measured using the time-varying weights proposed by Lumsdaine and Prasad (2003), where $w_{it} \equiv \tilde{h}_{it}^{-1} / \sum_i \tilde{h}_{it}^{-1}$,

[3] These countries are: Austria, Belgium, France, Germany, Greece, Italy, Netherlands, Portugal, Sweden, and the United Kingdom. All results we obtain for first moments hold when we use quarterly GDP growth data instead of IPG data.

[4] As shown in Solnik and Roulet (2000), under the assumption that the data generating process for a sufficiently large set of variables is described by a factor model, the evolution of their cross-sectional dispersion is inversely related to their pairwise correlation.

and variances $\tilde{h}_{it}$ are obtained by estimates of model (1)-(3) without the common factor. This specification embeds the assumption that the relative conditional standard deviation is a measure of the degree of commonality of countries' real fluctuations.

Stock and Watson (2005) have documented a reduction in the volatility of G-7 business cycles, and argued that this has been associated with a reduction in the magnitude of common shocks. Have reductions of volatility and the magnitude of common shocks occurred in Europe? The answer is affirmative. Note that by construction, F_t is described by an EGARCH(1,1) model. As shown in Figure 1, the estimated conditional variance and the residuals of both series appear to exhibit a downward trend. Furthermore, we tested for such a downward trend by estimating the EGARCH model for F_t with a trend both in the mean and variance equations. As shown in Table 1, the coefficient of the time trend in the conditional mean and variance is negative and highly significant.

To obtain a model for the cross-country variance of IPG and its volatility, note that the conditional mean and variance of X_{it} are given by $m_{t-1}(X_{it}) \equiv \alpha_{it} + \beta_i E_{t-1}F_t + \gamma X_{it-1}$ and by $\operatorname{var}_{t-1}(X_{it}) \equiv \beta_i^2 \sigma_F^2(t) + h_{it}^2$ respectively. Assume that the coefficients $\{\alpha_{it}, \beta_i, a_i\}$ are distributed cross-sectionally with means $\{\alpha_t, \beta, a\}$ and variances $\{\sigma_{\alpha t}^2, \sigma_\beta^2, \sigma_a^2\}$, and that covariances among all these random variables, as well as that of X_{it-1} and F_t and each of these are approximately nil. Under these assumptions, the *cross-sectional variances* of $m_{t-1}(X_{it})$ and h_{it}^2 are given by

$$\sigma_X^2(t) \equiv E(m_{t-1}(X_{it}) - Em_{t-1}(X_{it}))^2 = \sigma_{\alpha t}^2 + \sigma_\beta^2 (E_{t-1}F_t)^2 + \gamma^2 \sigma_X^2(t-1) \tag{3}$$

$$\sigma_{h^2}^2(t) \equiv E(h_{it}^2 - Eh_{it}^2)^2 = \sigma_{at}^2 + b^2 \sigma_{\varepsilon^2}^2(t-1) + c^2 \sigma_{h^2}^2(t-1) \tag{4}$$

Increased synchronization in real activity occurs if $\sigma_{\alpha t}^2$ and/or σ_{at}^2 exhibit a declining path. Note that a decline in $\sigma_X^2(t)$ exclusively driven by a decline in the magnitude of common shocks ($(E_{t-1}F_t)^2$) (which we have shown above has occurred) would *not* necessarily indicate increased integration, since disconnected economies hit by the same shock would exhibit the same decline.

We estimate the following counterpart of model (3)-(4) :

$$\bar{\sigma}_X^2(t) = A_0 + A_1 t + A_2 (E_{t-1}F_t)^2 + A_3 \bar{\sigma}_X^2(t-1) + H_t \eta_t \tag{5}$$

$$\log H_t^2 = B_0 + B_1 t + B_2 \eta_{t-1}^2 + B_3 \log H_{t-1}^2 \tag{6}$$

Two measures for $\bar{\sigma}_X^2(t)$ are used. The first one is the sample cross-sectional variance of IPG rates. The second one is the variance of *deviations* of IPG of each country from its own trend, obtained by applying the relevant HP filter.[5] This second measure is used to gauge the extent to which detrended and non-detrended dynamics differ. For both measures, we test whether A_1 and/or B_1 are negative.

Table 2 reports estimates of model (5)-(6). Both the trend coefficients in the mean equation (6) *and* the variance equation (7) are negative and significant. Moreover, the estimates of these coefficients remain virtually unchanged when the cross-sectional variance of *deviations* of IPG from trend is used. Most important, the relevant trend coefficients remain negative but become highly significant. This indicates that business cycle convergence is the primary driver of the decreasing dispersion of IPG rates. Notably, increased synchronization has occurred not only in the form of increased correlation of IPG fluctuations across countries, but also in terms of increased correlation of their (country-specific) volatilities.

To gauge the approximate timing of increased synchronization, we estimated model (1)-(2) for each country with dummies for different decades in both the mean and variance equations. As shown in Table 3, increased synchronization in the form of a decline of the cross-country variance of IPG rates started to occur in the early 1980s By contrast, the cross-country dispersion in the variance of IPG volatility does not exhibit a decline. This result, coupled with the significant decline found earlier, suggests that convergence in volatility is either driven by a subset of countries in the sample or has occurred at different points in time in some countries, or both.

Summing up, synchronization in real activity appears to have increased since the early 1980s. It has been primarily driven by increases in business cycle synchronization, and is not the mechanical outcome of a decline in the magnitude of common shocks.

III. Equity Markets Integration

One difficulty in testing advances in equity market integration rests on disentangling pricing effects from the effects of fundamental shocks. Here we tackle this problem by using a version of the methodology proposed by Flood and Rose (2005) (FR henceforth), which exploits the pricing of "idiosyncratic risk," as opposed to systematic risk. As detailed below, an advantage of this methodology is that it does not require taking a stand on a particular asset pricing model.

Consider the standard intertemporal asset pricing equation:

$$p_t^j = E_t(m_{t+1}x_{t+1}^j) = COV_t(m_{t+1}, x_{t+1}^j) + E_t m_{t+1} E_t x_{t+1}^j \qquad (7)$$

[5] For data at monthly frequency, here and in the sequel we use the value of the smoothing parameter for the HP filter derived by Ravn and Uhlig (2002), equal to 129,600.

where p_t^j is the price of asset *j* at date t, E_t is the expectations operator, COV_t is the covariance operator conditional on information available at date t, and m_{t+1} is the rate used to discount the income x_{t+1}^j accruing to the holder of the asset at date $t+1$. Equation (8) can be re-written as:

$$x_{t+1}^j = \delta_t (p_t^j - COV_t(m_{t+1}, x_{t+1}^j)) + \varepsilon_{t+1}^j, \qquad (8)$$

where $\delta_t \equiv 1/E_t m_{t+1}$ is the inverse of the expected discount factor (IEDF), and $\varepsilon_{t+1}^j \equiv x_{t+1}^j - E_t x_{t+1}^j$ is a prediction error orthogonal to information available at date t. If all assets traded in a given market are discounted at the same rate, then such asset market is said to be integrated.

As our focus is not on assessing integration per se, but *changes* in integration, we take the *dynamics* of the cross-country variance of estimated IEDFs across different equity markets as our measure of changes in integration. If markets become increasingly integrated, this variance should decline. If they moved towards perfect integration, this variance should converge to zero.

Estimates of IEDFs are obtained as follows. Let the time series vector Z_t denote the set of factors that capture *all* systematic components of (log) returns. Then, $p_t^j = p_{t-1}^j \exp(\beta' Z_t + v_t^j)$, where v_t^j is the idiosyncratic part of asset j return. Following FR, define the "systematic price" $\tilde{p}_t^j$ as the value of p_t^j conditional on idiosyncratic information available at date t set to zero. Thus, $\tilde{p}_t^j \equiv p_{t-1}^j \exp(\beta' Z_t)$. Normalizing equation (8) by such price yields:

$$x_{t+1}^j / \tilde{p}_t^j = \delta_t (p_t^j / \tilde{p}_t^j) - \delta_t COV_t(m_{t+1}, x_{t+1}^j / \tilde{p}_t^j)) + \varepsilon_{t+1}^j \ = \delta_t \exp(v_t^i) + u_{t+1}^j \qquad (9),$$

where $u_{t+1}^j \equiv \varepsilon_{t+1}^j - \delta_t COV_t(m_{t+1}, x_{t+1}^j / \tilde{p}_t^j)$.

Estimates of the IEDF δ_t can thus be obtained through regressions (9) by means of the following two-step procedure. In the first step, the "systematic price" $\tilde{p}_t^j$ of value weighted industry portfolios for each stock market is estimated by OLS, using the set of principal components of returns to factor out systematic risks. Their number is identified by standard statistical procedures. In the second step, returns are normalized with the estimated systematic price $\hat{p}_t^j$, and the IEDF estimates for each equity market and date are obtained by means of OLS cross-sectional regressions of the type:

$$x_{t+1}^j / \hat{p}_t^j = c_t + \delta_t \exp(v_t^i) + u_{t+1}^j \qquad (10)$$

As stressed by Marshall (2005), the constant is needed to control for date-specific (aggregate) shocks that can still be embedded into the IEDF estimates. This estimation procedure was applied to the 13 sectoral portfolios and 9 countries for which monthly data from Datastream were available for the 1975:01-2004:12 period.[6]

All IEDF estimates exhibit correlation with future returns and first-order autocorrelation not significantly different from zero. They also exhibit high volatility, but standard tests reject the hypothesis of ARCH effects. It turns out that the dynamics of the IEDFs for country i at date t, denoted by M_{it}, is well represented by a simple random walk with drift. Thus, we gauge whether equity markets integration has advanced by testing the significance of a time trend in the following equation for the cross-country variance of IEDFs, denoted by $\bar{\sigma}_M^2(t)$:

$$\bar{\sigma}_M^2(t) = A_0 + A_1 t + \eta_t \qquad (11)$$

Table 4 reports estimates of (11), specified with a time trend as well as with a set of decade-long dummies. As shown in Panel A, the trend coefficient is negative and significant. As shown in Panel B, increased integration appears to have occurred approximately since the early 1990s. This is also confirmed by simple tests of differences in slopes associated with decade-long dummies. As shown in Panel C, these results are further validated by estimated time trends for the IEDF for each country, since the cross-country variance of the decade-long dummies exhibits a decline from the early 1990s.

In sum, European equity market integration appears to have advanced since the early 1990s. This result is consistent with the conjectures advanced by Adjaouté and Danthine (2004), and with the finding of Baele and others (2004), who document European stock returns and volatility as increasingly affected by "common" European shocks.

IV. Systemic Risk and Integration

A. Measures of Systemic Risk

Our indicators of systemic risk are distance-to-default (DD) measures of "portfolios" of sets of publicly traded, systemically important European banks and insurance companies. These measures are based on the structural valuation model of Black and Scholes (1973) and

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[6] The sectors covered are: Banks, Insurance, Financials, Non-Financials, Basic Industries, Cyclical Consumer Goods, Cyclical Services, General Industrials, Information Technology, Non-Cyclical Services, Non-Cyclical Consumer Goods, Resources, and Utilities. The countries are: Austria, Belgium, Denmark, France, Germany, Ireland, Italy, Netherlands, and the United Kingdom. In all first step regressions, the first two principal components were sufficient to capture common risks according to standard statistical criteria.

Merton (1974) (BSM hereafter).[7] In the BSM model, the portfolio's equity is viewed as a call option on the portfolio's assets, with strike price equal to the current book value of total liabilities. When the value of the portfolio's assets is less than the strike price, its equity value is zero. The market value of assets is not observable, but can be estimated using equity values and accounting measures of liabilities.

Under the assumption that asset values follow a lognormal process, the DD of a *portfolio* of N firms (indexed by i) is given by:

$$DD_t = \frac{Ln(V_t^P / L_t^P) + (\mu_P - 0.5\sigma_P^2)}{\sigma_P}$$

where $V^P = \sum_i V_t^i$ and $L_t^P = \sum_{i=1}^{N} L_t^i$ are the total value of assets and liabilities, respectively. The mean and variance of the portfolio are respectively given by $\mu_P = \sum_i w_t^i \mu^i$ and $\sigma_P = \sum_i \sum_j w_t^i w_t^j \sigma_{ij}$, where $w_t^i = V_t^i / \sum_i V_t^i$ and σ_{ij} is the asset return covariance of firm i and j. Thus, the "portfolio" DD embeds the structure of risk interdependencies among firms. "Default" at date $t+1$ occurs when $V_t^P < L_t^P$. Thus, the DD indicates how many standard deviations $Ln(V_t^P / L_t^P)$ has to deviate from its mean in order for default to occur. Since $V_t^P = L_t^P + E_t^P$, where E_t^P is the value of equity, declines in V_t^P / L_t^P imply declines in capitalization (E_t^P / L_t^P).

Lower (higher) levels of the "portfolio" DD imply a higher (lower) probability of firms' joint failure. Since positive and negative variations in the DD of individual firms are allowed to offset each other, the DD of a portfolio is always higher than the (weighted) sum of the DDs of the individual firms.[8] As a result, the probability of "failure" associated with the "portfolio" DD is always lower than that associated with the actual probability of joint failures of sets of firms in the portfolio. Thus, the "portfolio" DD can be viewed as tracking the evolution of a *lower bound* to the joint probabilities of failure of the firms composing a portfolio. For this reason, and because of the distributional assumptions underlying its derivation,[9] the portfolio DD measure is a *conservative* measure of systemic risk, that is, it is likely to *underestimate* systemic risk.

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[7] Risk measures obtained from structural models, such as the BSM model, have been shown to have predictive power for supervisory ratings, bond spreads, and rating agencies' downgrades as well as actual defaults (see Krainer and Lopez, 2001; Gropp, Vesala, and Vulpes, 2006; Arora, Bohn and Zhu, 2005; and Tarashev, 2005).

[8] This fact can be also seen as an implication of Jensen's inequality.

[9] Recall that under the assumption that asset values follow a lognormal process, DD measures do not necessarily capture extreme events adequately. In addition, the simplifying assumption that the liability structure is composed of only equity and debt with fixed maturity for all firms, and no rollover of debt, may lead to underestimates of interest rate risks and other risks associated with contingent (derivative) liabilities.

We constructed portfolios for all banks and insurance companies included in the relevant Datastream indexes during the period 1991.01-2004.12.[10] The monthly DD measures were estimated using the methodology described in Vassalou and Xing (2004). At each date, the value of asset, the return on assets and its volatility were derived using the option valuation formula of the BSM model, using one year of daily equity return data preceding the estimation date, and the accounting value of liabilities for the relevant year. This procedure was repeated for each month, and the relevant estimates were used to construct the "portfolio" DD measures at a monthly frequency. As shown by Duan, Gauthier and Simonato (2004), this procedure yields maximum likelihood estimates of implied asset returns and volatility.

B. Trends in Systemic Risk

Figure 2 depicts the evolution of bank systemic risk measures and their trend computed applying an HP filter. Over the period 1990-2004, bank systemic risk does not appear to have declined.

One explanation of these dynamics rests on the changes in the composition of sources of income that have occurred during the period examined. European banks exhibited a substantial increase in noninterest income in the past decade (ECB, 2004). As documented in De Nicolò and others (2005), the volatility of noninterest income growth was significantly larger than that of interest income growth at large banks since 1997. Moreover, the correlation between interest and noninterest income growth has been high (0.79 for the EU-15), indicating *decreasing* diversification benefits across traditional and nontraditional business lines. As banks' earnings have increasingly relied on income generated through financial market activity, most large banks have experienced significant increases in asset return volatility since the early 1990s. Substantial increases in capitalization and improvements in returns have occurred as well, but they have not been sufficient to offset increases in asset return volatility. Thus, large European banks may have supported higher-risk/higher-return investments with larger capital buffers. Yet, risk-adjusted asset returns have not increased, and overall risk profiles have not declined. Using a different systemic risk metrics but a smaller sample of European financial institutions, Hartmann, Straetmans and de Vries (2005) provide further evidence consistent with our results.

These findings, and the attendant interpretation, do not characterize only European banks. A similar pattern appears to have characterized the evolution of risk profiles of U.S. banks as well, as documented by De Nicolò, Hayward, and Vir Bhatia (2004) for U.S. large complex banking groups, and by Stiroh (2004), Hartmann, Straetmans, and de Vries (2005), Stiroh and Rumble (2006), and Houston and Stiroh (2006) for a large set of U.S. bank holding companies, using different systemic risk metrics. Using a term aptly coined by Stiroh and

[10] As of end-2004, the Datastream indices included 63 banks and 53 insurance companies, whose identities and asset sizes are reported in the Appendix.

Rumble, the "*dark side of diversification*" has materialized for U.S. banks as well during the same period.

The dynamics of systemic risk profiles for insurance companies is depicted in Figure 3. While in most European countries these dynamics are similar to those of banks, cross-country heterogeneity is more marked. In some instances, the systemic risk measures indicate that a decline has occurred recently.

C. Convergence of Systemic Risk Measures

Hartmann, Straetmans and de Vries (2005) provide evidence of increased systemic risk in the 1990s for a set of large European (and U.S.) banks in the form of increased correlation of measures of extreme realizations of bank stock excess returns. Unlike these measures, our measures of systemic risk are directly related to firms' joint probability of failures, since they take into account not only the evolution of bank returns, but also their volatility and firms' capitalization. Do our measures of systemic risk point at increased correlation in the form of convergence? The answer is affirmative.

We test convergence in both levels *and* volatility of our systemic risk measures. Denote the sample cross-sectional variance of "portfolio" DDs by $\bar{\sigma}^2_{DD}(t)$. We posit and estimate the following EGARCH-type model for $\bar{\sigma}^2_{DD}(t)$:

$$\bar{\sigma}^2_{DD}(t) = A_0 + A_1 t + A_2 Y_t^2 + A_3 \bar{\sigma}^2_{DD}(t-1) + H_t \eta_t \qquad (12)$$

$$\log H_t^2 = B_0 + B_1 t + B_2 \eta_{t-1}^2 + B_3 \log H_{t-1}^2 \qquad (13)$$

As remarked previously, assessing convergence requires controlling for the magnitude of common shocks, since financial firms operating in totally disconnected economies may exhibit increased comovements in their risk profiles just because the economies in which they operate are hit by the same shock. This motivates the introduction of a proxy measure of "common" risks in the mean equation (12), which is simply measured by the average of each country financial sector DD, $Y_t = \sum_i DD_{it} / N$. Convergence in systemic risk profiles of the banks and insurance sectors is assessed by testing whether the coefficients A_1 and/or B_1 are negative.

Table 5 reports estimates of model (12)-(13). Bank systemic risk profiles exhibit convergence in both mean *and* the variance, since the trend coefficients are negative and highly significant in both the mean and variance equations. These results provide strong support to the conjecture that risk interdependencies have increased remarkably. By contrast, insurance risk profiles do not exhibit convergence either in the mean or in the variance.
In sum, convergence in systemic risk profiles has occurred for banks, but there is no evidence that it has occurred for insurance companies.

D. The Sensitivity of Systemic Risk Measures to Real and Financial Shocks

Have increased real synchronization and advances in financial markets integration affected the dynamics of systemic risk profiles? We address this question by assessing whether the sensitivity of risk profiles of banks and insurance companies to both real and financial shocks common to all countries considered has significantly increased. The impact of such shocks is simply proxied by the common component of real activity estimated previously, and by a value-weighted index of European stock market returns.

An increased sensitivity of the dynamics of systemic risk profiles to the common component of real activity would indicate a greater impact of common real shocks to institutions' exposures, in part due to increased synchronization of real activity. Similarly, an increased sensitivity of these profiles to common financial shocks may be a result of increased financial integration. This is supported by our results on convergence in European IEDFs, as well as by the increased correlation of European stock market returns documented by Bekaert, Hodrick, and Zhang (2005),

Changes in these sensitivities are gauged as follows. Let $\rho_t^i \equiv DD_{it} - DD_{it-1}$ denote *monthly changes* in the DD for banks and insurance sectors in country i. Standard tests for ρ_t^i reject ARCH effects for both banks and insurance companies. We estimate a version of the following simple model for ρ_t^i in each country:

$$\rho_t^i = \alpha + \beta_1(t)F_t + \beta_2(t)R_t + \gamma\rho_{t-1}^i + \varepsilon_t \qquad (14),$$

where F_t denotes the common component of real activity estimated previously, and R_t denotes the Datastream European stock market index. Variables F_t and R_t are likely to capture distinct sources of real and financial shocks, since their contemporaneous correlation was only 0.06 during the entire 1991.1-2004.12 period.

We wish to test whether the coefficients $\beta_1(t)$ and $\beta_2(t)$ have increased. Given the short length of the sample, regressions (14) are simply estimated allowing these coefficients to differ for three periods approximately four-years long: 1991.1-1994.12, 1995.1-1998.12, and 1999.1-2004.12.

Table 6 reports regressions (14) for banks, where the coefficients for the three periods considered are denoted by β_{1j} and β_{2j}, $j=1,2,3$, and the relevant indicator functions I_j, $j=1,2,3$. The sensitivity of bank systemic risk measures to common shocks has increased in all countries but Austria, Greece, Italy, and Norway, where it has remained approximately constant. In most cases, the relevant coefficients have turned from negative to positive, and significantly so. By contrast, the sensitivity of bank risk profiles to financial shocks has changed differently across countries, increasing in Austria, France, Germany, Greece, Italy, the Netherlands, and Portugal, but decreasing in Belgium, Ireland, Norway, Spain, Sweden, and the United Kingdom.

The results for insurance companies are similar to those for banks with respect to common real risks, but exhibit heterogeneity with respect to financial risks. As shown in Table 7, the sensitivity of insurance systemic risk measures to common real shocks has increased in all countries but Austria, Denmark, Italy, and the United Kingdom, where it has remained approximately constant. On the other hand, the sensitivity to financial shocks has increased in France Germany, Italy, and the Netherlands, but has decreased in Denmark, Ireland, and Norway.

Summing up, we find a significant increase in the sensitivity of bank systemic risk profiles to real shocks. In no country have such sensitivities have declined. We also find a significant increase in the sensitivities to financial shocks for institutions located in all large countries but Spain and the United Kingdom. The results for insurance risk profile mirror those for banks with regard to increased exposures to common real shocks, but exhibit heterogeneity with respect to common financial shocks. However, the sensitivity of insurance risk profiles to both common real and financial shocks has increased for most institutions located in the largest countries.

V. Conclusion

In this paper we have assessed whether synchronization in real activity has increased and equity market integration has advanced, and have examined one dimension through which systemic risk profiles at large, systemically important European banks and insurance companies may have been affected by changes in real synchronization and financial markets integration.

We found increased synchronization of real activity starting in the early 1980s, and increased integration in the equities markets starting in the early 1990s. We also found that our measures of bank systemic risk profiles have not declined over the last 15 years, and have converged both in levels and volatility. This evidence suggests that banks may have opted for investment strategies targeting higher-risk/higher-expected returns.

Furthermore, we assessed whether the sensitivity of bank and insurance systemic risk profiles to common real and financial shocks have changed during this period. We found that for banks, the sensitivity of risk profiles to common real and financial shocks has significantly increased in most countries. The sensitivity of risk profiles of insurance companies to common real shocks has significantly increased as well in most countries, while their sensitivity to common financial shocks appears to have increased only for institutions located in the large continental European countries.

Overall, these findings suggest that increased real synchronization and advances in financial integration may not have necessarily resulted in heightened financial stability. Thus, enhanced monitoring of increased interdependencies in risk profiles among institutions and through markets appears an important task European supervisors may face as integration progresses.

Figure 1: EGARCH estimates of IPG Common Component

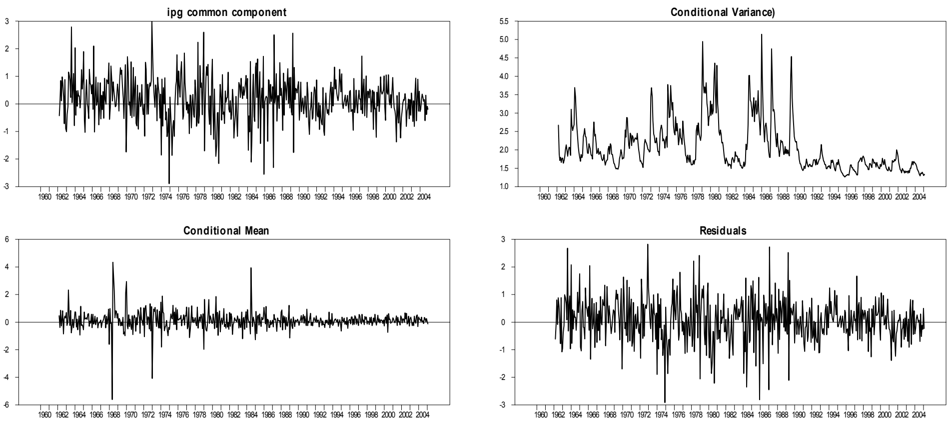

Table 1. EGARCH Estimates for the Common Components of IPG

Mean Equation: $$F_t = A_0 + A_1 t + A_2 F_{t-1} + H_t \eta_t$$

Variance Equation: $$\log H_t^2 = B_0 + B_1 t + B_2 \eta_{t-1}^2 + B_3 \log H_{t-1}^2$$

	Coefficients	Standard Error	T-Statistic	p-value
Mean Equation				
A0	0.33118	0.07129	4.64574	0.00000
A1	**-0.00057**	**0.00018**	**-3.22896**	**0.00124**
A2	0.03188	0.03612	0.88267	0.37741
Variance Equation				
B0	-0.15833	0.19829	-0.79851	0.42457
B1	**-0.00267**	**0.00076**	**-3.51361**	**0.00044**
B2	0.38005	0.08970	4.23701	0.00002
B3	-0.12188	0.24345	-0.50065	0.61662

Table 2. EGARCH Estimates for Cross-Country Variances of IPG and De-Trended IPG

Mean Equation: $\bar{\sigma}_X^2(t) = A_0 + A_1 t + A_2(E_{t-1}F_t)^2 + A_3\bar{\sigma}_X^2(t-1) + H_t\eta_t$

Variance Equation: $\log H_t^2 = B_0 + B_1 t + B_2\eta_{t-1}^2 + B_3 \log H_{t-1}^2$

	Coeff	Std Error	T-Stat	Signif
Mean Equation				
A0	5.832508368	2.292758087	2.54388	0.01096278
A1	**-0.007229695**	**0.004513876**	**-1.60166**	**0.10923082**
A2	2.918317416	0.859319970	3.39608	0.00068359
A3	0.085131670	0.084094149	1.01234	0.31137665
Variance Equation				
B0	4.814365906	1.578460677	3.05004	0.00228812
B1	**-0.006901057**	**0.002589526**	**-2.66499**	**0.00769909**
B2	0.588642141	0.152287022	3.86535	0.00011093
B3	-0.026846689	0.203262590	-0.13208	0.89492192
	De-trended			
Mean Equation				
A0	5.303880223	0.950224807	5.58171	0.00000002
A1	**-0.006814521**	**0.001873768**	**-3.63680**	**0.00027605**
A2	7.069362688	3.455381054	2.04590	0.04076625
A3	0.233748490	0.069387844	3.36872	0.00075517
Variance equation				
B0	4.617319622	0.890776496	5.18348	0.00000022
B1	**-0.008062957**	**0.001681891**	**-4.79398**	**0.00000164**
B2	0.454190765	0.139146278	3.26412	0.00109803
B3	0.226598798	0.114381371	1.98108	0.04758215

Table 3. Country-by-Country EGARCH Estimates for IPG

Mean Equation: $X_{it} = D60 + D70 + D80 + D9004 + \beta_i \overline{X}_t + \gamma X_{it-1} + h_{it}\varepsilon_{it}$

Variance Equation: $Ln(h_{it}^2) = D60 + D70 + D80 + D9004 + b\varepsilon_{it-1}^2 + cLn(h_{it-1}^2)$

	Mean Equation				Variance Equation			
	D60	D70	D80	D9004	D60	D70	D80	D9004
Country								
Austria	-0.02	0.36	0.13	0.36	0.76	-1.09	-1.15	-0.82
Belgium	0.09	0.02	0.06	0.13	-0.14	0.27	0.23	0.21
France	-0.01	0.24	0.07	0.07	1.27	-2.35	-2.72	-3.01
Germany	0.21	-0.07	0.03	0.04	0.44	-0.83	-0.58	-1.19
Greece	0.70	0.63	0.22	-0.04	0.51	-0.53	-0.30	-0.29
Italy	0.16	0.29	0.08	0.00	0.13	0.15	-0.21	-0.90
Netherlands	0.50	0.14	0.12	0.10	-0.17	0.44	0.91	0.62
Portugal	0.35	0.67	0.41	0.10	0.61	-0.56	-0.84	-0.89
Sweden	0.17	0.04	0.08	0.20	1.10	-1.68	-0.67	-2.30
U.K.	-0.01	0.04	0.07	-0.03	-0.83	1.59	1.00	0.40
Mean	0.21	0.24	0.13	0.09	0.37	-0.46	-0.44	-0.82
Variance	**0.06**	**0.07**	**0.01**	**0.01**	**0.40**	**1.28**	**1.15**	**1.34**

Table 4. Dependent Variables: Cross-Country Variance of IEDFs and Country IEDFs

Panel A: $\bar{\sigma}_M^2(t) = A_0 + A_1 t + \eta_t$

Panels B: $\bar{\sigma}_M^2(t) = D702 + D801 + D802 + D901 + D902 + D00 + \eta_t$

Panels C: $EDF_i(t) = D702 + D801 + D802 + D901 + D902 + D00 + \eta_t$

	Coeff	Std Error	T-Stat	Signif
Panel A				
A0	0.238763917	0.032929671	7.25072	0.00000000
A1	**-0.000240336**	**0.000106836**	**-2.24957**	**0.02447599**
Panel B				
D702	0.1727069830	0.0193907237	8.90668	0.00000000
D801	0.2497064481	0.0464092453	5.38053	0.00000007
D802	0.1860275694	0.0201381090	9.23759	0.00000000
D901	0.1888773756	0.0223010268	8.46945	0.00000000
D902	0.1544279148	0.0150023740	10.29357	0.00000000
D00	0.1431732182	0.0150554668	9.50972	0.00000000

Panel C

	d702	**d801**	**d802**	**d901**	**d902**	**d00**
AUSTRIA	1.20645	1.10617	1.29210	1.16723	1.19304	1.20955
BELGIUM	1.13181	1.17612	1.22143	1.22645	1.17590	1.26687
DENMARK	1.11991	1.27833	1.22076	1.23424	1.26985	1.15297
FRANCE	1.17015	1.19635	1.24437	1.28162	1.22491	1.20120
GERMANY	1.30347	1.25389	1.14590	1.15146	1.12503	1.13513
IRELAND	1.05380	1.03319	1.27659	1.26040	1.28902	1.19700
ITALY	1.30551	1.26973	1.27198	1.28658	1.34620	1.24998
NETHERLANDS	1.20677	1.20968	1.23937	1.24176	1.25930	1.15309
U.K.	1.23885	1.25970	1.13021	1.20395	1.27444	1.26789
Mean	1.19297	1.19813	1.22697	1.22819	1.23974	1.20374
Variance	**0.00704**	**0.00684**	**0.00315**	**0.00221**	**0.00449**	**0.00252**

Figure 2: Bank DDs

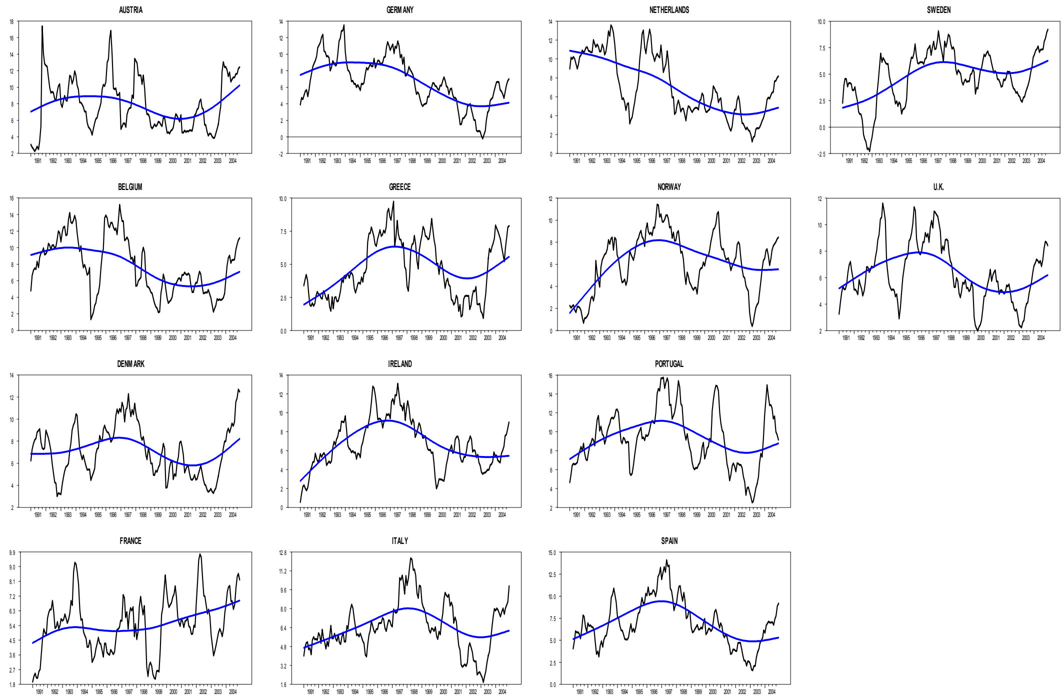

Figure 3: Insurance DDs

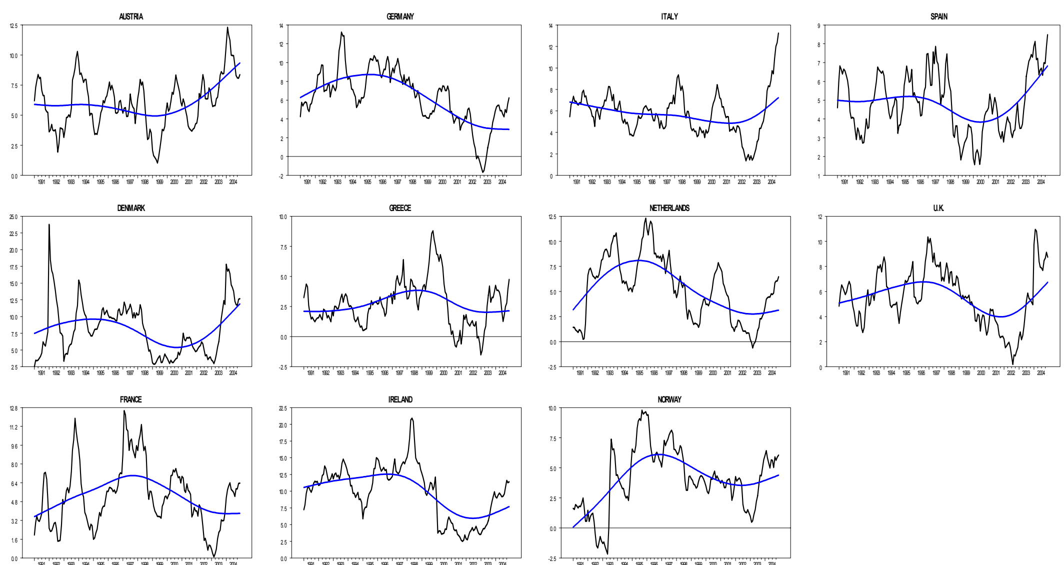

Table 5. Dependent Variables: Cross-Country Variance of Portfolios' DDs

Mean Equation: $\bar{\sigma}^2_{DD}(t) = A_0 + A_1 t + A_2 Y_t^2 + A_3 \bar{\sigma}^2_{DD}(t-1) + H_t \eta_t$

Variance Equation: $\log H_t^2 = B_0 + B_1 t + B_2 \eta_{t-1}^2 + B_3 \log H_{t-1}^2$

	Coeff	Std Error	T-Stat	Signif
BANKS				
Mean Equation				
A0	2.130758233	0.796056529	2.67664	0.00743641
A1	**-0.004987358**	**0.001985143**	**-2.51234**	**0.01199330**
A2	0.005940051	0.003149941	1.88577	0.05932652
A3	0.858994960	0.039575910	21.70500	0.00000000
Variance Equation				
B0	6.070978192	2.226300055	2.72694	0.00639254
B1	**-0.017596387**	**0.005921549**	**-2.97158**	**0.00296267**
B2	0.220411658	0.116434721	1.89301	0.05835703
B3	-0.224892329	0.226904246	-0.99113	0.32162055
INSURANCE				
Mean Equation				
A0	1.103339887	2.667662223	0.41360	0.67916850
A1	**0.003887521**	**0.004944093**	**0.78630**	**0.43169399**
A2	0.057381532	0.021335058	2.68954	0.00715502
A3	0.719393328	0.103899125	6.92396	0.00000000
Variance Equation				
B0	9.234640107	9.860517900	0.93653	0.34900198
B1	**-0.021483407**	**0.023667905**	**-0.90770**	**0.36403563**
B2	0.010679293	0.393523834	0.02714	0.97834998
B3	-0.470348664	0.936137459	-0.50244	0.61536123

Table 6. Dependent Variable: Banks DDs Changes

Models: (1) $\Delta\rho_t^i = \alpha + \beta_1 F_t + \beta_2 R_t + \gamma\Delta\rho_{t-1}^i + \varepsilon_t^i$; (2) $\Delta\rho_t^i = \alpha + \sum_{j=1}^{3}\beta_{1j} I_j F_t + \sum_{j=1}^{3}\beta_{2j} I_j R_t + \gamma\Delta\rho_{t-1}^i + \varepsilon_t^i$

	β_1	β_{11}	β_{12}	β_{13}	β_2	β_{21}	β_{22}	β_{23}
AUSTRIA	**0.22914**	**0.19882**	**0.24446**	**0.19005**	**3.06991**	**-2.58253**	**5.08501**	**4.14558**
t-stat	1.12680	0.48277	0.74375	0.86648	0.90713	-0.31624	0.88052	2.02906
BELGIUM	**-0.05524**	**-0.14530**	**-0.18260**	**0.12222**	**6.79376**	**7.18137**	**6.00944**	**7.22582**
t-stat	-0.44064	-0.83982	-0.48629	0.89236	3.71733	2.21134	1.41646	4.12920
DENMARK	**0.18350**	**-0.02602**	**0.08777**	**0.50247**	**5.39206**	**11.29102**	**5.53111**	**1.83205**
t-stat	1.72894	-0.21526	0.35315	2.98560	4.54716	5.23163	2.81885	1.05308
FRANCE	**-0.06485**	**-0.21530**	**-0.07057**	**0.06281**	**8.51009**	**6.23099**	**10.61516**	**7.25105**
t-stat	-0.86576	-2.08099	-0.37863	0.58821	6.68370	2.43581	5.36341	4.64868
GERMANY	**0.00863**	**-0.08972**	**-0.12743**	**0.14603**	**6.01768**	**1.50707**	**5.94823**	**8.47721**
t-stat	0.10507	-0.52650	-0.64834	1.93410	4.15413	0.24985	3.36277	5.78293
GREECE	**0.00882**	**-0.10041**	**0.14396**	**0.02024**	**6.84393**	**4.94287**	**9.23776**	**5.07508**
t-stat	0.10323	-0.90929	0.64083	0.15302	5.54959	2.61422	5.00959	2.54594
IRELAND	**-0.08240**	**-0.26604**	**-0.08318**	**0.10216**	**5.67918**	**6.03562**	**5.79232**	**4.84149**
t-stat	-1.01429	-1.88952	-0.49246	0.83259	4.19292	3.09929	2.26681	2.32658
ITALY	**0.21024**	**0.25366**	**0.11337**	**0.17804**	**7.30423**	**2.14074**	**10.67059**	**7.15589**
t-stat	2.50871	1.80220	0.77431	1.41244	6.47755	0.86133	7.00629	4.21428
NETHERLANDS	**-0.02262**	**-0.23540**	**-0.03518**	**0.14693**	**5.91218**	**1.99414**	**6.59478**	**6.83980**
t-stat	-0.26792	-1.62760	-0.16432	1.81176	4.79348	0.59233	3.15099	4.37547
NORWAY	**0.17415**	**0.20640**	**0.10871**	**0.18771**	**5.42550**	**5.60672**	**5.62960**	**5.31900**
t-stat	1.95444	1.09798	0.72036	1.61691	4.36156	1.73398	2.78827	3.66942
PORTUGAL	**0.14310**	**-0.14880**	**0.35741**	**0.23421**	**7.23641**	**2.33354**	**8.10958**	**7.98958**
t-stat	1.55419	-1.09203	2.06801	1.41386	5.71466	0.82094	3.66198	4.03926
SPAIN	**-0.00595**	**-0.06114**	**-0.14175**	**0.15393**	**8.99014**	**10.51475**	**9.79983**	**7.39503**
t-stat	-0.07638	-0.45176	-0.78550	1.52710	6.44645	2.56563	4.43565	4.20194
SWEDEN	**0.11139**	**-0.05850**	**0.01928**	**0.35596**	**5.62820**	**7.54971**	**6.35453**	**3.66768**
t-stat	1.44782	-0.47774	0.11013	3.77615	4.85987	3.18056	2.92426	3.14802
U.K.	**-0.11513**	**-0.40599**	**-0.09382**	**0.15302**	**4.95129**	**5.10395**	**5.11531**	**3.94157**t-
stat	-1.39310	-2.93993	-0.62166	1.18845	4.43553	2.00226	2.62350	2.81685

Table 7. Dependent Variable : Insurance DDs Changes

$$\text{Models : (1) } \Delta\rho_t^i = \alpha + \beta_1 F_t + \beta_2 R_t + \gamma\Delta\rho_{t-1}^i + \varepsilon_t^i \text{ ; (2) } \Delta\rho_t^i = \alpha + \sum_{j=1}^{3}\beta_{1j} I_j F_t + \sum_{j=1}^{3}\beta_{2j} I_j R_t + \gamma\Delta\rho_{t-1}^i + \varepsilon_t^i$$

	β_1	β_{11}	β_{12}	β_{13}	β_2	β_{21}	β_{22}	β_{23}
AUSTRIA	**-0.07401**	**-0.13646**	**-0.02889**	**-0.05242**	**5.56877**	**4.79820**	**6.68891**	**4.74129**
t-stat	-0.87164	-0.79823	-0.18099	-0.41560	3.93998	1.12355	3.95795	2.21433
DENMARK	**0.35582**	**1.05606**	**0.12418**	**-0.00905**	**11.31496**	**28.15192**	**7.08159**	**8.84322**
t-stat	1.32135	1.36990	0.52799	-0.04400	3.67787	1.89994	3.42040	2.21464
FRANCE	**-0.19178**	**-0.48789**	**-0.20667**	**0.08307**	**10.62458**	**8.60484**	**12.58048**	**9.19347**
t-stat	-2.11906	-2.58970	-1.10573	0.89256	7.15602	2.15961	4.77712	5.59050
GERMANY	**0.02595**	**-0.03629**	**0.01163**	**0.08253**	**6.17503**	**4.73298**	**3.90193**	**9.01931**
t-stat	0.29904	-0.18959	0.06824	0.84674	3.85809	0.77777	1.72722	6.90630
GREECE	**-0.00128**	**-0.16637**	**0.31959**	**-0.05217**	**5.78269**	**4.96145**	**5.78071**	**5.30061**
t-stat	-0.01313	-1.81309	1.48146	-0.33157	4.71844	2.88784	2.51895	2.65559
IRELAND	**-0.00002**	**-0.12271**	**0.04893**	**0.09791**	**4.27298**	**5.76075**	**6.61989**	**0.92890**
t-stat	-0.00143	-0.92617	0.13156	0.39044	2.58317	1.78139	1.97196	0.44966
ITALY	**0.13099**	**0.12708**	**0.05859**	**0.12922**	**5.67917**	**0.60276**	**7.62463**	**6.70161**
t-stat	1.99638	1.09772	0.50392	1.24325	4.58143	0.19621	3.87340	4.68354
NETHERLANDS	**0.02564**	**-0.14301**	**0.01596**	**0.12346**	**5.43702**	**-1.57370**	**8.48470**	**5.82751**
t-stat	0.30738	-1.06652	0.07301	1.42235	3.59210	-0.41880	3.98888	3.69937
NORWAY	**0.04063**	**0.00638**	**0.08005**	**0.08555**	**5.45010**	**8.69135**	**4.54006**	**4.48679**
t-stat	0.46890	0.04253	0.41735	0.73726	4.95299	2.80595	2.57227	2.96369
SPAIN	**0.02762**	**-0.10887**	**0.12016**	**0.09305**	**5.97838**	**5.90317**	**7.39693**	**4.33736**
t-stat	0.39628	-1.16996	0.75689	0.84544	5.60565	4.09959	3.59187	3.03786
U.K.	**-0.14484**	**-0.28911**	**0.17216**	**-0.19506**	**5.39866**	**7.48984**	**2.26799**	**6.49323**
t-stat	-1.57067	-2.35482	0.66822	-1.30092	3.21487	3.25397	0.89055	2.04962

Appendix Table 1. Banks and Insurance Companies

Total Assets, end 2004
(In millions of euro)

Austria	
Banks	
BANK AU.CREDITANSTALT	145,680
ERSTE BANK	139,390
Insurance	
GENERALI HOLDING	10,430
UNIQA	15,125
WIENER STAEDT VZ	12,525
Belgium	
Banks	
ALMANIJ	259,629 *
DEXIA	349,463
FORTIS (BRU)	521,524
KBC BKVS.HDG.	225,587
Denmark	
Banks	
DANSKE BANK	248,949
JYSKE BANK	16,687
SYDBANK	10,453
Insurance	
ALM BRAND	2,897
CODAN	5,358
TOPDANMARK	4,516
France	
Banks	
BNP PARIBAS	905,001
CREDIT AGRICOLE	814,654
SOCIETE GENERALE	600,897
Insurance	
AGF-ASR.GL.DE FRN.	103,549
APRIL GROUP	419
AXA	440,744
EULER HERMES	5,716
FINAXA	4,973
SCOR	12,542
Germany	
Banks	
BANKGESELLSCHAFT BERLIN	152,041
BAYER.HYPO-UND-VBK.	463,496
COMMERZBANK	419,674
DEUTSCHE BANK	836,368
Insurance	
ALLIANZ	958,579
AMB GENERALI HDG.	85,632
AXA KONZERN	38,438
AXA VERSICHERUNG	7,219
DBV-WINTERTHUR HOLDING	22,398
ERGO VERSICHERUNG	108,988
GERLING	4,327
HANNOVER RUCK.	30,615
KOELN.RUCK.	9,390
KOELN.VERWALT.GESELL.	69
MLP	2,378
MUNCH.RUCK.REGD.	203,501
WUESTENROT & WUERTT.	54,380
Greece	
Banks	
ALPHA BANK	32,917
BANK OF GREECE	32,810
BANK OF PIRAEUS	16,591
EFG EUROBANK ERGASIAS	31,760
EMPORIKI BK.OF GREECE	18,236
NAT.BK.OF GREECE	52,877
Insurance	
ETHNIKI GREEK GEN IN CO	1,621
Ireland	
Banks	
ALLIED IRISH BANKS	102,042
ANG.IR.BK.	34,305
BANK OF IRELAND	106,431
Insurance	
FBD HOLDINGS	1,394
Italy	
Banks	
UNICREDITO ITALIANO	264,791
SAN PAOLO IMI	209,627
CAPITALIA	131,163
BANCA INTESA	273,181
BANCA MONTE DEI PASCHI	128,662
BCA.NAZ.LAVORO	78,111
Insurance	
CATTOLICA ASSICURAZIONI	14,773
FONDIARIA-SAI	31,381
GENERALI	252,542
MILANO ASSIC.	9,804
PREMAFIN-HLDG.DI PART.	31,493
RAS	66,229
UNIPOL	32,201
Netherlands	
Banks	
ABN AMRO HOLDING	607,263
FORTIS (AMS)	521,524
Insurance	
ING GROEP CERTS.	866,201
Norway	
Banks	
DNB NOR	86,097
SPAREBANKEN ROGALAND	7,152
Insurance	
STOREBRAND	20,871
Portugal	
Banks	
BANCO BPI	26,166
BNC.ESPR.SANTO (BESCL)R	45,894
BNC.TOTTA & ACORES	28,824 *
BCP R	71,678

Appendix Table 1. Banks (concluded)

	Total Assets, end 2004 (In millions of euro)
Spain	
Banks	
BANCO ESPANOL DE CREDITO	66,257
BANCO POPULAR ESPANOL	62,522
BANCO SANTANDER CENTRAL HISPANO	569,795
BBV ARGENTARIA	306,218
Insurance	
CORP.MAPFRE 'R'	18,033
GRUPO CATALANA OCCIDENTE	3,536
Sweden	
Banks	
FNSPK. A	112,758
NORDEA BANK	262,523
SEB A	175,698
SVENSKA HANDBKN	149,071
UK	
Banks	
BARCLAYS	735,337
HBOS	623,776
HSBC HDG.	935,023
LLOYDS TSB GP.	394,145
RYL.BK.OF SCTL.	821,784
STD.CHARTERED	103,769
Insurance	
ADMIRAL GROUP	708
ALEA GP.HDG.(BERMUDA)	4,646
AMLIN	2,858
BEAZLEY	1,136
BENFIELD GROUP	6,052
BRIT INSURANCE HOLDINGS	3,563
CATLIN GROUP	2,437
CHAUCER HOLDINGS	1,074
COX IN.HOLDINGS	1,104
DOMESTIC & GENERAL GP.	474
HISCOX	2,269
JARDINE LLOYD THOMPSON	3,171
KILN	707
ROYAL & SUN ALL.IN.	28,279
WELLINGTON UNDERWRITING	1,841

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