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Time-varying Betas of the Banking Sector

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Abstract:

This paper analyses the evolution of systematic risk of banking industries in eight advanced countries using weekly data from 1990 to 2012. The estimation of time-varying betas is done 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 largely across countries. Finally, our results do not support the previous findings that systematic risk of the banking sector was underestimated before the last financial crisis.

Keywords: CAPM, Time-varying Beta, Multivariate GARCH, Bayesian State Space Models, Stochastic Volatility

JEL: C11, G12, G21

1 Introduction

The concept of capital asset pricing model (CAPM[1]) 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 (asset's beta) as the proper measure of the asset's systematic risk. This risk is determined by general market conditions and cannot be diversified away.

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

Looking at the properties of systematic risk, it is now widely held that beta is not time-invariant. However, no consensus has been found on the methodology for estimating time-varying betas. We extend the current literature by employing a Bayesian state space model with stochastic volatility to estimate time-varying betas of banking sectors in eight advanced countries. This approach combines the advantages of both Kalman filter approach (modelling beta as an unobservable process in a state-space model) and the approach based on M–GARCH model (allowing for heteroskedasticity of residuals).

This innovative approach allows us to study both cross-country differences and time evolution of the betas. We focus on banking sectors in eight advanced countries after 1990. The choice has been driven by the specific development of the banking sector in recent years and its role during the financial crisis. Banking internationalization and globalization, documented largely in the literature, certainly contributed to the transmission of the financial shocks worldwide. So pricing the risk of the banking sector could reflect more the global factor in more inter-connected banking sectors. Moreover, key question for the financial stability is whether the risk of banking stocks are systematically mispriced in tranquil times when the inherent instability is built up. Our method should be more suitable as the noise present in M–GARCH estimates is filtered out and the estimation is not dependent on the size of the window in a rolling regression.

The paper is organized as follows. Chapter 2 introduces the concept of beta and its time-varying nature with a specific focus on banking sector studies. The third chapter presents the methodology of estimating beta using the M–GARCH and the state space model with stochastic volatility used in this paper. The last chapter presents the comparison of results across the different methods and main findings, including the analysis of sensitivity of the systematic risk to the global factor.

[1]The capital asset pricing model was introduced independently by Sharpe (1964), Lintner (1965) and Mossin (1966)

2 Systematic risk in the literature

2.1 Beta and its time-varying nature

CAPM beta is a widely-used measure of systematic risk of an asset. It is derived in a general equilibrium context and measures the sensitivity of asset's returns to the movements in the stock market. The equilibrium condition from the CAPM model can be written as:

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

where r_f is return on the risk-free asset, $\widetilde{R}_i = R_i - r_f$ is an excess return on asset i and $\widetilde{R}_m = R_m - r_f$ is an excess return on market portfolio. It states that in equilibrium, 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:

$$\widetilde{R}_{it} = \alpha_i + \beta_i \widetilde{R}_{mt} + \epsilon_{it}, \qquad \epsilon_{it} \sim N(0, \sigma_i^2) \tag{2}$$

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 a random coefficient, which could explain a large variance of betas estimated using OLS, a poor performance in estimating the returns on assets and the rejections of the CAPM model in many stock markets.

Despite the consensus on the time-varying nature of the beta coefficient, the literature uses several approaches to estimate time-varying beta of a stock. Basically, two streams exist. The first one is based on the property of the linear regression coefficient $\beta = \frac{\mathrm{Cov(R_{it}, R_{mt})}}{\mathrm{Var(R_{mt})}} = \rho \frac{\sigma_i}{\sigma_M}$. The studies assume usually that ρ is constant and put certain assumptions on the volatility process. For example, Bollerslev et al. (1988) estimates the volatility processes as a multivariate GARCH process. Another approach is to model volatilities of market and asset returns as a latent stochastic volatility process and assume constant correlation between the two (Mergner and Bulla, 2008).

The second approach regards beta as an unobservable component process, puts several assumptions on its evolution and estimates it using Kalman filter and MLE. The state space model usually assumed is:

$$\widetilde{R}_{it} = \alpha_{it} + \beta_{it} \widetilde{R}_{Mt} + e_t, \qquad e_t \sim N(0, Q) \tag{3}$$

$$B_t = T B_{t-1} + \eta_t, \qquad \eta_t \sim N(0, R) \tag{4}$$

where $B_t = (\alpha_{it}, \beta_{it})'$ is a vector of time-varying parameters. When $T = I$ is an identity matrix, we obtain a random-walk model. The estimating technique to this type of model can found for example in (Kim and Nelson, 1999). The drawback is that Equation 4 assumes that the variance Q is constant. However, there is sizeable evidence, that returns on assets exhibit heteroskedasticity and volatility clustering. This assumption is not innocuous in that we would obtain only implausible confidence intervals but also incorrect estimates of B_t. This is because in times of high volatility, Q is underestimated and the change in B_t is overestimated by Kalman filter.

Another approach is by Jostova and Philipov (2005), who estimate a mean reverting process, not in the state space framework, of beta using Bayesian inference. They show that this procedure is more precise than competing models (based on GARCH and rolling regression) even if the underlying data generating process comes from these models.

The approaches have been compared only rarely. Faff et al. (2000) concludes that only models based on Kalman filter perform consistently better than the market (i.e. the time invariant) model. Particularly the specification when beta is assumed to follow a random walk achieves lowest in-sample MSE. In addition, the models differ significantly and their errors are independent, which suggests that each method captures a different type of time variation.

2.2 Systematic risk of the banking sector

No similar study to that in this paper, i.e. the comparison of time-varying betas in banking sector in different countries, can be found in the literature. Betas of banking sectors have been usually estimated in the literature as a part of sectoral analyses in the financial sector. For example, Mergner and Bulla (2008) estimate 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. The estimation on an individual stock level is performed by Lie et al. (2000), who estimate time varying betas of 15 financial sector companies in Australia on daily data. They use GARCH model and 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 until 2005 in all countries, except for Japan, when they started to rise. The decline in the costs reflects both the declining beta and declining risk-free rate. He also suggests that the low beta may point to mispricing of the banking shares.

More recently, Caporale (2012) performs tests for structural breaks in the 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 underestimated), as the banks took highest leverage and risk in this time, while expected risk was low.

Rather limited attention has been paid explicitly to the determinants of the sensitivity of banking sector returns to market risk (beta). For banking sector supervision and financial stability purposes, the cost of equity (which is determined based on beta) is still a key issue, largely covered in the literature. A recent paper by Yang and Tsatsaronis (2012) extends this stream to show that leverage and business cycle influence systematic component of its risk, so bank equity financing is cheaper in the boom and dearer during a recession. Altunbas et al. (2010) identify several determinants of individual bank riskiness, accounting for banking sector characteristics like GDP, housing prices or yield curve. The impact of banking globalization on the 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 the banks. The banking globalization has been shown by Cetorelli and Goldberg (2012) as a way of increasing the global transmission of shocks, so increased financial linkages between banking sectors worldwide increase their vulnerability to financial shocks.

3 Approaches to the estimation of systematic risk

For the purposes of this paper (estimating betas of the banking sectors), we consider the standard CAPM result in Equation 2. As we have stressed in the previous chapter, there is a large body of evidence that this relation is time-dependent and various approaches to estimating time-varying betas lead to different results (e.g. Faff et al. (2000), Mergner and Bulla (2008), Lie et al. (2000)). 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 M–GARCH model introduced by Bollerslev (1990), which is based on estimating conditional covariances between returns on market portfolio and an 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 the 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 the sensitivity to the choice of the window size and the sensitivity of OLS to outliers. As this method is used only as a benchmark to which we compare the latter 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 $(\varepsilon_{it}, \varepsilon_{Mt})' = H_t^{1/2} z_t$, and $z_{jt} \sim N(0, 1)$ are uncorrelated. Since $\varepsilon_{jt}|\Psi_{t-1} \sim N(0, H_t)$, the equation (5) then represents a conditional covariance matrix between the banking sector returns and the market returns.

$$H_t = \begin{pmatrix} h_{ii,t} & h_{iM,t} \\ h_{Mi,t} & h_{MM,t} \end{pmatrix} \tag{5}$$

We have chosen a GARCH(1,1) process as suggested by previous analysis by Rippel and Jansky (2011), which leads to an M–GARCH model described by a vector equation (6). The same equation can be rewritten in a more compact way (Equation 8) using a *vech* operator that stacks in one column all non–redundant elements of a symmetric matrix that are either on a diagonal or below the diagonal (Hamilton, 1994).

$$\begin{pmatrix} h_{ii,t} \\ h_{iM,t} \\ h_{MM,t} \end{pmatrix} = \begin{pmatrix} c_{11} \\ c_{12} \\ c_{22} \end{pmatrix} + \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \times \begin{pmatrix} \varepsilon^2_{i,t-1} \\ (\varepsilon_{i,t-1})(\varepsilon_{M,t-1}) \\ \varepsilon^2_{M,t-1} \end{pmatrix} + \tag{6}$$

$$\begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix} \times \begin{pmatrix} h_{ii,t-1} \\ h_{iM,t-1} \\ h_{MM,t-1} \end{pmatrix} \tag{7}$$

$$(vech)\mathbf{H_t} = \mathbf{C} + \mathbf{A}(vech)\varepsilon + \mathbf{B}(vech)\mathbf{H_{t-1}} \tag{8}$$

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 is growing at a polynomial rate as the number of time series involved rises (Pagan, 1996). Some authors, such as Bollerslev (1990), suggest to set all coefficients above and below the diagonal to zero. This simplification leads to a substantially reduced form of the general equation and it allows us to describe the model by equations (9), (11) and (10) with only seven coefficients. The correlation between the returns of a banking sector and the market, denoted ρ, is by Bollerslev (1990) assumed to be constant. This simplification leads to the following system of equations:

$$h_{ii,t} = c_{11} + a_{11}\varepsilon^2_{i,t-1} + b_{11}h_{ii,t-1} \tag{9}$$

$$h_{MM,t} = c_{22} + a_{33}\varepsilon^2_{M,t-1} + b_{33}h_{MM,t-1} \tag{10}$$

$$h_{iM,t} = \rho\sqrt{h_{ii,t}h_{MM,t}} \tag{11}$$

Having estimated the three equations above, the time–varying beta can be easily calculated. The standard CAPM model calculates the β as a ratio of covariance between an asset and the market and 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 respective conditional covariance matrix H_t. In other words, a time–varying beta calculated using an M–GARCH model has a form described by the following equation:

$$\beta_{it} = \frac{cov_t(\tilde{R}_{it}, \tilde{R}_{Mt})}{var_t(\tilde{R}_{Mt})} = \frac{h_{iM,t}}{h_{MM,t}} \tag{12}$$

3.3 Bayesian state space model with stochastic volatility

As we have noted in the literature review, the standard approach based on Kalman filter suffers from a bias due to the assumption of homoskedastic residuals. Therefore, we relax this assumption and assume the following state-space model (note that the analysed asset's index i is omitted):

$$\widetilde{R}_t = \alpha_t + \beta_t \widetilde{R}_{mt} + u_t, \qquad u_t \sim N(0, \sigma_t^2), \qquad t = 1, 2, ..., T \tag{13}$$

$$B_t = \begin{pmatrix} \alpha_t \\ \beta_t \end{pmatrix} = \begin{pmatrix} \alpha_{t-1} \\ \beta_{t-1} \end{pmatrix} + \begin{pmatrix} v_{\alpha,t} \\ v_{\alpha,t} \end{pmatrix}, \qquad \begin{pmatrix} v_{\alpha,t} \\ v_{\alpha,t} \end{pmatrix} \sim N(\mathbf{0}, \Sigma) \tag{14}$$

$$\log \sigma_t = \log \sigma_{t-1} + \eta_t, \qquad \eta_t \sim N(0, W) \tag{15}$$

In this state space model, we assume a variant of stochastic volatility, i.e. the volatility is modelled as a latent process σ_t, which is not a simple function of the past or current values of observables, as is the case of a GARCH process for example. We assume the simplest version of the stochastic volatility process, where volatility follows a geometric random walk.

This kind of models is usually estimated using Bayesian inference, that overcomes the problem of failing to find local maxima, as is the case of the MLE approach. In addition, the Bayesian methods in this context are relatively easy to be implemented and can be extended for finding the posterior distributions of parameters in very complex models. The major difference between the MLE and Bayesian approach to state space modelling is that the latter one 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 they 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 priors on the hyperparameters and the starting values of state variables, and solving for posterior densities of 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.

3.3.1 The choice of priors

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

$$\begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} \sim N\left(\begin{pmatrix} \widehat{\alpha}_{OLS} \\ \widehat{\beta}_{OLS} \end{pmatrix}, 3\,.\,\widehat{\Sigma}_{OLS} \right) \tag{16}$$

$$\log \sigma_0 \sim N(\log \hat{\sigma}_{OLS}, 1) \tag{17}$$

$$\Sigma \sim IW(t_o\,.\,k_Q^2.\hat{\Sigma_{OLS}}, t_0) \tag{18}$$

$$W \sim IG(4\,.\,k_W^2, 4) \tag{19}$$

The mean of the initial values of state variables ($\alpha_0, \beta_0, \log \sigma_0$) have been set at their OLS values but with a larger variance. The prior on the error variance of B

(the distribution of Σ) has been set to belong to the inverse-Wishart family, with the scale parameter set as a fraction of the OLS variance of estimates of B. The degrees of freedom parameter has been chosen as t_0. This is in line with the interpretation of the inverse-Wishart distribution parameters: sum of squared errors and the number of observations. It is worth to note 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 to the volatility process, W was chosen as a noninformative conjugate prior from the inverse-gamma distribution.

3.3.2 Gibbs sampling

The state space model in this subsection is a relatively complex one and we simulate it by drawing from the posterior density. The variables of interest are not only variances Σ and W, but also state variables. Together, we sample from the joint posterior distribution of the following vector of random variables: $\Omega = \{B^T, \sigma^T, \Sigma, W\}$[2].

Draws from joint posterior density functions in state space models is done by means of the Gibbs sampler, which draws in turns from conditional posterior densities of each block of random variables. If the sampling is performed a sufficient number of times, the distribution of draws generated using Gibbs sampler converges to draws from 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 $p(B^T|y^T, \sigma^T, \Sigma, W)$
3. Draw σ from $p(\sigma^T|y^T, B^T, \Sigma, W)$
4. Draw Σ from $p(\Sigma|B^T, \sigma^T, W)$
5. Draw W from $p(W|B^T, \sigma^T, \Sigma)$

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 the vector B^T. Conditional on draws B^T and variance hyperparameters, we can obtain the estimates of 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 a standard one of drawing the covariance matrix in a SURE model when we assume a conjugate inverse Wishart prior. Finally, Step 4 is a standard one of drawing the variance in a linear regression model, assuming a conjugate inverse gamma prior.

[2]The symbol x^T denotes $x_1, x_2, ..., x_T$

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

Table 1: Data used for the analyss

4 Time-varying betas of banking sectors

4.1 Data used for the analysis

We estimate time-varying betas of banking industries in 8 advanced countries - United States, United Kingdom, Germany, France, Switzerland, Japan, Hong Kong and Australia. The countries were chosen based on their market capitalization and the number of banks. The major stock market indices were used as the indices representing the market portfolio. In some cases, banking sector indices are published by stock exchanges but to ensure the consistency, we opted for banking sector indices constructed by Thomson Reuters. Finally, risk-free rate of most countries were chosen as those recommended by Datastream[3] , 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 A.1.

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

4.2 Results: systematic risk of the banking sectors

We have estimated time varying betas of each banking sector using 3 approaches - rolling regression, multivariate GARCH and finally using state space model with stochastic volatility. Figure B.1 presents the results from rolling regression with a window spanning 50 observations, which corresponds approximately to one year. This approach has two major drawbacks - there is no means of estimating an 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 C.1 and Figure C.2 present estimates using the multivariate GARCH. Its drawback is that the resulting time series contain a large amount of noise, which causes the time series to be very erratic. Since each new observation affects volatility of both market and the sectoral index and therefore the beta, changes between two subsequent observations should be interpreted cautiously.

[3]Available on Datastream intranet, for example

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

All three approaches strongly support the idea of time-varying nature of beta and several important features are apparent. First, we cannot 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 the 20-year period, with substantial increase only in the latest period. He used the bank-level estimates that are lower than the equity subindices estimates we employ. The differences are considerable mainly 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 measure exactly the cost of equity for financial stability purposes.

Second, our more precise estimate of beta indicates that the banking sector risk in tranquil times can still be priced in. As for the period after 2005, it is often argued in the literature that the 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 the mispricing of this instability built-up took place. The US banking beta started to rise as soon as in July 2006 from levels close to 0.6, growing steadily to 1.5 two years later, when the financial crises fully developed. Similarly, the sovereign debt crisis was expected to hit mainly 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 French banking sector started to rise again, reaching 2.5 at the end of 2011.

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

In the following part we will try to shed more light on this last issue. Our aim is to understand why the evolution of banking sector betas for some countries seems to be more synchronized by identifying the global factor.

4.3 Extension: Exploring the global development in 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 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 perceived riskiness of some banking sectors are more sensitive to global shocks in some countries than in others. To quantify the hypothesis that systematic risk of some banking sectors are more isolated to global developments, we extract a common (global) factor to all betas and compute the proportion of explained variation of each beta by the global factor. If more variation is explained, the banking sector is more sensitive to global development.

One approach to extracting the global component is the 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:

$$y_t = Pf_t + u_t, \quad u_t \sim MN(0, \Sigma_u) \tag{20}$$

$$f_t = Af_{t-1} + \nu_t, \quad \nu_t \sim AR(1) \tag{21}$$

where y_t stacks the estimated betas transformed to achieve stationarity.

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 or the 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 has not been rejected by Dickey-Fuller test[4]. To achieve stationarity, we have first normalized the original time series and then differenced them, so the value of the transformed series has the interpretation as the deviation from the mean, where the unit of measurement is the standard deviation on the estimated sample.

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

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	0.3	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

Table 2: Percentage of variations 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.

[4]the same conclusion is made based on KPSS test

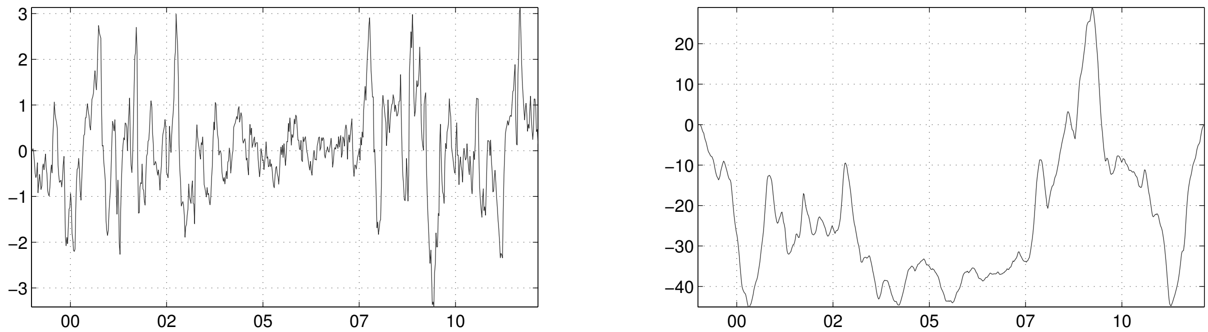

Figure 4.1: The global factor of the systematic risk of the banking sector and its cumulative sum

Next we want to examine how the proportion of variation explained by the global factor has changed over the analysed period. To this end, we estimate the following linear regression:

$$y_{it} = a_i + b_i \hat{f}_t + \eta_{it} \tag{22}$$

and examine R^2.

First, we estimate a regression over the whole period and another two regressions over two sub-periods - 1999-2006 and 2006-February 2012[5]. Next, in order to check the robustness of the results, we estimate another two factors, one for each sub-period and estimate Equation 22 over the sub-periods. This step is done to make sure that the results do not change when the 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 which would test for the equality of the two approaches, since different dependent variables are used, so the differences are assessed only informally.

The results are reported in Table 2. The highest percentage of variations 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 other hand, beta for Japan seems unrelated to global developments.

One potential explanation for the level of sensitivity to global developments can be a degree to which countries are financially interconnected. Ideally, internationalization per se is a diversification strategy reducing the risk of a bank, which depends on the correlation between domestic and foreign assets and on the volatility of the foreign markets. However, Buch et al. (2010a) for example found that internationalization increases the risk of German banks, but the results depend strongly on the type and 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. The internationalization dominated banking in the last ten years, when the amount of global

[5]The choice of 2006, apart to check the robustness, was driven by two reasons. First, we wanted to include in the second the onset of the crisis in the US. Then, according to Garratt et al. (2011), in Q1 2006 a substantial shift in international banking occurred 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.

international claims increased by 400% since 2000, mainly in advanced countries. Cetorelli and Goldberg (2012) show how globally active banks contribute to international propagation of shocks. To any domestic liquidity shock a global bank responds by adjusting funds internationally. The financial stability dimension of global banking led to several attempts to limit these activities (BIS, 2009).

Therefore an interesting question arises whether the investors are aware of cross country banking sector linkages when pricing the risk. Still there is no simple measure of a degree to which country's banking sector is internationally integrated. The first simple measure could be the amount of loans from non-resident banks on GDP (presented in Table 3). Switzerland, Hong Kong and UK 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 of the offshore activities which are related to operations of hedge funds and shadow banking. The country ranking is similar.

More sophisticated measures are based on BIS bilateral claims database, taking into account both debtor and creditor positions. Garratt et al. (2011) use this dataset to identify crucial financial centers. Using an information map equation they divide banking groups from 21 countries in structure which shows a map of 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 UK, US, Germany and Japan. In 2006 Japan and Switzerland left the dominant position while France gained this position. In 2009 the most influential centers were US, UK, France and Germany, which is in line with our findings on beta. Any identification of the determinants of pricing the perceived risk is behind the scope of this paper, but the most influential financial centers exhibit highest sensitivity of betas to global factor.

5 Conclusion

In this paper, we have estimated time-varying betas of banking sectors in eight advanced countries. We have shown that systematic risk of the sectors varies considerably over time using three approaches - the rolling regression model, the M–GARCH model and a Bayesian state space model. The variation reflects the inherent nature of the banking sector, which bridges the real and financial sector in an economy and makes the sector vulnerable to both real and financial shocks.

We have shown that 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. Contrary to some previous literature, we have not found strong evidence of declining systematic risk before the recent financial and sovereign crisis (which would signal mispricing of the risk, according to the literature).

We believe that our innovative approach to estimating time-varying betas is superior to M–GARCH or the rolling regression in that it subtracts noise from the data (similarly to the Kalman filter approach) but assumes heteroskedastic residuals at the same time (similarly to the M–GARCH approach). This is certainly worth exploring further in several other dimensions. First, tests of asset pricing models could be repeated using the results of our model. Also, forecasting performance of this model could be compared with the competing models. Then, more interestingly, the model can be used to extend the current literature on estimating the cost of equity for fi-

		Loans from non-resident banks (amt. outstanding / GDP)	Offshore bank deposits / domestic bank deposits
United Kingdom	1999	83.30%	10.50%
	2004	112.30%	23.50%
	2009	204.70%	21.10%
Germany	1999	24.50%	6.30%
	2004	30.10%	9.20%
	2009	35.70%	8.70%
United States	1999	13.90%	9.00%
	2004	17.80%	13.10%
	2009	33.80%	23.00%
Hong Kong, China	1999	172.00%	11.70%
	2004	90.30%	15.60%
	2009	129.70%	38.60%
France	1999	27.40%	5.70%
	2004	35.90%	9.80%
	2009	72.00%	12.00%
Switzerland	1999	101.30%	18.60%
	2004	137.90%	29.40%
	2009	284.40%	61.80%
Japan	1999	15.00%	0.50%
	2004	12.40%	1.20%
	2009	11.50%	2.40%
Australia	1999	14.00%	4.50%
	2004	12.60%	5.10%
	2009	26.80%	4.10%

Table 3: Banking sector external relations: cross country comparison, source: Beck et al. (2009)

nancial stability purposes. Finally, a rather limited attention has been paid to the determinants of the banking sector risks. In this sense it would be highly interesting to investigate, for example, whether monetary policy affects bank risk taking, i.e. whether a period of pro-longed low interest rates contributed to the inherent built-up of instability in the banking sector.

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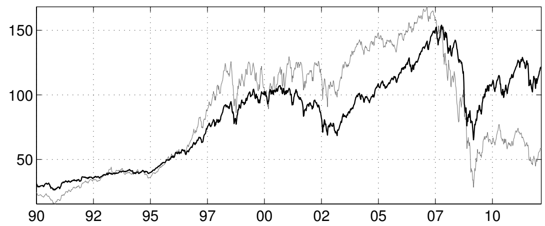
Appendices

A Banking and Stock Market Indices



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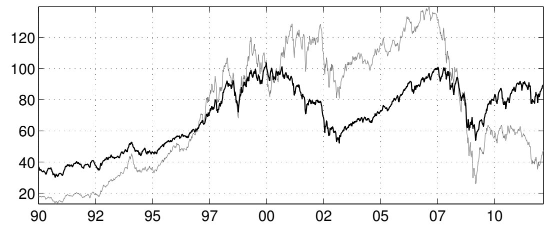

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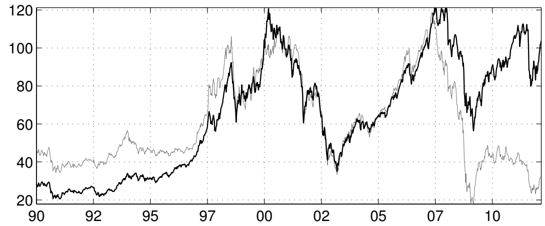

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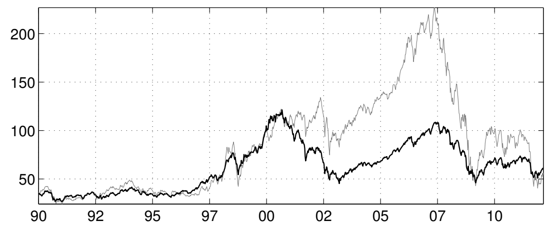

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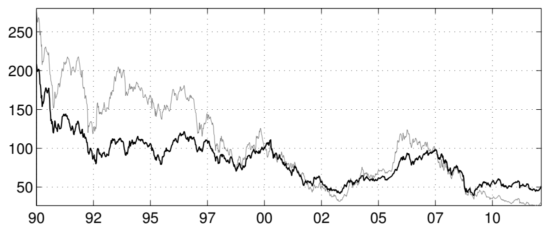

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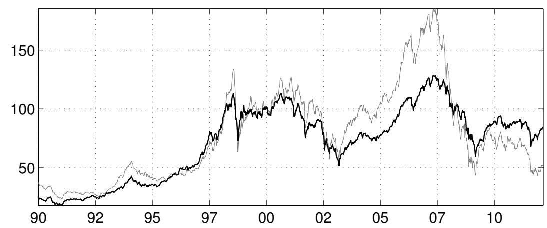

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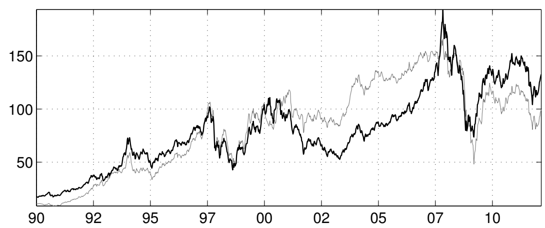

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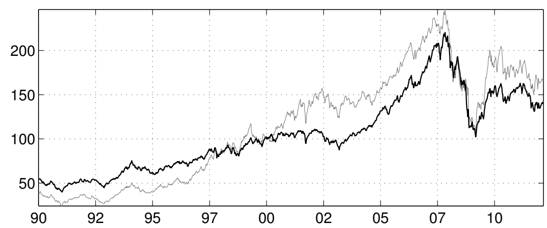
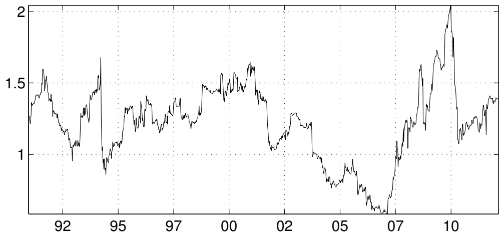


(h) Australia

Figure A.1: Stock market (dark line) and banking sector indices used for the analysis, weekly values. The values were normalized so that their values are 100 in the first week of 2000.

B Banking Sector Betas - estimation using rolling regression



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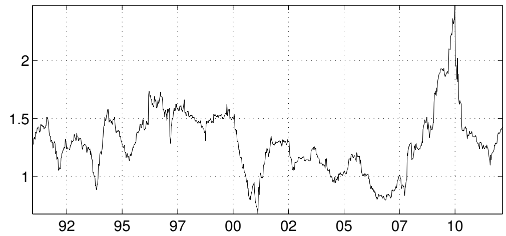

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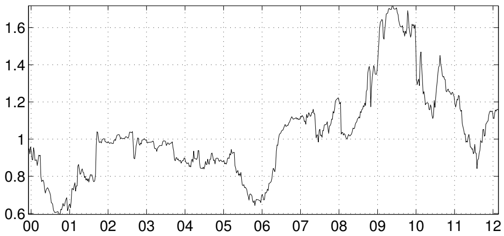

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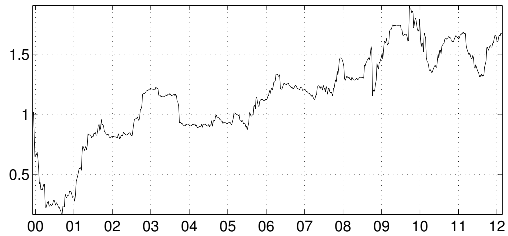

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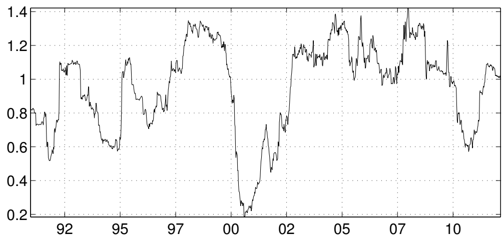

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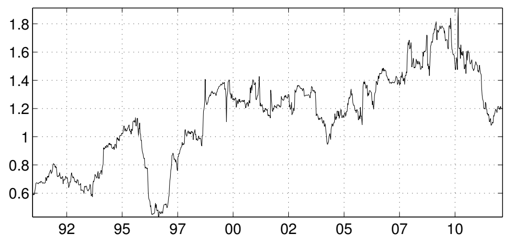

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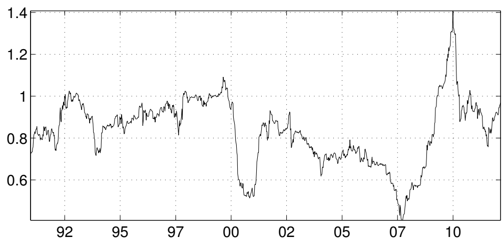

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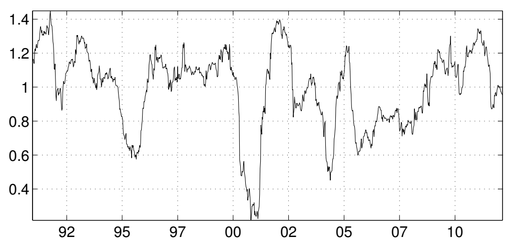
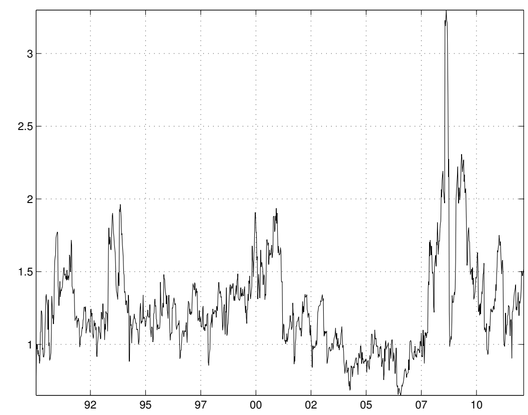


(h) Australia

Figure B.1: Rolling regression estimates of banking betas over windows of 50 observations

C Banking Sector Betas - estimation using M–GARCH model



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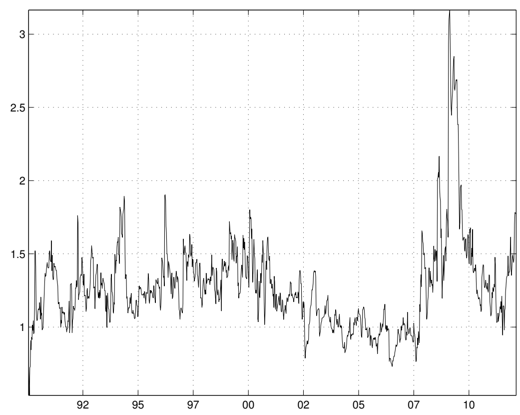

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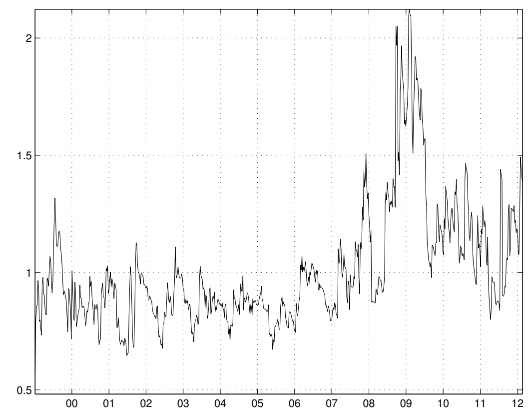

(c) Germany

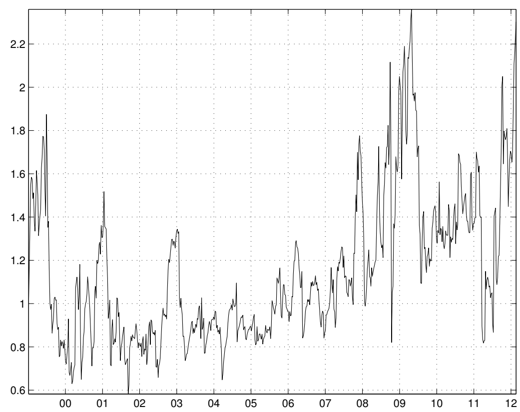

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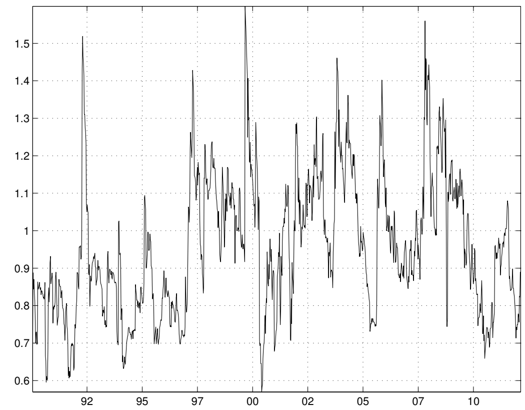
Figure C.1: Betas estimated using M-GARCH model



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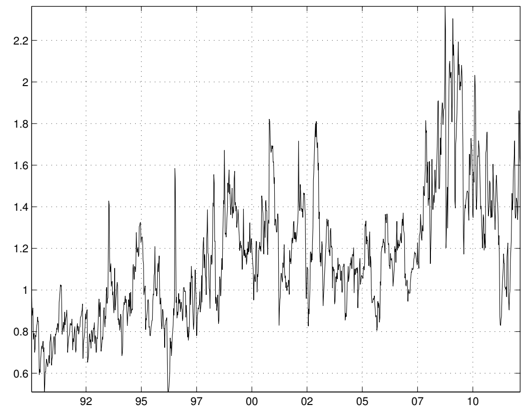

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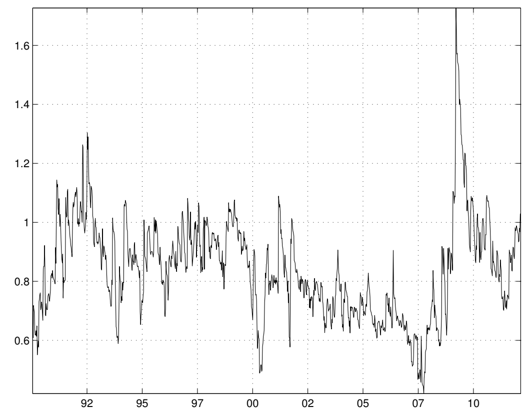

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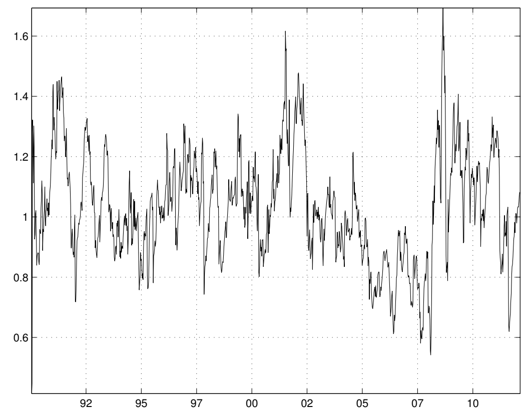

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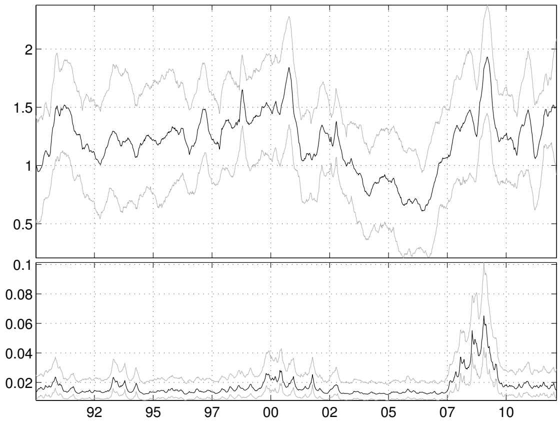
Figure C.2: Betas estimated using M-GARCH model

D Banking Sector Betas - estimation using Bayesian state space model with stochastic volatility



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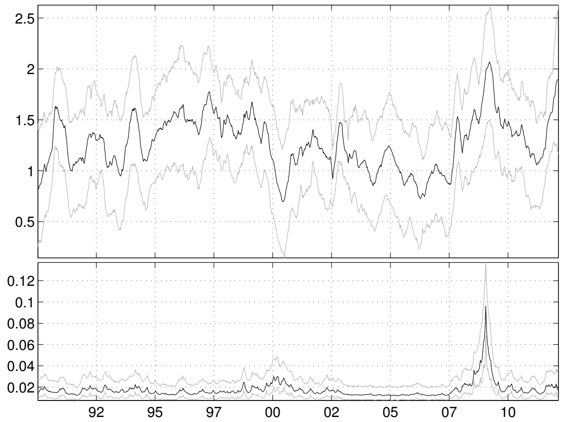

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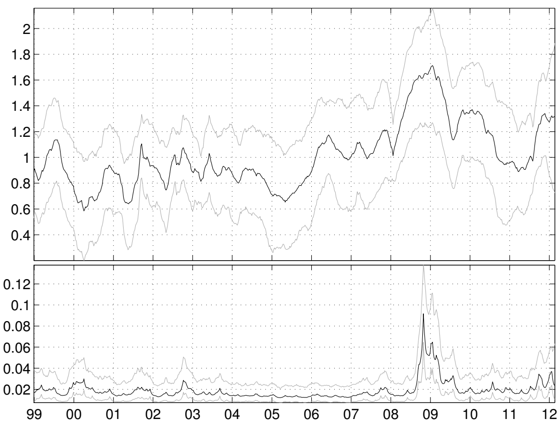

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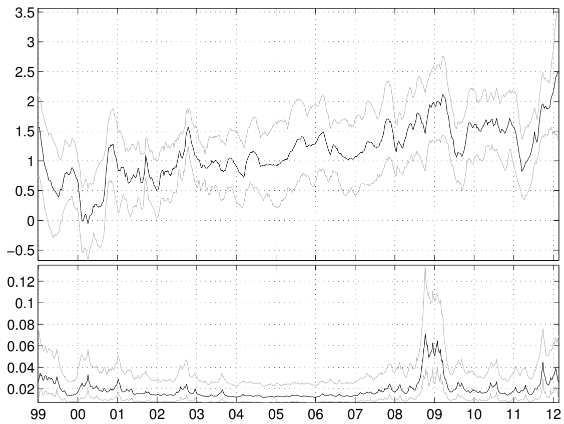
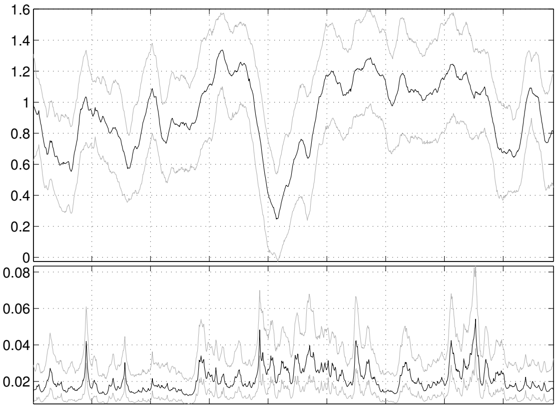
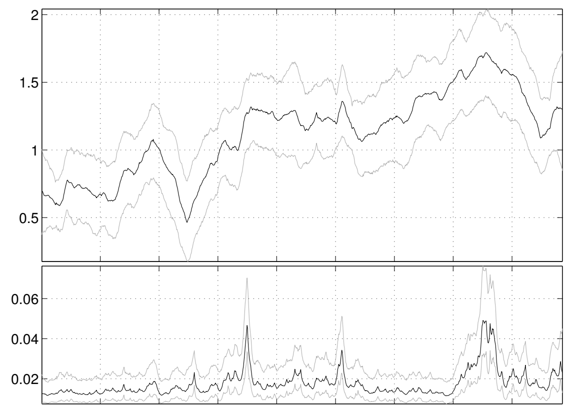


(d) France

Figure D.1: Posterior medians, 5-th and 95-th percentiles of betas (upper panels) and stochastic volatility (lower panels)



(a) Japan



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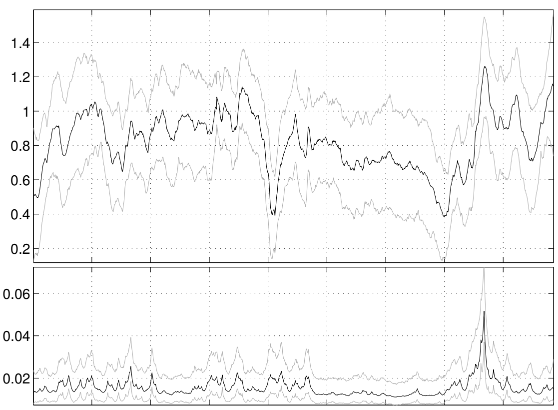

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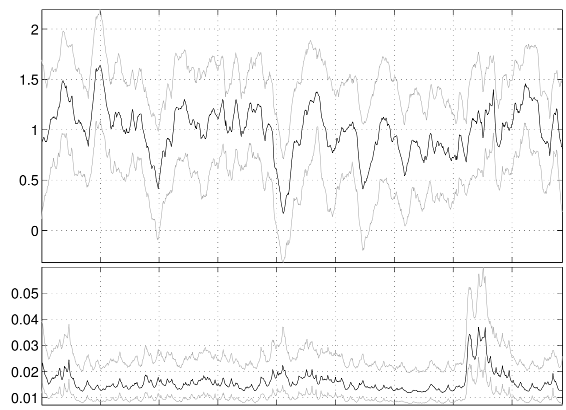

(d) Australia

Figure D.2: Posterior medians, 5-th and 95-th percentiles of betas (upper panels) and stochastic volatility (lower panels)

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