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Time-Varying Betas of Banking Sectors*

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Abstract

This paper analyzes the evolution of the systematic risk of the banking industries in eight advanced countries using weekly data from 1990 to 2012. Time-varying betas are estimated by means of a Bayesian state-space model with stochastic volatility, whose results are contrasted with those of the standard M-GARCH and rolling-regression models. We show that both country-specific and global events affect the perceived systematic risk, while the impact of the latter differs considerably across countries. Finally, our results do not support the previous findings that the systematic risk of the banking sector was underestimated before the last financial crisis.

1. Introduction

Systematic risk has been among the most studied issues in the financial literature, particularly when systematic risk of banking sectors is considered. The inherent fragility of banks and the opacity of their businesses raise the question of whether markets are able to price the risk correctly. The excessive risk-taking by US banks before the market meltdown in 2007 is an example of a period when the correct evaluation of risk is questionable. Surprisingly, not even the ex-post literature provides any clear-cut answer to this question, so it is not clear whether markets were aware of the risks connected with mortgage loan securitization. As we show in this paper, the results depend on how the systematic risk is estimated.

The paper extends the evidence from the current literature in several ways. First, it applies a Bayesian state-space model with stochastic volatility for the estimation of the CAPM betas of banking sectors. According to the CAPM theory, the betas should capture the systematic risk of the industry. It is now widely held that betas are not time invariant, and methods such as the rolling-regression model, classic state-space models, and the GARCH model have so far been used frequently to estimate the evolution of betas. Still, these methods have several shortcomings, such as arbitrary choice of window size (in the case of rolling regression), assumed homoskedasticity of residuals (in both the rolling-regression and the state-space approaches), and a large amount of noise present in the estimates (estimation based on the GARCH model). On the other hand, the model that we use links the advantages of both the Kalman filter approach (estimating the beta as an unobservable process in a state-space model) and the approach based on the M-GARCH model (allowing for heteroskedasticity of residuals).

* The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors and do not represent the views of any of the above-mentioned institutions.

Next, the paper presents the results for three methods—the rolling-regression model, the GARCH model, and the state-space model with stochastic volatility—and, on the example of US banking betas in the pre-crisis period, shows how these estimates can be useful for policy makers. This period was characterized by a build-up of instability in the banking sector, which was not reflected in stock prices according to some studies. Nevertheless, our analysis shows that the banking sector risk in tranquil times could still be priced in if the estimation techniques used in this paper were employed.

Third, as a novelty, we analyze the time-varying betas of banking sectors across different advanced countries. The previous literature has investigated the betas of financial sectors as a whole or has investigated trends between sub-sectors in one individual country. On the other hand, our estimation allows us to look at potential global trends in the perceived riskiness of banking sectors. To evaluate the degree of co-movement, we estimate a global factor and calculate the percentage of the variation explained by the global factor for individual countries. It seems that the banking sectors in some countries (the US, the UK, and Germany) share similar patterns in the evolution of their systemic risk, while the sectors in other countries (Japan and Australia) look more isolated. The paper presents one of many possible explanations: the degree to which the countries are financially interconnected. Thus, we compare our results with previous findings on international banking and the transmission of financial stress. It seems that the most influential financial centers exhibit the highest sensitivity to global developments and the degree to which the banking sector is internationalized can be reflected in the sector's systemic risk.

We believe that our suggested estimation method has substantial empirical value for equity capital investors and bank managers as well as for financial supervision. This innovative approach can be applied to the banking sector as a whole or to individual banks' data. Hence, it can be used to estimate the cost of capital more accurately or to identify the determinants of systemic risk. It may also help in the identification of instability accumulation in tranquil times, as this paradox remains a crucial issue for financial stability.

2. Systematic Risk and the Banking Sector

The concept of the capital asset pricing model (CAPM) has been under constant attention of both academicians and practitioners for almost 50 years. One of the most important implications of this model is that we can use the contribution of an asset to the variance of the market portfolio (the asset's beta) as a measure of the asset's systematic risk. This risk is determined by general market conditions and cannot be diversified away.

The assessment of systematic risk is vital both for academic research when testing asset-pricing models and market efficiency, and for investment decisions such as portfolio choice, capital budgeting, and performance evaluation. In recent years, it has also become used for financial stability purposes to estimate the cost of equity (Barnes and Lopez, 2006) or even to measure the level of financial stress.

Our study is unique in that it compares time-varying betas in banking sectors across different countries. Betas of banking sectors have usually been estimated in the literature as a part of sectoral analyses in the financial sector. For example, Mergner and Bulla (2008) estimate the time-varying betas of a financial sector (including insurance companies) in a pan-European portfolio. A similar exercise is performed by Groenewold and Fraser (1999) on Australian sectors. Estimation is performed on an individual stock level by Lie et al. (2000), who estimate the time-varying betas of 15 financial sector companies in Australia on daily data. They use the GARCH model and the Kalman filter, which generates better results based on in-sample MAE and MSE.

Another pure banking-sector analysis is by King (2009), who estimates the costs (required rate of return) of capital in six developed countries using rolling regression. He claims that the costs declined in all countries except for Japan until 2005, when they started to rise. The decline in costs reflects both a declining beta and a declining risk-free rate. He also suggests that a low beta may point to mispricing of banking shares.

More recently, Caporale (2012) performs tests for structural breaks in a market model of the US banking sector. He identifies three structural breaks—1960.12, 1989.09, and 2000.03, after which banking betas were at historical lows (the sample ends in 2008). He suggests that the risk was mispriced (systematic risk was under-estimated), as the banks took highest leverage and risk in this time, while the expected risk was low. On the other hand, Bhattacharyya and Purnanandam (2011) look at the evidence of excessive risk-taking of US banks in the pre-crisis period on an individual bank level. They conclude that financial markets were able to identify banks engaged in risky operations before the meltdown.

This brings us to a stream of literature dedicated to the determinants of systematic risk. Several studies have covered both US and European banking institutions, and the question of whether more leveraged banks are more risky is discussed in particular. While Yang and Tsatsaronis (2012) show a positive correlation between leverage and beta on a sample of 50 banks from OECD countries, di Base and Elisabetta (2012) do not find a strong link in the Italian sector. Also, the cost of equity (which is determined based on beta) is still a key issue mainly for banking sector supervision and financial stability purposes. A recent paper by Yang and Tsatsaronis (2012) extends this stream by showing that leverage and business cycles influence the systematic component of banking risk, so bank equity financing is cheaper in booms and dearer during recessions. Altunbas et al. (2010) identify several determinants of individual bank riskiness, accounting for banking sector characteristics such as GDP, housing prices, and the yield curve.

The impact of banking globalization on banking sector risk has never been studied in this context. Individual bank data from Germany were used by Buch et al. (2010b), who show that internationalization increases the riskiness of banks. Similarly, Cetorelli and Goldberg (2012) show that banking globalization is a way of increasing the global transmission of shocks, so increased financial linkages between banking sectors worldwide increase their vulnerability to financial shocks.

3. Estimating Time-Varying Betas

For the purposes of this paper (estimating the betas of banking sectors), we consider the standard CAPM result, summarized in the following equation:

$$E\left[\tilde{R}_i\right] = \beta_i E\left[\tilde{R}_m\right] \tag{1}$$

where $\widetilde{R}_i = R_i - r_f$ is the excess return on asset i (r_f is the return on the risk-free asset) and $\widetilde{R}_m = R_m - r_f$ is the excess return on the market portfolio. This asserts that in equilibrium, the returns on an asset depend linearly only on the returns on the market portfolio (thus, it is a one-factor model). This model should hold ex-ante, but it can be estimated only on historical data, so the following market model regression is used for the estimation:

$$\tilde{R}_{it} = \alpha_i + \beta_i \tilde{R}_{mt} + \varepsilon_{it},\ \varepsilon_{it} \sim N\left(0, \sigma_i^2\right) \tag{2}$$

The original model implies an equilibrium relation, which should be stable or time-invariant. However, the stability of this relation has been challenged several times in the literature and there is now a consensus that β_i is not constant. For instance, Fabozzi and Francis (1978) claim that betas may be random coefficients, which could explain the large variance of betas estimated using OLS, the poor performance in estimating the returns on assets, and the rejection of the CAPM in many stock markets. Despite these findings, no consensus has been found on the method for estimating time-varying betas. Usually, a Kalman filter or a GARCH model are used (e.g., Faff et al., 2000; Mergner and Bulla, 2008; Lie et al., 2000), with differing results.

In order to draw credible conclusions, we employ three approaches to estimating betas and compare their results. The first approach is based on a simple rolling-regression model. The second approach is based on the M-GARCH model introduced by Bollerslev (1990), which is based on estimating the conditional covariances between the returns on the market portfolio and the asset under consideration. The third approach is based on a Bayesian state-space model with stochastic volatility, which estimates betas as an unobserved component and allows for time-varying variance of shocks.

3.1 Rolling Regression

As a starting point, we employ a method based on rolling-regression estimates, where time-varying betas are estimated by OLS on a moving window of a given number of observations. The drawback of this method is its sensitivity to the choice of window size and the sensitivity of OLS to outliers. As this method is used only as a benchmark against which we compare the other two methods, the size of the window is chosen informally.

3.2 M-GARCH

First, let us assume without loss of generality that $\tilde{R}_{jt} = \varepsilon_{jt}$, where $j = i, M$, and the error terms are assumed to be $\left(\varepsilon_{it}, \varepsilon_{Mt}\right)' = H_t^{1/2} z_t$, and $z_{jt} \sim N\left(0,1\right)$ are uncorrelated. Since $\varepsilon_{jt} \mid \Psi_{t-1} \sim N\left(0, H_t\right)$, equation (3) then represents a conditional covariance matrix between the banking sector returns and the market returns:

$$H_t = \begin{pmatrix} h_{ii,t} & h_{iM,t} \\ h_{Mi,t} & h_{MM,t} \end{pmatrix} \tag{3}$$

As suggested by a previous analysis by Rippel and Jansky (2011), we chose a GARCH(1,1) process, which leads to the M-GARCH model described by the vector equation (4). The same equation can be rewritten in a more compact way (equation (6)) using a *vech* operator that stacks in one column all non-redundant elements of a symmetric matrix that are either on or below the diagonal (Hamilton, 1994).

$$\begin{pmatrix} h_{ii,t} \\ h_{iM,t} \\ h_{MM,t} \end{pmatrix} = \begin{pmatrix} c_{11} \\ c_{12} \\ c_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} x \begin{pmatrix} \varepsilon_{i,t-1}^2 \\ \varepsilon_{i,t-1}\varepsilon_{M,t-1} \\ \varepsilon_{M,t-1}^2 \end{pmatrix} + \tag{4}$$

$$+ \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} x \begin{pmatrix} h_{ii,t-1} \\ h_{iM,t-1} \\ h_{MM,t-1} \end{pmatrix} \tag{5}$$

$$(\text{vech})H_t = C + A(\text{vech})\varepsilon + B(\text{vech})H_{t-1} \tag{6}$$

A disadvantage of the multivariate M-GARCH model is its overparameterization. For example, the M-GARCH(1,1) model has 21 unknown coefficients, and the number of coefficients grows at a polynomial rate as the number of time series involved rises. Some authors, such as Bollerslev (1990), suggest setting all coefficients above and below the diagonal to zero. This simplification leads to a substantially reduced form of the general equation and allows us to describe the model by equations (7), (8), and (9) with only seven coefficients. The correlation between the returns of a banking sector and the market, denoted ρ, is assumed by Bollerslev (1990) to be constant. This simplification leads to the following system of equations:

$$h_{ii,t} = c_{11} + a_{11}\varepsilon_{i,t-1}^2 + b_{11}h_{ii,t-1} \tag{7}$$

$$h_{MM,t} = c_{22} + a_{33}\varepsilon_{M,t-1}^2 + b_{33}h_{MM,t-1} \tag{8}$$

$$h_{iM,t} = \rho\sqrt{h_{ii,t}h_{MM,t}} \tag{9}$$

Having estimated the three equations above, the time-varying beta can be easily calculated. The standard CAPM calculates β as the ratio of the covariance between the asset and the market to the market volatility. Since the variance-covariance matrix in the M-GARCH model is time dependent, the time-varying beta can be calculated using the relevant conditional covariance matrix H_t. In other words, a time-varying beta calculated using the M-GARCH model has the form described by the following equation:

$$\beta_{it} = \frac{cov_t\left(\tilde{R}_{it}, \tilde{R}_{Mt}\right)}{var_t\left(\tilde{R}_{Mt}\right)} = \frac{h_{iM,t}}{h_{MM,t}} \tag{10}$$

3.3 Bayesian State-Space Model with Stochastic Volatility

The drawback of the previous approach is that it contains a lot of noise because the betas can change substantially every period, which is not plausible. To overcome this problem, we model the betas as an unobservable process which follows a random walk. We assume the following state-space model (note that the analyzed asset's index i is omitted):

$$\tilde{R}_t = \alpha_t + \beta_t \tilde{R}_{mt} + u_t, u_t \sim N\left(0, \sigma_t^2\right), t = 1, 2, ..., T \tag{11}$$

$$B_t = \begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix} = \begin{pmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{pmatrix} + \begin{pmatrix} v_{\alpha,t} \\ v_{\beta,t} \end{pmatrix}, \begin{pmatrix} v_{\alpha,t} \\ v_{\beta,t} \end{pmatrix} \sim N(0, \Sigma) \tag{12}$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t, \eta_t \sim N\left(0, W\right) \tag{13}$$

This state-space model is similar to those used in the literature. However, those models, estimated using the Kalman filter, assume that the residuals u_t are homoskedastic, i.e., σ_t is fixed. This can bring bias into the results (i.e., the betas can be overestimated or underestimated, depending on the value of σ_t), because σ_t is used in the Kalman filtering and presumably varies over time. Therefore, we assume a variant of stochastic volatility, i.e., the volatility is modeled as a latent process σ_t which is not a simple function of the past or current values of the observables, as is the case with a GARCH process, for example. We assume the simplest version of the stochastic volatility process, where the volatility follows a geometric random walk.

This kind of model is usually estimated using Bayesian inference, which overcomes the problem of failure to find local maxima, as is the case with the MLE approach. In addition, Bayesian methods in this context are relatively easy to implement and can be extended to find the posterior distributions of parameters in very complex models. The major difference between the MLE and Bayesian approaches to state-space modeling is that the latter assumes that the parameters of the state/ /observational equations (i.e., the variances of the error terms) are not fixed parameters to be estimated, but are random variables. In addition, the state variables (B_t and σ_t) are regarded as random variables as well. The estimation starts by assuming the prior distributions of the hyperparameters and the starting values of the state variables, and solving for the posterior densities of all these variables (by means of Bayes' theorem). Because the joint posterior density function is intractable in this case, a simulation using Markov chain Monte Carlo methods is performed. Its details are described in the *Appendix*.

4. Time-Varying Betas of the Banking Sectors

4.1 Data Used for the Analysis

We estimate the time-varying betas of the banking industries in eight advanced countries—the United States, the United Kingdom, Germany, France, Switzerland, Japan, Hong Kong, and Australia. The countries were chosen based on their market capitalization and the number of banks operating in the country. The major stock market indices were used as the indices representing the market

Table 1 Data Used for the Analysis

Country	Risk-Free Rate	Stock Market Index
United Kingdom	UK Interbank 3M	FTSE 100
France	Euribor 3M	CAC 40
Germany	Euribor 3M	DAX 30
Switzerland	Swiss Liquidity Financing Rate 1M	SMI
United States	US 3M T-Bill	NYSE COMPOSITE
Japan	3M Interbank	NIKKEI 225
Hong Kong	HKD Depo 1M	Hang Seng
Australia	Dealer bill 90 day rate	ALL ORDS

Source: Thomson Reuters Datastream

portfolio. In some cases, banking sector indices are published by stock exchanges, but to ensure consistency we opted for banking sector indices constructed by Thomson Reuters. Finally, the risk-free rates of most countries were chosen as those recommended by Datastream (available on its intranet, for example), while the risk-free rate of Hong Kong was chosen based on the literature. All the data were downloaded from Datastream and are summarized in *Table 1*. The normalized stock indices are plotted in *Figure C.1* in *Appendix*.

Weekly data spanning January 1990 to February 2011 are used for the analysis. The exceptions are Germany and France, whose data start in January 1999, when the Euribor was introduced. The sample could have been extended by using the national money market rates before 1999, but we wanted to ensure consistency of the results, so this extension was skipped.

4.2 Results: Systematic Risk of the Banking Sectors

We estimated the time-varying betas of each banking sector using the three approaches mentioned in the previous section—the rolling-regression model, the multivariate GARCH model, and finally the state-space model with stochastic volatility. *Figure D.1* in *Appendix* presents the results from the rolling regression with a window spanning 50 observations, which corresponds to approximately one year. This approach has two major drawbacks—there is no means of estimating the optimal size of the window, and the technique is sensitive to outliers. Therefore, the figure would look different if the size of the window was chosen in a different way.

Next, *Figure E.1* and *Figure E.2* in *Appendix* present estimates using the multivariate GARCH. Its drawback is that the resulting time series contain a large amount of noise, which causes them to be very erratic. Since each new observation affects the volatility of both the market and the indices and, therefore, the betas, changes between two consecutive observations should be interpreted cautiously.

Finally, *Figure F.1* and *Figure F.2* in *Appendix* present the posterior medians and two posterior quantiles of the latent processes of the betas and the stochastic volatility simulated using the Gibbs sampler. The burn-in sample has 8,000 iterations and the following 2,000 iterations were used to form the quantiles. We can see that the largest differences between this approach and the former two occur at times of increased volatility, which is because the last method filters out the noise brought about by every new observation. This is also why we employ this third method.

All three approaches strongly support the idea of the time-varying nature of the beta, and several important features are apparent. First, we do not observe any steady decline in the banking sector beta after 1990. This is in contrast with King (2009), who concludes that the bank betas trended downward for most countries over a 20-year period, with a substantial increase only in the latest period. He used bank-level estimates that are lower than the equity sub-index estimates we employ. The differences are particularly large in the case of the UK and increased during the recent crisis period (mainly due to a different weighting and sample). Still, our aim is to follow investors' reasoning (perceived riskiness) and global factors for the most important banking groups rather than to measure exactly the cost of equity for financial stability purposes.

Second, our more precise beta estimates indicate that the banking sector risk in tranquil times could still be priced in. As for the period after 2005, it is often argued in the literature that market expectations of banking risk in the US were low while bank leverage and risk-taking were rising during the housing market credit boom. Still, we cannot fully agree that this instability build-up was mispriced. The US banking beta started to rise as early as July 2006 from levels close to 0.6, growing steadily to 1.5 two years later when the financial crisis had fully developed. Similarly, the sovereign debt crisis was expected to hit mainly the French banking sector, so its beta remained at elevated levels (more than 1.6) in most of 2010. In the first months of 2011, the beta for the French banking sector started to rise again, reaching 2.5 at the end of 2011.

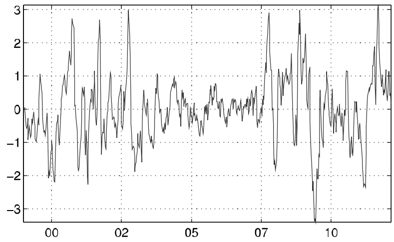
Third, the reaction of the markets to the recent crises also differed substantially. While the dot-com bubble in 2000 increased the perceived riskiness of the American banking sector and lowered it for other countries, the global financial crisis increased the betas of many banking sectors all around the world at the same time. The same pattern, to a lesser extent, can be found in the data for the more recent euro area sovereign debt crisis. This may be due to the systemic nature of the crisis, as the transmission of shocks was facilitated by the international banking network. The growth of banking sector linkages between several countries (such as the US, the UK, and Germany) could have contributed to higher perceived riskiness of their banking sectors.

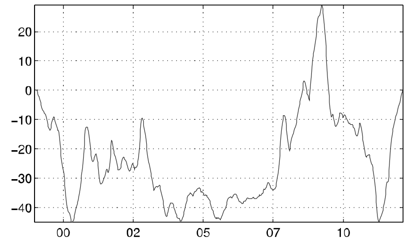
To explore the similarities among the movements of banking sector betas across countries more precisely, we estimate a global factor of systematic risk and assess its synchronization with the individual countries' betas.

4.3 Extension: Exploring the Global Development of Systematic Risk

As we have pointed out, some banking sectors share similar patterns in the evolution of their systematic risk. That is, in most countries the betas declined generally until 2005, after which they started to rise. Australia and Japan were exceptions, and the systematic risk of their banking sectors looks isolated to a large extent from global developments. Therefore, it seems that changes in the perceived riskiness of some banking sectors are more sensitive to global shocks in some countries than in others. To quantify the hypothesis that the systematic risk of some banking sectors is more isolated from global developments, we extract a common (global) factor to all the betas and compute the proportion of the variation of each beta explained by

Figure 4.1 The Global Factor of the Systematic Risk of the Banking Sector and Its Cumulative Sum





the global factor. If more variation is explained, the banking sector is more sensitive to global developments.

For further analysis, we use posterior medians estimated using Bayesian inference as described above. This is because this method filters out noise and outliers that are present in the results estimated by the GARCH and rolling-regression models. Since we have assumed that the process of betas follows a random walk, it is not surprising that the hypothesis of a unit root is not rejected by the Dickey-Fuller test.[1] To achieve stationarity, we first normalized the original time series and then differenced them, so the value of the transformed series has the interpretation of the deviation from the mean, where the unit of measurement is the standard deviation of the estimated sample.

The dynamic factor model, described in the *Appendix*, was estimated using the MLE approach and the Kalman filter, and the estimated global factor is plotted along with its cumulative sum in *Figure 4.1.* The magnitude of the factor is not directly interpretable, but one can observe that the sharp decline in the beta after the dot-com bubble in 2000 was followed by a period when the average beta for our sample rose and moved around unity. At the beginning of 2003, the betas of the banking sectors in several countries fell sharply again. The trend reversed only in 2007, when the financial crisis spread globally. The sovereign debt crisis had a smaller impact than the financial crisis, but the betas in several countries (France, UK, and Germany, among others) still rose substantially.

To quantify the extent to which the global factor explains the dynamics of each beta, we estimate a regression over the whole period and another two regressions over two sub-periods: 1999–2006 and 2006–February 2012.[2] Next, in order to check the robustness of the results, we estimate another two factors, one for each sub-period, and estimate equation (20) over the sub-periods. This step is done to make sure that the results do not change when matrix **P** is estimated using the split sample. If the results are to be robust, R^2 should not differ much. Unfortunately, there is no statistical test to test for the equality of the two approaches, since different dependent variables are used, so the differences are assessed only informally.

[1] The same conclusion is made based on the KPSS test.

[2] The choice of 2006 was driven by two reasons in addition to a robustness check. First, we wanted to include in the second sub-period the onset of the crisis in the US. Then, according to Garatt et al. (2011), a substantial shift in international banking occurred in 2006Q1, when Switzerland moved away from the most important financial centers in the sense of financial stress transmission. This structure remained broadly unchanged until recently. For further explanation see the remaining text.

Table 2 Percentage of the Variation Explained by the Global Factor
The first part of the table shows the results when the global factor is estimated for the whole period. The second part shows the results when two factors are estimated for the two sub-periods.

Factor	Time period	US	UK	DE	FR	JP	CH	HK	AU
Factor 1	1999–2012Feb	0.27	0.38	0.19	0.31	0.01	0.17	0.23	0.13
	1999–2006	0.15	0.32	0.15	0.32	0.01	0.14	0.24	0.14
	2006–2011	0.37	0.44	0.24	0.32	0.01	0.22	0.22	0.13
Factor 2	1999–2006	0.11	0.30	0.16	0.31	0.02	0.13	0.28	0.19
Factor 3	2006–2012Feb	0.39	0.46	0.23	0.32	0.01	0.2	0.22	0.12

The results are reported in *Table 2.* The highest percentage of the variation explained by the global factor both across sub-samples and over the whole sample is for the United Kingdom, while its value increased over time as well. It is followed by the United States, France, and Germany. On the other hand, the beta for Japan seems unrelated to global developments.

4.3.1 Systematic Risk and Global Banking

One potential explanation for the level of sensitivity to global developments is the extent to which countries are financially interconnected. Ideally, internationalization per se is a diversification strategy reducing a bank's risk, which depends on the correlation between domestic and foreign assets and on the volatility of foreign markets. However, Buch et al. (2010a), for example, found that internationalization increases the risk of German banks, although the results depend strongly on the type and the size of the bank.

Also the global financial crisis has shown that international integration exposes banks to additional risk, especially through the global banking network. Internationalization has dominated banking in the last ten years, with the amount of global international claims having increased by 400% since 2000, mainly in advanced countries. Cetorelli and Goldberg (2012) show how globally active banks contribute to international propagation of shocks. A global bank responds to a domestic liquidity shock by adjusting its funds internationally. The financial stability dimension of global banking has led to several attempts to limit these activities (BIS, 2009).

Therefore, an interesting question arises whether investors are aware of cross-country banking sector linkages when pricing risk. There is still no simple measure of the degree to which a country's banking sector is internationally integrated. One possible simple measure is the amount of loans from non-resident banks as a percentage of GDP (presented in *Table 3*). Switzerland, Hong Kong, and the UK have had a dominant position in international lending during the last ten years, while Japan and Australia have remained rather isolated. Another important development is the rise in offshore activities, which are related to operations of hedge funds and shadow banking. The country ranking is similar.

More sophisticated measures are based on the BIS bilateral claims database, taking into account both debtor and creditor positions. Garatt et al. (2011) use this dataset to identify crucial financial centers. Using an information map equation they divide banking groups from 21 countries into a structure which shows a map of

Table 3 Banking Sector External Relations: Cross Country Comparison (in %)

		Loans from non-resident banks (amt. outstanding / GDP)	Offshore bank deposits / / domestic bank deposits
United Kingdom	1999	83.3	10.5
	2004	112.3	23.5
	2009	204.7	21.1
Germany	1999	24.5	6.3
	2004	30.1	9.2
	2009	35.7	8.7
United States	1999	13.9	9.0
	2004	17.8	13.1
	2009	33.8	23.0
Hong Kong, China	1999	172.0	11.7
	2004	90.3	15.6
	2009	129.7	38.6
France	1999	27.4	5.7
	2004	35.9	9.8
	2009	72.0	12.0
Switzerland	1999	101.3	18.6
	2004	137.9	29.4
	2009	284.4	61.8
Japan	1999	15.0	0.5
	2004	12.4	1.2
	2009	11.5	2.4
Australia	1999	14.0	4.5
	2004	12.6	5.1
	2009	26.8	4.1

Source: Beck et al. (2009)

financial stress contagion. They conclude that the most influential centers became smaller but more contagious. As for the structure, the most prestigious centers in 2000 were the UK, the US, Germany, and Japan. In 2006, Japan and Switzerland ceased to be dominant while France became dominant. In 2009, the most influential centers were the US, the UK, France, and Germany, in line with our beta findings. Any identification of the determinants of the pricing of perceived risk is beyond the scope of this paper, but the most influential financial centers exhibit the highest sensitivity of betas to the global factor.

5. Conclusion

In this paper, we estimated the time-varying betas of the banking sectors in eight advanced countries. We showed that the systematic risk of the sectors varies considerably over time using three approaches—a rolling-regression model, an M-GARCH model, and a Bayesian state-space model. The choice of method can have a substantial impact on the assessment of whether markets are able to price the risk correctly. Our method, based on Bayesian inference, provides some new evidence, and, contrary to some previous literature, we do not find strong evidence of declining systematic risk before the recent financial and sovereign crises; according to the literature, such a decline would have signaled mispricing of the risk.

Finally, we investigated the cross-country differences in banking sector betas. The systematic risk of banking sectors is determined by domestic factors, but some countries share a degree of co-movement in their banking sector betas. The subsequent discussion showed that the growth of international banking linkages and easier transmission of financial shocks could have contributed to more significant co-movement in some countries.

APPENDICES

A. Estimating the CAPM in a Bayesian State-Space Framework

As we noted in the main body of the text, we use a relatively standard approach for estimating a state-space model with stochastic volatility. This approach is described well in a multivariate setting in Primiceri (2005) and Koop and Korobilis (2010). Here, we only review our choice of priors and the Gibbs sampling.

Choice of priors

Before the vector of parameters can be sampled from their joint posterior distribution, the prior distributions and their hyperparameters must be chosen. For our purposes, the priors were set broadly in line with Primiceri (2005). That is, we chose a training sample of size t_0, on which the starting values of the time-varying parameters were estimated. The OLS estimates on the training sample were used as a reference value for the priors:

$$\begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} \sim N\left(\begin{pmatrix} \hat{\alpha}_{OLS} \\ \hat{\beta}_{OLS} \end{pmatrix}, 3.\hat{\Sigma}_{OLS} \right) \tag{14}$$

$$\log \sigma_0 \sim N\left(\log \hat{\sigma}_{OLS}, 1 \right) \tag{15}$$

$$\Sigma \sim IW\left(t_0 k_Q^2 \hat{\Sigma}_{OLS}, t_0 \right) \tag{16}$$

$$W \sim IG\left(k_W^2, 2 \right) \tag{17}$$

The means of the initial values of the state variables ($\alpha_0, \beta_0, \log \sigma_0$) were set at their OLS values, but with a larger variance. The prior on the error variance of B (the distribution of Σ) was set to belong to the inverse-Wishart family, with the scale parameter set as a fraction of the OLS variance of the estimates of B. The degrees-of-freedom parameter was chosen as t_0. This is in line with the interpretation of the inverse-Wishart distribution parameters: the sum of the squared errors and the number of observations. It is worth noting that the choice of the inverse-Wishart distribution implies that covariance matrix Σ is not diagonal, i.e., shocks to α_t and β_t may be correlated (this is not the case in some studies using the Kalman filter). Finally, the prior on the variance of the error term for the volatility process, W, was chosen as a non-informative conjugate prior from the inverse-gamma distribution.

Gibbs sampling

The state-space model in this subsection is a relatively complex one and we simulate it by drawing from its joint posterior density function. The variables of interest are not only the variances Σ and W, but also the state variables. Together, we sample from the joint posterior distribution of the following vector of random variables: $\Omega = \{B^T, \sigma^T, \Sigma, W\}$.[3]

Draws from the joint posterior density functions in the state-space models are made by means of the Gibbs sampler, which draws in turns from the conditional posterior densities of each block of random variables. If the sampling is performed a sufficient number of times, the distribution of the draws generated using the Gibbs sampler converges to that of the draws from the joint posterior density. The conditional sampling is done in the following five steps:

1. Initialize B^T, σ^T, Σ, W
2. Draw B^T from $p\left(B^T \mid y^T, \sigma^T, \Sigma, W\right)$
3. Draw σ from $p\left(\sigma^T \mid y^T, B^T, \Sigma, W\right)$
4. Draw Σ from $p\left(\Sigma \mid B^T, \sigma^T, W\right)$
5. Draw W from $p\left(W \mid B^T, \sigma^T, \Sigma\right)$

The blocks are initialized at their OLS values and then a large number of repetitions n of steps 2–5 are performed. In order to skip draws before the Markov chain converges, we omit the first n_1 burn-in observations. The remaining $n - n_1$ observations are used for the analysis.

Step 2 is performed using a variant of the Bayesian simulation smoother of state-space models, proposed by Carter and Kohn (1994). In this step, we obtain draws from the posterior density of vector $\mathbf{B}^\mathbf{T}$. Conditional on the draws $\mathbf{B}^\mathbf{T}$ and the variance hyperparameters, we obtain estimates of the residuals u^T and apply the algorithm by Kim et al. (1998) combined with the previous algorithm to obtain draws of a latent stochastic volatility process. The steps are summarized in the appendix of Primiceri (2005). Step 3 is the standard one of drawing the covariance matrix in a SURE model, where we assume a conjugate inverse Wishart prior. Finally, Step 4 is the standard one of drawing the variance in a linear regression model, assuming a conjugate inverse gamma prior.

B. Estimating the Global Factor

One approach to extracting a global component of banking sector betas is principal components analysis, which is widely used in similar settings. However, as we want to allow for autocorrelation of shocks to the global factor, we estimate it as an unobserved component *f* in the following dynamic factor model:

[3] The symbol x^T denotes $x_1, x_2, \ldots, x_T$.

$$y_t = Pf_t + u_t, u_t \sim MN\left(0, \Sigma_u\right) \tag{18}$$

$$f_t = Af_{t-1} + v_t, v_t \sim AR\left(1\right) \tag{19}$$

where y_t stacks the estimated betas transformed to achieve stationarity (this is described in the text).

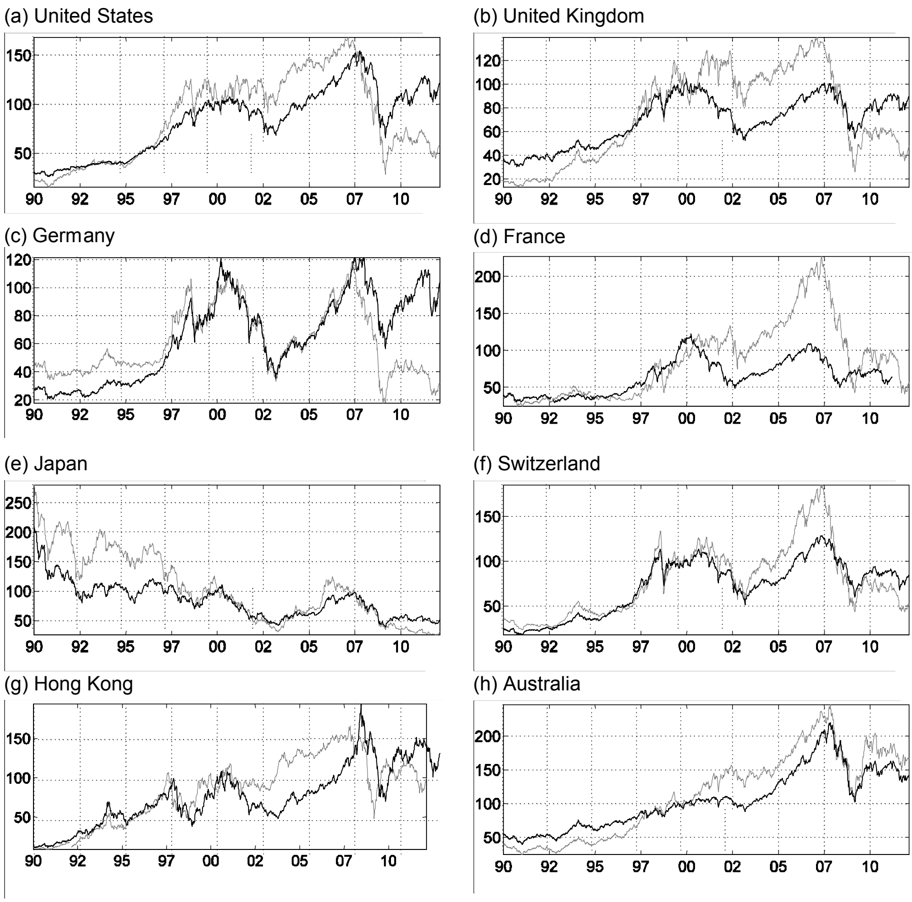
The proportion of the variation explained by the global factor is estimated by estimating the following linear regression:

$$y_{it} = a_i + b_i \hat{f}_t + \eta_{it} \tag{20}$$

and examining R^2. A higher R^2 indicates that the global factor explains the sector beta better.

C. Banking and Stock Market Indices

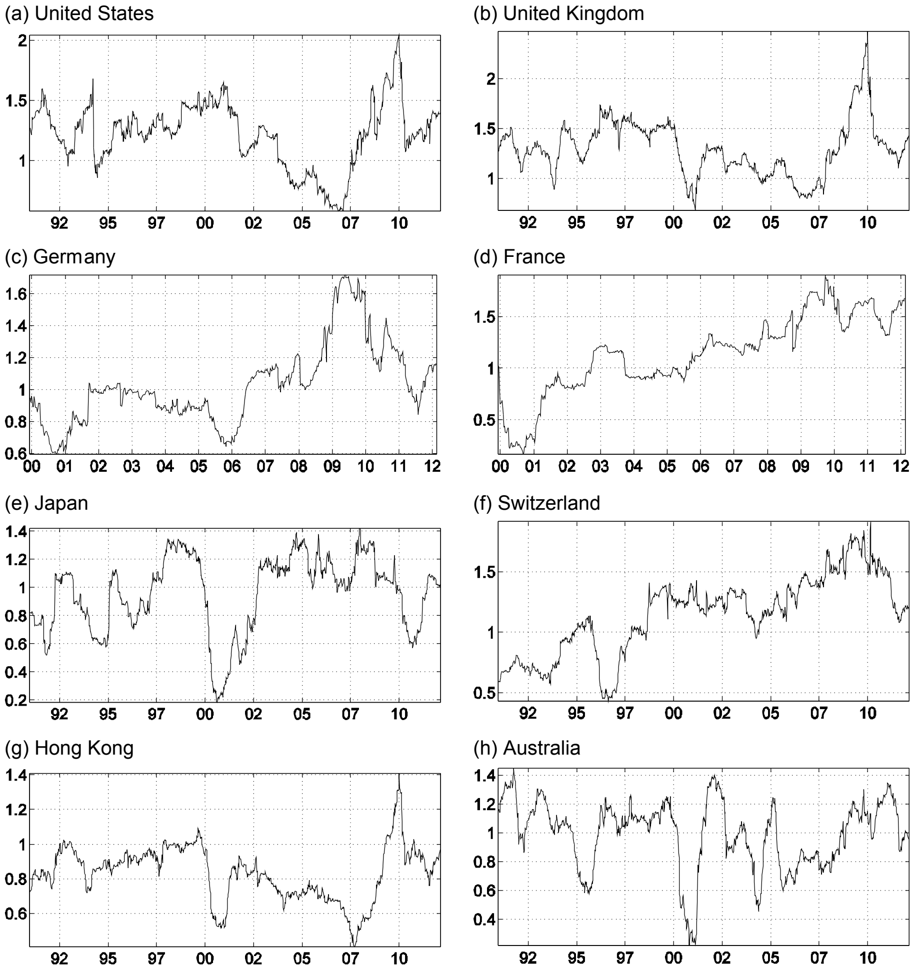
Figure C.1 Stock Market (Dark Line) and Banking Sector Indices Used for the Analysis



Note: Weekly values. The values were normalized so that their values are 100 in the first week of 2000.
Source: Thomson Reuters Datastream

D. Banking Sector Betas—Estimation Using Rolling Regression

Figure D.1 Rolling Regression Estimates of Banking Betas over Windows of 50 Observations



E. Banking Sector Betas—Estimation Using M–GARCH Model

Figure E.1 Betas Estimated Using M-GARCH Model

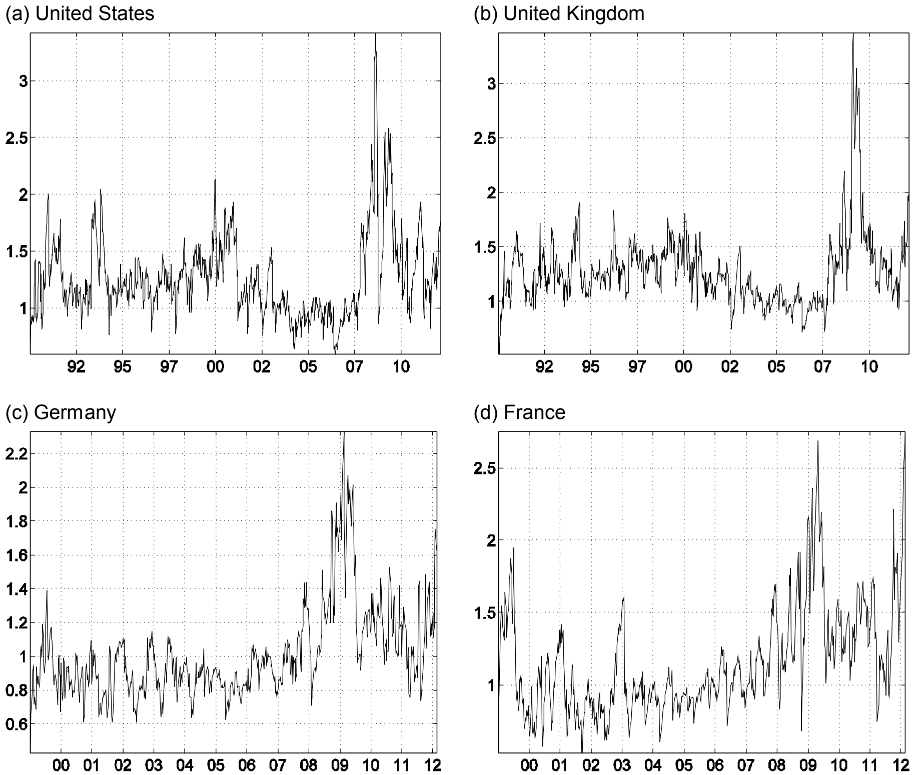
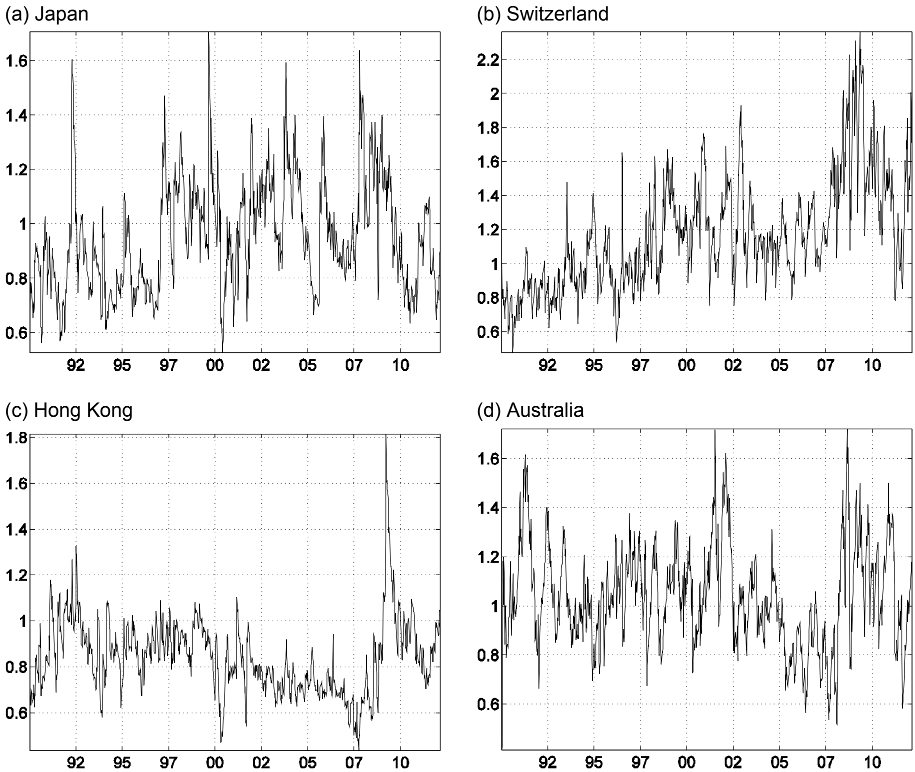


Figure E.2 Betas Estimated Using M-GARCH Model



F. Banking Sector Betas—Estimation Using Bayesian State Space Model with Stochastic Volatility

Figure F.1 Posterior Medians, 5-th and 95-th Percentiles of Betas (upper panels) and Stochastic Volatility (lower panels)

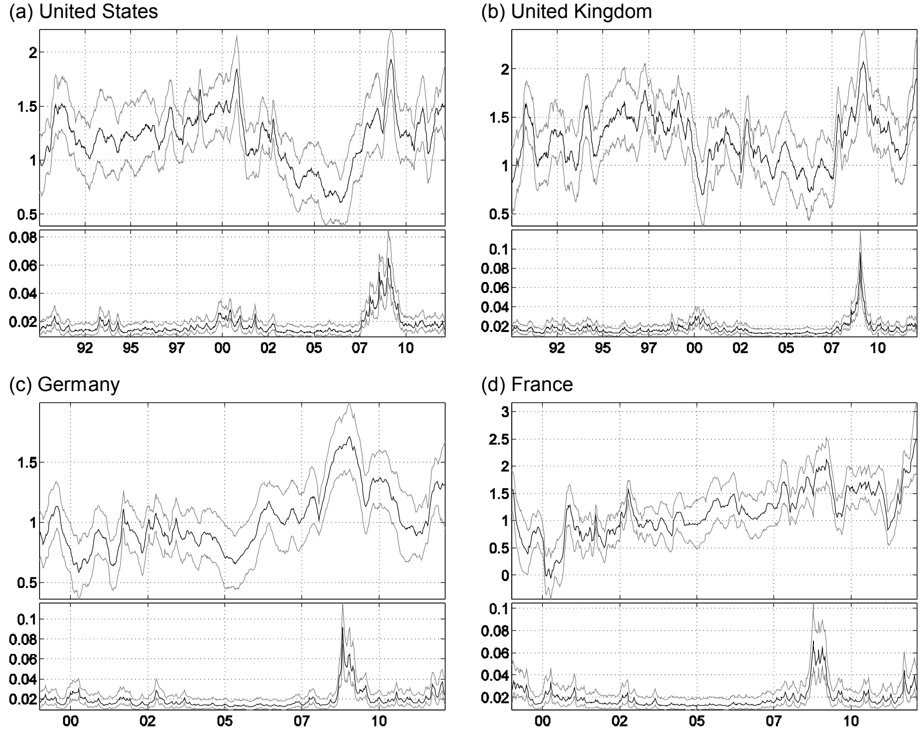
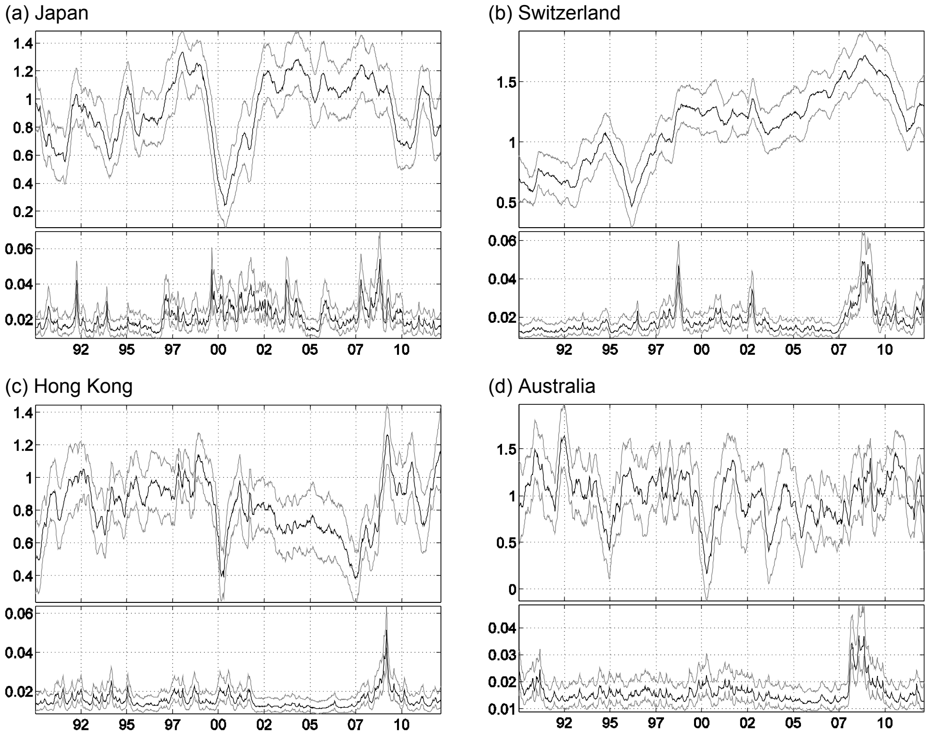


Figure F.2 Posterior Medians, 5-th and 95-th Percentiles of Betas (upper panels) and Stochastic Volatility (lower panels)



REFERENCES

Altunbas Y, Gambacorta L, Marques-Ibanez D (2010): Bank risk and monetary policy. *Journal of Financial Stability*, 6(3):121–129.

Bank for International Settlements (2009): *BIS Annual Report 2008/2009*.

Barnes ML, Lopez JA (2006): Alternative measures of the Federal Reserve Banks' cost of equity capital. *Journal of Banking & Finance*, 30(6):1687–1711.

Beck T, Demirguc-Kunt A, Levine R (2009): Financial institutions and markets across countries and over time data and analysis. *World Bank Policy Research Working Paper Series*, no. 4943.

Bhattacharyya S, Purnanandam A (2011): Risk-taking by banks: What did we know and when did we know it? *AFA 2012 Chicago Meetings Paper*.

Biase P di, Elisabetta DA (2012): The Determinants of Systematic Risk in the Italian Banking System: A Cross-Sectional Time Series Analysis. *International Journal of Economics and Finance*, 4(11):152–164.

Bollerslev T (1990): Modeling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *The Review of economics and Statistics*, 72(3):498–505.

Bollerslev T, Engle RF, Wooldridge JM (1988): A capital asset pricing model with time-varying covariances. *The Journal of Political Economy*, pp. 116–131.

Buch C, Koch CT, Kötter M (2010a): Margins of international banking: Is there a productivity pecking order in banking, too? *CESifo Working Paper Series,* no. 2891.

Buch C, Koch CT, Kötter M (2010b): Do banks benefit from internationalization? Revisiting the market power-risk nexus. *Deutsche Bundesbank Discussion Paper*, no. 09/2010.

Caporale T (2012): Time varying CAPM betas and banking sector risk. *Economics Letters*, 115(2):293–295.

Carter CK, Kohn R (1994): On Gibbs sampling for state space models. *Biometrika*, 81(3):541–553.

Cetorelli N, Goldberg LS (2012): Follow the Money: Quantifying Domestic Effects of Foreign Bank Shocks in the Great Recession. *NBER Working Paper,* no. 17873

Fabozzi FJ, Francis JC (1978): Beta as a random coefficient. *Journal of Financial and Quantitative Analysis*, 13(1):101–116.

Faff RW, Hillier D, Hillier J (2000): Time varying beta risk: An analysis of alternative modelling techniques. *Journal of Business Finance & Accounting*, 27(5-6):523–554.

Garratt RJ, Mahadeva L, Svirydzenka K (2011): Mapping systemic risk in the international banking network. *Bank of England Working Paper*, no. 413..

Groenewold N, Fraser P (1999): Time-varying estimates of CAPM betas. *Mathematics and Computers in Simulation*, 48(4):531–539.

Hamilton JD (1994): *Time Series Analysis*. Princeton University Press.

Kim S, Shephard N, Chib S (1998): Stochastic volatility: likelihood inference and comparison with ARCH models. *The Review of Economic Studies*, 65(3):361–393.

King MR (2009): The cost of equity for global banks: a CAPM perspective from 1990 to 2009. *BIS Quarterly Review*, no. 59.

Koop G, Korobilis D (2010): Bayesian Multivariate Time Series Methods for Empirical Macroeconomics. *Foundations and Trends in Econometrics*, 3(4):267–358.

Lie F, Brooks R, Faff R (2000): Modelling the equity beta risk of Australian financial sector companies. *Australian economic papers*, 39(3):301–311.

Mergner S, Bulla J (2008): Time-varying beta risk of Pan-European industry portfolios: A comparison of alternative modeling techniques. *The European Journal of Finance*, 14(8):771–802.

Pagan A (1996): The econometrics of financial markets. *Journal of Empirical Finance*, 3(1):15–102.

Primiceri GE (2005): Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies*, 72(3):821–852.

Rippel M, Jansky I (2011): Value at Risk forecasting with the ARMA-GARCH family of models in times of increased volatility. Charles University in Prague, Faculty of Social Sciences, *Working Papers IES,* no. 2011/27.

Yang J, Tsatsaronis K (2012): Bank stock returns, leverage and the business cycle. *BIS Quarterly Review*, 45.