Financial Stability and Extreme Market Conditions

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Abstract

This paper analyzes the role of systemic risk in normal and extreme market conditions. We argue that systemic risk can significantly contribute to the amplification of financial crisis and can hence also have contagious effects. We interpret a constant (or decreasing) impact of systemic risk in extreme market situations as a fundamental condition for financial market stability since common shocks are not amplified. Empirical results for a number of emerging and developed markets show that the impact of systemic risk varies and is significantly larger in highly volatile regimes for some markets. The findings also display the fact that developed markets exhibit a constant dependence on systemic risk and hence meet an essential condition for financial market stability. The focus of the paper and the use of the quantile regression model circumvent the ad hoc definition of a crisis origin and a crisis period which is prevalent in the contagion literature.

JEL Classification: C22, C51, G15
Keywords: Financial stability, Systemic risk, Contagion, Quantile regression

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1 Introduction

The recent crises in East Asia, Russia and Brazil have raised concerns about the adequate functioning and the stability of financial systems. This has triggered a large literature on contagion that mainly assesses the spread of idiosyncratic shocks from one country to another (e.g. see Forbes and Rigobon (2002)). The effect of systemic shocks, on the other hand, has not been studied in such an extent. This is surprising since shocks that do not have an idiosyncratic character but are common to many markets simultaneously can significantly affect the stability of the financial system and it can also be argued that such shocks can be contagious. For instance, if the system is partially infected, then any (inter)dependence with this system is potentially contagious. It is also surprising that there is yet no accepted definition of “financial stability” which resembles the situation a couple of years ago when there was no definition for “contagion”.

This paper investigates the effect of systemic shocks in different market conditions and suggests that one key element of financial stability is the constant impact of shocks on financial markets. We also argue that systemic shocks can be contagious if their propagation mechanism increases and show that this view is consistent with a definition of contagion and interdependence proposed by Forbes and Rigobon (2002).

The paper is structured as follows: section 2 presents definitions of financial stability and proposes a model to test the degree of financial stability and the existence of contagion. Section 3 presents the empirical results obtained by a quantile regression analysis, section 4 shows a small artificial example to explain the results. Finally, section 5 summarizes our findings and concludes.

2 Financial Stability and an Econometric Test

There is no clear consensus of what is “financial stability” and people seem to find it more convenient to define financial instability (see Padoa-Schioppa (2003)). We present one
definition of financial stability and one of financial instability and deduce an econometric test from these. The first definition is: “Financial stability is a condition whereby the financial system is able to withstand shocks without giving way to cumulative processes, which impair the allocation of savings and investments opportunities and the processing of payments in the economy.” (Padoa-Schioppa (2003), page 2). The second definition on financial system instability can be found in the IMF report on financial stability (International Monetary Fund (2003), page 63): “The degree to which shocks to the financial system are amplified and propagated across markets or across institutions is a key element of financial system instability.” These definitions clarify that financial stability can be viewed as a condition where the impact of shocks is not increasing in some circumstances and hence not amplifying its effects.

As stated in the introduction, this paper focusses on broad or systemic shocks that affect many markets simultaneously. Thus, we propose the following model to test whether such shocks have an increasing impact in some circumstances:

\[
r_{it} = \alpha_i + \beta_i f_t + u_{it}, \quad Q_{r_{it}}(\tau | f_t) = \alpha_i(\tau) + \beta_i(\tau) f_t
\]

where \( r_{it} \) is the market return at \( t \) for country \( i \), \( f_t \) represents a systemic shock given by a regional factor (e.g. EMF Asia) or a global factor (e.g. world index) and \( u_{it} \) represents the idiosyncratic shock of market \( i \) at time \( t \). \( Q_{r_{it}}(\tau | f_t) \) denotes the \( \tau \)-th conditional quantile of \( r_{it} \), assumed to be linearly dependent on \( f_t \).

The model is estimated with the quantile regression method and can thus assess the different impact of systemic shocks \( f_t \) on different conditional quantiles of \( r_{it} \), i.e. different market conditions (see Koenker and Bassett (1978) or Buchinsky (1998) for an introduction to quantile regression). The focus of the analysis and the use of the quantile regression model circumvent ad hoc definitions of crisis origins and crisis periods that are usually encountered in the analysis of the impact of shocks during periods of financial turbulence.
The model given by equation (1) can also serve as a test for contagion à la Forbes and Rigobon (2002): Forbes and Rigobon interpret constant co-movement as interdependence and increased co-movement as contagion. We interpret \( \beta_i(\tau) \) as a measure of co-movement and view a non-increasing parameter for extreme values of \( \tau \) (e.g. \( \tau < 0.1 \) or \( \tau > 0.9 \)) as no contagion and an increasing parameter as evidence for contagion. Since the quantile regression model accounts for heteroscedasticity in the data, we do not face any bias which can, in contrast, arise if the analysis is based on the correlation coefficient. In addition, a small simulation study will show that an increased variance of the systemic shock does not lead to an increased estimate of the propagation (or amplification) of such shocks.

In order to control for different states of volatility, we additionally include the estimated conditional variance of the regional/global factor obtained by an EGARCH(1,1)-estimation:

\[
Q_{ri}(\tau) = \alpha_i(\tau) + \beta_i(\tau)f_t + \gamma_i(\tau)\hat{h}_f_t
\]  

(2)

We also analyze conditional densities derived from this econometric model that can reveal the varying impact of different (extreme) values of \( f_t \) and \( \hat{h}_f_t \) on market \( i \).

3 Empirical Analysis

We use daily (close-to-close) continuously compounded index returns of twenty international stock markets calculated in U.S. dollars\(^1\). Furthermore, four regional stock indices are analyzed: Emerging Markets Free Asia\(^2\), Emerging Markets Free Latin America, Europe and North America. The indices span a time-period of six and a half years from April, 30th 1997 until October, 22th 2003. The number of observations is \( T = 1690 \). Table 1 presents several descriptive statistics for the 24 time series.

\(^1\)The data is provided by Morgan Stanley Capital International Inc. (MSCI) and can be retrieved under www.mscidata.com.

\(^2\)The MSCI Free indices reflect investable opportunities for global investors by taking into account local market restrictions on share ownership by foreigners.
Table 1: Descriptive statistics for the twenty countries and four regional indices utilized in the analysis (1690 observations from 30/04/1997 to 22/10/2003)

<table>
<thead>
<tr>
<th>market</th>
<th>median</th>
<th>mean</th>
<th>std dev</th>
<th>min</th>
<th>max</th>
<th>skewness</th>
<th>kurtosis</th>
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<td>China</td>
<td>-0.0004</td>
<td>-0.0008</td>
<td>0.0235</td>
<td>-0.1444</td>
<td>0.1274</td>
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<td>6.7425</td>
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<td>0.0195</td>
<td>-0.1377</td>
<td>0.1601</td>
<td>0.1772</td>
<td>11.0052</td>
</tr>
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<td>India</td>
<td>0.0001</td>
<td>0.0001</td>
<td>0.0170</td>
<td>-0.0732</td>
<td>0.0782</td>
<td>-0.1901</td>
<td>5.3206</td>
</tr>
<tr>
<td>Japan</td>
<td>-0.0004</td>
<td>-0.0001</td>
<td>0.0159</td>
<td>-0.0716</td>
<td>0.1227</td>
<td>0.3765</td>
<td>6.0370</td>
</tr>
<tr>
<td>Korea</td>
<td>0.0000</td>
<td>0.0002</td>
<td>0.0322</td>
<td>-0.2167</td>
<td>0.2688</td>
<td>0.3021</td>
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<tr>
<td>Malaysia</td>
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<td>0.0246</td>
<td>-0.2424</td>
<td>0.2568</td>
<td>1.1203</td>
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<tr>
<td>Philippines</td>
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<td>-0.0009</td>
<td>0.0203</td>
<td>-0.1036</td>
<td>0.2197</td>
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<td>-0.1113</td>
<td>0.0739</td>
<td>0.0389</td>
<td>4.9489</td>
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<tr>
<td>Thailand</td>
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<td>-0.0005</td>
<td>0.0270</td>
<td>-0.1489</td>
<td>0.1644</td>
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<td>Argentina</td>
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<tr>
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<td>0.0002</td>
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<td>United Kingdom</td>
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<td>0.0689</td>
<td>-0.1097</td>
<td>4.3515</td>
</tr>
<tr>
<td>France</td>
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<td>-0.0634</td>
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<td>-0.1026</td>
<td>4.3517</td>
</tr>
<tr>
<td>USA</td>
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<td>0.0561</td>
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<td>5.1883</td>
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<tr>
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<td>-0.1302</td>
<td>0.0764</td>
<td>-0.6630</td>
<td>8.5361</td>
</tr>
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<td>0.0153</td>
<td>-0.0753</td>
<td>0.0761</td>
<td>-0.0163</td>
<td>4.9233</td>
</tr>
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<td>Europe</td>
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<td>0.0159</td>
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<td>4.5628</td>
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<tr>
<td>North America</td>
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<td>0.0001</td>
<td>0.0129</td>
<td>-0.0688</td>
<td>0.0555</td>
<td>-0.0694</td>
<td>5.2198</td>
</tr>
</tbody>
</table>

3.1 Asian Markets

Prior to our analysis, all time series are standardized to ease the interpretation of the coefficients. Figures 1 to 3 present the estimation results of model 2 for Malaysia. Figure 1 shows the standardized return of Malaysia along with its estimated 1−, 50− and 99−percent conditional quantiles. It can be seen that the estimated conditional distribution varies significantly over time. The right side of the graph pictures the constant $\alpha(\tau)$ for 99 different quantiles ($\tau \in \{0.01, \ldots, 0.99\}$).

Figure 2 shows the coefficients of the EMF Asia market return ($\beta(\tau)$) and its estimated volatility ($\gamma(\tau)$), again for 99 different values of $\tau$. The market coefficient on the left side exhibits a pronounced “u-shape”. At middle quantiles (Malaysian returns near to zero), the market coefficient has a value of around 0.3. At extreme quantiles (either positive or negative), the values increase over 0.6, thus implying an increased impact of systemic risk in extreme market conditions. This increased impact shows that systemic shocks are propagated and even amplify their normal (average) impact.
The left side of figure 3 presents the estimated distributions of the Malaysian market, conditional on four different values of the EMF Asia return. The right part of figure 3 shows the same analysis for its volatility. The densities have been calculated by applying a kernel density estimation on 99 conditional quantile estimates obtained from each QR model (see the appendix for a detailed description). It can be seen that the EMF Asia return mainly influences the mean of the conditional distribution, whereas the variance of the Malaysian return seems to be rather unaffected. In contrast, the volatility of the Asian index affects the Malaysian variance but not the mean.

Figures 4 and 5 show the influence of the EMF-Asia index on eight different Asian markets. The countries can be divided into two classes: (i) “emerging” markets (Indonesia, Malaysia, Philippines and Thailand) that exhibit a “u-shaped” coefficient of the market index and (ii) “mature” markets (Hongkong, Japan, Korea and Taiwan) with a rather constant effect of the index at all conditional quantiles. It can also be seen that the average value of the coefficient ranges from around 0.4 to 0.7 thus indicating different degrees of market integration.

Figure 6 shows the goodness of fit measure developed by Koenker and Machado (1999) and denoted as $R^1(\tau)$ for the four “emerging” markets (Indonesia, Malaysia, Philippines and Thailand). The u-shaped graphs indicating a higher explanation power in extreme market conditions are in line with the coefficients presented earlier (figure 4). Furthermore, this result strengthens our argument that the analysis of systemic shocks is important and that a focus on only idiosyncratic shocks is insufficient.

3.2 Worldwide Analysis

Figures 7 and 8 present the world market coefficient for eight different countries. It can be stated that four Latin American markets (Argentina, Brazil, Chile and Mexico) exhibit a slightly u-shaped coefficient curve, whereas its shape is flat for three European countries (United Kingdom, Germany and France) and the United States. It can also be
seen that the average values are higher for the latter countries reflecting a higher degree of market integration.

Figure 9 shows the results from a regression of four regional indices (EMF Asia, EMF Latin America, Europe and North America) on the world market. Again, the rather “emerging” indices exhibit a u-shape, whereas the “developed” indices show a flat curve. The low integration of the Asian index probably stems from non-synchronous trading hours. Figure 10 presents the according densities of the regional indices conditional on different values of the world market. It can be seen that the higher market integration of North America leads to a more accurate prediction.

4 Artificial Example

In order to clarify our approach, we present a little example with artificially constructed values. We arbitrarily set the length of the dataset to 4000 and assume a “crisis period” between observation 1801 and 2200. Then we construct a time series $\varepsilon_t$ following an EGARCH(1,1)-process and drawn from a student t-distribution with five degrees of freedom (according to Campbell, Koedijk, and Kofman (2000) and Bae, Karolyi, and Stulz (2003) daily stock returns can be well described by t distributions with degrees of freedom ranging between 3 and 6).\footnote{The EGARCH-parameters ($a = 0.01$, $b = -0.05$, $c = 0.15$ and $d = 0.97$) are taken from an estimation on the EMF Asia time series of our dataset.}

$\varepsilon_t = \sigma_t \cdot t_5$

$\ln \sigma_t^2 = a + b(\varepsilon_{t-1}/\sigma_{t-1}) + c(|\varepsilon_{t-1}/\sigma_{t-1}| - \sqrt{2/\pi}) + d \ln \sigma_{t-1}^2$

In the same way, we (independently) construct a time series $\nu_t$ and subsequently generate a market return $f_t = \varepsilon_t$ and a country return $r_{1t} = f_t + \nu_t$. During the crisis period, we consider four different cases: (i) a benchmark model with no change in the propagation mechanism, (ii) an increased volatility of the underlying factor, (iii) increased volatilities
of both the factor and the country, and (iv) an increased transmission mechanism. Table 2 summarizes the exact adjustments. Finally, all values are standardized to allow an intuitive interpretation of the results.

Table 2: Constructed behaviour during the crisis period

<table>
<thead>
<tr>
<th>Model</th>
<th>Market Return</th>
<th>Country Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>bench</td>
<td>(f_t = \varepsilon_t)</td>
<td>(r_{1t} = f_t + \nu_t)</td>
</tr>
<tr>
<td>volf</td>
<td>(f_t = 4 \cdot \varepsilon_t)</td>
<td>(r_{1t} = f_t + \nu_t)</td>
</tr>
<tr>
<td>volb</td>
<td>(f_t = 4 \cdot \varepsilon_t)</td>
<td>(r_{1t} = f_t + 4 \cdot \nu_t)</td>
</tr>
<tr>
<td>transm</td>
<td>(f_t = \varepsilon_t)</td>
<td>(r_{1t} = 4 \cdot f_t + \nu_t)</td>
</tr>
</tbody>
</table>

Figure 11 presents the market coefficient for the four cases. The first three graphs show rather flat curves of the coefficient \(\beta(\tau)\). In contrast, the fourth picture exhibits a pronounced u-shape similar to the results obtained for emerging markets in the previous section. As the fourth case with an increased propagation mechanism during the crisis period can be interpreted as contagion (see Pericoli and Sbracia (2003) for different definitions of contagion), we argue that the higher impact of systemic risk in extreme market conditions obtained in the previous section can also be seen as evidence of contagion. Figure 12 shows the influence of the estimated volatility. The graphs underline the fact that the fourth case coincides with the empirical results obtained for emerging markets.

5 Conclusions

In this paper, we present definitions of financial stability and deduce an econometric model from these. We find that the dependence of individual emerging markets on a regional or world index is increasing in extreme market conditions. Including the fact that the goodness of fit also increases in the tails of the conditional distribution, we argue that systemic shocks become more important and predictive for emerging markets in times of stress. In contrast, we do not find any increased propagation mechanisms for developed countries. Comparing our results with an artificial example, we show that the increased influence of the common factor can also be interpreted as evidence of contagion.
According to the used definition of financial stability, we can conclude that many emerging markets do not exhibit financial stability. This result obviously depends on the underlying definition and should be viewed as an initial step that points to the necessity of a clear idea of the term and its implications. Future work will hopefully follow this path.

Appendix

Quantile Regression

Given a random variable $y$ with right continuous distribution function $F_y(a) = P(y \leq a)$, the quantile function $Q_y$ can be defined by

$$[0, 1] \rightarrow \mathbb{R}$$

$$Q_y(\tau) = F_y^{-1}(\tau) = \inf \{a \mid F_y(a) \geq \tau\}$$

Similarly, taking a random sample $y_1, y_2, \ldots, y_n$ with empirical distribution function $\hat{F}_y(a) = \frac{1}{n} \#\{y_i \leq a\}$, the empirical quantile function is defined by

$$\hat{Q}_y(\tau) = \hat{F}_y^{-1}(\tau) = \inf \{a \mid \hat{F}_y(a) \geq \tau\}$$

The quantiles may also be formulated as the solution to a minimization problem:

$$\hat{Q}_y(\tau) = \arg\min_a \left\{ \sum_{i: y_i \geq a} \tau|y_i - a| + \sum_{i: y_i < a} (1 - \tau)|y_i - a| \right\}$$

$$= \arg\min_a \sum_i \rho_\tau(y_i - a)$$

with the check function

$$\rho_\tau(z) = \begin{cases} \tau z & : z \geq 0 \\ (\tau - 1)z & : z < 0 \end{cases}$$

Assuming that $y$ is linearly dependent on a vector of exogenous variables $x$, the linear conditional quantile function can be written as

$$Q_y(\tau|x) = \inf \{a \mid F_y(a|x) \geq \tau\}$$

$$= \sum_k \beta_k(\tau)x_k = x^\prime \beta(\tau)$$
In analogy to equation (6), the quantile regression coefficients are obtained by solving with respect to \( \beta(\tau) \):

\[
\hat{\beta}(\tau) = \arg\min_{\beta(\tau) \in \mathbb{R}^k} \left\{ \sum_{i : y_i \geq x_i' \beta(\tau)} \tau |y_i - x_i' \beta(\tau)| + \sum_{i : y_i < x_i' \beta(\tau)} (1 - \tau) |y_i - x_i' \beta(\tau)| \right\}
\]

\[
= \arg\min_{\beta(\tau)} \sum_i \rho_\tau (y_i - x_i' \beta(\tau)) \tag{8}
\]

As the check function \( \rho_\tau \) in equation 8 is not differentiable at the origin, there is no explicit solution for the regression coefficients. However, the minimization problem can be formulated as a linear program and solved by an algorithm suggested by Koenker and d’Orey (1987) with desirable computing properties for small to medium number of observations. In addition, an interior point method for linear programming proposed by Portnoy and Koenker (1997) has been shown to be comparable to least squares in computation time even for very large data sets. The calculations in this paper have been carried out using the software package STATA (Stata Corporation 2003).

**Conditional Densities**

Consider a linear quantile regression model with \( y \) dependent on \( K \) standardized regressors \( x_k \):

\[
Q_{yt}(\tau|x_{t1}, \ldots, x_{tK}) = \beta_0(\tau) + \sum_{k=1}^{K} \beta_k(\tau) x_{tk} \forall t \in 1, \ldots, T \tag{9}
\]

Now assume that we are interested in the effect of one distinct regressor (denoted as \( x_l \) with \( l \in \{1, \ldots, K\} \)) on the distribution of \( y \). As all regressors are standardized to have a mean of zero, we omit the other covariates and estimate a simplified model that includes only the constant and \( x_l \) for 99 different quantiles (\( \tau = 0.01, \ldots, 0.99 \)). This results in 99 estimated coefficients \( \hat{\beta}_0(\tau) \) and \( \hat{\beta}_l(\tau) \). So, for any value of \( x_l \) (say \( x_l^* \)), we can calculate 99 conditional quantiles of \( y \):

\[
\hat{Q}_y^*(\tau|x_l^*) = \hat{\beta}_0(\tau) + \hat{\beta}_l(\tau) x_l^* \tag{10}
\]

These 99 values constitute a rough estimation of the empirical quantile function (and the empirical cumulative distribution function as its inverse). The resulting (discrete) empirical probability density function consists of 99 spikes of equal height and we can directly apply a kernel density estimation\(^4\) to get an approximation of the estimated density of \( y \) conditional on \( x_l^* \). In our application, we chose for each regressor its unconditional 2\%-st, 10\%-st, 90\%-st and 98\%-st quantile as values of \( x_l^* \) to examine the different impacts on \( y \). Of course, one could also think of calculating not only 99 but all different conditional quantiles (which are of order \( O(T \ln T) \)). In this case, the different heights of the spikes of the empirical probability function would have to be accordingly included into the kernel density estimation process.

\(^4\)We used STATA’s \texttt{kdensity} command with an Epanechnikov kernel (see Stata, 2003). We tried several bandwidth values and finally chose the automatic (“optimal”) selection procedure. The number of evaluation points was set to 1000.
A disadvantage of this procedure is the fact that any additional information contained in the other regressors is neglected. Trying to incorporate this information, we have to be aware of possible relationships among the regressors. So, we first conduct a (simple least square) auxiliary regression of each of the other variables on $x_l$. Subsequently, we include their estimated values $\hat{x}_k^*(k \neq l)$ into the full model:

$$Q_y^*(\tau|x_l^*) = \hat{\beta}_0(\tau) + \hat{\beta}_l(\tau)x_l^* + \sum_{k=1}^{K} \hat{\beta}_k(\tau)\hat{x}_k^* \forall k \neq l$$

(11)

So, we again calculate 99 estimated conditional quantiles of $Y$ enabling us to determine the density estimation of the regressand dependent on any desired value of $x_l^*$.

Figures

Figure 1: Conditional quantiles and constant for Malaysia. The left figure shows the standardized returns of the Malaysian market as red dots for every point of time $t$ along with the estimated conditional 1%- , 50% - and 99%-quantiles superimposed as green, orange and blue lines, respectively. The right graph pictures the constant ($\alpha(\tau)$) of model (2) for 99 different quantiles ($\tau \in \{0.01, \ldots, 0.99\}$). The respective values are connected as a solid red line; the least squares value is included as a horizontal blue solid line.
Figure 2: Market and volatility Coefficient for Malaysia. The two figures present the coefficients $\beta(\tau)$ (regional market index EMF-Asia) and $\gamma(\tau)$ (estimated volatility) for 99 different quantiles ($\tau \in \{0.01, \ldots, 0.99\}$). Again, the respective values are connected as a solid red line with the least squares result added as a horizontal blue solid line.

Figure 3: Conditional densities. The left figure shows the estimated distribution of the Malaysian market conditional on four different values of the market return (to be precise: the unconditional 2%- (solid blue line), 10%- (long-dashed red line), 90%- (dashed green line) and 98%-quantile (short-dashed orange line) of the EMF-Asia index). The right graph pictures the influence of the estimated market volatility.

Figure 4: Market coefficient for Indonesia, Malaysia, Philippines and Thailand. The figures show the influence of EMF-Asia ($\beta(\tau)$) on four “emerging” Asian markets.
Figure 5: Market coefficient for Hongkong, Japan, Korea and Taiwan. The figures show the influence of EMF-Asia ($\beta(\tau)$) on four “mature” Asian markets.

Figure 6: Goodness of fit for Indonesia, Malaysia, Philippines and Thailand. The four graphs show the values of $R^2(\tau)$ for 99 different quantiles ($\tau \in \{0.01, \ldots, 0.99\}$) at four “emerging” Asian markets. The measure is calculated as $R^2(\tau) = 1 - \hat{V}(\tau)/\tilde{V}(\tau)$ with $\hat{V}(\tau)$ and $\tilde{V}(\tau)$ referring to the unrestricted and restricted quantile regression minimization problems, respectively. The horizontal blue line depicts the goodness of fit ($R^2$) from the least squares regression.

Figure 7: World market coefficient for Argentina, Brazil, Chile and Mexico. The figures show the influence of the world market ($\beta(\tau)$) on four Latin American countries.

Figure 8: World market coefficient for UK, Germany, France and USA. The figures show the influence of the world market ($\beta(\tau)$) on three European markets and the United States.
Figure 9: World market coefficient for EMF Asia, EMF Latin America, Europe and North America. The figures show the influence of the world market ($\beta(\tau)$) on four regional indices.

Figure 10: Densities conditional on world market coefficient for EMF Asia, EMF Latin America, Europe and North America. The figures show the estimated distributions of four regional indices conditional on four different values of the world market return (compare figure 3).

Figure 11: Artificial market coefficient. The figures show the influence $\beta(\tau)$ of the constructed factor $f_t$ on $r_{1t}$ in the four cases discussed in section four.

Figure 12: Artificial volatility coefficient. The figures show the influence $\gamma(\tau)$ of the estimated volatility $\hat{h}_{ft}$ on $r_{1t}$ in the four cases discussed in section four.
References


